With the contribution of the LIFE Programme of the European Union

LIFE 15 IPE IT 013

prepAIR

Po Regions Engaged to Policies of Air

AIR QUALITY ASSESSMENT 2022

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Beneficiary responsible for implementation ARPAE Emilia-Romagna and ARPA Piemonte.

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1. INTRODUCTION

The Integrated project "Po Regions Engaged to Policies of Air" LIFE-IP PREPAIR supports the implementation of regional air quality plans (AQPs) and of Po Valley agreements on a larger scale, acting in a synergic way, so to strengthen the sustainability and durability of the results. Although the most critical area studied in the project is the Po Valley, the field of study is extended to Slovenia in order to assess and reduce transboundary pollutants transport. Regarding air quality, in fact, all the Regions located south of the Alps face the same adverse climatic conditions, which require higher technical and financial efforts to settle compliance problems, in comparison with other Regions. The Po Valley, a densely populated and heavily industrialised area, represents a non-attaining zone for PM (Particulate Matter), NO_2 (Nitrogen Dioxide) and O_3 (Ozone). Previous experience demonstrates that coordinated and large-scale actions are necessary in this area. A comprehensive policy, acting on a large scale and on several sources of pollutant precursors of PM and O_3, is essential to further reduce pollution levels. For this purpose, all the Regions have clustered in the so-called Po Basin Board and planned actions with the aim of further reducing the emission of pollutants and their precursors.

This third assessment report of action D5 provides a synthetic view on the state of air quality in the Po Valley and Slovenia for year 2022 and examines PM10, PM2.5, nitrogen dioxide and ozone, which are the pollutants whose concentration values more frequently exceed legislation thresholds. However this report is not intended to be a formal air quality assessment which is responsibility of the regional authorities. The assessment was carried out with data fusion techniques using model output and monitoring data collected within the PREPAIR project. Even though five CTM and data fusion modelling systems with different setup (resolution, boundary condition, meteorological data and data fusion technique) have been used, the model outputs are similar to each other. In this report the assessment methodology, the data fusion technique and results of the most critical indicators compared to the limit values established by the 2008/50/EC Directive are shown.

2. ASSESSMENT METHODOLOGY

The assessment of air quality status in Po Valley and Slovenia for year 2022 is produced using the same methodology as in the previous “Action D5 - Air Quality Assessment” on year 2020[1] and “Action D5 - Air Quality Assessment” on year 2021[2]

This methodology is a state-of-the-art technique for air quality assessment and considers an integrated approach that exploits two different types of information:

- the air quality monitoring network data, accurate but available only in a limited number of locations;
- high spatial resolution concentration fields produced by means of a chemical transport model (CTM).

Currently, within the PREPAIR project, several CTM modelling systems running operationally and air quality data are shared daily by all partners through action C1. Then, concentration fields and air quality monitoring data have been integrated using different data fusion techniques, one for each modelling system.

The assessment is carried out taking into account the most critical indicators compared to the limit values established by the 2008/50/EC Directive:

1. PM10 annual mean concentration values (the limit value set by EU legislation is 40 µg/m^3) ;
2. PM2.5 annual mean concentration values (the limit value set by EU legislation is 25 µg/m^3 for stage I and 20 µg/m^3 for stage II);
3. NO_2 (nitrogen dioxide) annual mean concentration values (the limit value set by EU legislation is 40 µg/m^3) ;
4. 90.4 percentile of PM10 daily mean concentration values corresponding to the 36th highest daily mean of the year (the limit value set by EU legislation is 50 µg/m^3);
5. 93.15 percentile of O_3 (ozone) maximum daily 8-hour average concentration values corresponding to the 26th highest daily maximum of the running 8-h mean of the year (the target value set by EU legislation is 120 µg/m^3)

In the following paragraphs, input data (air quality measurements and CTM models) are first briefly described (paragraph 2.1), then the data fusion techniques (paragraph 2.2) and the results of the validation task (paragraph 2.3) are presented.

[1] https://www.lifeprepair.eu/?smd_process_download=1&download_id=9890
[2] https://www.lifeprepair.eu/index.php/azioni/air-quality-and-emission-evaluation/#toggle-id-12

2.1. DATA FUSION INPUT DATA

2.1.1. AIR QUALITY DATA

The observational database used in data fusion procedures for the present assessment, was built with the support of PREPAIR partners providing revised validated data. This dataset is composed of pollutant concentrations measured by monitoring stations, which are divided into urban, sub-urban and rural categories (zone type classification). Moreover, some stations represent the background level (B), whereas some others represent the industrial (I) or traffic (T) level (station type classification). Table 1 summarises the main stations classification, while Figure 1 shows the spatial distributions of monitoring stations.

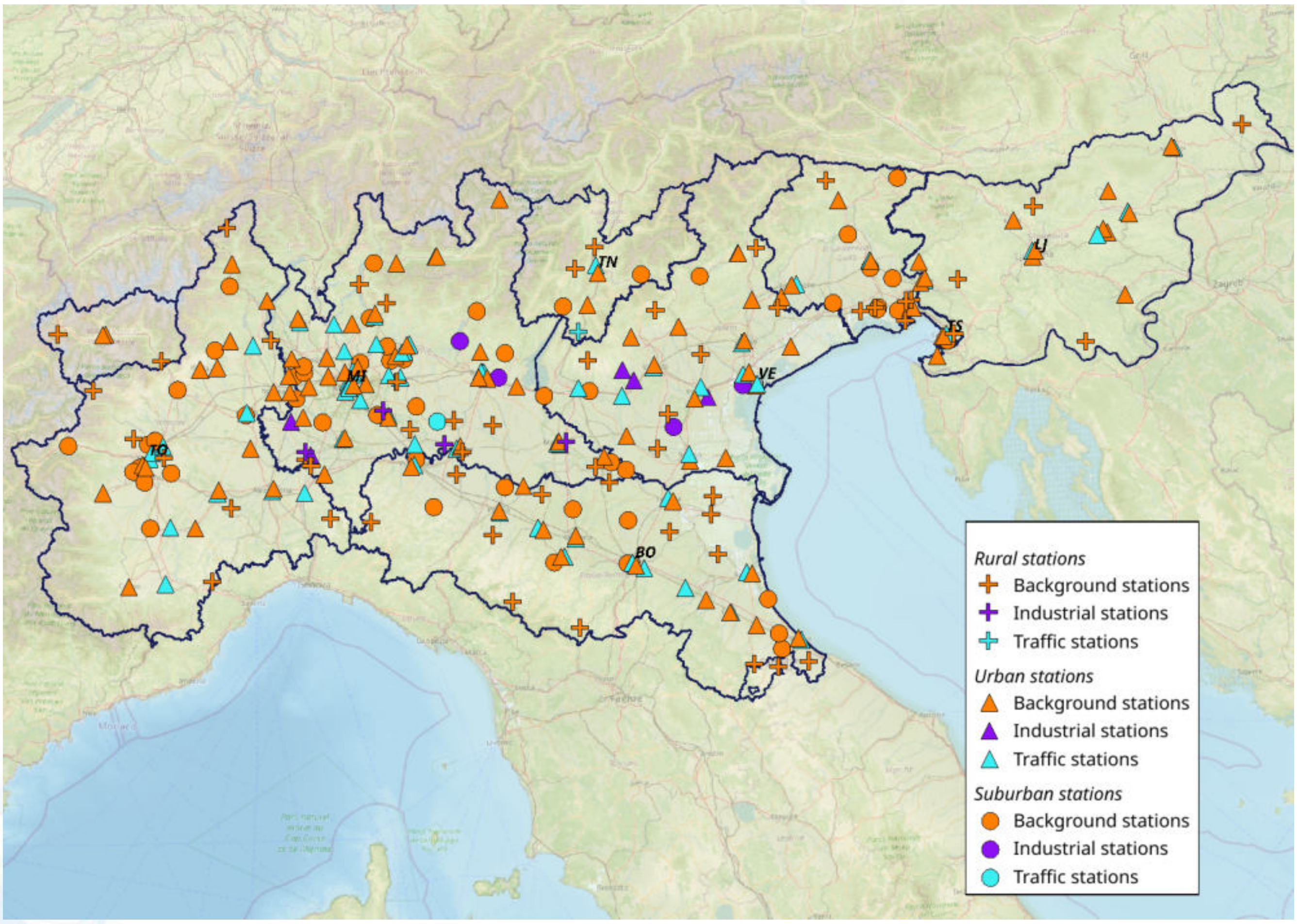

Figure 1. Spatial distribution of monitoring stations available in observation dataset.

The dataset contains hourly measurements of nitrogen dioxide (NO_2), and ozone (O_3), hourly and daily measurements of particulate matter PM10 and PM2.5 (see Table 1). The data are aggregated to obtain the air quality indicators (annual mean and percentiles) used in the assessment.

Region	Rural				Sub-urban				Urban				Total	Pollutant			
	B	I	T	Tot	B	I	T	Tot	B	I	T	Tot		NO2	O3	PM10	PM25
Emilia-Romagna	14	-	-	**14**	9	-	-	**9**	12	-	12	**24**	**47**	47	34	44	25
Friuli-Venezia-Giulia	7	-	-	**7**	12	-	-	**12**	9	-	4	**13**	**30**	20	19	27	14
Lombardia	10	4	-	**14**	18	2	1	**21**	29	3	26	**58**	**87**	92	51	73	37
Piemonte	8	-	-	**8**	13	-	-	**13**	15	-	11	**26**	**46**	46	30	43	27
Trentino	2	-	1	**3**	2	-	-	**2**				**3**	**8**	8	6	8	3
Valle d'Aosta	2	-	-	**2**	-	-	-	**-**	2	-	-	**2**	**4**	4	4	2	2
Veneto	7	-	-	**7**	2	2	-	**4**	13	3	9	**25**	**34**	35	26	32	15
Slovenia	4	-	-	**4**	-	-	-	**-**	12		5	**17**	**27**	11	12	18	5
Total	**54**	**4**	**1**	**59**	**56**	**4**	**1**	**61**	**94**	**6**	**68**	**168**	**288**	**263**	**182**	**249**	**128**

Table 1. Observation dataset: monitoring stations grouped according to data supplier (rows), station type classification, zone type classification and measured pollutant (columns).

Among all the stations included in the dataset, the database is chosen based on the following criteria:

- station type: background stations (urban, suburban or rural); this choice is consistent with the resolution of the modelling systems described in paragraph 2.1.2;
- data capture percentage: stations with data capture percentage not less than 75%; this value allows to have enough stations in all regions of the domain, as shown in the Figure 2;
- location of monitoring station: for each pollutant, a dataset with homogeneous distribution and sufficient spatial coverage to capture the complexity of different territorial contexts is built; if multiple stations fall in the same cell of computational domain, the station with the highest data capture percentage is selected (this

leads to different datasets for each different modelling system described in paragraph 2.1.2).

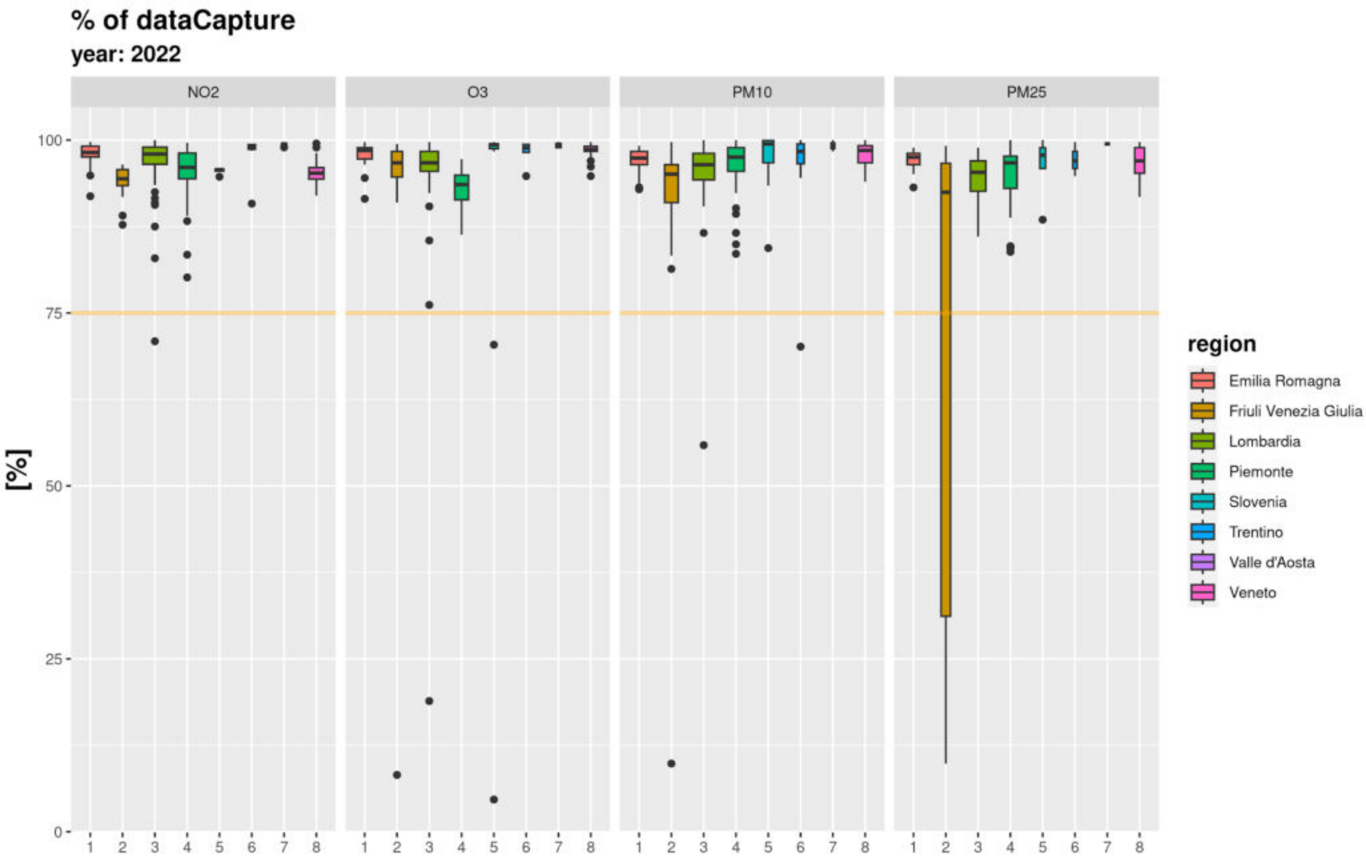

Figure 2. Observation dataset: data capture percentage for each pollutant and for each data supplier.

Finally, an exploratory analysis on the measured data in 2022 is carried out, with the aim of checking and validating the assessment results obtained by means of data fusion procedures (see paragraph 3). The results of this exploratory analysis are presented in Appendix A.

2.1.2. CTM MODELS

Among all the CTM running operational within the PREPAIR project, five modelling systems have been used for the assessment: NINFA-ER (Arpae Emilia-Romagna), PieAMS (ARPA Piemonte), SMAL-LO (ARPA Lombardia), CAMx-SLO (ARSO) and, starting from this report, SPIAIR (ARPA Veneto).

2.1.2.1. Emission data for CTM model

In the PREPAIR Project several activities have been performed for the development of emission datasets also with the aim to support the elaboration of CTM model simulations. In Action A1, the first common emission inventory covering the entire Po basin was developed, referring to the year 2013. Currently, all CTMs working within the PREPAIR project use the emission dataset (with municipal detail) updated to 2017 in Action D2 (Marongiu et al., 2022)

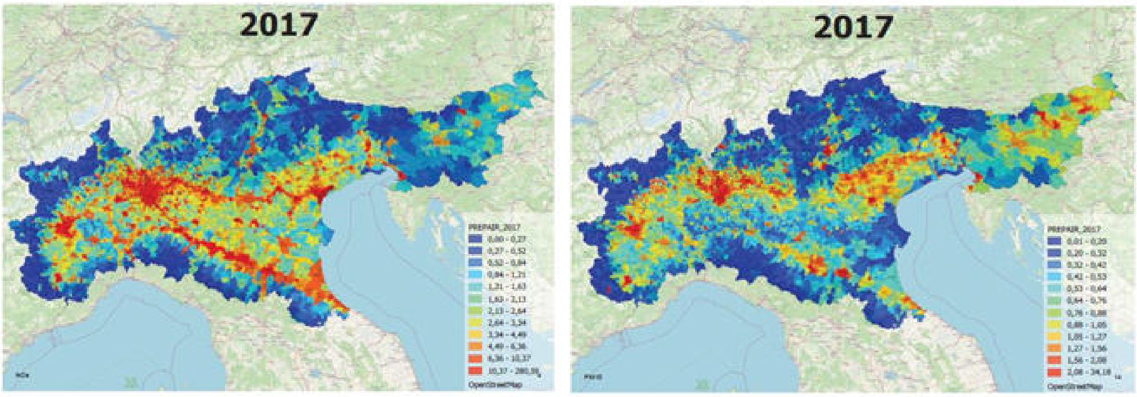

Figure 3. Emission maps for 2017 representing PM10 (right) and N0x (left).

2.1.2.2. Arpae Emilia-Romagna Model (NINFA-ER)

NINFA (Northern Italy Network to Forecast Aerosol pollution) is the operational AQ model of the Environmental Agency of the Emilia-Romagna Region (Arpae). The model suite includes a Chemical Transport Model, a meteorological model and an emissions pre-processing tool. The chemical transport model is CHIMERE, (http://www.lmd.polytechnique.fr/chimere/) an eulerian-type numerical model, which simulates transport, dispersion, chemical transformations and deposition (dry and wet) of air pollutants and aerosols. Starting from the emission data for the Po Valley, Slovenia and the other regions/countries in the model domain, (http://www.lifeprepair.eu/wp-content/uploads/2017/06/Emissions-dataset_final-report.pdf), emissions are allocated to the model grid by using specific proxy variables for each emission activity SNAP3 (i.e. road network for traffic emission, population and urban fabric for domestic heating, and so on). The meteorological hourly input is provided by COSMO, the National NWP model used by the National Civil Protection Department. COSMO is a non-hydrostatic, limited-area atmospheric prediction model, based on the primitive thermo-hydrodynamical equations describing compressible flow in a moist atmosphere, with a variety of physical processes taken into account by dry and moist parameterization schemes. The time-dependent boundary conditions (with hourly frequency) in PREPAIR project are provided by CAMS service (https://doi.org/10.3390/atmos11050447)

The AQF (Air Quality Forecast) modelling system performs simulations over four nested domain

• a background domain covering Europe with a horizontal resolution of 20 km (KAIROS MEDL);

• a national background domain covering the whole Italian Peninsula with a horizontal resolution of 7 km (KAIROS ITA7);

• an inner domain nested to ITA7 with 5 km horizontal resolution, including Northern Italy and Slovenia (PREPSLO). This domain is considered for the present assessment.

• an inner domain nested to ITA7 (EMR3), with 3 km horizontal resolution, centred over Emilia-Romagna region (EMR3) ;

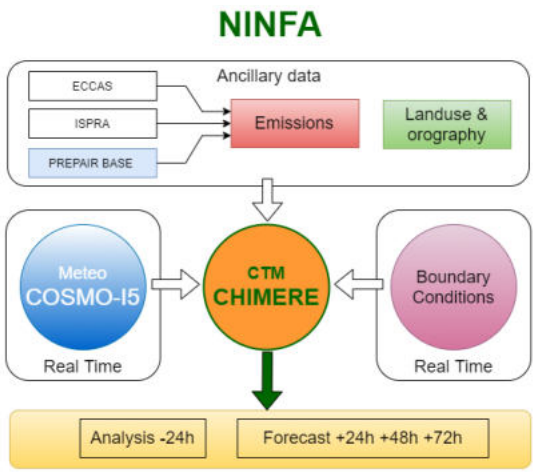

Figure 3. NINFA model scheme

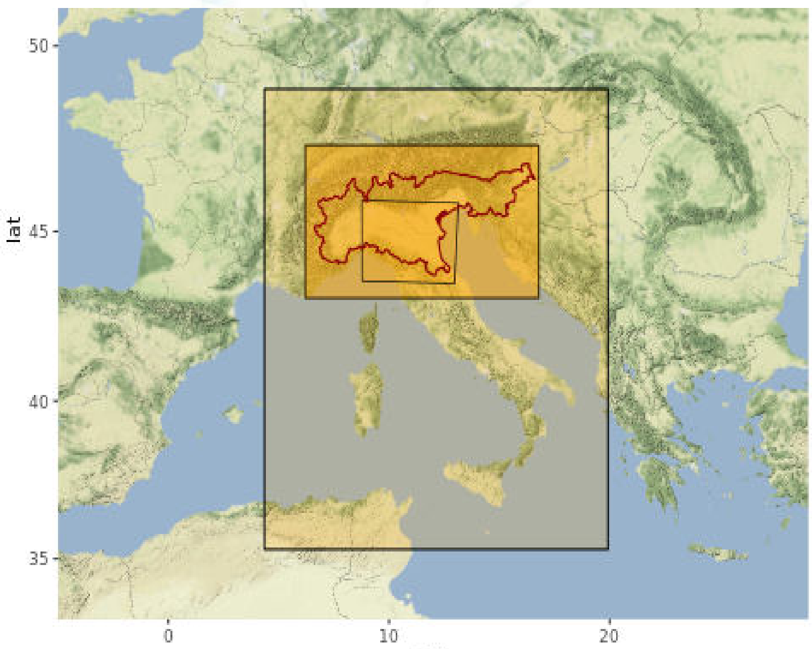

Figure 4. NINFA PREPSLO domain nested to KAIROS ITA7 domain. The area covered by region/country project partners is shown in red. The inner EMR3 domain is also shown.

Domain	MEDL	ITA7	PREPSLO	EMR3
Bounding Box	Lon: -24.8 - 33.49 Lat : 27.04 - 54.99	Lon: 4.36 - 19,12 Lat : 35.2 - 48.88	Lon: 6.25 - 16.75 Lat : 43.1 - 47.35	xUTM : 482.4 - 821.4 yUTM: 4824.5- 5079.5
Vertical Resolution	9 level up to 500 hPA	9 level up to 500 hPA	9 level up to 500 hPA	15 level up to 500 hPA
Horizontal Resolution	0.18 * 0.17 degree	0.09 * 0.07 degree	0..07 * 0.05 degree	3 * 3 km
CTM Model	CHIMERE2017	CHIMERE2017	CHIMERE2017	CHIMERE2017
BC	CAMS	kAIROS (MEDL)	kAIROS (ITA7)	kAIROS (ITA7)
METEO	COSMO5I	COSMO5I	COSMO5I	COSMO5I/COSMO2I
EMISSION	TNO-MACC III	ISPRA, TNO-MACCIII	Prepair, ISPRA TNO-MACCIII	Prepair, ISPRA TNO-MACCIII
OUTPUT	Hindcast, +72 hours forecast	Hindcast, +72 hours forecast	Hindcast, +72 hours forecast	Hindcast, +72 hours forecast

Table 2. Main configurations of NINFA-ER modelling system.

2.1.2.3. ARPA Piemonte Model (PieAMS)

The PieAMS (Giorcelli et al, 2013) model is the operational AQF model of the Environmental Agency of the Piemonte Region (ARPA Piemonte). The forecasting system has been built by using state-of-the-art techniques for atmospheric transport and dispersion modelling. The computational system architecture (Figure 5) is modular, so that the model inter-dependence is limited, in order to facilitate system improvements without modifying the general structure.

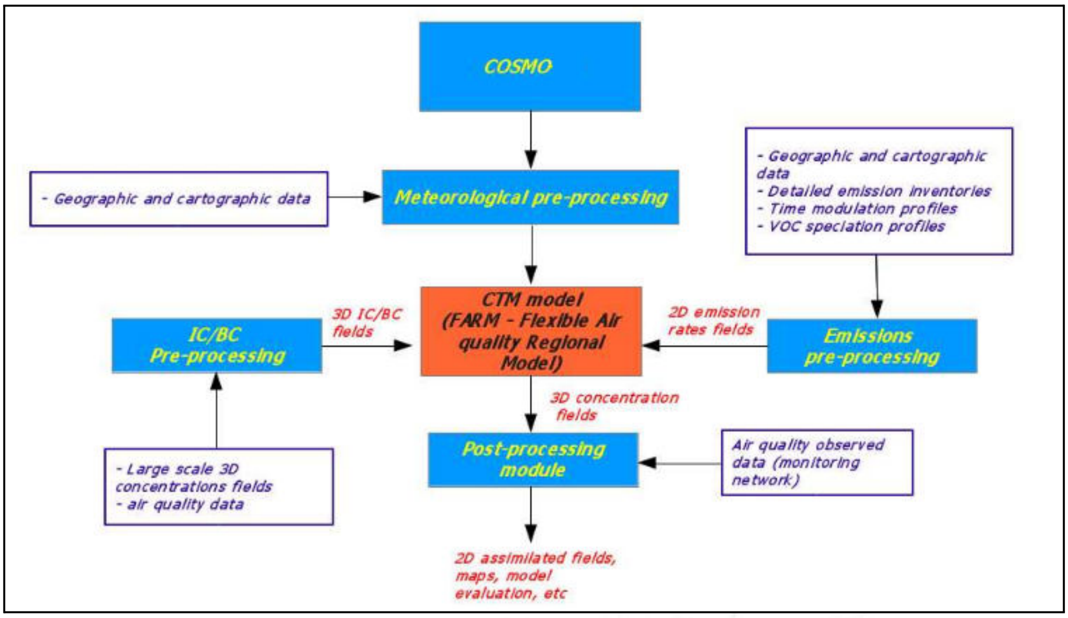

Figure 5. PieAMS computational system architecture

The core of the system is represented by the air quality model FARM (Flexible Air Quality Model, Gariazzo et al, 2007; Silibello et al, 2008), a three-dimensional Eulerian model that accounts for transport, chemical conversion and deposition of atmospheric pollutants. The forecasting system needs a series of detailed input datasets: emission inventories, geographic and physiographic data (to describe topography, surface land cover and urban details), large scale air quality and meteorological forecasts. Some specific modules are needed to process these data in order to produce emissions, meteorological fields and boundary conditions necessary as input to the air quality model. Emission data (point, line and area sources) coming from different resolution inventories available over all computational domains are processed by a specific emission module in order to produce gridded hourly emission rates for all the chemical species considered by the air quality model. This preprocessing system allows non-methanic hydrocarbon speciation and flexible space and time disaggregation, according to cartographic thematic layers and specific time modulation profiles (yearly, weekly and daily). The meteorological fields are provided by 00 UTC runs of COSMO, the National NWP model used by the National Civil Protection Department. The COSMO model levels fields are directly interpolated and adjusted (forced to be non-divergent) over all the computational domains by an interface module Starting from topography and land-use data managed by the modelling system and gridded fields of meteorological variables provided by COSMO, a diagnostic model computes three-dimensional fields of horizontal and vertical diffusivity and two-dimensional fields of deposition velocities for a given set of chemical species. The initial and boundary conditions for the background domain are obtained by continental scale air quality forecasts provided by PrevAir European Scale Air Quality Service (http://www.prevair.org). The AQF modelling system performs simulations over the following three nested domains (two-way nesting), as shown in Figure 6:

- a background domain (g1, blue line), covering Po valley basin and the Alps, with a horizontal resolution of 8 km;
- a regional target domain (g2, black line), covering the whole Piemonte Region with a horizontal resolution of 4 km;
- an inner domain (g3, red lines), with 1 km horizontal resolution, centred over Torino metropolitan area.

