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José A. Garcia-Moya
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Papers

For How Long Should What Data Be Assimilated for the Mesoscale Forecasting of Convection and Why? Part I: On the Propagation of Initial Condition Errors and Their Implications for Data Assimilation

FRÉDÉRIC FABRY

McGill University, Montreal, Quebec, Canada

JUANZHEN SUN

For How Long Should What Data Be Assimilated for the Mesoscale Forecasting of Convection and Why? Part II: On the Observation Signal from Different Sensors

FRÉDÉRIC FABRY

McGill University, Montreal, Canada

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Introduction

- Predictability as a function of scale key in Data Assimilation.
- Computer resources and data availability seem to be the main factors for the quality of DA
- Fitting data beyond their time of predictability has a negative impact.
- Mesoscale structures have shorter predictability than synoptic scale ones.

Questions?

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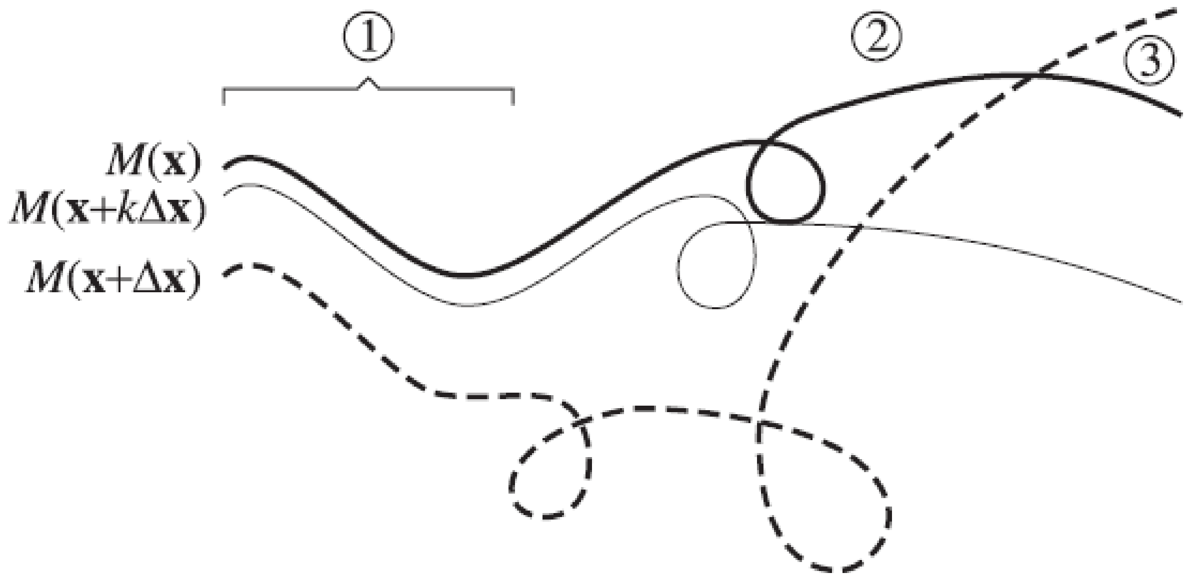
- Propagation of initial condition errors from one variable to the next.
  - How well we can detect errors in fields by observing the time evolution of another?
- How does predictability affects the assimilation period to be used for different fields?
- Which initial condition errors cause the worst forecast and should they be detected in priority?
- Should the assimilation time window be modified according with the propagation of errors in the initical conditions?

