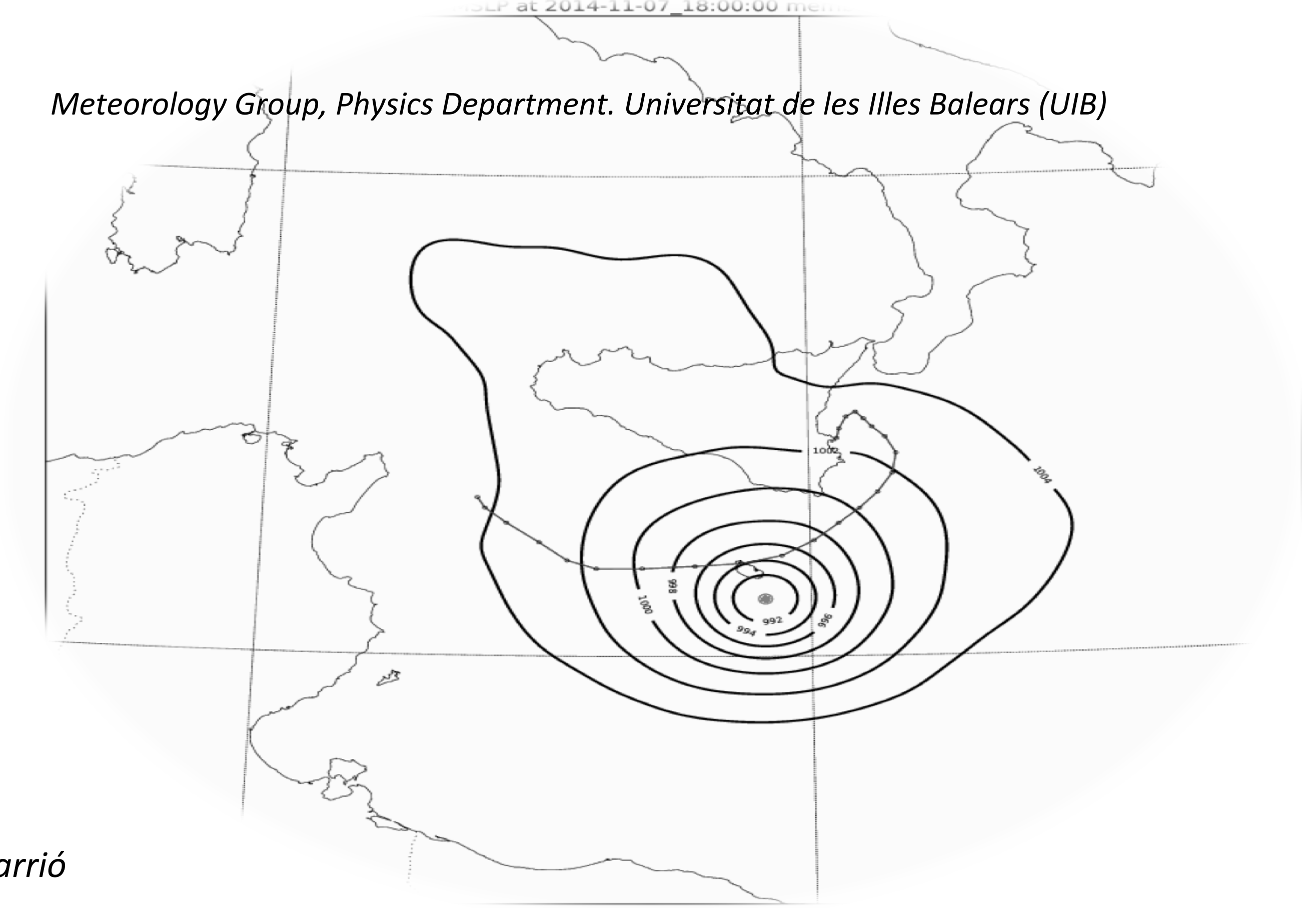
Assimilation of remote sensing data over the Western Mediterranean. Experiences with EnKF

Meteorology Group, Physics Department. Universitat de les Illes Balears (UIB)



Universitat de les Illes Balears

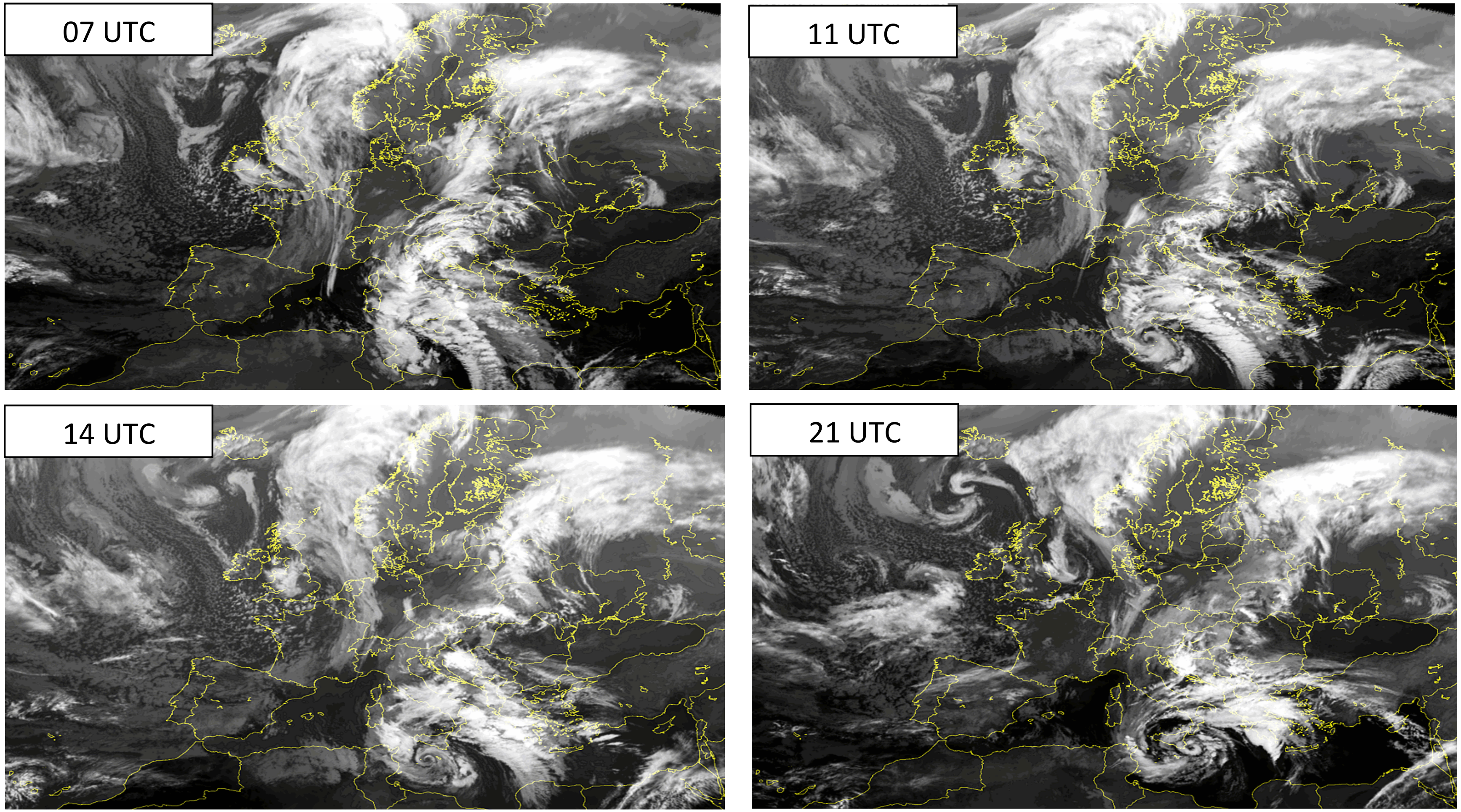
Diego Saúl Carrió Carrió

24th May 2018

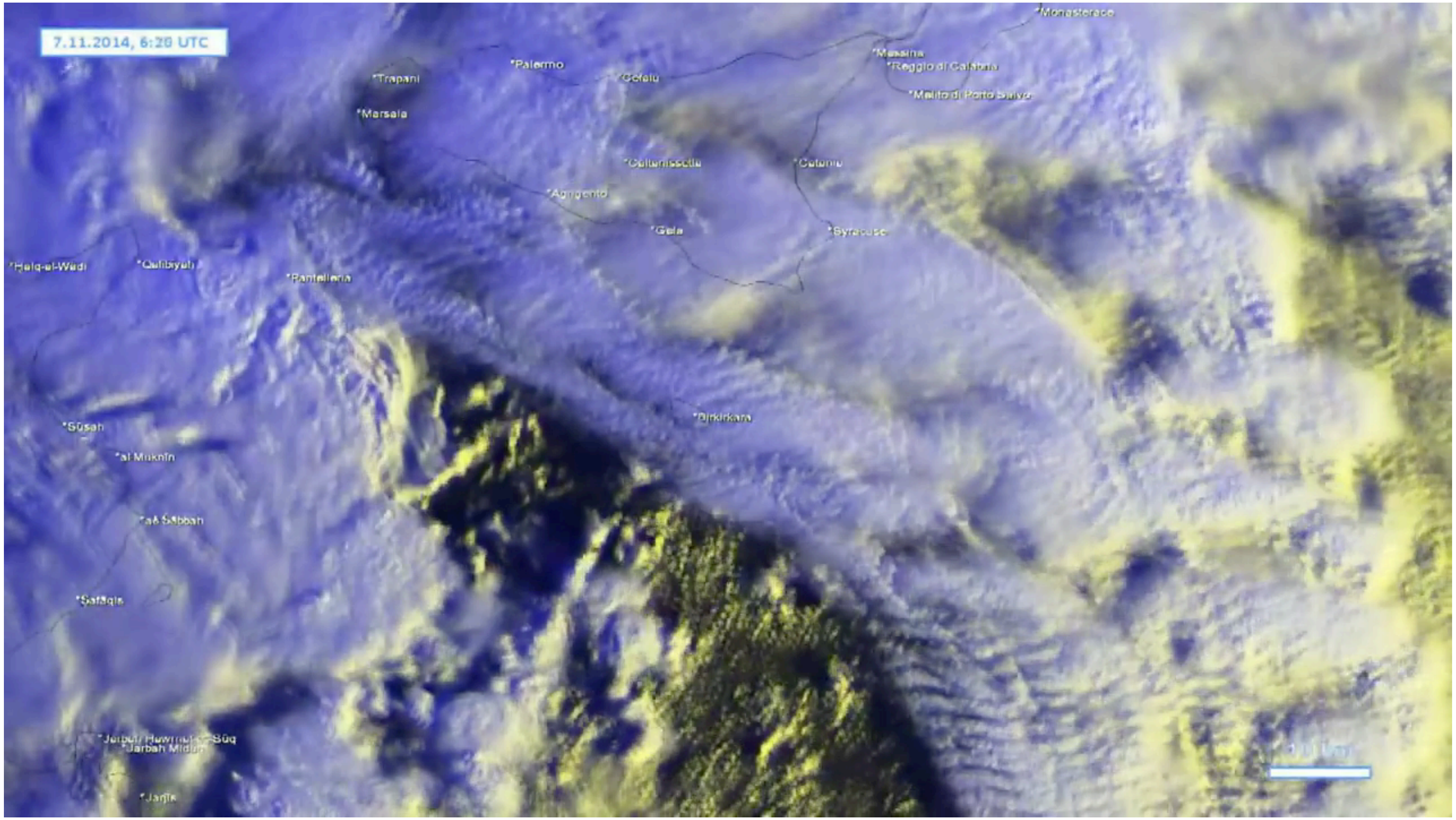
CONTENT

1. INTRODUCTION

1. INTRODUCTION: Brief overview of the 7 November 2014 medicane

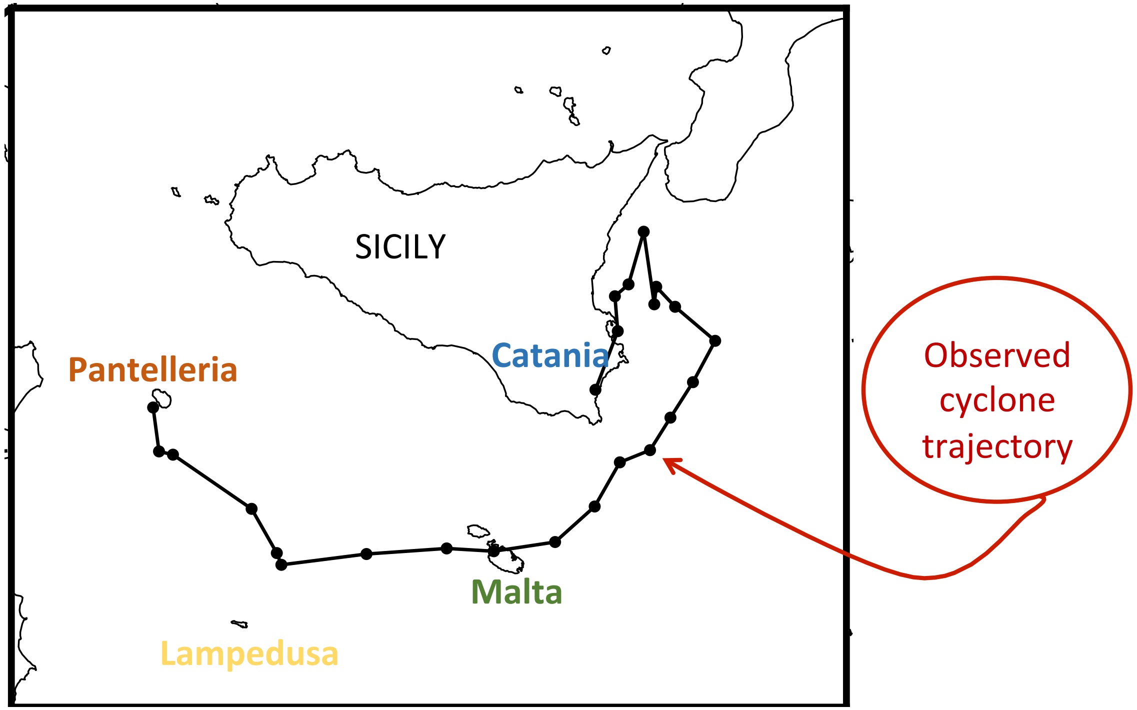


1. INTRODUCTION: Brief overview of the 7 November 2014 medicane



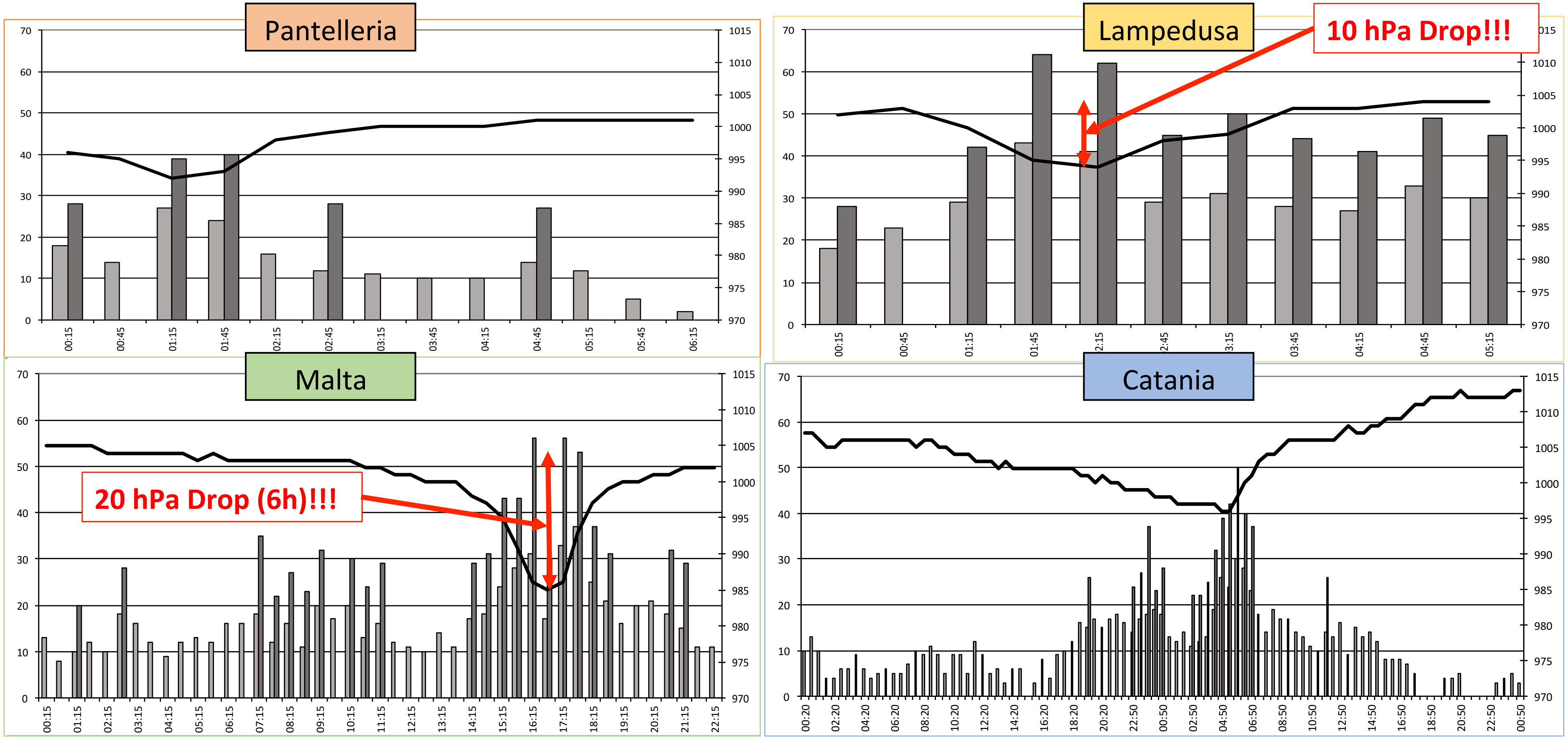
1. INTRODUCTION: Brief overview of the 7 November 2014 medicane

- Cyclone's **track obtained from satellite imagery**
- Limited number of *in-situ* observations available
- We use **METARs** (Meteorological Aerodrome Reports) observations from:



1. INTRODUCTION: Brief overview of the 7 November 2014 medicane

- METAR observations: **surface pressure** (hPa, solid line), **sustained and gust winds** (m s-1, light and dark grey bars resp.)
- Indicated times in UTC of 7 November 2014



1. INTRODUCTION: Objective

- Improving numerical **predictability of extreme weather events** initiated and developed over maritime bodies, such as the Mediterranean Sea, **remains nowadays a challenge**.

- For the Mediterranean Sea, this is mainly due to the **lack of in-situ observations available**, strong heat fluxes associated to the relative warm sea, and finally the interaction with the complex topography surrounding the Mediterranean basin.

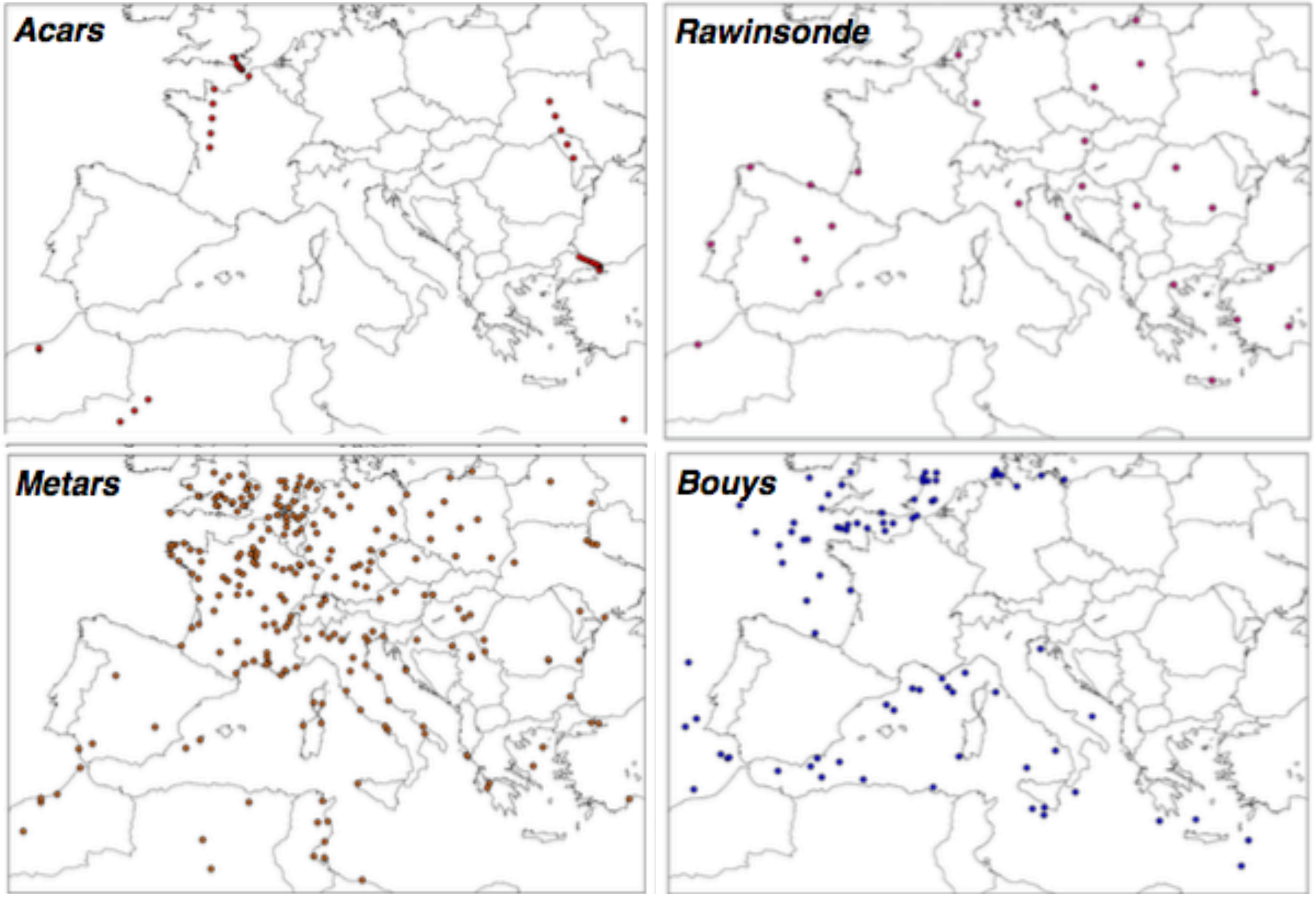
- **Data Assimilation** could help to improve the predictability of such extreme events!!

