Uncertainty in weather prediction

Where does it come from and what does it look like?

George C. Craig

Meteorologisches Institut
Fakutät für Physik, LMU München

Outline

1. A meteorologist's picture of weather
2. Quantitative forecasting
3. Uncertainty and ensembles of forecasts
4. Probabilities and decision making
5. Why we need new ways of looking at data

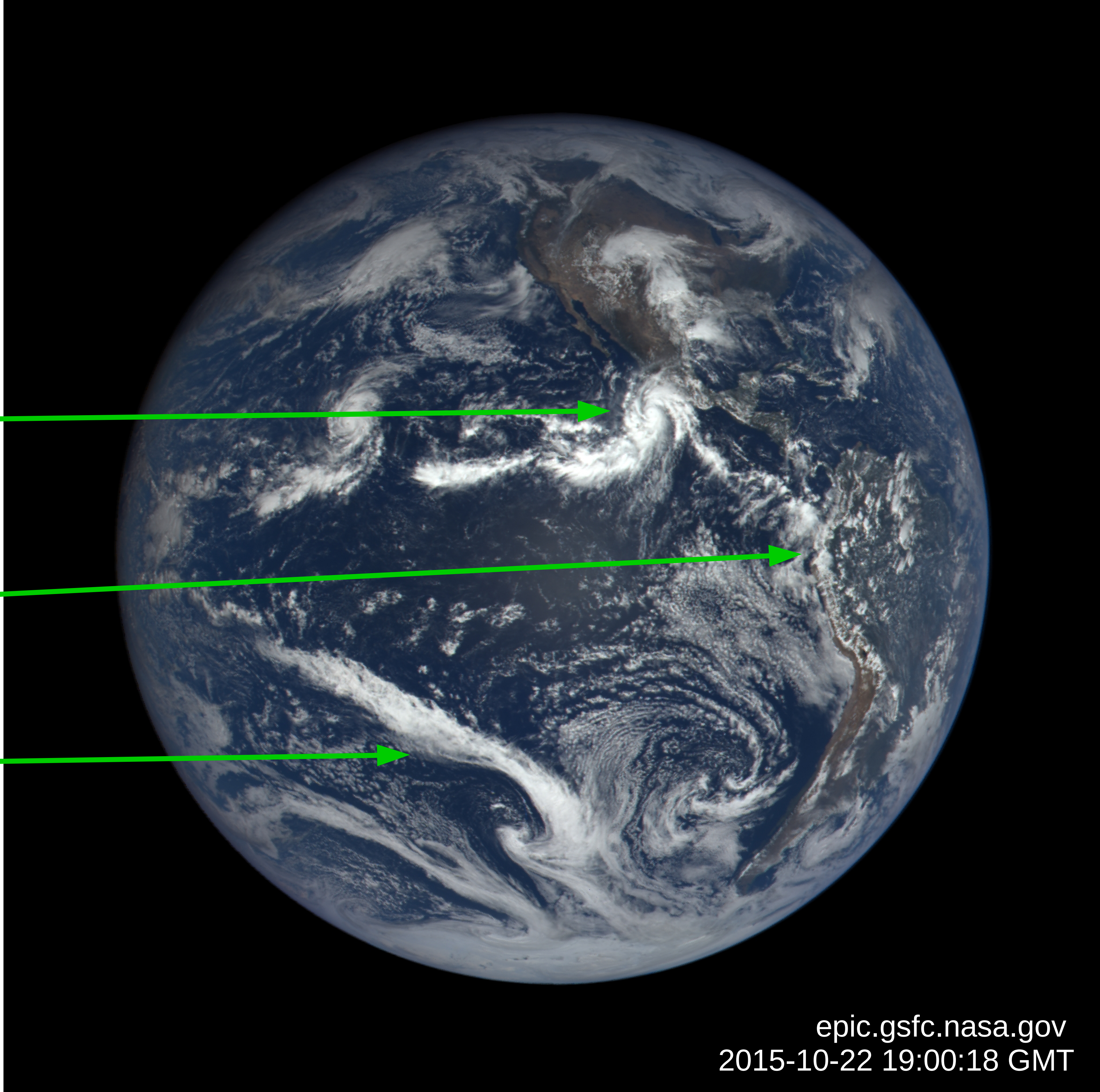
Weather objects

