Ensemble forecasting

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Overview

- Introduction
  - Why do forecast go wrong?
  - Observations, model, “chaos”
- The ECMWF ensemble
  - How does the ENS represent uncertainties?
  - Configuration of the ENS
- ENS products
  - Very short overview – much more in rest of course
- Evaluation of the ENS
- Use of ENS
  - Probabilities and decision support

Sources of forecast uncertainty

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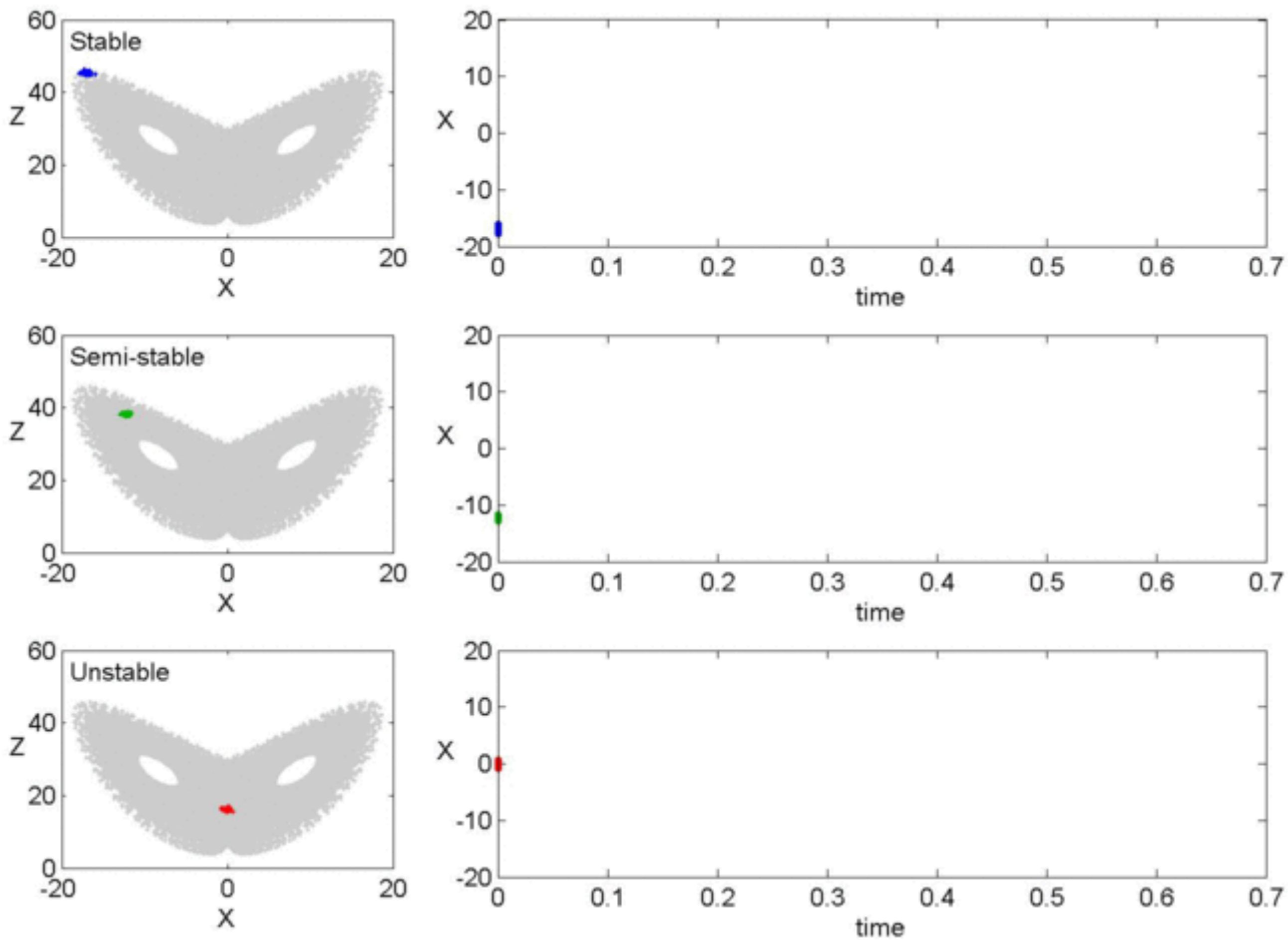
Why are forecasts sometimes wrong?

- Initial condition uncertainties
  - Lack of observations
  - Observation error
  - Errors in the data assimilation
- Model uncertainties
  - Limited resolution
  - Parameterisation of physical processes
- Boundary condition uncertainties
- The atmosphere is chaotic
  - small uncertainties grow to large errors (unstable flow)
  - small scale errors will affect the large scale (non-linear dynamics)
  - error-growth is flow dependant

Even very good analyses and forecast models are prone to errors

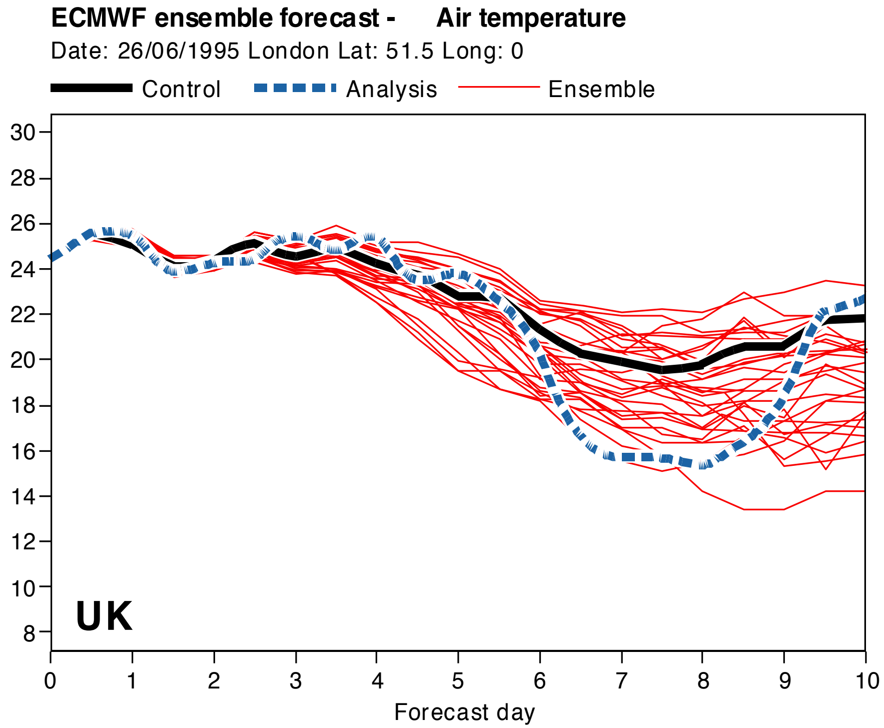
Chaos - the Lorenz attractor



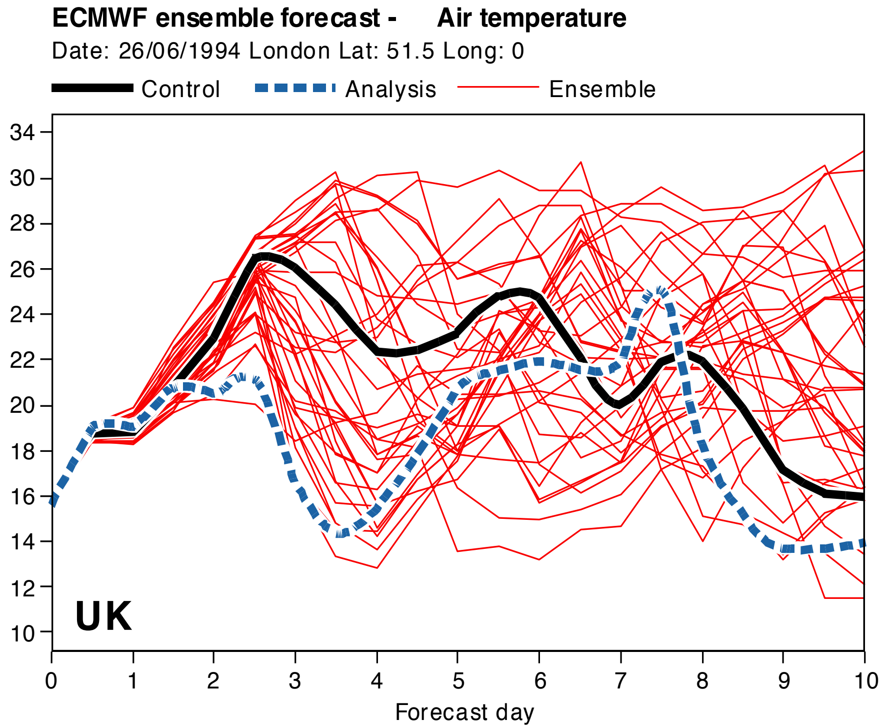
Tim Palmer, Oxford University

Flow dependence of forecast errors

26th June 1995



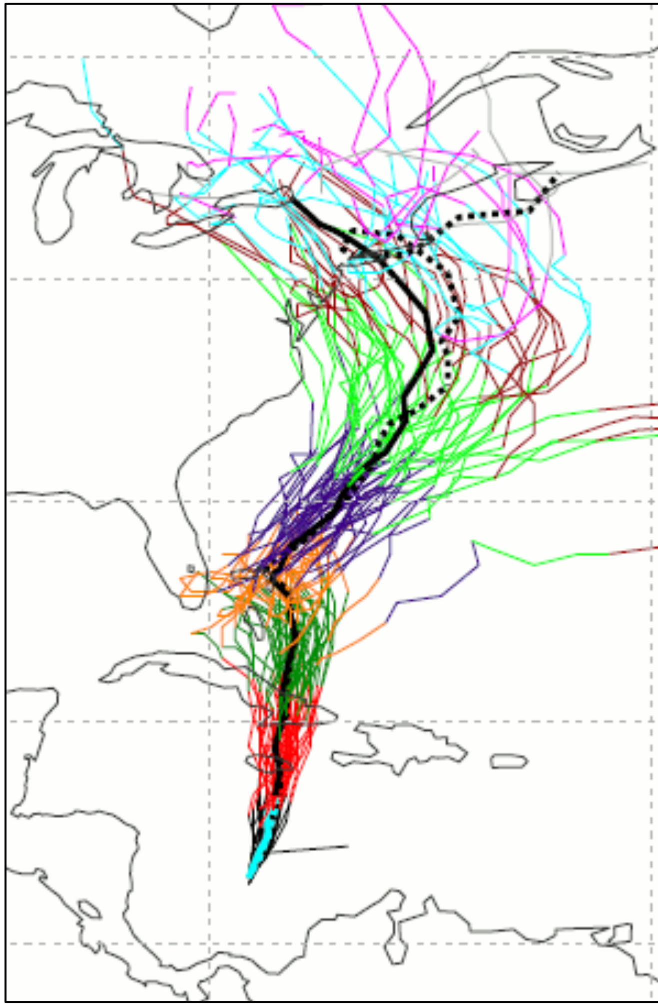
26th June 1994



If the forecasts are coherent (small spread) the atmosphere is in a more predictable state than if the forecasts diverge (large spread)

Representing uncertainty - ensemble forecasts

- A set of forecasts run from slightly different initial conditions to account for initial uncertainties
- The forecast model also contains approximations that can affect the forecast evolution
  - Model uncertainties are often represented using "stochastic physics"
- The ensemble of forecasts provides a range of future scenarios consistent with our knowledge of the initial state and model capability
  - Provides explicit indication of uncertainty in today's forecast



Ensembles: quantifying forecast uncertainy

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Global medium-range ensembles

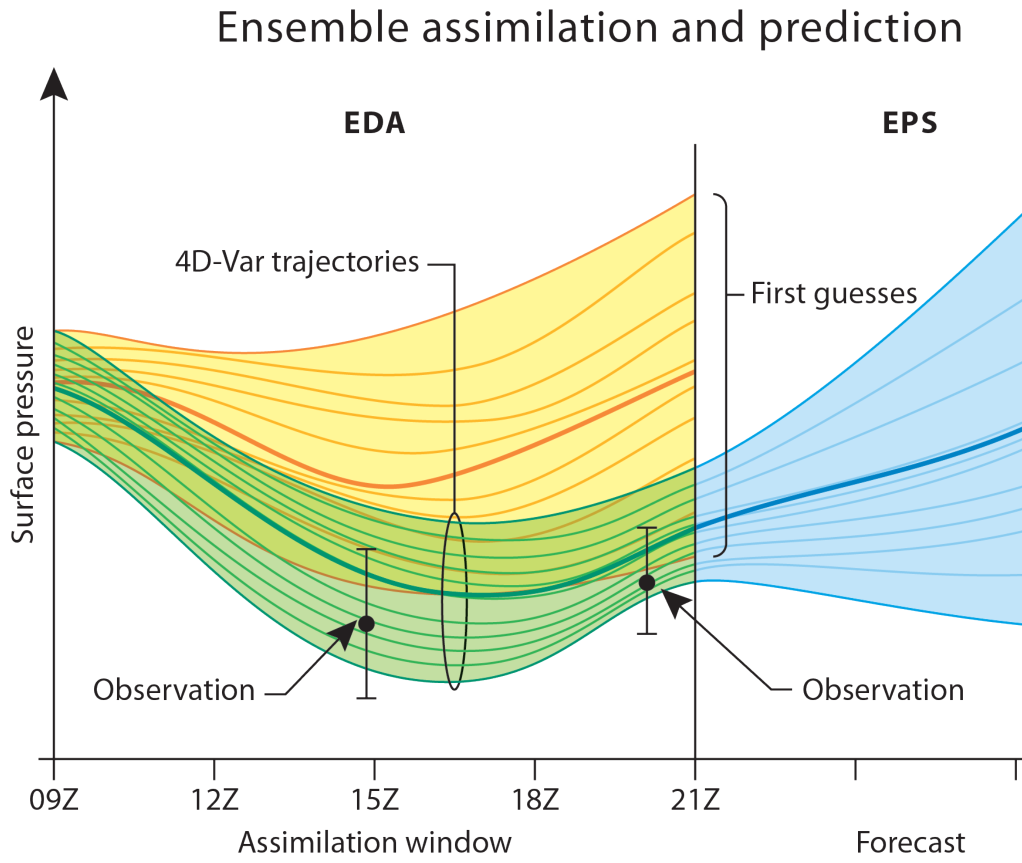
- All operational global medium-range ensemble systems represent initial uncertainty
- Most also include some representation of model uncertainty
- Different centres use different approaches
- Some centres combine ensembles from different start times to increase ensemble size (lagged)

