European Radiation Protection Week - 2023

Clustering and selection of relevant meteorological scenarios for short-range atmospheric dispersion during nuclear accident

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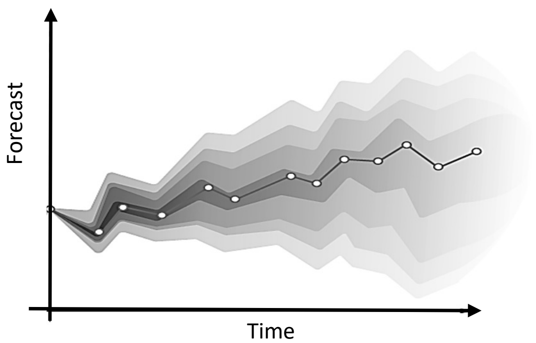

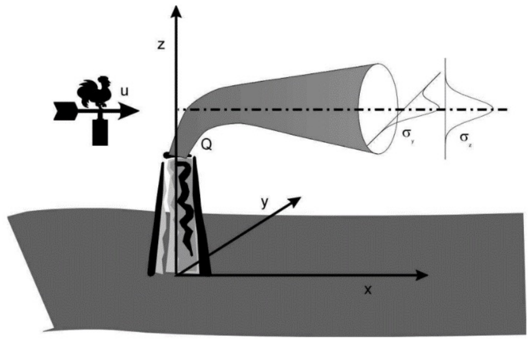

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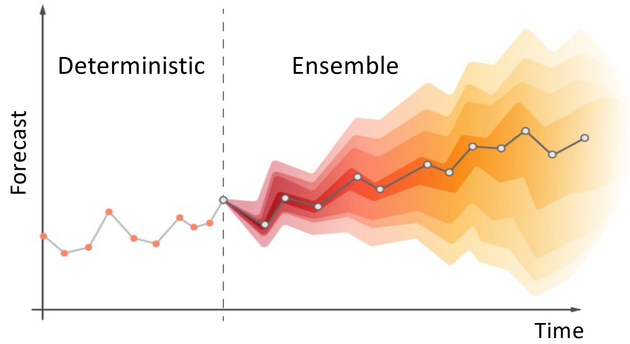
Context and motivations

Atmospheric dispersion models and nuclear emergency management

- Atmospheric dispersion models are used to predict the radiological consequences of the nuclear accidents.

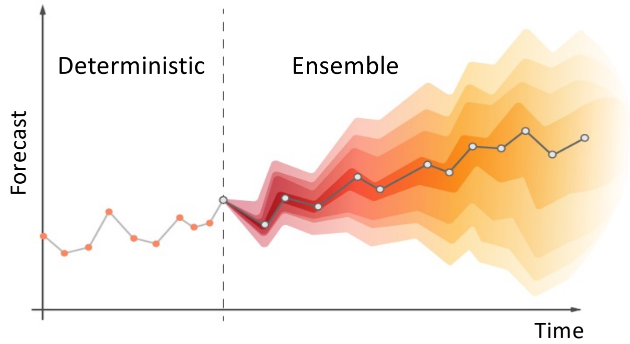
- The use of fine-scale «probabilistic» meteorological forecasts instead of a single deterministic forecast improves atmospheric dispersion forecasting (El-Ouartassy et al., 2022).



Context and motivations

Atmospheric dispersion models and nuclear emergency management

- Atmospheric dispersion models are used to predict the radiological consequences of the nuclear accidents.
- The use of fine-scale ensemble («probabilistic») meteorological forecasts instead of a single deterministic forecast improves atmospheric dispersion forecasting (Leadbetter et al., 2020; El-Ouartassy et al., 2022).



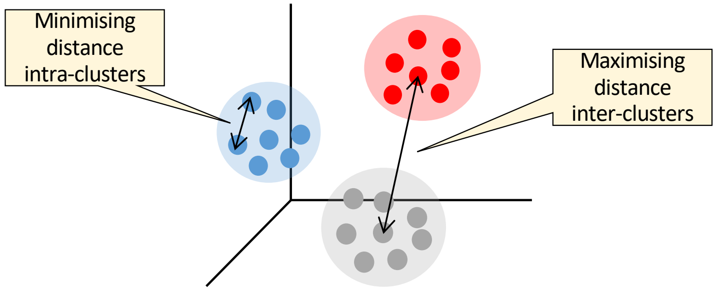
- The use of a high-resolution ensemble approach in an accidental context requires the optimization of the calculation time: data transfer and processing + dispersion calculation.

