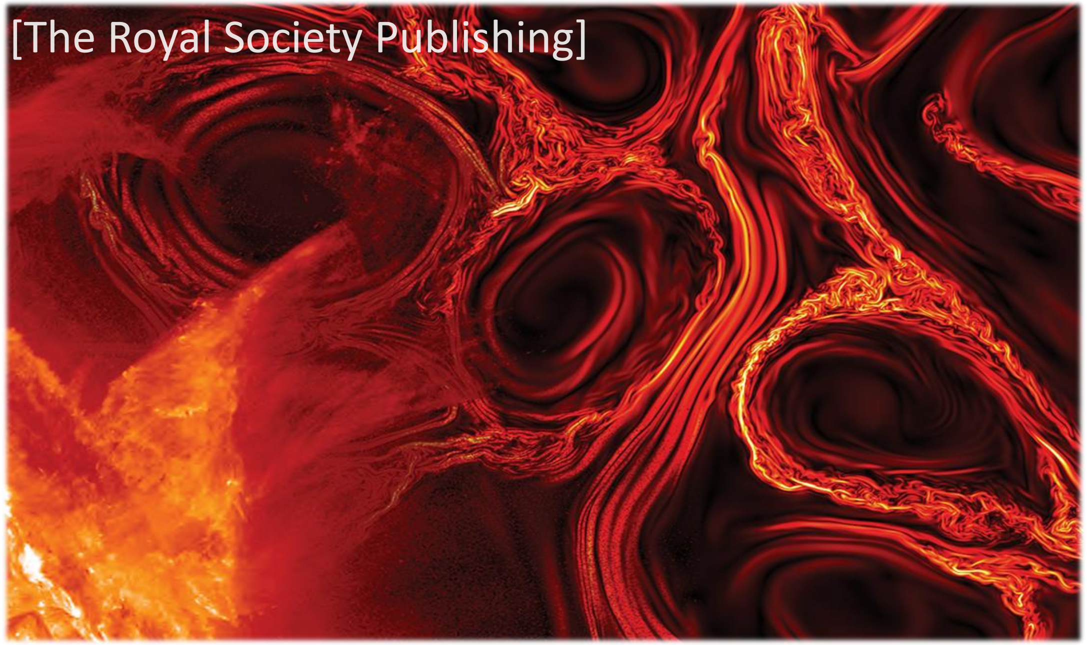
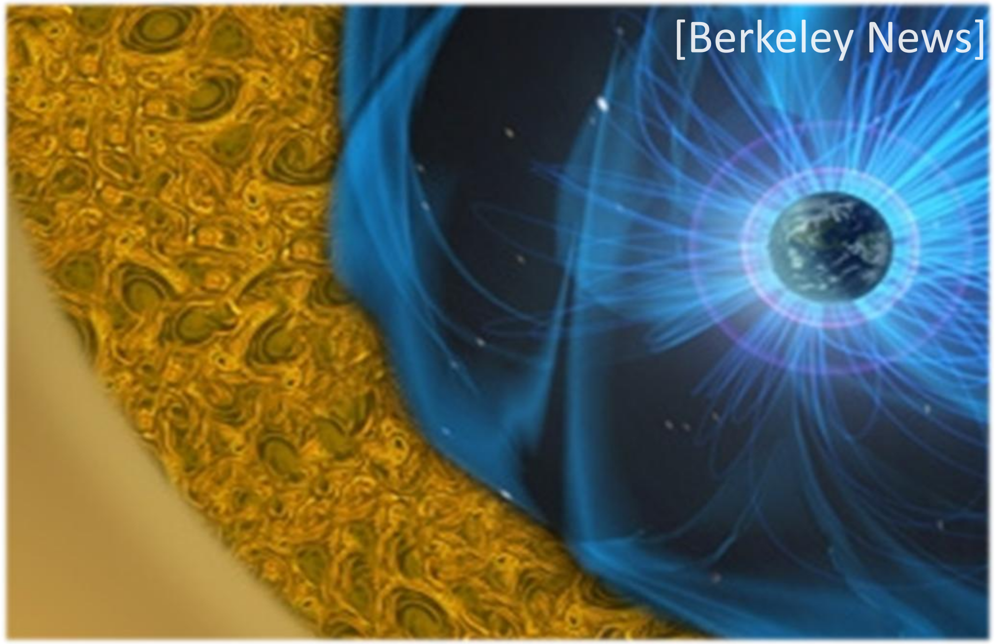
Insight on forecasting techniques from their application to the solar wind





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2. Department of Meteorology, University of Reading, Reading, UK

