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Italiadomani PIANO NAZIONALE DI RIPRESA E RESILIENZA
CNR ISMAR ISTITUTO DI SCIENZE MARINE

Probabilistic wave and storm surge forecasting at regional scale using reduced ensemble forcings

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[3] University of Padua, Padua, Italy.
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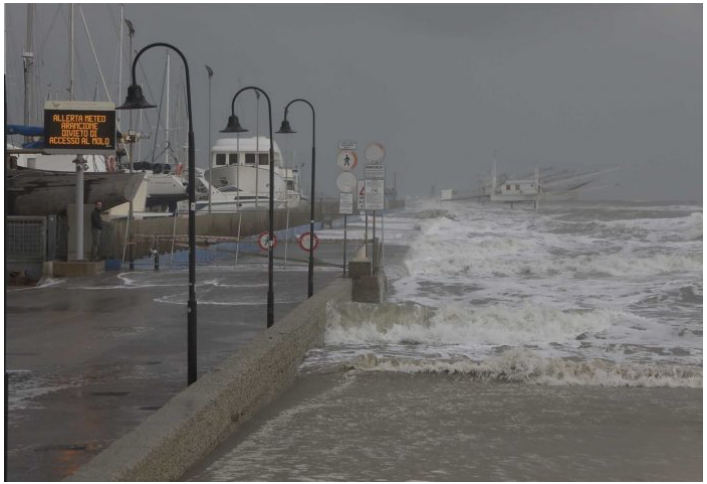
Santander, 26 September 2025

Motivations: a solution to a practical problem

AIM: **marine hazards** (coastal flooding, sea storms, …) **EARLY-WARNING** at **REGIONAL/LOCAL scale**.



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TOOL: numerical weather prediction

- **wind** and pressure (**ATM** models)
- **waves** and **sea level** (**WAVE** and **OCEAN** models, **coupled**)
- **high-resolution** spatial grids
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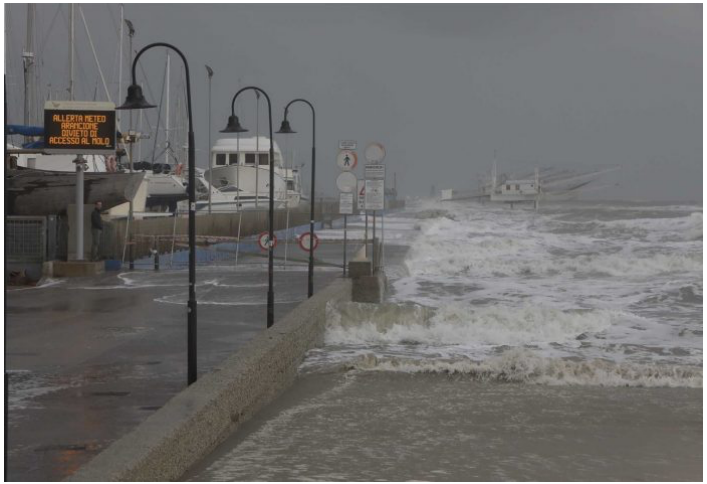

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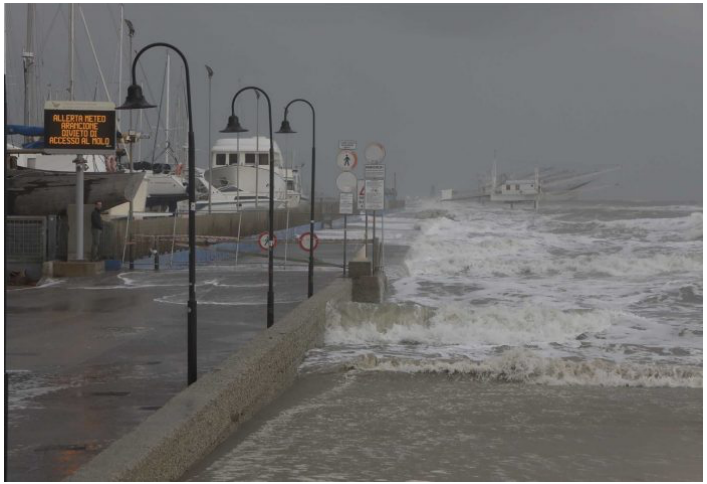

Computational demanding, not for regional forecasting centres

Motivations: a solution to a practical problem

ENS weather **FORECASTING** requires (CONs):

- **n (=50, ECMWF)** IC+BC forcings
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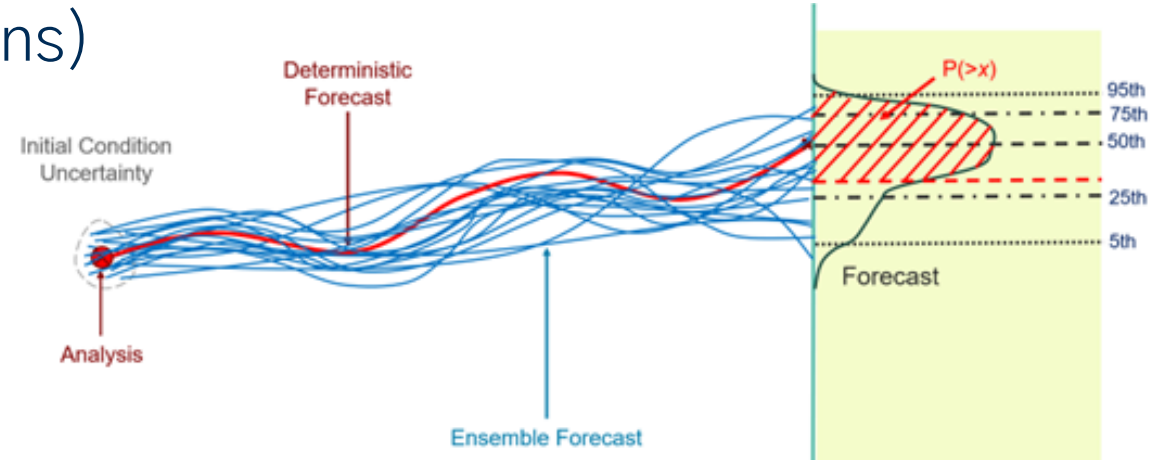
- n OW runs



www.rmets.org

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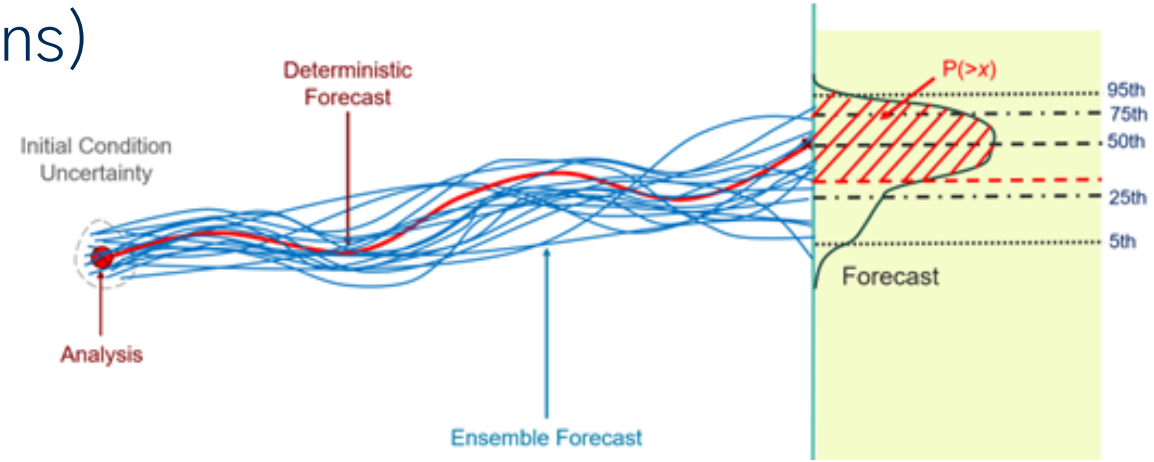

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But provides (PROs):

- Forecast **uncertainty**
- **Probability** of Exceedance (**WARNING**)

Objectives

Would it be possible to reduce the ensemble size (n<<50) preserving most of the ensemble information?

