Ensemble weather forecasting scenarios tailored to users' needs

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Context

Probability forecasting

Taking into account

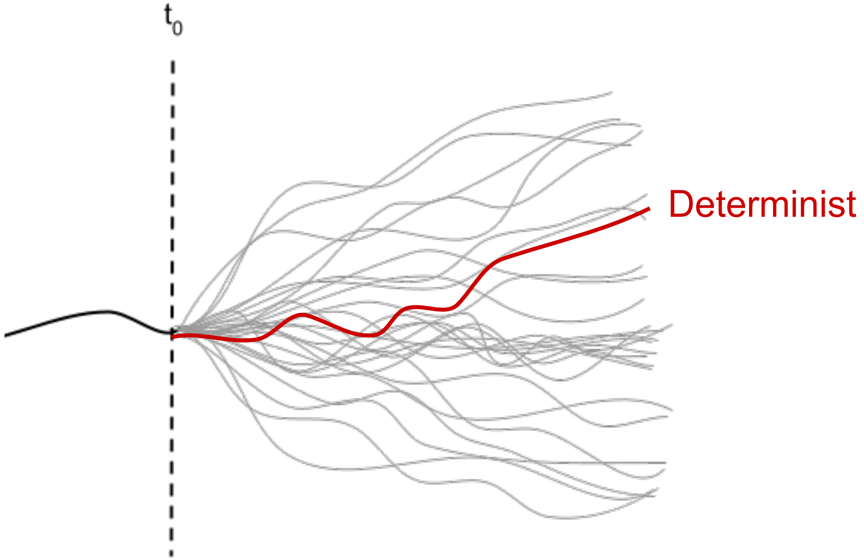
- Calculation errors
- Uncertainties in decision-making
- Extreme events

Nowadays, at Météo-France

- ARPEGE-EPS: 35 members
- AROME-EPS: 24 (+1) members

60 fields to consult

For each member: Ignore it? Follow it? With which trust?



How to, among all those pieces of information, identify **essential information** for decision making?

Aim

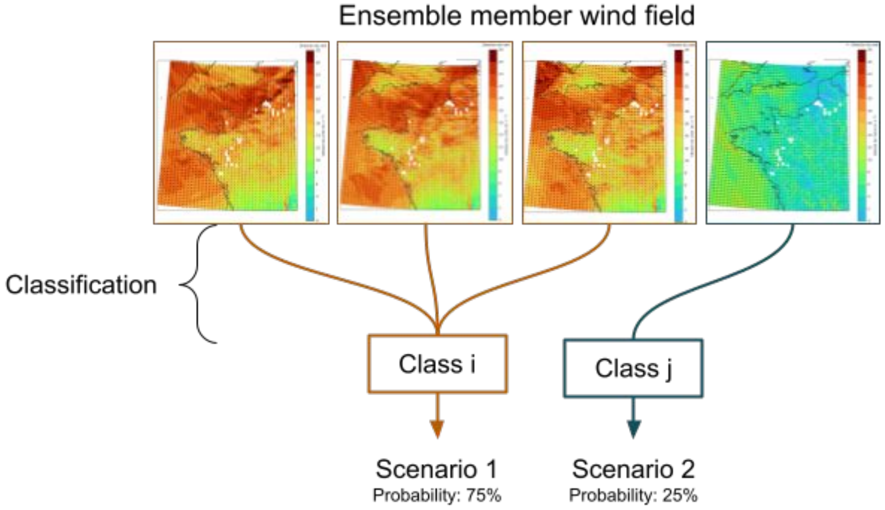
From AROME-EPS to a synthesis in scenarios, adapted to a user

Methodology
Adapted from Mounier et al. (2025)

1) Defining climatological classes, while introducing non-meteorological variables

2) Operational use: assigning each ensemble member to a class

→ Representing the main class (Scenario 1) AND the minor classes/scenarios



Mounier, A., Raynaud, L., Rottner, L., Plu, M., & Arbogast, P. (2025). Rainfall classification of kilometer-scale ensemble forecasts using convolutional neural networks and soms. *Artificial Intelligence for the Earth Systems*. https://doi.org/10.1175/AIES-D-24-0108.1

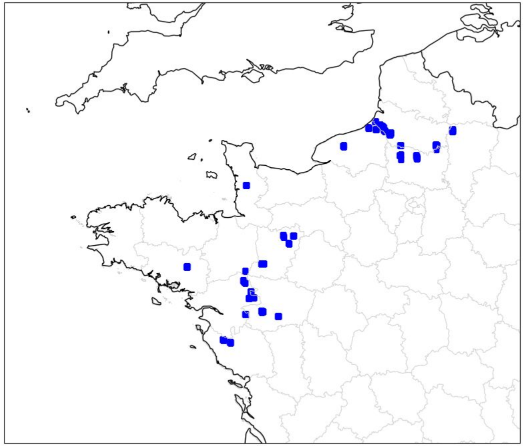
Study case and dataset

Compagnie Nationale du Rhône (CNR)

Collaboration with the CNR on their **renewable wind energy**

Wind farms from northern and western France

CNR wind energy delivery points



CNR variable: Electrical production

Database's time range: 6 years (2017-2022)

CNR **hourly average** electrical energy output on all delivery points

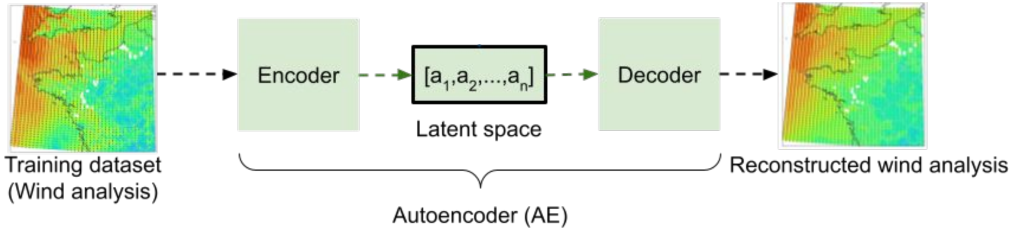
Meteorological fields: Wind field

U and V hourly analysis from AROME, **at 100m height**, on the north-west quarter of France

Data dimension: **over 190 000**

Methodology

1) Dimension reduction



Methodology

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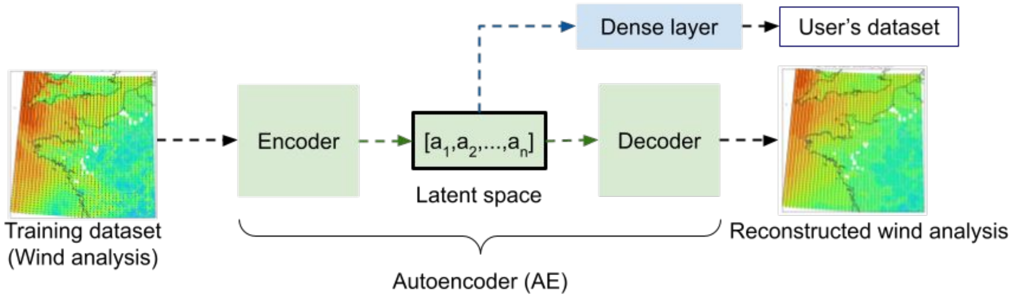

