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Displaying air quality forecast data

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Abstract

Air pollution is one of the most pressing environmental challenges of the 21st century, with significant impacts on human health, ecosystems, and climate. Reliable forecasts are essential to support public policies, raise awareness, and inform daily decision-making. The Copernicus Atmosphere Monitoring Service (CAMS) provides high-quality forecasts of atmospheric composition worldwide, but existing platforms for accessing these data often involve a trade-off between scientific rigor and usability: expert-oriented tools require advanced technical skills, while public-facing applications simplify the information at the cost of analytical depth.

This work presents the design and implementation of online visualization platform that fills this void by providing a user-friendly interface to explore CAMS air quality forecasts. The system is entirely client-side and leverages open technologies such as Leaflet.js for mapping and Highcharts for dynamic time-series visualization. Key features include hourly forecast handling with an interactive time slider, pollutant value extraction at any clicked location, historical trend plotting, customizable color scales, and animation of forecast evolution. The platform automatically retrieves and processes CAMS WMS layers, ensuring scalability and adaptability to different pollutants and regions.

The results demonstrate that the developed platform successfully combines accessibility and analytical capability, enabling users to visualize and interpret complex atmospheric forecasts without specialized software or expertise. Beyond its academic value, this tool can support public awareness, educational purposes, and environmental monitoring initiatives. Future work will focus on integrating observational datasets for validation and incorporating advanced statistical analyses.

Contents

List of Figures

List of Tables

Listings

1 Introduction

Air contamination has become one of the most urgent environmental issues of the 21st century. Poor air quality has direct and well-documented impacts on human health, contributing to respiratory and cardiovascular diseases, and is linked to millions of premature deaths globally each year [1]. Among the most critical atmospheric pollutants are ozone (O_3), nitrogen dioxide (NO_2), and particulate matter (PM)[2]; these pollutants also have detrimental effects on ecosystems, reduce agricultural productivity[3], and play a significant role in climate change processes [4].

Nitrogen dioxide (NO_2) is a reactive gas primarily produced by high-temperature combustion in traffic, power generation, and industrial processes [5]. Short-term exposure to NO_2 can irritate the respiratory tract and increase susceptibility to respiratory infections, particularly in vulnerable populations such as children and individuals with asthma [6]. Long-term exposure is associated with the development of chronic respiratory diseases, including asthma, and with reduced lung function [7].

Ground-level ozone (O_3), in contrast to the protective ozone layer in the stratosphere, is a harmful secondary pollutant formed through photochemical reactions between nitrogen oxides (NO_x) and volatile organic compounds (VOCs) in the presence of sunlight [5]. Due to its low solubility in water, ozone can penetrate deep into the lungs, inducing oxidative stress, airway inflammation, and reductions in lung function, particularly among sensitive groups such as individuals with asthma [9]. Exposure to high concentrations of ground-level ozone has been associated with decreased lung function, exacerbation of asthma, increased hospital admissions, and a higher risk of respiratory morbidity, especially during summer smog events [8].

Particulate matter (PM) is another key air pollutant, consisting of a complex mixture of solid and liquid particles suspended in the air [5]. PM_{10} refers to coarse particles smaller than 10 micrometers in diameter, which can reach the upper respiratory tract and cause irritation and respiratory symptoms [10]. $PM_{2.5}$ refers to fine particles smaller than 2.5 micrometers; due to their small size, they can penetrate deep into the lungs and enter the bloodstream [11]. $PM_{2.5}$ exposure has been strongly linked to cardiovascular disease, stroke, lung cancer, and premature mortality [12]. Because of these health risks, both

PM_{10} and $PM_{2.5}$ are widely used as key indicators in international air quality standards.

Beyond human health, these pollutants have severe environmental consequences. Elevated ozone concentrations damage crops and forests, reducing agricultural productivity and biodiversity [13]. Nitrogen oxides and particulate matter contribute to soil acidification, water eutrophication, and climate forcing, disrupting natural ecosystems and accelerating global warming [14]. As a result, monitoring and forecasting air quality have become essential tools for environmental policy, public health planning, and raising public awareness.

The urgency of this challenge is also recognized at the political and institutional level. Within the framework of the United Nations 2030 Agenda for Sustainable Development, several goals are directly related to the problem of air pollution. Goal 3 (Good Health and Well-Being) emphasizes the need to reduce illnesses caused by hazardous chemicals and air pollution; Goal 11 (Sustainable Cities and Communities) calls for improving urban air quality and reducing environmental impacts of cities; and Goal 13 (Climate Action) highlights the interconnections between air pollutants, greenhouse gases, and the fight against climate change. The European Union has also aligned its environmental policies with these objectives, reinforcing the importance of reliable air quality data for informed decision-making.

Here we have an image showing the referenced goals (Figure 1.1). A direct link can be found at the Sustainable Development Goals.

Figure 1.1: Sustainable development goals.[1]

[1] https://sdgs.un.org/goals

1.1 The Role of CAMS in Air Quality Forecasting

To address the challenges posed by air pollution, advanced monitoring and forecasting systems are essential. One of them is the Copernicus Atmosphere Monitoring Service (CAMS) [15], operated by the European Centre for Medium-Range Weather Forecasts (ECMWF) [16], which is one of the core components of the European Union's Earth observation programme Copernicus. You can think of CAMS as a weather forecast service for air pollution: instead of predicting rain or temperature, it predicts the state of the atmosphere and the levels of air pollutants.

CAMS provides continuous, detailed information about the atmosphere, including daily forecasts for Europe and the whole world. It tracks a wide range of air pollutants, including those already introduced (PM2.5, PM10, O_3, NO_2, SO_2), and also several additional compounds. Among them is carbon monoxide (CO), a colorless and odorless gas mainly emitted through incomplete combustion processes in vehicles, power generation, and industrial activities. At elevated levels, CO can impair the blood's oxygen-carrying capacity, posing risks particularly for individuals with cardiovascular or respiratory conditions [17]. CAMS also tracks ammonia (NH_3), a gas predominantly released by agricultural activities, including fertilizer application and livestock farming. In the atmosphere, ammonia contributes to the formation of secondary particulate matter, thus indirectly impacting both health and environmental quality [18].

Moreover, CAMS monitors methane (CH_4), a potent greenhouse gas that, while not directly toxic at ambient concentrations, plays a crucial role in long-term air quality and climate regulation by affecting atmospheric chemistry and radiative forcing [19]. Similarly, carbon dioxide (CO_2), the principal anthropogenic greenhouse gas driving climate change, is included in CAMS observations due to its indirect effects on pollutant transport and weather patterns [20]. Lastly, CAMS accounts for natural contributors to air quality such as dust, composed of fine soil particles lifted into the atmosphere by wind. These particles can significantly degrade air quality and cause respiratory irritation, especially in sensitive populations.

A key aspect of CAMS is its air quality forecasting system. In order to predict how pollution levels will evolve in different regions and over time, CAMS uses what are known as chemical transport models. These are sophisticated mathematical tools that simulate how pollutants behave and move through the atmosphere. Because weather conditions such as wind, temperature, and humidity affect how pollutants are dispersed, these models are closely coupled with meteorological forecasts.

To make these simulations as accurate as possible, CAMS incorporates real-world data from multiple sources. Satellite observations play a crucial role in capturing information about the atmosphere from space. These are complemented by in place measurements taken at ground level by air quality monitoring stations spread across different countries. By combining satellite data, surface observations, and advanced modeling, CAMS is able to produce near real-time analyses and forecasts.

The forecasting system works at both global and European scales. On a global level, CAMS provides forecasts with a spatial resolution of around 40 km, while in Europe, higher resolution models offer more detailed predictions down to scales of about 10 km.

This makes CAMS a key infrastructure for researchers, decision makers, and developers working on climate and environmental services

Here we include the CAMS logo (Figure 1.2). A direct link to the service is available at the CAMS webpage.

Figure 1.2: Copernicus Atmosphere Monitoring Service (CAMS).[2]

1.2 Motivation: Combining Visualization and Technical Analysis

Although CAMS provides a large set of high-quality scientific data, accessing and using these data is not always straightforward for non-experts. Many of the available tools fall into two extremes. On the one hand, some platforms are designed mainly for researchers and specialists, offering the data in formats that require technical knowledge to be used. A common example is the so-called WMS (Web Map Service), which is a standardized way of delivering map images over the internet. In practice, a WMS layer is like a “raw map” containing pollutant concentrations, but it usually appears as a static image with little or no interactivity. Extracting numerical values or comparing pollutants across time and regions often requires additional software and expertise.

On the other hand, simplified applications focus only on highly aggregated indicators, such as the Air Quality Index (AQI). While these are easy to understand, they often hide important details, for example which specific pollutants are driving the problem, or how concentrations evolve during the day.

