

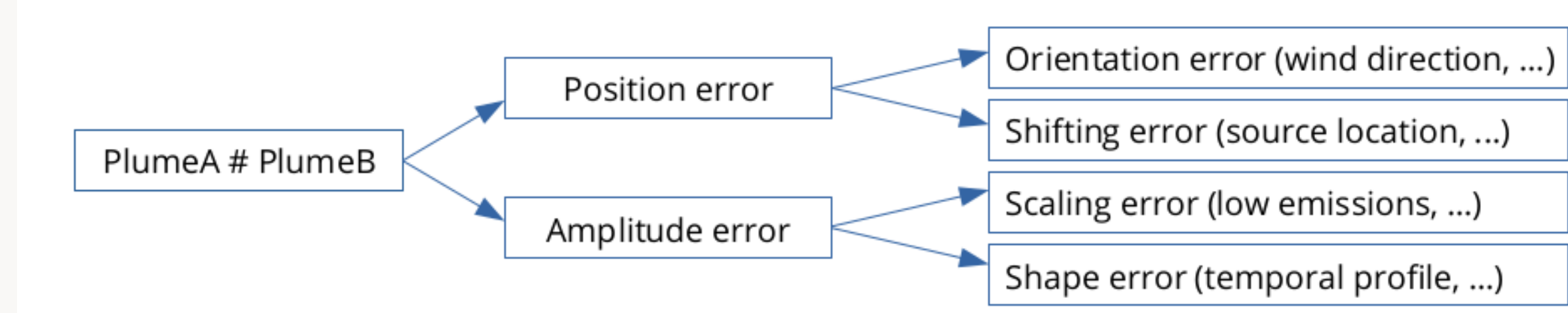
Non-local metrics applied to the comparison of CO₂ plumes and their sensitivities to mesoscale meteorology

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What are we aiming for?

- Design smarter metrics to compare plumes from high-resolution satellite images (like Sentinel-5P) to simulation results to give less credit to errors due to meteorology.
- Use these metrics in an inverse method relying on atmospheric transport models to update emission inventories.

Categorisation of discrepancies between the images



Strategy

- Develop new non-local metrics for the comparison of plume objects.
- Remove the position error to have comparison less sensitive to meteorology.
- Detection and segmentation of plume objects are discussed in Joffrey's poster.

Compared metrics

- Usual metric integrated over the image:

$$d(A, B) = \sqrt{\int (A(\mathbf{x}) - B(\mathbf{x}))^2 d\mathbf{x}} \quad (1)$$

- Usual metric with upstream position correction:

$$d_F(A, B) = \sqrt{\int (A(\mathbf{x}) - B(F(\mathbf{x})))^2 d\mathbf{x}} \quad (2)$$

where F is the best plane transformation that minimise the distance.

- Wasserstein metric:

$$w(A, B) = \sqrt{\inf_T \int \|\mathbf{x} - T(\mathbf{x})\|^2 \hat{A}(\mathbf{x}) d\mathbf{x}} \quad (3)$$

where T is the best transport plan that transport the normalised \hat{B} to \hat{A} .