Methodology

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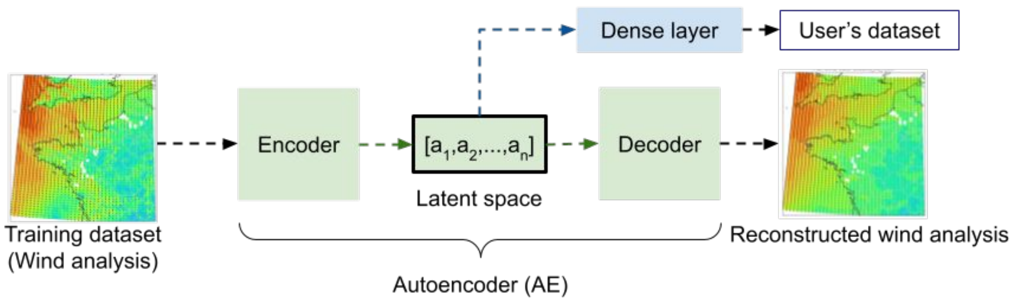
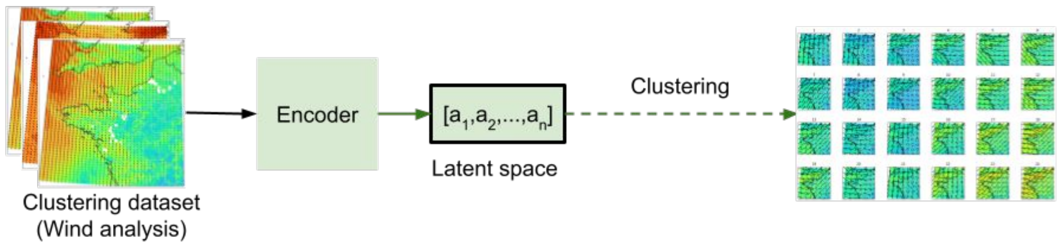


2) Dataset reduction and clustering



Methodology

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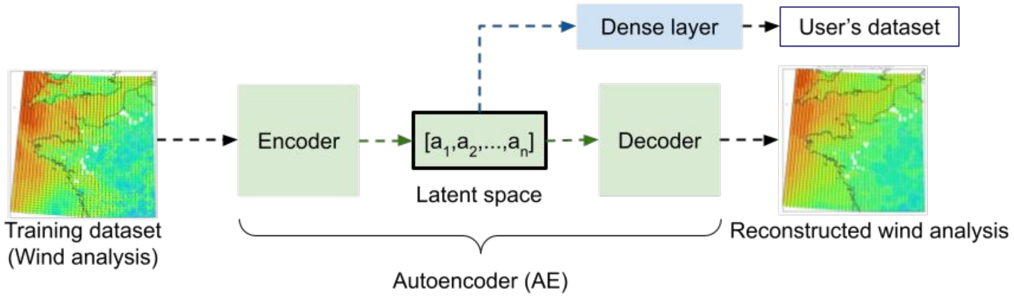

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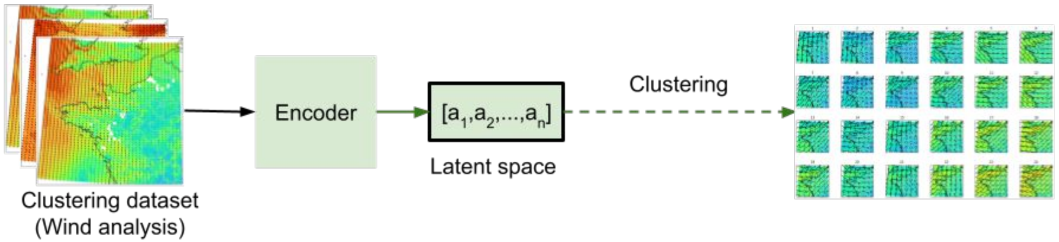
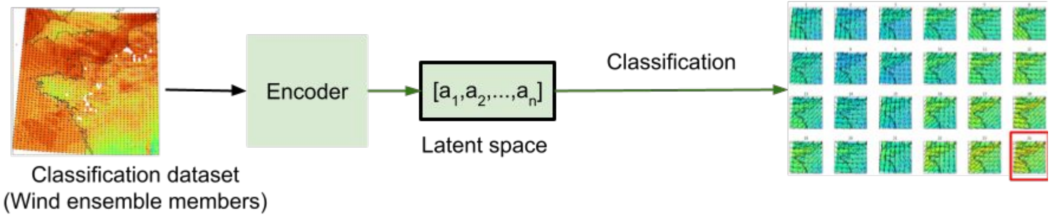
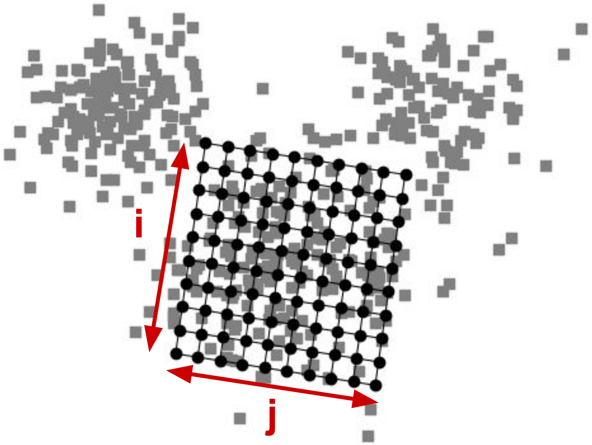