This project is motivated by the need to bridge this gap: to build a visualization tool that can take the detailed forecasts provided by CAMS and present them in a way that is both scientifically accurate and easy to explore. The idea is to allow users to interact

[2] https://atmosphere.copernicus.eu/

with the data, select pollutants of interest, compare regions, and understand not only the overall air quality but also the underlying factors.

1.3 Objectives of the Project

The goal of this project is to make the advanced air quality forecasts provided by CAMS more accessible and understandable to a wider audience, while also gaining a deeper understanding of how these forecasts are produced and validated. To achieve this, the project pursues six main objectives that build on each other:

- Understand CAMS forecasting models: Study how the system works, including the type of data it receives (from satellites, monitoring stations, and meteorological inputs) and how this information is processed to generate forecasts.
- Examine forecast evaluation methods: Analyze how the quality of CAMS predictions is checked against real-world measurements, identifying strengths and limitations of the current system.
- Explore WMS data access and pollutants representation: Investigate how Web Map Services (WMS) are used to deliver CAMS forecast layers, how pollutants are encoded and visualized, and what challenges arise when transforming these "raw map" layers into interactive formats.
- Develop a visualization platform: Create a web-based tool that transforms CAMS forecasts into interactive and user-friendly visualizations, enabling users to explore pollutant levels, compare regions, and better understand the factors driving air quality changes.
- Select relevant forecast variables: Review the full range of atmospheric variables predicted by CAMS, understand their meaning and relevance, and make a reasoned selection of those to be included in the visualization platform.
- Assess tools and implementation choices: Review the available software libraries and frameworks for working with CAMS data, compare their advantages and limitations, and document the reasoning behind the choices made for the visualization platform.

Together, these objectives aim not only to enhance the scientific understanding of air quality forecasting, but also to provide a practical tool that bridges the gap between complex data and accessible information for decision-makers and the general public.

2
State of art

In this chapter, we review the main approaches to air quality monitoring and forecasting. Several initiatives exist worldwide, both public and private, aimed at predicting pollutant levels, supporting policy decisions, and raising public awareness. Among the most relevant are the Copernicus Atmosphere Monitoring Service (CAMS), national monitoring networks, and independent platforms that aggregate air quality data.

We focus on the models and methods behind these forecasts, how they are validated, the platforms available for dissemination, and current challenges. This provides a clear picture of the state of the art and highlights gaps that justify the development of new visualization tools.

2.1 Air Quality Forecasting and Chemical Transport Models (CTMs)

Air quality forecasting relies on complex computational tools known as Chemical Transport Models (CTMs). These models simulate how pollutants are emitted, transported, chemically transformed, and ultimately removed from the atmosphere. In essence, CTMs help answer questions such as: Where do pollutants come from? How do they react in the air? Where are they transported? And how are they deposited or removed from the atmosphere [21].

To generate accurate forecasts, CTMs require multiple types of input data. Meteorological information like wind speed and direction, temperature, humidity, solar radiation, and atmospheric pressure. These information strongly influences the transport and transformation of pollutants. This data is typically provided by Numerical Weather Prediction (NWP) systems. In addition, detailed emission inventories are needed, which describe the quantity, source, timing, and location of pollutants released from traffic, industry, agriculture, or natural sources. Preparing these emissions correctly is crucial, as they must be adapted to the model's spatial and temporal resolution and, in some cases, chemically speciated to reflect their composition [21].

Once pollutants enter the atmosphere, CTMs simulate their chemical reactions, interactions with natural emissions, and removal processes, such as dry and wet deposition. To enhance accuracy, data assimilation techniques are employed, which integrate observational data from satellites and ground-based monitoring stations to correct and refine the model's outputs. This combination of simulation and observation allows CTMs to provide reliable forecasts of air pollution levels over time and across different regions.

Despite their utility, CTMs are computationally demanding and require careful configuration and expert interpretation. The quality of their predictions depends not only on the complexity of the model itself as well as on the accuracy and resolution of input data. Continuous development in both modeling approaches and observational networks is therefore essential to meet the increasing demand for reliable air quality information [21].

2.2 The Copernicus Atmosphere Monitoring Service (CAMS)

The **Copernicus Atmosphere Monitoring Service (CAMS)** is a core component of the European Union's Copernicus Earth observation programme [15], operated by the European Centre for Medium-Range Weather Forecasts (ECMWF) [16]. CAMS provides continuous, comprehensive information about the state of the atmosphere, producing forecasts of air pollutants at both global and regional scales. In simple terms, CAMS can be thought of as a "weather forecast for air quality": instead of predicting rain or temperature, it predicts concentrations of pollutants and their evolution over time.

At the global scale, CAMS uses the IFS-COMPO system, which is based on the ECMWF Integrated Forecasting System enhanced with atmospheric composition modules. This system produces analyses every six hours and forecasts up to five days ahead, with a horizontal resolution of approximately 40 km. The global system tracks major gases, including ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), methane (CH_4), carbon dioxide (CO_2), and formaldehyde (HCHO). It also monitors particulate matter (PM_{10} and $PM_{2.5}$), the Aerosol Optical Depth (AOD) by type (such as dust or smoke), black carbon, and sea salt. In addition, the system includes greenhouse gases and the UV index, providing a comprehensive view of atmospheric composition on a global scale [22].

For European regions, CAMS operates a high-resolution ensemble system combining multiple chemical transport models (CTMs) developed by different European research institutes. Each model within this ensemble implements its own chemical mechanisms, aerosol parameterizations, and data assimilation methods. By merging these outputs, CAMS produces more robust forecasts, reducing biases inherent in individual models. The ensemble system typically provides forecasts at horizontal resolutions of 5–10 km, which is particularly useful for understanding air quality variations in urban areas and regions with complex terrain [23].

At the regional European scale, CAMS provides detailed information on a wide range of pollutants: carbon monoxide (CO), nitric oxide (NO), nitrogen dioxide (NO_2), ozone (O_3), particulate matter (PM_{10} and $PM_{2.5}$), formaldehyde (HCHO), ammonia (NH_3), non-methane volatile organic compounds (NMVOCs), peroxyacetyl nitrates (PANs), and organic and elemental carbon (OC/EC) mainly from residential sources. It also tracks biological contaminants such as pollen (e.g., birch, olive, grass), which are highly relevant for public health.

In addition to these model systems, CAMS applies statistical post-processing techniques known as Model Output Statistics (MOS). MOS uses near-real-time observations from ground stations, combined with meteorological predictors, to correct systematic biases and improve the accuracy of near-surface pollutant forecasts. This allows CAMS to deliver reliable, actionable information for policymakers, researchers, and the general public [24].

By combining advanced chemical transport modeling, high-quality meteorological input, and observational data from satellites and ground networks, CAMS provides an integrated platform for monitoring and forecasting air pollution across Europe and the world [15]. This service is operated and maintained by the European Centre for Medium-Range Weather Forecasts (ECMWF) [16].

Together, these systems allow CAMS to provide a comprehensive suite of products, accessible via the Atmosphere Data Store (ADS). The information is delivered as multi-day hourly predictions and can be obtained in different formats: through web services such as WMS (Web Map Service) and WCS (Web Coverage Service), which allow users to visualize or directly download map-based data; through APIs (Application Programming Interfaces), which enable automated access for software and applications; or in scientific file formats such as NetCDF (Network Common Data Form), commonly used for storing and analyzing large climate and atmospheric datasets.

2.3 Evaluation and Validation of Air Quality Forecasts

Reliable air quality forecasts are essential for public health protection, policy decision-making, and citizen engagement. Therefore, systematic evaluation and validation of forecasts is a critical component of CAMS operations. To support this, CAMS uses two complementary frameworks:

Evaluation and Quality Control (EQC): EQC ensures continuous, near-real-time monitoring of forecast quality. Every day, forecasts are compared with independent datasets (EEA stations, ozone sondes, AERONET, satellites, IAGOS aircraft). Statistical indicators such as Bias, RMSE, MNMB, FGE, MFB and MFE are automatically computed and published in dashboards and reports. For example, if the Normalized Mean Bias (NMB) for NO_2 is –0.25, this indicates that the model underestimates average concentrations by 25%. EQC also makes use of graphical tools such as Taylor diagrams and Target diagrams to visualize skill across models and regions. According to the CAMS Global Services portal, the EQC server provides quick-look graphics and validation reports for analyses, forecasts, and reanalyses [25].

Evaluation and Quality Assurance (EQA): EQA goes beyond daily performance monitoring and focuses on long-term robustness and compliance with pre-defined quality standards. It verifies that methodological updates (e.g. changes in emission inventories or data assimilation schemes) genuinely improve forecast quality. For instance, an update is considered successful if it reduces RMSE at more than 80% of stations while maintaining correlation above 0.7. In the FAIRMODE framework, this is quantified through the Model Quality Indicator (MQI), which compares model error against observation uncertainty. Models are deemed "fit-for-purpose" if MQI < 1 for at least 90% of monitoring sites. The CAMS Global Services website emphasizes that EQA reports also document daily forecast quality, planned upgrades, and reanalyses [25].