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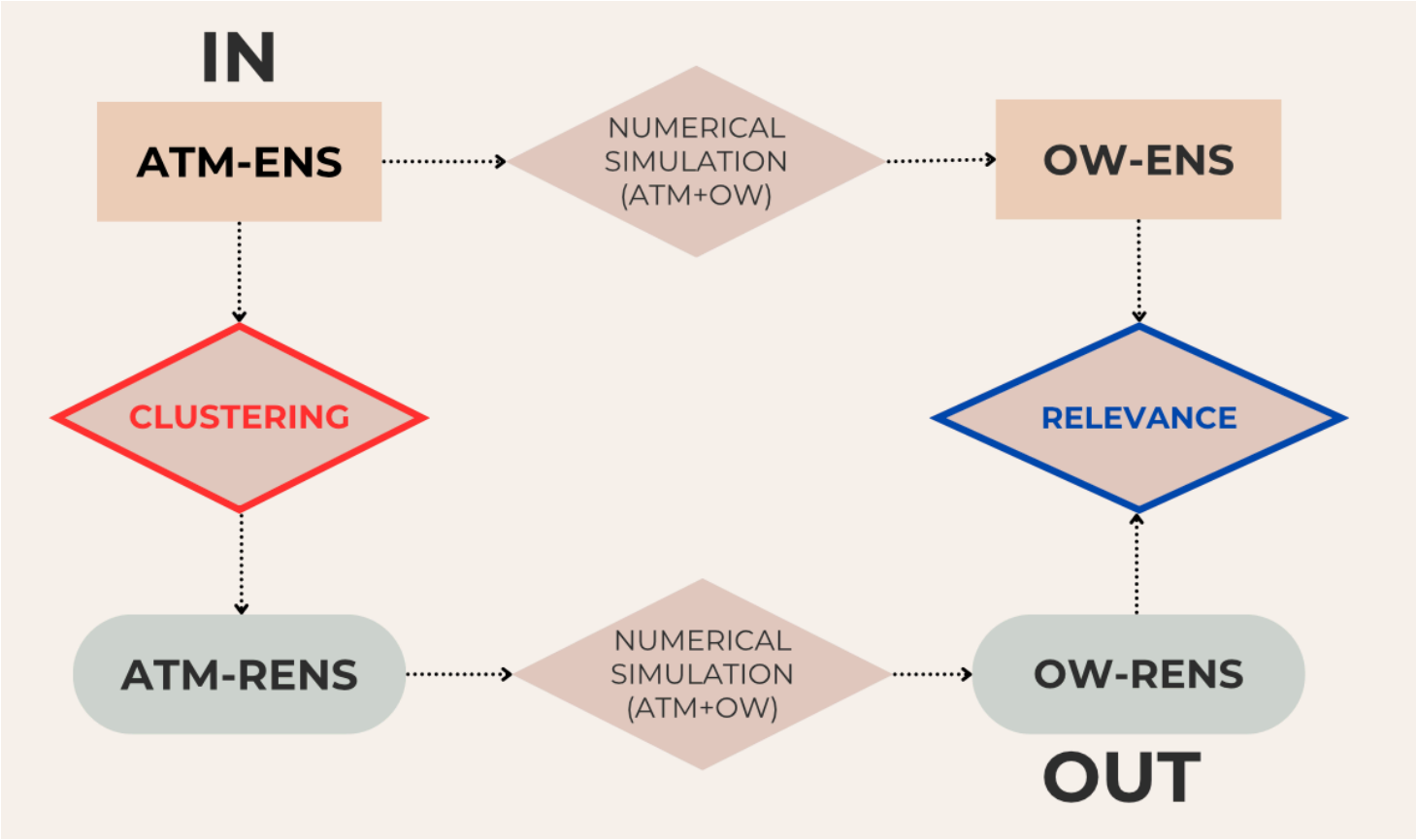
1. Overarching goal, to develop a **METHODOLOGY** to obtain a **REDUCED ENSEMBLE (RENS)**, resembling the COMPLETE ENSEMBLE (ENS)
2. Here, we test the methodology in **1 REAL-CASE event**:
   - low-predictability
   - coastal impact
   - using a prototype EARLY-WARNING FORECASTING SYSTEM (ensemble, coupled, high-resolution)

Methodology



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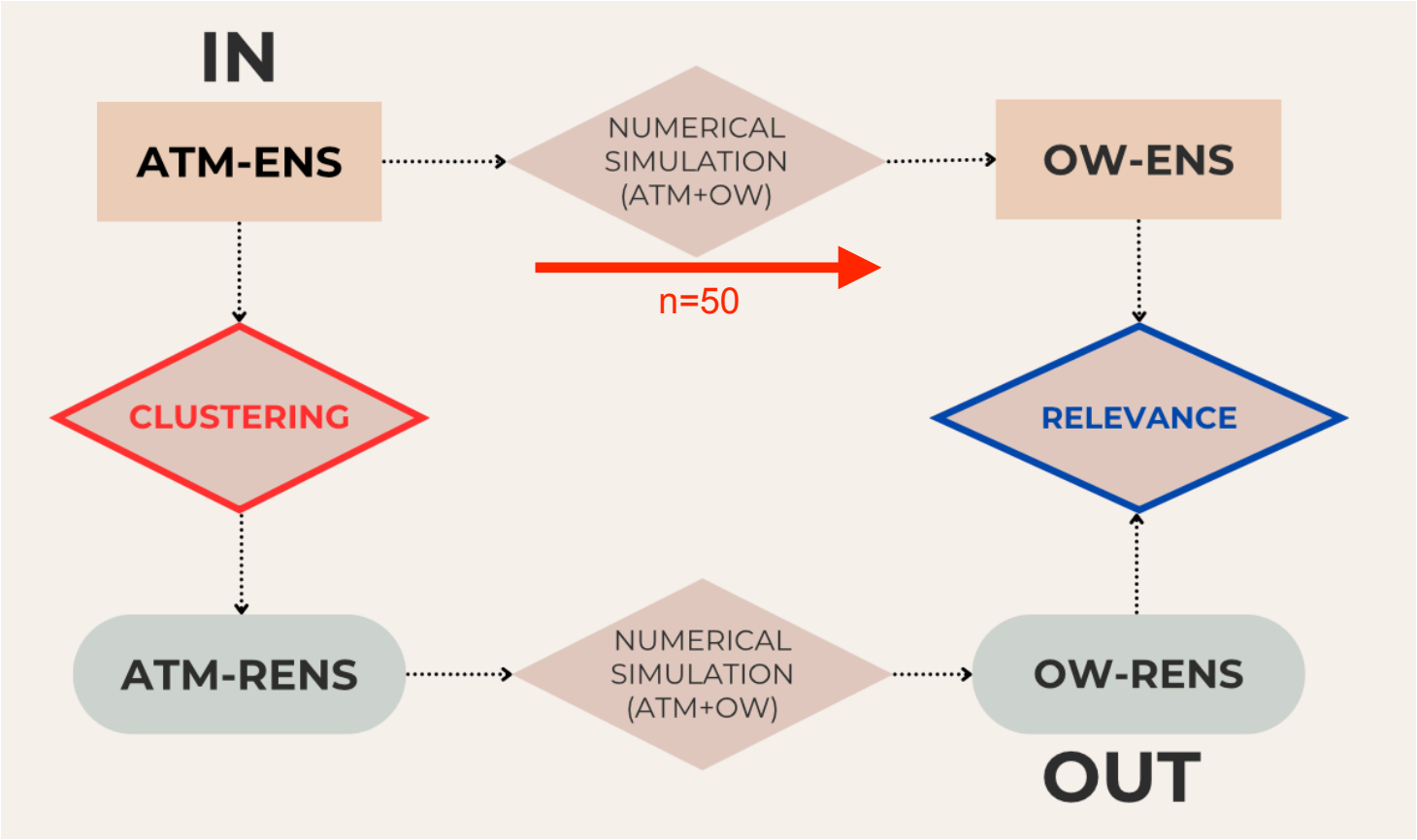

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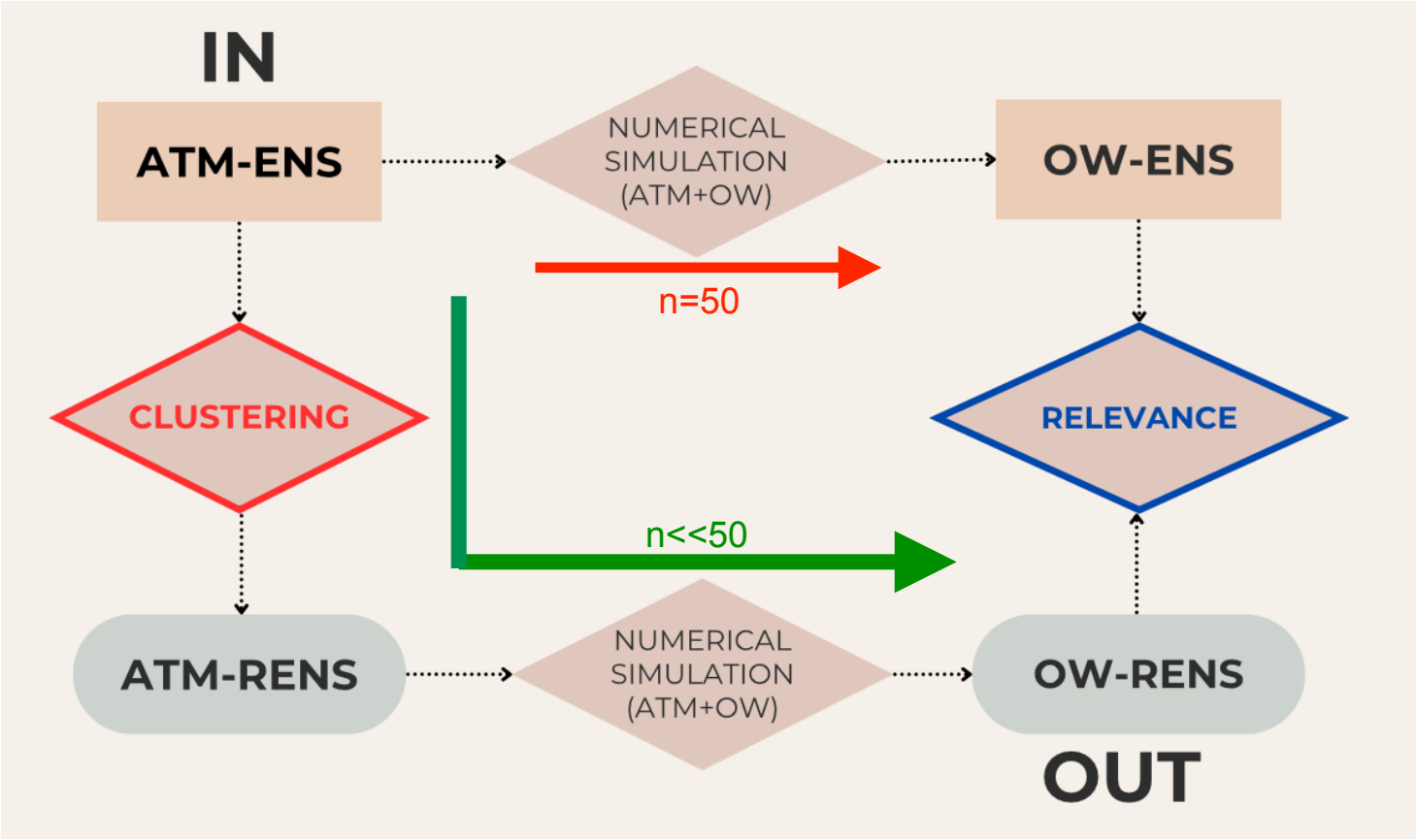

