

ENSEMBLE PREDICTION AND PROBABILISTIC FORECASTS

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ACKNOWLEDGMENTS

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- This material has been prepared with the aid of lectures and material available in the Internet. Papers and books are cited at the end of this lecture.
- COMET modules on Ensemble Forecasting (<u>http://www.meted.ucar.edu/nwp/pcu1/ensemble/index.htm</u>)
- Analysis, diagnosis and short range forecast tools

(http://www.meted.ucar.edu/nwp/anldiagfcsttools/index.htm)

- Sources of uncertainty (EC/TC/PR/RB-L1) by Robert Buizza (ECMWF)
- Introduction to Chaos by Tim Palmer (ECMWF)
- Convective scale ensembles for data assimilation, Migliorini et al., U of Reading.
- Representation of model error in a convective-scale ensemble 2012 Alison Rudd et al U of Reading. Interrnational Conference on Ensemble Methods in Geophysical Sciences

OUTLINE

- Sources of numerical forecast errors
- Predictability and chaotic systems
- Ensemble forecasts
- Probabilistic Forecasts
- Sources of uncertainty at convective scales
- Examples

MAIN CHALLENGES FOR A GOOD NUMERICAL FORECAST

- Quality of the forecast system (this includes both the Numerical Model and the Assimilation System)
- Quality (and quantity) of the observations





Forecast errors and Forecast Uncertainty



"Why have meteorologists such difficulty in predicting the weather with any certainty? Why is it that showers and even storms seem to come by chance ... a tenth of a degree (C) more or less at any given point, and the cyclone will burst here and not there, and extend its ravages over districts that it would otherwise have spared. If (the meteorologists) had been aware of this tenth of a degree, they could have known (about the cyclone) beforehand, but the observations were neither sufficiently comprehensive nor sufficiently precise, and that is the reason why it all seems due to the intervention of chance"

Poincaré, 1909

GOING A LITTLE DEEPER IN OUR UNDERTSTANDING OF ATMOSPHERIC PREDICTABILITY

- In his 1951 paper on NWP, Charney indicated that he expected that even as models improved, there would still be a limited range to skillful atmospheric predictions, but he attributed this to inevitable model deficiencies and finite errors in the initial conditions
- In a series of remarkable papers, Lorenz (1963a, 1963b, 1965, 1968) made the fundamental discovery that even with perfect models and perfect observations, the chaotic nature of the atmosphere would impose a finite limit of about two weeks to the predictability of the weather.

GOING A LITTLE DEEPER IN OUR UNDERTSTANDING OF ATMOSPHERIC PREDICTABILITY

Weather forecasts lose skill because of:

- the growth of errors in the initial conditions (initial uncertainties)
- numerical models describe the laws of physics only approximately (model uncertainties).

As a further complication, predictability (i.e. error growth) is flow dependent.

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THE FUNDAMENTAL THEOREM OF PREDICTABILITY (LORENZ, 1963A, 1963B)

 Unstable systems have a finite limit of predictability, and conversely, stable systems are infinitely predictable (since they are either stationary or periodic)



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ILLUSTRATING CHAOTIC FLOWS LORENZ 3-D MODEL



 This model could mimic our interest of forecasting when are we going to move from a "warm" phase to a "cold phase"

A SMALL CHANGE IN THE INITIAL CONDITION...



According to Lorenz, 2006, deterministic Chaos can be thought as:

"WHEN THE PRESENT DETERMINES THE FUTURE BUT THE APPROXIMATE PRESENT DOES NOT APPROXIMATELY DETERMINE THE FUTURE"

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THE ERRORS OF THE DAY







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- A set of slightly different initial conditions is used to represent the uncertainty in the initial conditions
- From each initial condition we obtain different "future states": we can get an idea of the forecast uncertainty.
- This uncertainty depends on the flow

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AN EXAMPLE IN THE ATMOSPHERE

 ECMWF Surface Temp.
Forecasts for London on 2 different summer days



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AN ENSEMBLE PREDICTION SYSTEM (EPS)

A more complete description of a future state can be derived from the PDF of this state. Ensemble forecasts are used to represent the PDF of these future states. Our forecast will provide the probability of occurrence of a given event



ENSEMBLE FORECASTS AS AN ALTERNATIVE TO QUANTIFY UNCERTAINTY

Error and Uncertainty Growth with Time



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NOAA/NWS/Caribou ME WFO

CONCEPTUALLY

- Running an EPS gives us a sample of possible forecasts from a much greater population of forecast possibilities. From this sample, we can then draw *inferences* about the central tendency ("*middleness*"), variability, and shape of the distribution for the population of all potential forecast outcomes
- However, we still have statistical caveats: it is possible that the ensemble forecast data set (i.e., the data sample) is *not* representative of all possible forecast outcomes

GOOD ENSEMBLES VS. BAD ENSEMBLES



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- Represent initial conditions uncertainty
- Represent model uncertainty
- Represent boundary conditions uncertainty

THROUGH:

- Good sampling of different initial states
- Stochastic physics or multi model ensemble
- Perturbed boundary conditions (could refer to land-ocean or lateral boundaries)

ENSEMBLE GENERATION

 Ensemble technique is well established at synoptic-scale, but suitable for convectionresolving scales?

eg. selective sampling: the idea that not all the initial errors (e.g. perturbations) will grow at the same rate is valid at synoptic scales (baroclinic instability)



WHAT CAN ENSEMBLES PROVIDE?