Together, EQC and EQA provide a dual guarantee: EQC ensures day-to-day reliability of forecasts, while EQA safeguards their long-term scientific and regulatory validity.

2.3.1 Observational Datasets for Validation

To validate CAMS forecasts, outputs are compared against a large number of independent measurement datasets, ensuring robust evaluation across spatial and temporal scales. These datasets include:

- **Surface in situ measurements:** Continuous ground-based observations from monitoring stations (e.g., EEA) for key pollutants.
- **Surface remote sensing:** Networks such as AERONET provide aerosol optical depth and other atmospheric properties.
- **Routine aircraft measurements:** In-situ observations along flight paths (e.g., IAGOS) providing vertical profiles of atmospheric composition.
- **Balloon measurements:** Ozone sondes capturing vertical ozone profiles and supporting upper-air validation.
- **Satellite observations:** Instruments such as Sentinel-5P, MODIS, and IASI providing global and regional coverage of trace gases and aerosols.

These diverse sources allow CAMS to perform both EQC and EQA, improving model forecasts through data assimilation and rigorous validation [26].

2.3.2 Statistical Metrics for Forecast Evaluation

The commonly employed statistical metrics are shown in Table 2.1. These metrics provide complementary perspectives on forecast performance, helping to identify both systematic biases and the ability of the model to capture temporal and spatial variations.

Explanation of Symbols: In these formulas, M_i represents the model forecast at observation point i, O_i the corresponding observed value, $\overline{M}$ and $\overline{O}$ are the mean values of the forecasts and observations, and N is the total number of paired observations.

Metric	Description	Formula
RMSE (Root Mean Square Error)	Emphasizes large errors by penalizing higher deviations. Useful for detecting occasional extreme forecast errors.	$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(M_i - O_i)^2}$
MAE (Mean Absolute Error)	Measures the average magnitude of forecast errors, without considering their direction. Less sensitive to outliers than RMSE.	$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\lvert M_i - O_i\rvert$
Mean Bias (MB)	Indicates systematic overestimation (positive) or underestimation (negative) of the forecast.	$\text{MB} = \frac{1}{N}\sum_{i=1}^{N}(M_i - O_i)$
Pearson Correlation (R)	Measures the strength and direction of the linear relationship between forecasts and observations. High values indicate good temporal/spatial pattern reproduction.	$R = \frac{\sum_{i=1}^{N}(M_i-\overline{M})(O_i-\overline{O})}{\sqrt{\sum_{i=1}^{N}(M_i-\overline{M})^2\sum_{i=1}^{N}(O_i-\overline{O})^2}}$

Table 2.1: Standard statistical metrics used to evaluate air quality forecasts.

Interpretation, Usage, and Limitations: Each metric has specific characteristics that should be understood together to properly assess forecast quality. The RMSE is sensitive to extreme values and highlights occasional large errors, which can be critical in public health applications, such as pollution peaks. In contrast, the MAE provides a robust measure of average forecast error and is preferred when outliers should not dominate the evaluation. The Mean Bias (MB) helps detect systematic over- or under-prediction tendencies; a persistent bias may indicate issues in emission inventories, chemical mechanisms, or meteorological inputs. Finally, the Pearson correlation (R) assesses how well the forecast reproduces temporal or spatial variations, independently of absolute magnitude; a high R value does not guarantee accuracy in absolute terms if bias exists. It is important to note that RMSE can overemphasize extreme events while MAE may underrepresent them, MB alone does not reflect the magnitude of errors, and correlation does not capture systematic over- or underestimation. Therefore, it is recommended to consider multiple metrics together to obtain a comprehensive understanding of model performance.

Practical Example: Consider a model predicting daily $PM_{2.5}$ concentrations over one week at a monitoring station. Suppose the RMSE is 15 μg/m^3, MAE is 10 μg/m^3, Bias is

$+5\ \mu g/m^3$, and Pearson R is 0.85. Interpretation:

- The model captures the temporal variations well (high R).
- On average, predictions are moderately accurate (MAE).
- Large deviations exist (RMSE > MAE), possibly due to one or two days with extreme errors.
- There is a slight tendency to overestimate concentrations (positive Bias).

This example illustrates why multiple metrics are necessary to fully assess forecast performance.

2.3.3 Advanced Metrics for CAMS Forecast Evaluation

Beyond standard metrics, CAMS employs advanced statistical indicators to better capture performance nuances and improve model assessment. These metrics are particularly useful when evaluating ensemble forecasts, assessing bias sensitivity, or comparing updated model versions. These advanced metrics are shown in Table 2.2.

Metric	Description	Formula
MNMB (Modified Normalized Mean Bias)	Normalizes the bias with respect to both observed and modeled values to reduce sensitivity to extreme values.	$\mathrm{MNMB} = \frac{1}{N}\sum_{i=1}^{N}\frac{M_i - O_i}{M_i + O_i}$
MAB (Mean Absolute Bias)	Measures the average magnitude of bias regardless of direction, emphasizing overall forecast deviation.	$\mathrm{MAB} = \frac{1}{N}\sum_{i=1}^{N}\lvert M_i - O_i\rvert$
FGE (Fractional Gross Error)	Expresses the error proportionally to the sum of observed and predicted values. Less sensitive to large outliers.	$\mathrm{FGE} = \frac{1}{N}\sum_{i=1}^{N}\frac{\lvert M_i - O_i\rvert}{M_i + O_i}$
Improvement / Deterioration Scores	Track systematic performance changes by comparing updated forecasts against control runs.	$\mathrm{DiffMB} = \mathrm{MB}_{\mathrm{new}} - \mathrm{MB}_{\mathrm{control}}$

Table 2.2: Advanced metrics used in CAMS forecast evaluation.

Explanation of Symbols: M_i denotes the forecast value at observation i, O_i the corresponding observation, and N the total number of paired data points. $\mathrm{MB}_{\mathrm{new}}$ and $\mathrm{MB}_{\mathrm{control}}$ refer to mean bias values for the updated and reference model versions, respectively.

Interpretation, Usage, and Limitations: Advanced metrics provide additional insight into forecast performance, particularly for ensemble models or pollutants with high variability. The Modified Normalized Mean Bias (MNMB) reduces sensitivity to extreme concentrations by normalizing the bias relative to both observed and modeled values; values near zero indicate minimal systematic bias. The Mean Absolute Bias (MAB) quantifies the average magnitude of deviation without regard to direction, useful for assessing overall forecast accuracy. The Fractional Gross Error (FGE) expresses errors proportionally to the sum of observed and forecasted values, providing a balanced assessment when pollutant concentrations vary widely. Improvement or Deterioration Scores (DiffMB) track systematic changes in forecast performance by comparing updated model runs against reference runs, helping developers identify whether modifications enhance or degrade forecast quality. It is important to note that MNMB and FGE assume non-zero denominators, so caution is needed for near-zero concentrations; MAB does not indicate bias direction and should be interpreted alongside MNMB or MB; and improvement scores are meaningful only if the control run is representative. Using these metrics together allows for a comprehensive evaluation of both magnitude and proportional errors, providing a more nuanced understanding of forecast performance than standard metrics alone.

Practical Example: Consider a 5-day forecast for daily $PM_{2.5}$ at a monitoring site:

$$M = [18, 25, 30, 28, 20]\ \mu\text{g/m}^3, \quad O = [20, 22, 27, 30, 18]\ \mu\text{g/m}^3.$$

We compute:

- MNMB $= \frac{1}{5} \sum \frac{M_i - O_i}{M_i + O_i} \approx 0.03$, indicating very low systematic bias.
- MAB $= \frac{1}{5} \sum |M_i - O_i| = 2.4\ \mu\text{g/m}^3$, showing the average deviation magnitude.
- FGE $= \frac{1}{5} \sum \frac{|M_i - O_i|}{M_i + O_i} \approx 0.08$, reflecting proportional error relative to observed + forecast values.

These metrics together provide a comprehensive understanding of forecast performance, highlighting both magnitude and proportional errors, and allowing comparison across models or time periods.

Origin and Rationale: Many of these metrics were introduced in the context of European air quality model intercomparison exercises and the FAIRMODE initiative, which aimed to harmonize model evaluation practices across Member States. For example, the Modified Normalized Mean Bias (MNMB) and Fractional Gross Error (FGE) are now considered reference indicators within FAIRMODE because they treat over- and underestimation symmetrically and are less affected by extreme outliers [27]. The Mean Fractional Bias (MFB) and Mean Fractional Error (MFE) are likewise recommended when comparing pollutants with different scales, since they provide percentage-like interpretations.