Methodology – CLUSTERING of atm. forcings

Built upon "**Molteni et al (2001) – A strategy for high-resolution ensemble prediction. I: Definition of representative members and global-model experiments. QJRMS**"

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U_{10} and mslp fields, on the sea, over time

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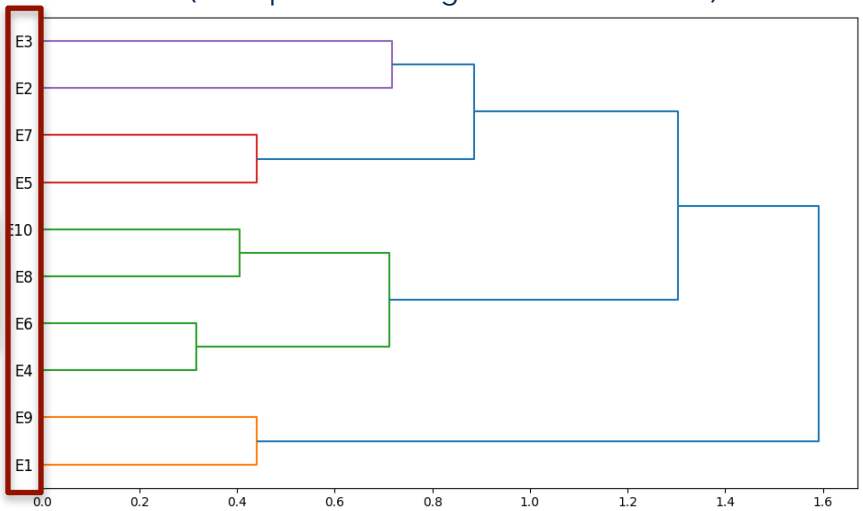
(complete linkage distance crit.)



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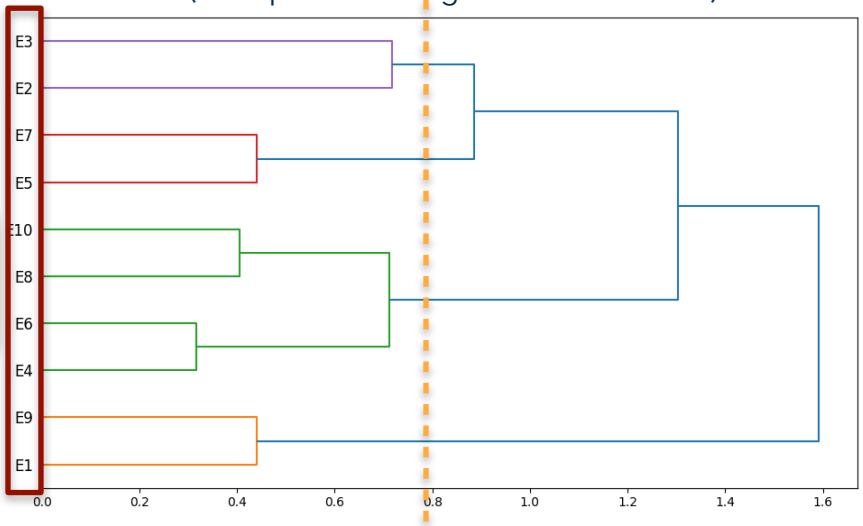

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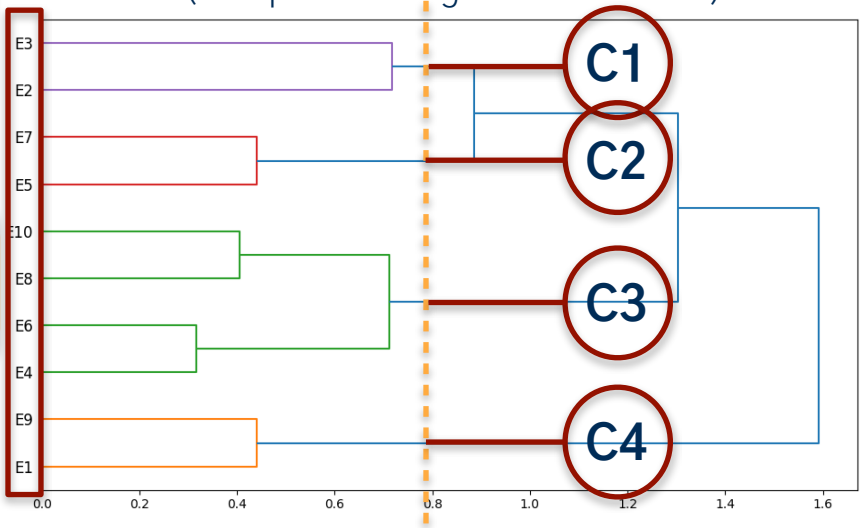

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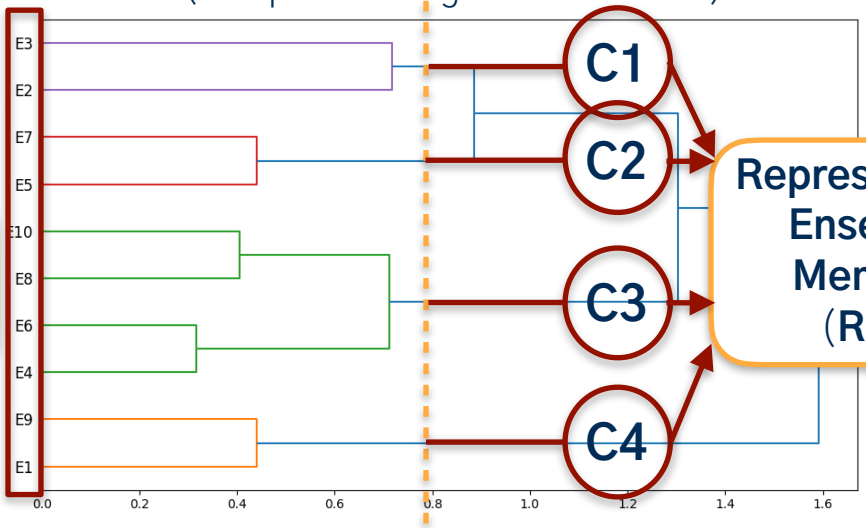

Representative Ensemble Members (REM)

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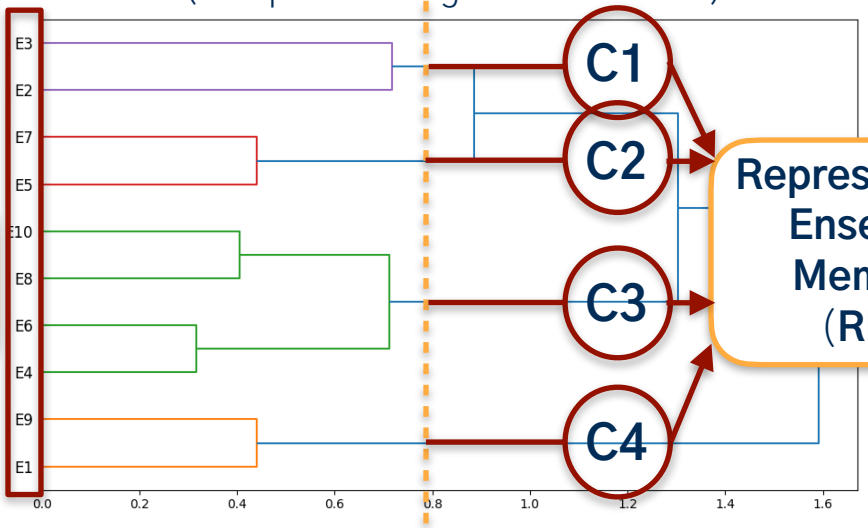

Representative Ensemble Members (REM)

RENS
U_{10} and mslp fields, on the sea, over time

weighted (according to cluster population)

Methodology – RELEVANCE of reduced ensemble

RELEVANCE: capability of **RENS** to **capture** the main features of the **probability distribution of ENS.** NOT a verification against OBSERVATIONS

