AI4EO

A bridge between EO and AI

Air Quality & Health Challenge

Summary

1 Introduction

The Copernicus Programme and NewSpace constellations have strongly increased the availability of **Earth Observation** (EO) data and of derived information services, including information from complex geophysical models and measurements from in situ instruments. Nowadays, a large amount of that information is easily accessible and can be obtained free of charge. The availability of several information sources allows the implementation of novel applications thanks to the introduction of **Artificial Intelligence** (AI) techniques that are enabling the speed-up and integrated analysis of EO data and other information layers. In particular the application of AI and Machine Learning are demonstrating their effectiveness in revealing patterns among different kind of heterogenous data and are enabling to easily discover relationships between EO and in situ measurements. This means that the EO community can immensely profit from AI and that the AI community can provide an invaluable contribution for monitoring and understanding the processes and transformations happening on our Planet.

2 Aim of the Challenge

The aim of the challenge is to develop novel AI based algorithms for improving air quality monitoring and, specifically, of $PM_{2.5}$ and NO_2.

$PM_{2.5}$

PM stands for particulate matter of solid particles and liquid droplets present in the air. Some particles, such as dust, dirt, soot, or smoke, are large or dark enough to be seen with the naked eye. Others are so small they can only be detected using an electron microscope. This type of pollutant includes:

- PM_{10} : inhalable particles, with diameters that are generally 10 micrometers and smaller;
- $PM_{2.5}$: fine inhalable particles, with diameters that are generally 2.5 micrometers and smaller.

PM particles are so small that they can be inhaled and cause serious health problems. PM_{10} can get deep into your lungs and some may even get into your bloodstream. $PM_{2.5}$ pose the greatest risk to health.

NO_2

Nitrogen Dioxide (NO_2) is one of a group of highly reactive gases known as oxides of nitrogen or nitrogen oxides (NOx). NO2 is used as the indicator for the larger group of nitrogen oxides. NO_2 primarily gets in the air from the burning of fuel. NO2 forms from emissions from cars, trucks and buses, power plants, and off-road equipment.

Breathing air with a high concentration of NO_2 can irritate airways in the human respiratory system. Such exposures over short periods can aggravate respiratory diseases, particularly asthma, leading to respiratory symptoms (such as coughing, wheezing or difficulty breathing), hospital admissions and visits to emergency rooms. Longer exposures to elevated concentrations of NO_2 may contribute to the development of asthma and potentially increase susceptibility to respiratory infections. People with asthma, as well as children and the elderly are generally at greater risk for the health effects of NO_2.

NO_2 along with other NOx reacts with other chemicals in the air to form both particulate matter and ozone. Both of these are also harmful when inhaled, due to effects on the respiratory system.

3 The Earth Observation contribution

PM_x and NO_x can be measured by *in situ* stations, which provide local information on their concentrations and evolution, as well as by satellites and modelling approaches, which provide a synoptic view of such parameters' concentration and their spatial distribution over geographical areas.

The in-situ data provide the most precise information in terms of concentration accuracy of the measured parameter but, on the other hand, the spatial variation of the parameters cannot be directly measured by the in-situ stations.

The main advantage of satellite Earth Observation and modelling approaches is the possibility of obtaining homogenous information over large areas without any constraint on the location of the in-situ stations. In this case the spatial information is provided as a geolocated grid cells each of them containing the value of each parameter in the geolocated grid. This means that the concentration of the parameters is averaged within each cell of the geolocated grid. The dimension of the cell composing a geolocated grid can be referred as the **spatial resolution** of the data.

An example of the Copernicus Atmosphere Monitoring Services (CAMS) map for the $PM_{2.5}$, over Europe, is shown in figure 1.

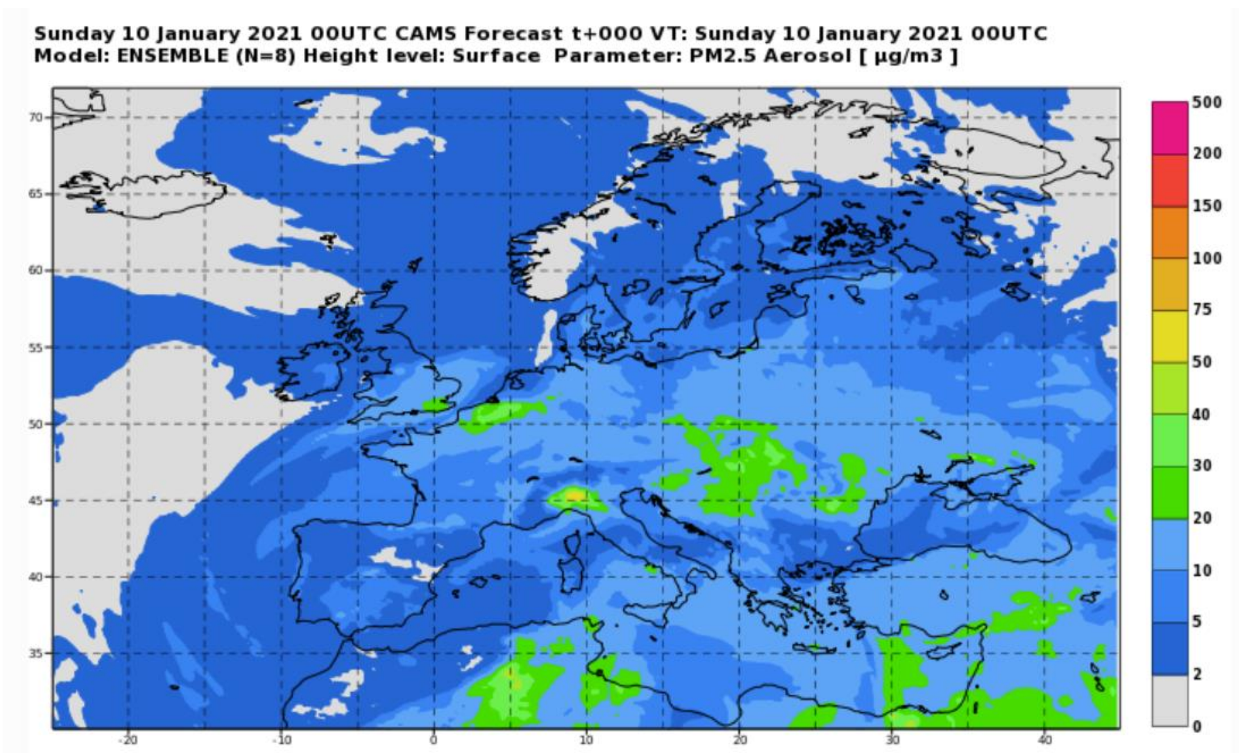

Figure 1 Example of PM2.5 information produced by the Copernicus CAMS Core Service

In the "Air Quality & Health" challenge, the participants have to analyse the datasets provided by AI4EO and to prototype an AI based solution for improving the spatial resolution of the air quality monitoring information provided by the Copernicus Atmosphere Monitoring Service (for $PM_{2.5}$) and by ESA Sentinel-5 product (for NO_2).