	Initial uncertainty	Model uncertainty	Time-range days	Resol. (km)	Ens. Size	Freq.
ECMWF	SV (NH, SH, Tr) +EDA (globe)	YES	15/46	18/36	51	00/12
UKMO	ETKF (globe)	YES	7	60	24	00/12
NCEP	ETR (globe)	YES	16	90/120	21	00/06/12/18
EC	EnKF	YES	16/32	75	21	00/12
JMA	SV (NH, SH, Tr)	YES	11	50	33	00/12
KMA	ETKF (globe)	YES	10	40	24	00/06/12/18
CMA	BV (globe)	NO	10	70	15	00/12
CPTEC	EOF (40S-30N)	NO	15	120	15	00/12

Ensemble of data assimilations (EDA)

- EDA (initial EPS perturbations since June 2010)
  - Control + 25 ensemble members using 4D-Var assimilations
  - TCo639 (18km) outer loop
  - TL191 inner loop (reduced number of iterations)
  - Model error: Stochastically Perturbed Parametrization Tendencies
  - Randomly perturbed observations and SST fields

- EDA perturbations are not sufficient by themselves
  - Additional initial perturbations based on “singular vectors”



Initial uncertainties – singular vectors

- The number of ensemble members is limited by available computer resources. How can we produce suitable perturbations?
- Look for perturbations that will grow fastest
- Singular vectors: perturbations that produce the greatest (linear) difference (total energy) over a fixed time interval (48 hours)
  - Uses the same tangent-linear and adjoint models as used for the 4D-Var analysis
- 50 perturbations generated by random (Gaussian) sampling from 50 singular vectors. Amplitude tuned to match error
- Tropical cyclones:
  - Up to 6 areas centred on existing tropical cyclones
  - 5 singular vectors per area, Gaussian (random) sampling
  - “moist SVs” – TL includes diabatic processes (large-scale condensation, convection, radiation, gravity-wave drag, vert. diff. and surface friction)

ENS initial perturbations

- SV- and EDA-based perturbations have different characteristics:
  - EDA-based perturbations are less localized than SV-based perturbations. They have a larger amplitude over the tropics. EDA-perturbations are more barotropic than SV-based perturbations, and grow less rapidly.
  - At initial time, SV-based perturbations have a larger amplitude in potential than kinetic energy, while EDA-based perturbations have a similar amplitude in potential and kinetic energy

- Since June 2010 SV- and EDA-based perturbations are used together to construct the initial perturbations for the EPS

- The perturbations are constructed so that all perturbed members are equally likely

- All perturbations are flow-dependent: they are different from day to day

Model uncertainties – stochastic physics

- Parametrization – represent effects of unresolved (or partly resolved) processes on the resolved model state
- Statistical ensemble of sub-grid scale processes within a grid box; in equilibrium with grid-box mean flow
- Stochastic physics represents statistical uncertainty
  – allows for energy transfer from sub-grid scale to resolved flow, non-local effects

tochastically Perturbed Parametrization Tendencies
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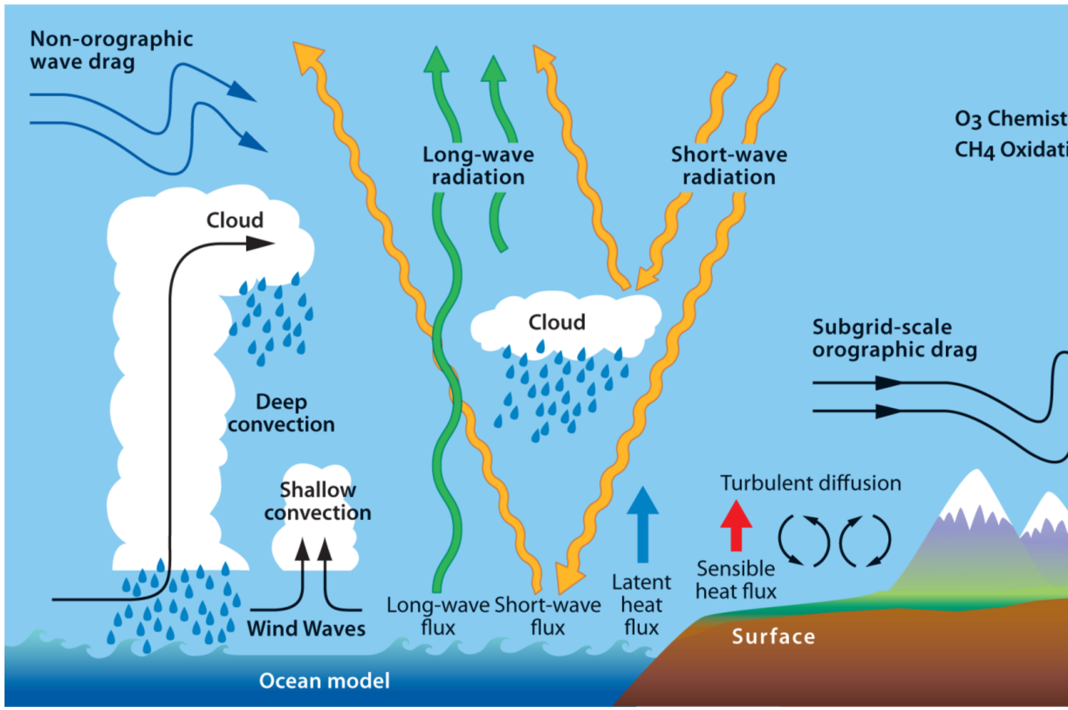
– Random pattern of perturbation to model fields

pectral stochastic backscatter scheme (SPBS)

– A fraction of the dissipated energy is backscattered upscale and acts as streamfunction forcing for the resolved-scale flow



ECMWF medium-range forecasts

- High-resolution forecast (9 km grid, 137 levels) runs twice every day to 10 days
- Ensemble: same model but run at lower resolution (18 km, 91 levels; 32 km after day 15)
  - ensemble control (run from high-resolution analysis, no perturbation)
  - 50 perturbed members (account for initial and model uncertainties)
  - Ensemble coupled to ocean model from start of forecast
- Ensemble extended to 46 days twice per week for monthly forecast (00 Thursday, Monday)

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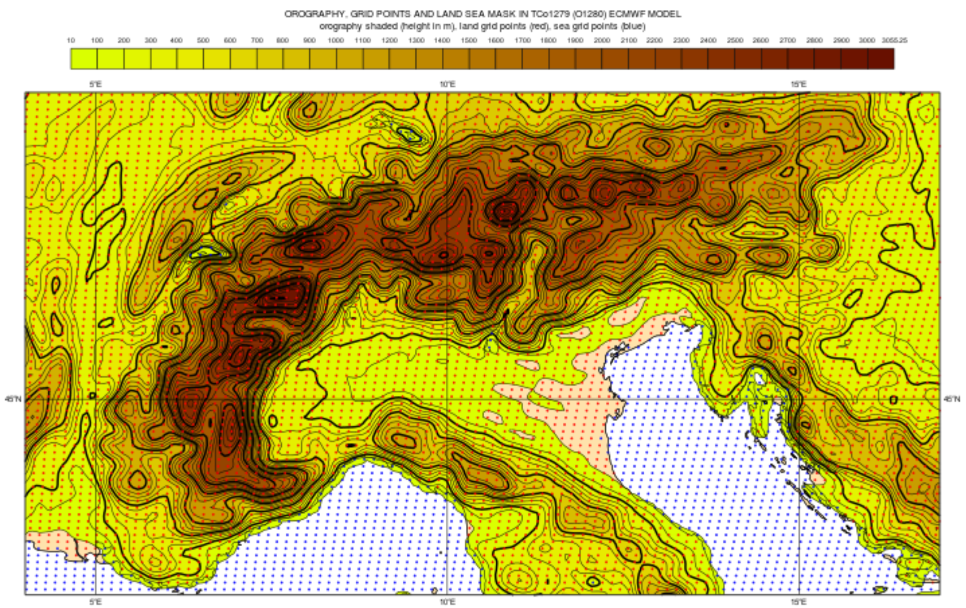

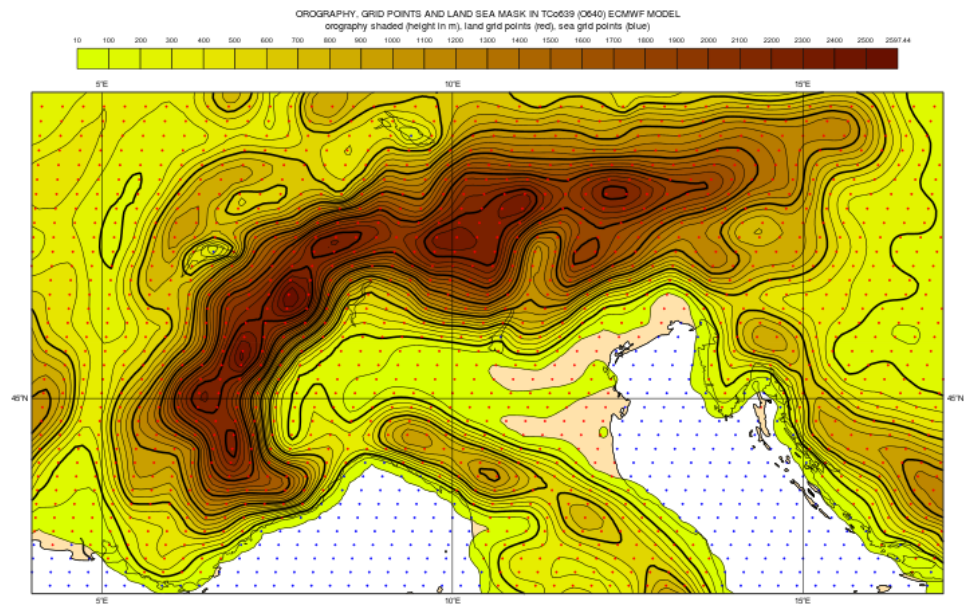

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Forecast products – extracting the information from the ensemble

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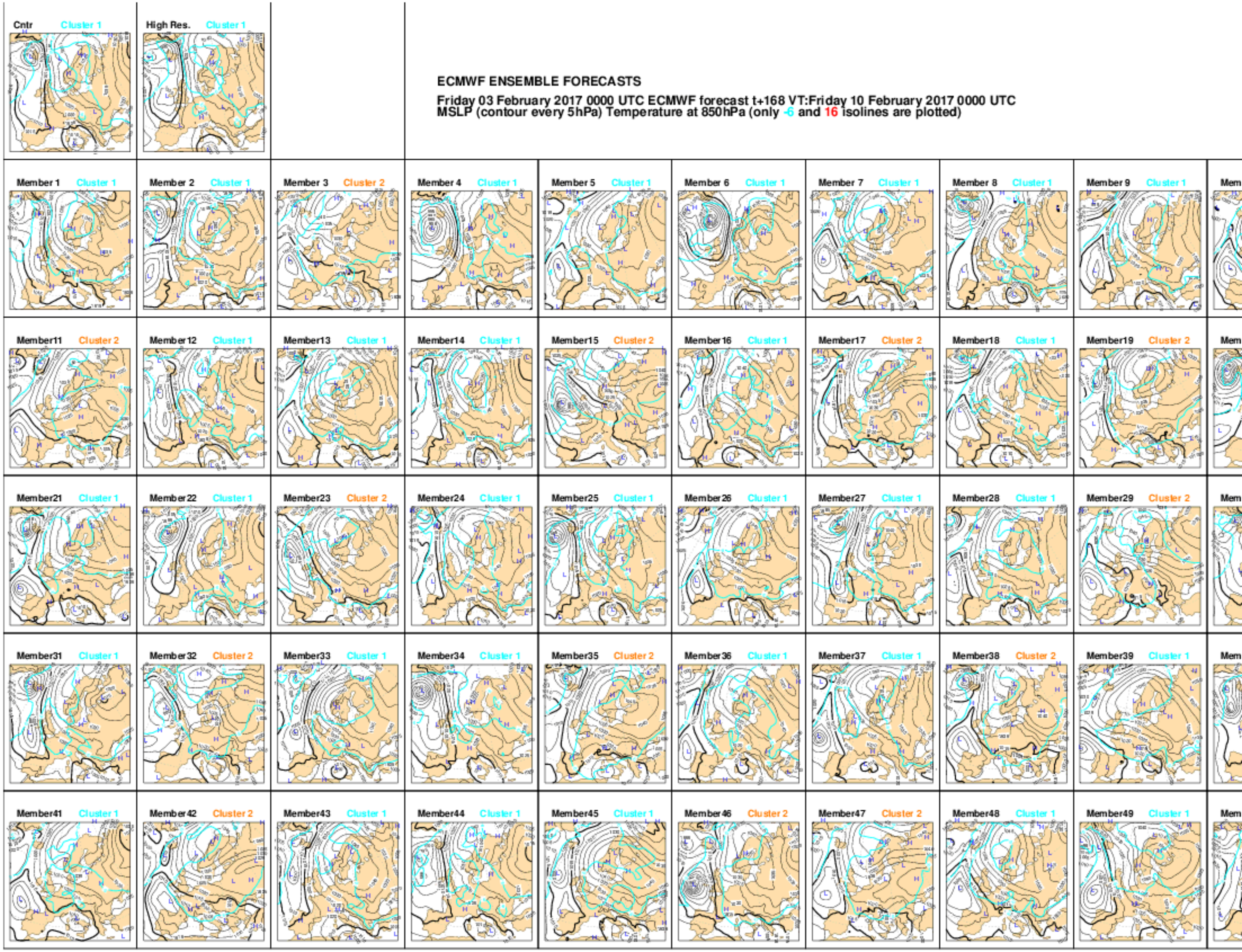