This multi-scale approach allows to take into account the effect of sources located outside the target areas, and to better describe phenomena characterised by large spatial scales, such as photochemical smog and particulate matter accumulation processes. The forecasting system runs on a daily basis in order to produce air quality forecasts for the current day and the two days after, with one hour time resolution.

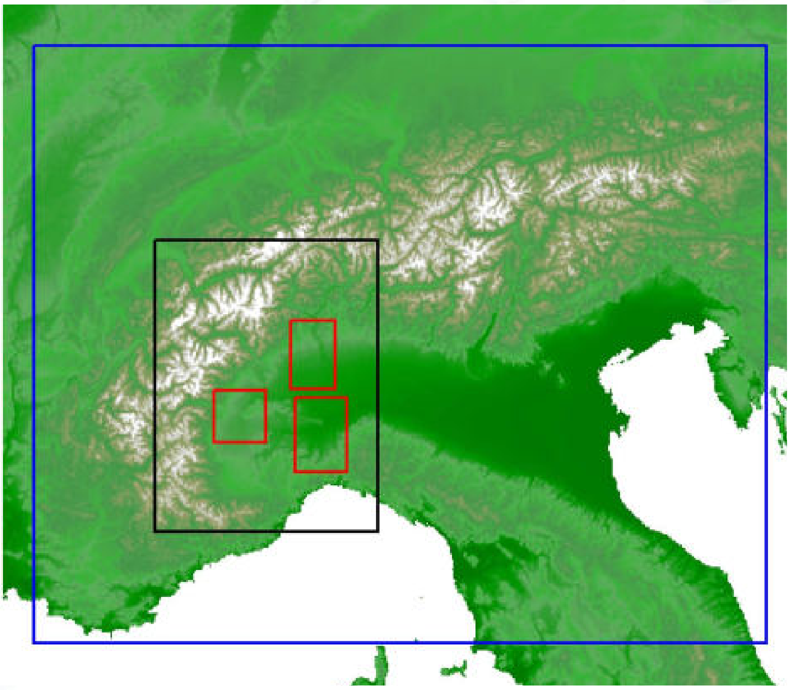

Figure 6. PieAMS computational domains.

Domain	***g1***	***g2***	***g3***
Bounding Box	Lon: 191000-911000 Lat: 4765000-5349000	Lon: 309000-529000 Lat: 4875000-5159000	Lon: 367500-418500 Lat:4961500-5012500
Vertical Resolution	16 level up to 7500 a.g.l	16 level up to 7500 a.g.l	16 level up to 7500 a.g.l
Horizontal resolution	8km x 8km (4kmx4km for KED)	4km x 4km	1km x 1km
CTM model	FARM v4.13	FARM v4.13	FARM v4.13
BC	PrevAir services	Two-way nesting with g1 grid	One-way nesting with g2 grid
Meteo model	COSMO5I	COSMO5I	COSMO5I
Emission data	Prepair, IREA, ISPRA, EMEP	Prepair, IREA, ISPRA, EMEP	IREA (Piemonte regional inventory)
Output	+72 hours forecast, air quality indicators, air quality maps	+72 hours forecast, air quality indicators, air quality maps	+72 hours forecast, air quality indicators, air quality maps, air quality index

Table 3. Main configurations of PieAMS modelling system.

2.1.2.4. ARPA Lombardia Model (SMAL-LO)

The air modelling system of ARPA Lombardia (SMAL-LO) is based on ARIA Regional developed by AriaNET srl. There are two different domain extension: one for Regione Lombardia (in Figure 7 represented by red line named g3) and one for the PREPAIR project (in Figure 7 represented by blue line named g2) which includes the Po basin extended from western (Piemonte and Valle d'Aosta Regions) to eastern part (Slovenia) and from northern (Trento Province and Friuli Venezia Giulia Regions) to southern (Emilia-Romagna Region). The PREPAIR model domain consists of 105 rows x 210 columns with a cell resolution of 4 km and is vertically discretized into 16 different levels till 4960 m a.s.l.. The main workflow of modelling architecture is composed by (Figure 8):

- WRF suite: SMAL-LO model uses the Weather Research and Forecasting (WRF) model, version 4.1.1, at 4 km horizontal resolution with 33 levels from 20 m up to 20 km.
- SURFPro suite: estimation of micrometeorological fields linked to atmospheric turbulence (i.e., mixing height, atmospheric stability classes, vertical and horizontal diffusivity), dry deposition velocity for several chemical species and natural emissions (from vegetation to winds action).

- EMMA: spatial (i.e. gridding on domain cells) and temporal (i.e. hourly) attribution of the inventory emission data (INEMAR). Furthermore, COV and particulate matter speciation are considered into FARM. Mainly, in order to use the database developed by Action D2, a harmonization procedure of the tables which associate SNAP codes for each inventory to spatial proxy and to contaminants speciation have been applied.
- IC/BC: initial condition for chemical species concentration in the model domain and at the beginning of simulation and boundary condition representing the chemical concentration in the border of the domain time-independent during all the simulation process (provided by QualeAria: http://www.qualearia.it)).
- FARM: WRF, IC/BC and Emission Inventories are the input for the 3D chemical transport model (CTM) which is a multi-grid Eulerian model for dispersion (wet and dry), transformation and deposition (droplet and gas-phase chemistry) of air pollutants in gas and aerosol phases. This is the core of the modelling system.

The main output consists of the estimation of pollutant concentrations (i.e., PM10, NO_2 and O_3). Moreover, these can be corrected based on the observed air quality data provided by the regional monitoring network (i.e. OI, Optimal Interpolation Method, see the paragraph 2.2.3). These techniques have been applied on hourly simulated concentrations by the modelling system.

Domain	g2	g3
Bounding Box	Lon: 254506-1112902 Lat: 4808039-5235127	Lon: 452013-699319 Lat:4935490-5170980
Vertical Resolution	16 level up to 4960 a.g.l	16 level up to 4960 a.g.l
Horizontal resolution	4km x 4km	1km x 1km
CTM model	FARM	FARM
BC	QualeAria: http://www.qualearia.it	QualeAria: http://www.qualearia.it
Meteo model	WRF	WRF
Emission data	Prepair, INEMAR, EMEP, ISPRA	Prepair, INEMAR, EMEP
Output	+96 hours forecast, air quality indicators, air quality maps	+96 hours forecast, air quality indicators, air quality maps, air quality index

Table 4. Main configurations of SMAL-LO modelling system.

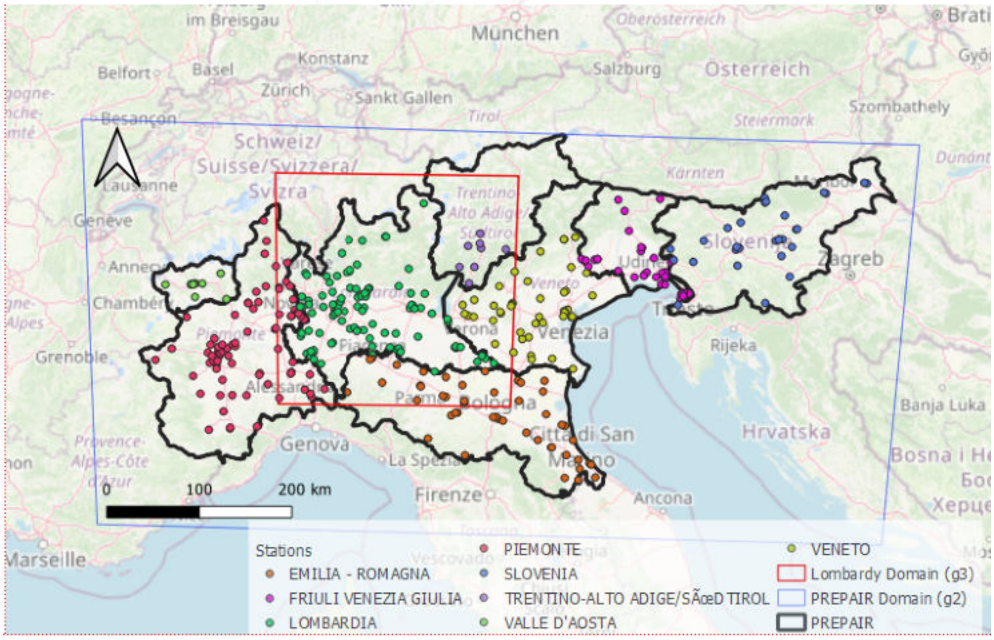

Figure 7. PREPAIR domain of SMAL-LO modelling system

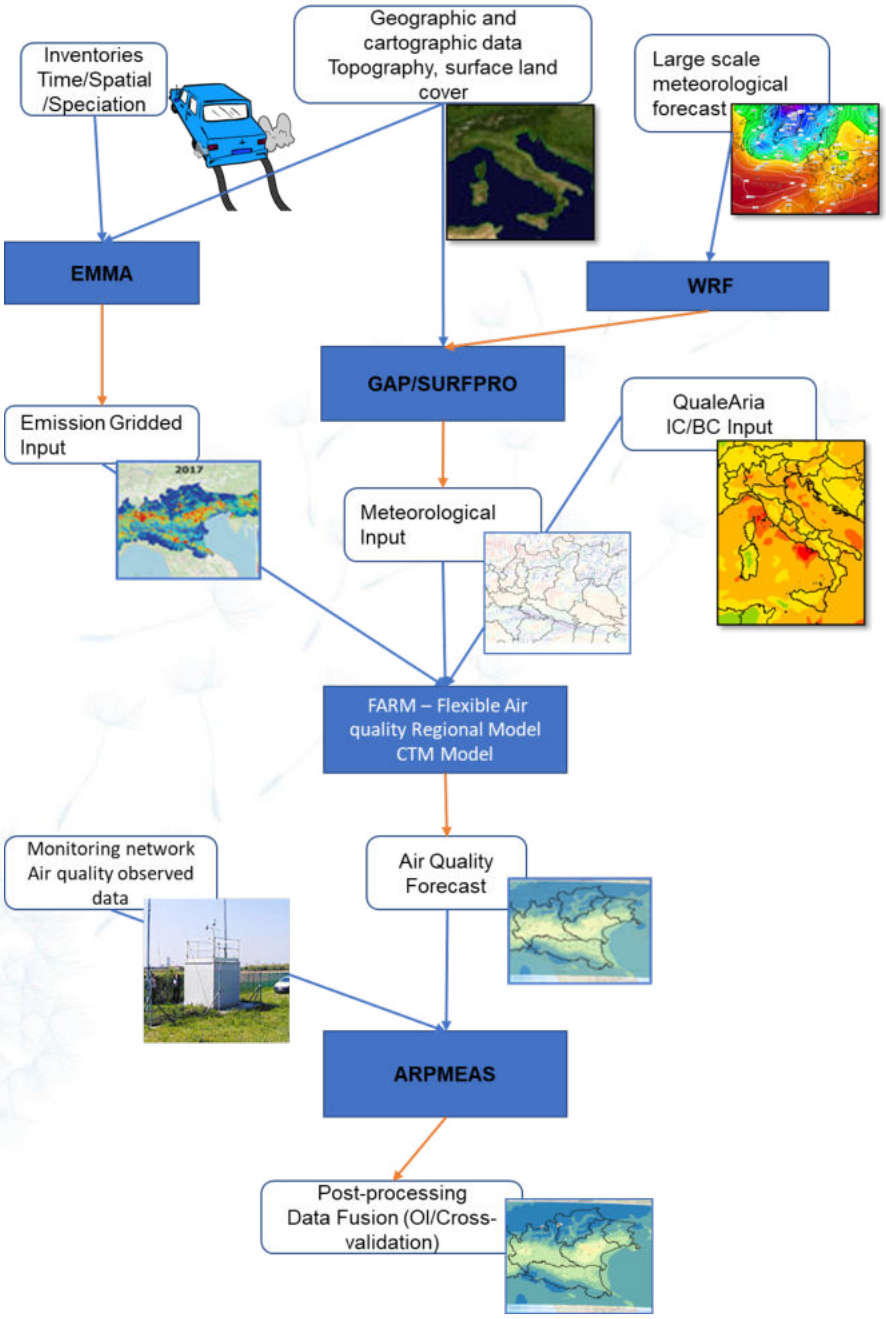

Figure 8. The architecture of SMAL-LO modelling system.

2.1.2.5. ARSO Model (CAMx-SLO)

ALADIN/SI-CAMx modelling system consists of chemical transport CAMx model (Comprehensive Air Quality Model with Extensions) coupled offline in 1 hour interval with the operational meteorological ALADIN/SI model.

ALADIN/SI model is a hydrostatic model, in which the hydrostatic approximation replaces the vertical momentum equation (http://www.umr-cnrm.fr/aladin/). Setup of the model is as follows (Slovenian Environmental Agency, ALADIN/SI Model Products, http://meteo.arso.gov.si/):

- Model with the Central Europe domain (figure 1). Horizontal resolution: 4.4 km, 421 x 421 model points.
- Vertical resolution: 87 levels (first model level 10 meters above the surface, 19 levels below the pressure surface of 900 hPa, 23 levels below the pressure surface of 850 hPa).
- Meteorological fields for the CAMx input: pressure, temperature, wind, specific humidity, cloud water, rainwater, snow water, falling ice crystal volume, optical cloud thickness, vertical turbulent diffusivity coefficient and the surface temperature field.

CAMx is an Eulerian model, able to simulate transport, dispersion, chemical transformations and deposition (dry and wet) of air pollutants (ENVIRON International Corporation. CAMx Ozone Particulates TOxics User's Guide, Comprehensive Air Quality Model With Extensions Version 6.2. Novato, California. https://www.camx.com/). The model setup of is as follows:

- Model domain is smaller than the ALADIN/SI domain, but still large enough to cover the entire Po Valley region, Slovenia and the surrounding countries (Figure 9);
- Horizontal resolution: 4.4 km, 270 x 210 model points;
- Vertical resolution: lower 68 levels of the ALADIN/SI's 87 levels;
- Chemical initial conditions: from previous run;
- Chemical boundary conditions: Global model system IFS-TM5 (The European centre for Medium-Range Weather Forecasts, ECMWF). MACC reanalysis, http://pps.ecmwf.int/datasets/data/macc-reanalysis/);
- 3 different anthropogenic emission databases:

1) Emissions over Slovenia: National inventory for year 2016 (resolution: 100 m)

2) Emission over Po Valley (i.e. PREPAIR area): PREPAIR emission database for year 2017

3) Emissions outside Slovenia and PREPAIR area: European TNO-MACC-III for 2011.

- Chemical mechanism used: SAPRC07TC ("Toxics" version of SAPRC07, with additional model species to explicitly represent selected toxics species, https://intra.engr.ucr.edu/~carter/SAPRC/)

Among above listed input data, some additional input data is also required by the CAMx.

These include geographical variables: land use (CORINE database, https://land.copernicus.eu/pan-european/corine-land-cover), Leaf area index (from ALADIN/SI model) and total amount of ozone in the atmosphere (Global model system IFS-TM5 (The European centre for Medium-Range Weather Forecasts, ECMWF. MACC reanalysis, (http://pps.ecmwf.int/datasets/data/macc-reanalysis/)).

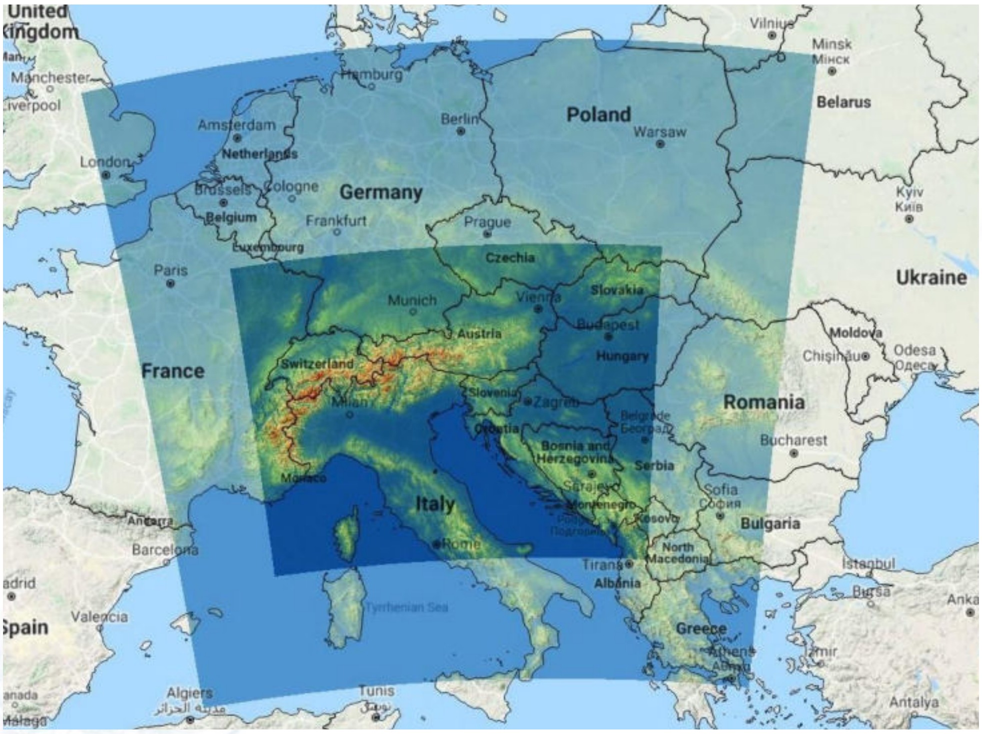

Figure 9 – Model domain of ALADIN/SI and CAMx-SLO model.

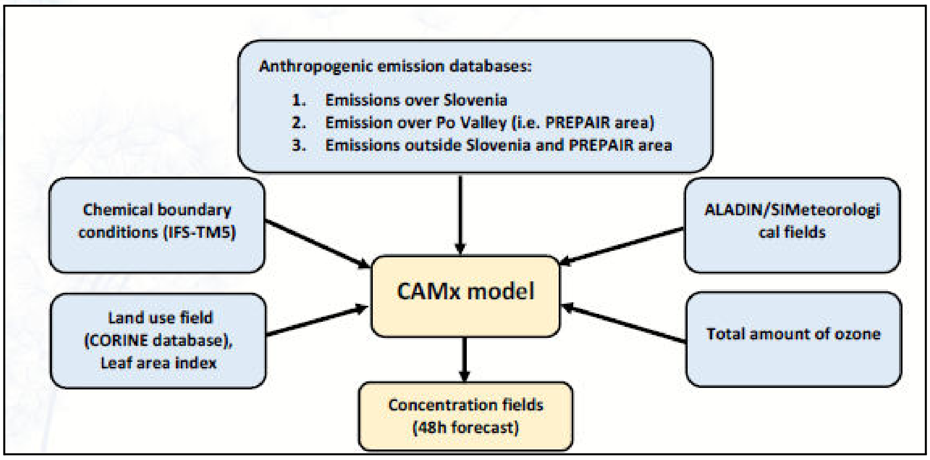

Figure 10 – Input data for CAMx model.

2.1.2.6. ARPA Veneto Model (SPIAIR)

The SPIAIR system is based on the CAMx model (www.camx.com); CAMx is an open-source, multi-scale photochemical modelling system for gas and particulate air pollution. Meteorological inputs are supplied by the COSMO model, the National NWP model used by the National Civil Protection Department. Boundary conditions are supplied by the model kAIROS, based on an implementation of CHIMERE at national level (https://www.snpambiente.it/prodotti/previsioni-qualita-dellaria-in-italia/il-modello-previsionale-kairos/).

Chemical Transport model	CAMx, version 6.5
Vertical levels	11 levels up to 6000 m a.g.l. Coordinates are heights terrain-following, first half level is 10 m.
Horizontal grid and resolution	4 km. 146 x 96 cells.
Boundary conditions	kAIROS at 7 km
Meteorological model	COSMO5I at 5 km
Emissions	PREPAIR, EMEP, ISPRA

Table 5. Main configurations of SPIAIR modelling system.

The model domain is shown in the Figure 11, it includes the whole Po valley (Slovenia is not included). The system runs on a daily basis and provides hourly analysis of the previous day and forecasts up to three days. The COSMO meteorological fields are processed by the GAP-SURFPRO suite, anthropogenic emissions are processed by the EMMA software (both are developed and maintained by the company ARIANET) and biogenic emissions are estimated by means of the MEGAN module. Sea salt emissions and windblown dust are accounted for by specific processors supplied with the CAMx model. Gridded (diffuse) emissions are assigned to the first model level whereas for point sources the level is assigned at each model time step according to its release height.

Figure 11 – Model domain of SPIAIR model.

2.2. DATA FUSION TECHNIQUES

2.2.1 NINFA-ER and Observations Data Fusion

The pollutant concentration output by the CTM NINFA can well represent the spatial distribution of pollutants while, on the other hand, in situ measurements are more quantitatively accurate. A data fusion post processing is then applied to CTM simulations in order to get the most benefit from both CTM spatial representativeness and observation precision.

A geostatistical algorithm is used in Arpae to merge data from different sources. The pollutant background concentration can be regarded as a phenomenon measured by two variables, one more precise but known at only few locations (the observations) and one less accurate but known in the whole domain (the CTM on a regular grid), so Kriging with External Drift (KED) is a suitable technique to be applied to this dataset.

The considered domain is characterised by a complex orography, so that the elevation above the sea level (h) is considered as a further spatial explanatory variable. A cross validation including or not including elevation was performed to verify the improvement introduced by the second explanatory variable.

Let the statistical process we are estimating (either annual mean concentration or percentile) at X location be Y(X), in KED it is assumed that its expectation E[Y(X)] is equal to a combination of the two explanatory variables, CTM model (m) and elevation (h):

$$E[Z(X)] = a + b \cdot m(X) + c \cdot h(X)$$

(Wackernagel, 2003)

With this assumption on the mean part of the process, the residuals are estimated. To fulfil the hypothesis of a gaussian process, before fitting the variogram, a Box-Cox transformation with fixed zero lambda parameter is done. Moreover the covariance function is estimated assuming an exponential variogram.
The KED algorithm has been implemented for the present work by means of the geoR R package (Ribeiro and Diggle, 2001; Diggle and Ribeiro, 2007). For the present assessment, the main indexes are evaluated with the described KED method: PM10 annual mean, PM10 90.41 percentile, PM2.5 annual mean, NO2 annual mean, O3 93.10 percentile.
The KED spatial prediction is performed at the NINFA model grid, i.e. at about 5 X 5 km^2 resolution, on PREPSLO domain.
To test the prediction skill of the used KED method, a cross validation has been carried out and the results are shown in section 2.3.

2.2.2 PieAMS and Observations Data Fusion

In order to make pollutant model outputs more realistic and their spatial distribution more representative, PieAMS concentration fields were fused with the observed data through kriging with external drift method (KED, Wackernagel 2003) by employing the geoR package in R (Development Core Team 2010; Ribeiro and Diggle, 2001). Specifically, the kriging was applied on the observations while the external drift was represented by the PieAMS model output, since KED is a particular case of universal kriging, where the trend component is the CTM output (Ignaccolo et al, 2013; Ghigo et al 2017). To make observed data approximately normally distributed with constant variance, a Box-Cox transformation (Box and Cox 1964) was applied separately per pollutant.

Therefore, transformed observations were interpreted as realisations of a Gaussian spatial process Y (s) at spatial location s, in the domain S, that has the following structure:

$$Y(s) = \mu(s) + w(s) + \varepsilon(s),$$

where:

$\mu(s) = X\beta$ is the spatial trend component, $\beta = \{\beta_0, \beta_1, \beta_2\}$ is the unknown parameter vector, X = [1, PieAMS(s), HGT (s)] is the deterministic variable including PieAMS model output as well as orography (HGT): the addition of this variable as auxiliary covariate had the purpose to introduce information about the complex Po basin terrain. w(s) is a zero-mean stationary Gaussian random process with sill σ^2 that takes into account the spatial correlation between observations by means of the spatial correlation function $\rho(\cdot)$ with range φ. Finally, $\varepsilon(s)$ is the error term characterised by the variance τ^2 (nugget). The leave-one-out cross-validation method was performed to choose the spatial covariance function and the best results were obtained with the exponential function, on all pollutants. To fit the model, firstly the parameters of the Box-Cox transformation and then the covariance parameters were estimated by the use of a restricted maximum likelihood method.