More specifically, the goal of the challenge is to implement an AI based model for improving the spatial resolution of the $PM_{2.5}$ and NO_2 data provided respectively by Copernicus and ESA:

- **$PM_{2.5}$:**
  - **From 10km x 10km over North Italy to the final resolution of 1km x 1km;**
  - **From 40km x 40km over South Africa and California to 10km x 10km to the final spatial resolution of:**
- **NO_2: from 7km x 7km to the final resolution of 1km x 1km**

We draw your attention to the fact that, in relation to the NO_2 parameter, there is a difference between the data provided by the ground stations, CAMS data and Sentinel-5p data. The data of the ground stations, as well as the CAMS data, measure or estimate the concentration of NO_2 near the Earth surface while the Sentine-5p data measure the integrated amount of NO_2 over the whole tropospheric column (approximately the lower 10km of the atmosphere). Even if the measures at Earth surface and of the tropospheric column are of a different nature, the possible correlation between them can be exploited by ML algorithms to improve their final solution. Please, keep in mind that the goal of your solution for the NO_2 parameter is not to approximate the ground stations data but to use such data, in combination with all the other provided data, to increase the spatial resolution of the Sentinel-5p NO_2 data.

4 Challenge Areas of Interest

The three Areas of Interest (AoI) of the challenge are presented in Figure 2, 3 and 4.

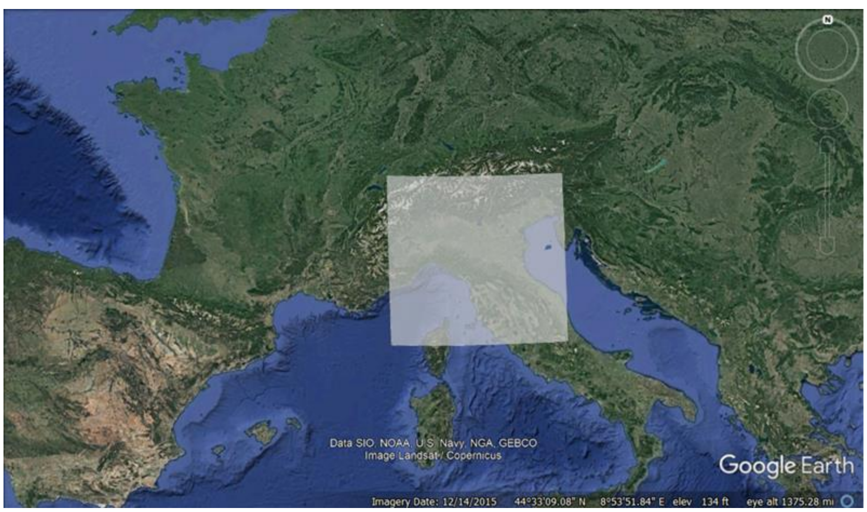

Figure 2 North Italy Area of Interest

Figure 3 South Africa Area of Interest

Figure 4 California Area of Interest

It has to be noted that the challenge execution <u>must be performed on all the three geographical areas:</u>

- North Italy
- South Africa
- California

Challenge concept

The "Air Quality & Health" challenge is based on a wide range of data which includes a number of information made available by the Copernicus Programme and other players:

- Satellite data
- Geospatial layers
- *In situ* data

Besides the two main datasets of $PM_{2.5}$ and NO_2, respectively provided by the models of Copernicus Atmosphere Monitoring Service and the Sentinel 5P Level2 satellite data, a large set of additional data are provided on order to develop the AI based model aimed at improving the spatial resolution of the $PM_{2.5}$ and NO_2 maps.

All the provided datasets are spatially geo-referenced and relevant to the same time intervals, so that AI approaches can be more easily developed for the purpose of the challenge. The “Air Quality & Health” challenge concept is exemplified in the diagram in figure 5.

