

Climate predictions for energy

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EERA JP Wind annual event, 17th-18th September 2018, Amsterdam





Context and motivation

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



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





Context and motivation

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





Climate predictions

Weather forecasts

1-15 days

Climate predictions
Sub-seasonal Seasonal

10-32 days 1-15 months

Decadal

1-30 years

Climate-change projections

20-100 years

Time

Initial-value driven

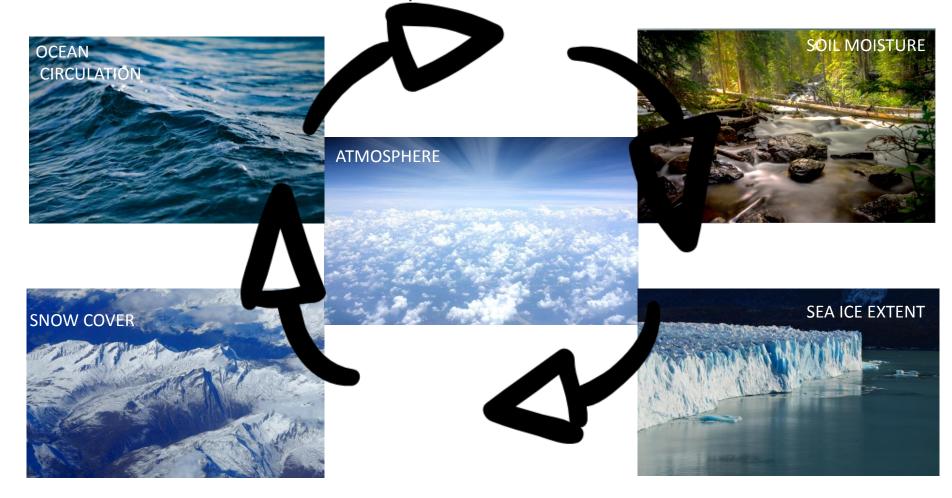
Boundary-condition driven

Adapted from: Meehl et al. (2009)



Predictability

How 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.

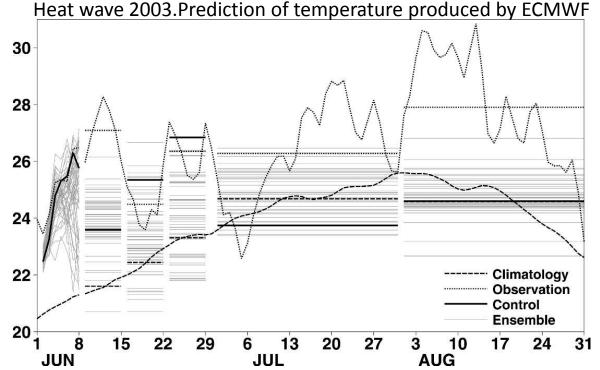


Objective



Objective

S2S4E will offer an innovative service to improve RE variability management by developing new research methods exploring the frontiers of weather conditions for future weeks and months. The main output of S2S4E will be a user co-designed Decision Support Tool (DST) that for the first time integrates sub-seasonal to seasonal (S2S) climate predictions with RE production and electricity demand.



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



Applications

Weather forecast

Climate predictions

Sub-seasonal

Seasonal

1-30 years

Decadal

Climate projections or multidecadal

20-100 years

Time

1-15 days

10 d-1 month

1-6 months

1-30 years

Applications for wind/solar/hydro generation

Post-construction decisions ! Post-

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

Applications for demand

Daily operation decisions

Grid operators:

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

Energy traders: Anticipate energy prices.

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

Mid-term planning

Grid operators:

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

Energy traders:

Anticipate energy prices.