The KED procedure was applied to the concentration fields of PM10 annual mean, PM10 90.41 percentile, PM2.5 annual mean, NO2 annual mean, O3 93.1 percentile produced by the PieAMS modelling system on the g1 grid but with a resolution of 4km (see paragraph 2.1.3.2). Therefore before the kriging procedure, we interpolated the results of model concentration fields on the g1 grid with a resolution of 8 km to the g1 grid with a resolution of 4 km.

The model output post-processing performs well. Moreover, we carried out a cross-validation analysis in order to evaluate the KED performance and it showed that kriging results are satisfactory. The results of this analysis are reported shortly in paragraph 2.3

2.2.3 SMAL-LO and Observations Data Fusion

ARPMEAS (ARchive Plus MEASurements) combine background 2/3D fields with observed data. The OI (Optimal Interpolation) approach is implemented for the data fusion process. The Optimal Interpolation allows to interpolate arbitrarily located observations to a regular grid using a background field as first guess. The observations and the background fields may contain errors. Optimal interpolation merges observations and background taking their expected variances into account. The merged field is optimal in the sense that it has the lowest error variance. The error correlation function of the background field is assumed to decrease exponentially with the square of the distance. The correlation length in every dimension must be specified by the user. ARPMEAS implements the code developed by Alexander Barth.

Within the OI framework, the analysed (optimal) state vector x^A is given by:

$$x^A=x^G+BH^T(HBH^T+R)^{-1}.(Y-Hx^G)$$

where x^G is the background state vector, Y is the observation vector; H is the observation operator that extracts from a state vector the corresponding values at the location of the observations; B is the background error covariance matrix, R is the observation error covariance matrix. K $(BH^T(HBH^T+R)^{-1})$ is the so-called Kalman gain matrix. The following assumptions are made: the observation errors are uncorrelated, e.g. off-diagonal elements of R are zero and R is consequently assumed to be diagonal: $R=\sigma^2 OI$ where I is the Identity matrix and $\sigma^2 O$ is the observation error variance defined as follows:

$$\sigma^2 O = \langle \epsilon^2 o \rangle \text{ where } \epsilon^2 o = Y - Hx^T$$

x^T is the "true state" and B is assumed to decrease exponentially with the square of the distance along each dimension:

$$B(i,j) = \sigma_o^2 . e^{\frac{-d_h^2(i,j)}{L_h^2}} . e^{\frac{-\delta z_{i,j}^2}{L_z^2}}$$

Here $d^2_h(i,j)$ is the horizontal distance between the i-th and the j-th grid points, Δz_{ij} is their vertical distance, $\sigma^2 B$ is the background error variance and L_h and L_z are the horizontal and vertical scaling distances. The implication of assuming B as exponentially decreasing is to spread out spatially the information from local observations that contribute to corrections of state variables in neighbouring locations. Defining ε^2 as the ratio of the observation error variance to the background error variance ($\varepsilon^2=\sigma^2 o/\sigma^2 B$) and dividing the two error covariance matrixes R and B by $\sigma^2 B$, the diagonal elements of R become equal to $\varepsilon^2 I$ and the parameter ε^2 becomes a single tuning parameter.

2.2.4 CAMx-SLO and Observations Data Fusion

Data fusion is considered one of the techniques of data assimilation (Lahoz et al. 2014), where we combine the results of numerical models and the point measurements (Schneider et al, 2015). There are known various statistical and geostatistical approaches to the data fusion (Berrocal et al, 2012). In our case the used statistical method for data fusion was geostatistical approach of kriging with external drift (Cressie, 1993)).

Kriging with external drift is a geostatistical algorithm where the value of a variable (interpolated value) at any grid point is calculated as a linear combination of measurements of the surrounding measuring points. The coefficients of this linear combination are calculated under assumption, that the mean square of the differences between the measured and interpolated values at the measurement points (kriging variance) are the smallest. In addition to this assumption (smallest mean square error), when calculating the coefficients of a linear combination, we also take into account the outcome of the spatial relationship of the variable, which is described by the variogram function (Cressie, 1993). The average of the considered variable may also depend on other explanatory variables, such as the altitude. In such a case, we express the average as a linear combination of explanatory variables and look for a spatial correlation only for the residues of this function.

In our case, we performed Kriging with external drift in two stages. In the first stage, we interpolated the results of model concentration fields with a resolution of 4.4 km to the model grid with a resolution of 1 km, taking into account the altitude field and the field of geographical coordinates (latitude and longitude) with 1 km resolution as external variables. In the second stage, we interpolated the measurement points to a model grid with 1 km resolution, taking into account the interpolated field of model values (i.e. the result from the first step) and the field of geographical coordinates (latitude and longitude) at 1 km resolution.

2.2.5 SPIAIR and Observations Data Fusion

Concentrations from the model analysis were merged with observations in order to get an improved spatial representation of pollutants. The implemented method (Horalek et al, 2007) follows a procedure in two steps:

1. A linear regression is performed with observations as dependent variable and model output and terrain elevation as independent variables. A field Z is obtained applying the linear transformation to each grid point i :

   $$Z_i = a\, M_i + b\, h_i + c$$

   where M is the model output and h the terrain elevation; a, b and c are the coefficients of the regression.

2. the residuals R given by the difference between the Z field and the measurements are calculated at station sites and interpolated to each grid point by means of a IDW (inverse distance weight) algorithm:

   $$Ri = (\sum_j R_j/d_{ij}^2)/(\sum_j 1/d_{ij}^2)$$

where d_{ij} is the distance between the grid point i and station j and the j index ranges from 1 to the number of stations.

The final field is obtained by subtracting the residuals from the Z field.

This procedure has been applied to the concentration fields of PM10 annual mean, PM10- 90.41 percentile, PM2.5 annual mean, NO2 annual mean, O3- 93.1 percentile produced by the SPIAIR system.

2.2.6 D5 Ensemble model

For each indicator considered in the assessment, the results produced by the five modelling systems after the data fusion procedure are combined into an ensemble model. The model ensemble is defined on the PREPSLO grid of the NINFA-ER modelling system; first all results of the data fusion are interpolated on the PREPSLO grid, then for each grid point the ensemble is built using, the median value of all data fusion systems. The advantage of an ensemble over a single model is that it benefits from a set of concentration fields of similar general skill, the performance of each individual model being overall equivalent. The slight differences between models allows assessment of uncertainty: the more similar the individual fields, the lower the uncertainty. Since the ensemble is built on the median value, its uncertainty is calculated using interquartile range IQR. The ensemble uncertainty maps are shown in the Appendix B, while the concentration maps are commented and discussed together with the results of the five modelling systems.

2.3. DATA FUSION VALIDATION

For all models the data fusion simulation is validated by means of a cross validation. The one-leave-out methodology has been applied to obtain a set of independent observations to verify the spatial prediction performance. The results are presented either in qualitative terms by means of scatter plots, or in quantitative terms by means of statistical performance indexes. The scatter plots of observed/simulated data for each air quality index are shown: PM10 annual mean, PM10 90.41 percentile, PM2.5 annual mean, NO_2 annual mean, O_3 93.1 percentile.

In the following plots the lines defining the admitted model percentage discrepancy (in terms of percentage relative uncertainty) and the EU limit value are depicted for each pollutant index.

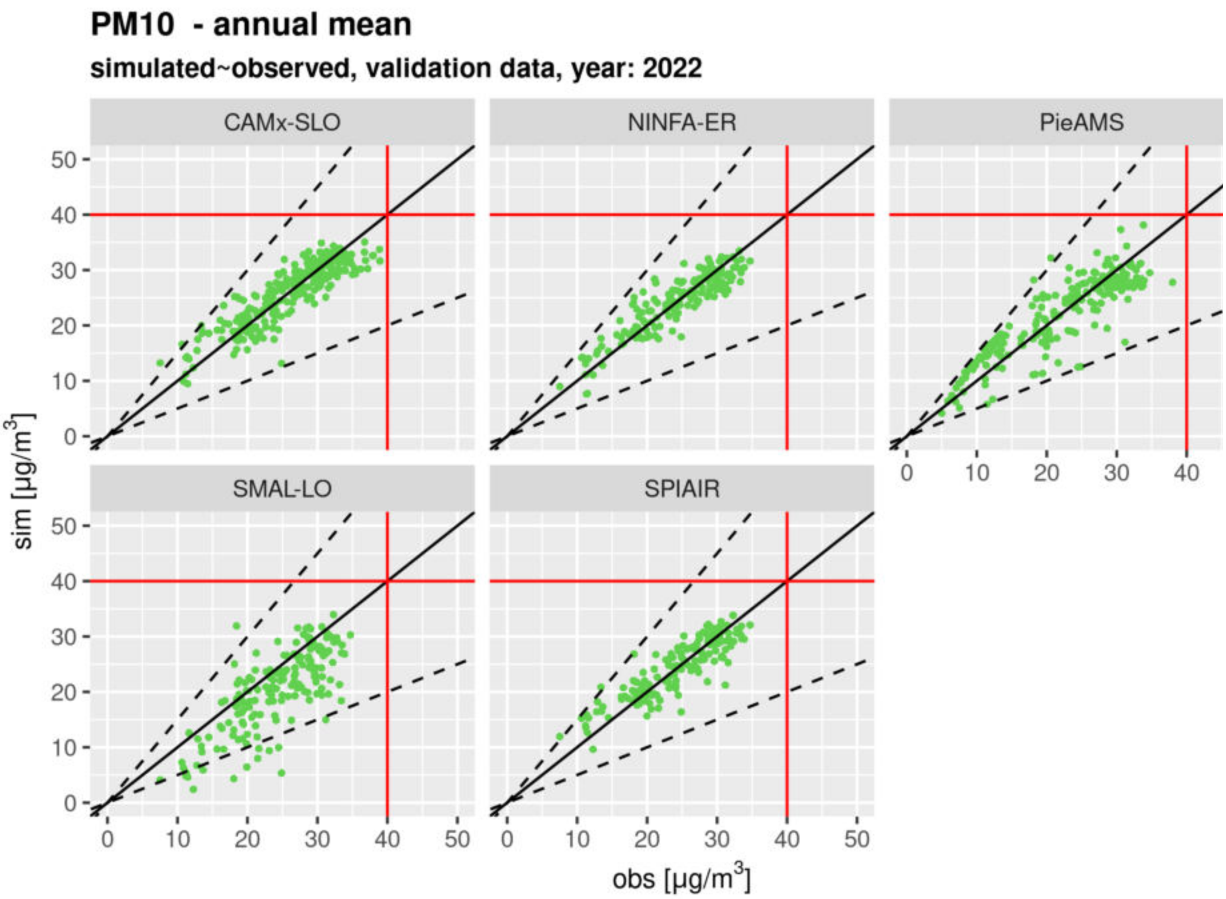

Figure 12. PM10 annual mean: cross validation scatter plot for CAMx-SLO (top left), NINFA-ER (top central), PieAMS (top right), SMAL-LO (bottom left and SPIAIR (bottom central). The dashed lines represent the admitted relative uncertainty (50% for PM10 annual mean), while the red lines indicate the EU limit value (40 µg/m^3).

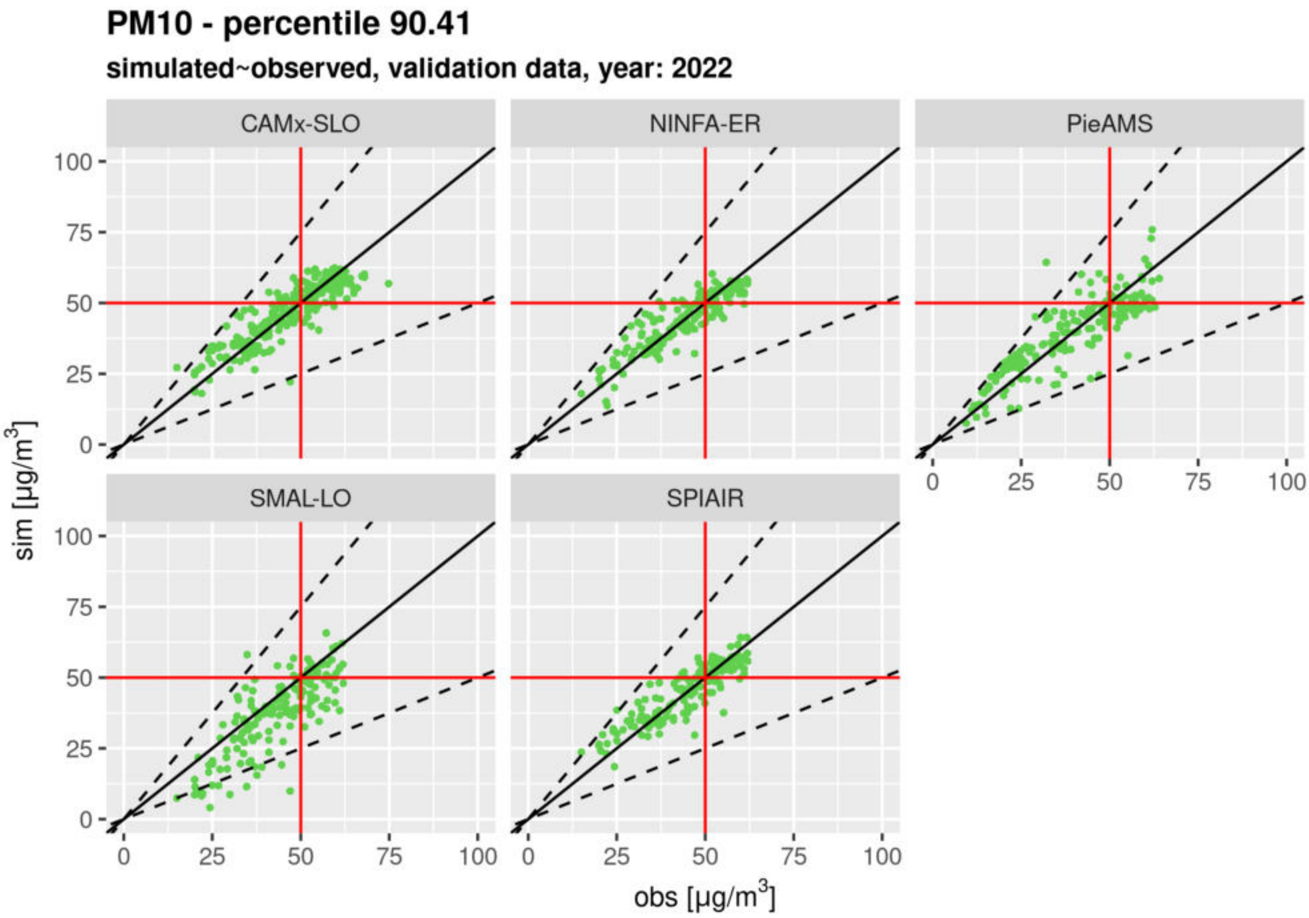

Figure 13. PM10 percentile 90.41: cross validation scatter plot for CAMx-SLO (top left), NINFA-ER (top central), PieAMS (top right), SMAL-LO (bottom left) and SPIAIR (bottom central). The dashed lines represent the admitted relative uncertainty (50% for PM10 annual mean), while the red lines indicate the EU limit value (50 µg/m³).

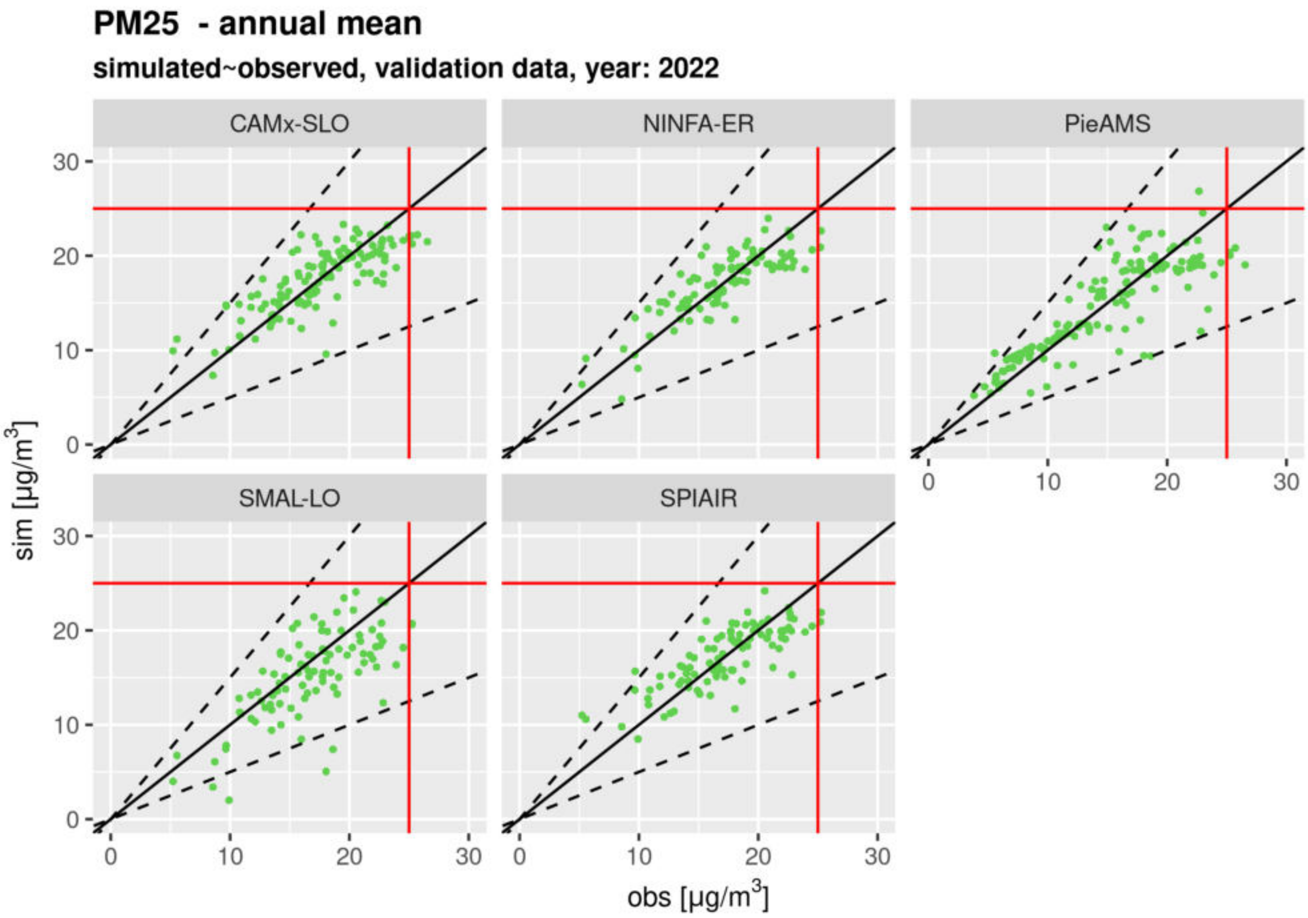

Figure 14 PM2.5 annual mean: cross validation scatter plot for CAMx-SLO (top left), NINFA-ER (top central), PieAMS (top right), SMAL-LO (bottom left) and SPIAIR (bottom central). The dashed lines represent the admitted relative uncertainty (50% for PM10 annual mean), while the red lines indicate the EU limit value (25 µg/m^3).

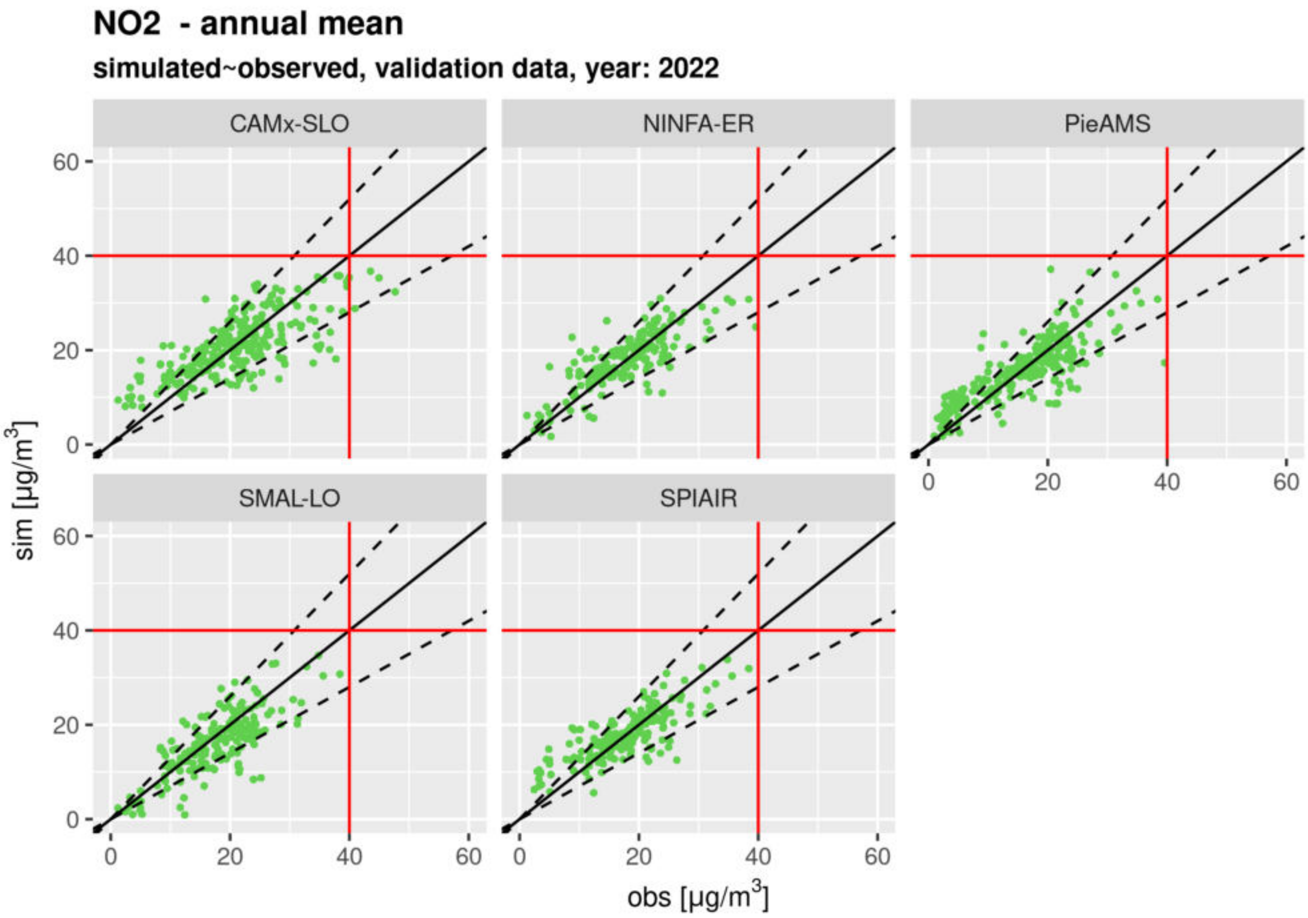

Figure 15. NO_2 annual mean: cross validation scatter plot for CAMx-SLO (top left), NINFA-ER (top central), PieAMS (top right), SMAL-LO (bottom left) and SPIAIR (bottom central). The dashed lines represent the admitted relative uncertainty (50% for PM10 annual mean), while the red lines indicate the EU limit value (40 µg/m^3).

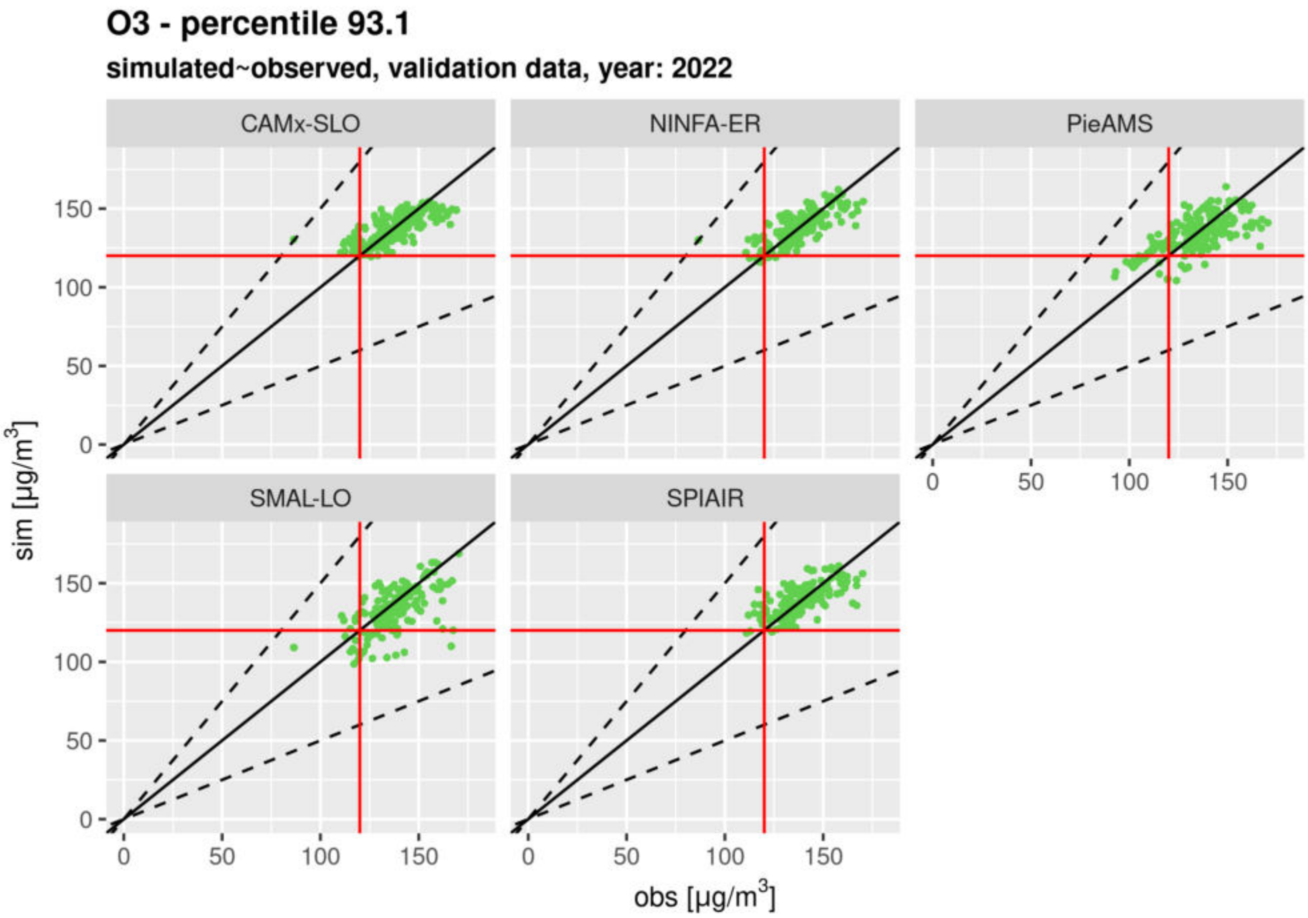

Figure 16. O3 percentile 93.1: cross validation scatter plot for CAMx-SLO (top left), NINFA-ER (top central), PieAMS (top right), SMAL-LO (bottom left) and SPIAIR (bottom central). The dashed lines represent the admitted relative uncertainty (50% for PM10 annual mean), while the red lines indicate the EU target value (120 µg/m^3).