ECMWF forecast products

Summarise information in HRES and ENS

Represent uncertainty

Broad-scale evolution out to 15 days

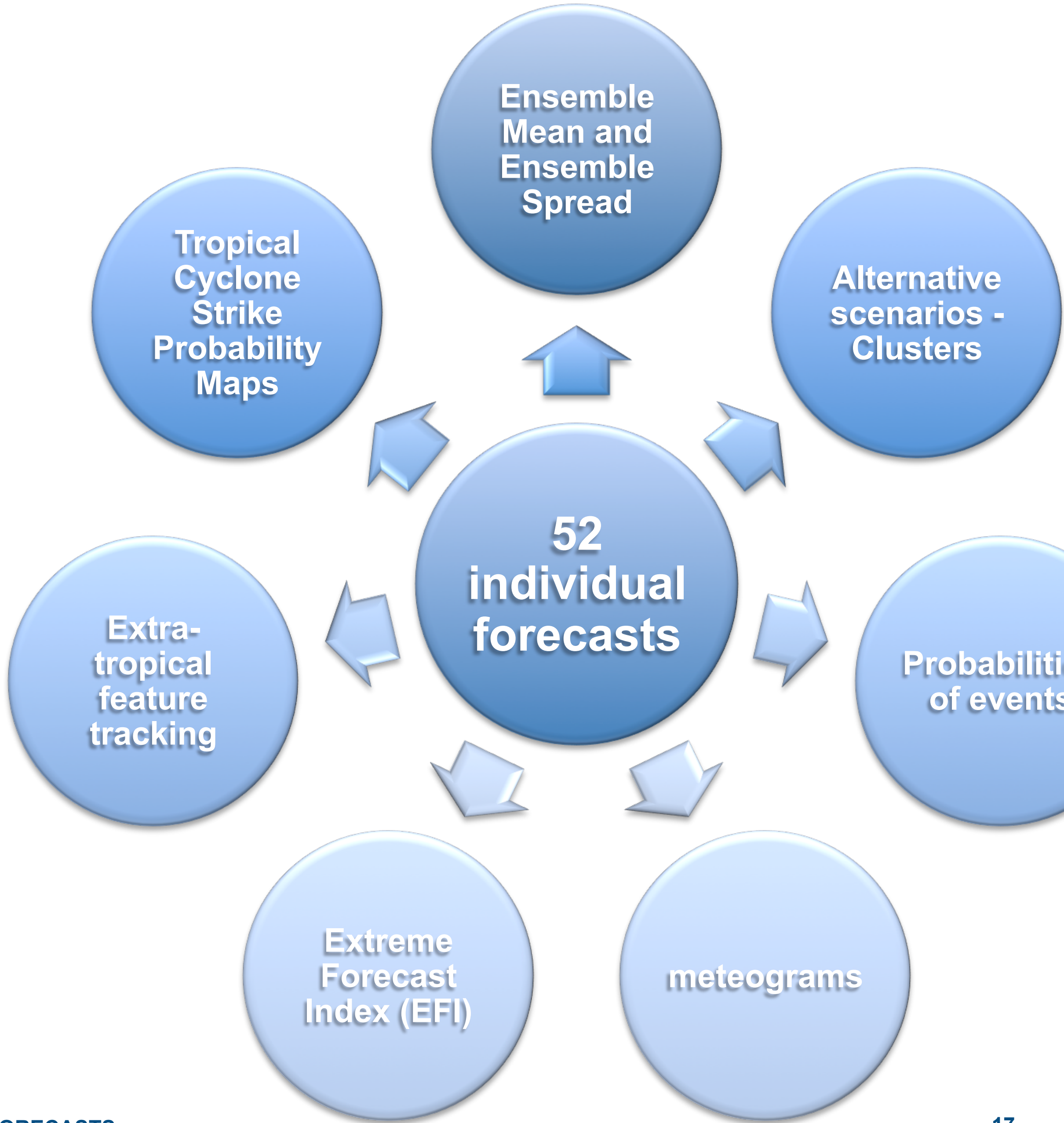
Changes in weather regime

Highlight potential for severe weather few days ahead

Monthly and seasonal outlooks

To assist operational forecasters (in Member States)

Users generate their own tailored products for specific applications



Ensemble mean and spread

he ensemble mean is the average over all
nsemble members

 will smooth the flow more in areas of large
ncertainty (spread)

his cannot be achieved with a simple filtering of
 single forecast

 there is large spread, the ensemble mean can
e a rather weak pattern and may not represent
ny of the possible states

he ensemble mean should always be used
ogether with the spread

he mean may not be the best option for
arameters with skewed (non-gaussian)
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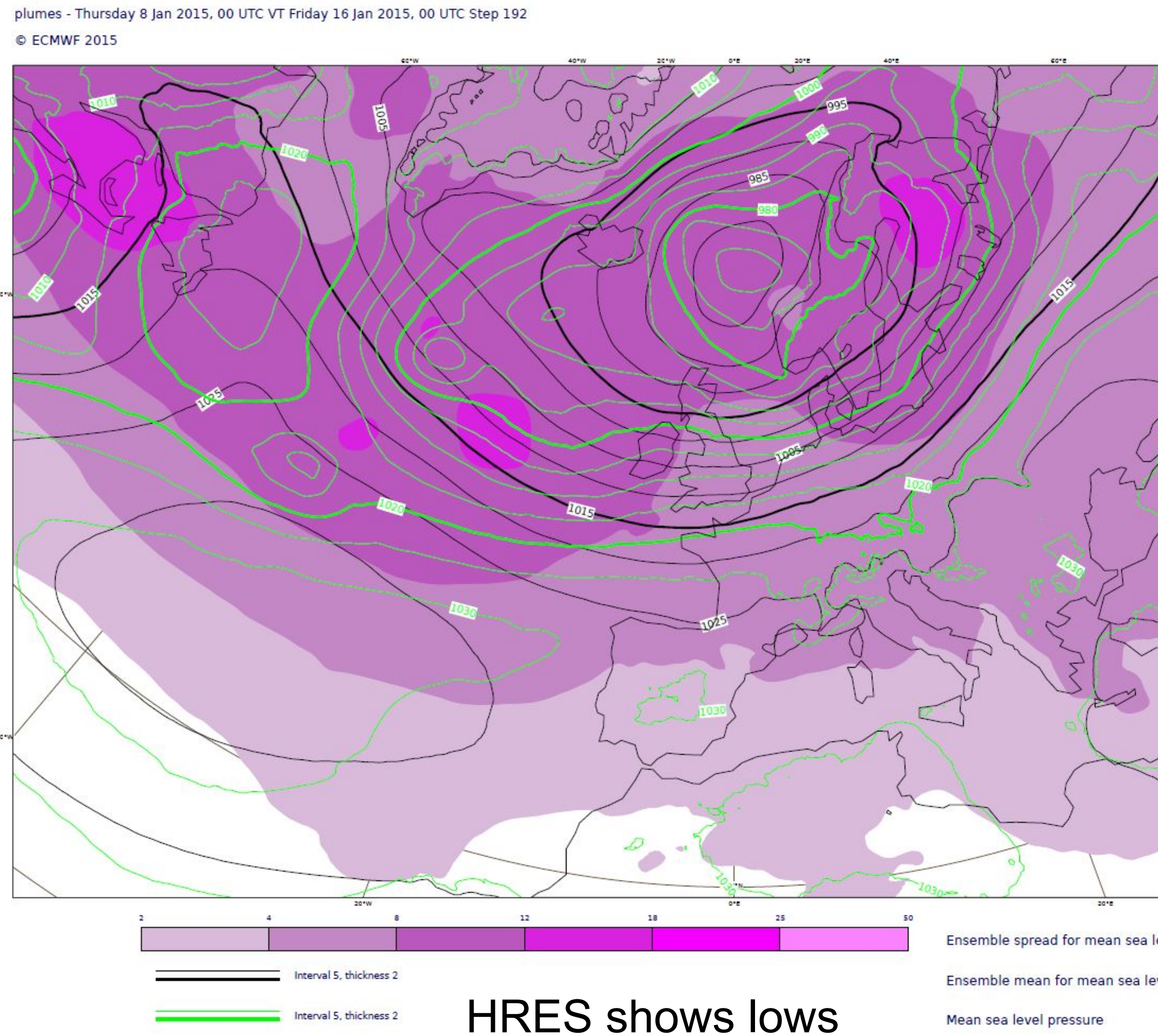
Day 8, green = HRES, black=ENS Mean



HRES shows lows

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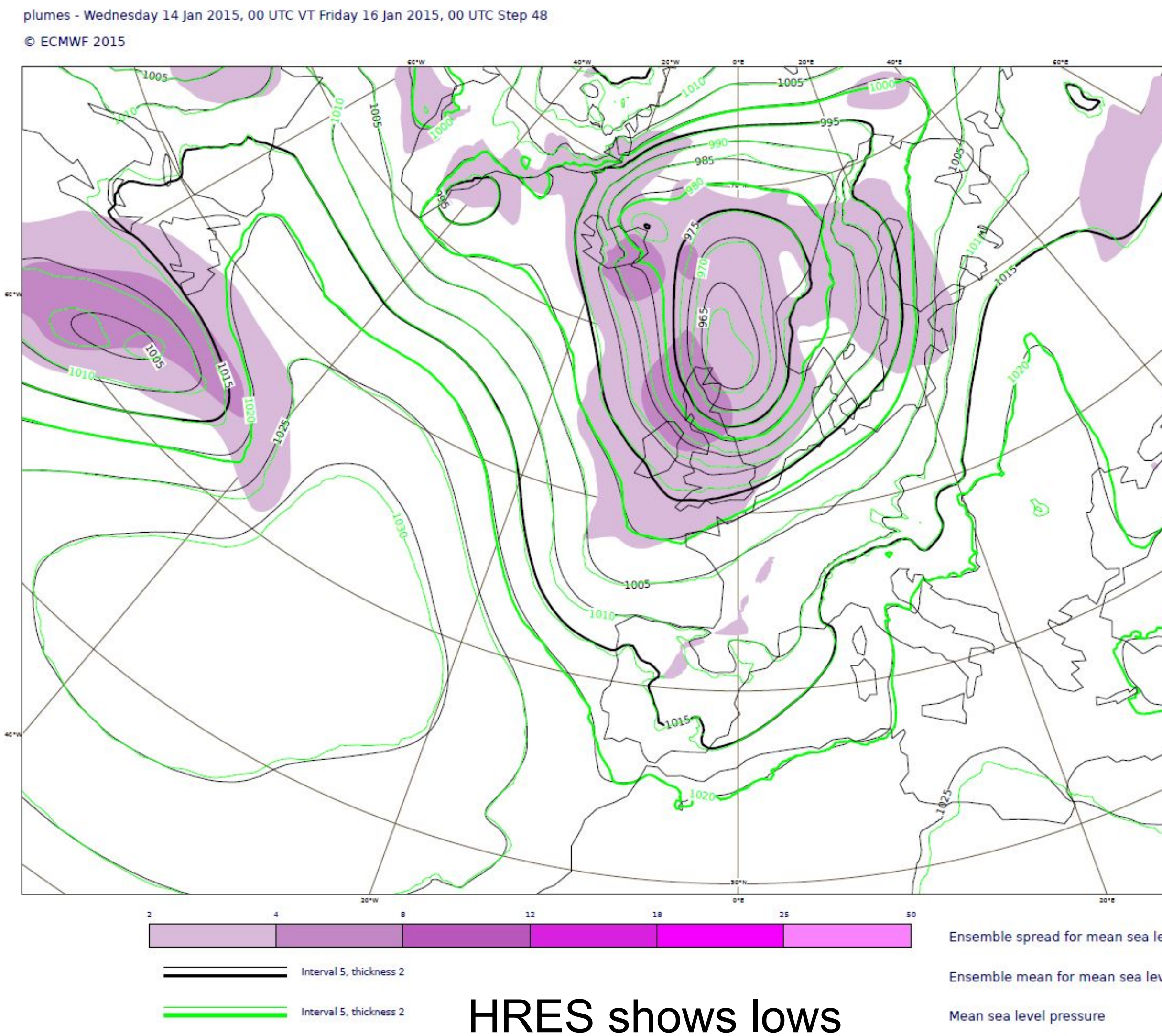
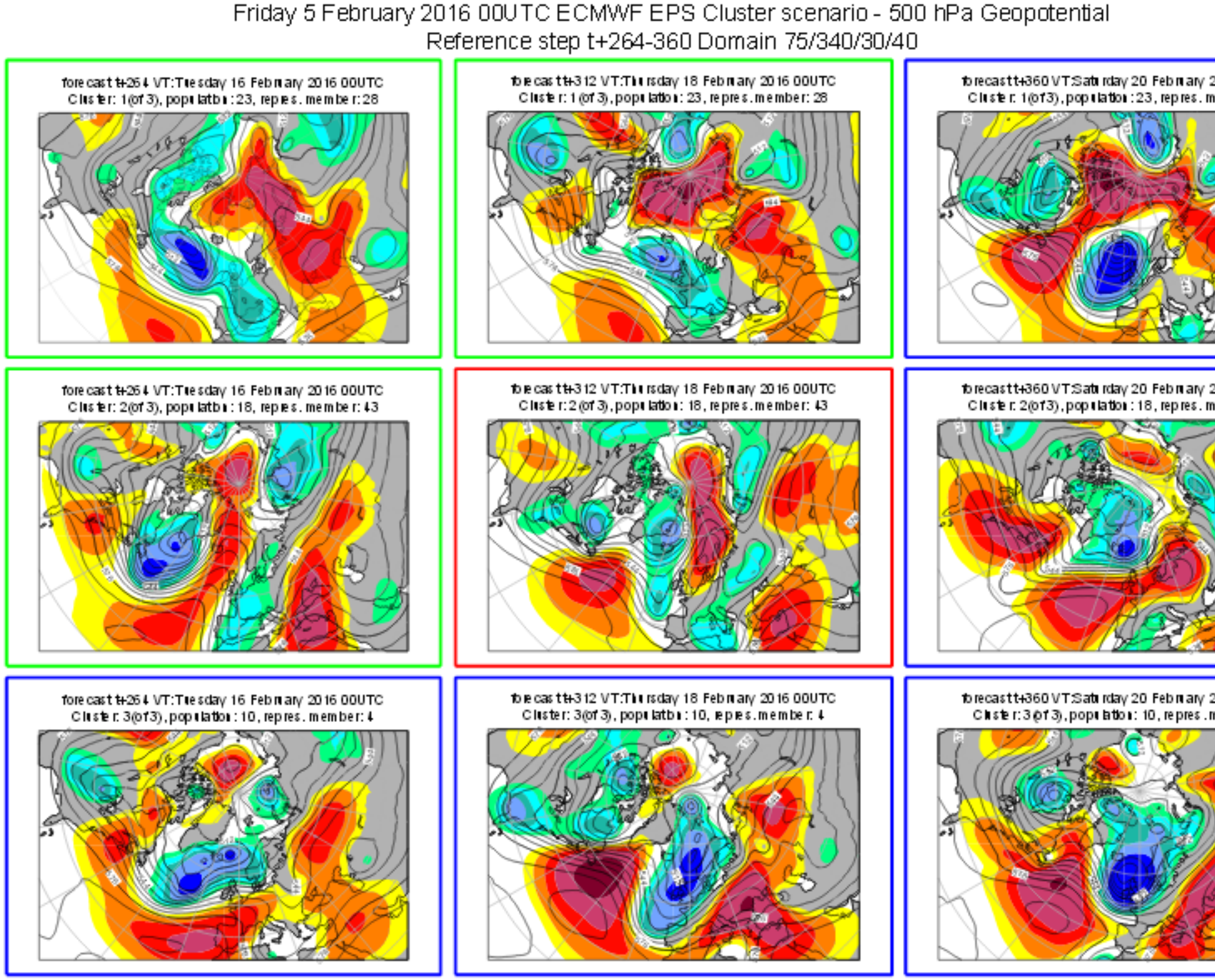
Day 2, green = HRES, black=ENS Mean



HRES shows lows

Clusters – alternative scenarios

- lustering based on 500 hPa geopotential orecast fields. Time windows: 3-4 days, 5-7 ays, 8-10 days, 11-15 days.
- NS members in the same cluster display a imilar synoptic evolution of 500 hPa eopotential over the chosen time window
- Veather scenarios, defined as ensemble nember closest to centroid of each cluster
- ach scenario is associated to one of 4 pre-efined large scale climatological regimes, ndicated by frame colour of each plot
  - Blocking (red), positive NAO (blue), negative NAO (green), Atlantic ridge (violet).