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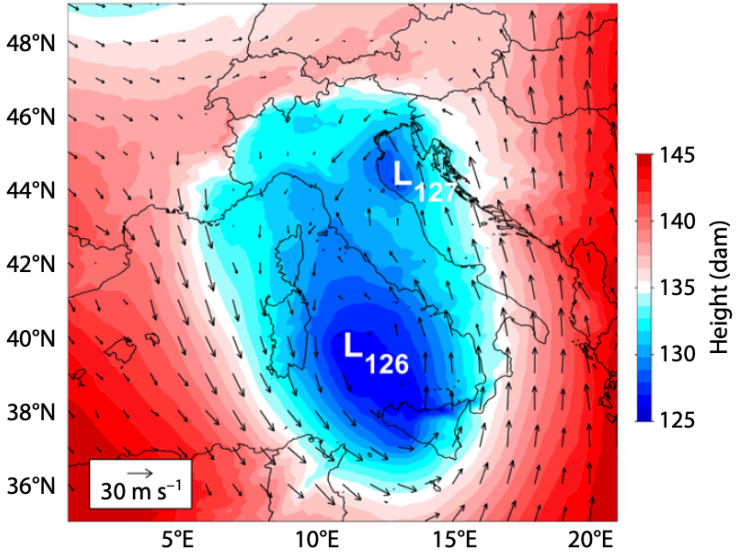
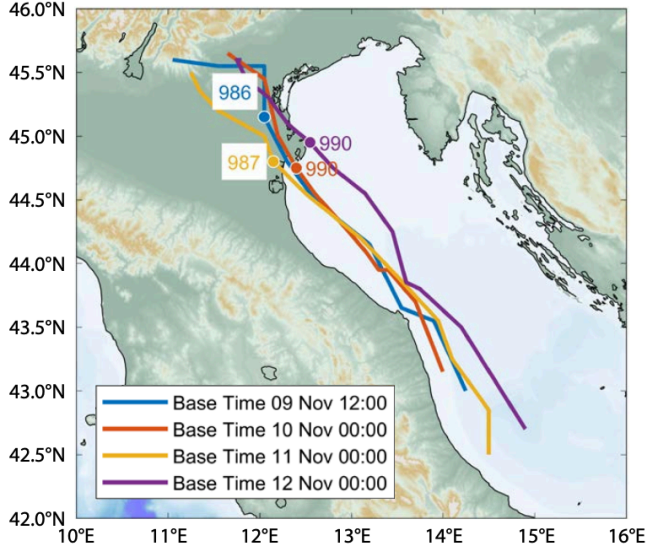
- EXPECTED U_{10}, H_s: **ensemble mean**
- UNCERTAINTY/VARIABILITY: **ensemble spread** (standard deviation)
- PROBABILITY DISTRIBUTION: **Wilkoxon test** of pdfs, % of X with **p–value > 5%** (reject null hypothesis, i.e., ENS and RENS pdfs belong to the same probability distribution)

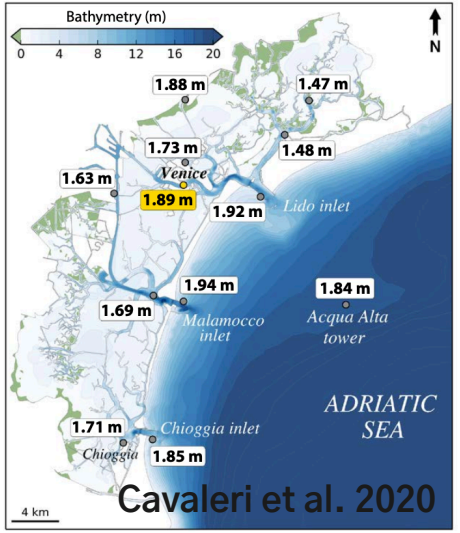
Methodology – TEST CASE

DETLEF cyclone (12/11/2019)

- Mediterranean cyclone with 2 pressure minima, the smallest one (moving northward over the Adriatic until Venice) was difficult to predict
- Impact on Italian coasts: 2nd highest flooding (Acqua Alta) in Venice





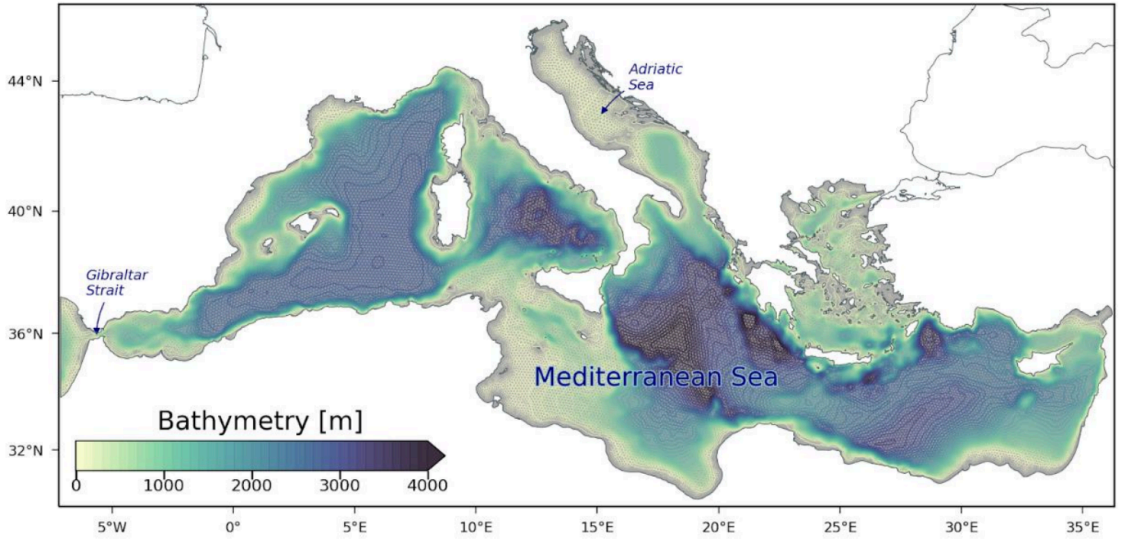


Methodology – DATA&MODELS

DATA

ECMWF–IFS ENS forecast:

- wind speed U_{10}
- mslp
- Run 11/11/2019–12UTC, 0h–48h, step 1h



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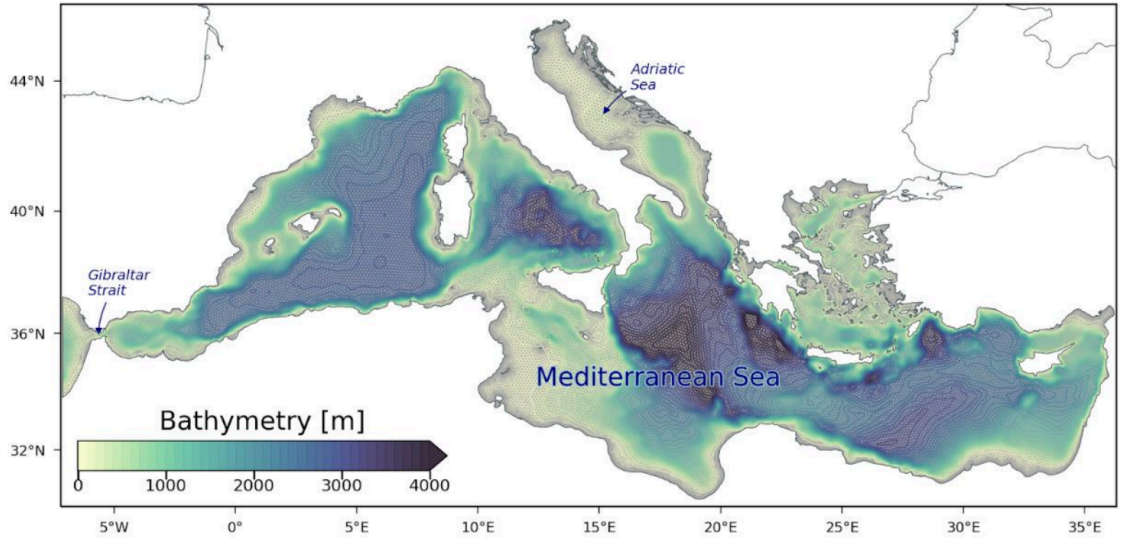

NUMERICAL MODELS

- Atmosphere downscaling: WRF, 9km over Europe, 3km over Italian seas
- Ocean and wave modeling: SHYFEM hydrodynamic model coupled to WAVEWATCH III spectral wave model – unstructured grid (500m–2km)

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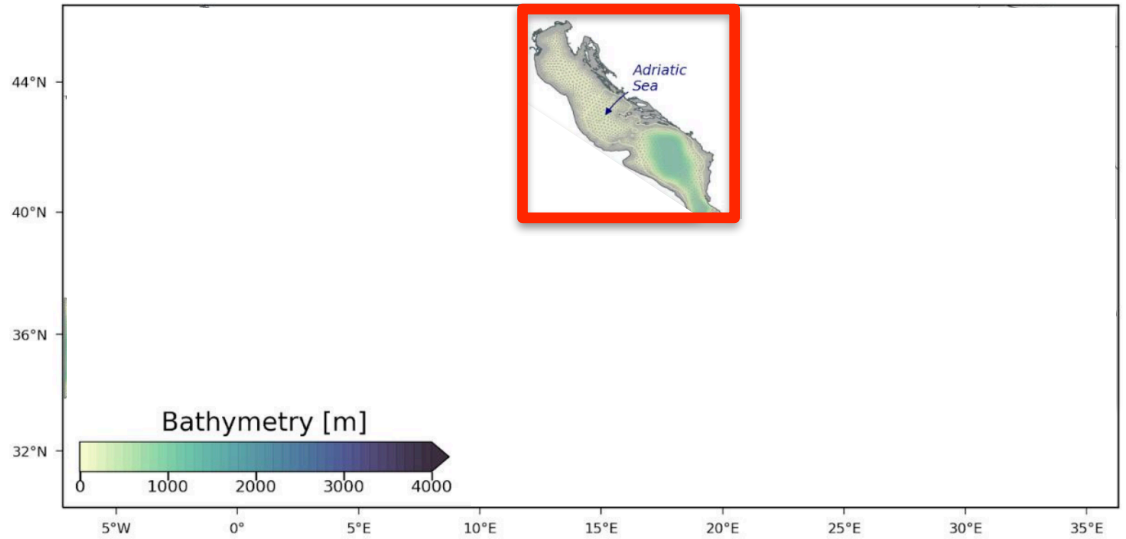