Overall, a good agreement between observed and simulated data for all the data fusion simulations can be observed. The bulk of PM10 predictions, either annual mean or 90.41 percentile, lie within the tolerance area; only for a few stations the simulated data are located beyond the admitted model discrepancy. Almost all PM2.5 annual mean simulations are within the tolerance or very close and for the O_3 93.1 percentile all the points are within tolerance for the five models.,

For NO_2 annual mean the results show a significant correlation between simulations and observations, however the scatter plots show, for all the simulations, points not included in the tolerance area, with local overestimation or underestimation. This behaviour is probably due to high spatial variability of NO2 concentrations and local peculiarities which cannot be reproduced at chemical transport model resolution (from 4 to 8 km).

In the following table the main performance statistical scores are summarised for the validation datasets. Three typical indexes based on the differences between predicted and observed data that provided meaningful information are here considered: mean error (ME), unbiased root mean squared error (URMSE) and Pearson correlation (Yu et al, 2006; Denby et al, 2011).

The results reported in Table 6 show satisfying performances for data fusion methodologies for almost all air quality indexes.

For all the pollutants and indicators CAMx-SLO, NINFA-ER, PieAMS and SPIAIR have positive and close to 0 ME; SMAL-LO have for all indexes and pollutants negative ME values (slight tendency to underestimation) The Pearson correlation ranges from (0.61 to 0.90 with higher values for PM10 annual mean and 90.41 percentile Lower correlations are generally shown for O_3 indicators. The URMSE have in general the lowest values for PM10 and Pm2.5 annual mean and the higher values for O_3.

model	index	pollutant	ME	URMSE	PEARSON
CAMx-SLO	*annualMean*	*PM10*	0.00	3,04	0,88
NINFA-ER	*annualMean*	*PM10*	0,02	2,65	0,90
PieAMS	*annualMean*	*PM10*	0,01	3,90	0,88
SMAL-LO	*annualMean*	*PM10*	-3,77	4,65	0,77
SPIAIR	*annualMean*	*PM10*	0,05	2,87	0,88
CAMx-SLO	*annualMean*	*PM2.5*	0,03	2,66	0,78
NINFA-ER	*annualMean*	*PM2.5*	0,03	2,31	0,84
PieAMS	*annualMean*	*PM2.5*	0,02	3,01	0,85
SMAL-LO	*annualMean*	*PM2.5*	-1,6	3,38	0,71
SPIAIR	*annualMean*	*PM2.5*	0,04	2,6	0,78
CAMx-SLO	*annualMean*	NO_2	0.00	5,77	0,74
NINFA-ER	*annualMean*	NO_2	0,15	4,25	0,81
PieAMS	*annualMean*	NO_2	0,02	4,86	0,8

model	index	pollutant	ME	URMSE	PEARSON
SMAL-LO	*annualMean*	NO_2	-1,51	4,56	0,78
SPIAIR	*annualMean*	NO_2	0,16	4,14	0,80
CAMx-SLO	*perc-90.4*	*PM10*	0,05	5,48	0,88
NINFA-ER	*perc-90.4*	*PM10*	0,05	5,05	0,89
PieAMS	*perc-90.4*	*PM10*	0,02	7,38	0,87
SMAL-LO	*perc-90.4*	*PM10*	-5,64	8,06	0,8
SPIAIR	*perc-90.4*	*PM10*	0,24	5,14	0,89
CAMx-SLO	*perc-93.1*	O_3	0,17	9,23	0,72
NINFA	*perc-93.1*	O_3	0,15	8,8	0,74
PieAMS	*perc-93.1*	O_3	0,01	11,54	0,69
SMAL-LO	*perc-93.1*	O_3	-3,93	12,12	0,61
SPIAIR	*perc-93.1*	O_3	0,47	9,23	0,68

Table 6. Cross-validation results: statistical scores.

3. ASSESSMENT RESULT

3.1. PM10

The spatial distributions of the PM10 annual mean and 90.41 percentile produced by all the data fusion systems (Figure 17 and Figure 18 respectively) are similar to each other, showing the same main patterns. The areas with the highest concentrations are located in the Lombardia and Veneto plains, along the main road axis in Emilia-Romagna, around the agglomeration of Turin and in the areas between Asti and Alessandria. Nevertheless, we can see some differences between the models. First of all in the eastern part of Lombardia, in the plains between Cremona and Mantua, NINFA-ER, PieAMS, CAMx-SLO and SPIAIR show higher concentrations with more homogeneous spatial distribution than SMAL-LO. Furthermore, SPIAIR and CAMx-SLO simulate higher PM10 levels than the other three models in the Alps and in the hills between Asti and Alessandria. These differences are mainly related to the different data fusion techniques used (as set out in section 2.2.). This is confirmed by the D5 ensemble concentration maps (top of Figure 17 and Figure 18) and the ensemble uncertainty maps (in the Appendix B for both indicators).

No model estimates annual average concentration beyond the threshold value of 40 μg/m^3, while all the models report PM10 concentrations above the EU daily limit value for the flat area of the Po Valley among Lombardia, Veneto and Emilia-Romagna regions and for the Turin metropolitan area.

Figure 19 shows boxplots of grid point distribution grouped by region for each data fusion system. The distributions are quite similar: NINFA-ER, PieAMS and D5 ensemble have very close median values, CAMx-SLO and SPIAIR show slightly higher median values while SMAL-LO shows the lowest median levels. The largest differences between the four models occur in Slovenia and in the Alpine regions of Valle d'Aosta and Trentino. These differences can be attributed to diverse data fusion approaches: PieAMS, NINFA-ER, CAMx-SLO use similar methodologies (kriging), though CAMx-SLO datafusion archives a finer resolution, SPIAR uses a non-geostatistical algorithm to spatialize the residuals, while SMAL-LO has implemented a conceptually different approach.

PM10, 2022 annual mean

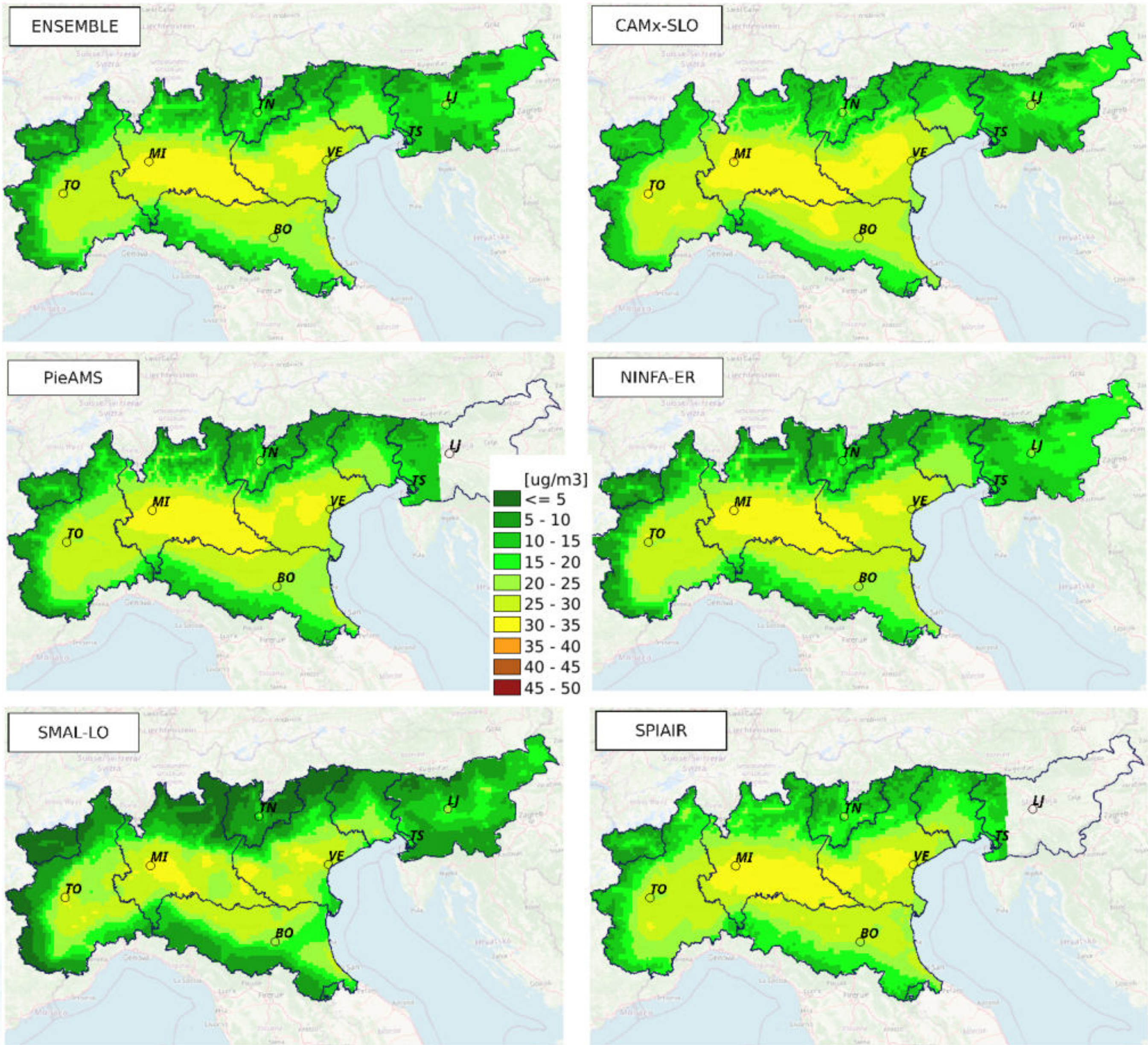

Figure 17. Maps of PM10 annual mean produced by the five data fusion systems and by the D5 ensemble (top left of the figure).

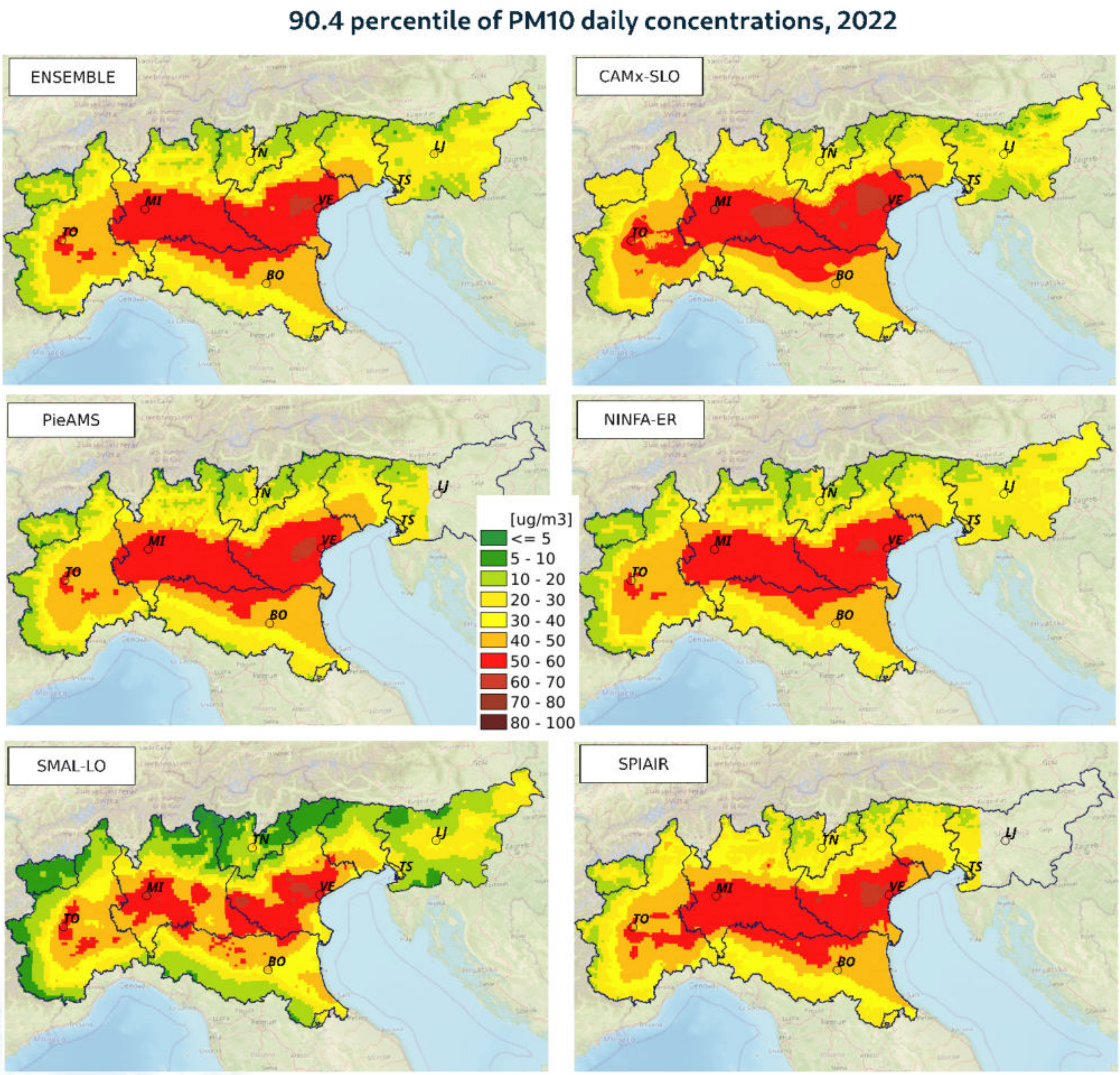

Figure 18. Maps of PM10 90.41 percentile produced by the five data fusion systems and by the D5 ensemble (top left of the figure).

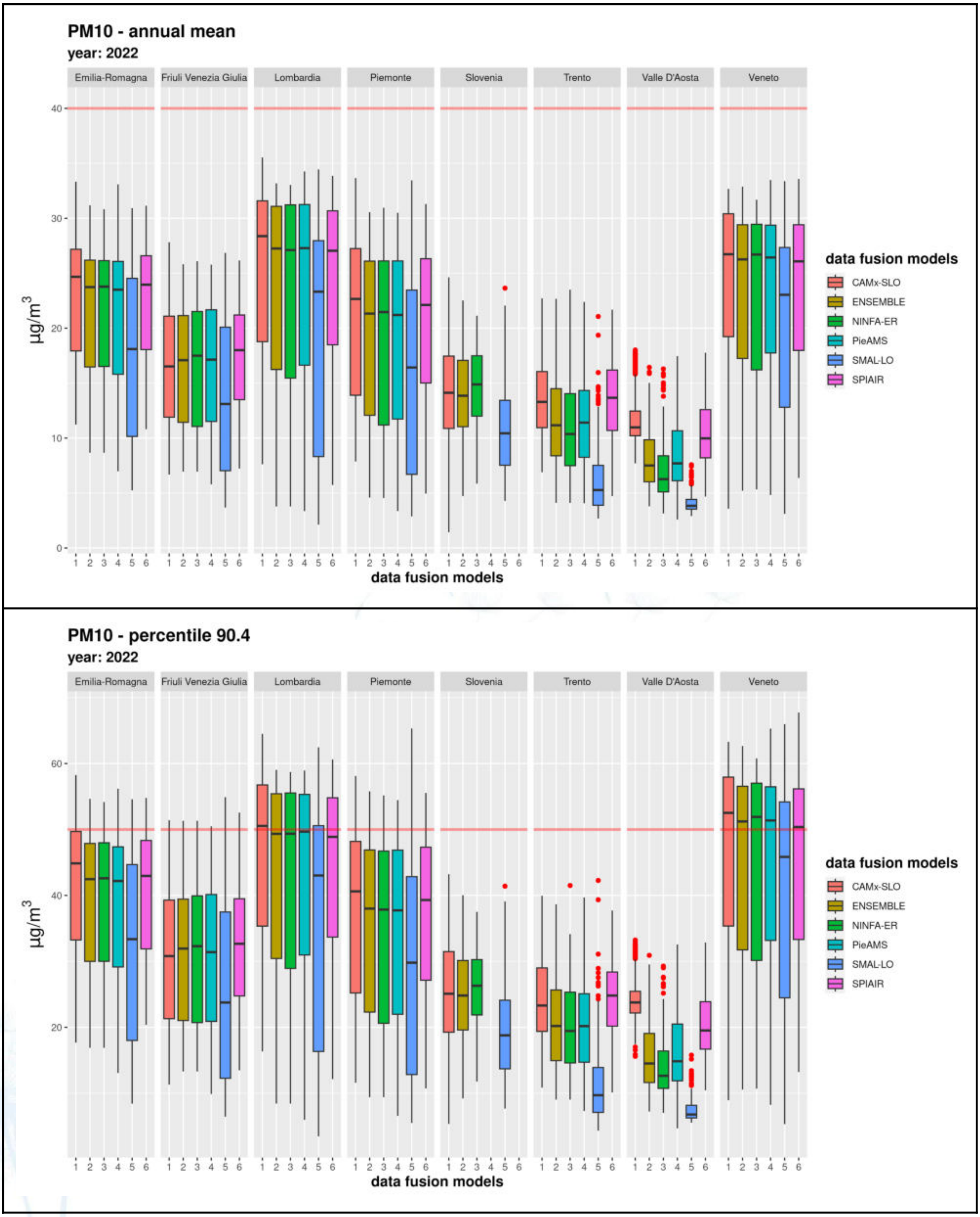

Figure 19 Boxplots of grid point concentration distributions grouped by model and region. Left: PM10 annual mean; right percentile 90.4 of PM10 daily values. The red lines indicate the EU limit value (40 and 50µg/m^3 respectively)

3.2. PM2.5

All models agree in estimating average annual values of PM2.5 above 20 µg/m3 (EU limit for the stage II) around the Milan and Turin metropolitan area and in some areas of Lombardia and Veneto plains. NINFA-ER, SPIAIR and SMAL-LO also show exceedances in the south-western part of Piemonte region. Moreover, SMAL-LO shows lower average annual concentrations of PM2.5 over the south-eastern Lombardia and over the central part of Veneto region.

The PM2.5 concentration is below the EU limit value (stage I) for the annual mean throughout the domain for all the modelling systems.

The comparison between the spatial structure of the fields confirms what has already been highlighted for PM10. However, in Veneto and the south-eastern part of Lombardia region the spatial differences between NINFA-ER, PieAMS, CAMX-SLO, SPIAIR, on one hand, and SMAL-LO on the other, are not negligible. Figure 21 shows boxplots of grid point distribution grouped by region for each data fusion system. The distributions are quite similar: As with the PM10, SMAL-LO shows the lowest median levels and the largest differences between the five models occur in the Alpine regions of Valle d'Aosta and Trentino.

PM25, 2022 annual mean

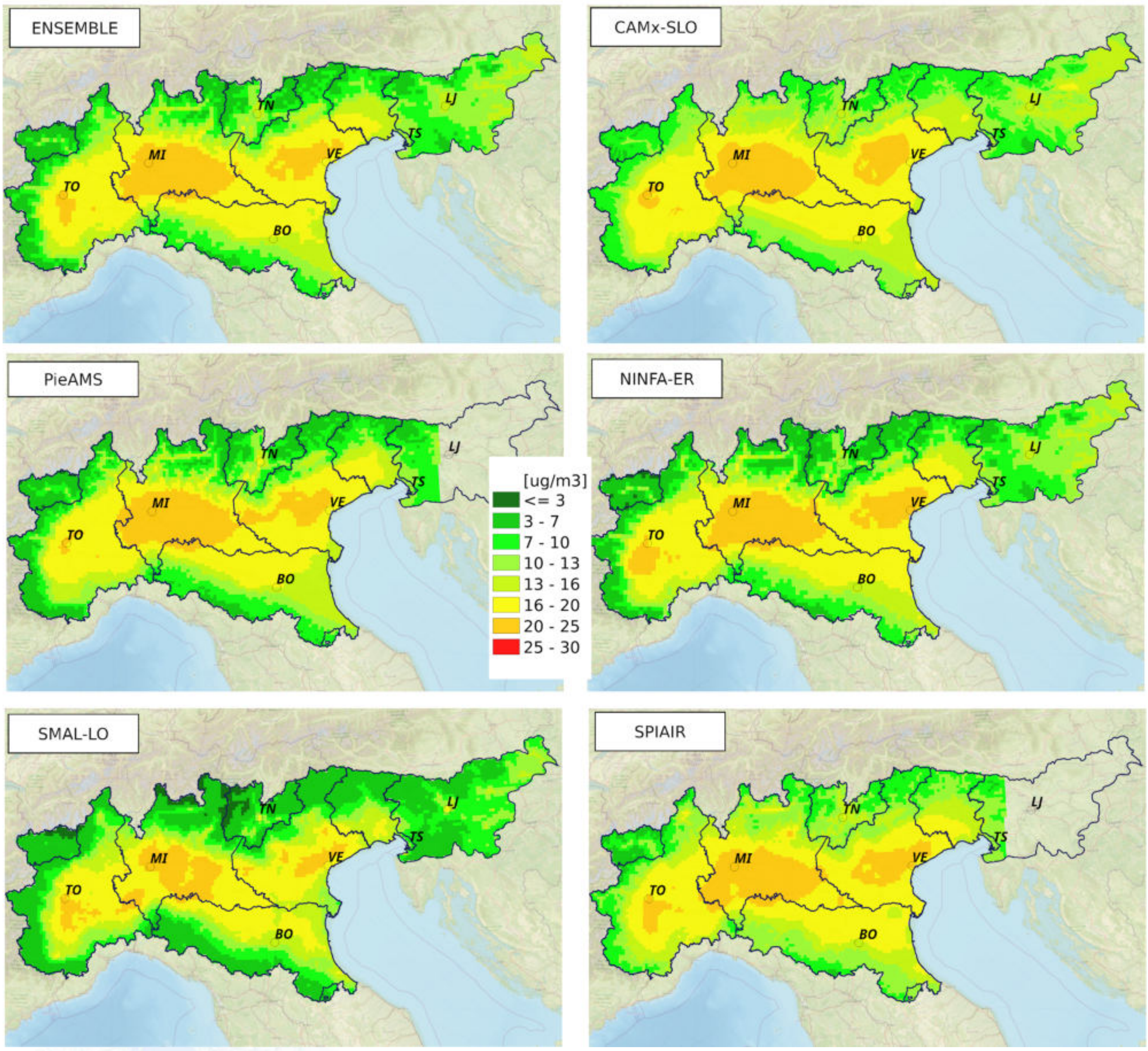

Figure 20 Maps of PM2.5 annual mean produced by the five data fusion systems and by the D5 ensemble (top left of the figure).

