On the scale-dependence of precipitation predictability

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Acknowledgements: Adam J. Clark, Ming Xue, Fanyou Kor

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Atmospheric predictability

**Intrinsic**
Related to the *non-linear nature of atmospheric dynamics*: very small errors in ICs grow exponentially to result in a finite limit of atmospheric predictability

\[
\begin{align*}
\frac{dx}{dt} &= \sigma(y-x), \\
\frac{dy}{dt} &= x(\rho-z) - y, \\
\frac{dz}{dt} &= xy - \beta z.
\end{align*}
\]

Chaotic behaviour for: \(\sigma = 10, \beta = 8/3 \text{ and } \rho = 28\).

**Practical**
Related to the loss of predictability due to *errors in ICs and model physics* that could be potentially resolved

\[
\text{Initial conditions} \rightarrow \text{Governing equations} + \text{Parameterizations}
\]

Lorenz (1969)
What do we know about intrinsic predictability?

• Predictability is scale-dependent
  
  • Lorenz 1969, Lilly 1990, Kalnay 2003: predictability at scales ~ 10 km is $O(1h)$, at scales ~1000 km is $O(10 \text{ days})$
  
  • Errors grow faster at convective scales than at synoptic scales (Hohenegger and Schar 2007)
  
  • Error growth at convective scales is amplified by moist convection (Hohenegger and Schar 2007, Zhang et al. 2002)
  
  • Once errors saturate at convective scale, they propagate upscale where they continue to grow – the three stage error growth model (Zhang et al. 2007, Selz and Craig 2015):
    
    • 1st stage: error growth and saturation due to moist convective instability
    
    • 2nd stage: geostrophic adjustment
    
    • 3rd stage: continuing growth at synoptic scales through baroclinic instability
Intrinsic versus practical predictability

- While in some cases intrinsic predictability limitations can lead to a very rapid loss of forecasts skill (Zhang et al. 2003, Melhauser and Zhang 2012), generally practical predictability limitations are the main reason for forecast errors (Durran and Gingrich 2014).

- Most previous studies were based on a limited set of cases.

- Investigate the intrinsic and practical limitations for convection-allowing models using a large data set of storm-scale ensemble forecasts.
Quantify the limits of precipitation predictability

**Intrinsic**
- Investigate the growth of very small IC perturbations in model simulations

**Practical**
- Characterizing the growth of different types of model perturbations in model simulations
- Comparing forecasts to observations
- Evaluating forecast skill

*Model predictability of the atmospheric state*
Methodology

• A statistical approach to studying predictability

  • Use a large set of data
  • Quantify predictability as a function of spatial scale
  • Determine the role of different types of errors forensemble predictability
  • Characterize the relationship between predictability limits and the environment
Large data set

Acknowledging Adam Clark (NSSL), Ming Xue (OU, CAPS) and Fanyou Kong (OU, CAPS)

Storm-scale ensemble forecasting system
WRF-based, 4-km grid spacing, radar DA
Multi-physics, multi-model

Now more than 10 years of high-resolution ensemble forecasts during the severe weather season in the US.
Our experience in mesoscale predictability

Ensemble precipitation forecasts

- IC/LBC perturbations from regional-scale ensemble - resolution of 32-45 km
- Random IC perturbations
- Random correlated IC perturbations - small-scale (12 km horizontal, 3 km vertical)

Initial conditions

- Governing equations (DYNAMICS) + Parameterizations (PHYSICS)
- Boundary conditions

- Varied MP scheme
- SKEB
- Varied PBL scheme

Practical predictability limits

Intrinsic predictability limits

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Precipitation forecasts from CAPS SSEF.
Radar derived QPE.
Stage IV precipitation.
All remapped on the Stage IV grid using nearest neighbor interpolation.