3) Operational use

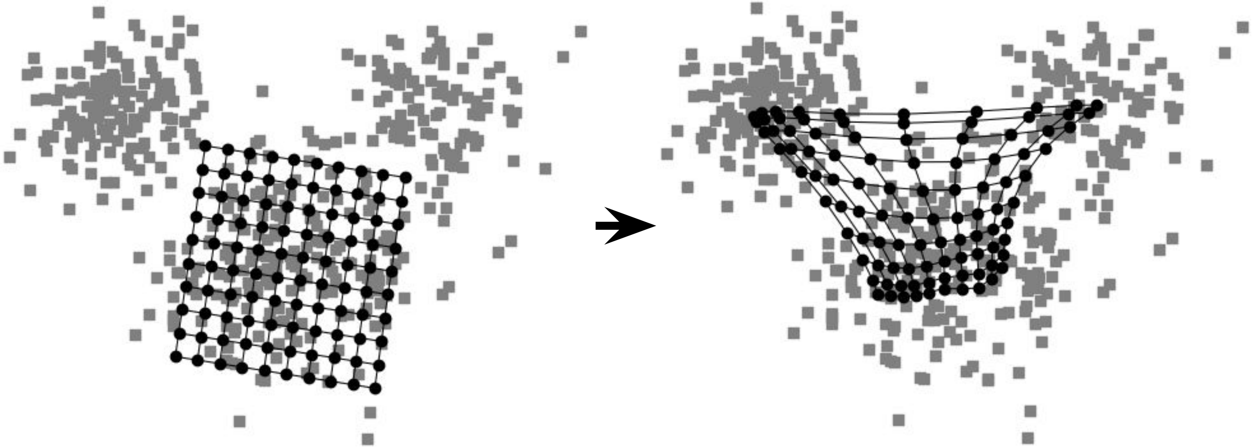


Self Organizing Maps (SOMs)



initialization

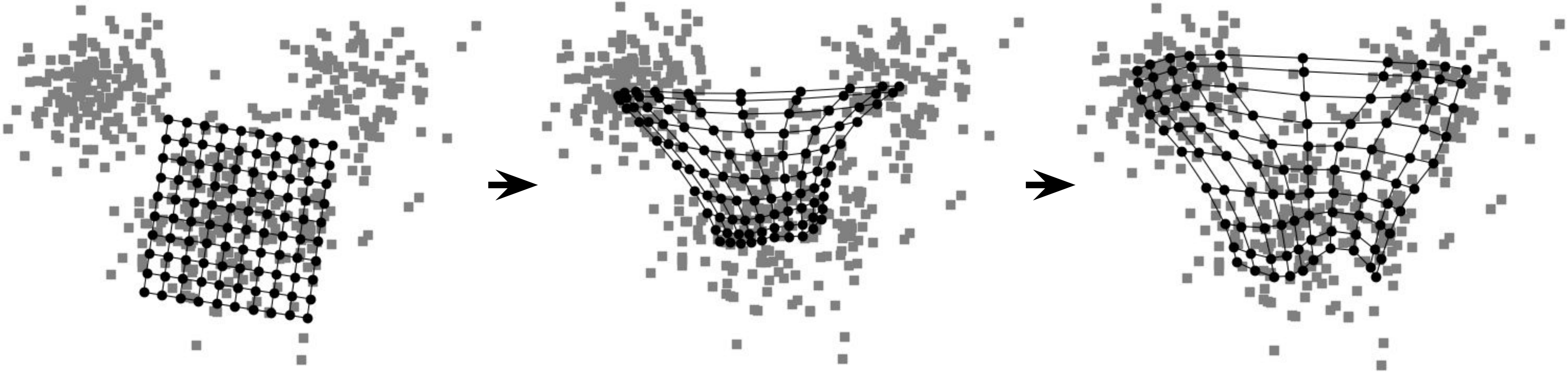
Self Organizing Maps (SOMs)



initialization

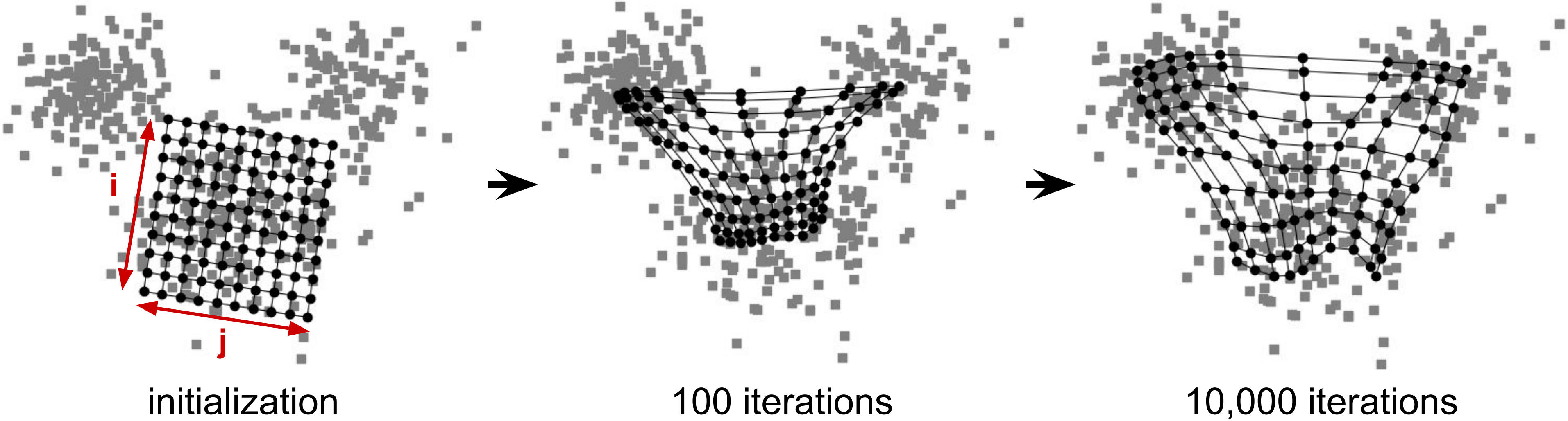
100 iterations

Self Organizing Maps (SOMs)



initialization — 100 iterations — 10,000 iterations

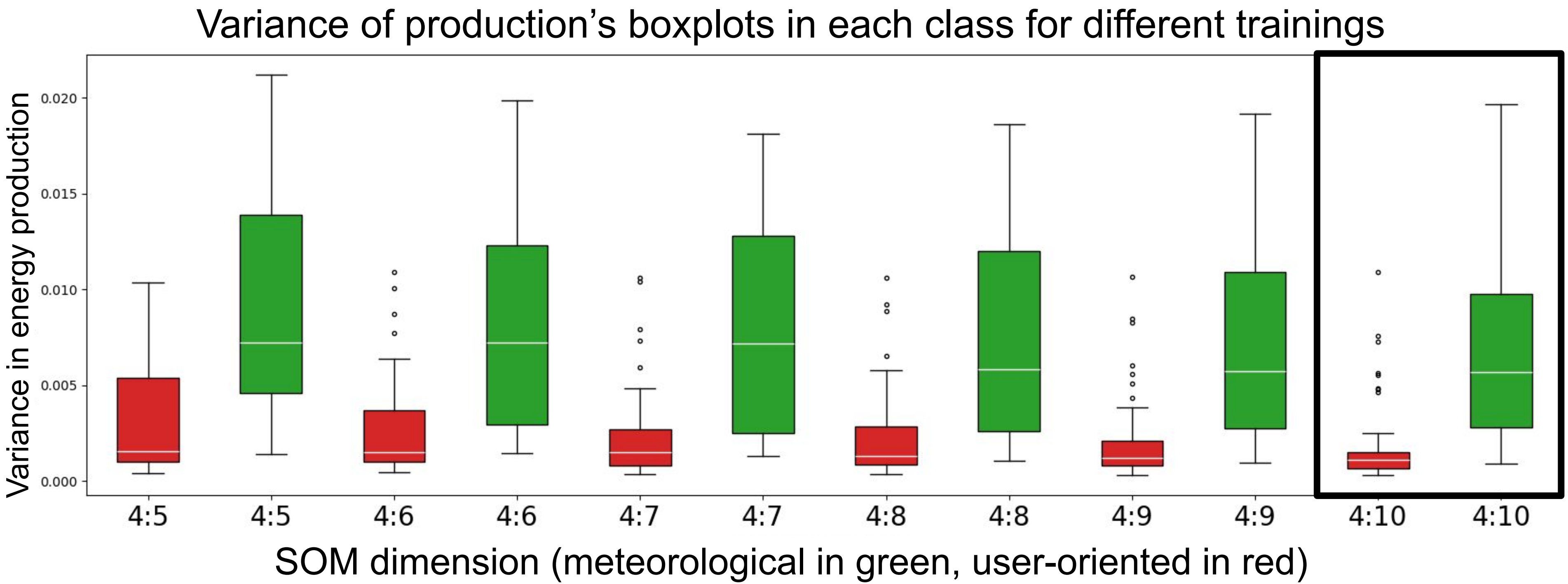
Self Organizing Maps (SOMs)



