An object-oriented methodology for the verification of cyclone trajectories in an ensemble forecasting system

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Introduction

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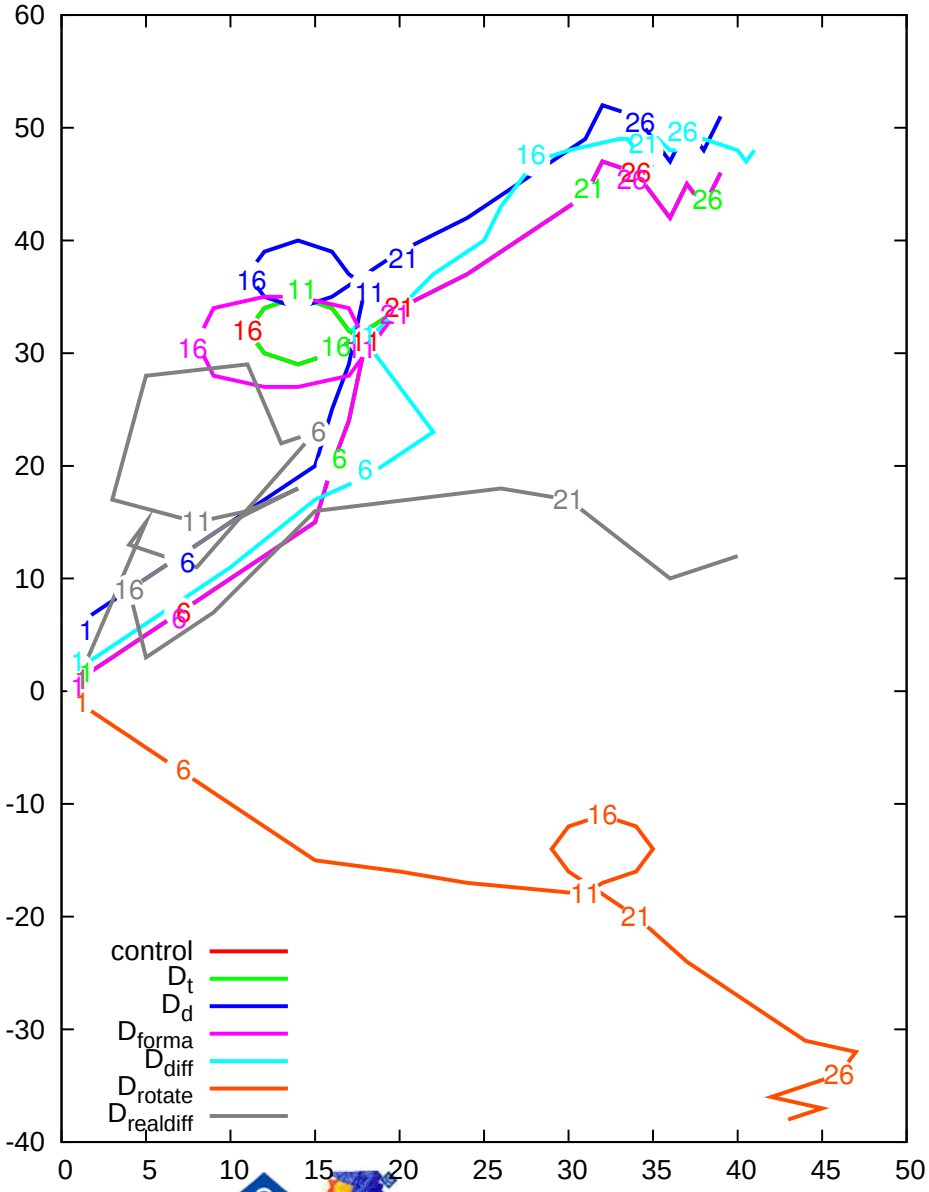
Control trajectories



D_t= Same trajectory as control, but faster at initial phase

D_d= Same trajectory but 5 grid points spatially shifted on direction $\hat{e}_y$

D_{forma}= Same trajectory, but bigger loop

D_{diff}= Similar trajectory

D_{rotate}= Same trajectory rotated $\pi/2$

$D_{realdiff}$= Completely different trajectory

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- Complexity of a trajectory as function of its smoothing

$$\mathcal{T}(i)_{smth} = \left[\frac{1}{3} \sum_{k=-1}^{1} (x_{i+k}, y_{i+k}) \right]^{n}$$

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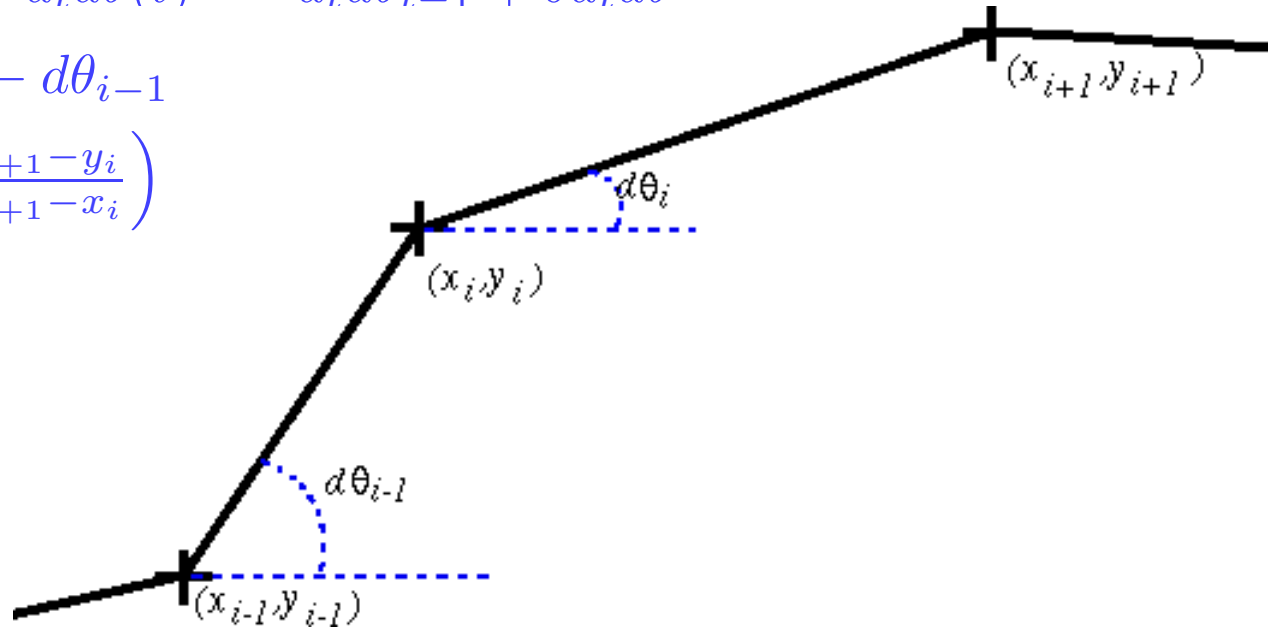
  Piece: Consecutive points of the trajectory with similar shape of evolution (similar $d_t d\theta_i,\ i = \{n, n+1, ..., n+m\}$). Similarity: ($\delta d_t d\theta = \%\sigma_{d_t d\theta}$)

  $d_t d\theta_{t-1} - \delta d_t d\theta \ \leq \ d_t d\theta(t) \ < \ d_t d\theta_{t-1} + \delta d_t d\theta$

  - $d_t d\theta_i = d\theta_{i+1} - d\theta_{i-1}$
  - $d\theta_i = atan\left(\frac{y_{i+1} - y_i}{x_{i+1} - x_i}\right)$



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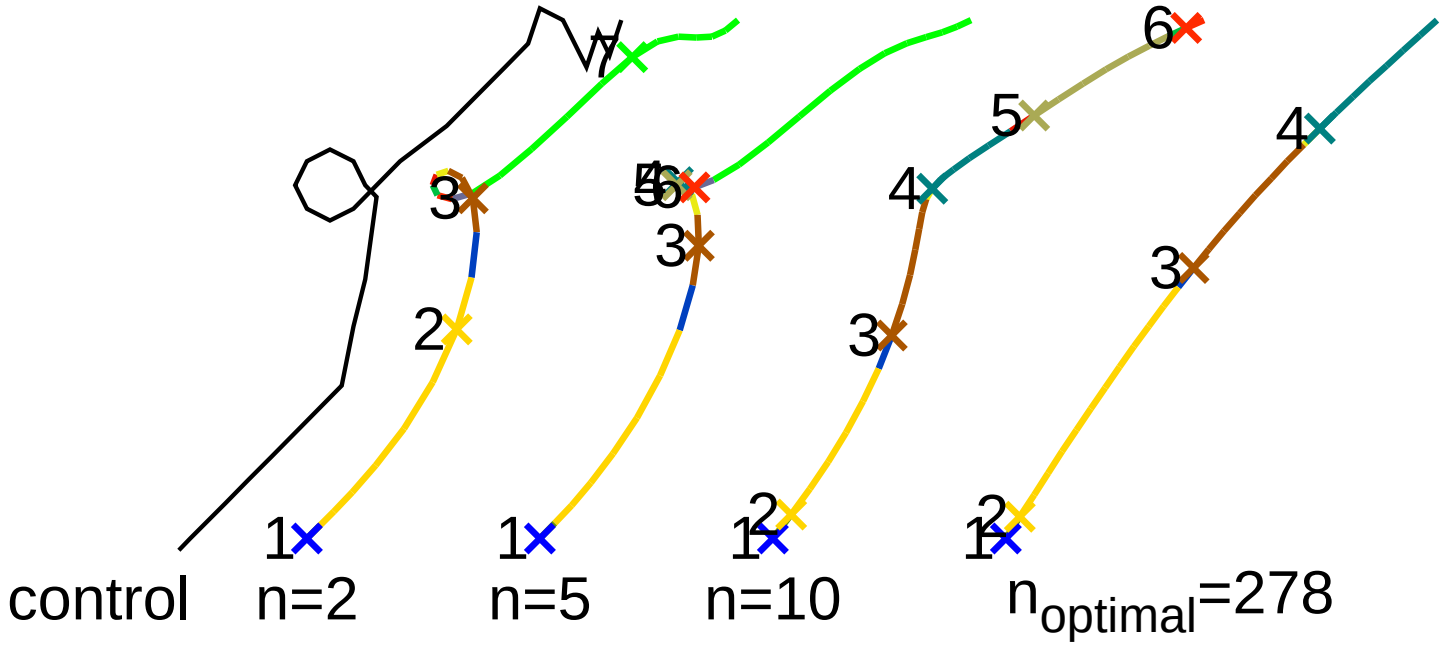
$$\forall i \begin{cases} |x_i^{n+1} - x_i^n| \leq \varepsilon = \sigma \times 10^{-\alpha} \\ |y_i^{n+1} - y_i^n| \leq \varepsilon = \sigma \times 10^{-\alpha} \\ \alpha = min(\alpha_x, \alpha_y) \end{cases}$$