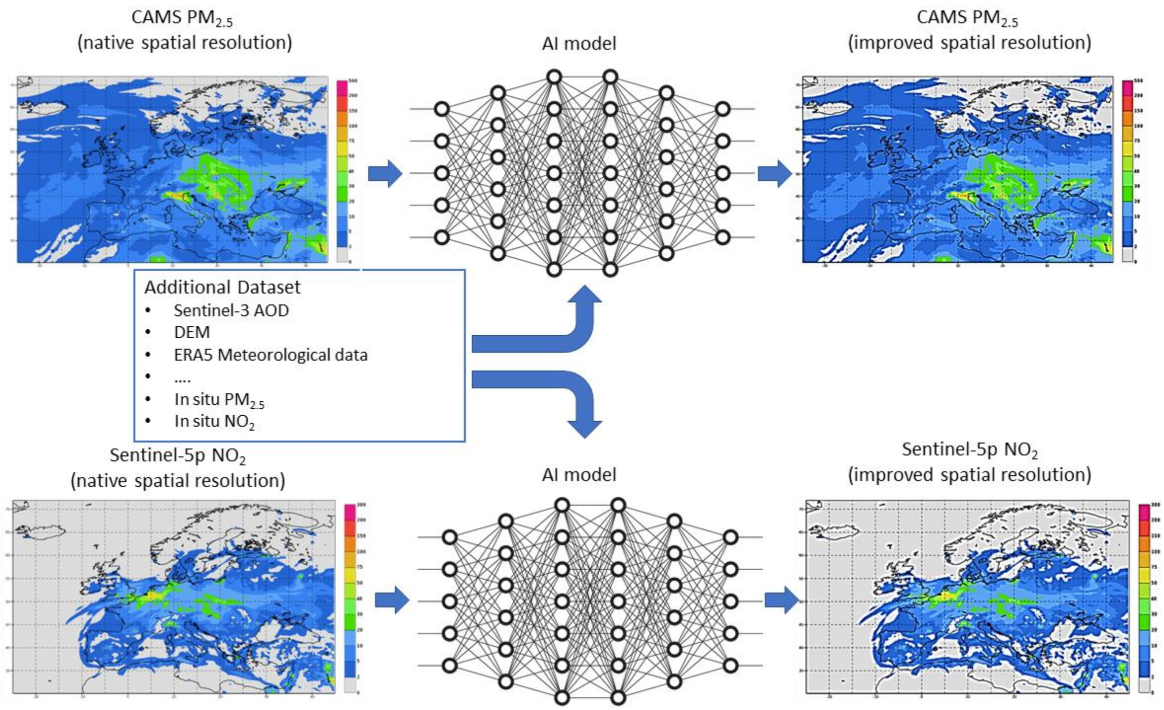

Figure 5 The “Air Quality & Health” challenge concept

The challenge is articulated in three main phases:

- Training of AI models
- Improvement of AI models
- Final scoring of results

The aims of the three main phases are reported in figure 6.

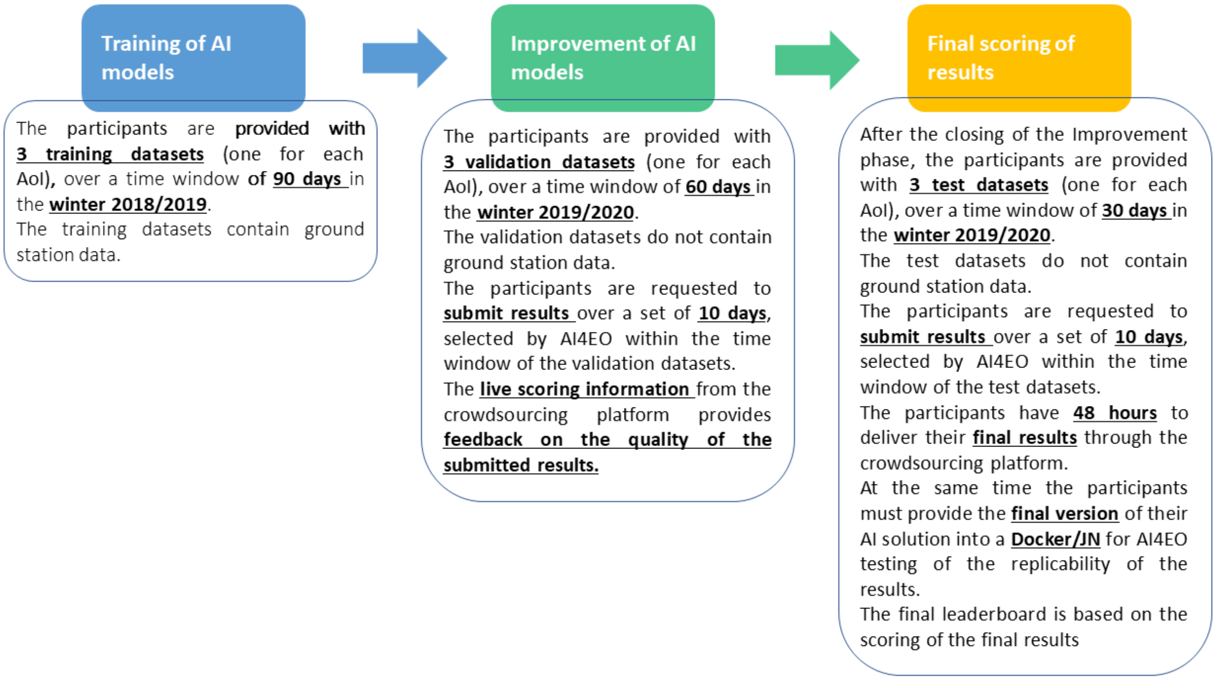

Figure 6 Three main phases of the "Air Quality & Health" challenge

5 "Air Quality & Health" Datasets

The datasets used in the challenge are reported in Table 1.

Table 1 – Challenge Datasets

Dataset	North Italy	South Africa	California	Raster/ Vector	Purpose	Training dataset (winter 2018/2019	Validation dataset (winter 2019/2020	Temporal Resolution
CAMS model $PM_{2.5}$ data	10x10Km	40x40Km	40x40Km	R-mono	Main input data to the AI model (parameters to be downscaled)	X	X	hourly
Sentinel 5p observed NO_2 data	7x7Km	7x7Km	7x7Km	R-mono	Main input data to the AI model (parameters to be downscaled)	X	X	daily
CAMS model NO_2 data	10x10Km	40x40Km	40x40Km	R-mono	Additional input for training/application of the AI model for downscaling of main parameters	X	X	hourly
Sentinel-5p observed UV Aerosol Index	7x7Km	7x7Km	7x7Km	R-multi	Additional input for training/application of the AI model for downscaling of main parameters	X	X	daily
Sentinel-3 Aerosol Optical Depth	300x300m	--	300x300m	R-multi	Additional input for training/application of the AI model for downscaling of main parameters	X	X	daily
MODIS Aerosol Optical Depth	1x1Km	1x1Km	1x1Km	R-multi	Input for training/application of the AI model for downscaling of main parameters	X	X	daily

ECMWF ERA5 meteorological parameters	31x31Km	31x31Km	31x31Km	R-mono	Input for training/application of the AI model for downscaling of main parameters (account for meteorology effects)	X	X	hourly
Copernicus Land cover products (CORINE)	25x25m	--	--	R-mono	Input for training of the AI model for updated land cover	X	X	2018
Copernicus Global Land Service (CGLS-LC100)	--	--	100x10m	R-mono	Input for training of the AI model for updated land cover	X	X	2018
South African National Land-Cover (SANLC)	--	20x20m	--	R-mono	Input for training of the AI model for updated land cover	X	X	2018
SPOT 6/7	1,5x1,5m	--	--	R-multi	Input to consider updated information on land cover with high level of details	X	X	2018/2019
Copernicus DEM	25x25m h: +/- 7m	100x100m h: +/- 10m	100x100m h: +/- 10m	R-mono	Input for training/application of the AI model for downscaling of main parameters (account for effects of topography)	X	X	2016
$PM_{2.5}$, NO_2 ground station measurements (location of stations on shape file)	Point measure	Point measure	Point measure	Vector	Generating target data for the training phase of the AI model	X	--	daily