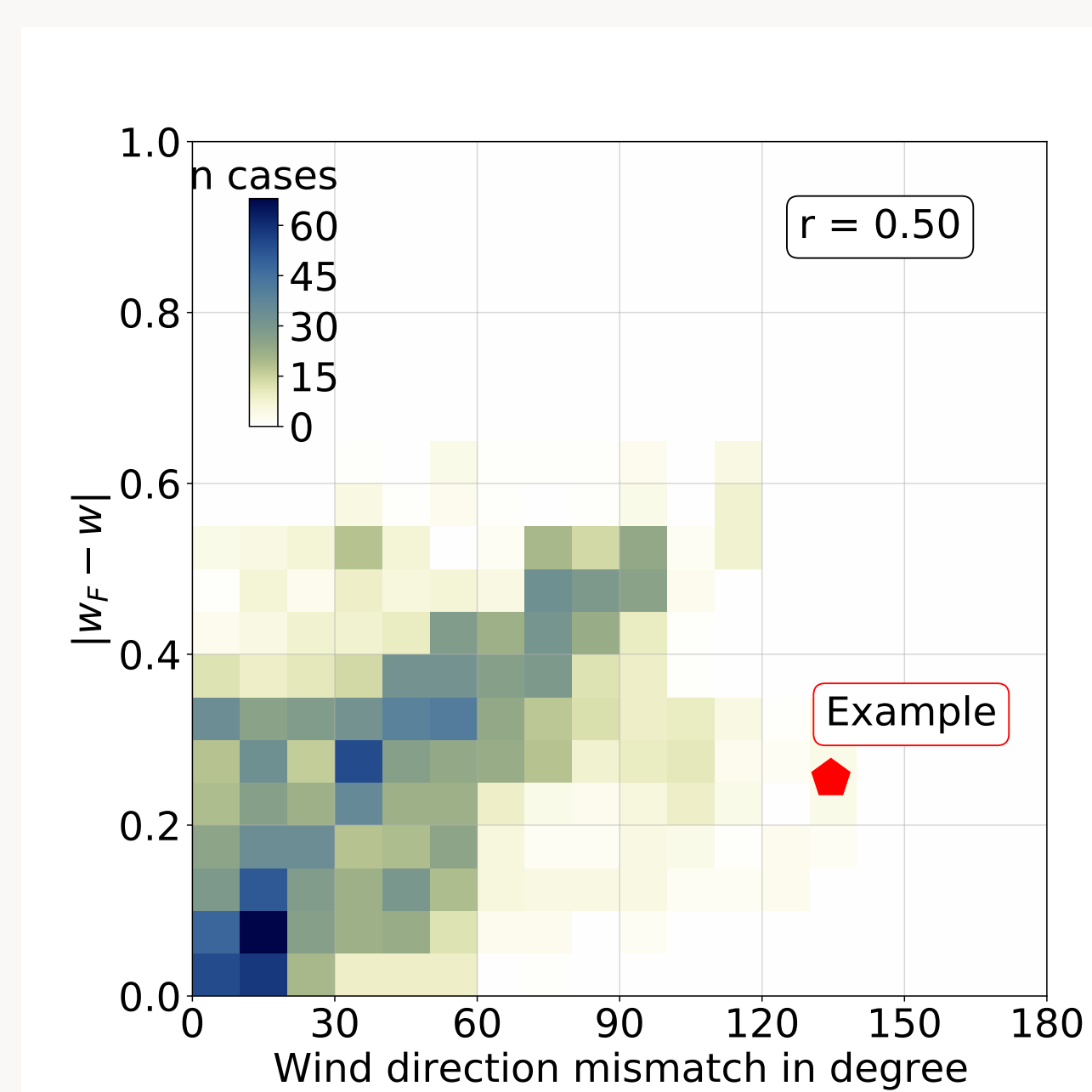
- Wasserstein metric with position correction:

$$w_F(A, B) = \sqrt{\text{Tr}((\text{Cov}(\hat{A})^{\frac{1}{2}} - \text{Cov}(\hat{B})^{\frac{1}{2}})^2)} \quad (4)$$

assuming plumes are Gaussian-like histograms.

Evaluation over meteorology criteria

- Meteorology changes are represented by changes in: mean wind direction, mean wind intensity, standard deviation of the wind direction and standard deviation of the wind intensity.