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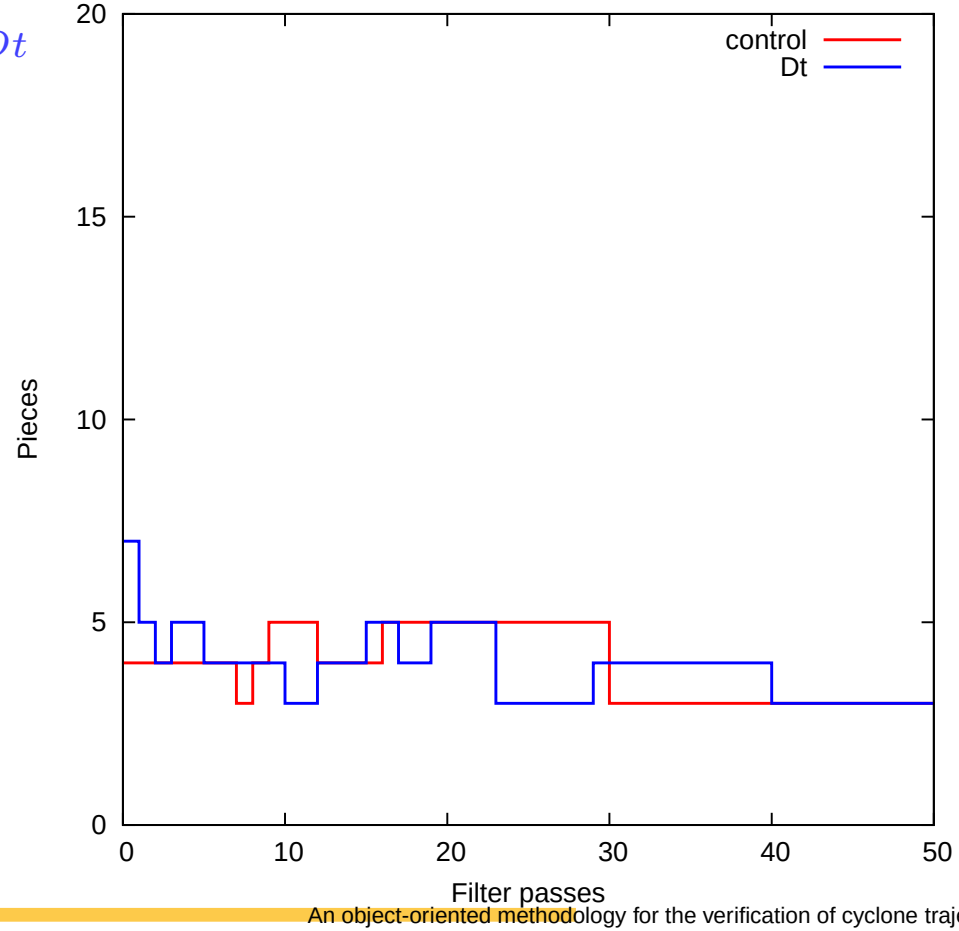

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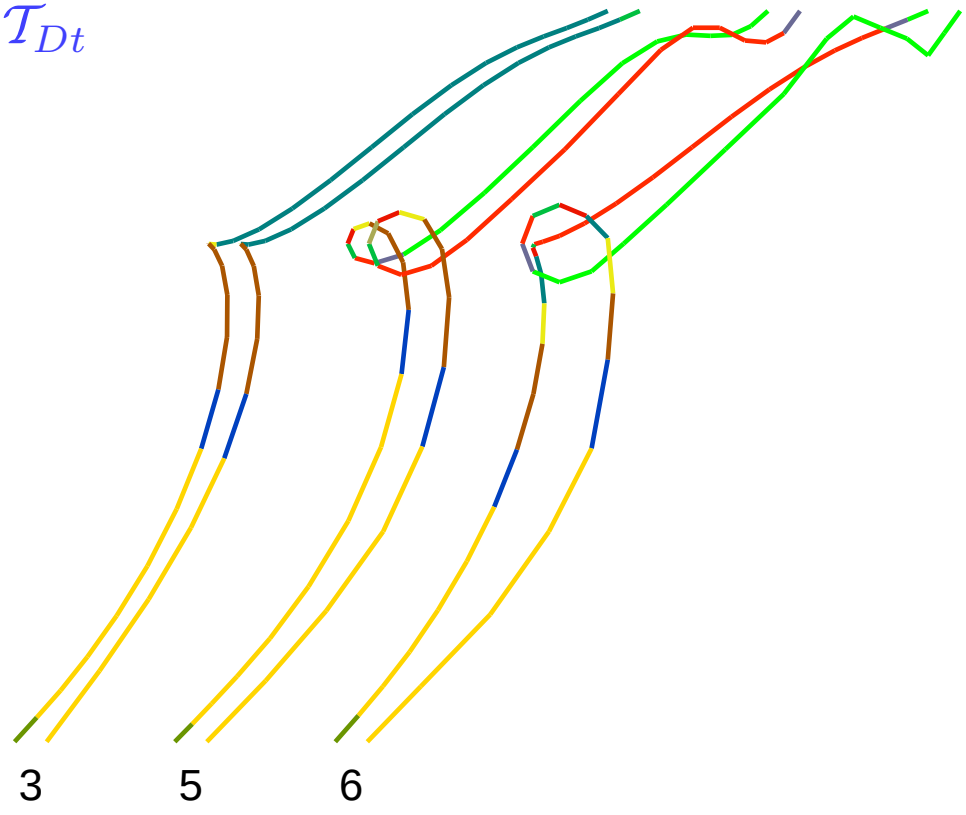

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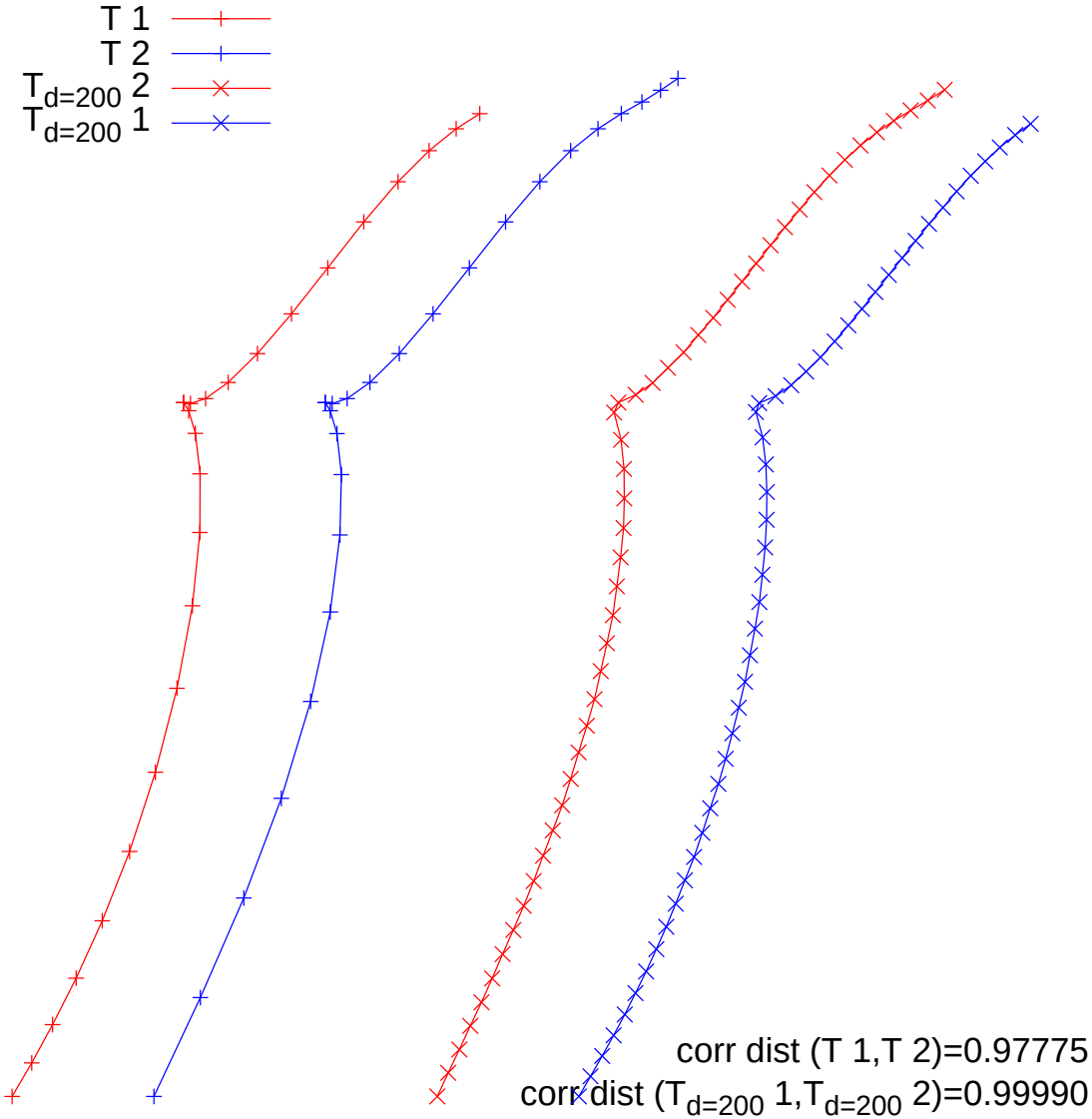