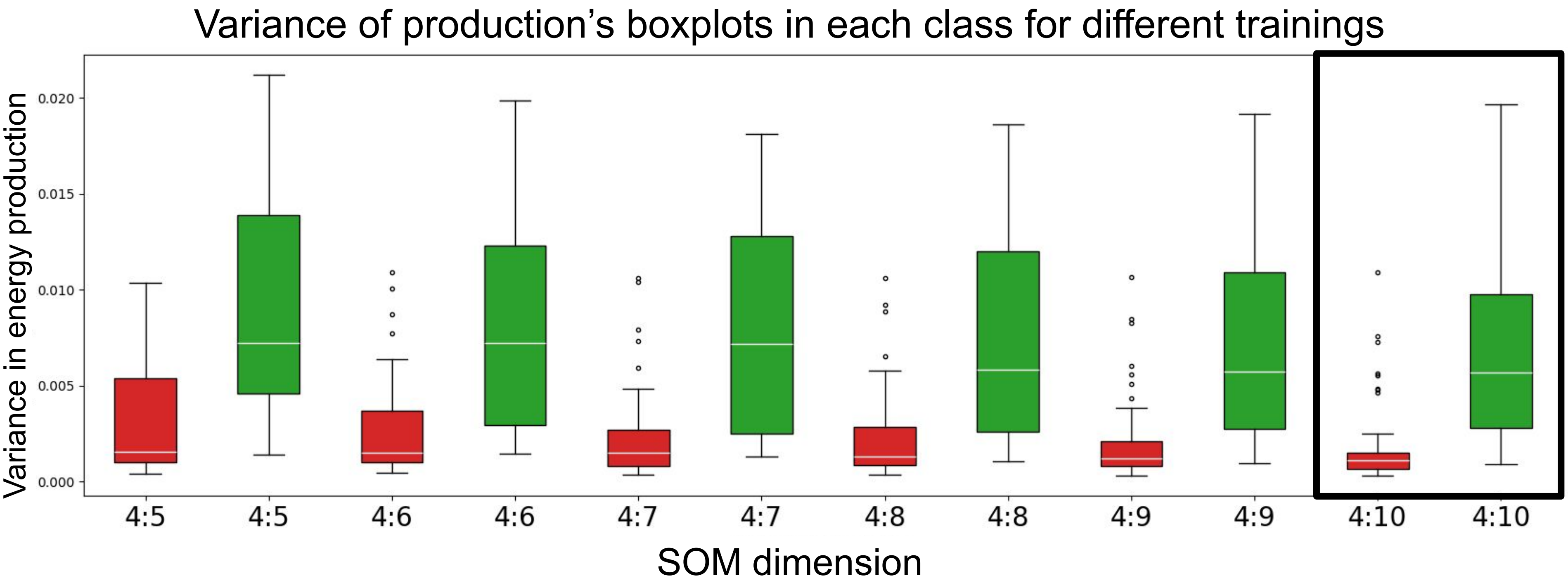
Hyperparameter's (i:j) selection criterias

