Seasonal climate forecasting for the energy and water industries in SECLI-FIRM

Andrea Alessandri (KNMI) and WP2 Team

FIRM

Stakeholder Workshop, 17 January 2019 Milan (Italy)





Outline

- ✓ On the probabilistic nature of Seasonal Predictions
- ✓ Use of Grand-MME seasonal forecasts in SECLI-FIRM
- ✓ Optimization of Seasonal Climate prediction in SECLI-FIRM (WP2)
- ✓ Discussion: Q&A



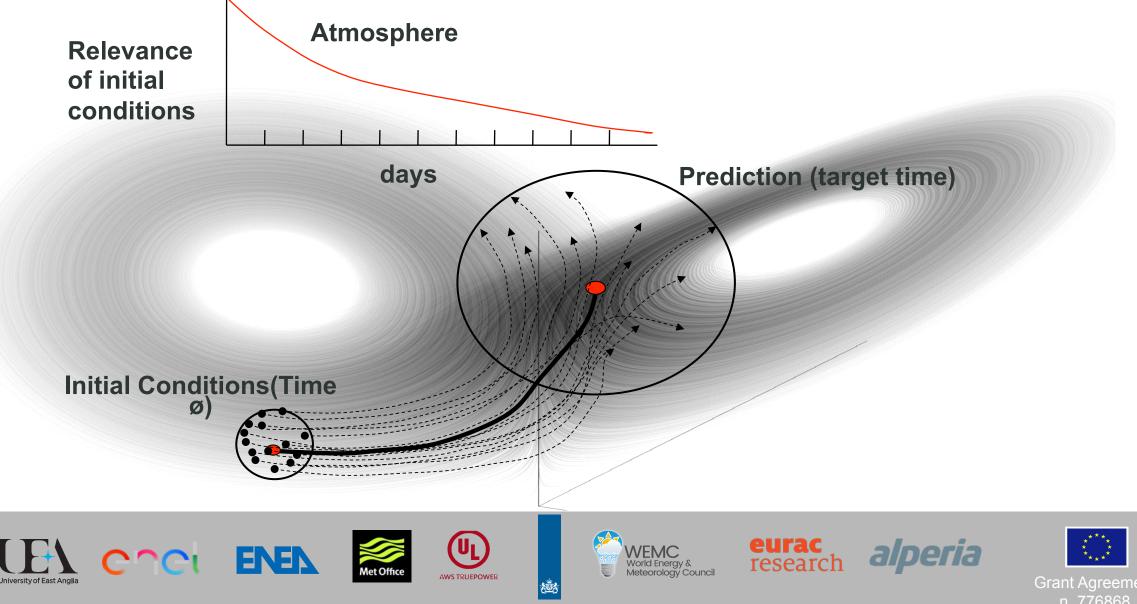


On the probabilistic nature of Seasonal Predictions

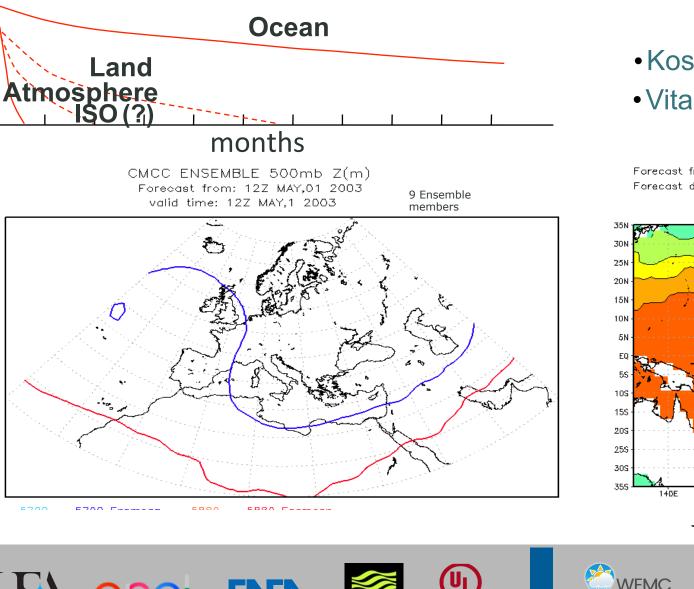


On the probabilistic nature of Seasonal Predictions





On the probabilistic nature of Seasonal Predictions



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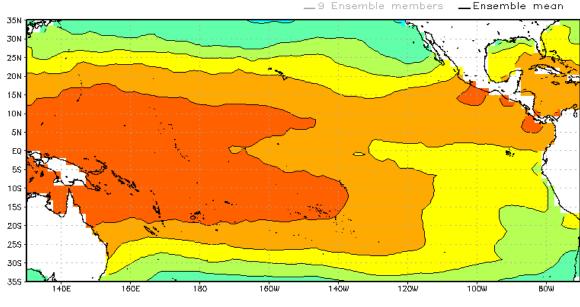
• Koster et al., 2004; 2010