Three periods



① Linear regime: $M(\mathbf{x}+\Delta\mathbf{x}) \approx M(\mathbf{x}) + \Delta\mathbf{x}\ (\partial M/\partial\mathbf{x})$
$\rightarrow M(\mathbf{x}+k\Delta\mathbf{x}) - M(\mathbf{x}) \approx k\,[M(\mathbf{x}+\Delta\mathbf{x}) - M(\mathbf{x})]$

② Nonlin. regime: $M(\mathbf{x}+k\Delta\mathbf{x}) - M(\mathbf{x}) \neq k\,[M(\mathbf{x}+\Delta\mathbf{x}) - M(\mathbf{x})]$

③ Contradictory region: Adjusting $\mathbf{x}$ towards $\mathbf{x}+k\Delta\mathbf{x}$ at the initial time worsens the fit with the data from $M(\mathbf{x}+\Delta\mathbf{x})$

Model

- WRF:
  - 1600 x 1600 Km^2 domain.
  - 28 vertical levels.
  - 4 Km horizontal resolution.
  - Running every 9 hours for 12 hours forecast.
  - 6-days of convective activity (10-16 June)

Experiments

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- Control: Full data assimilation.
- Experiments with errors in the initial conditions.
  - Perturbing one field at a time (10 perturbations):
    - Winds: low, mid and high levels.
    - Temperature: low, mid and high levels.
    - Moisture: low and mid levels.
    - Condensate at all levels.
    - Soil moisture at all depths.
- Vertical scaling of errors.

- Part I: signal in model variables.
- Part II: skill of measurements to pull out a useful signal.

Computing errors in forecast

- Energy different of two similar model states, one control and one perturbed.

$$E = \frac{1}{2}\int_D \left[\Delta u^2 + \Delta v^2 + \frac{c_p}{T_r}\Delta T^2 + RT_r\left(\frac{\Delta p_s}{p_r}\right)^2 \right] dD, \qquad (2)$$

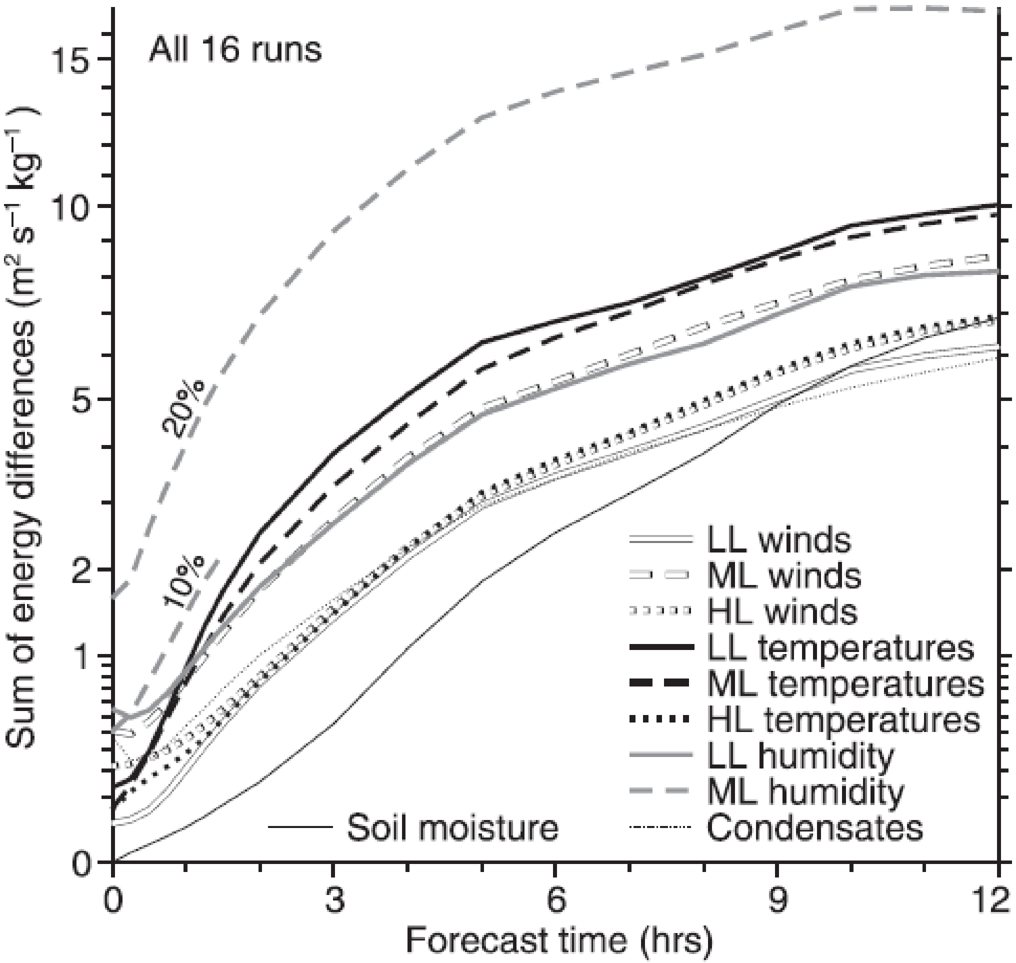
$$\mathrm{KED} = \frac{1}{2}\int_D (\Delta u^2 + \Delta v^2)\, dD$$