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>IC/LBC</td>
<td>SREF-derived IC/LBC perturbations</td>
<td>2008</td>
</tr>
<tr>
<td>IC/LBC/MIX</td>
<td>SREF-derived IC/LBC perturbations and mixed PHYS</td>
<td>2008–11, 2013</td>
</tr>
<tr>
<td>RAND</td>
<td>Uncorrelated random noise added to the initial moisture and temperature fields</td>
<td>2010</td>
</tr>
<tr>
<td>RC</td>
<td>Correlated random noise added to the initial moisture and temperature fields</td>
<td>2010</td>
</tr>
<tr>
<td>MP</td>
<td>Microphysical parameterization scheme different than for CN (Thompson)</td>
<td>2010–13</td>
</tr>
<tr>
<td>PBL</td>
<td>Planetary boundary layer scheme different than for CN (MYJ)</td>
<td>2010–13</td>
</tr>
<tr>
<td>SKEB</td>
<td>Stochastic kinetic energy backscatter scheme</td>
<td>2012</td>
</tr>
</tbody>
</table>
Quantify predictability as a function of scale

- As mentioned before, Zhang et al. 2003 etc. – errors saturate with scale and forecast time

- Does this apply to our definitions of predictability and to our data set?

- Determine the range of scales where predictability is lost: **the decorrelation scale**
The decorrelation scale

- Define the power ratio for a pair of precipitation fields:

\[ R(\lambda) = \frac{\text{Var}_X(\lambda) + \text{Var}_Y(\lambda)}{\text{Var}_{X+Y}(\lambda)} \]

\( X, Y \) are 2D precipitation fields and \( \text{Var}_X(\lambda) \) and \( \text{Var}_Y(\lambda) \) represent the variance of the fields at scale \( \lambda \).

- When the power ratio is 1, the two precipitation fields are fully decorrelated.

- The variance at a given scale is obtained by computing the power spectrum of precipitation using the Discrete Cosine Transform.

Example of the power ratio for a pair of two precipitation forecasts, one unperturbed, one with IC/LBC perturbations.

At 10-hour lead time, the decorrelation scale is 103 km. This means that IC/LBC errors in this case cause predictability loss at scales smaller than 100 km after 10 forecast hours!
The decorrelation scale as a function of forecast lead-time averaged over all cases of SE2008

Power ratios averaged over all cases

\[ \lambda_o(t) = 13 t^{0.9} \]

\[ \lambda_o = 103 \text{ km} \]
Other measures to quantify predictability

- **The Normalized Root Mean Square Error:**

\[
\text{NRMSE} = \frac{\sum_{i=1}^{I} \sum_{j=1}^{J} [X(i,j) - Y(i,j)]^2}{\sum_{i=1}^{I} \sum_{j=1}^{J} [X(i,j) + Y(i,j)]^2}
\]

X, Y are precipitation fields of dimensions \(I\) and \(J\).

This measure is also applied to band-pass components of the fields.

- **The Fractions Skill Score (FSS, Roberts and Lean 2005)**

\[
\text{FSS} = 1 - \frac{\sum_{i=1}^{I} \sum_{j=1}^{J} [f_X(i,j) - f_Y(i,j)]^2}{\sum_{i=1}^{I} \sum_{j=1}^{J} f_X^2(i,j) + \sum_{i=1}^{I} \sum_{j=1}^{J} f_Y^2(i,j)}
\]

\(f_X, f_Y\) are fraction fields.
Results – the decorrelation scale

Results are presented for hourly rainfall accumulations and averaged for 22 cases during 2008.

Predictability of the model state – effect of IC/LBC/PHYS errors
Results – the decorrelation scale

Results are presented for hourly rainfall accumulations and averaged for 22 cases during 2008.

Predictability of the model state – effect of IC/LBC/PHYS errors.

Model predictability of the atmospheric state – effect of IC/LBC/PHYS errors on forecast skill.

Predictability is lost very rapidly. Significant difference between spread and skill.
2008-2013 averages

Forecast error: IC/LBC/PHYS+RC  IC/LBC/PHYS  MP  RC  PBL  RAND  Radar DA  SKEB

Our experience in mesoscale predictability

2008

2009

2010

2011

2012

2013
Our experience in mesoscale predictability

2008-2013 averages

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<tr>
<th>Forecast error</th>
<th>IC/LBC/PHYS+RC</th>
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IC/LBC errors most important – spread comparable to forecast error after 20 h.

MP perturbations most important

PHYS perturbations

Practical predictability limits far from intrinsic predictability limits

Random perturbations: 0.5 K and 5 % humidity – larger than usually used for intrinsic predictability studies
Case-to-case variability

Predictability is not only scale-dependent, but also case-dependent.

Impossible to build the entire atmospheric attractor, so different indicators of where we are situated in the atmospheric attractor are necessary.