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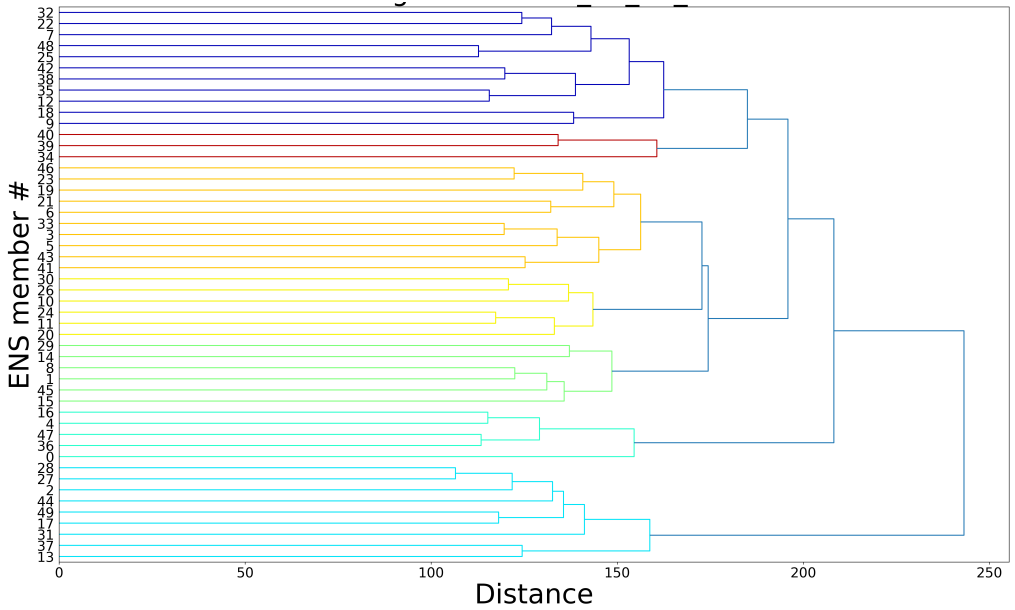
in this presentation ONLY WAVES

Results – CLUSTERING

- **no PCA**
- **Time WINDOW**:
  12h–48h, step 6h

- similar distances btw members/clusters
- #clusters/REMS: **8**



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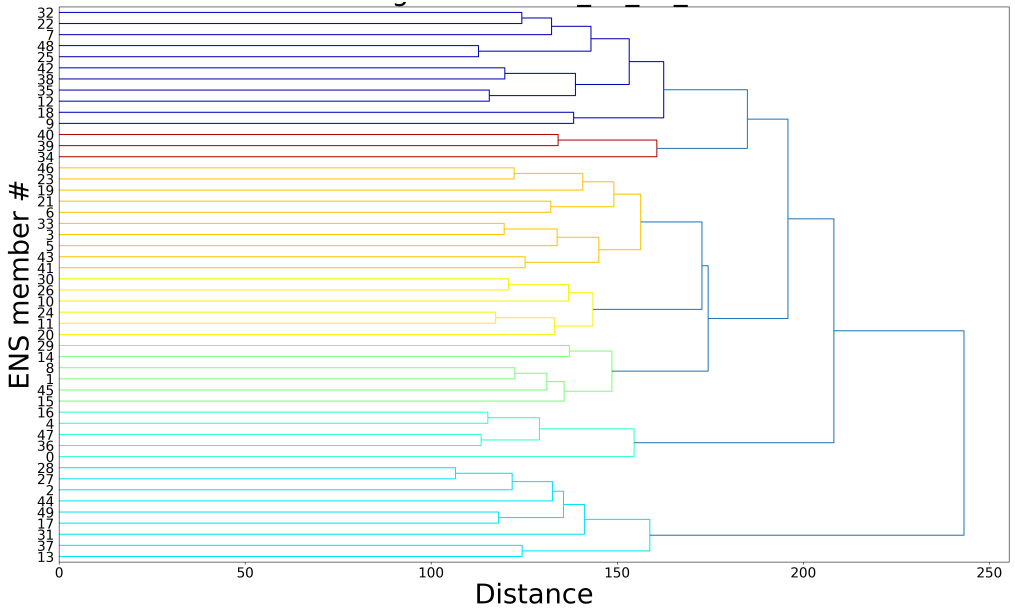
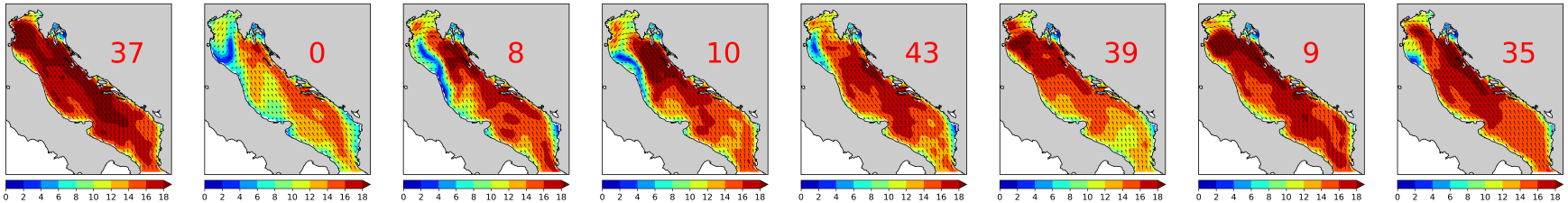


Representative ensemble members (REM)
wind speed (m/s) at 2019/11/12-18UTC



Results – PCA+CLUST

- **PCA** (80% explained variance – 25 PCs
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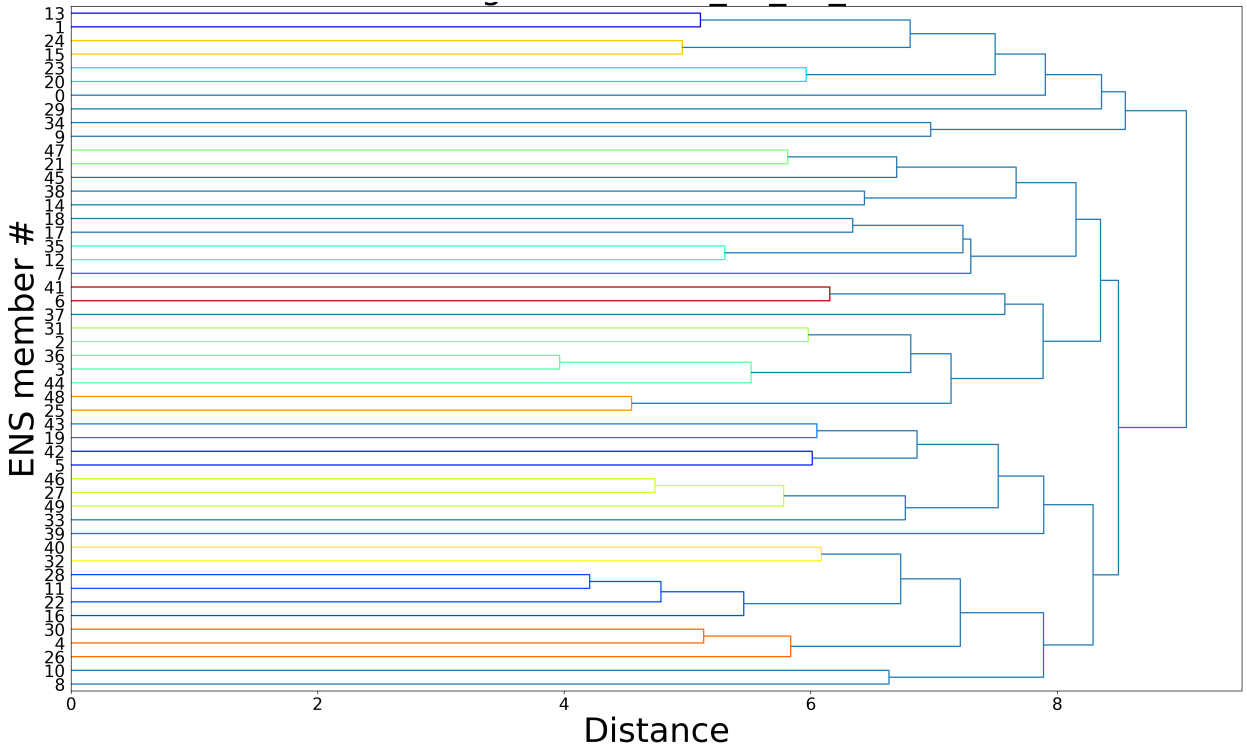

