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NEW EUROPEAN WIND ATLAS
newa

First results on predictability assessment

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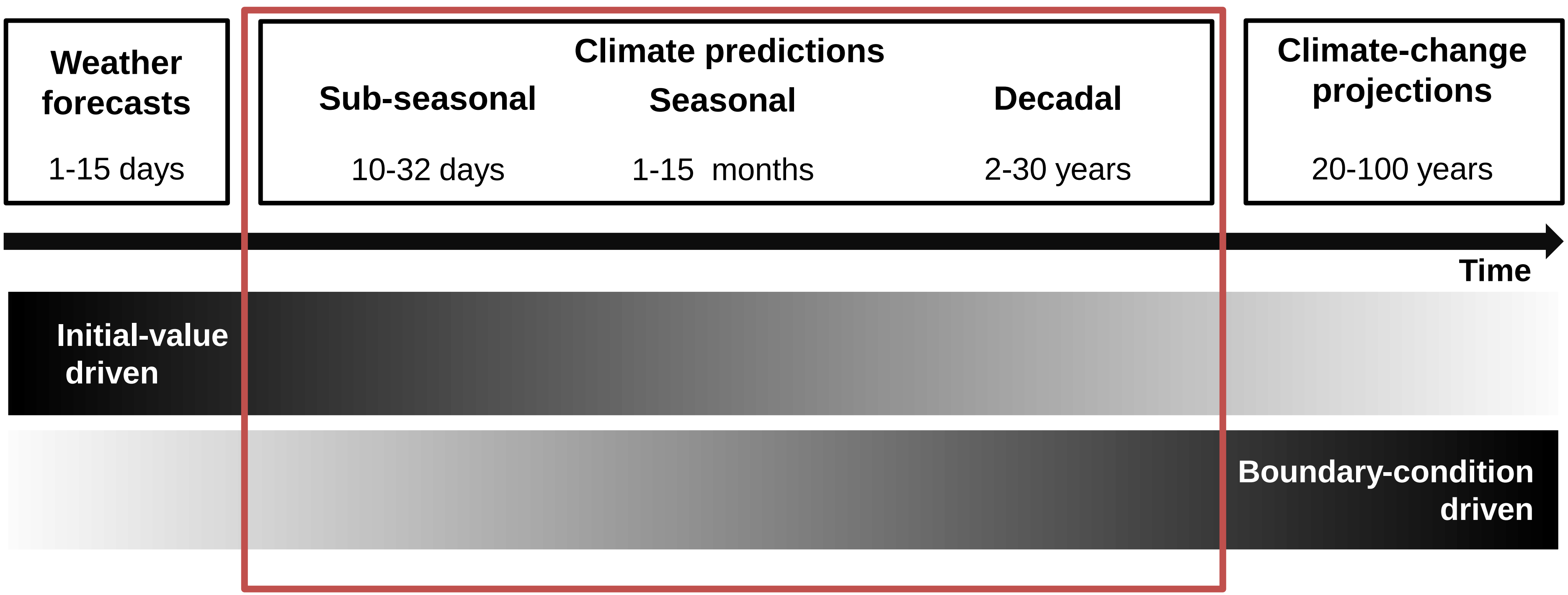
Objective

1. **Introduction to climate predictions**
2. **Sources of predictability**
3. **Methodology**
4. **Preliminary results**
5. **Conclusions and future work**

- Weather forecasting: Initial-value problems
- Climate projections: forced boundary condition problem.
- **Climate predictions** (sub-seasonal, seasonal and decadal) in the middle.



Adapted from: Meehl et al. (2009)

Introduction to climate services

- Wind energy sector routinely uses weather forecast up to 15 days. Beyond this time horizon, climatological data are used.
- In other sectors, climate information on seasonal-to-interannual time scales have already been illustrated for management decisions.

Hydroelectric power management

INTERNATIONAL JOURNAL OF CLIMATOLOGY
Int. J. Climatol. **27**: 1691–1705 (2007)
Published online in Wiley InterScience
(www.interscience.wiley.com) DOI: 10.1002/joc.1608

RMetS
ROYAL METEOROLOGICAL SOCIETY

Forecasting precipitation for hydroelectric power management: how to exploit GCM's seasonal ensemble forecasts

Marta Benito García-Morales* and Laurent Dubus
EDF Research and Development Division, Electricité de France, France

Electricity demand

ELSEVIER

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

AppliedEnergy

Seasonal climate forecasts for medium-term electricity demand forecasting

CrossMark

Matteo De Felice [a,*], Andrea Alessandri [a,b], Franco Catalano [a]

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[b] *International Pacific Research Center, University of Hawaii at Manoa, Honolulu, HI, USA*

HIGHLIGHTS

- During the ten years, seasonal climate forecasts have improved their skill.
- We analyzed the link between summer average temperature and demand over Italy.
- Both deterministic and probabilistic forecasting approaches are here considered.

Heat wave 2003.Prediction of temperature produced by ECMWF

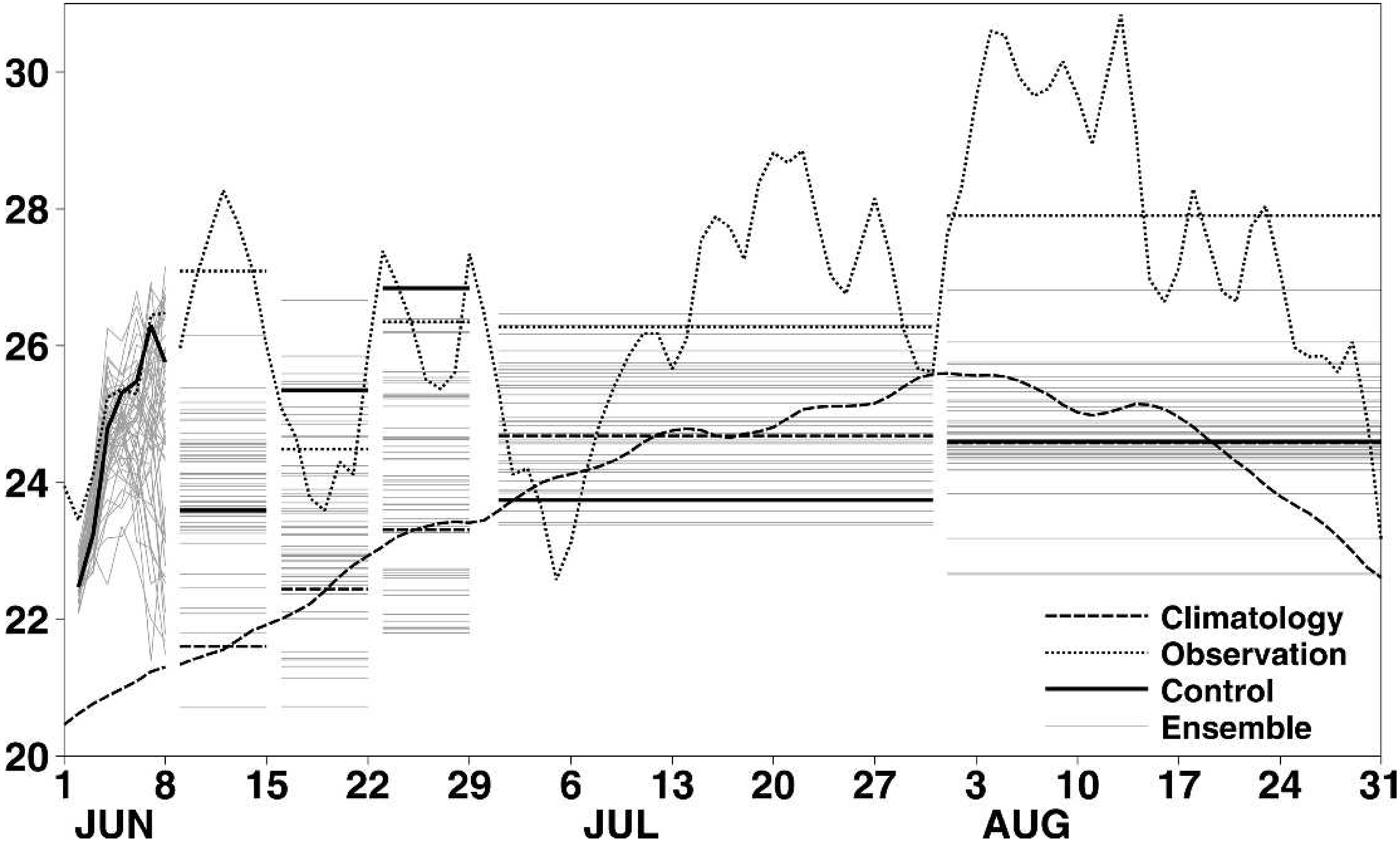

Fig. Observations (dotted) and forecasts (solid) made by ECMWF at the beginning of June of European 2-m land temperatures (°C). (Source: Rodwell and Doblas-Reyes, 2006)

Introduction. Decision-making

MONTHLY TO SEASONAL TIMESCALES

- **Energy producers:** Resource management strategies
- **Energy traders:** Resource effects on markets
- **Wind farm operators:** Planning for maintenance works
- **Wind farm investors:** Optimise return on investments

ANNUAL TO DECADAL TIMESCALES

- **Wind farm planners:** Site selection
- **Wind farm investors:** Evaluate return on investments
- **Policy makers:** Understand changes to energy mix

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Sources of predictability

How can we predict climate for the coming season if we cannot predict the weather next week?

Weather forecasts

The forecasts are based in the initial conditions of the **atmosphere**, which is highly variable and develops a chaotic behaviour after a few days

Climate predictions

The predictions are based in the initial conditions of the **sea surface temperature**, **snow cover** or **sea ice**, which have a slow evolution that can range from few months to years.

Sources of seasonal predictability

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ENSO is the most important source of predictability at seasonal timescales (see e.g. Doblas-Reyes et al. 2013)

