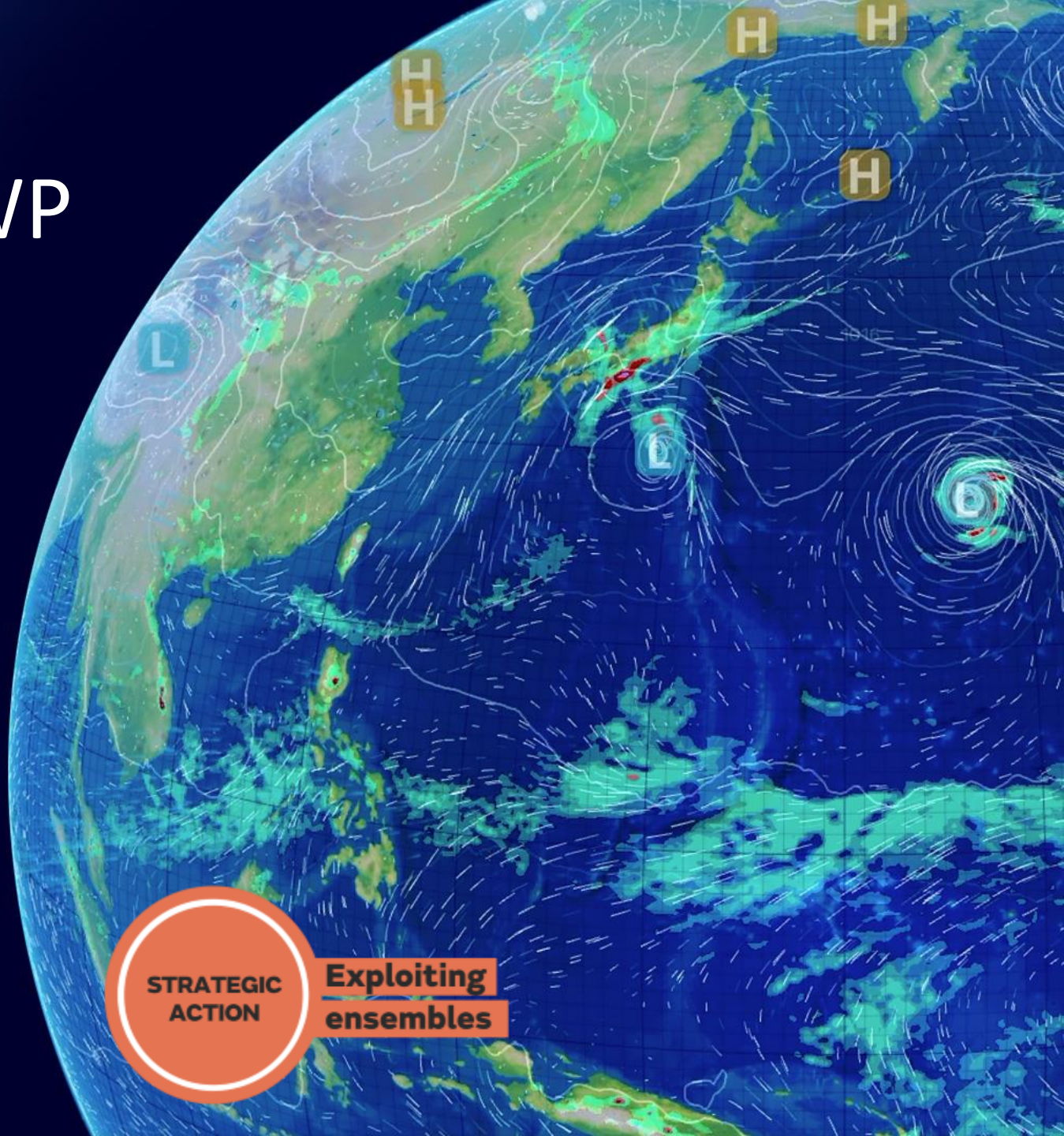
# Exploiting Ensemble NWP Forecasts

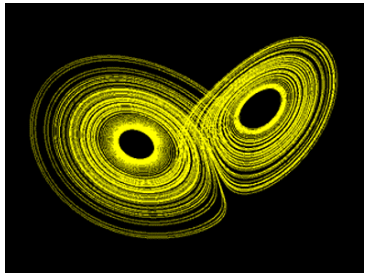

## Ken Mylne

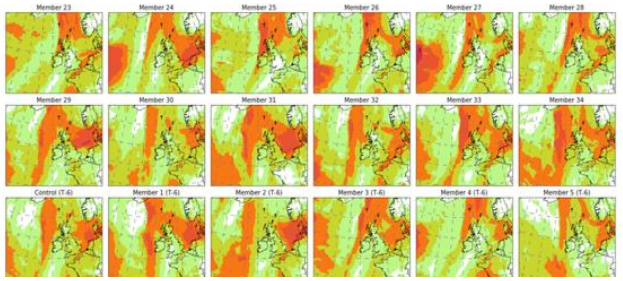
Science Fellow in Exploitation of Ensembles

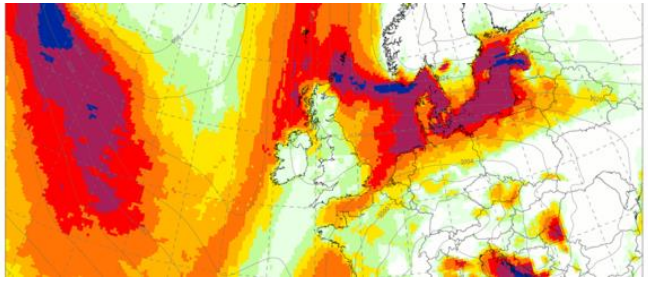
Contributions from: David Walters, Oak Wells
Nigel Roberts, Steve Willington,
Rosa Barciela, Rose Jones and
Steve Ramsdale


ECMWF UEF Meeting
6th June 2023





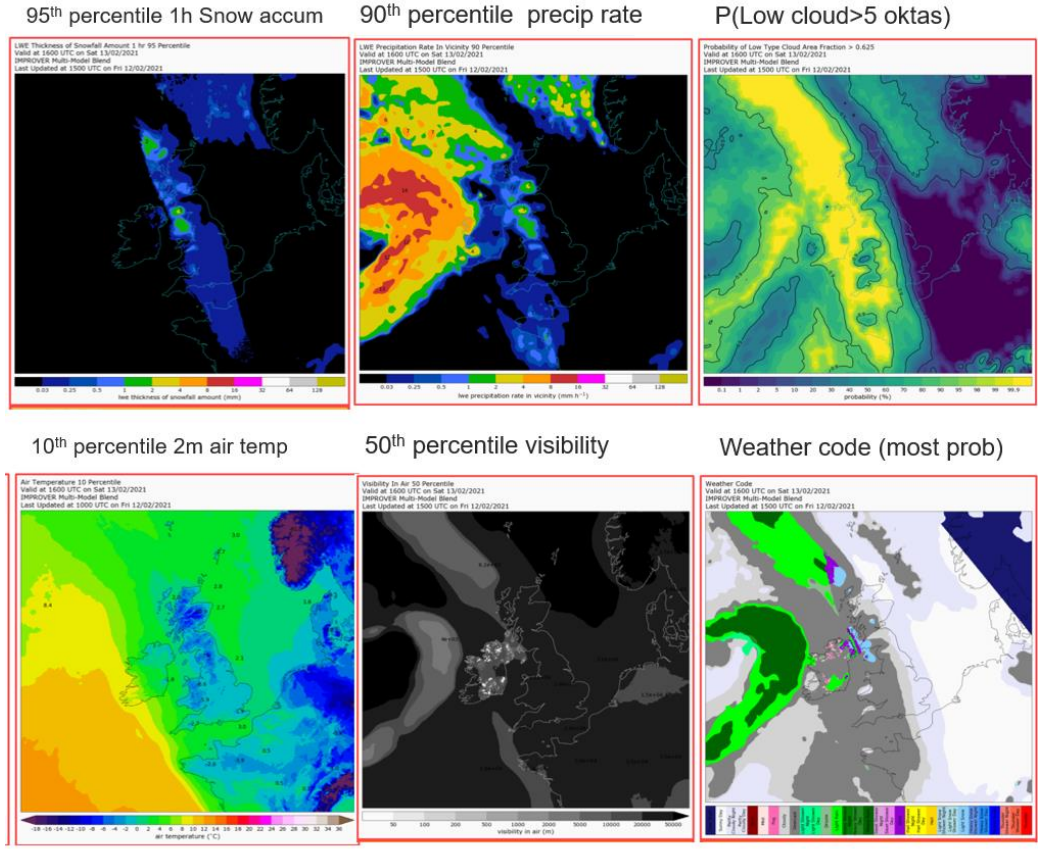




# 30 years of ensemble forecasting

- ECMWF and NCEP both started medium-range EPS in 1992
- COSMO-LEPS regional started c. 1999
- Met Office MOGREPS-Regional 2005
- MOGREPS-UK convective-scale 2012
- IMPROVER blended post-processing

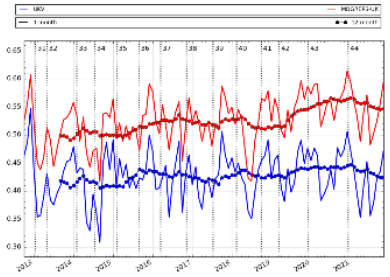

- …***so why aren't we using them more?***

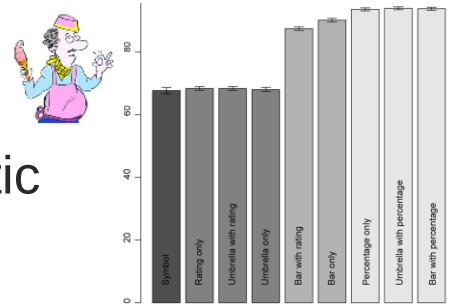


# The problem…

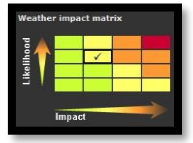
## Science

- Huge HPC investments in ensembles £££…
- HPC promises delivered ✓
- Verification shows ensembles provide greater skill than deterministic ☺
- Research consistently shows that people make better decisions when presented with probabilistic forecasts *






## Services



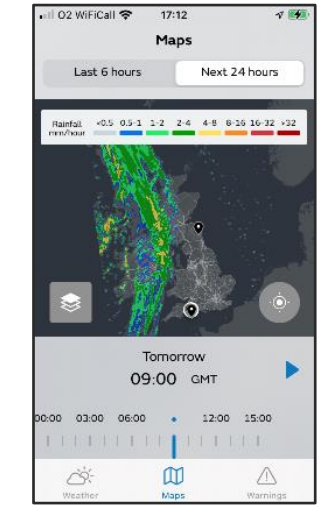

Users just want a decision

The Public won't understand

We don't know how to use it so we can't explain to customers

Too much data

Ensemble doesn't tell the story I want to tell




* e.g. Elisabeth M. Stephens, David J. Spiegelhalter, Ken Mylne, and Mark Harrison **The Met Office Weather Game** Geosci. Commun., 2, 101–116, 2019

Met Office

STRATEGIC ACTION Exploiting ensembles

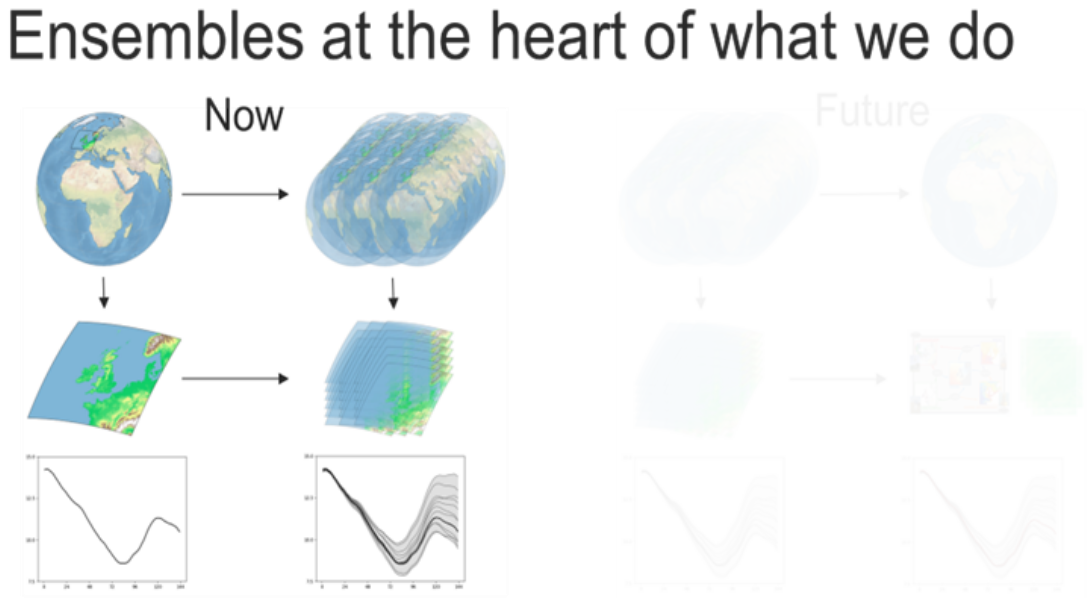
# Ensemble Exploitation

A Met Office wide strategic action to ensure **all our products and services are underpinned by our ensemble forecasting systems**.

- Make better use of ensembles across our advice and services
- Ensure we are developing our forecasting systems recognising how ensembles are used

# Vision

*We are **already using ensembles** but want to **fully exploit and extract maximum value** from our **NWP-based ensemble systems,** for underpinning all our **services,** in order to support users and customers in their **decision-making**, particularly in terms of **risk** of high **impact** weather events by …*

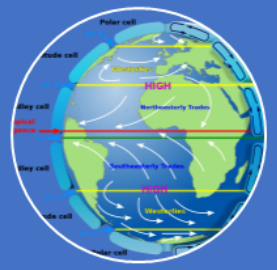



1. *Increasing the number of forecasts products and services exploiting ensembles.*
2. *Engaging with customers to exploit, and make more use of, our ensembles.*
3. *Developing our models to recognise user requirements and how ensembles are being used .*
4. *Provide a common language.*
5. *Changing the culture.*

Rosa Barciela and Rose Jones MOSAC talk

Met Office

## 5. Communicating our work and thought leadership



2. Ensemble Development

3. Developing our tools, processes and people


4. Engaging and supporting our users

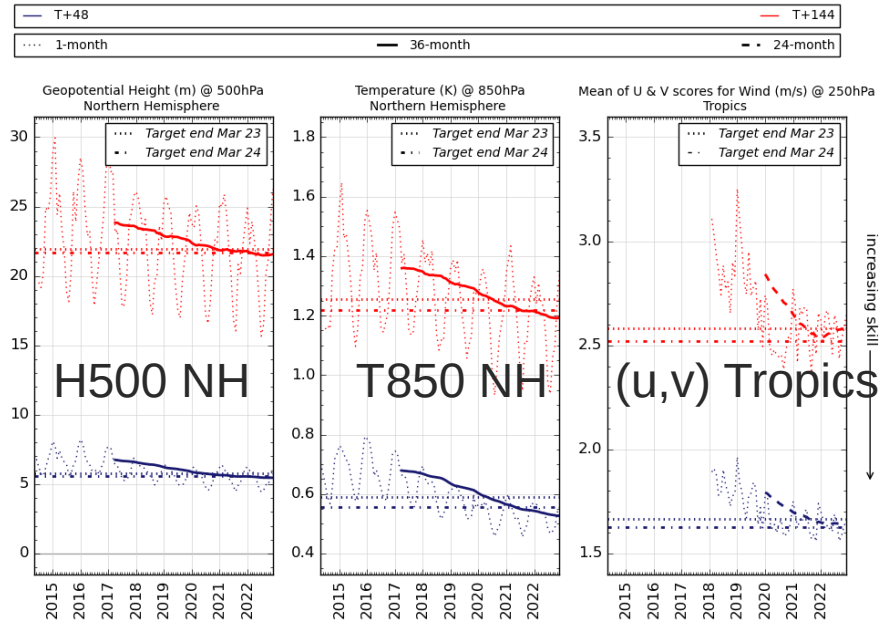
## 1. Underpinning research

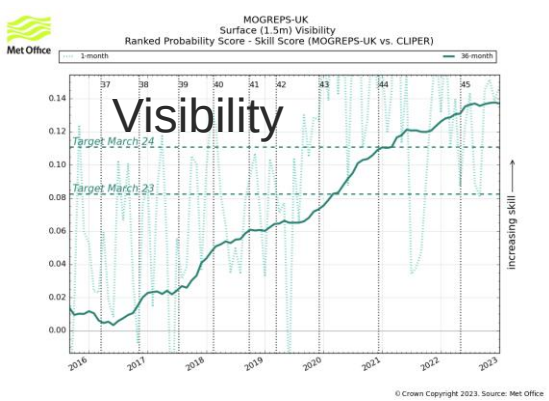
**WP1:** Nigel Roberts & Steve Willington **WP2:** Chiara Piccolo & Keith Williams **WP3:** Mike Gray & Ken Mylne
**WP4:** Teil Howard & Patrick Sachon **WP5:** Oak Wells & David Walters

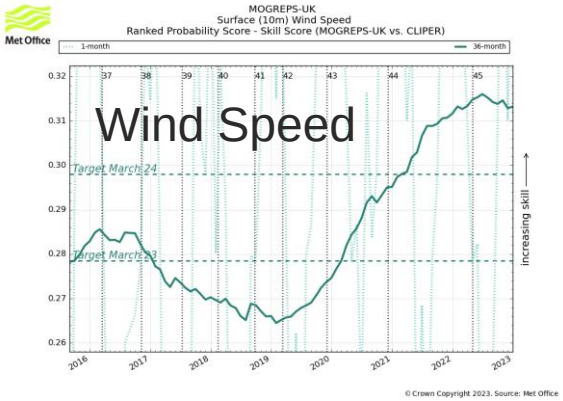
# Measuring performance – Corporate KPIs

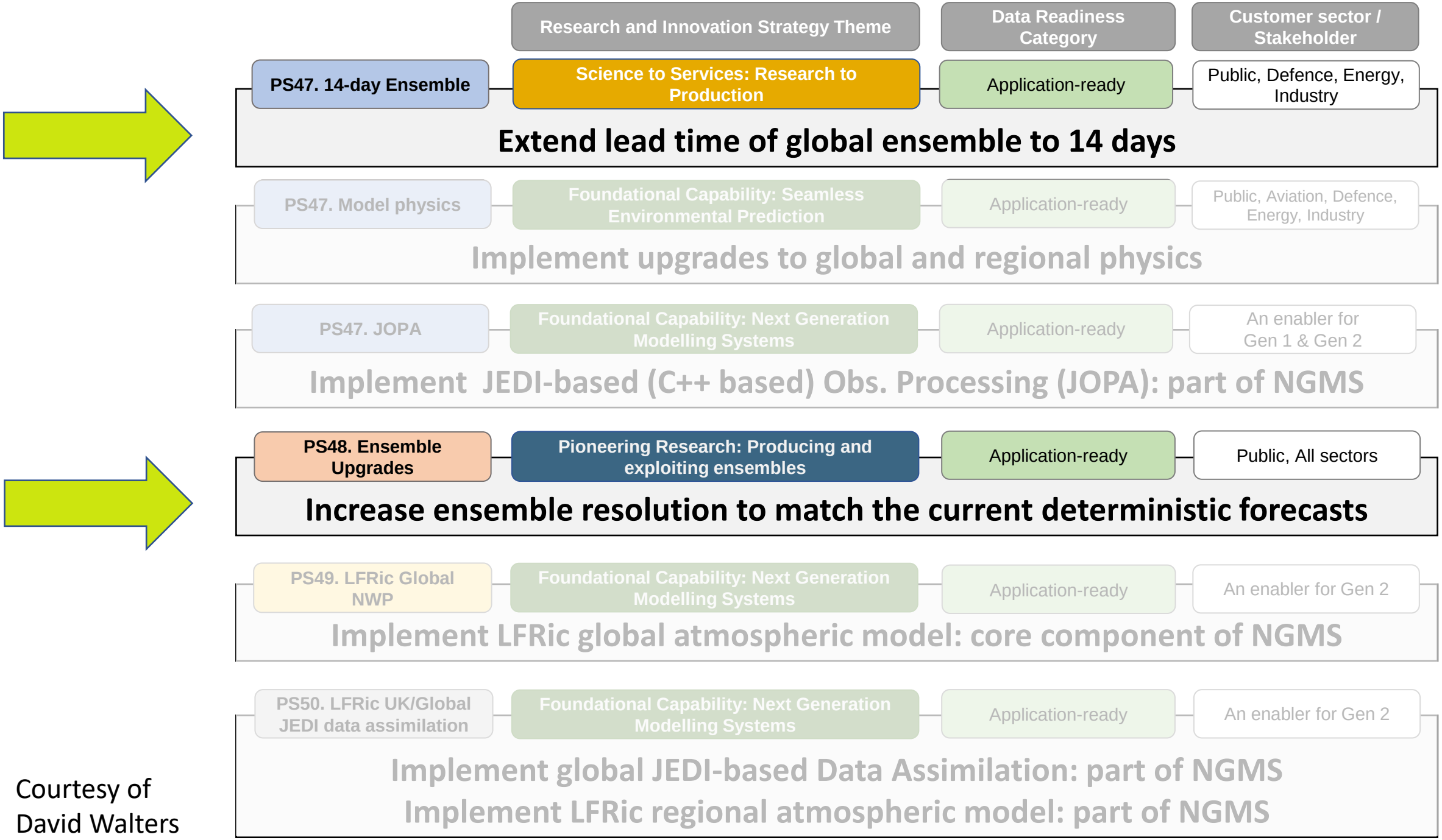
| Area | Component | 202211 | | 202212 | |
|---|---|---|---|---|---|
| | | T+48 (2 days) | T+144 (6 days) | T+48 (2 days) | T+144 (6 days) |
| NH | GPH @500hPa | 0.3 | 0.46 | 0.3 | 0.41 |
| | Temp @850hPa | 0.06 | 0.06 | 0.06 | 0.06 |
| TR | Temp @850hPa | 0.07 | 0.1 | 0.07 | 0.1 |
| | (u,v) Wind @250hPa | 0.02 | 0.0 | 0.02 | -0.0 |
| SH | GPH @500hPa | 0.38 | 0.77 | 0.38 | 0.76 |
| | Temp @850hPa | 0.05 | 0.04 | 0.05 | 0.04 |