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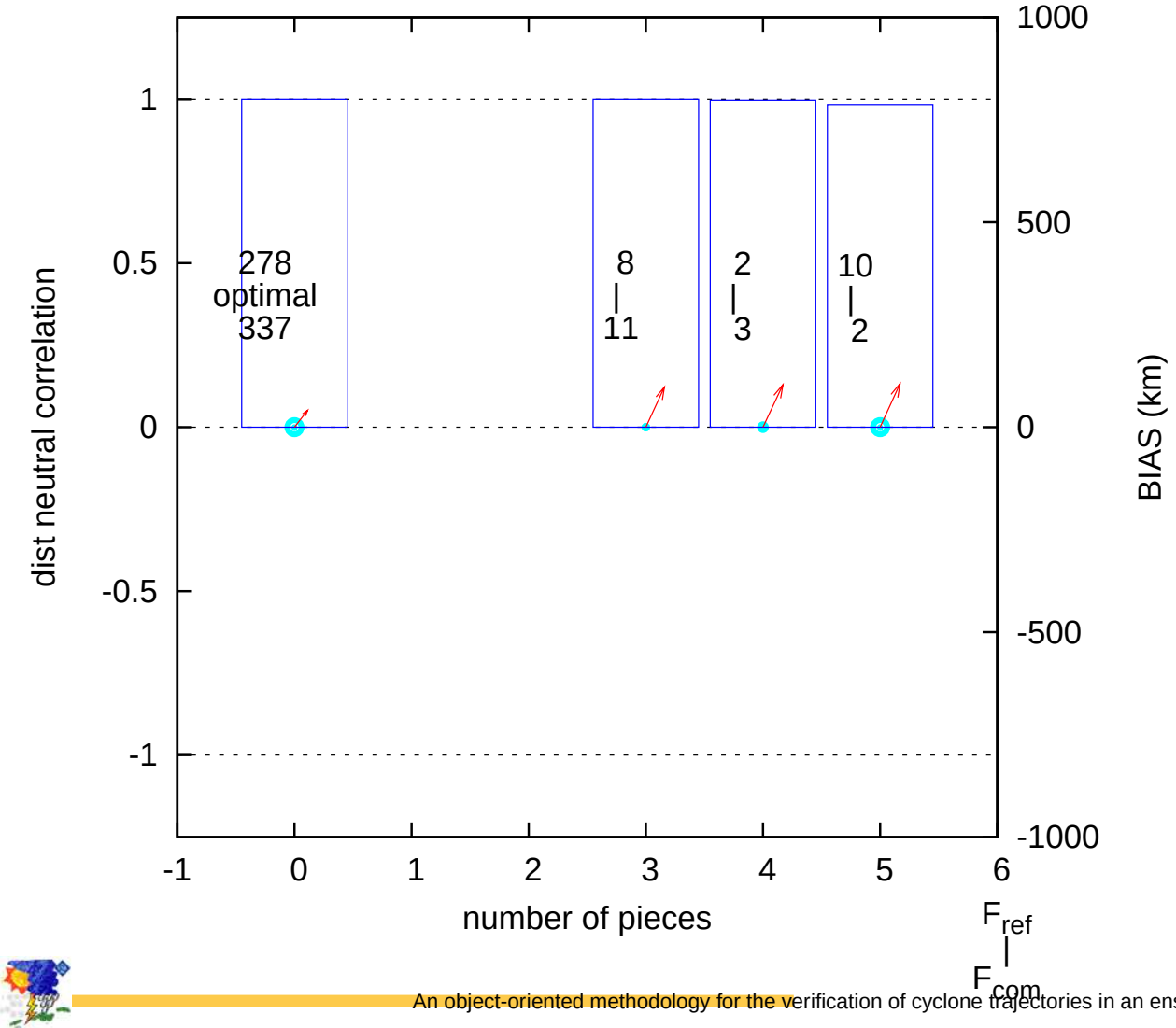
  - Temporal evolution $\Delta\mathcal{D} = \sum_{t=1}^{\mathcal{T}_{tot}} [dist_{com}(t+1,t) - dist_{ref}(t+1,t)]$

Control results

Dt



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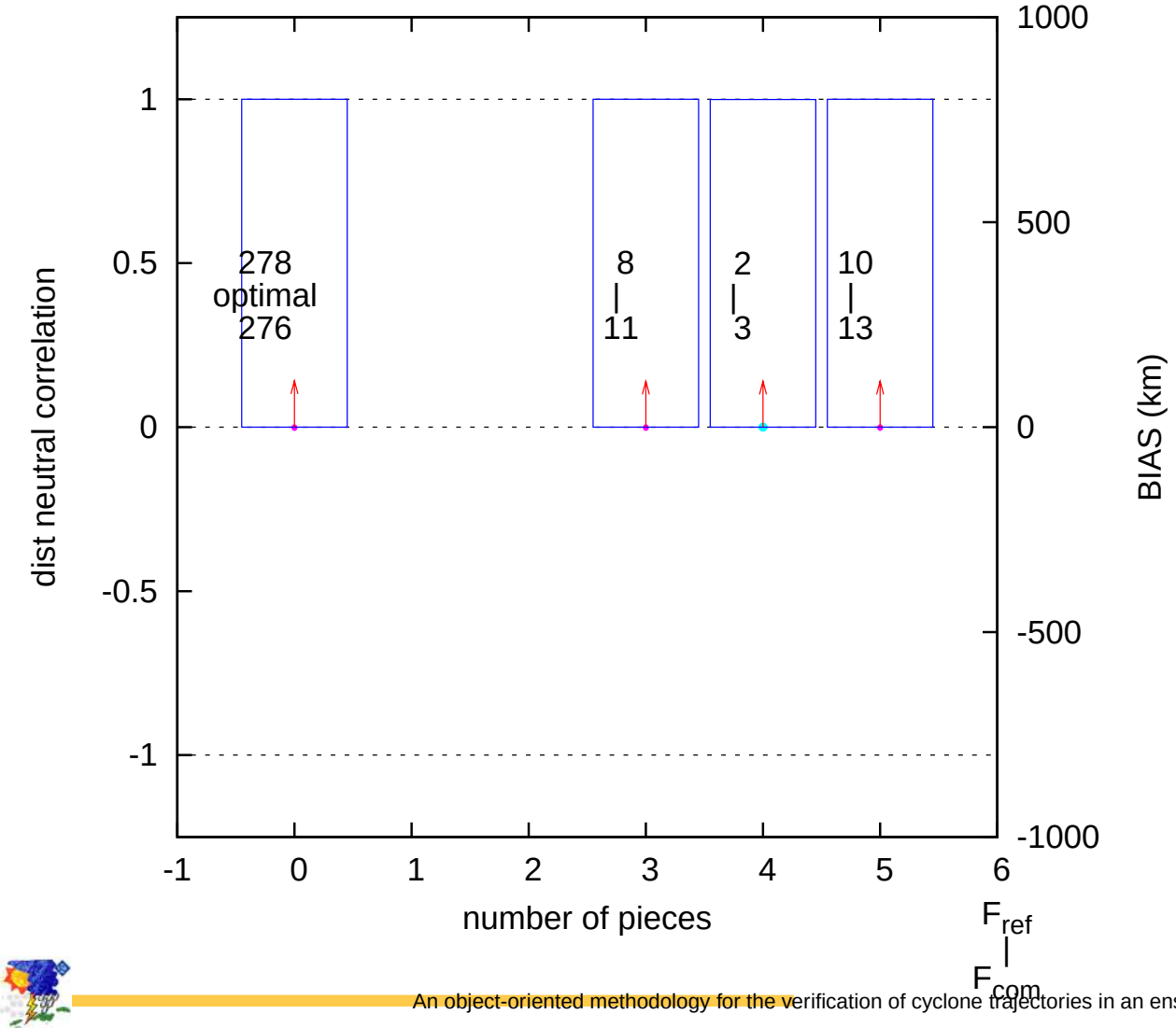
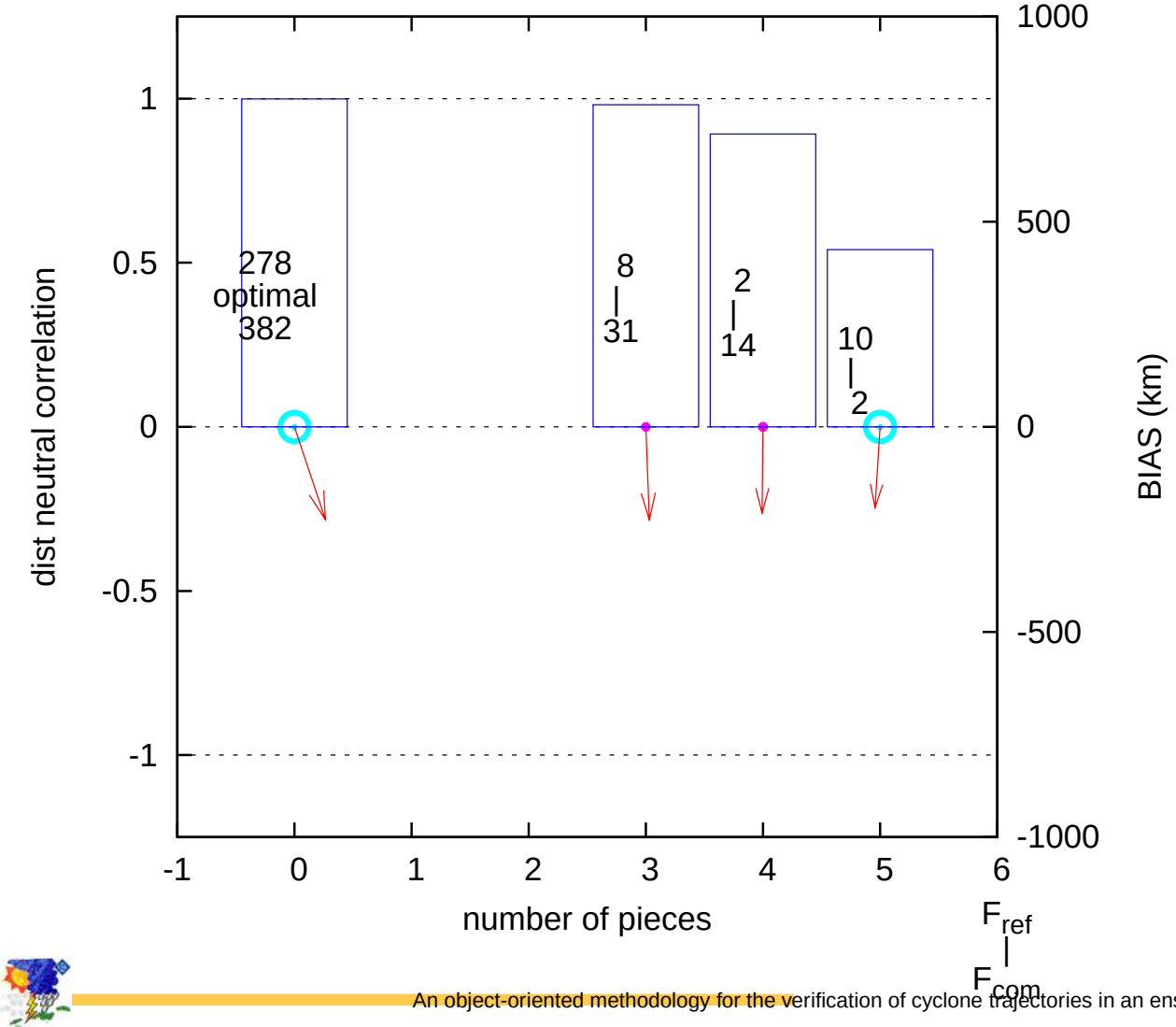