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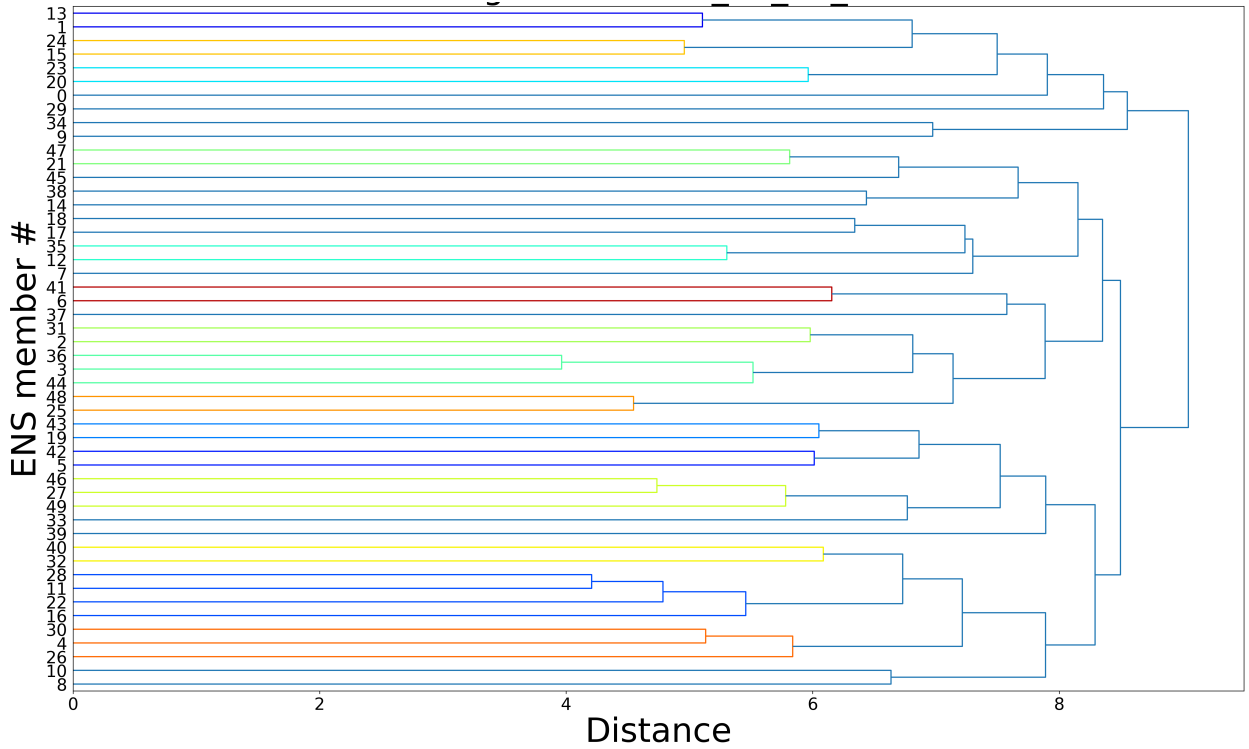

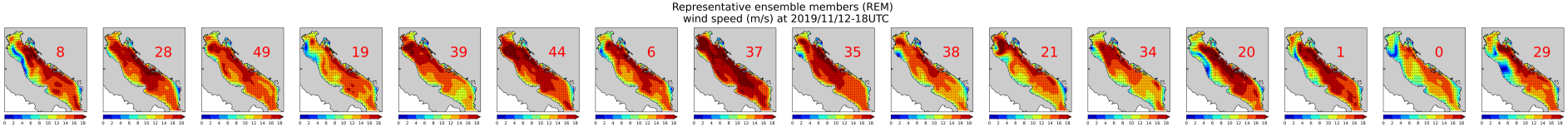

Results – mean&spread

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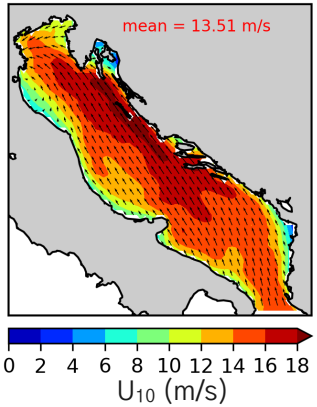
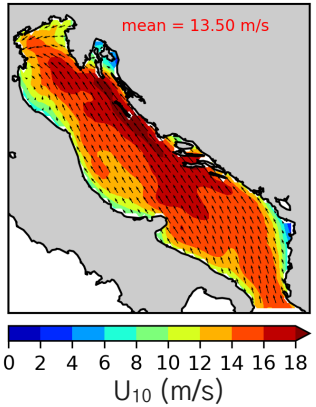


RENS mean



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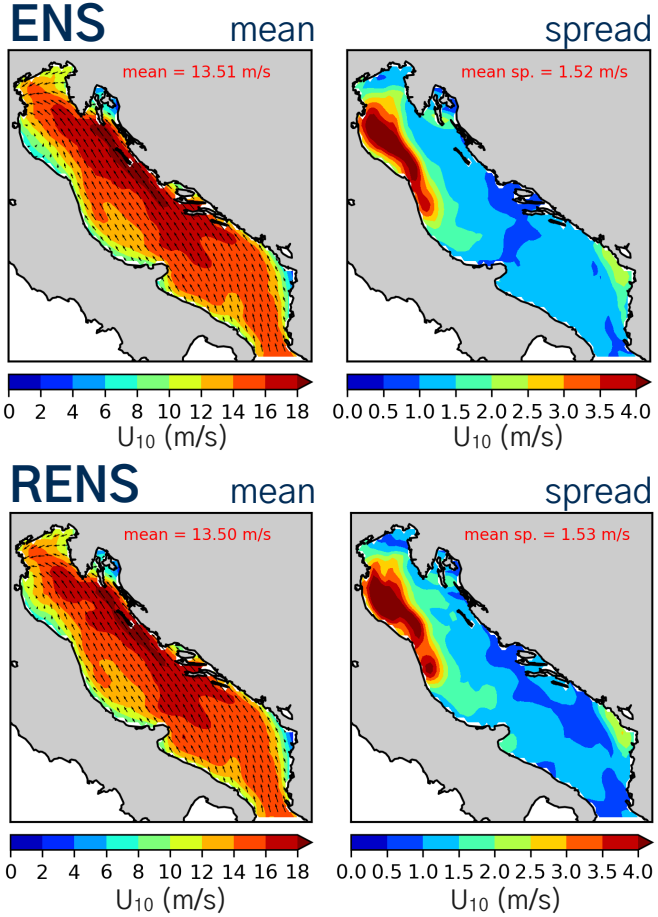

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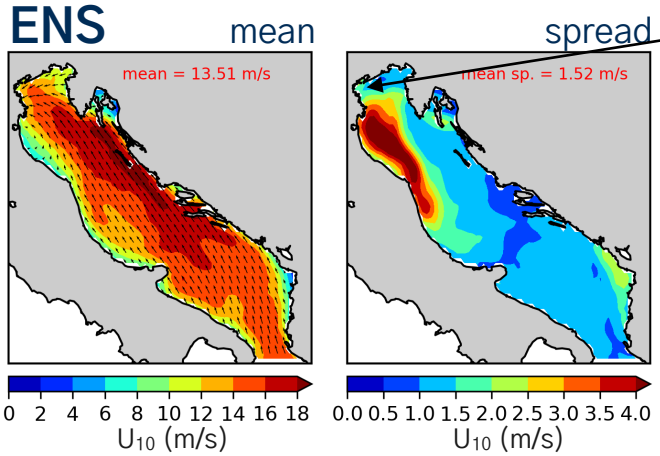
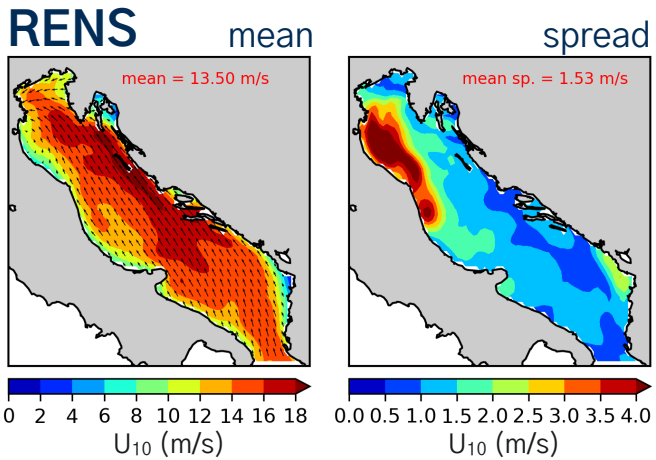
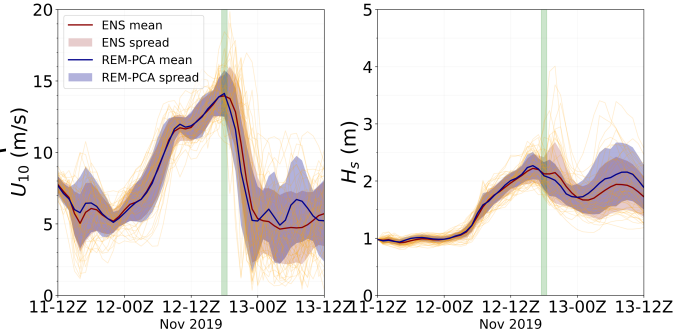