- Corporate Key Performance Indicators for forecast accuracy now based on ensembles
- Global MOGREPS CRPS to WMO standards
- UK HiRA scores for 6 surface weather components



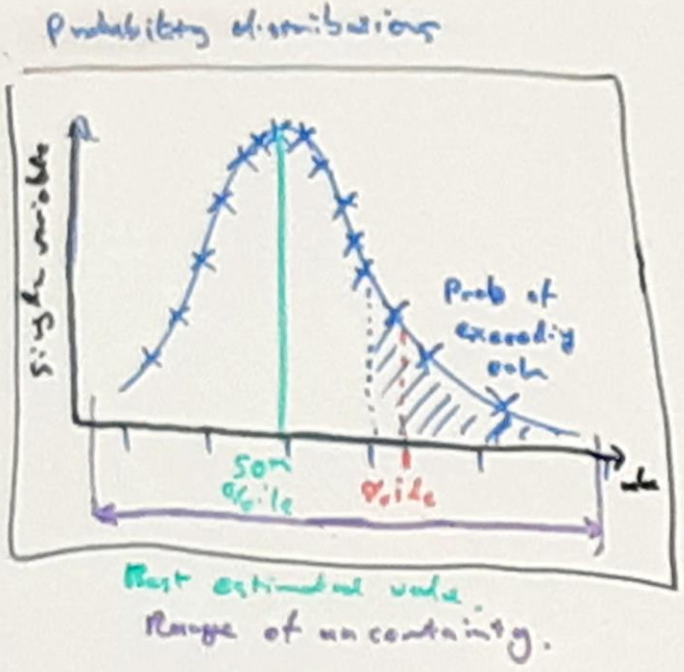



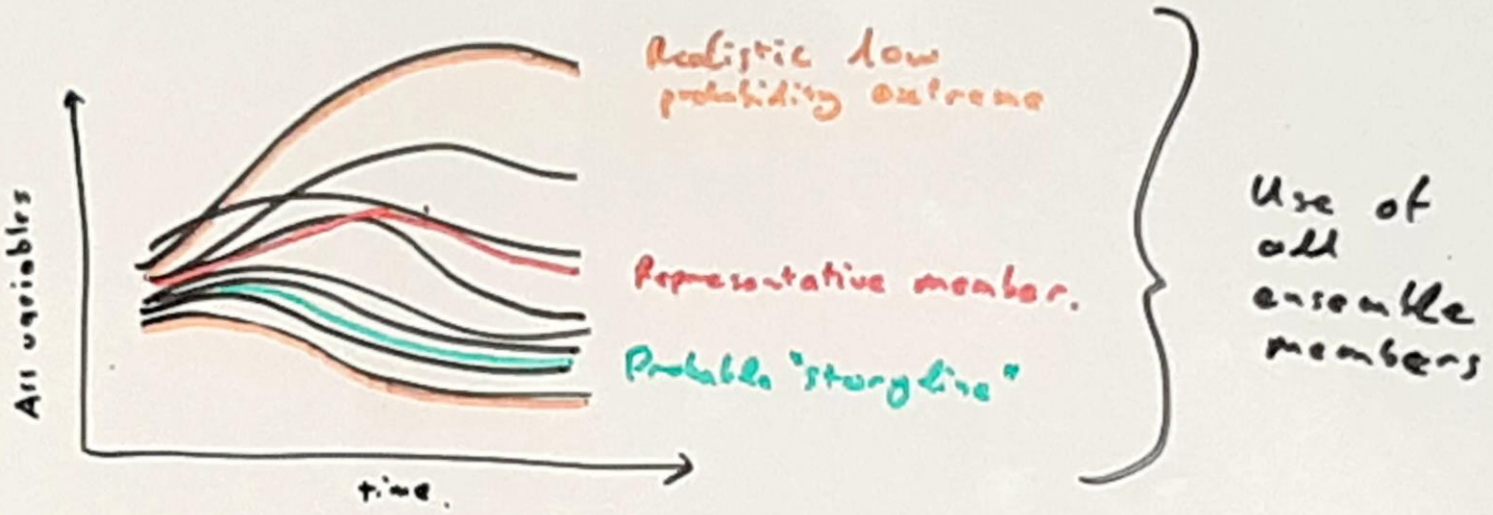






Courtesy of David Walters

# An illustration of use cases….

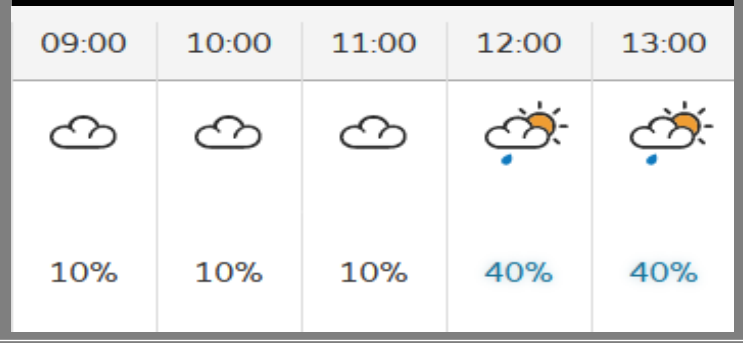


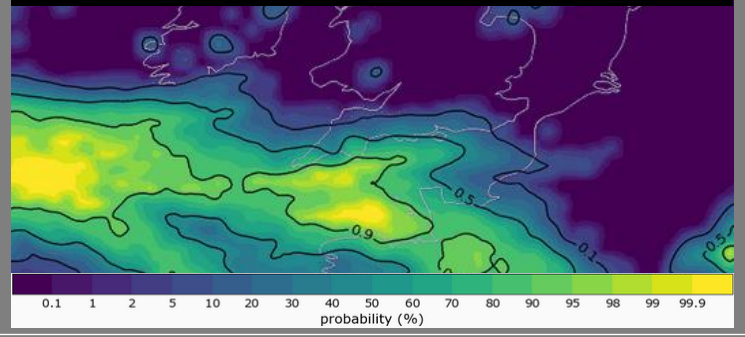
# Classes of use cases for ensembles

1) Use cases for ensemble stats

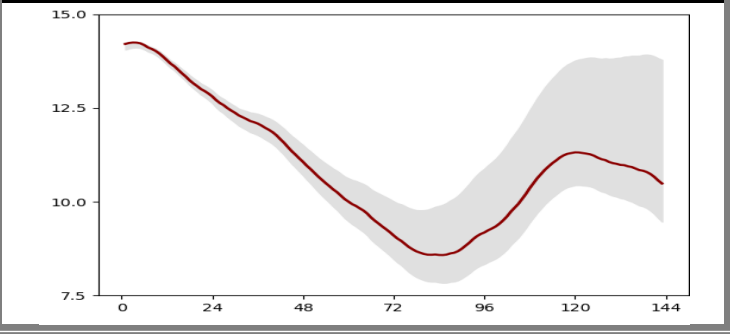
## 1a. Best estimated values




## 1b. Probability distributions

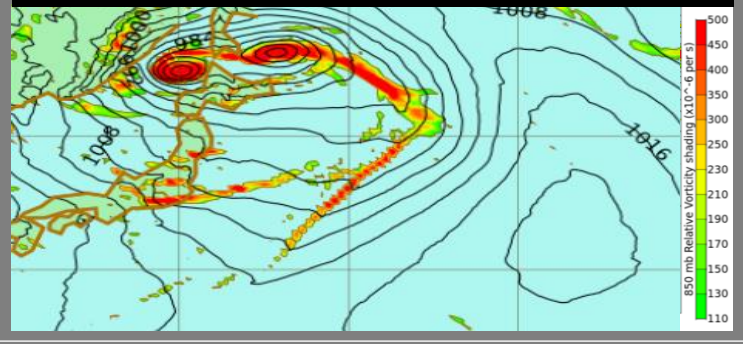



## 1c. Ranges of uncertainty

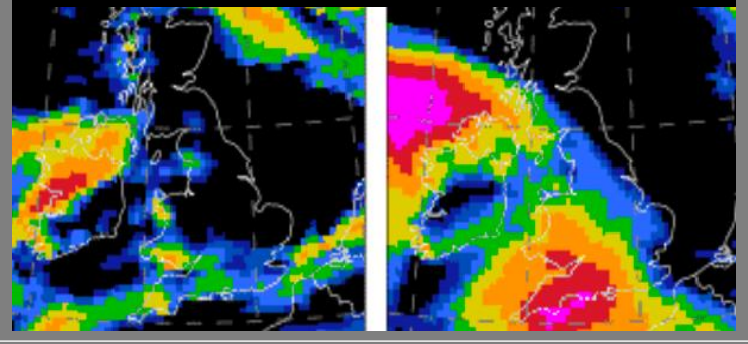



2) Use cases for 1 or more members

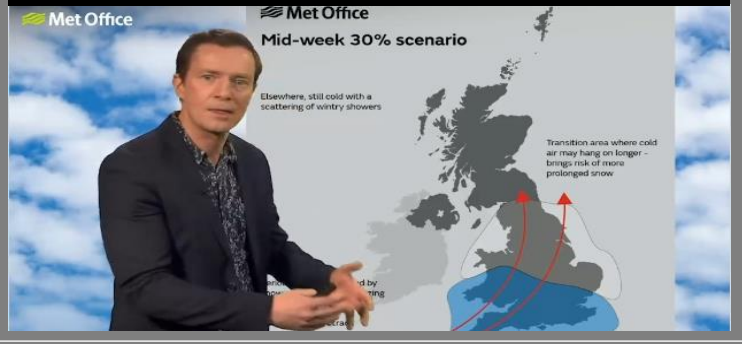
## 2a. Representative member




## 2b. Realistic low-prob. extremes

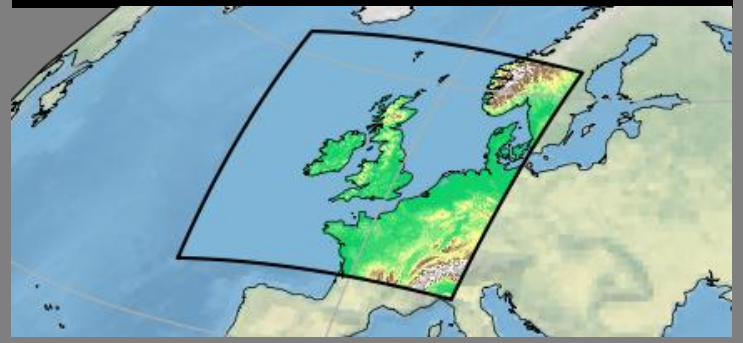


## 2c. Probable “storylines”



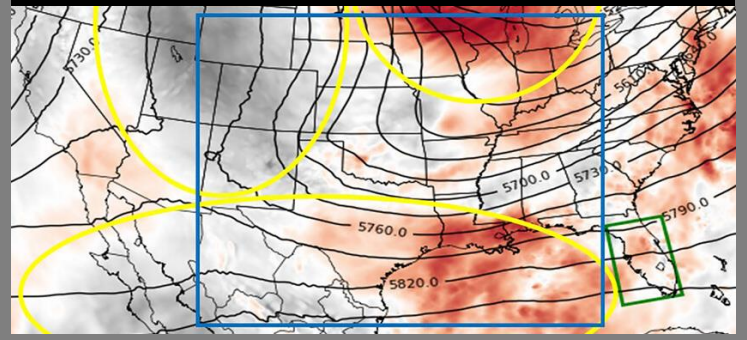

3) Use cases for all members

## 3a. Driving downstream models

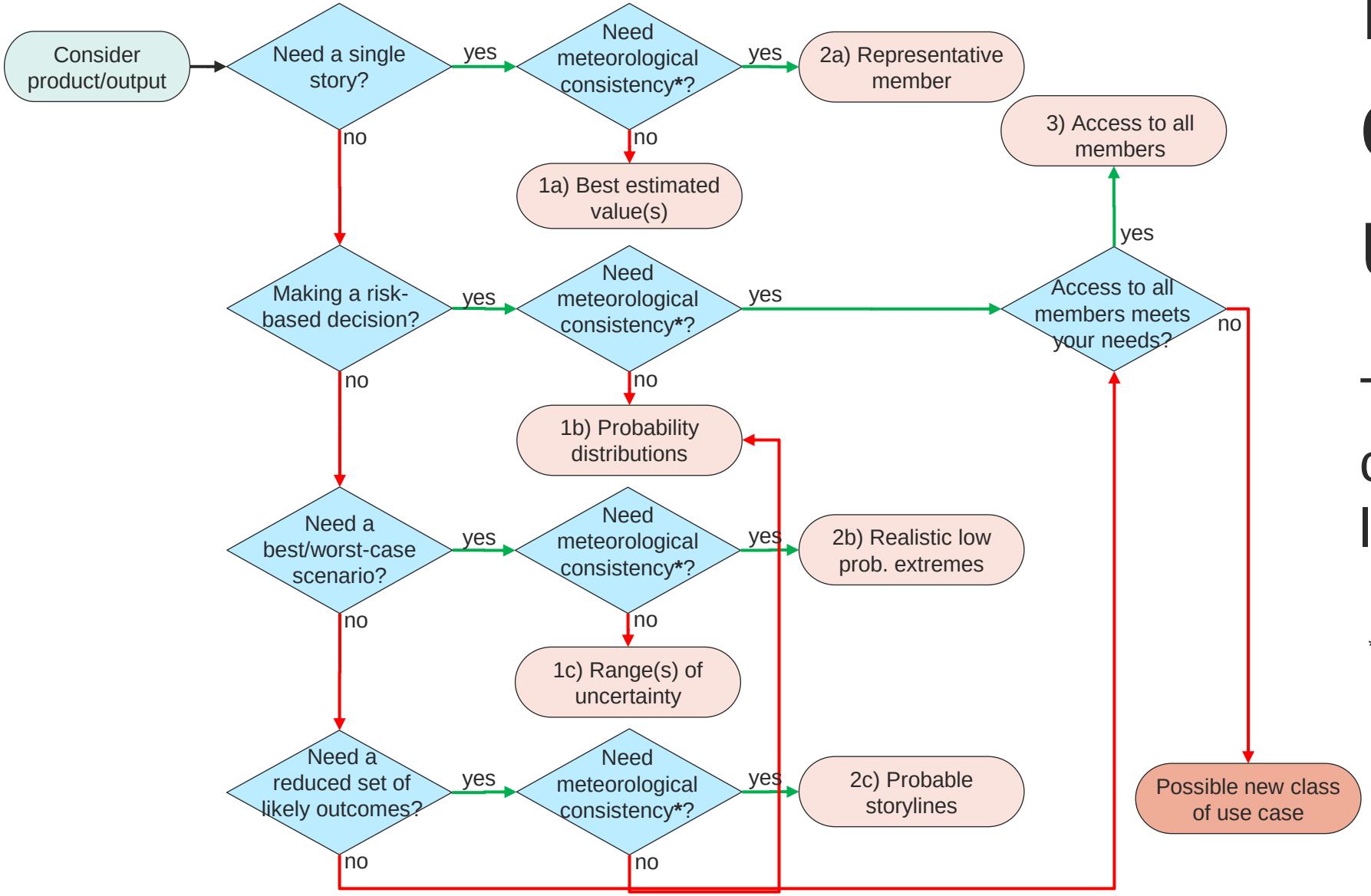


## 3b. Correlated prob. distribution

## 3c. Extra ensemble processing



# Developing classes of use cases

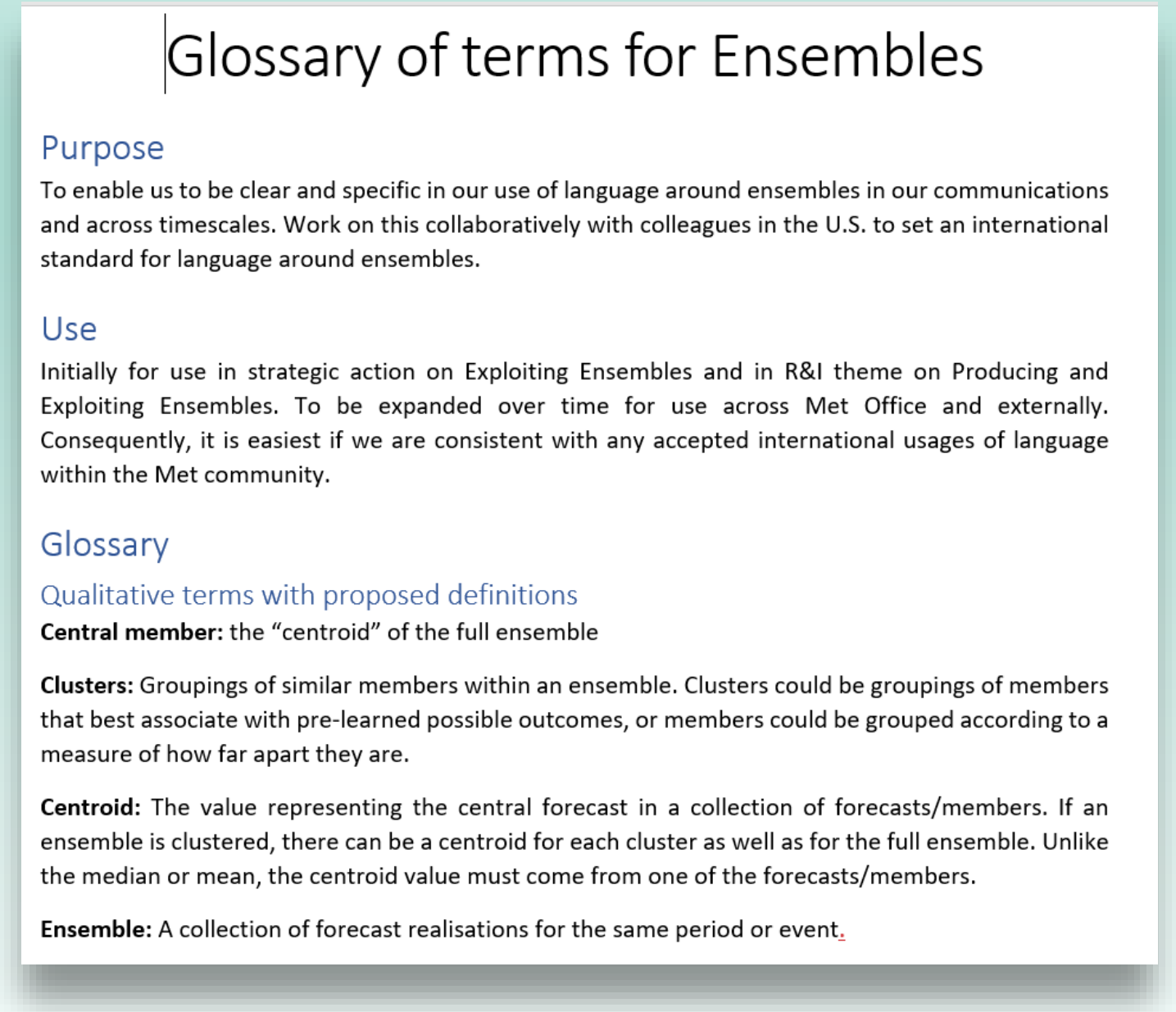



Test potential use cases using something like this framework?

* Meteorological consistency means consistency between different variables, spatial locations and forecast ranges.

# Glossary of terms

We have started to create a glossary of terms around ensembles and probabilistic forecasts.
We are working with NOAA and hope possibly to aim for an international standard.



## Glossary of terms for Ensembles

### Purpose

To enable us to be clear and specific in our use of language around ensembles in our communications and across timescales. Work on this collaboratively with colleagues in the U.S. to set an international standard for language around ensembles.

### Use

Initially for use in strategic action on Exploiting Ensembles and in R&I theme on Producing and Exploiting Ensembles. To be expanded over time for use across Met Office and externally. Consequently, it is easiest if we are consistent with any accepted international usages of language within the Met community.

### Glossary

#### Qualitative terms with proposed definitions

**Central member:** the "centroid" of the full ensemble

**Clusters:** Groupings of similar members within an ensemble. Clusters could be groupings of members that best associate with pre-learned possible outcomes, or members could be grouped according to a measure of how far apart they are.