$$\mathrm{TED} = \frac{c_p}{2T_r}\int_D \Delta T^2\, dD.$$

$$\mathrm{LED} = \frac{L^2}{2c_p T_r}\int_D \Delta r_v^2\, dD,$$

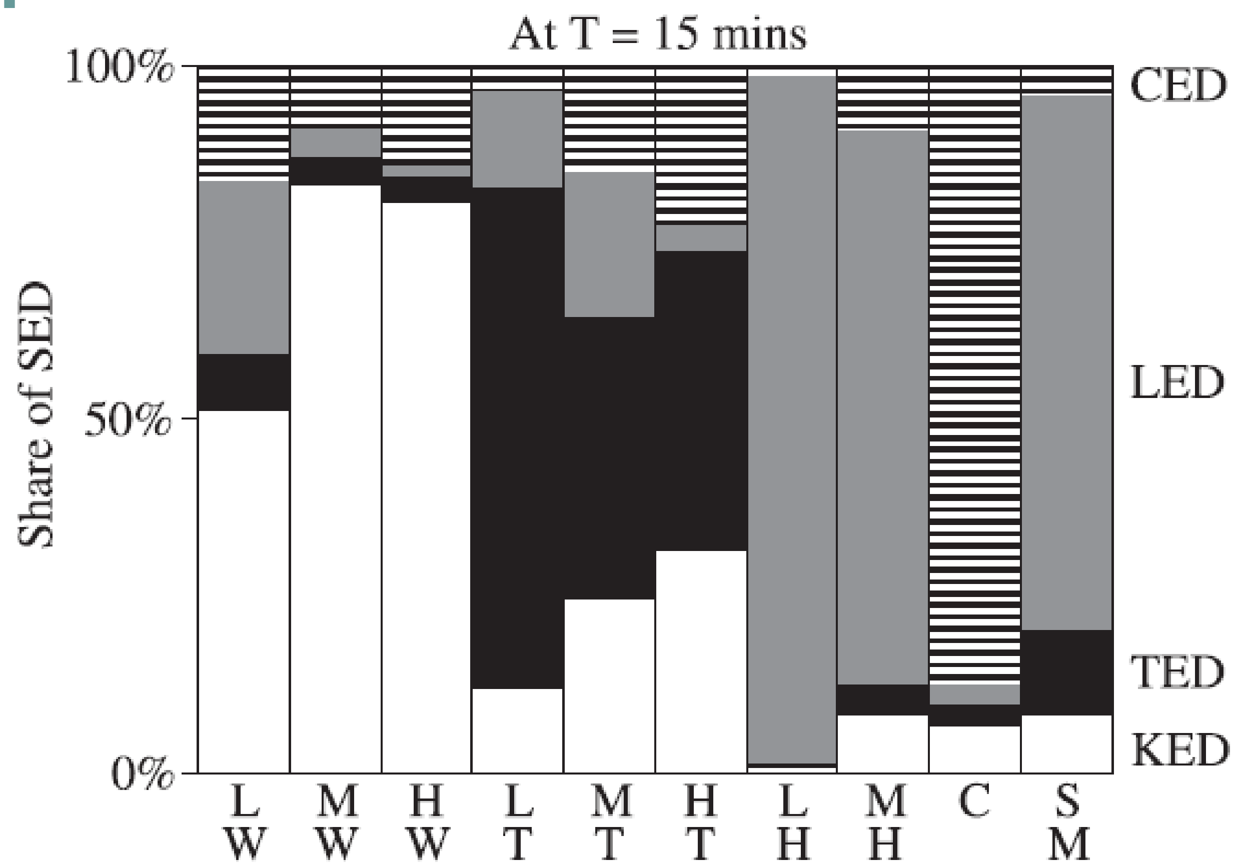
- Components of E

Results



Influence of perturbations in the forecast

Results: 15’ forecast



Most of the influence of perturbations in the same field:

Wind → KED

Temperature → TED

Moisture → LED

FIG. 6. Share of the SED among its different components [KED (white), TED (black), LED (gray), and CED (stripes)] (top) 3 h

Results: 3 h. forecast

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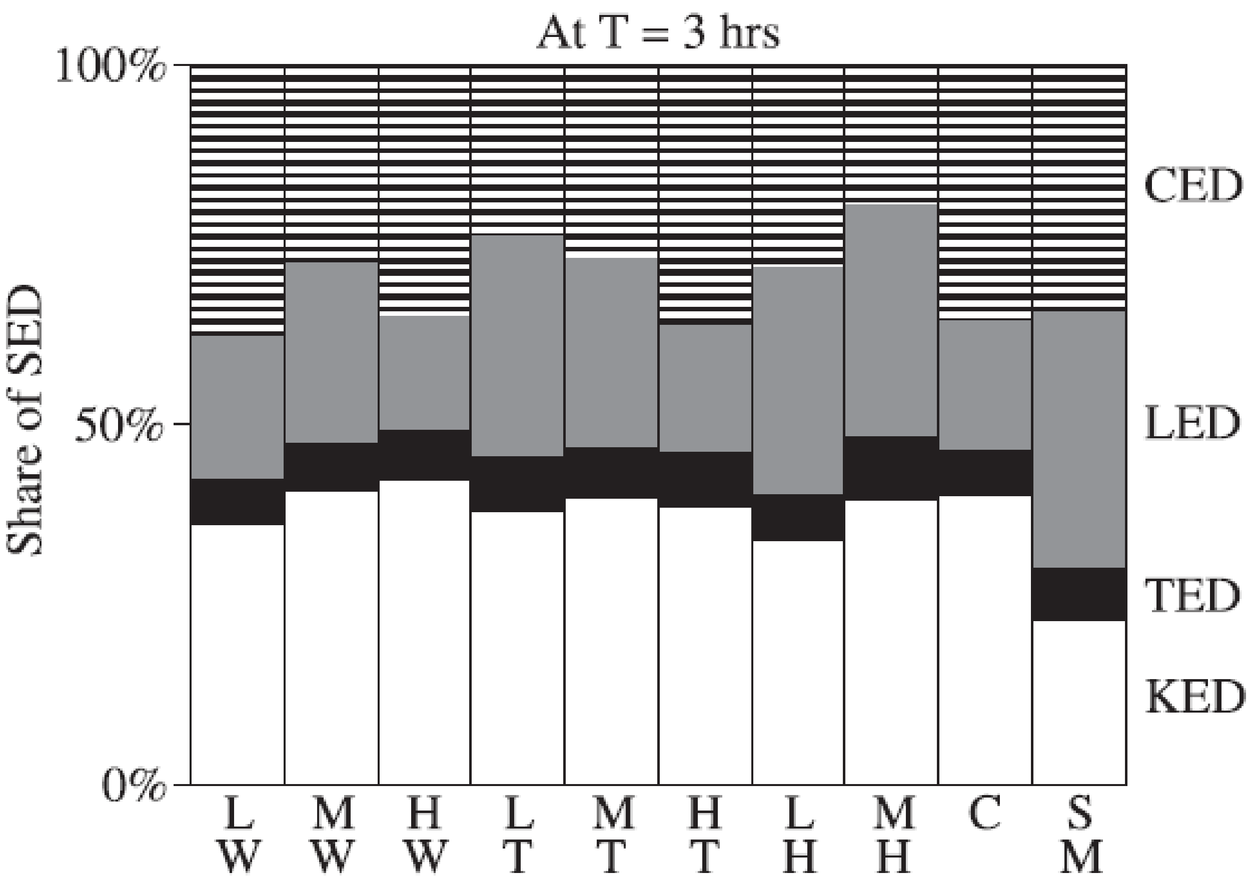