Tropical cyclone Patricia

Thunderstorms

Cold front

Features in space and time



Synoptic Chart

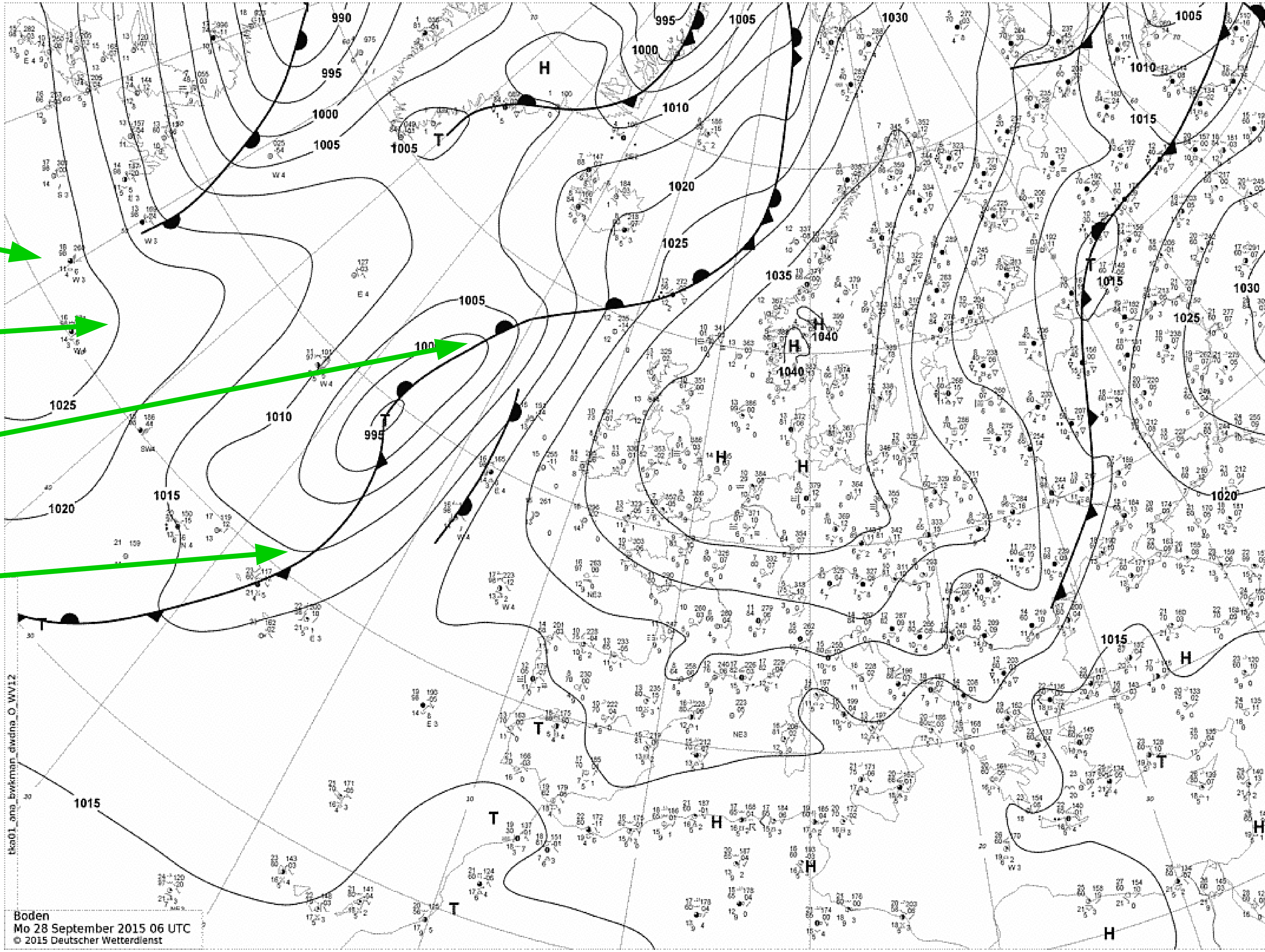
Observations

Isobars

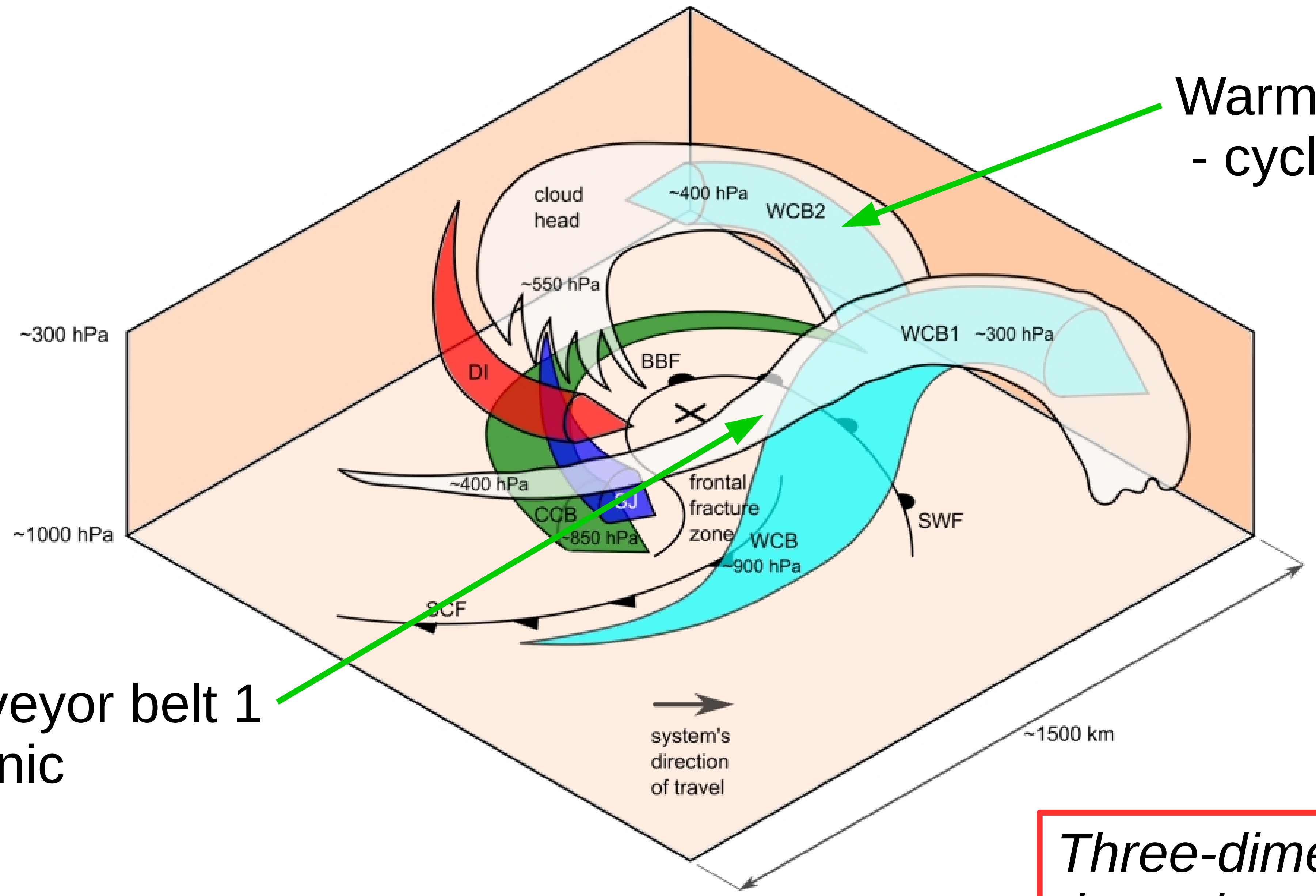
Warm front

Cold front

Conceptual model



A modern coneptual model



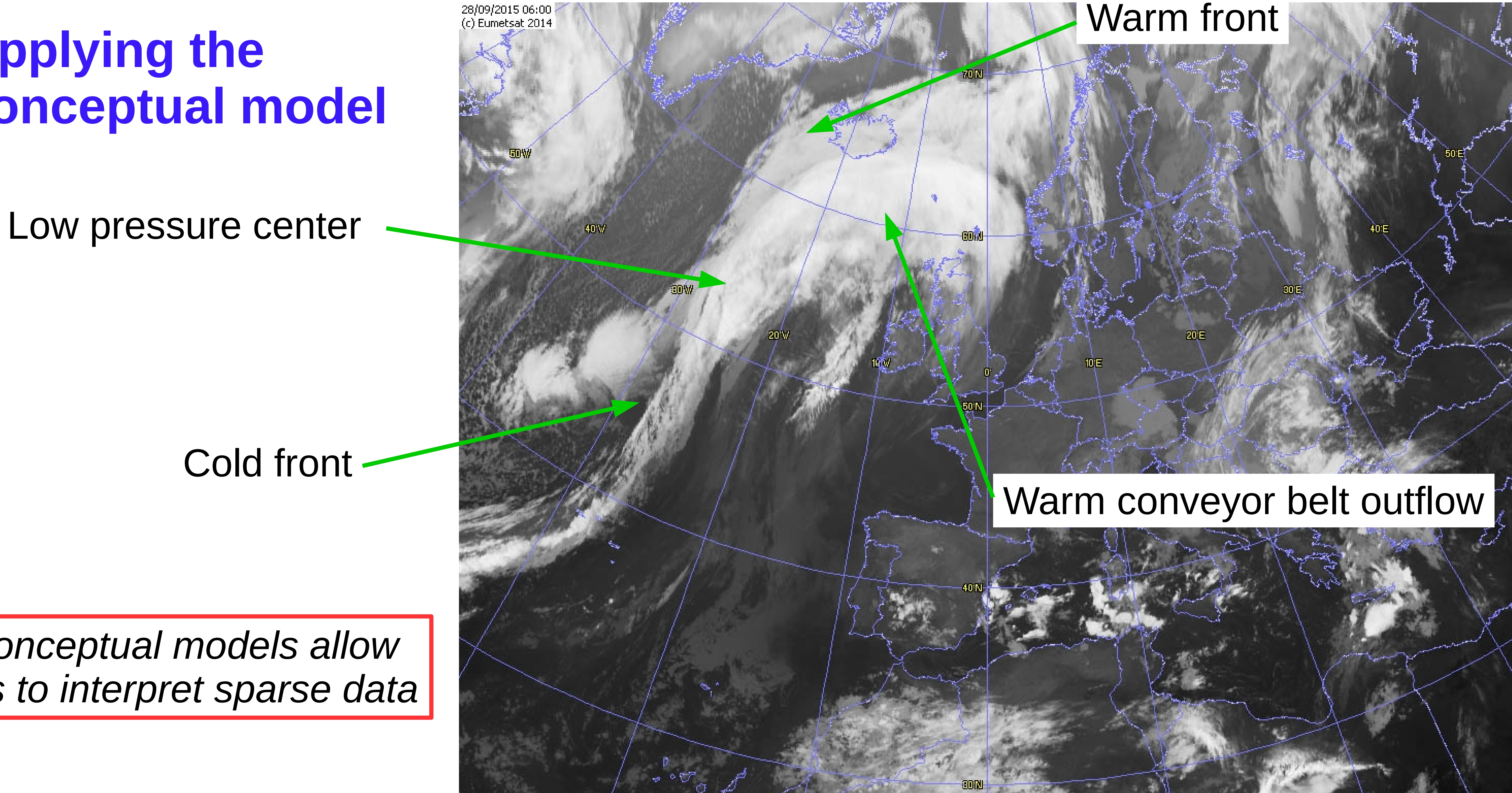
Warm conveyor belt 2
- cyclonic

Warm conveyor belt 1
- anticyclonic

Three-dimensional flow of air through weather system