Practical Use Cases:

- **Ozone (O_3)**: MNMB is preferred due to strong seasonal variability and high concentration ranges.
- **Particulate matter (PM_{10}, $PM_{2.5}$)**: FGE and MFE are often used to capture proportional errors in urban vs. rural sites.
- **Episode detection (peaks)**: Correlation (Pearson, Spearman) is critical to assess whether the timing of high pollution events is reproduced, even if absolute magnitudes are biased.

Limitations: Although these metrics overcome some drawbacks of standard scores, they are not free of issues. For example, fractional metrics become unstable when observed concentrations are very low, while correlation coefficients may mask systematic overestimation. Therefore, CAMS adopts a multi-metric approach, reporting several indicators simultaneously rather than relying on a single number.

2.4 Platforms for Dissemination and Accessibility

The forecasts produced by CAMS are made accessible through a variety of platforms, each targeting different audiences and offering distinct levels of complexity. These platforms range from highly intuitive, user-oriented interfaces to scientific portals that require expert knowledge. Understanding their functionalities and limitations is essential to identify the gaps that motivate the development of new visualization tools.

One of the most popular public-facing platforms is **Windy.com**[1], which integrates CAMS data into its interactive global weather maps. Windy is widely used due to its highly visual interface: users can navigate the globe, zoom into regions of interest, and overlay layers of air pollutants such as $PM_{2.5}$, NO_2, or O_3. This makes it an effective tool for raising awareness among the general public. However, Windy focuses on visualization rather than analysis: it does not provide access to underlying numerical values or allow generation of graphs directly. Therefore, while it excels in accessibility and interactivity, it is limited for scientific or technical work (Figure 2.1).

At the other end of the spectrum, the **CAMS Atmosphere Data Store (ADS)**[2] provides full access to forecast datasets in scientific formats such as NetCDF and GRIB. Through ADS, expert users can download multi-day, hourly predictions of pollutants, meteorological variables, and greenhouse gases at global or regional scales. This platform offers maximum flexibility and scientific robustness, but requires specialized knowledge of data processing tools (Python, R, GIS software). For many non-experts, this represents a significant barrier. To illustrate, Figure 2.2 shows the ADS interface alongside a capture of the installation instructions for the CDS API, demonstrating the technical steps required to access the data programmatically.

[1] https://www.windy.com
[2] https://ads.atmosphere.copernicus.eu/

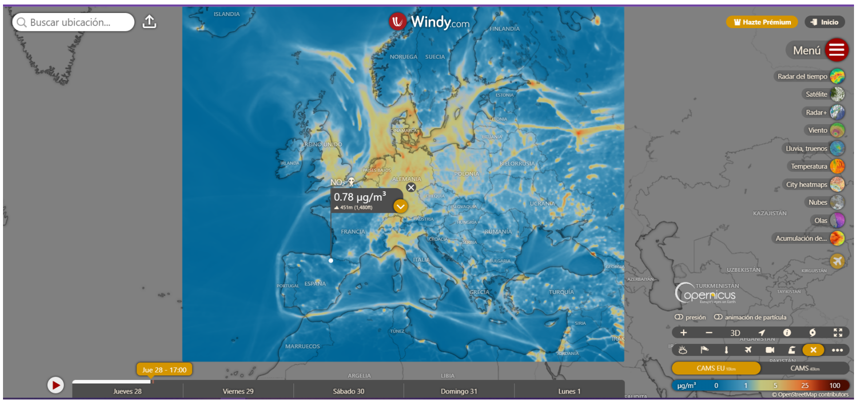


Figure 2.1: Example of CAMS air quality layers integrated in Windy.com.

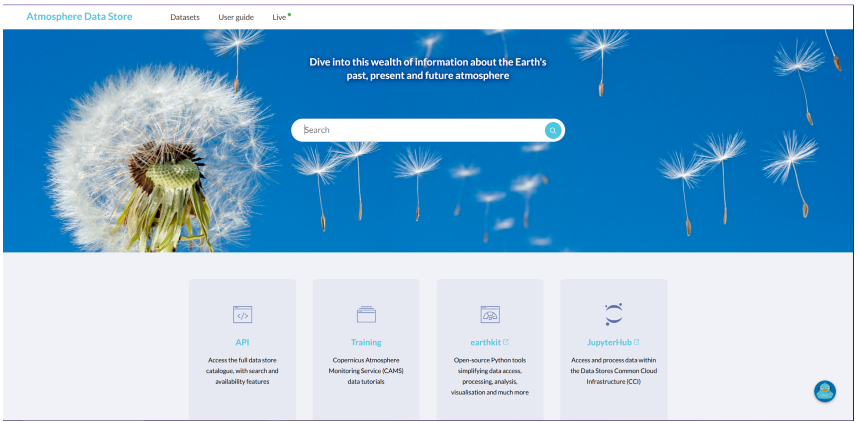


Figure 2.2: Interface of the CAMS Atmosphere Data Store (ADS).

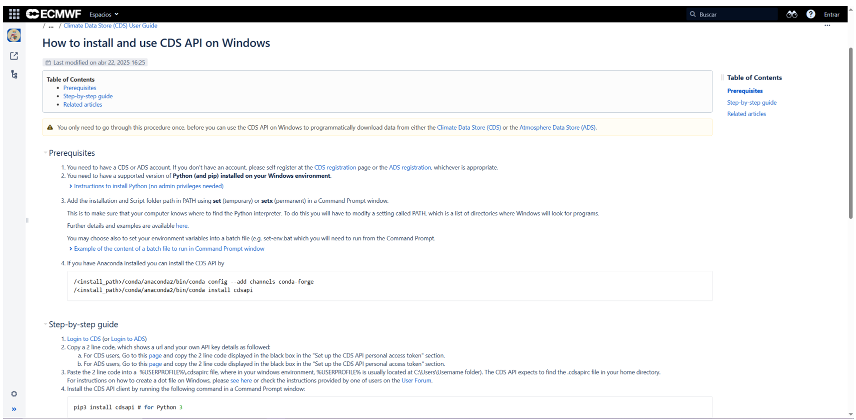


Figure 2.3: Screenshot illustrating the installation and setup of the CDS API for accessing ADS data.

Between these extremes, the **CAMS Regional Air Quality Viewer**[3] is designed specifically to display European forecasts with higher spatial resolution (5–10 km). It presents interactive maps for pollutants such as ozone, nitrogen dioxide, and particulate matter. Unlike ADS, this platform allows users to visualize pollutant distributions graphically, including plots of predicted values over time. However, users cannot extract raw numerical data directly from the graphs, limiting its usefulness for advanced analysis (Figures 2.4 and 2.5).

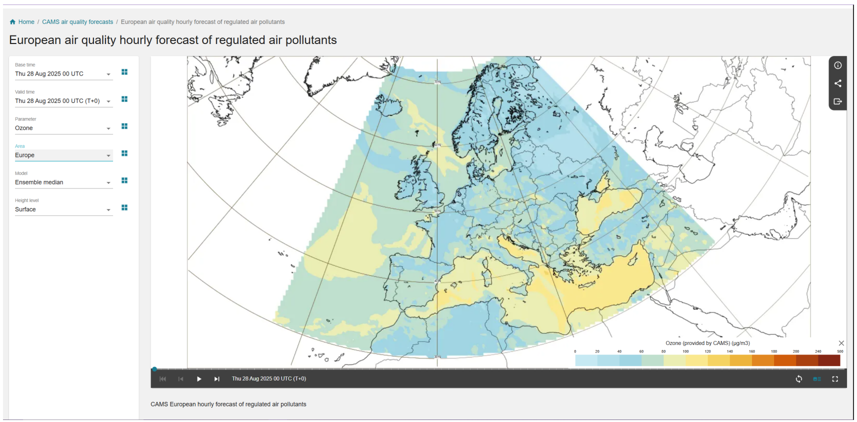


Figure 2.4: CAMS Regional Air Quality Viewer, showing forecast maps for Europe.

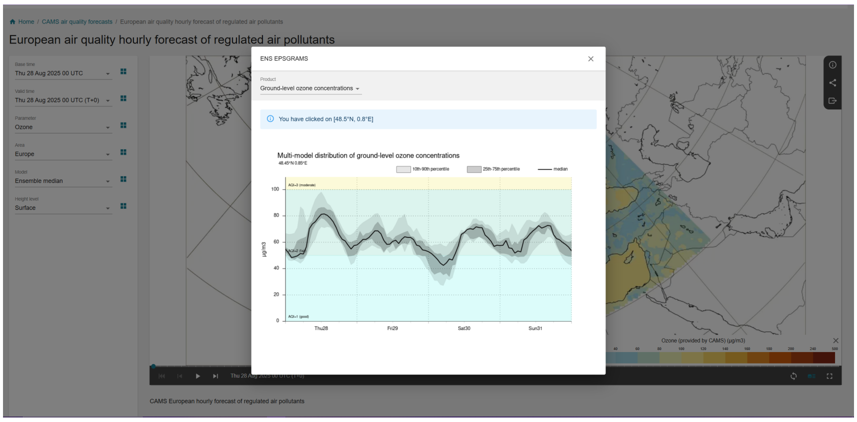


Figure 2.5: Example of a graph in the CAMS Regional Air Quality Viewer, showing predicted pollutant values over time for a selected location.