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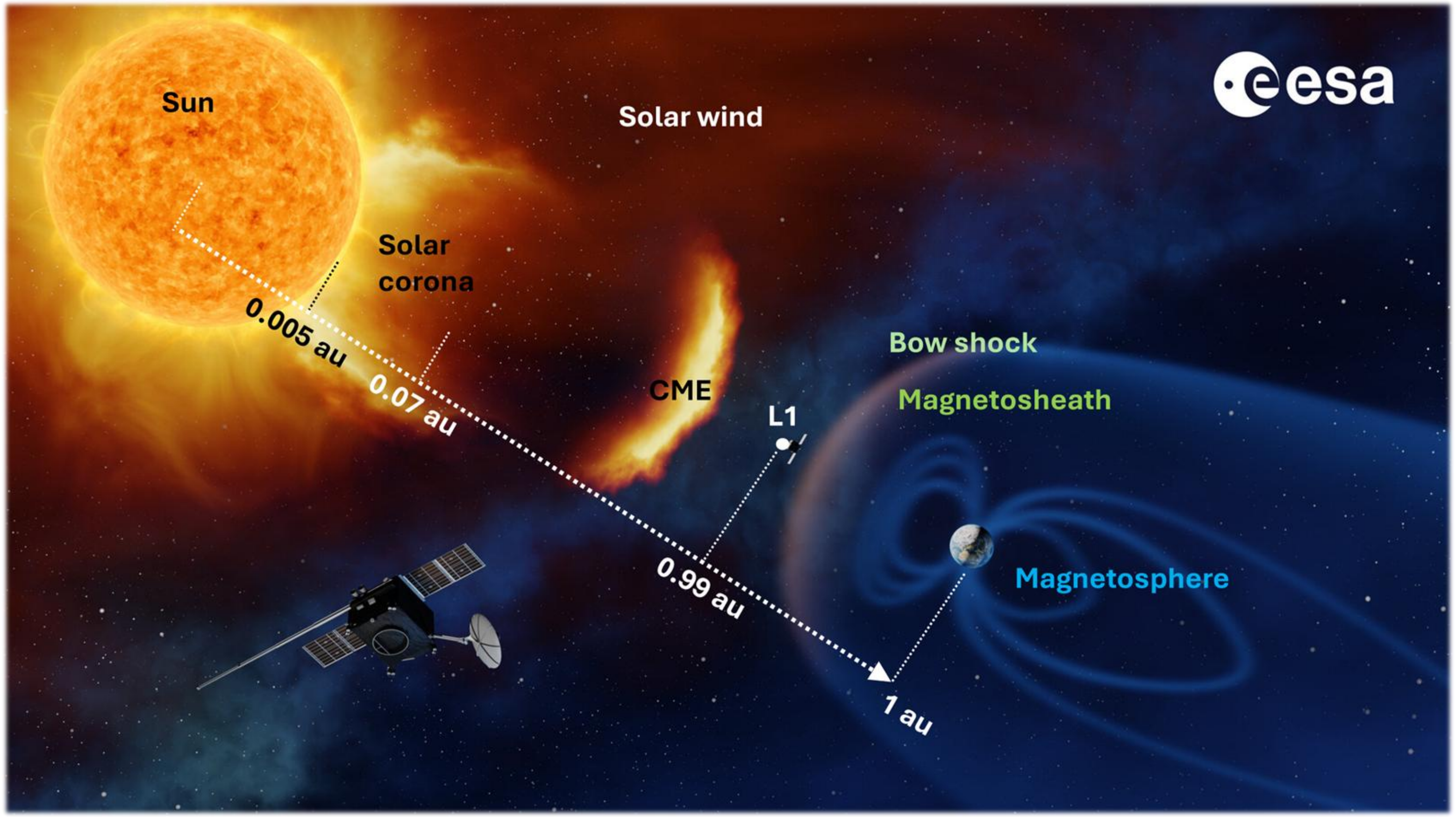
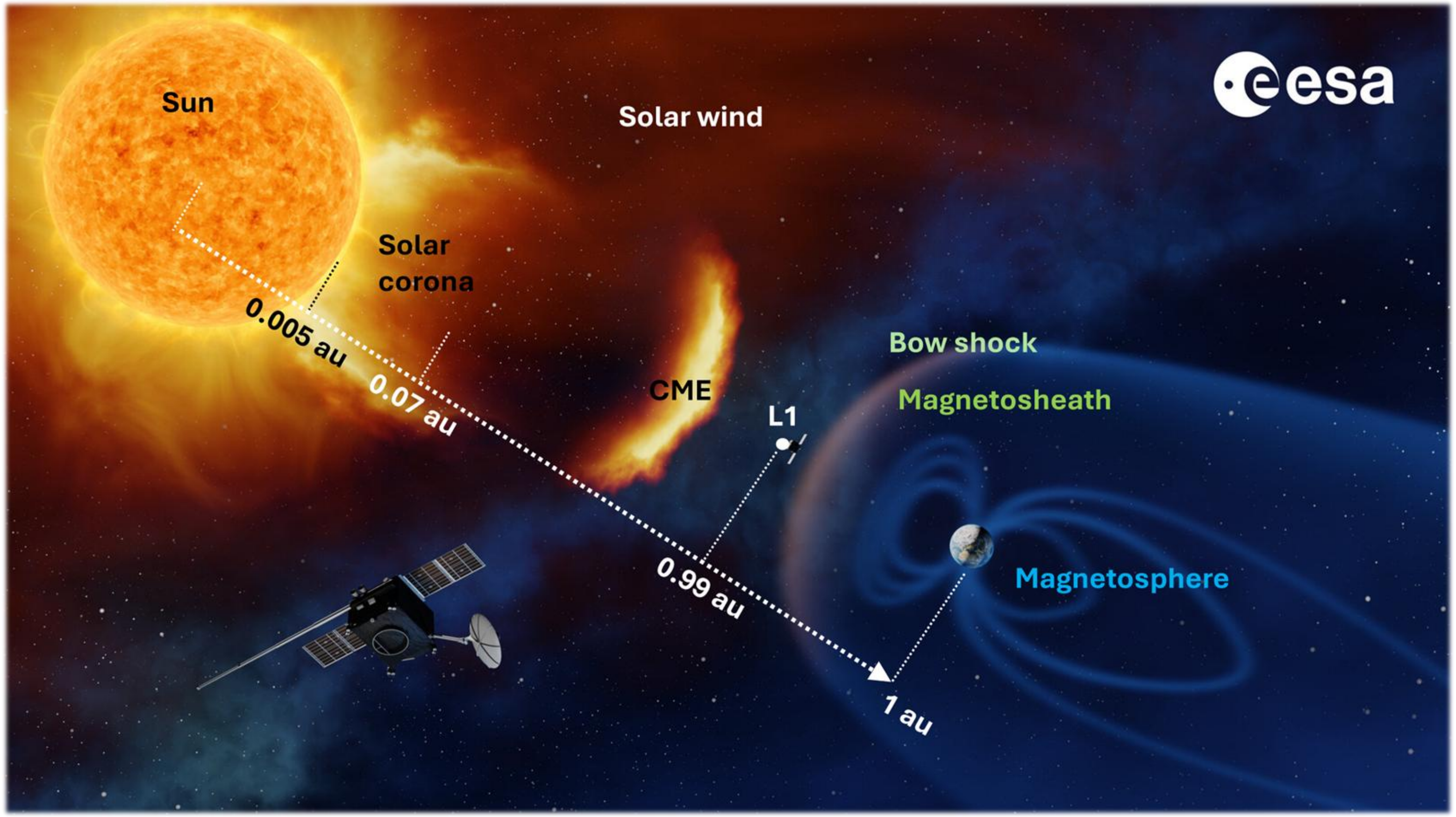
Forecasting multiscale system

The solar wind



The solar wind



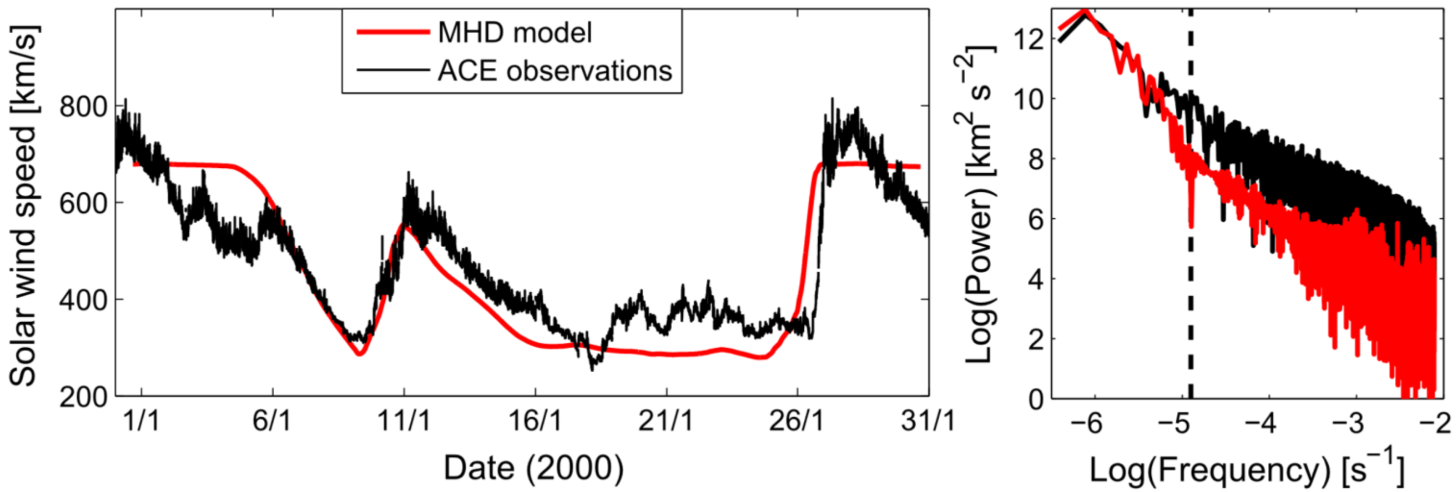
<u>Solar wind-magnetosphere coupling during a substorm</u>
[Ala-Lahti, 2024]

Scales > 1 day
=> Capture the enhancement of the geomagnetic activity but wrong starting time and magnitude

Scales > 15 min
=> Capture the bulk of the coupling interaction

Scales ~ 2 min (ULF)
=> Local enhancement of geomagnetic activity, location of the energy transfer