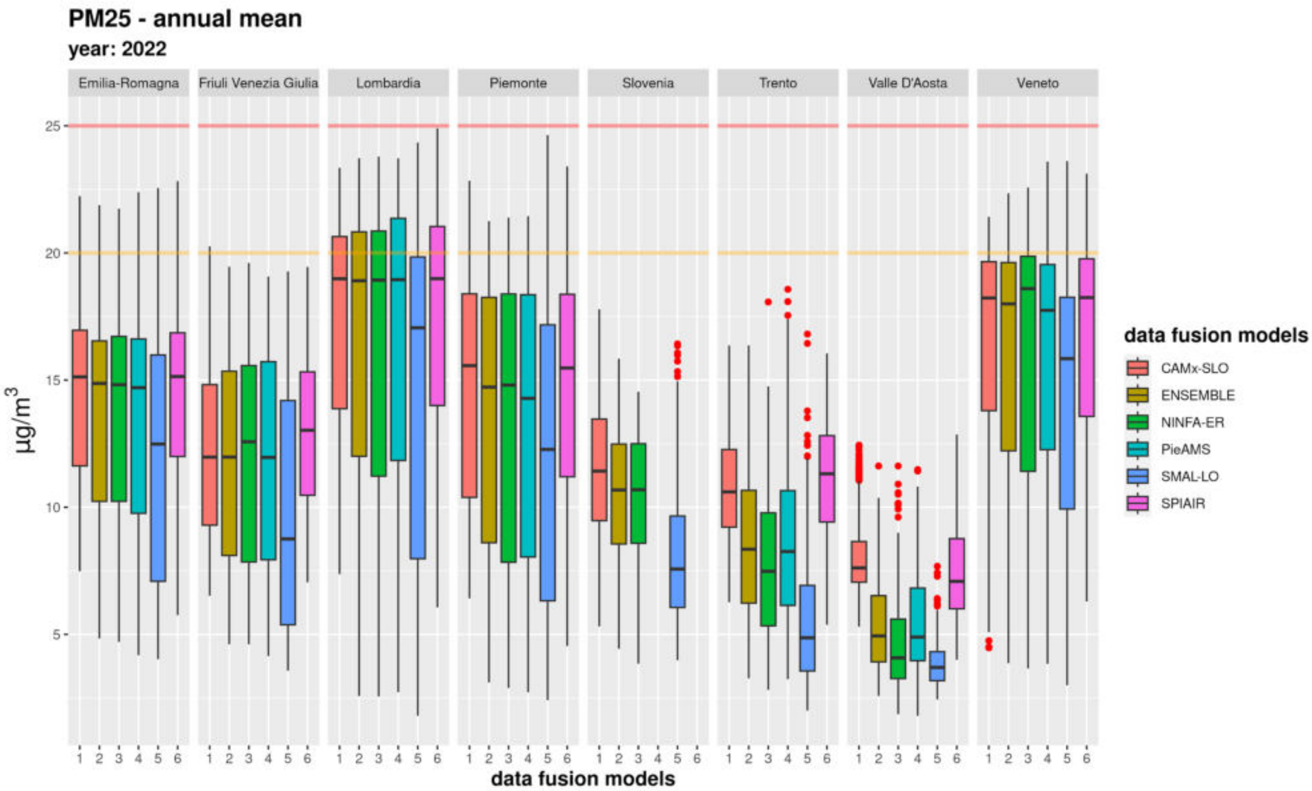

Figure 21. PM2.5, annual mean: boxplots of grid point concentration distributions grouped by model and region. The red lines indicate the EU limit value for stage I (25 µg/m³), while the orange one for stage II (20 µg/m³).

3.3. NO_2

Maps reported in Figure 22 show a quite similar spatial distribution of NO_2 annual mean: all the models identify the main urban agglomerations as areas with the highest values. It is possible to highlight the location of the main highways, in particular from the results of the SMAL-LO and CAMx-SLO modelling systems (due to the higher resolution of the grid). Only one model out of five (SMAL-LO) estimates the annual mean of NO_2 concentration above the EU limit value in a very small area around Milan metropolitan area. Figure 23 confirms the considerations expressed in paragraphs 3.1 and 3.2 regarding the differences between the spatial distributions of the various data fusion systems.

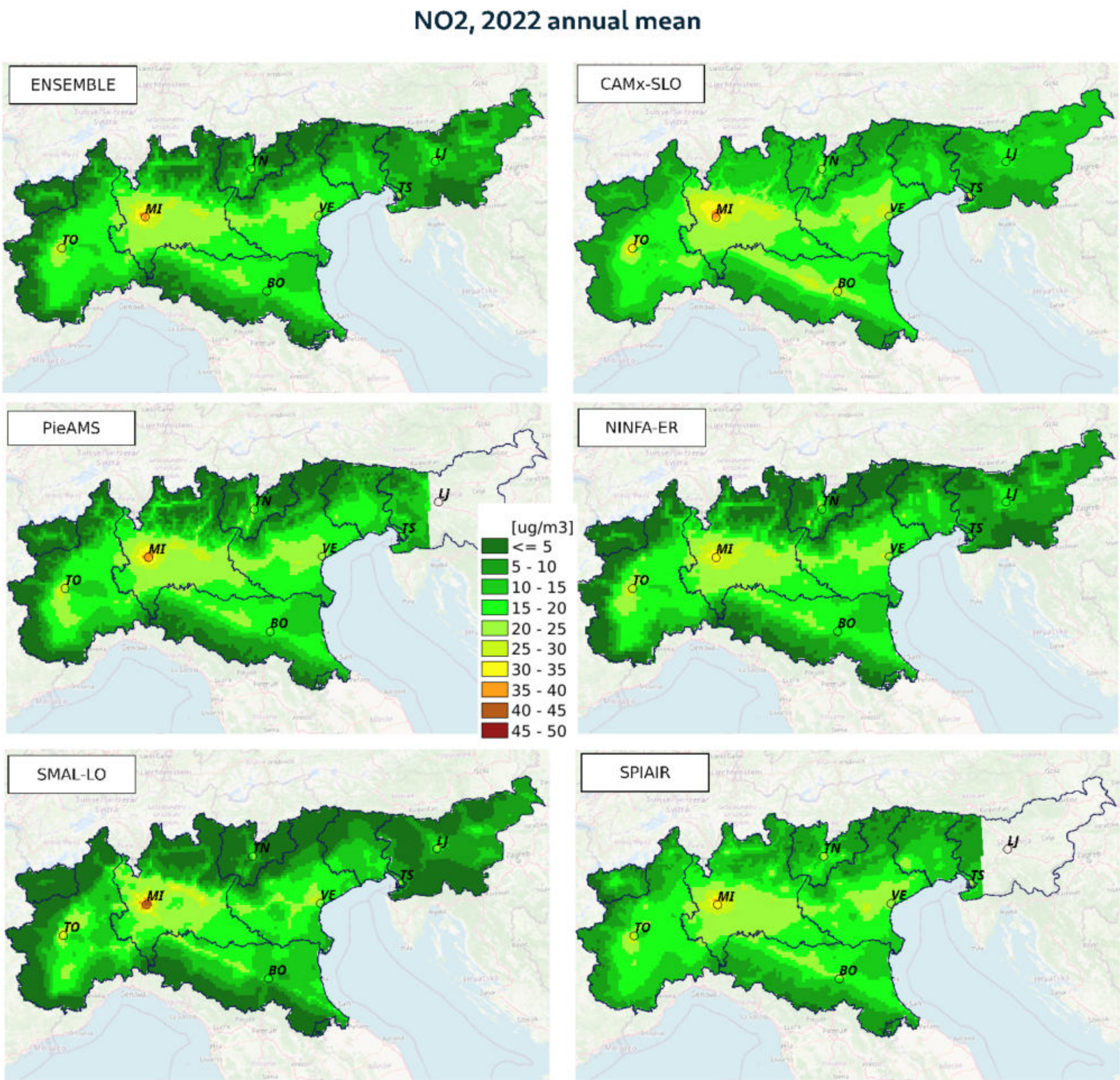

Figure 22. Maps of NO_2 annual mean produced by the five data fusion systems and by the D5 ensemble (top left of the figure).

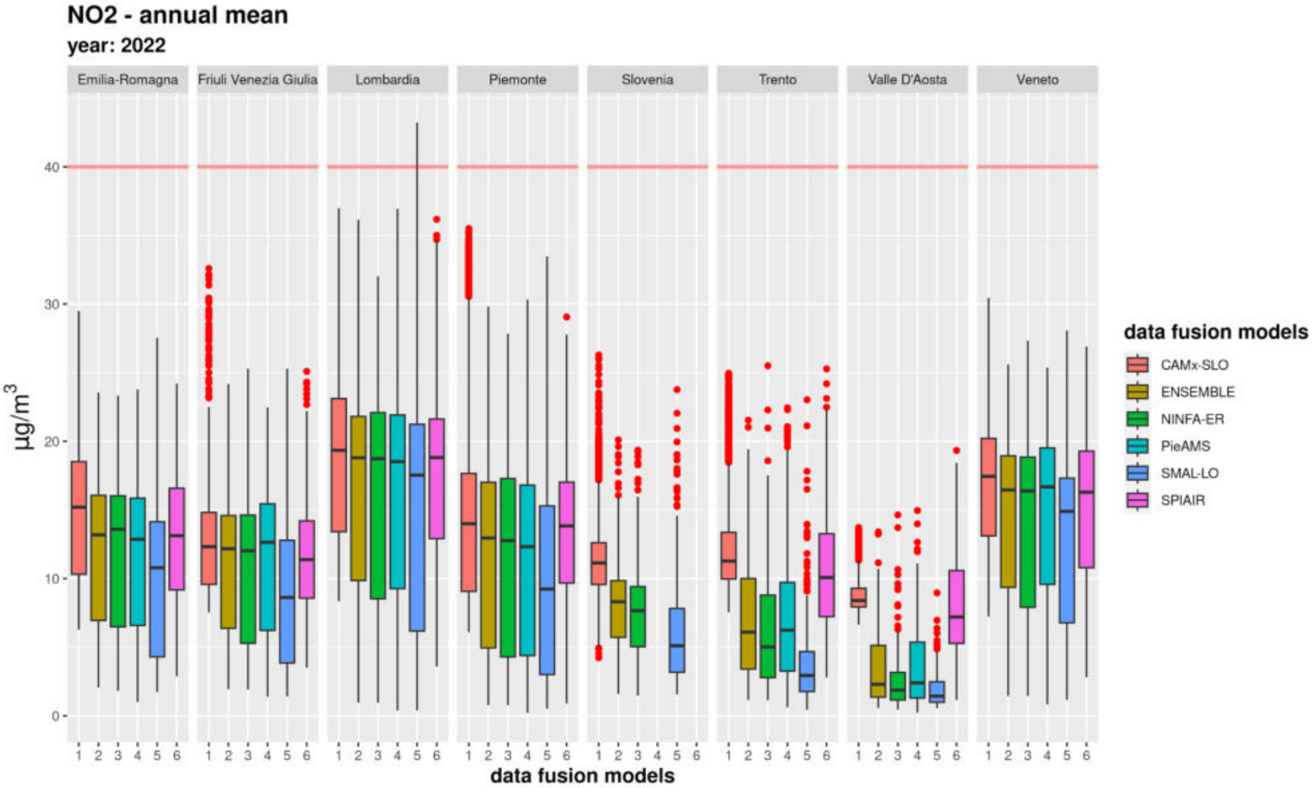

Figure 22. NO_2 annual mean: boxplots of grid point concentration distributions grouped by model and region. The red lines indicate the EU limit value (40 µg/m^3)

3.4. O3

The maps in Figure 23 show the spatial distribution of O_3 maximum daily 8-hour mean concentration values. All the models estimate concentration above the 120 µg/m^3 threshold, implying an exceedance of the target value in almost the entire Po Valley. Nevertheless we can see some differences between the models, especially in the Apennine area of the Emilia-Romagna region, where SMAL-LO and SPIAIR show a different spatial distribution, both among themselves and with respect to the other three systems. Moreover, SMAL-LO also shows on the Alps lower ozone levels than all other models, while SPIAIR has very high concentrations in Piemonte region (see Figure 24); higher values are localised on a small area in the mountains near the border with France where the model foreseas a peak of ozone.

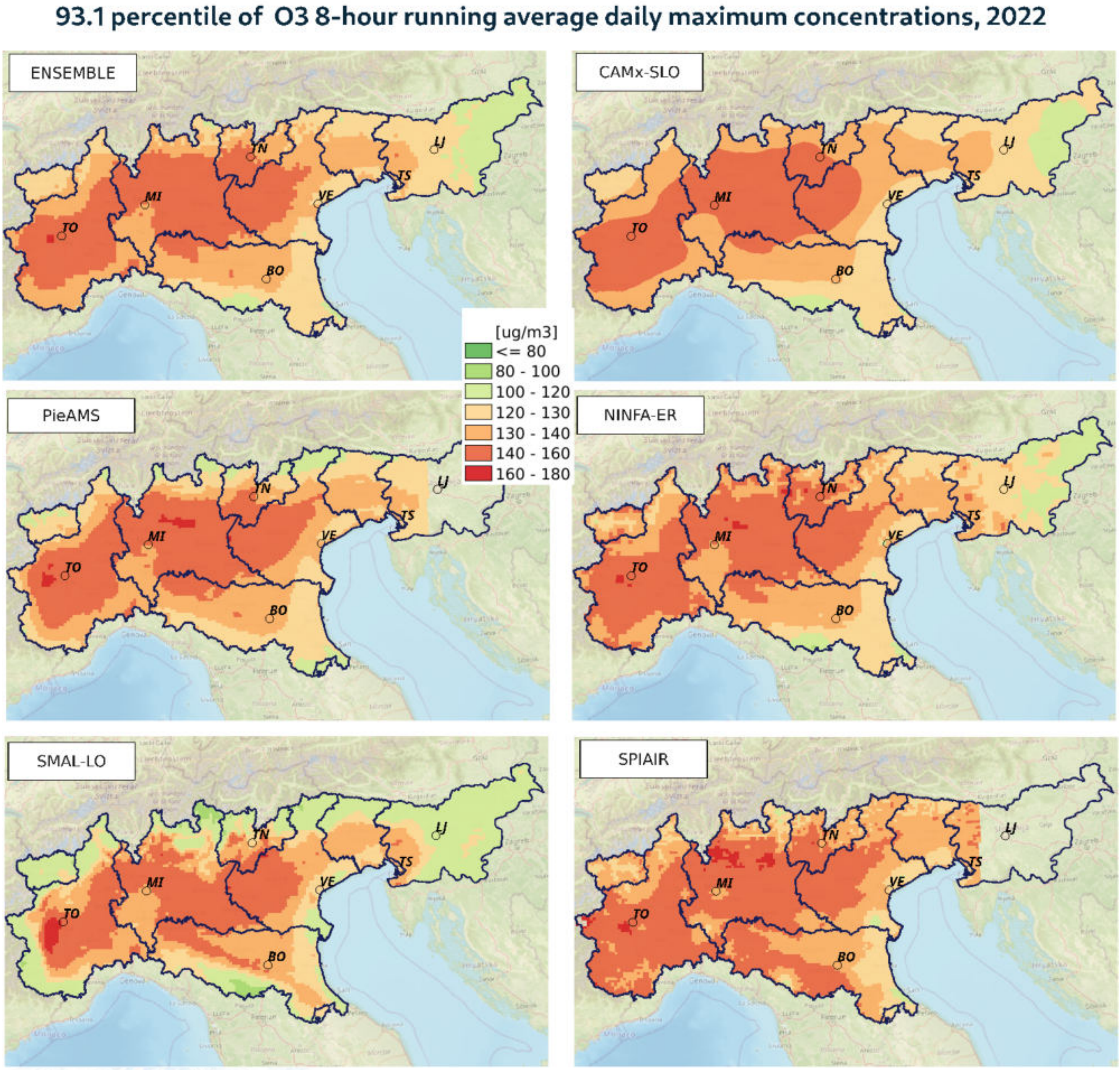

Figure 23 Maps of O_3 93.1 percentile produced by the five data fusion systems and by the D5 ensemble (top left of the figure).

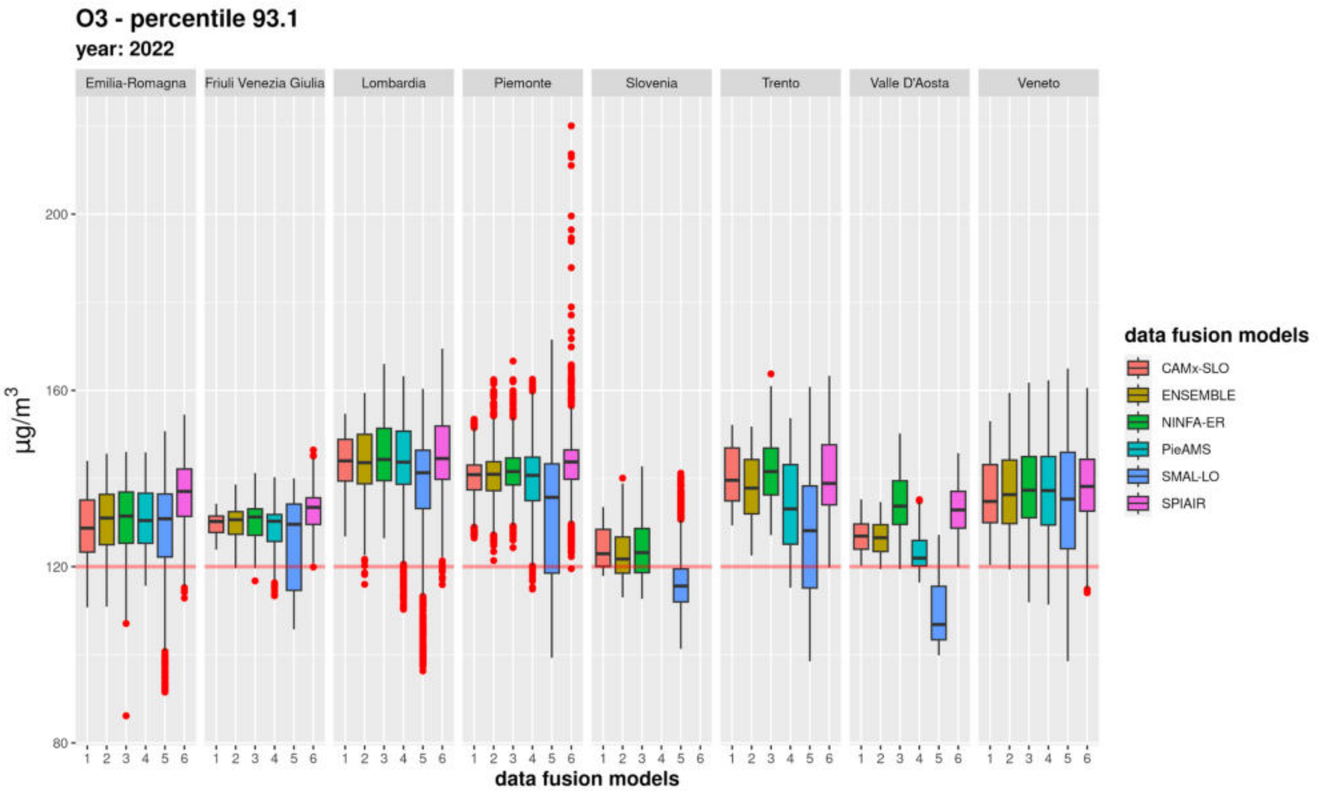

Figure 24. O_3 93.1 percentile: boxplots of grid point concentration distributions grouped by model and region. The red lines indicate the EU target value (120 µg/m^3)

3.5. ATTAINMENT STATUS/POPULATION EXPOSURE

The following Figure 25 and Figure 26 show the maps of the four air quality indicators produced by the five data fusion and by the D5 ensemble systems with a traffic light classification that highlights the attainment green areas and the nonattainment red areas. In summary, it can be stated that:

- there are no nonattainment areas for the annual mean of PM10 (Figure 25, left), as also confirmed by the monitoring data reported in Appendix A;
- there are no nonattainment areas for the annual mean of NO_2 (Figure 26, right); only one model predicts one very small nonattainment near Milan; the monitoring data, as show in Appendix A, record exceedances only in a few traffic stations located in Lombardia, and in one traffic station located in Turin metropolitan area;
- for the percentile 90.41 of PM10 (Figure 25, right) the nonattainment area extends across the whole flat area of the Po Valley; the monitoring data in Appendix A show exceedances in Piemonte, Lombardia,

Veneto, Emilia-Romagna (only for traffic stations) and in Friuli Venezia Giulia regions (only one background monitoring station in this case);

- there are no nonattainment red areas or PM2.5 annual mean regarding EU limit of 25 µg/m^3; instead considering the limit of 20 µg/m^3 the nonattainment area (yellow areas in Figure 26, left) extends across a significant part of Lombardia and minority part of Veneto and Piemonte. The same scenario is described by monitoring data reported in Appendix A, but with exceedances also in Emilia Romagna region;
- for the percentile 93.15 of O_3 the nonattainment area extends across almost the whole Po Valley, confirmed by the monitoring data reported in Appendix A (it is to notice that the legal definition of the target value considers not only 1 year but the average over 3 years).

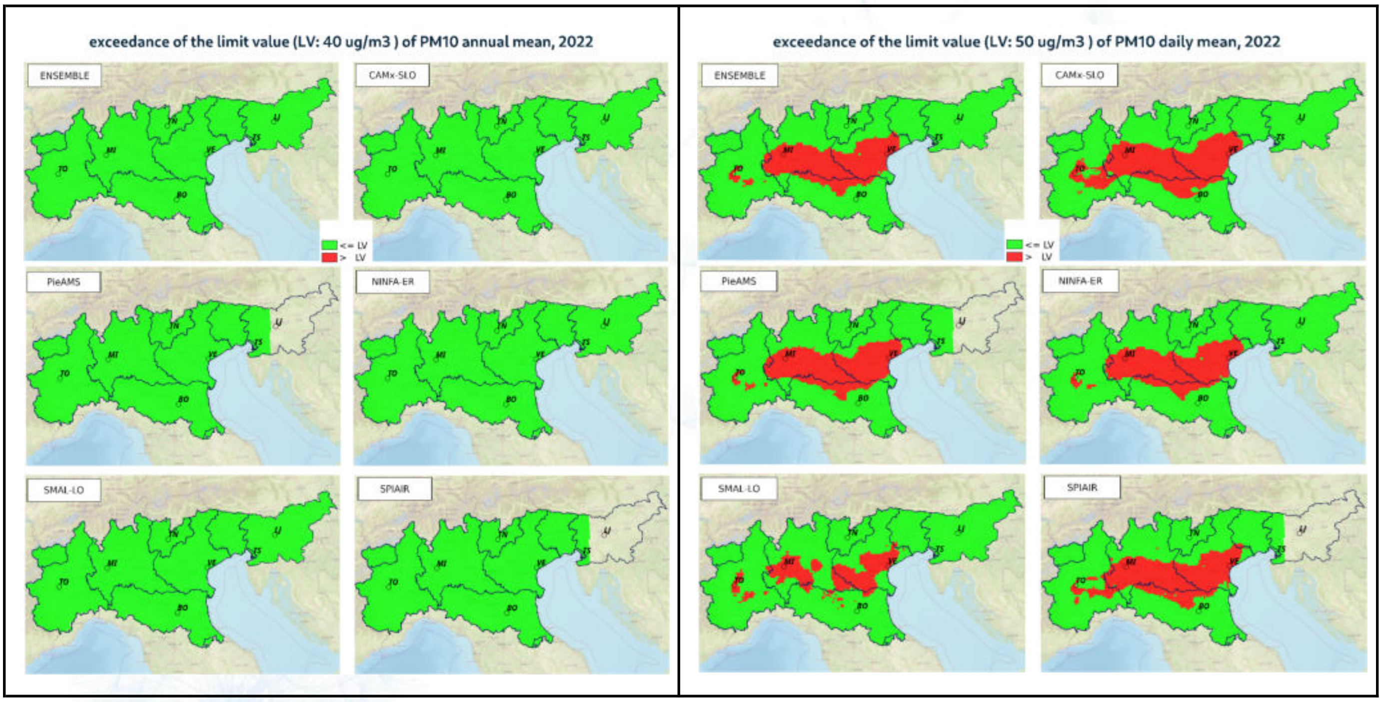

Figure 25. Attainment (green) and nonattainment (red) areas for PM10 annual mean (left) and PM10 percentile 90.41 (right).

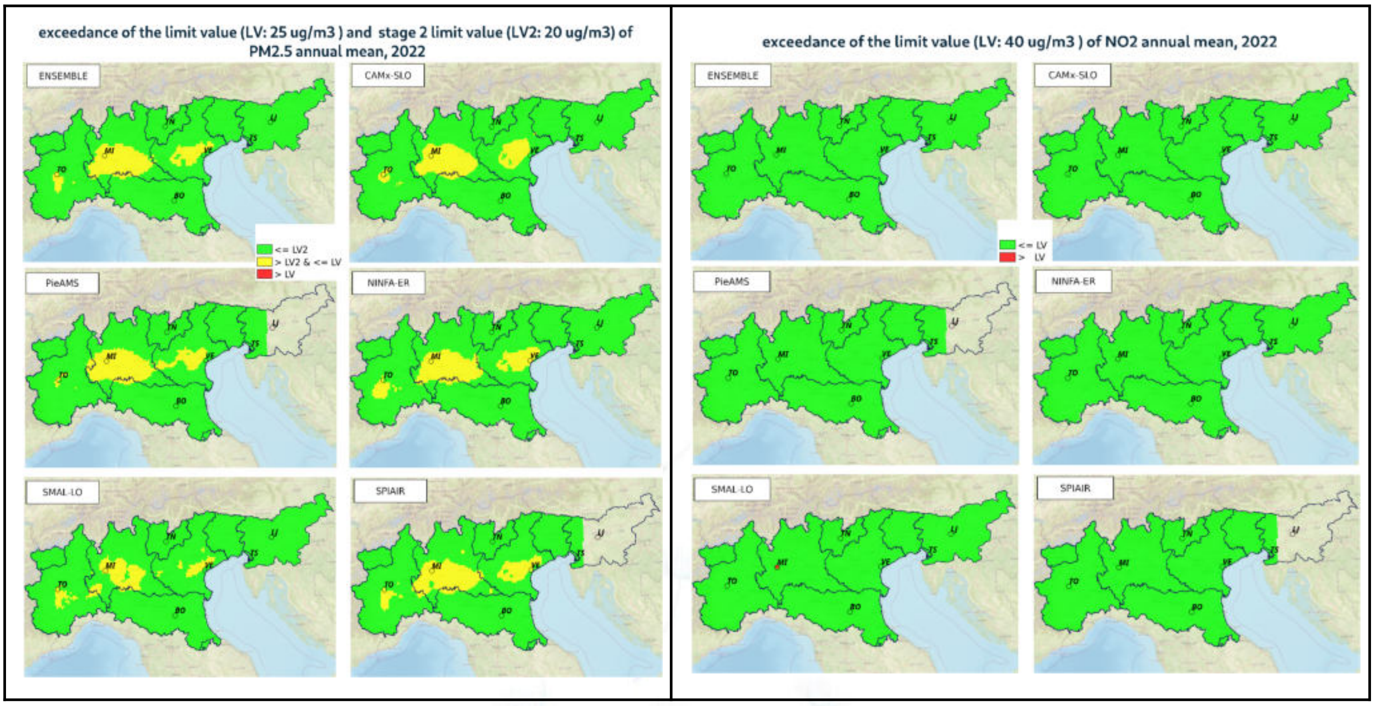

Figure 26. Attainment (green) and nonattainment (red) areas for PM2.5 annual mean (left) and NO_2 annual mean (right). In the PM2.5 maps yellow areas indicate attainment regarding the EU limit of 25 µg/m^3 and nonattainment for EU limit of 20 µg/m^3.