S2S4E project

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



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



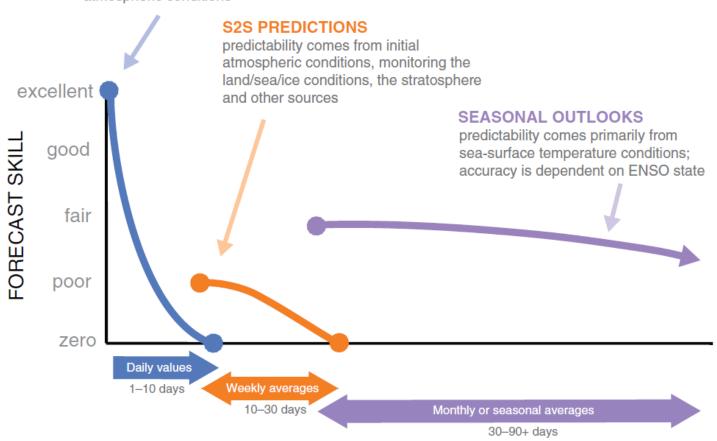
Challenges and opportunities



S2S Forecast range and skill

WEATHER FORECASTS

predictability comes from initial atmospheric conditions

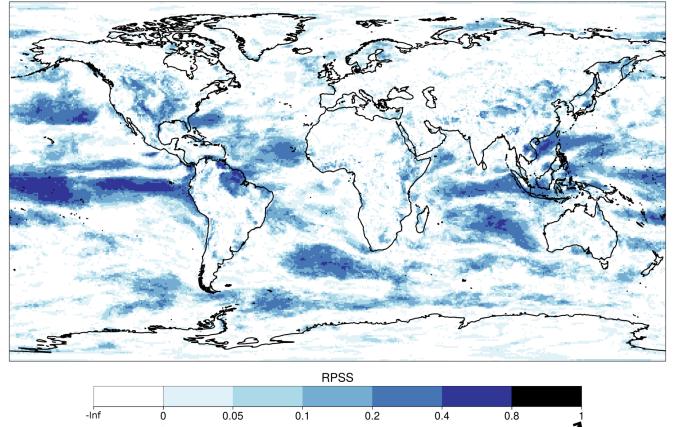


FORECAST RANGE

Qualitative estimate of forecast skill based on forecast range from short-range weather forecasts to long-range seasonal predictions, including potential sources of predictability. Relative skill is based on differing forecast averaging periods. (Source: White et al., 2017)

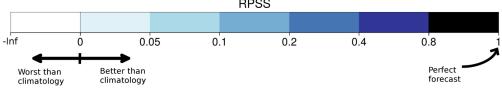


Skill



Skill assessment for DJF (1981-2013)

Displaying: Ranked **Probability Skill Score** [RPSS]

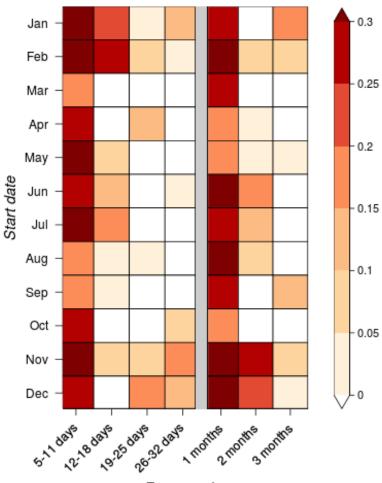


"A prediction has no value without an estimate of forecasting skill based on past performance"



NEWA project, predictability

FairRPSS of ECMWF 10-m wind speed for 1996-2015 over Europe







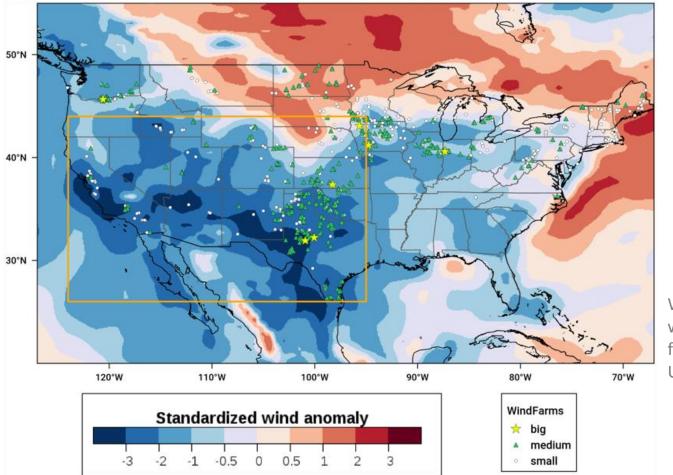
Case study: wind drought in US

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



Wind drought in US

During the first quarter of 2015 the United States experienced a widespread and extended episode of low surface wind speeds. This episode had a strong impact on wind power generation. Some wind farms did not generate enough cash for their steady payments, and the value of wind farm assets decreased.