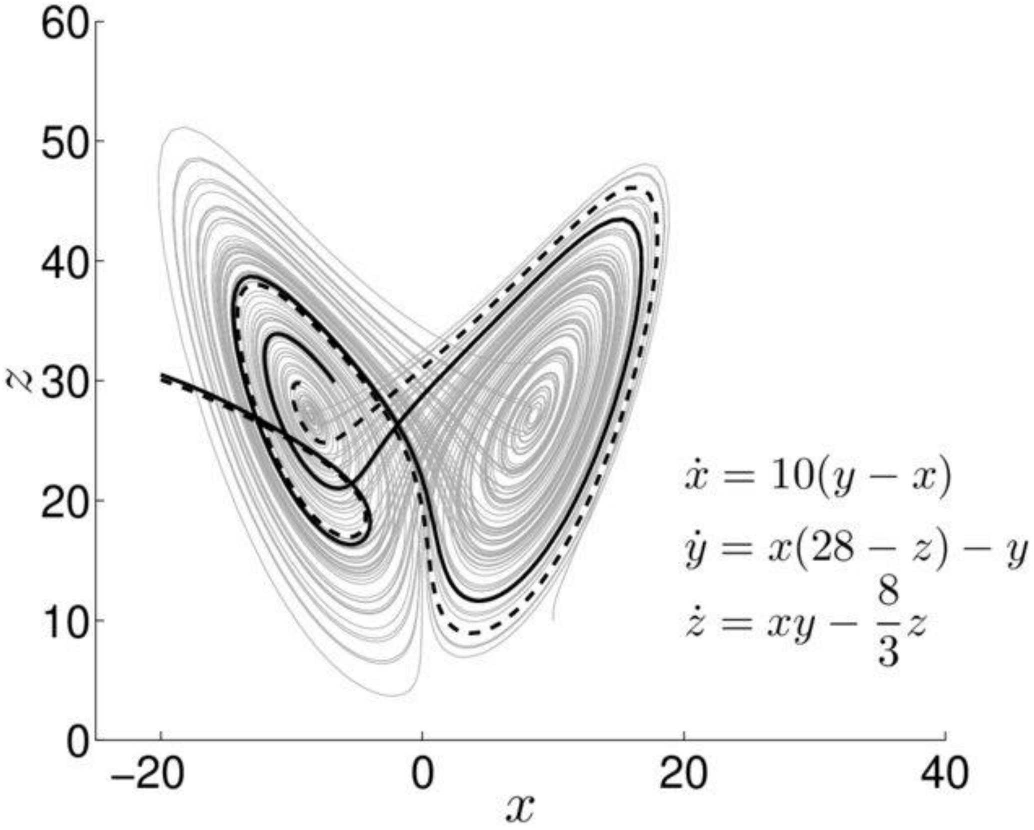
Multiscale challenge on forecasting the solar wind



Is there a forecast method that can preserve a maximum of scales?

[Owens et al, 2014]

Analogue forecast: Lorenz 1969

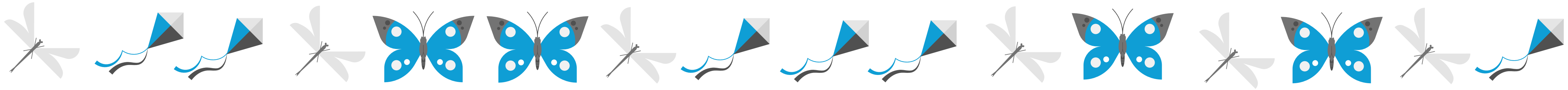


Analogues
Trajectories that have similar initial conditions

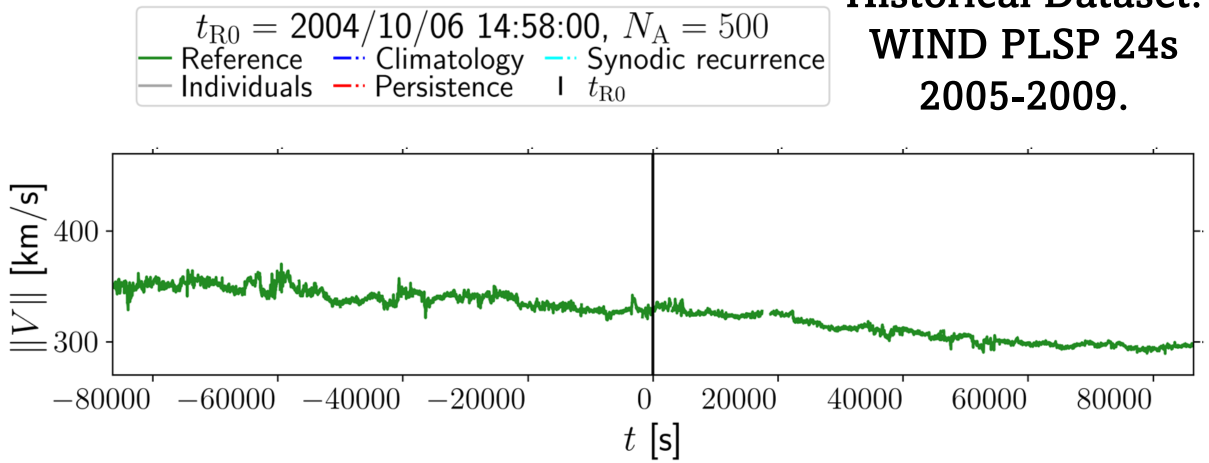
[Kabiraj, 2012]

Analogue Ensemble forecast: the principle

HISTORICAL DATASET (potential analogues)

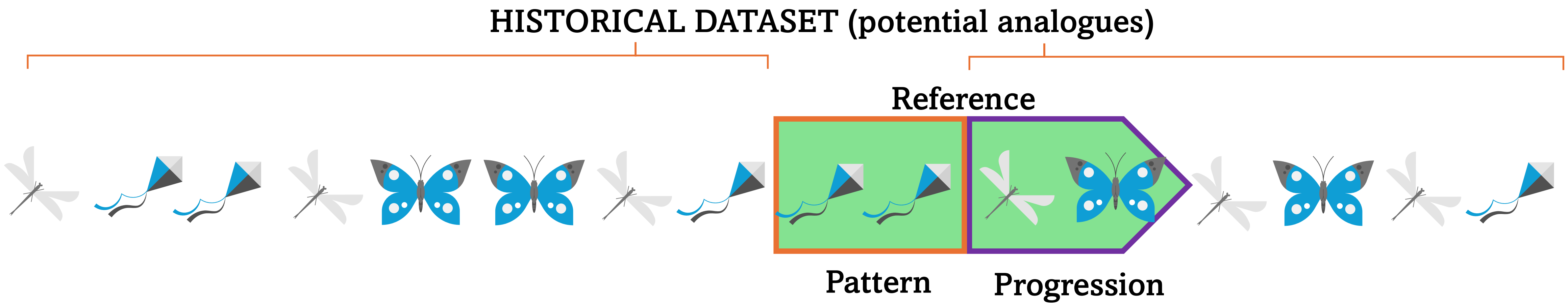


Historical Dataset: WIND PLSP 24s 2005-2009.



Principle:
Using the progression of an ensemble of historical analogues, similar to the present, to forecast the future.

Analogue Ensemble forecast: the principle



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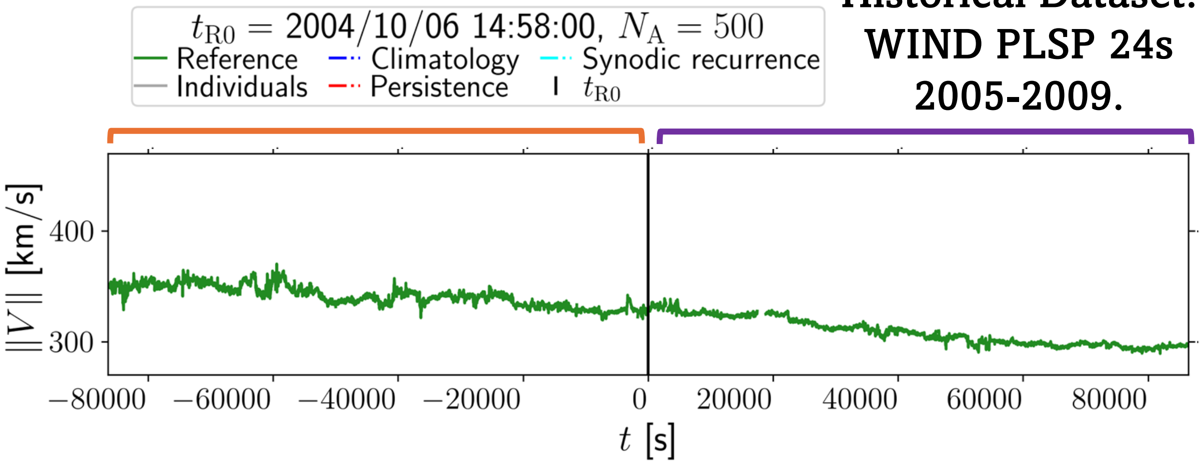