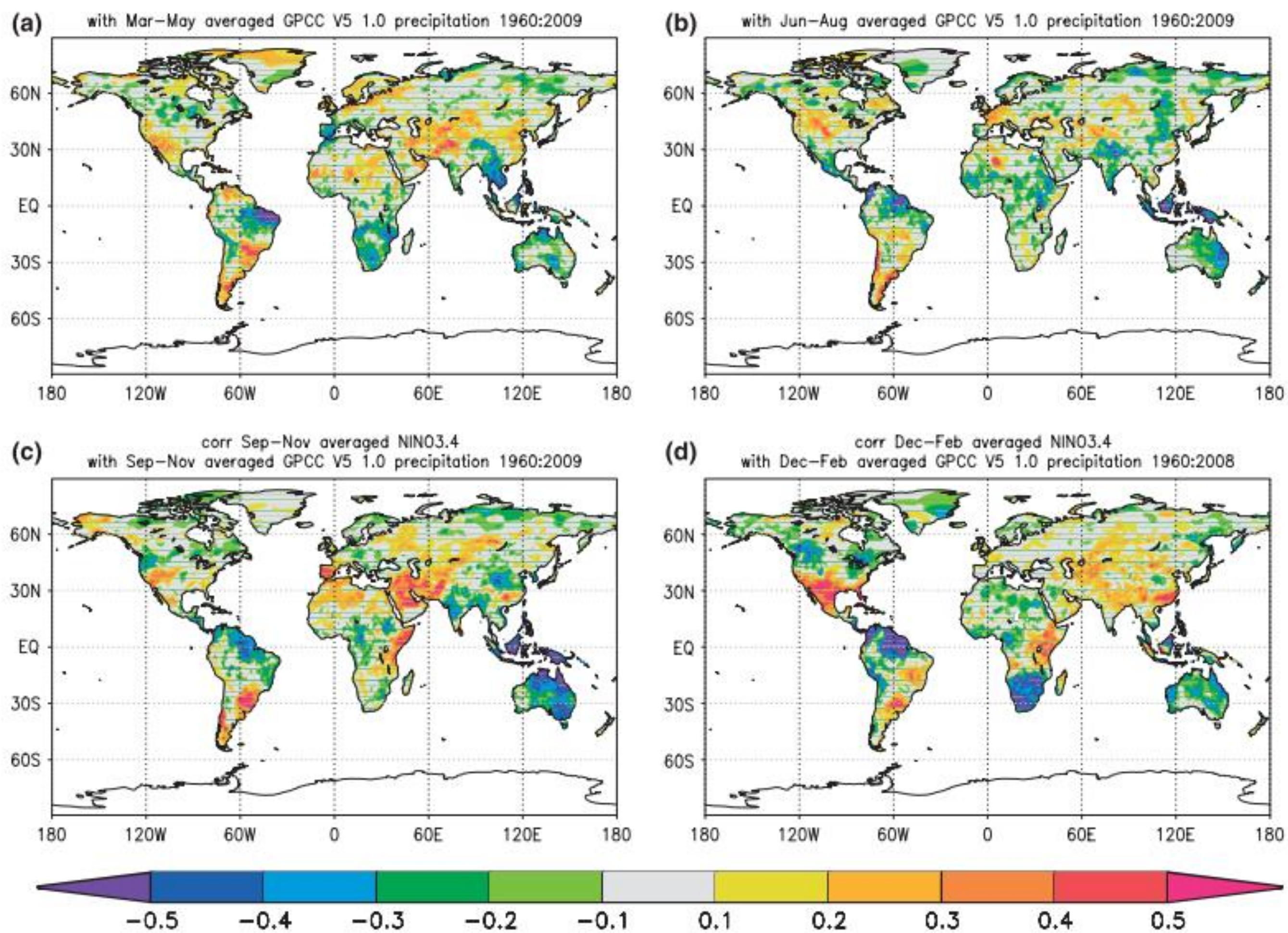
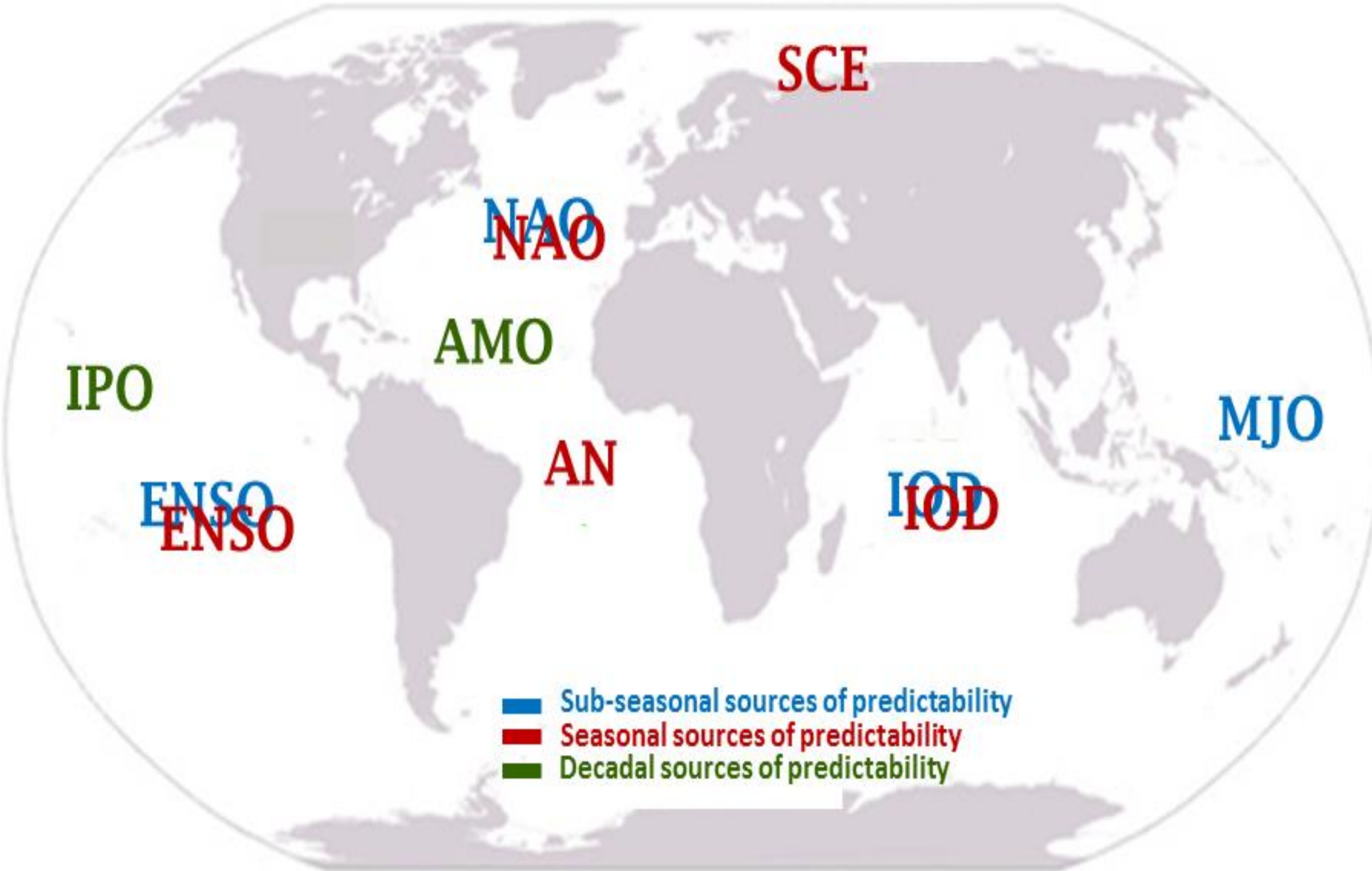


FIGURE 1 | Correlation between the ERSST[38] SST Niño 3.4 index (average temperature over 5°N–5°S, 170°–120°W) and the GPCCv5[39] gridded precipitation over the period 1960–2009. (a) March to May, (b) June to August, (c) September to November, and (d) December to February.

Sources of predictability of wind



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Methodology

Methodology

Download climate predictions:

- Sub-seasonal
- Seasonal
- Decadal

Comparison with observations

Sources of predictability

Predictability assessment

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Preliminary results: Sub-seasonal predictions

Sub-seasonal prediction systems

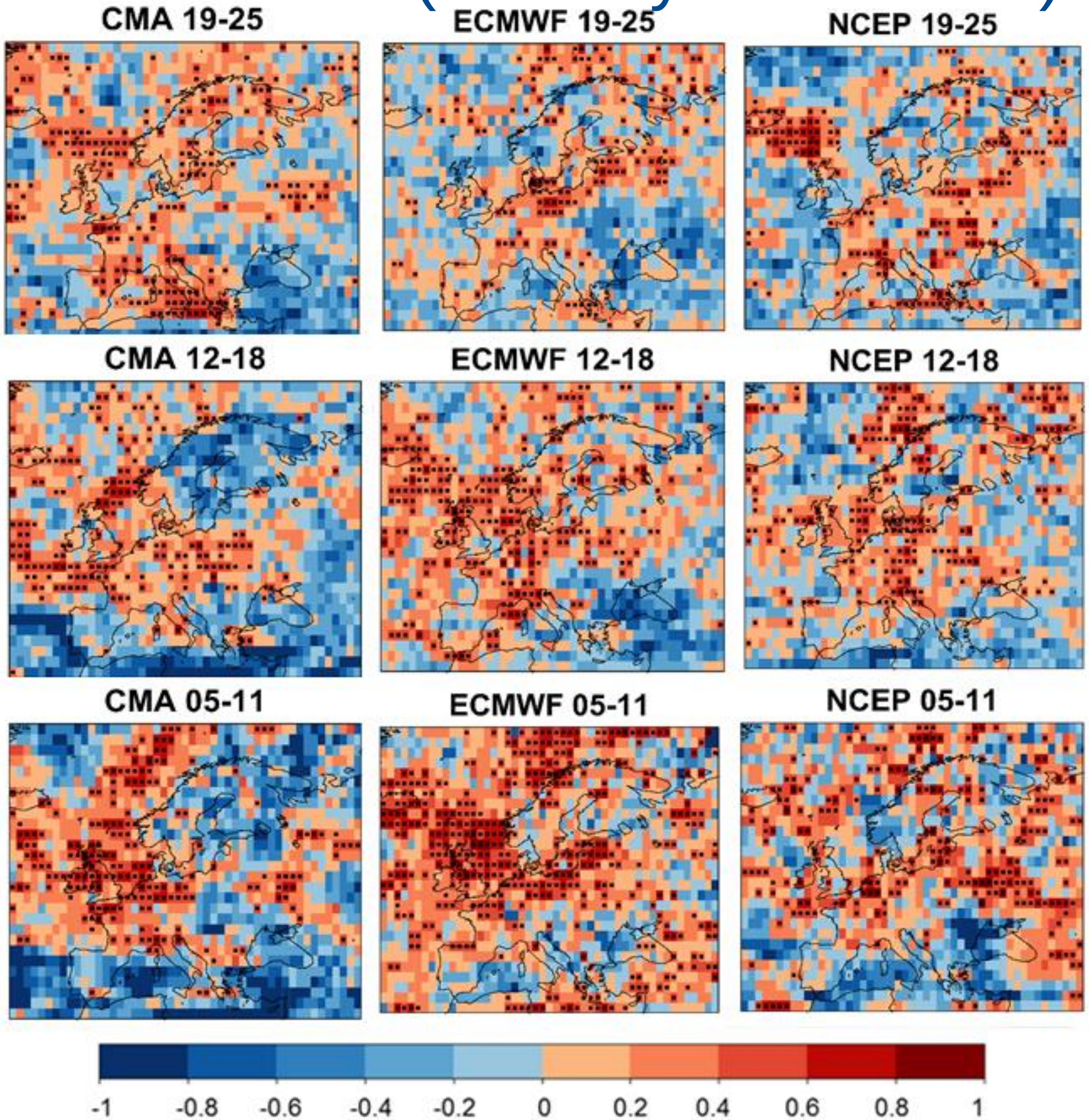
Subseasonal-to-Seasonal S2S Prediction Project

http://s2sprediction.net

Status on 1st July 2015	Time range	Resolution	Ens. Size	Frequency	Re-forecasts	Rfc length	Rfc frequency	Rfc size
BoM (ammc)	d 0-60	T47L17	33	2/week	fix	1981-2013	6/month	33
CMA (babj)	d 0-60	T106L40	4	daily	fix	1994-2014	daily	4
EC (cwao)	d 0-32	0.6x0.6 L40	21	weekly	on the fly	1995-2012	weekly	4
ECMWF (ecmf)	d 0-46	T639/319 L91	51	2/week	on the fly	past 20 years	2/week	11
ISAC-CNR (isac)	d 0-32	0.75x0.56 L54	40	weekly	fix	1981-2010	6/month	1
HMCR (rums)	d 0-63	1.1x1.4 L28	20	weekly	fix	1985-2010	weekly	10
JMA (rjtd)	d 0-34	T319L60	25	2/week	fix	1981-2010	3/month	5
KMA (rksl)	d 0-60	N216L85	4	daily	on the fly	1996-2009	4/month	3
Météo-France (lfpw)	d 0-61	T255L91	51	monthly	fix	1993-2014	2/monthly	15
NCEP (kwbc)	d 0-44	T126L64	16	daily	fix	1999-2010	day	4
UKMO (egrr)	d 0-60	N216L85	4	daily	on the fly	1996-2009	4/month	3