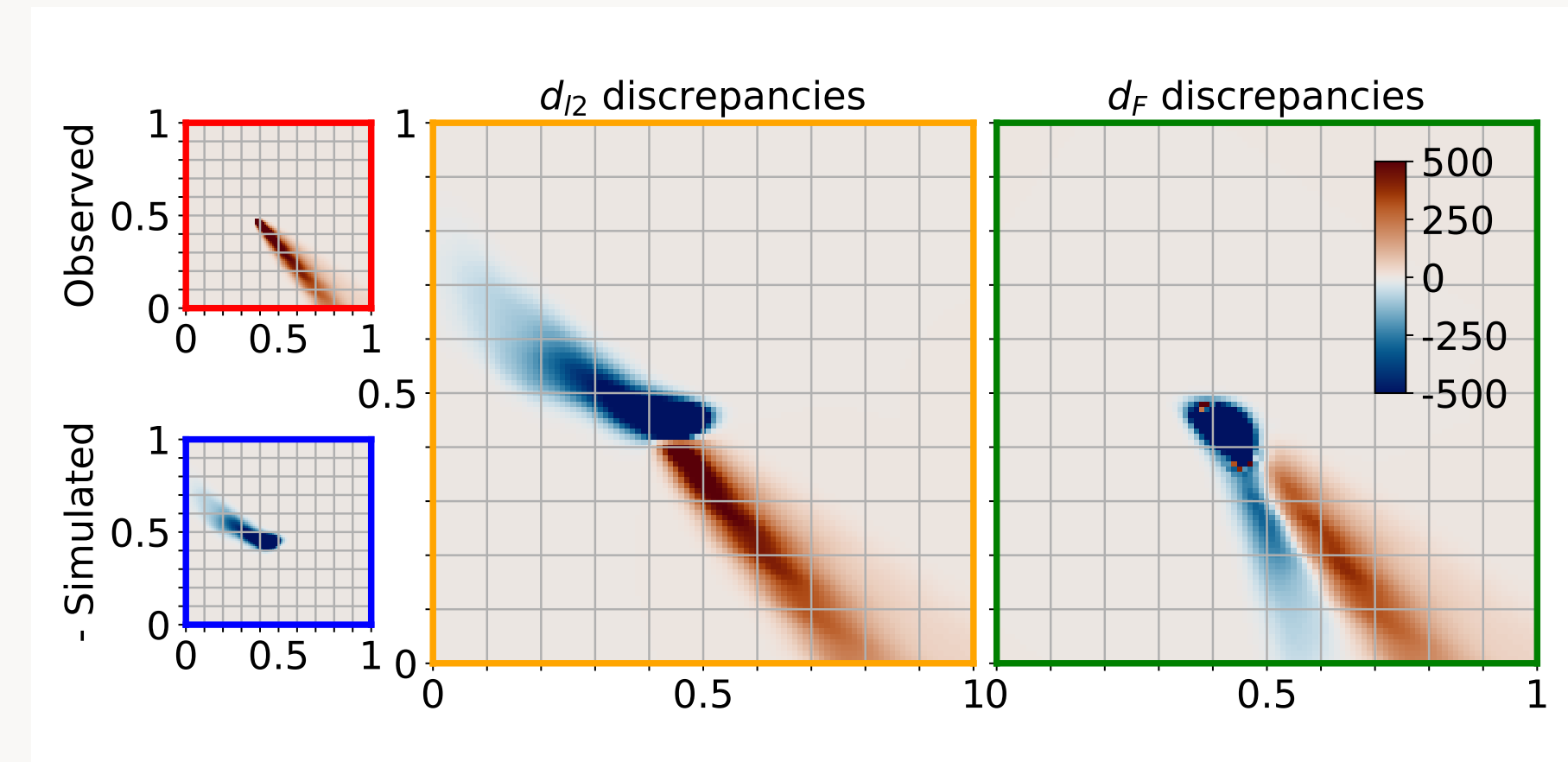


Correlation between the reduction $|w - w_F|$ and changes in the mean wind direction

- r is the Pearson correlation.
- The chosen example is represented by the red pentagon.
- Both corrected metrics lead to less sensitivity to mean meteorology changes.
- The corrected metrics are mainly driven by changes in the standard deviation of the wind.

What is a non-local metric?