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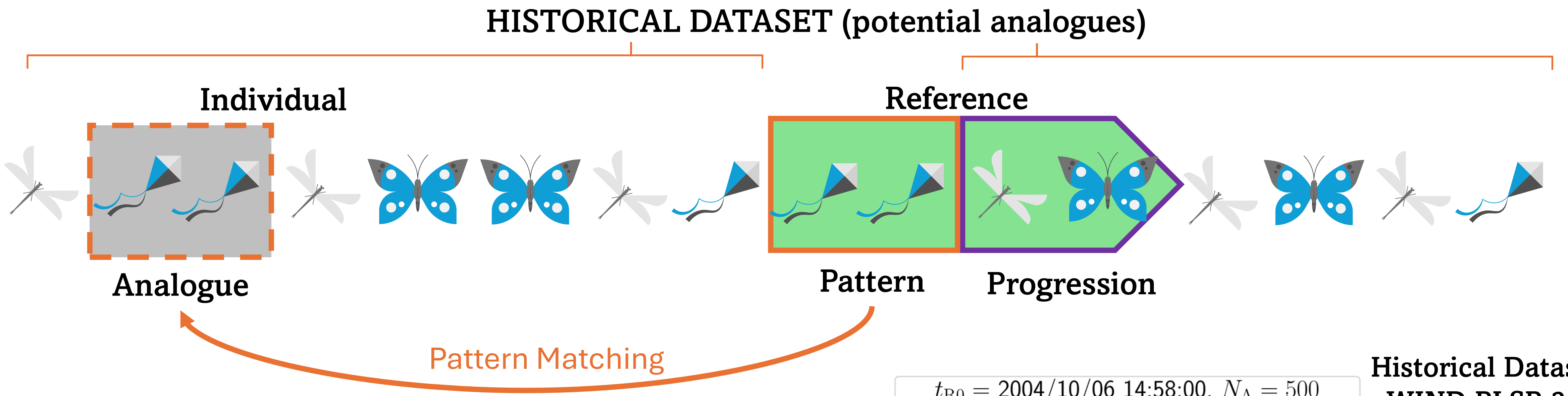
Analogue Ensemble forecast: the principle



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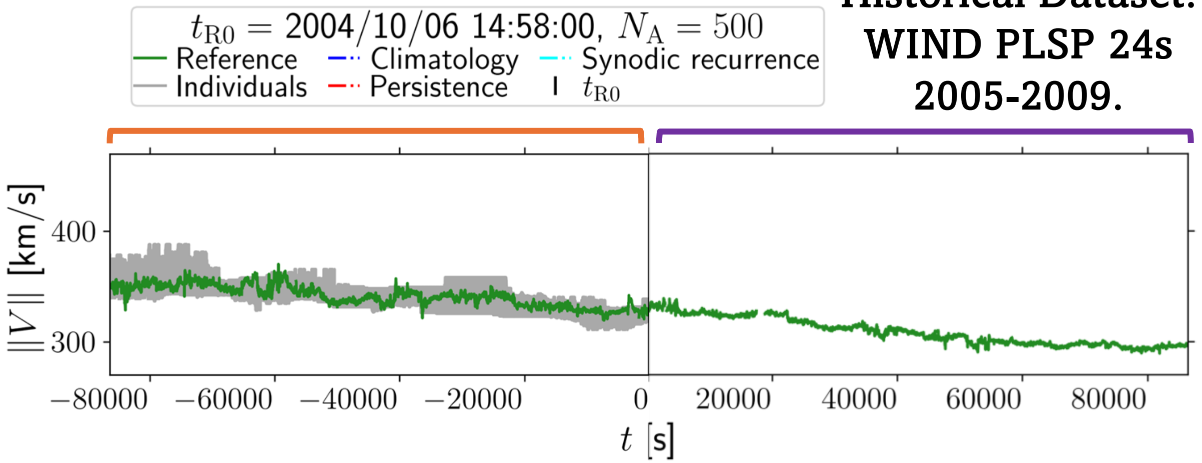

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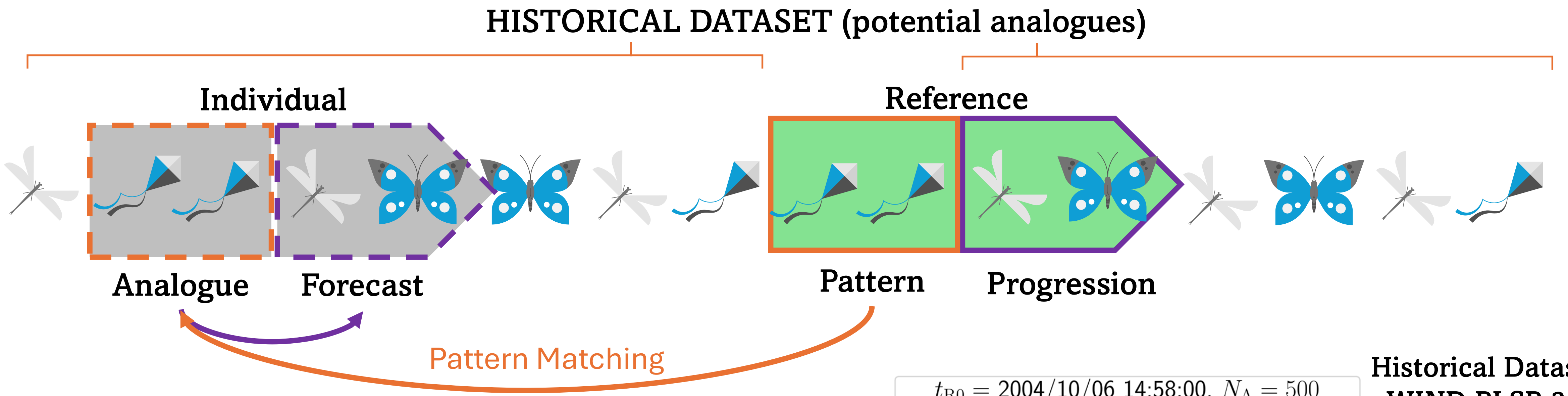
Analogue Ensemble forecast: the principle



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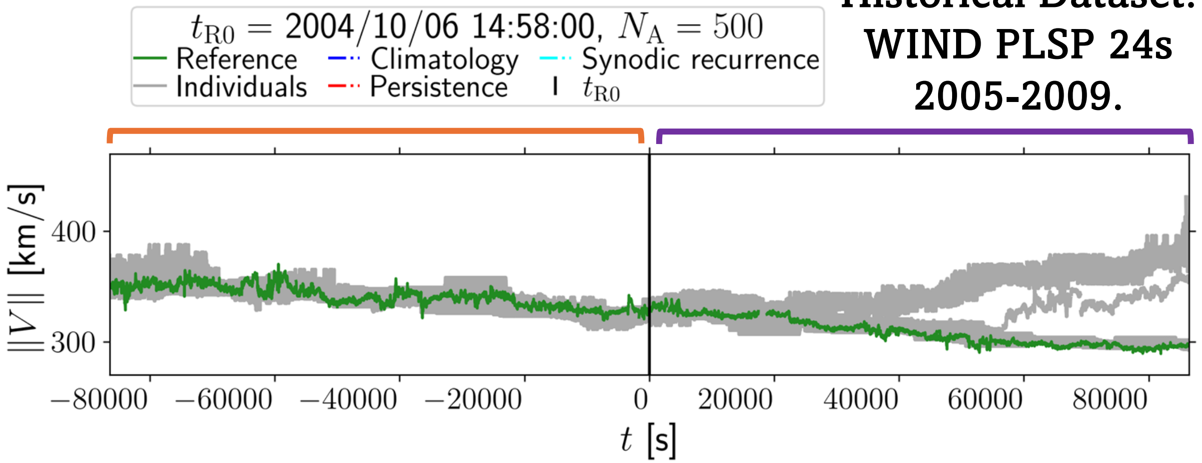