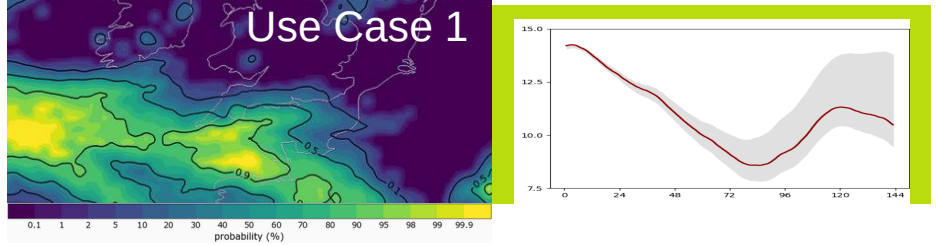
**Centroid:** The value representing the central forecast in a collection of forecasts/members. If an ensemble is clustered, there can be a centroid for each cluster as well as for the full ensemble. Unlike the median or mean, the centroid value must come from one of the forecasts/members.

**Ensemble:** A collection of forecast realisations for the same period or event.

# Progress…some use cases…

Met Office

| 09:00 | 10:00 | 11:00 | 12:00 | 13:00 |
|---|---|---|---|---|
| | | | | |
| 10% | 10% | 10% | 40% | 40% |

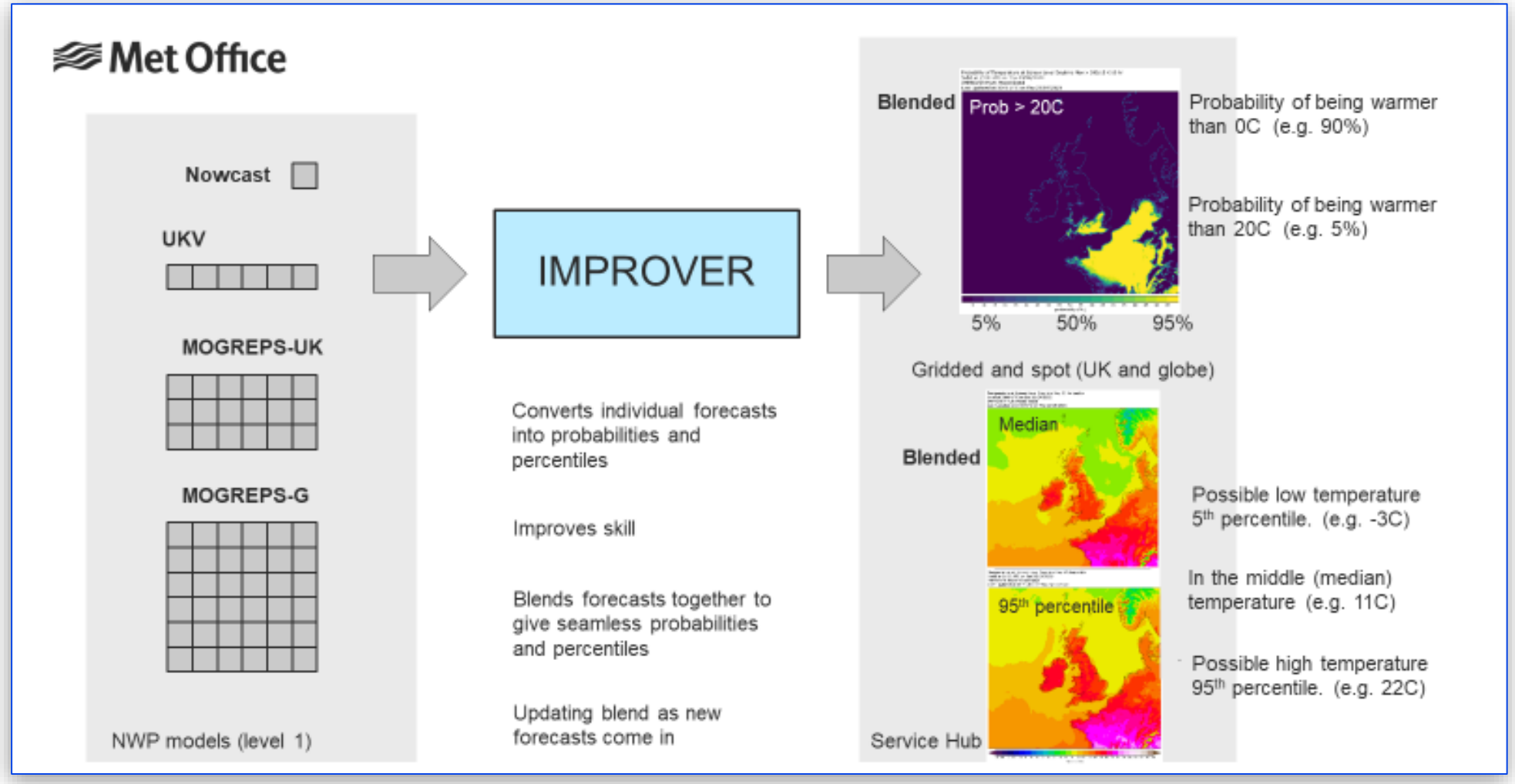



**IMPROVER**
serves use case 1 – ensemble stats

Includes:

- ***most likely***
- ***Extremes***
- ***Reasonable worst case***

…but on a local point-by-point basis



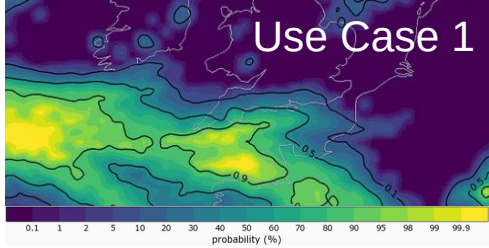
# "*People don't understand probabilities*" – or do they?

Literature review provides overwhelming evidence that:

**"1) average people can make sense of and use probability information if consideration is given to information presentation and**

**2) assuming appropriate presentation, probability information generally improves decision quality."**

Ripberger *et al* (2022)




# Cost-Loss – *rational decision-making*

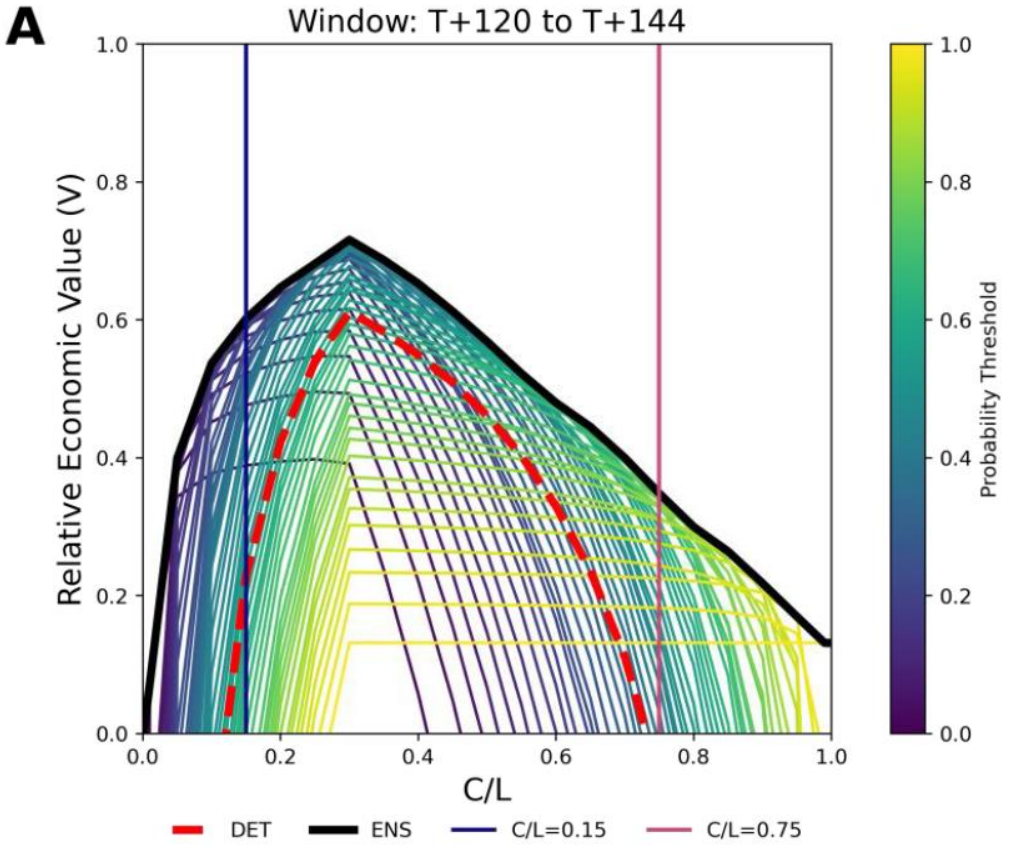
- Scientists long promoted a simple yes/no decision model:
  - Cost of protection = C
  - Potential loss from event = L
  - Take action if:

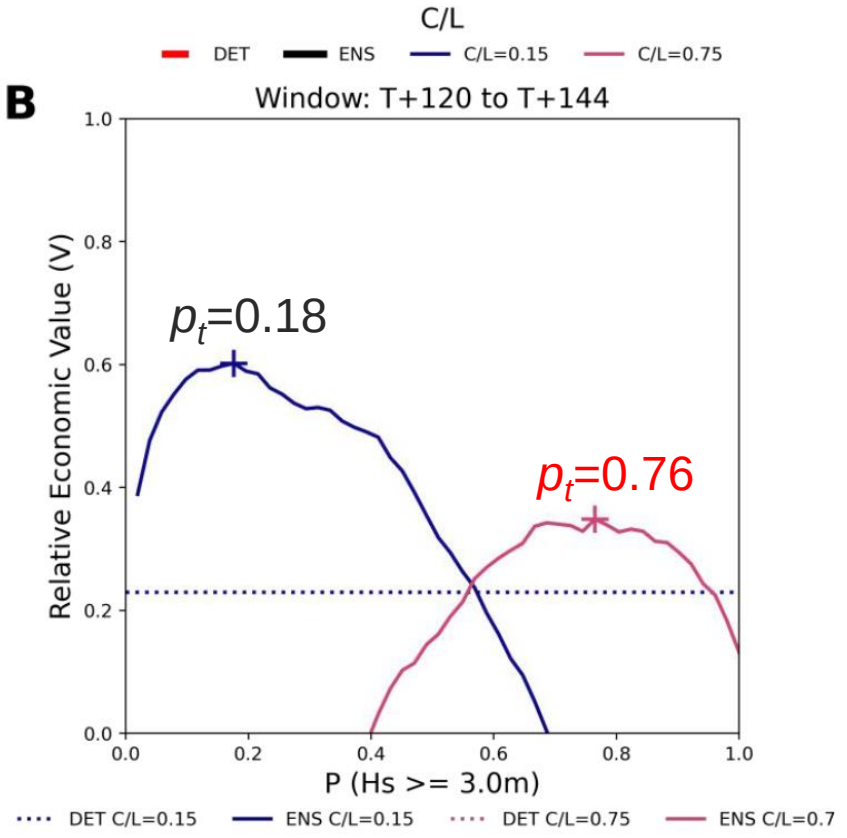
$$p(event) > C/L$$

Real-world decision-making is rarely this simple


- Estimating losses difficult – need to understand Hazard Impacts

# Verification of past forecasts shows the Relative Economic Value for different C/L ratios (left) or probabilities (right)




For user with *C/L*=0.15 verification shows that value is maximised for $p_t$=0.18

Built-in calibration



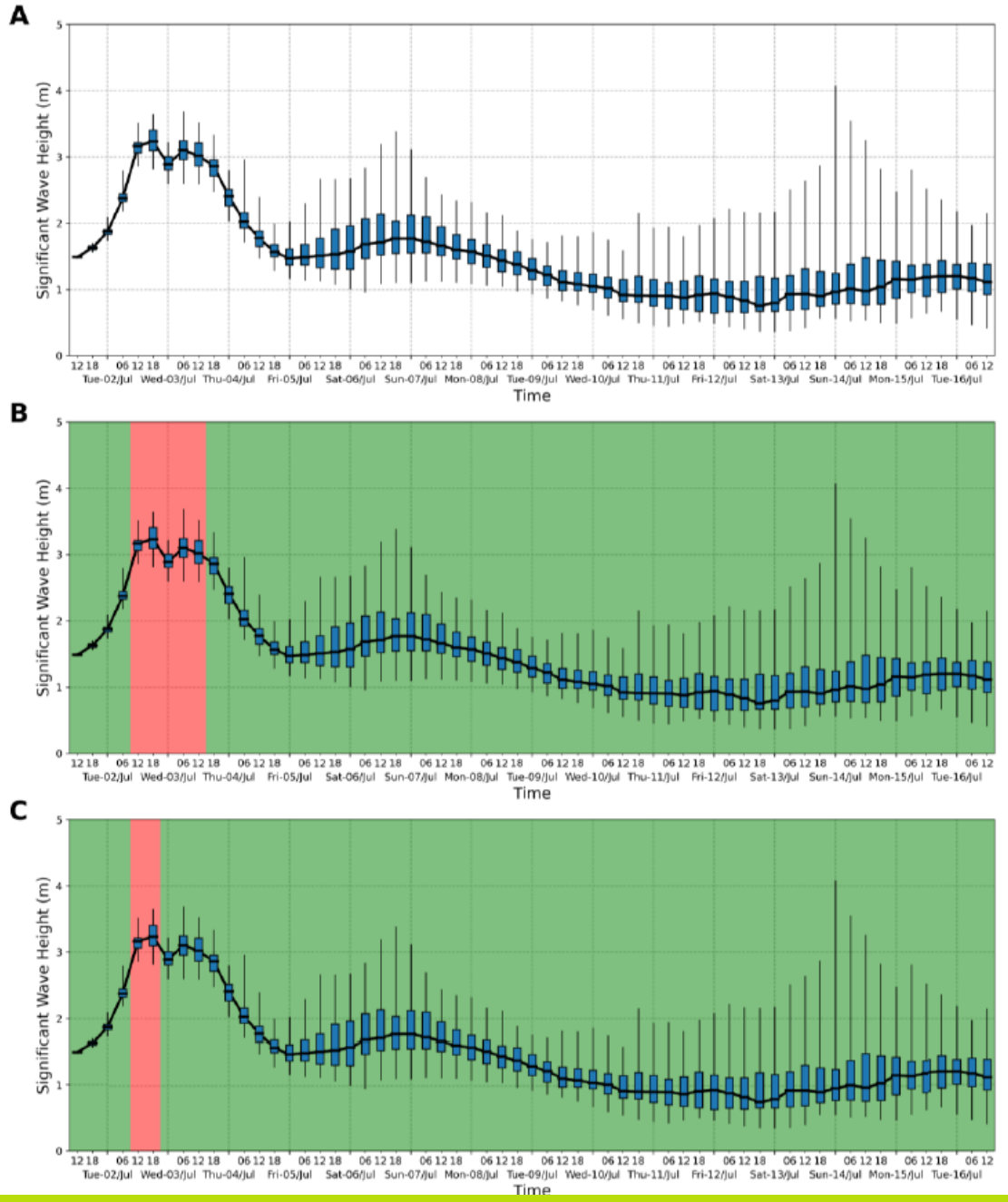
Courtesy: Ed Steele *et al*

# Using Cost-Loss Decision-Making

- Used here with ECMWF ensemble significant wave height forecasts for offshore pipe-laying operations.
- A – Standard ensemble meteogram
- B – Highlighting optimal decision for $p_t$=0.18 (C/L = 0.15)
- C – same for $p_t$=0.76 (C/L = 0.75)

- RED - Postpone operations

- Trained on past verification to select optimal $p_t$ decision threshold – built-in calibration

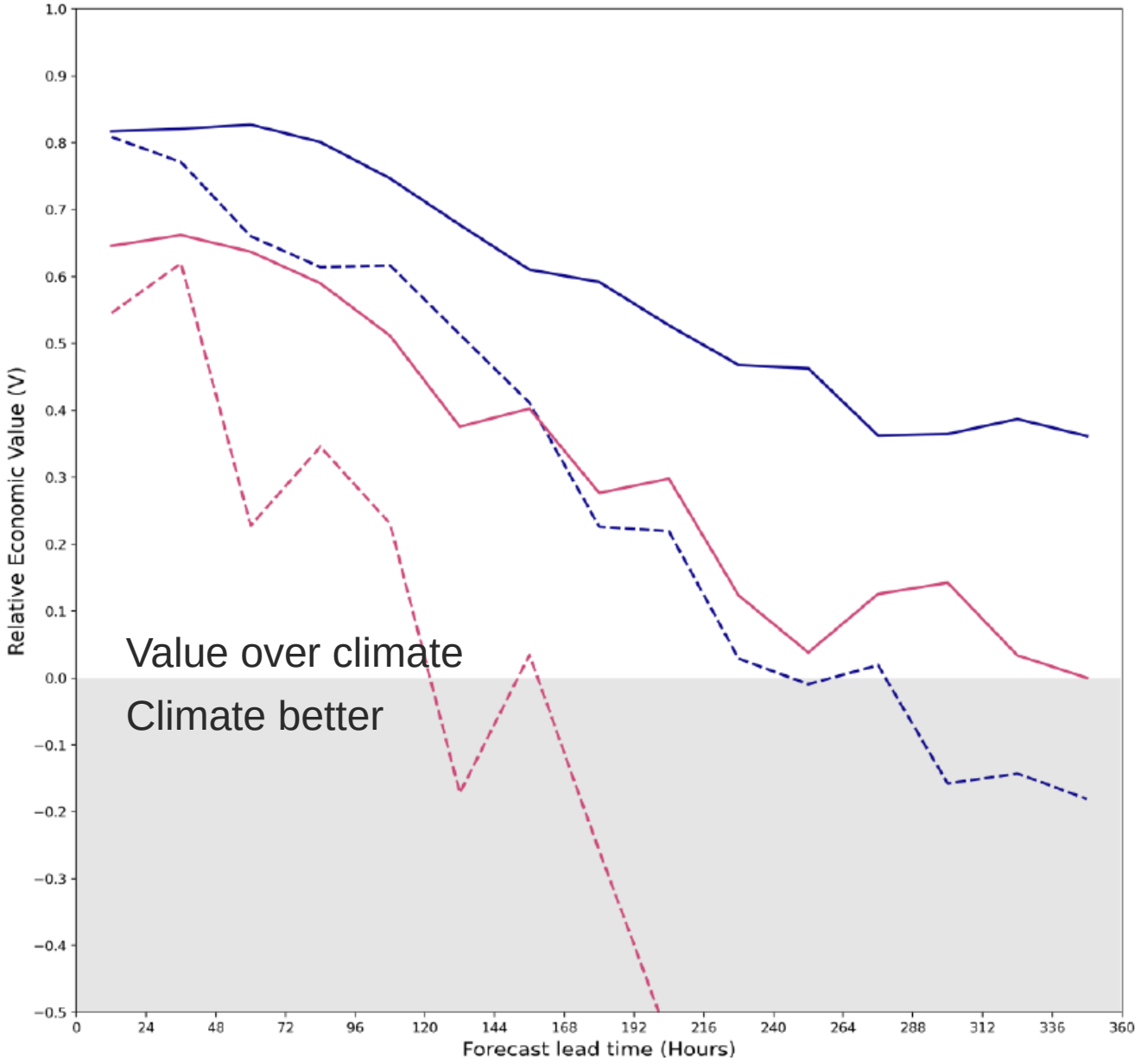





Courtesy: Ed Steele *et al*

# Verification

- Verification from independent test period (9 months)
- Blue *(C/L=0.15)*
- Red *(C/L=0.75)*
- Solid Ensemble Probs
- Dashed Deterministic Control