❖ How can we reduce the number of meteorological members used at the input of dispersion models while retaining some statistical properties of the complete ensemble?

Clustering

Definition and principle

- A set of machine learning algorithms designed to identify homogeneous groups within a population.
- Given a set of points (the meteorological members, in our case) and a similarity metric defined between them, find a number of clusters (classes, groups, segments) such that :
  - The points within the same cluster are very similar to each other,
  - Points belonging to different groups are very dissimilar.



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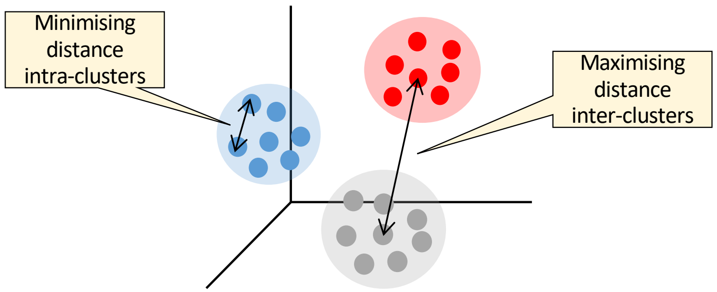


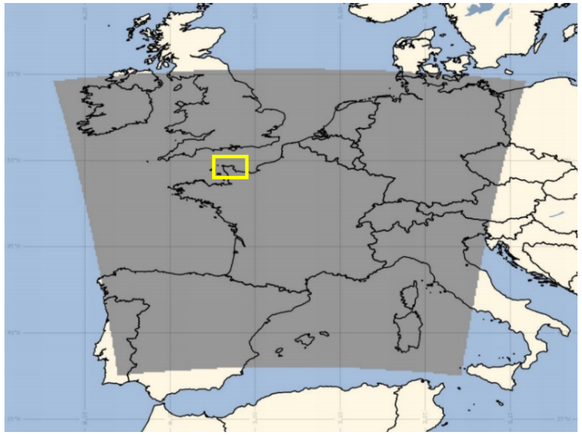
Issues

- ❑ What is the nature of the data (binary, qualitative, numerical, etc.)?
- ❑ What is the appropriate metric for measuring similarity (Euclidean, DTW, Wasserstein, etc.)?
- ❑ How many clusters can be identified in the data set (K=1, 2, 3,...)?
- ❑ Which learning algorithm?
- ❑ Comparison of different clustering results ...

Case study

AROME Esemble Prediction System (AROME-EPS, Météo-France)

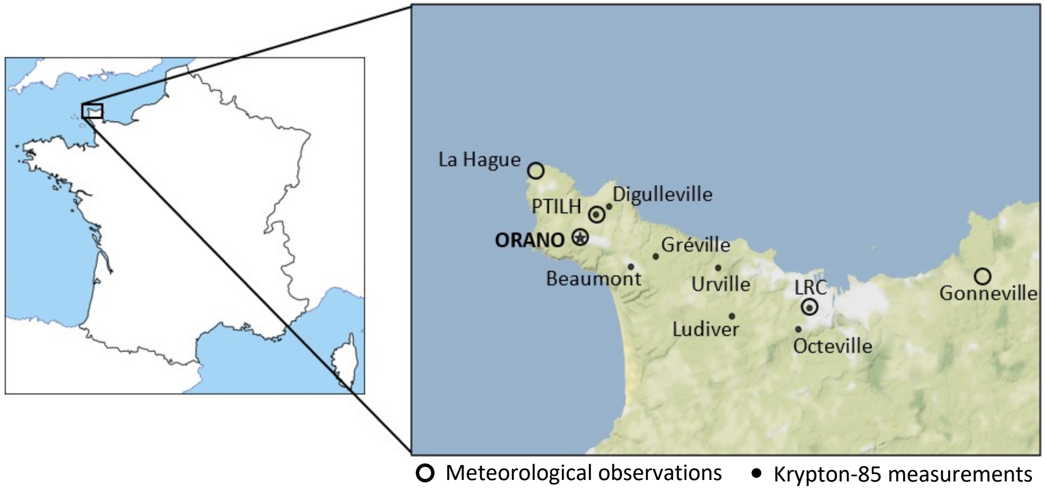
- 16 members at a horizontal resolution of 2.5 km.
- 25 vertical levels [10 – 3000m].
- Hourly forecasts.