(*) R-mono: raster mono-band, R-multi: raster multi-band

Raster and Vector data types

The challenge datasets include different type of data which can be categorized into:

- Vector data
- Raster data

Vector data

Vector data represent real world features through points, lines and polygons defining the shape of spatial objects (figure 7)

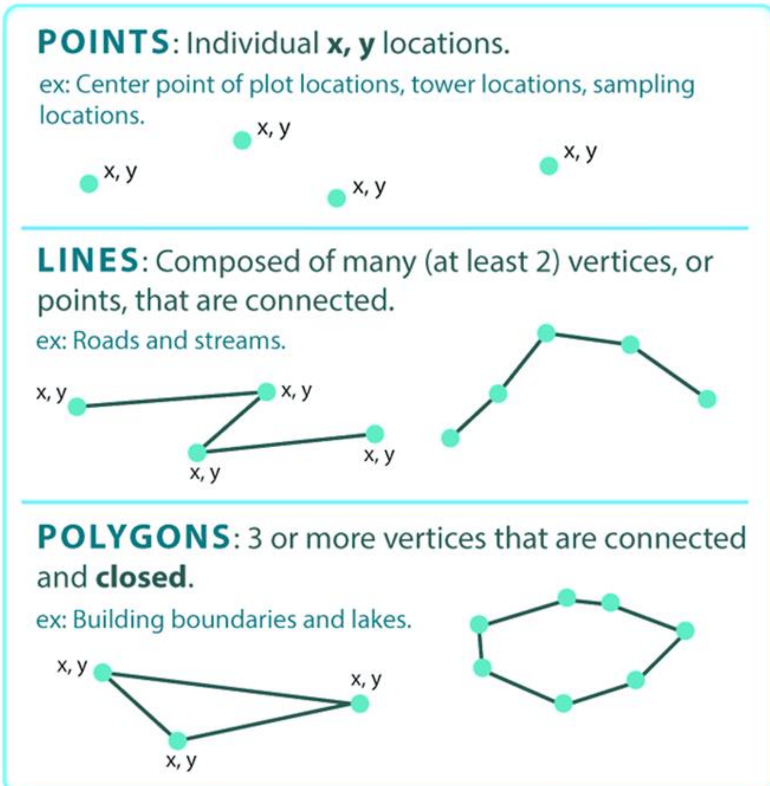

Figure 7 The three possible vector data types

A feature can be imagined as anything you can see on a landscape image as houses, roads, trees, rivers, and so on (see next figure). In general, vector features have attributes, which consist of text or numerical information that describe the features' properties. In figure 8 different examples of vector features are highlighted over a landscape image.

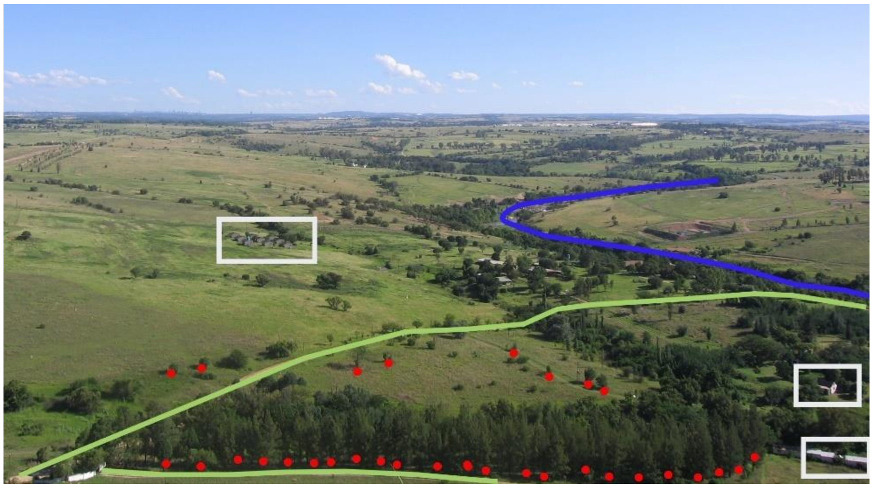

Figure 8 Example of vector data types

Raster data

Raster data are made up of a matrix (or grid) of pixels (also called cells), each containing a value that represents the conditions for the area covered by that cell (see figure 9). In general the dimension of pixel (also known as pixel size) is fixed for all the pixels of the matrix. As we can see in the following paragraph, often (but not always) the pixel size is coincident with the spatial resolution of the data.

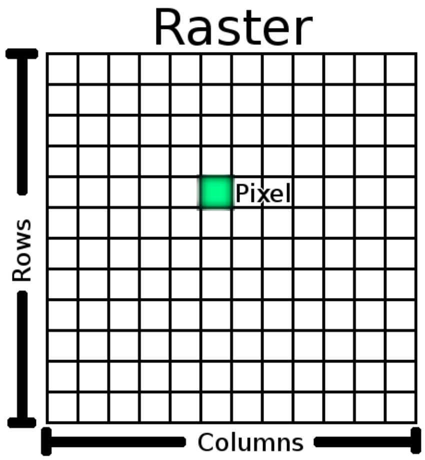

Figure 9 Representation of a raster data type as a matrix composed of rows and columns of pixels (also known as cells).

Raster data is used in EO and GIS applications when we want to display information that is continuous across an area and cannot easily be divided into vector features. Point, polyline and polygon features work well for representing some features such as trees, roads and building footprints. For mapping the continuous variation of a feature (like the color variation of the grass in the picture) the raster format is the best option. In this case each pixel of the raster matrix represents a unique value associated to the parameter which is reported in the raster. In the case of the air quality, each pixel of a raster dataset reports the value of a specific parameter, e.g. the $PM_{2.5}$ and NO_2 over the portion of surface sampled by the pixel.

In general, a raster contains more than one matrix. In this case the data format can be schematised as a stack of over imposed matrices. In this case the data is often referred as multiband raster, while in the case of a single matrix we refer the data as single band raster.