In addition to forecast-oriented services, **OpenAQ** plays an important complementary role by aggregating real-time observational data from thousands of monitoring stations worldwide. Unlike CAMS platforms, OpenAQ focuses on measurements rather than modeled forecasts, making it particularly valuable for validation purposes. Researchers and

[3] https://atmosphere.copernicus.eu/european-air-quality-forecast-plots

developers can access its open API to retrieve raw observations, enabling integration into independent applications. While it does not provide predictive capability, OpenAQ exemplifies how open data platforms can foster transparency and community engagement.

In summary, existing platforms present a clear trade-off between usability and scientific depth. Public-facing tools like Windy.com offer engaging visualizations but little analytical flexibility, while scientific portals such as ADS provide full datasets at the expense of accessibility. Intermediate solutions, like the CAMS Regional Viewer, address part of this gap but remain limited in interactivity. This fragmentation highlights the need for tools that are at once scientifically robust and user-friendly, providing accessible, interactive ways to explore CAMS data without requiring advanced technical expertise.

2.5 Challenges and Open Gaps

I decided to develop my own platform for air quality forecasting because existing tools, although comprehensive, do not offer the flexibility needed to visualize information interactively and customize it according to specific regions and pollutants. Traditional platforms often provide static maps or pre-determined reports, whereas this application allows users to select different regions, choose specific pollutants, and observe their hourly variations through a slider, complemented by historical time-series charts. The integration of WMS layers and dynamic map visualization enables a more intuitive experience, allowing users to explore data in real time and obtain precise information by clicking on a given location. This approach contrasts with previous systems, which typically limit interactivity and do not allow combining visualizations from multiple sources dynamically. By developing this platform, the goal was to merge data accuracy with usability and analytical capability, resulting in a tool that is both accessible and versatile for public, academic, or environmental monitoring purposes.

Overall, existing tools successfully deliver high-quality air quality forecasts but exhibit trade-offs between usability and analytical depth. This motivates the creation of a new visualization platform that bridges this gap, offering a scientifically robust, interactive, and user-centered interface that facilitates exploration, comparison, and interpretation of atmospheric data.

3

Implementation

This chapter describes the implementation process of the web platform developed for the visualization of atmospheric pollutant forecasts. The main objective is to detail the technical decisions made, the system architecture, and the different components that enable dynamic interaction with environmental data in real time.

3.1 System Architecture

The platform developed to visualize atmospheric pollutant forecasts is based on a **client-only web application running entirely in the browser**. This means that the user does not need to install specialized software or download large datasets to interact with maps and graphs. All interactions occur dynamically and in real time.

The architecture follows a typical pattern for modern web applications. There is a **presentation layer** responsible for displaying information and enabling user interaction, and a **data flow** connecting this layer to external services that provide atmospheric data. In this case, the data is offered by CAMS (Copernicus Atmosphere Monitoring Service) through ECMWF's *ecCharts* platform, which exposes pollutant concentration fields at both global and European scales using the OGC Web Map Service (WMS) standard.

The browser manages interaction and rendering using standard web technologies: HTML for structure, CSS for styling, and JavaScript for interactive logic. Within this layer, *Leaflet* displays interactive maps onto which pollutant layers are overlaid via WMS requests, while *Highcharts* generates on-demand time-series plots of pollutant concentrations at user-selected locations.

For clarity, the architecture can be visualized as illustrated in Figure 3.1, the client interacts directly with CAMS servers using WMS requests. The **web browser** executes the application and issues WMS requests to CAMS servers via the Internet. CAMS servers act as the information provider, rendering pollutant concentration maps (GetMap) and returning pixel values at clicked points (GetFeatureInfo). The data flow is strictly *on demand*: data is only requested when the user selects a pollutant, adjusts the time slider, or clicks on the map.

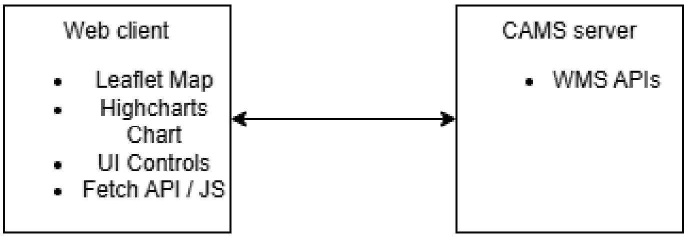


Figure 3.1: System architecture: interaction between the web client and CAMS servers via WMS APIs.

3.2 Choice of Mapping Library

One of the key decisions in the design of the visualization system was the selection of a mapping library capable of rendering geospatial data and providing interactive functionality. This choice is critical because it determines not only the technical possibilities of the system but also its accessibility for future users and developers.

The first option considered was **Google Maps API**, a service that is widely recognized and extensively documented. At first sight, it might appear to be the easiest solution, since it provides polished interfaces and reliable infrastructure. However, it is not well suited for the objectives of this project. Being a proprietary tool, it imposes licensing restrictions that limit its free use and redistribution. Furthermore, it offers only limited support for geospatial standards such as WMS (Web Map Service), which are essential when working with scientific or institutional sources of environmental data.

Another possibility was **OpenLayers**, an open-source library that is highly regarded in the professional field of web mapping. Its main strength lies in its native compatibility with OGC standards, including WMS, WFS, and WMTS. This makes it an extremely powerful and flexible option for complex applications. Nevertheless, this power comes at the cost of a higher degree of complexity. The learning curve for OpenLayers is steeper, and for a project intended to be both educational and easy to prototype, this could represent an unnecessary barrier for development and future maintenance.

The final choice was **Leaflet.js**, a lightweight and widely adopted library for interactive web maps. Although its built-in support for WMS services is more basic than that of OpenLayers, it can be extended with a rich ecosystem of plugins, such as *leaflet.wms* or *leaflet.timeDimension*. These extensions allow seamless integration of external services, including the CAMS datasets used in this project, and make it possible to explore temporal variations in air quality data through interactive layers.

Leaflet was selected because it offers the best balance between simplicity and functionality. Its design allows developers to build interactive maps with only a few lines of code, accelerating the prototyping process. The library is very lightweight (less than 40 KB), which ensures quick loading times even on devices with limited resources, thereby improving accessibility. Since it is entirely open-source and free to use, it also aligns with the philosophy of this project, which aims to rely on open technologies to guarantee reproducibility and long-term usability. Finally, Leaflet benefits from an active and large community that provides tutorials, documentation, and practical examples, making it easier to learn, troubleshoot, and sustain over time.

In summary, Leaflet represents an optimal solution for this project. It is powerful enough to handle CAMS WMS layers and interactive visualizations, while remaining simple and approachable for future users or developers who may wish to extend or adapt the tool without requiring advanced expertise in geospatial technologies.

3.3 Discovering Available Layers

To determine which pollutants and forecast products are available from CAMS, it is necessary to inspect the WMS service capabilities. ECMWF provides documentation of the CAMS WMS service, but the official page does not contain the complete list of layers. Therefore, the full set of available layers is obtained through a `GetCapabilities` request, which returns an XML document describing them. Each layer entry includes its internal identifier, descriptive title, units (if defined), and the time dimension specifying the forecast horizon.

The process can be automated using a Python script, shown in Listing 3.1. It sends a request to the CAMS server, parses the XML, and prints out the available layers with their metadata:

```python
import requests
import xml.etree.ElementTree as ET

url = "https://eccharts.ecmwf.int/wms/?token=public&request=GetCapabilities&version=1.3.0"

response = requests.get(url)
xml_content = response.content

root = ET.fromstring(xml_content)

ns = {'wms': 'http://www.opengis.net/wms'}

layers = root.findall('.//wms:Layer/wms:Layer', ns)

print(f"Found {len(layers)} layers:\n")

for layer in layers:
name = layer.find('wms:Name', ns)
title = layer.find('wms:Title', ns)
units = layer.find('wms:Units', ns)
dimension = layer.find("wms:Dimension[@name='time']", ns)

print("Layer:")
print(f"  Name:   {name.text if name is not None else 'N/A'}")
```

```
        print(f"  Title:  {title.text if title is not None else 'N/A'}")
        print(f"  Units:  {units.text if units is not None else 'N/A'}")
        print(f"  Time:   {dimension.text[:50] + '...'}" if dimension is not None else "  Time:   N/A")
        print("-" * 40)
```

Listing 3.1: Python script to extract CAMS layers from WMS GetCapabilities

When executed, the script returns a list of all the layers exposed by CAMS. Each entry contains the pollutant or variable identifier, its description, the units, and the available time stamps. in Listing 3.2.

```

Found 121 layers:
...

Layer:
Name: composition_o3_surface Title: Ozone at surface [ppbv] (provided by CAMS, the Copernicus Atmosphere Monitoring Service)
Units: N/A Time: 2025-08-23T03:00:00Z,2025-08-23T06:00:00Z/2025-09-...
----------------------------------------

Layer:
Name:
composition_europe_o3_analysis_surface
Title: Ozone at surface [ug/m3] (provided by CAMS, the Copernicus Atmosphere Monitoring Service)
Units: N/A
Time: 2022-11-28T00:00:00Z,2022-11-29T00:00:00Z/2023-01-...
----------------------------------------

Layer:
Name: composition_pm10
Title: PM10 - coarse particulate matter [ug / m3] (provided by CAMS)
Units: N/A
Time: 2025-08-23T03:00:00Z,2025-08-23T06:00:00Z/2025-09-...
----------------------------------------

...
```

Listing 3.2: Truncated output of the GetCapabilities request

This information is essential for dynamically populating the pollutant menu and enabling correct requests for specific forecast hours.