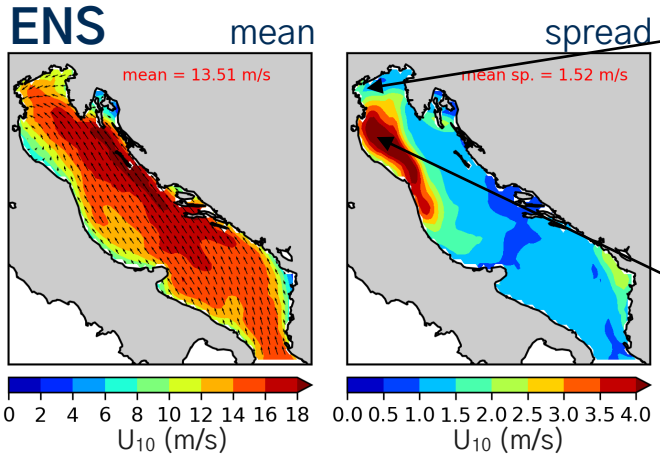


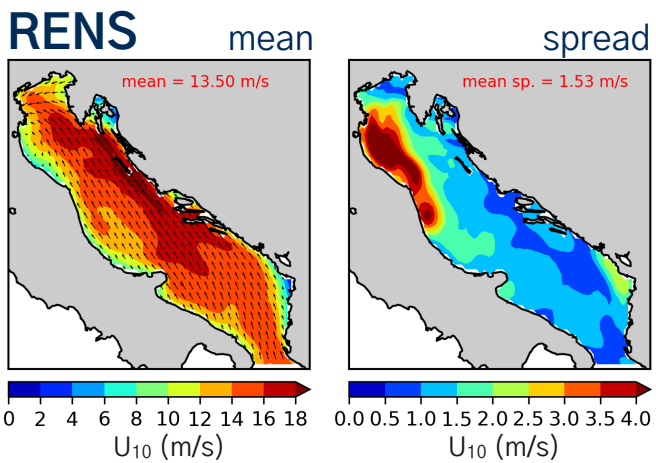


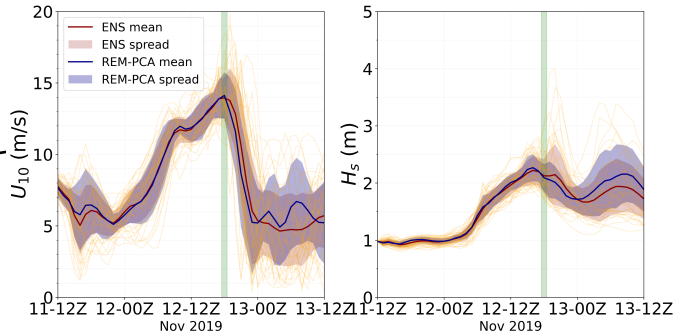
AAOT

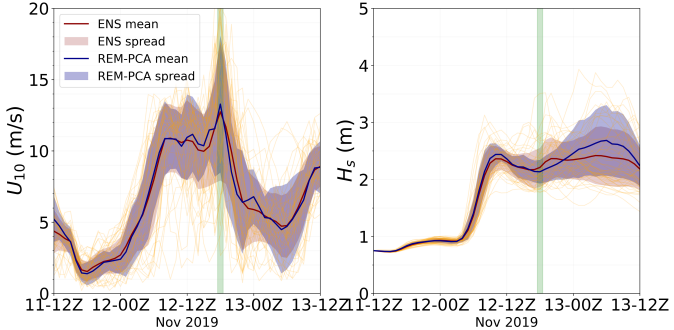
NMAE(U_{10} mean) = 6%
NMAE(U_{10} spr.) = 12%
NMAE(H_s mean) = 4%
NMAE(H_s spr.) = 19%

Results – mean&spread









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High spread

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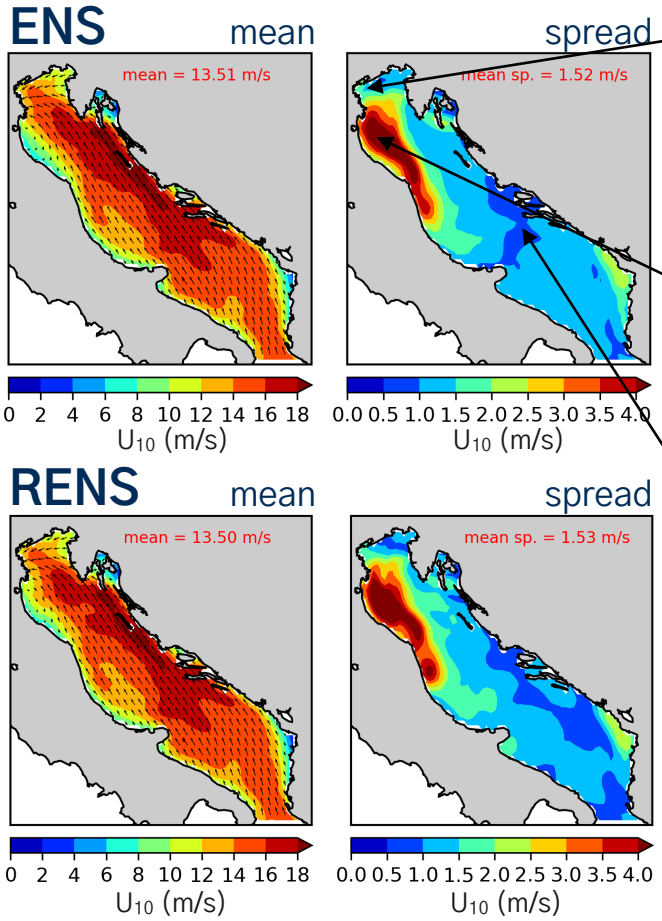
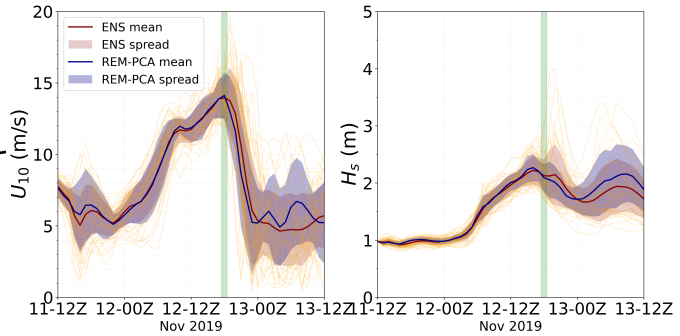
Results – mean&spread





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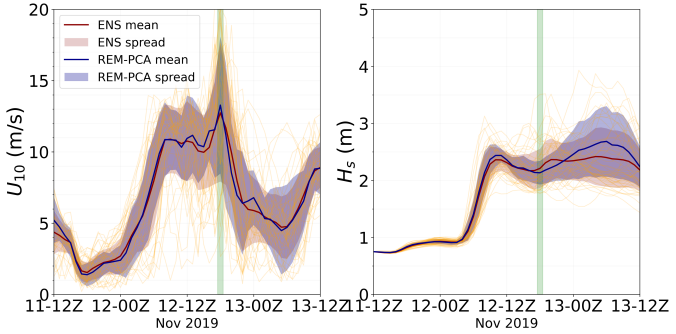

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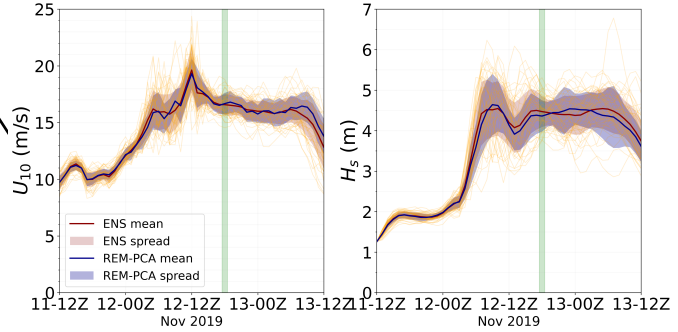
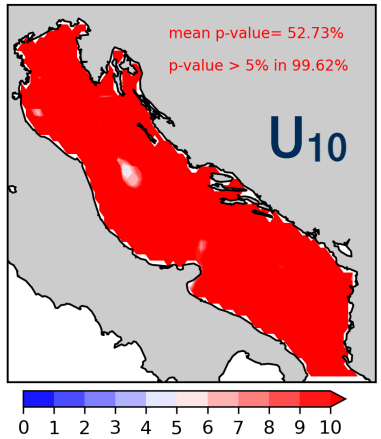


Low spread

NMAE(U_{10} mean) = 2%
NMAE(U_{10} spr.) = 15%
NMAE(H_s mean) = 2%
NMAE(H_s spr.) = 15%

Results – probabilities

p-value (%) at 2019/11/12-18UTC



Results – probabilities

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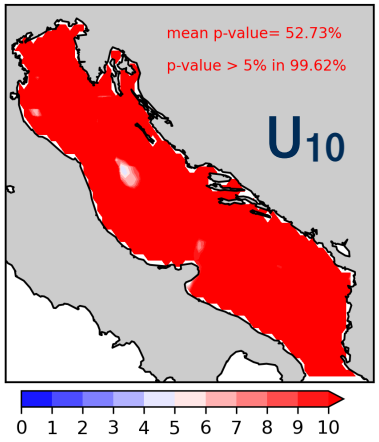

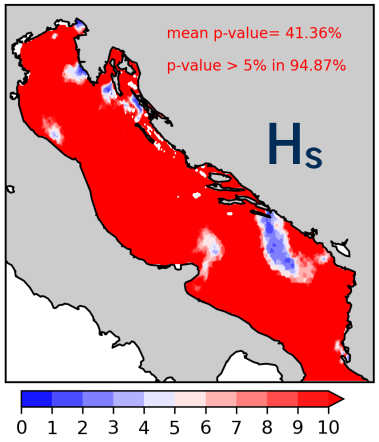

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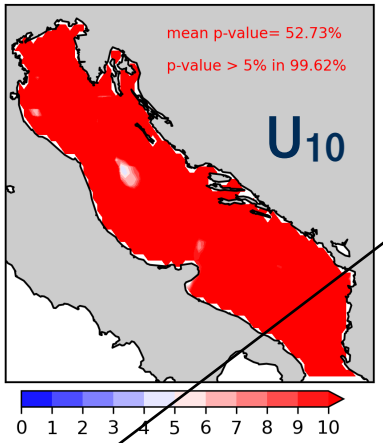