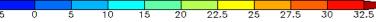
research

World Energy & Meteorology Council

• Vitart et al., 2006; Wang et al., 2009

CMCC ENSEMBLE Sea Surface Temperature degC Forecast from: 12Z FEB,01 1997 Forecast day: 1 , time 12 Z





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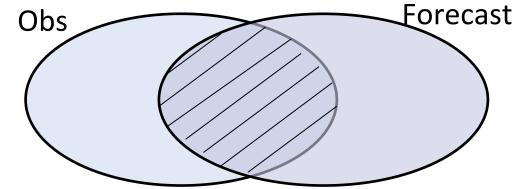
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On the probabilistic nature of Seasonal Predictions



On a fundamental level, probabilistic verification/calibration involves investigation of the joint distribution of forecasts and observations (Murphy and Winkler 1987). That is, verification data-set consists of a collection of forecast/observation pairs whose joint behavior can be exploited to assess forecasts performance.

Joint distribution of observed and forecast outcomes



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For Joint distribution to be tractable: dichotomous (Yes, No) events need to be identified as well as suitable discretization of the model probabilities performed.

After discretizing probability forecasts to finite set of values $(y_1, y_2, ..., y_i; I = 1, ..., I)$, the joint distribution of forecasts and dichotomous observations (oj; yes j = 1; no j = 0) can be denoted by:

$$\Pr(y_i \cap o_j) = p(y_i, o_j)$$
$$i = 1, 2, \dots, I$$
$$i = 0, 1$$

 y_i model probability forecasts

 o_j observed events :

above normal (i.e : > upper tercile) below normal (i.e : < lower tercile)







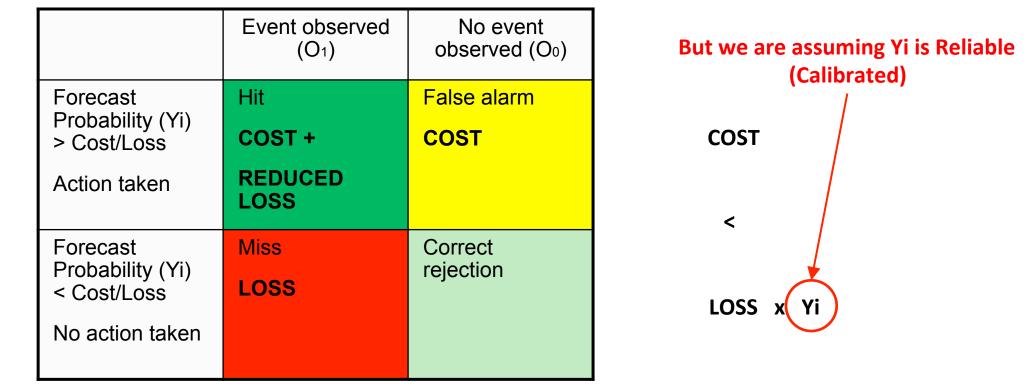
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Prediction of adverse event [E+] – Probabilistic case

Potential Economic Value (**Cost-Loss** decision model; Richardson, 2003)



[E+] implies financial Loss if no preventive action is taken at a financial Cost



Steele et al. (2017), OTC, pp. 1-8; Steele et al. (2018), OTC, pp. 1-8; Alessandri et al., 2018

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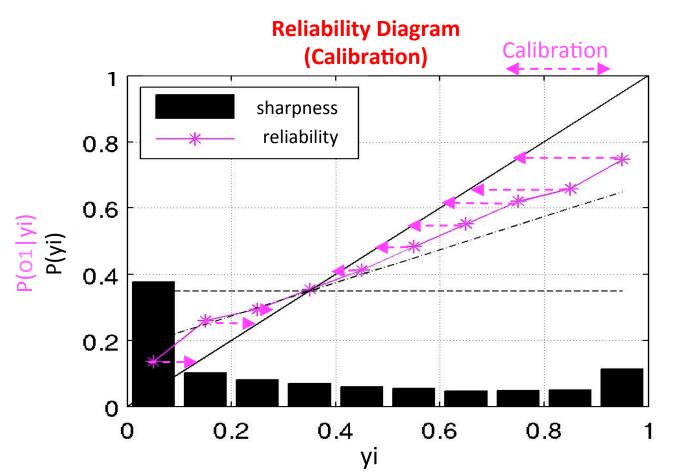




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On the reliability of probabilistic information from ensemble forecasts: shall we trust ensemble forecast raw outcomes or do we need any calibration?