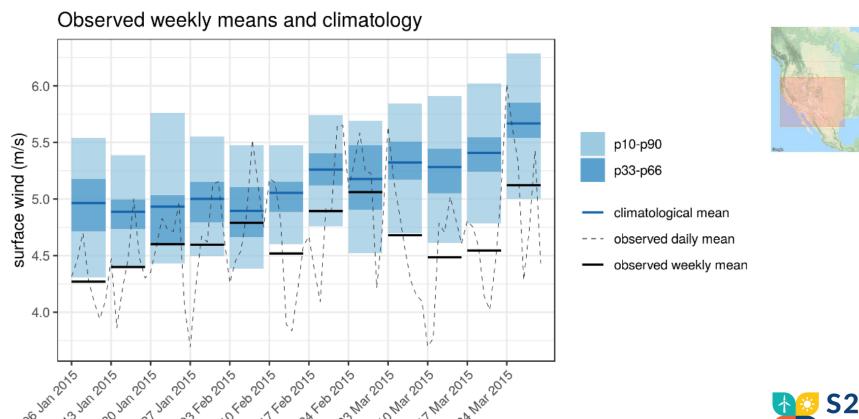


Wind speed anomalies reflecting the wind drought over the United States for the first trimester of 2015. The US wind farm fleet is also shown.



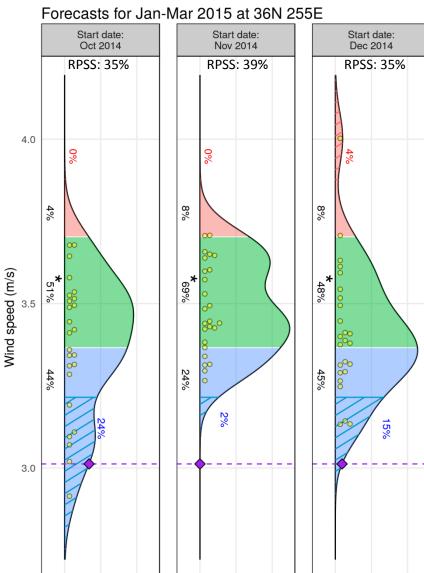
Wind drought in US

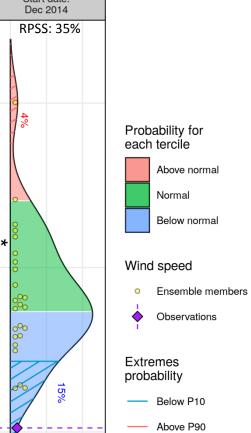
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Available seasonal forecast





System: ECMWF S4
Reanalysis: ERA-Interim
Bias adjusted –calibrated
Hindcast: 1993-2015

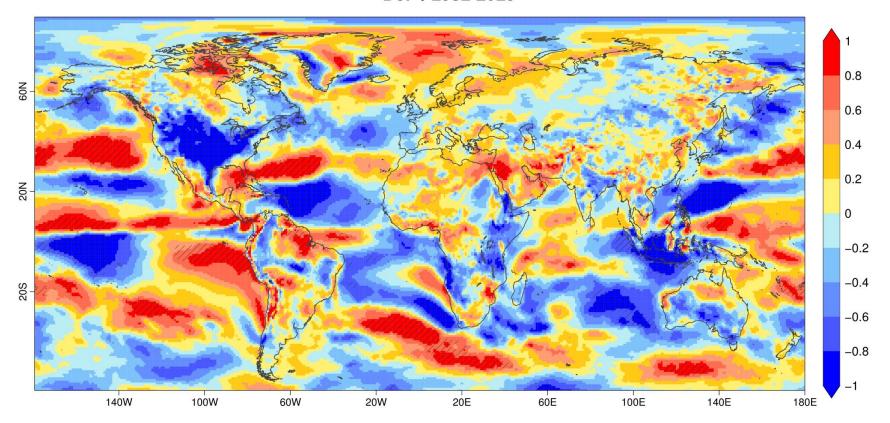
37N 105W

Which decisions would you take in view of those forecasts?