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- Middleness and spread (to assess, on average, the most likely outcome and uncertainty in the forecast)
- **Probability distribution** of ensemble forecasts (to assess the usefulness of the above two measures)
- Probability of exceeding critical thresholds (to assess the need for watches, warnings, etc.)
- It is highly desirable that ensemble spread could represent forecast error (e.g. being able to forecast "forecast skill")

Probabilistic forecasts

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PROBABILISTIC FORECASTS ARE NOT NEW....

Before having NWP-EPS, forecasters used:

- Local climatology to assess likely future value of forecast variables
- Current values for meteorological variables in making the forecast (persistence)
- Past evolution of the atmosphere in similar situations (forecast analogues)

PROBABILISTIC FORECASTS DERIVED FROM SINGLE NWP

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It turns out that the mean for the analysis sample is 14.6°C with a standard deviation of 2.9°C. The 24-hour forecasts, however, have a mean of 15.1°C with (for simplicity) the same standard deviation.

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Some DISADVANTAGES

- Relationships between model forecasts and the subsequent verification are often flow regime dependent, which means that application of these relationships in at least some cases will not be valid.
- We also do not get a quantitative sense of how predictable the flow regime might be.

ENSEMBLE FORECASTS BECOME A GOOD ALTERNATIVE TO OVERCOME THESE PROBLEMS

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WHAT DO ENSEMBLES TAKE INTO ACCOUNT?

- Current initial condition uncertainty and atmospheric predictability
- Current flow regime effect on NWP model predictability and bias
- Current model configuration (i.e. previous versions of the NWP model may have different characteristic errors and biases)

HOW TO USE PRODUCTS OBTAINED FROM EPS

For several practical, traditional and psychological reasons categorical (single- value) forecasts are the most requested from the end-users.

- Deterministic statement like the mean (the best estimate), the most likely and the median can easily be extracted from probability distributions.
- The *ensemble mean is obtained by averaging all ensemble forecasts. This has* the effect of filtering out features of the forecast that are less predictable.

PROS AND CONS OF USING THE ENSEMBLE MEAN

- beyond the short range, exhibits higher accuracy than the Control for "dry" fields (with low spread)
- Higher degree of day-today consistency
- Less jumpiness (because of filtering smaller scales features)
- do not constitute genuine, dynamically three-dimensional representations of the atmosphere, so it can show inconsistencies between different fields

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 Is less able to represent extreme or anomalous weather events (unless they appear in most of the ensemble members)

ENSEMBLE SPREAD²⁹

- The ensemble spread is a measure of the difference between the members and is represented by the standard deviation (Std) *with respect to the EM*.
- On average, small spread indicates a high a priori forecast accuracy and large spread a low a priori forecast accuracy



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Sunday 4 August 2013 12UTC ECMWF Forecast t+24 VT: Monday 5 August 2013 12UTC Mean sea level pressure (MSLP) Ensemble Mean and Normalised Standard Deviation (shaded)



Sunday 4 August 2013 12UTC ECMWF Forecast t+24 VT: Monday 5 August 2013 12UTC Mean sea level pressure (MSLP) Deterministic Forecast and Standard Deviation (shaded)





Sunday 4 August 2013 12UTC ECMWF Forecast t+120 VT: Friday 9 August 2013 12UTC Mean sea level pressure (MSLP) Ensemble Mean and Normalised Standard Deviation (shaded)



Sunday 4 August 2013 12UTC ECMWF Forecast t+120 VT: Friday 9 August 2013 12UTC Mean sea level pressure (MSLP) Deterministic Forecast and Standard Deviation (shaded)





Sunday 4 August 2013 12UTC ECMWF Forecast t+216 VT: Tuesday 13 August 2013 12UTC Mean sea level pressure (MSLP) Ensemble Mean and Normalised Standard Deviation (shaded)



Sunday 4 August 2013 12UTC ECMWF Forecast t+216 VT: Tuesday 13 August 2013 12UTC Mean sea level pressure (MSLP) Deterministic Forecast and Standard Deviation (shaded)



24hr_rainfall (mm) forecast valid for 12Z04DEC2012 initialized on 12Z03DEC2012





34S

57W 56W 55W 54W 53W 52W 51W 50W



150

120

100

75

Example from CHUVA



57W 56W 55W 54W 53W 52W 51W 50W





57W 56W 55W 54W 53W 52W 51W 50W

Matsudo et al., 2013



GETTING MORE INFORMATION³⁵ FROM THE EPS: MOVING INTO PROBABILITIES



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EXAMPLES AT THE SYNOPTIC SCALE



SYNTHESIZING THE ³⁷ INFORMATION FROM AN EPS

City of London

Five day maximum temperature range



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- The theory underlying EPS has been designed to handle the problem of uncertainty at the synoptic scales.
 - It filters out "unpredictable" short scales

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 It states that the problem can be treated in a deterministic way for the first hours (even 3 or more days in advance)

...BUT... CAN WE THINK IN THIS WAY IF WE ARE DOING NOWCASTING?