In the challenge context, you will meet both single and multi-bands raster data, with different spatial resolution. Anyhow, all the raster data have been georeferenced; this means that each pixel of the matrix has a position over the Earth surface provided in terms of geographical coordinates.

The spectral bands of the Sentinel-3, Sentinel-5p, MODIS and SPOT-6/7 satellites are reported in in figure 10, 11, 12 and 13, respectively.

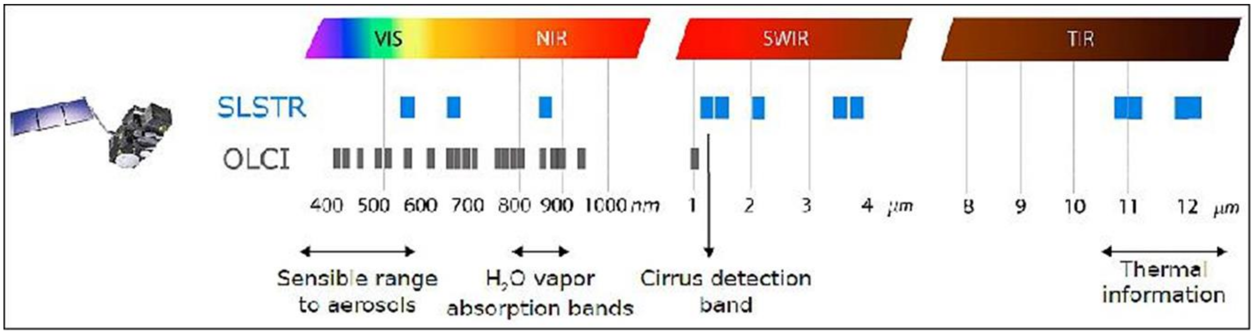

Figure 10 Sentinel-3 spectral bands

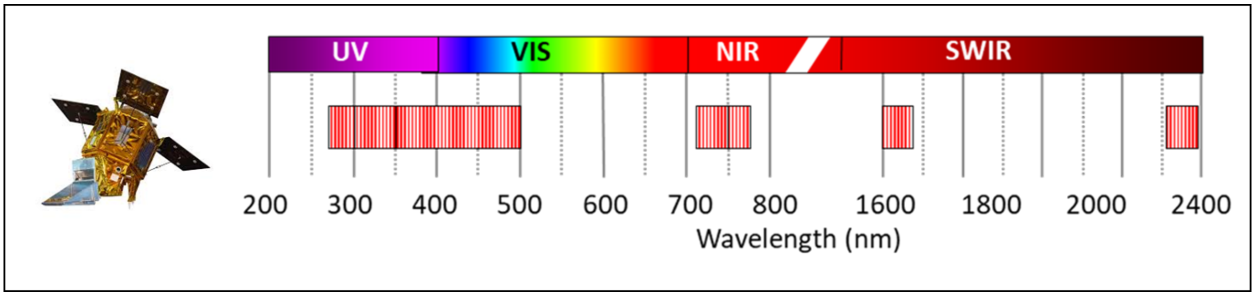

Figure 11 Sentinel-5p spectral bands

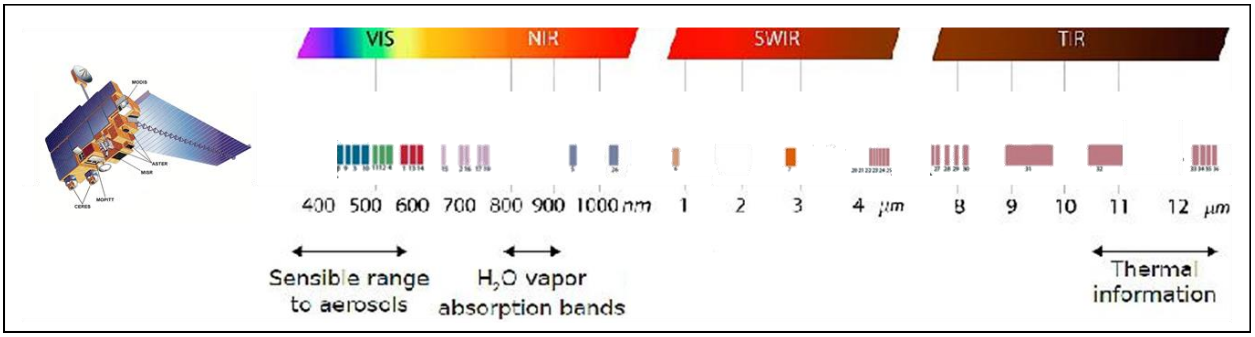

Figure 12 MODIS spectral bands

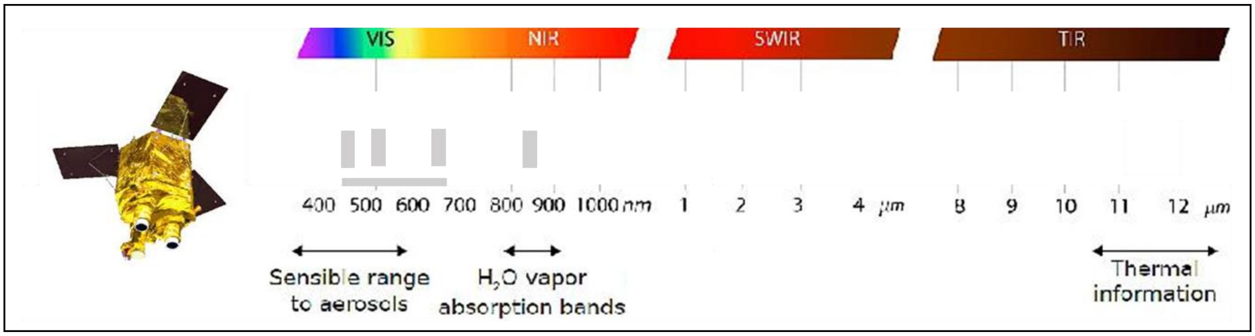

Figure 13 SPOT-6/7 spectral bands

6 Details on the "Air Quality & Health" Datasets

In Table 2 the additional information about the different data included in the challenge datasets are reported.