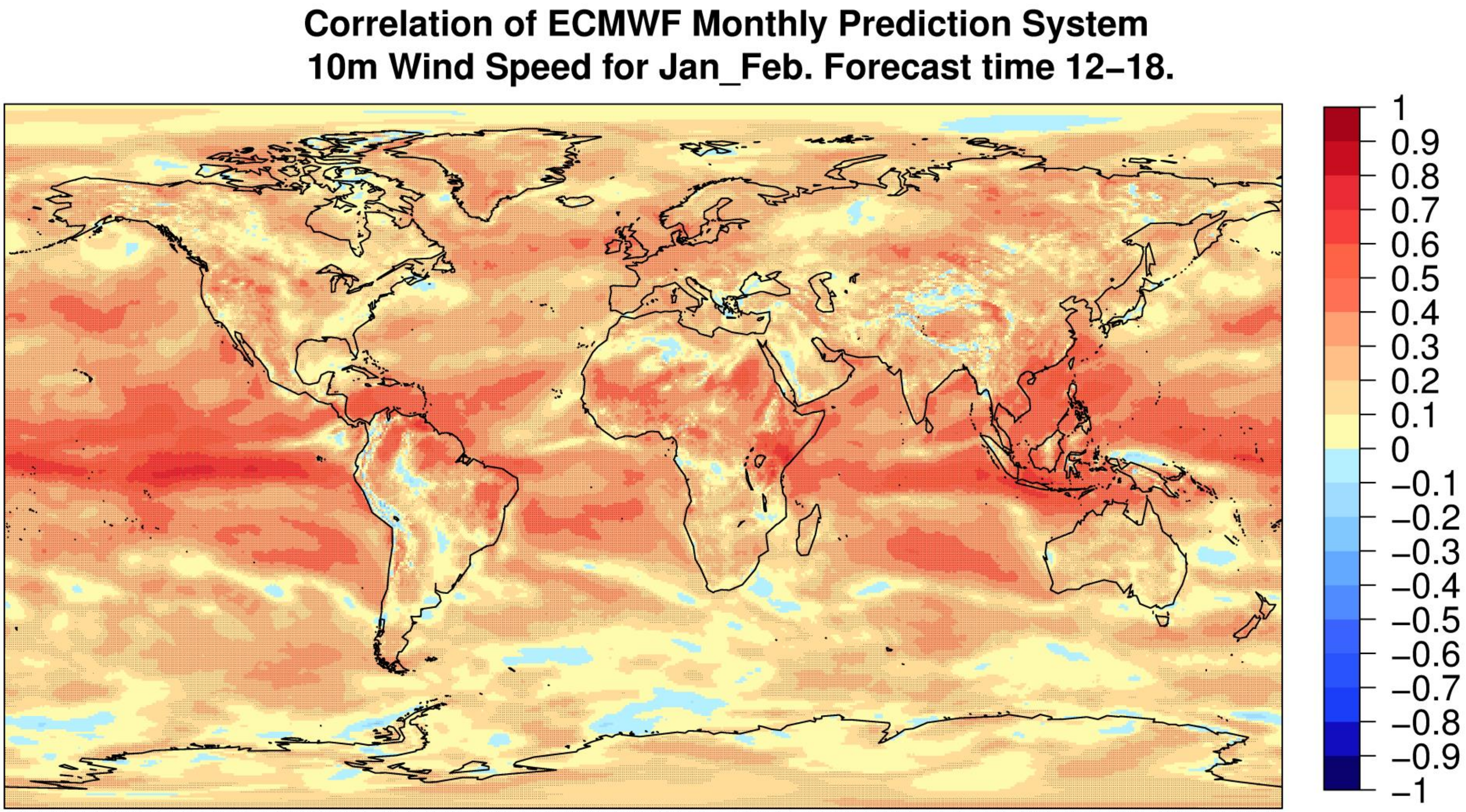
- Comparison of the different subseasonal prediction systems.
- Evolution of the skill with the lead time for the 10m wind speed predictions.

Correlation (January 1995-2014)



- The CMA prediction system displays lower correlations than those from ECMWF and NCEP.
- The considered S2S prediction systems show statistically significant levels of correlation for the three lead times.
- The results enhance our confidence in the ability of the systems to forecast wind speed, however the sources of predictability need to be further explored.

Sub-seasonal predictability



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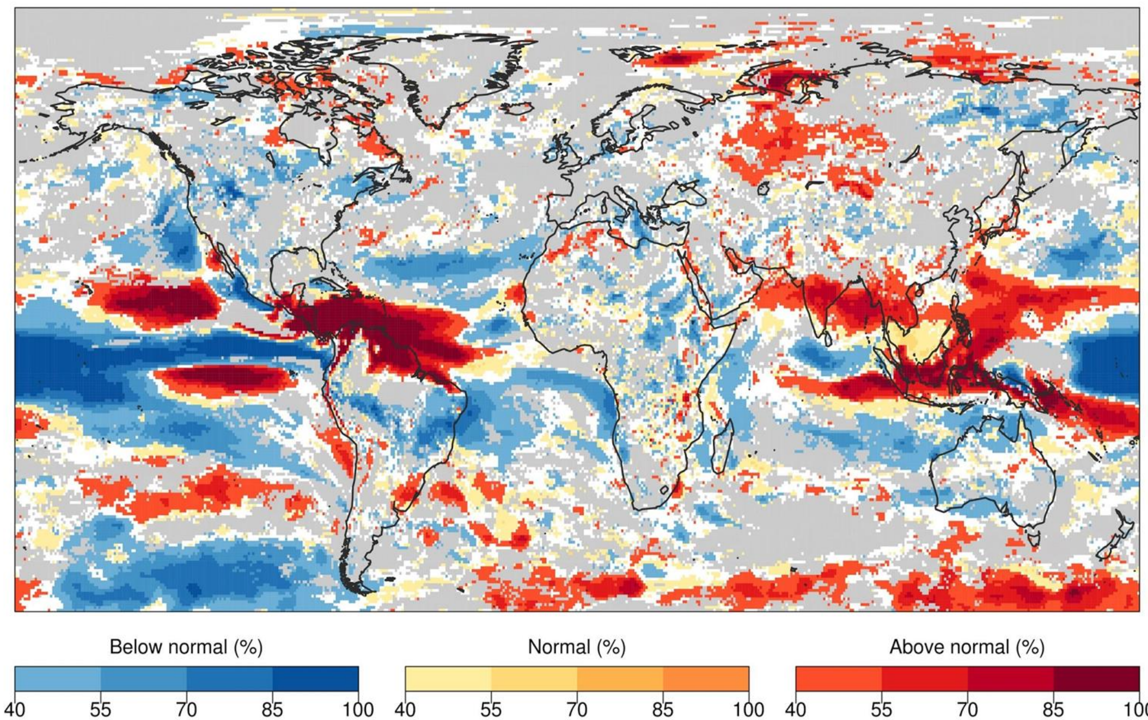
Preliminary results: Seasonal predictions

Seasonal prediction system

- Data from **ECMWF** (European Centre for Medium-Range Weather Forecasts)
- We assess the global behavior providing **probabilistic predictions**
- Aggregated output in **terciles**:
  - Above normal
  - Normal
  - Below normal



Wind speed prediction for June 1st - August 31st 2015, issued on May 1st 2005.
The most likely wind power category (below normal, normal or above normal), and its percentage probability to occur is shown. "Normal" represents the average of the past. White areas show where the probability is <40% and approximately equal for all three categories. Grey areas show where the climate prediction model does not improve upon the standard and current approach, which projects past climate data into the future.

Seasonal predictability in Europe

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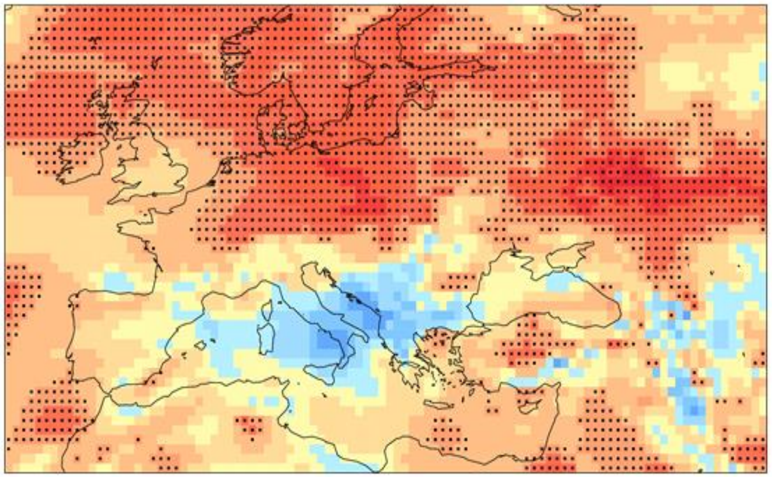
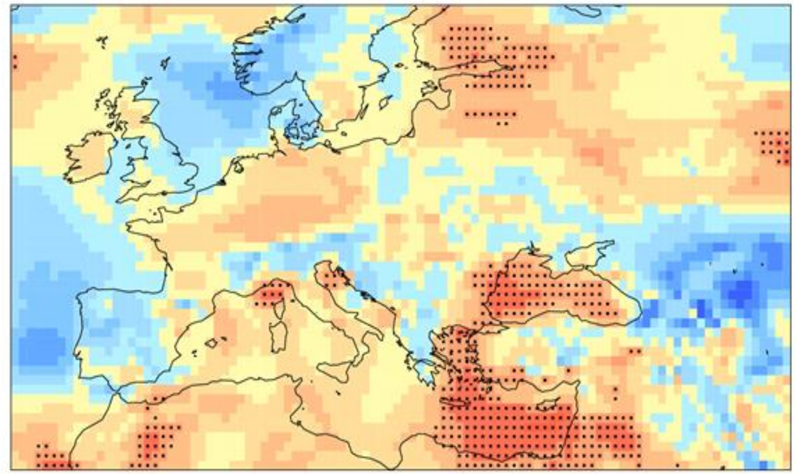
Correlation Skill Score. 10-m wind speed. ECMWF S4 with starts dates once a year on first of December and ERA-Interim from 1981 to 2013. Raw data.