Palmer 1993
Where do the events situate in the atmospheric attractor?

- Use several indices to characterize the events:
  - Fractional precipitation coverage
  - The convective adjustment time scale (Done et al. 2006, Keil et al. 2014) - An indicator of whether convection is in equilibrium with the large-scale flow or not - proxy for strength of large-scale forcing.

\[
\tau_c \sim \frac{\text{CAPE}}{d(\text{CAPE})/dt}.
\]

\[
\tau_c = \frac{1}{2} \frac{\text{CAPE}}{P} \times 49.58 \text{ mm s}^3 \text{ m}^{-2} \text{ h}^{-1}.
\]

Average the spatial convective-adjustment time-scale over all regions of hourly rainfall accumulations larger than 1 mm.
Where do the events situate in the atmospheric attractor?
Relate predictability to precipitation coverage and $\tau_c$

- The decorrelation scale does not show any case-dependence

- Case-dependence of spread and skill measures at large scales (more than $\sim 200$ km)

- Spread measures:

\[
S_{\text{NRMSE}} = \frac{1}{N} \sum_{\text{all members}} \text{NRMSE}_{\text{member-CN}}
\]

\[
S_{\text{FSS}} = \frac{1}{N} \sum_{\text{all members}} \text{FSS}_{\text{member-CN}}
\]
Relate predictability to precipitation coverage and $\tau_c$

Correlation coefficient between spread and precipitation coverage or $\tau_c$.

Solid lines – IC/LBC/PHYS ensemble
Dashed lines – MP ensemble

Relationship is not statistically significant during the diurnal cycle precipitation minimum.

No apparent difference between the two types of ensembles.

Forecasting skill at scales $> 256$ km shows more relation to event type than spread.
Do the error sources considered in this system ever capture the entire forecast error?

How does the effect of IC/LBC/PHYS/RC perturbations compare to forecast skill?

During the first 12 forecast hours the spread is insufficient.

After 24 hours, the errors considered generate sufficient spread, and at medium scale (128-256 km) the error caused by the perturbations is even larger than forecast error.

No relationship to the type of event.
Maybe the distribution of cases we have is not wide enough!

Averages for each case - total of 179 cases over 6 years

For most of the case, most of the variability in fractional precipitation coverage is explained by the diurnal cycle of precipitation.
Summary

- We were interested in characterizing the precipitation predictability limits by convection-allowing models.

- Indeed, predictability at small scales is short lived.

- Furthermore, while there seems to be some relationship between predictability at scales larger than ~200 km and type of event, predictability is always lost rapidly at convective scales.

- Despite the many types of errors sampled by the ensemble system used here, spread for short lead times (<12 h) is still insufficient.
Impacts

• Serious implications of these findings:
  • Small scale predictability always rapidly lost – what does this mean for data assimilation of storm scale observations? How long can the duration of the effect of assimilating such data be?
  • Producing operational forecast products - information is lost rapidly at small scales, therefore, shouldn’t probabilistic forecasts of precipitation reflect that?
    • Schwartz and Sobash 2016: neighbourhood approaches for producing POPs
    • The neighbourhood size should change with forecast lead time – work in progress
    • Already explored for lagrangian extrapolation nowcasting systems (ex. MAPLE, Germann and Zawadzki 2004)
    • Careful interpretation of ensemble mean products, which become increasingly filtered with increasing forecast time.
Caveats

• Main problem of our study: using data produced for other purposes made it difficult to control the experiment

• Only precipitation data available – How do predictability estimates differ when other variables are analyzed?

  • Expecting less spread for other variables such as temperature and wind – problem for DA!

  • Understanding the relationship between error growth in mass variables and error growth in precipitation is important

• No perfect knowledge of the IC perturbation structure which is needed to properly understand error growth

• Predictability estimates are sensitive to the model used for estimation
To end the presentation

• An example of how difficult convective scale predictability could be
Same intensity echo

Different intensity echo

16:3
Fire
15 min 17:5

Outflo
Triggering of the storm
Tornad to CP2 radar 19:45 less than 2h after triggering of the storm
This is a very extreme case – but what is the impact of other smaller anthropogenic perturbations such as rush hour traffic effects?

Lorenz 1969: is the system represented by convection-allowing models non-deterministic? How can we account for these stochastic effects?

Thank you!