

Accessible air quality forecasts for Arctic communities: how AI can help citizens and policy-makers

The Real-World Impact of AI in the Polar Regions

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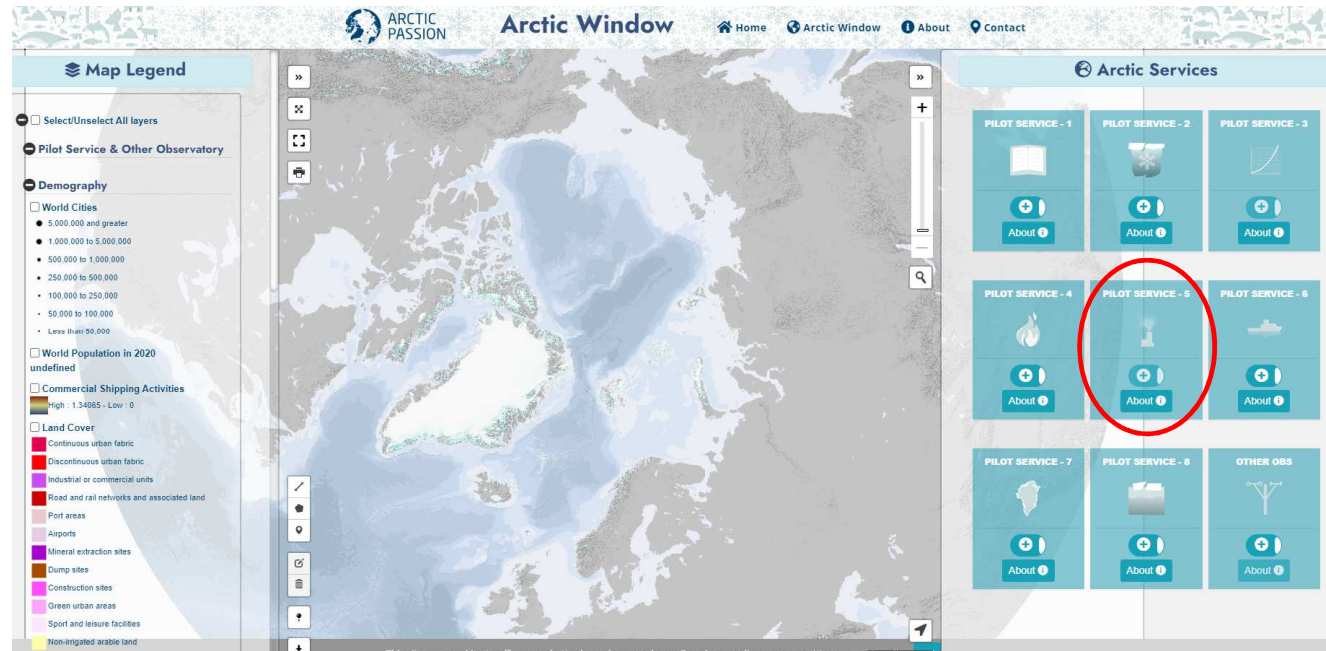
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Arctic PASSION H2020 Project

Arctic PASSION
Pan-Arctic Observing
System of Systems
Implementing Observations for Societal Needs



PARTNERS: 43 partners from 17 countries including Indigenous communities across the Arctic