Annual values of the five air quality indexes considered in this report, as estimated by the five considered chemistry-transport models, are compared with the population data on the same grids, i.e. on the grid of each model, in order to assess the population exposure. Population data have been provided by the Italian Statistical Institute ISTAT for the Italian regions, on the census units, referring to 2011, and for Slovenia by the Statistical Office of the Republic of Slovenia SURS, on a regular grid of 100m resolution, referring to 2019. Population data have been splitted (in the Italian regions only, given the irregularity of the census units) and reaggregated (both in Italy and in Slovenia), proportionally to the surface, in order to estimate the population residing in each cell of each model.

Finally, for each air quality index, each model and each considered region, the population exposed to different index values was estimated, assuming that each inhabitant is exposed to the concentration that was estimated in the cell in which it resides. In particular, the population exposed to values exceeding the thresholds established by EU legislation has been estimated.

According to all models, in 2022 no citizens were exposed to values beyond the threshold for the PM10 annual average.

Only one model out of five estimates that there were inhabitants exposed to values above the threshold for the NO_2 annual average (about 920000 in Lombardia region er). The other four models remain under the limits across their domain.

All the models agree in estimating that a significant part of the population of Lombardia, Veneto and Piemonte was exposed to average PM2.5 annual values above 20 μg/m^3. Only a small fraction of the population of Emilia-Romagna are exposed for this index; for Slovenia there is little agreement between the three models that cover that area.

About seven million from Lombardia, three million and a half from Veneto, two million from Piemonte, one million and half from Emilia-Romagna and even 65,000 from Friuli Venezia Giulia were exposed to more than 35 daily PM10 exceedances in 2022.

Almost nine and half million Lombards, about five million from Veneto, four and a half from Piemonte, almost four from Emilia-Romagna, about two hundred thousand from Friuli Venezia Giulia, half a million from Trentino Alto Adige and one and half million Slovenes and even some thousands of inhabitants of the Valle d'Aosta were exposed to more than 25 daily ozone exceedances in 2022.

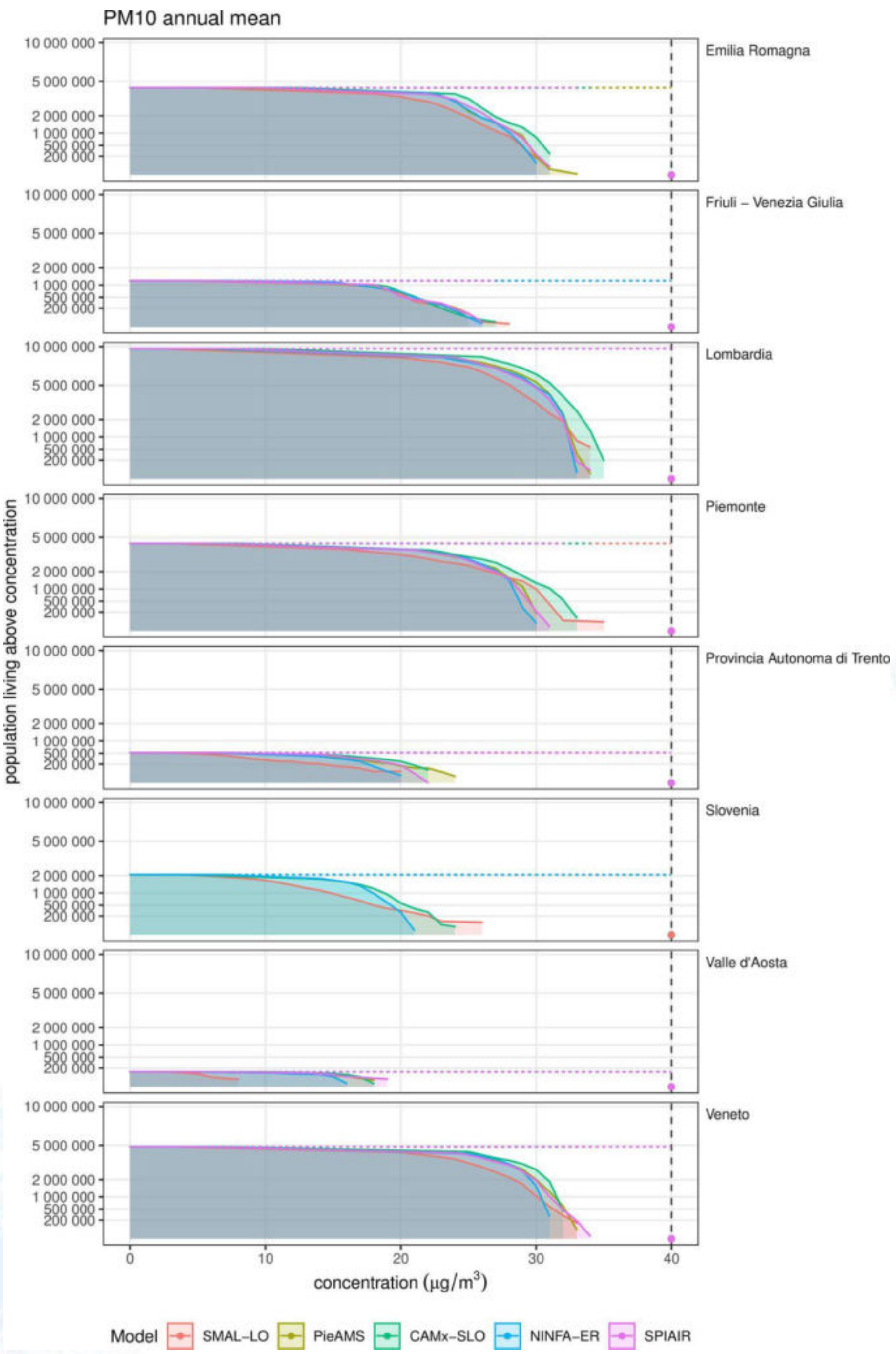

Figure 26. Population exposure estimate for PM10 annual mean.

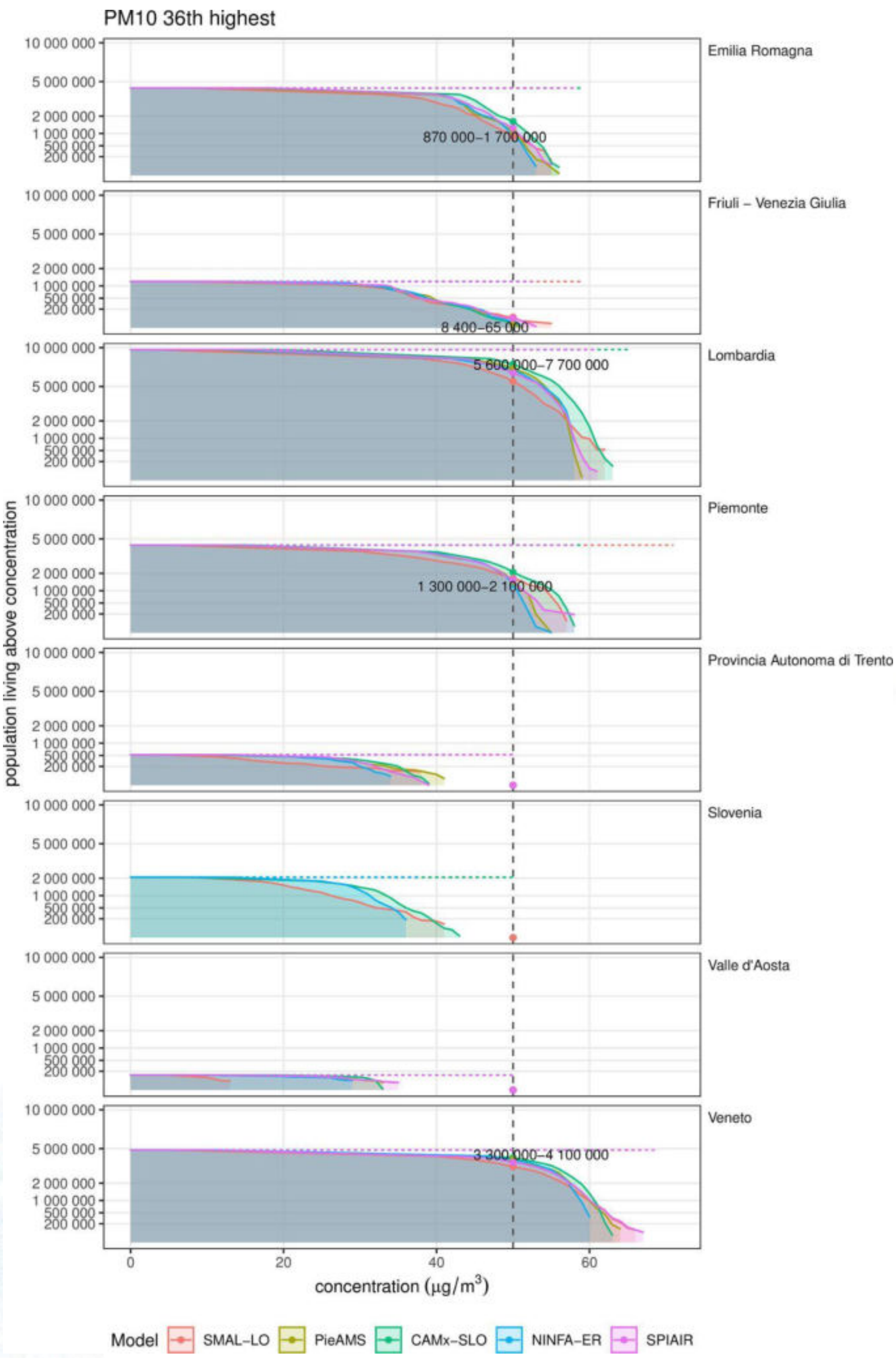

Figure 27. Population exposure estimate for percentile 90.41 of PM10.

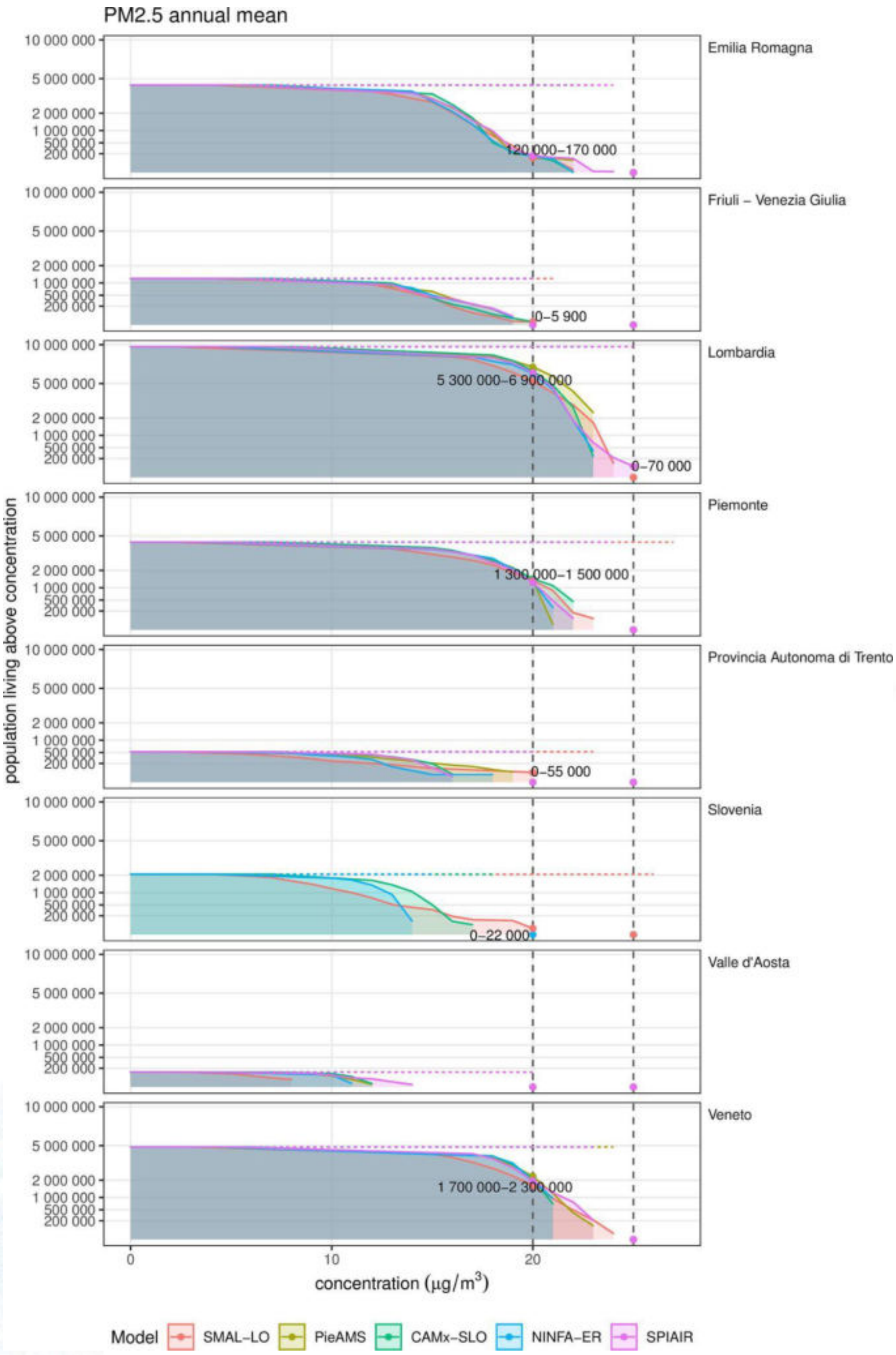

Figure 28. Population exposure estimate for PM2.5 annual mean.

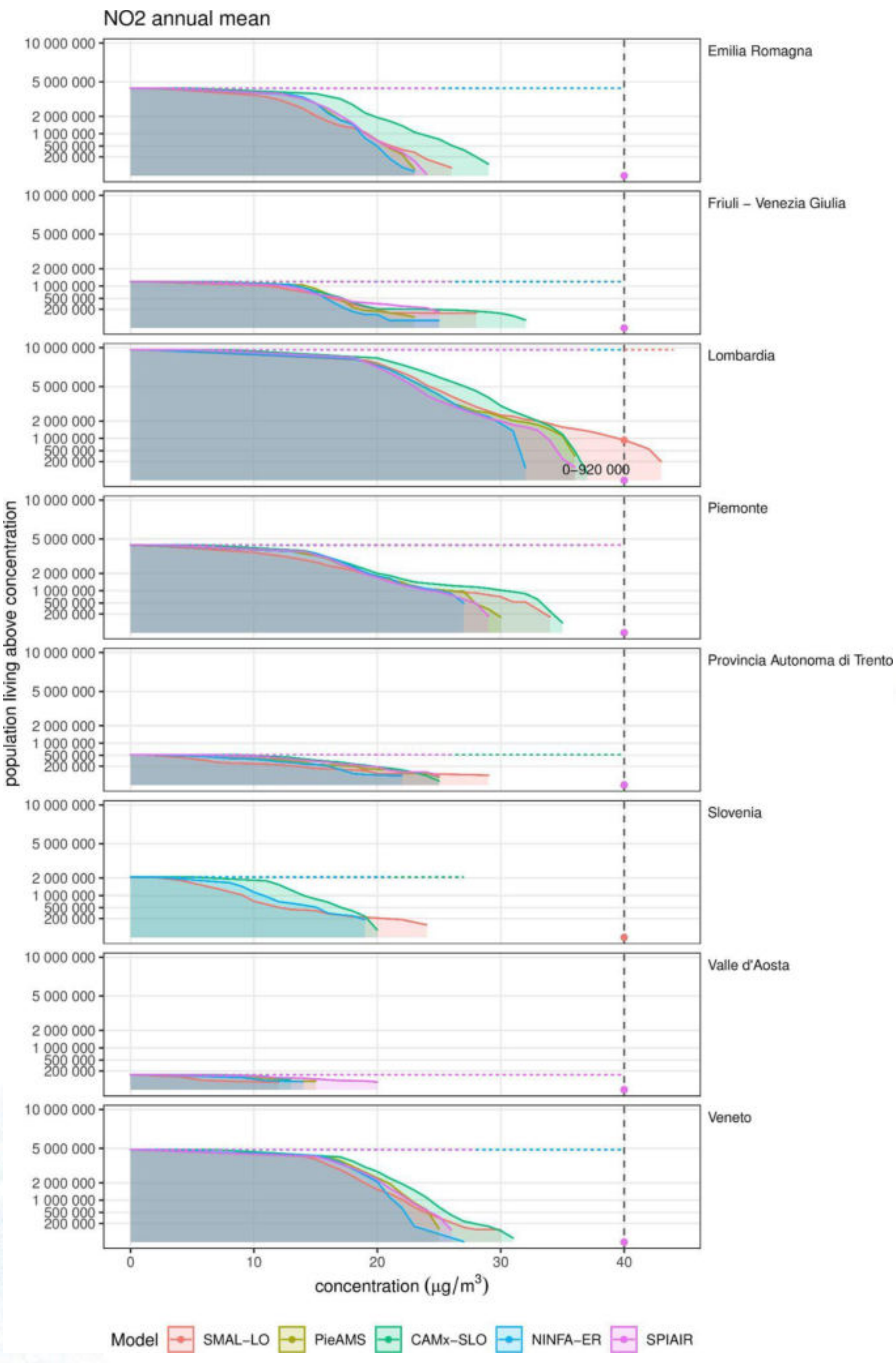

Figure 29. Population exposure estimate for NO_2 annual mean.

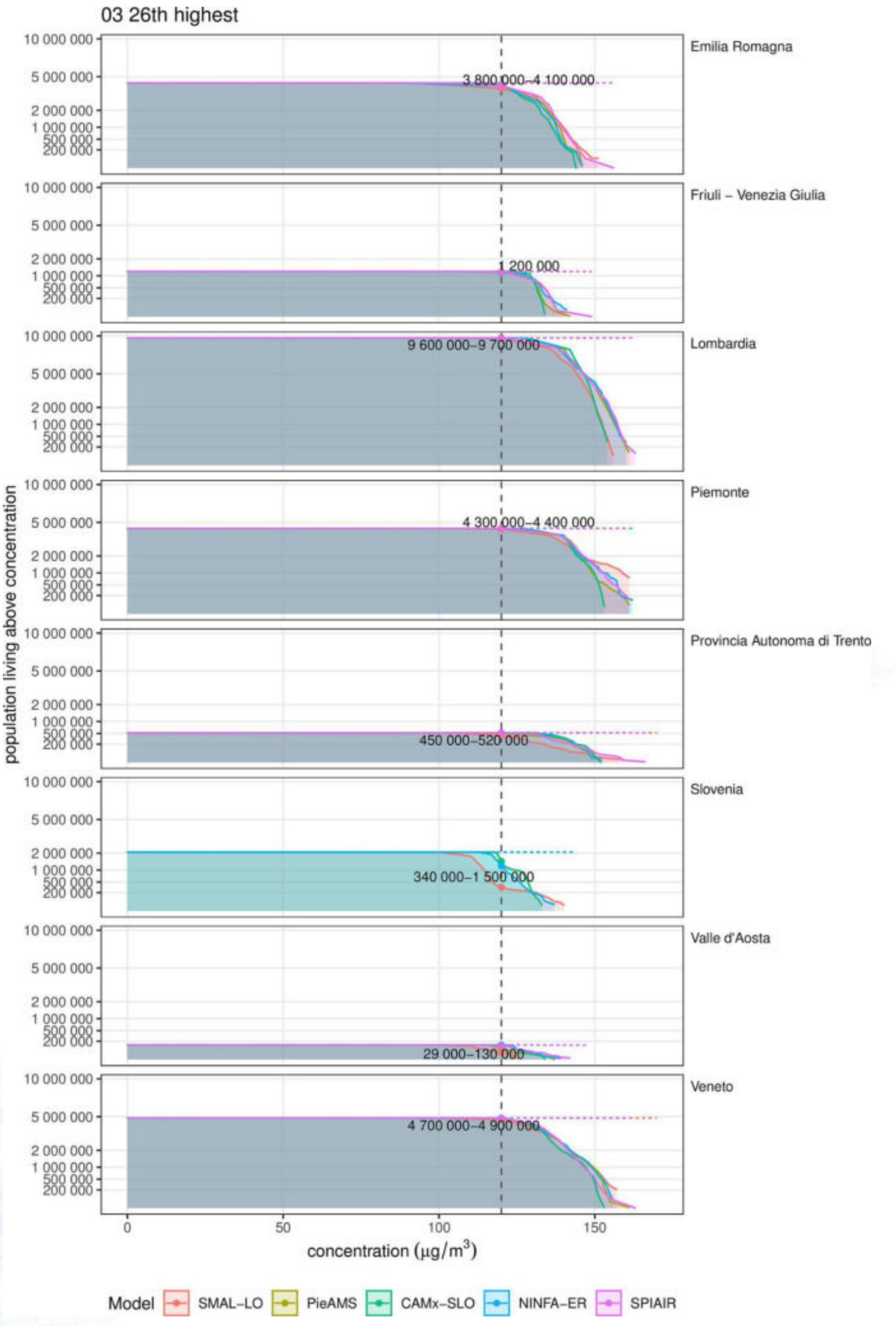

Figure 30. Population exposure estimate for ozone percentile 93.10.

4. DISCUSSION

This third Air Quality Assessment report provides a synthetic view on the state of air quality in Po Valley and Slovenia for year 2022 and examines PM10, PM2.5, nitrogen dioxide and ozone, which are the pollutants whose values more frequently exceed legislation thresholds.

The assessment was carried out with a state-of-art approach that uses data fusion techniques to integrate information coming from air quality monitoring networks and CTM modelling systems. Among all the CTM running operational within the PREPAIR project, five modelling and data fusion systems have been used for the 2022 assessment.

No data fusion system estimates PM10 annual average concentrations beyond the threshold value of 40 µg/m^3, while all the models report PM10 concentrations above the EU daily limit value for the flat area of the Po Valley, thereby a large percentage of the population is exposed to values beyond the daily limit value.

A significant percentage of populations, especially in Lombardia, Veneto and Piemonte is exposed to average annual values of PM2.5 above the stage II limit (20 µg/m^3); nevertheless, no data fusion system estimates PM2.5 annual average concentrations beyond the stage I limit (25 µg/m^3)

All the data fusion systems identify the main urban agglomerations as areas with the highest values of NO2 concentrations. Only one model out of five estimates the annual mean average of NO2 concentration above the EU limit value in a very small area around Milan.

All the data fusion systems show ozone concentration above the 120 µg/m^3 threshold, implying an exceedance of the target value in almost the entire Po Valley and more than 24 million of inhabitants exposed to value beyond EU limit.

It should be noted that the purpose of this report is informative, it does not replace the annual air quality assessment and reports required by EU directives and decisions (2008/50/EU and 2011/850/EU).

Finally, it must be underlined that although the five CTM systems have different setup (resolution, boundary condition, meteorological data and data fusion technique), the model outputs are similar to each other showing the reliability of the assessment contained in the report.

Glossary

ALADIN	a numerical weather prediction system (Aire Limitée Adaptation dynamique Développement InterNational)
APPA/ARPA/Arpae	environment protection agency of one of the Italian regions or autonomous provinces
AQF	air quality forecast
ARSO	Slovenian environment agency
CAMS	Copernicus Atmosphere Monitoring Service
CAMx	Comprehensive Air Quality Model with Extensions
COSMO	Consortium for Small-scale Modelling
CTM	chemistry-transport model
ECMWF	European Centre for Medium-Range Weather Forecasts
EMEP	European Monitoring and Evaluation Programme

FARM	Flexible Air quality Regional Model
IC/BC	initial conditions/boundary conditions
INEMAR	INventario EMissioni ARia
ISPRA	Italian Institute for Environmental Protection and Research (Istituto Superiore per la Protezione e la Ricerca Ambientale)
KED	kriging with external drift
NINFA	Northern Italy Network to Forecast Aerosol pollution
NWP	numerical weather prediction
PREPAIR	Po Regions engaged to Policies of Air
SAPR	chemical mechanism, part of the chemistry-transport models (originally developed by the Statewide Air Pollution Research Center)
SNAP	emitting sources classification (originally defined in the framework of the “Significant New Alternatives Policy” program of US-EPA)
SNPA	the Italian national system for environmental protection (Sistema nazionale per la protezione dell’ambiente)
WRF	Weather Research and Forecasting model

Bibliography

Berrocal VJ, Gelfand AE, Holland DM (2012). Space-time data fusion under error in computer model output: an application to modelling air quality. Biometrics 68(3): 837–48.