Martinez-Alvarado et al. *Monthly Weather Review* 2014

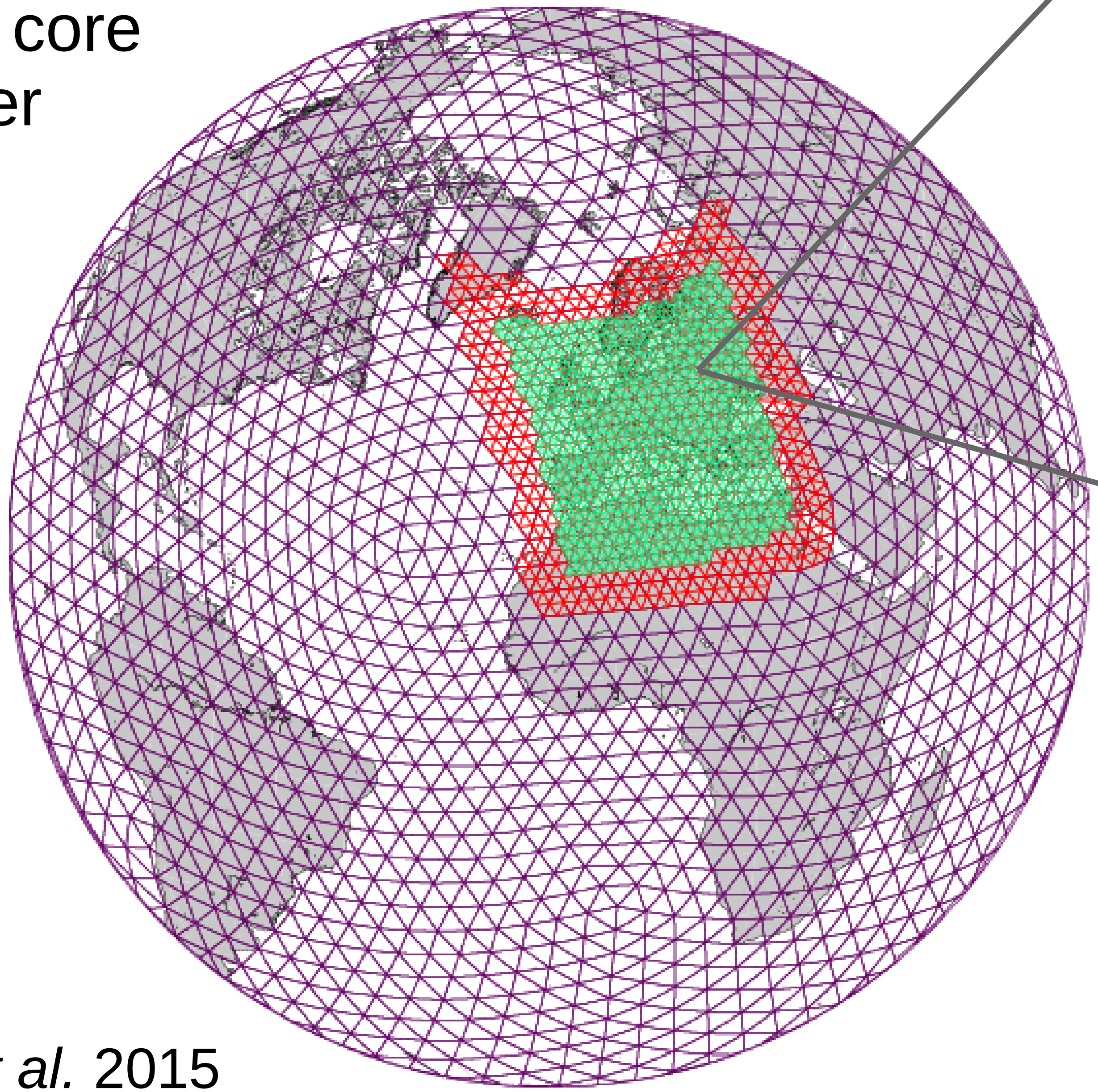
Applying the conceptual model



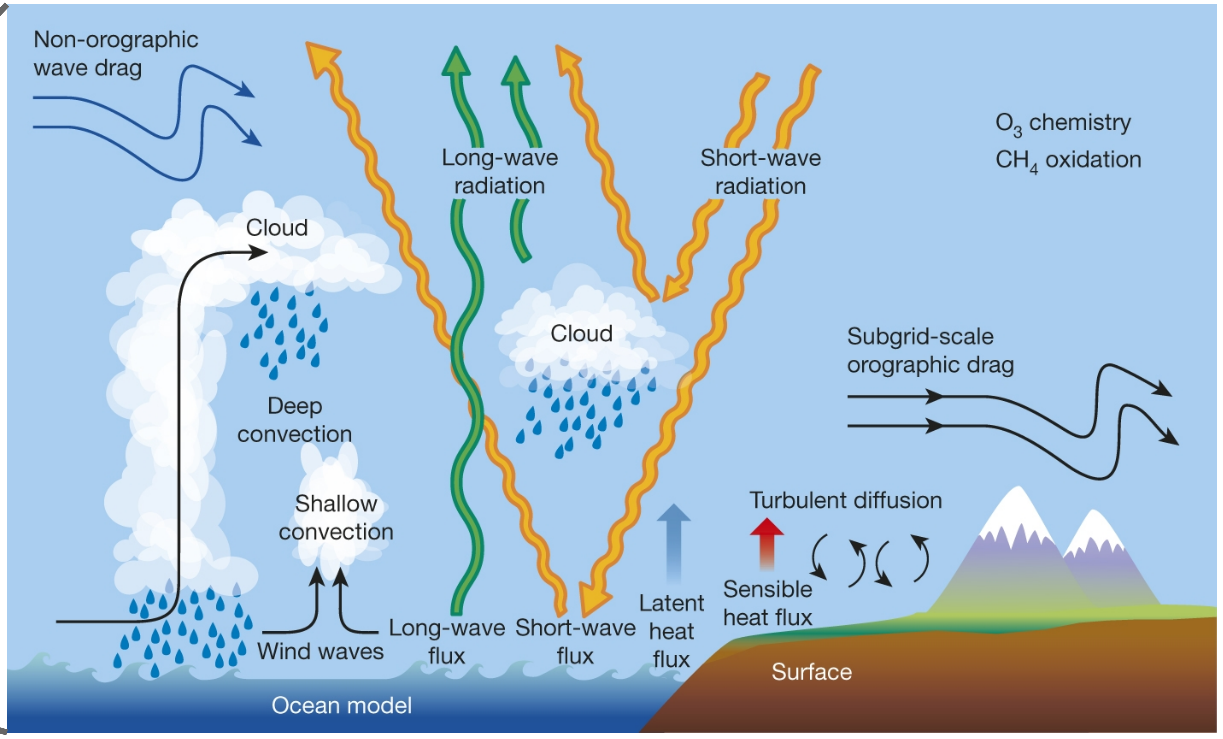
Conceptual models allow us to interpret sparse data

Numerical weather prediction

Dynamical core
- fluid solver



Zängl *et al.* 2015



Bauer *et al.* 2015

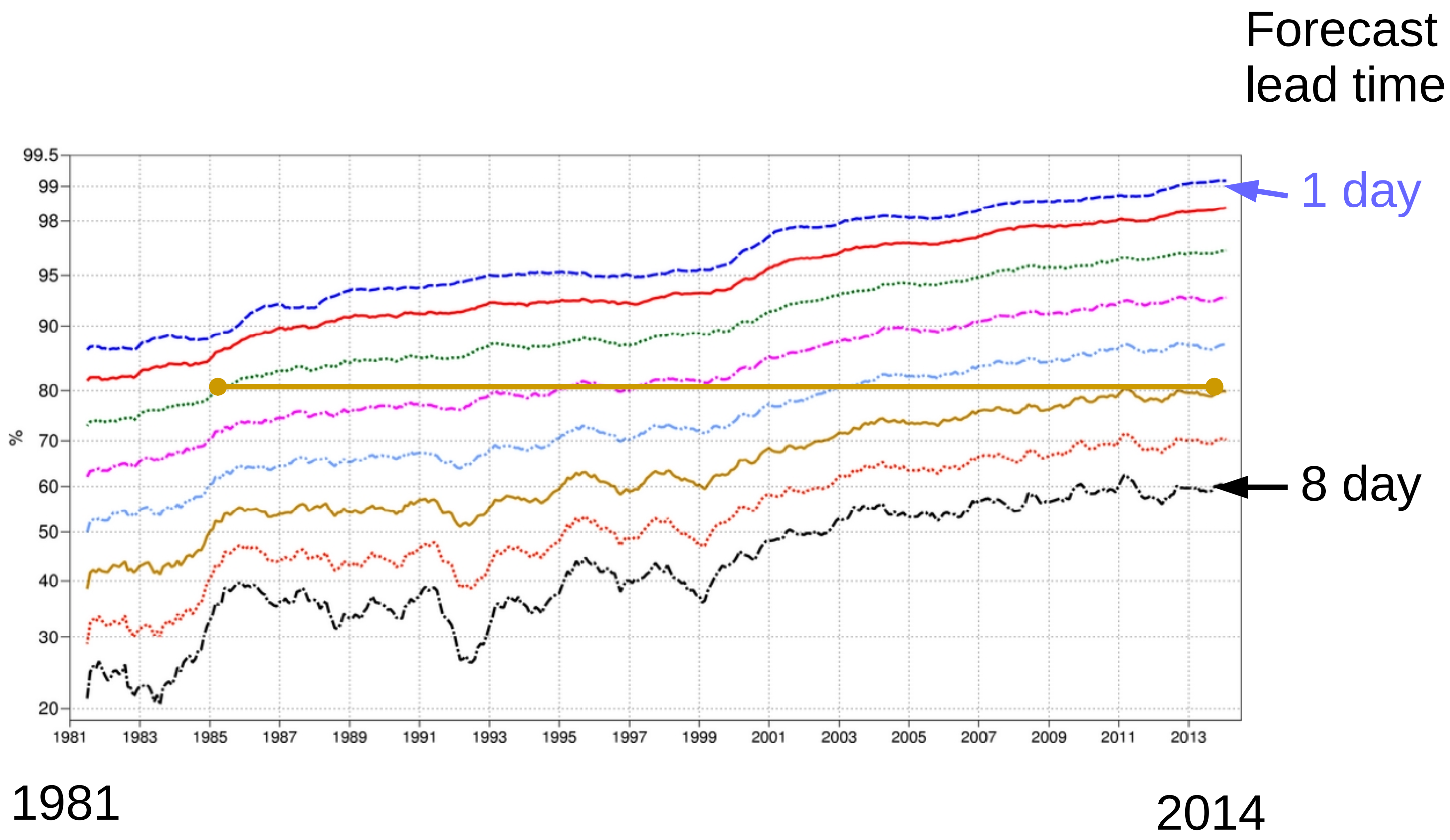
Parameterizations
- additional physical processes