Table 2 – Additional information about challenge Datasets

Dataset	Description
CAMS model $PM_{2.5}$ and NO_2 data	This dataset provides daily air quality forecasts for Europe at a spatial resolution of 0.1 degree (approx. 10km). The production is based on an ensemble of nine air quality forecasting systems across Europe. The analysis combines modelling approach and data with observations provided by the European Environment Agency (EEA) for producing forecast available at hourly time steps at seven height levels. Only the data at the first level (0m a.s.l.) are considered in the North Italy datasets. Outside Europe the same modelling approach is applied for producing the CAMS reanalysis data with a spatial resolution of approximately 40 km. For sub-daily data the analyses are available 3-hourly. Also in this case, the data are 3-dimensional and only the data at the first level (0m a.s.l.) are considered in the South Africa and the California datasets. For the three AoIs the $PM_{2.5}$ model data are provided as main inputs, while the NO_2 model data are included as additional inputs.

Sentinel 5p observed NO_2 and UV Aerosol Index data	The Sentinel-5 Precursor (Sentinel-5P) polar orbiting satellite is an active ESA mission founded under the Copernicus Earth Observation Sentinel-5P carries the TROPOspheric Monitoring Instrument (TROPOMI) spectrometer. This instrument senses ultraviolet (UV), visible (VIS), near (NIR) and short-wave infrared (SWIR). Outputs from these sensors are used to generate different atmospheric monitoring data (e.g. ozone, methane, formaldehyde, nitrogen dioxide, aerosol, etc.). These data are known as level 2 products since are derived from the radiometric measurement. In the challenge we consider the NO_2 tropospheric column data as the main input for the three AoIs. In order to comply with the SI unit definitions, the Sentinel-5P NO_2 data gives trace gas concentrations in mol/m^2, rather than in the commonly used unit $molec/cm^2$. The following multiplication factor enabling the user to easily make the conversions[1]: The multiplication factor to convert mol/m^2 to $molec/cm^2$ is 6.02214×10^{19} So that for converting the native Sentinel-5P NO_2 data from mol/m^2 to $molec/cm^2$ the following formula must be applied: $NO_2\ [molec/cm^2] = NO_2\ [mol/m^2] * 6.02214\times10^{19}$ In order to be comparable with the NO_2 ground station measures, which unit is $\mu g\ m^{-3}$, an additional conversion formula[2] must be applied to the Sentinel-5P NO_2 (e.g. for computing the Pearson's Correlation coefficient): $NO_2\ [\mu g\ m^{-3}] = NO_2\ [molec/cm^2] * 1.0\times10^{-15} * 1.9125$ This formula is merely an empirical approximation that can be used (with caution) because of the scarcity of directly comparable observations.

[1] https://sentinels.copernicus.eu/documents/247904/2474726/Sentinel-5P-Level-2-Product-User-Manual-Nitrogen-Dioxide

[2] https://www.sciencedirect.com/science/article/pii/S1352231012011144

	The UV Aerosol Index data, which are correlated to the presence of other air pollutant (like NOx and PM) are provided as additional dataset.
MODIS **Aerosol Optical Depth**	The data acquired by the Moderate Resolution Imaging Spectroradiometer (MODIS) on board of the Aqua and Terra satellite mission by NASA are used to compute Aerosol Optical Depth Level-2 data. This data (identified by MCD19A2 name) are correlated with the atmospheric proprieties as influenced by the presence of different gasses and aerosols. MODSI Aerosol Optical Depth data are provided as additional inputs data for the three AoIs.
Sentinel-3 Aerosol Optical Depth	The data acquired by the Copernicus Sentinel-3 mission are used to develop estimation of Aerosol Optical Depth. The latter are obtained exploiting the combination of two different sensor on board of Sentinel-3: the SLSTR and the OLCI. The Sentinel-3 Aerosol Optical Depth data are included as additional inputs to provide a further information on the atmosphere for the North Italy and the California AoIs. At present, such data are not available over the South Africa in the time windows considered.
ECMWF ERA5 meteorological parameters	ERA5 models provide estimates of the state of the atmosphere covering the period 1950 to the present and is produced at the European Centre for Medium-Range Weather Forecasts (ECMWF) by the EU Copernicus Climate Change Service (C3S). The estimates are produced with a procedure known as "Reanalysis", which creates an optimal combination of measurements of natural variables with information from a numerical weather forecast model. In the datasets for the three AoIs, the Relative air humidity, the Specific rain water content and the wind information have been selected from the ERA5 modeled variables for the inclusion as additional inputs. Such parameters can be taken into account in the AI model for considering the meteorological effects.
Copernicus Land cover products (CORINE)	The Corine Land Cover (CLC) dataset is produced within the frame of the Copernicus Land Monitoring Service. The included dataset over the North Italy refers to land cover / land use status of year 2018 and can be considered in the AI model for taking into account the

	effect of the land cover classes (e.g. due to soil consumption and to the presence of factories) on the spatial distribution of the NO_2 and $PM_{2.5}$.
Copernicus Global Land Service (CGLS-LC100)	The Copernicus Global Land Service (CGLS) is a component of the Land Monitoring Core Service (LMCS) of Copernicus. The CGLS-LC100 data are provided for the 2018 on the California AoI. The dataset can be considered in the AI model for taking into account the effect of the land cover classes (e.g. due to soil consumption and to the presence of factories) on the spatial distribution of the NO_2 and $PM_{2.5}$.
South African National Land-Cover (SANLC)	The new South African National Land-Cover 2018 dataset has been generated from 20 meter multi-seasonal Sentinel 2 satellite imagery. The imagery used represents the full temporal range of available imagery acquired by Sentinel 2 during the period 01 January 2018 to 31 December 2018. The SANLC 2018 dataset can be considered in the AI model for taking into account the effect of the land cover classes (e.g. due to soil consumption and to the presence of factories) on the spatial distribution of the NO_2 and $PM_{2.5}$.
SPOT 6/7 data	Images acquired over the North Italy AoIs by the AIRBUS SPOT-6/7 satellites are included as additional dataset for providing a more detailed overview of the land cover. Indeed, the data, are characterized by a spatial resolution of 1,5x1,5m.
Copernicus DEM	The Copernicus DEM is a Digital Surface Model (DSM) which represents the surface of the Earth including buildings, infrastructure and vegetation. This DEM is derived from an edited DSM named WorldDEM™. The Copernicus DEM is provided in 3 different instances named EEA-10, GLO-30 and GLO-90. The EEA-10 is the European data, characterized by a spatial resolution of 25x25m (and vertical resolution h: +/- 7m) and it is provided for the North Italy AoIs. The GLO-30 is a world wide dataset with a spatial resolution of 100x100m (and vertical resolution h: +/- 10m) and it is provided for the South Africa and the California AoIs. The DSM information can be considered in the AI model for taking into account the effect of the topography.