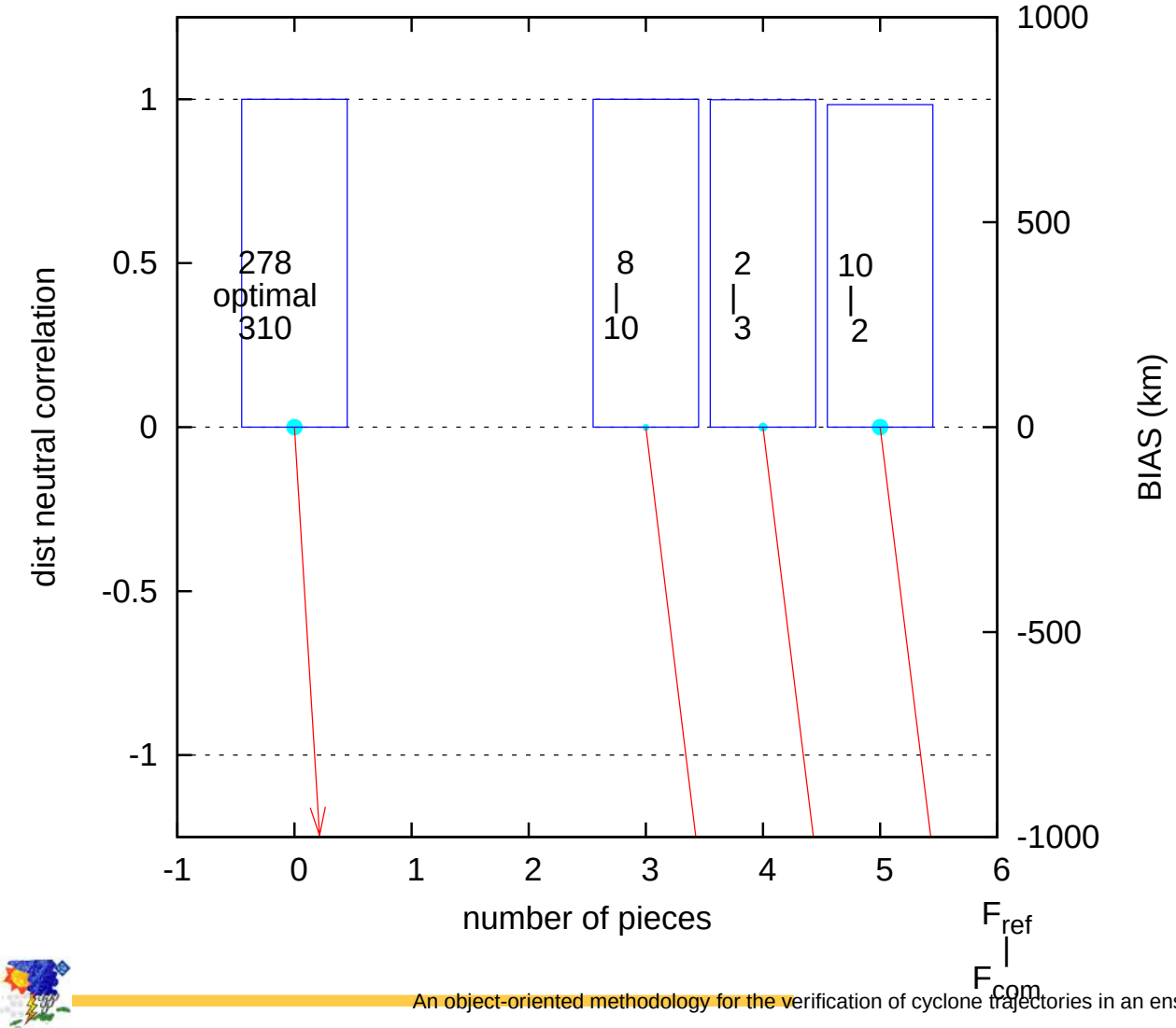
Control results

Drealdiff



Control results

Drotate



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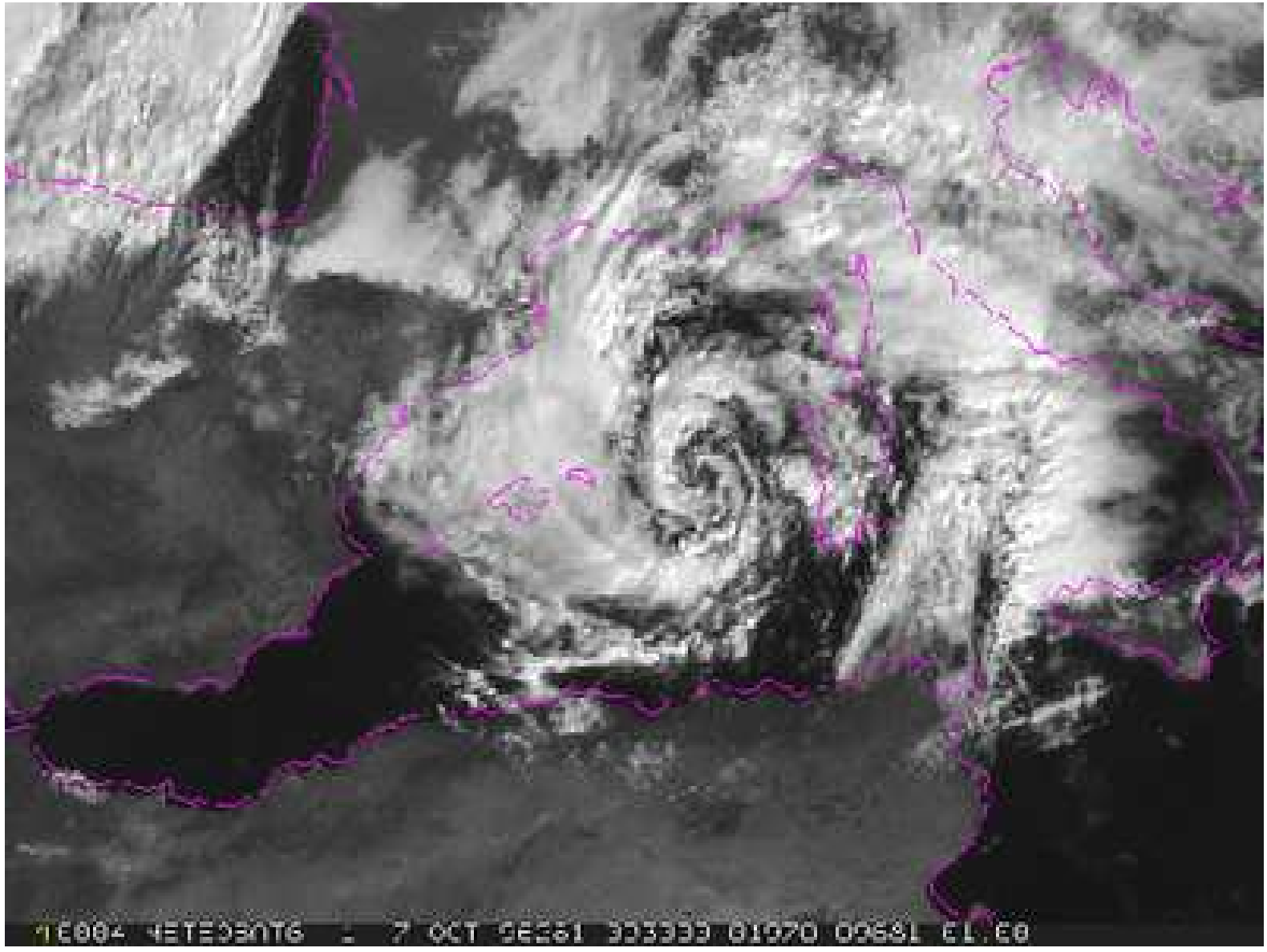