- We were interested in **assess the impact of assimilating** both **conventional** and **Atmospheric Motion Vectors (AMVs)** using the EnKF in improving the predictability of Mediterranean Hurricane (medicane) that hit Malta at ~18 UTC on 07 November 2014 (Carrió, D. S. et al., 2017).

2. AVAILABLE OBSERVATIONS

2. AVAILABLE OBSERVATIONS: *In-situ* Conventional (SYN)

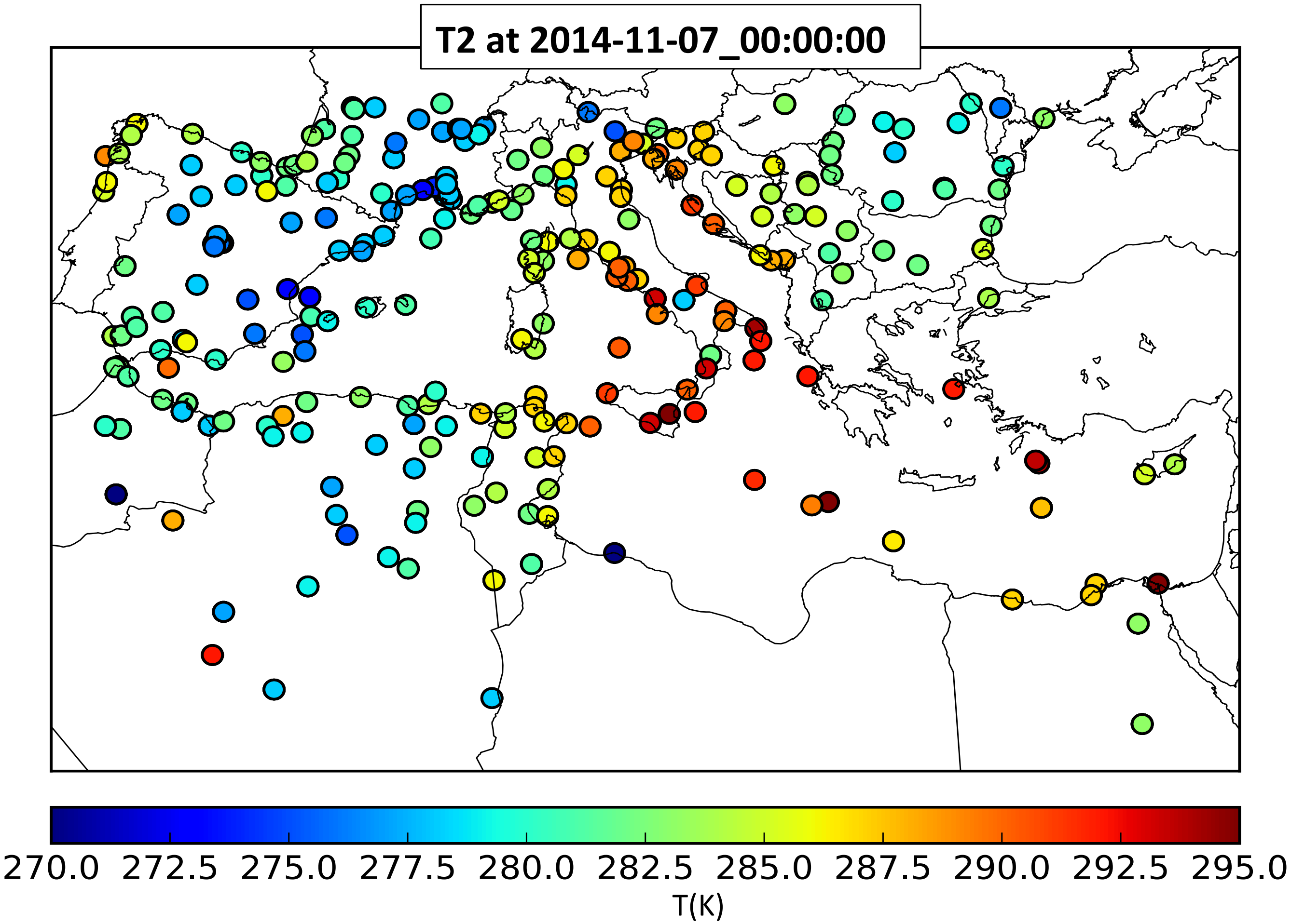
Observations used from **NCEP-MADIS** (Meteorological Assimilation Data Ingest System)



2. AVAILABLE OBSERVATIONS: *In-situ* Conventional (SYN)

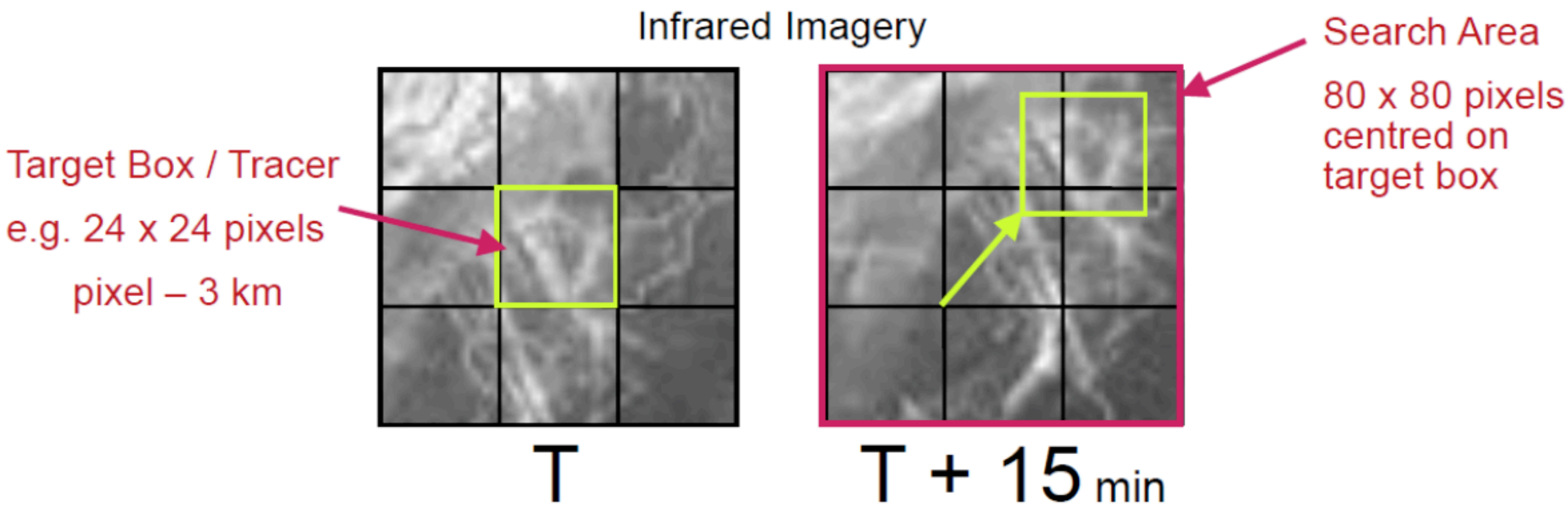
Observations used from **NCEP-MADIS** (Meteorological Assimilation Data Ingest System)

- Temporal resolution: 1-h
- Quality Controlled data
- E.g.: **Temperature at 2m** from MADIS observations



2. AVAILABLE OBSERVATIONS: Rapid Scan Atmospheric Motion Vectors (AMVs)

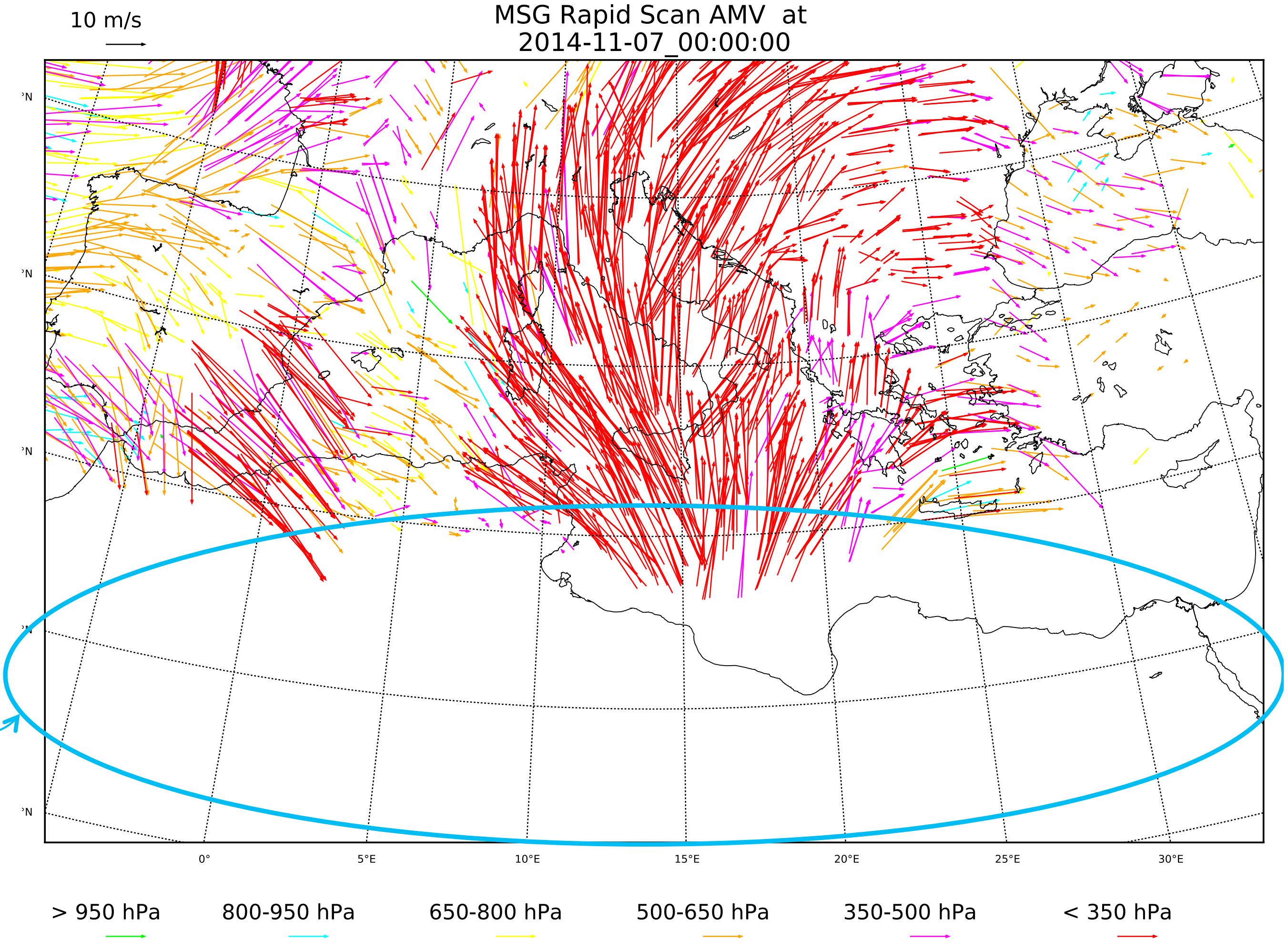
- Radiometer SEVIRI instrument onboard Meteosat Second Generation (MSG)
- **Scanning frequency: 5-min**
- Data available in EUMETSAT database **at temporal resolution** : **20-min** (*average of four 5-minutes* vector components)
- Spatial resolution: 60-120 km



2. AVAILABLE OBSERVATIONS: Rapid Scan Atmospheric Motion Vectors (AMVs)

Rapid Scan Amospheric Motion Vectors:

Southern part of parent domain not covered by RS-AMV observations!!!!!

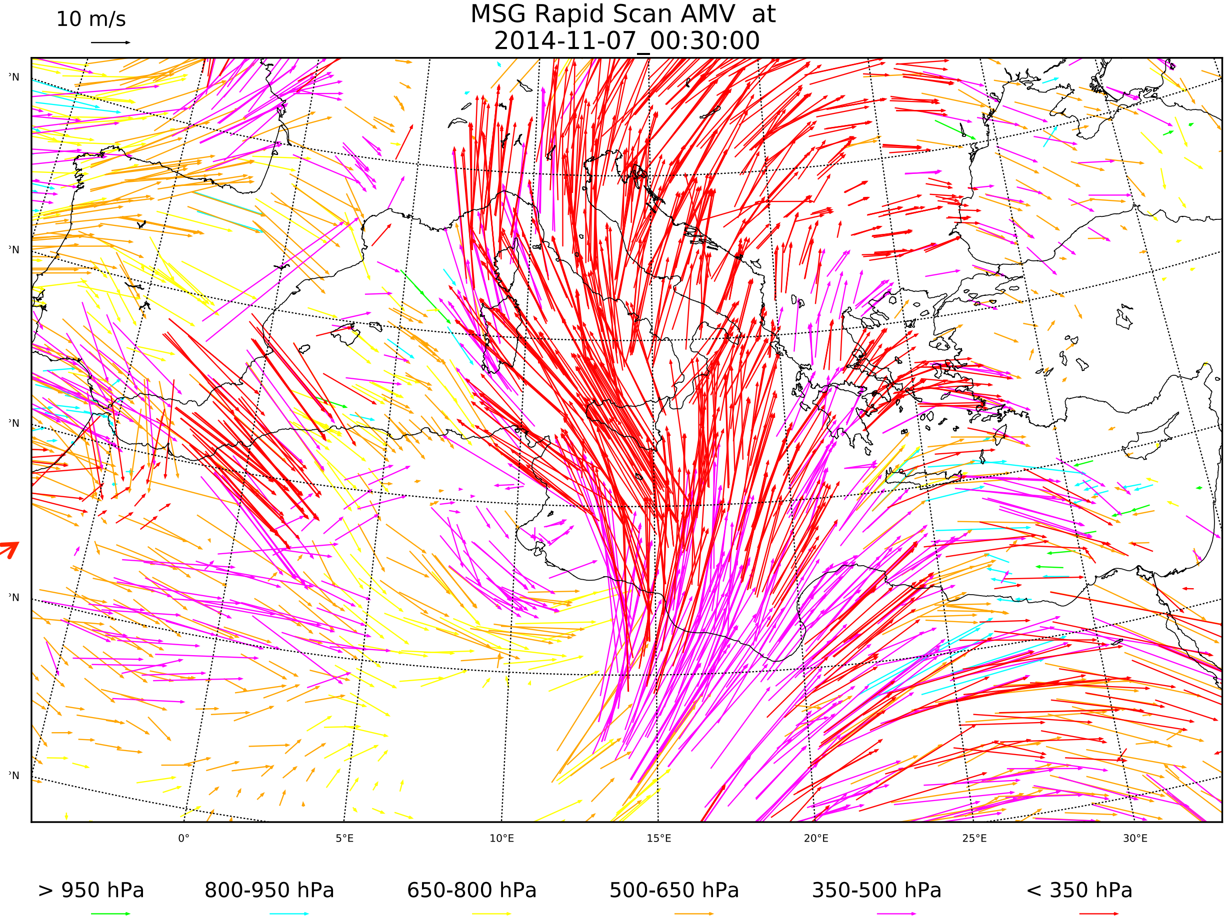


2. AVAILABLE OBSERVATIONS: Rapid Scan Atmospheric Motion Vectors (AMVs)

Amospheric Motion Vectors (global):

Temporal resolution: 1-h

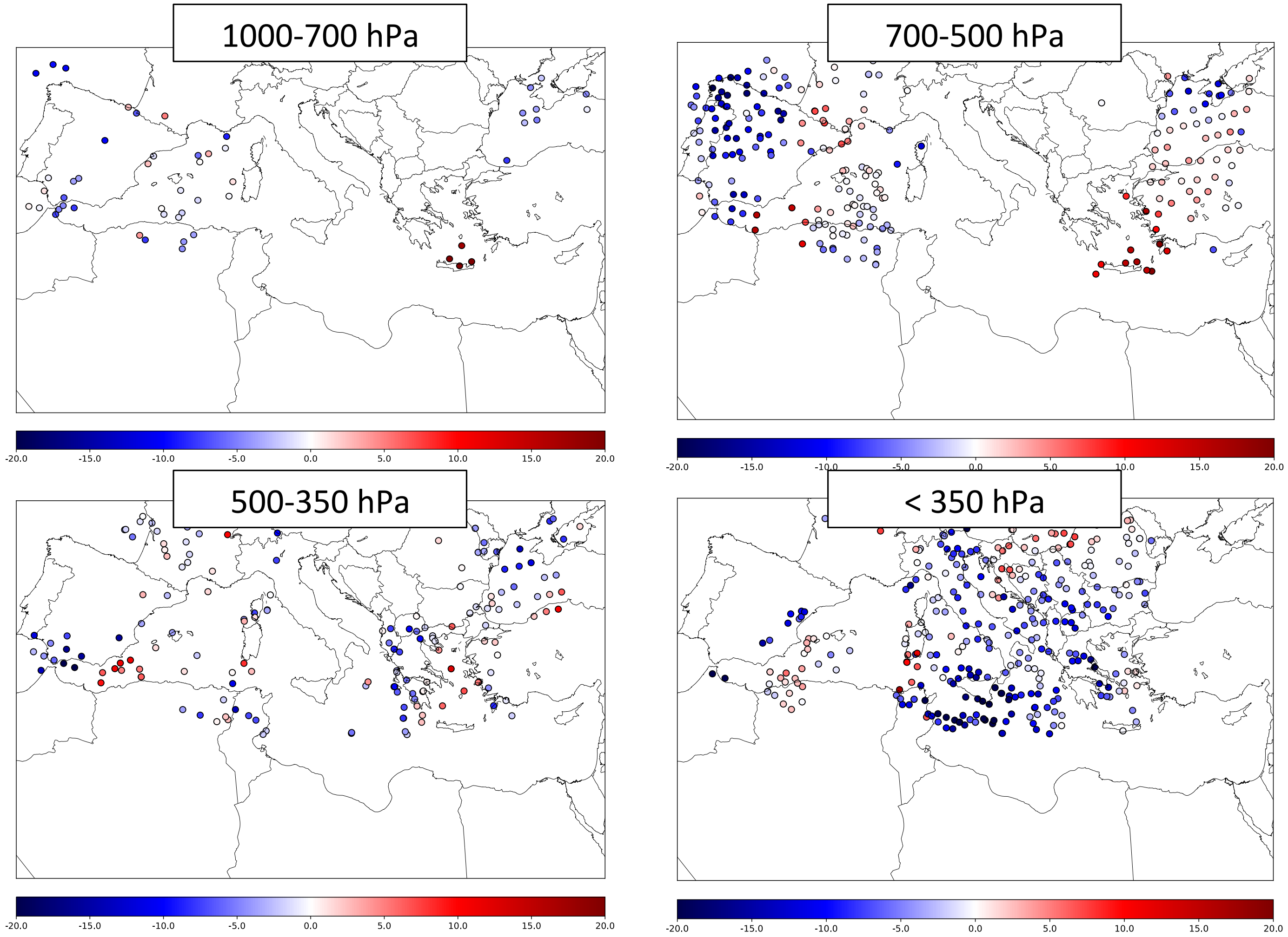
Full spatial cover over parent domain!!!!!