<https://arcticpassion.eu/>



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PM₁₀ in North Europe

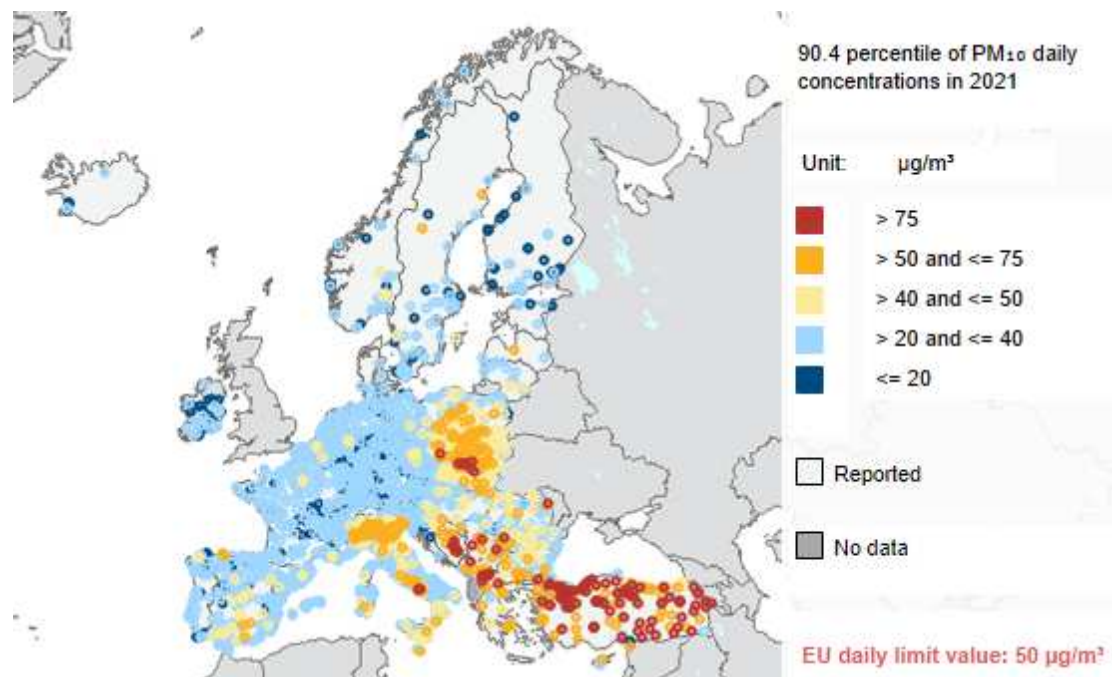
PM₁₀ is a complex mixture of solids and aerosols with a diameter of 10 microns or less

It is inhalable into the lungs and can induce adverse health effects (respiratory, cardiovascular, etc.)

WHO 2021 recommendations

15 µg/m³ mean annual concentration

45 µg/m³ mean daily concentration



Source: European Environmental Agency (www.eea.europa.eu/)

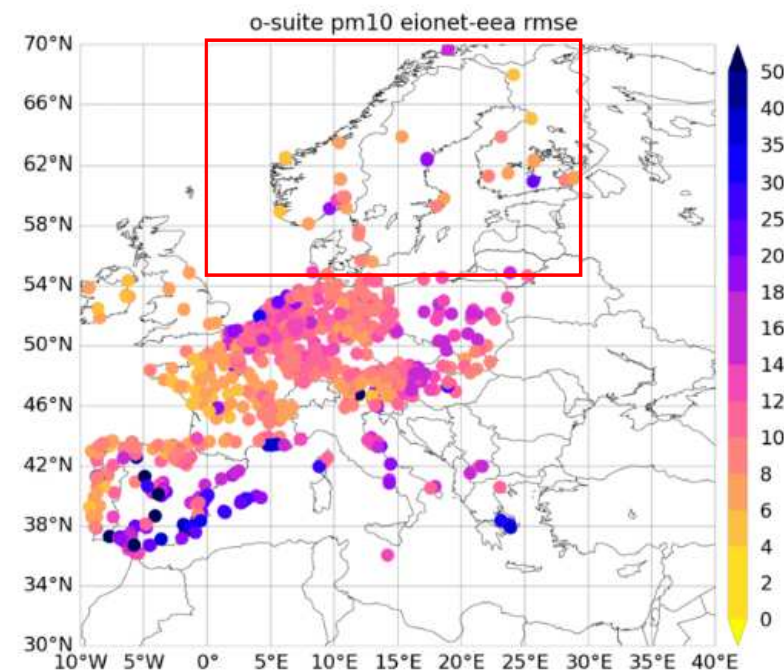
Limits of CAMS PM₁₀ forecast

Forecast performances

- High error for CAMS forecast vs in-situ measurements
- Limited number of in-situ monitoring stations data used for assimilation (less than 20 for all North Europe)

Data accessibility

- Data available only in professional users' format
- Manual download needs some knowledge of modelling vocabulary and technical knowledge and/or programming skills
- Absence of a unique platform to access near-real time air pollution data (EEA) and forecast (CAMS)

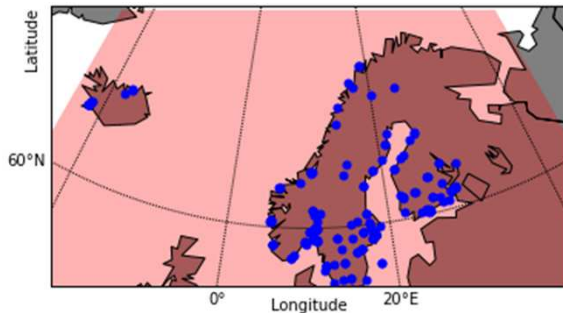


RMSE for 24-hour forecasts (at 3hourly basis) of CAMS for the 1 June – 31 August 2021 and 3 hourly PM₁₀ from EIONET measurements (Ramonet et al. 2021)