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- Control trajectory taken from satellite imagery

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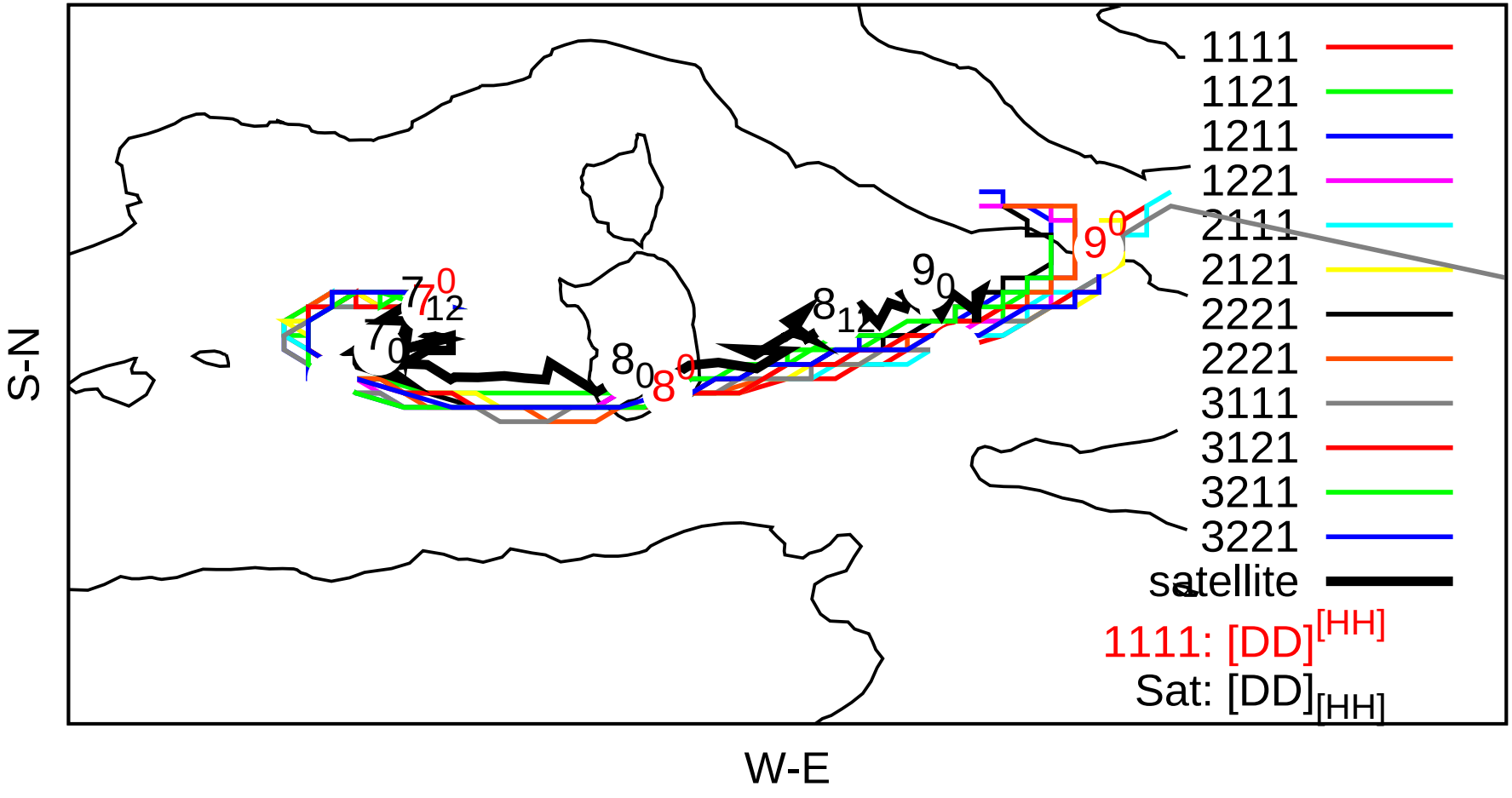
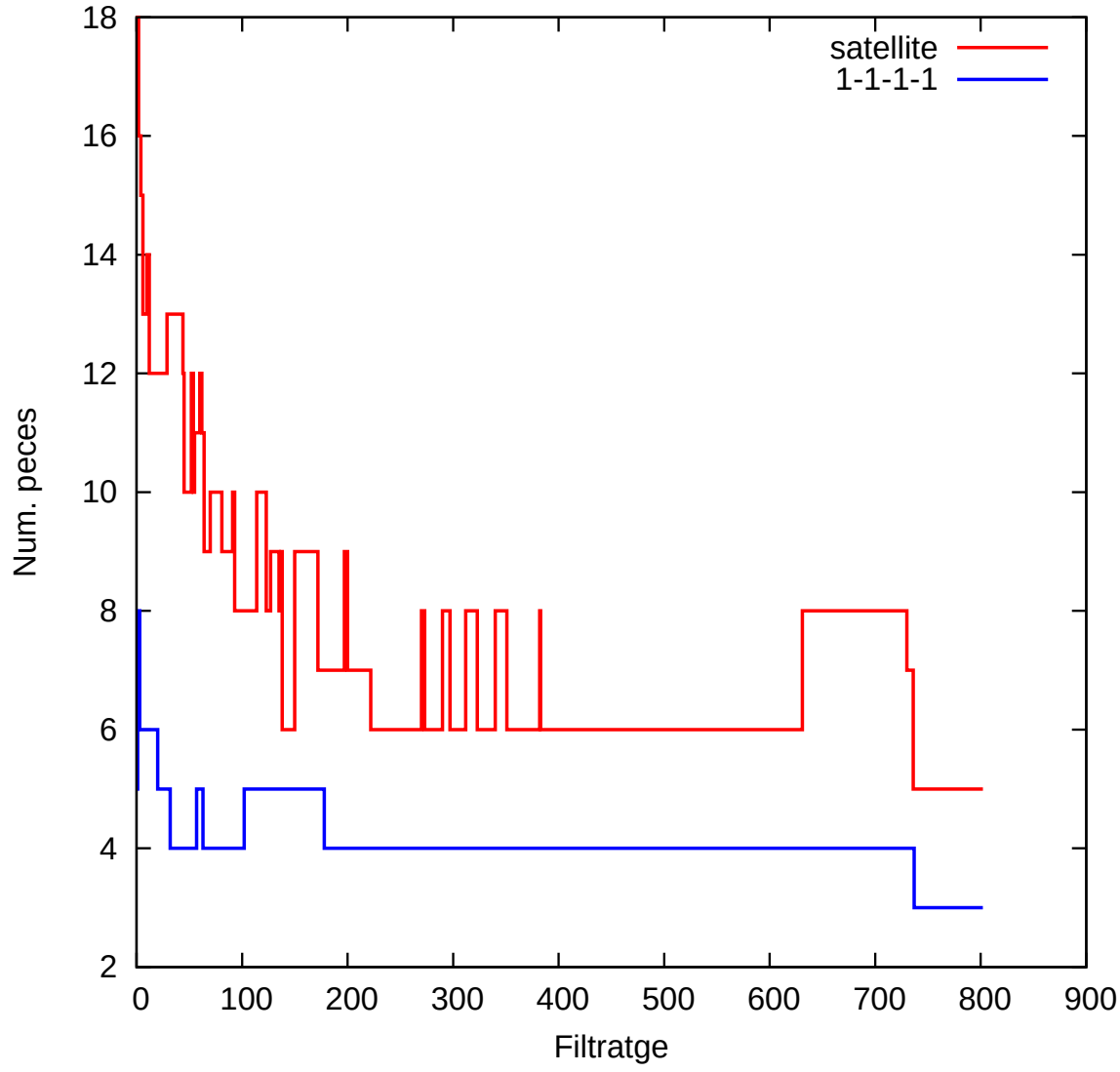