Complex numerical codes, based on physical concepts

Measuring forecast skill

- Root mean square error (here 500 hPa geopotential, NH extratropics)
- Reference forecast - persistence
- Skill score
  - 100% → no error
  - 0% → no better than persistence

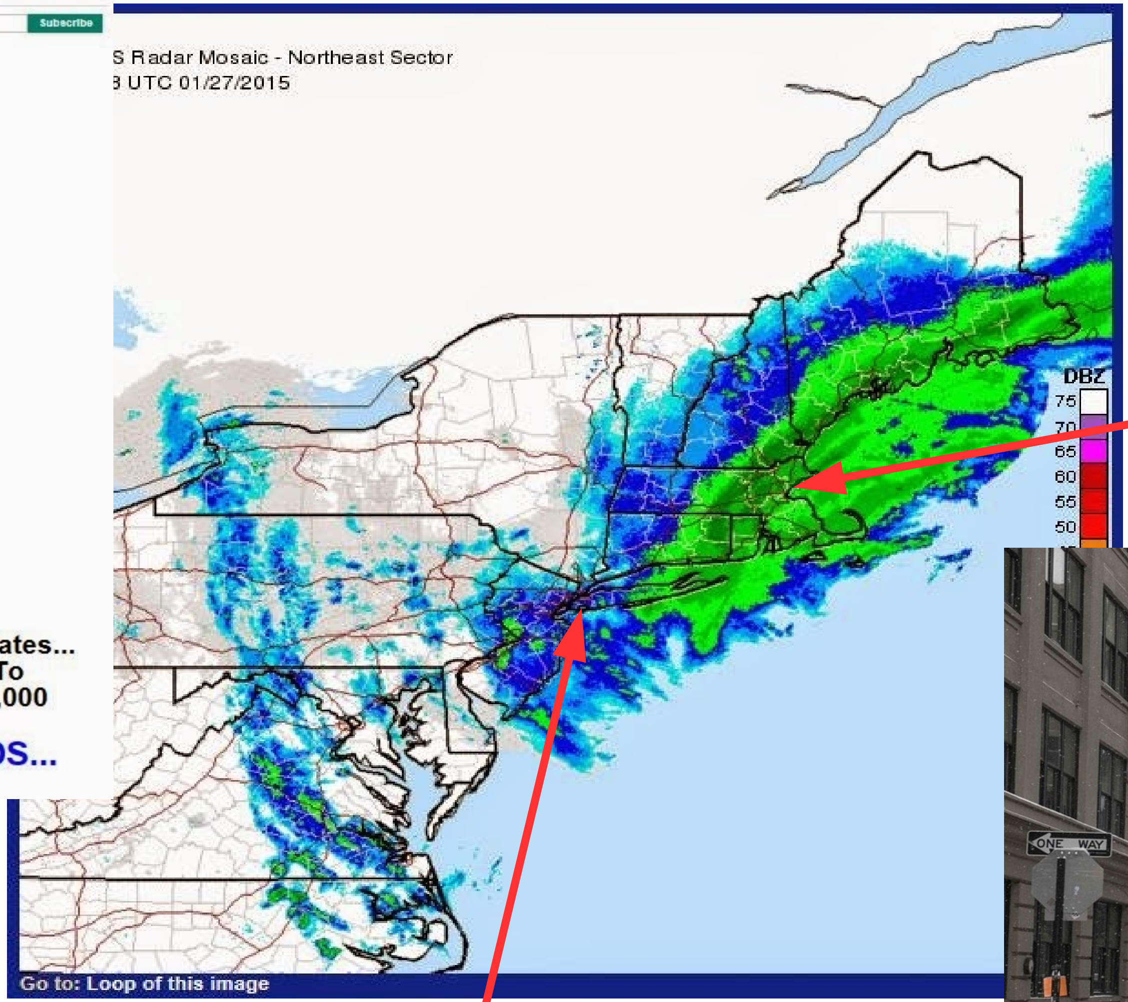
Improvement of 1 day per decade



Haiden et al., ECMWF, 2014

A bad forecast!

New York Storm
Jan. 27, 2015



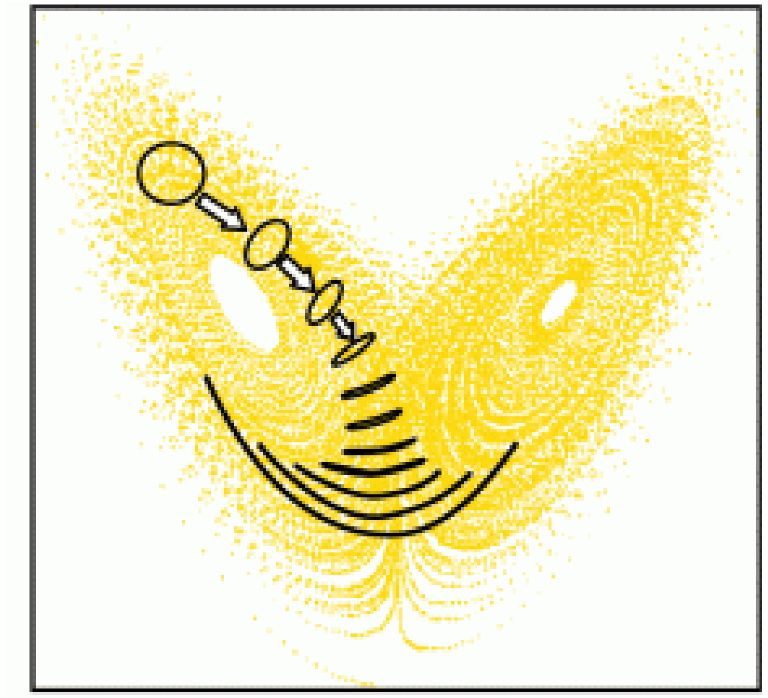
… but hit Boston!

Record winter storm forecast for New York

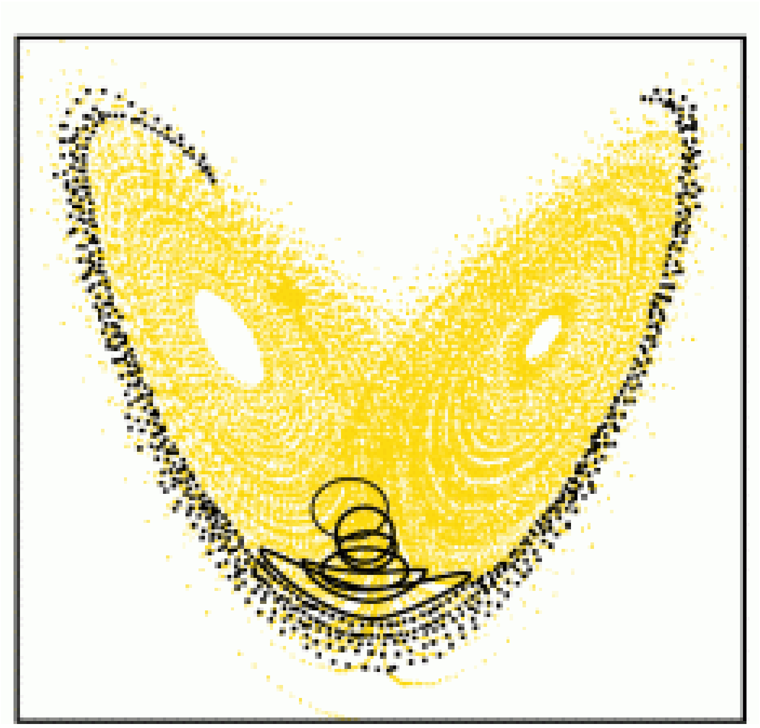
Storm missed New York, ...