1. Improve forecast performances with AI

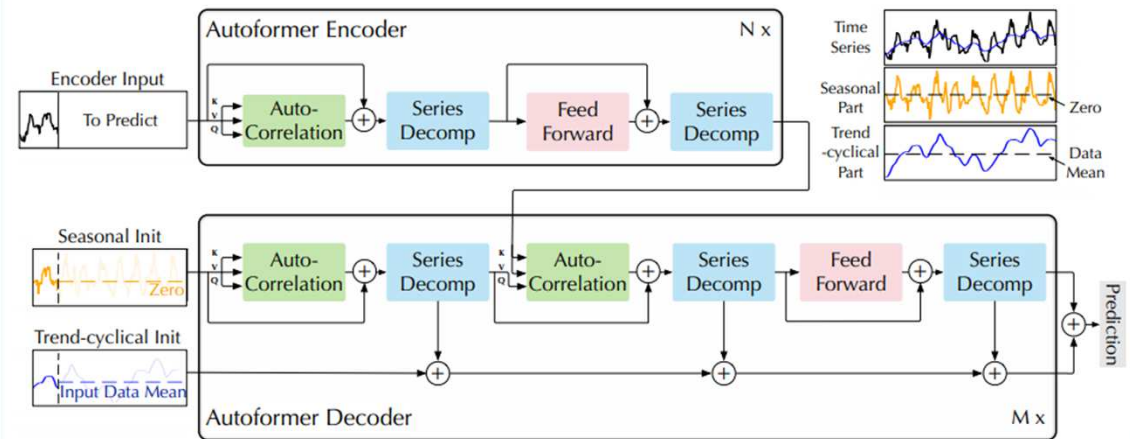
Input data

- PM₁₀ data at hourly frequency from ~ 100 monitoring stations (June 2020-June 2023)
- CAMS PM₁₀ forecast (48 hours) at each station
- Meteorological variables (temperature, boundary layer, wind components, precipitation, m.s.l. pressure) at each station (ECMWF)



Deep learning models

- LSTM-networks used as baseline for long series forecasting
- Transformer architectures better track long-term dependencies exploiting time series decompositions and correlations

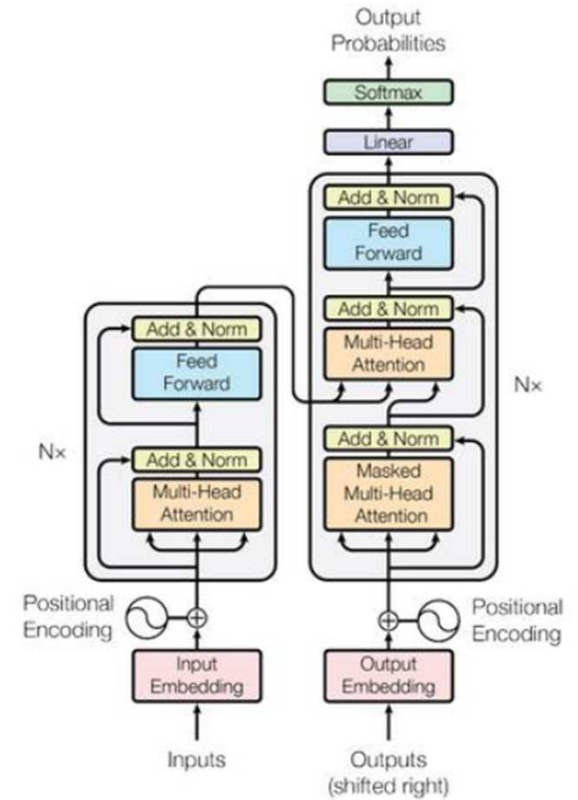
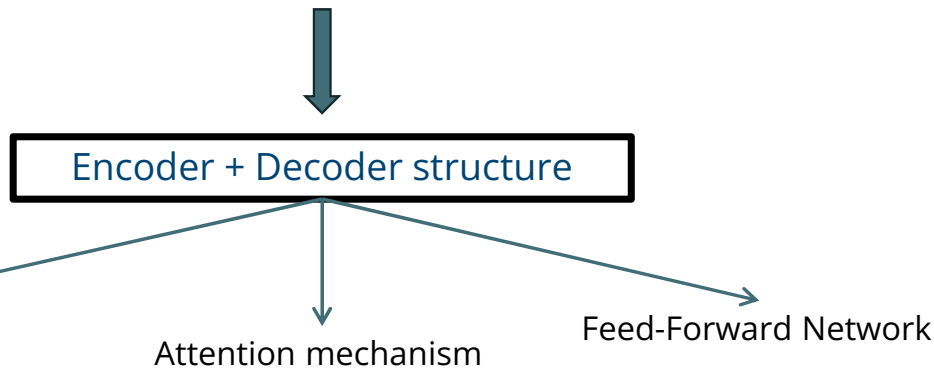