$PM_{2.5}$, NO_2 ground station measurements (location of stations on shape file) for EEA	European air quality information reported by the European Environmental Agency (EEA) consists of a multi-annual time series of air quality measurement data and calculated statistics for a number of air pollutants. It also contains meta-information on the monitoring networks involved, their stations and measurements, as well as air quality zones, assessment regimes and compliance attainments reported by the EU Member States and European Economic Area countries. EEA data have been included in the North Italy dataset for providing the in-situ variation of $PM_{2.5}$ and NO_2.
PM2.5, NO2 ground station measurements (location of stations on shape file) form US EPA	The Air Quality System (AQS) contains ambient air pollution data collected by the US Environmental Protection Agency (EPA). The AQS databases consist of a multi-annual time series of air quality measurement data and calculated statistics for a number of air pollutants. It also contains meta-information on the monitoring networks involved, their stations and measurements. EPA AQS data have been included in the California dataset for providing the in-situ variation of $PM_{2.5}$ and NO_2.
PM2.5, NO2 ground station measurements (location of stations on shape file) form the South African Air Quality Information System (SAAQIS)	The South African Air Quality Information System (SAAQIS), provides a common platform for managing air quality information in South Africa. It makes data available to stakeholders including the public and provides a mechanism to ensure uniformity in the way air quality data is managed i.e. captured, stored, validated, analysed and reported on in South Africa. SAAQIS data have been included in the South Africa dataset for providing the in-situ variation of $PM_{2.5}$ and NO_2.

7 Challenge Evaluation

The evaluation of the solutions submitted will be performed in two stages: live scoring of the accuracy of your solution throughout the challenge, which will be visible on the leaderboard on this platform; and an evaluation by a jury consisting of experts after the final submission of your code.

The total score of a participant will be calculate as follows:

- 75/100 will be based on an automatic calculation of the accuracy of your output datasets, using objective metrics (see next paragraph)

- 25/100 will be based on an evaluation by a jury, who will consider the extent to which you effectively used or incorporated the datasets provided and the methodologies you applied, in addition to uniqueness, quality, reproducibility and contribution to open science of your solution.

The objective evaluation will produce a total score that will be calculated by a weighted combination of the score for each pollutant, as follows:

- 37.5/75 for PM2.5
- 37.5/75 for NO2

The solution submitted by the participants have to be reproducible by the challenge organisers, starting only from the test data set.

The qualitative jury evaluation will produce a qualitative jury score what will be based on the following parameters:

- How well code is documented
- Level of creativity and originality
- Contribution to Open Science
- Completeness and scalability of the released code.

Objective evaluation metrics

In the scoring of the participants' results different metrics will be applied. The first set of metrics will be computed on a point basis by comparing the values of the AI models' outputs for the $PM_{2.5}$ and NO_2 parameters at improved spatial resolutions with the values of the ground monitoring stations.

This first set of metrics (point-based metrics) include:

- **Root Mean Square Error (RMSE):**
  The RMSE is the square root of the mean of the square of all the errors. Formally, letting S_i be the predicted values of a variable, O_i the observations, and n the total number of observations,

$$\boldsymbol{RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2}}$$

- **Pearson's Correlation (Corr)**
  It is a statistic that measures the linear correlation between two variables X and Y, in our case the ground station measurements (X) and the AI models outputs (Y). It has a value between +1 and −1. A value of +1 is a total positive linear correlation, 0 is no linear correlation, and −1 is a total negative linear correlation. It can be formally defined as:

$$\boldsymbol{\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y}}$$

  where $cov(X,Y)$ is the covariance of two random variables X and Y, and σ_α is the standard deviation of the random variable α.

- **Factor of 2 (Fact2)**
  The "factor of 2" score is defined by the fraction of data satisfying the criterion
  $$0.5 \leq \frac{predictions}{observations} \leq 2$$

The second set of metrics are applied to evaluate the spatial variation consistency of the improved spatial resolution $PM_{2.5}$ and NO_2 AI models' outputs with respect to the data at their native spatial resolution.

This second set of metrics (area-based metrics) include:

- **False Alarm Ratio (FAR), Probability of Detection (POD), Diagnostic Odd Ratio (OddR), Intersection Over Union (IOU)**
  Let the following denote the number of true/false positive/negative predictions with respect to a ground truth reference data:
  TP: Number of True Positives
  TN: Number of True Negatives
  FP: Number of False Positives
  FN: Number of False Negatives

$$\boldsymbol{FAR = \frac{FP}{TP + FP}}$$

$$\boldsymbol{POD = \frac{TP}{TP + FN}}$$

$$\boldsymbol{IOU = \frac{TP}{TP + FN + FP}}$$

$$\boldsymbol{OddR = \frac{TP/FP}{FN/TN}}$$

To perform the comparison of the spatial variation consistency, the AI models' output is subsampled to the resolution of the native $PM_{2.5}$ and NO_2 data provided by CAMS and ESA.

Application of point-based metrics to Sentinel-5p NO_2 data

In order to make comparable the unit of Sentinel-5p NO_2 tropospheric column data with the unit of the ground station data, the conversion formulas reported in Table 2 can be applied.

The result of the conversion formulas is merely an empirical approximation that can be used (with caution) because of the scarcity of directly comparable observations and lower values in the achieved scoring could reflect that it is not a perfectly robust measurement of skill.

Anyhow, also if the NO_2 measures of ground stations and of the tropospheric column are of a different nature, the possible correlation between them can be exploited by ML algorithms to improve their final solution for achieving the goal of improve the spatial resolution of the Sentinel-5p NO_2 tropospheric column data.

8 Leaderboard formation

The different metrics reported above will be computed by the live scoring tool on the AI4EO platform, after each submission of the teams. The values obtained by each team in the different metrics, for each parameters ($PM_{2.5}$ and NO_2) and for all the geographic Areas of Interest (North Italy, South Africa, California) will determine the position of the team in the overall leaderboard.

