Barcelona Supercomputing Center
Centro Nacional de Supercomputación

EXCELENCIA SEVERO OCHOA

Climate services for clean energy

A. Soret, Ll. Palma, C. Delgado, Ll. Lledó, N. González-Reviriego, J. Ramon, F.J. Doblas-Reyes…

27/09/2022

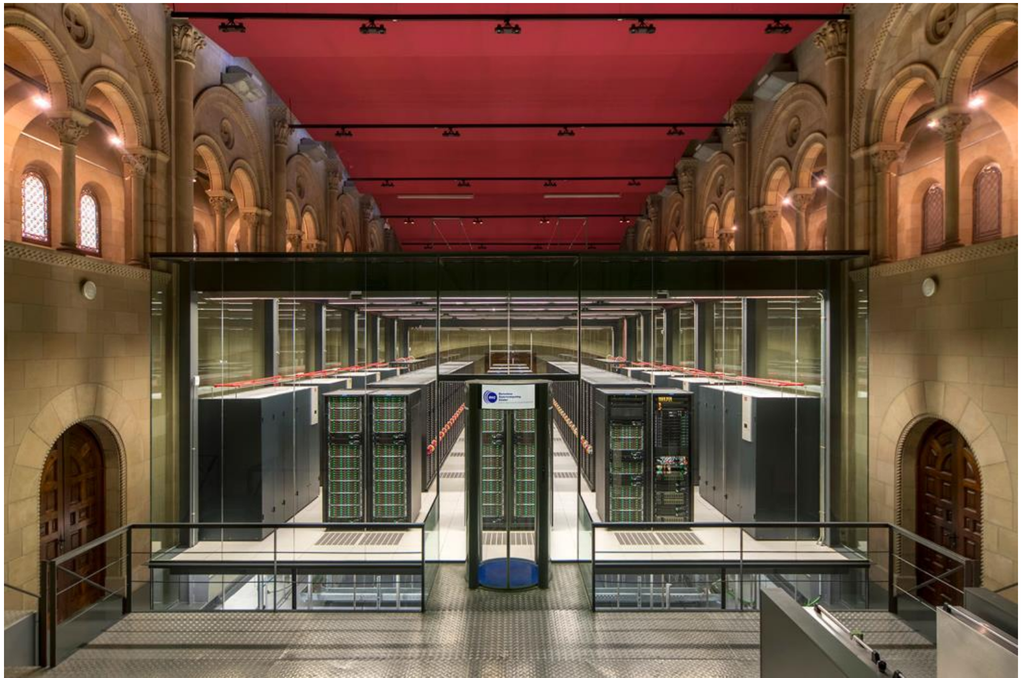
CAFE FINAL CONFERENCE

Barcelona Supercomputing Center

- Research, develop and manage information technology and facilitate its application in society

Created in **2005**	**650** employees	MareNostrum 4	**PRACE** network

50,000 **Cores** **100,8** **TB main memory** **3** **PB disk storage**



Earth Science Department

- Environmental modelling and forecasting, with a particular focus on weather, climate and air quality

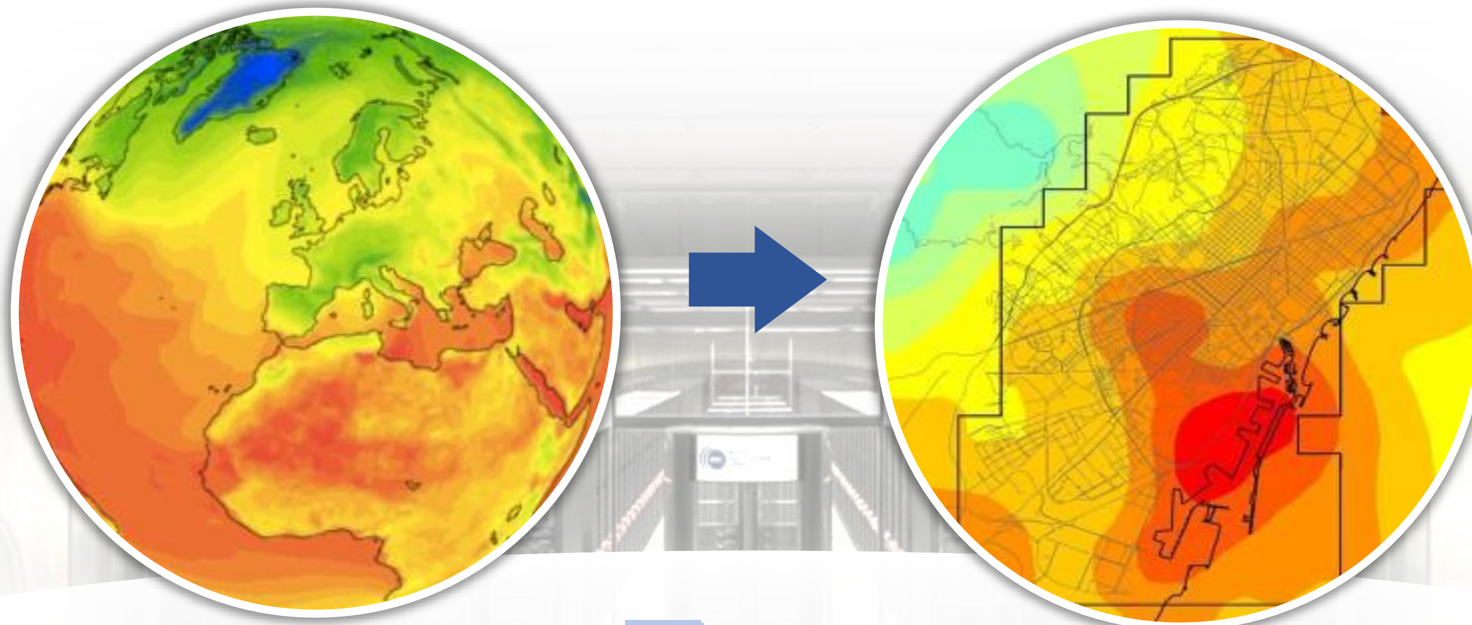
Director: **Francisco Doblas-Reyes**

- ~ 120 people
- Leading: H2020 projects, ERC Consolidator Grant and hosts an AXA Chair

Climate and Air quality modelling

From real world to models

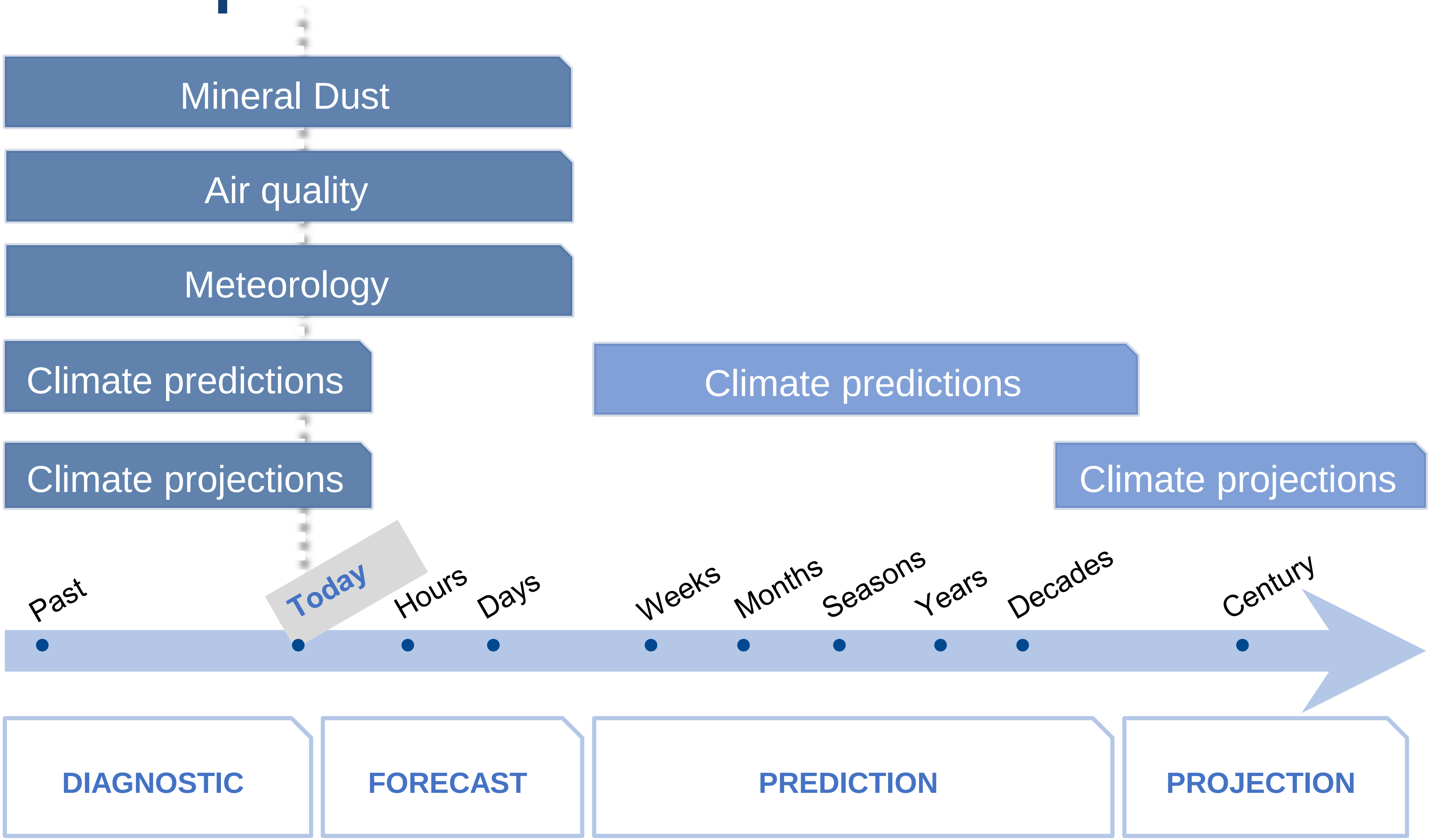
Spatial scales



Multi-scale models

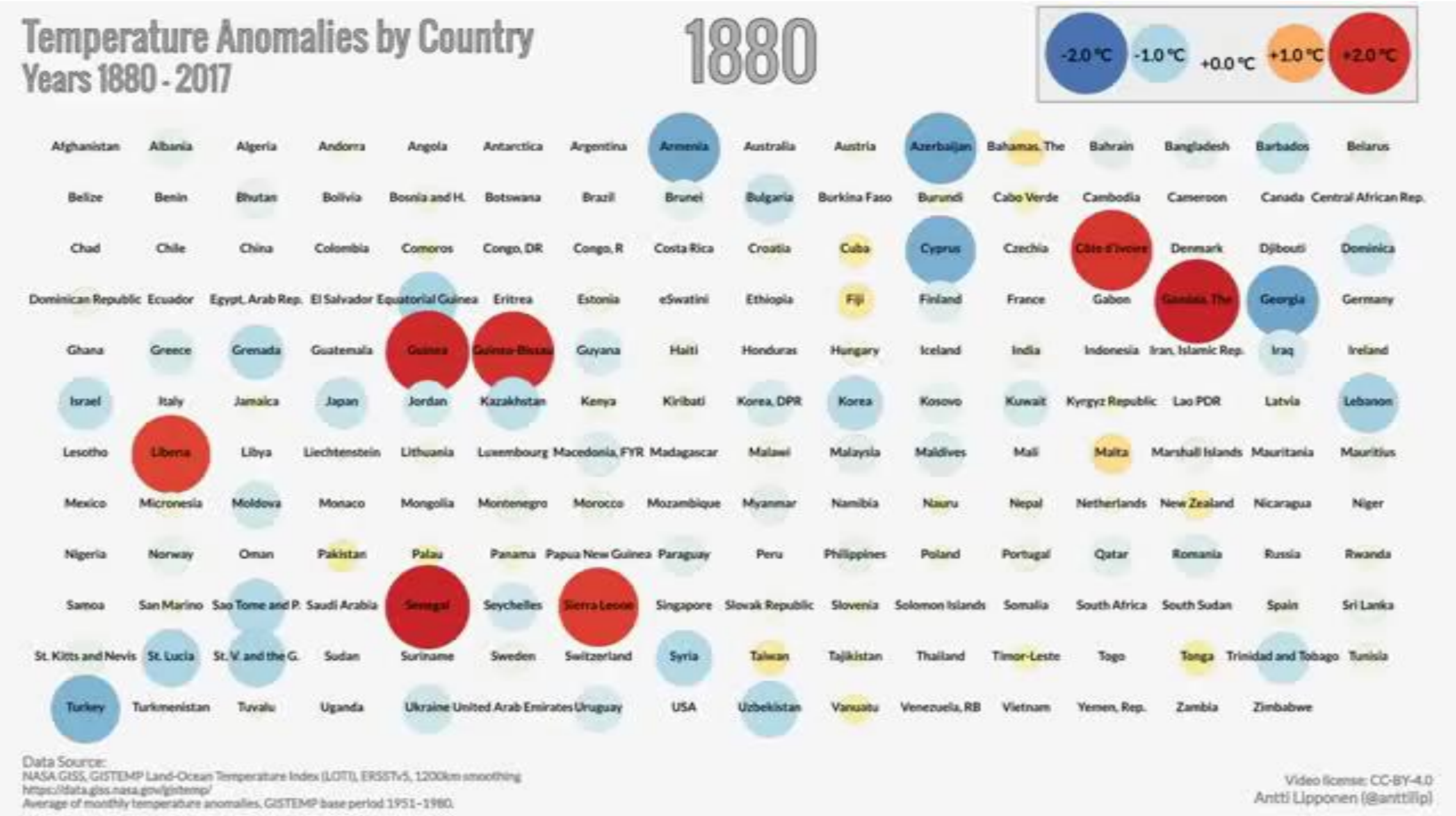
- Global
- Regional
- Local

Temporal scales



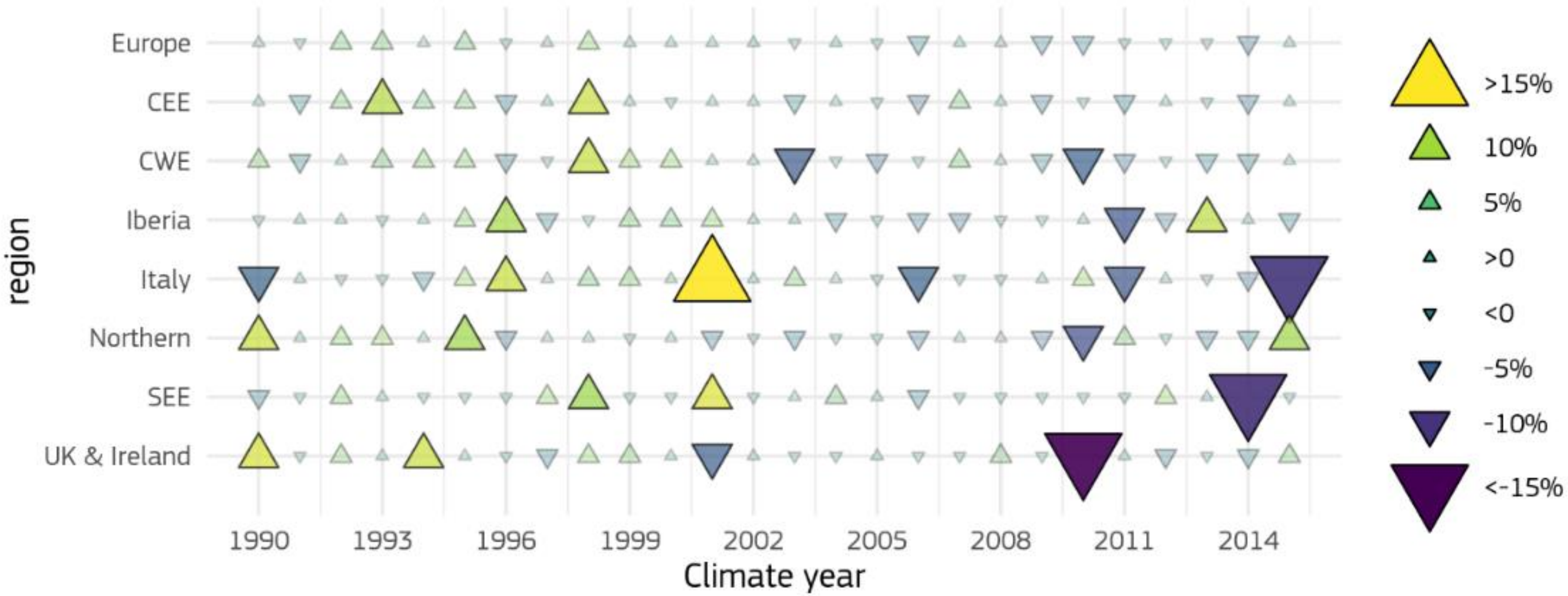
Weather forecast is a familiar concept …

… and climate change too, but what about climate variability?