Source: Wu et al. 2021

Transformer Architecture

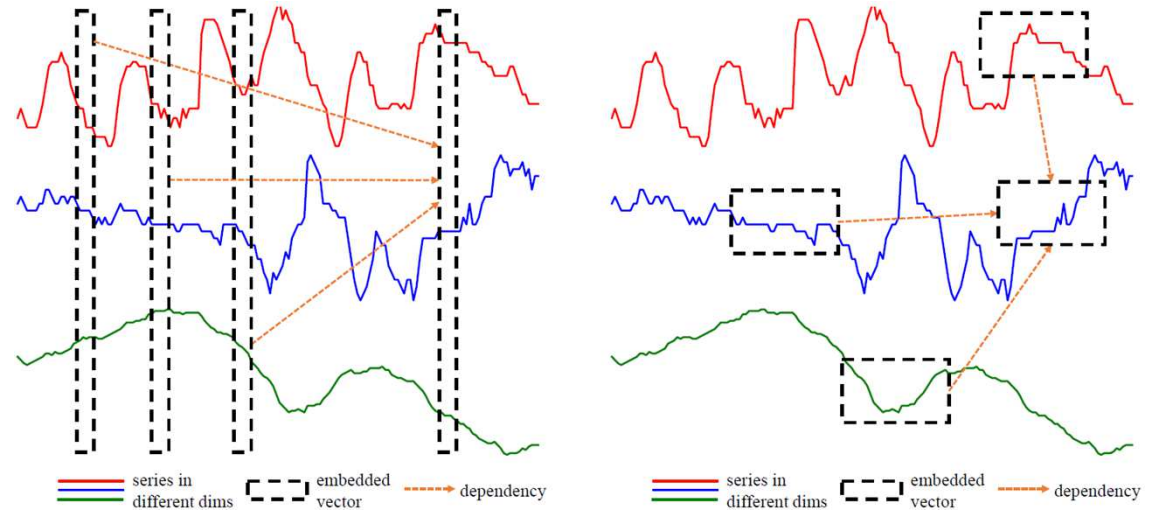
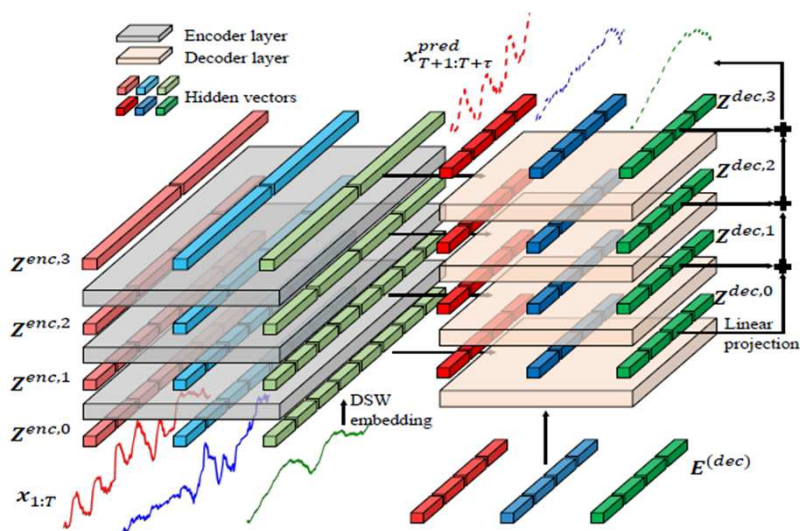
In recent developments, time series forecasting is turning away from RNNs as new models coming from Natural Language Processing are being adapted to time series analysis tasks as they:

- better incorporate sequential data and thus historical information
- prove to be more suited for long sequence forecasting
- Better encode temporal and cross dimensional information



Original Transformer Architecture as defined in Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. Attention is all you need. CoRR, abs/1706.03762, 2017

Variation: Incorporating Cross-Dependencies



Original Crossformer Architecture as represented in Zhang, Y. and Yan J., Crossformer: Transformer Utilizing Cross-Dimension Dependency for Multivariate Time Series Forecasting, International Conference on Learning Representations, 2023

- Most Transformer architectures try to capture cross dependencies amongst features within embedding and forward stages, while it is possible to incorporate a cross-dimension stage within an encoder layer as a two-step attention block
- The embedding also considers segment-wise decomposition in order to track correlations between subsequences

2. Improve data accessibility

The Air Quality Forecast for Arctic Communities (AURORAE) service website

The screenshot shows the AURORAE website interface with several callouts highlighting key features:

- Download .txt files:** A callout points to the "Download Daily Bulletin" button in the top navigation bar.
- Choose between near-real time data and forecast:** A callout points to the "Display PM₁₀ concentrations:" section, which includes radio buttons for "Measured", "Forecast 1-Day", and "Forecast 2-Days".
- Intuitive legend:** A callout points to the legend for PM₁₀ concentrations, which includes categories: "No data", "Good (0 - 25 µg/m³)", "Moderate (25 - 45 µg/m³)", "Unhealthy (45 - 100 µg/m³)", and "Very unhealthy (> 100 µg/m³)".
- Interactive map:** A callout points to the map of the Arctic region showing various monitoring stations.
- PM₁₀ concentration + forecast + information on the station:** A callout points to the "SELECTED STATION" section, which displays:
 - Station Name: **Vågen**
 - Station Code: **NO_5_73250**
 - PM₁₀ Measured: **7.4849 µg/m³**
 - PM₁₀ Forecast: **0.0000 µg/m³**
- Historical data (2020-today):** A callout points to the "Historical Data" graph, which shows PM₁₀ concentration (µg/m³) from July 2021 to January 2024.
- Last week data + forecast:** A callout points to the "Last Days" graph, which shows PM₁₀ concentration (µg/m³) from 00:00 on June 21, 2024, to 12:00 on June 25, 2024.

A tool for citizens and policymakers

- AURORAE improves the available 2 days PM₁₀ forecast for municipalities in North Europe and in the European Arctic
- Non-scientific users can easily navigate the interactive map and access air pollution data
- The service empowers Nordic and Arctic communities on air quality topic and its effects on public health
- AURORAE helps to promptly take action in case of episodes of high level of air pollution

We'd love to hear you feedback!

To take part in our Slido survey scan the QR code!





THANK YOU!

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References

- Fazzini, P., Montuori, M., Pasini, A., Cuzzucoli, A., Crotti, I., Campana, E. F., Petracchini, F., & Dobricic, S. (2023). Forecasting PM10 Levels Using Machine Learning Models in the Arctic: A Comparative Study. *Remote Sensing*, 15(13), 3348. <https://doi.org/10.3390/rs15133348>
- Ramonet, M., N. Sudarchikova, M. Schulz, Q. Errera, H. J. Eskes, S. Basart, A. Benedictow, Y. Bennouna, A.-M. Blechschmidt, S. Chabrillat, Christophe, Y., E. Cuevas, A. El-Yazidi, H. Flentje, P. Fritzsche, K.M. Hansen, U. Im, J. Kapsomenakis, B. Langerock, A. Richter, V. Thouret, A. Wagner, T. Warneke, C. Zerefos, Validation report of the CAMS near-real-time global atmospheric composition service: Period June – August 2021, Copernicus Atmosphere Monitoring Service (CAMS) report, CAMS84_2018SC3_D1.1.1_JJA2021.pdf, November 2021, doi:10.24380/6x8f-9630
- Wu H., Xu J., Wang J., Long M. (2021). Autoformer: Decomposition Transformers with Auto-Correlation for Long-Term Series Forecasting, <https://doi.org/10.48550/arXiv.2106.13008>
- Zhang, Y. and Yan J. (2023). Crossformer: Transformer Utilizing Cross-Dimension Dependency for Multivariate Time Series Forecasting, International Conference on Learning Representations, <https://openreview.net/forum?id=vSVLM2j9eie>