2. AVAILABLE OBSERVATIONS: Rapid Scan Atmospheric Motion Vectors (AMVs)

U-AMVs

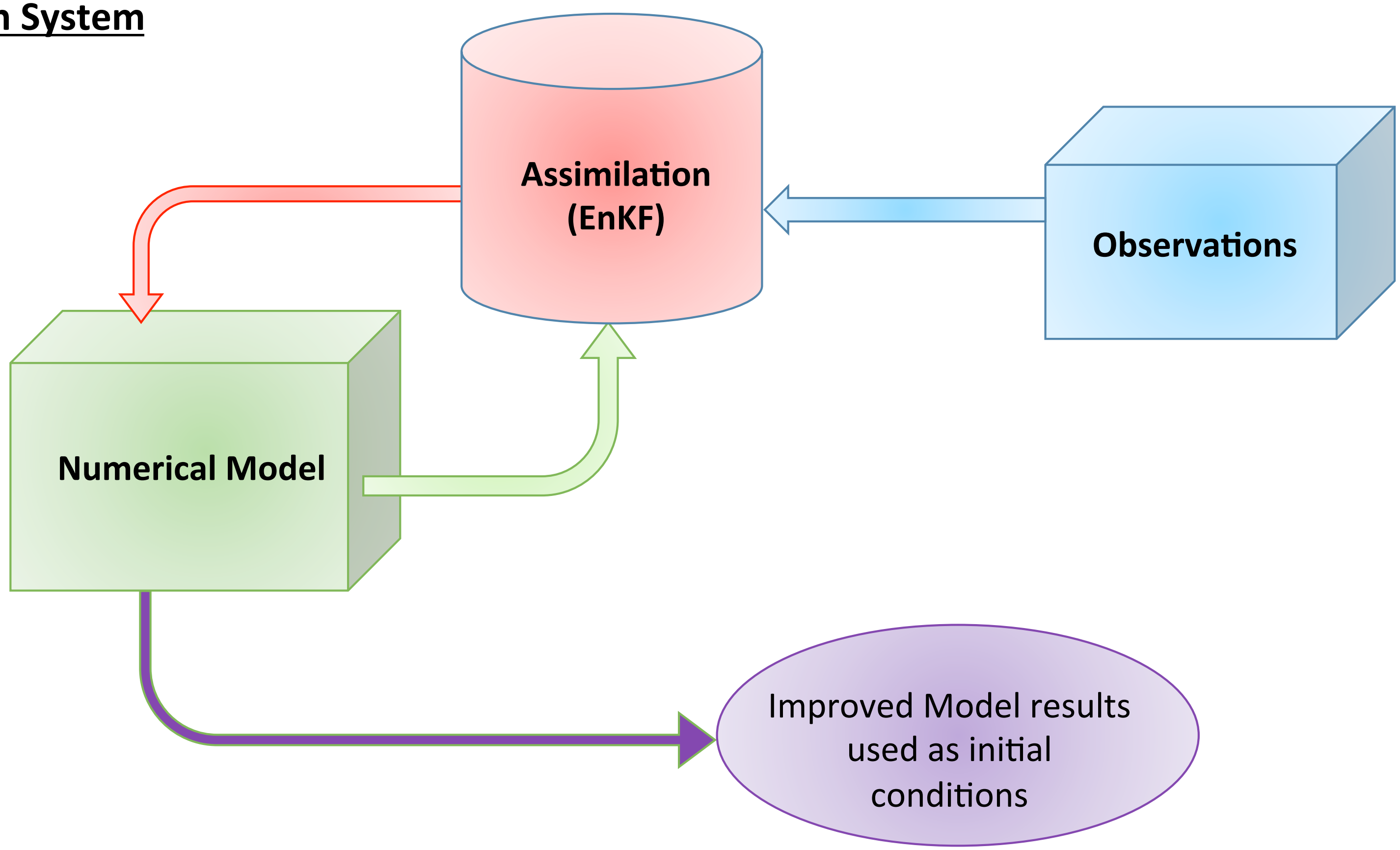
Prior Increments (**obs-background**)



3. METHODOLOGY

3. METHODOLOGY: Numerical Model

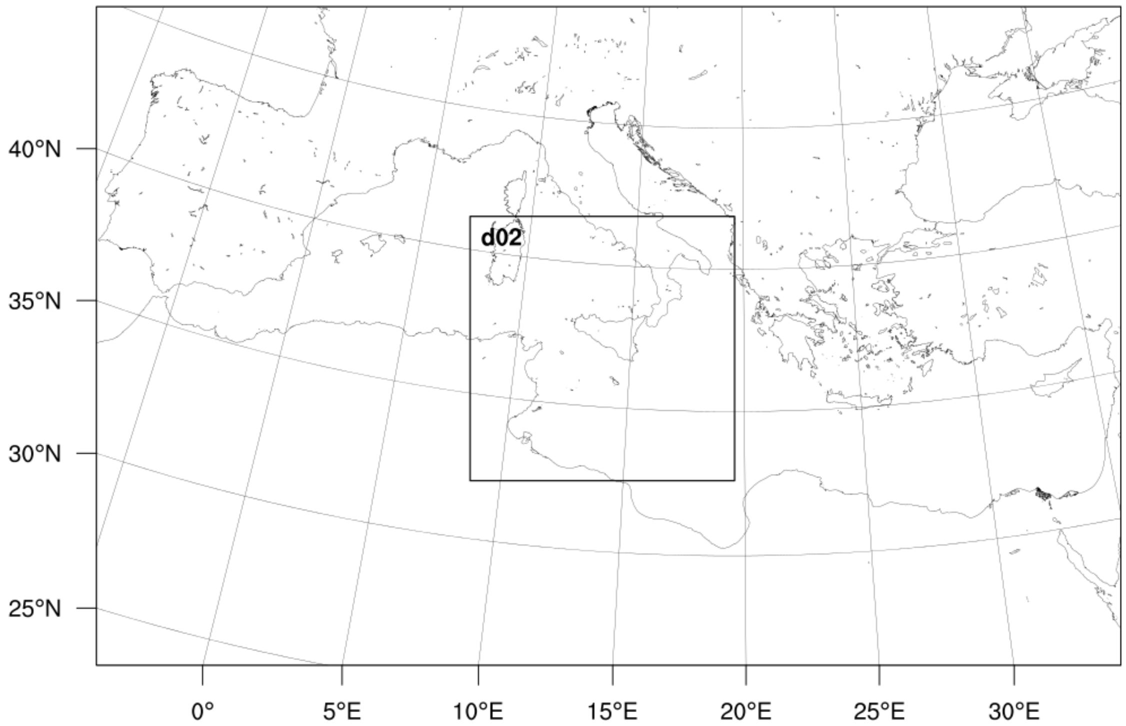
<u>Data Assimilation System</u>



3. METHODOLOGY : Numerical Model

<u>Numerical Model Configuration:</u>

- **WRF-ARW** model V3.7.1: Fully compressible, non-hydrostatic model
- Initial and Boundary Conditions from **EPS-ECMWF** (~16 km horizontal grid resolution)
- **One way-nesting:**
  - ➢ D01: $\Delta x = \Delta y = \mathbf{16\ km}$ **(**245x253x51**)**
  - ➢ D02: $\Delta x = \Delta y = \mathbf{4\ km}$ $(253x253x51)$
  - ➢ 51 terrain-following etha levels up to 50 hPa
- <u>Start simulation time</u>: 12 UTC 6 November 2014
- <u>End simulation time</u>: 12 UTC 8 November 2014



3. METHODOLOGY : Numerical Model

Numerical Model Configuration:

- Ensemble of 36 members using different physical parameterizations:

Multiphysic Configuration					
Ensemble Members	Microphysics	Cumulus	PBL	Land Surface	SW/RW radiation
1	Thompson	KF	YSU	Noah	Dudhia
2		KF	YSU		RRTMG
3		KF	MYJ		Dudhia
4		KF	MYJ		RRTMG
5		KF	MYNN2		Dudhia
6		KF	MYNN2		RRTMG
7	Thompson	GF	YSU	Noah	Dudhia
8		GF	YSU		RRTMG
9		GF	MYJ		Dudhia
10		GF	MYJ		RRTMG
11		GF	MYNN2		Dudhia
12		GF	MYNN2		RRTMG
13	Thompson	Tiedke	YSU	Noah	Dudhia
14		Tiedke	YSU		RRTMG
15		Tiedke	MYJ		Dudhia
16		Tiedke	MYJ		RRTMG
17		Tiedke	MYNN2		Dudhia
18		KF	MYNN2		RRTMG
19	Thompson	KF	YSU	Noah	Dudhia
20		KF	YSU		RRTMG
21		KF	MYJ		Dudhia
22		KF	MYJ		RRTMG
23		KF	MYNN2		Dudhia
24		KF	MYNN2		RRTMG
25	Thompson	GF	YSU	Noah	Dudhia
26		GF	YSU		RRTMG
27		GF	MYJ		Dudhia
28		GF	MYJ		RRTMG
29		GF	MYNN2		Dudhia
30		GF	MYNN2		RRTMG
31	Thompson	Tiedke	YSU	Noah	Dudhia
32		Tiedke	YSU		RRTMG
33		Tiedke	MYJ		Dudhia
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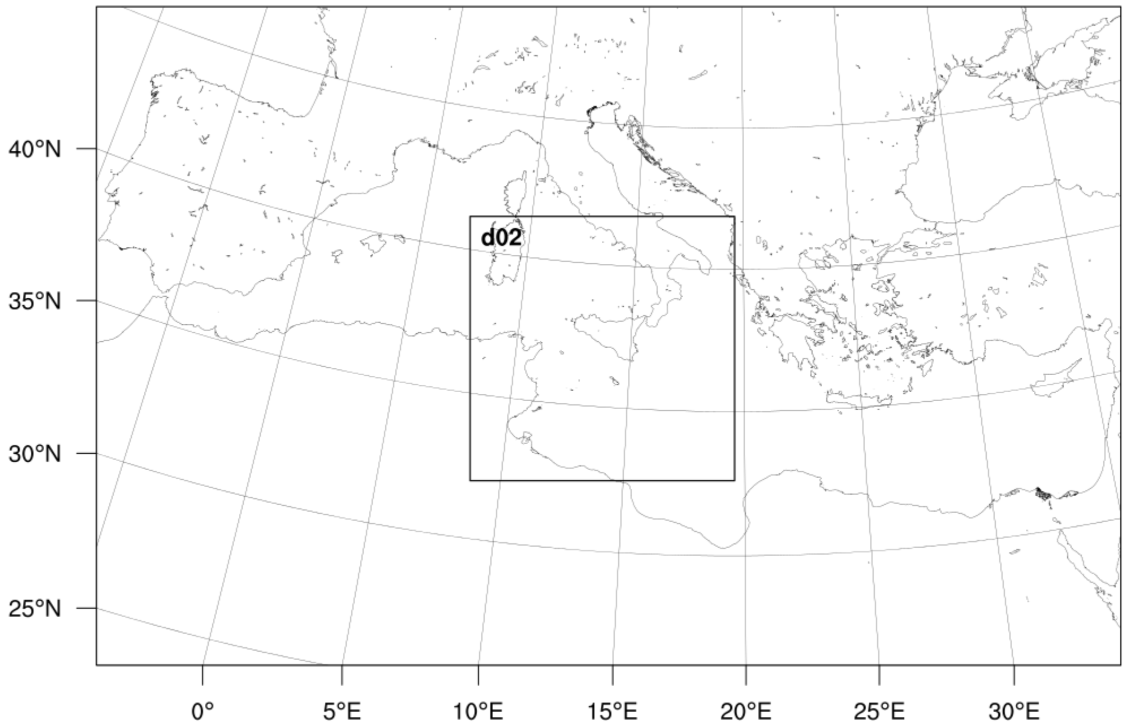
35		Tiedke	MYNN2		Dudhia
36		Tiedke	MYNN2		RRTMG



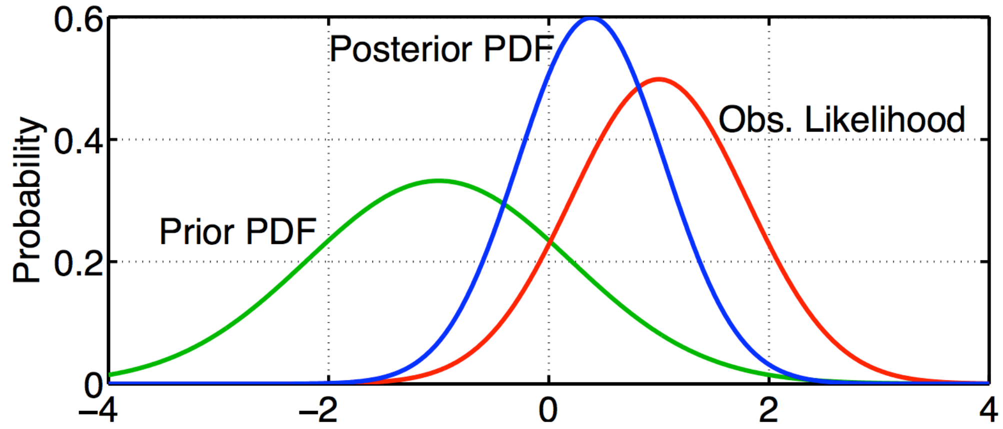
3. METHODOLOGY : Ensemble Kalman Filter (EnKF)

Kalman Filter (KF):

- State vector model with Gaussian probability distribution (**prior**) p(x)
- Error distribution of data with Gaussian probability distribution and no-correlated (d)
- Probability density of the data conditional of the system state x (**obs. Likelihood)** p(d|x)
- **Bayes theorem** allow to combine the pdf of the state and the data likelihood to give a new pdf of the system state conditional on the data d (**the posterior**, also Gaussian):

$$Pxd \propto Pdx\ \ P(x)$$

Posterior Likelihood Prior



3. METHODOLOGY : Ensemble Kalman Filter (EnKF)

Kalman Filter (KF):

- After some statistical assumptions (**minimum-variance** analysis), we can formulate the analysis state vector $\mathbf{X_a}$ as follows:

$$\boldsymbol{x}_a = \boldsymbol{x}_b + \boldsymbol{K}(\boldsymbol{d} - H(\boldsymbol{x}))$$

Where:

$\mathbf{X_b}$ is the "background" or "first guess"

$\mathbf{d\text{-}H(X_b)}$ is the "observational increment" or "innovation"

H is the observation operator which transform model variables to observed magnitudes.

K is the "Kalman gain matrix" (determines the weight given to the observations)

- The Kalman gain matrix is defined as:

$$K = P_b H^T (H P_b H^T + R)^{-1}$$

Where:

$\mathbf{P_b}$ is the covariance of the background error matrix

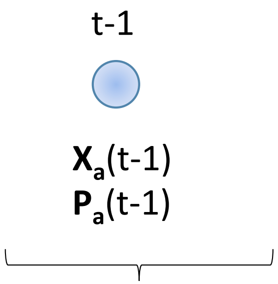
R is the covariance of the observational error matrix

- The larger the background error covariance compared with the observation error covariance, the larger the correction to the first guess.

3. METHODOLOGY : Ensemble Kalman Filter (EnKF)

Kalman Filter (KF):

- **Cycle** of of assimilation => **Forecast** Step + **Update** Step
- In a schematic way, we can represent a **cycle** of the Kalman Filter as following:



Assume that initially the analysis state and its error covariance matrix is given.

3. METHODOLOGY : Ensemble Kalman Filter (EnKF)

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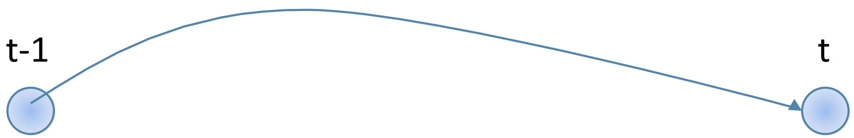

$\mathbf{X}_a(t-1)$
$\mathbf{P}_a(t-1)$

1. Move the model forward
$$\boldsymbol{X}_b(t)=M(\boldsymbol{X}_a(t-1))$$

2. Predict the error cov.
$$\boldsymbol{P}_a(t)=M\boldsymbol{P}_a(t-1)M^T+\boldsymbol{R}(t)$$

Forecast Step

Non-linear numerical model

3. METHODOLOGY : Ensemble Kalman Filter (EnKF)

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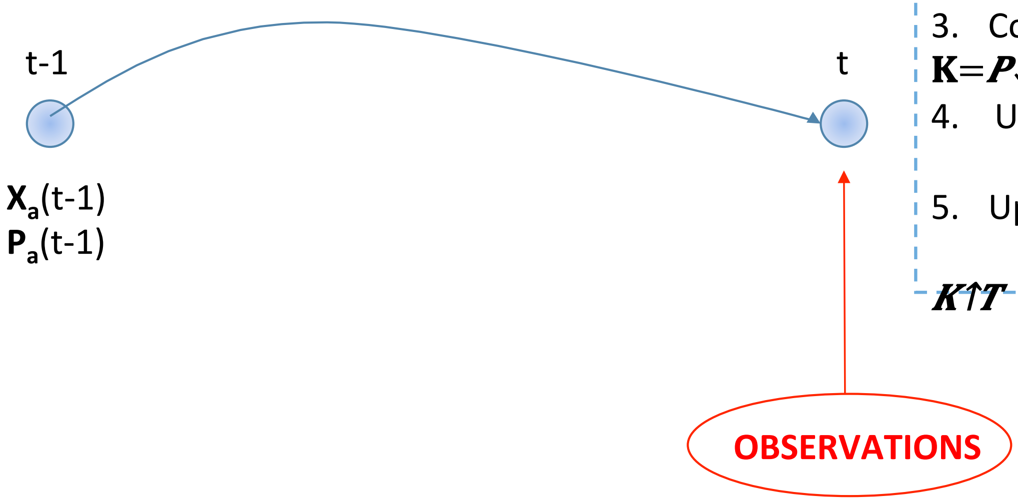


3. Compute the Kalman gain

$$\mathbf{K} = \boldsymbol{P}_b H^T (H \boldsymbol{P}_b H^T + \boldsymbol{R})^{-1}$$

4. Update state estimate

$$\boldsymbol{X}_a(t) = \boldsymbol{X}_b(t) + \boldsymbol{K}(\boldsymbol{d} - H(\boldsymbol{X}_b(t)))$$

5. Update error state estimate

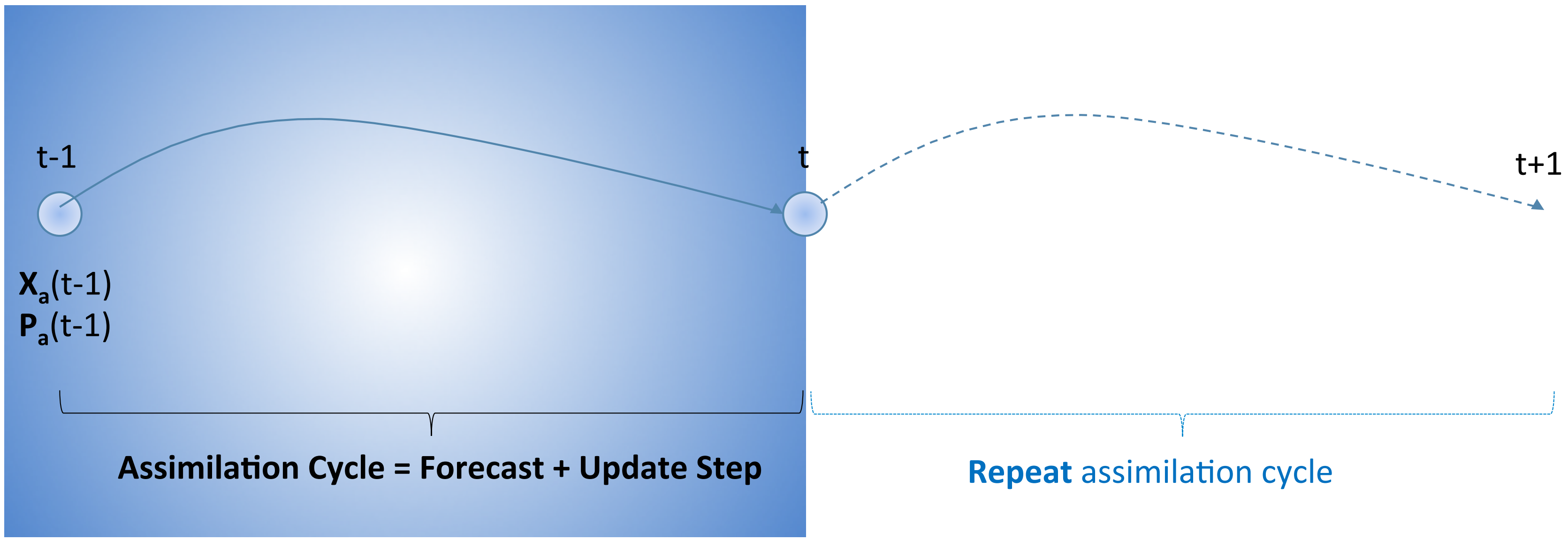
$$\boldsymbol{P}_a(t) = (I - \boldsymbol{K}H)\, \boldsymbol{P}_b(t)(\boldsymbol{I} - \boldsymbol{K}H)^T + \boldsymbol{K}\boldsymbol{R}\boldsymbol{K}^T$$

Update Step

3. METHODOLOGY : Ensemble Kalman Filter (EnKF)

Kalman Filter (KF):

- **Cycle** of of assimilation => **Forecast** Step + **Update** Step
- In a schematic way, we can represent a **cycle** of the Kalman Filter as following:

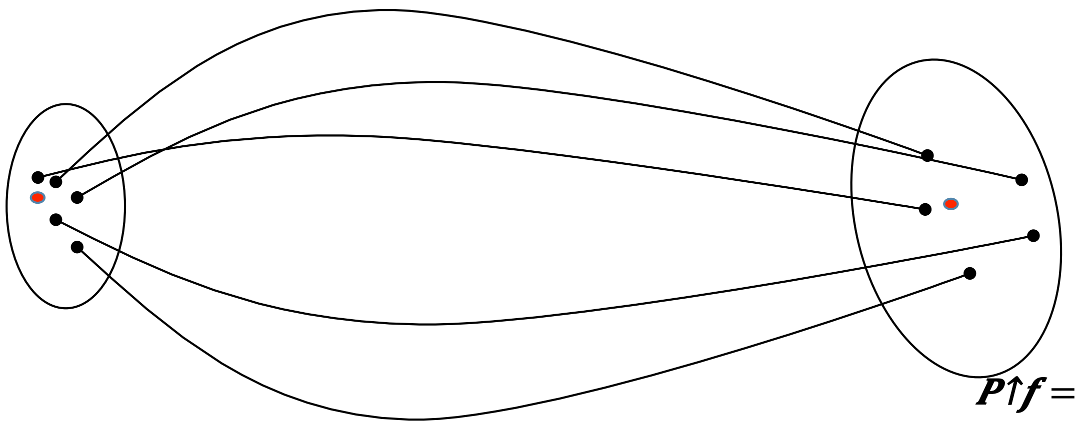


3. METHODOLOGY : Ensemble Kalman Filter (EnKF)

Ensemble Kalman Filter (EnKF):

- Kalman Filter is **computationally high-cost** for large dimensional systems (performance of large covariance matrix errors)
- Ensemble Kalman Filter (EnKF) gives a **statistical approximation to the KF by sampling the errors** of the forecast and analysis (Monte Carlo approach)
- Error **covariances in EnKF are constructed as sample covariances from an ensemble** of background/analysis fields
- The main property of EnKF is that the error **covariances are implicitly propagated** in time through the ensemble forecasts

Initial Time:
N samples, $\mathbf{x}_i$ from the background



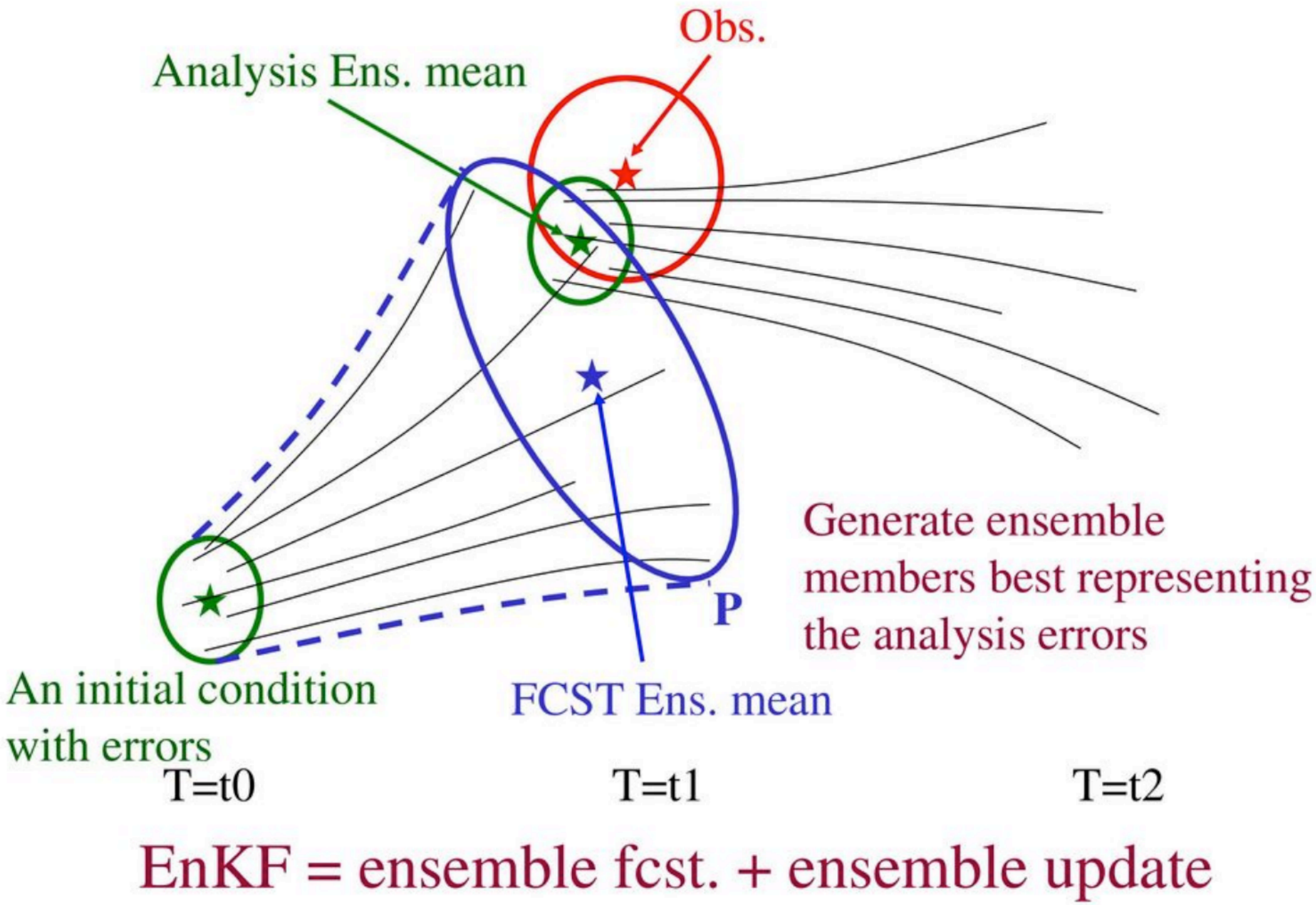
Later Time:

$$\boldsymbol{x} = 1/N-1 \sum_{i}^{N} M(\boldsymbol{x}_{\boldsymbol{i}})$$

$$\boldsymbol{P}^{\boldsymbol{f}} = 1/N-1 \sum_{i}^{N} (M(\boldsymbol{x}_{\boldsymbol{i}}) - \boldsymbol{x})^{T} (M(\boldsymbol{x}_{$$

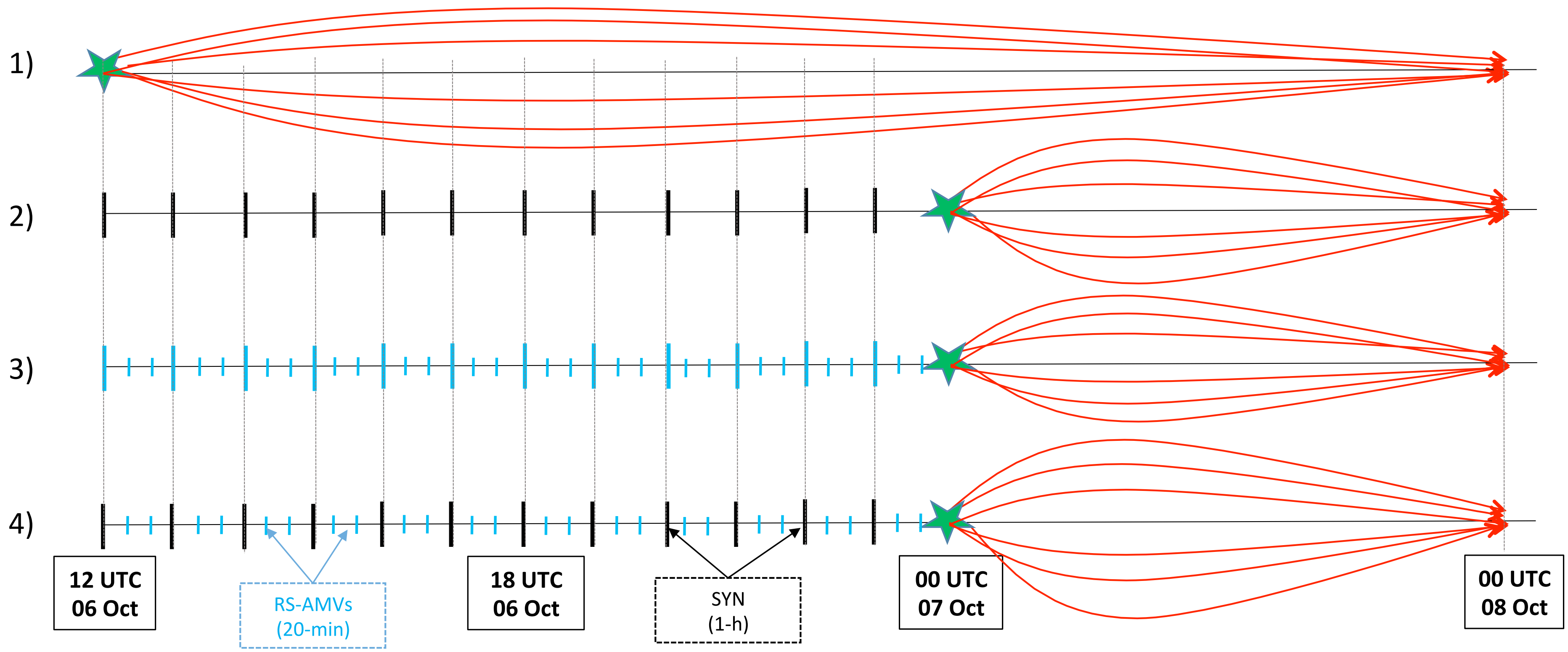
3. METHODOLOGY : Ensemble Kalman Filter (EnKF)

Ensemble Kalman Filter (EnKF):



3. METHODOLOGY : Experimental Design

1) **NODA** (No data assimilation)
2) **SYN** (hourly conventional data assimilation from MADIS database)
3) **RS-AMV** (20-min Rapid Scan Atmospheric Motion Vector data assimilation)
4) **CNTRL** (SYN+RS-AMV data assimilation)



4. PRELIMINAR RESULTS

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For the experiment **RS-AMV** experiment we performed several tests tuning the following parameters:

1. Observational errors:

Several numerical simulations reducing the observational error (5%, 25%, 50%, 75%)

4. PRELIMINAR RESULTS

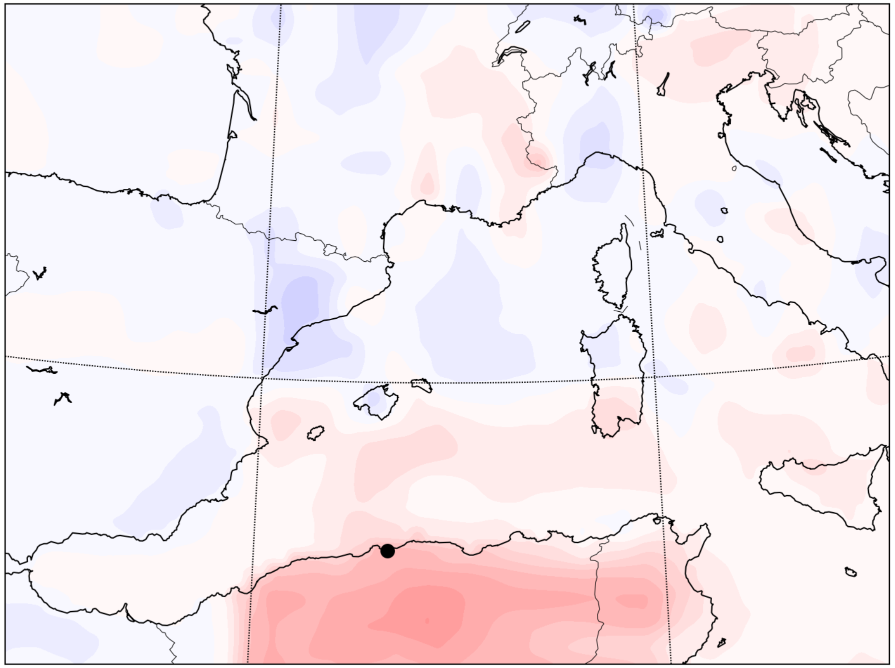
For the experiment **RS-AMV** experiment we performed several tests tuning the following parameters:

1. *Observational errors*
2. ***Covariance influence***

   Check the effect of using different localizations:

   500, 300, 250, 100 km radii of covariance

Covariance T2m



4. PRELIMINAR RESULTS

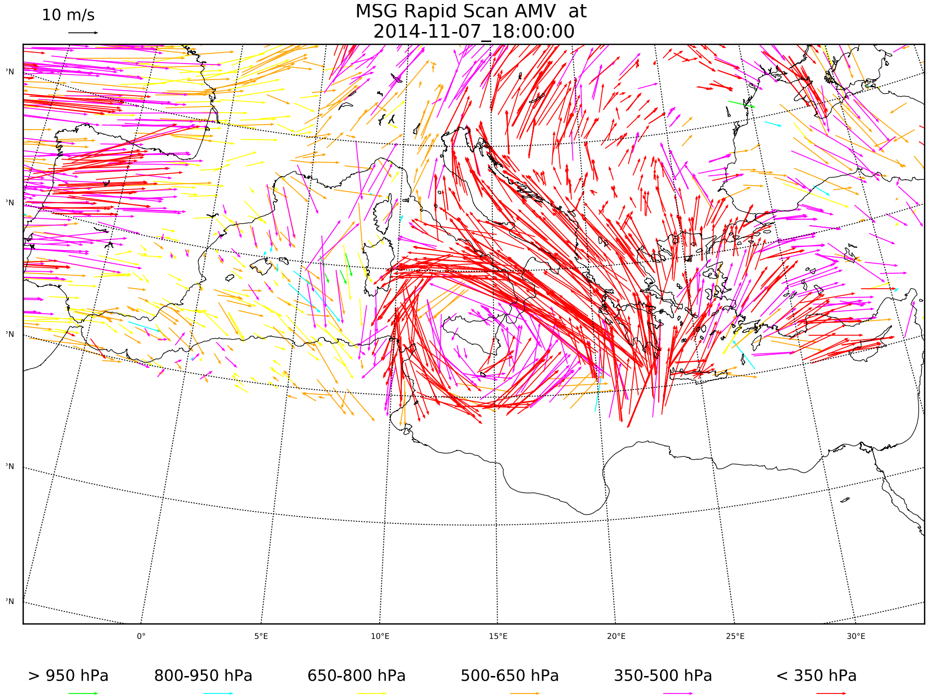
For the experiment **RS-AMV** experiment we performed several tests tuning the following parameters:

1. *Observational errors*
2. *Covariance influence*
3. ***Superobbing***

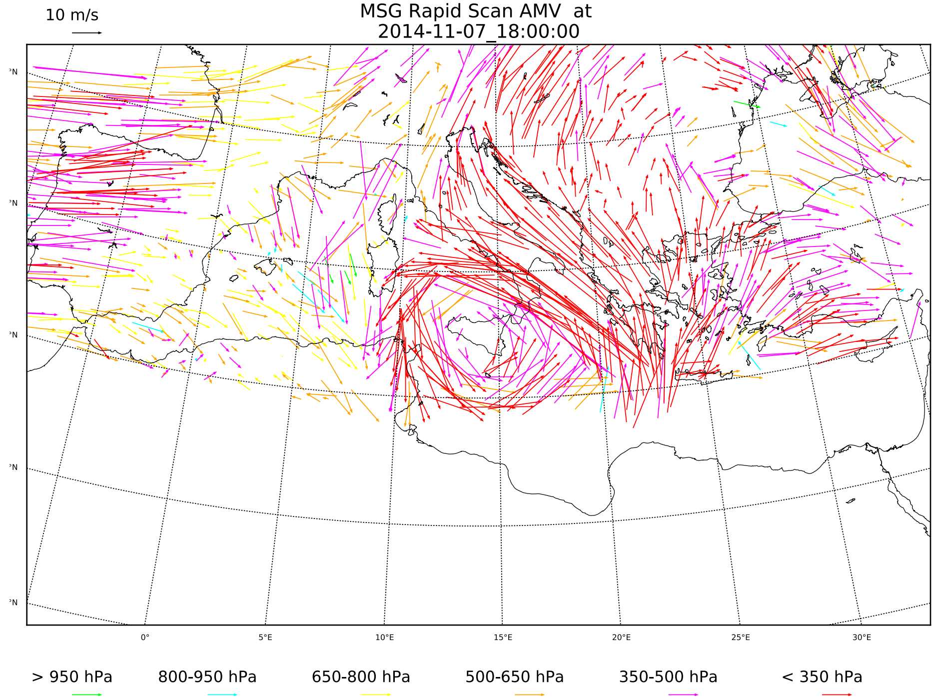
4. PRELIMINAR RESULTS

SUPERROBBING: In this case, we average available observations using prisms of 96 km x 96 km x 25 hPa

RAW RS-AMVs



SUPEROBBING RS-AMVs



4. PRELIMINAR RESULTS

- ***Which of these experiment is the most suitable as analysis to start the forecast stage?***

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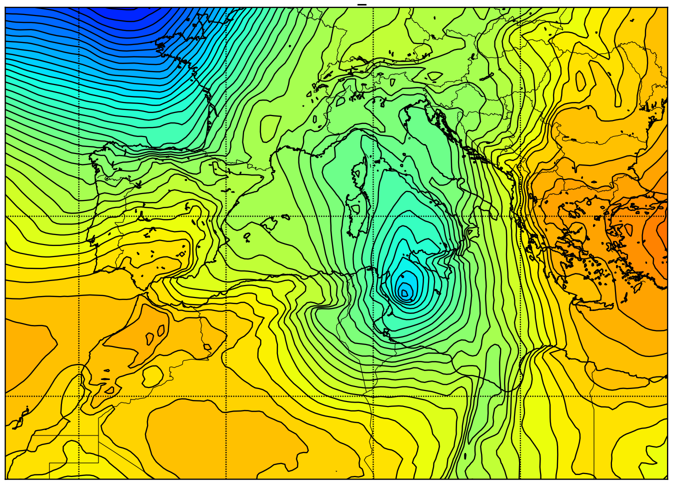
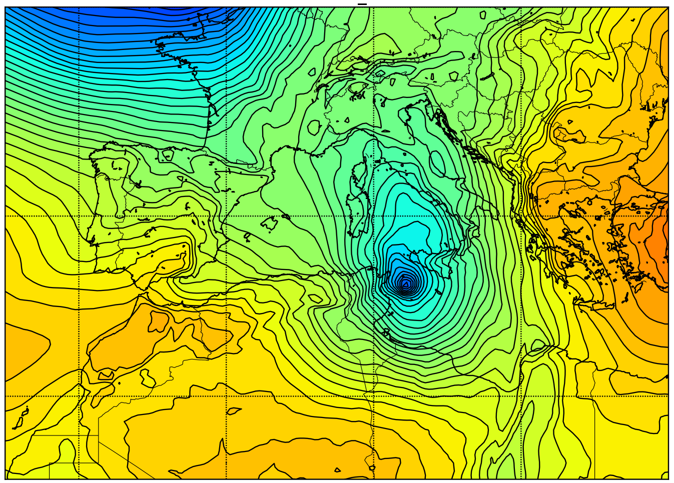
- ***Which of these experiment is the most suitable as analysis to start the forecast stage?***

- To answer this question we look for the analysis that best correlates with the **ERA5 reanalyses** (15 km grid resolution) from ECMWF at the analysis time (00 UTC on 07 November)