Predictability and chaos

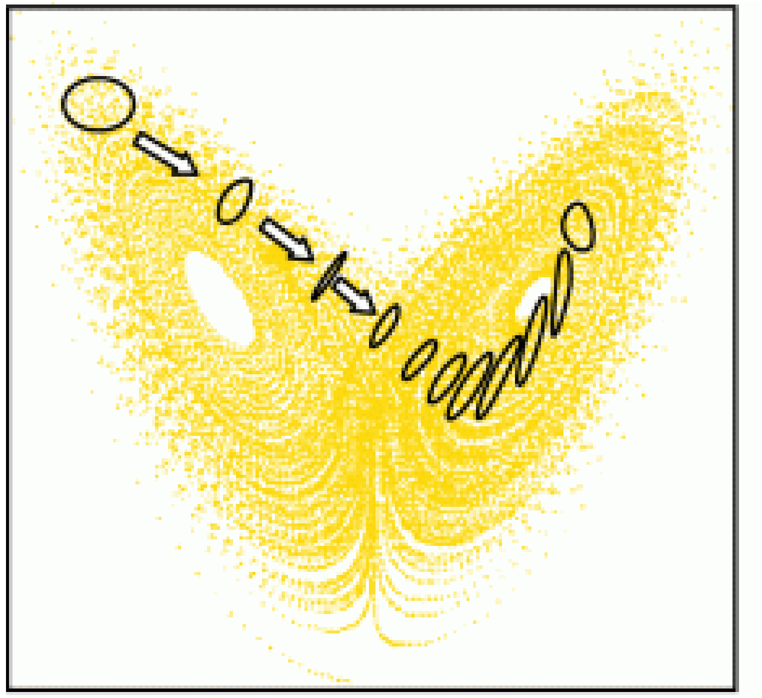
Simple dynamical system with three degrees of freedom
… but nonlinear Lorenz (1963)



Uncertainty in initial conditions grows rapidly



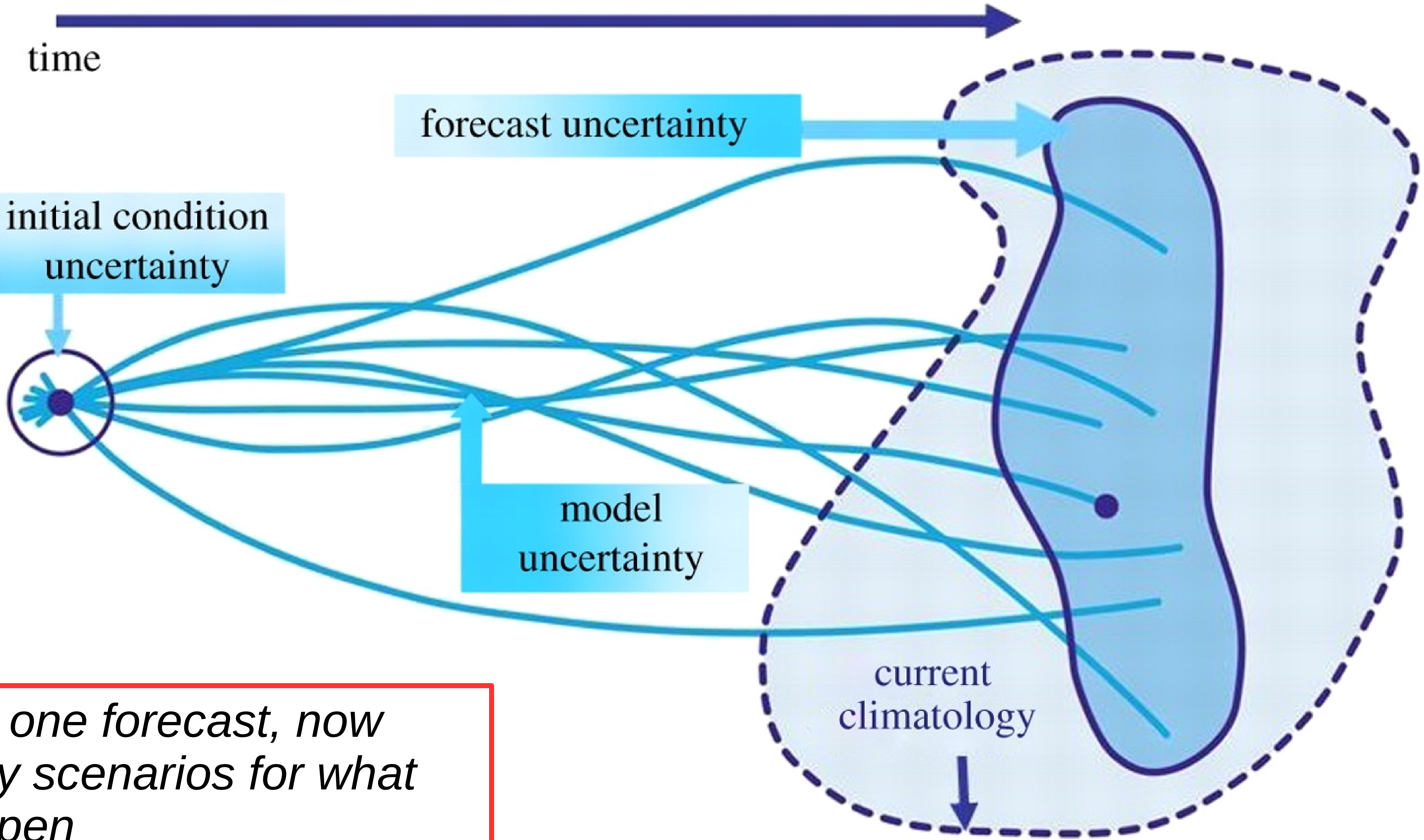
can lead to complete loss of predictability in finite time