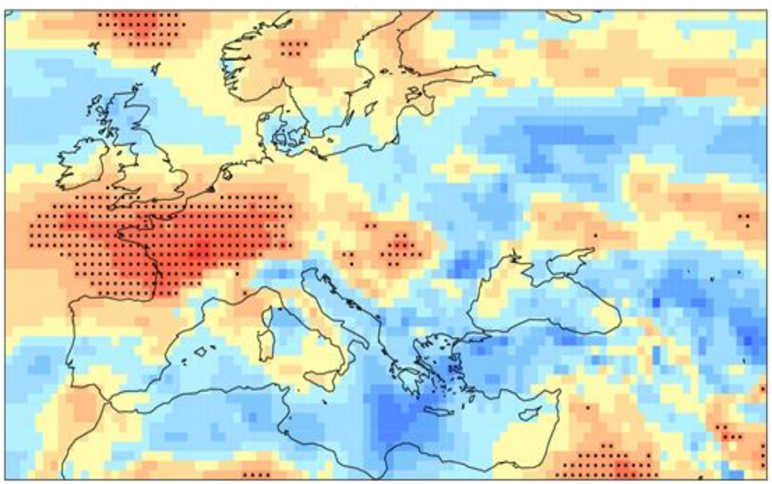
Lead 0. Average over months 1-3



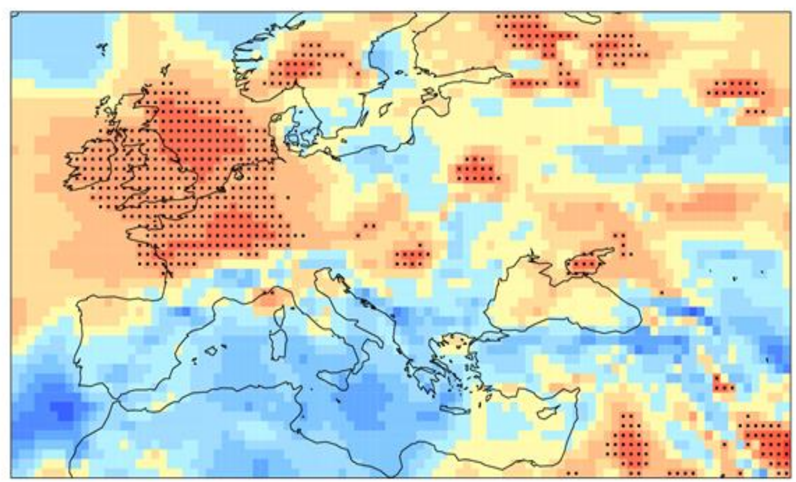
Lead 1. Average over months 2-4

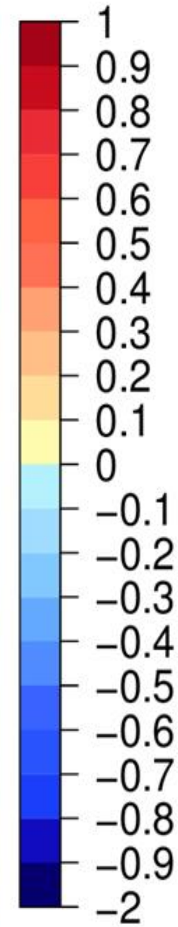


Lead 2. Average over months 3-5

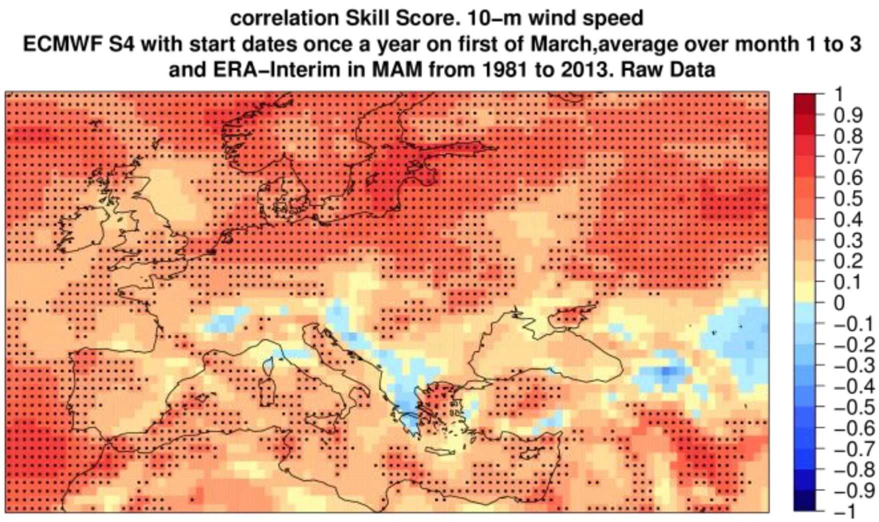


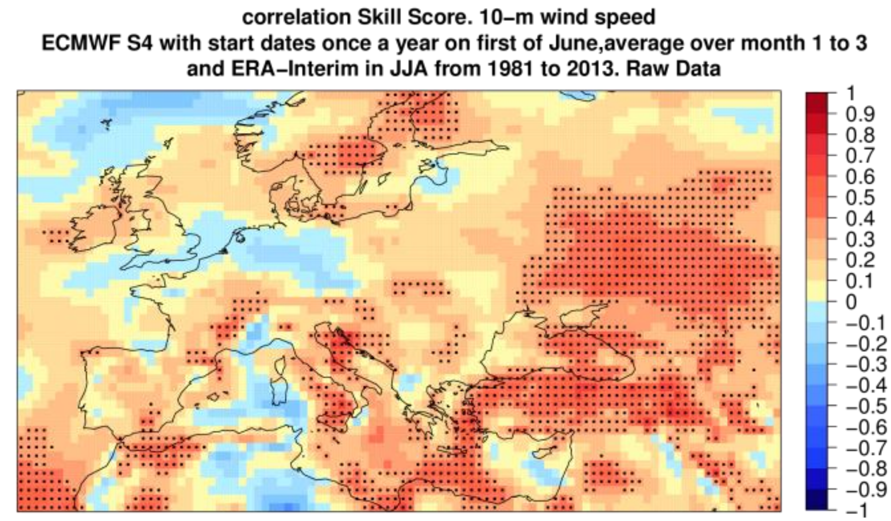
Lead 3. Average over months 4-6

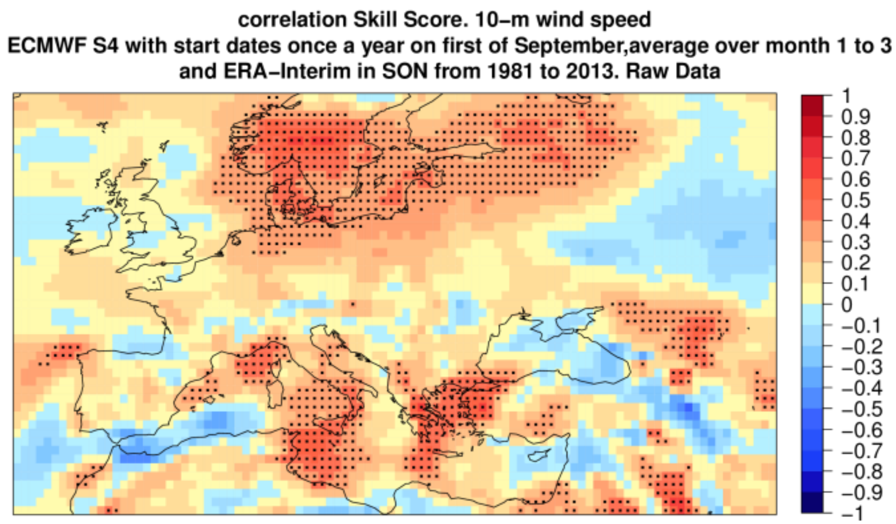


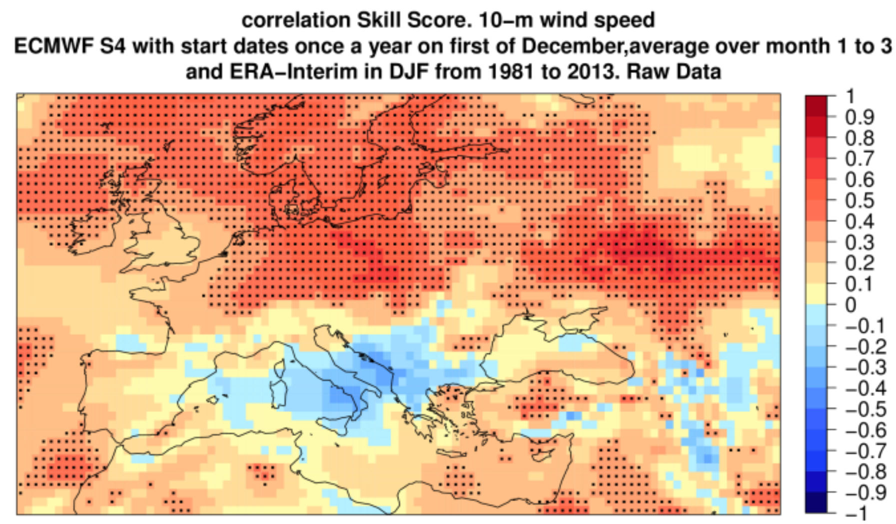


Seasonal predictability in Europe









Seasonal predictability in Europe

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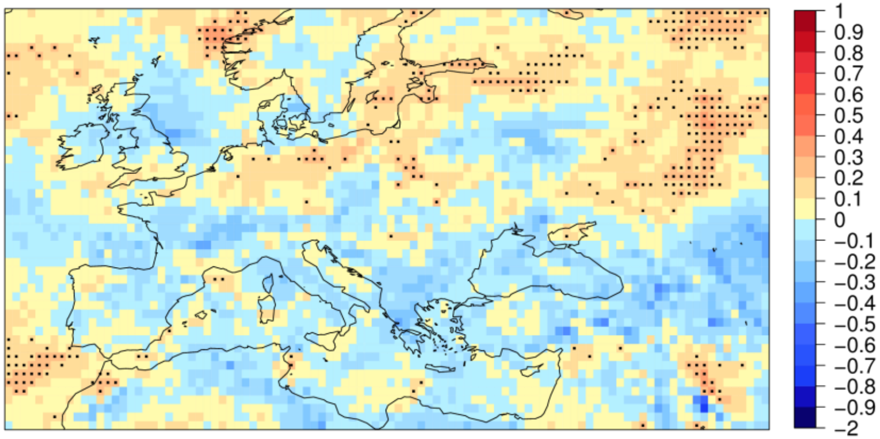
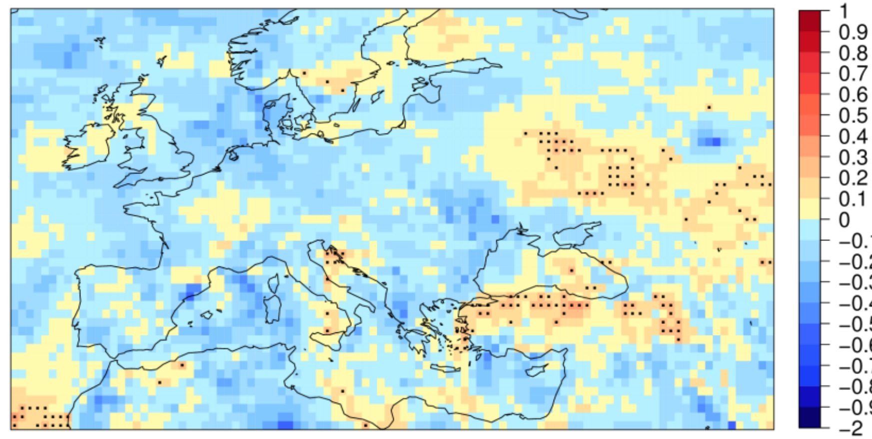
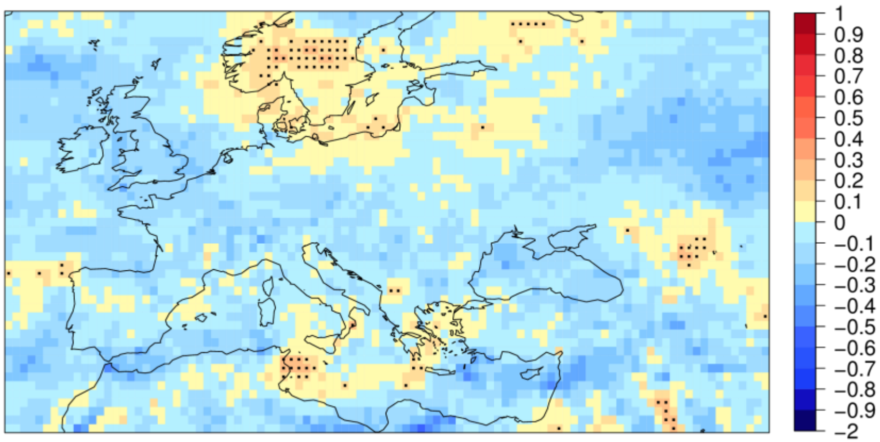
RPSS Skill Score. 10−m wind speed
ECMWF S4 with start dates once a year on first of March,average over month 1 to 3
and ERA−Interim in MAM from 1981 to 2013. Raw Data