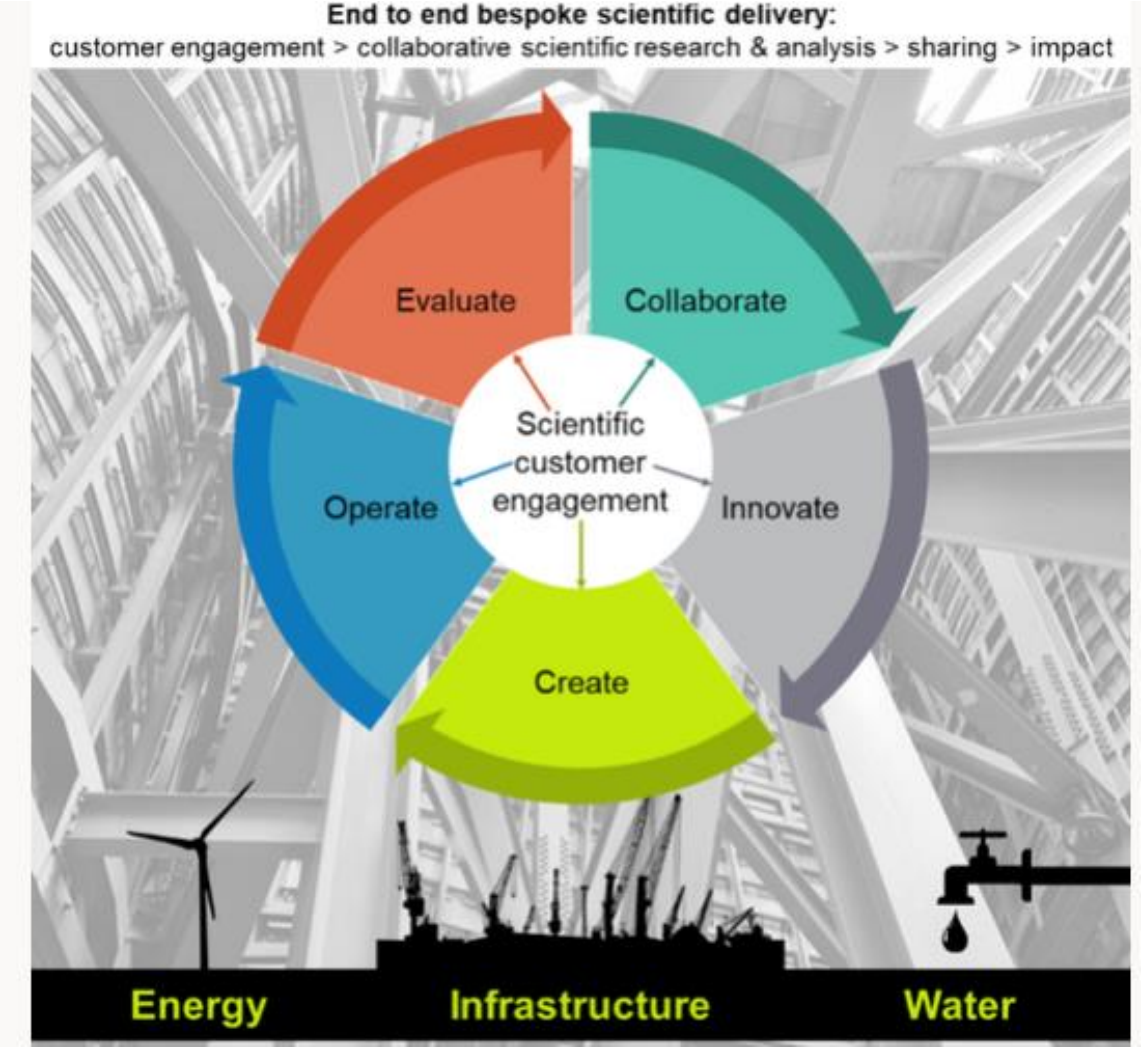





Courtesy: Ed Steele *et al*

# Co-Development framework

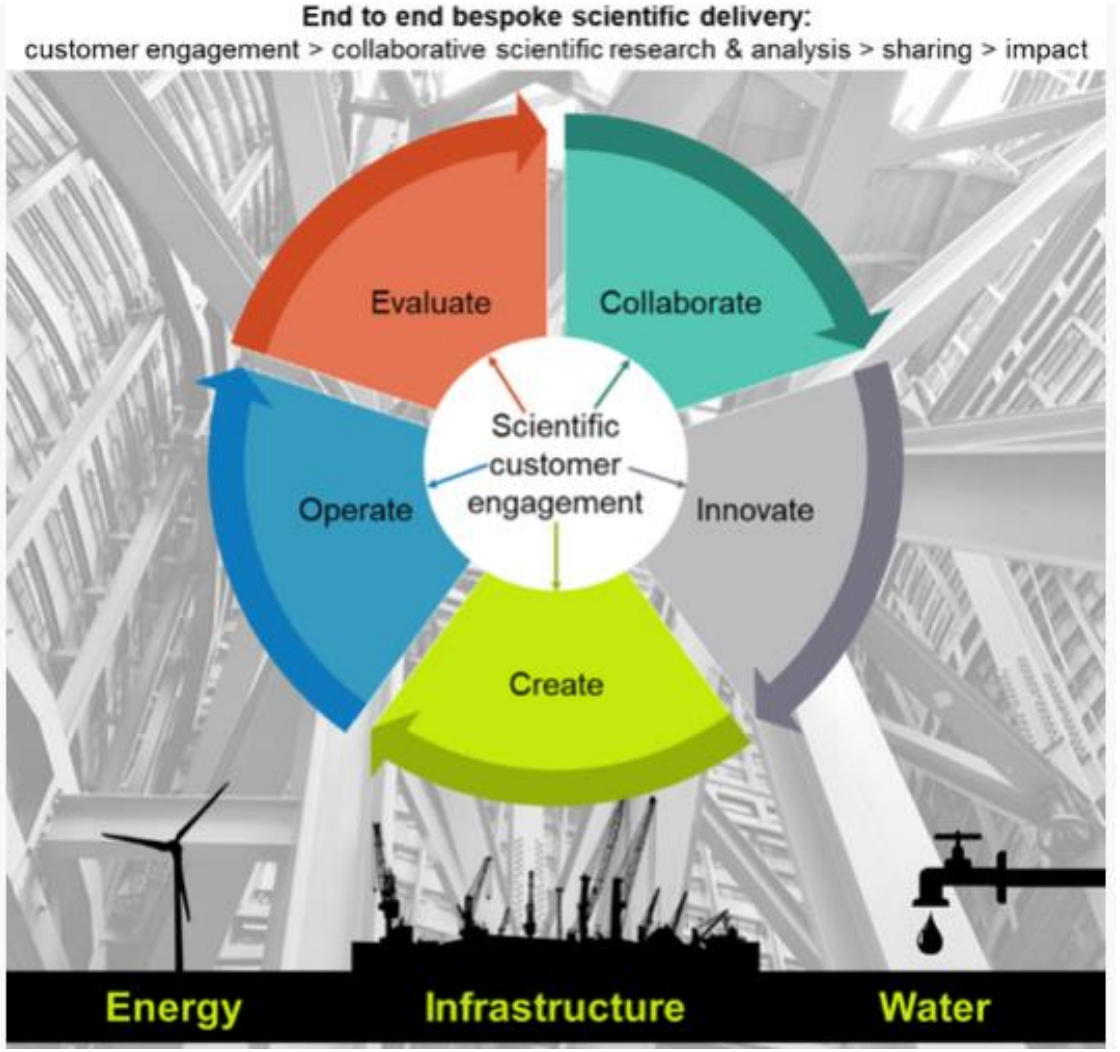
- **Collaborate** - Work with stakeholders and partners to identify and prioritise weather related business impacts.
- **Innovate** - Characterise the hazards, or adverse events, that cause the business impacts identified projections.
- **Create** - Combine cutting-edge statistical modelling techniques and innovative research with industry knowledge.
- **Operate** - Deliver services that support decisions ranging across timescales, from short-range weather prediction through to 50-year ahead climate.
- **Evaluate** – Evaluate performance of service including relevant performance metrics, value add and customer feedback.



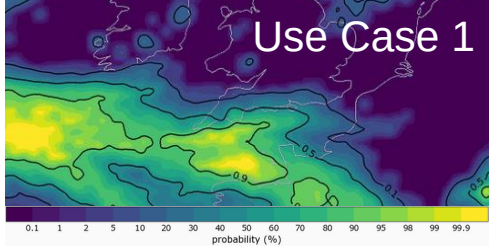
# Co-Development framework

- **Collaborate** - Work with stakeholders and partners to identify and prioritise weather related business impacts.
- **Innovate** - Characterise the hazards, or adverse events, that cause the business impacts identified projections.
- **Create** - Combine cutting-edge statistical modelling techniques and innovative research with industry knowledge.
- **Operate** - Deliver services that support decisions ranging across timescales, from short-range weather prediction through to 50-year ahead climate.
- **Evaluate** – Evaluate performance of service including relevant performance metrics, value add and customer feedback.

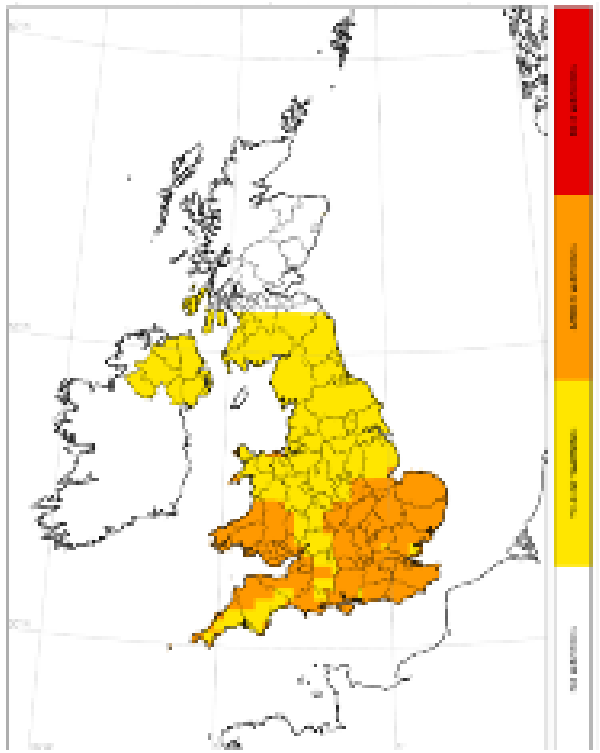
More examples I can show anyone interested later



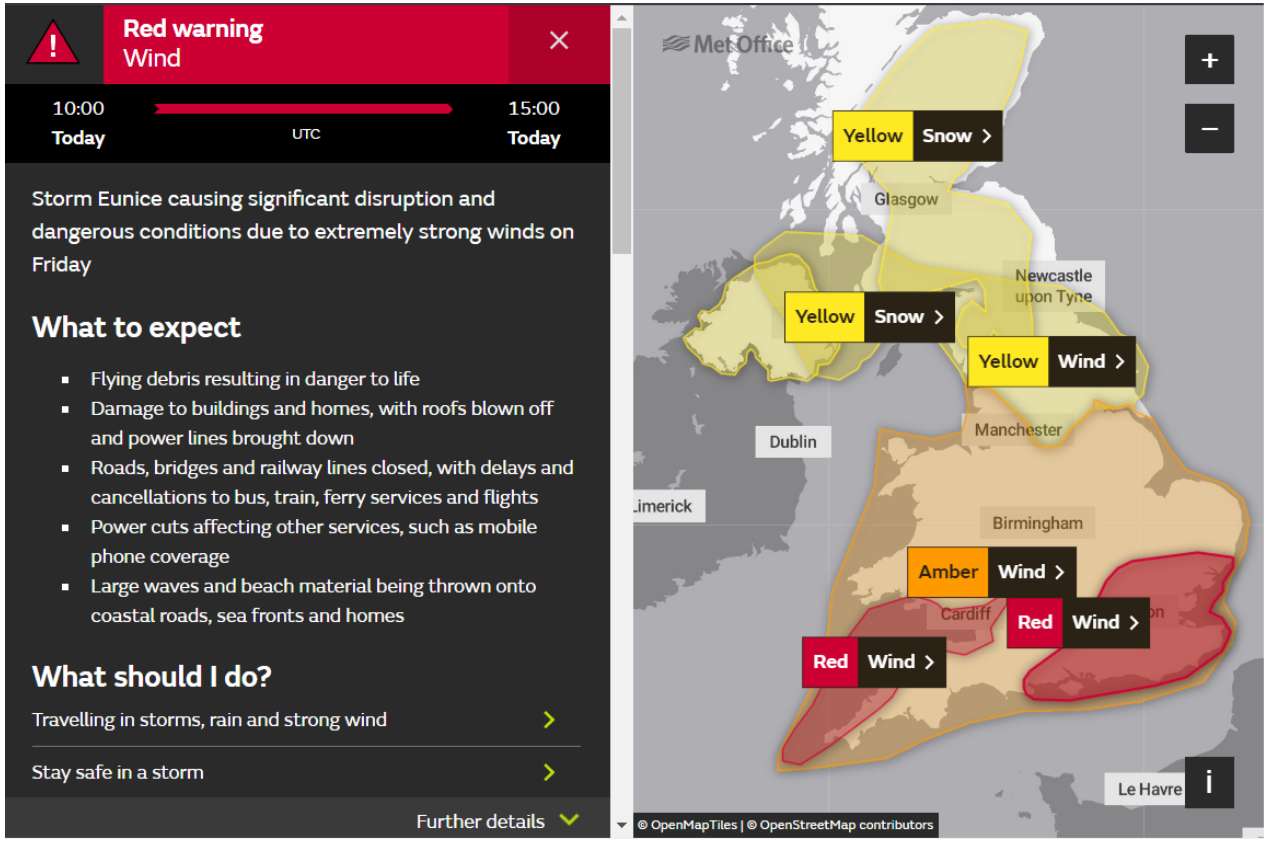
# National Severe Weather Warning Service




- Impact-based warnings – combination of impact and likelihood



Ensemble-based first-guess warnings help guide forecasters

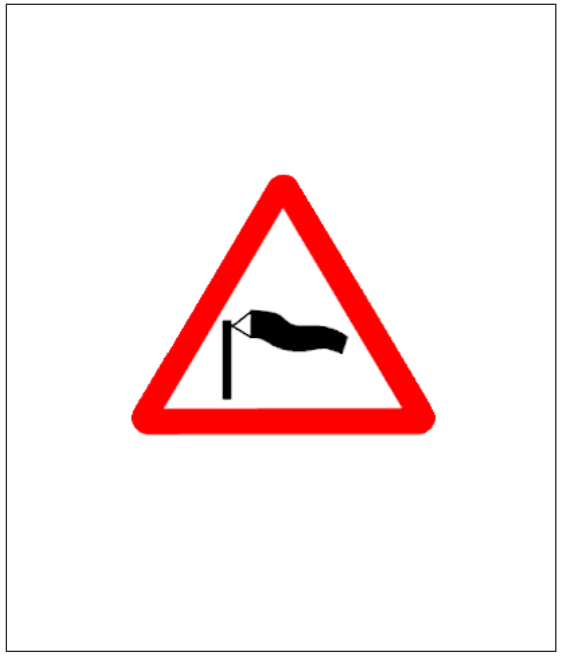



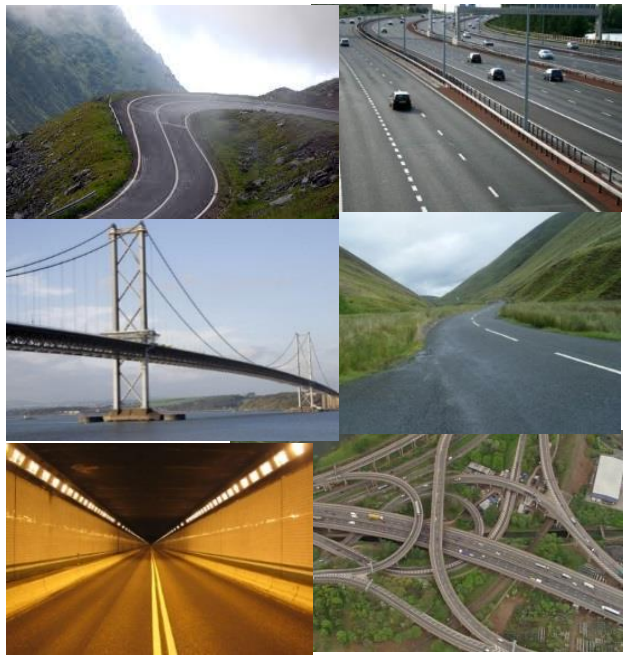

Warnings for **Storm Eunice**, 17 Feb 2022

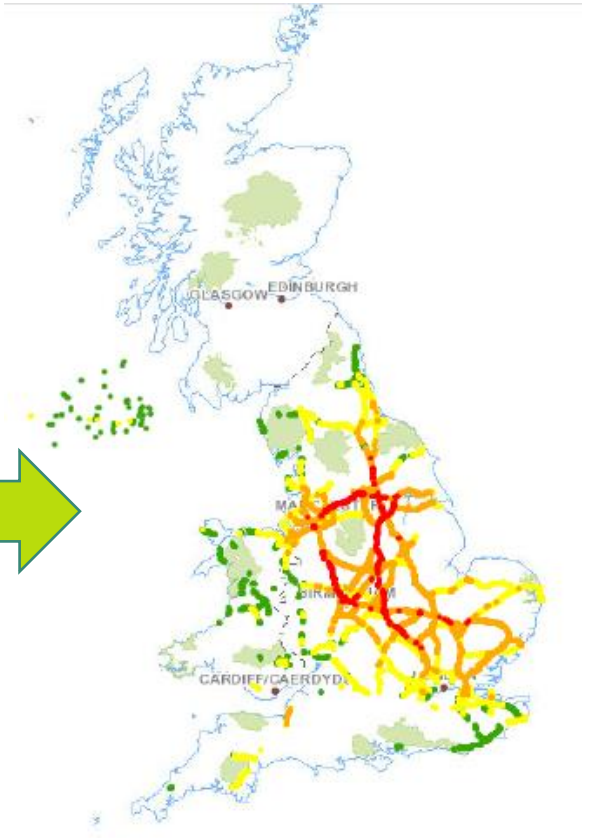
Met Office

# Risk = Prob(Hazard) X Vulnerability X Exposure

# Hazard Impact Model - Vehicle OverTurning








## Hazard

Probability of wind gusts exceeding thresholds

## Vulnerability

- Altitude
- Number of lanes
- Other features e.g. bridge
- Road orientation

## Exposure

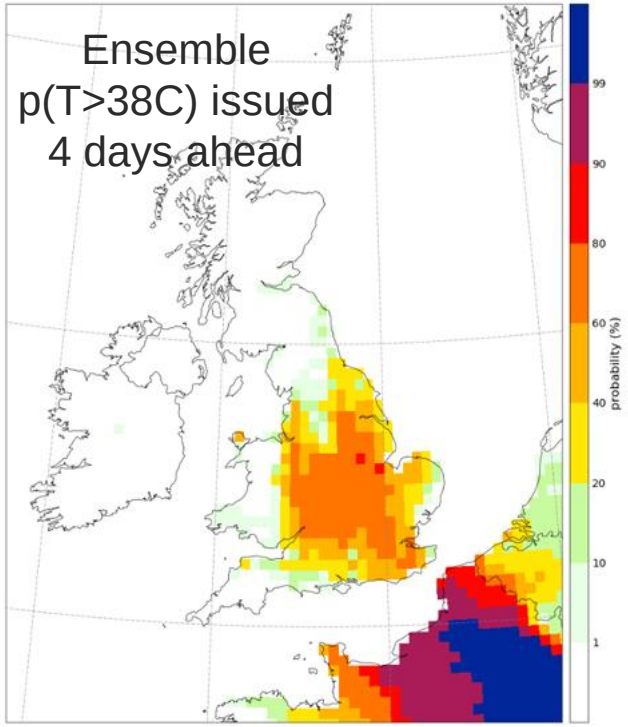
Number of vehicles on road

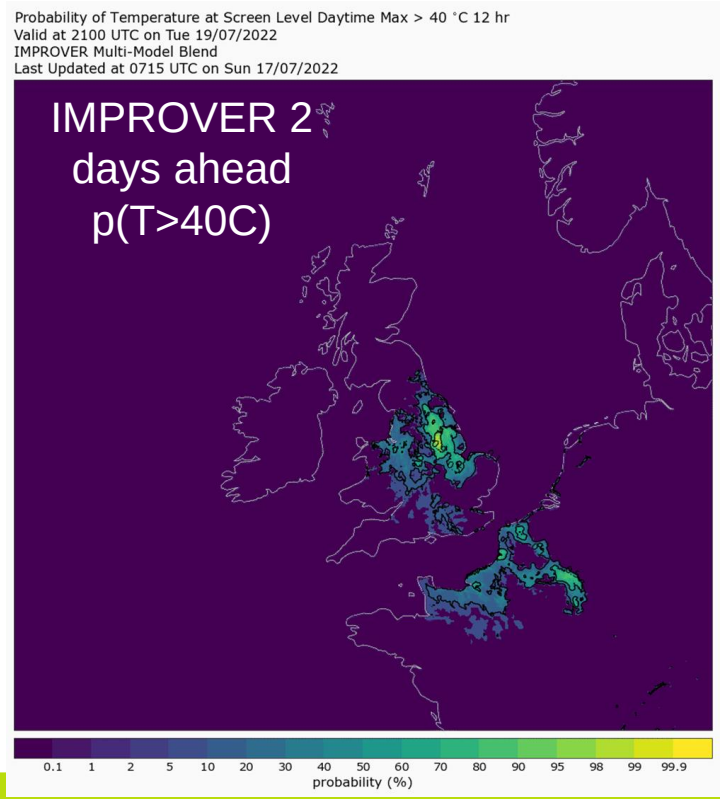
***Storm Doris***

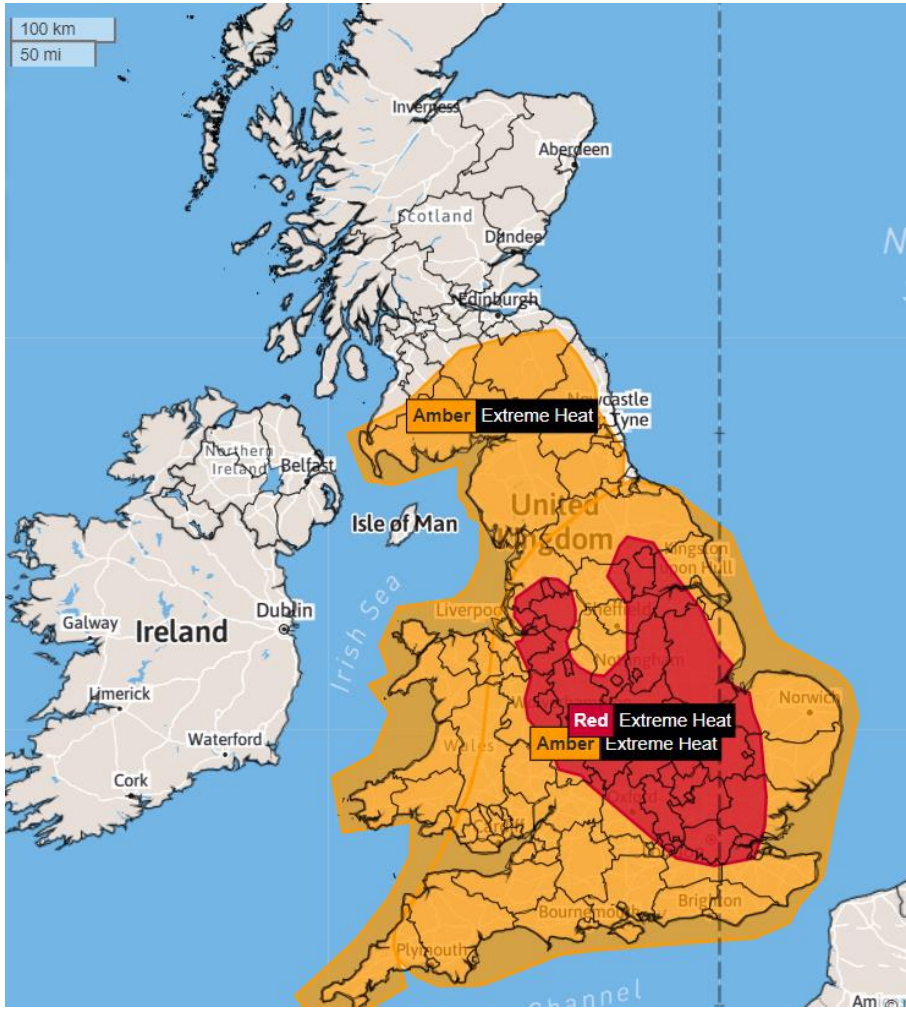
Vulnerability and exposure information – partnership – social science