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

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





Causes

120E

40E

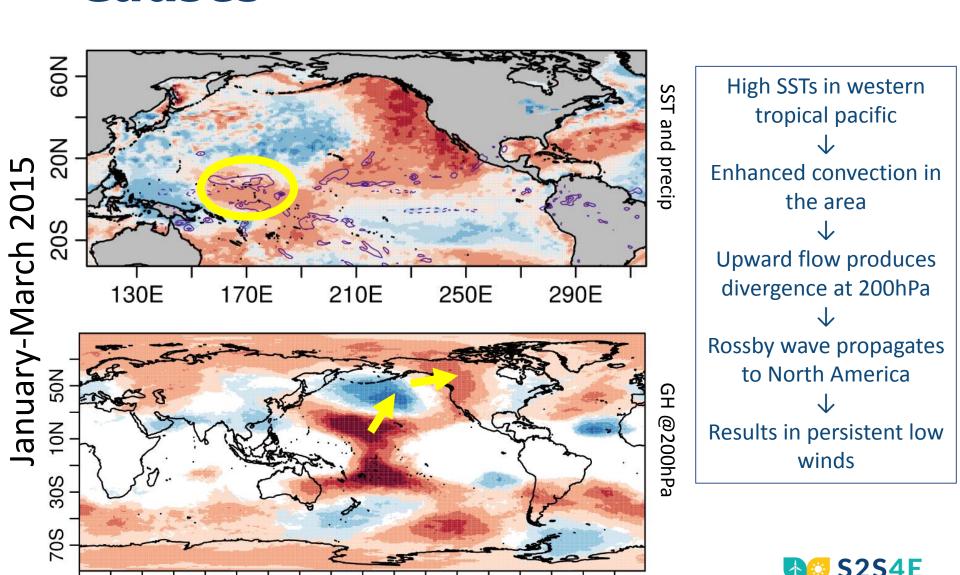
80E

160E

200E

240E

280E



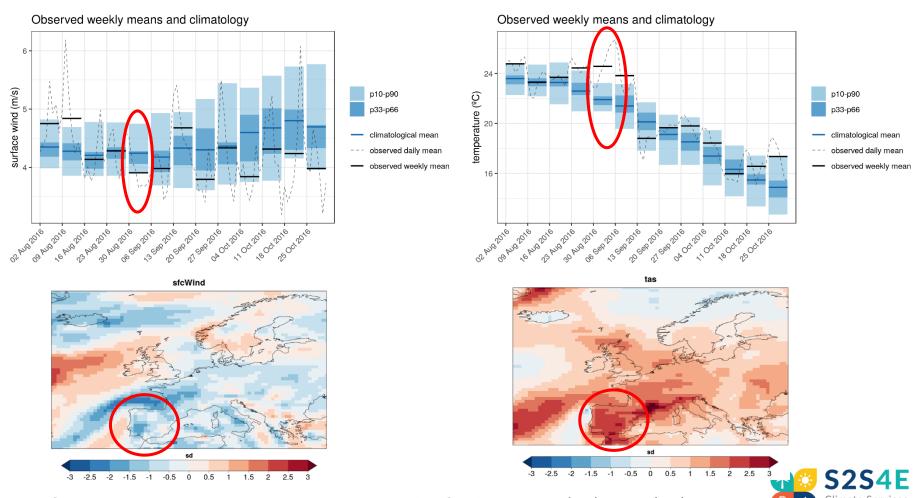
320E

System: EC-EARTH

Case study: heat wave and wind drought in Spain. Sep 2016

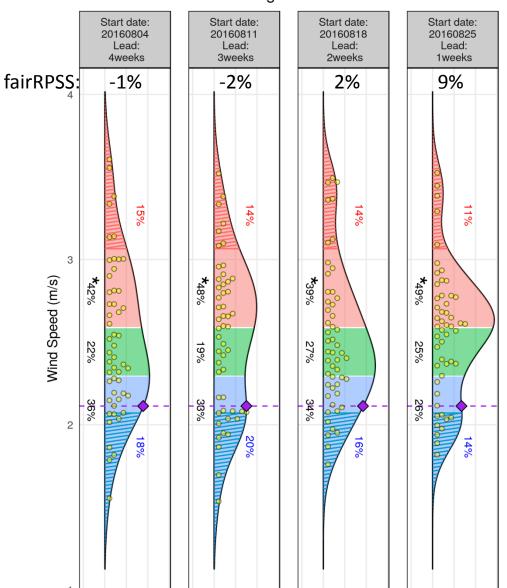


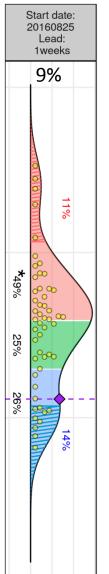
Heat wave and wind drought in Spain. Sep 2016



Forecast available: wind speed

Forecasts for week starting 2016-08-30