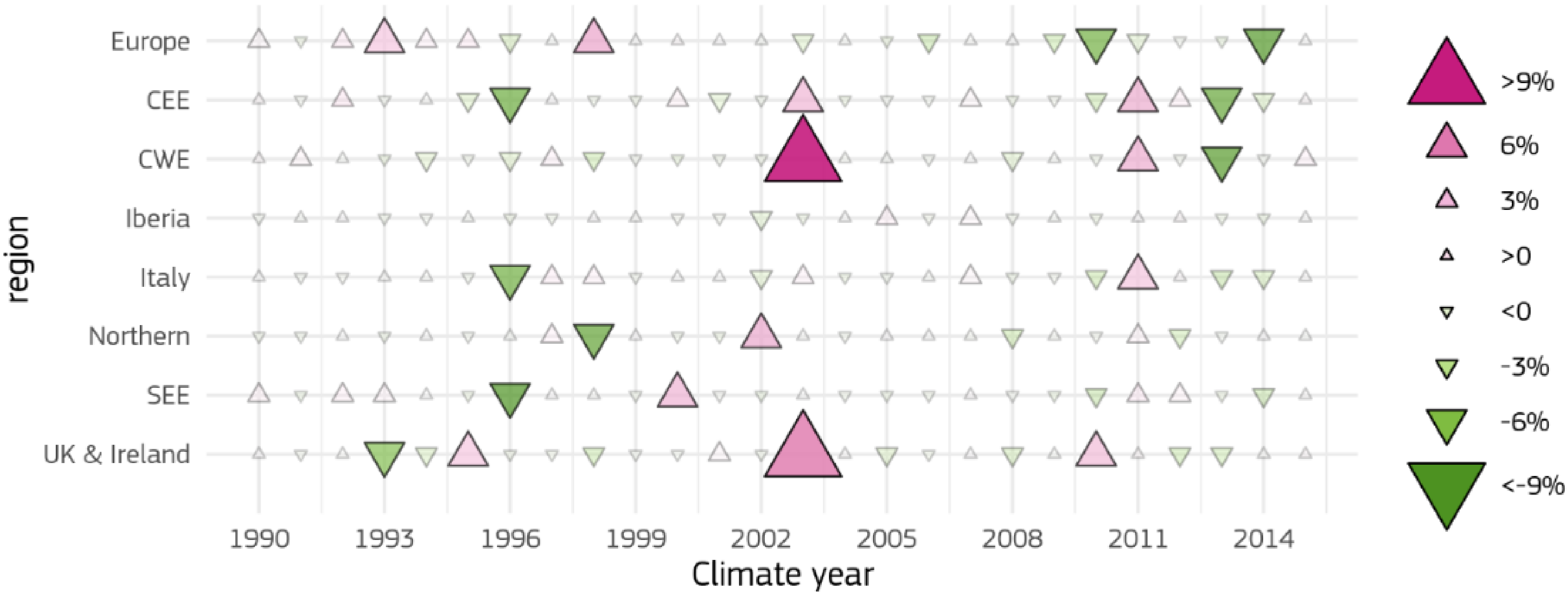
Link: https://youtu.be/PhbdyNnUliM

Energy. Context and motivation



Annual variability (percentage deviation from the average) of onshore wind resources in the 26 climate years for the considered regions. Source: JRC, 2020

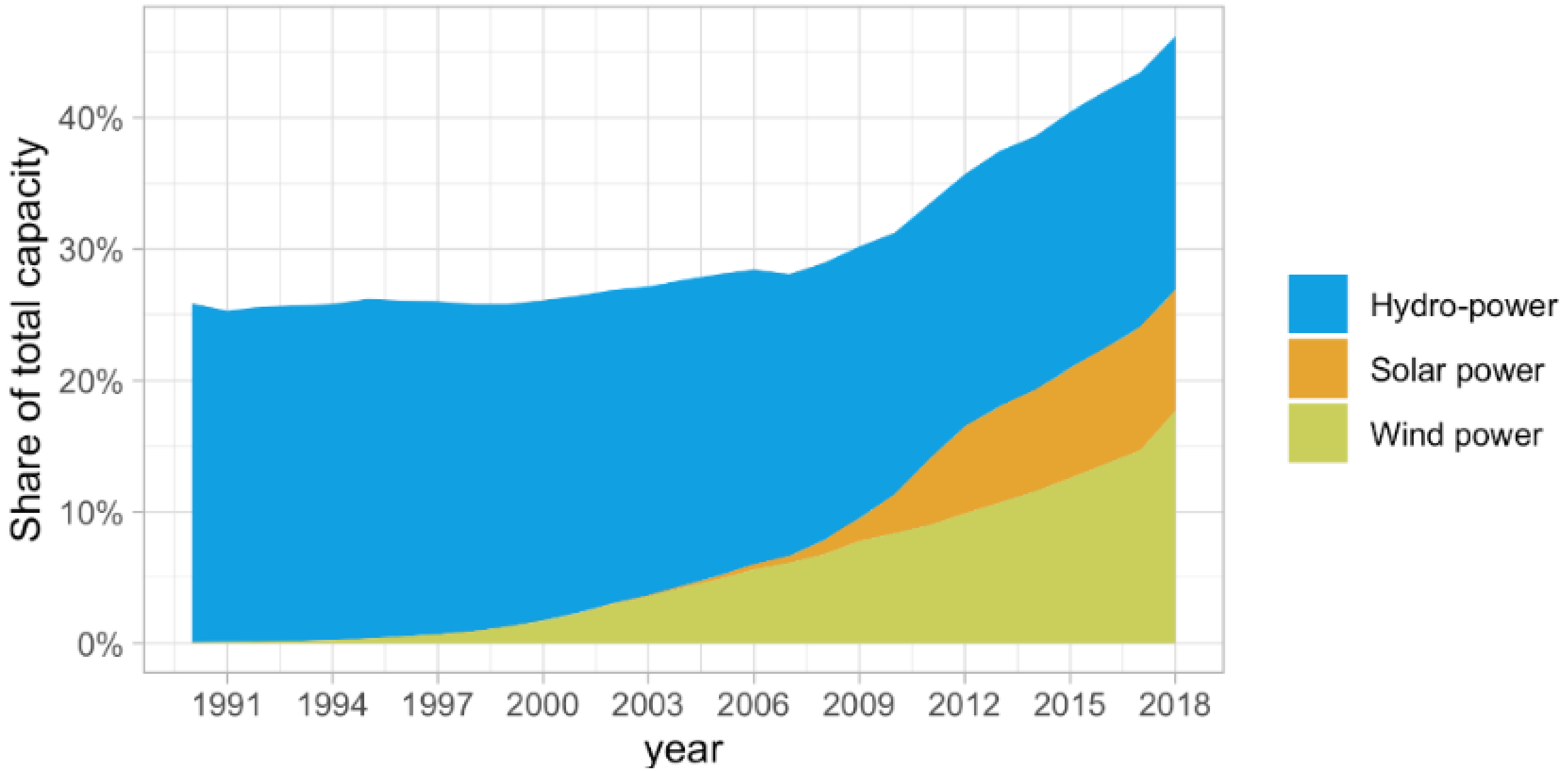
Energy. Context and motivation



Annual variability (percentage deviation from the average) of solar resources in the 26 climate years for the considered regions. Source: JRC, 2020

Energy. Context and motivation

- Renewable energy is growing fast to decarbonize the energy system.
  –> Challenge: Energy security



Fraction of the hydro, solar and wind power capacities with respect to the total electricity generation capacities for the European countries. Source: EUROSTAT

Energy. Context and motivation

- Both energy supply and demand are strongly influenced by atmospheric conditions and its evolution over time in terms of climate variability and climate change.

Like 15M

Thursday, Aug 30th 2018 1PM 25°C 4PM 26°C 5-Day Forecast

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Britain's turbines are producing 40% less energy as wind 'disappears' for six weeks across the UK causing record low electricity production

- Britain got 15 per cent of its power from wind last year — twice as much as coal
- Since the start of June, wind farms have been producing almost no electricity
- The 'wind drought' has seen July 2018 be 40% less productive than July 2017
- In the still weather, solar energy has increased by 10% to help cover the drop-off

By JOE PINKSTONE FOR MAILONLINE

PUBLISHED: 15:48 BST, 18 July 2018 | UPDATED: 17:29 BST, 18 July 2018

Context and motivation

- Energy sector routinely uses weather forecast up to several days. Beyond this time horizon, climatological data are used.

Met mast on Gwynt y Môr offshore wind farm (source: solar wheel)

Applications

Weather forecast	Climate predictions			Climate projections or multidecadal
	Sub-seasonal	Seasonal	Decadal	
1-15 days	15 d-1 month	1-6 months	1-10 years	20-100 years

Time

Applications for wind/solar/hydro generation

Post-construction decisions

Energy producers: commit energy sales for next day

Grid operators: Market prices and grid balance

Energy traders: Anticipate energy prices

Plant operators: planning for cleaning and maintenance

Post-construction decisions

Energy producers: Resource management strategies

Energy traders: Resource effects on markets

Plant operators: Planning for maintenance works, especially offshore wind O&M

Plant investors: anticipate cash flow, optimize return on investments

Pre-construction decisions

Power plant developers: Site selection. Future risks assessment.

Investors: Evaluate return on investments

Policy-makers: Asses changes to energy mix

River-basin managers: understand changes to better manage the river flow

Applications for demand

Daily operation decisions

Grid operators: Anticipate hot/cold days. Schedule power plants to reinforce supply.

Energy traders: Anticipate energy prices.

Mid-term planning

Grid operators: Anticipate hotter/colder seasons Schedule power plants to reinforce supply.

Energy traders: Anticipate energy prices.

Long-term planning

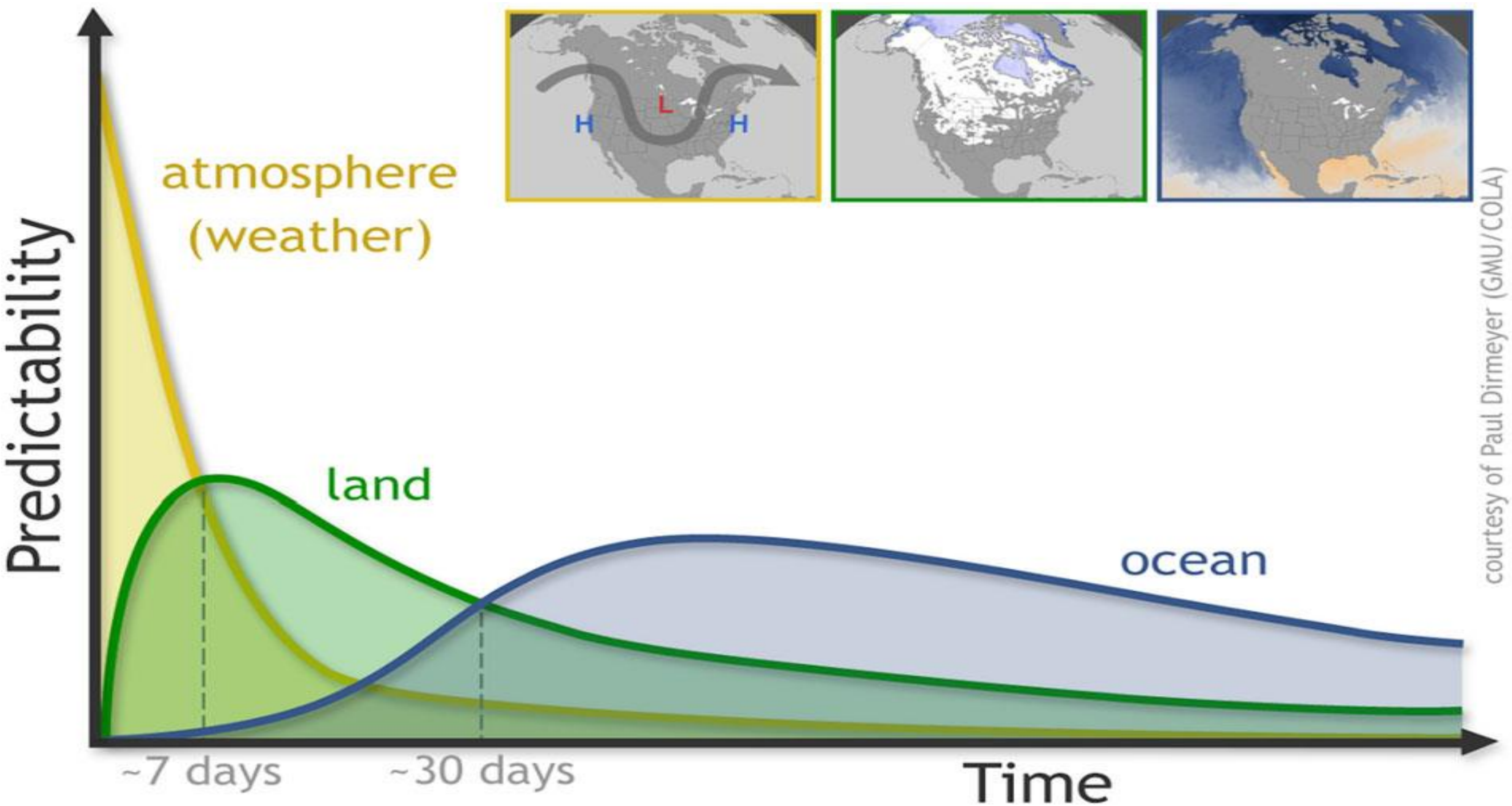
Grid operators: Anticipate addition of more capacity. Adaptation of transmission lines

Policy-makers: Plan addition of more capacity. Understand changes to energy mix

Predictability

- Why can we predict climate for the coming season if we cannot predict the weather next week? Slow components (sea surface temperature, soil moisture, etc.) force the atmosphere.

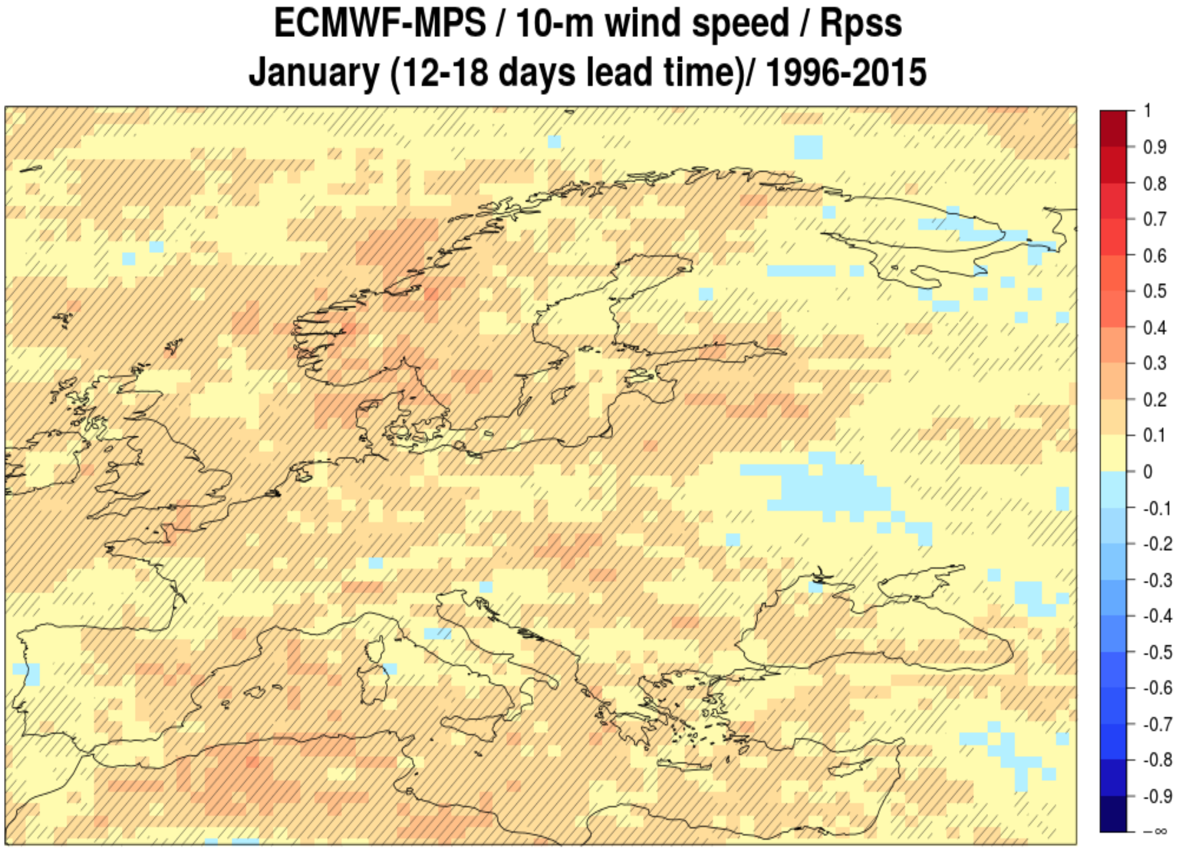
S2S Forecast range and skill



(Source: Mariotti et al. 2018)

S2S skill

- A prediction has no value without an estimate of forecasting skill based on past performance



RPSS of 10-m wind speed for the Monthly Prediction System of January (1996-2015). Locations where the RPSS is significant (95%) are hatched.