Point forecasts: timeseries (meteogram)

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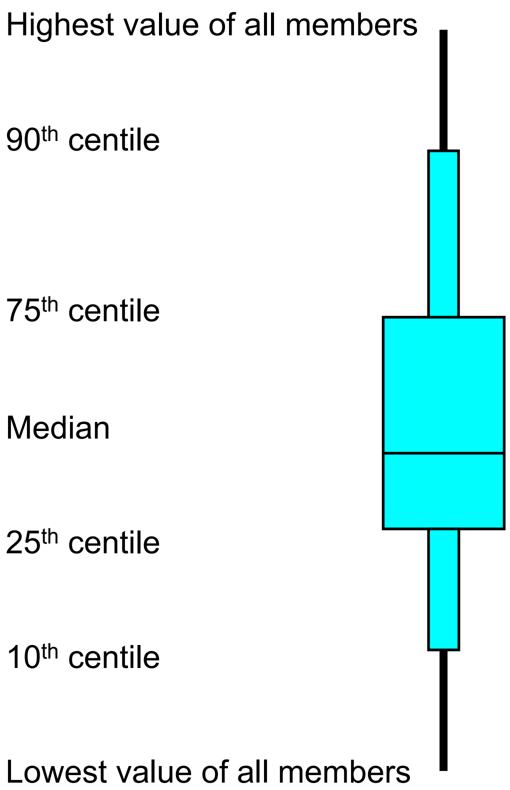

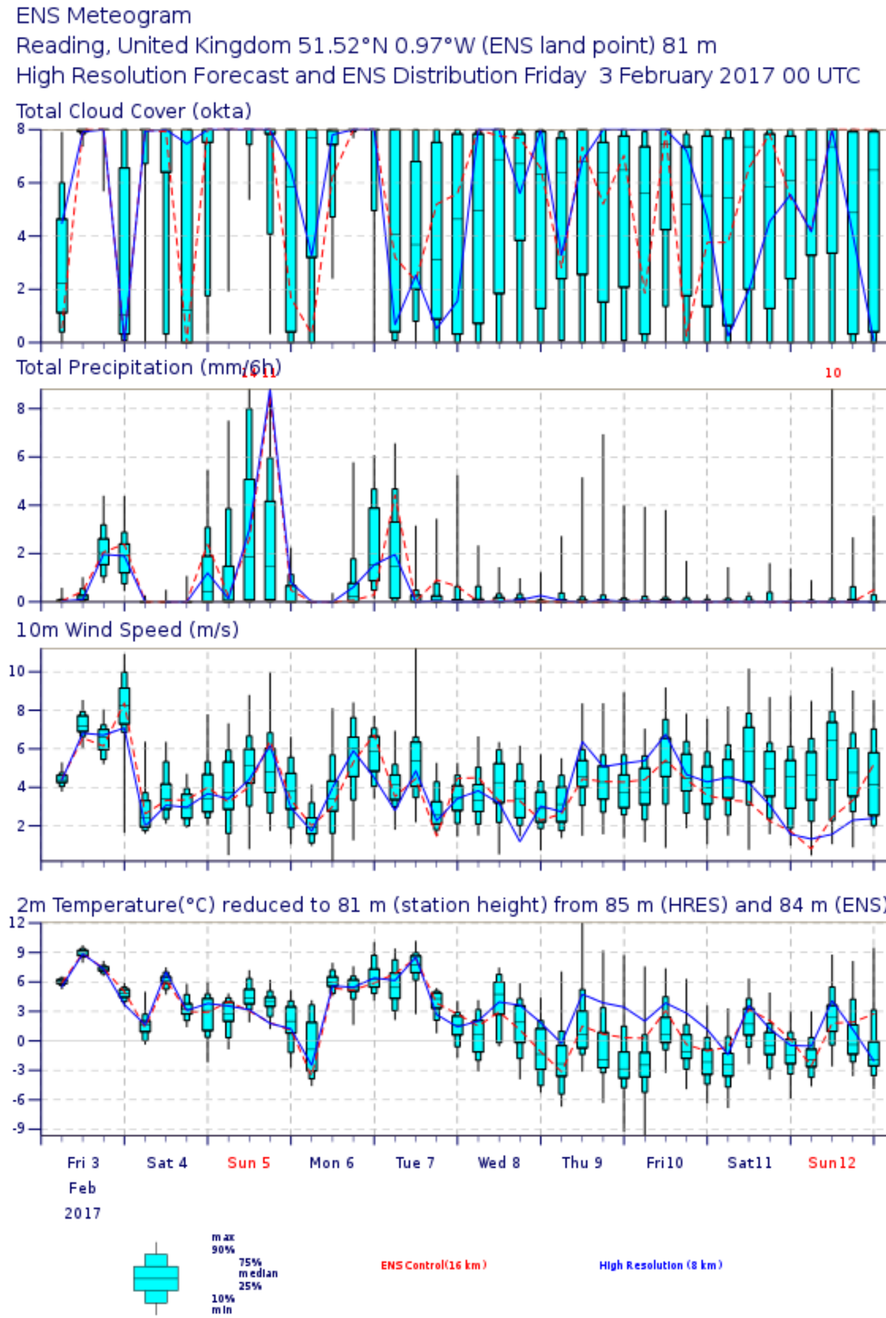

Point forecasts: timeseries (meteogram)

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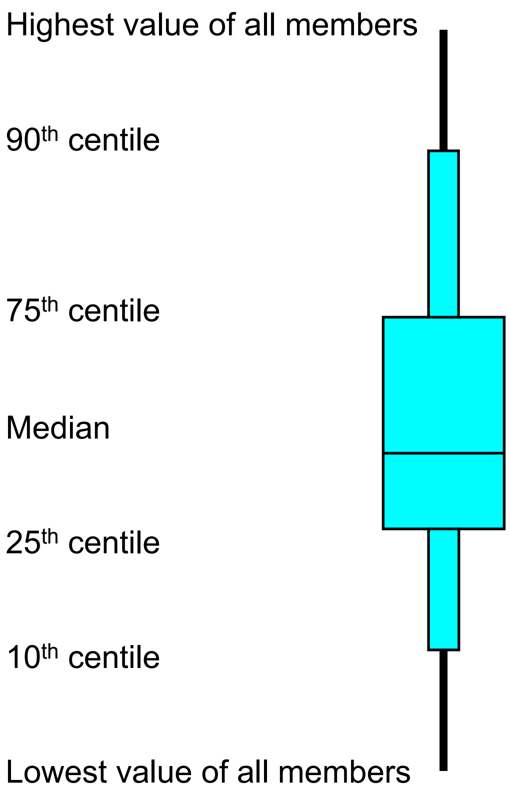

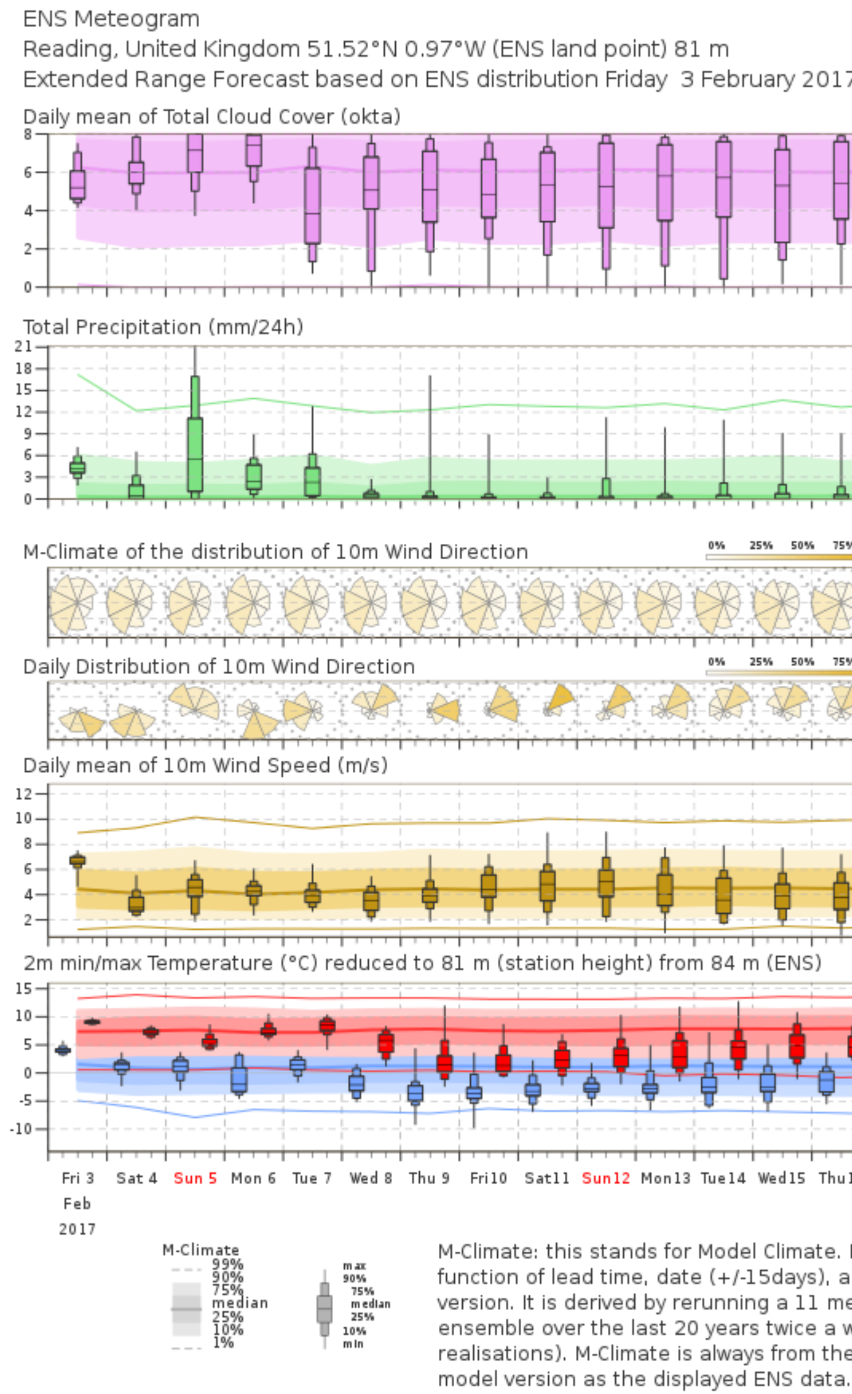

Extra-tropical cyclonic feature tracking

ecast cyclonic
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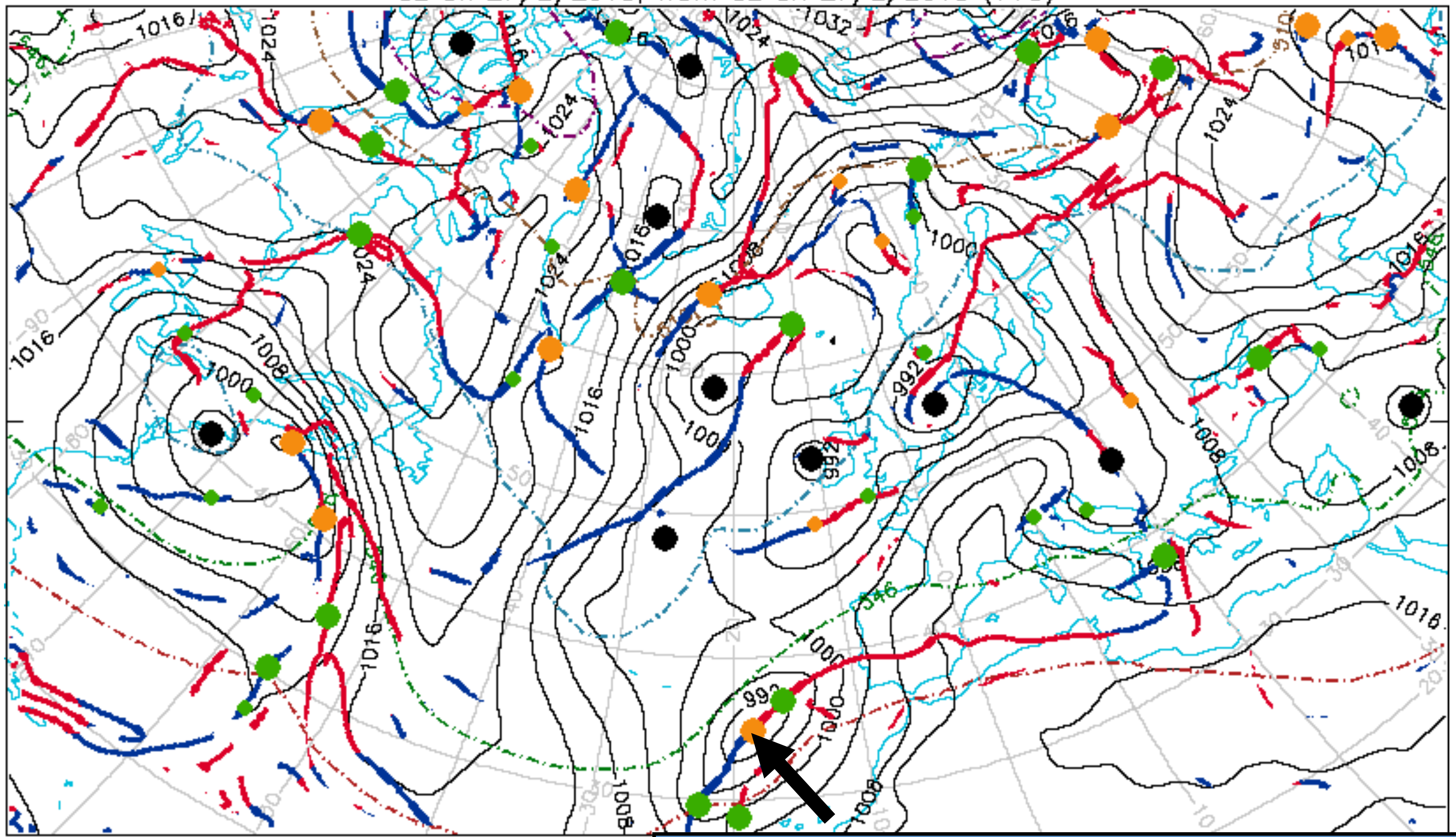
ES, control, ENS