... but not always

Palmer 2014

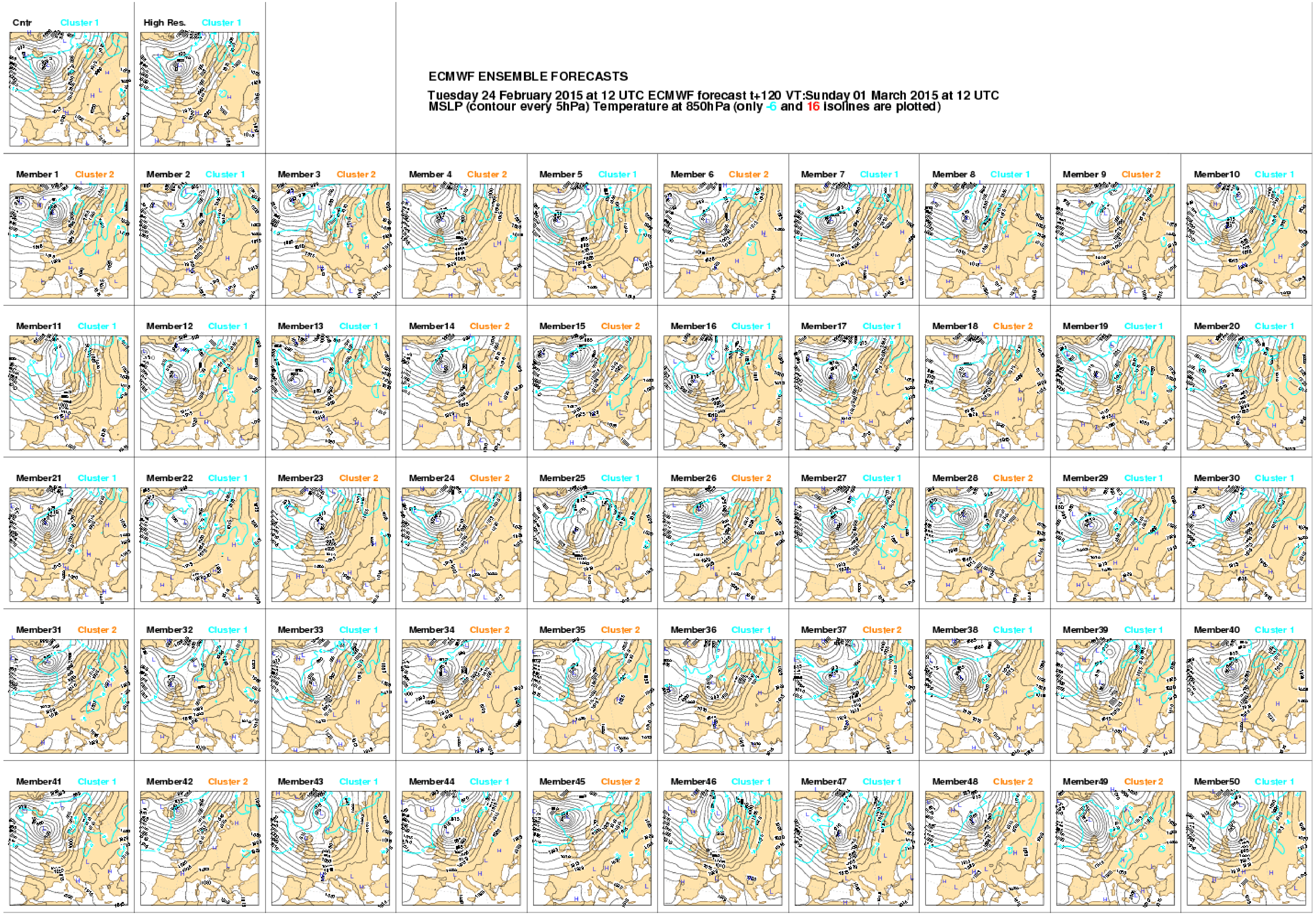
Ensemble prediction systems



Instead of one forecast, now have many scenarios for what might happen

Slingo and Palmer 2011

50 forecasts from ECMWF



Now what?

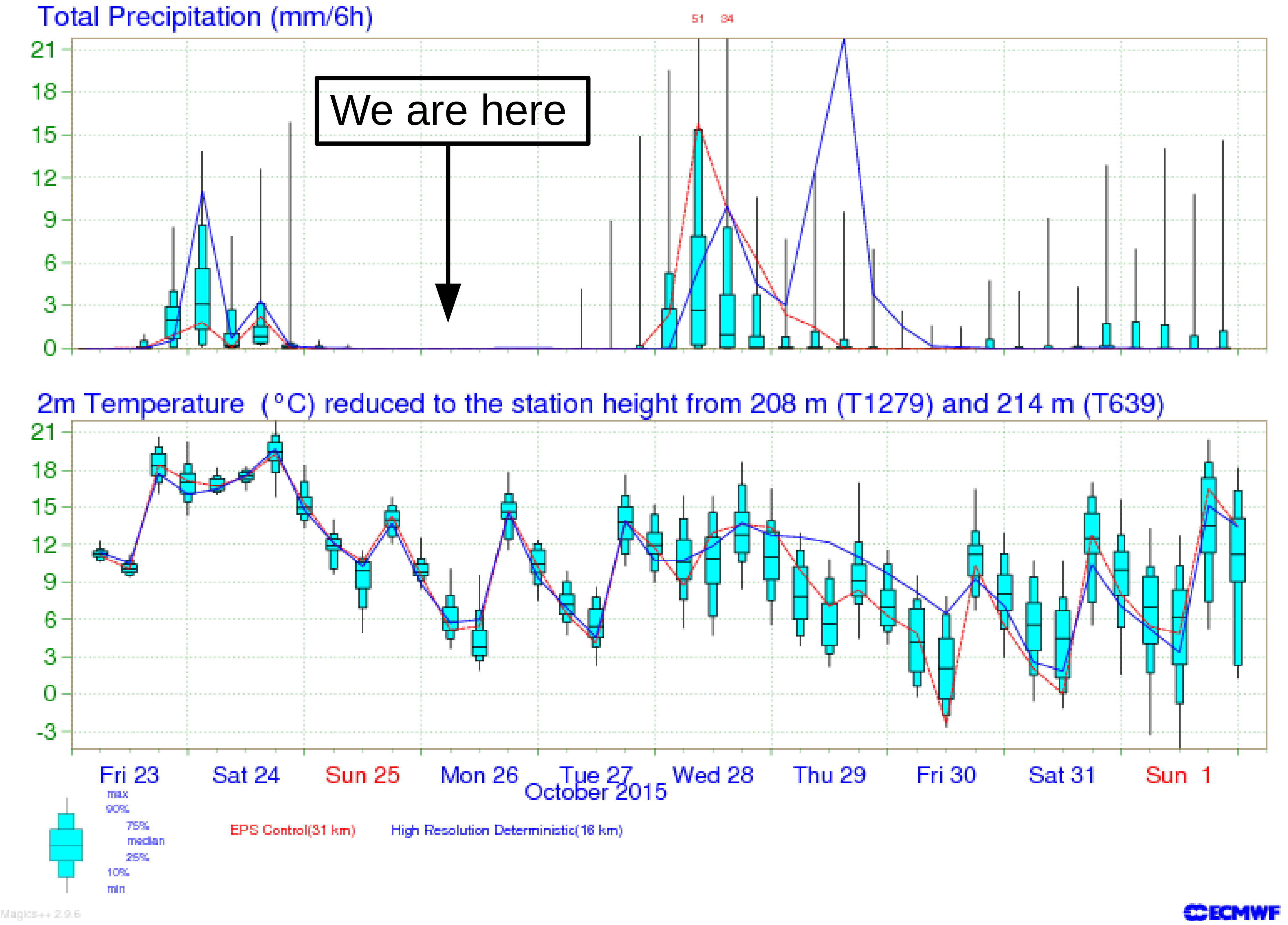
Meteogram

Forecast for Chicago from Friday

Precipitation
- scenarios

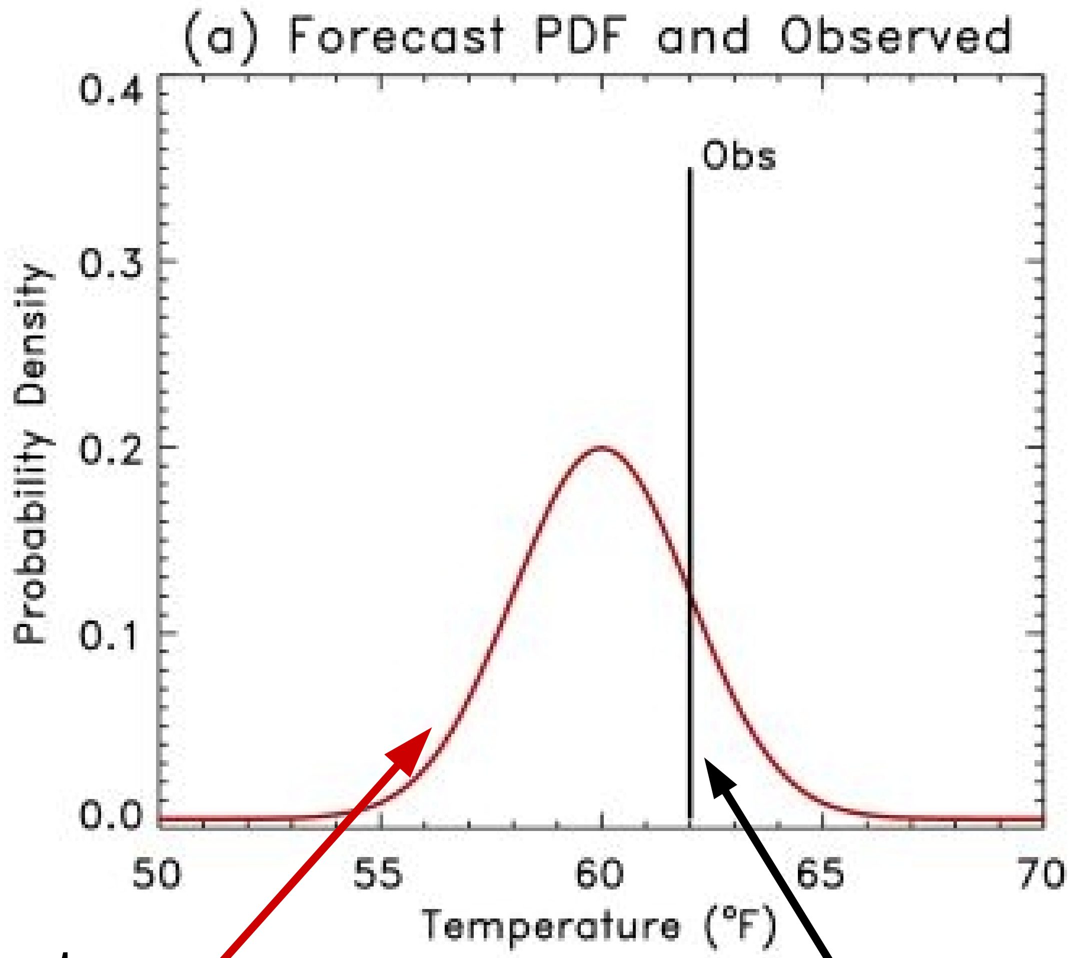
Temperature
- spread increases with time

Forecast is the probability of an event



What is a good probabilistic forecast?