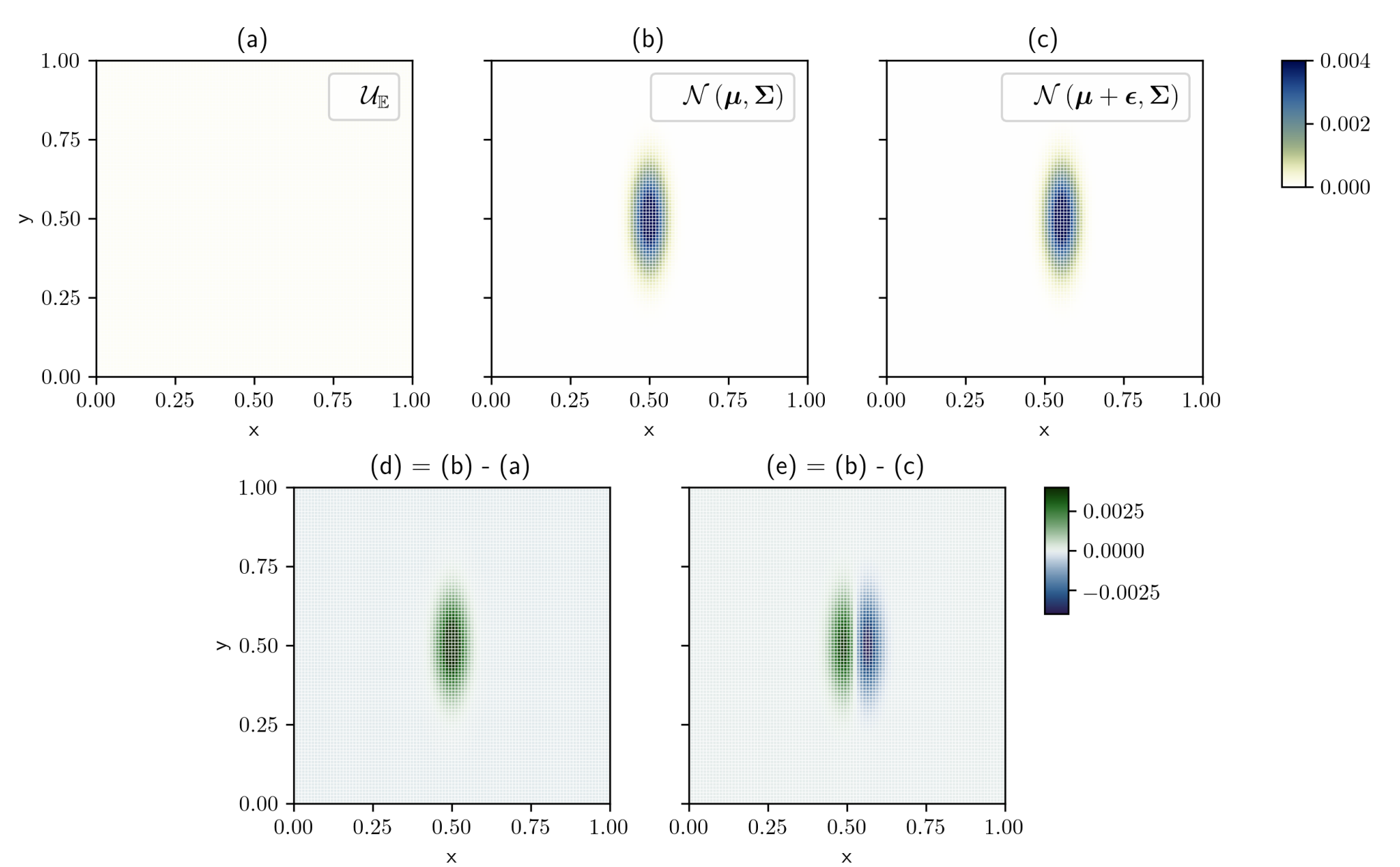
- *local* ~ pixel-wise comparison and thus consider only the cost of amplitude differences pixel by pixel leading to the double penalty issue.
- *non-local* ~ histogram comparison which consider the cost of the displacement and the change in amplitude to match the two histogram.



Example of discrepancies map seen by the usual *local* metric (d_{L2}) and the *non-local* metric (d_F)

What is the double penalty issue?