AROME domain and the study area

Study area: La Hague experimental site

- Regular release of ^{85}Kr, which is a good tracer of atmospheric dispersion (no deposition, $\tau_{1/2}$=10.7 years).
- Well known Source Term (Orano La Hague).
- The AROME-EPS-pX dispersion ensembles have already been validated in this area during the period [Dec. 2020 – Jan. 2021] : (DISKRYNOC project, El-Ouartassy et al.,2022).



Methodology

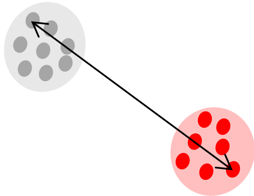
Number of clusters

- The number of clusters chosen in this work is $K = 4$.

Clustering algorithms used :

- ***Agglomerative clustering:***
  - Complete Linkage: The similarity between two clusters is the distance between their most distant individuals.
  - Ward : The similarity between two clusters is the variance of their union.
- **Partitional clustering:**
  - K-means : Based on the minimization of a cost function..

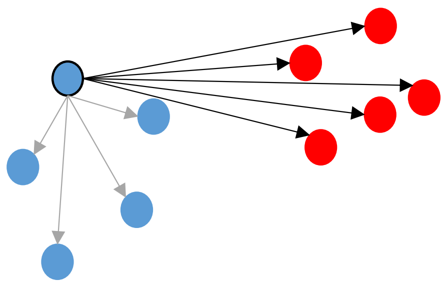
Complete Linkage



Representative member of each cluster:

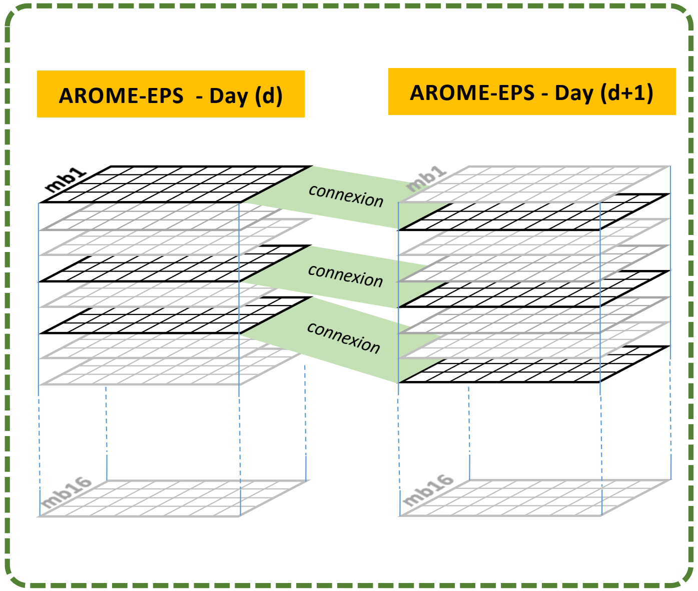
- the member who minimizes the representativeness index : $\mathrm{I} = \frac{a}{b}$

  where : a is the average distance of the member from members of the same cluster,
  b is the average distance of the member from members of other clusters.