0Z on 27/2/2010, from 0Z on 27/2/2010 (T+0)



User can click on any spot (= cyclonic feat
to see how that feature evolves in the fore

Extra-tropical cyclonic feature tracking

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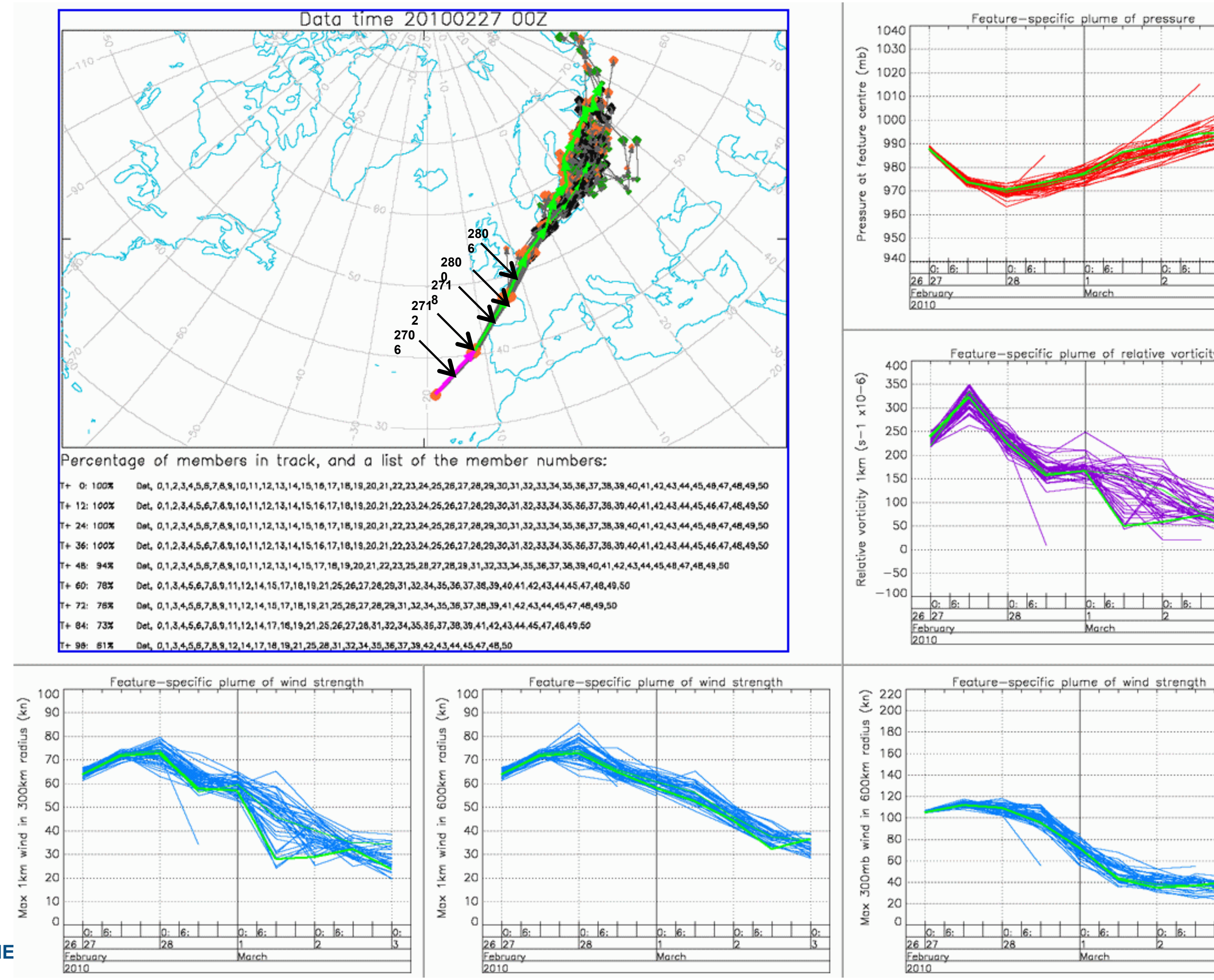
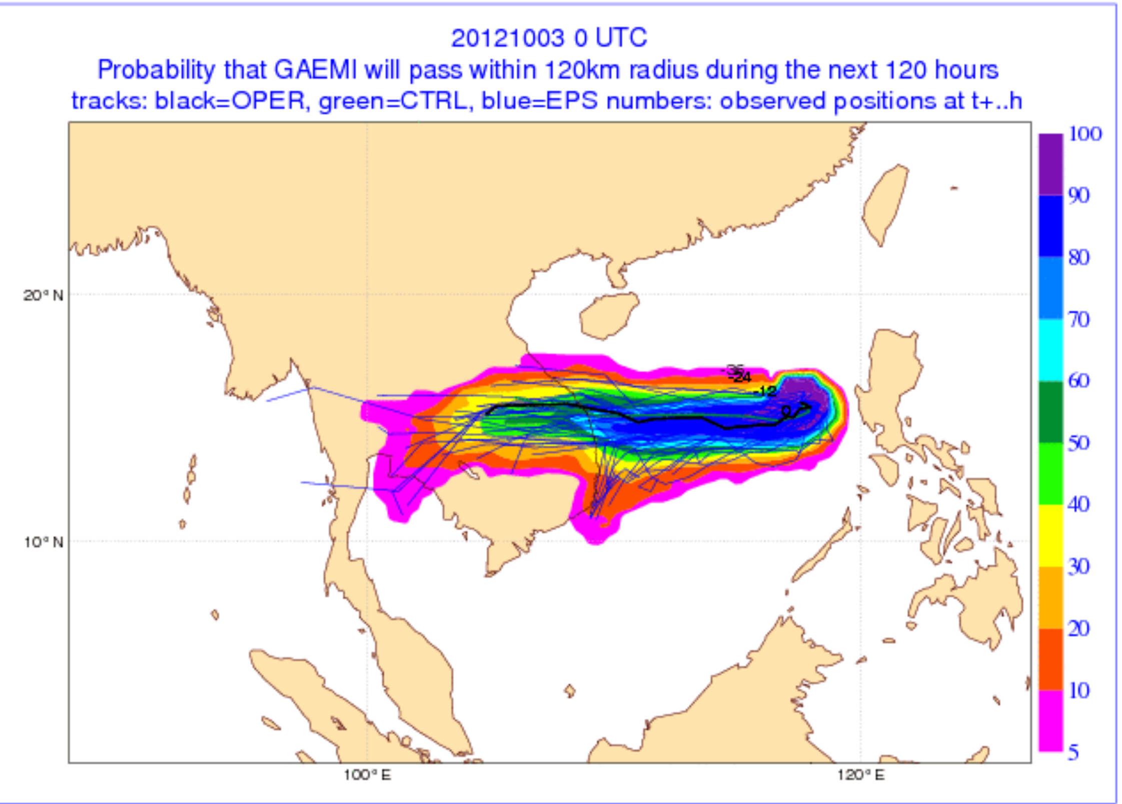
ES, control, ENS

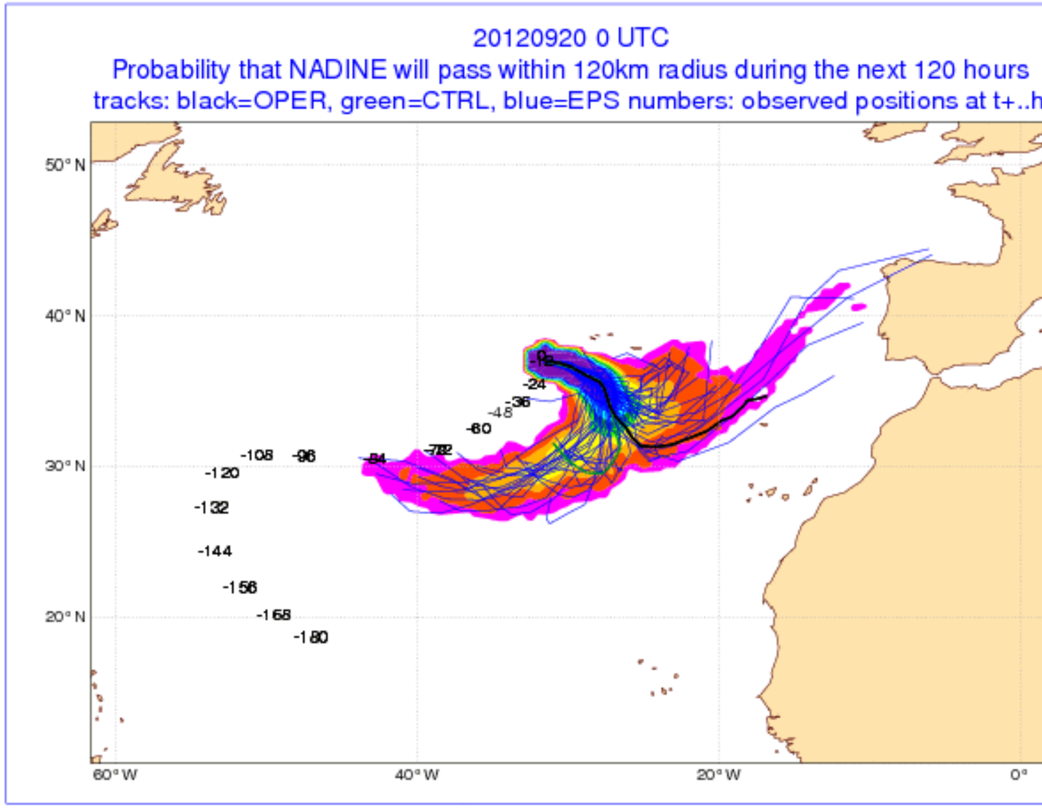


Tropical cyclones

cks of TCs present at start of forecast

ES, control, ENS





strike probability

Tropical cyclones – extended-range forecasts

TCs including
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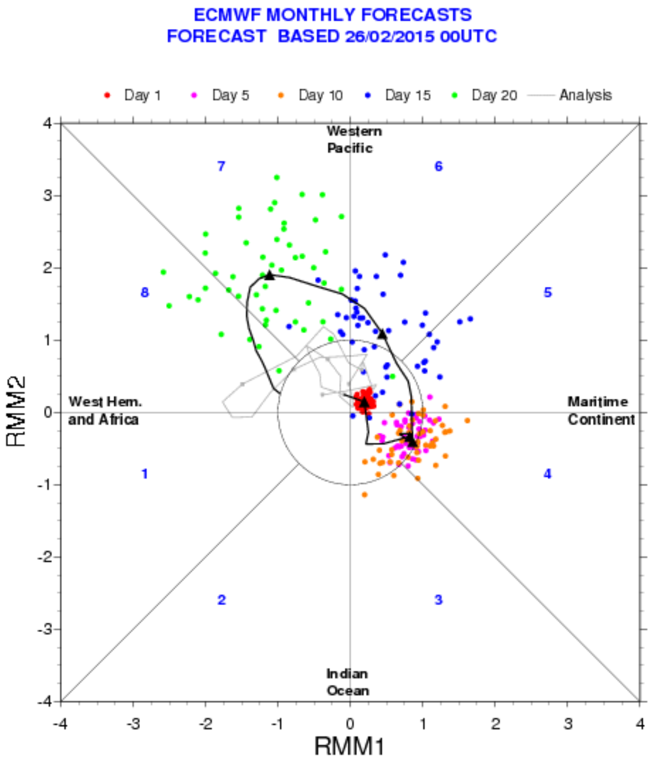

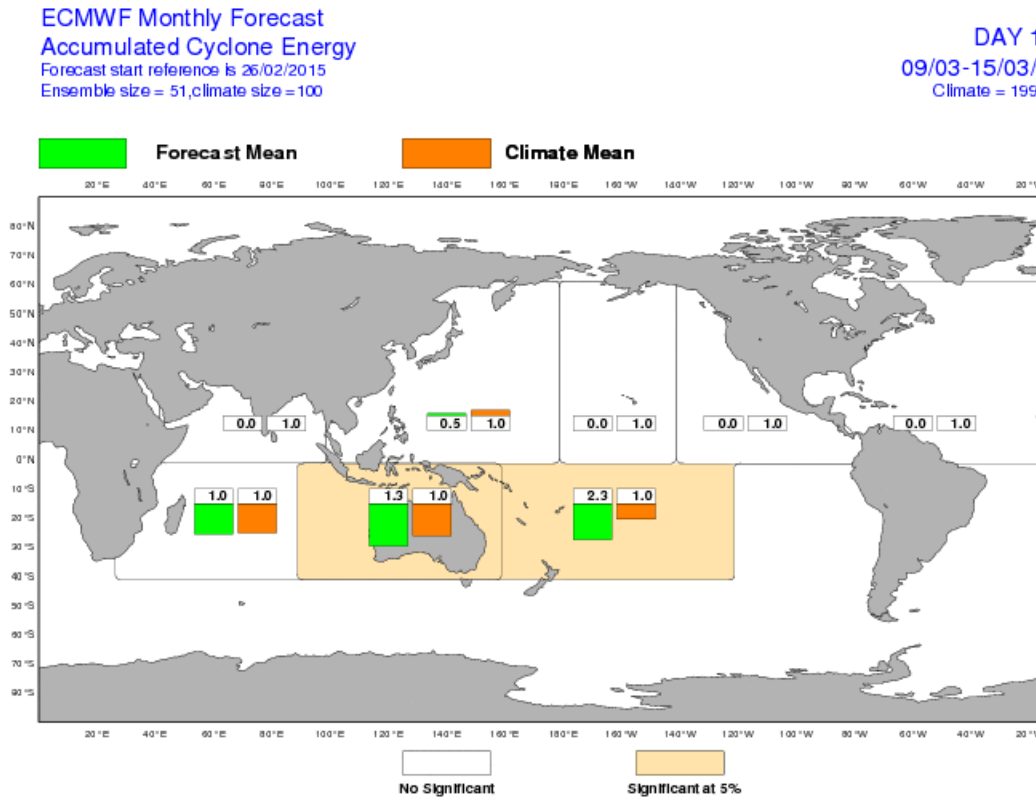

Extreme forecast index (EFI)