4. PRELIMINAR RESULTS

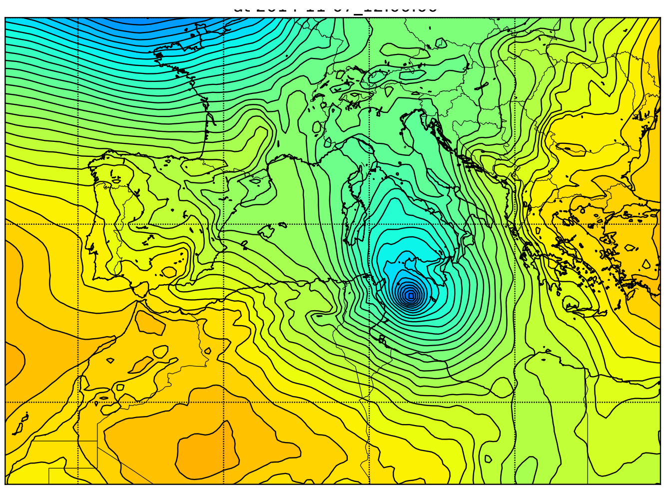
07 Nov
00 UTC

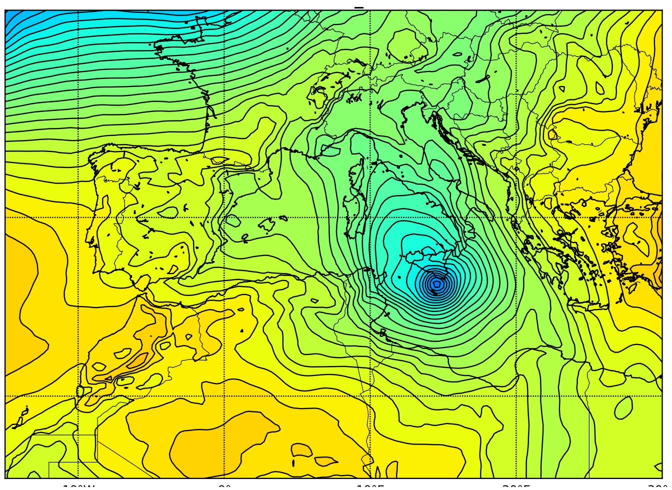




07 Nov
06 UTC

07 Nov
12 UTC

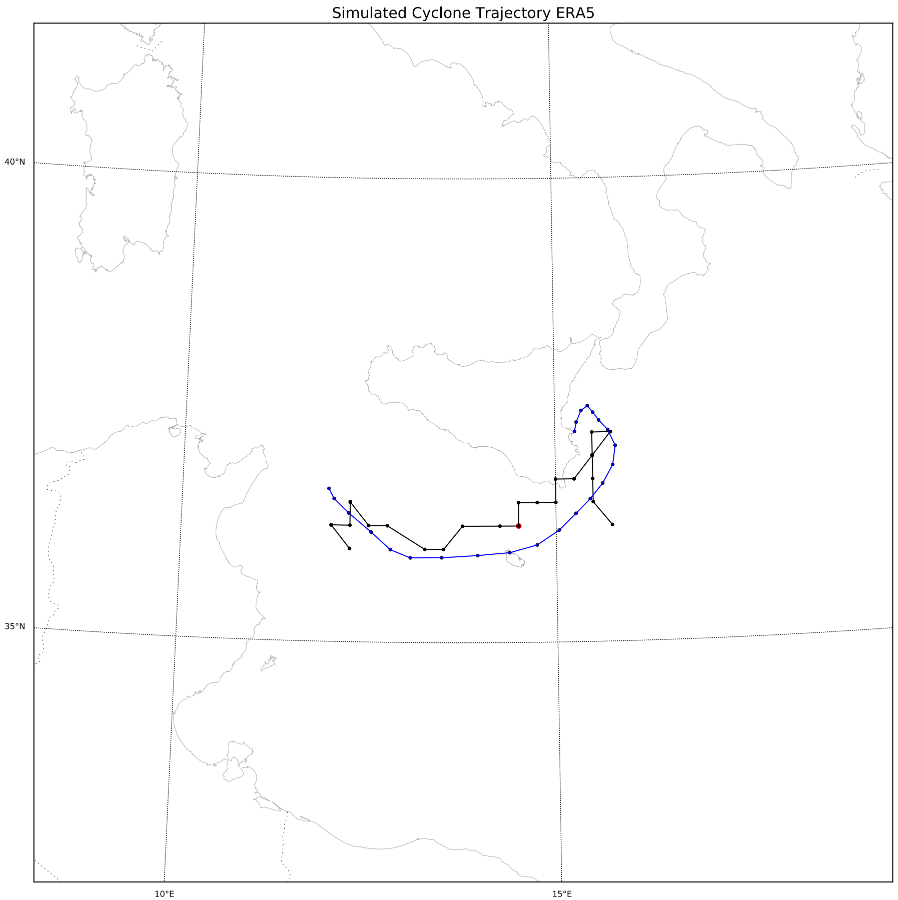


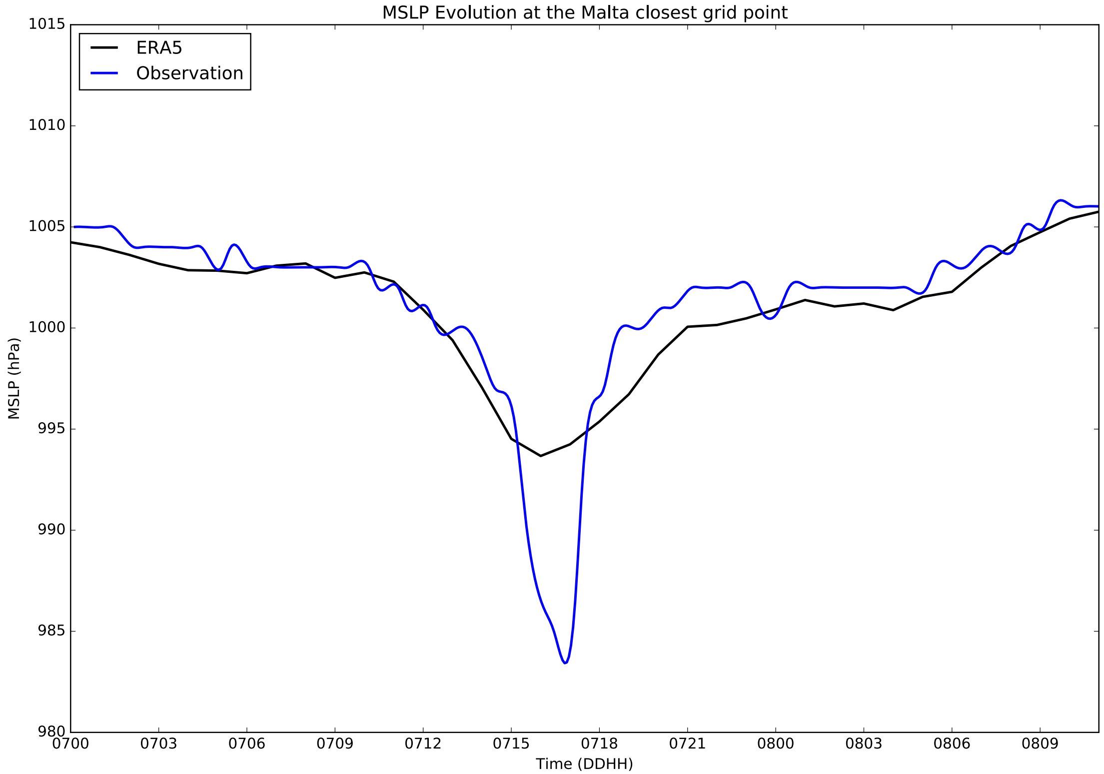


07 Nov
18 UTC

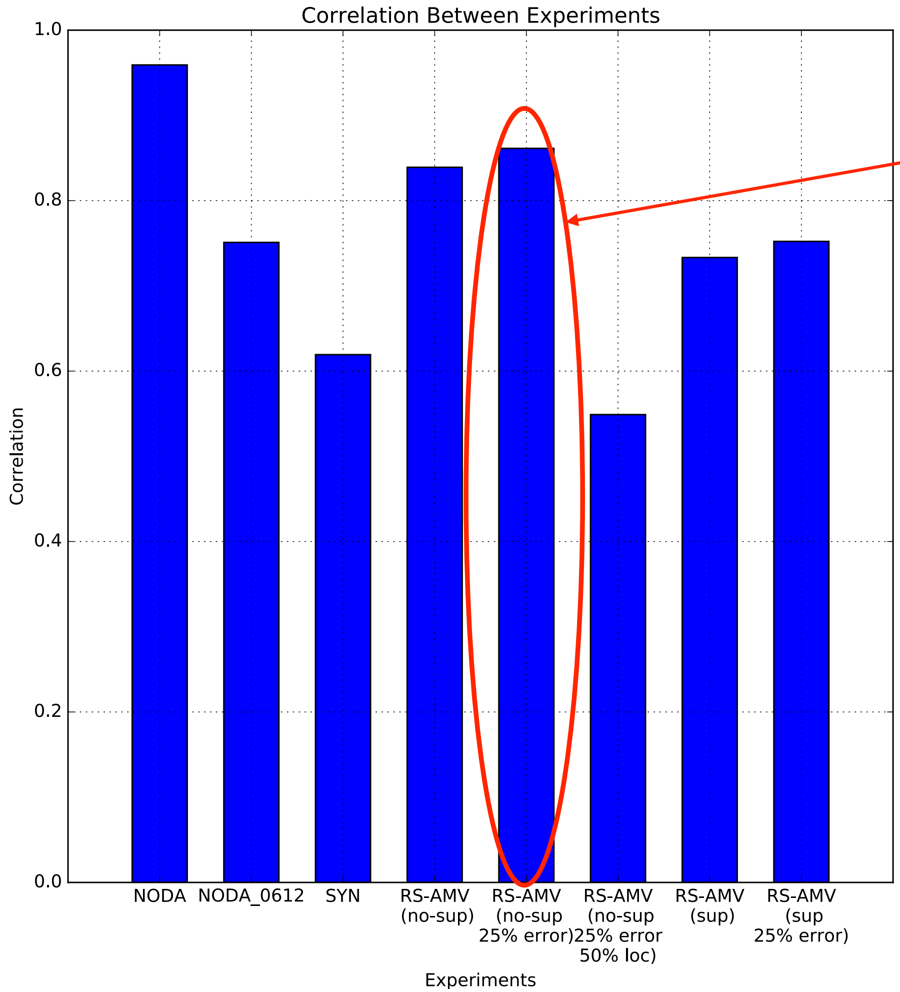
4. PRELIMINAR RESULTS

ERA5 Track and MSLP Verification:





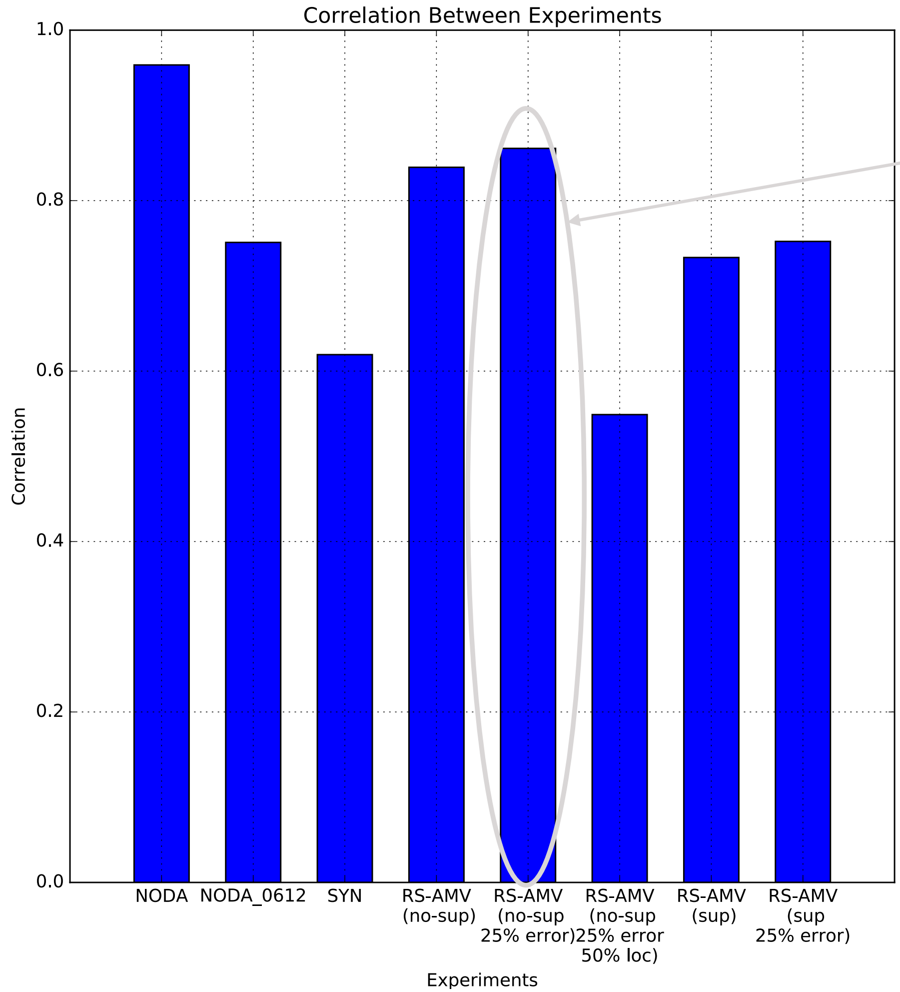
4. PRELIMINAR RESULTS



Assimilation of AMVs without performing superobbing and reducing 25% of the ECMWF error statistics

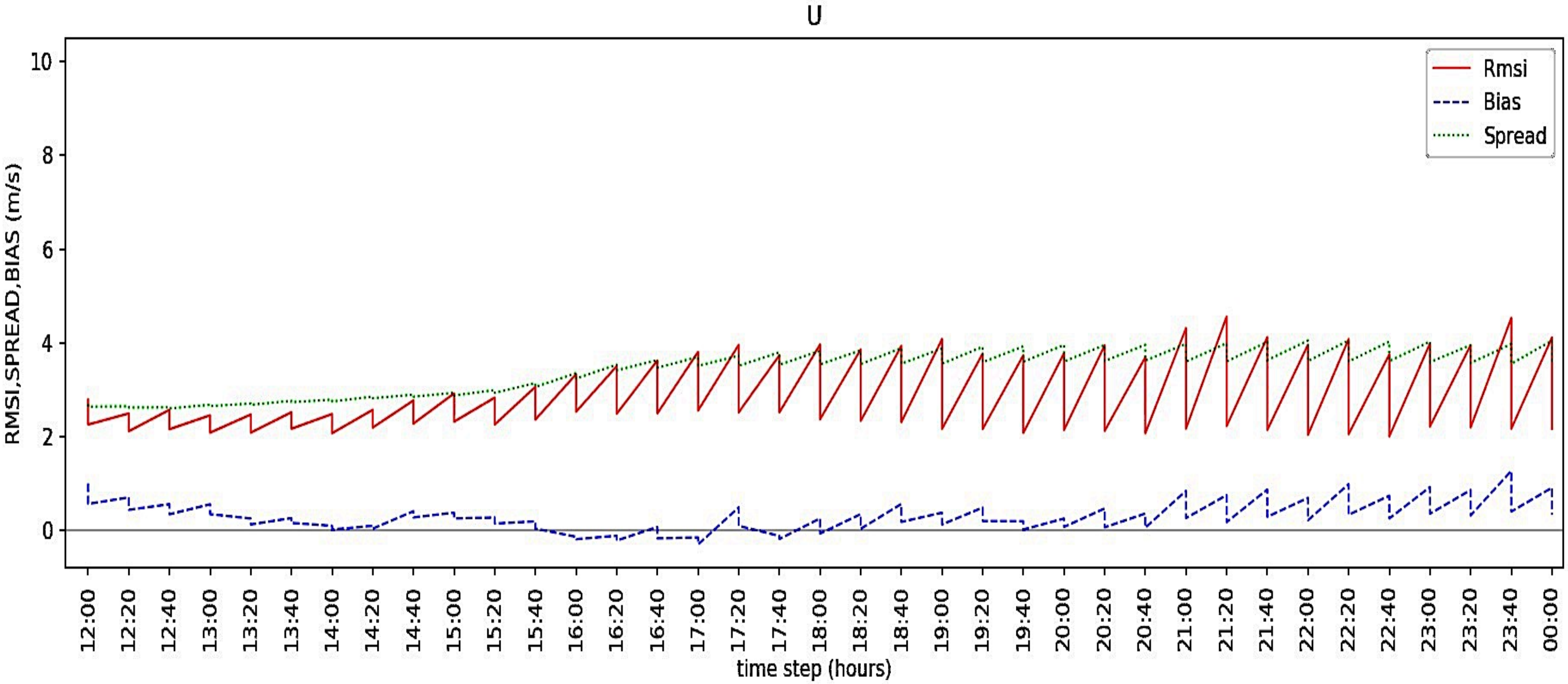
4. PRELIMINAR RESULTS

For the CONTROL simulation we are going to choose the RS-AMV (no-superobbing and with observational errors reduced) and the conventional observations!!



Assimilation of AMVs without performing superobbing and reducing 25% of the ECMWF error statistics

4. PRELIMINAR RESULTS



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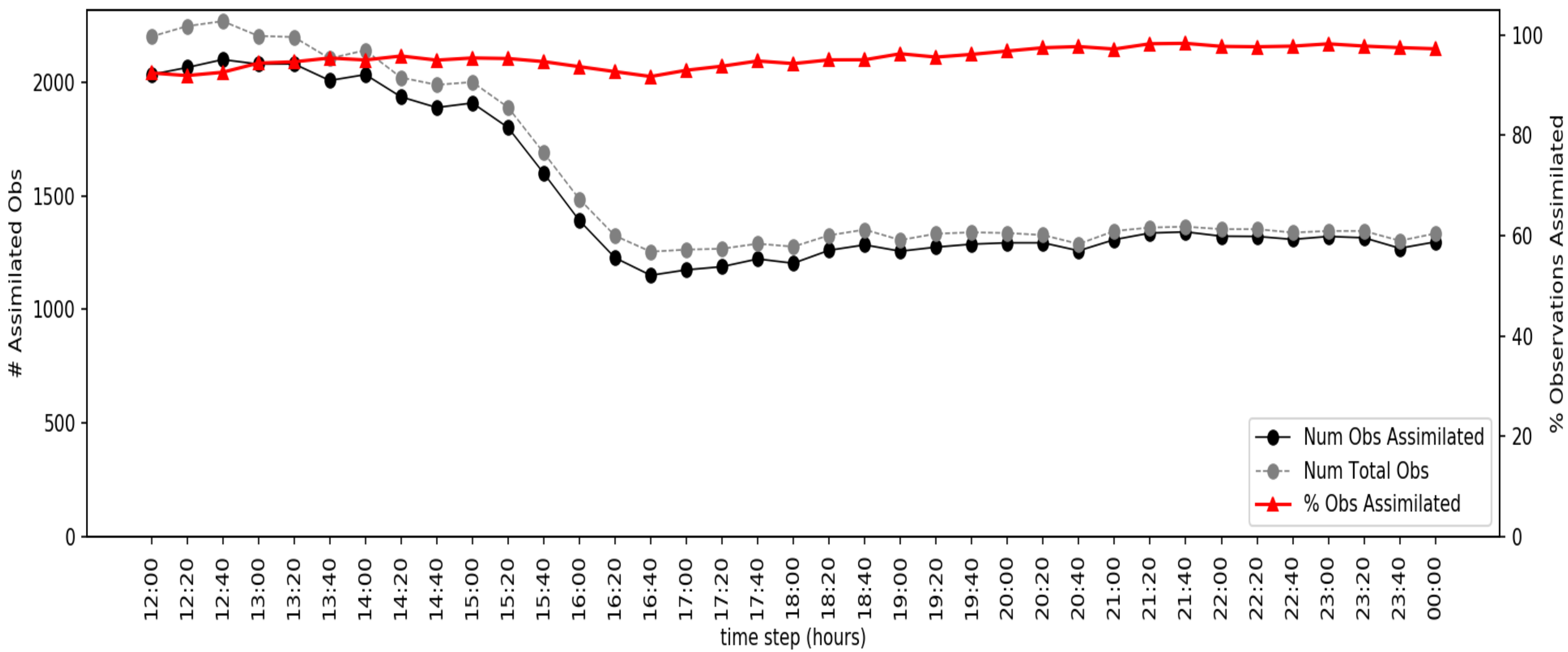
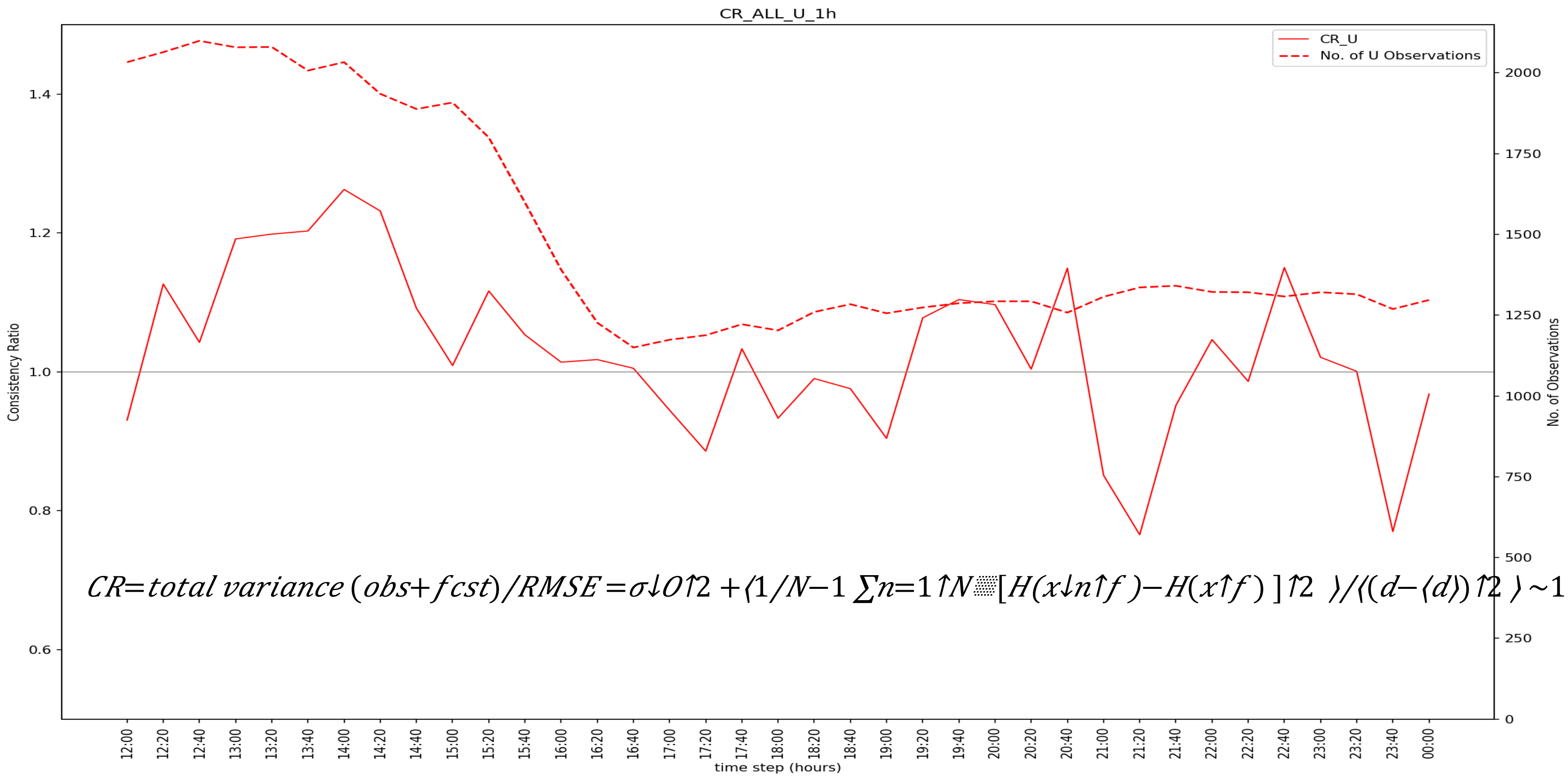