Methodology

Overview

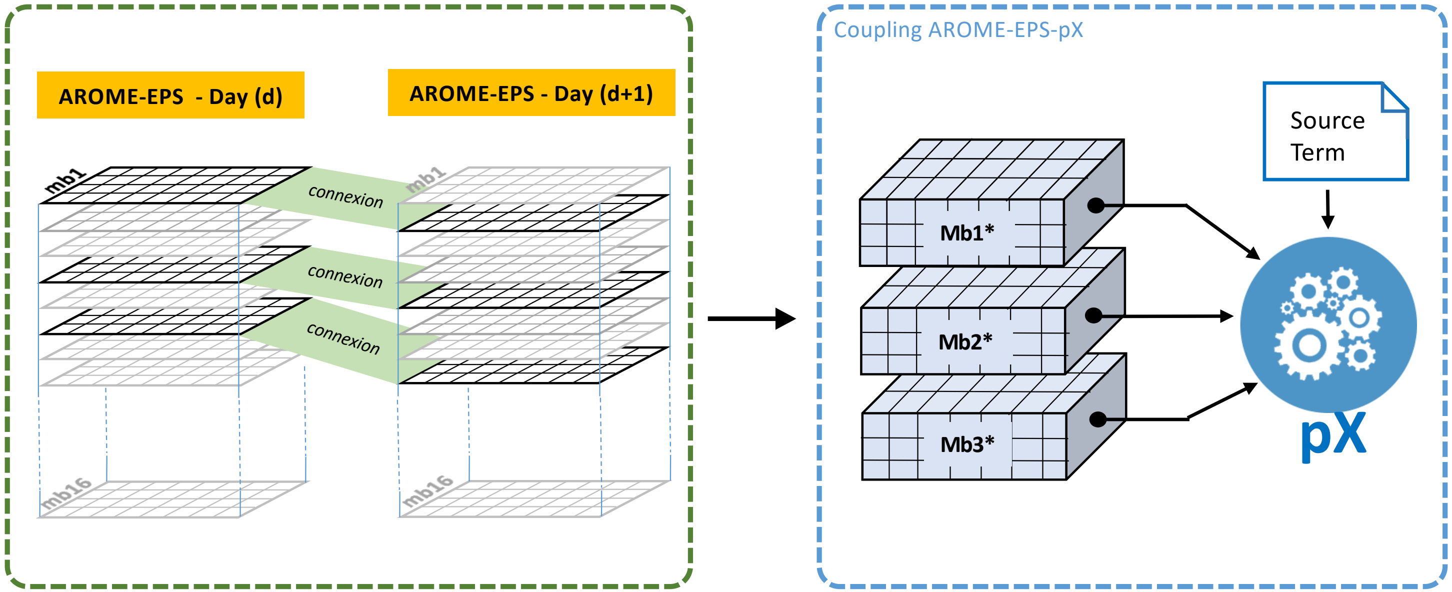


Clustering and calculation of the representative member

1

Methodology

Overview



Clustering and calculation of the representative member

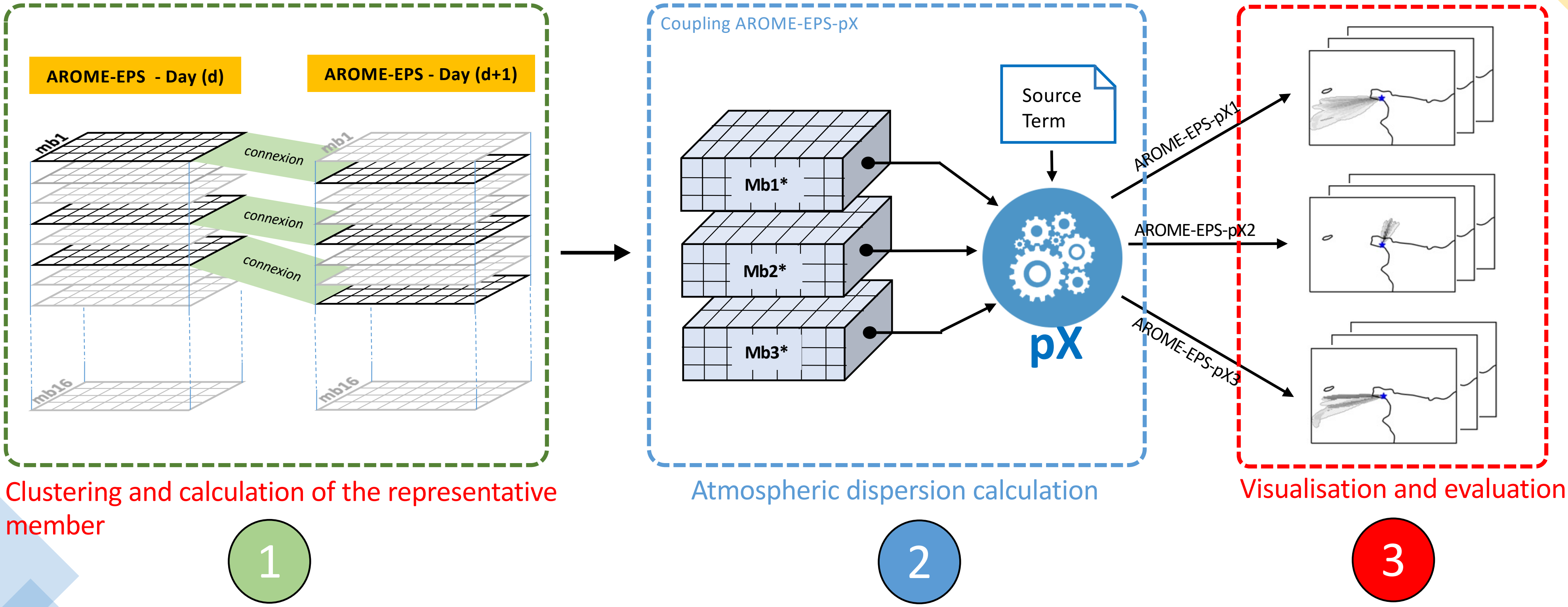
1

Atmospheric dispersion calculation

2

Methodology

Overview

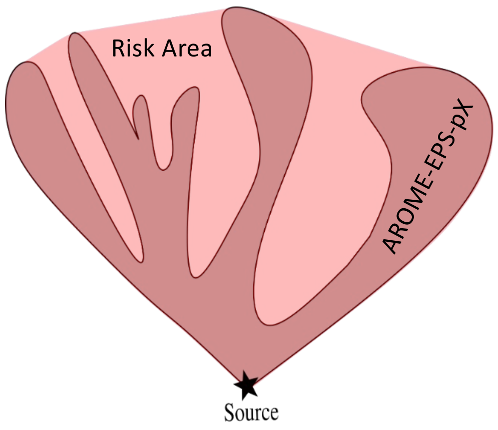


Methodology

Evaluation strategy for dispersion maps

What areas would be potentially contaminated in the next few hours following an atmospheric radioactive release ?