- Topographic error
- Within-class energy production variance

SOMs - variance in energy production



SOMs - variance in energy production



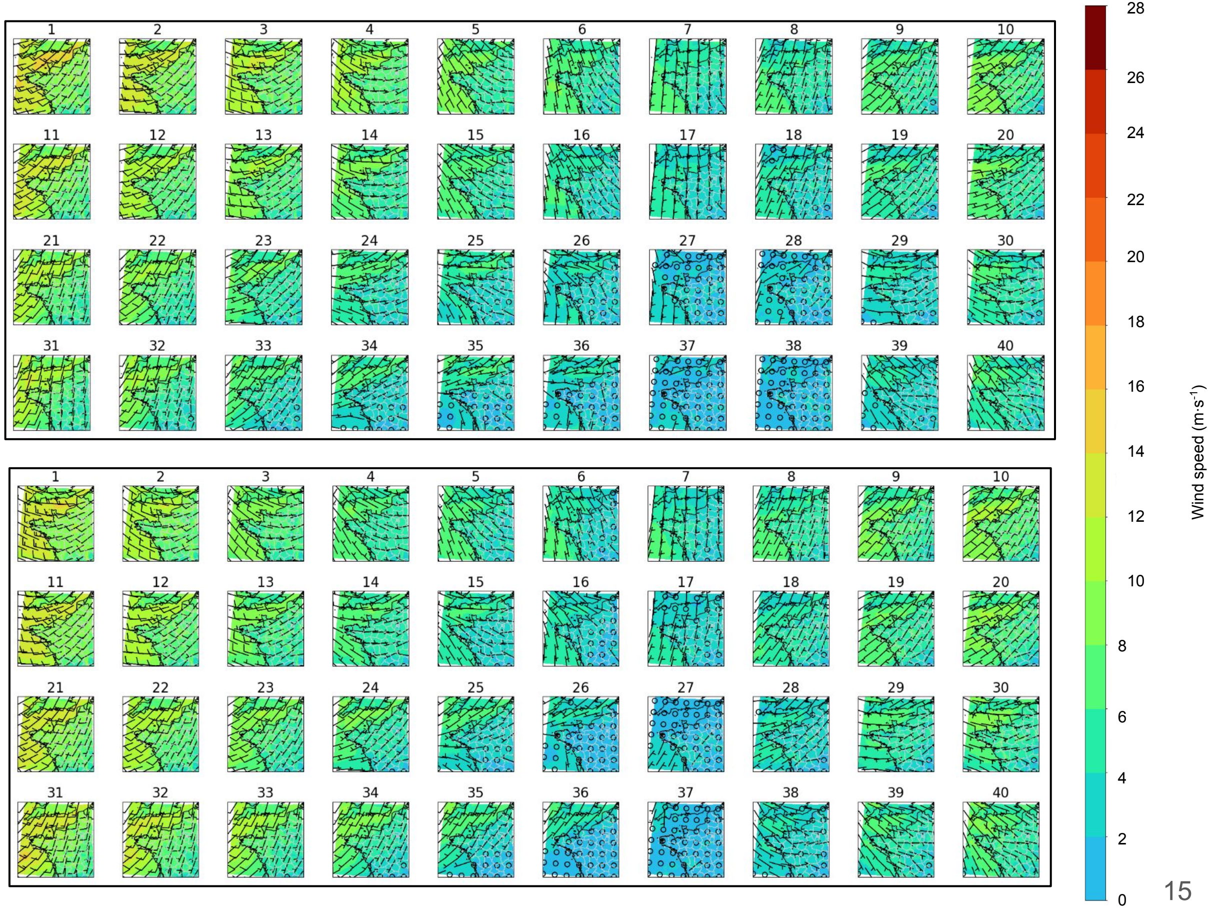
Initial hypothesis validation

Taking into account the impact variable ⇒ User adapted clusters obtained

SOMs - visualization of nodes' wind fields

Meteorological

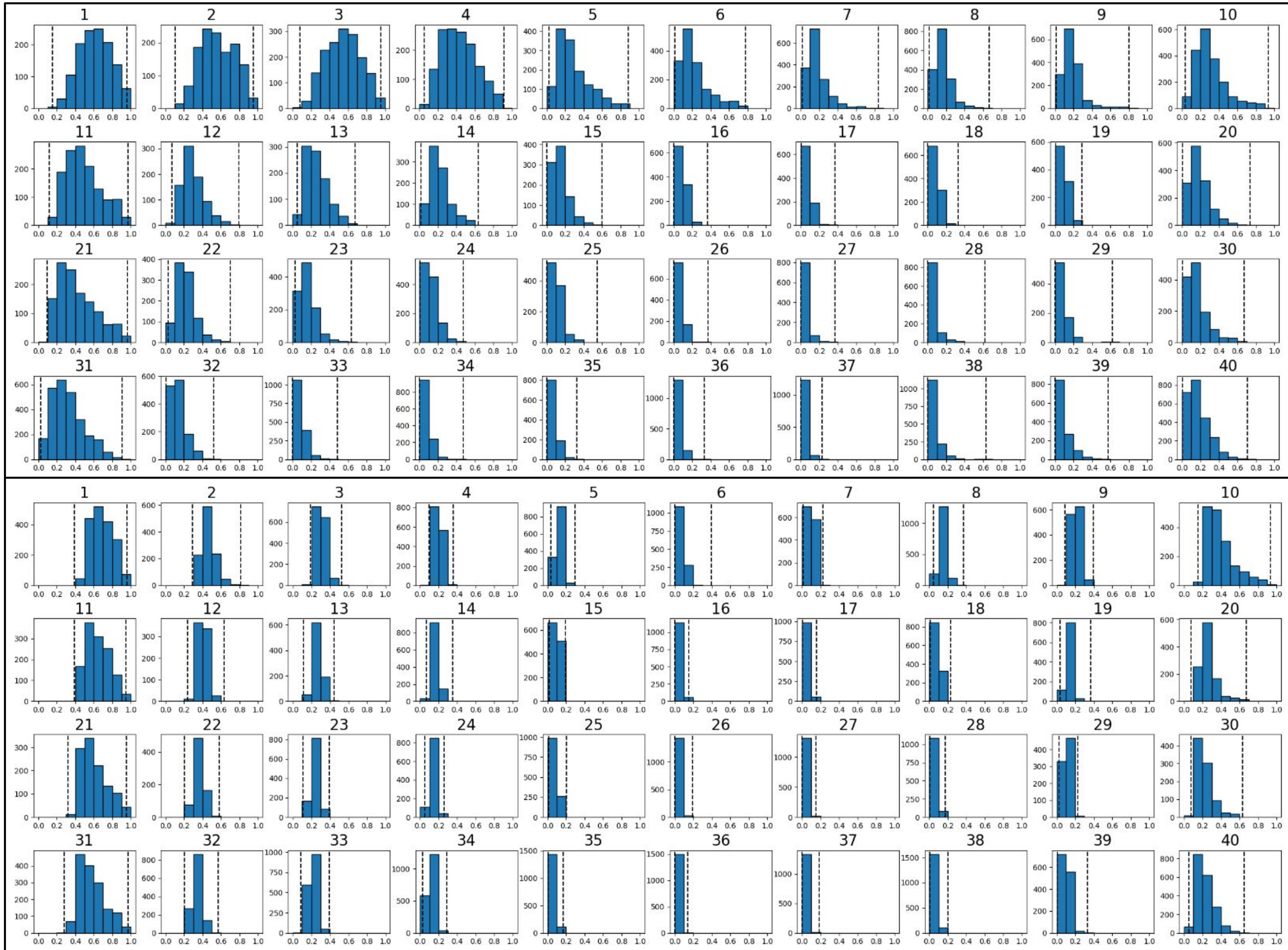
User-oriented



SOMs - distribution of energy production by class

Meteorological

User-oriented



Methodology

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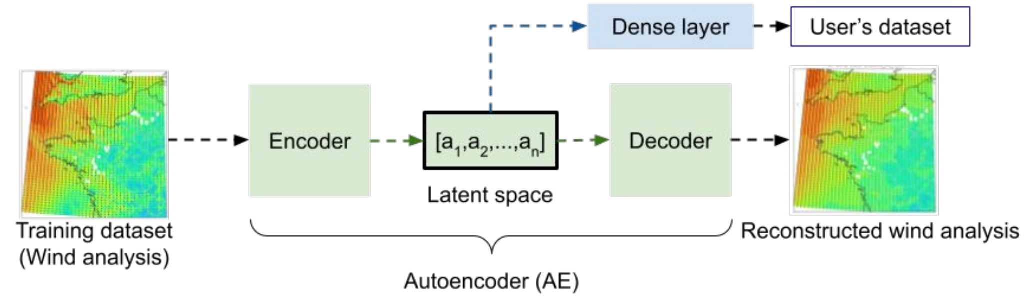