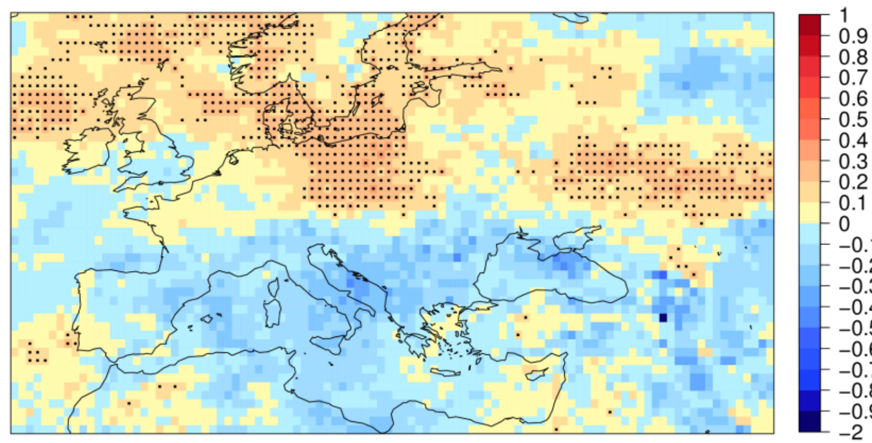
RPSS Skill Score. 10−m wind speed
ECMWF S4 with start dates once a year on first of June,average over month 1 to 3
and ERA−Interim in JJA from 1981 to 2013. Raw Data



RPSS Skill Score. 10−m wind speed
ECMWF S4 with start dates once a year on first of September,average over month 1 to 3
and ERA−Interim in SON from 1981 to 2013. Raw Data

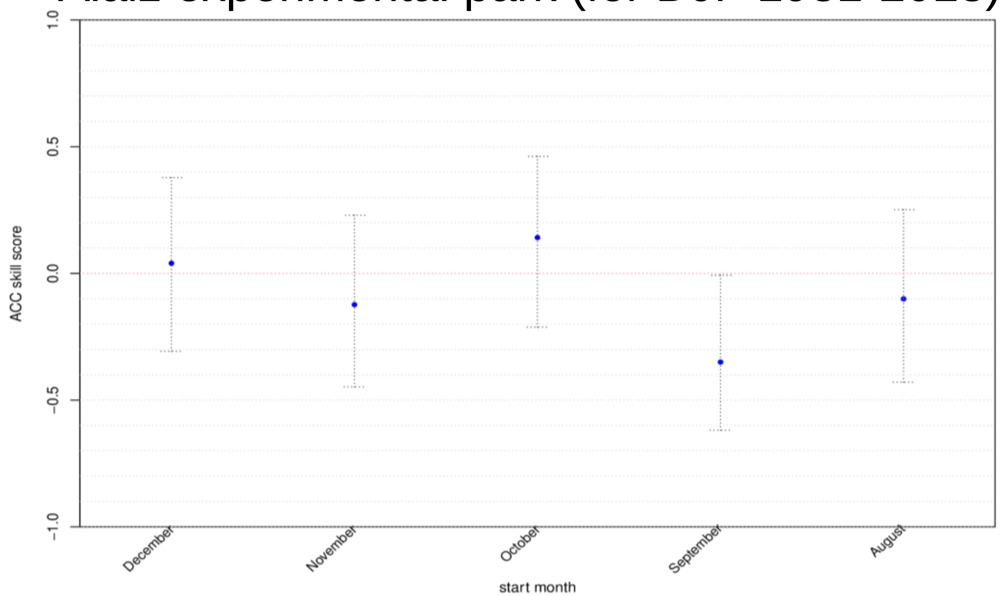


RPSS Skill Score. 10−m wind speed
ECMWF S4 with start dates once a year on first of December,average over month 1 to 3
and ERA−Interim in DJF from 1981 to 2013. Raw Data

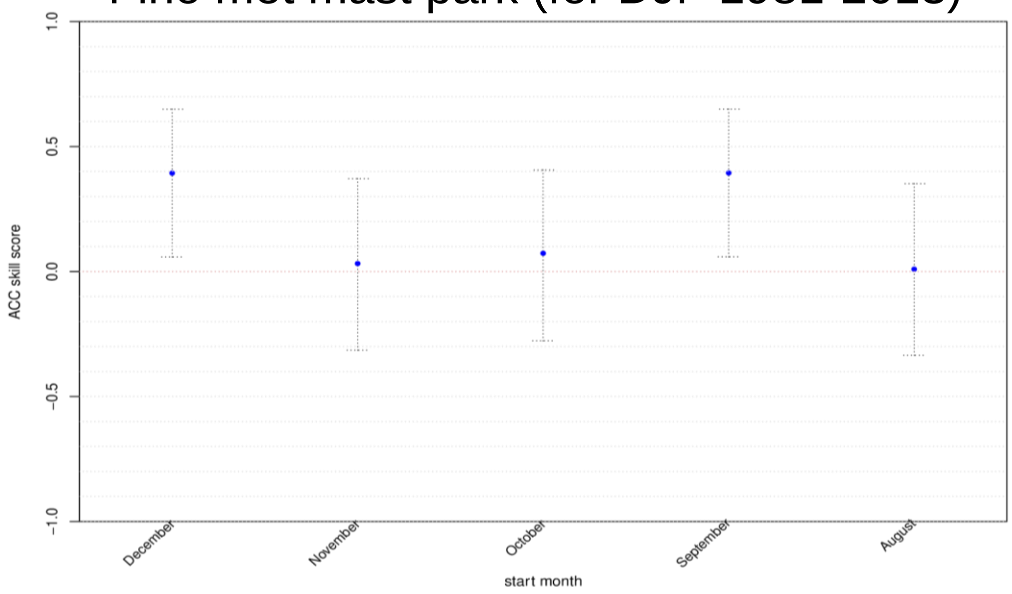


Seasonal predictability at specific sites

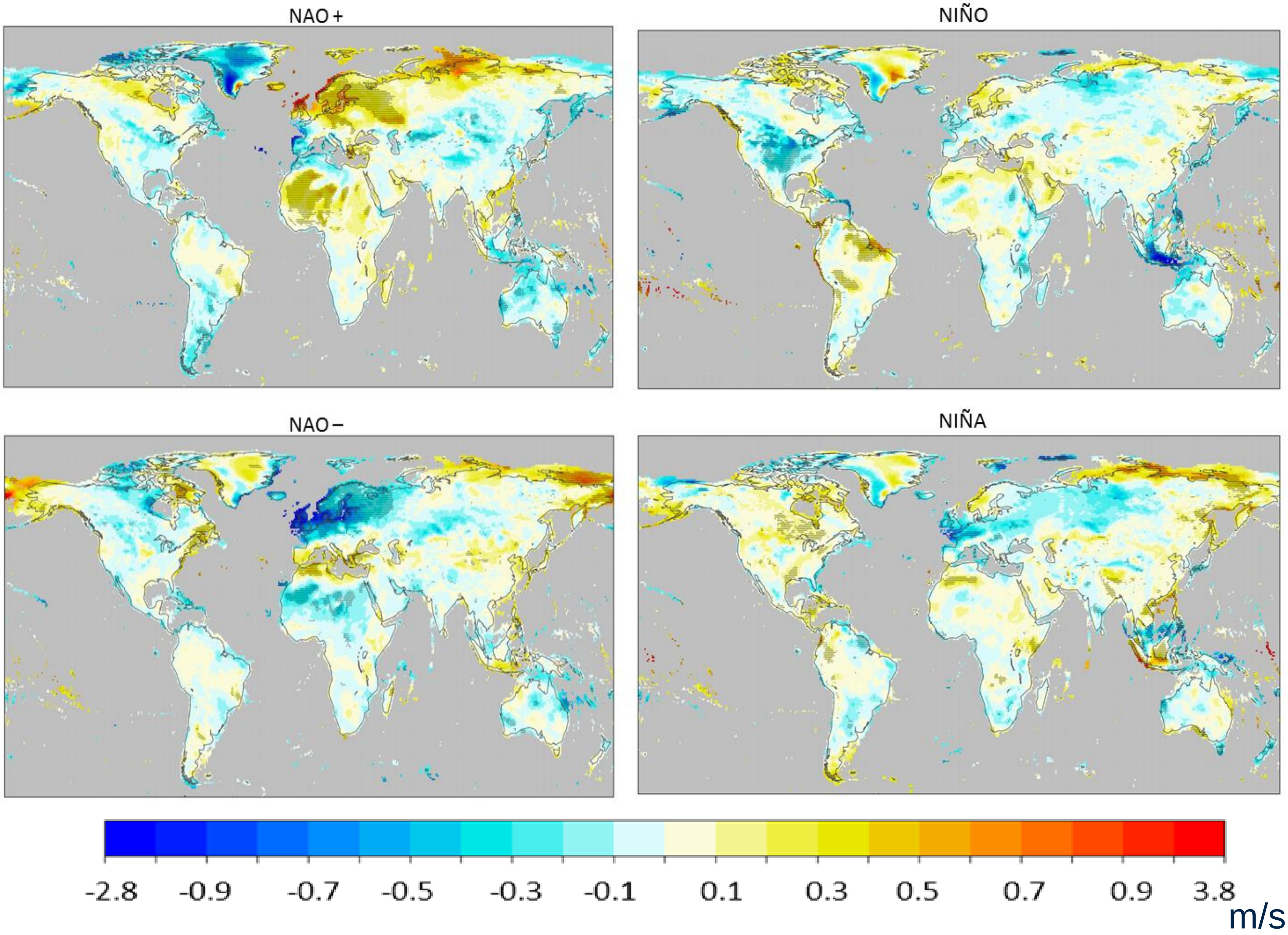
Alaiz experimental park (for DJF 1981-2013)



Fino met mast park (for DJF 1981-2013)



Wind speed drivers: ENSO and NAO



Conclusions and future work

Conclusions

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- Preliminary results detected at least two windows of opportunity (potential forecast skill) over Europe:
    - Sub-seasonal; lead time of 12-18 days
    - Seasonal scale; lead time of one month.
    - Central and Northern Europe
    - Winter months of December-February.

- For further information, see D3.2. Description of the predictability assessment methodology.