- ❑ Each ensemble/subensemble is assigned a risk area defined as the smallest convex surface surrounding the ensemble.



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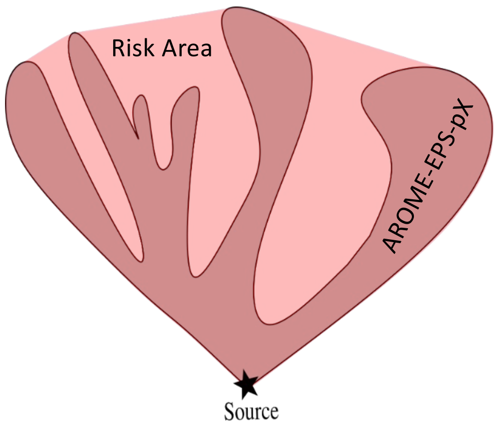
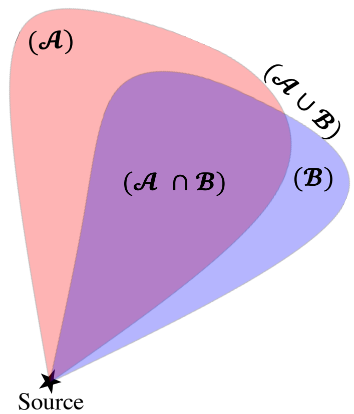


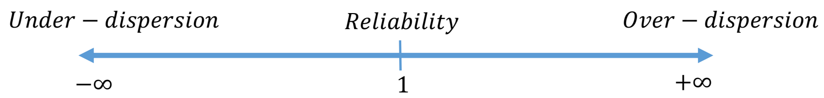
- We calculate the FMS (Figure of Merit in Space) temporal evolution of the risk areas of the clustering sub-ensemble ($\mathcal{B}$) in relation to the risk zone of the PEARO-pX set ($\mathcal{A}$):

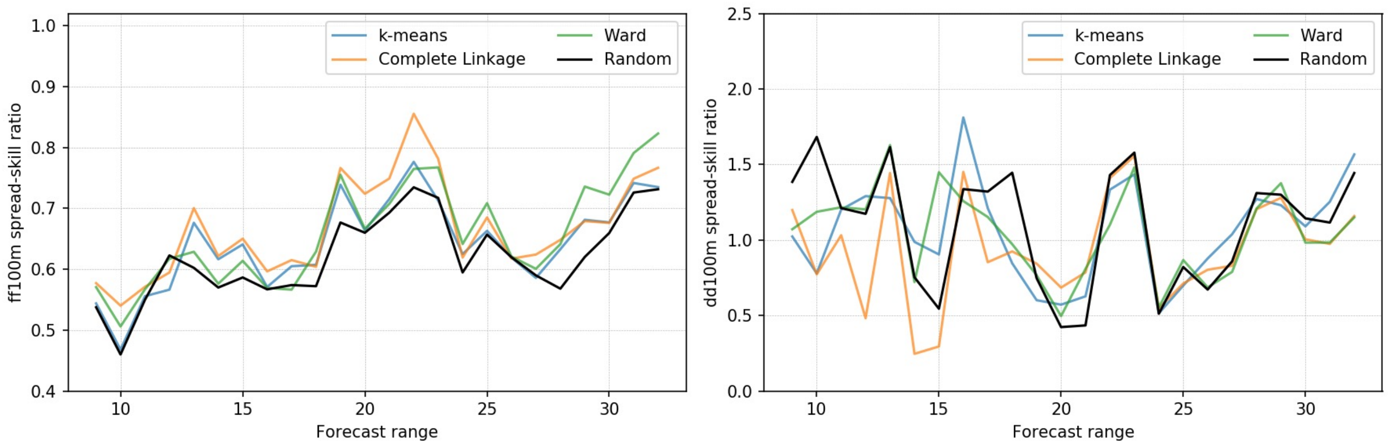
$$FMS = \frac{\mathcal{A} \cap \mathcal{B}}{\mathcal{A} \cup \mathcal{B}} \times 100$$