# Heatwave Warnings

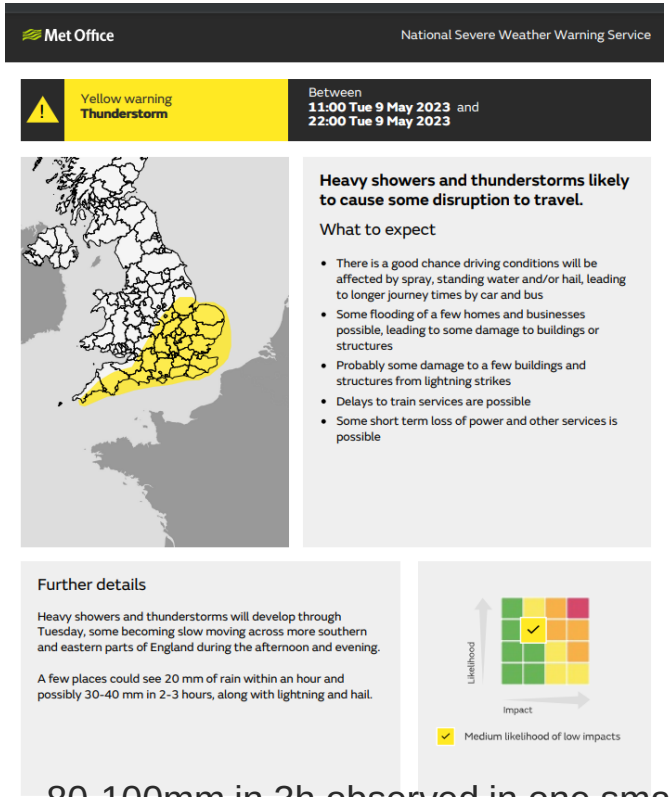
- UK temperature record of 40.3C set 19 Jul 2022
- Strong ensemble consistency and high probabilities gave confidence to issue warnings several days ahead – earliest ever Red warning

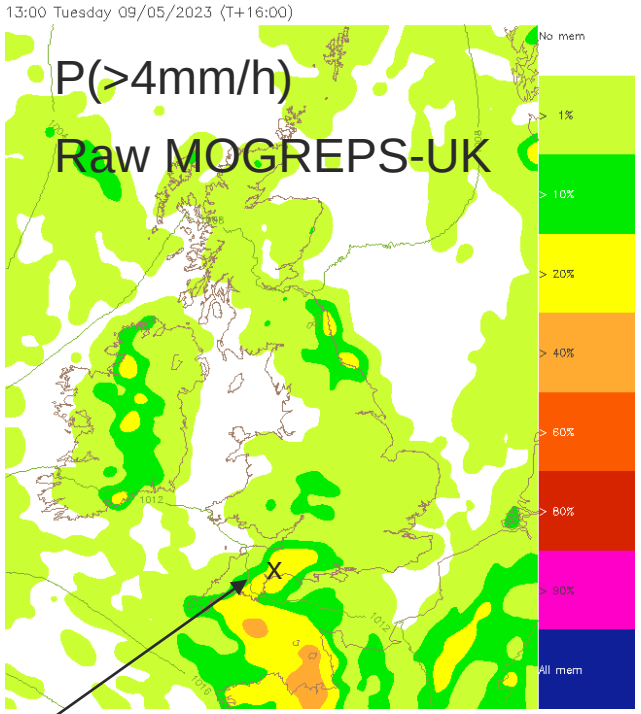


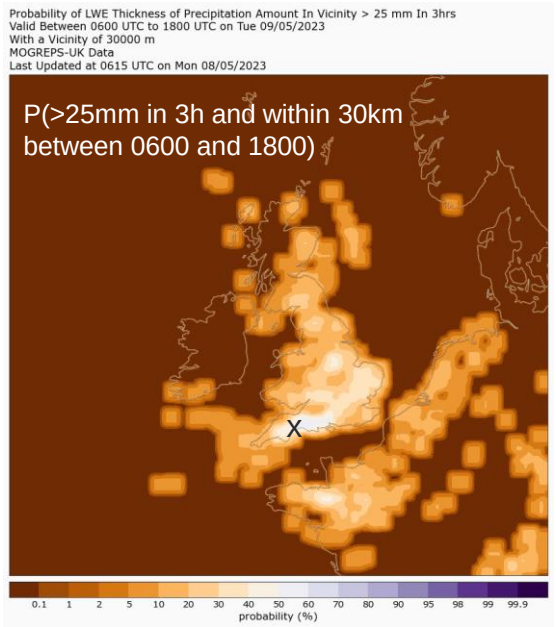



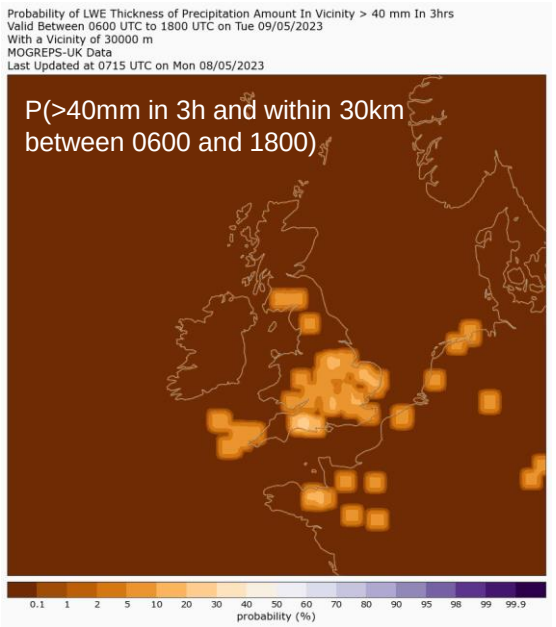



# Localised flash floods, East Devon 9th May 2023



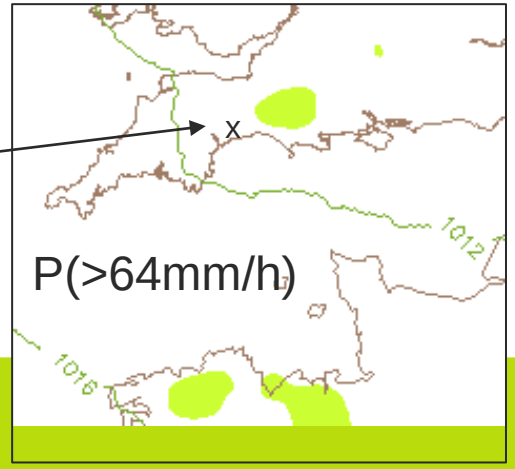



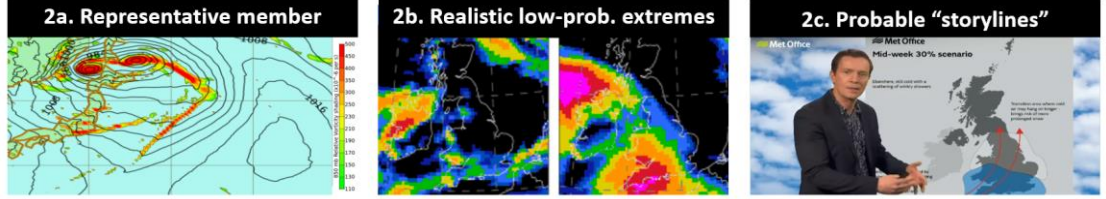



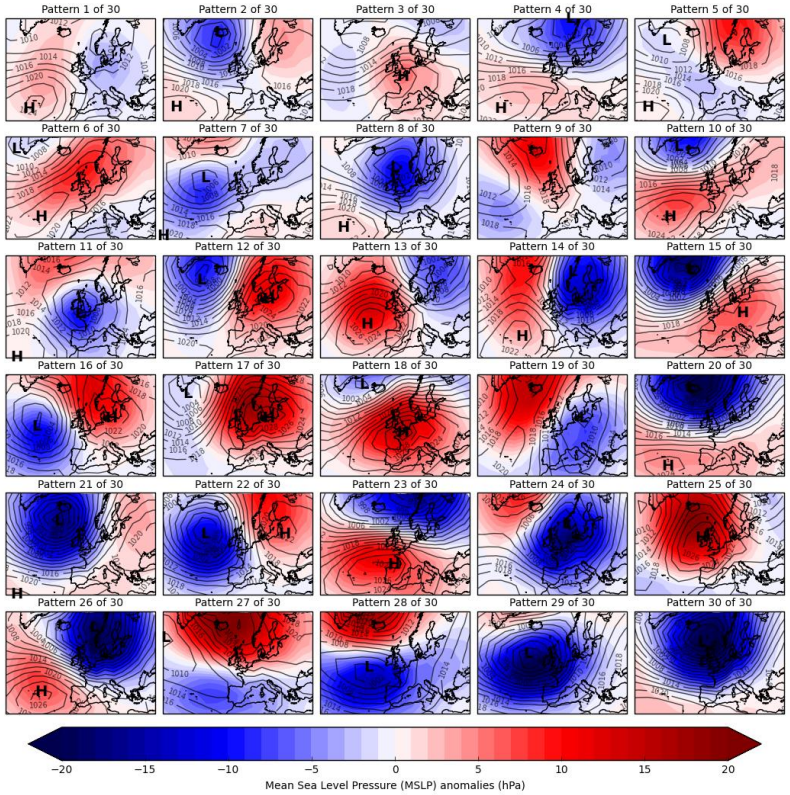

- Broad area Yellow warning low prob
- Raw MOGREPS-UK ensemble captures only low probabilities of heavy rain rates – 1 member
- Appropriate post-processing with IMPROVER for in-vicinity accumulations suggests highest risk in affected area, but:
  - Greatly underestimates max accumulations
  - Significant false alarm rate

80-100mm in 3h observed in one small area (<10km$^2$)



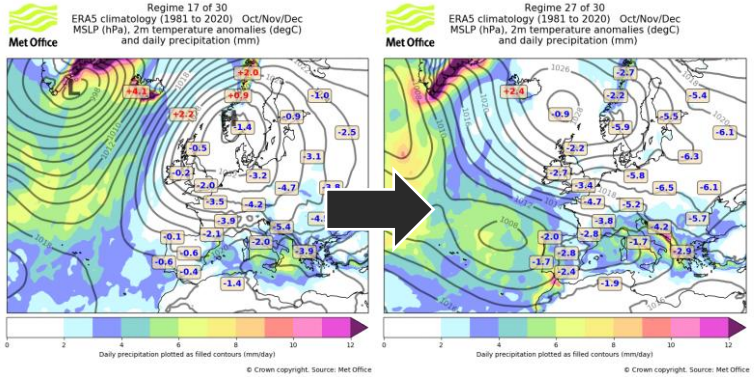
# DECIDER
# Weather patterns




| | Mon 28 Nov | Tue 29 Nov | Wed 30 Nov | Thu 1 Dec | Fri 2 Dec | Sat 3 Dec | Sun 4 Dec | Mon 5 Dec | Tue 6 Dec | Wed 7 Dec | Thu 8 Dec | Fri 9 Dec | Sat 10 Dec | Sun 11 Dec | Mon 12 Dec | Regime Descriptions (UK) | Historic Occurrence O/N/D |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Regime 1 | | | | | | | | | | | | | 2 | | | Unbiased NWly | 2.6% |
| Regime 2 | | | | | | | | | | | | | | | | Cyclonic SWly, returning Pm airmass | 3.7% |
| Regime 3 | | | | | | | | | | | | | | | | Anticyclonic SWly, ridge over N France | 3.3% |
| Regime 4 | | | | | | | | | | | | | | | | Unbiased Wly | 3.5% |
| Regime 5 | 100 | | | | | | | | | | | | 2 | | 2 | Unbiased Sly, high over Scandinavia | 3.3% |
| Regime 6 | | | | | | | | | | | | | | | | Anticyclonic, Azores high ext. | 3.3% |
| Regime 7 | | | | | | | | | | | | | | 4 | | Cyclonic SWly, low WNW of Ireland | 2.8% |
| Regime 8 | | | | | | | | | | | | | | | | Cyclonic Wly, low near Shetland | 3.8% |
| Regime 9 | | | | | | | | | | | | | | | 2 | Anticyclonic N-NEly, high near Iceland | 3.5% |
| Regime 10 | | | | | | | | | | | | | | 2 | | Anticyclonic W-SWly, slight Azores ridge | 3.7% |
| Regime 11 | | | | | | | | | | 2 | | 2 | 2 | | 4 | Cyclonic, low centred over southern UK | 3.1% |
| Regime 12 | | 4 | | | | | | | | | | | | | 4 | Anticyclonic Sly, high over Poland | 4.5% |
| Regime 13 | | | | | | | | | | | 2 | | | | 2 | Anticyclonic NWly, high SW of Ireland | 4.3% |
| Regime 14 | | | | | | | | | | | 2 | | | | | Cyclonic N-NWly, low near S Sweden | 4.1% |
| Regime 15 | | | | | | | | | | | | | | | | Unbiased SWly, very windy NW Britain | 4.3% |
| Regime 16 | | 96 | | | | | | | | | | 2 | 8 | 4 | 4 | Anticyclonic S-SEly, high E of Denmark | 3.1% |
| Regime 17 | | | 100 | 100 | 43 | | | 4 | | | | | | 2 | 2 | Anticyclonic E-SEly high over Denmark | 3.9% |
| Regime 18 | | | | | | | | | | | | | | | | Anticyclonic SWly, high over N France | 3.9% |
| Regime 19 | | | | | | | | | 2 | 4 | 12 | 10 | 8 | 6 | 12 | Unbiased Nly, low E of Denmark | 3.8% |
| Regime 20 | | | | | | | | | | | | | | | | Cyclonic Wly, intense low near Iceland | 3.5% |
| Regime 21 | | | | | | | | | | | | | | | | Cyclonic SWly, deep low S of Iceland | 3.7% |
| Regime 22 | | | | | | | | | | | | 2 | | | | Cyclonic Sly, low W of Ireland | 2.8% |
| Regime 23 | | | | | | | | | | | | | | | | Unbiased Wly, windy in N | 2.9% |
| Regime 24 | | | | | | | | | | | 2 | | | 2 | 4 | Cyclonic Nly, low in N Sea | 2.9% |
| Regime 25 | | | | | | 6 | 10 | 10 | 12 | 6 | | 4 | 4 | 6 | 4 | Anticyclonic Nly, high centre Irish Sea | 3.0% |
| Regime 26 | | | | | | | | | | | | | | | | Cyclonic NWly, low near Norway, windy | 3.0% |
| Regime 27 | | | | | 57 | 94 | 90 | 86 | 86 | 86 | 67 | 57 | 43 | 35 | 31 | Anticyclonic Ely, high in Norwegian Sea | 2.8% |
| Regime 28 | | | | | | | | | | 2 | 16 | 24 | 31 | 35 | 22 | Cyclonic SEly, low SW of UK | 2.1% |
| Regime 29 | | | | | | | | | | | | | | 4 | 6 | Cyclonic S-SWly, deep low W of Ireland | 2.3% |
| Regime 30 | | | | | | | | | | | | | | | 2 | Cyclonic W-SWly, deep low SE of Iceland | 2.4% |
| Total Members | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | --- | --- |

Weather pattern probabilities from the 51 member ECMWF ensemble (00 UTC run on 28th November 2022)




The most likely transition, showing pattern climatologies for November

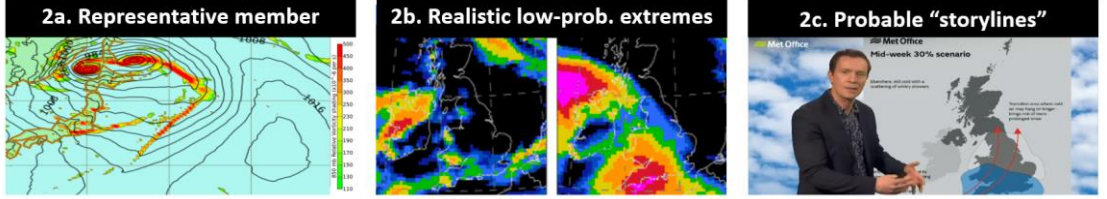
| | Mon 28 Nov | Tue 29 Nov | Wed 30 Nov | Thu 1 Dec | Fri 2 Dec | Sat 3 Dec | Sun 4 Dec | Mon 5 Dec | Tue 6 Dec | Wed 7 Dec | Thu 8 Dec | Fri 9 Dec | Sat 10 Dec | Sun 11 Dec | Mon 12 Dec | Regime Descriptions (UK) | Historic Occurrence O/N/D |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Regime 1 | | | | | 57 | 100 | 100 | 96 | 100 | 100 | 94 | 96 | 88 | 82 | 75 | Blocked (NAO-) | 21.7% |
| Regime 2 | | | | | | | | | | | | | | | 2 | Zonal (NAO+) | 19.0% |
| Regime 3 | | | | | | | | | | | | 6 | | 2 | 2 | North-westerly variants | 13.9% |
| Regime 4 | | 4 | | | | | | | | | | | | | 4 | South-westerly variants | 16.3% |
| Regime 5 | 100 | 96 | 100 | 100 | 43 | | | 4 | | | | | 4 | 10 | 6 | Scandinavian high | 13.2% |
| Regime 6 | | | | | | | | | | | | | | | | High pressure centred on English Channel | 7.1% |
| Regime 7 | | | | | | | | | | | | | | | 8 | Southerly tracking low west of Ireland | 5.0% |
| Regime 8 | | | | | | | | | | | | | | | 2 | Azores high | 3.7% |
| Total Members | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | 51 | --- | --- |

Aggregated probabilities for a set of 8 regime groups

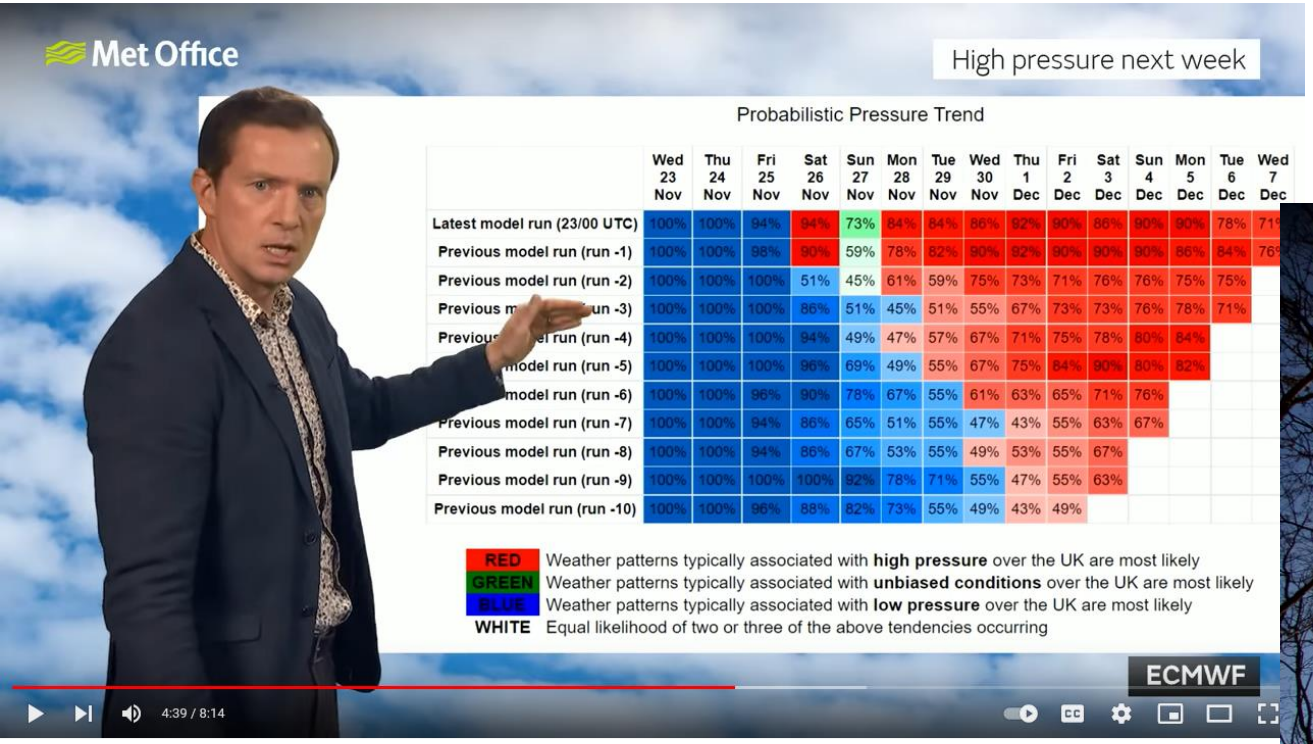
- Weather pattern definitions from Neal et al. (2016) in *Meteorol. Appl.*
- Derived by clustering 154 years of daily MSLP data
  - → 30 gridded definitions
  - → Daily historical classifications (1850 to present)