Future work

Next steps

1) Verification against other data bases: NCEP reanalysis, JRA, 10m measurements

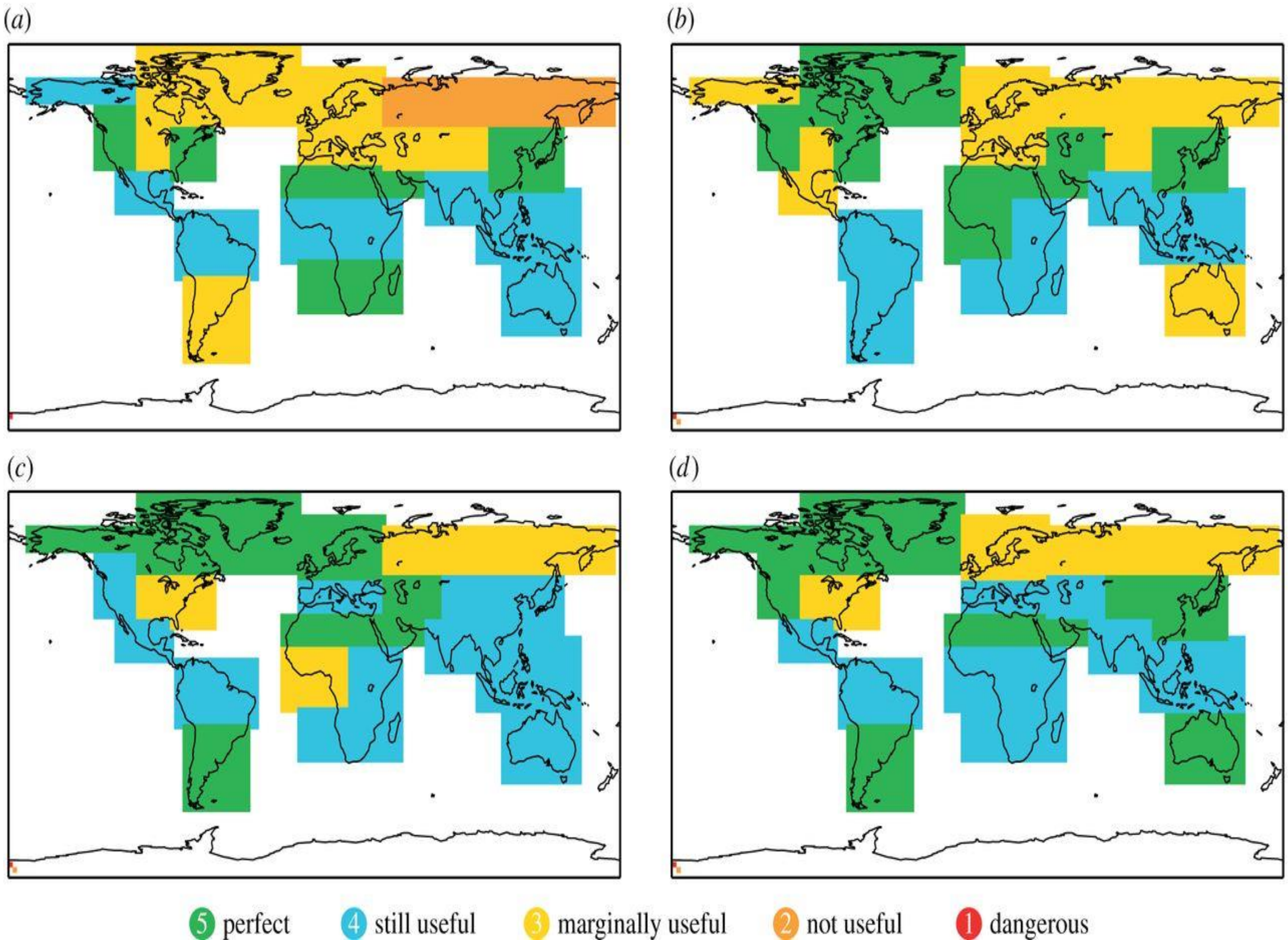
2) Apply bias-correction techniques

3) Assessment of different forecast systems

4) Categorization of regions

5) Summarize all information in easy interpretable format

Future work


(a)
(b)
(c)
(d)
5 perfect
4 still useful
3 marginally useful
2 not useful
1 dangerous

Further discussion:

1) Which format/kind of information will be uploaded to the GIS wind resources map? Rasters? Vectorial layers? Both? Could each geographical point have value tables or graphs associated?

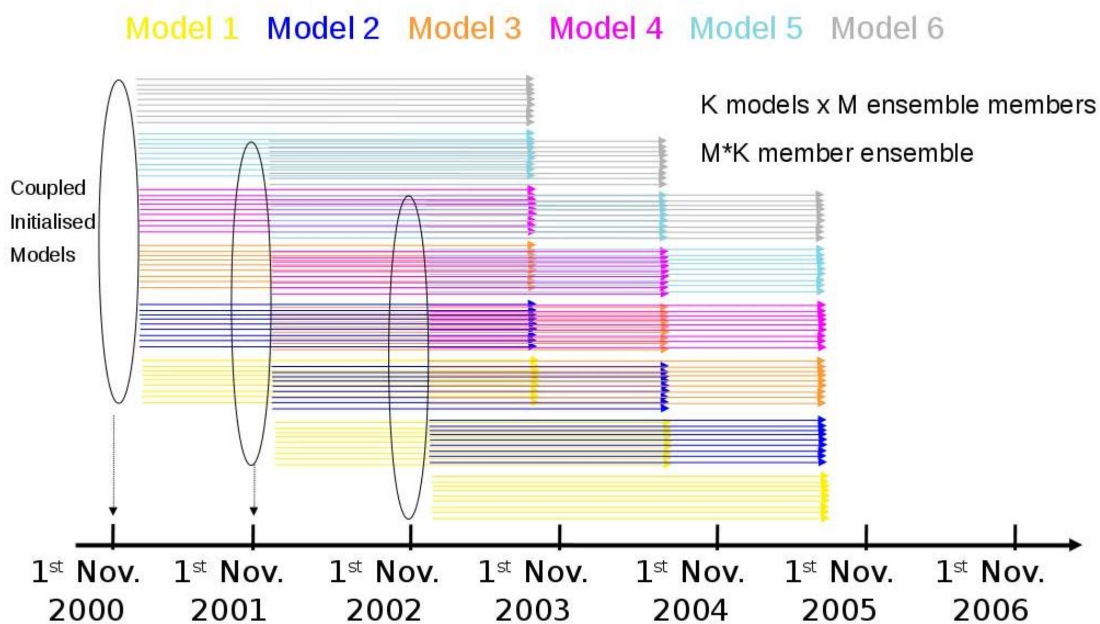
2) When the 10m European data base will be available?

http://project-ukko.net/

Methodology description

Decadal predictions are a field of research that is on early stages, so we lack examples illustrating the methodology

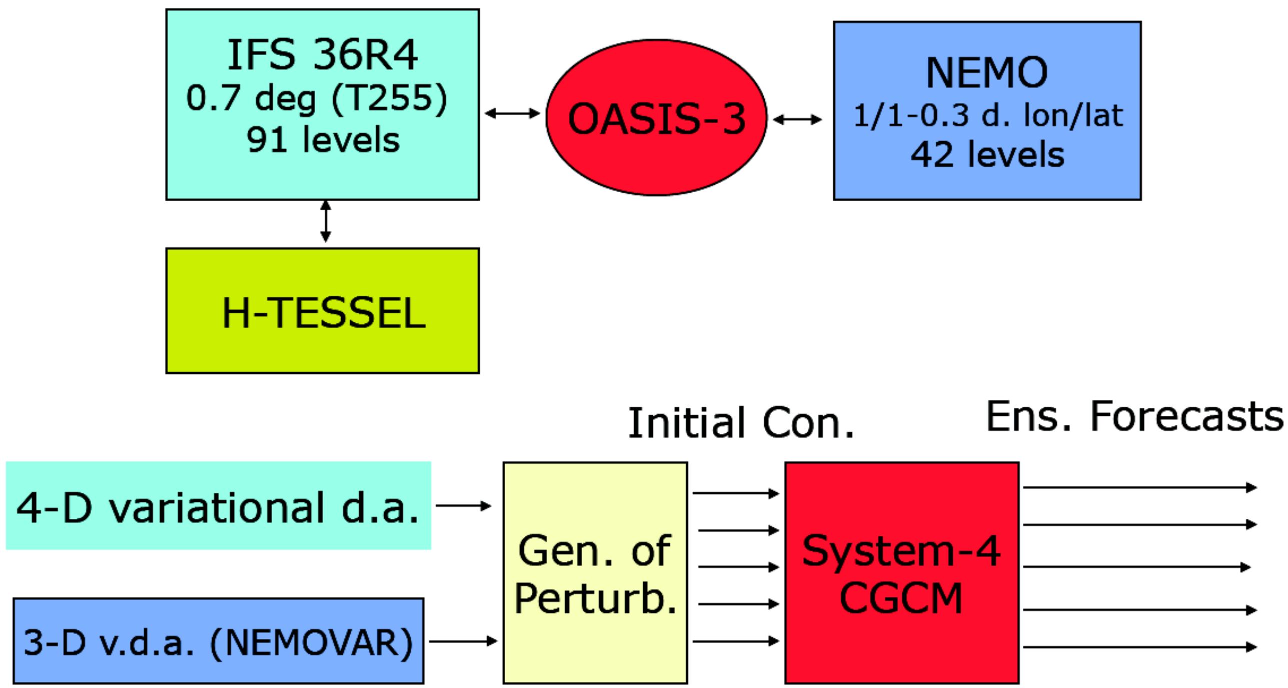
Multimodel approach: CMIP5 decadal dataset



Planned analyses

- Skill evaluation of individual models and comparison with the skill of the multi-model by means of a Taylor diagram.
- The worst models are then discarded and the remaining models are used to generate the new, improved multi-model.
- Assessment of the AMO and IPO roles in the wind speed variability at decadal time-scales.