Most of the influence of perturbations spread out over all fields

FIG. 6. Share of the SED among its different components [KED (white), TED (black), LED (gray), and CED (stripes)] (top) 3 h

Results

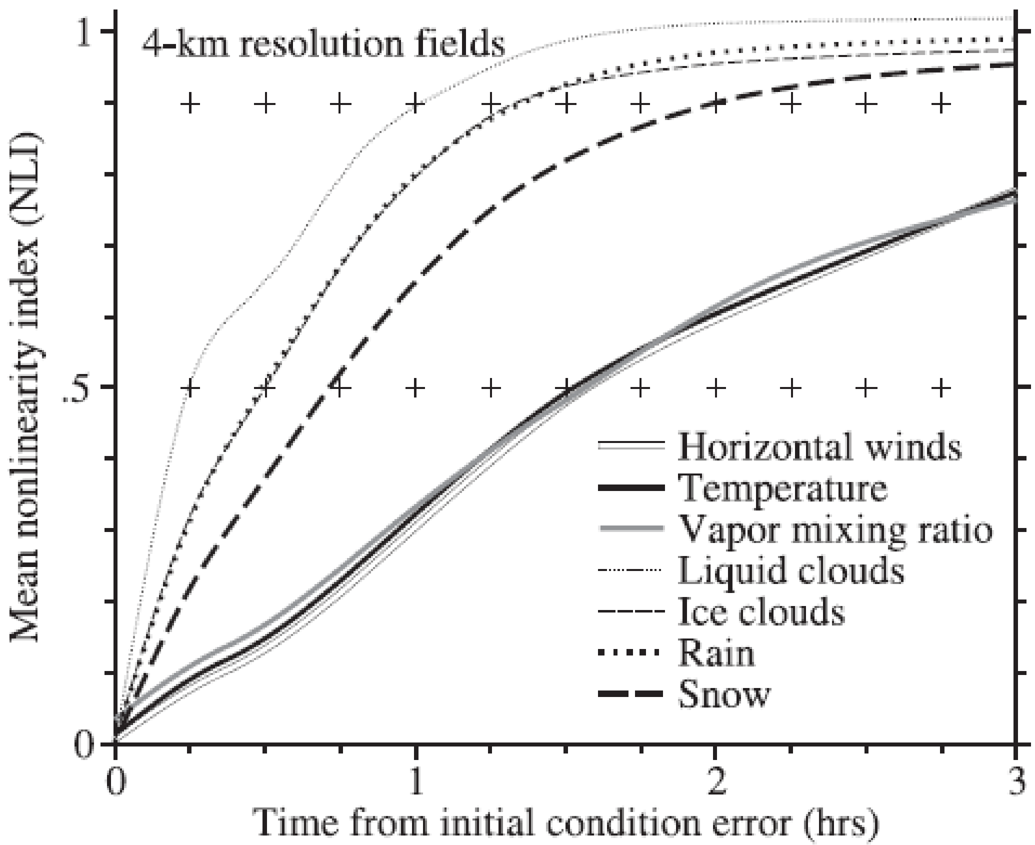
Memory of initial conditions is lost before 3 hours of forecast