Case study 3
Heat wave and wind drought in Spain – Sep 2016
Subseasonal forecasts

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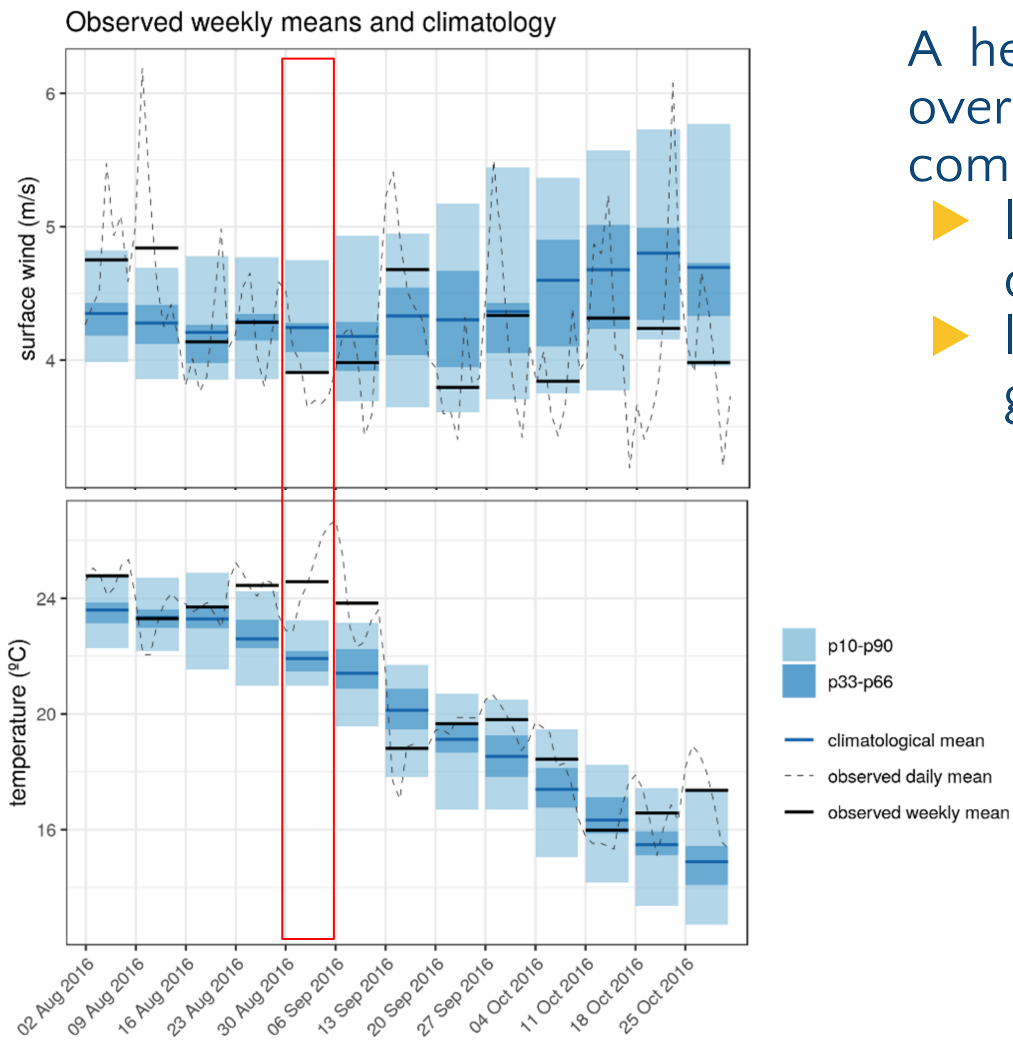
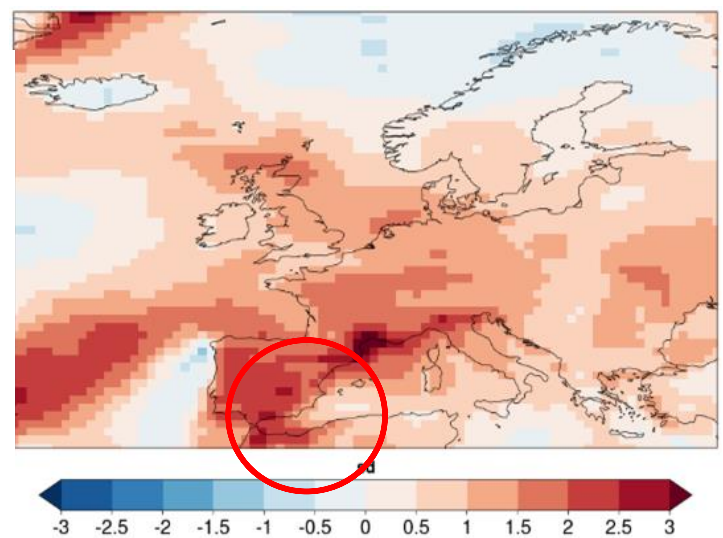
Heat wave and wind drought in Spain. Sep 2016



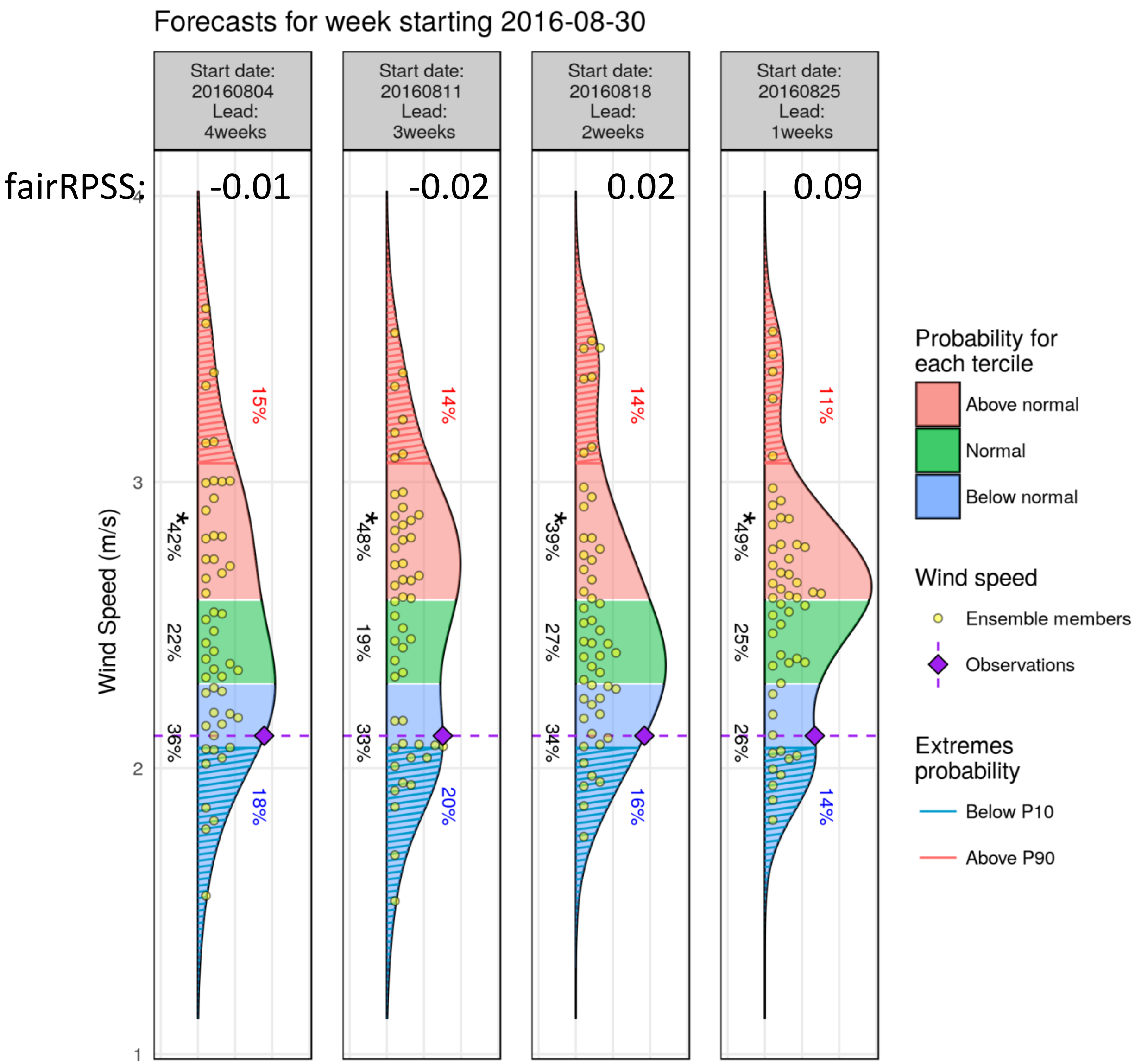
A heat wave and wind drought over Iberian Peninsula created a combination of:

- large increase in electricity demand
- lower than usual wind power generation



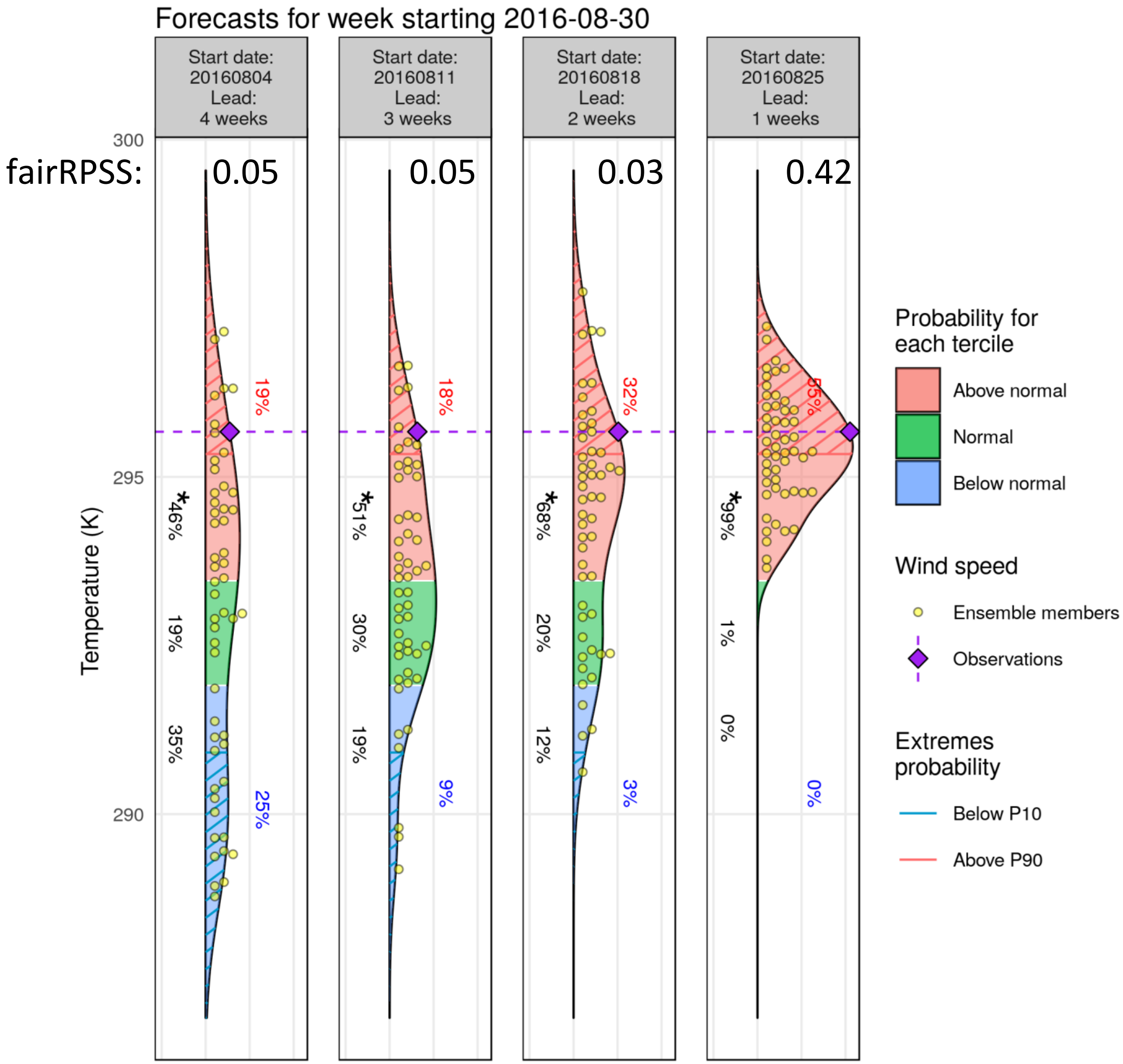
Surface wind and temperature anomalies for the week 30/08/2016-5/09/2016. ERA-Interim with respect to climatology (1981-2017)

Wind speed forecasts



System: ECMWF monthly prediction system
Reanalysis: ERA-Interim
Bias adjusted –calibrated
Hindcast: 1996-2015
Lat= 40.5 N/Lon = 358.5 E

Temperature forecasts:



System: ECMWF monthly prediction system
Reanalysis: ERA-Interim
Bias adjusted –calibrated
Hindcast: 1996-2015
Lat= 40.5 N/Lon = 358.5 E