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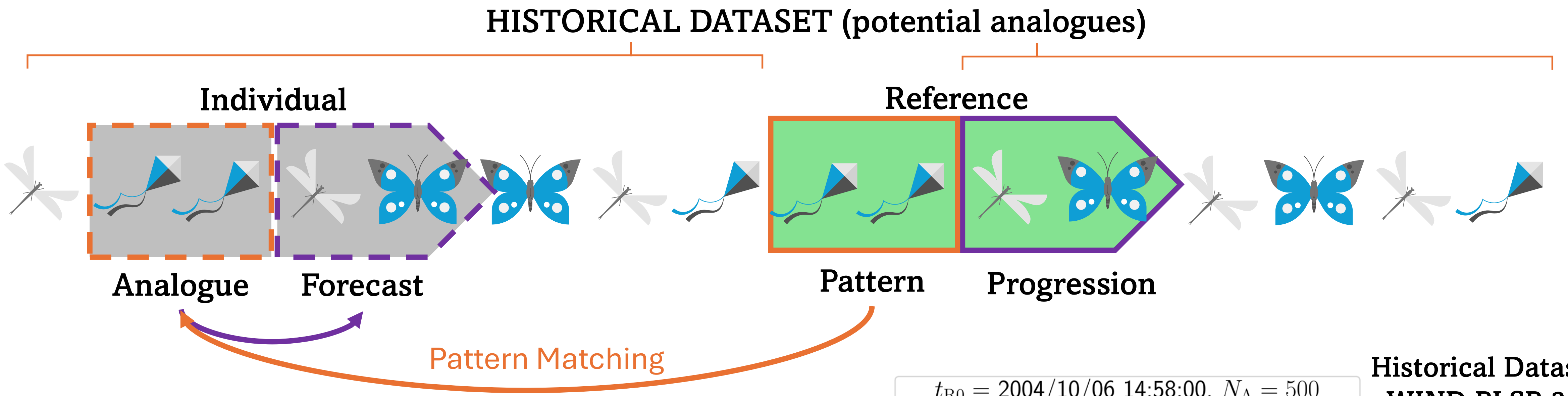
Analogue Ensemble forecast: the principle



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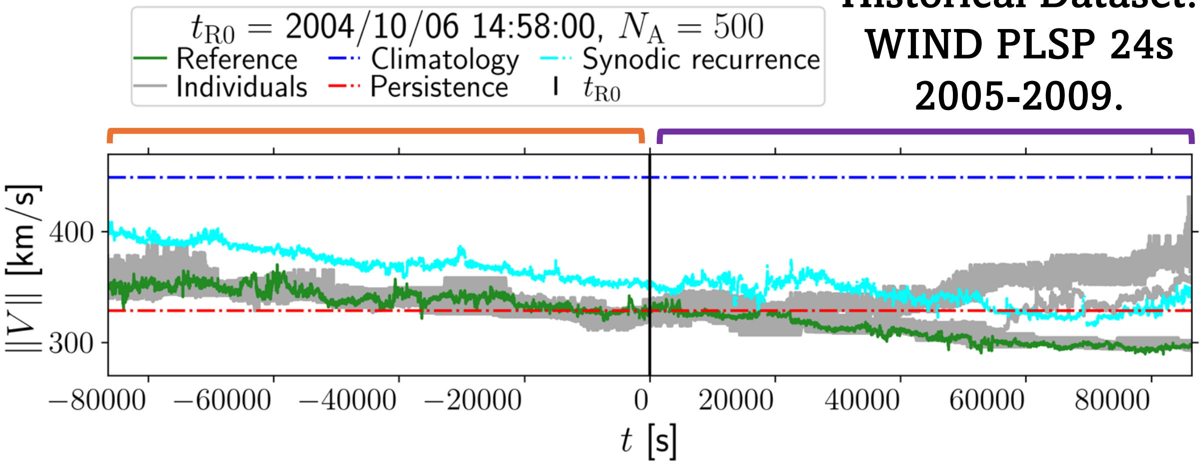
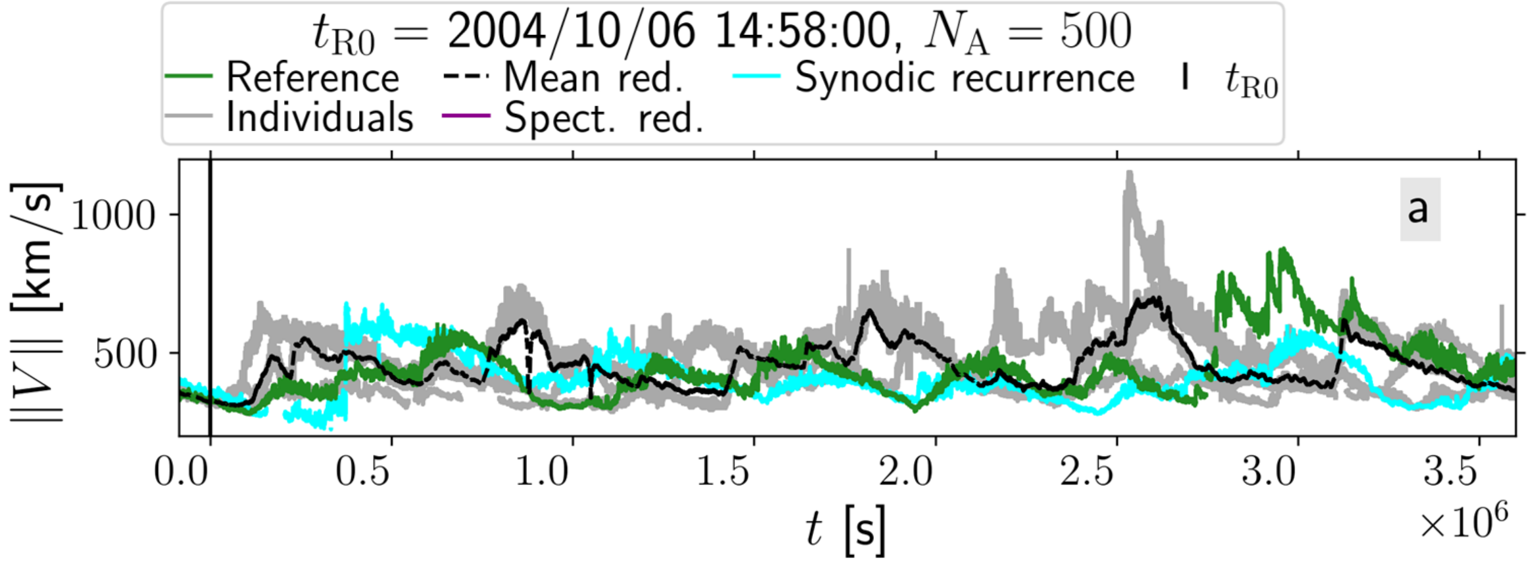