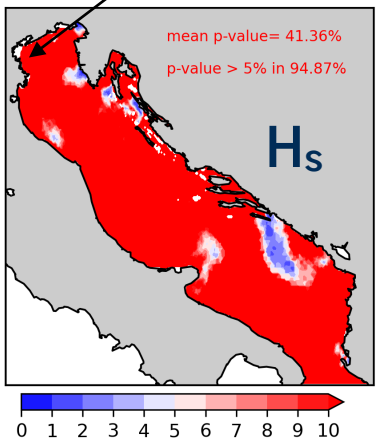

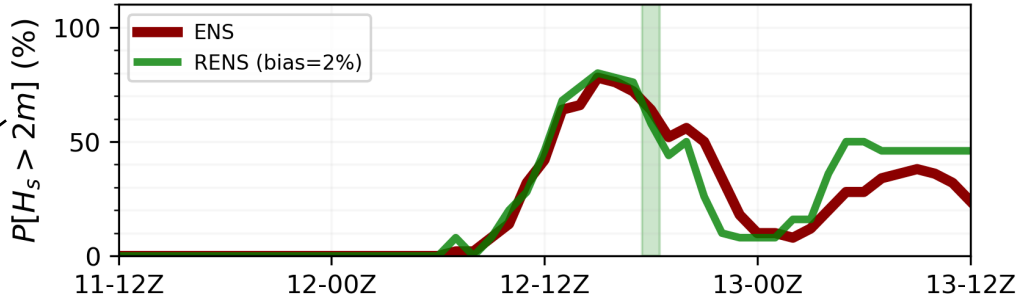

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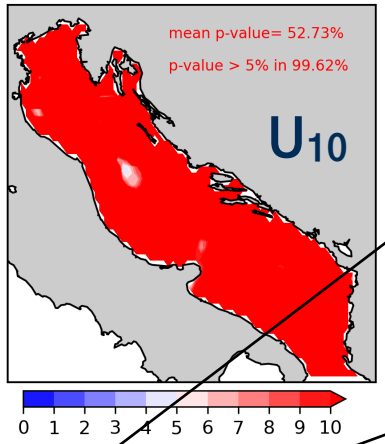
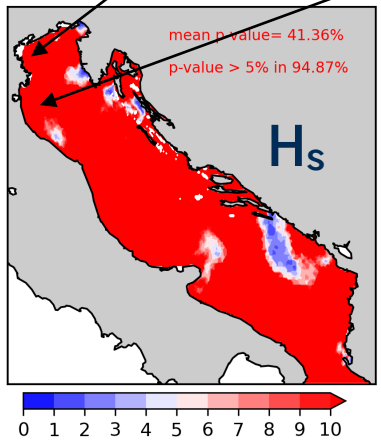
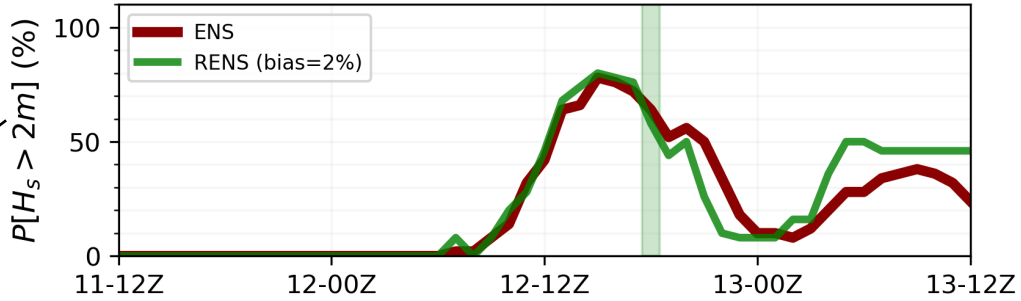
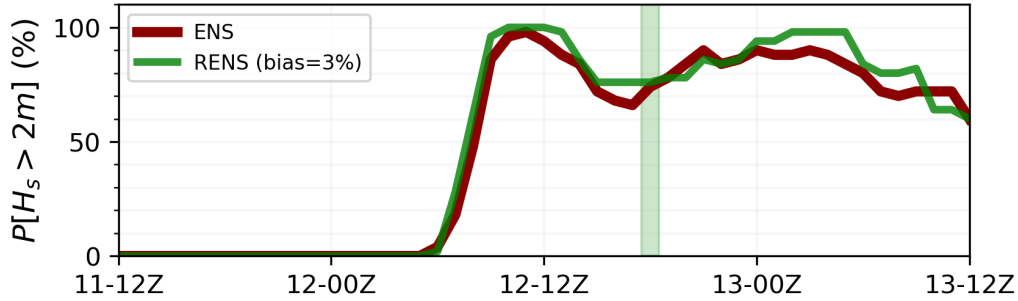
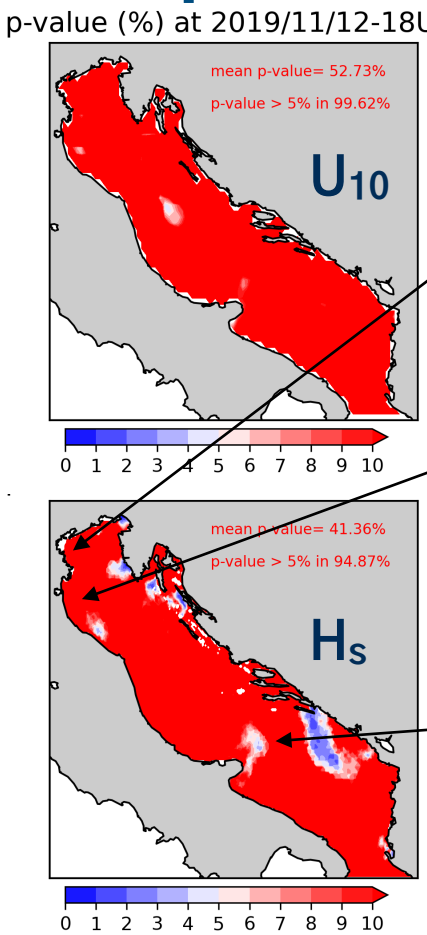


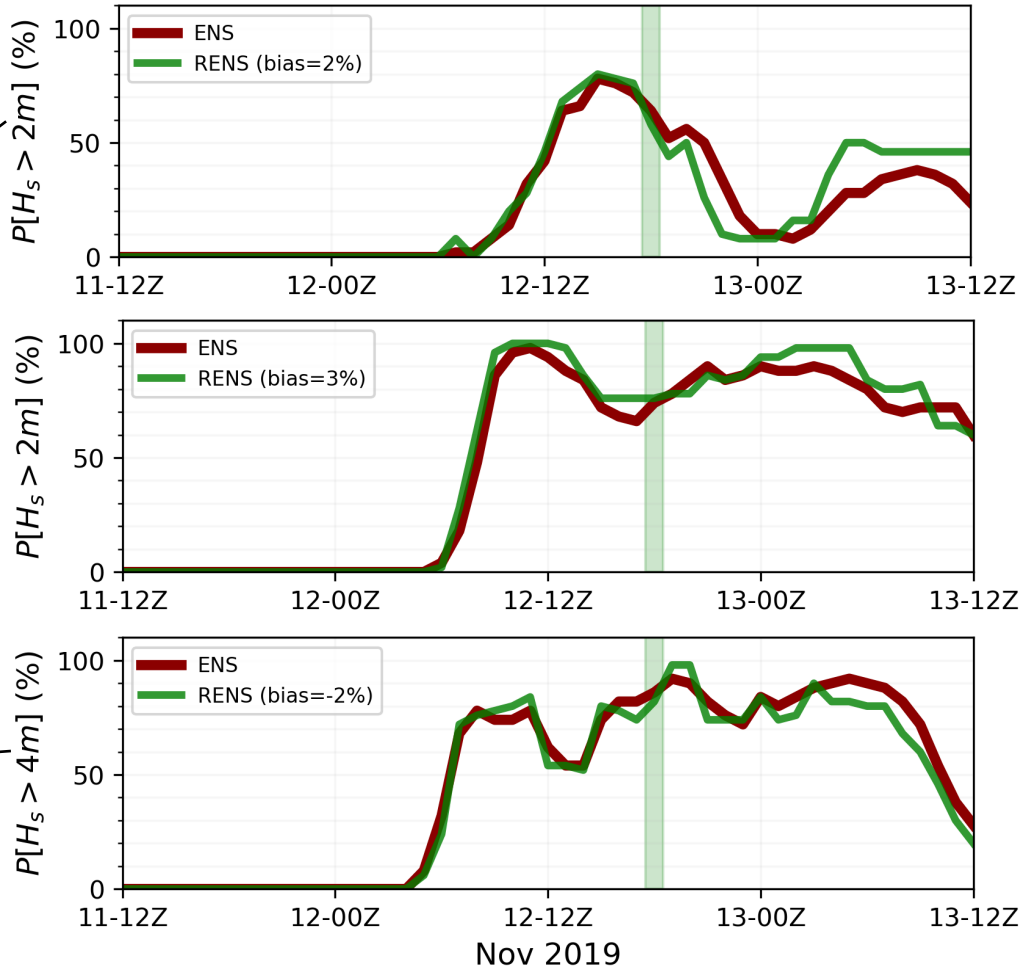






Results – probabilities





Discussion

Results depends strongly on the choices (Molteni et al., 2001) – confirmed

- **PCA:** improves the relevance of REMs, but increases #clusters/REMs (until a certain level, curse of dimensionality)
- Other preprocessors (e.g. **AUTO-ENCODERS, w/ pattern recognition**) tested: no significant improvement
- **# clusters**: w/ automatic selection there should be an **upper limit** linked to computational **resources available**
- **time window:** ensures time evolution is accounted for, but which window depends on the forecasting/warning needs

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Random picking: potentially performant in terms of mean/spread/probability, but **no repeatability/control. Clustering is better (Ferranti&Corti, 2011)**

Summary (of an ongoing work)

- A promising solution to a practical problem: NWP of coastal hazards for early-warning
- For **regional/coastal applications** it might be preferable to use the computer resources to run **less ensemble members at high resolution**, rather than the whole ensemble with only a modest resolution increase.
- **Trade-off btw ensemble reduction and relevance** (the smaller, the faster, but less relevant – for PCA, not a monotonic #PCs-relevance relationship).
- A single case test has been presented, **need for generalisation**
  - more study on the effect of **clustering choices**
  - extensive **testing on events**
- **Storm surge**: add mslp to clustering and test the methodology

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Thanks for the attention!
Questions?

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