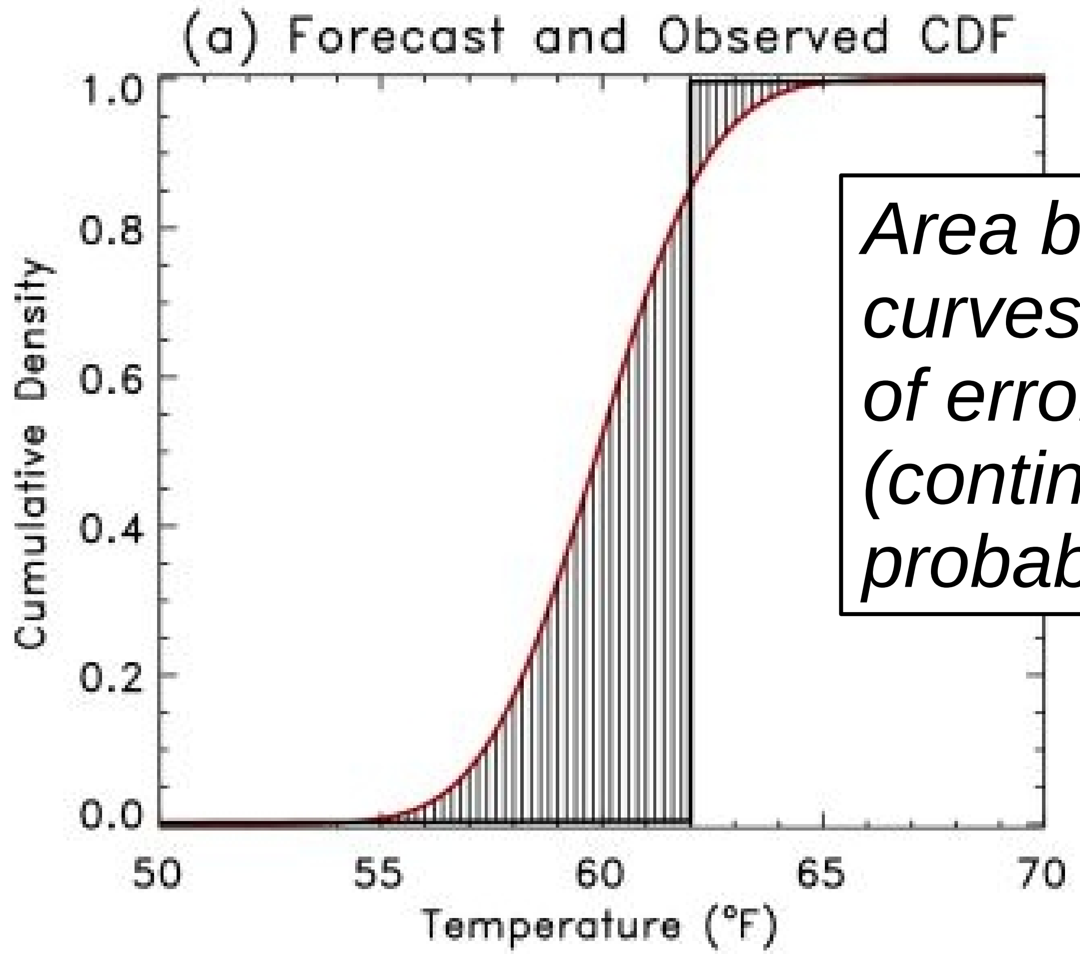
Probability density
Will this temperature occur?



Forecast probability

Observation

Cumulative density
Will this temperature be exceeded?

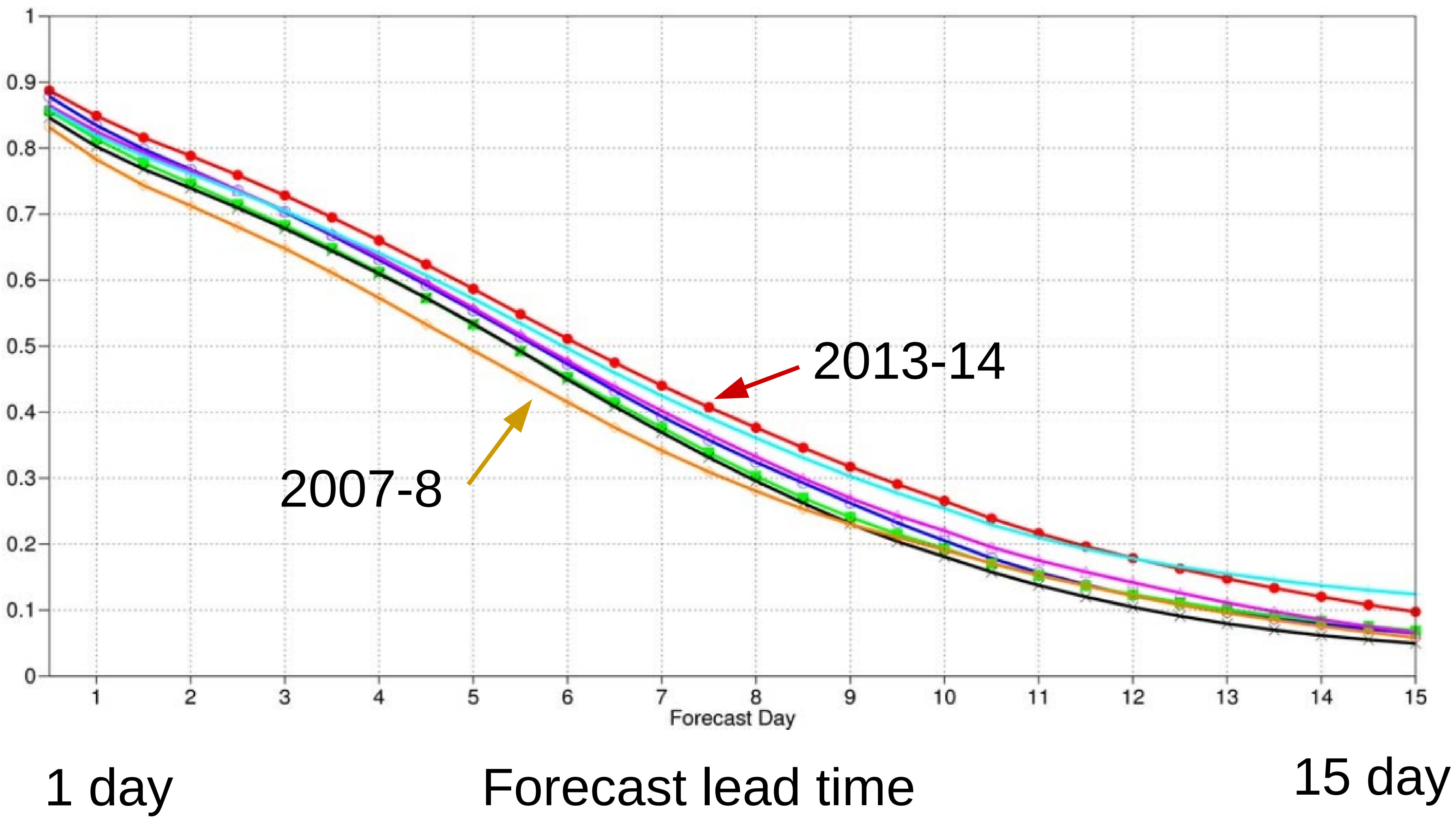


Area between curves is measure of error: CRPS (continuous ranked probability score)

Forecast errors - too low (reliability)
- too vague (sharpness)

Measuring probabilistic forecast skill

- CRPS (here 850 hPa temperature, NH extratropics)
- Reference forecast - persistence
- Skill score
  - 1 → no error
  - 0 → no better than persistence



Rapid improvement – but is it useful?

Haiden et al., ECMWF, 2014

A toy decision model

A static cost-loss model

- L: *Loss* due to an adverse event
- C: *Cost* of an action protecting against the loss. Arises whether or not event occurs
- C < L (or never take action!)