System: ECMWF monthly

prediction system

Reanalysis: ERA-Interim Bias adjusted -calibrated

Hindcast: 1996-2015

Lat= 40.5 N/Lon = 358.5 E

Wind speed

Probability for

Normal

Above normal

Below normal

each tercile

- Ensemble members
- Observations

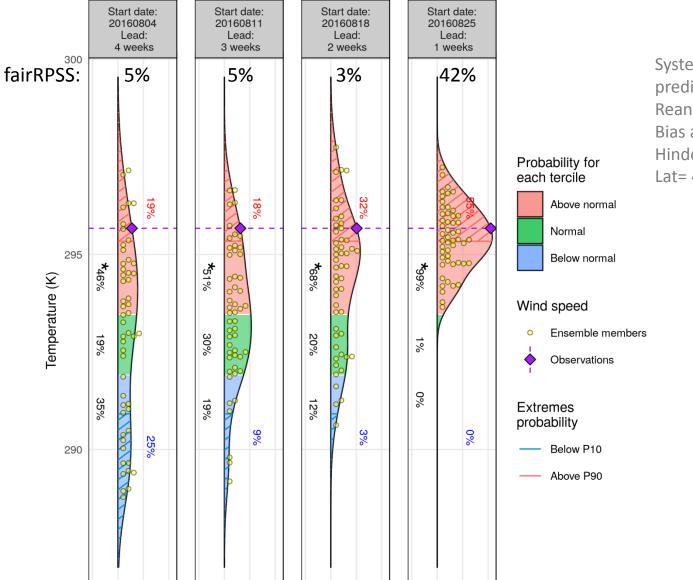
Extremes probability

- Below P10
- Above P90



Forecast available: temperature





System: ECMWF monthly

prediction system

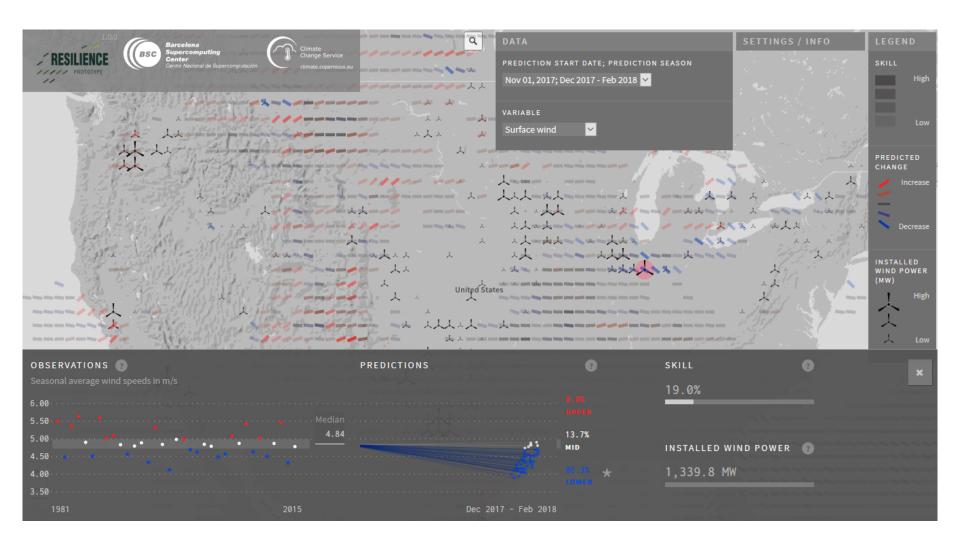
Reanalysis: ERA-Interim Bias adjusted —calibrated