The new ECMWF Seasonal forecast system (Sys-4)



ECMWF System 4: main features (1)

- **New ocean model : NEMO v. 3.0 + 3.1 coupling interface**

ORCA-1 configuration (~1-deg. resol., ~0.3 lat. near the equator)
42 vertical levels, 20 levels with z < 300 m

- **Variational ocean data assimilation (NEMOVAR)**

3-D var with inner and outer loop
Collaboration with CERFACS, UK Met Office, INRIA
First re-analysis (1957-2009), no assim. of sea-level anomalies
Final re-analysis (ORA-S4) and real-time system including SLA

- **IFS model cycle: 36r4 (op. Nov. 2010-May 2011), T255-L91**

New physics package, including H-TESSEL land-surface scheme, new snow model, new land surface initialization

- **Prescribed sea-ice conc. with sampling from recent years**

ECMWF System 4: main features (2)

- **Operational forecasts**

51-member ensemble from 1st day of the month
released on the 8th
7-month integration

- **Experimental ENSO outlook**

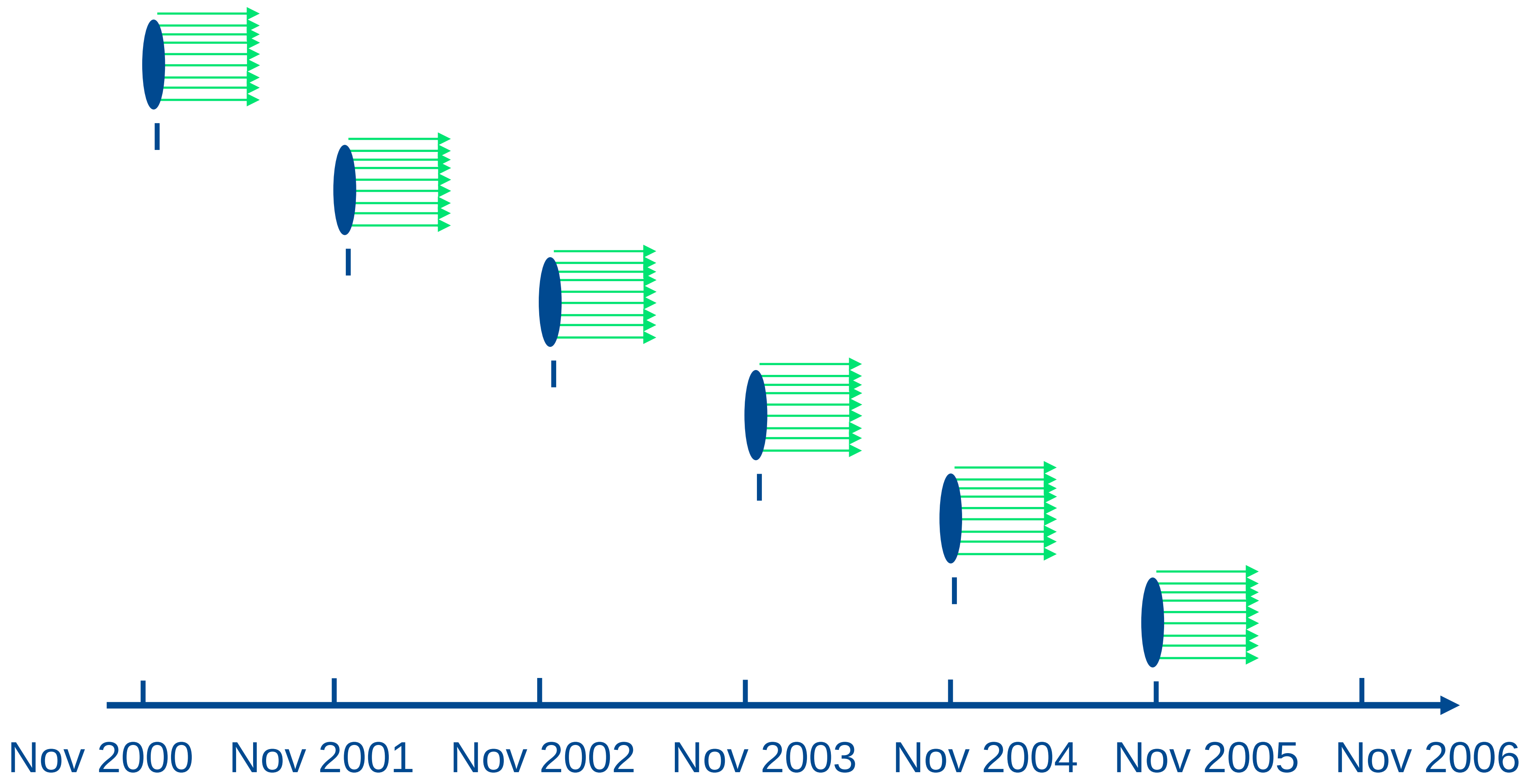
13-month extension from 1st Feb/May/Aug/Nov
15-member ensemble

- **Re-forecast set**

33years, start dates from 1 Jan 1981 to 1 Dec 2013
15-member ensembles, 7-month integrations
51-member ensembles from 1st Feb/May/Aug/Nov
13-month extension from 1st Feb/May/Aug/Nov

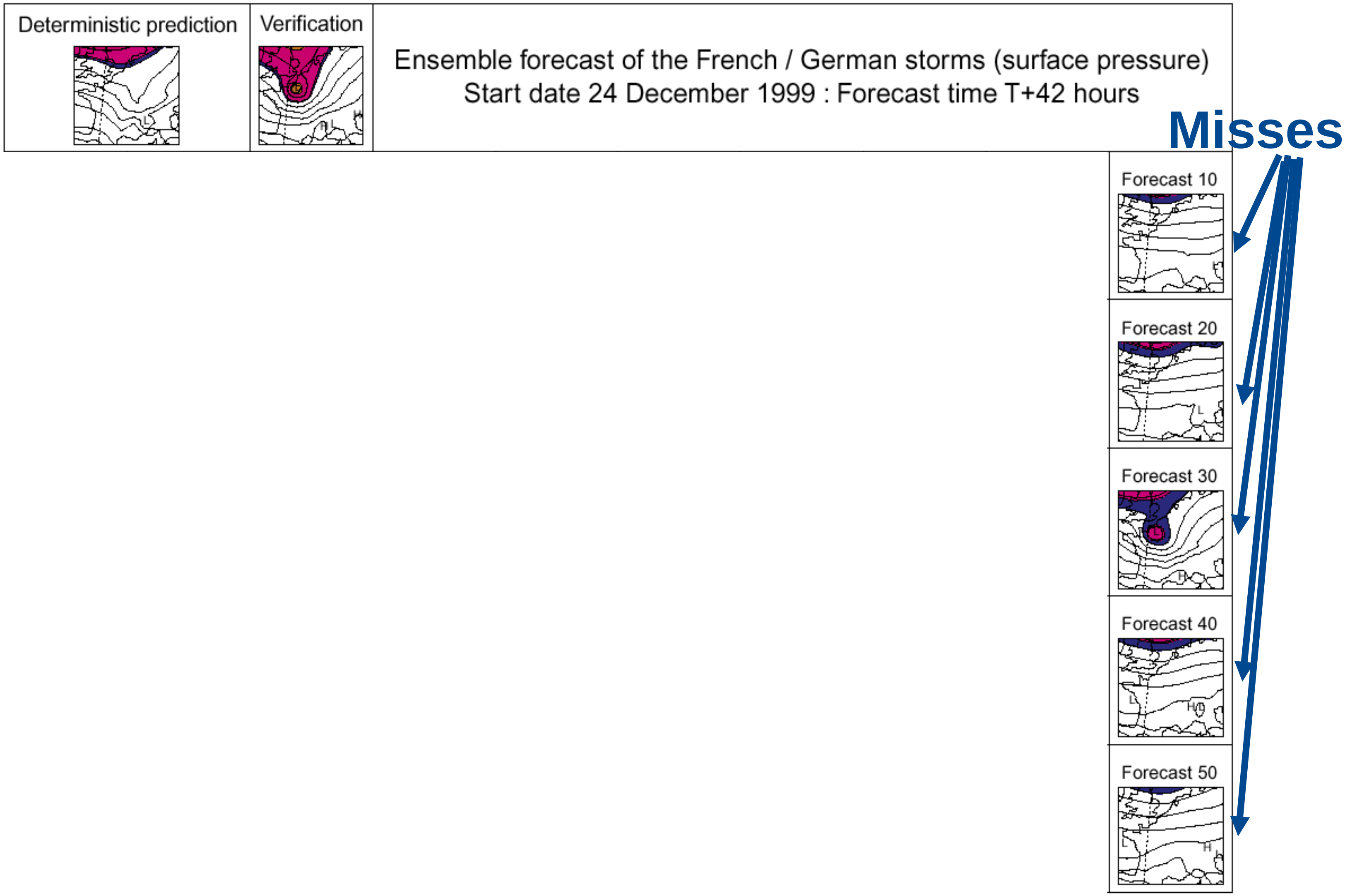
Ensemble predictions

Ensemble forecast system



How many members: ensemble size

ECMWF forecasts (D+42) for the storm Lothar



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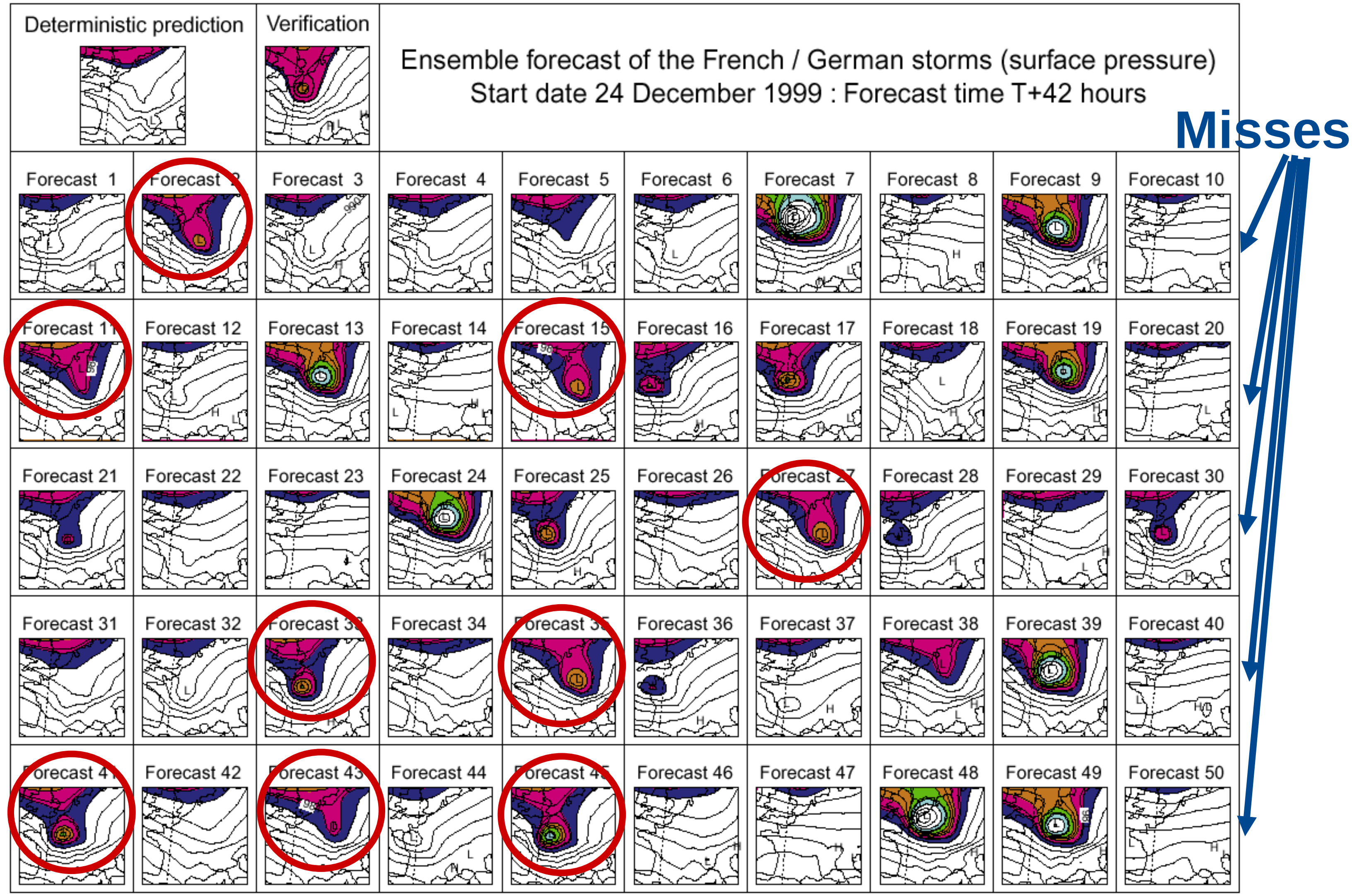