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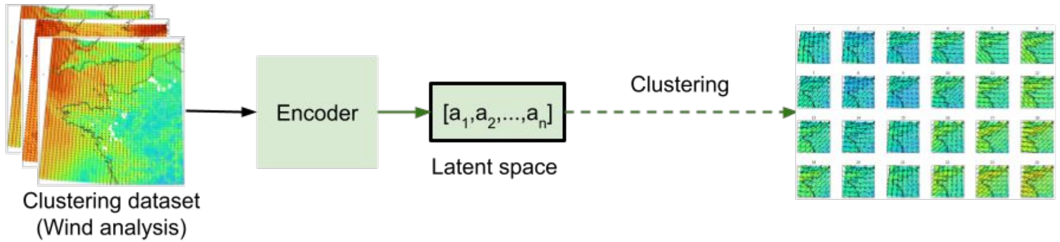
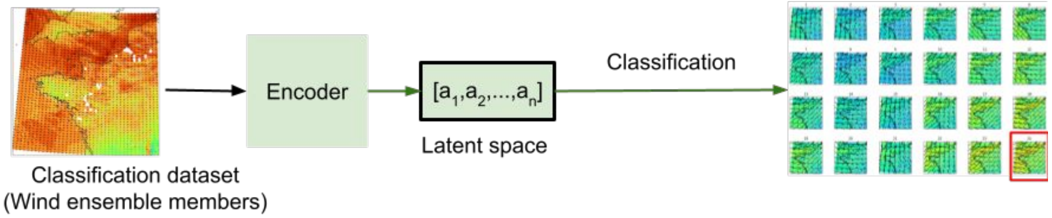


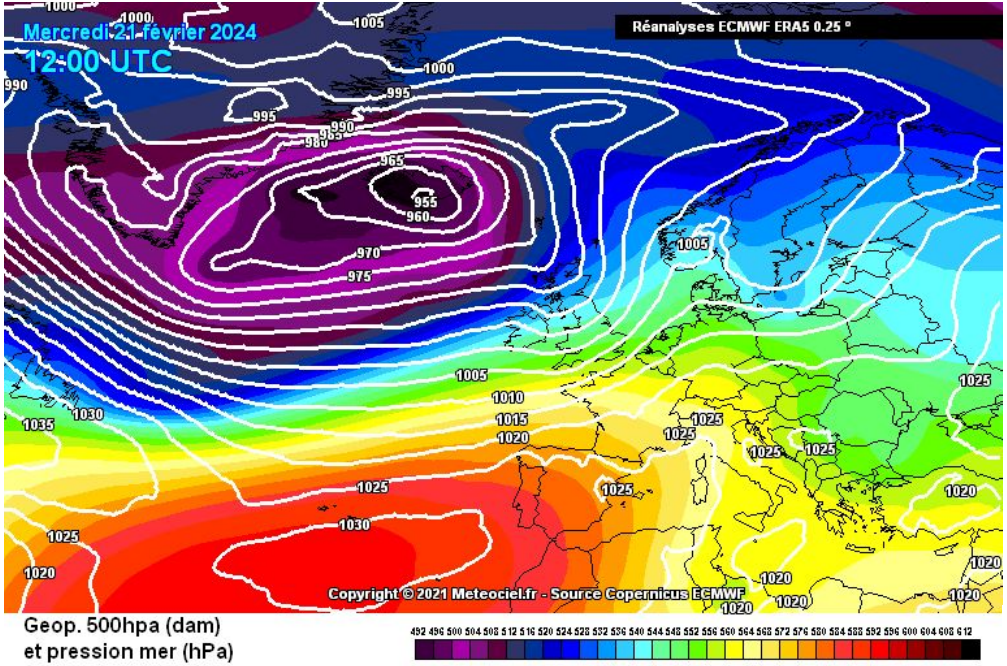
3) Operational use



Study case - 02/21/2024

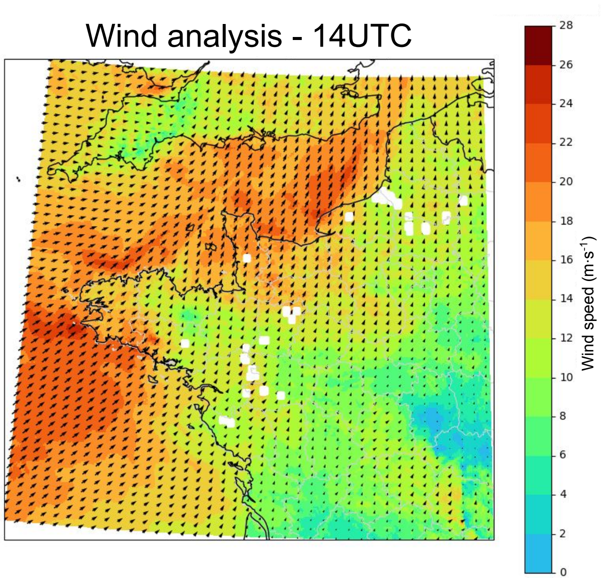
Synoptical situation

- Low-pressure area centered over Iceland
- Warm front across northwestern France
- Wind power production: ramp effect