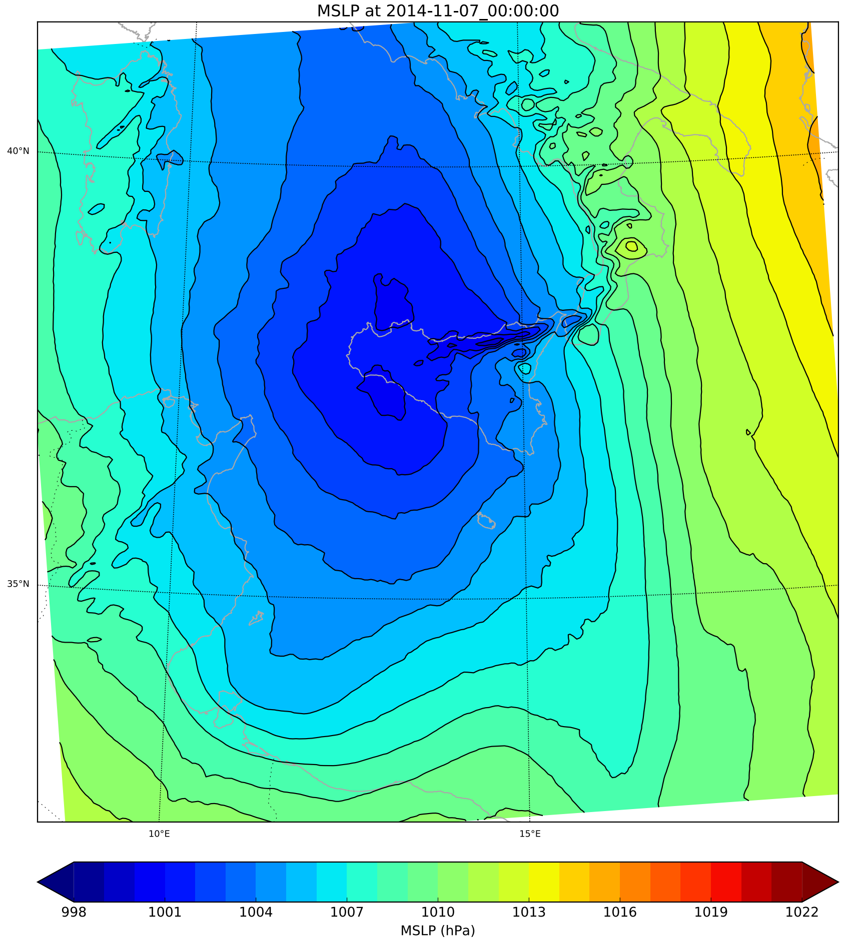
4. PRELIMINAR RESULTS



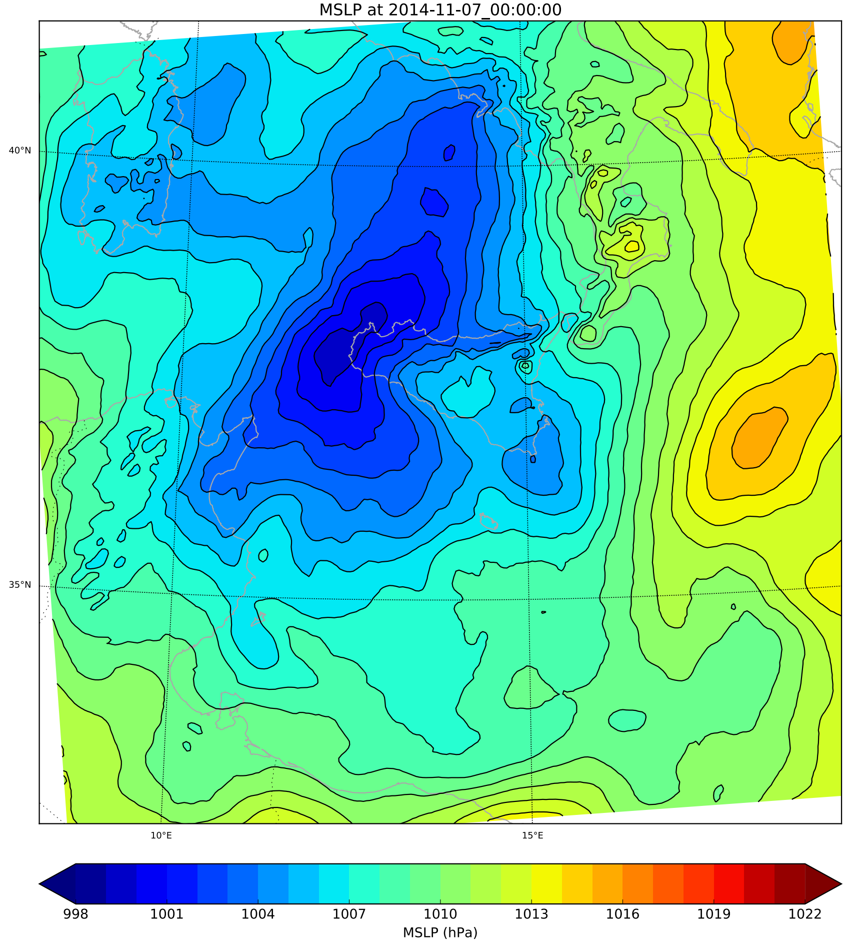
$$CR = \frac{\text{total variance}\,(obs+fcst)}{RMSE} = \frac{\sigma_O^2 + \left\langle \frac{1}{N-1}\sum_{n=1}^{N}\left[H(x_n^f) - H(x^f)\right]^2 \right\rangle}{\left\langle (d - \langle d \rangle)^2 \right\rangle} \sim 1$$

4. PRELIMINAR RESULTS

NODA



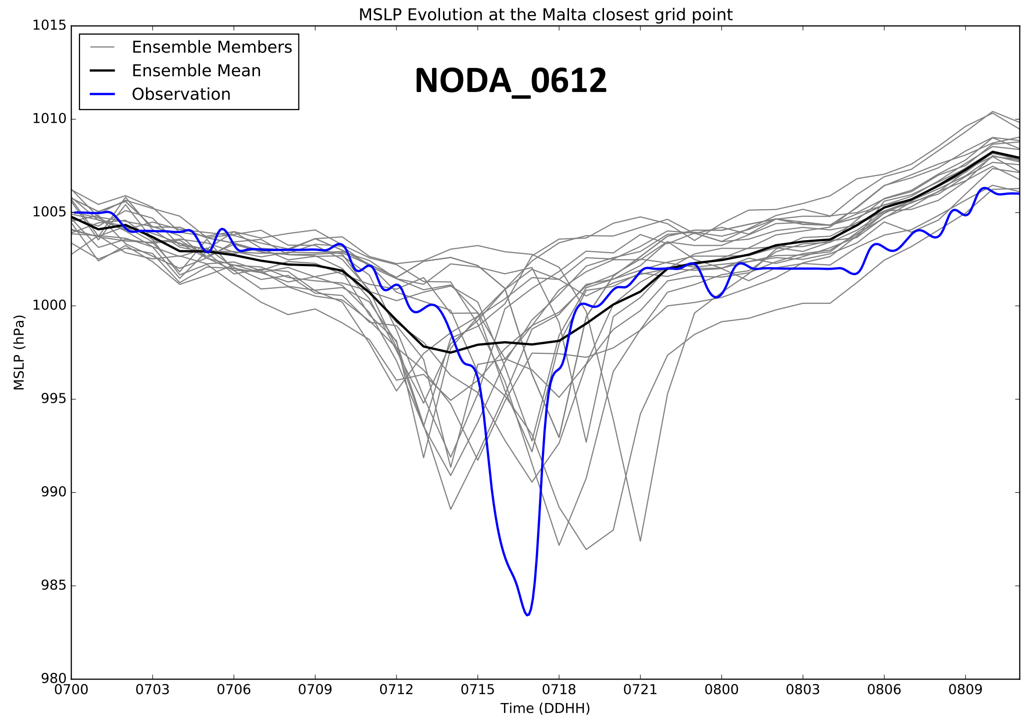
CNTRL

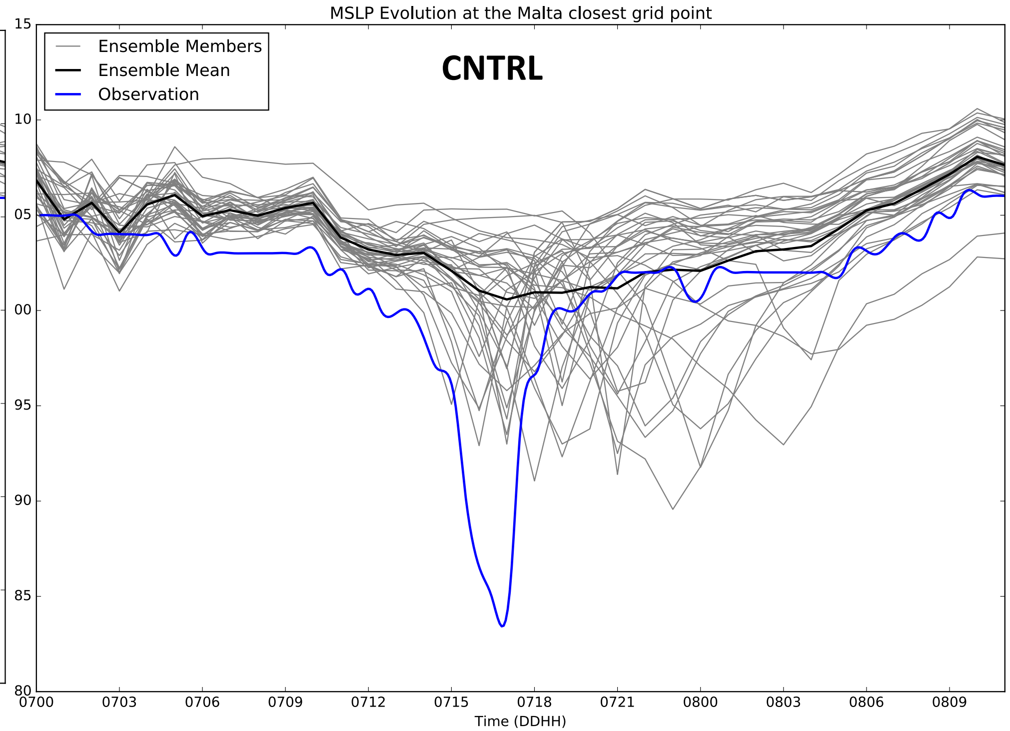


4. PRELIMINAR RESULTS

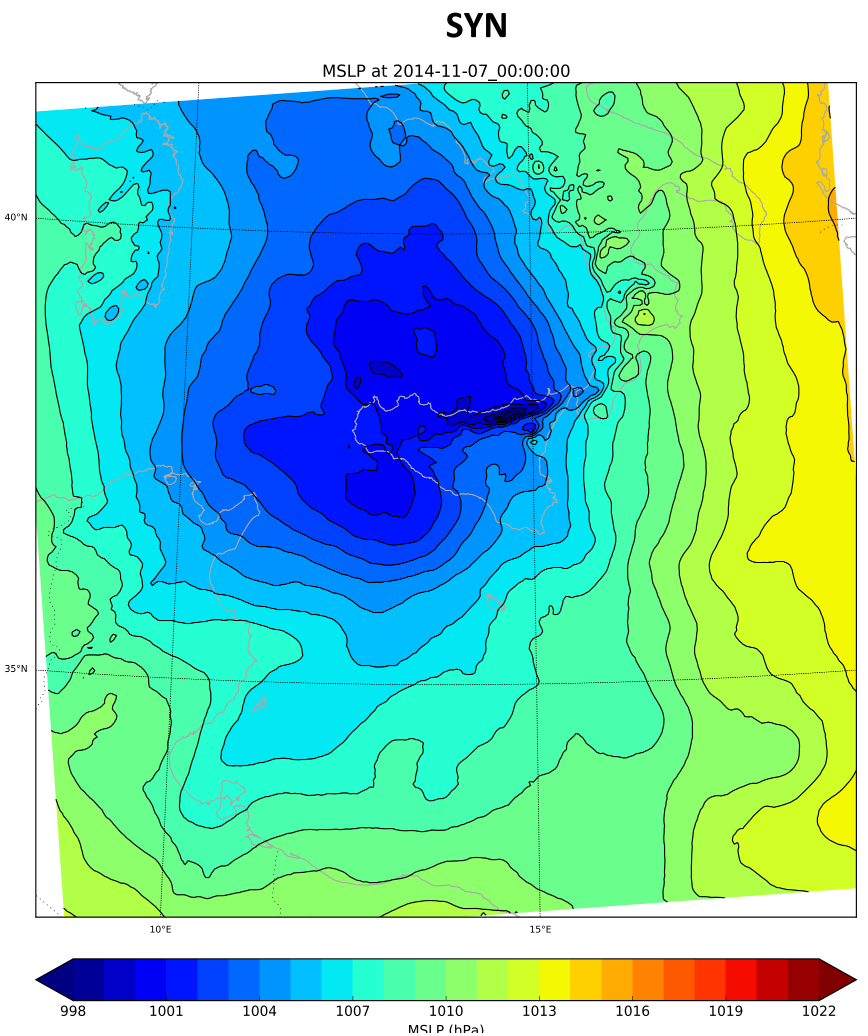
- CNTRL experiment (assimilation of both sources of obs) depicts a temporal shifting towards posterior hours.

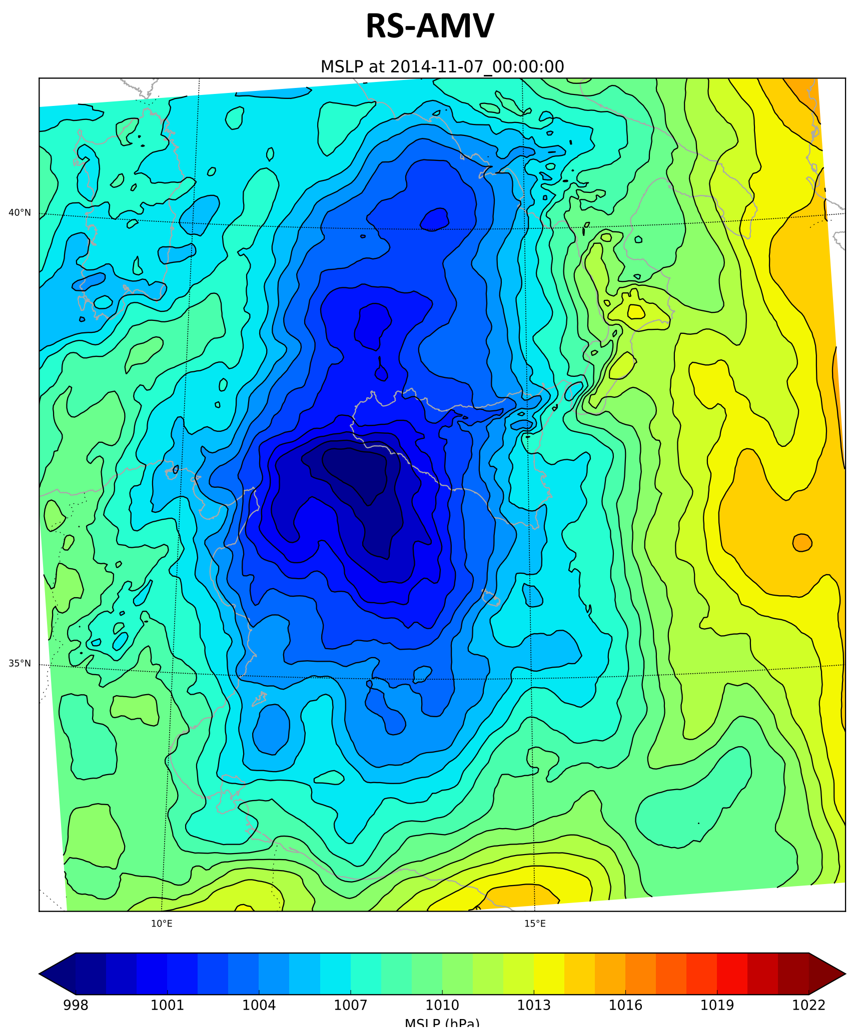
- **What is the problem of the assimilation? Why the assimilation of both kind of observations does not help to better depict the observed pressure drop in Malta?**





4. PRELIMINAR RESULTS

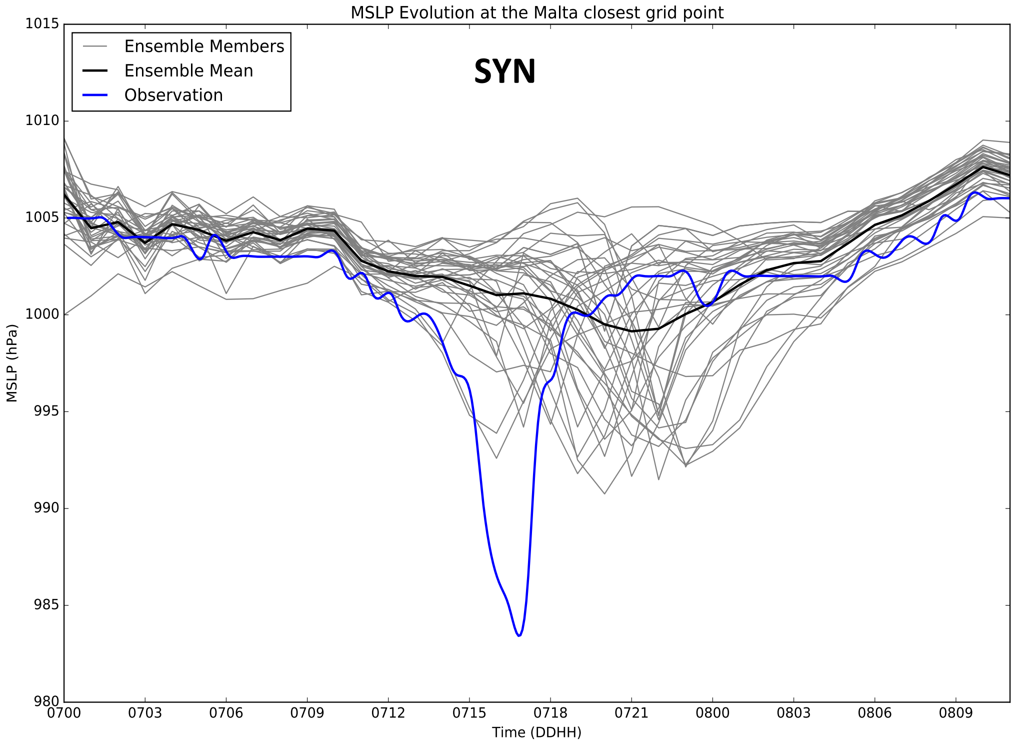


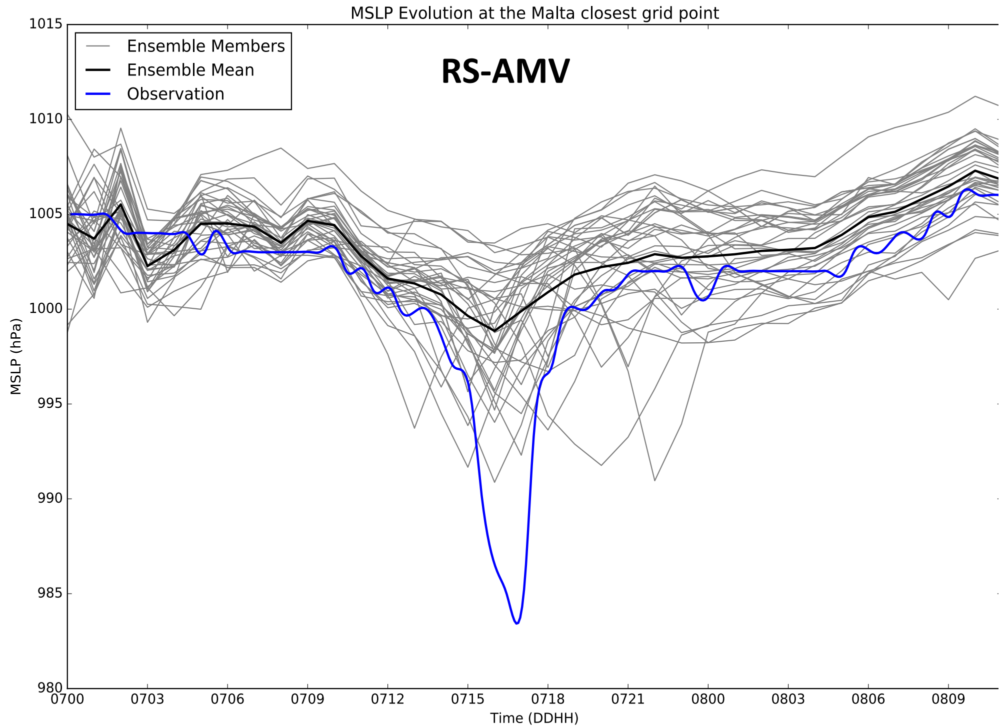


4. PRELIMINAR RESULTS

- To better understand what is going on in the CNTRL experiment I perform the experiments 2) **SYN** and 3) **RS-AMVs independently**.