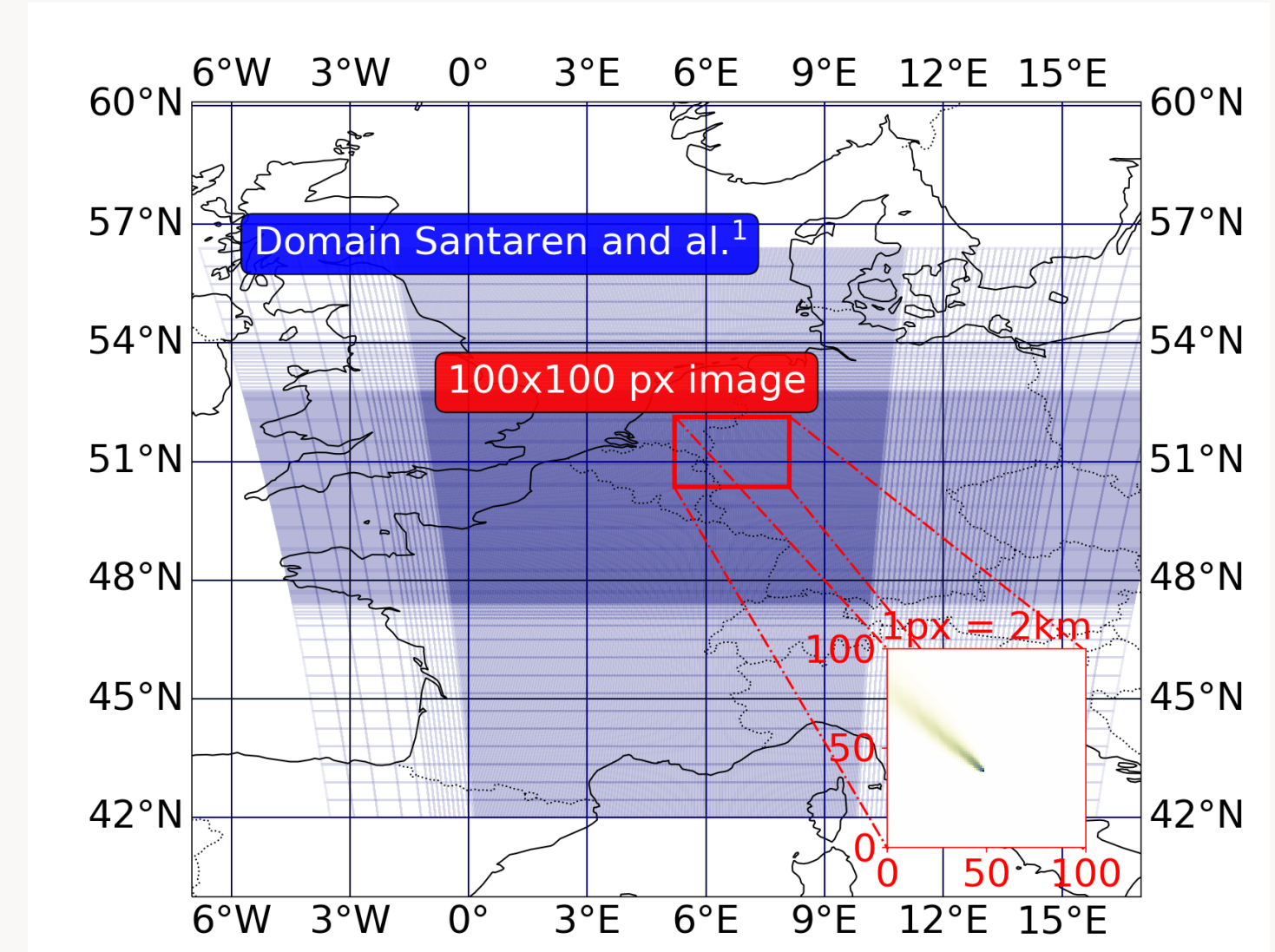
- When two identical pixels are shifted from each other, pixel-wise comparison will penalise the shifting by twice the amplitude of the pixels.
- Conversion of any position error into amplitude error.



Comparison of Gaussian histograms shifted from each other. The discrepancies maps lead to the same d_{L2} value.

Which images are compared?

- Pulsating power plant simulated over 14 days with a 2 km × 2 km resolution [1].
- 100 × 100 pixel images centered on the power-plant.
- We conserved 2208 pairs of CO₂ plumes ($A(\mathbf{x})$, $B(\mathbf{x})$) where only the meteorology change.



Simulated domain [2]

Synthesis

- Position correction in the new metrics lead to comparison that are less sensitive to change in the mean direction of the wind and/or its intensity.
- Small-scale meteorology still impacts the comparison between the plumes through the shape error.
- Wasserstein distance is not subject to the double penalty issue.
- Optimal transport metrics need to use normalised images and thus an additional term representing the scaling error is required for the inversion.
- These results are submitted to the AMT journal.

Bibliography

- [1] D. Santaren, G. Broquet, F.-M. Bréon, F. Chevallier, D. Siméoni, B. Zheng, and P. Ciais. A local- to national-scale inverse modeling system to assess the potential of spaceborne CO₂ measurements for the monitoring of anthropogenic emissions. *Atmospheric Measurement Techniques*, 14(1):403–433, 2021. doi: 10.5194/amt-14-403-2021. URL <https://amt.copernicus.org/articles/14/403/2021/>.
- [2] E. Potier, G. Broquet, Y. Wang, D. Santaren, A. Berchet, I. Pison, J. Marshall, P. Ciais, F.-M. Bréon, and F. Chevallier. Complementing xCO₂ imagery with ground-based CO₂ and ¹⁴CO₂ measurements to monitor CO₂ emissions from fossil fuels on a regional to local scale. *Atmospheric Measurement Techniques Discussions*, 2022:1–44, 2022. doi: 10.5194/amt-2022-48. URL <https://amt.copernicus.org/preprints/amt-2022-48/>.