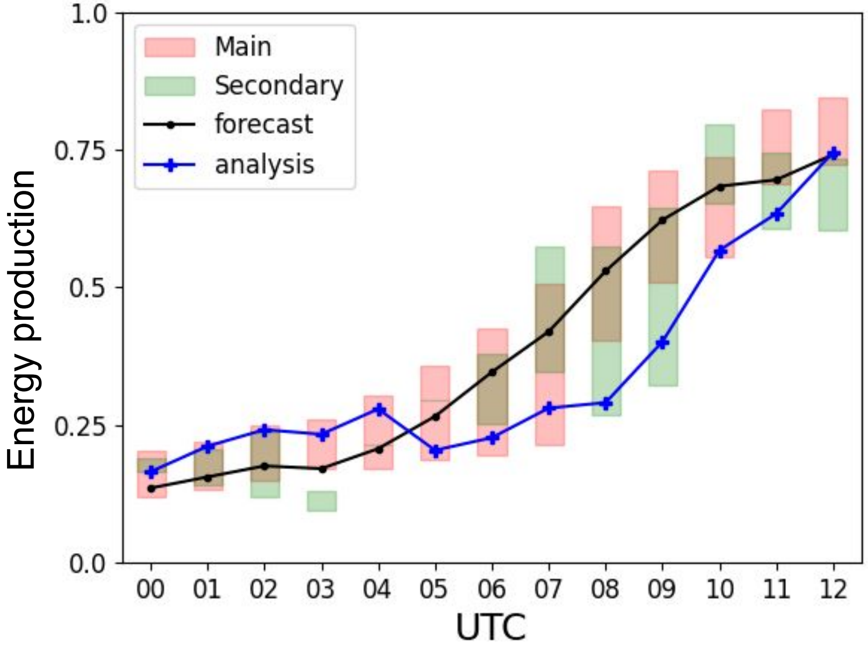
Z500 and Sea Level Pressure

Wind analysis - 14UTC

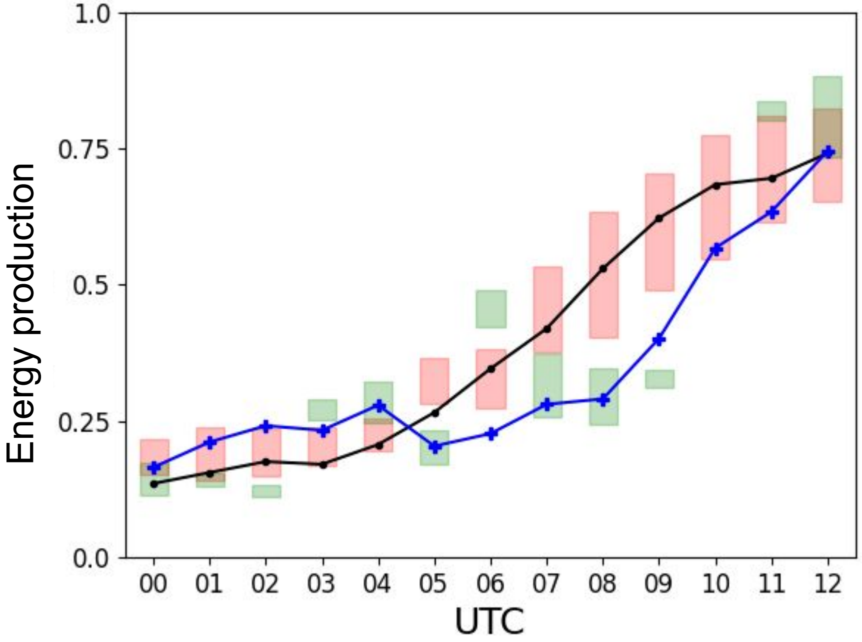


Study case - Scenarios’ energy production

Meteorological



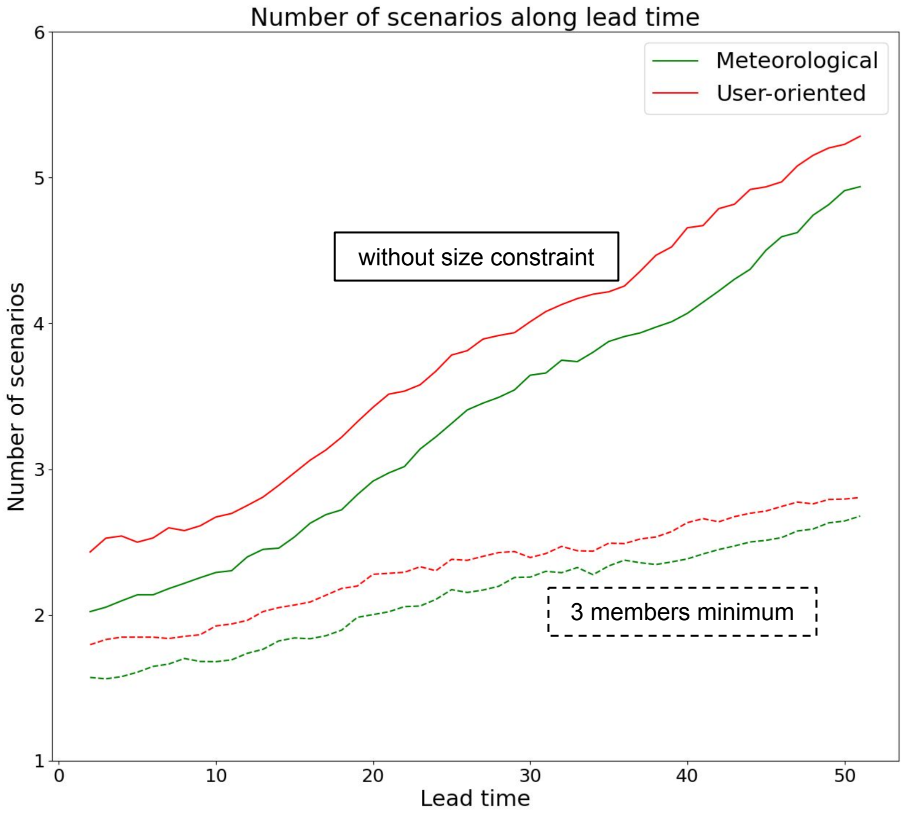
User-oriented



2 EPS information processing ⇒ Very different operational conclusions

User-oriented: **Better discrimination skill** as a decision support tool for users

Meteorological versus user-oriented scenarios



Clustering scores from the user's point of view

Davies-Bouldin / Calinski-Harabasz

- Minimize within-classes variance
- Maximize between-classes variance

No-Overlap

- Proportion of disjointed main and secondary scenarios
- Generalizing the study case's comparison

Score	Meteorological	User-oriented
Davies-Bouldin	19.72	**8.12**
Calinski-Harabasz	3.19	**9.7**
No-Overlap	9.01%	**26.11%**