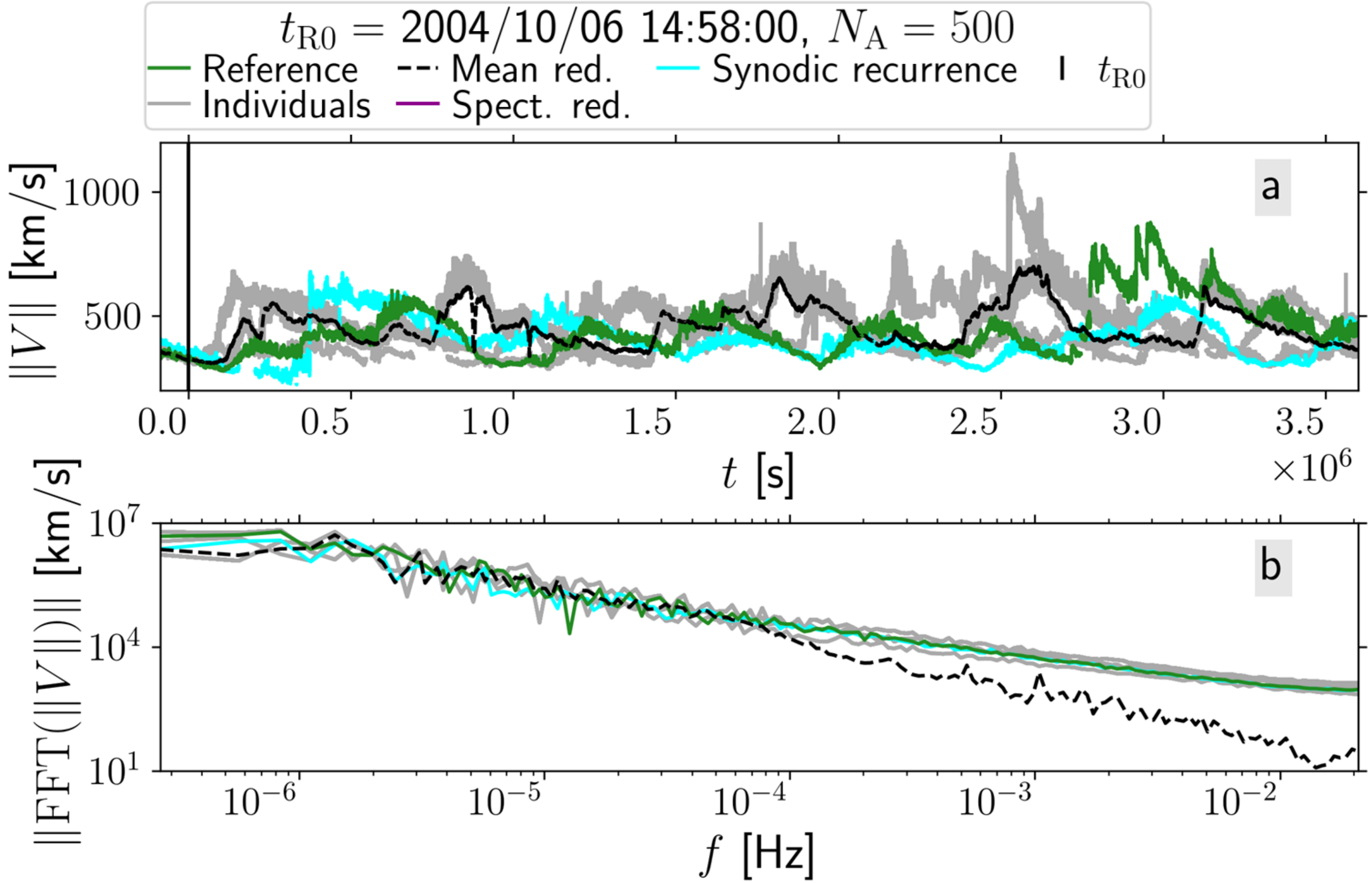
Historical Dataset: WIND PLSP 24s 2005-2009.

Analogue Ensemble forecast: Case study



Choosing a reduction algorithm is needed to compare the ensemble to baselines or other forecasts.

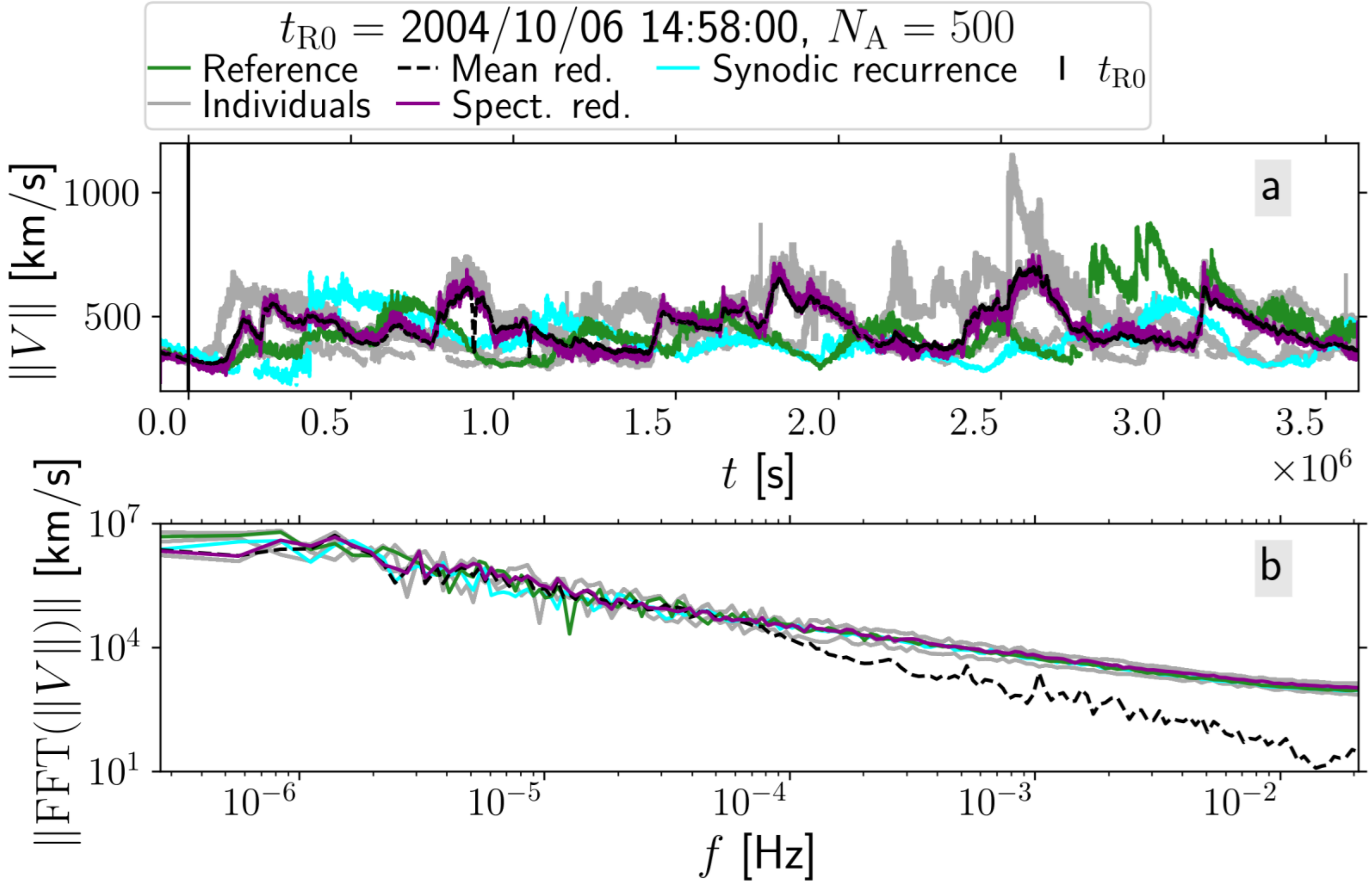
Analogue Ensemble forecast: Case study



Choosing a reduction algorithm is needed to compare the ensemble to baselines or other forecasts.

Time-by-time average lost the small-scale information.

Analogue Ensemble forecast: Case study



Choosing a reduction algorithm is needed to compare the ensemble to baselines or other forecasts.