Case study 6
US wind drought – JFM 2015
Seasonal forecast

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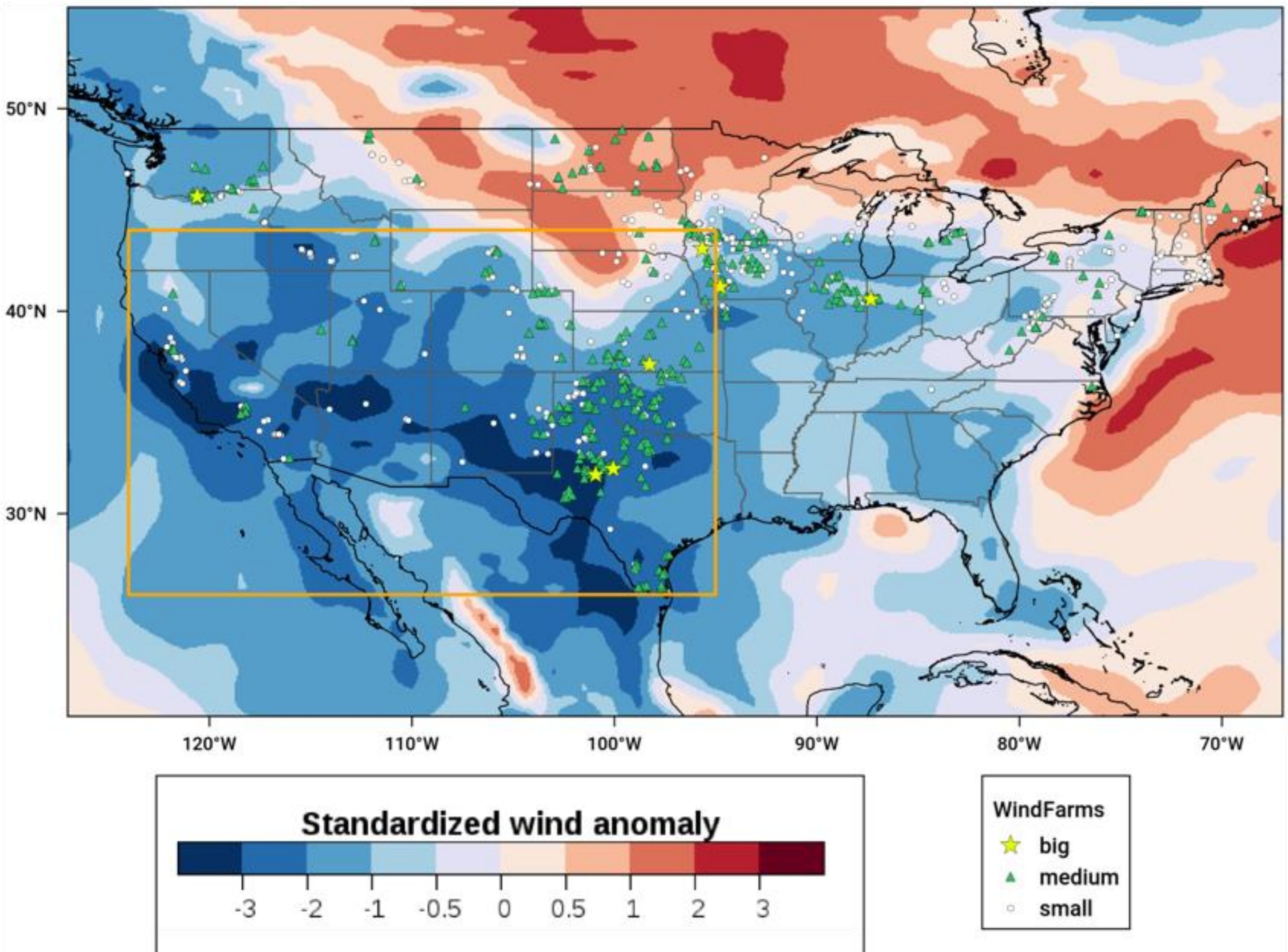
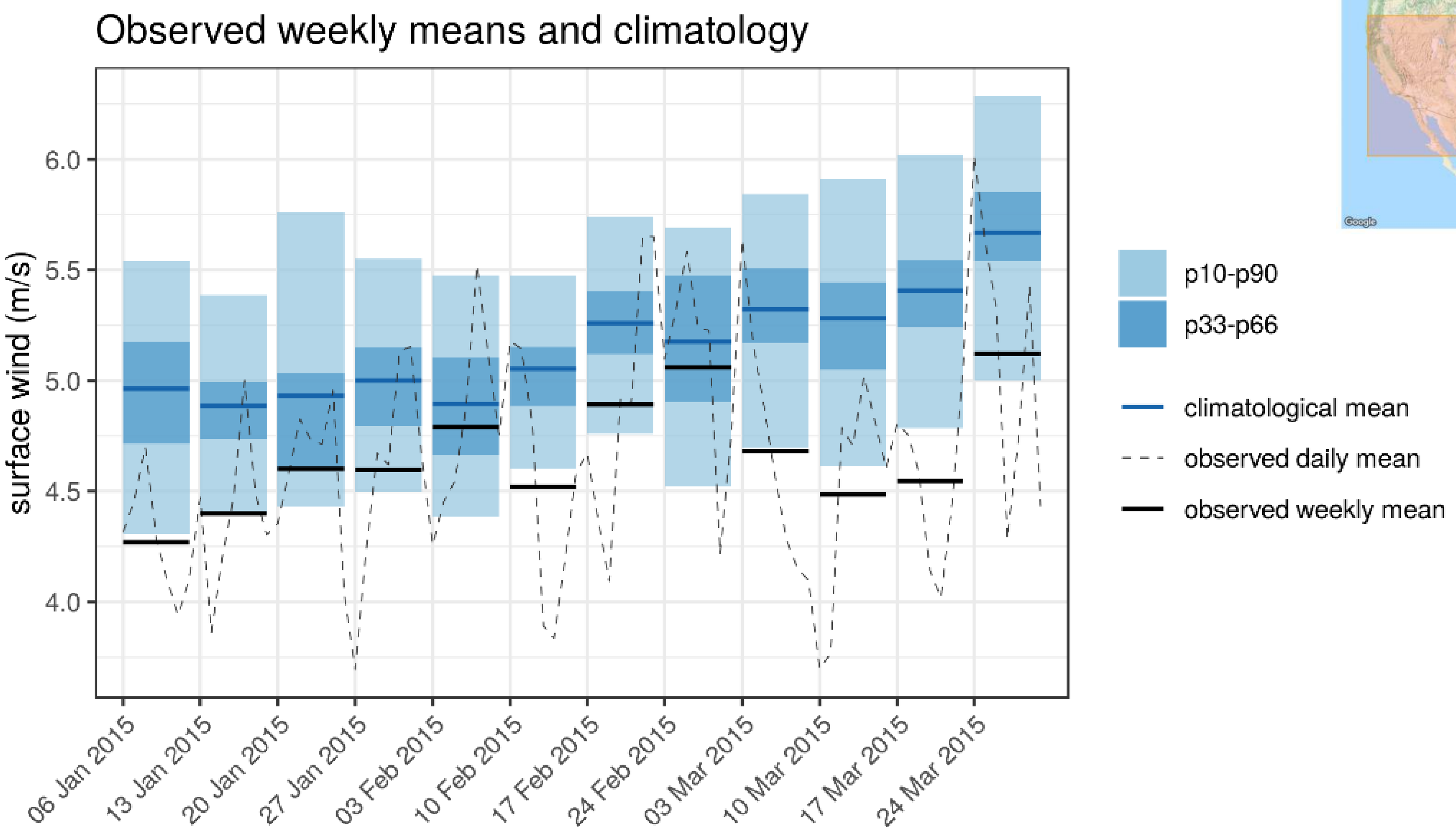
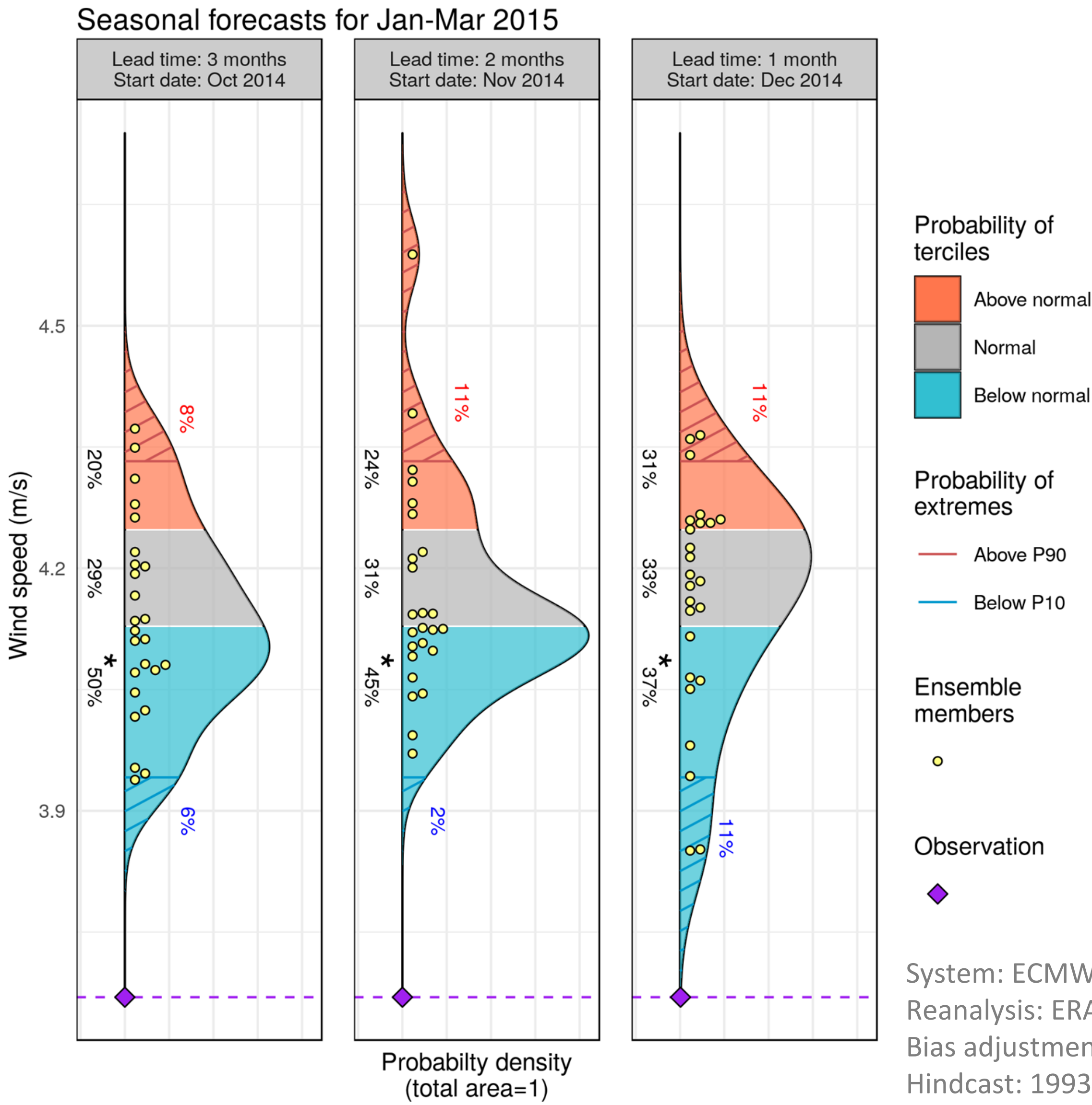
Wind anomaly Q1 2015



Widespread and extended in time



Fcsts available 3 to 1 months ahead



System: ECMWF SEAS5
Reanalysis: ERA-Interim
Bias adjustment: calibration
Hindcast: 1993-2015

Associated Skill Scores

	Start Date		
	Oct	**Nov**	**Dec**
RPSS	0.35	0.39	0.35
BS P10	−0.07	−0.27	−0.16
BS P90	0.1	0.04	0.07
CRPSS	0.14	0.11	0.14
EnsCorr	0.55	0.54	0.51

Event impacts

"US clean energy suffers from lack of wind"
Financial Times, September 2015.

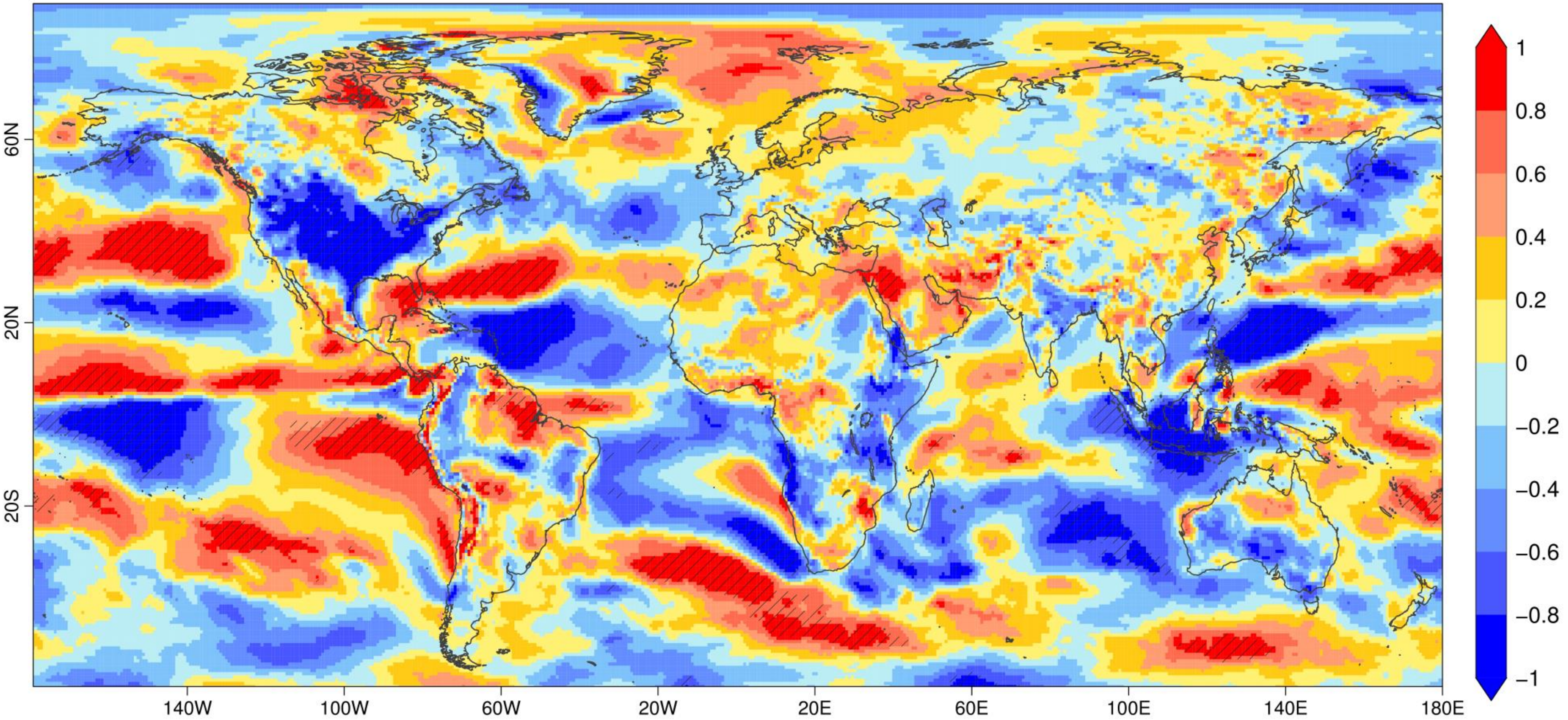
"El Niño Buffers U.S. Wind Power Dreams"
Wall Street Daily, September 2015.

"El Niño blowing down wind projections in US"
Fierce Energy, July 2015.

"We never anticipated a drop-off in the wind resource as we have witnessed over the past six months"
David Crane, RNG, September 2015.

NIÑO3.4 teleconnection

ERA-Interim / 10m wind speed / NIÑO3.4 positive minus neutral impact
DJF / 1981-2015



Bias correction: none
Hatched area:siginficant at 95% confidence level from a two tailed Student's t-test
Mask: sea depth below 50m

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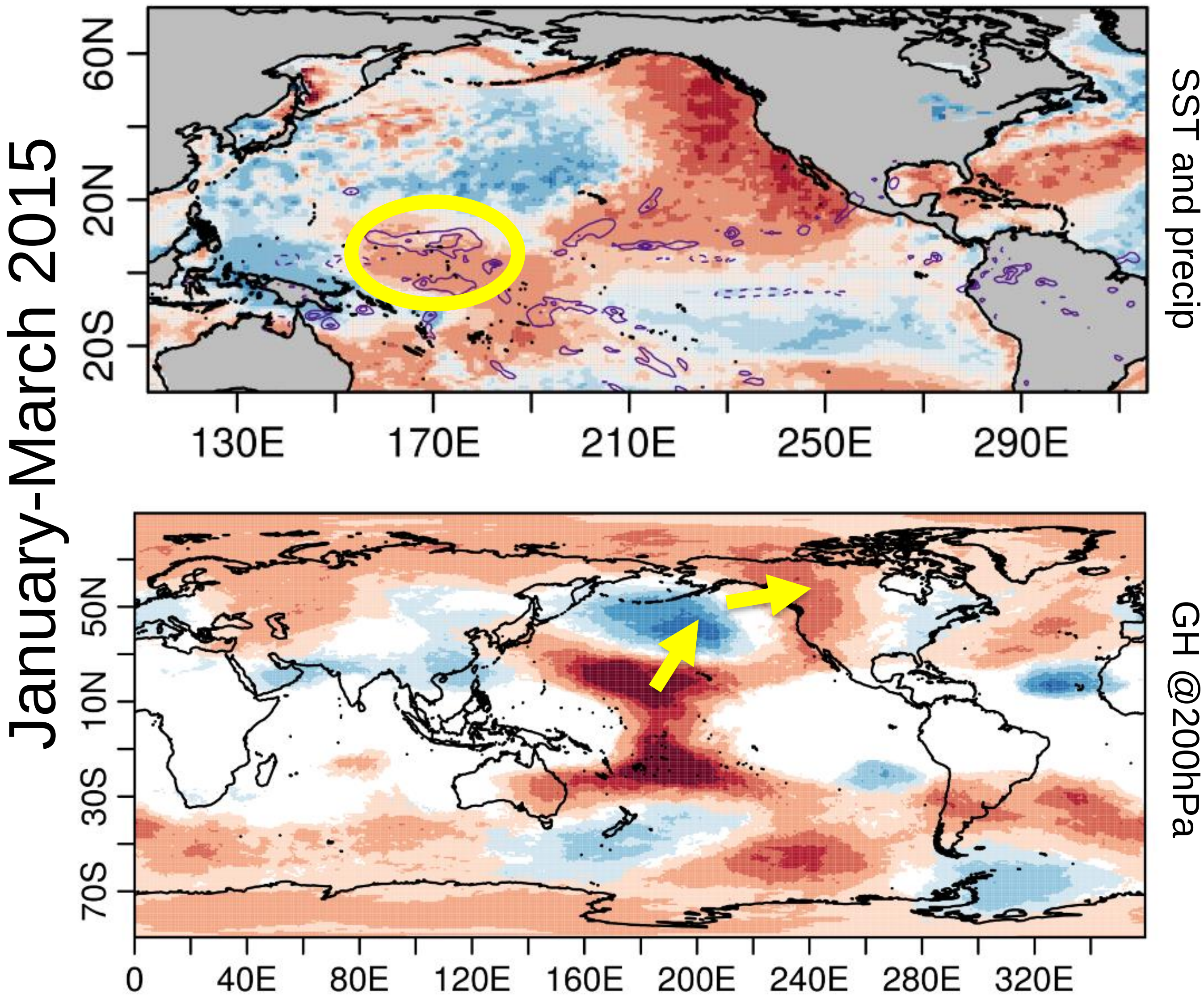
Impact maps between NIÑO3.4 teleconnection index 10m wind speed from ERA-Interim reanalysis.