Box GEP, Cox DR (1964) An analysis of transformations. J R Stat Soc Ser B 26:211–246

Cressie NAC (1993). Statistics for Spatial Data. 2nd. New York: Wiley

2011/850/EU: Commission Implementing Decision of 12 December 2011 laying down rules for Directives 2004/107/EC and 2008/50/EC of the European Parliament and of the Council as regards the reciprocal exchange of information and reporting on ambient air quality (notified under document C(2011) 9068) GU L 335 del 17.12.2011, pagg. 86–106, http://data.europa.eu/eli/dec_impl/2011/850/oj

Daley R (1991). Atmospheric data analysis, Roger Daley, Cambridge Atmospheric and Space Science Series, Cambridge University Press

Daley, R., Atmospheric Data Analysis, Cambridge University Press, New York, 1991

Denby B, Georgieva E, Lükewille A (2011) The application of models under the European Union's Air Quality Directive: a technical reference guide. Technical Report 10/2011, European Environmental Agency, Copenhagen

Development Core Team (2010) A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna

Diggle, P.J. and Ribeiro Jr. P. J. (2007) Model-based Geostatistics, Springer

Directive 2008/50/EC of the European Parliament and of the Council of 21 May 2008 on ambient air quality and cleaner air for Europe GU L 152 dell' 11.6.2008, pagg. 1–44, http://data.europa.eu/eli/dir/2008/50/oj

Elbern, H., et al. "Emission rate and chemical state estimation by 4-dimensional variational inversion." Atmospheric Chemistry and Physics 7.14 (2007): 3749-3769.

Gariazzo C, Silibello C, Finardi S, Radice P, Piersanti A, Calori G, Cecinato A, Perrino C, Nusio F, Cagnoli M, Pelliccioni A, Gobbi GP, Di Filippo P (2007) A gas/aerosol air pollutants study over the urban area of rome using a comprehensive chemical transport model. Atmos Environ 41:7286–7303

Ghigo, S.; Bande, S; Ciancarella, L.; Mircea, M.; Piersanti, A.; Righini, G; Baldasano, J.M.; Basagaña, X; Cadum, E. (2017) Mapping air pollutants at municipality level in Italy and Spain. Mapping air pollutants at municipality level in Italy and Spain in support to health impact evaluations. Air Quality, Atmosphere & Health, DOI 10,1007/s 11869-017+0520-x

Giorcelli M., Bande S., Muraro M., Milelli M.(2013) Operational multiscale modelling system for air quality forecast. COSMO NEWSLETTER, vol. 13, p. 58-63

Jan Horálek, Bruce Denby, Peter de Smet, Frank de Leeuw, Pavel Kurfürst, Rob Swart, Twan van Noije Spatial mapping of air quality for European scale assessment. ETC/ACC Technical Paper 2006/6, March 2007.

Ignaccolo R, Ghigo S, Bande S (2013) Functional zoning for air quality. Environ Ecol Stat 20(3):321–339

Lahoz W, Schneider P (2014). Data assimilation: making sense of Earth Observation. Front Environ Sci 2(16): 1–28

Mailler S., L. Menut, D. Khvorostyanov, M. Valari, F. Couvidat, G. Siour, S. Turquety, R. Briant, P. Tuccella, B. Bessagnet, A. Colette, L. Letinois, and F. Meleux, CHIMERE-2017: from urban to hemispheric chemistry-transport modelling, Geosci.ModelDev.,10,2397-2423, https://doi.org/10.5194/gmd-10-2397-2017

Marongiu, A. , Angelino, E. , Moretti, M. , Malvestiti, G. and Fossati, G. (2022) Atmospheric Emission Sources in the Po-Basin from the LIFE-IP PREPAIR Project. Open Journal of Air Pollution, 11, 70-83. doi: 10.4236/ojap.2022.113006

Pielke Sr, Roger A. Mesoscale meteorological modelling. Academic press, 2013.

Raffaelli, K.; Deserti, M.; Stortini, M.; Amorati, R.; Vasconi, M.; Giovannini, G. Improving Air Quality in the Po Valley, Italy: Some Results by the LIFE-IP-PREPAIR Project. Atmosphere 2020, 11, 429. https://doi.org/10.3390/atmos11040429

Ribeiro JR, Diggle PJ (2001) geoR: a package for geostatistical analysis. R-NEWS 1(2):15–18

Silibello C, Bolignano A, Sozzi R, Gariazzo C (2014) Application on chemical transport model and optimized data assimilation methods to provide air quality assessment. Air Quality Atmosphere & Health https://doi.org/10.1007/s11869-014-0235-1

Stortini, M.; Arvani, B.; Deserti, M. Operational Forecast and Daily Assessment of the Air Quality in Italy: A Copernicus-CAMS Downstream Service. Atmosphere 2020, 11, 447. https://doi.org/10.3390/atmos11050447

Wackernagel H (2003) Multivariate geostatistics: an introduction with applications. Springer, Berlin

Yu S, Eder B, Dennis R, Chu S, Schwartz S. 2006. New unbiased symmetric metrics for evaluation of air quality models. Atmospheric Science Letters 7: 26–34.

Zhan, X., Houser, P. R., Walker, J. P., & Crow, W. T. (2006). A method for retrieving high-resolution surface soil moisture from hydros L-band radiometer and radar observations. IEEE Transactions on Geoscience and Remote Sensing, 44(6), 1534-1544.

Appendix A Air Quality Data

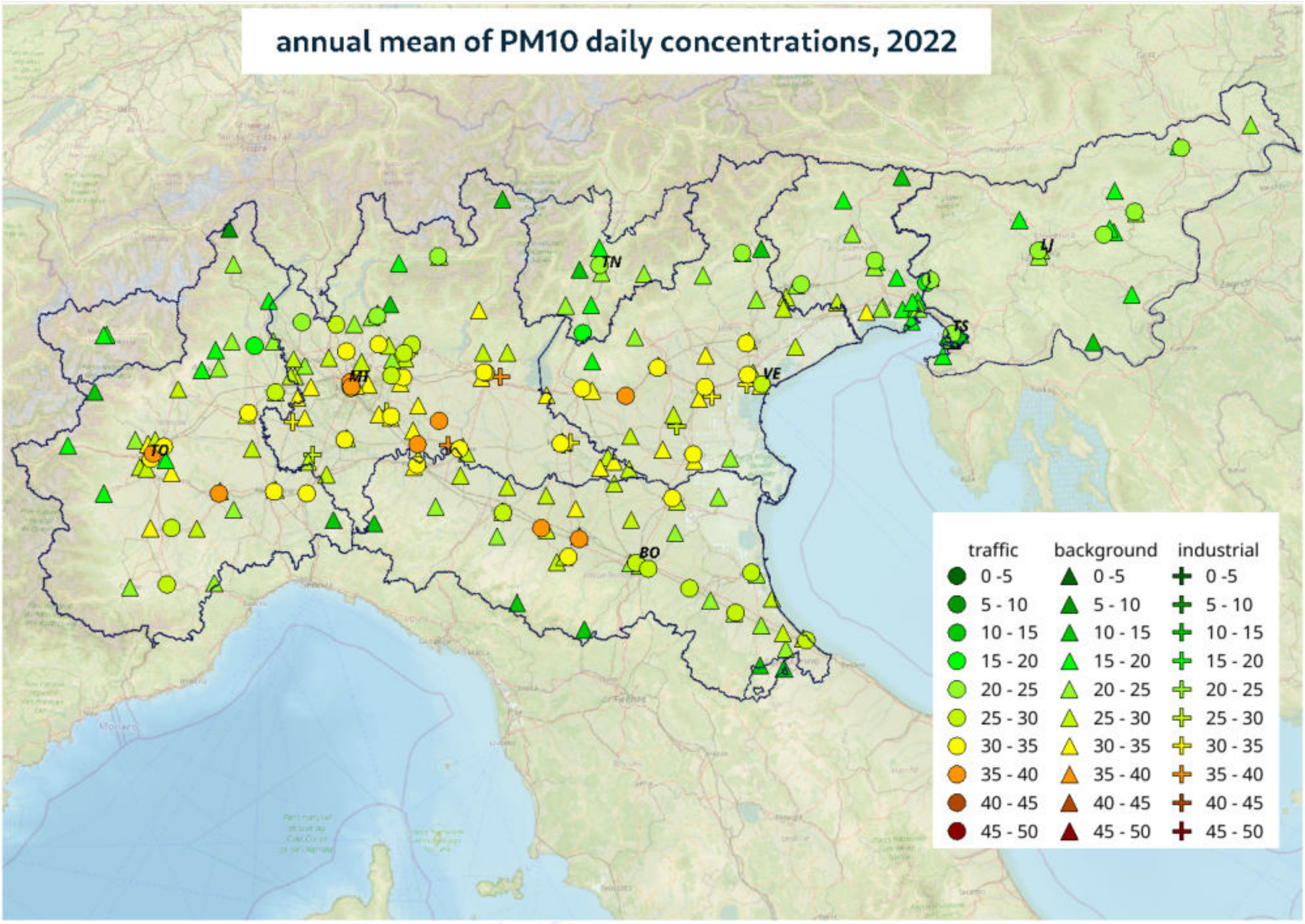

Figure A1. PM10 annual mean: maps of observed data, monitoring stations are grouped by station classification.

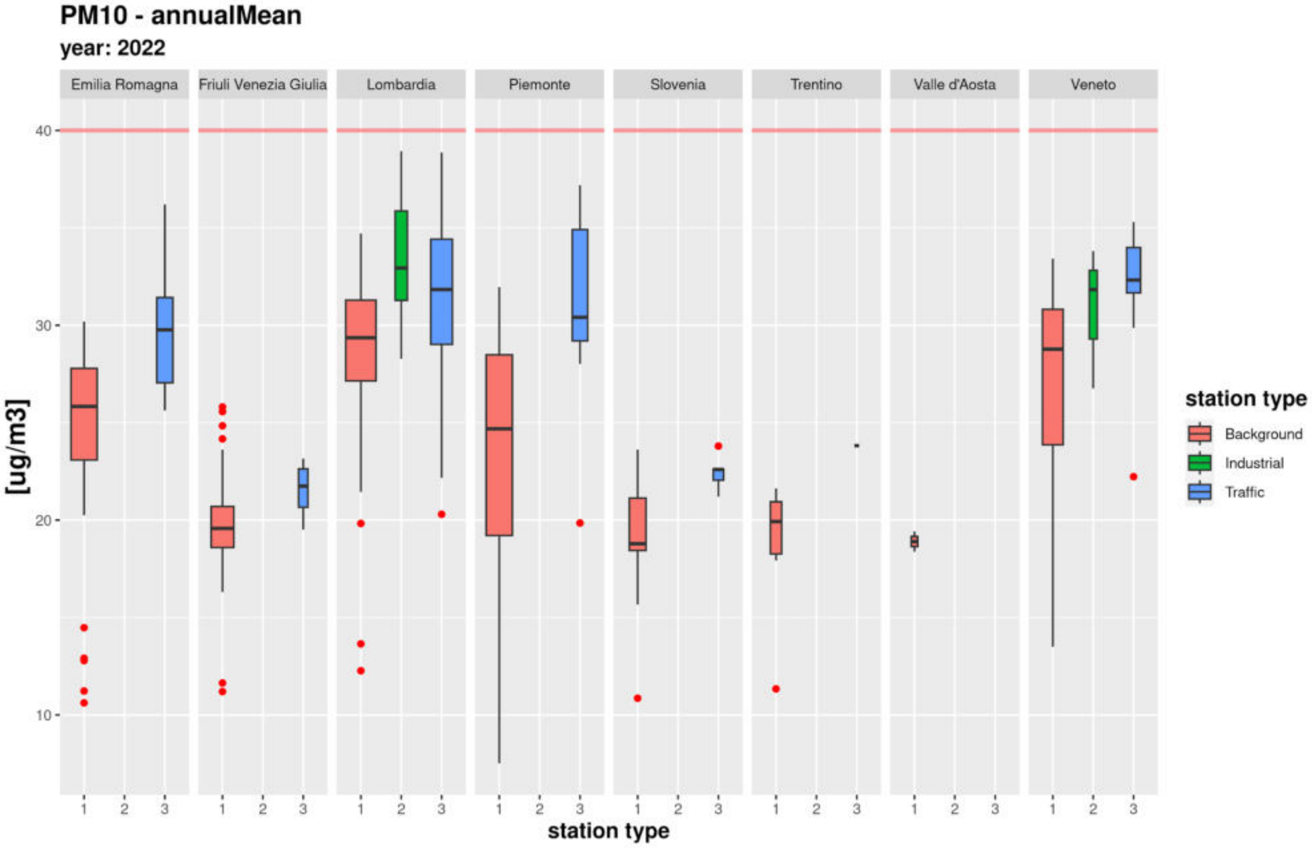

Figure A2. PM10 annual mean: boxplots of observed data grouped by station type and region.

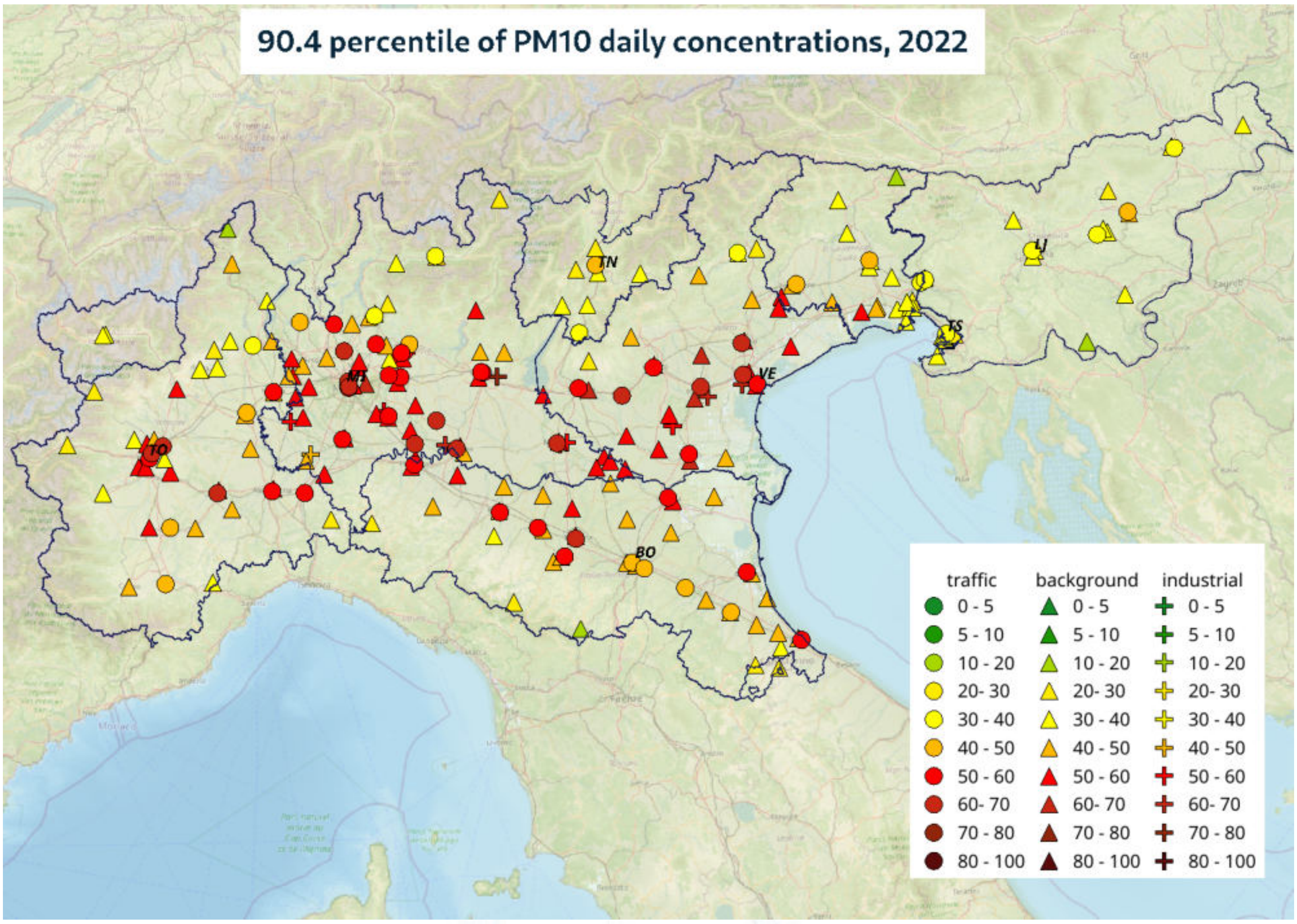

Figure A3. PM10 percentile 90.41: maps of observed data, monitoring stations are grouped by station classification.

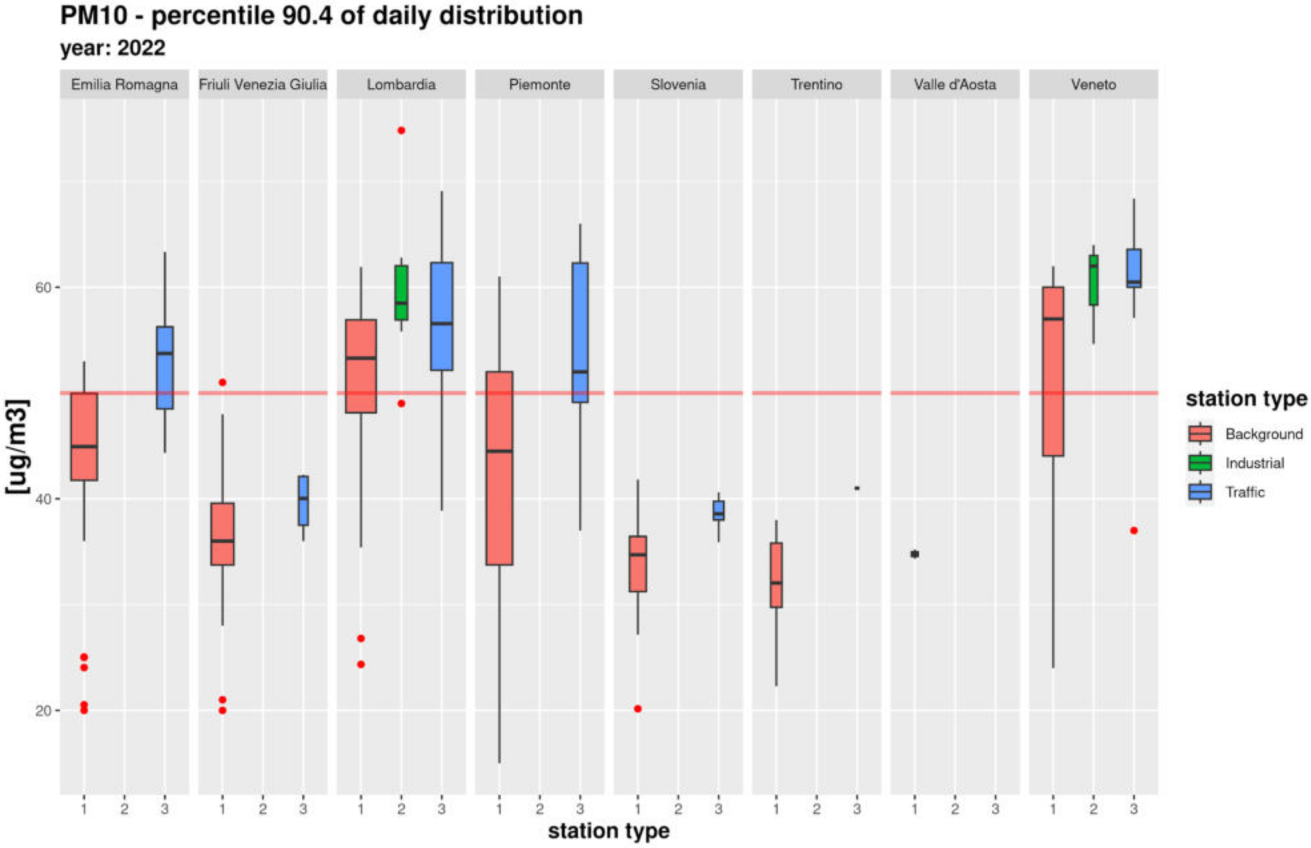

Figure A4. PM10 percentile 90.41: boxplots of observed data grouped by station type and region.

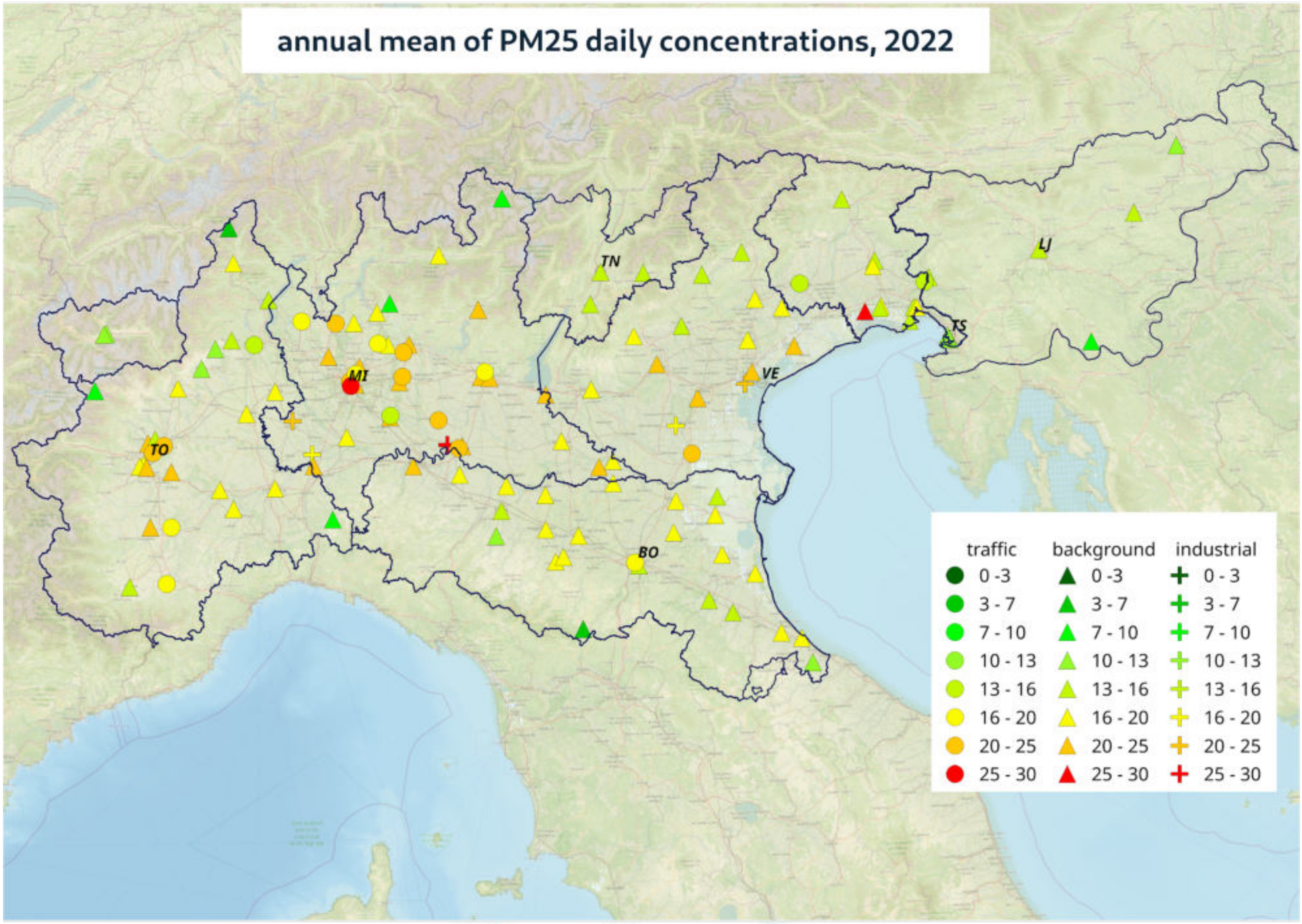

Figure A5. PM2.5 annual mean: maps of observed data, monitoring stations are grouped by station classification.

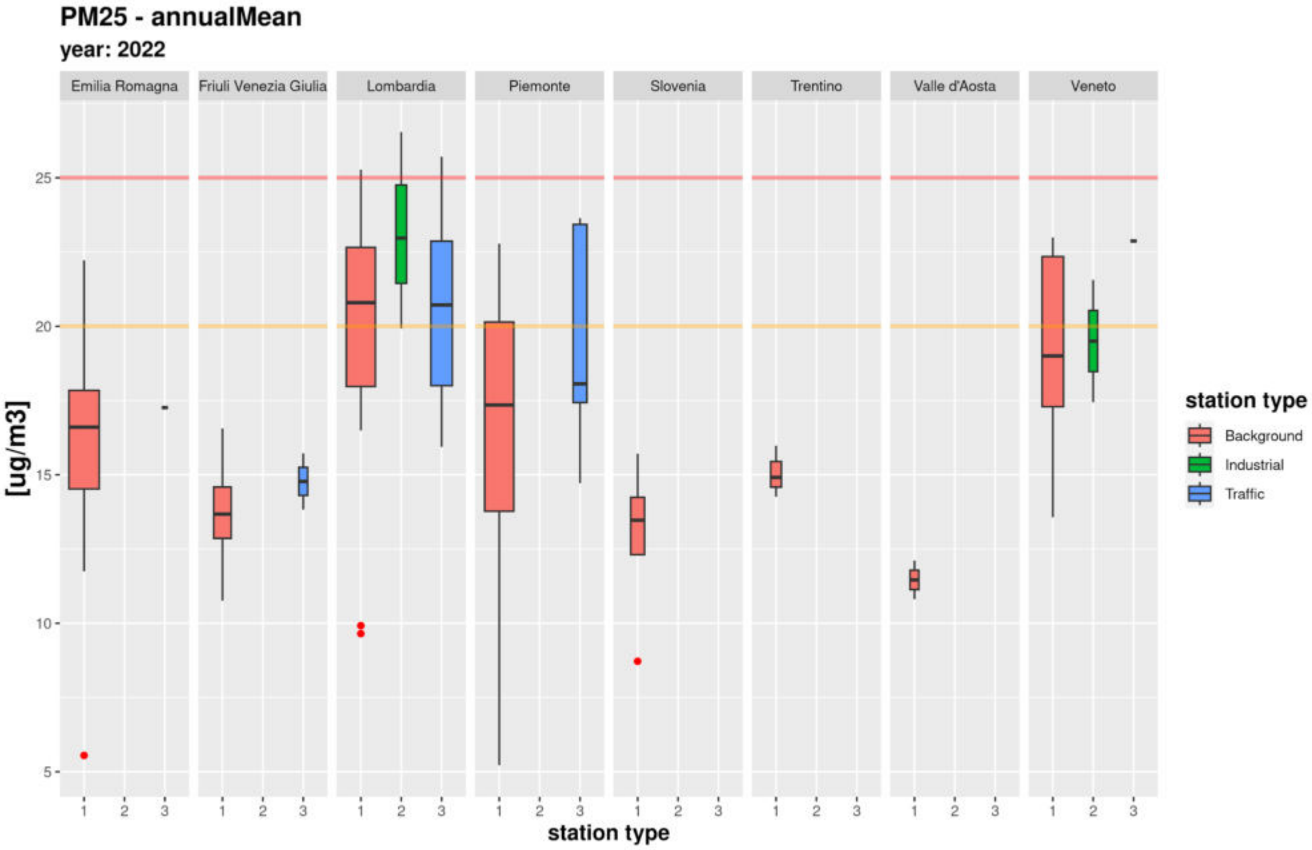

Figure A6. PM2.5 annual mean: boxplots of observed data grouped by station type and region.