Time-by-time average lost the small-scale information.

=> Reduction process based on spectral composite.

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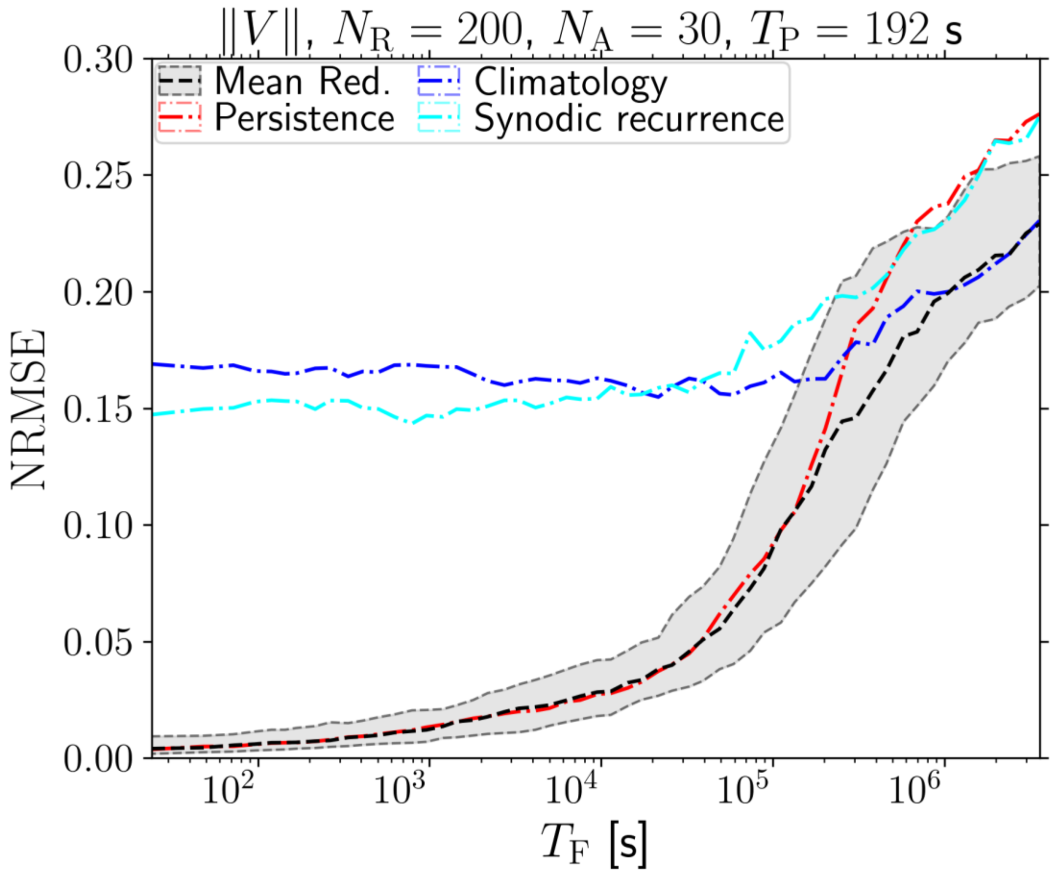
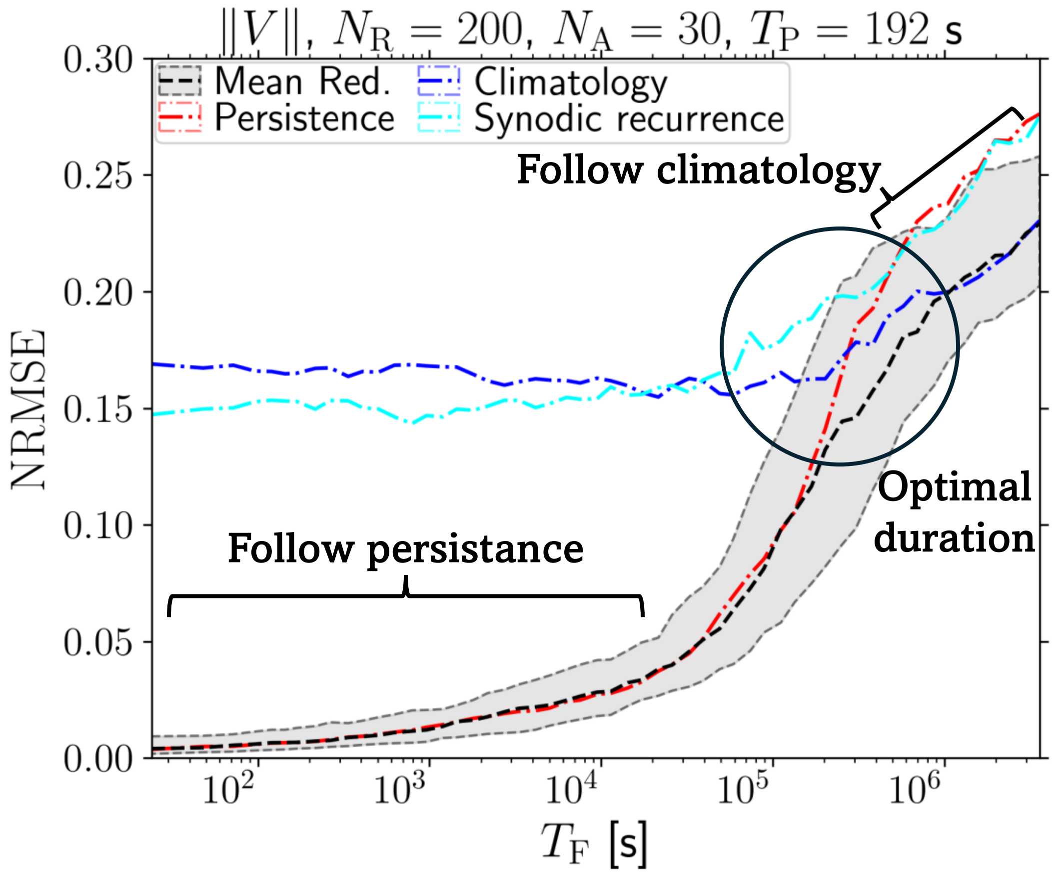
Analogue Ensemble forecast: statistical results



$$NRMSE = \sqrt{\frac{\langle (Forecast\ - Reference)^2 \rangle_{t\in[0;T_F]}}{\langle Reference^2 \rangle_{t\in[0;T_F]}}}$$