Impact of clustering on AROME-EPS sub-ensembles

- ❑ ***Spread-skill ratio:***





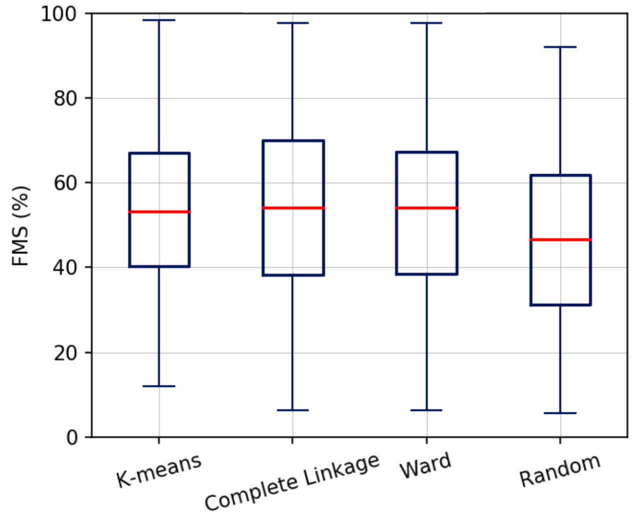
✓ In terms of wind speed, the clustering algorithms improve the dispersion of the subsets constructed to calculate dispersion, with a slight preference for the « complete-Linkage ».

✓ In terms of wind direction, the impact of the clustering algorithms is not obvious.

Results

Impact of clustering on the AROME-EPS-pX sub-ensembles

- ❑ ***Evaluation of ^{85}Kr dispersion maps***



✓ Clustering algorithms improve atmospheric dispersion forecasts on average.

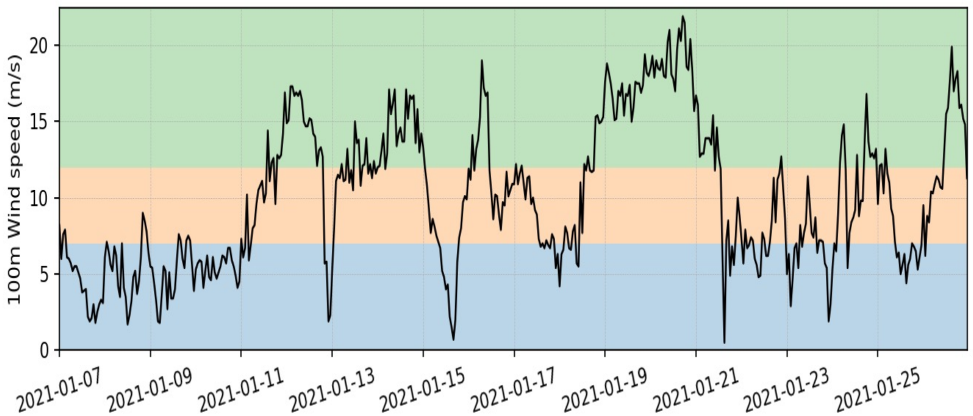
Results

Impact of clustering on the AROME-EPS-pX sub-ensembles

❑ *Sensitivity to wind conditions*

- A comparison of wind speed evolution and the impact of clustering on dispersion forecasts (FMS) shows that there is a correlation between these two variables.