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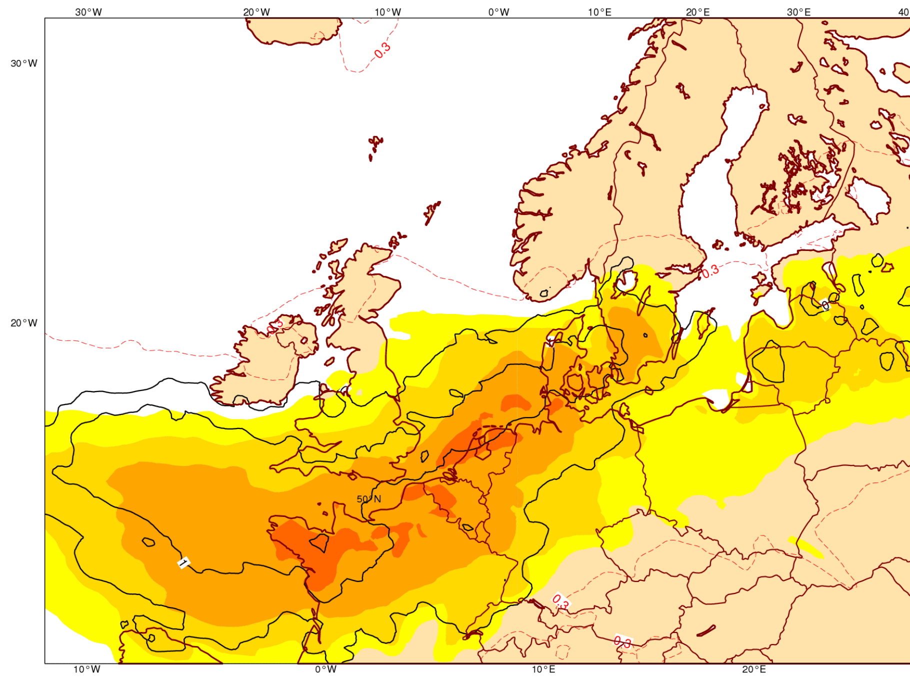
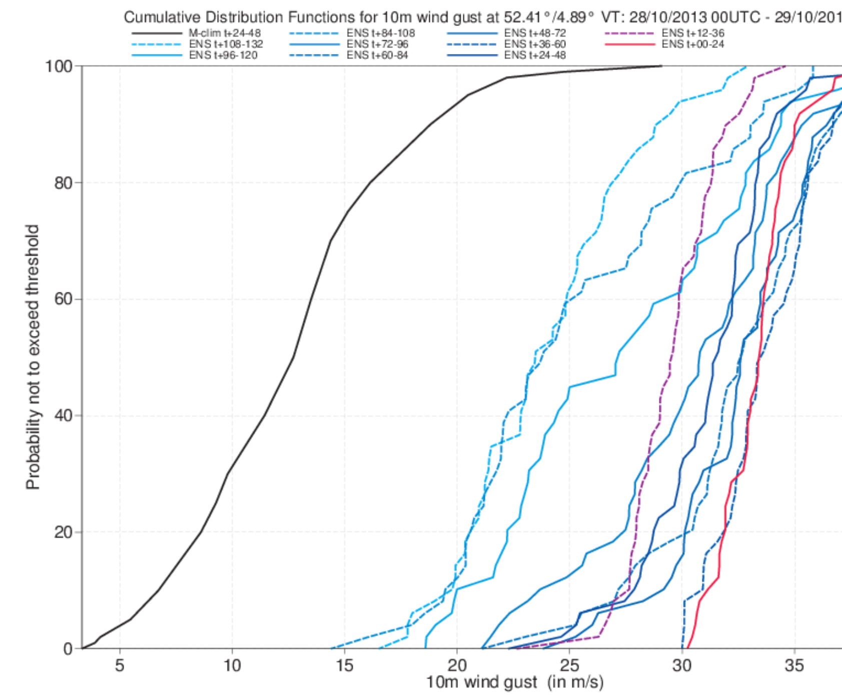
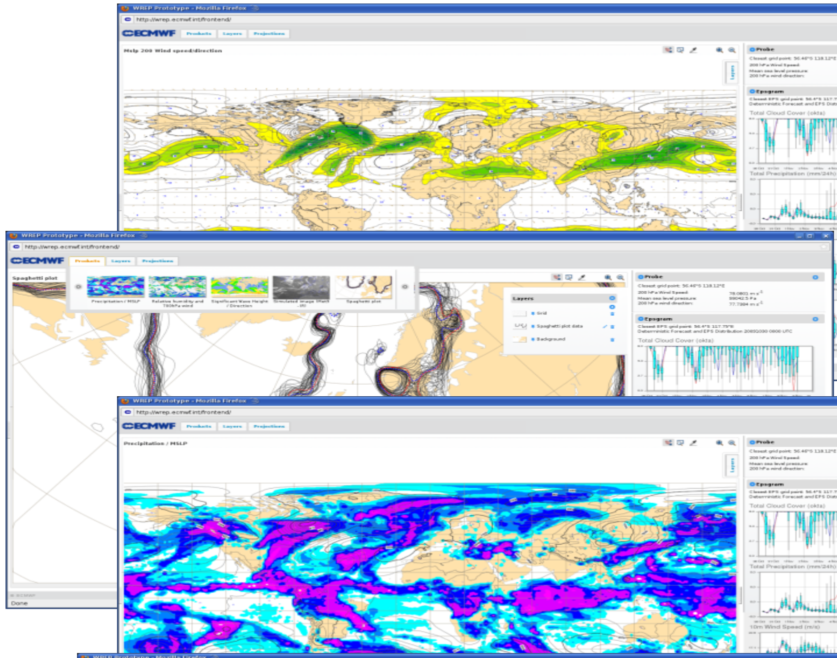
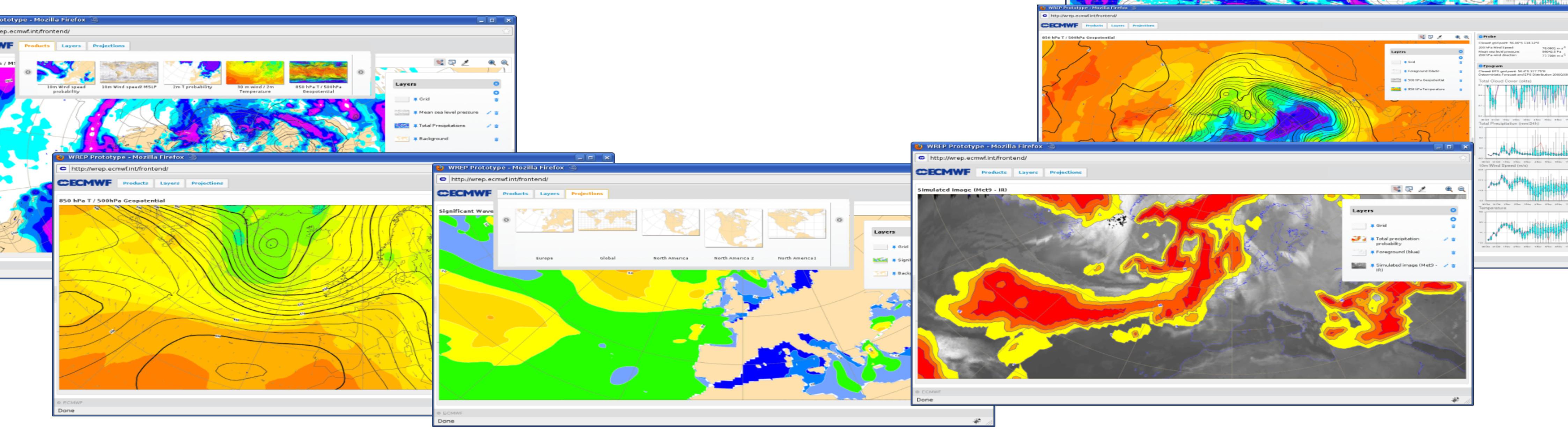




ecCharts

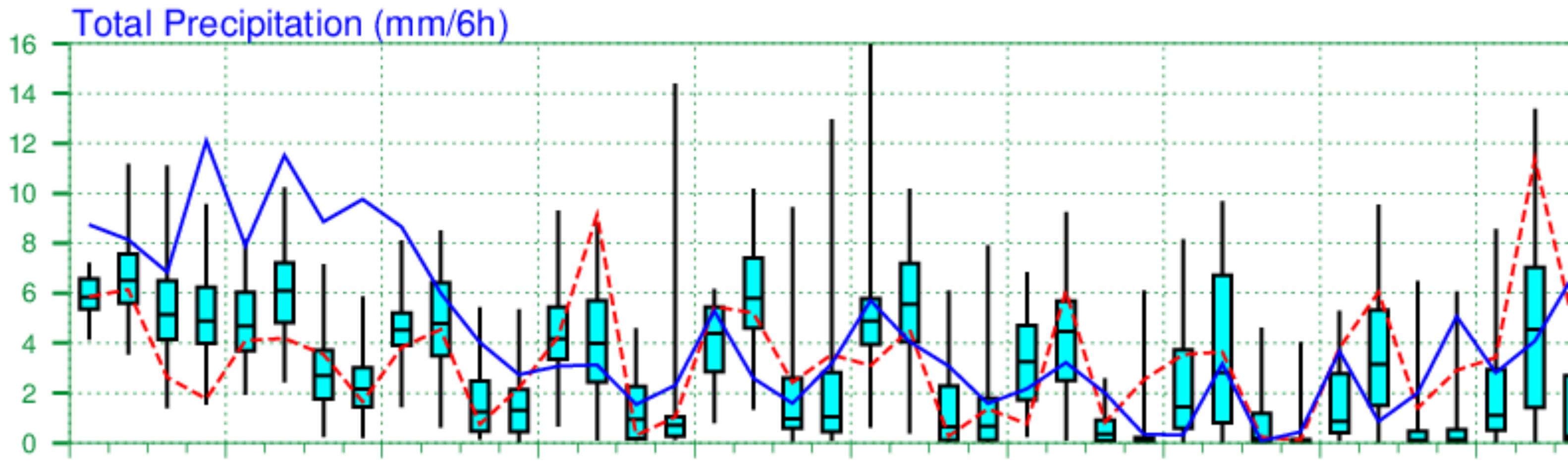
- Display HRES and ENS together
- Customisation:
  - Show/hide, add/remove layers
  - Probability thresholds, percentiles

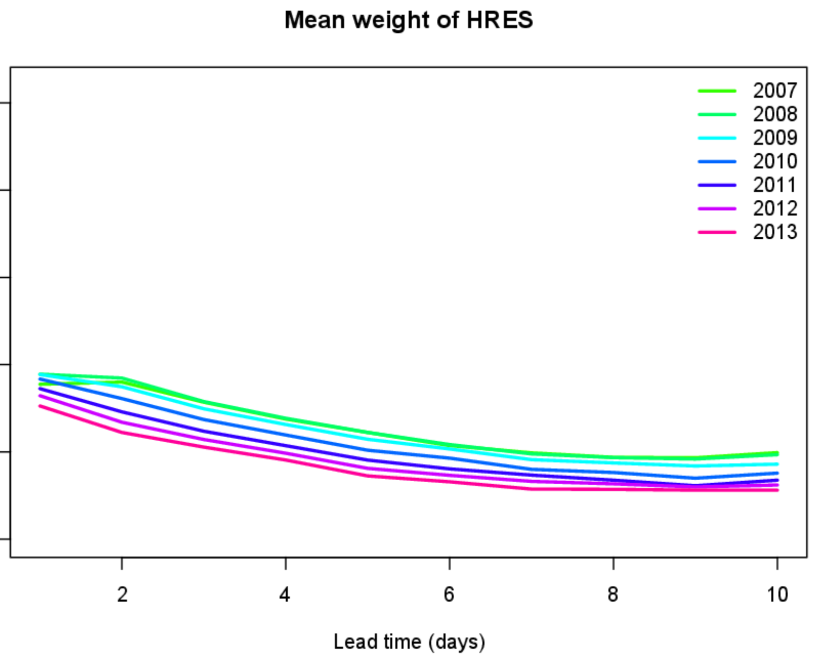


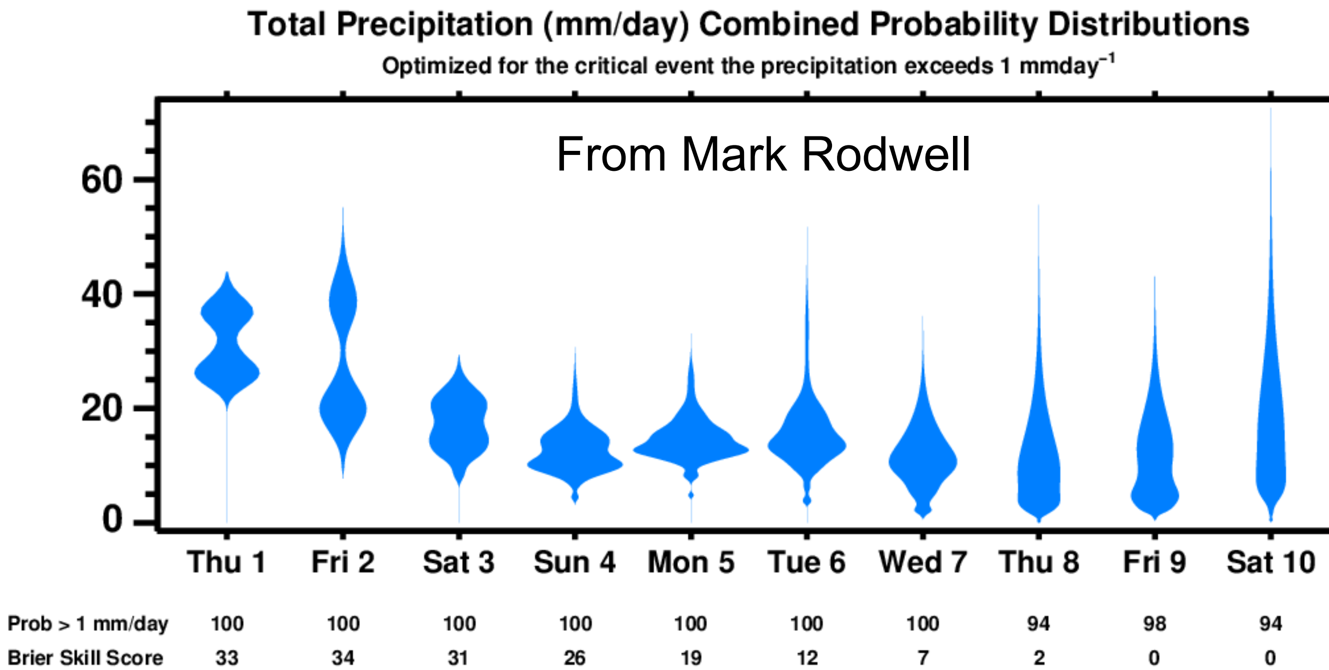


Combined HRES and ENS

- ght assigned to HRES?
- ivalent number of ENS
  mbers
- odal distribution?