How many members: ensemble size

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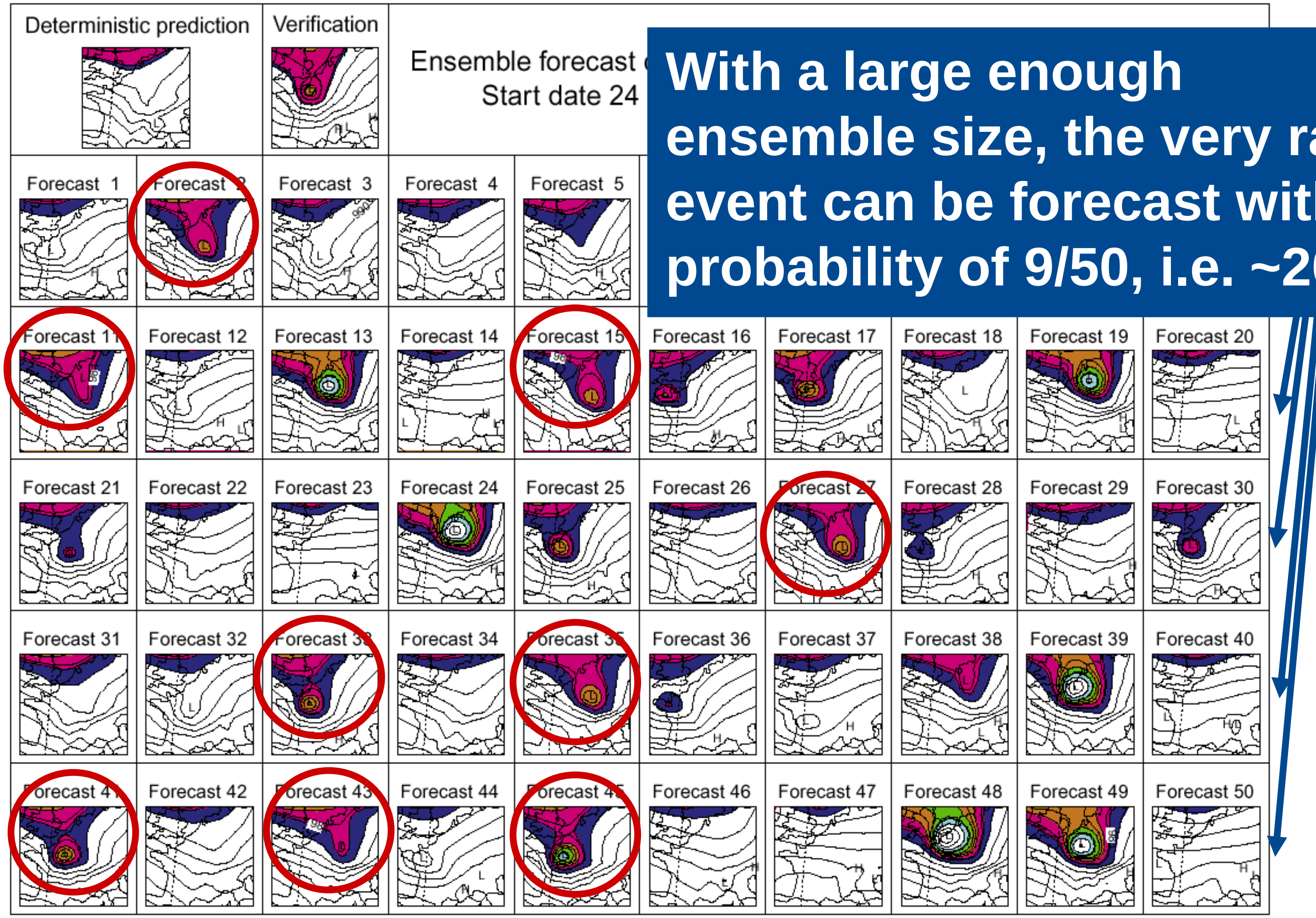
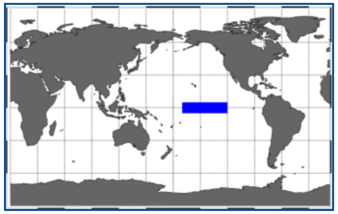
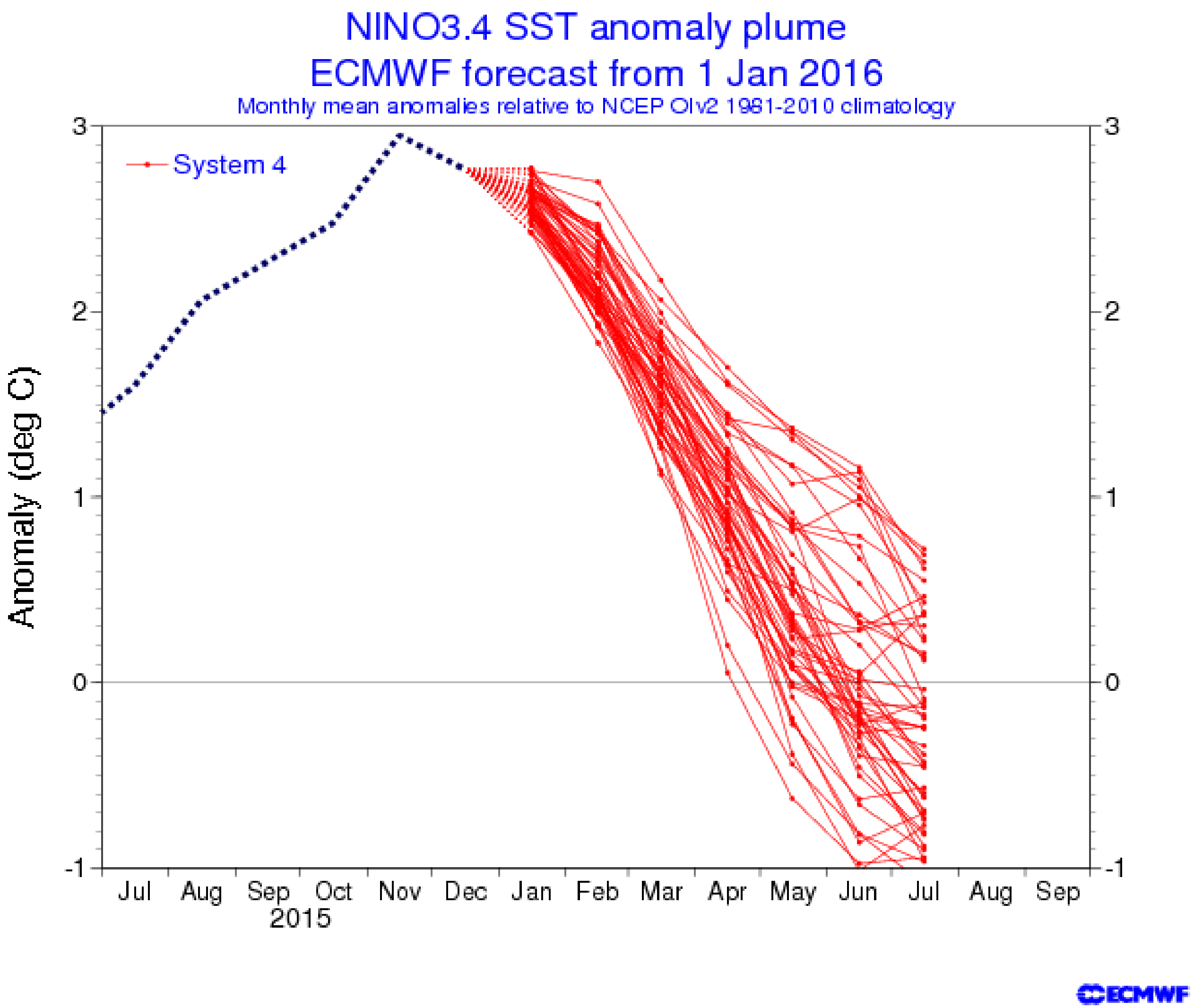


With a large enough ensemble size, the very rare event can be forecast with a probability of 9/50, i.e. ~20%

ENSO ensemble predictions

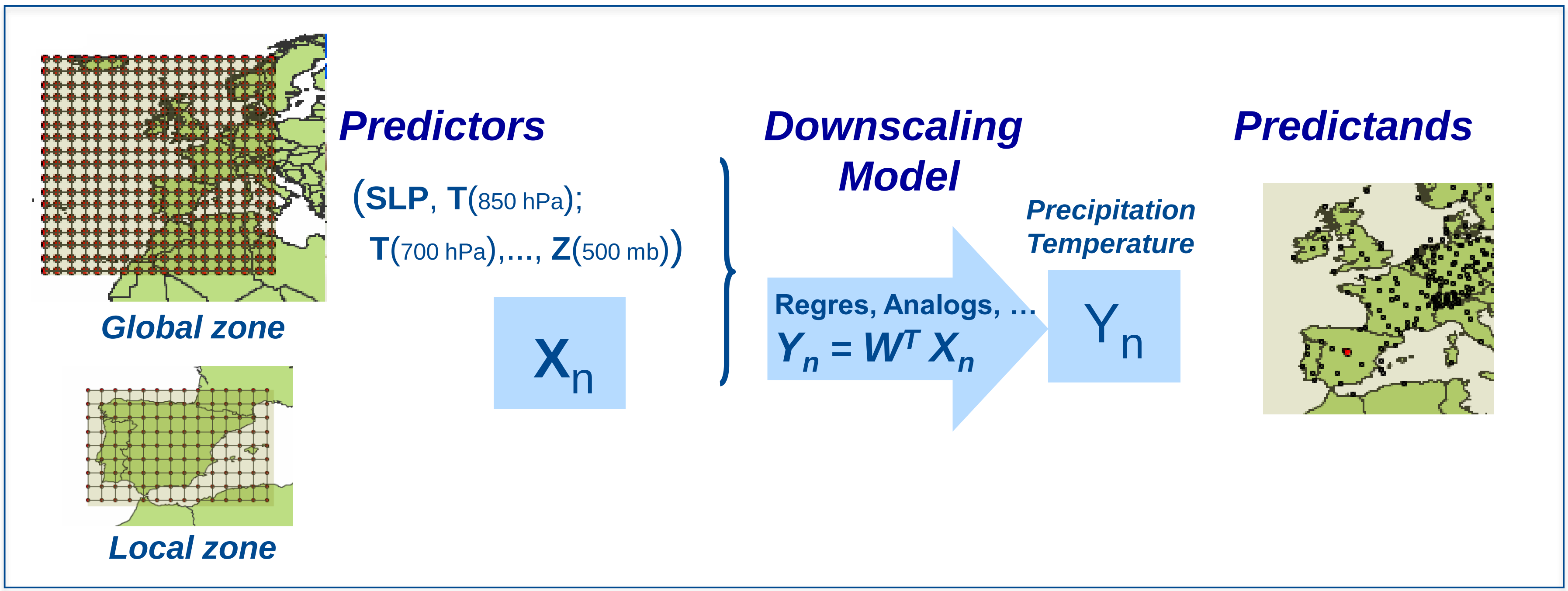




Bias correction/downscaling

Perfect prognosis approach:

- In the training phase the statistical model is calibrated using observational data for both the predictands and predictors (e.g. reanalysis data)
- Typical techniques: transfer functions, analogs, weather typing, weather generators, etc. (Maraun et al. 2010)



Source: José M. Gutiérrez, University of Cantabria