For each parameter in the three AoIs the computation of the scores of each team is performed as follows:

1. For each metric, the team with the best-performance is classified in the first position, the team with the second best-performance is classified in the second position and so on.
2. A score equal to 1 is assigned to the team in the first position, a score equal to 2 is assigned to the team in the second position and so on.

An example of the computation for a generic parameter and a generic AoI, considering 5 teams is reported below.

Metrics	***Values in each metric***					***Evaluation criteria***	***Score in each metric***				
	Team 1	***Team 2***	***Team 3***	***Team 4***	***Team 5***		***Team 1***	***Team 2***	***Team 3***	***Team 4***	***Team 5***
RMSE	0.25	0.28	0.37	0.42	0.23	*Min (Team 1 … N)*	2	3	4	5	1
CC	0.97	0.93	0.92	0.96	0.95	*Max (Team 1 … N)*	1	4	5	2	3
Factor 2	0.80	0.60	0.70	0.78	0.83	*Max (Team 1 … N)*	2	5	4	3	1
POD	0.98	0.53	0.87	0.97	0.78	*Max (Team 1 … N)*	1	5	3	2	4
FAR	0.23	0.24	0.27	0.28	0.19	*Min (Team 1 … N)*	2	3	4	5	1
Odd Ratio	0.65	0.69	0.78	0.63	0.45	*Max (Team 1 … N)*	3	2	1	4	5
Intersection Over Union	0.70	0.54	0.73	0.65	0.82	*Max (Team 1 … N)*	3	5	2	4	1
						AoI Score	**14**	**27**	**23**	**25**	**16**

3. The scores achieved in all metrics are then added together and the team which has obtained the smaller overall score is classified in the first position of the leaderboard, the team with the second smaller overall score is classified in the second position and so on. In case of parity of the total scores of one or more teams, the last but one total scores of the involved teams will determine the relative position between the involved teams.

An example of the computation for the leaderboard is reported below.

North Italy score	11	31	21	21	15	**$PM_{2.5}$**
South Africa score	27	23	25	16	27	
California score	26	29	32	20	20	
North Italy score	23	31	33	40	27	**NO_2**
South Africa score	37	30	38	23	27	
California score	26	29	32	33	20	
Total scores	**150**	**173**	**181**	**153**	**136**	
Leaderboard Position	**2**	**4**	**5**	**3**	**1**	

9 Instructions for data handling

The AI4EO team provided a set of technical tools for handling the different phases of the challenge. The set of tools include a dedicated Docker and a Jupyter Notebook for supporting the data handling as well as the development of the AI models, their tests and their application for producing the final results. The step-by-step set of instructions for the different data handling (reading, manipulation, plotting, ecc.) are included into a dedicated Jupiter notebook available at https://ai4eo.eu/.

The Docker and Jupyter Notebook can be download and installed on local servers as well as on a cloud environment.

The instruction to install the Docker are provided in the following.

AI4EO Docker Introduction

The AI4EO Docker is a virtualized Operative System that can be used to support all the technical operations needed to participate to the challenge.

The AI4EO Docker contains the following libraries, already installed and configured: python3.6, tensorflow-gpu, jupyter, gdal, scikit-learn, jupyterlab, keras, seaborn, matplotlib, numpy, scipy, pyarrow, fastparquet, pandas, xcube, rasterio, astropy, cartopy, eo-learn, torch, torchvision.

In the following sections the operations to install and use the Docker container are reported.

Getting Started

To create a container, one can simply type:
$sudo docker run --detach -it --name ai4eo-container ai4eo-public

To connect with a running container's terminal, e.g. the one called ai4eo-container, type:
$sudo docker container attach ai4eo-container

To reconnect to a container, e.g. the one called ai4eo-container, one has to first make sure that the container has been started. For executing that operation, type:
$sudo docker container start ai4eo-container

There are further possible parameters that can be considered during the container creation.

1. By default, the container is configured to run with an unprivileged user that can only access to its own home directory (/home/participant). To change the user, type:
   $[..] -u <uid>:<guid>
2. To link a directory with the container, making all the files in that location accessible within the container, type:
   $ [..] -v <host_path>:<container_path>
3. To make the docker reachable from the host' network, for example for using jupyter lab with a browser on the host machine, type:
   $[..] --ip <ip-address> --port <host_port>:<container_port>
4. To let the docker use a configured GPU on the host, type
   $[..] --runtime=nvidia

The Scripts

There are 3 suggested modes that have already been configured in 3 .sh scripts which implements:

1. A standard unprivileged user with read only access to the host working directory from which the script is executed. The GPU and the Jupyter are enabled. To use this mode, it is needed to run the dedicated .sh script by typing:
   $sh run_ai4eo.sh
2. A mode similar to the previous one, but with a user that has also write access to the host working directory from which the script is executed. To use this mode, it is needed to run the dedicated .sh script by typing:
   $sh run_ai4eo_uhost.sh
3. [Dangerous and not recommended] A mode with elevated privileges. To use this mode, it is needed to run the dedicated .sh script by typing:
   $sh run_ai4eo_root.sh

Example

Example usage with the standard mode:

1. Download the docker image and the scripts to a directory on the host. Let 'app/' be the name of this directory.
2. [Import the image in the docker]
3. Open a terminal and type:
   $sh run_ai4eo.sh
4. Type:
   $sudo docker container attach ai4eo-container
5. From the container command line, type:
   $jupyter lab --ip 0.0.0.0 --port 8888 --no-browser
6. Open a browser from the host and navigate to "localhost:8888".
7. Fill in the token spawned in the container's terminal to access the Jupyter lab.

Exporting the container for submission

Follow these steps for exporting the docker container to a tarball:

1. $docker export <container name> > <team_name>_docker.tar
2. Add the tarball to a zip folder containing the other requirements for the submission

IMPORTANT:

Please bear in mind that the docker export command does not export the contents of volumes associated with the container. If a volume is mounted on top of an existing directory in the container, docker export will export the contents of the underlying directory, not the contents of the volume. Therefore, the documents that are required for the challenge (e.g. the Jupyter Notebook, and the trained models) should always be included in the internal directories of the container.

Example

1. $docker export ai4eo-container > team1_docker.tar
2. $gzip team1_docker.tar