See talk from Rob Neal for more details

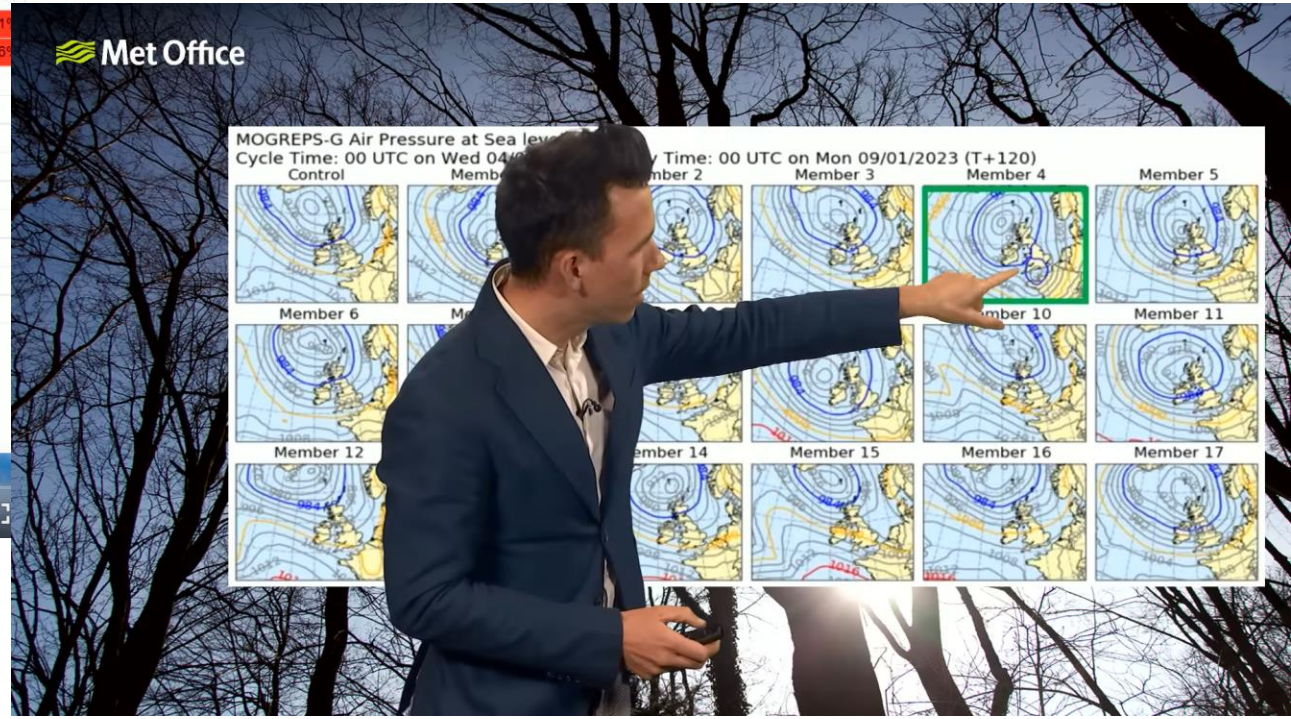
Met Office




# Presenting Ensembles to the Public



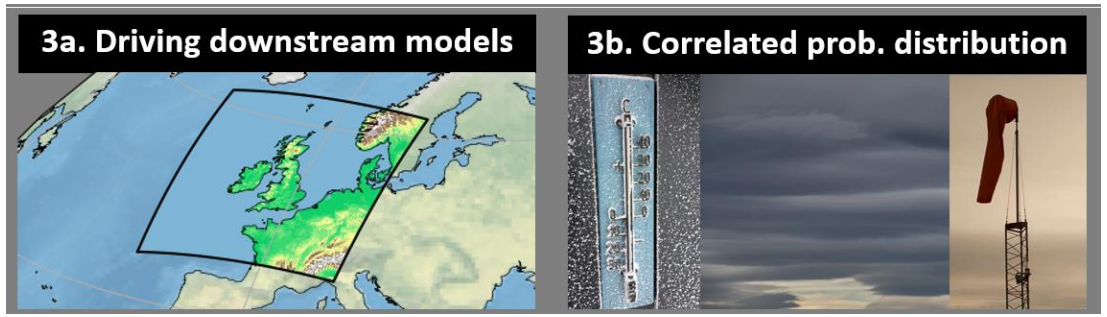

10 Day trend 23/11/22 - Drier for December - Met Office Weather Forecast

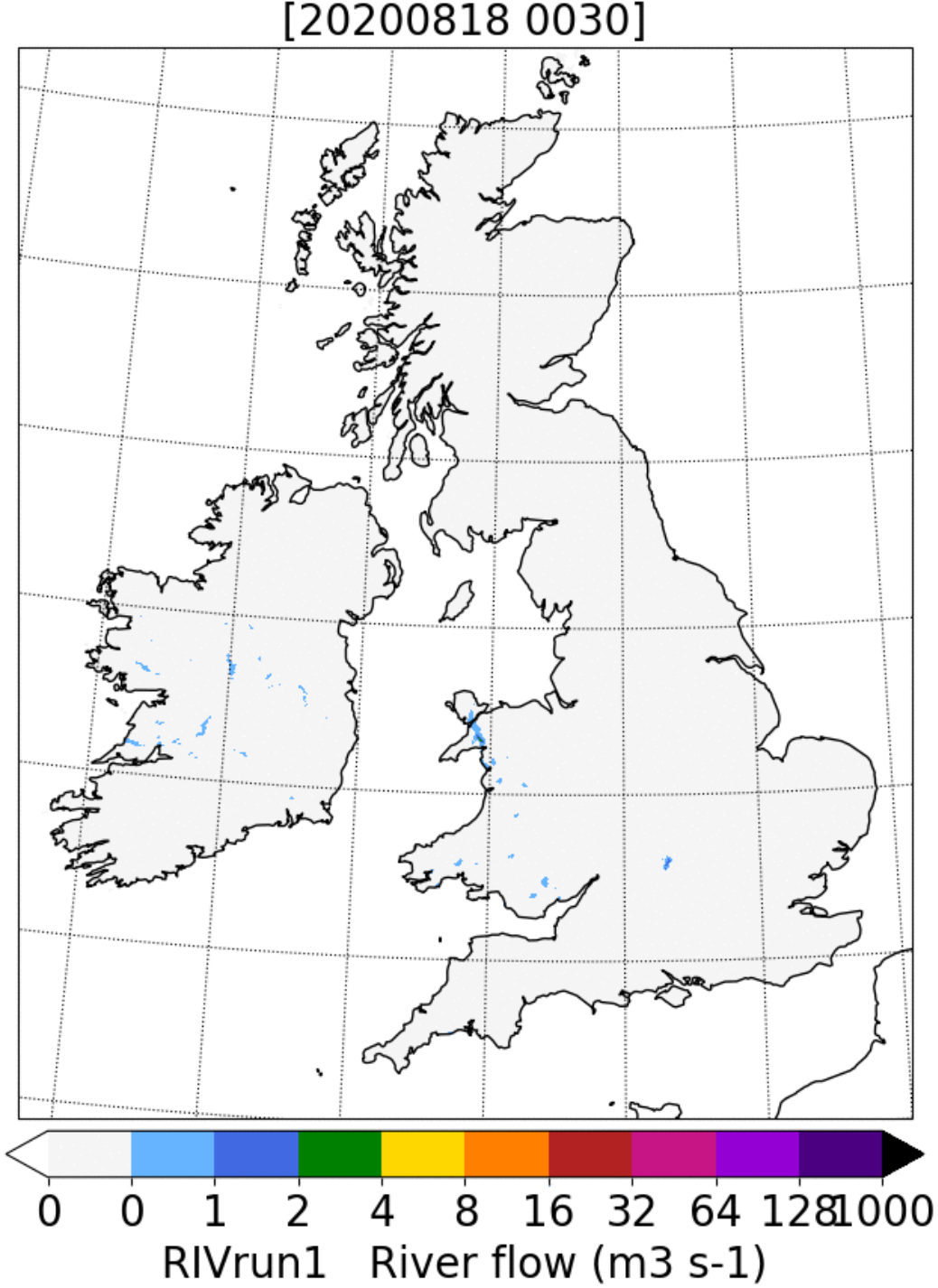


# Hydrological Modelling

Animation of hydrological run-off from different ensemble members, driven from MOGREPS-UK

- Good example of use case 3 where we must use every ensemble member



# Moving Forward - Forecast Process

Courtesy of Nigel Roberts and Steve Willington

# Research Challenge – spread metrics

**Ensemble science theory**

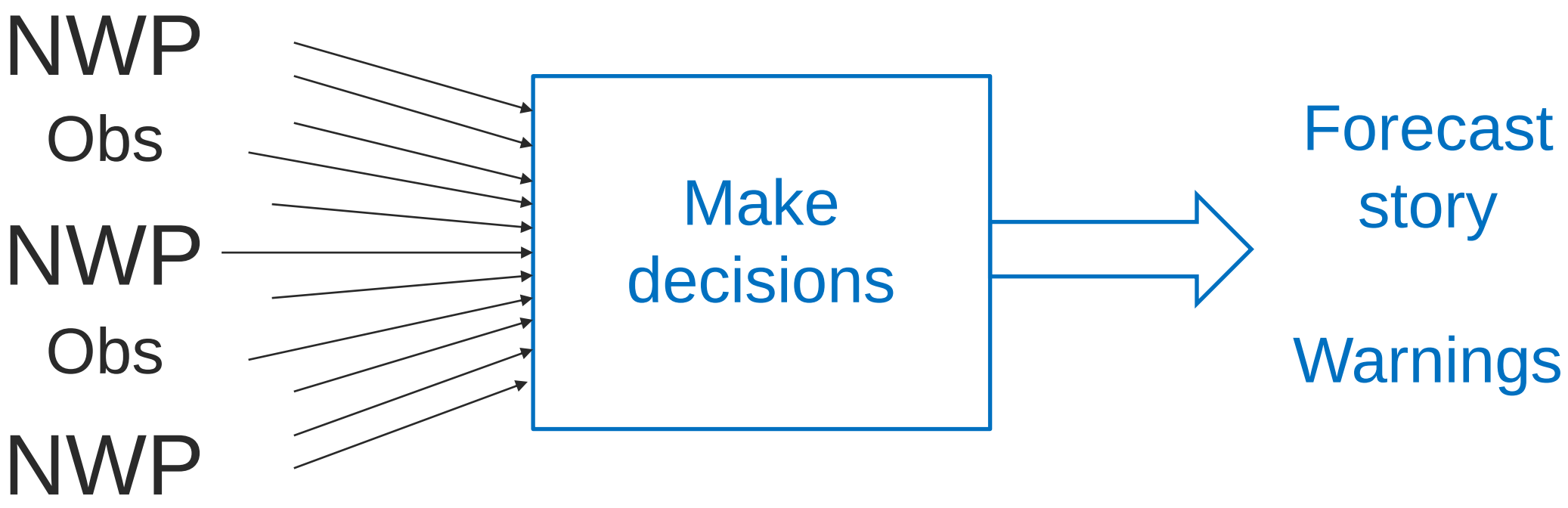
- Optimise probabilities
- Spread-error matching
- Minimise CRPS
- Often focus on synoptic scale and/or free atmosphere

**Operational Meteorologists**

- Capture events of interest – often extreme
- Scenarios and storylines
- High impact scenarios and weather components

**Can we find ensemble optimisation metric which meets needs and expectations of both communities?**

# Forecast process




Where to start with an ensemble first?

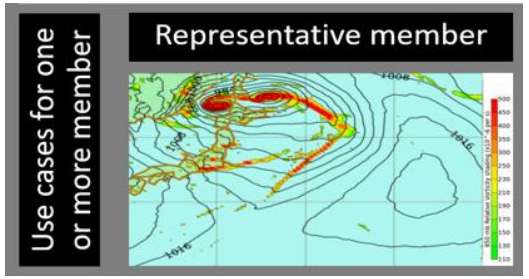
# Where to start with an ensemble?

If Op Mets don’t start with the global (or favourite) model, then what?

| | |
|---|---|
| Go through each member one by one? | Don’t think so! |
| Just look at probabilities/percentiles? | Useful, but actual realisations / context |
| Use the control? | Could be an outlier, may not exist! |
| Use the most representative member? | Could be viable? |
| Use quick access to different scenarios? | Could be viable! |

Select / group -> Clustering

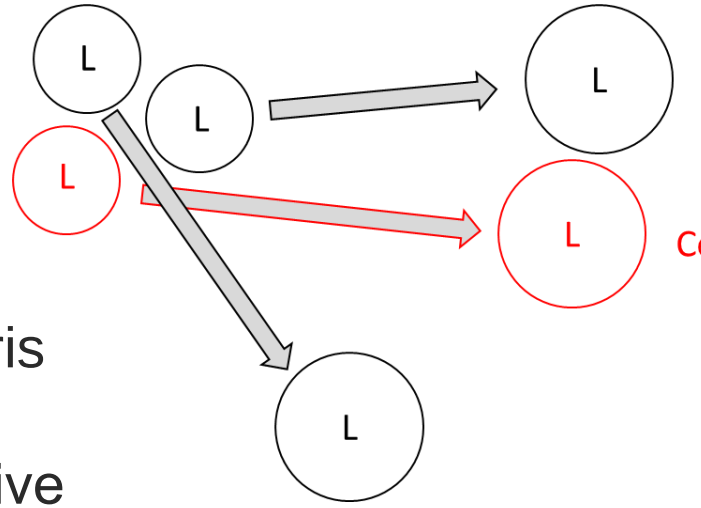
# Representative member




Method to find the most representative ensemble member

Many applications – essential if no control member

Central member – apply to a new pressure pattern diagnostic (or other variables)




Based around CASE PhD work at Reading University by Kris Boykin plus extensions.
Kris's approach examined in 2022 winter testbed with positive feedback and ideas for improvement.

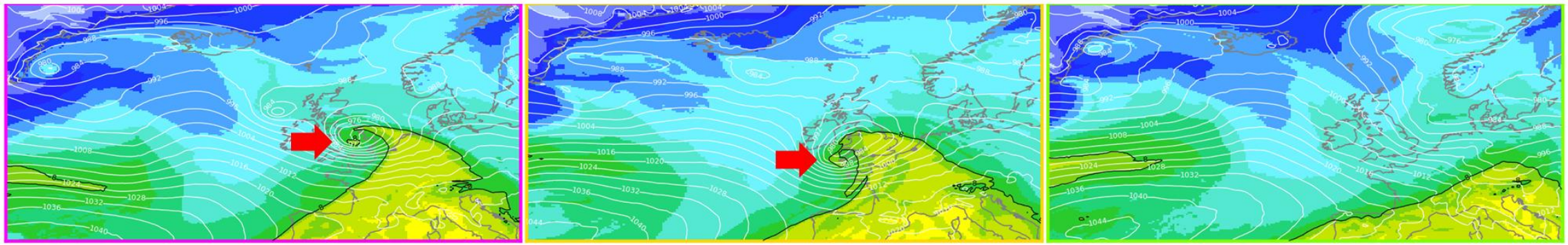
Same methodology extends to clustering and scenarios / storylines

# 5 day forecast clusters for Storm Eunice

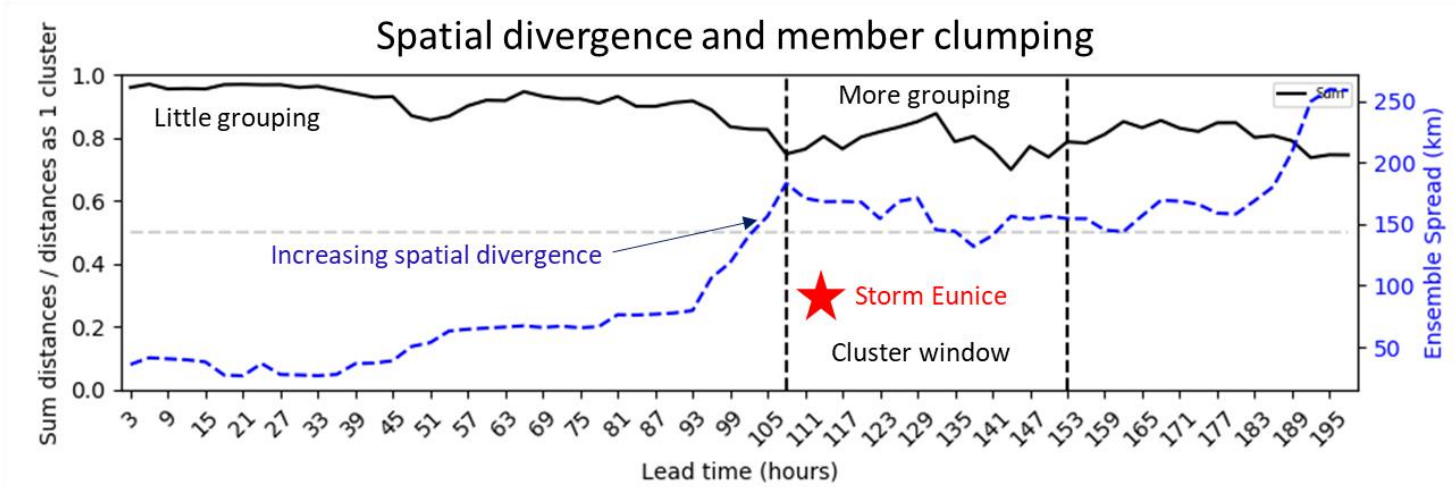
Cluster 0
Members 0, 20, 27, 28, 32

Cluster 1
Members 19, 23, 24, 26, 30,31,33,34

Cluster 2
Members 18, 21, 22, 25, 29




Wet-bulb potential temperature 850 hPa



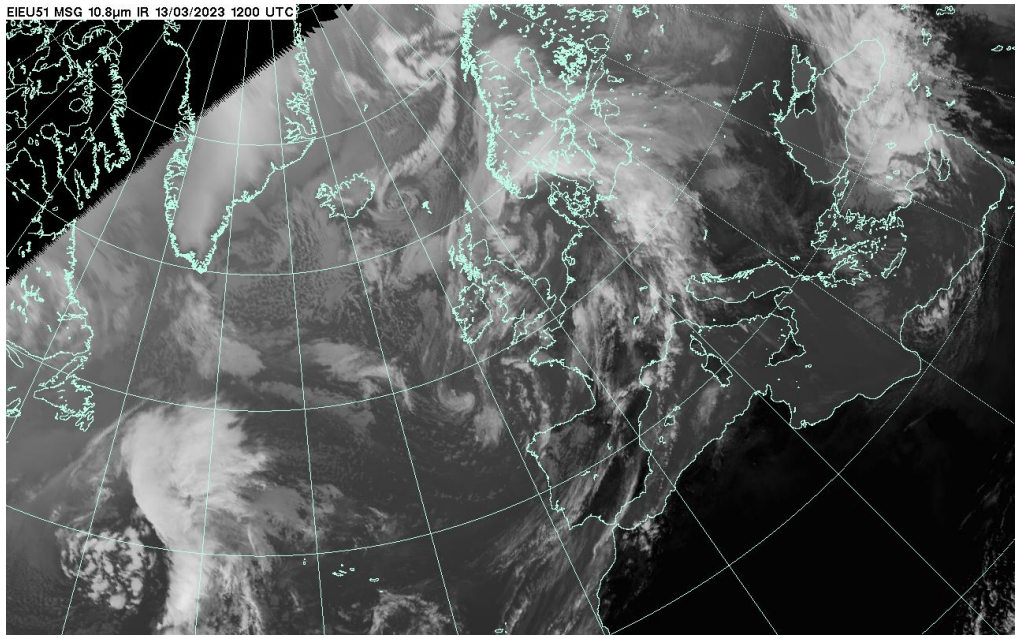

Kris Boykin PhD
John Methven, Tom Frame
University of Reading
Nigel Roberts, Stephen Moseley
Met Office