Hindcast: 1996-2015

Lat= 40.5 N/Lon = 358.5 E



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:

- multi-model ensembles
- to improve the utility of forecasts by incorporating skillful information of the large-scale teleconnection patterns at different time scales



Thank you

Get in touch for more information!



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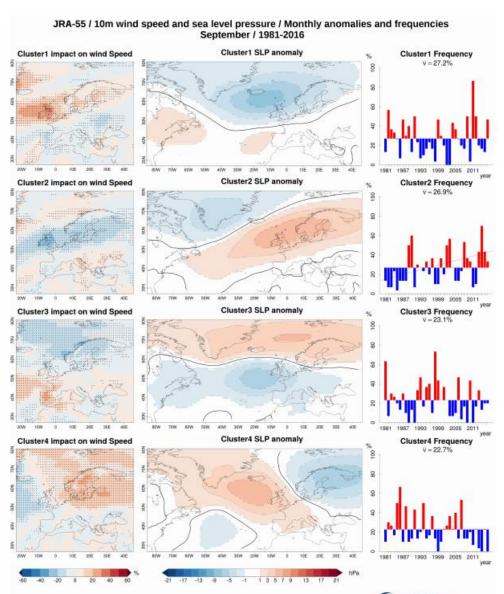


Consortium





Causes



Region. Left: Europe (26.9°N-80.6°N, 23.1°W-45.6°E). Right: North Atlantic (26.9°N-80.6°N, 86.1°W-45.6°E).

Reference dataset: JRA-55 reanalysis

Center column: monthly SLP anomalies (in hPa) corresponding to the four Euro-Atlantic clusters (weather regimes) in September over the period 1981-2016, in decreasing order of explained variance.

Right column: monthly frequency of occurrence of the four clusters in September for 1981-2016. Eventual presence of black lines indicate significant trends.

Left column: impact of the four clusters on 10-m wind speed. Impact (in %) is relative to the average wind speed for the month of September over the period 1981-2016. Black dots indicate significant points with a t-test at 95% confidence level. (Source: JRA-55 reanalysis)



Capacity factor

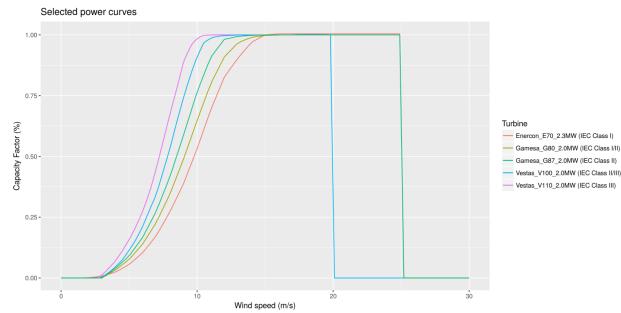
Capacity factor is a good indicator of wind power generation.