Causes



High SSTs in western tropical pacific
↓
Enhanced convection in the area
↓
Upward flow produces divergence at 200hPa
↓
Rossby wave propagates to North America
↓
Results in persistent low winds

System: EC-EARTH

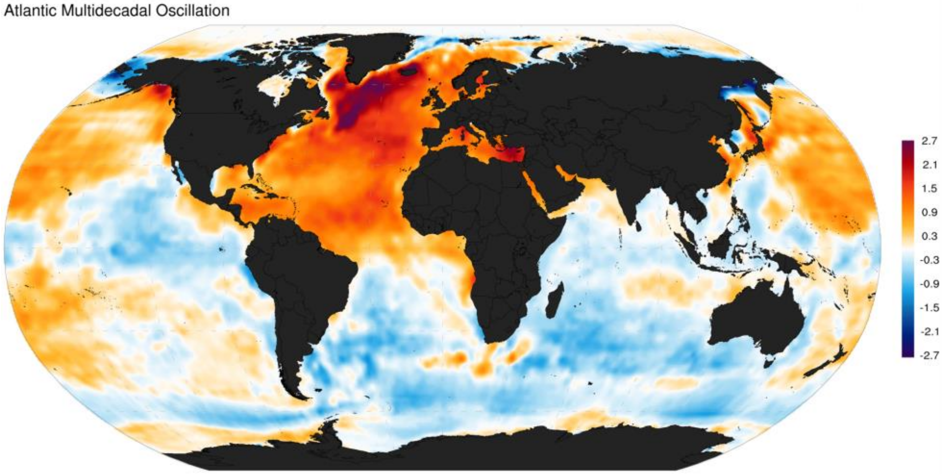
Lledó et al., 2018: Investigating the effects of Pacific sea surface temperatures on the wind drought of 2015 over the United States.

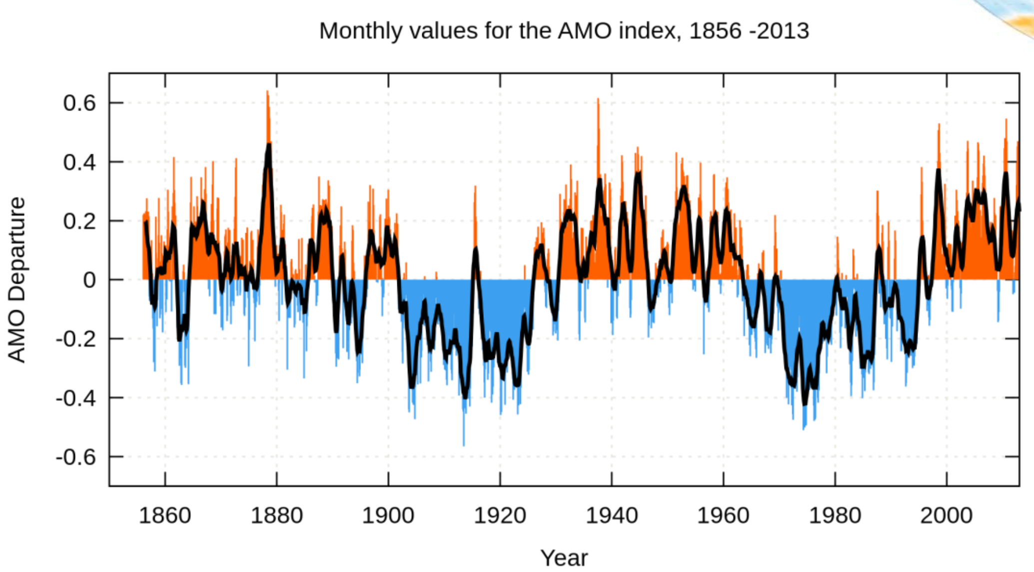
Decadal predictions

European Climate Prediction system

Decadal predictions

- Between seasonal predictions and climate projections
- Both initial value and boundary condition problems
- Different sources of predictability

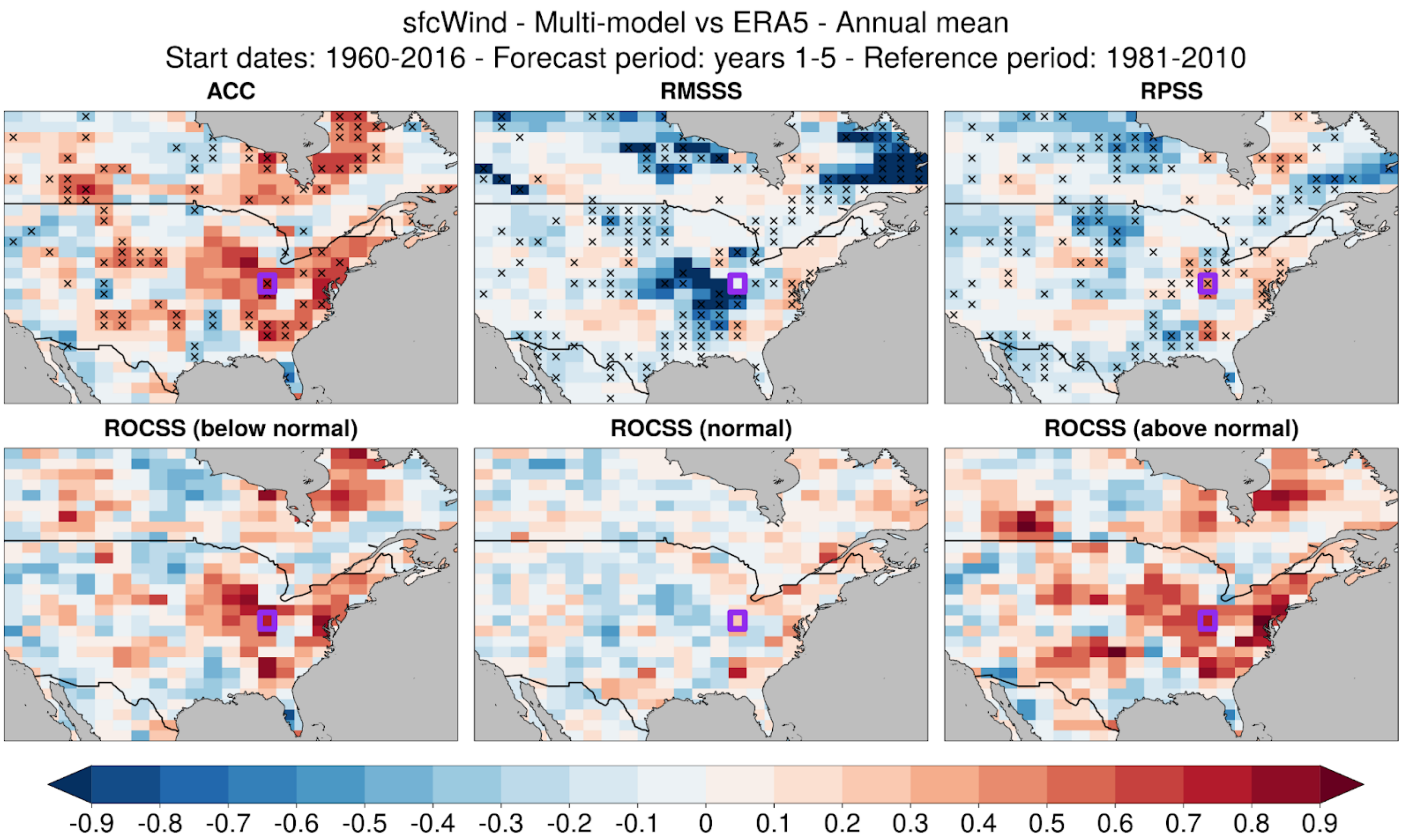




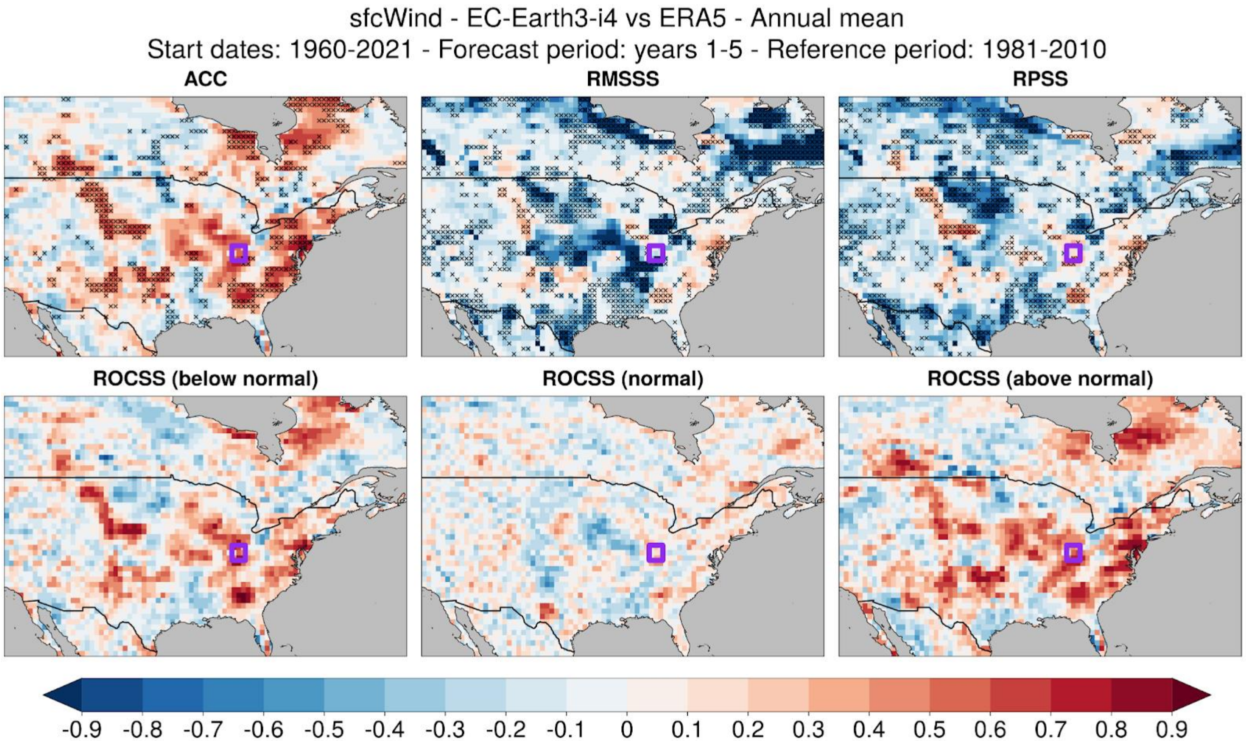
Decadal predictions

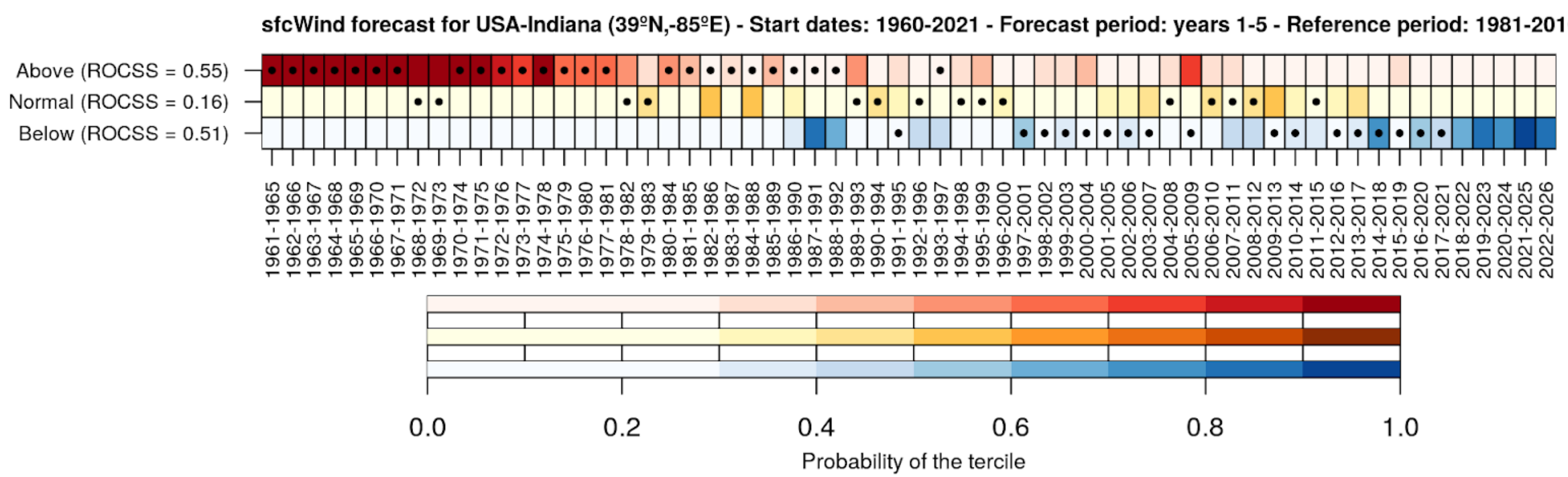
Table 2. Forecast systems that provide subdaily surface wind speed data contributing to the CMIP6/DCPP and their specifications (available simulations at the time of the study).

Forecast system	nº of DCPP members	Near-real time data	Spatial resolution	Month of initialisation	Reference
EC-Earth3-i1	10	No	0.7º x 0.7º	November	Bilbao et al. (2021)
EC-Earth3-i2	5	No	0.7º x 0.7º	November	Tian et al. (2021)
EC-Earth3-i4	10	Yes	0.7º x 0.7º	November	Bilbao et al. (2021)
IPSL-CM6A-LR	10	No	1.25º x 2.5º	January	Boucher et al. (2020)
MPI-ESM1.2-HR	10	No	0.9º x 0.9º	November	Müller et al. (2018)