3.4 Hourly Forecast Handling

The platform provides hourly forecasts of atmospheric pollutants, enabling users to explore both the spatial distribution of pollutants on a map and the temporal evolution at specific locations. Handling these hourly forecasts involves several interconnected components, including the time slider, the WMS requests to CAMS, the rendering of map layers, and the visualization of historical data.

The first key component is the time slider, which allows the user to select the forecast hour they wish to inspect. The application automatically calculates the range of available forecast hours based on the current UTC time and a forecast horizon of four days. For each hour within this range, an ISO-formatted timestamp is generated and associated with a position on the slider. When users select a global forecast, the application rounds the chosen hour to the nearest multiple of three, reflecting the temporal resolution of the global CAMS forecasts. The slider also displays labels that indicate the day of the forecast, providing an intuitive reference so users can easily identify which hours correspond to which day.

3.5 Conversion of Pollutant Values

Some of the data layers were not given in $\mu g/m^3$ (micrograms per cubic meter), but in ppbv (parts per billion by volume). To standardize the units, a pollutant-specific conversion factor was applied.

These factors are derived from the relationship between volumetric concentration and mass using the ideal gas law:

$$C_{\mu g/m^3} = C_{ppbv} \times \frac{M \cdot P}{R \cdot T} \cdot 10^3$$

where:

- $C_{\mu g/m^3}$ = concentration in micrograms per cubic meter ($\mu g/m^3$)
- C_{ppbv} = concentration in parts per billion by volume (ppbv)
- M = molar mass of the pollutant (g/mol)
- P = pressure (Pa)
- R = universal gas constant $8.314\,\mathrm{J/(mol \cdot K)}$
- T = absolute temperature (K)

The factors used in the code were calculated assuming standard pressure and temperature conditions ($P = 101325\,Pa$, $T = 298\,K$) and applying the equation above.

Note on temperature: $T = 298\,K$ corresponds to approximately $25\,°C$.

For example, for NO_2:

$$\text{NO}_2\text{ Factor} = \frac{46.0055\,[g/mol] \cdot 101325\,[Pa]}{8.314\,[J/(mol \cdot K)] \cdot 298\,[K]} \cdot 10^{-3} \approx 1.9125$$

This means that each ppbv of NO_2 corresponds approximately to $1.9125\,\mu g/m^3$. The code that performs the conversion is shown in Listing 3.3.

```
function convertPollutantValue(pollutant, rawValue) {
    let value = parseFloat(rawValue);
    let unit = "ug/m3";

    switch (pollutant) {
        case "NO2": value = value * 1.9125; break;
        case "SO2": value = value * 2.6609; break;
        case "CO":  value = value * 1.1642; break;
        case "CO2": value = value * 1.829; break;
        case "CH4": value = value * 0.666; break;
        case "O3":  value = value * 1.9957; break;
        default: value = value * 1; break;
    }

    return { value: Math.round(value * 100)/100, unit };
}
```

Listing 3.3: Conversion of pollutant values to $\mu g/m^3$

Each factor in the code corresponds to the calculation shown for NO_2, adjusted for the molar mass of each pollutant. This ensures all values are in the same unit ($\mu g/m^3$) for consistent analysis and comparison.

3.6 Dynamic Layer Updating

Whenever the user changes the selected region, pollutant, or forecast hour, the function `updateLayer()` is triggered. This function is responsible for updating the map with the correct pollutant layer for the chosen time. The implementation is shown in Listing 3.4. It first computes the exact time to request from the CAMS servers, taking into account region-specific rounding rules. Using the service URL provided by CAMS, it then constructs a WMS GetMap request, specifying the layer corresponding to the selected pollutant. If a color gradient style is defined for that pollutant, it is included in the request to ensure a meaningful visual representation. Before adding the new layer to the map, any previous pollutant layer is removed, ensuring that only the selected forecast is visible. The map legend is also updated at this point, reflecting the pollutant's concentration range and the color mapping used to represent different values.

```
function updateLayer() {
    if (wmsLayer) map.removeLayer(wmsLayer);
```

```

        const layerName = wmsInfo[region].layers[contaminante];
        const wmsUrl = wmsInfo[region].url;

        wmsLayer = L.tileLayer.wms(wmsUrl, {
            layers: layerName,
            format: 'image/png',
            transparent: true,
            opacity: 0.6,
            time: timeISO
        }).addTo(map);

        if (styleName) wmsLayer.setParams({ styles: styleName });

        leyendaDiv.textContent = = `Leyend: ${leyendas[contaminante
           ]} (Hour UTC: ${fechaReal.getUTCHours()}:00)`;
        renderLegend(contaminante);
    }
```

Listing 3.4: Updating the map layer for the selected pollutant and hour

3.7 Pollutant Value Extraction on Map Click

Users can click on any point of the map to obtain the forecasted concentration of the selected pollutant at that location. This is accomplished by an asynchronous function, which sends a WMS GetFeatureInfo request to the CAMS servers using the coordinates of the clicked point and the selected forecast hour. The response is parsed to extract the raw pollutant value, which is then converted to a standardized unit using predefined conversion factors specific to each pollutant. The result, including both the concentration and its unit, is displayed on the interface, allowing users to quickly understand the expected air quality at a given location.

3.8 Historical Data Visualization

In addition to showing the concentration at a single point in time, the platform allows users to explore the temporal profile of pollutant concentrations at a specific location. The function `getHistoricalDataForPollutant()` retrieves data for all available forecast hours in the slider. Each forecast hour is queried individually through a WMS GetFeatureInfo request, and the values are converted to consistent units. The resulting time series is plotted using Highcharts through the `plotPollutantHistory()` function, as shown in Listing 3.5. Producing an interactive line chart. This feature enables users to visualize how pollutant concentrations evolve over time and identify periods of higher risk.

```
    function plotPollutantHistory(data) {
        Highcharts.chart('chartContainer', {
```

```
            chart: { type: 'line', zoomType: 'x' },
            title: { text: 'Historial␣de␣Contaminantes' },
            xAxis: { type: 'datetime', title: { text: 'Fecha/Hora␣
               UTC' } },
            yAxis: { title: { text: 'Concentracion␣(ug/m3)' }, min:
                0 },
            series: [{ name: contaminanteSelect.value, data: data,
               turboThreshold: 0 }],
            credits: { enabled: false },
            exporting: { enabled: true }
        });
    }
```

Listing 3.5: Plotting historical pollutant data using Highcharts

3.9 Animation of Forecasts

To further facilitate understanding of pollutant trends, the platform provides a play/stop button that animates the forecast over all available hours. Activating this feature sequentially advances the slider, updating both the WMS layer on the map and the legend in real time. This animation helps users intuitively grasp the dynamics of pollutant distribution and evolution without manually adjusting the slider.

3.10 Color Gradients and Legends

Finally, each pollutant has a predefined color gradient and threshold levels stored in the application. When a layer is displayed, a floating legend is rendered on the screen. This legend visually represents the range of concentrations using the color gradient and indicates key values such as the minimum, 30%, 50%, 70%, and maximum thresholds. Additionally, the legend includes the name of the pollutant and the measurement unit.

The legend is generated by requesting the corresponding WMS layer, which returns an image containing the color gradient and associated threshold levels. From this image, it is posible to extract both the colors and the numerical values for each threshold. These extracted values are then combined with the pollutant-specific conversion factor, ensuring that the legend displayed in the interface matches the standardized units used in the map and in the time-series charts.

This approach ensures consistency between the visual representation of pollutant concentrations and the numerical data displayed, allowing users to intuitively interpret both current and forecasted air quality levels directly from the map.