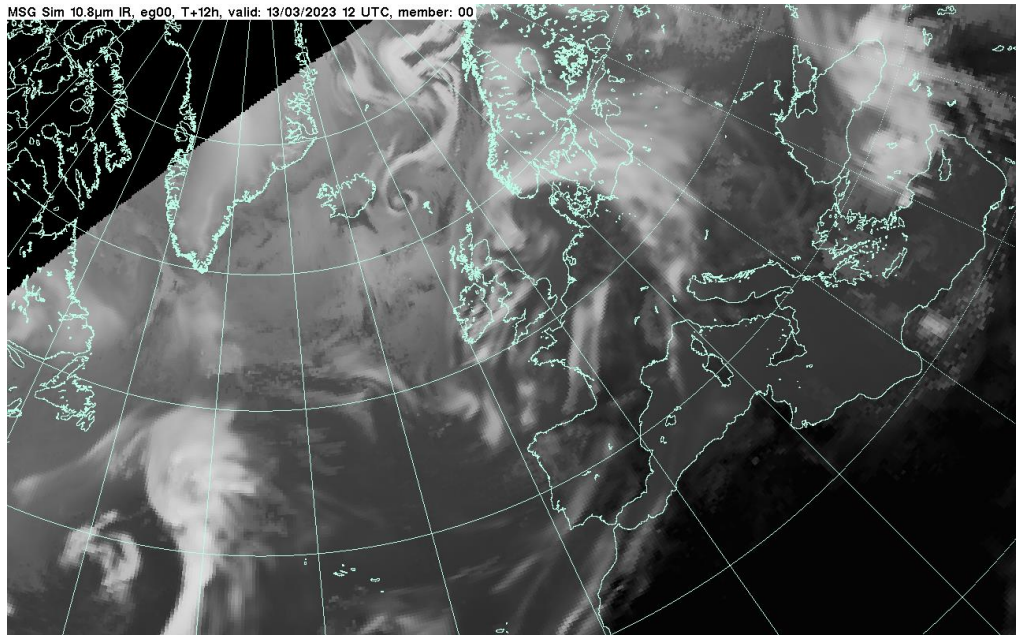
Forecast scenarios based on spatial clustering using wet-bulb potential temperature gradient objects
Different to traditional point-by-point methods

Paper in development

# Image Similarity

- Part of Guidance Unit role is to assess imagery in sensitive areas to judge model performance and potential changes to evolution

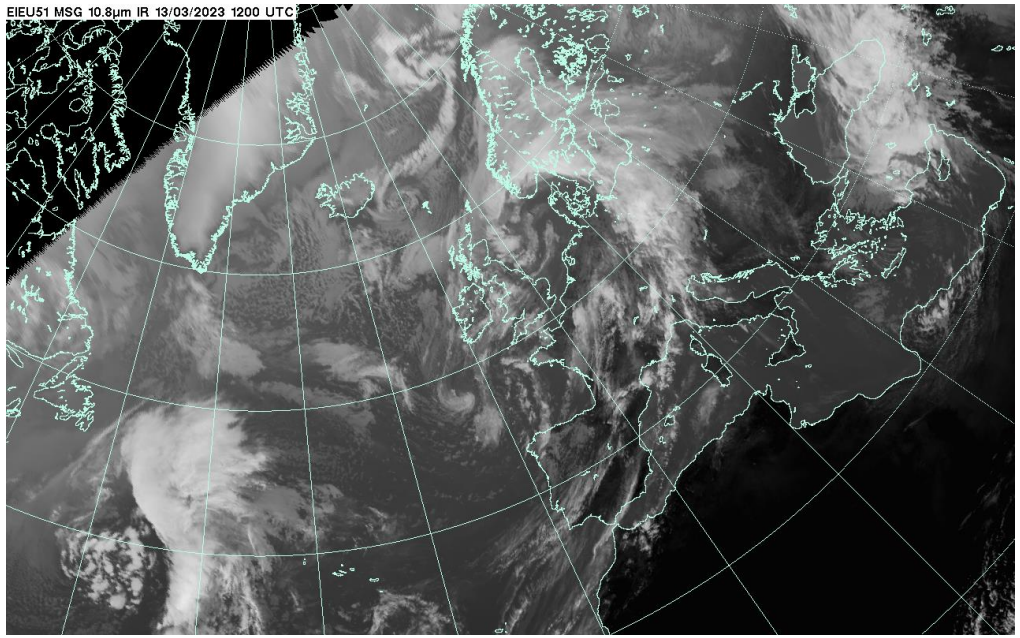


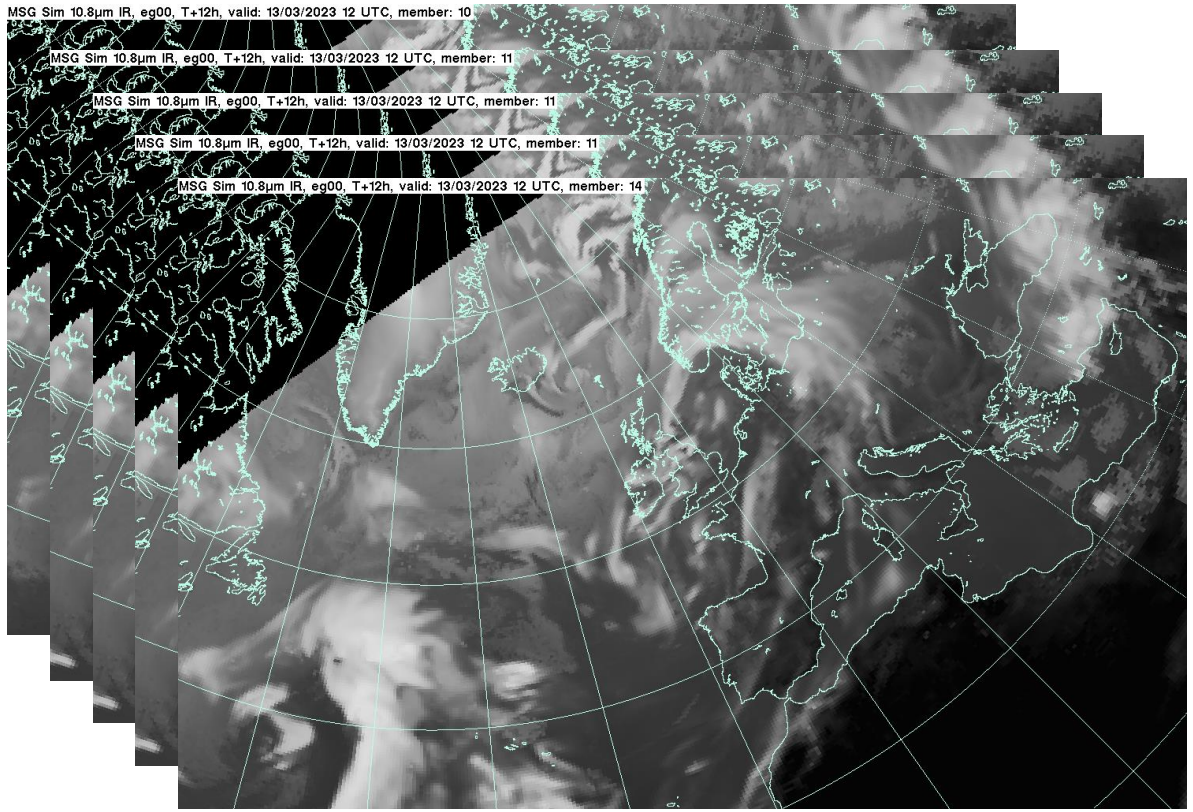




Courtesy of Steve Ramsdale

# Image Similarity

- Difficult enough in deterministic world – how can we do it in ensemble space




Courtesy of Steve Ramsdale

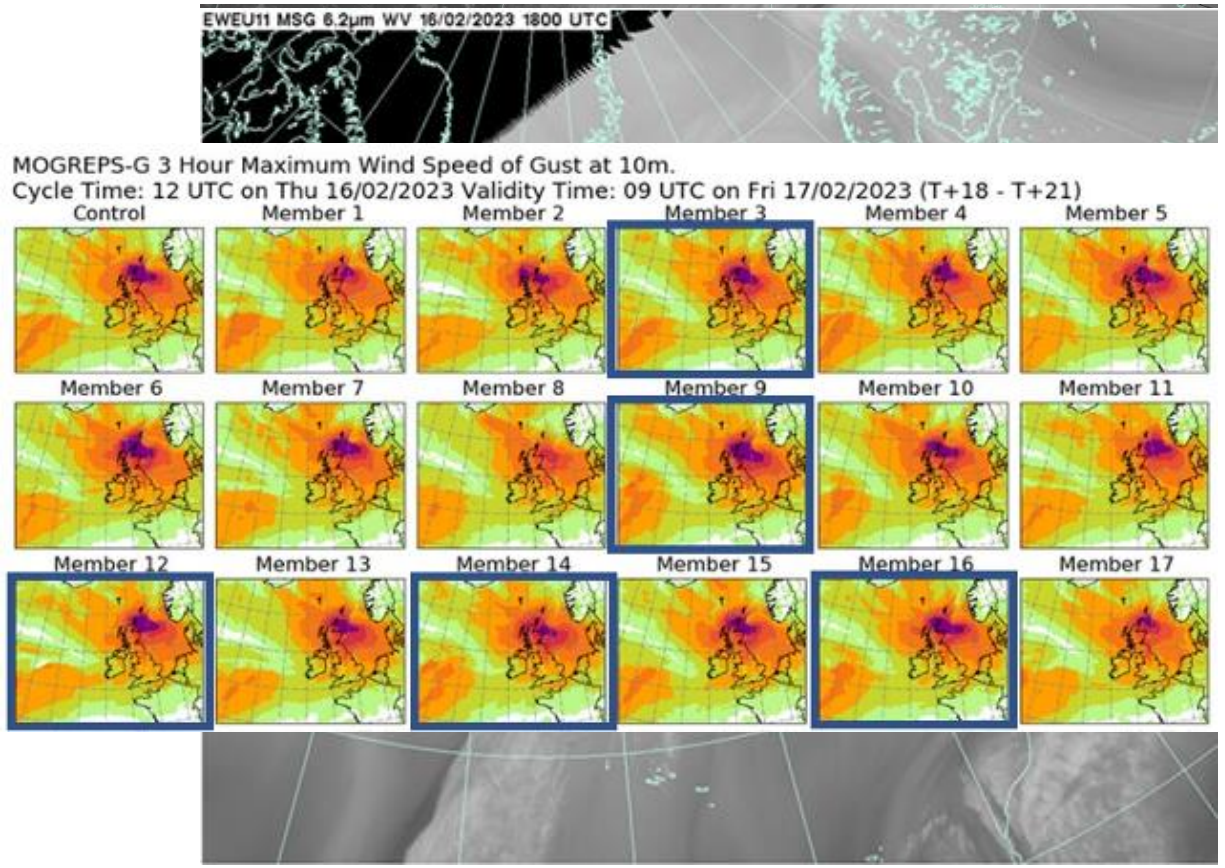
Met Office

# Image Similarity

- Algorithms exist to compare similarity between images (e.g. Structural Similarity Index)
- Combine meteorologist understanding of the most important areas of the forecast with automated comparison of these areas
- This process done for Storm Otto as part of short report on event…

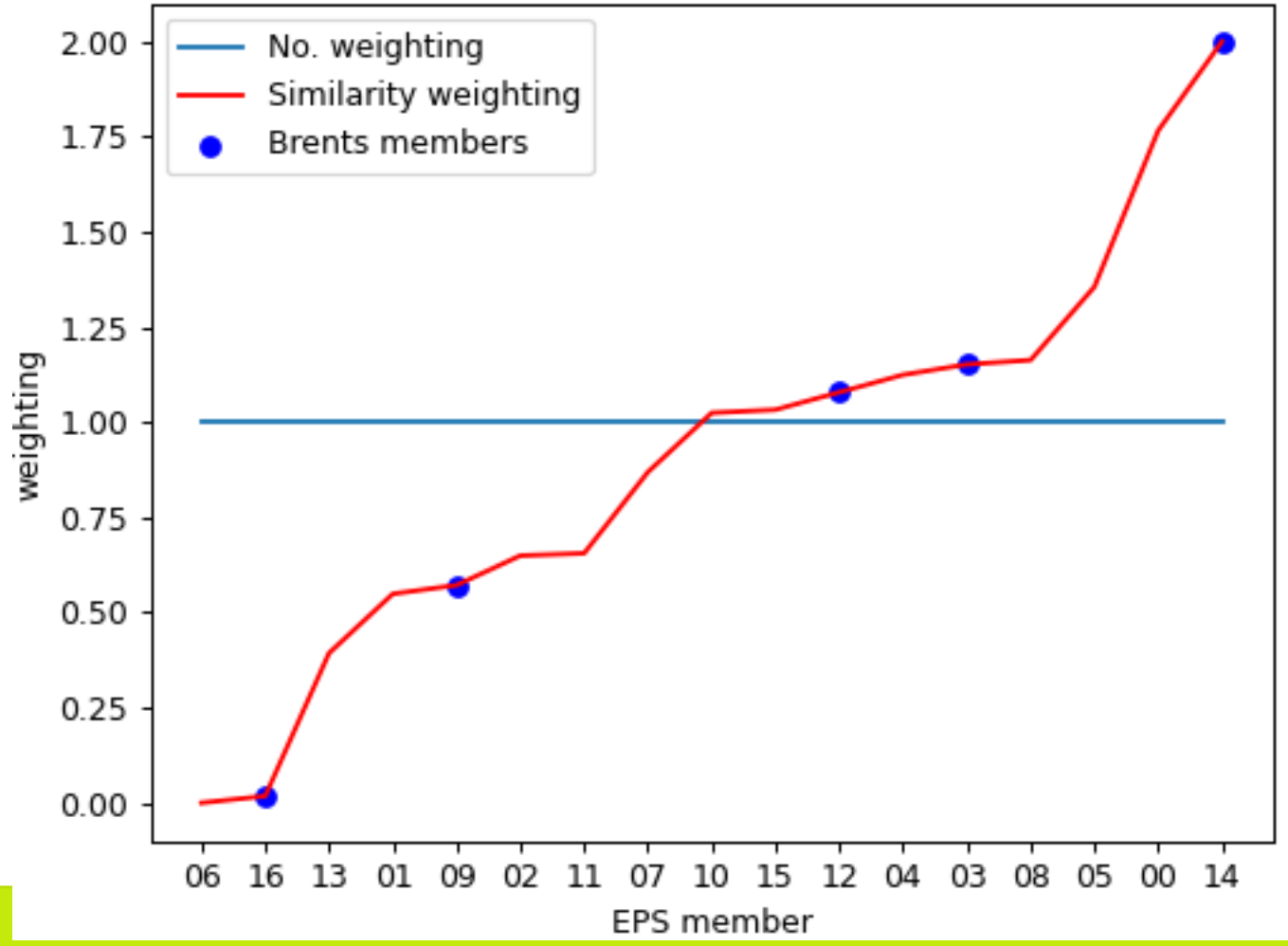
# Image Similarity – Storm Otto 17/02/23

- Meteorologist highlighted sensitive area the day before near Iceland
- Selected best fitting ensemble members by eye
- Assessed that likely increased likelihood of stronger winds over N Scotland



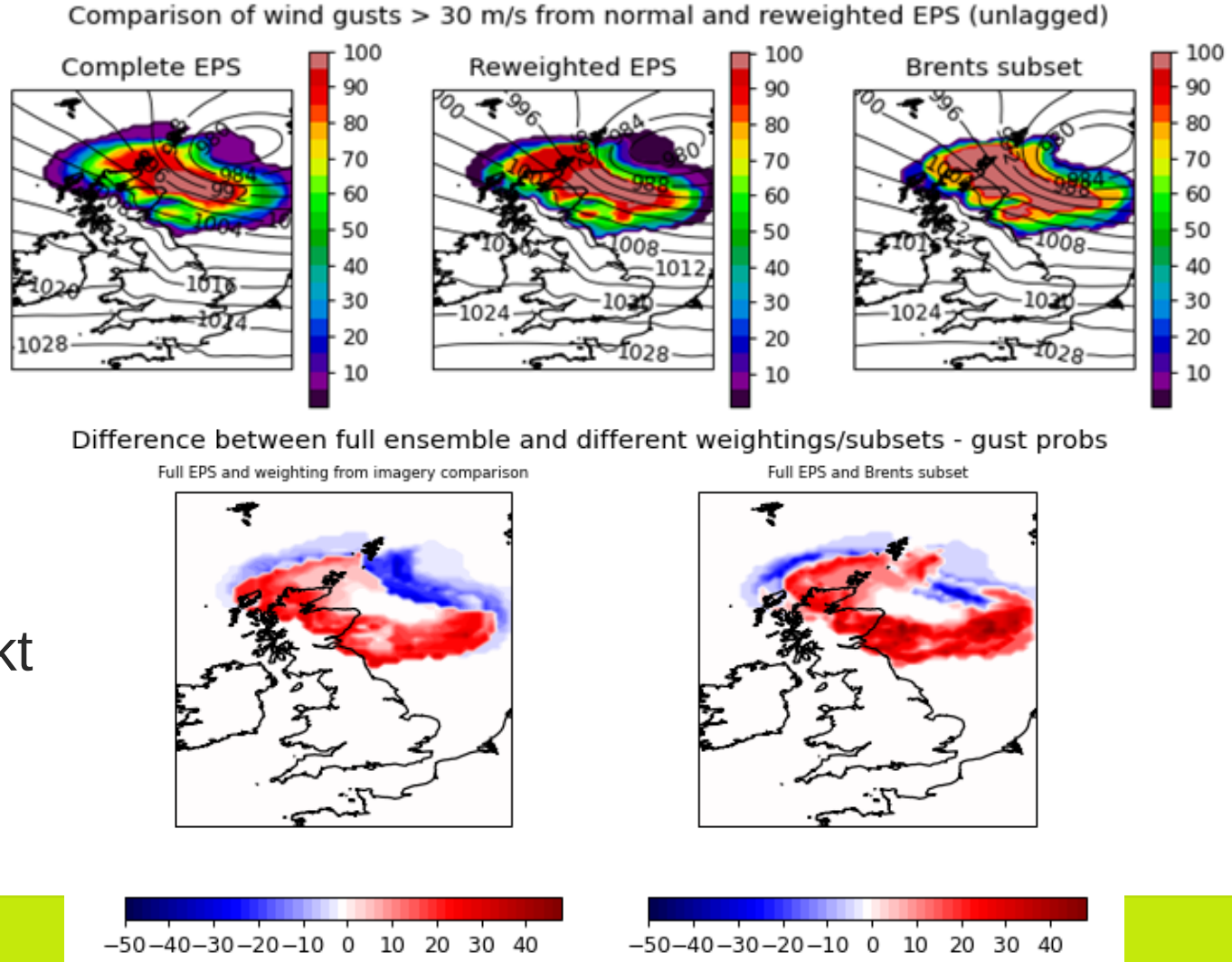
# Image Similarity – Storm Otto 17/02/23

- Application of the algorithmic comparison
- More objective and faster
- Ranks fit
- Some agreement in best fitting members between algorithm & human



# Image Similarity – Storm Otto 17/02/23

- Weighted ensemble according to results of human & automated comparison
- Shows agreement in movement of probabilities of higher winds
- Looks to fit better with observed gusts in this event – e.g. gusts >60kt over Western Isles



Met Office

# Questions?

**30 years of ensemble forecasting**

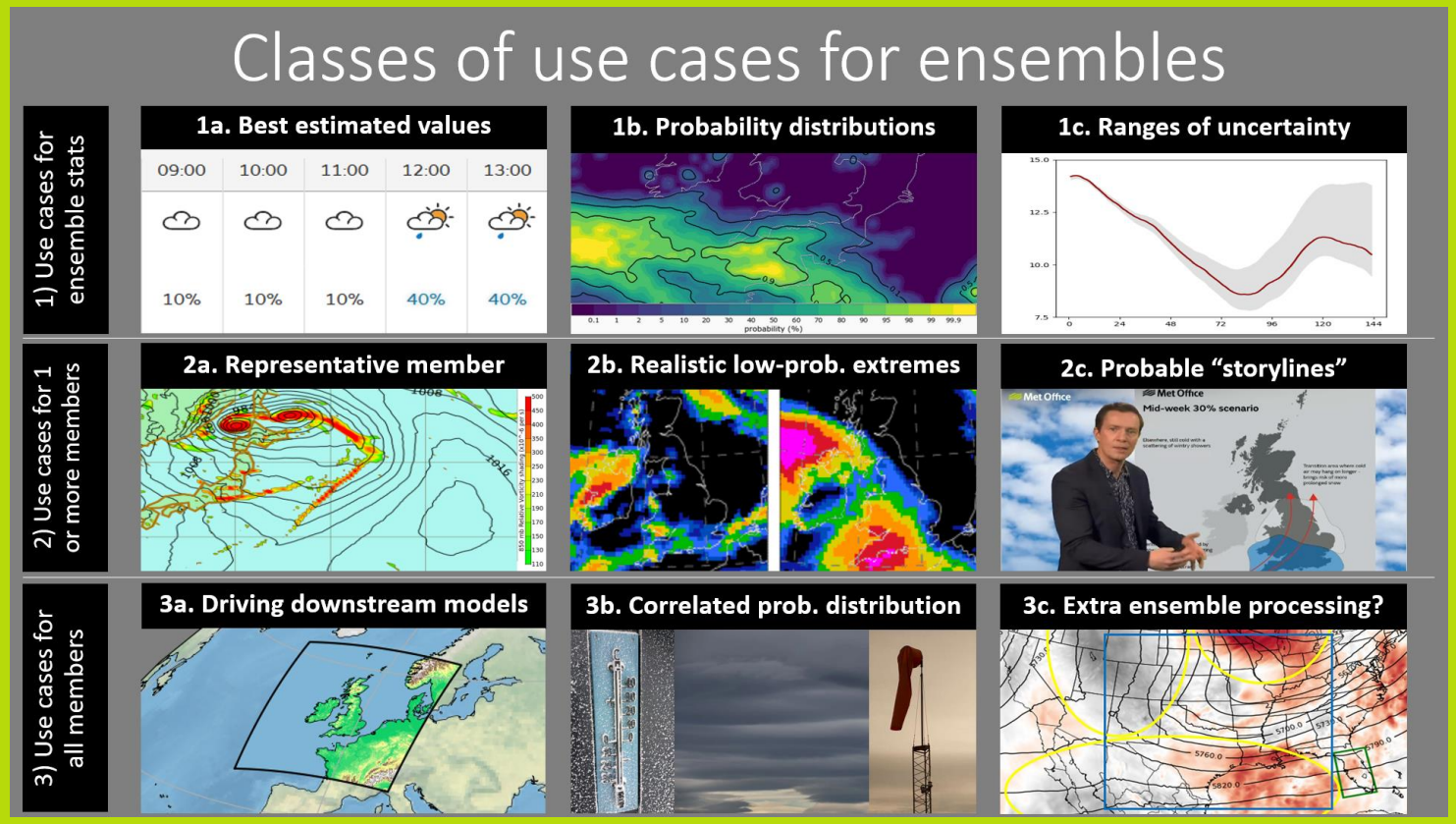
Science is proven

Potential benefits are demonstrated

…and some good examples

It's time for **Exploiting Ensembles**

STRATEGIC ACTION **Exploiting ensembles**



# Ensemble-based NWP

- Ensemble can provide improved single narrative and alternative potential “storylines” as well as additional information around likelihood and risk.
- **Retiring deterministic forecasts will not break products that do not need – or are unable – to exploit the full ensemble. These can use the control member.**
- Strategic action will help us exploit the additional information in the ensembles for different applications and users.
- Shift Science’s focus towards ensembles to accelerate improvements of NWP systems to best underpin our services.