- We define 3 wind intervals:

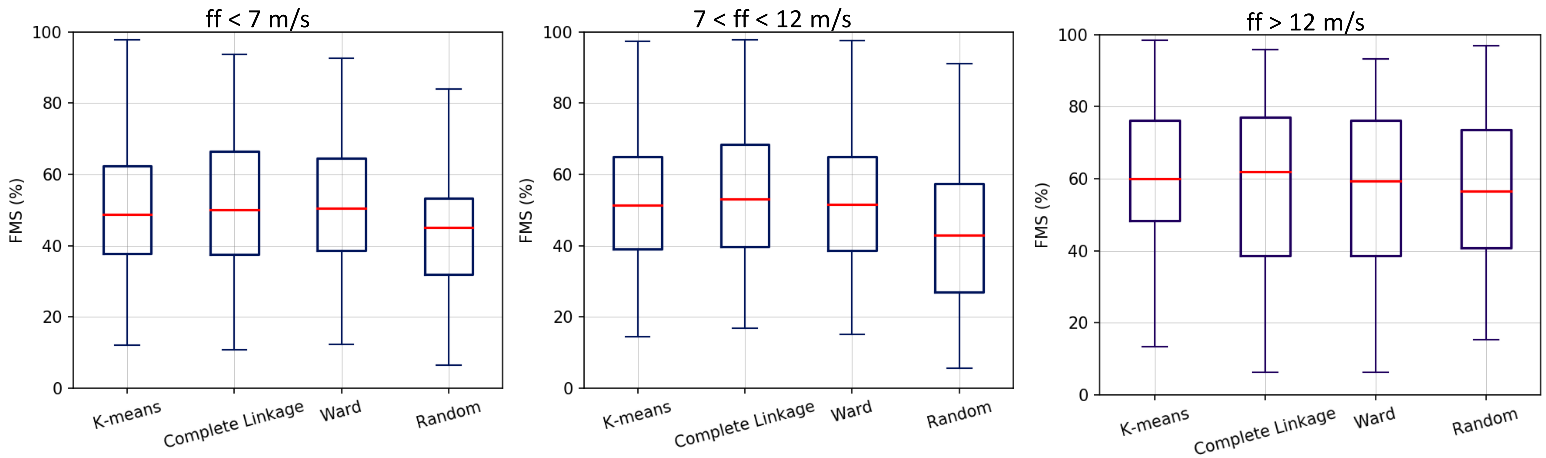


ff100 < 7 m/s : 136 samples
7 < ff100 < 12 m/s : 153 samples
ff100 > 12 m/s : 143 samples

Results

Evaluation of 85Kr dispersion maps

- ***Sensitivity to wind conditions***

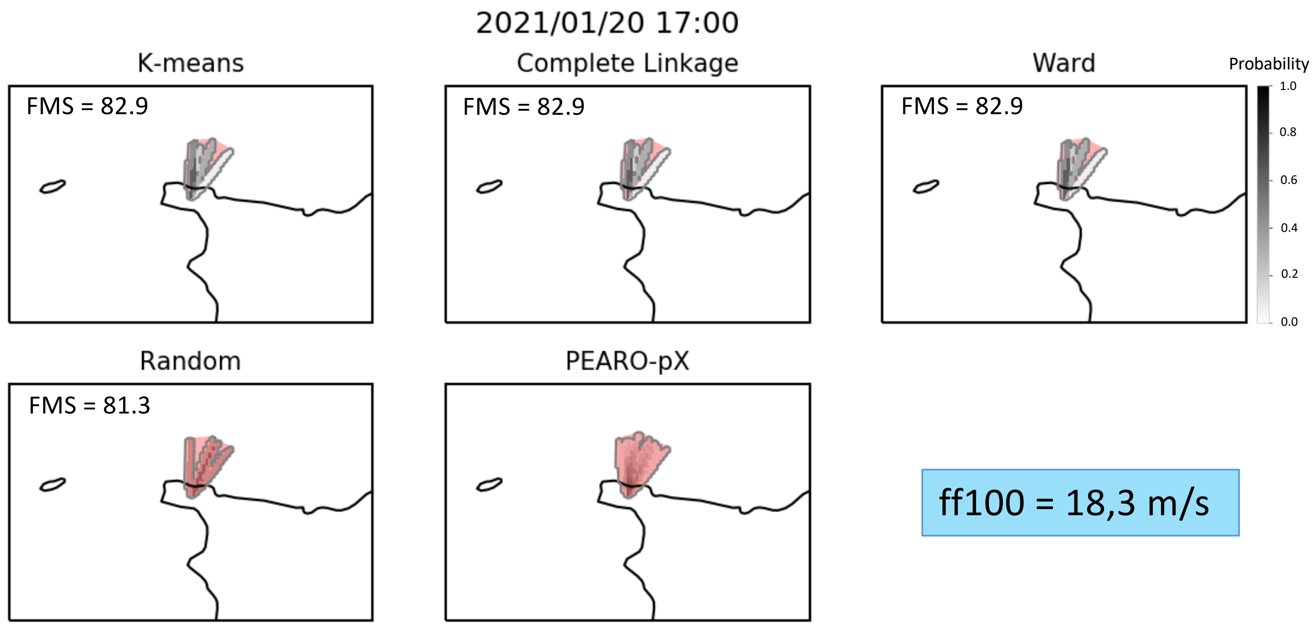


✓ Clustering has a higher impact in low/moderate wind situations.