4 Results

This chapter presents the outcomes obtained from the development and implementation of the web-based platform for visualizing air quality forecasts. The platform prototype enables users to interactively explore forecasts of atmospheric pollutants provided by the Copernicus Atmosphere Monitoring Service (CAMS), offering both spatial and temporal insights. In this chapter, the functionality and performance of the platform are analyzed, highlighting key features such as dynamic map layers, point-specific pollutant queries, time-series visualizations, forecast animations, and data export capabilities. Each section illustrates how the interface supports intuitive exploration of forecast data and facilitates interpretation of pollutant concentrations across different geographic domains and forecast horizons.

4.1 Main Interface

The application runs entirely in the web browser, so it does not require installation or additional configuration. Its central element is an interactive map, implemented with `Leaflet`, which displays pollutant concentration layers provided by CAMS through the WMS standard. Users can select both the geographic domain (Europe or Global) and the pollutant of interest through a drop-down menu. A time slider positioned below the map allows exploration of hourly forecasts up to four days ahead, while an adaptive legend facilitates interpretation of concentration values by associating each color range with a quantitative interval (Figure 4.2).

In addition to these basic elements, the platform includes complementary features designed to enhance usability and interactivity. The map itself is fully interactive: by clicking on any location, the application retrieves the forecasted pollutant value at that point and displays it in a dedicated text panel and also it will display the future values in the time-series plots. Animation controls enable sequential visualization of forecasts, helping users to perceive the temporal evolution of pollutant dispersion. These elements are illustrated in Figure 4.1, which highlights the pollutant and time indicators, the clickable map for pollutant extraction, and the animation controls. Furthermore, the interface integrates a charting component that generates time-series plots of pollutant concentrations at the selected location, together with export options that allow downloading the data for further analysis (Figure 4.2).

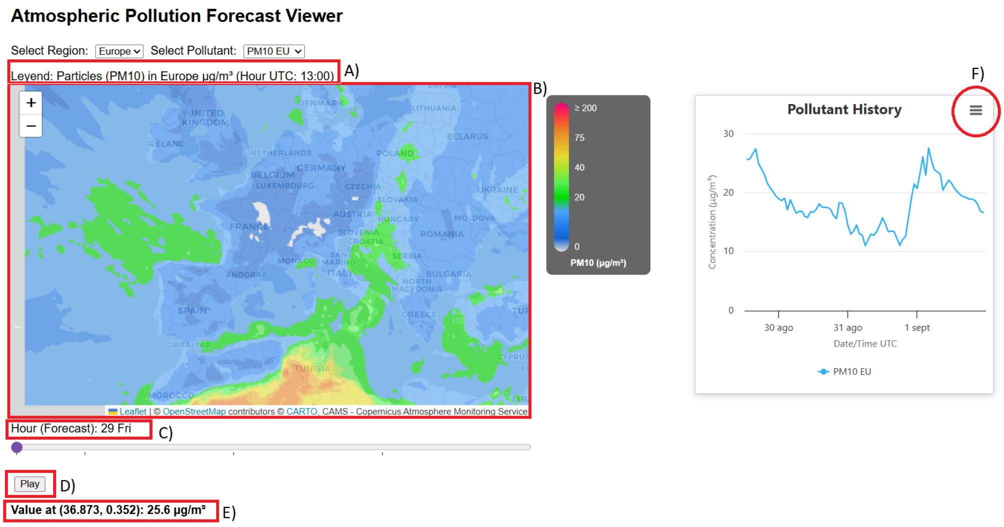


Figure 4.1: Main user interface of the developed platform. (A) Text panel indicating the selected pollutant and forecast hour. (B) Interactive map with clickable locations for pollutant value extraction. (C) Text panel showing the selected forecast day. (D) Animation controls for sequential forecast visualization. (E) Text panel displaying the clicked location and its pollutant value. (F) Menu for data download options from the chart.

4.2 Dynamic Layer Updating

One of the key features of the platform is the automatic update of pollutant layers whenever the user modifies any of the control parameters: selected region, pollutant, or forecast hour. The update process is triggered first through the region and pollutant selectors (A) in Figure 4.2, implemented as dropdown menus, which allow switching between the European or Global domain and choosing the pollutant of interest. Similarly, the time slider (B) in Figure 4.2 enables navigation across the hourly forecasts, and each movement of the slider synchronizes the map with the concentration values corresponding to the selected forecast hour. Finally, the clickable map interaction (B) in Figure 4.1 provides pollutant concentration values for any chosen location. When a location is clicked, the application retrieves the forecasted value for that point, displays it in the corresponding text panel, and simultaneously generates its temporal evolution in the time-series chart (D) in Figure 4.2. In this way, the interface ensures that all visual elements remain consistent with user selections, offering a smooth and responsive exploration of the CAMS forecast data.

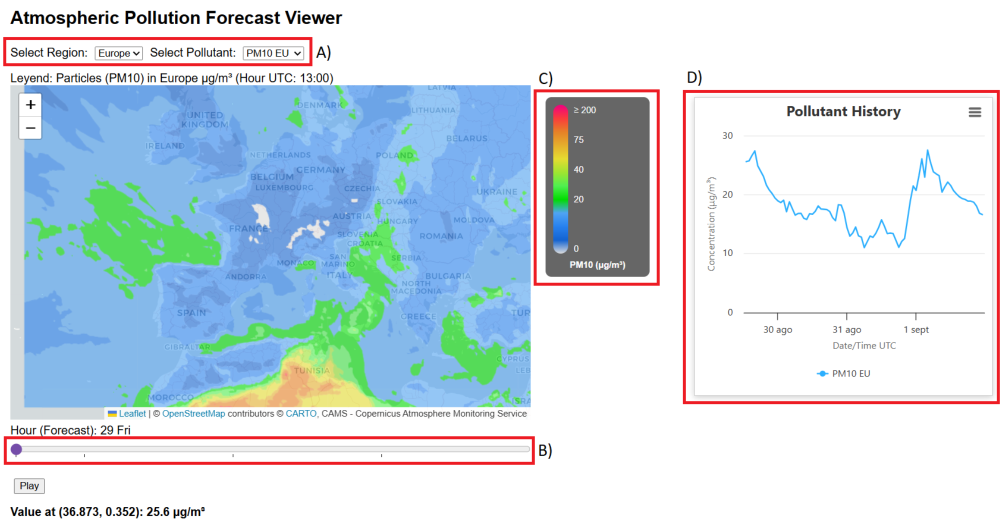


Figure 4.2: Extended view of the platform interface. (A) Region and pollutant selectors. (B) Time slider for navigating forecast hours. (C) Color scale legend indicating pollutant concentration levels. (D) Time-series chart showing the evolution of pollutant concentrations (example: PM_{10}) at the selected location.

4.3 Point Query of Concentrations

In addition to the dynamic update of pollutant layers, the platform allows users to query the concentration value at any geographic location by simply clicking on the map. This interaction triggers a `WMS GetFeatureInfo` request to the CAMS server, which returns the forecasted concentration for the selected pollutant and time.

Once retrieved, the raw value is automatically converted into standardized units (typically $\mu g/m^3$) through predefined conversion factors that account for the different formats used by CAMS layers. The resulting value is then displayed in the information panel (E) in Figure 4.1, alongside the geographic coordinates of the clicked location.

However, when the selected domain is restricted to Europe, the system also validates whether the clicked location lies inside the spatial coverage of the European forecast. If the query is made outside this domain, the application informs the user that the value is not available for that point. As an illustrative example, Figure 4.3 shows the result of clicking on a location outside the European forecast area, where the information panel explicitly indicates that the data are unavailable.

This functionality provides users not only with direct access to numerical values within the forecast domain, but also with clear feedback when attempting to query outside the valid region, thereby improving transparency and user experience.

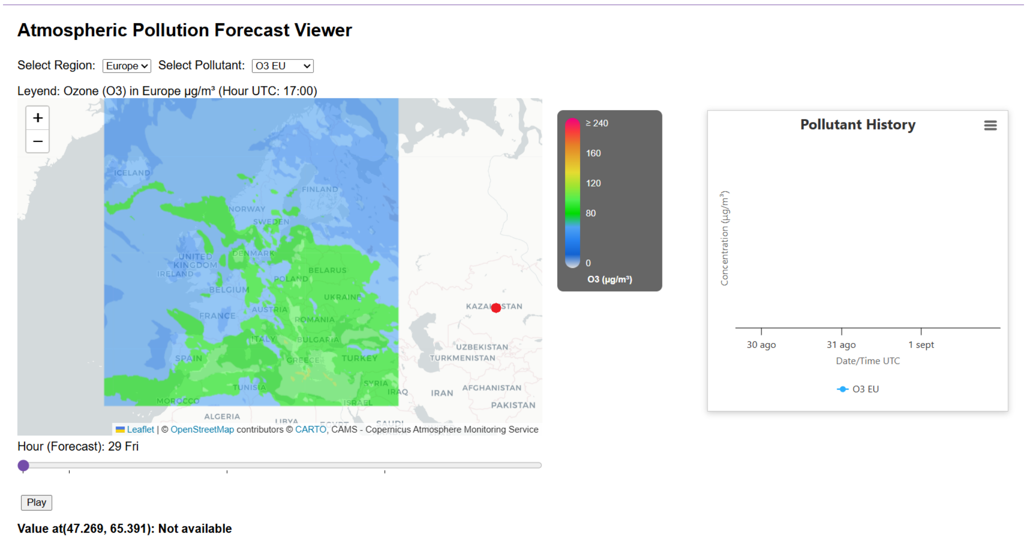


Figure 4.3: Example of point query outside the European forecast domain. The red point indicates the clicked location beyond the coverage area, and the information panel shows that the value is not available.