Decision strategy

Take decisions so that expenses are minimized over the long term

Cost-loss ratio determines how to react to a forecast

Expenses:

Decision is taken	event occurs: yes	event occurs: no
yes	*C*	*C*
no	*L*	*0*

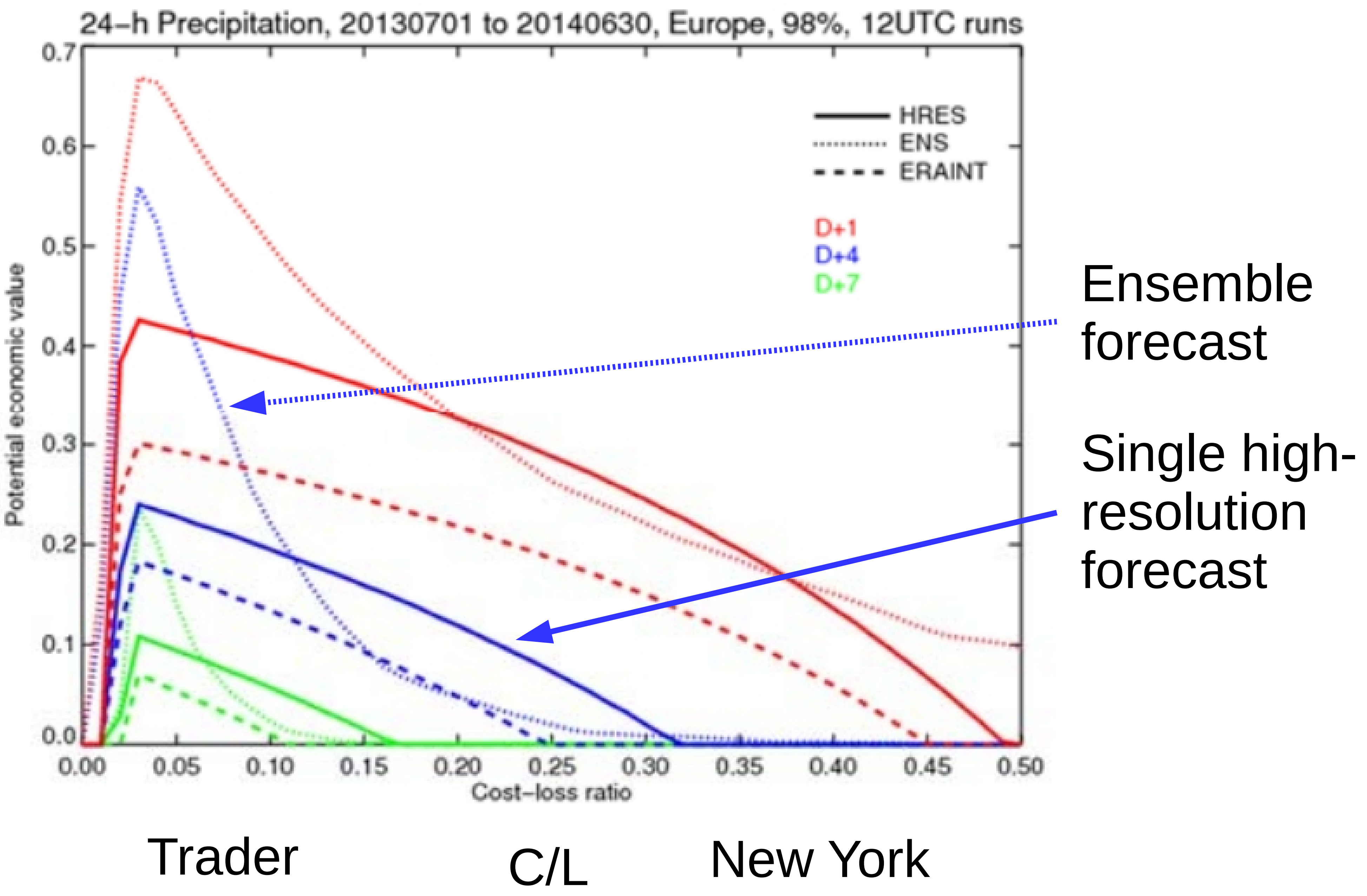
Different users have different cost-loss ratios

– Low C/L, e.g. energy trader
– High C/L, e.g. Mayor of New York

(Based on notes by Christoph Frei, Meteoswiss)

Potential economic value

- PEV for extreme precipitation (24 hr accumulation for Europe above 98th percentile)
- Reference forecast - climatology
- Skill score
  - 1 → expenses as low as for perfect forecast
  - 0 → no better than climatology



For some users, a deterministic forecast gives the best probabilites

Haiden et al., ECMWF, 2014

The need for new ways of looking at data

- Decision making

  … based on

- Probabilistic forecasts

  … based on

- Ensembles of scenarios

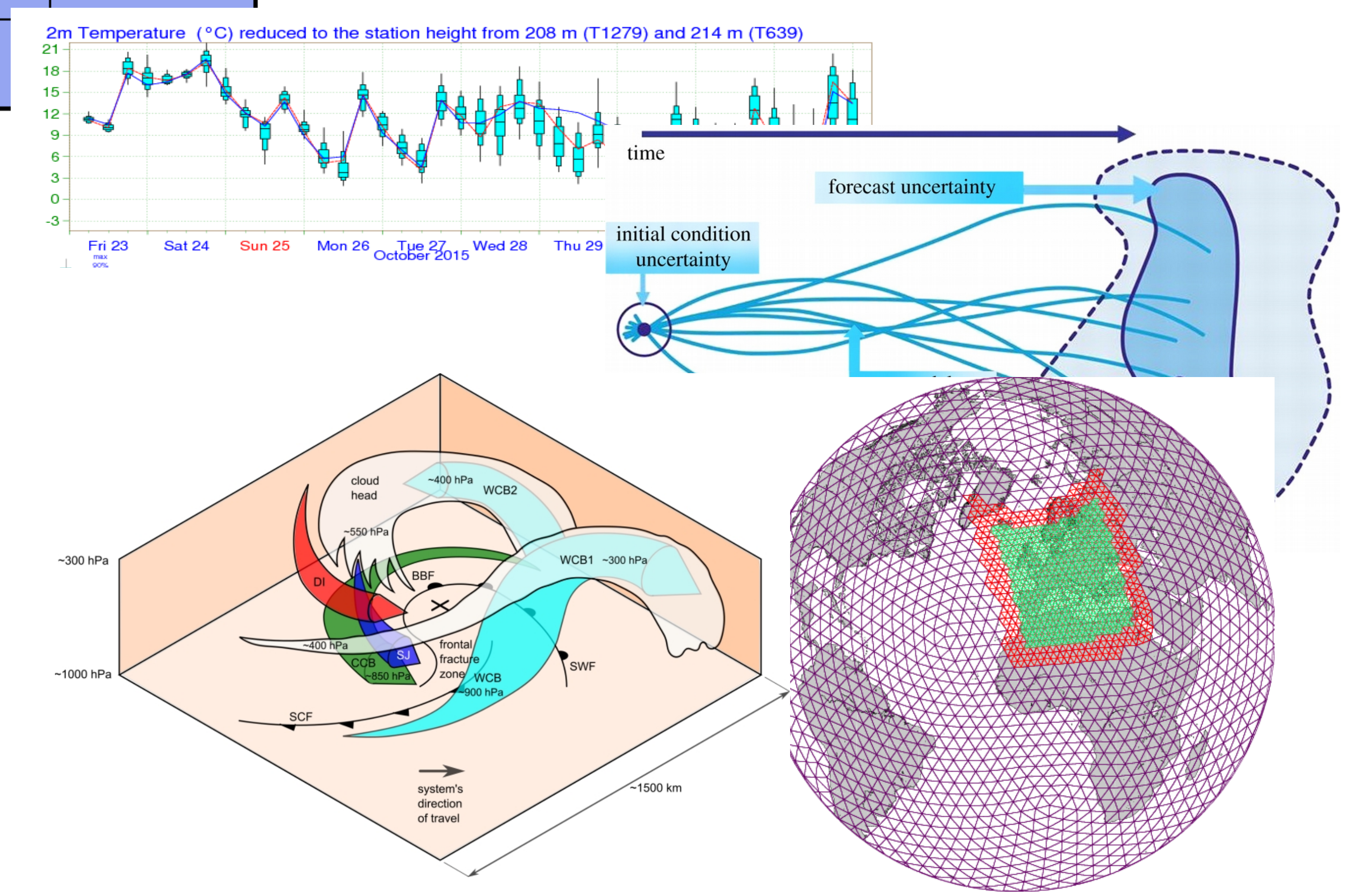
  … based on

- Numerical prediction models

  … based on

- Conceptual models that encapsulate physical understanding

Decision is taken	event occurs: yes	event occurs: no
yes	*C*	*C*
no	*L*	



How can we understand probabilistic and ensemble information using physically-based concepts and conceptual models?