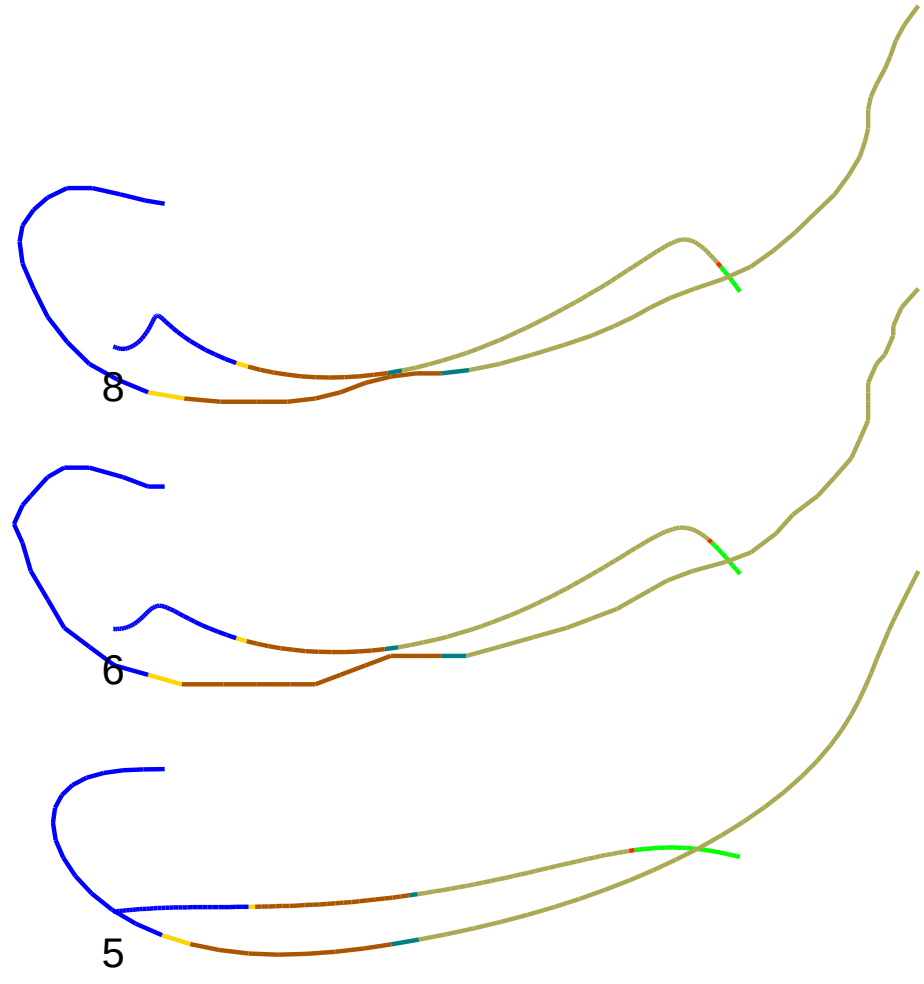
Results on PRECIOSO ensemble

- Evolution of pieces with filtering satellite & 1-1-1-1



Results on PRECIOSO ensemble

- Compared trajectories satellite & 1-1-1-1



Results on PRECIOSO ensemble

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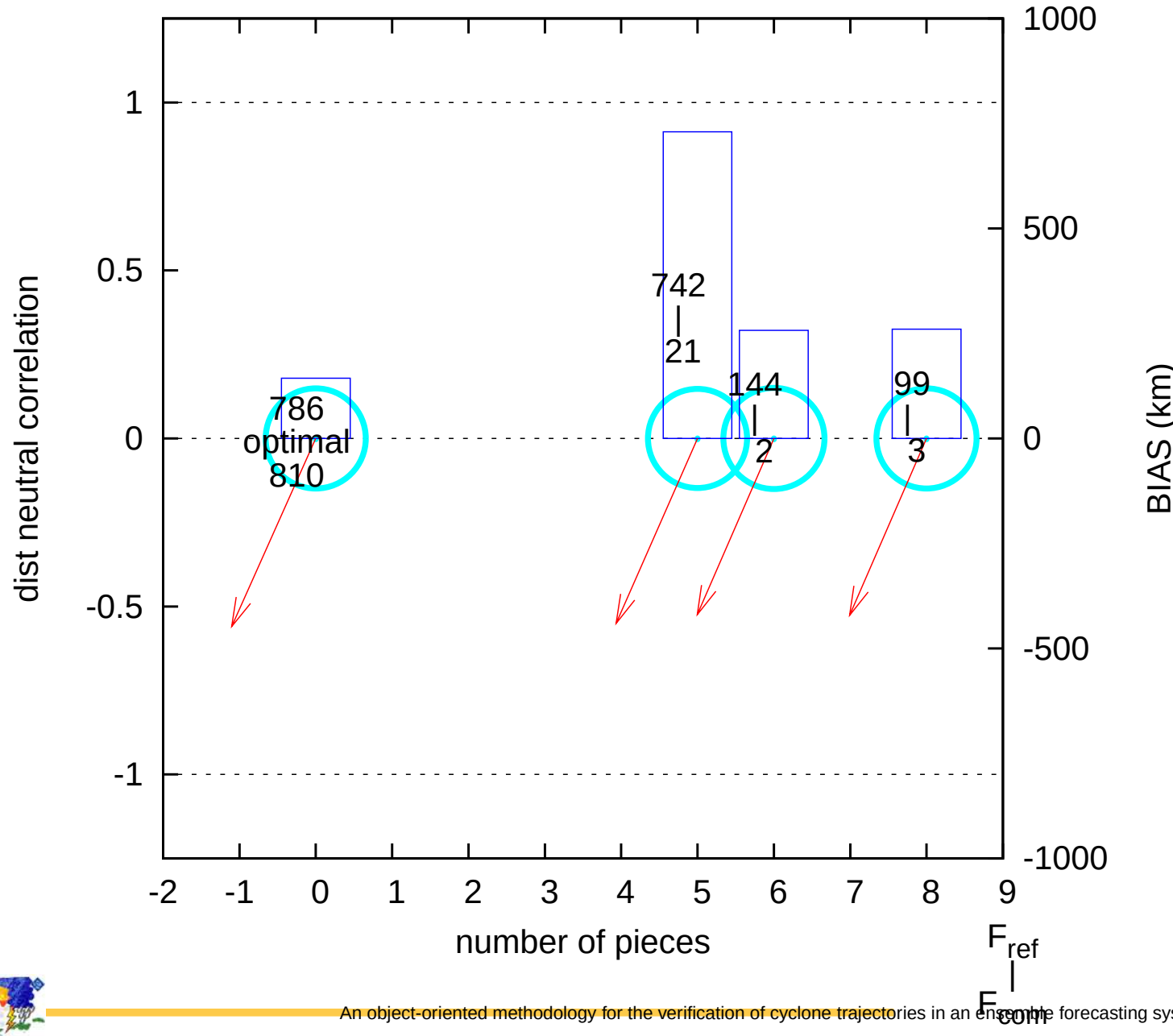
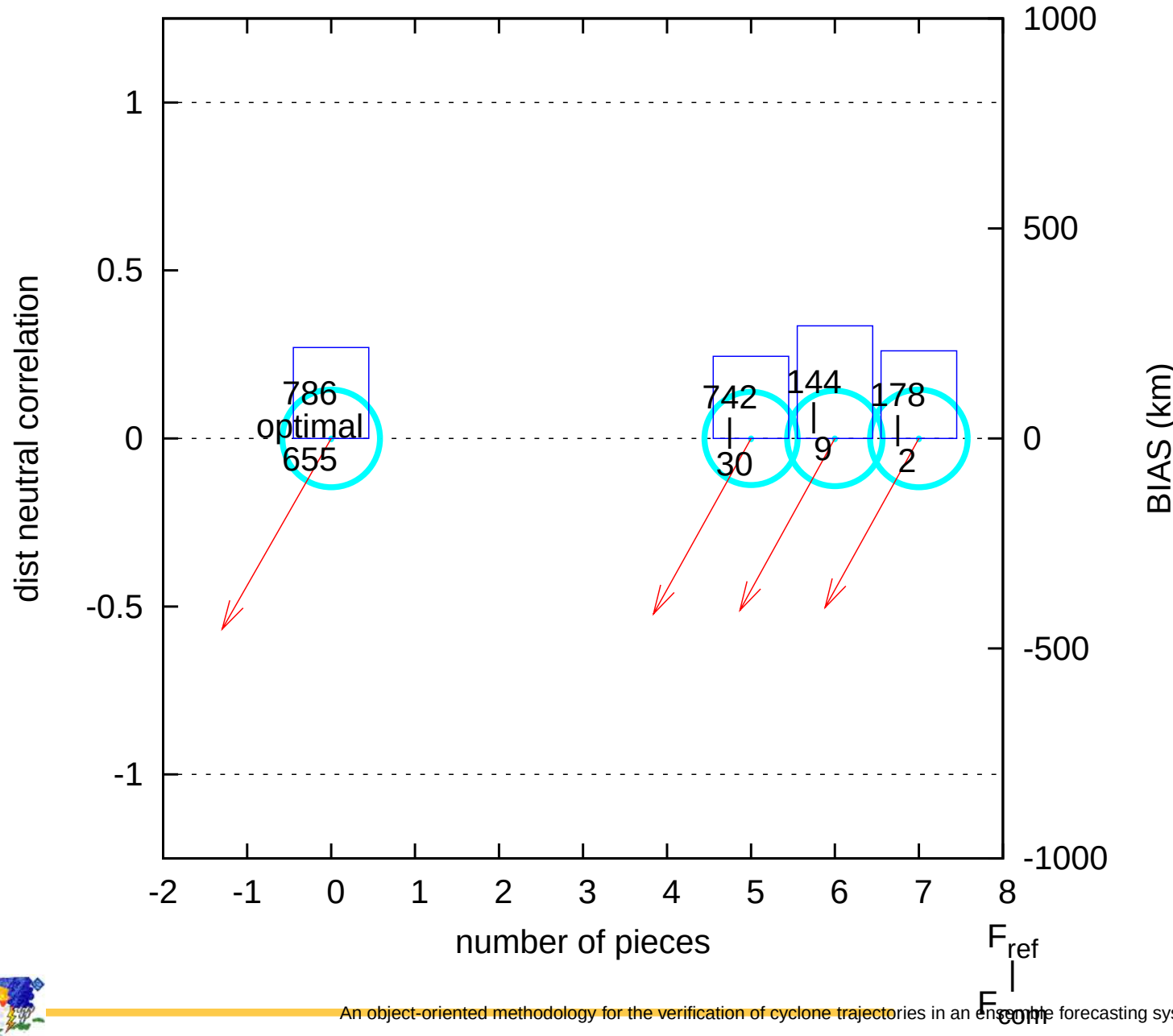