**Scientific detail**

Deterministic forecasts will become control member.

Will use same DA, run at same time and output same fields as GM/UKV.

Rest of ensemble will run at same time as control and provide more timely and higher resolution output than now.

In time, improve system and our ways of working to deliver the very best possible ensemble.

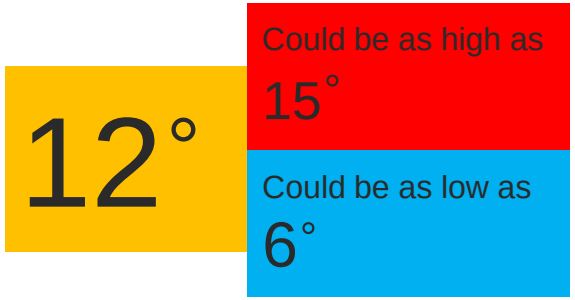
# Classes of use case – descriptions in development

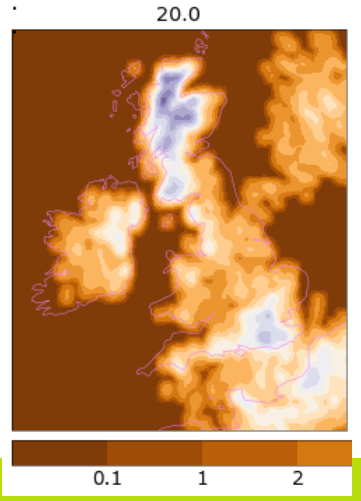
- **Best estimated value.** Best estimated value (e.g. ensemble mean). As is the case now, many applications will require this, but we could generate this more intelligently using ensemble data.
- **Probability distributions.** An accurate distribution of probabilities of atmospheric variables and associated outcomes. This is the primary use of ensembles to date and is a continuing requirement.
- **Range of uncertainty.** An estimate of the possible range/maximum uncertainty that includes all but the very least likely/probable events. Can be used to determine best- and worst-case values.
- **Representative member.** The identification and availability of a member close to the mean/mode/median for the whole forecast or a particular event or phenomenon for detailed exploration/interrogation. Intelligent selection could lead to more skill than the deterministic forecast.
- **Realistic low-probability extremes.** Realistic “extreme” members for detailed exploration/interrogation and measures of whether those extremes are becoming more or less likely over time.
- **Probable “storylines”.** The application of clustering (or sub-setting) could identify representative members for a given outcome, which could be explored in more detail.
- **Exposure of all individual ensemble members.** Exposing all members opens the possibility of further processing such as the ability to sub-set the full ensemble distribution either to add weight to specific members or produce conditional probabilities or conditional clusters.

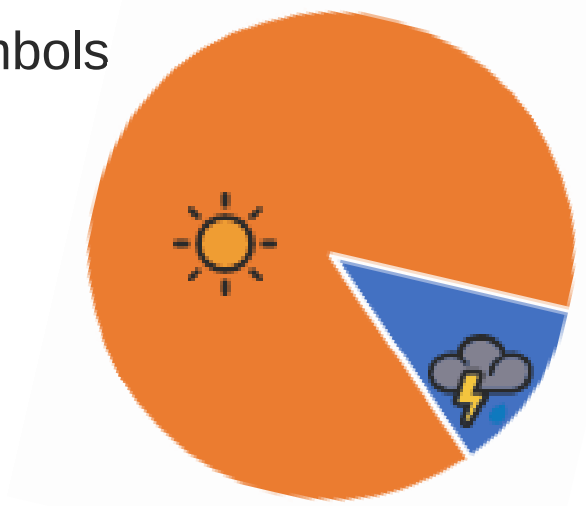
Met Office

# Can we present uncertainty better to the public?

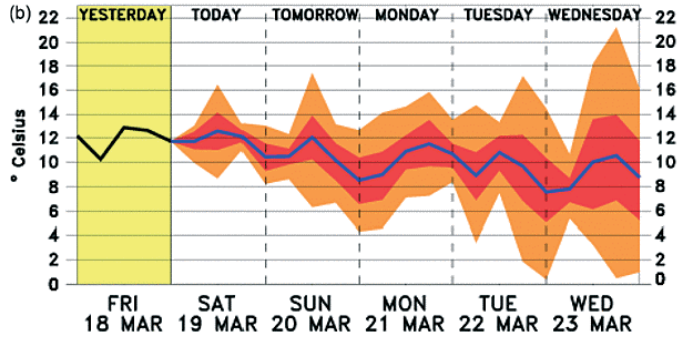

Options to present multiple symbols

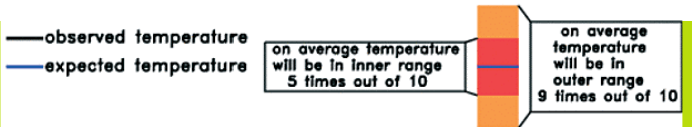


Graphical options



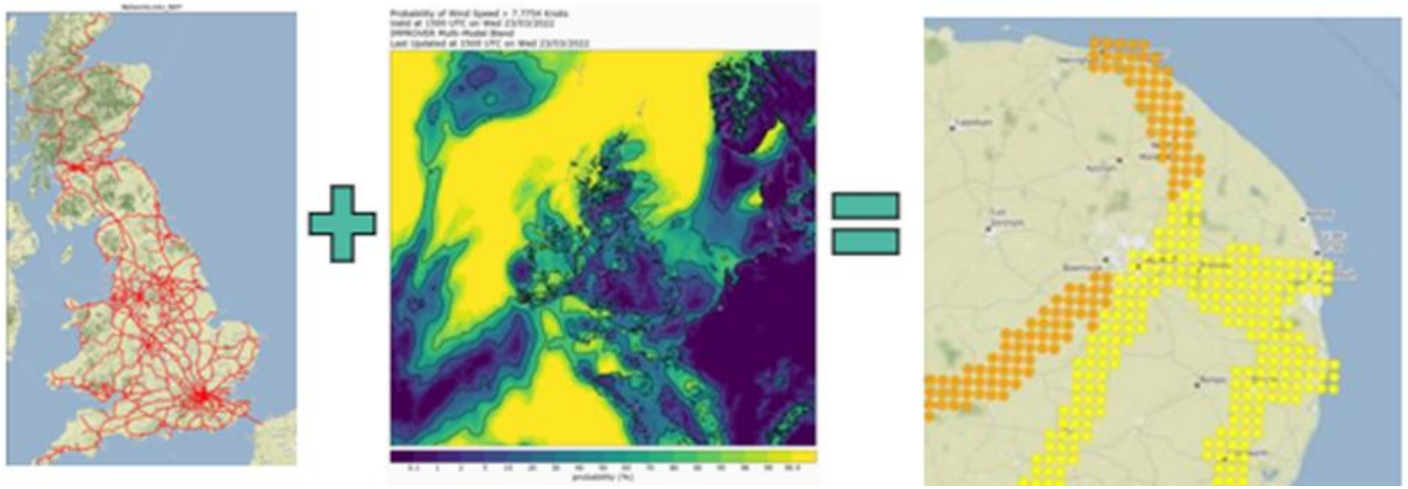



Risks of high-impact weather

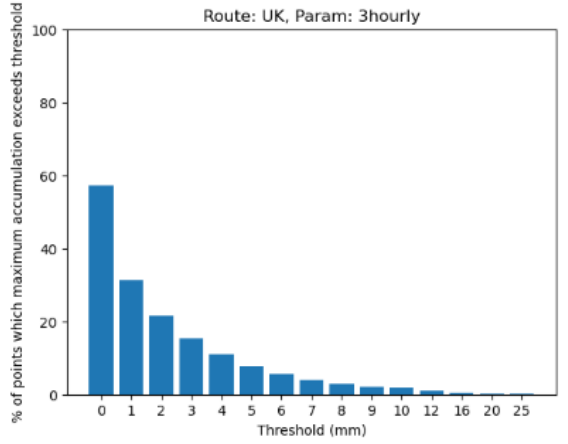
# Demonstrating state-of-the-art forecasting tools

**Method and data**

- IMPROVER forecasts were cut to the NR route for wind, rain and temperature
- For a range of case studies, RAYG alert statuses at various lead times were compared in detail to observations (e.g. radar, GPP analysis fields) and to NR incidents
  - For example, frequency of NR thresholds' exceedance in radar and nowcast data was used to ensure chosen IMPROVER thresholds were not over- or under-triggered

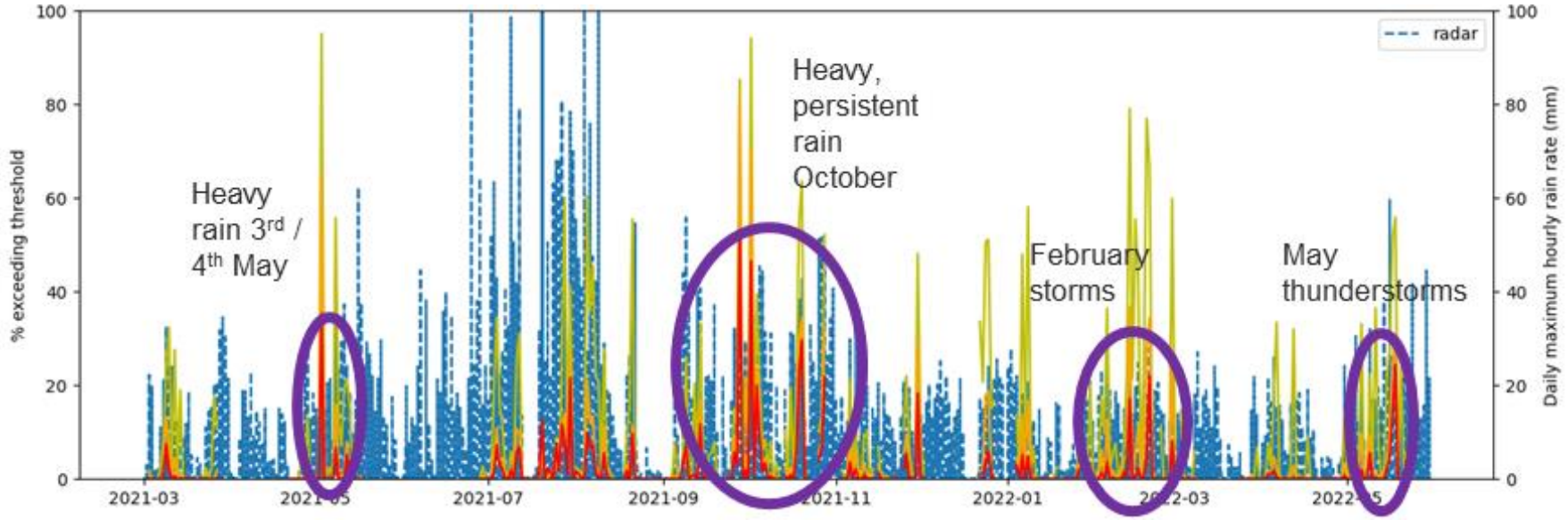


*Percentage of points on the NR route for which various three-hour rainfall accumulation thresholds are exceeded in rain radar data* →




**Acronyms:** RAYG = red-amber-yellow-green; NR = Network Rail; GPP = gridded post-processing; IMPROVER = Integrated Model postPROcessing and VERification

# Demonstrating state-of-the-art forecasting tools



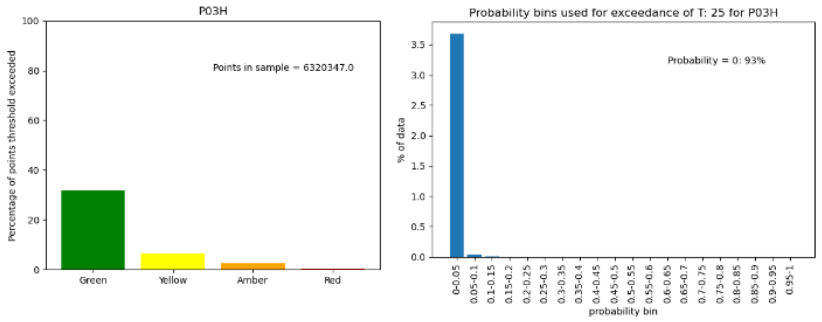

Key:

- Blue = observed rainfall (from radar)
- Red, amber, yellow = % of rail network exceeding relevant threshold

- Thresholds identify many known events (example shown for rainfall)

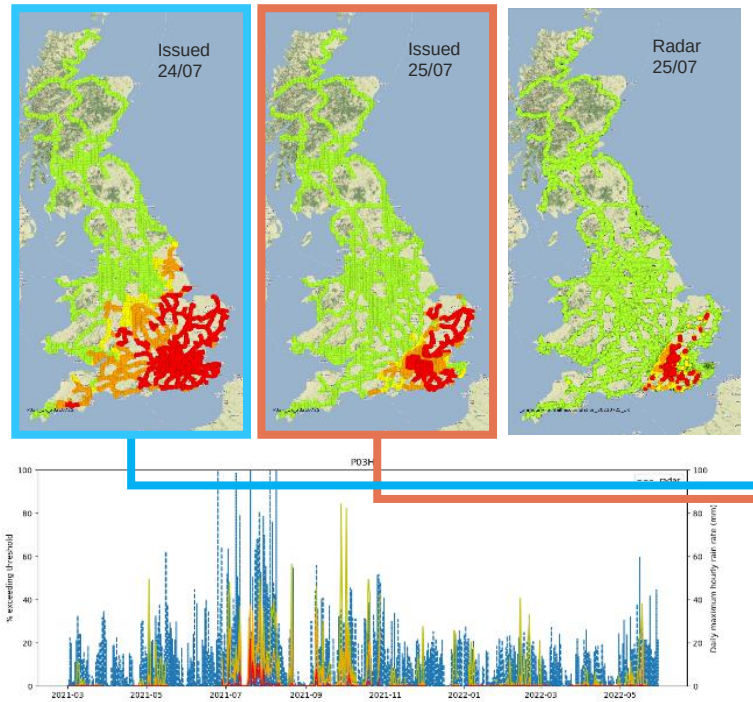
# Demonstrating state-of-the-art forecasting tools

IMPROVER forecasts the exceedance of thresholds with very low probabilities for some parameters, particularly rainfall.

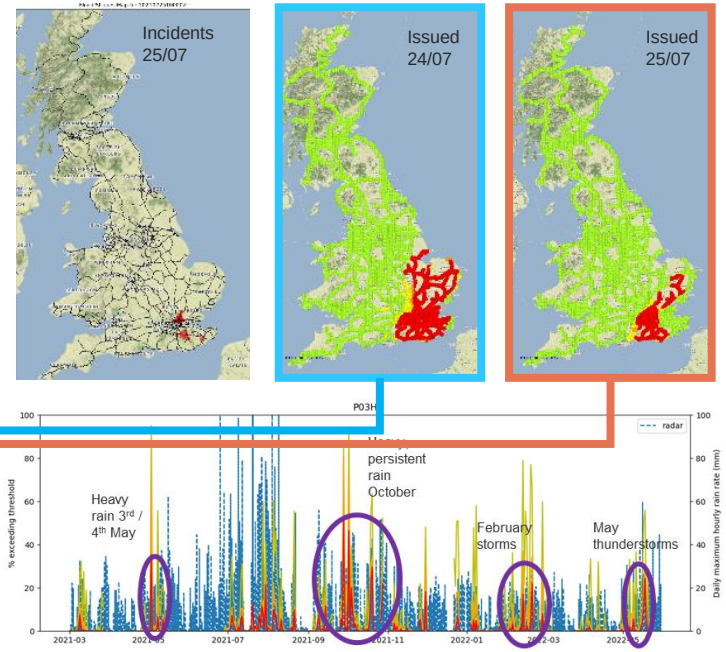



However, use of very low probabilities is not very stable with lead time.

First-guess thresholds using low probabilities of exceeding high rainfall thresholds:



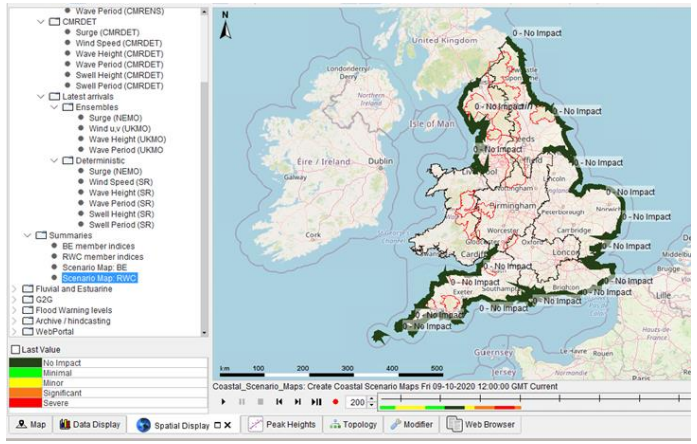

Refined thresholds better capture areas of greatest risk, even at longer lead times and identify more events.



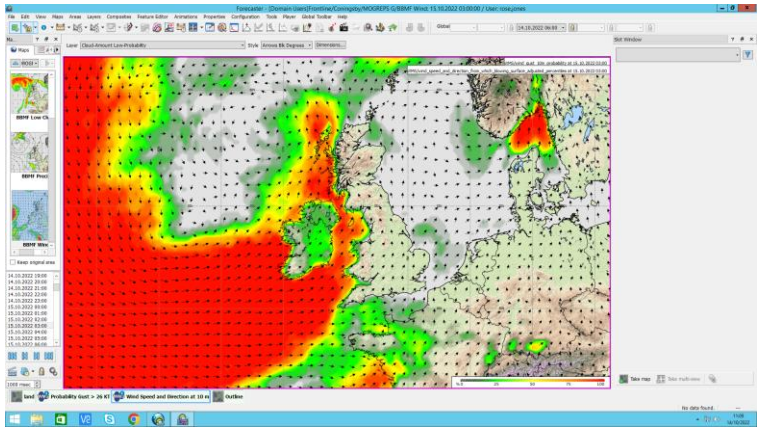

**Acronyms:** IMPROVER = Integrated Model postPROcessing and VERification

# Examples of user cases

- **Some early success**




**Ensemble-driven flood impacts decision tools.**
We are able to show likelihood and impact of coastal flooding across a 7 day period, using MOGREPS-G & Nemo Surge (driven by MOGREPS G) data. This helps us alert local authorities with increased notice, to trigger action to keep the public safe.



**Ensemble-driven planning products.**
This example shows a Red Amber Green probability of occurrence of a customer specified threshold, used for planning military flying of fragile WW2 aircraft. This product was re-designed from a deterministic, manually created risk table, to an automated MOGREPS-UK feed with great success. [p(gust>26kt)]



**Newly developed tools to exploit our ensembles.**
The Military MetOc Visualisation Hub (MMVH) is a web-based tool developed for the British military to ensure access to meteorological data, no matter how big the data, even with bandwidth limitations. It has allowed us to developed novel ways to display and utilise ensemble data.