Evaluation of ensemble forecast performance

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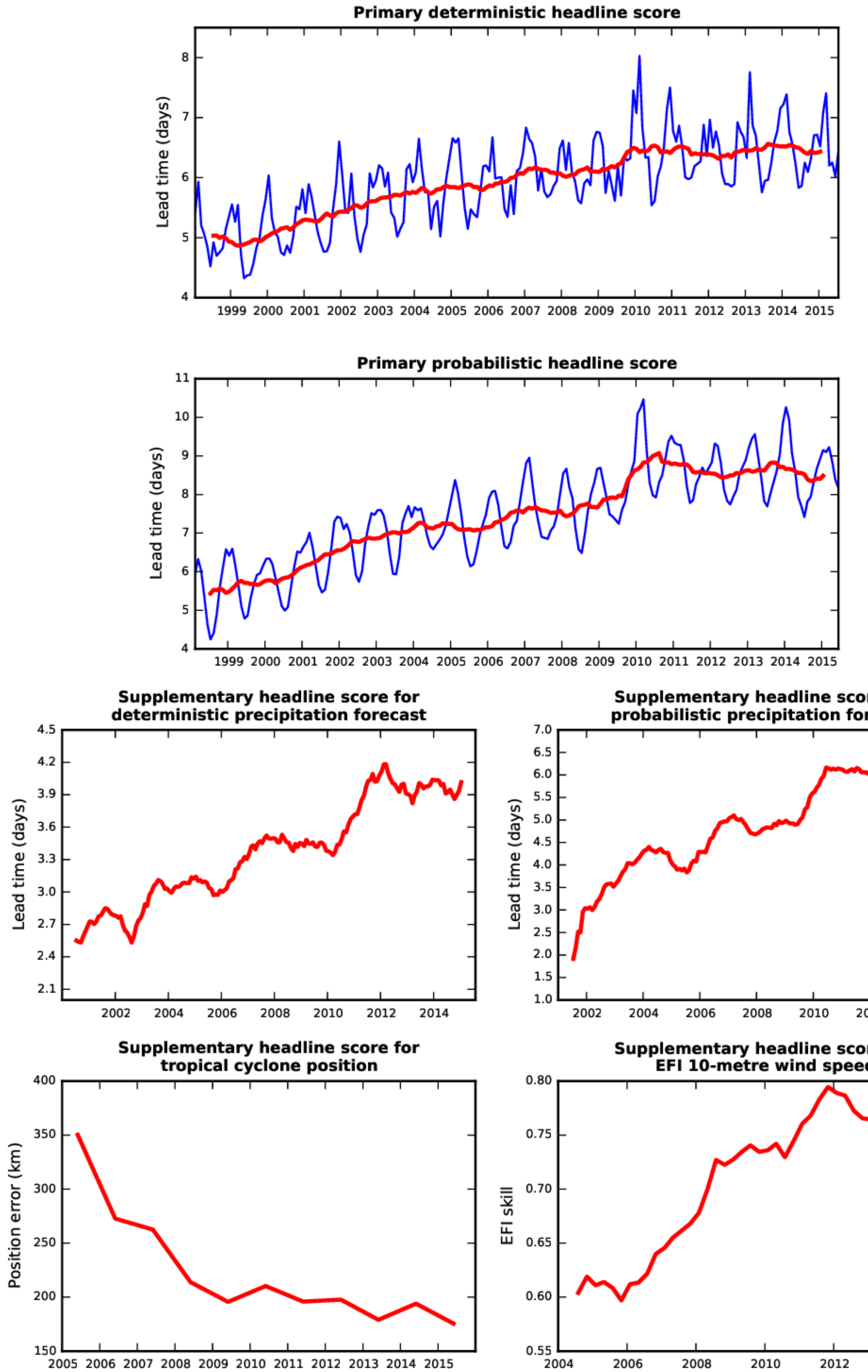
Forecast performance

- 6 headline scores
  - HRES and ENS upper-air skill
  - HRES and ENS precipitation
  - Severe weather: TC position and EFI for extreme wind
- Comparison with reference systems
- Comparison with other centres
- Evaluation for severe weather
- Additional verification and in-depth diagnostics
- See ECMWF web site for latest results

www.ecmwf.int/en/forecasts/quality-our-forecasts



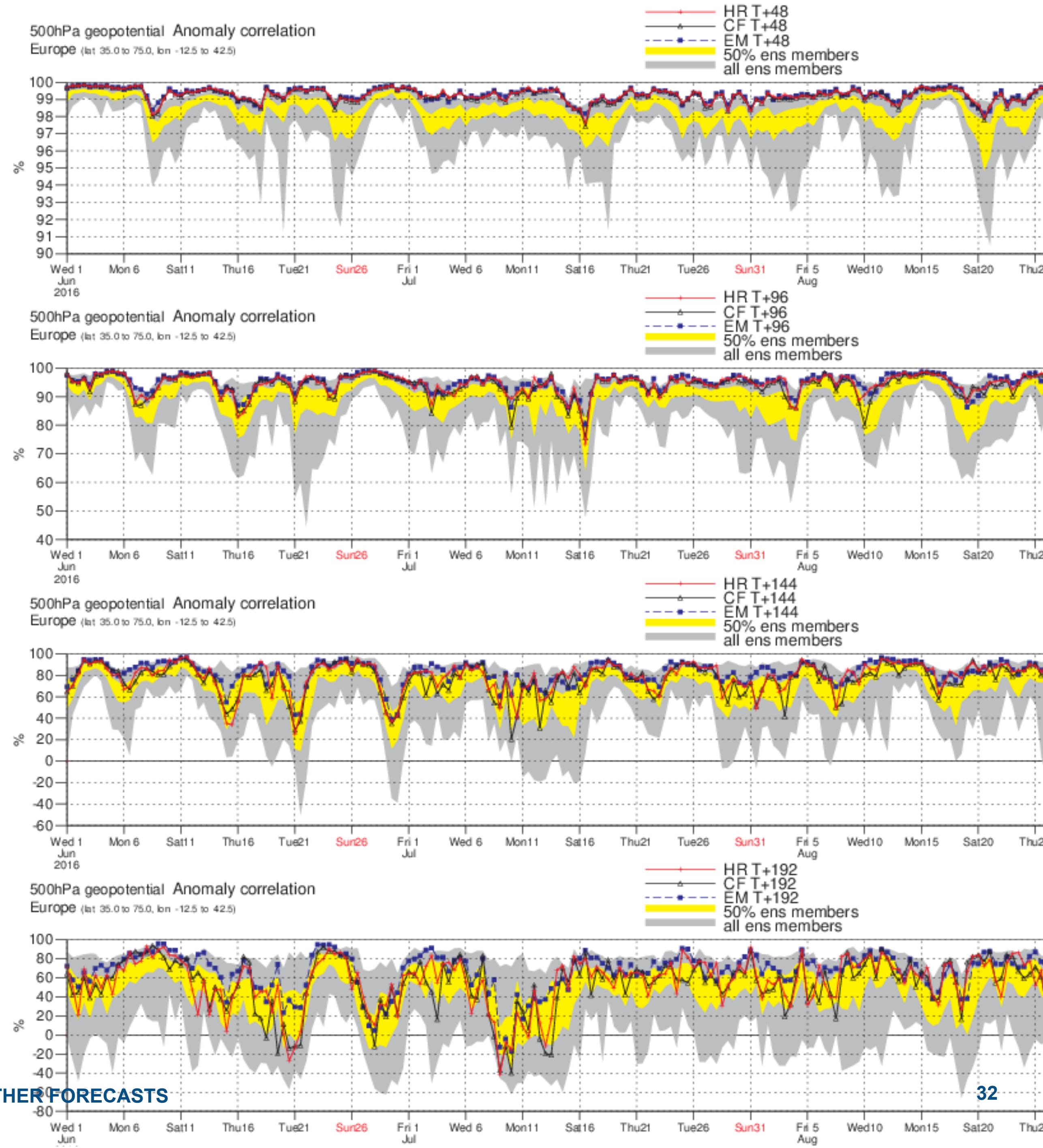
Ensemble skill Z500 Europe

Day 2: HRES best, except for a few days

Day 4

Day 6

Day 8: HRES generally not best in medium range



Ensemble skill Z500 Europe

RES the best consistent
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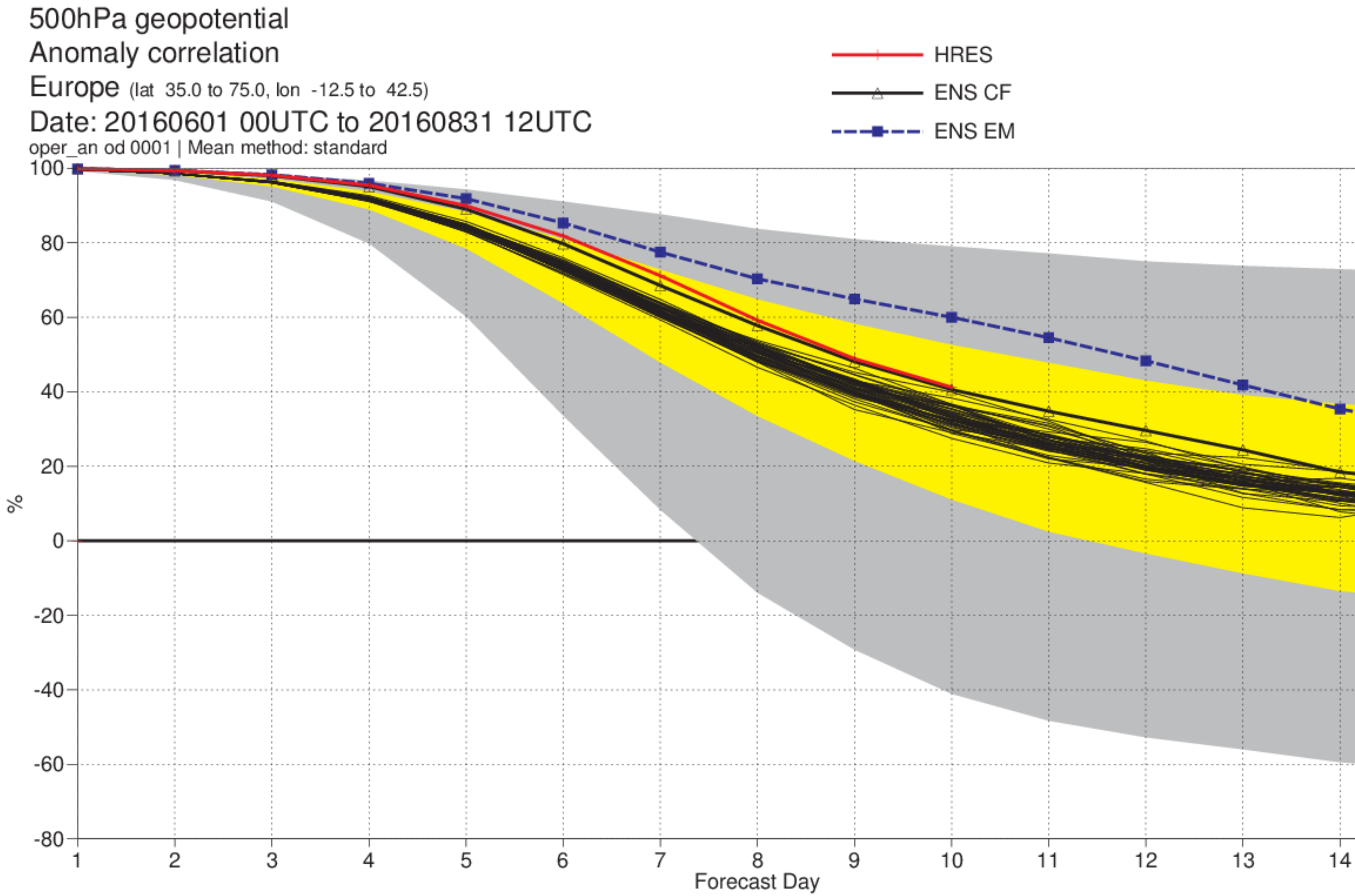