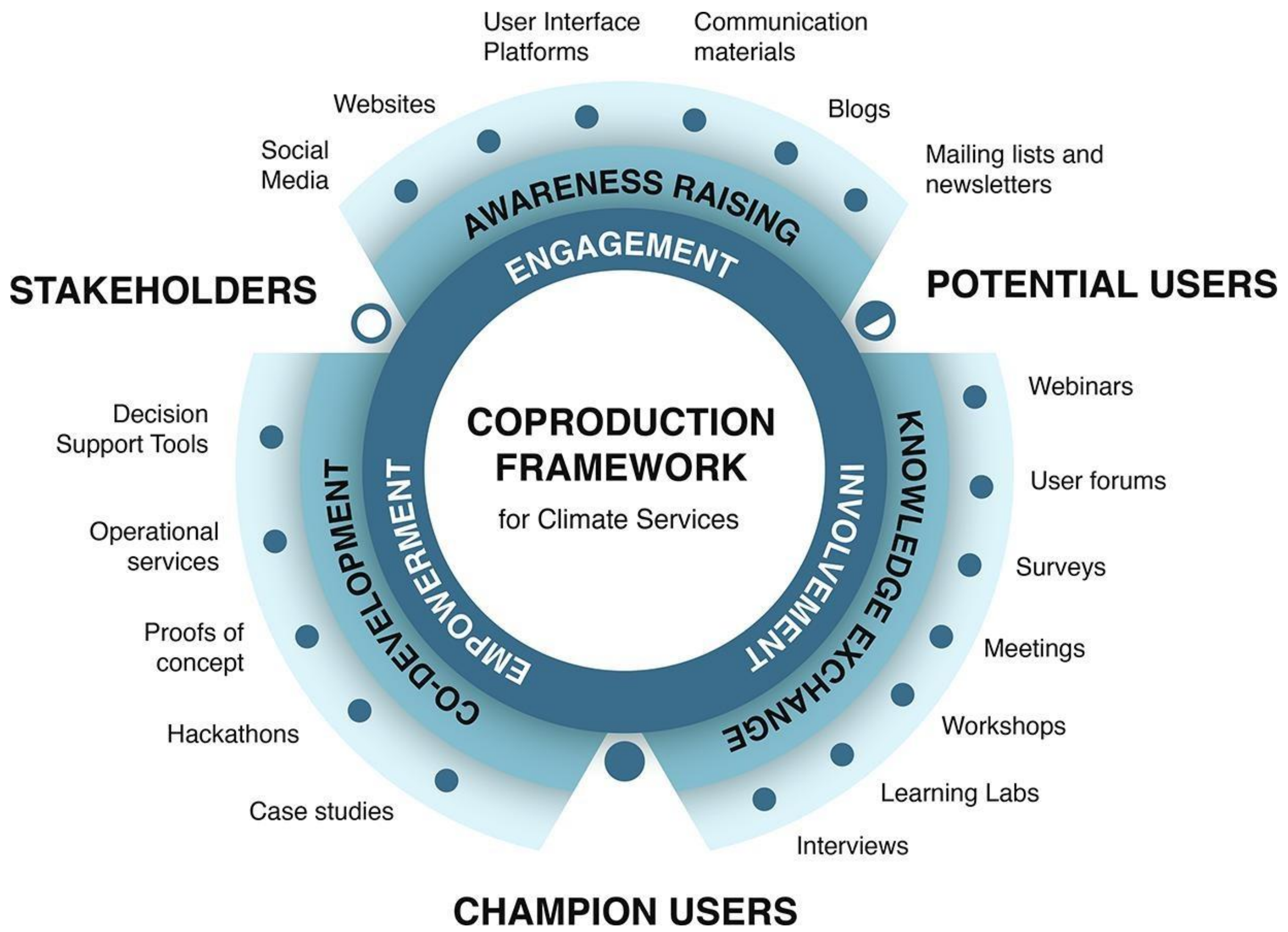
Decadal predictions





Tailored indicators

Coproduction



Bojovic et al, 2021. https://doi.org/10.1016/j.gloenvcha.2021.102271

Case study 5
Iccing in Romania – Feb 2014
Subseasonal forecasts

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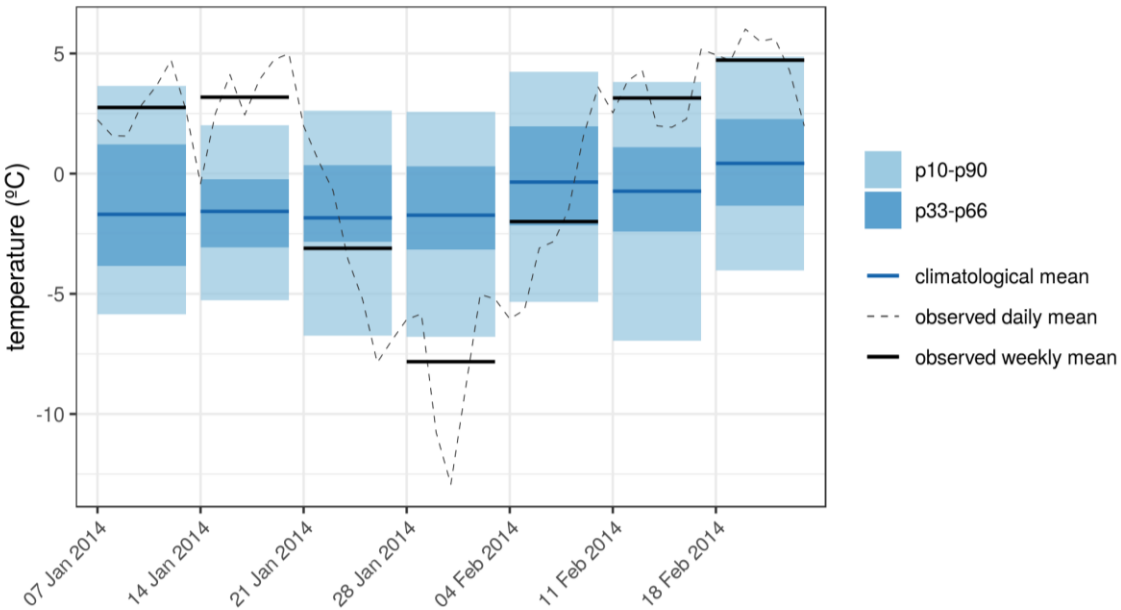
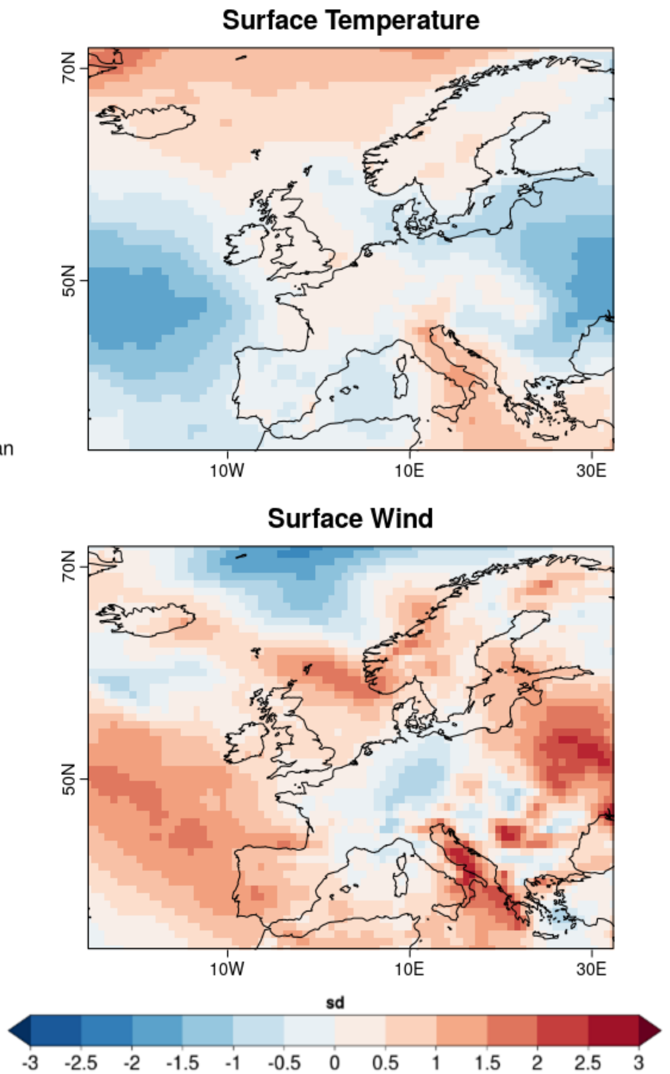
Extreme event, icing. Romania 2014

Extreme event, icing. Romania 2014

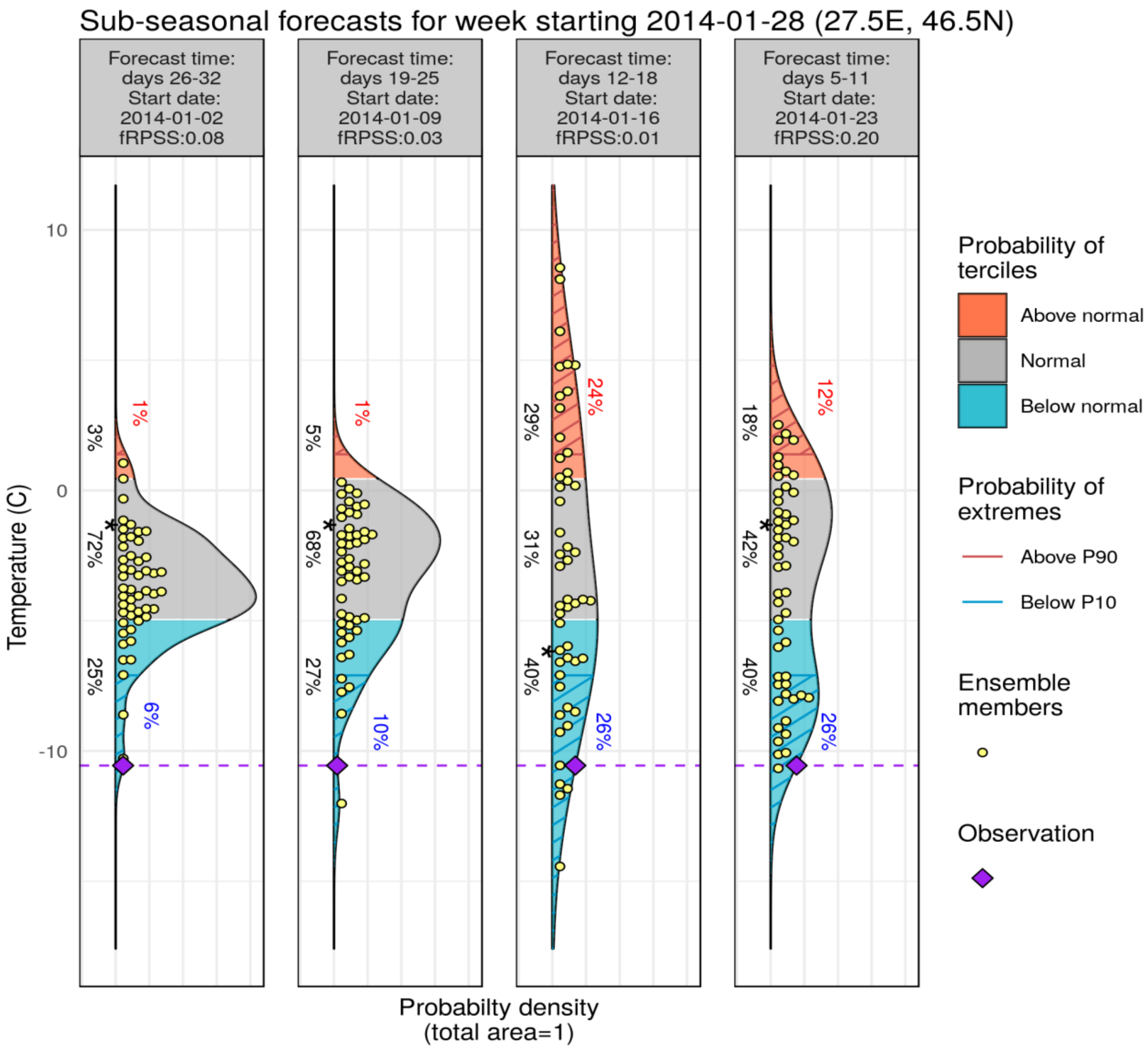


Temperature anomalies (at 27.5 oE, 46.5 oN during January and February 2014.). ERA-Interim with respect to climatology (1981-2017)



Surface wind and temperature anomalies. ERA-Interim with respect to climatology (1981-2017)

Temperature forecasts



System: ECMWF monthly prediction system
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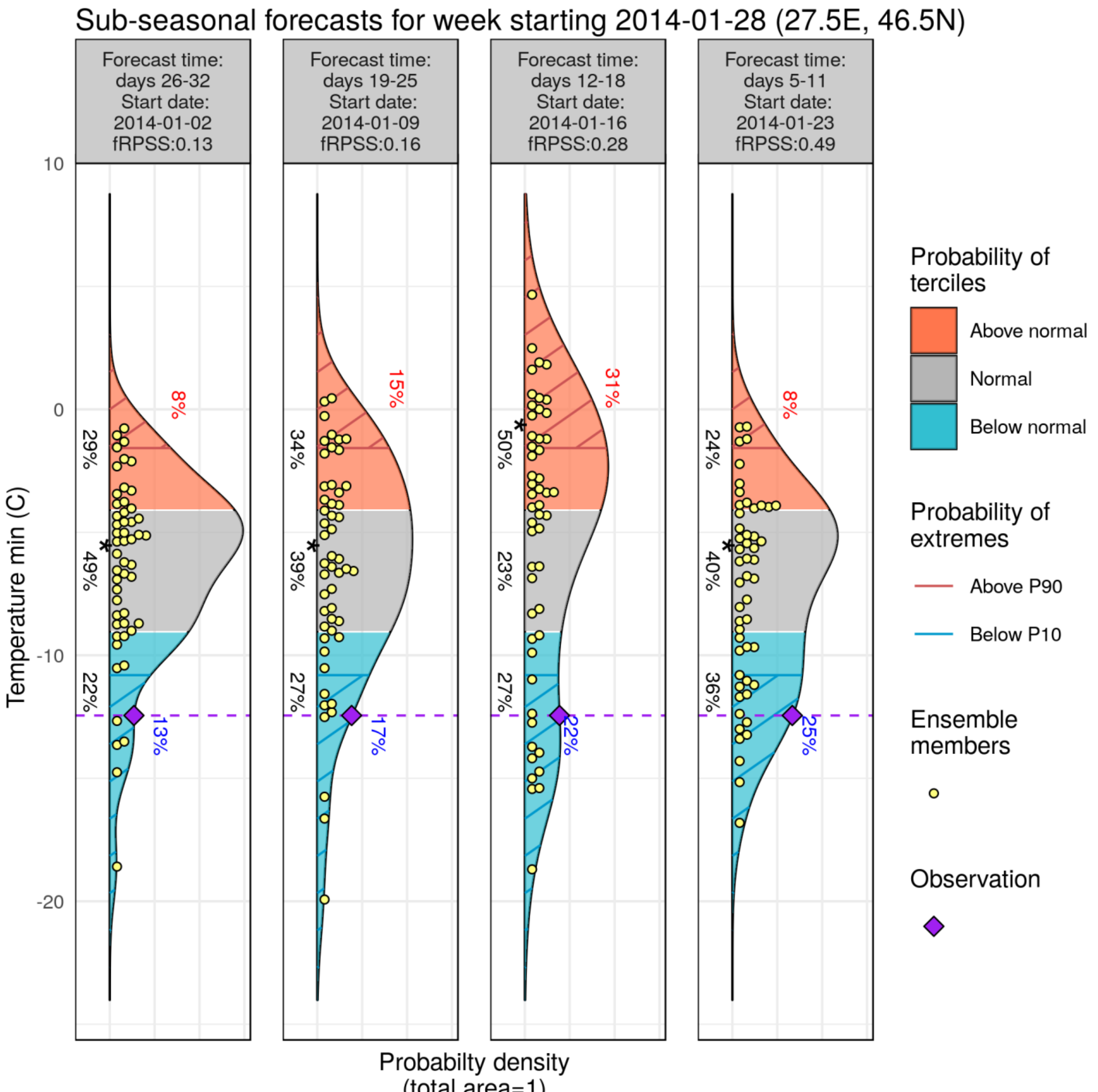
Hindcast: 1996-2015

Temp min forecasts



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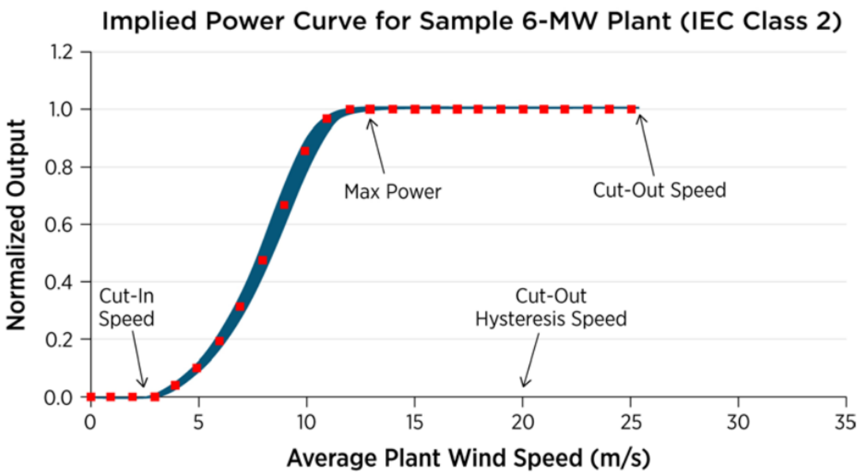
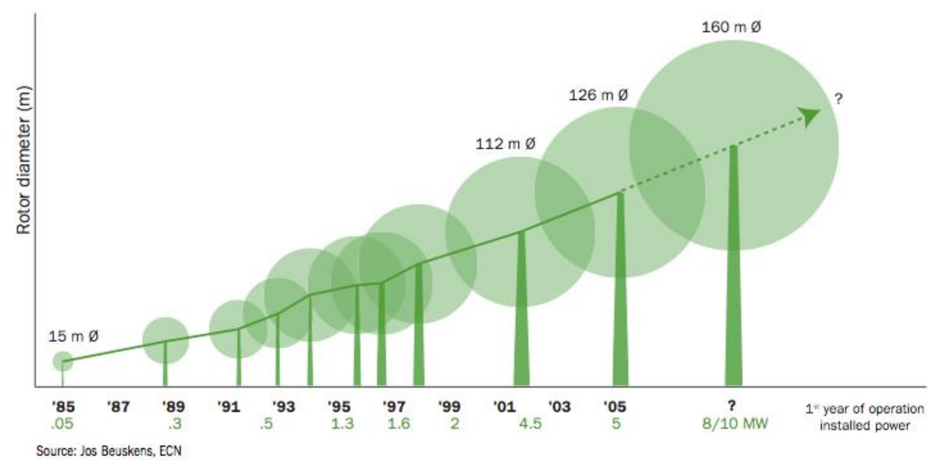
Capacity factor