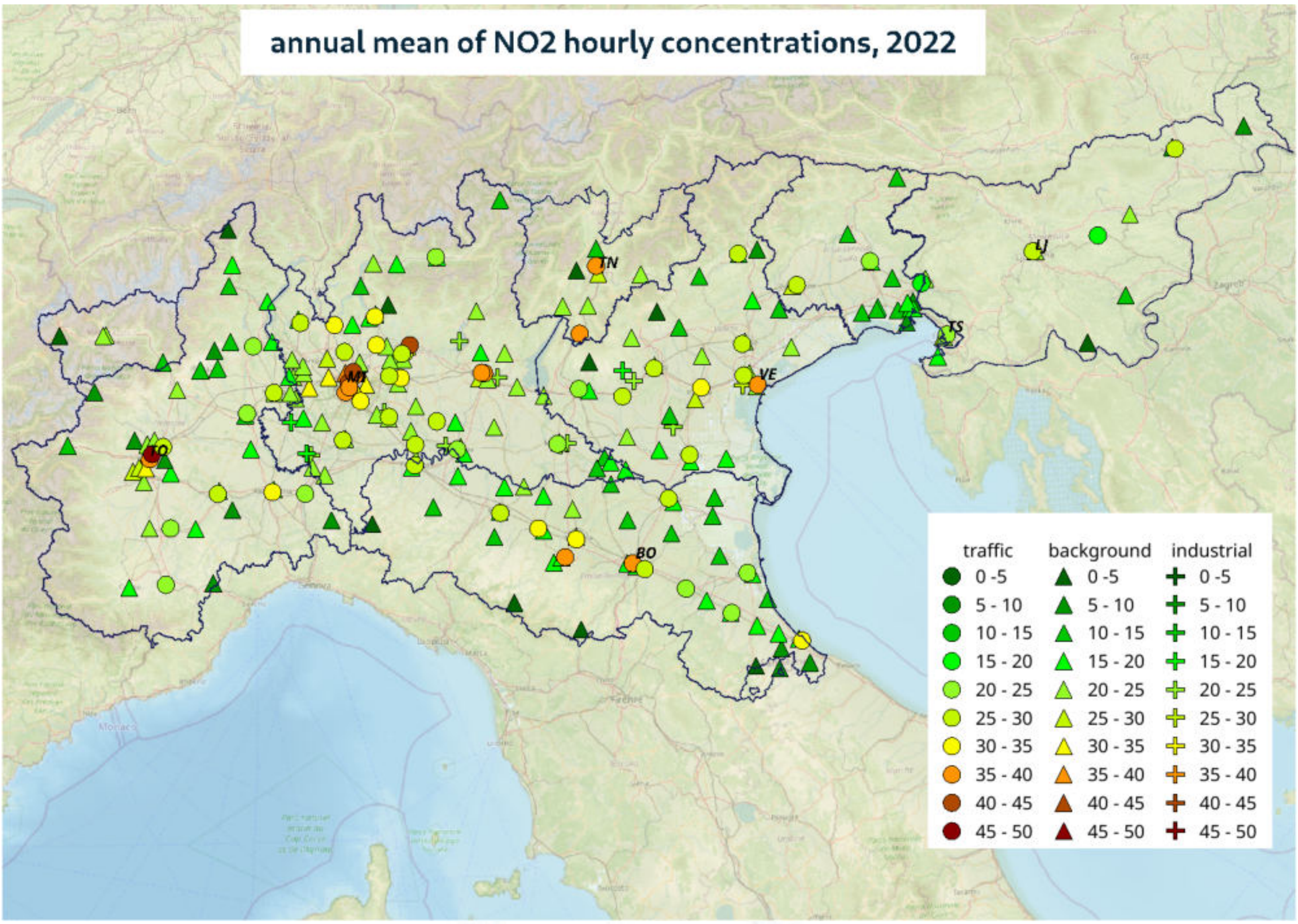

Figure A7. NO_2 annual mean: maps of observed data, monitoring stations are grouped by station classification.

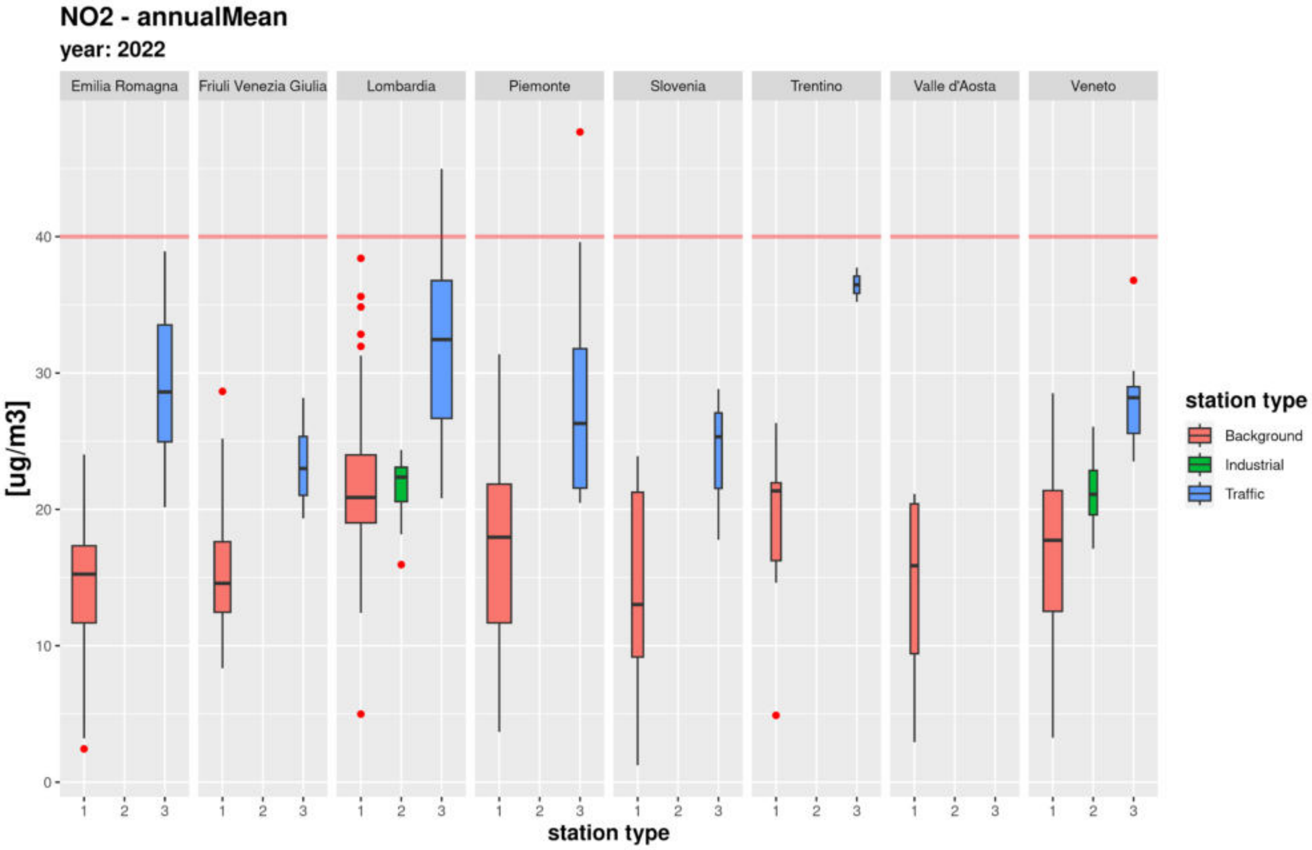

Figure A8. NO_2 annual mean: boxplots of observed data grouped by station type and region.

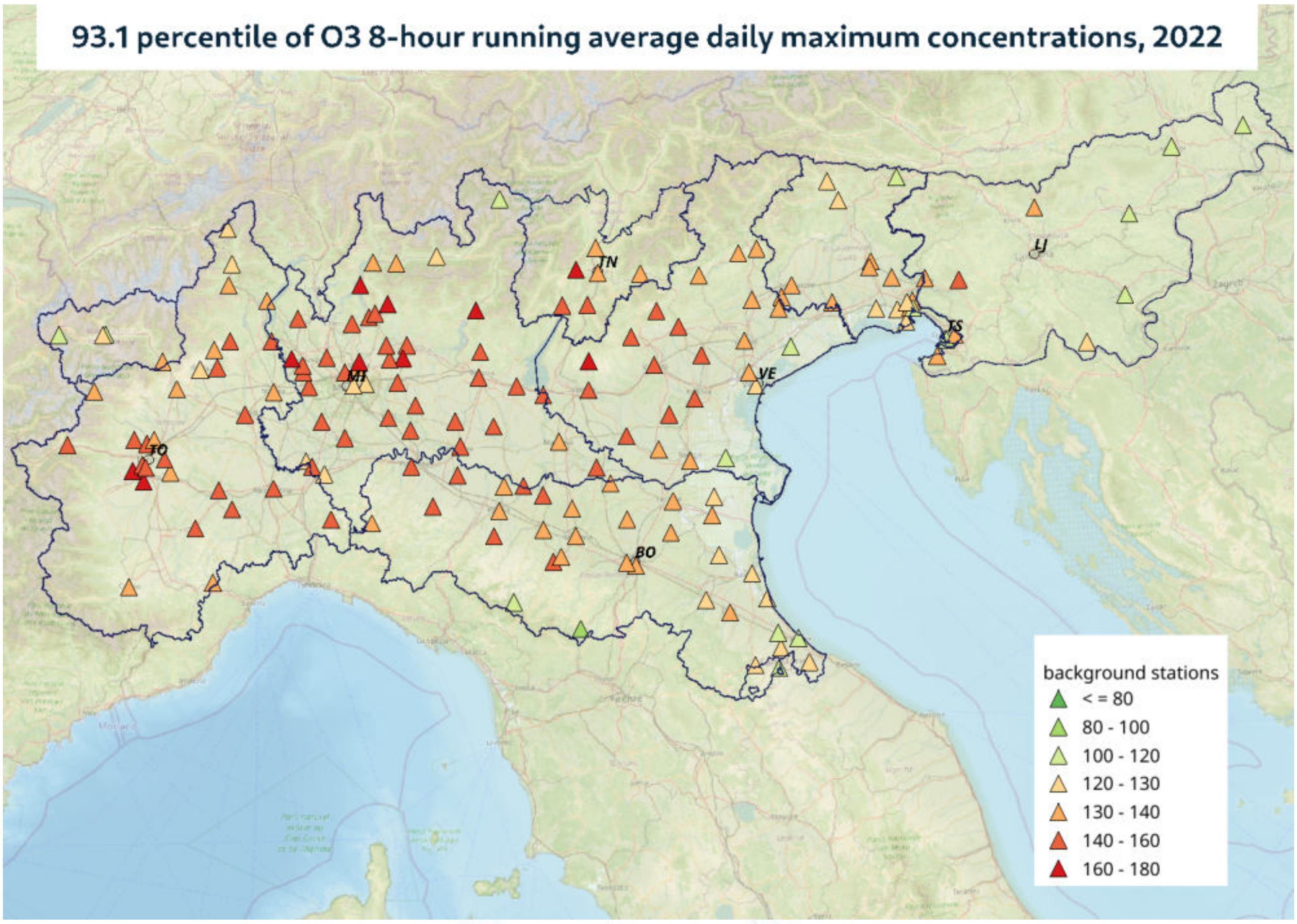

Figure A9. O_3 percentile 93.1: maps of observed data, monitoring stations are grouped by station classification.

Appendix B D5 ensemble maps.

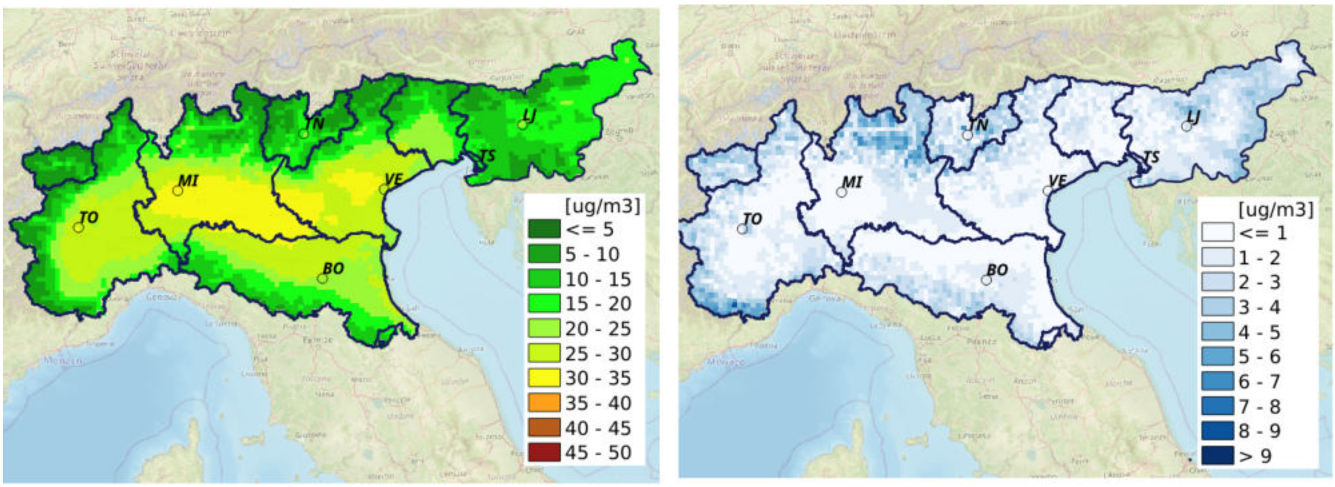

Figure B1. PM10 annual mean, D5 ensemble concentration map (left) and ensemble interquartile range map (right).

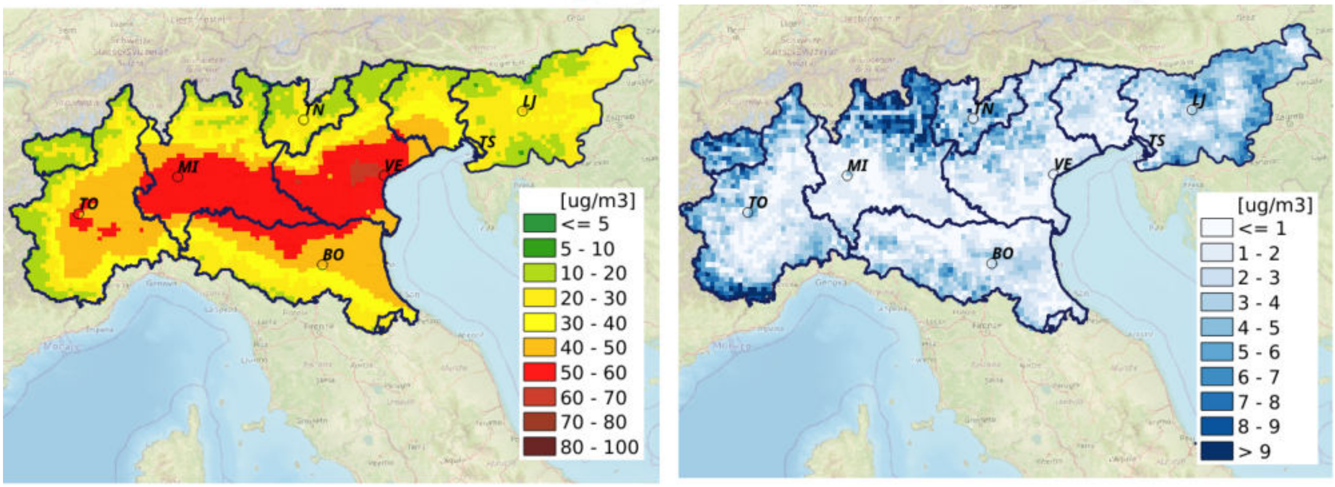

Figure B2 PM10 90.4 percentile, D5 ensemble concentration map (left) and ensemble interquartile range map (right).

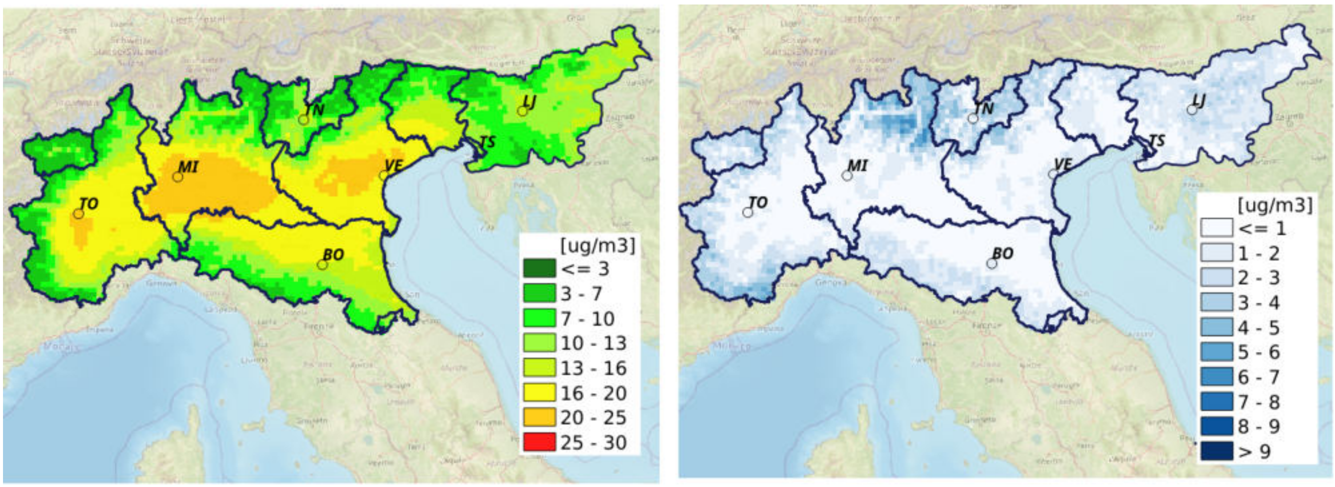

Figure B3. PM2.5 annual mean, D5 ensemble concentration map (left) and ensemble interquartile range map (right).

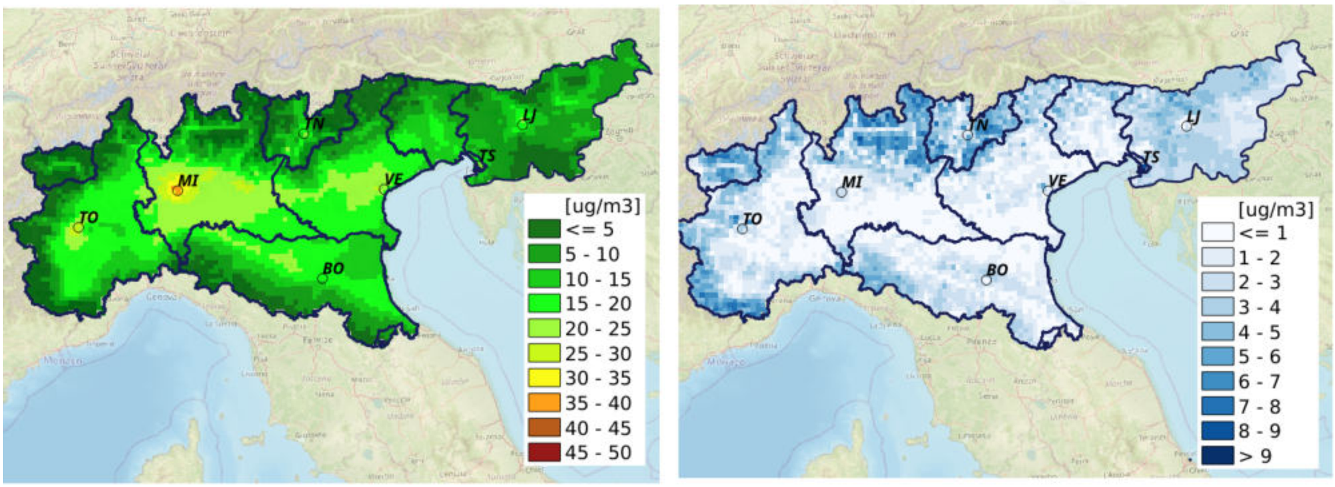

Figure B4. NO_2 annual mean, D5 ensemble concentration map (left) and ensemble interquartile range map (right

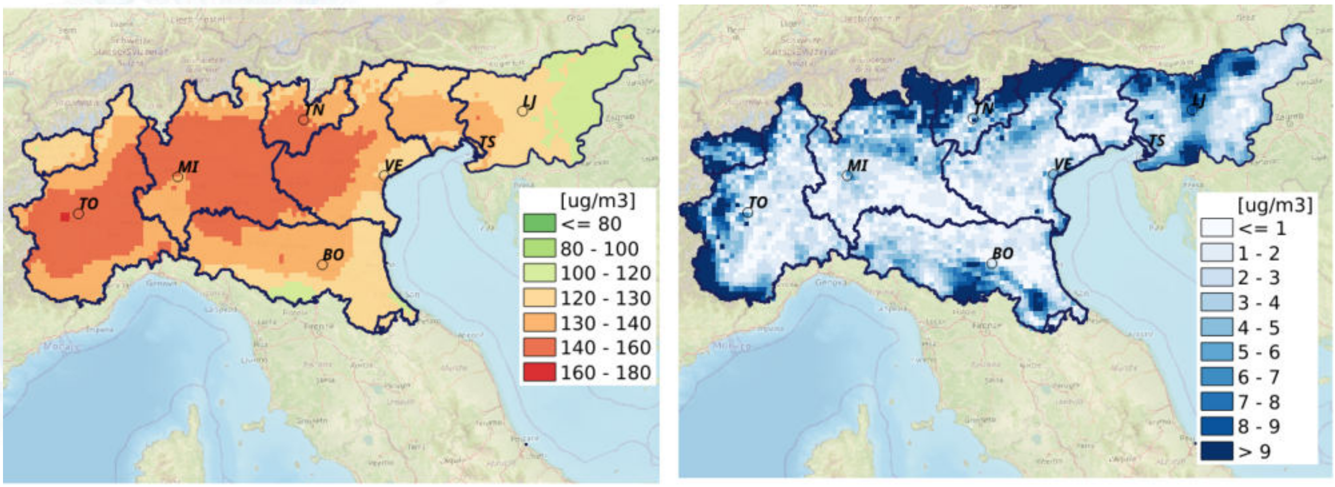

Figure B5. O_3 93.1 percentile, D5 ensemble concentration map (left) and ensemble interquartile range map (right

With the contribution of the LIFE Programme of the European Union

LIFE 15 IPE IT 013

prepAIR
Po Regions Engaged to Policies of Air

THE PROJECT PREPAIR

The Po Basin represents a critical area for the quality of air, as the limit values of fine powders, nitrogen oxides and ozone set by the European Union are often exceeded. The northern Italian regions re included in this area as well as the metropolitan cities of Milan, Bologna and Turin.

This area is densely populated and highly industrialized. Tons of nitrogen oxides, powders and ammonia are emitted annually into the atmosphere from a wide variety of polluting sources, mainly related to traffic, domestic heating, industry, energy production and agriculture. Ammonia, mainly emitted by agricultural and zootechnical activities, contributes substantially to the formation of secondary powders, which constitute a very significant fraction of total powders in the atmosphere.

Because of the weather conditions and the morphological characteristics of the basin, which prevent the mixing of the atmosphere, the background concentrations of the particulate, in the winter period, are often high.

In order to improve the quality of the air in the Po Valley, since 2005 Regions have signed Program Agreements identifying coordinated and homogeneous actions to limit emissions deriving from the most emissive activities.

The PREPAIR project aims at implementing the measures foreseen by the regional plans and by the 2013 Po Basin Agreement on a wider scale, strengthening the sustainability and durability of the results: in fact, the project involves not only the regions of the Po valley and its main cities, but also Slovenia, for its territorial contiguity along the northern Adriatic basin and for its similar characteristics at an emissive and meteoclimatic level.

The project actions concern the most emissive sectors: agriculture, combustion of biomass for domestic use, transport of goods and people, energy consumption and the development of common tools for monitoring the emissions and for the assessment of air quality over the whole project area.

DURATION

From February 1st 2017 to January 31 2024.

TOTAL BUDGET

17 million euros available to invest in 7 years: 10 million of which coming from the European Life Program.

COMPLEMENTARY FUNDS

PREPAIR is an integrated project: over 850 million euros coming from structural funds and from regional and national resources of all partners for complementary actions related to air quality.

PARTNERS

The project involves 17 partners and is coordinated by the Emilia-Romagna Region – General directorate for the territorial and environmental care.

www.lifeprepair.eu – info@lifeprepair.eu