ENS spread and error

0 hPa temperature, Northern
emisphere

IS spread (dashed),
/IS error of ensemble-mean
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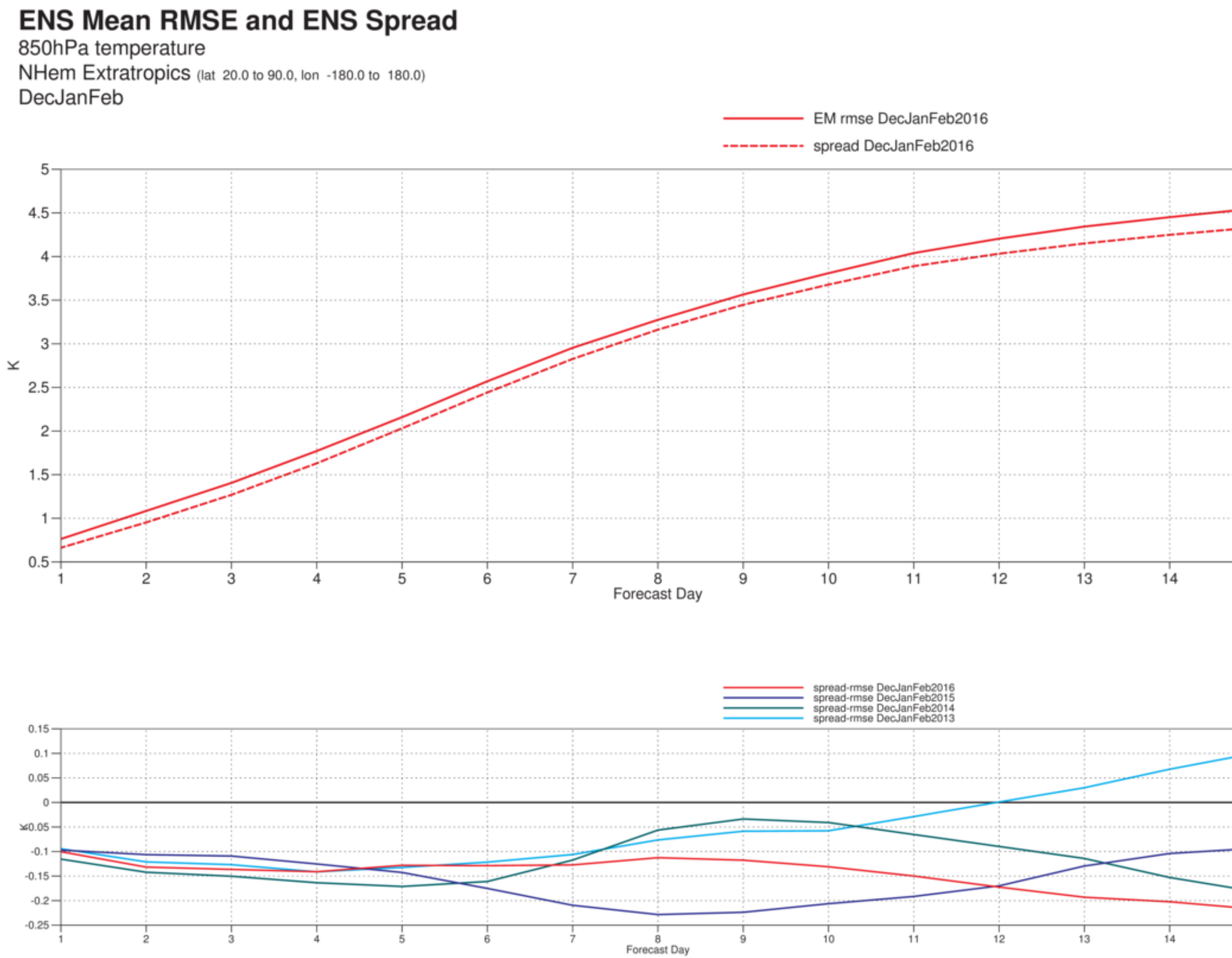
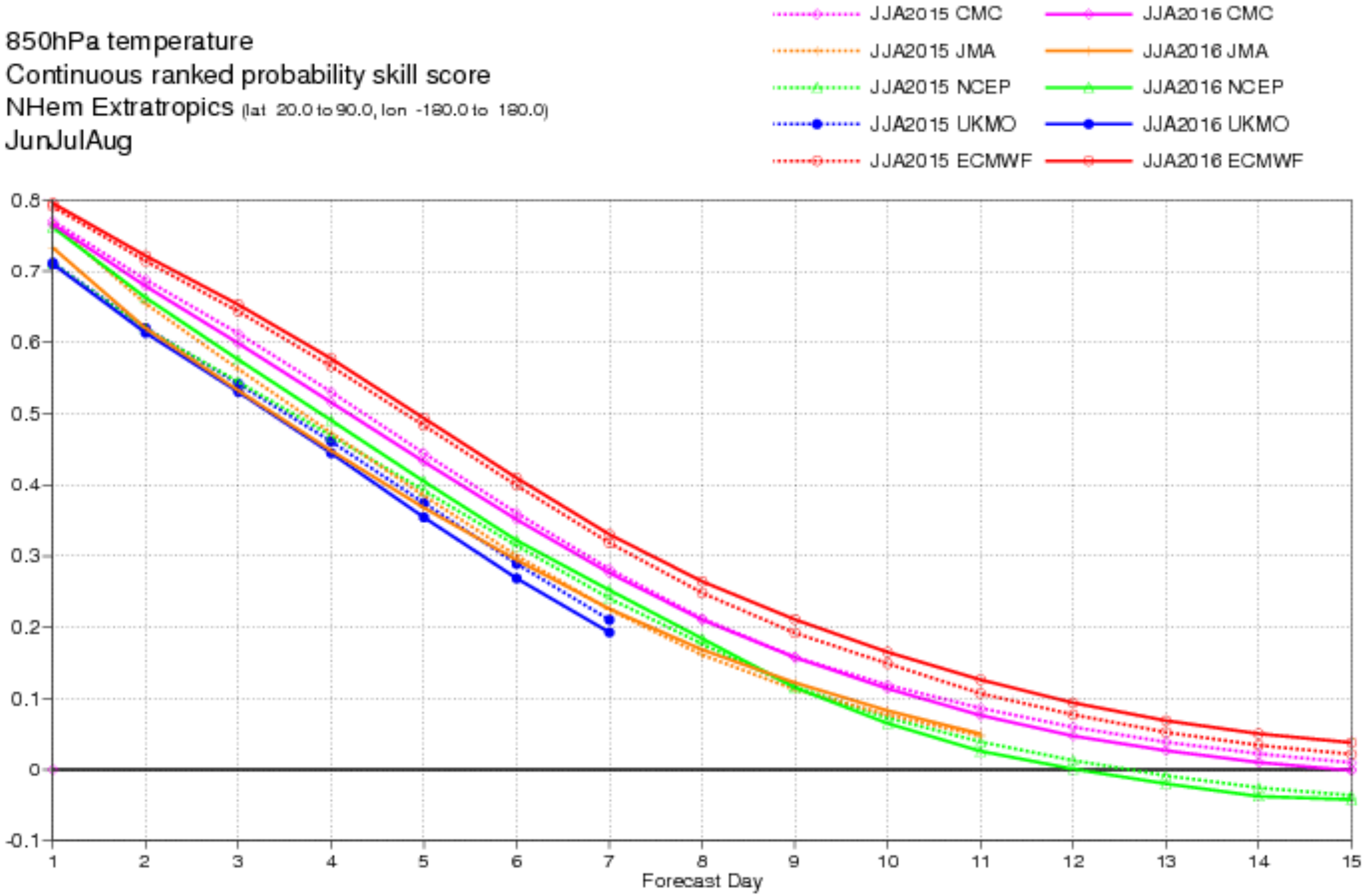


ENS skill compared to other centres



Ensemble forecasts: Communicating uncertainty

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ECMWF

Ensemble forecasts – communicating uncertainty

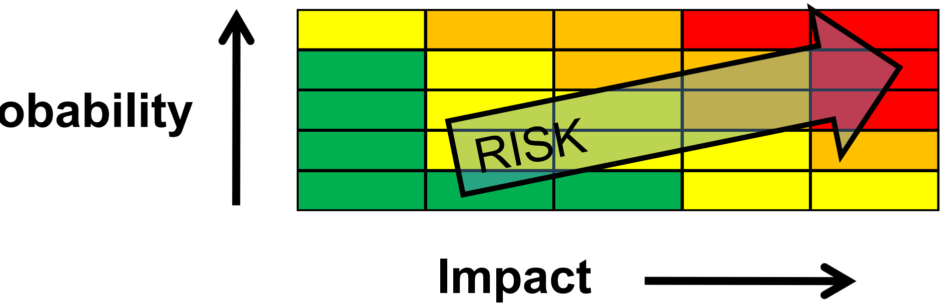
- All forecasts have errors
- It can be important for the user to know about the uncertainty in a forecast
  - what else could happen? what is the worst possibility?

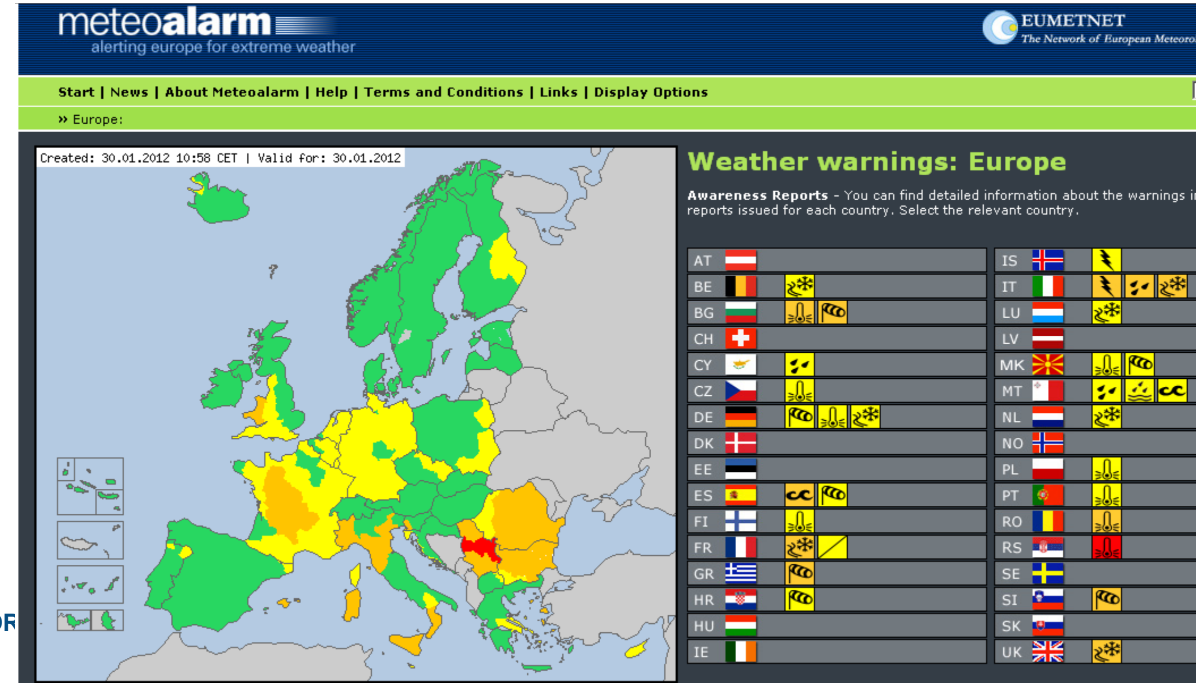
- This is not a new idea
  - Forecasters are used to adjusting their forecast with their experience of model errors (flow dependence, forecast range dependency)
  - Inconsistency of the forecasts (in time, from one model to the other) were used as indication of the (un-)predictability of scenarios

- Ensembles give more information – they provide an explicit, detailed representation of model uncertainties, and potential of unusual events

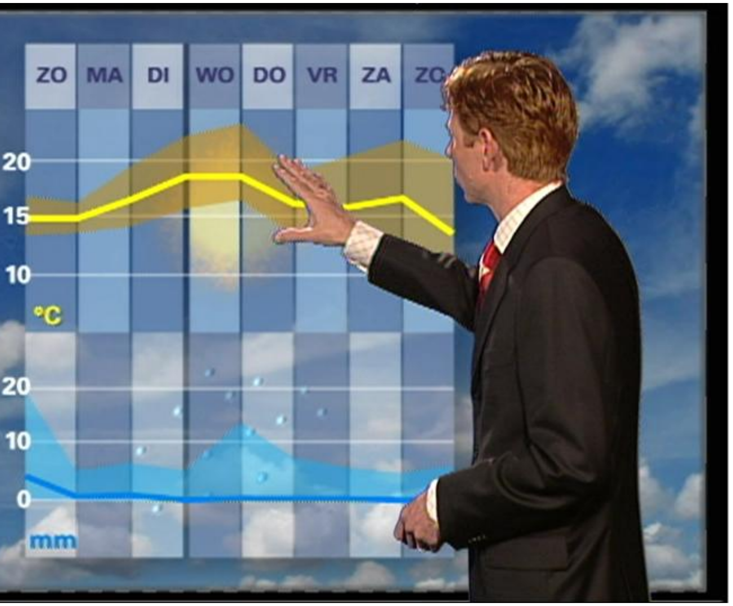
Value: the economic or societal worth of forecasts

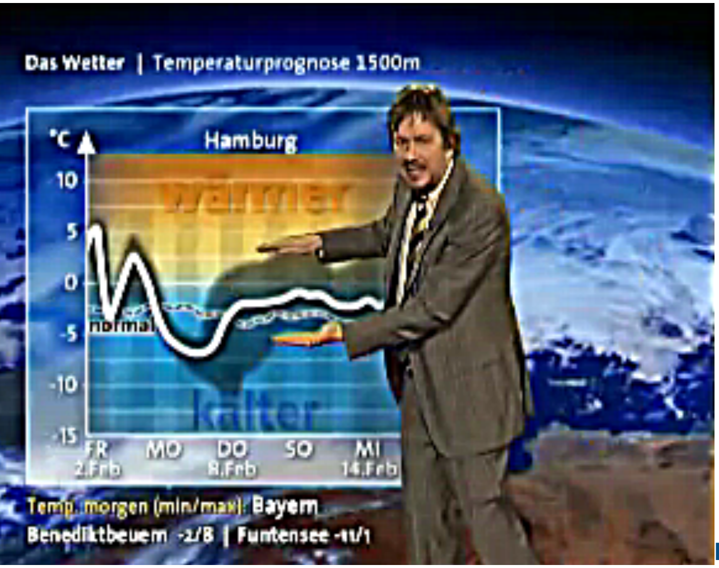
- Forecasts only have value if people use them
  - make a decision or take an action which would not otherwise have been made
- Decisions can be based on deterministic forecasts, but …
- Decisions involve assessment of risk
- Risk = probability x impact
- To make a good decision need to know the probability and the impact (consequence to the individual user)

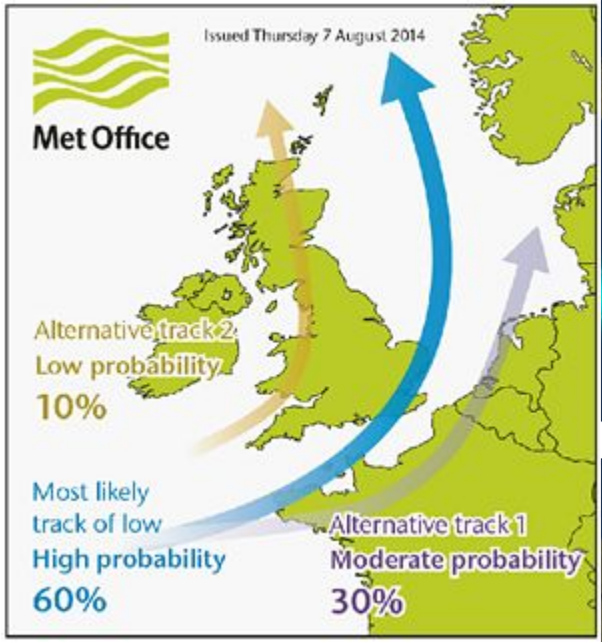




Communicating forecast uncertainty information to public







Summary - why do we run an ensemble?

- The best method we have to produce flow-dependent probabilistic weather forecasts

- The ensemble gives a range of future scenarios consistent with our knowledge of the initial state and model capability
  – explicit indication of uncertainty in today's forecast
  – Potential of high-impact events
  – Range of ensemble-based products for different users

- Ensembles provide the required input for a range of application models (hydrology, ship routing, energy demand), explicitly propagating the atmospheric uncertainty

- Read more in the ECMWF products User Guide
  – www.ecmwf.int/sites/default/files/User_Guide_V1.2_20151123.pdf

Ensemble references

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