Analogue Ensemble forecast: statistical results



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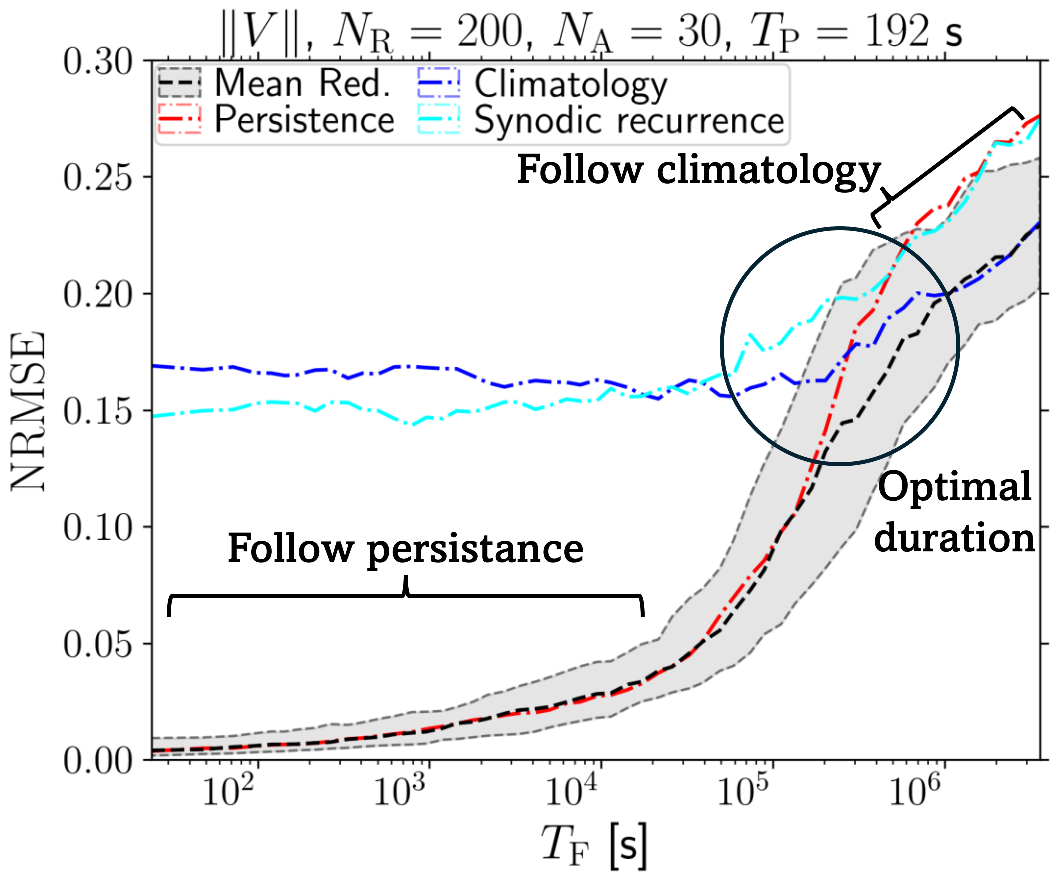
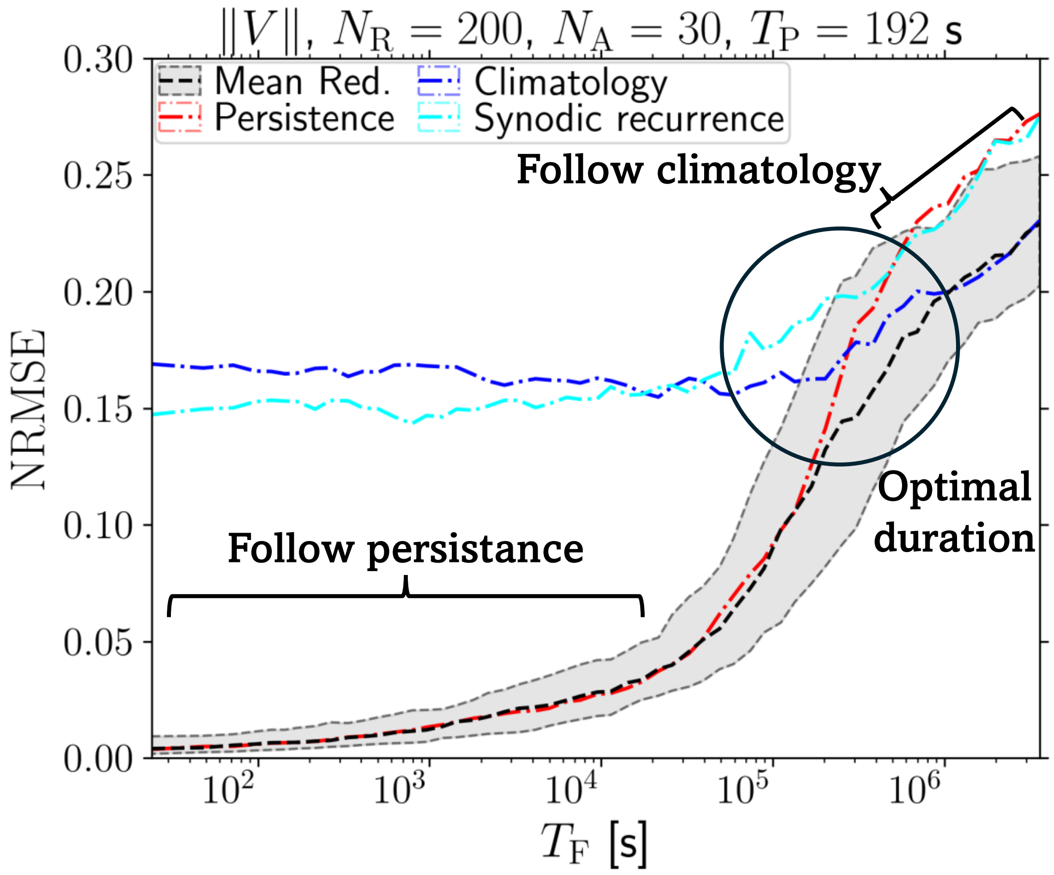
Analogue Ensemble forecast: statistical results



	$\|V\|$	V_x	V_y	V_z	$\|B\|$	B_x	B_y	B_z
Π [%]								
Mean red.	66	65	61	64	58	66	63	63
Spect. red.	59	58	56	52	47	56	54	53
T_L [s]								
Mean red.	3.8×10^5	3.8×10^5	3.9×10^4	3.3×10^4	1.7×10^5	1.3×10^5	2.5×10^5	1.4×10^4
Spect. red.	3.1×10^5	3.1×10^5	3.3×10^4	3.9×10^4	1.7×10^5	1.7×10^5	2.5×10^5	0.7×10^4
NRMSE								
Mean red.	0.152	0.153	0.747	0.940	0.317	0.934	0.957	0.918
Spect. red.	0.165	0.159	0.804	1.017	0.358	0.965	1.020	0.963
Synodic rec.	0.199	0.199	1.197	1.348	0.461	1.211	1.149	1.390
δ_{SR}								
Mean red.	−0.048	−0.053	−0.485	−0.513	−0.220	−0.457	−0.484	−0.484
Spect. red.	−0.145	−0.137	−0.163	−0.163	−0.118	−0.201	−0.209	−0.210
Synodic rec.	0.041	0.040	−0.011	−0.002	0.002	0.023	0.016	0.020

$$NRMSE = \sqrt{\frac{\langle (Forecast - Reference)^2 \rangle_{t \in [0;T_F]}}{\langle Reference^2 \rangle_{t \in [0;T_F]}}}$$

Analogue Ensemble forecast: statistical results



$$NRMSE = \sqrt{\frac{\langle (Forecast\ - Reference)^2 \rangle_{t\in[0;T_F]}}{\langle Reference^2 \rangle_{t\in[0;T_F]}}}$$

	$\|V\|$	V_x	V_y	V_z	$\|B\|$	B_x	B_y	B_z
Π [%]								
Mean red.	66	[illegible]	61	64	58	[illegible]	[illegible]	63
Spect. red.	59	58	56	52	47	56	54	53
T_L [s]								
Mean red.	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	2.5×10^5	1.4×10^4
Spect. red.	[illegible]	[illegible]	[illegible]	[illegible]	1.7×10^5	1.7×10^5	2.5×10^5	0.7×10^4
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Proportion of references better forecasted with AnEn than with persistence, climatology and synodic recurrence: ~ 60%

Associated progression duration

Main components: ~10^5s ~ days

Fluctuation components: ~10^4s ~ hours

Associated time series accuracy

Mean reduction = best

Spectral reduction = compromise

Synodic recurrence = worse

Associated spectral loss

Mean reduction = worse

Spectral reduction = compromise

Synodic recurrence = best

Conclusion

The An.En. method can be use as a baseline that work as well as persistence and climatology and better than the synodic recurrence. It can even do better than both, for around 60% of the set of 200 dates, for all quantities and a set of particular parameters.

A reduction of the ensemble based on the spectra of the individual forecast saves the forecast of the fluctuations. We still emphasize that the choice of reduction when working with ensemble of forecasts need precaution and to be fitted to the aim of the study.

[Simon et al., 2025, Space Weather]

THANK YOU EVERYONE FOR YOUR ATTENTION!