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SOME FACTS

- Experimental studies (e.g., Honegger and Schar 2007, Leoncini, 2010) show that error growth saturation time at convective-scales (2.2 km and 4 km horizontal resolution) is of the order of one day, with error doubling time of the order of a few hours.
- Similar studies with the ECMWF EPS (T255, 80 km) indicate instead an error saturation time of the order of 10 days, with error doubling time of the order of a few days.



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Hohenegger and Schar, BAMS, 2007

WHAT IS IMPORTANT AT CONVECTIVE SCALES?

- Presumably, uncertainty due to model parameterizations is a key component of model error at these scales.
 Synoptic scale uncertainty (provided with BC) are also a source of error. Ensembles system should capture this..
- What is known about predictability at convective scale:
 - Small errors grow faster (non-linear behavior).
 - Errors amplify faster in high-resolution convectionresolving simulations.
 - Moist convection is the primary mechanism for forecast error growth at small scales.
 - Mesoscale data assimilation can lead to improved and more realistic forecasts

ENSEMBLE FORECASTING AT CONVECTIVE SCALES

- Is at its early stage
- Needs further research in order to create proper optimal perturbations
- Is largely benefited from assimilating very high resolution data (e.g. reflectivity, doppler winds, cloud properties)
- Linear assumptions, used by some assimilation techniques, may not hold
- The large sensitivities to initial conditions and to model error motivates the need for probabilistic forecasts at convective scale

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EXAMPLE

- Impact of the Environmental Low-Level Wind Profile on Ensemble Forecasts of the 4 May 2007 Greensburg, Kansas, Tornadic Storm and Associated Mesocyclones DANIEL T. DAWSON II et al, 2012
- COMMAS Hi-res model
- Homogeneous initialization (radiosonde)
- 1 km horizontal resolution, 50 vertical levels, 140x160 km
- 30 members ensemble (EnKF) generated using random horizontal wind perturbations, with extra perturbation added over the regions with large reflectivity

THE GREENSBURG STORM

- The Greensburg storm itself first developed after a long series of cell splits and mergers near the Oklahoma–Kansas border between 0013 and 0038 UTC 5 May 2007, and first became tornadic around 0132 UTC.
- The storm produced at least four small and relatively short-lived tornadoes (rated EF0-EF1) before producing its first significant long-track tornado.
- The Greensburg tornado (was rated EF5) began at approximately 0200 UTC, struck the town of Greensburg just after 0245 UTC, and finally dissipated at approximately 0300 UTC (LU08). The Greensburg tornado had a mean path width of approximately 2.0 km

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FIG. 6. Individual 0–1-h vorticity swaths for the first 28 (of 30) ensemble members of experiment V0200I0200. For reference, overlaid in each are the tracks of the Greensburg tornado, as well as the two subsequent large tornadoes from the storm. The location of Greensburg, KS, is denoted by the yellow star. The scale is indicated in km in the lower left. Only a portion of the full model domain is shown.

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Between 0130 and 0315

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Between 0145 and 0315

Between 0200 and 0315

Vxxxxlyyyy: xxxx time of the hodograph yyyy initial time

REMAINING ISSUES

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- Calibration
- Verification
- Assimilation
- Operational implementation: strategies to run a convective scale EPS

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Generating a convective scale forecast ensemble

- MOGREPS-G (60 km) operational
- MOGREPS-R (18 km) operational
- ETKF-1.5 km research

southern UK domain

- Control and 23 ensemble members with perturbed initial conditions
- Hourly cycling
- Convection-permitting
- LBCs and IC perturbations from MOGREPS-R
- Grid-point based NWP model
- 70 vertical levels

MOGREPS: Met Office Global and Regional Ensemble Prediction System

540 km

Rudd et al 2012

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SOME REFERENCES

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- Cloud-Resolving Ensemble Simulations of Mediterranean Heavy Precipitating Events: Uncertainty on Initial Conditions and Lateral Boundary Conditions, Vie et al., 2011MWR
- Impact of the Environmental Low-Level Wind Profile on Ensemble Forecasts of the 4 May 2007 Greensburg, Kansas, Tornadic Storm and Associated Mesocyclones DANIEL T. DAWSON II et al, 2012, MWR.
- User guide to ECMWF forecast products, Andersson. ECMWF Technical Notes 2013