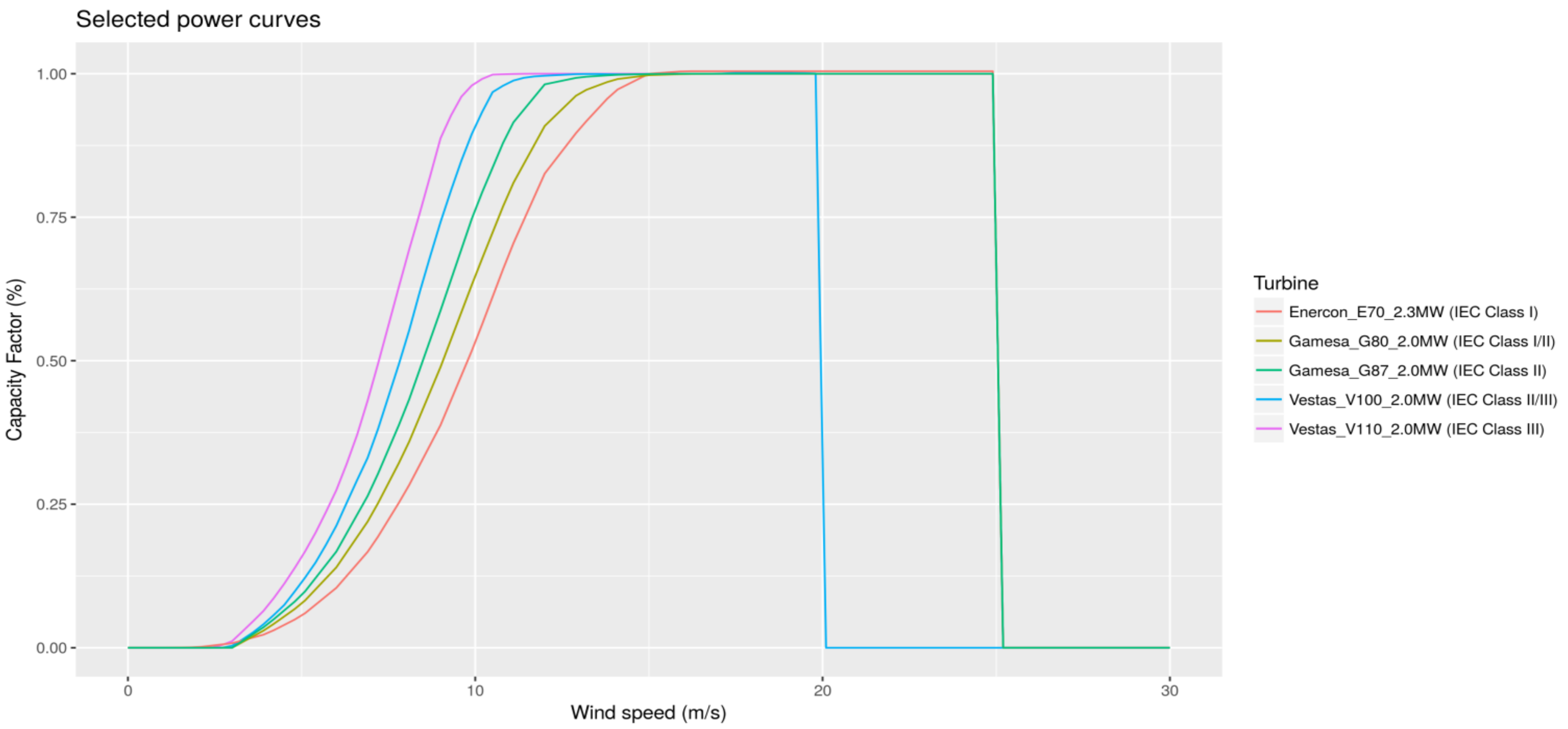
Aggregate power curve for a sample 6-MW wind power plant with theoretical power curve (red markers). Source: NREL

The capacity factor of a wind turbine is its average power output divided by its maximum power capability. On land, capacity factors range from 0.26 to 0.52. Offshore winds are generally stronger than on land, and capacity factors are higher on average, but offshore wind farms are more expensive to build and maintain.

The size of wind turbines at market introduction

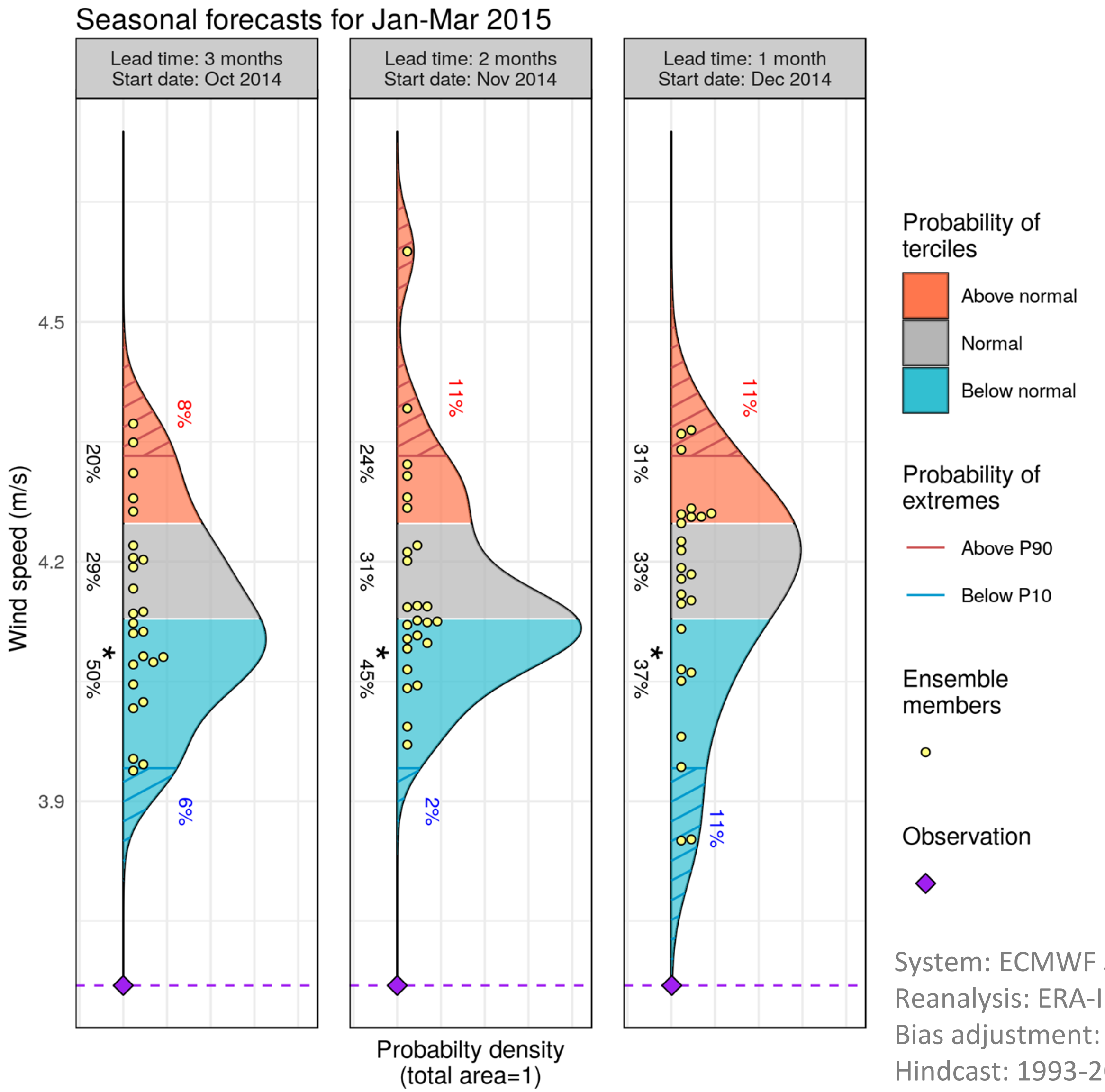


Capacity factor



The size of wind turbines at market introduction

Case study 6
US wind drought – JFM 2015



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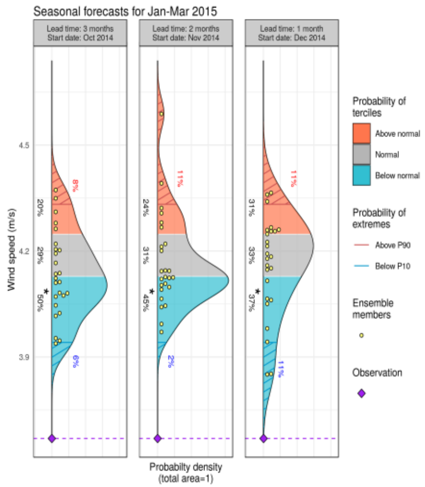
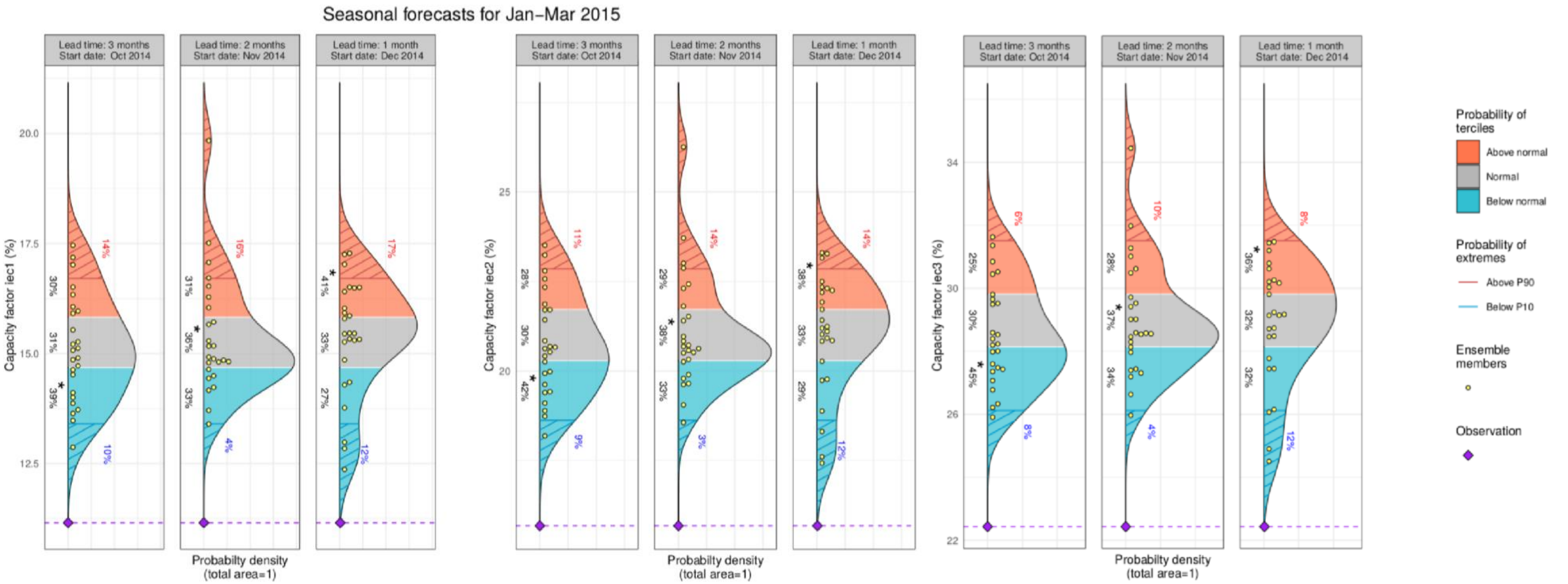
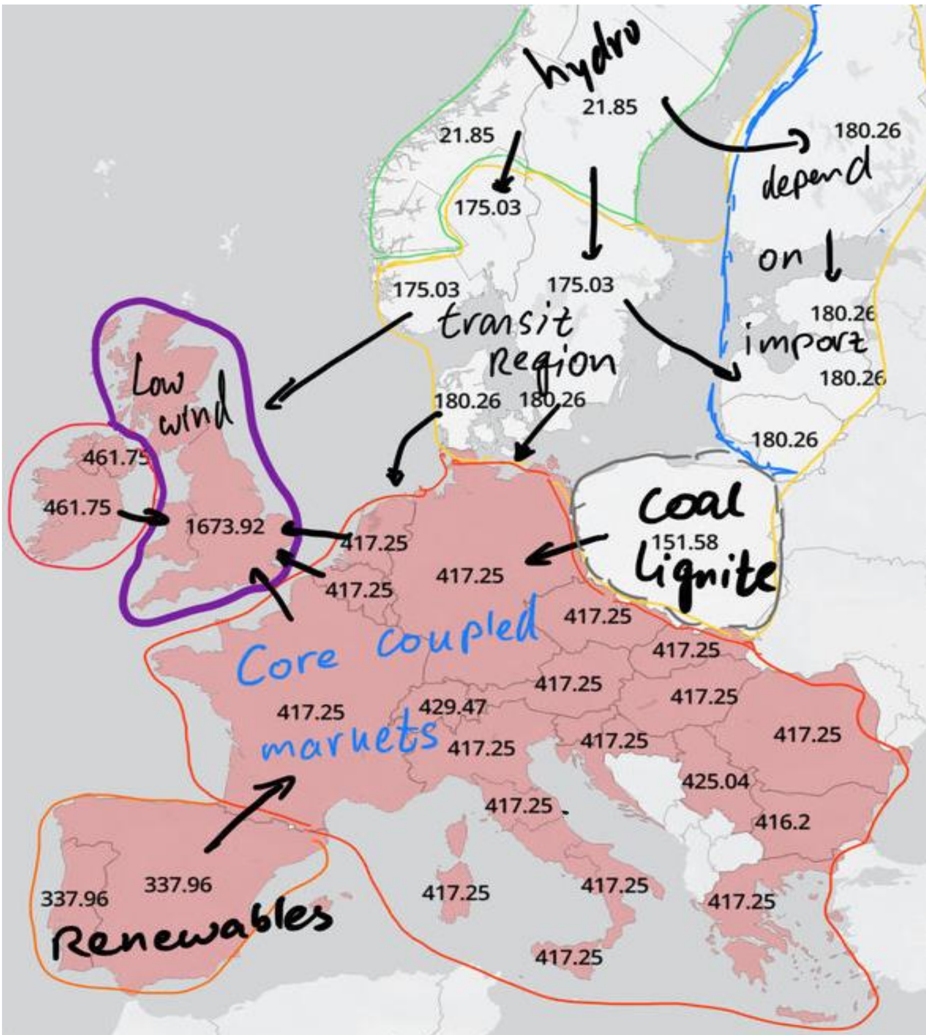




Economic assessment

Economic assessment



Day ahead prices for 16/12/2021. Large differences across the continent, with a core region around €420. UK prices are the highest in Europe due to low wind energy production, while Iberian system prices are the lowest due to high wind resources (source: EnAppSys).