Is independent of:

- number of installed turbines
- nameplate capacity of installed turbines

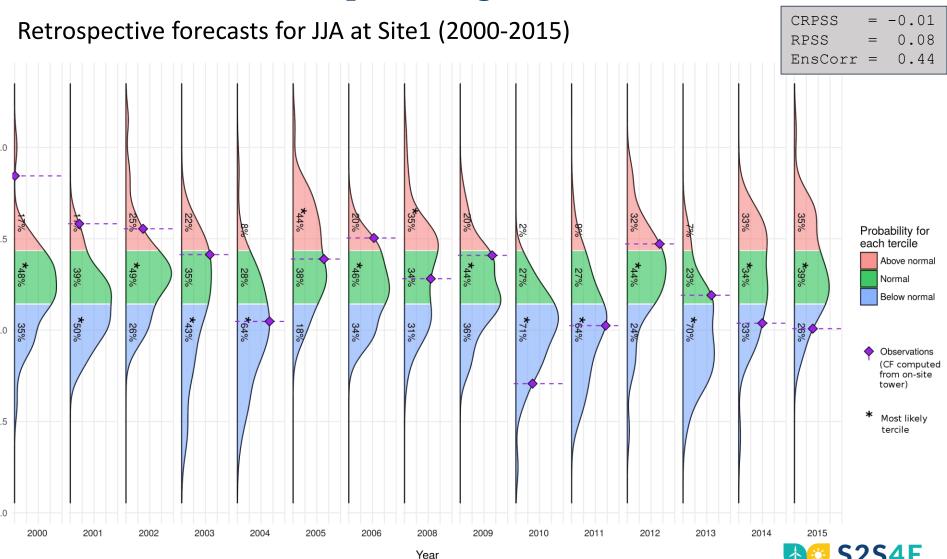
Using manufacturer power curves for three turbines representing IEC classes.

Fed with: 6-hourly model data, sheared at 100m.