Non-linearity index

$$\mathrm{NLI}(v, T, \Delta\mathbf{x}) = \frac{\int_D \left|[v(\mathbf{x}_o + k\Delta\mathbf{x}) - v(\mathbf{x}_o)] - k[v(\mathbf{x}_o + \Delta\mathbf{x}) - v(\mathbf{x}_o)]\right| dD}{\int_D \left|v(\mathbf{x}_o + k\Delta\mathbf{x}) - v(\mathbf{x}_o)\right| dD}.$$

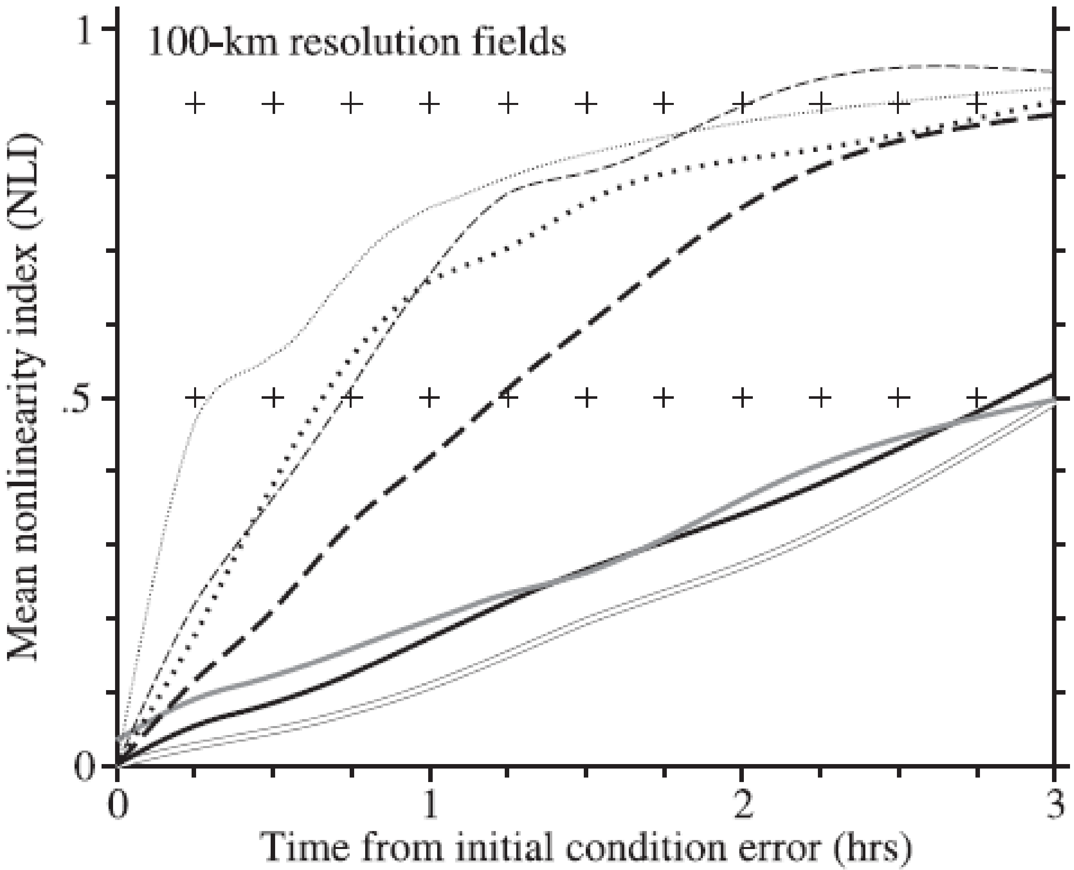
The NLI is hence a useful bulk quantity to measure the nonlinearity in the response of the model to a perturbation after a certain time. It is tied with predict-