Decision maps of weather and climate dependent

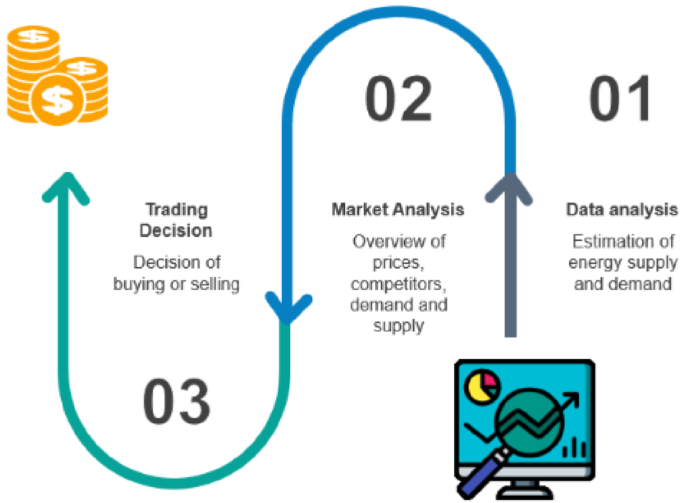


Figure 9: Energy trading decision-making process

Source: S2S4E. D2.1

Figure 10: Hedging decision-making process

Cold spell France 2018

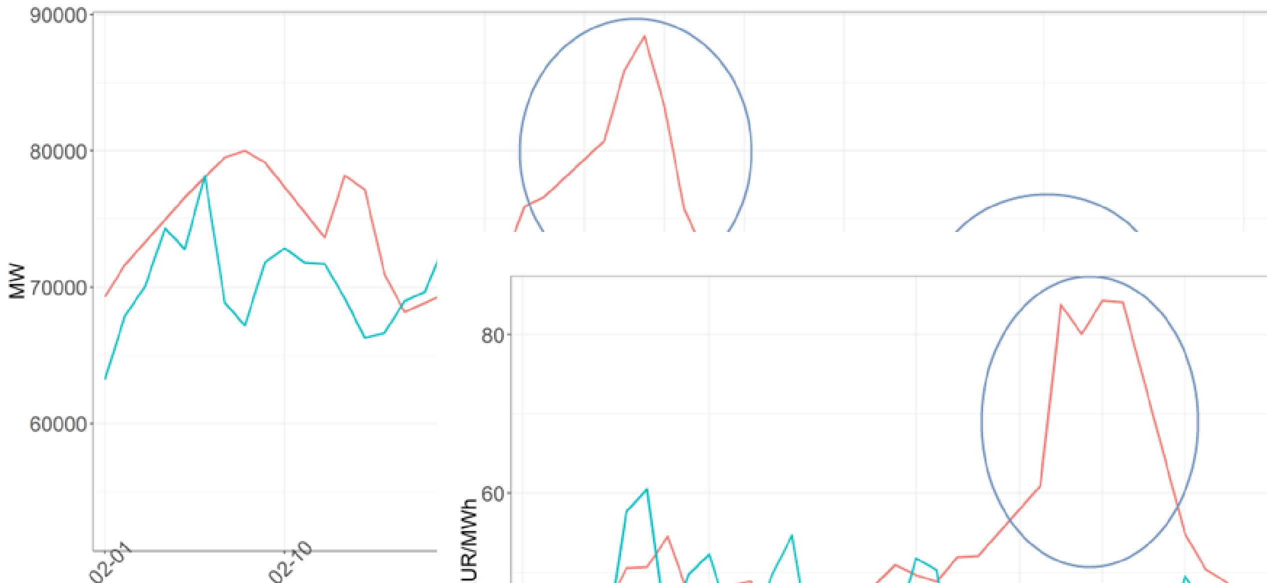


Figure 17: Daily average
week

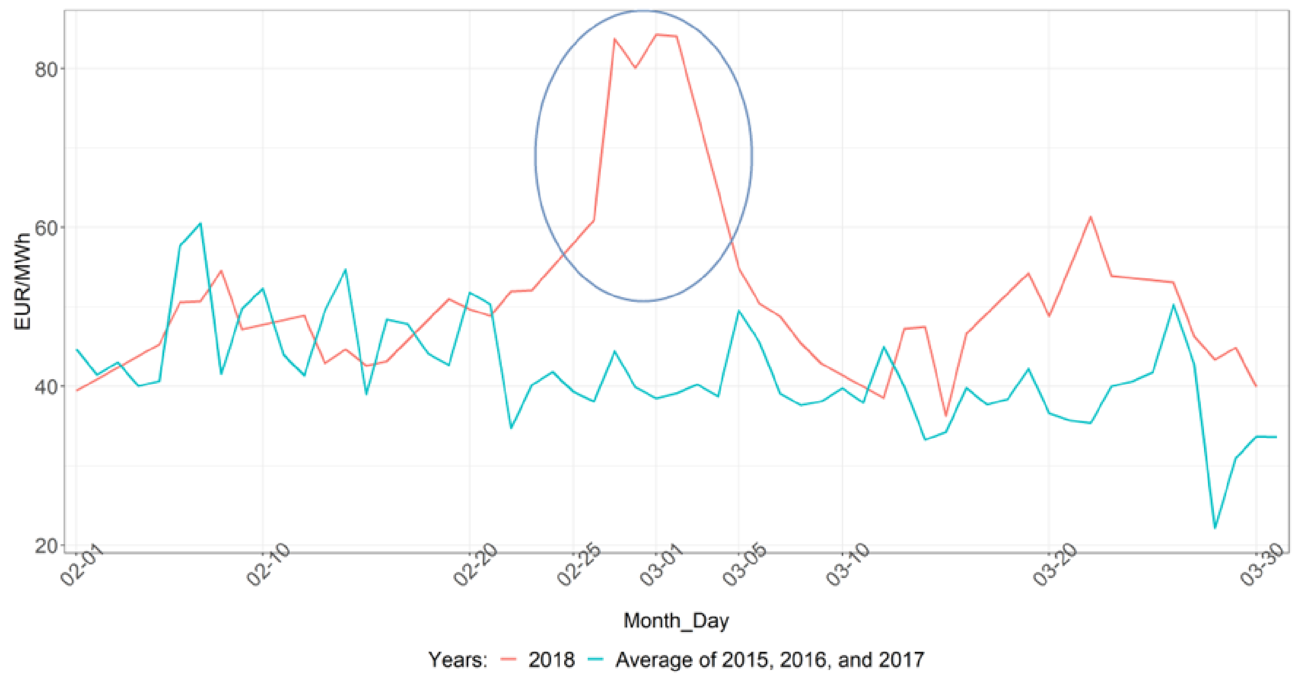
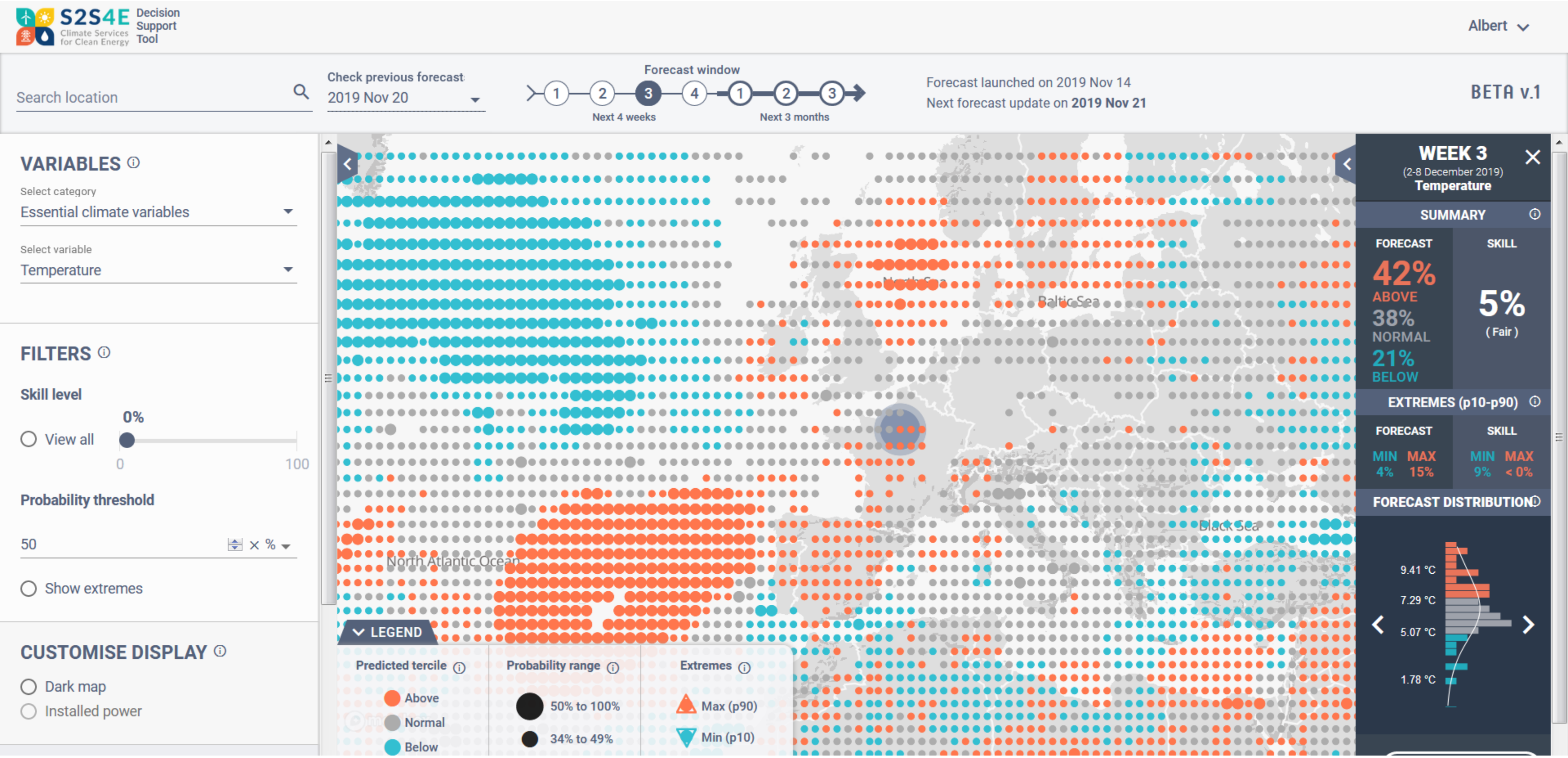


Figure 18: Day-ahead electricity prices in France in February-March 2018. Only weekdays are shown. Source: ENTSO-E

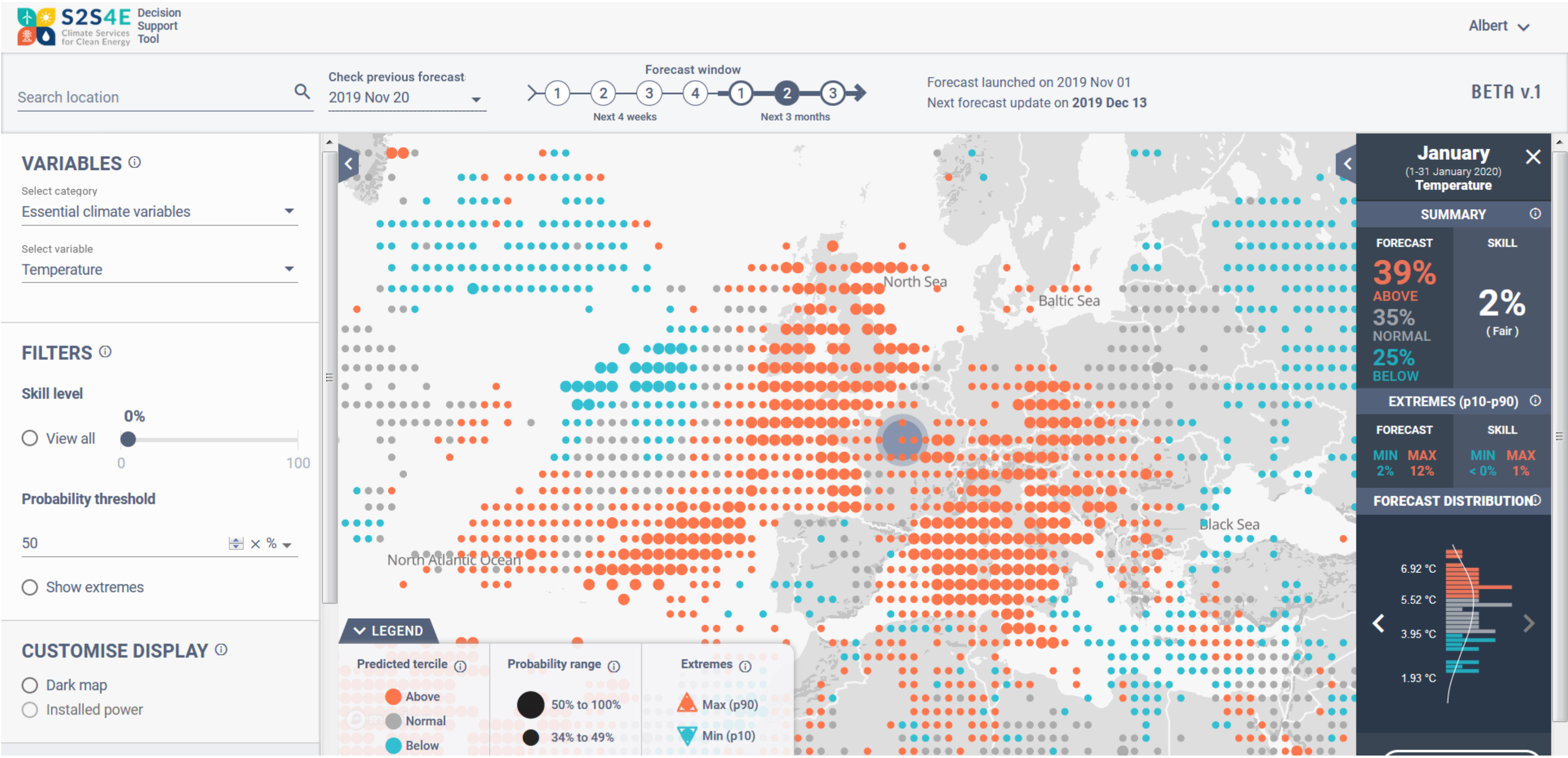
Codevelopment of a decission support tool

S2S4E DST



https://s2s4e.eu/dst

S2S4E DST



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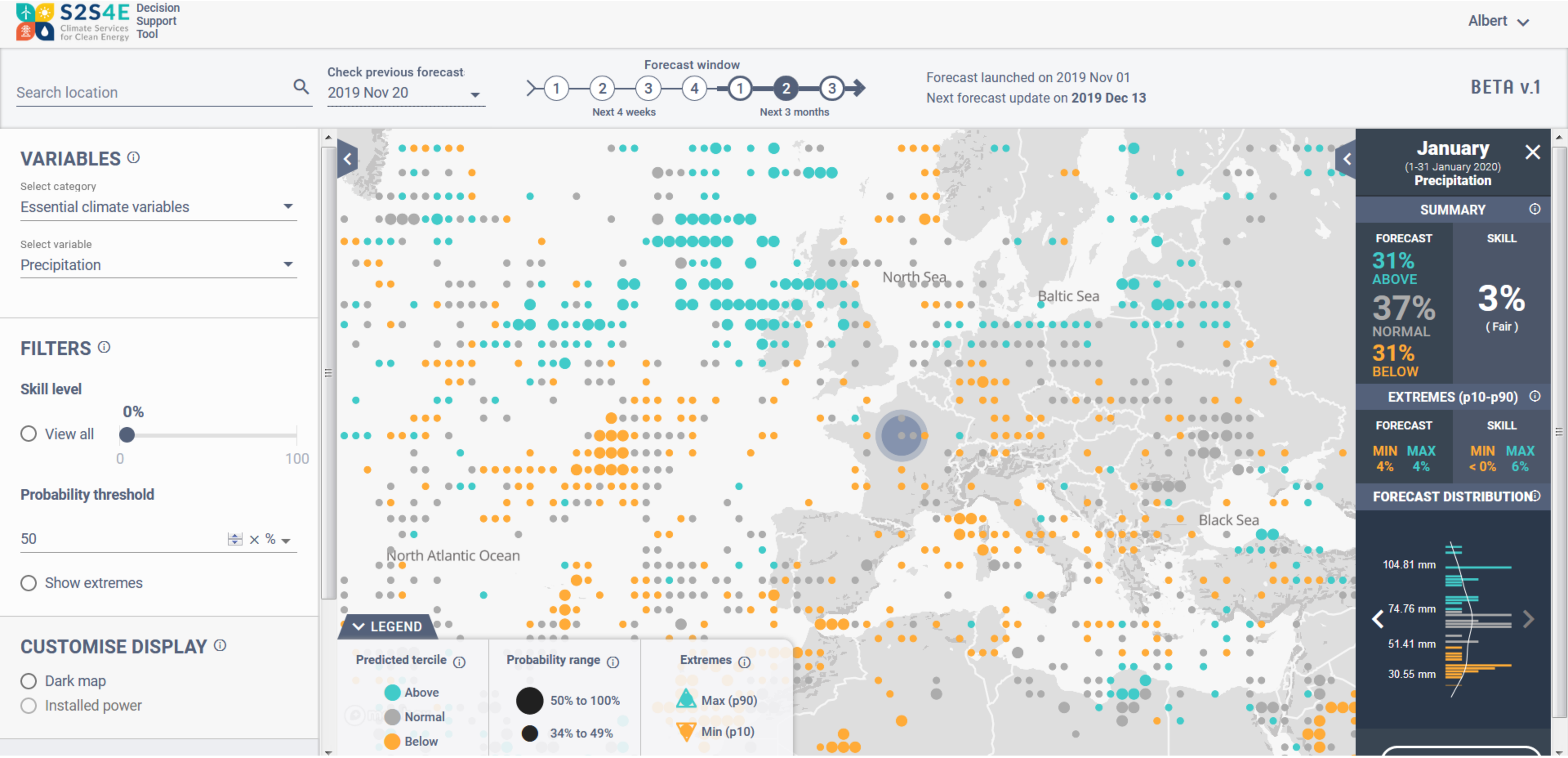
S2S4E DST



https://s2s4e.eu/dst

Final remarks

- Climate prediction systems have improved in the last decade demonstrating that probabilistic forecasting can inform better decision making at some temporal scales and regions
- Alongside the model development process, climate predictions need to be evaluated on past years to provide robust information before making decisions
- Tailored service helpful for several applications
- Interdisciplinary groups enhance the interaction with users to co-develop a service

Future work:

- Seamless prediction
- Take advantage of AI techniques

Thanks!

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