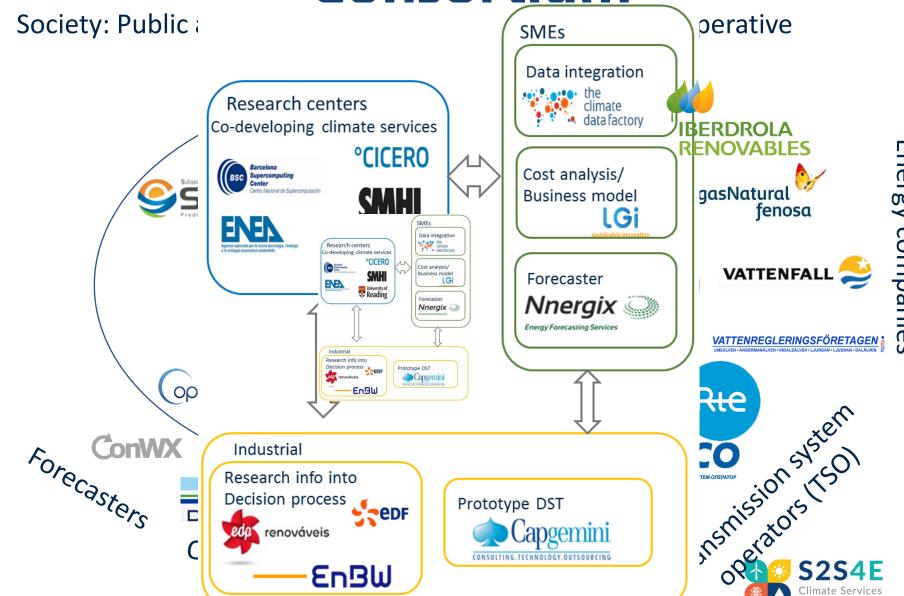


Capacity factor

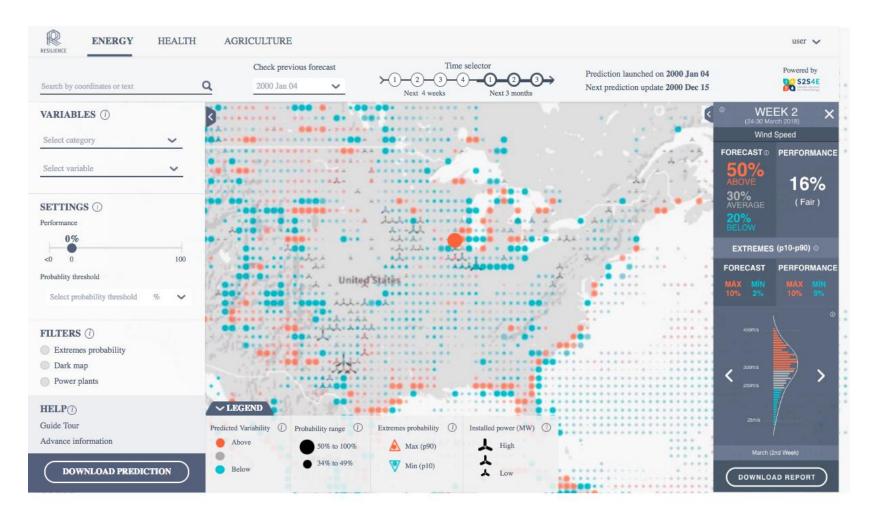


for Clean Energy

Consortium

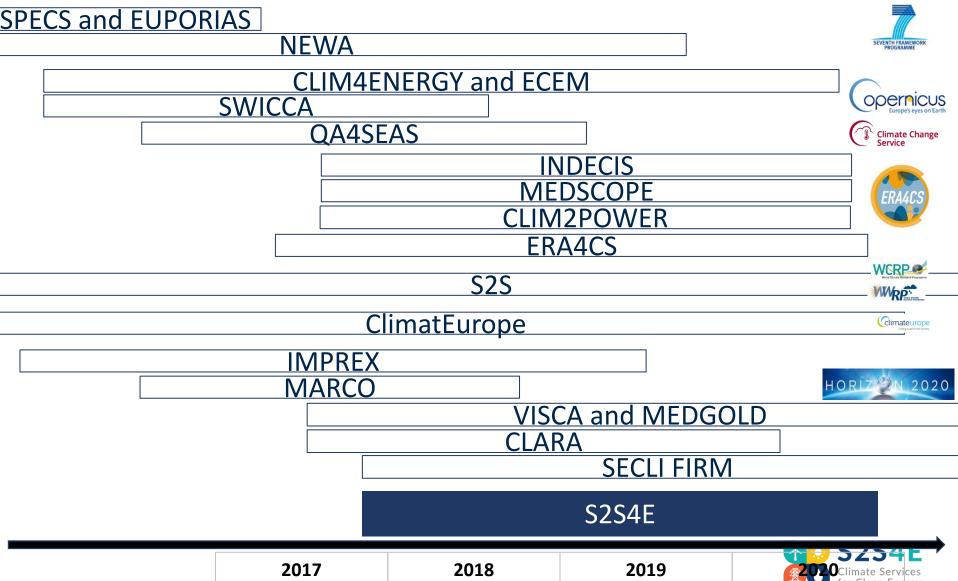


Success criteria is TRUST





Synergies with other projects

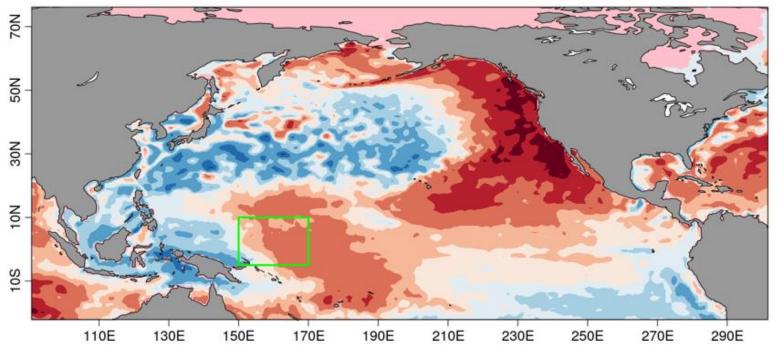


Why?

Using retrospective climate predictions, we find that high ocean temperatures in the western tropical Pacific Ocean played a central role to establish and maintain those wind anomalies. This is not a single event. This work shows that the wind speed variability in the United States is not only dominated by El Niño but also by the ocean temperatures in this region of the Pacific.

0.5

Standardized SST anomalies for Q1 2015



-0.5

Sea surface temperature anomalies in the Pacific Ocean during the same period. The green box shows the area under study.



Climate services