Results



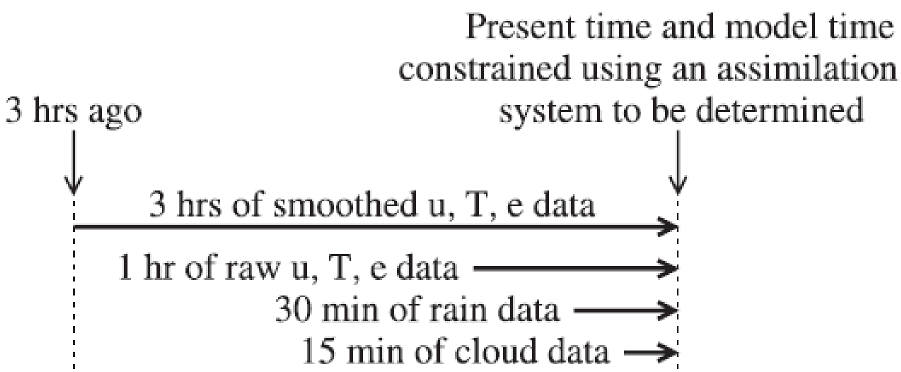
- Linear regime: NLI → 0
- Non-linear regime: NLI → 1

Results



- Synoptic scale fields keeps linear regime as double as mesoscale for T, wind and moisture perturbations

Results



Scenario 4: Real-time processing, new assimilation method

Ideal solution, but implementing it requires designing a data assimilation approach that constrains the model at the end time of the assimilation window, not at the beginning time as traditional formulations of 4D-Var do. Possible?

Part II: Observations

- Same methodology but for instruments, sensors and other source of observations.
- Not very clear methodology.
- Strength of the observational signal:

$$S_{y_i}(\Delta\mathbf{x}, T) = \sum_{i=1}^{N} \frac{[y_i(\mathbf{x}+\Delta\mathbf{x}, T) - y_i(\mathbf{x}, T)]^2}{\sigma(y_i)^2},$$