- Results indicate that the responsible to the **temporal shift of the pressure drop** of the majority of ensemble members is **due to the assimilation of conventional observations**.



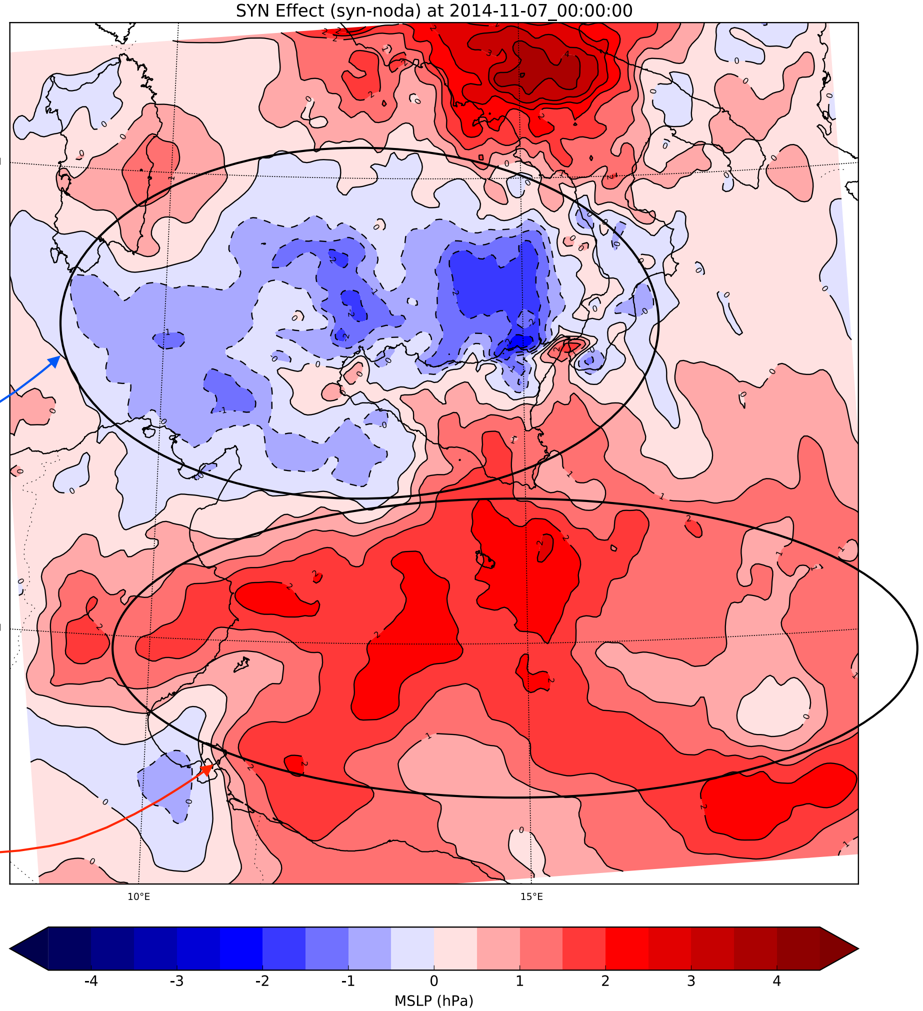


4. PRELIMINAR RESULTS

MSLP Increments (SYN-NODA)

The assimilation of conventional data reduces the pressure

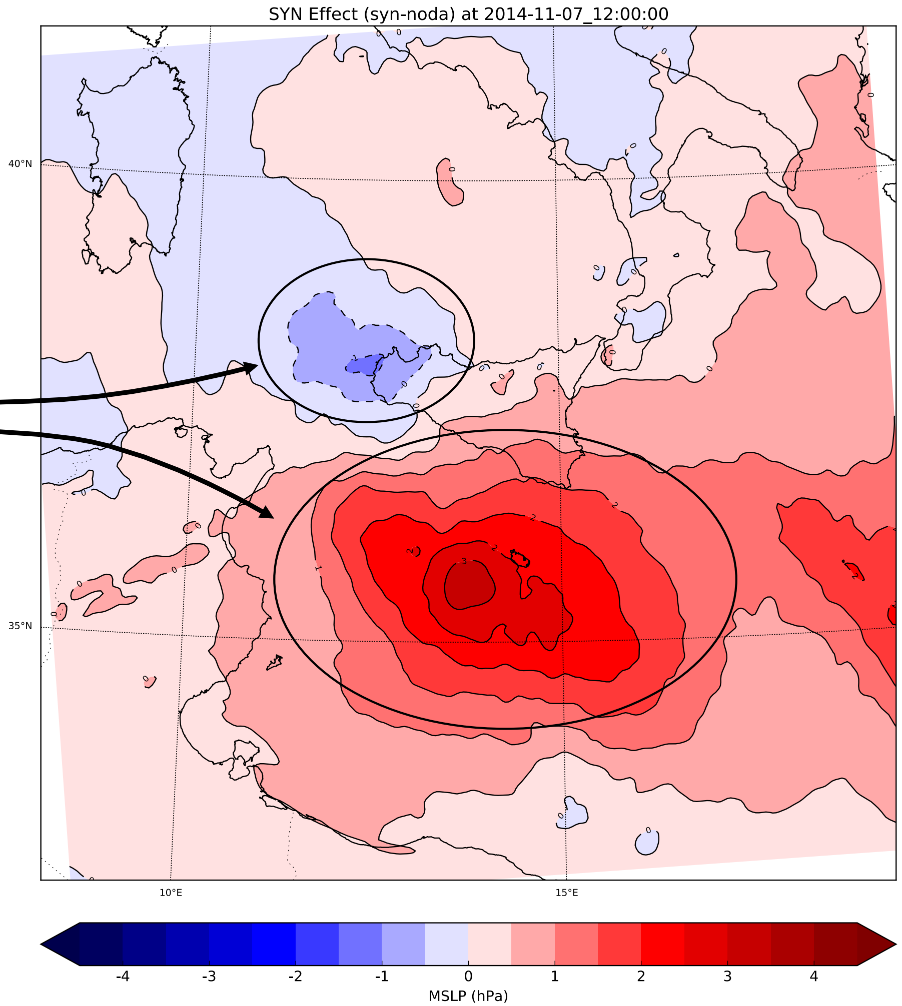
The assimilation of conventional data increases the pressure



4. PRELIMINAR RESULTS

MSLP Increments (SYN-NODA) 12 hours later.

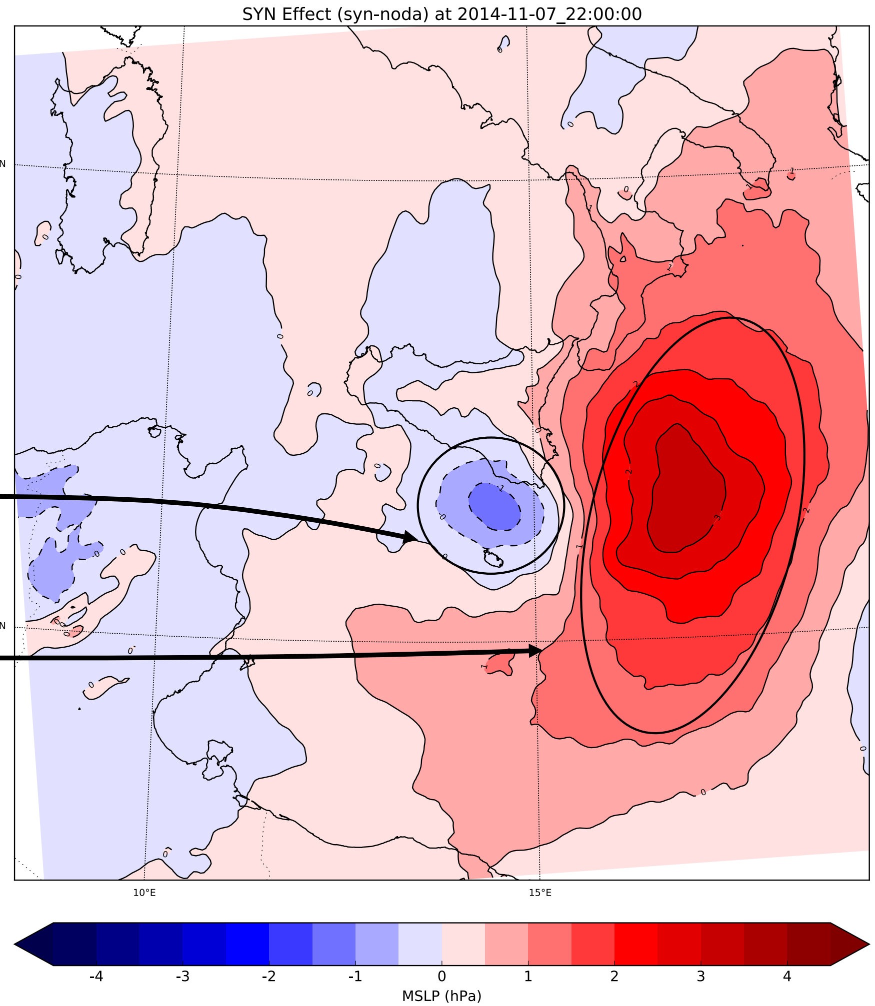
The assimilation of conventional data delays the cyclogenesis!!



4. PRELIMINAR RESULTS

MSLP Increments (SYN-NODA) 22 hours later.

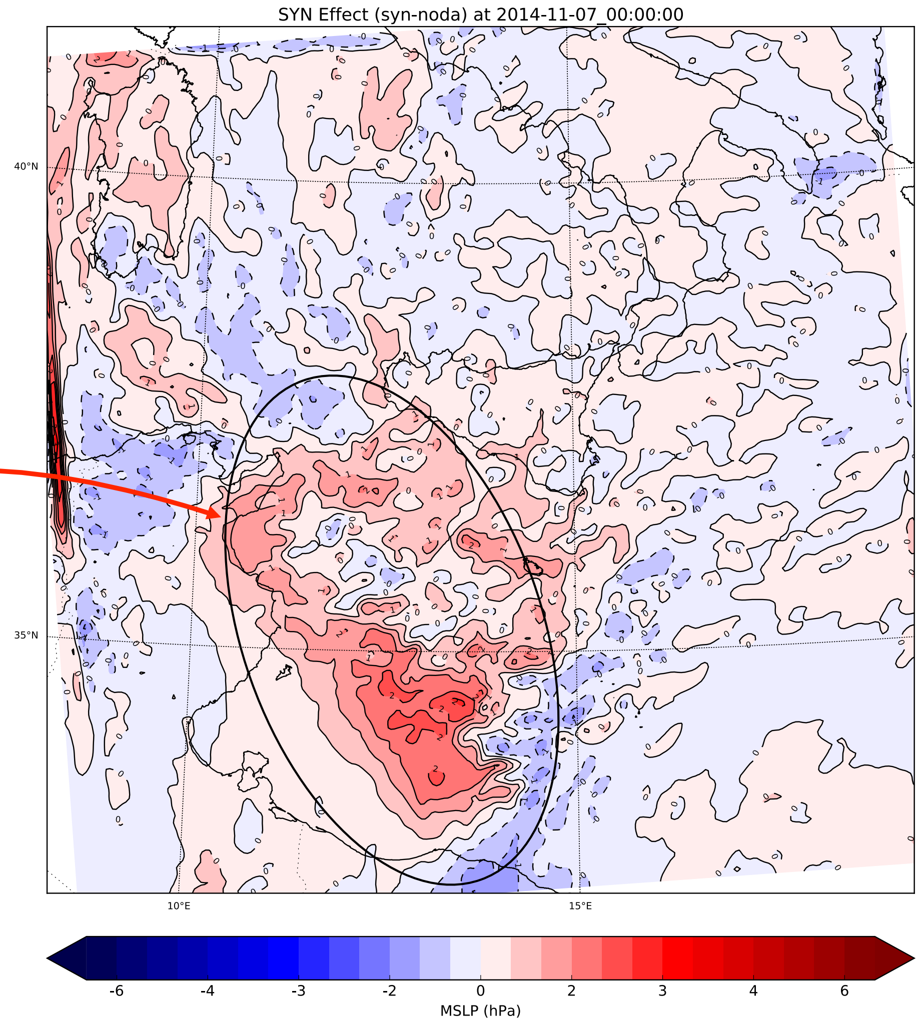
The assimilation of conventional data delays the cyclogenesis!!



4. PRELIMINAR RESULTS

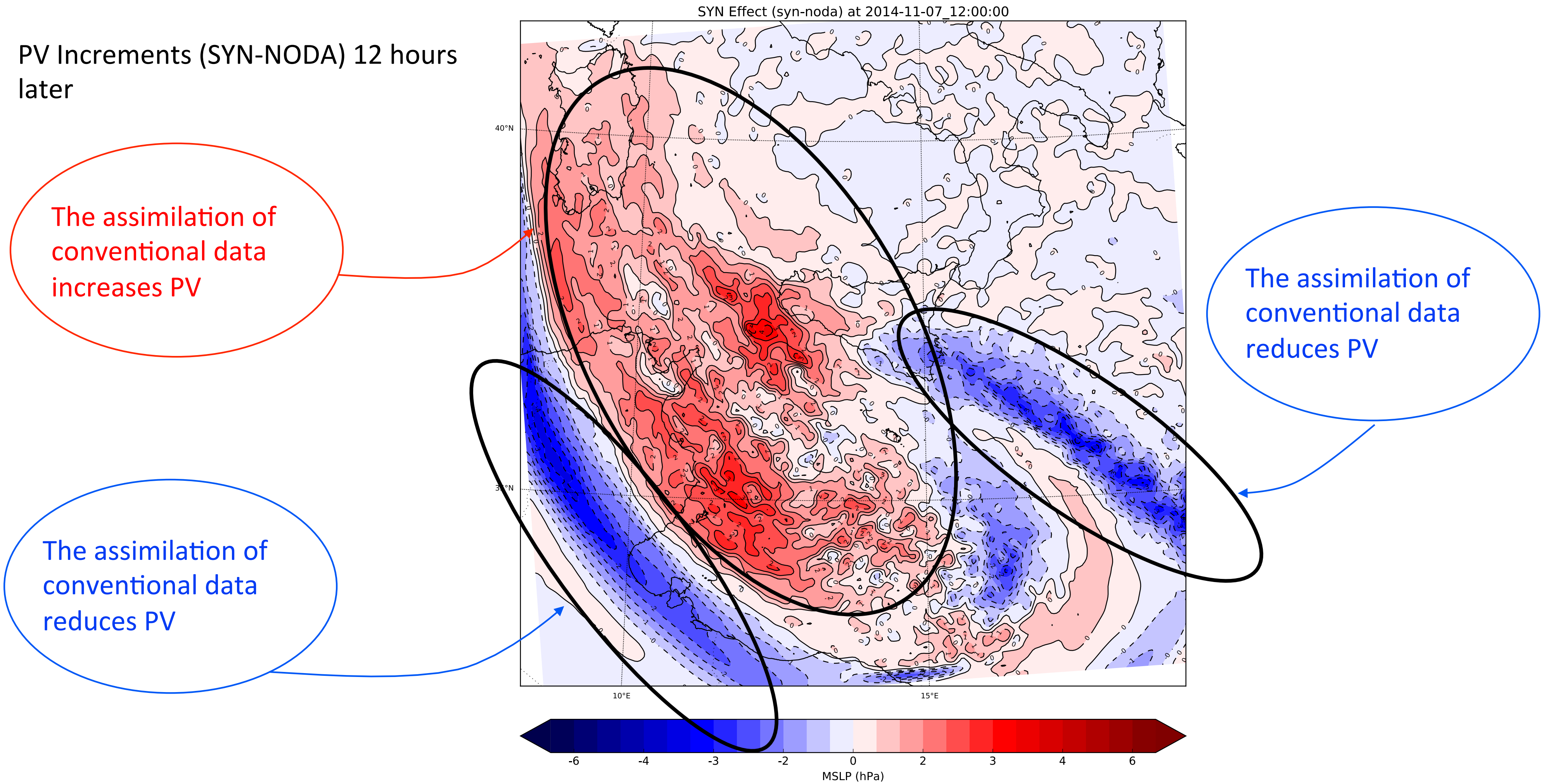
Potential Vorticity (PV) Increments (SYN-NODA)

The assimilation of conventional data increases the PV



4. PRELIMINAR RESULTS

PV Increments (SYN-NODA) 12 hours later



4. PRELIMINAR RESULTS

- For this reason, I focused on understanding why the assimilation of the conventional observations deteriorate the results.

- I performed **two additional experiments** with the main aim of improving the interpretation of the results: One experiment assimilating **only METAR** data and the other **only** assimilating **MARINE** observations.

In addition, I change the default observational errors to similar errors used in Romine et al. 2012.

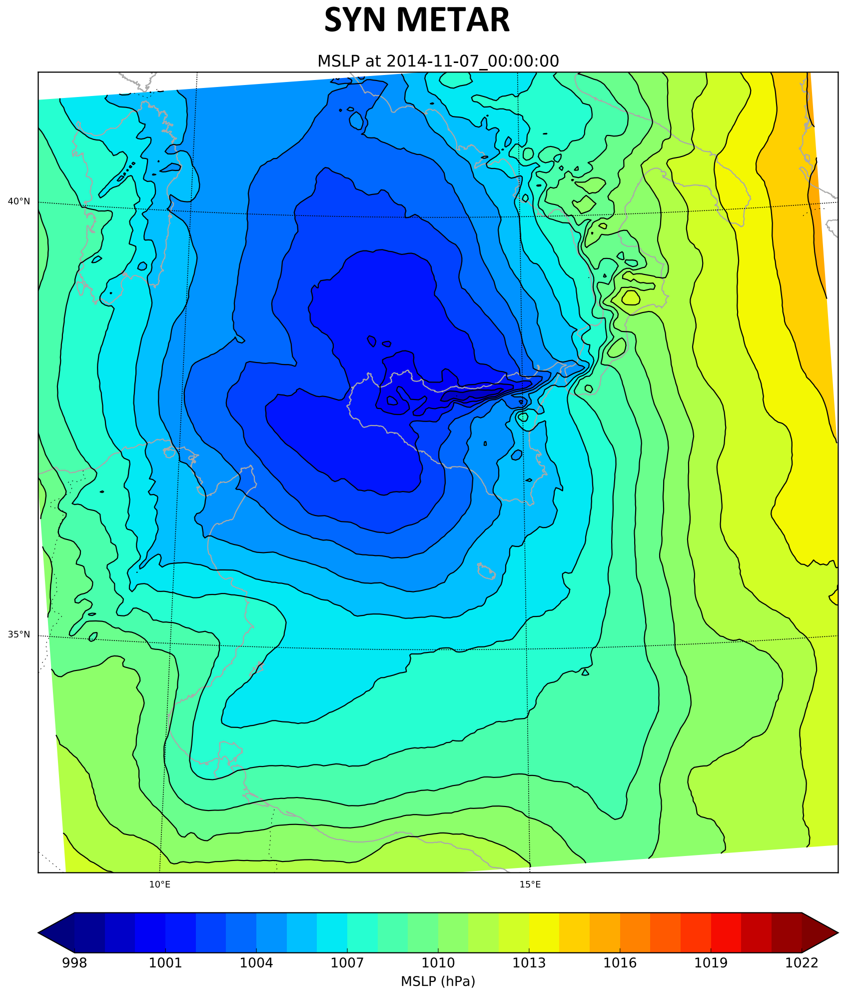
Default errors:

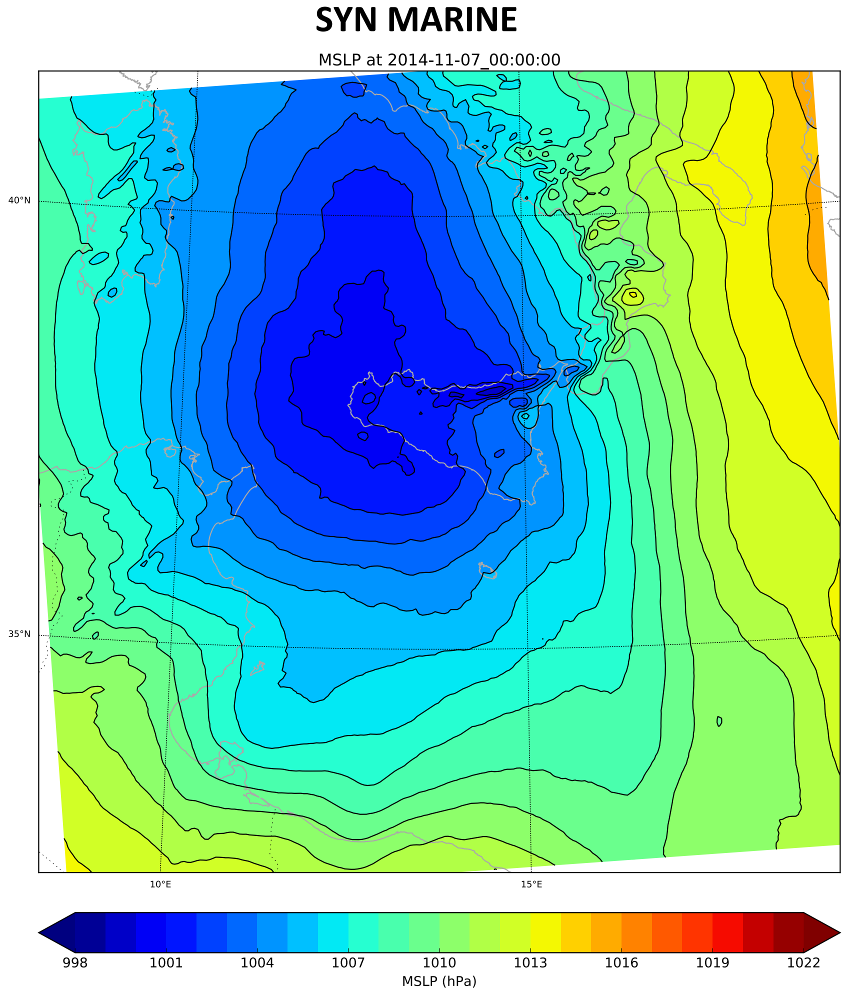
METAR:	T	1.75 K
	U/V	1.75 m/s
	Dewpoint	Lin and Hubbard (2004)
	Altimeter	1 hPa
Buoys and ship reports:	T	2.5 K
	U/V	1.75 m/s
	Dewpoint	Lin and Hubbard (2004)
	Altimeter	1.6 hPa

Modified errors according Romine et al. 2012:

METAR:	T	**2 K**
	U/V	1.75 m/s
	Dewpoint	Lin and Hubbard (2004)
	Altimeter	1 hPa
Buoys and ship reports:	T	**2 K**
	U/V	1.75 m/s
	Dewpoint	Lin and Hubbard (2004)
	Altimeter	**1 hPa**

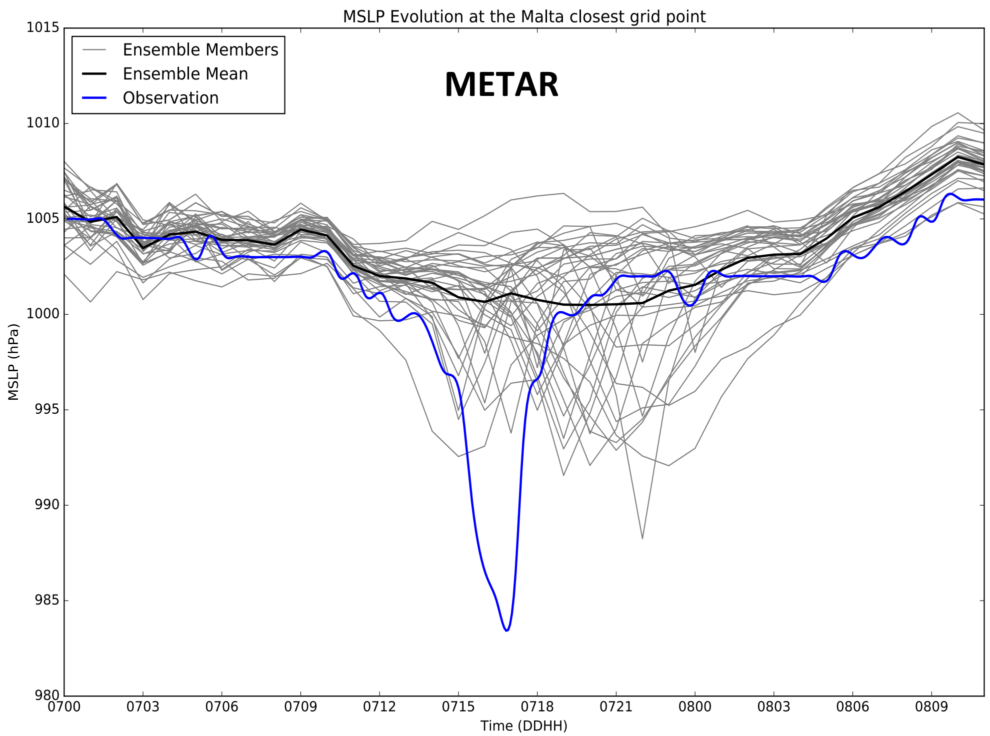
4. PRELIMINAR RESULTS

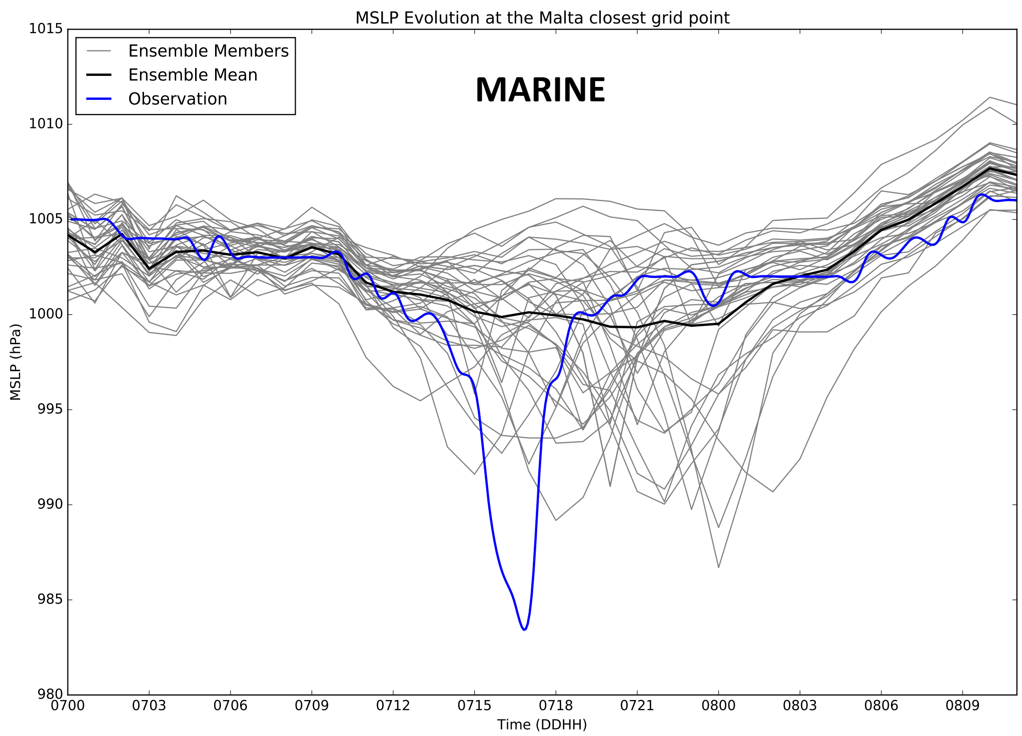




4. PRELIMINAR RESULTS

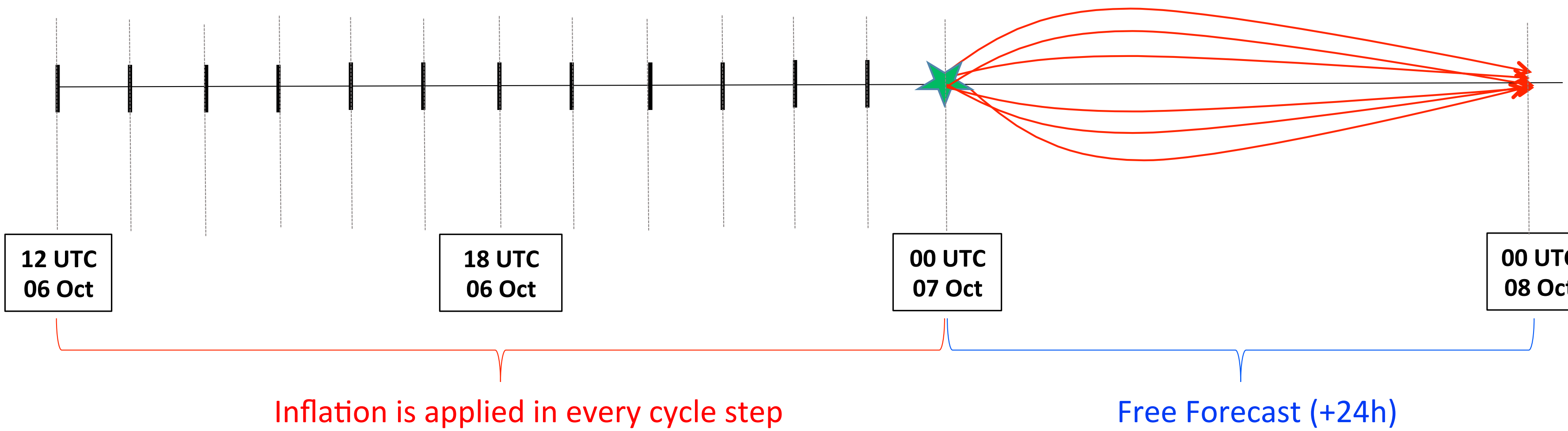
- Results still showing that both experiments still performing a significant temporal shifting towards posterior hours.





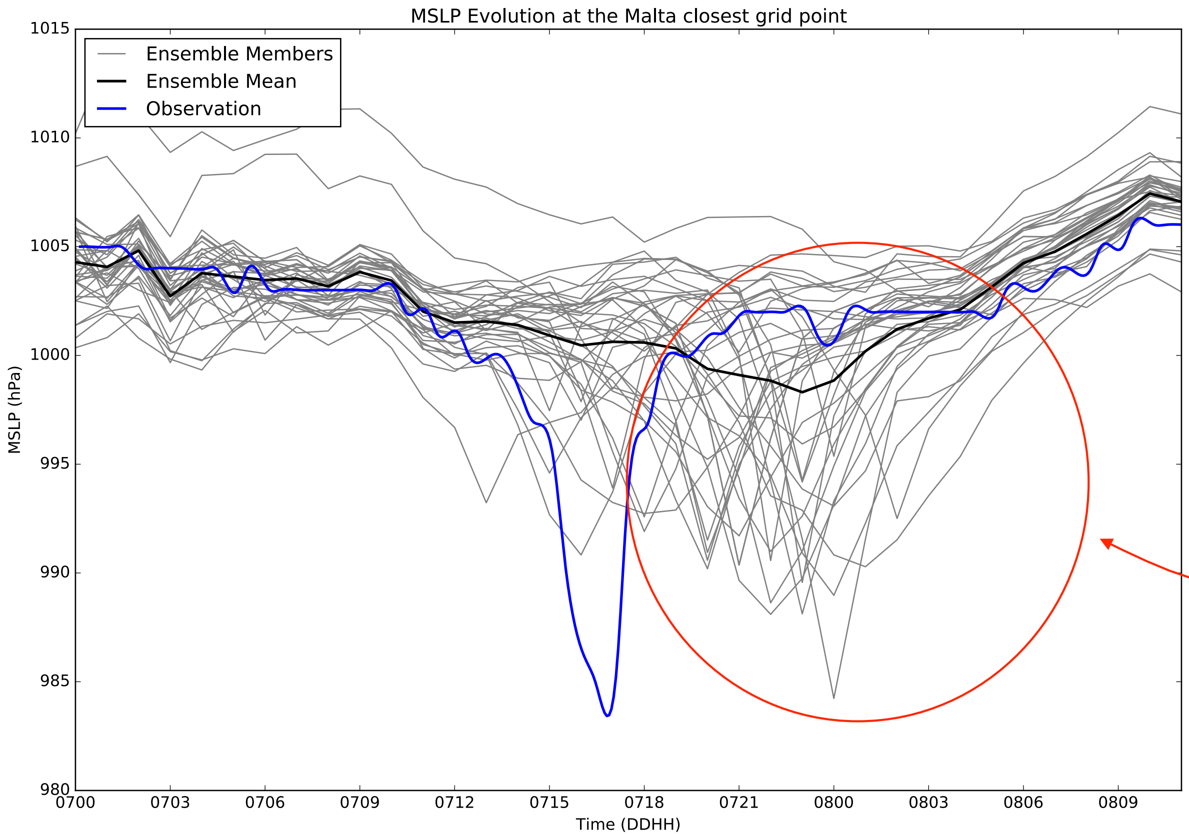
4. PRELIMINAR RESULTS

- A **new experiment** was performed **performing inflation but <u>without assimilating</u>** any kind of observation (**INFL_EXP**)



4. PRELIMINAR RESULTS

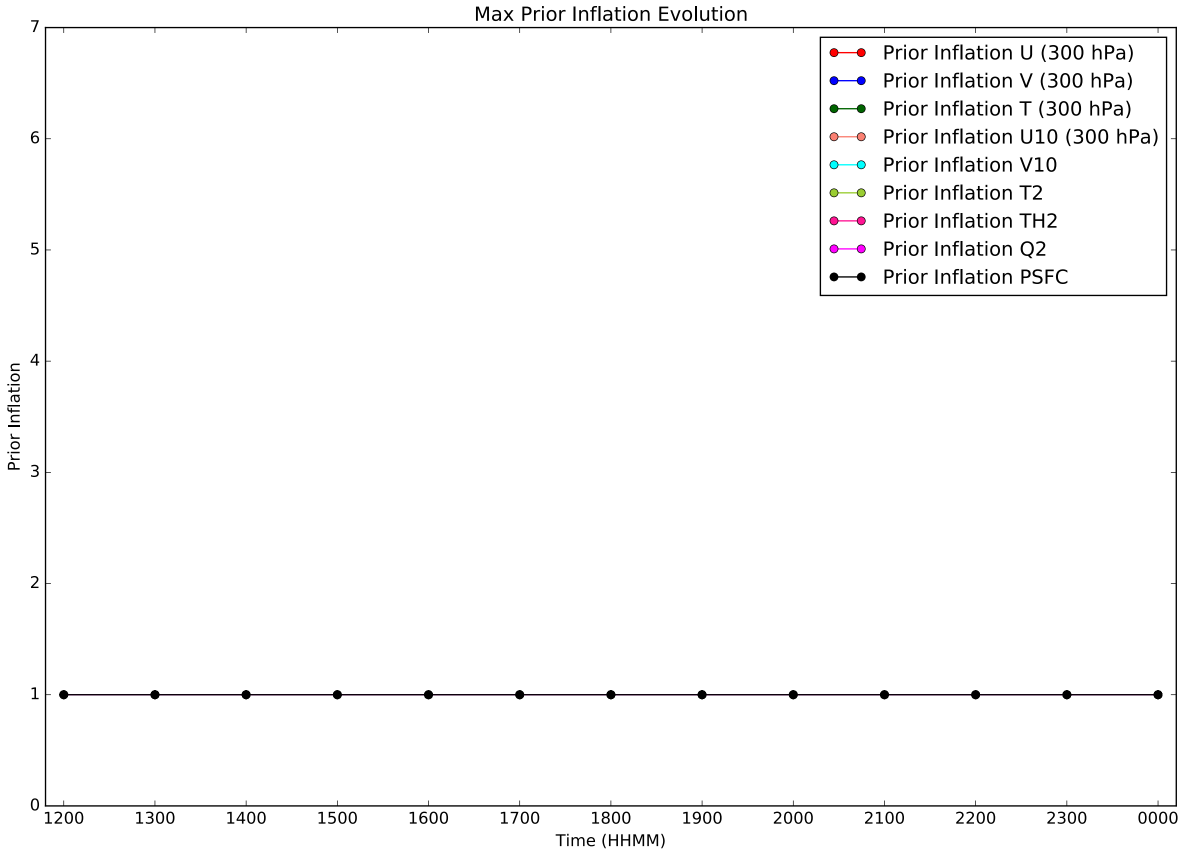
- A **new experiment** was performed **performing inflation but without assimilating** any kind of observation (**INFL_EXP**)



We still having the same behaviour than the observed in the SYN_EXPs

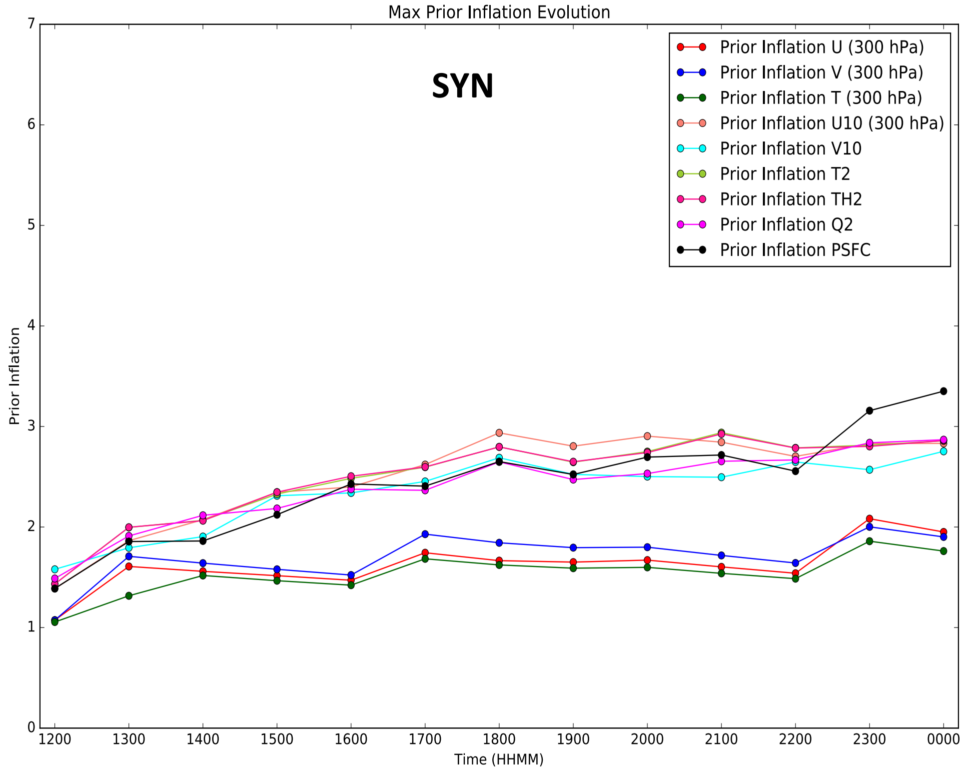
4. PRELIMINAR RESULTS

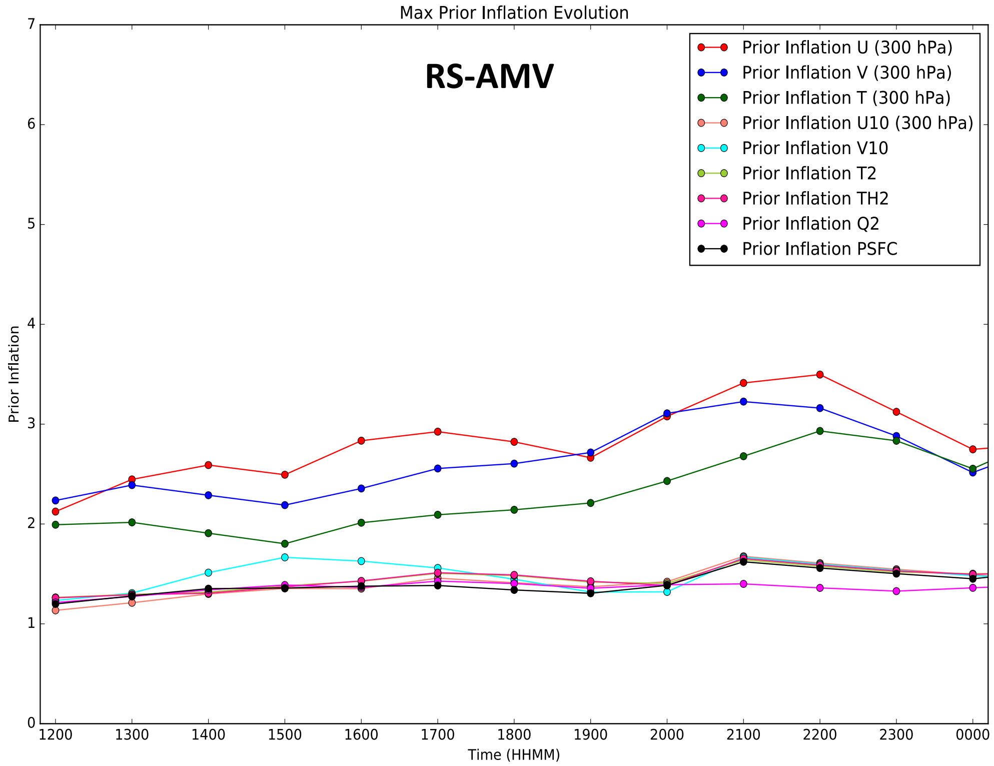
- **<u>Evolution of the maximum inflation</u>** nested domain for the **INFL_EXP**:



4. PRELIMINAR RESULTS

- A **new experiment** was performed **performing inflation but without assimilating** any kind of observation (**INFL_EXP**)





5. FUTURE WORK

- Understand key ingredients responsible of the mismatch between SYN_EXP and the observations
- Creation of a **black-list for the conventional observations**
- Investigate **role of the inflation** and its impact on the forecast
- Quantitative assessing of the DA experiments using **different probabilistic verification methods**
- Investigate **physical mechanisms modified by the assimilation** of observations, such as the upper-level dynamical forcing.

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