EPS synthesized in a **few discriminating scenarios** for end-users

Conclusion

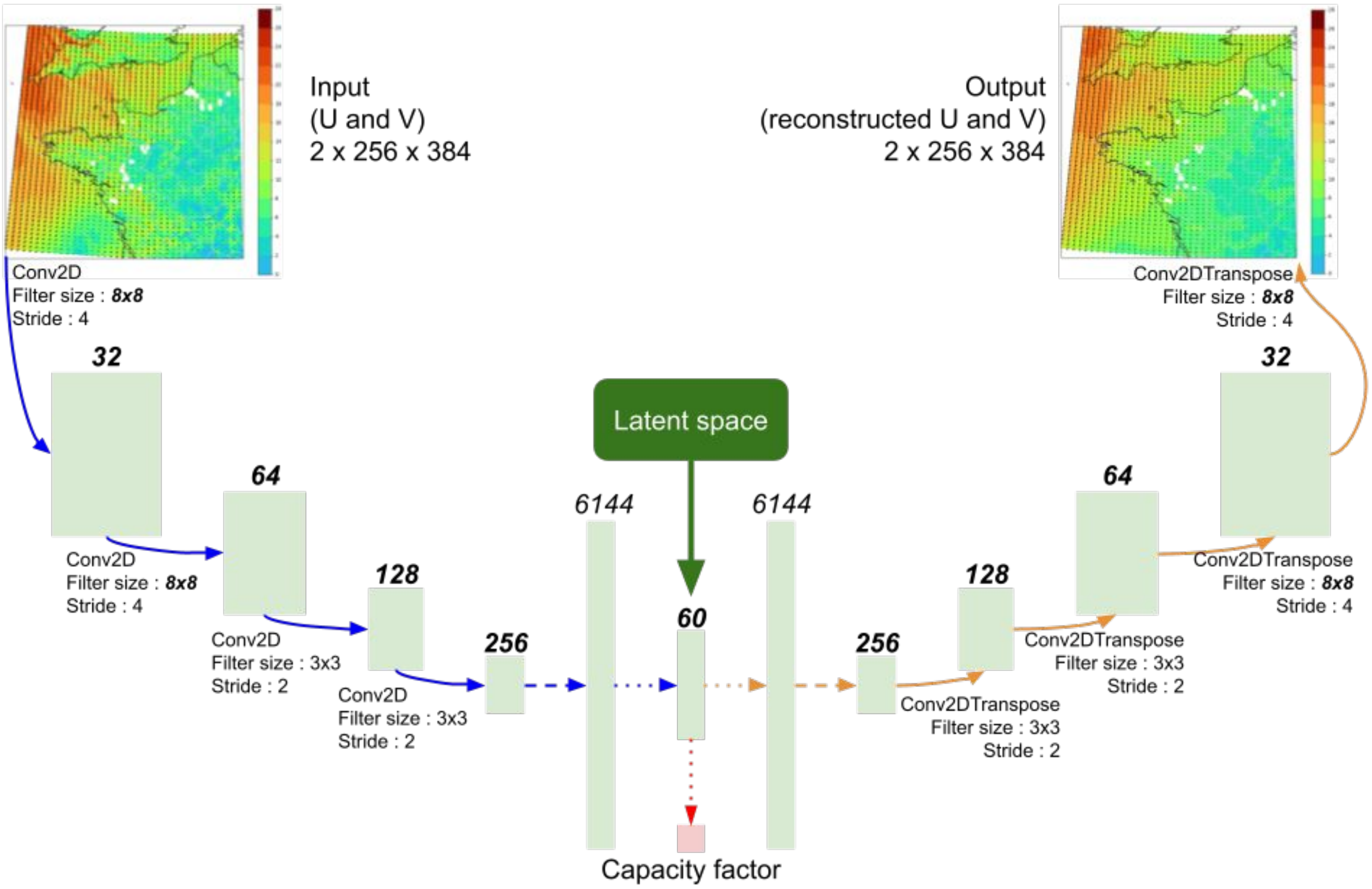
Done so far

- Meteorological and user-oriented classifications
- Comparison between both classifications
- Visible contribution from variable integration
- Study case and scores

In progress

- Other study cases
- Article submitted
- Manuscript currently being written

Appendix - Neural network architecture



Appendix - used losses

loss

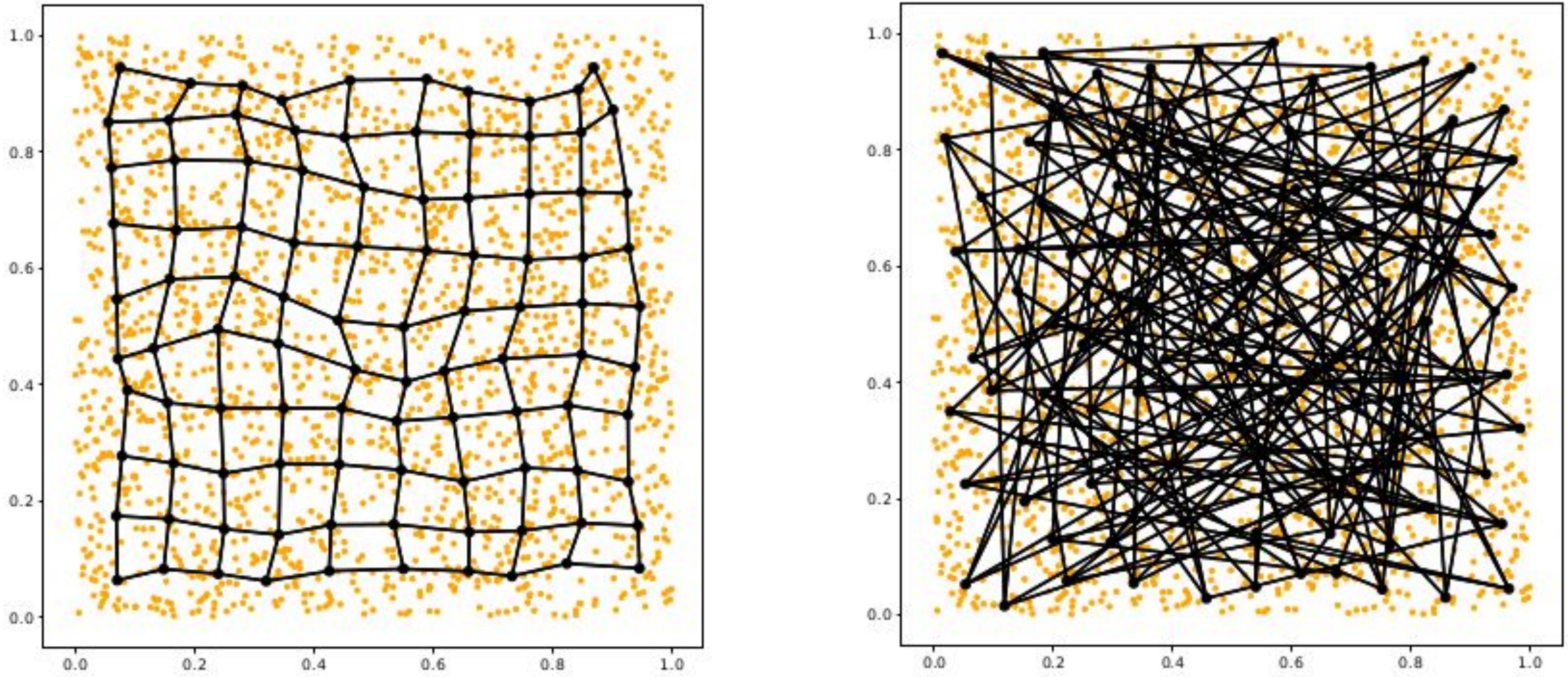
$$\text{loss} = \frac{k_{\text{meteo}}}{k_{\text{meteo}} + k_{\text{energy}}}\text{MSE}_{\text{meteo}} + \frac{k_{\text{energy}}}{k_{\text{meteo}} + k_{\text{energy}}}\text{MSE}_{\text{energy}}$$

changing arctan loss

$$\text{facteur} = \frac{\text{epoch}}{\text{epoch}_{max}}$$

$$\text{loss} = \left(\frac{1}{2} - \frac{1}{\pi}\text{arctan}(10 \times \text{facteur} - 5)\right)\frac{k_{\text{meteo}}}{k_{\text{meteo}} + k_{\text{energy}}}\text{MSE}_{\text{meteo}} + \left(\frac{1}{2} + \frac{1}{\pi}\text{arctan}(10 \times \text{facteur} - 5)\right)\frac{k_{\text{energy}}}{k_{\text{meteo}} + k_{\text{energy}}}\text{MSE}_{\text{energy}}$$

Appendix - topographic error



Source: Forest 2020

Appendix - topographic error: results