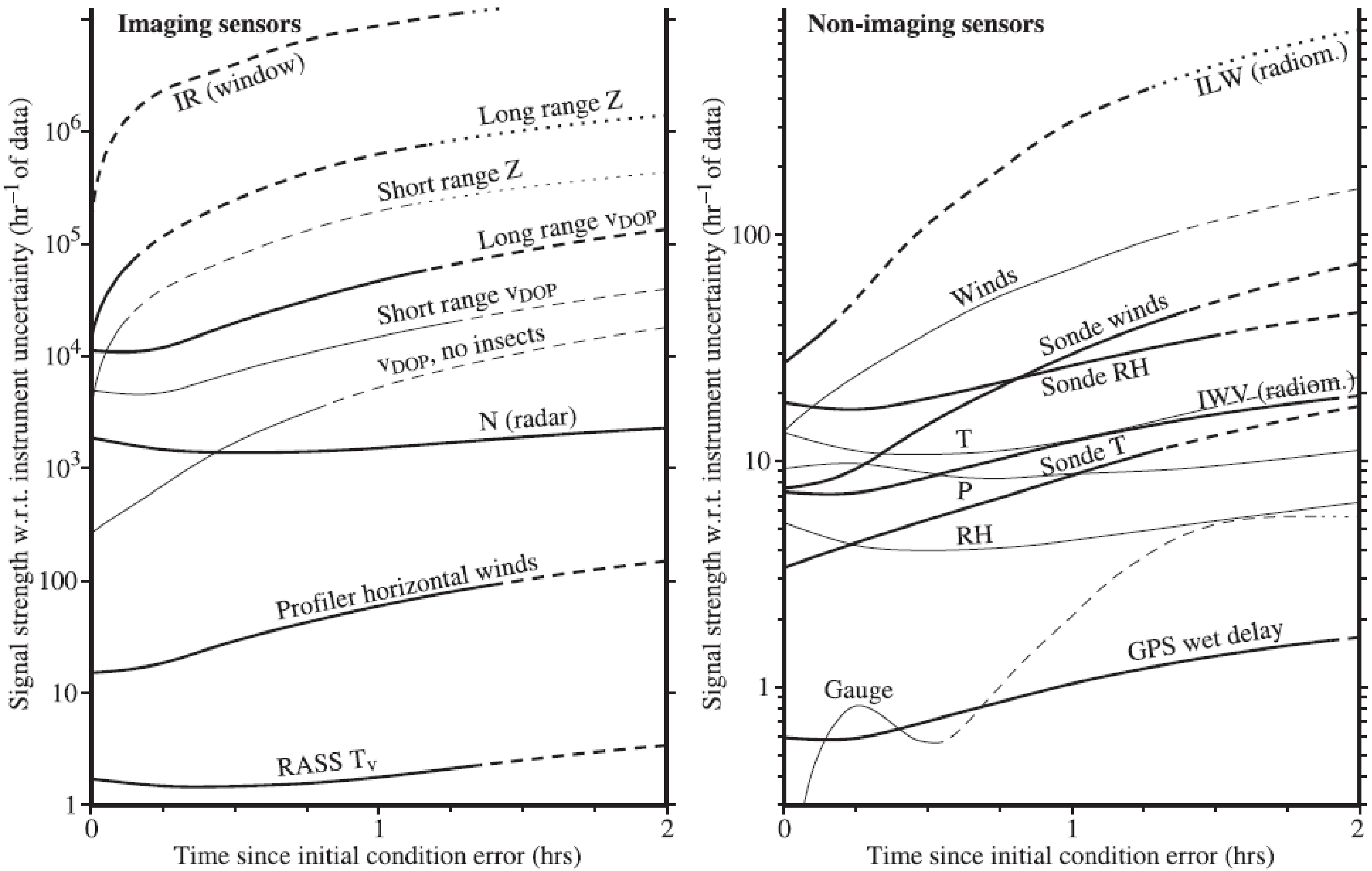
Part II: Observations

- NLI:

$$\mathrm{NLI}(y_i, T, \Delta\mathbf{x}) = \frac{\sum_{i=1}^{N} \left| [y_i(\mathbf{x}_o + k\Delta\mathbf{x}) - y_i(\mathbf{x}_o)] - k[y_i(\mathbf{x}_o + \Delta\mathbf{x}) - y_i(\mathbf{x}_o)] \right|}{\sum_{i=1}^{N} \left| [y_i(\mathbf{x}_o + k\Delta\mathbf{x}) - y_i(\mathbf{x}_o)] \right|},$$

N number of observations per hour

Results



- Influence by sensor

Conclusions

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- Predictability as a function of scale key in Data Assimilation.
- Fitting data beyond their time of predictability has a negative impact.
- Mesoscale structures have shorter predictability than synoptic scale ones.
- Perturbations of initial conditions spread out in less than 3 hours.
- Linearity at mesoscale lies between 15’ and 3 hours.

Conclusions

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In the end, the most valuable aspect of this study is the approach we used and what information it can provide, but the exercise needs to be repeated in the appropriate context to be most useful. The results presented here are

ments by radiosondes and surface stations. In the end, one can see that at the mesoscale, there is no magic bullet: to be successful, one must assimilate data from a variety of sources to properly initialize models.

sors. In Part I, we found that the greatest current source of forecast errors are due to 1) uncertainties in midlevel moisture and 2) uncertainties in low- and midlevel temperature, low-level humidity, and midlevel winds. Given

Future for Harmonie DA

- Repeat the exercise with Harmonie DA at 2.5 Km resolution.
- Running the model every 3 hours (8 times a day) up to 12 hours.
- Using two sets of experiments AROME and ALARO physics.
- Using ensemble techniques to strengthening results?