Results

Evaluation of ^{85}Kr dispersion maps

- ***Sensitivity to wind conditions***

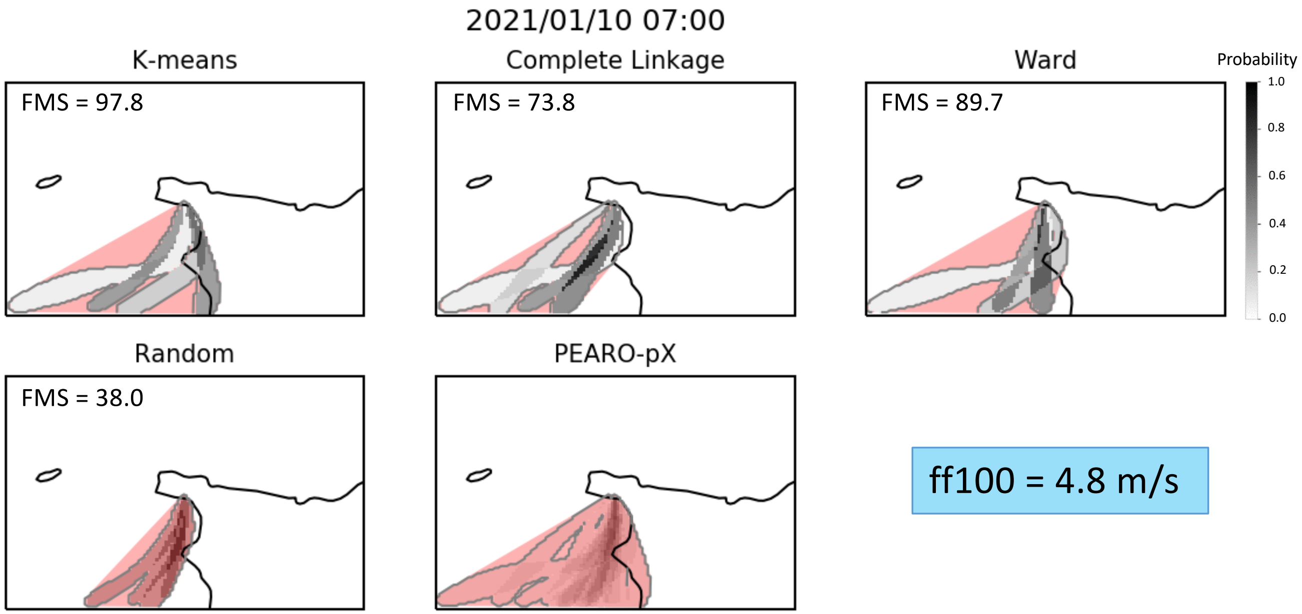


ff100 = 18,3 m/s

Results

Evaluation of 85Kr dispersion maps

- ***Sensitivity to wind conditions***



ff100 = 4.8 m/s

Conclusions and perspectives

Conclusions

- Clustering algorithms have an advantage over random sampling in predicting short-range atmospheric dispersion,
- Wind is the appropriate predictor variable for the calculation of clustering,
- Clustering results are efficient in low and medium wind conditions.

Conclusions and perspectives

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- ❑ Clustering algorithms have an advantage over random sampling in predicting short-range atmospheric dispersion,
- ❑ Wind is the appropriate predictor variable for the calculation of clustering,
- ❑ Clustering results are efficient in low and medium wind conditions.

Perspectives

- ❑ Application to an ensemble containing a relatively large number of members (PEARP, 35 members, 10km resolution),
- ❑ Implement more complicated algorithms wherever possible (calculation time!), using more efficient distances (Wasserstein distance) for calculating inter- and intra-cluster similarity,
- ❑ Study the sensitivity of the representative member of each cluster to the calculation method.

Thank you !

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