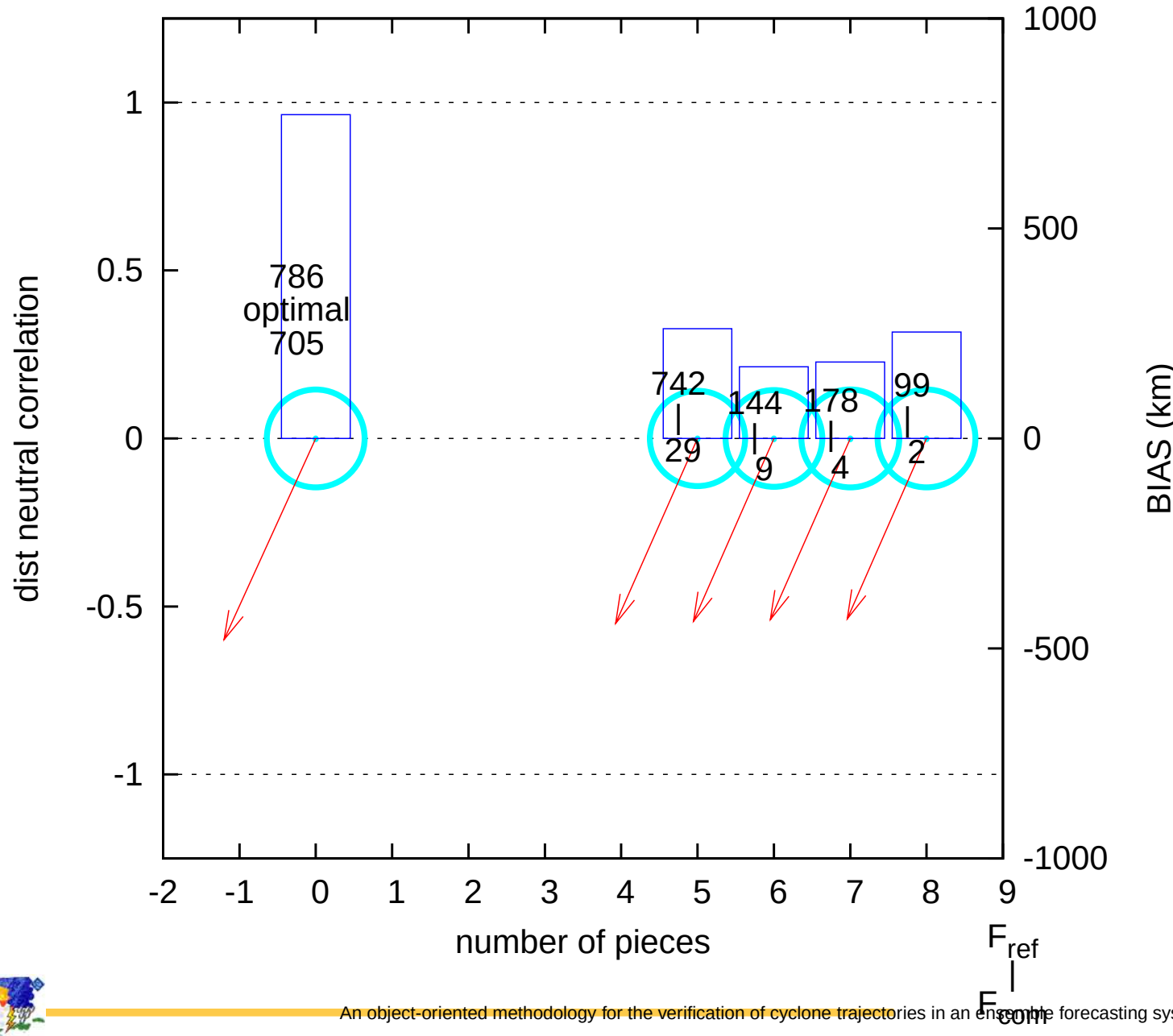
Results on PRECIOSO ensemble

- Results for satellite & 1-2-1-1



Results on PRECIOSO ensemble

- Results for satellite & 2-1-2-1



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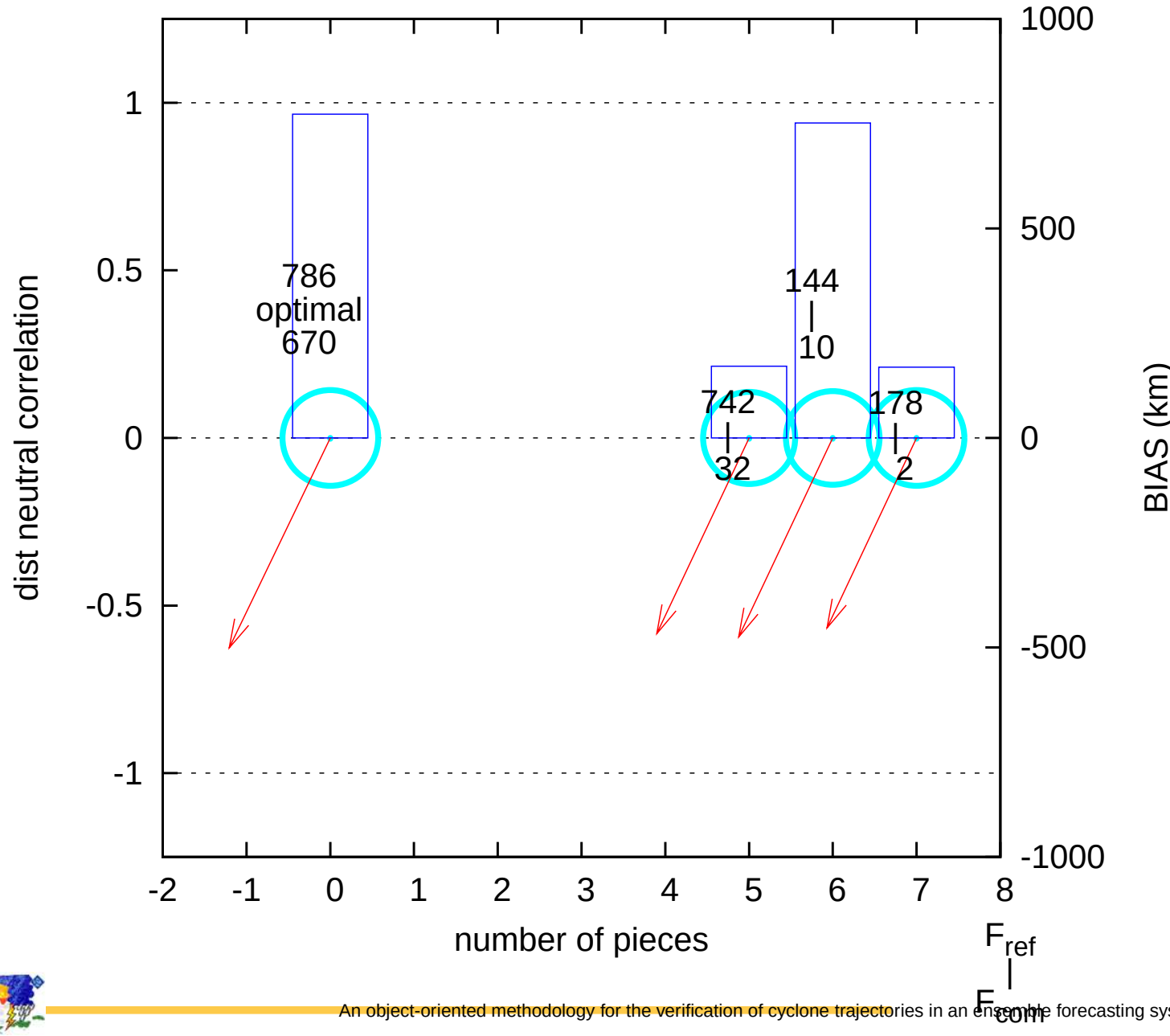
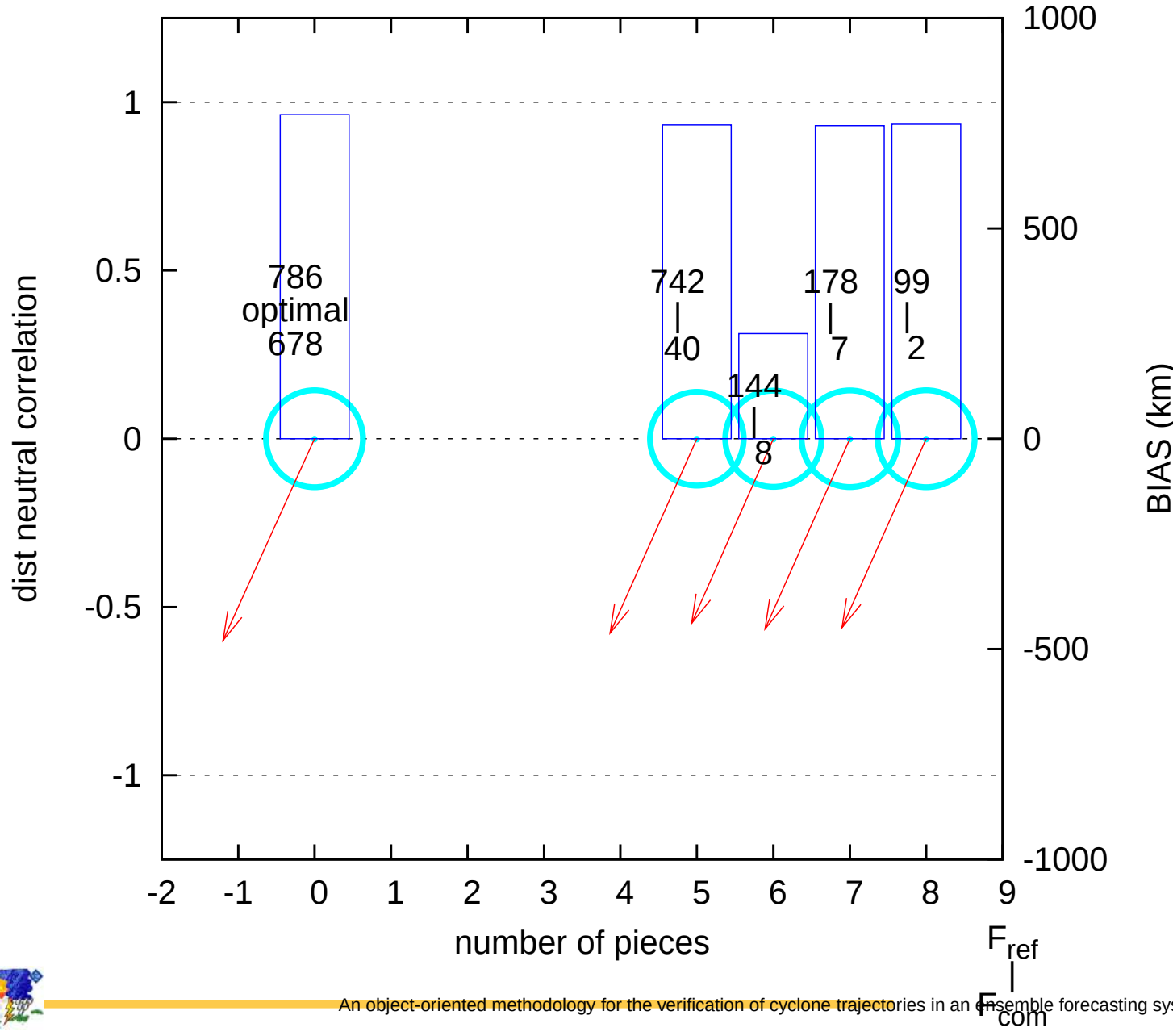