4.4 Time Series Visualization

The time-series visualization module provides users with an overview of the temporal evolution of pollutant concentrations at any selected location. Once a point is clicked on the interactive map, the platform automatically generates a chart showing the pollutant values for successive forecast hours. Users can also export the data displayed in the chart as a CSV or XLS file for further analysis. This feature facilitates offline processing, statistical analysis, or integration with other tools.

A key aspect of the CAMS forecasts is their temporal resolution, which differs between domains. The European domain delivers predictions at 1-hour intervals, so the concentration values in the chart change every hour, as illustrated in Figure 4.4. In contrast, the Global domain provides predictions at 3-hour intervals, causing the values to remain constant over each 3-hour block before updating at the next forecast step, as shown in Figure 4.5. This difference reflects the underlying temporal resolution of the numerical models and should be considered when interpreting pollutant trends.

4.4.1 Data Export

In addition to the time-series visualization, the platform allows users to export the pollutant data for further analysis. The chart interface provides a download button that lets users save the data in CSV or XLS format. This feature enables offline processing, statistical evaluation, or integration with other software tools.

Figure 4.6 shows an example of the export button in the chart interface and a sample of the downloaded CSV file.

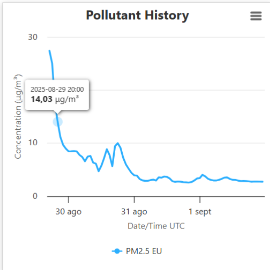


Figure 4.4: Time-series visualization of $PM_{2.5}$ concentrations at a selected location within the European domain. Values update every hour according to the temporal resolution of the forecasts.

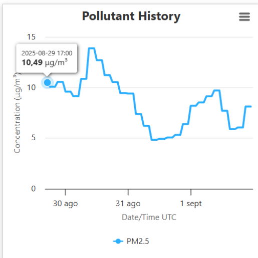


Figure 4.5: Time-series visualization of $PM_{2.5}$ concentrations at a selected location within the Global domain. Values remain constant over 3-hour intervals, corresponding to the temporal resolution of the CAMS forecasts.

4.5 Forecast Animation

To further enhance the understanding of temporal pollutant dynamics, the platform includes a forecast animation feature. By activating the play button, the application sequentially advances the time slider, updating the pollutant layer on the map and the associated legend in real time. This animation allows users to intuitively perceive the spread and evolution of pollutants over the selected domain without manually moving the slider. For illustration purposes, the UV Index was chosen as an example, since its changes are clearly visible as the slider moves (see Figure 4.7).

4.6 Summary of Results

The web-based platform developed in this work successfully enables interactive exploration of atmospheric pollutant forecasts from CAMS. The main interface allows users to select the geographic domain and pollutant of interest, navigate through hourly forecasts, and visualize pollutant concentrations both spatially and temporally. Key features include dynamic updating of map layers, point-specific pollutant queries, interactive time-series charts, forecast animation, and data export functionality.

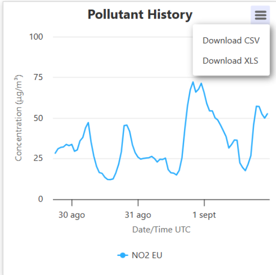
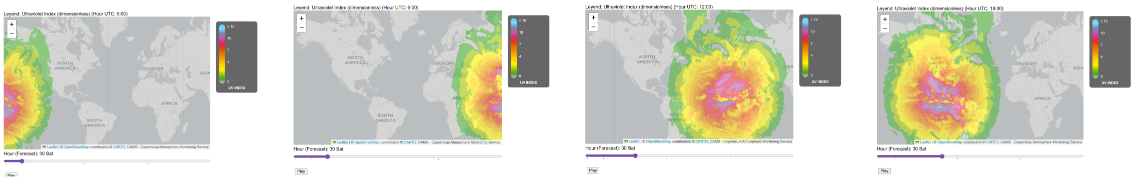


Figure 4.6: Export functionality for pollutant time-series data. Users can download the values displayed in the chart for further analysis.



(a) Hour 0 UTC (b) Hour 6 UTC (c) Hour 12 UTC (d) Hour 18 UTC

Figure 4.7: Snapshots of the UV Index forecast animation at different forecast hours, illustrating how the pollutant layer updates as the time slider moves.

The results demonstrate that the platform provides an intuitive and responsive user experience, supporting both educational and research-oriented applications. By standardizing units, integrating adaptive legends, and providing clear feedback for queries outside the forecast domain, the interface ensures consistency and transparency in data interpretation. Overall, the platform achieves its objective of making CAMS forecast data accessible and interpretable through a lightweight, browser-based solution, highlighting the potential of interactive web technologies for environmental monitoring and decision-making.

5 Conclusions and Future Work

In this work, a web-based platform was developed to allow interactive exploration of atmospheric pollutant forecasts provided by the Copernicus Atmosphere Monitoring Service (CAMS). The main goal was to create a tool that runs entirely in a standard web browser, so users do not need to install specialized software or download large datasets. This approach makes it easy for students, researchers, and the general public to access and understand air quality forecasts directly from their devices.

5.1 Conclusions

The platform integrates an interactive map where users can visualize pollutant concentrations over Europe or the entire globe. By selecting a pollutant and a forecast hour, the map updates dynamically, showing the predicted distribution of the selected pollutant. Users can click on any point within the forecast domain to obtain detailed numerical values, which are automatically converted into standard units, making interpretation straightforward. The system also provides time-series charts for the clicked location, allowing users to see how pollutant concentrations evolve hour by hour. These charts can be exported for offline analysis, which is particularly useful for research purposes or educational exercises.

Animations play a key role in helping users understand how pollution spreads over time. By sequentially moving through forecast hours, the platform offers a visual sense of pollutant movement, although the performance can be affected by internet speed or device capabilities. Overall, the platform demonstrates that it is possible to make high-resolution atmospheric forecasts accessible and understandable, combining scientific rigor with simplicity and interactivity. Its open-source and browser-based design ensures that it can be easily maintained and adapted in the future, while providing a consistent and transparent way to interpret air quality data.

5.2 Future Work

Although the platform functions effectively as a prototype, several improvements could enhance usability and performance. One clear opportunity is to make the map occupy most of the screen, reducing empty space and allowing users to focus on the visualization. Controls, such as pollutant selectors or the time slider, could be implemented as floating or collapsible panels. This design would make the interface cleaner, allowing users to expand or hide controls as needed, without overwhelming the main view.

Another area for improvement concerns the interaction between regions and pollutants. Currently, when a user switches from one geographic domain to another, the selected pollutant may reset to a default option even if the same pollutant exists in the new region. Ideally, the platform should automatically retain the selected pollutant if it is available in the new region, only changing to a default option when the pollutant is not present. This enhancement would make the interface more intuitive and reduce unnecessary adjustments by the user, improving the overall experience when exploring forecasts across different geographic scales.

User interaction with the map could also be enhanced. Adding a visible marker at the point selected for historical data would help users immediately identify which location the time-series chart corresponds to. Furthermore, clarifying on-screen that clicking on the map retrieves historical information would make this feature more intuitive, particularly for users without prior experience with environmental data services.

Performance improvements could be achieved by preloading multiple forecast hours or caching data locally. Currently, when the forecast animation moves hour by hour, the map sometimes does not update smoothly due to network delays. By storing several layers in advance, the system could display them instantly, providing a more fluid experience. Similarly, allowing the simultaneous download of multiple forecast elements would reduce waiting times and improve responsiveness, particularly for larger geographic domains or slower connections.

Future developments could also expand the platform's analytical capabilities. For example, users could overlay additional meteorological or environmental datasets to better understand factors influencing air quality. Customization of pollutant conversions or the addition of new variables would allow more detailed analyses, while optimizing the platform for mobile devices would make it accessible on a wider range of screens, from tablets to smartphones.

In summary, the platform provides an effective and intuitive way to visualize CAMS pollutant forecasts. While the current implementation already offers dynamic maps, point-specific queries, time-series visualization, and animations, there is significant potential for future enhancements. By improving usability, interactivity, and performance, the platform could serve as a comprehensive educational and research tool for understanding air quality and supporting informed decision-making regarding atmospheric pollution.

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Códigos extra