Results on PRECIOSO ensemble

- Results for satellite & ensemble mean trajectory



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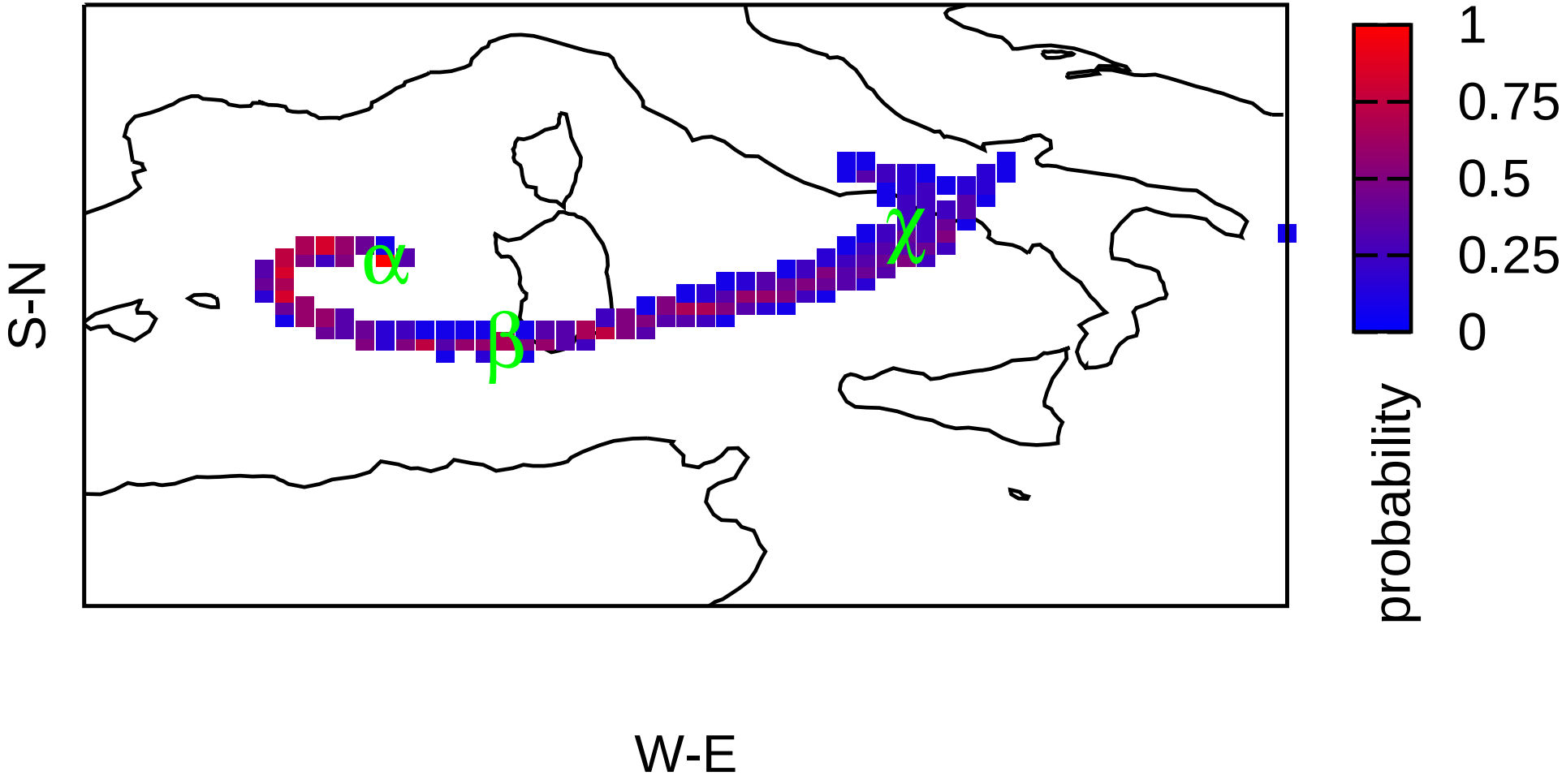
- Probabilistic map of the trajectory given by the ensemble



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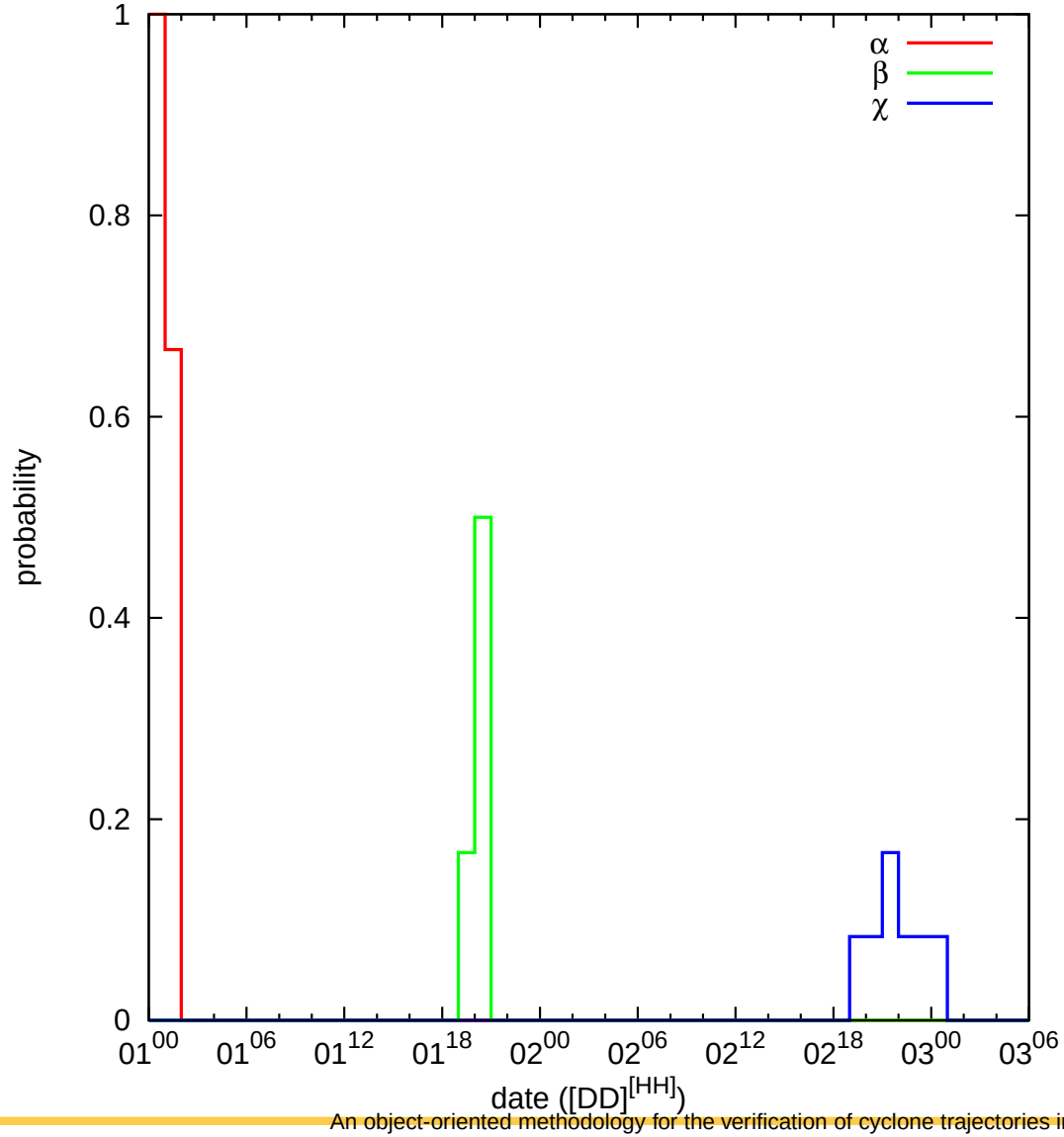
- Probability of medicane pass at a given place given by ensemble



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THANK YOU FOR YOUR ATTENTION !!