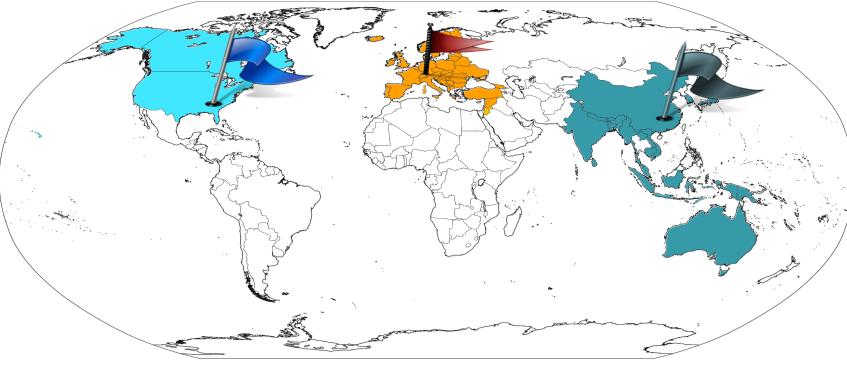
Grand MME in SECLI-FIRM

Task 2.1 – Development of multi-model seasonal prediction dataset from independent sources: European, North American and Asian Pacific (Lead UEA) [M1-M12]



Grand MME in SECLI-FIRM





"We'll collect (i) the Copernicus C3S seasonal forecasts product (C3S dataset;

<u>https://climate.copernicus.eu/seasonal-forecasts</u>) for the European community, (ii) the APEC Climate Center MME (APCC dataset;<u>http://www.apcc21.org/abt/model.do?lang=en</u>) for the Asian-Pacific community and (iii) the North American Multi-Model Ensemble (NMME dataset; <u>http://www.cpc.ncep.noaa.gov/products/NMME</u>)"

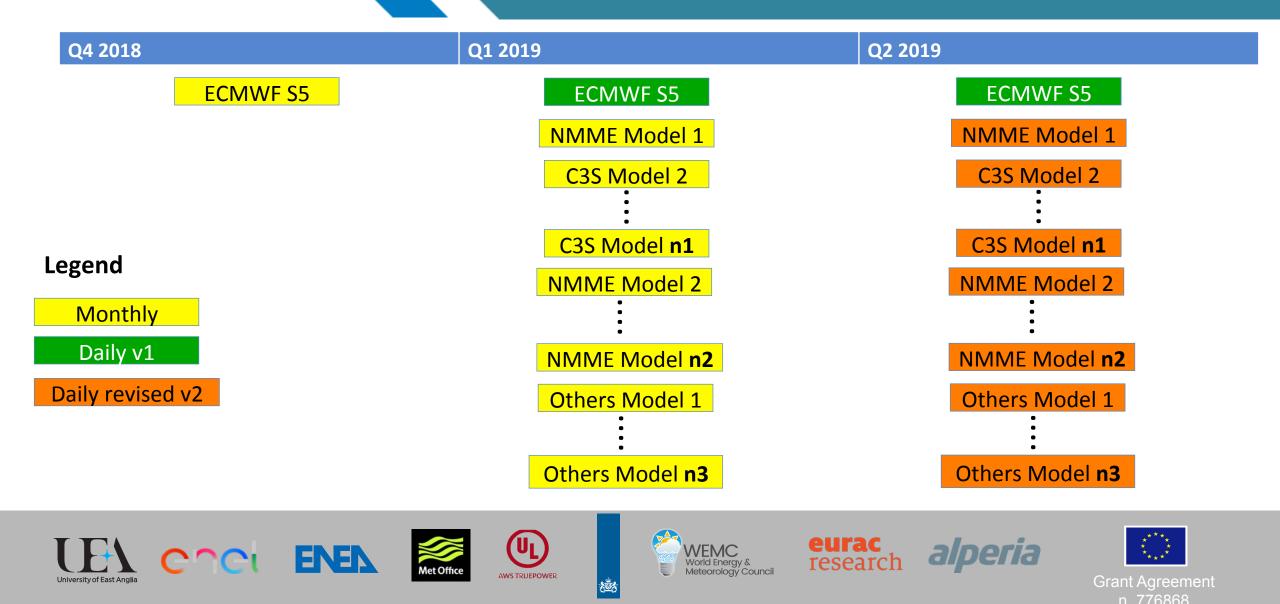
D2.1: Report on the development of the homogenized and calibrated Multi-Model seasonal predictions database. [Lead UEA; M12] MS2.1: Multi-Model seasonal predictions database made available [M12]











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Q4 2018	Q1 2019	Q2 2019
Decision on Monthly variables (it may need revision at later stage)	Decision on Daily variables (comprehensive set of variables and members) Decision on initial set of	Revise variables, ensemble members needed (after preliminary analysis)
	models to include in MME	Revise set of models to include in MME (daily fields)
	Decision on the calibration to apply to Monthly and Daily fields	Revise calibration to apply to Monthly and Daily
UEA HPC Access provided to	UEA HPC: 1 TB (fast) +3 TB (slow)	AWS: 10 TB (fast) + ~50 TB (slow)
partners	(can be upgraded to 1+10 TB storage)	(can be upgraded also looking to partner with MED-GOLD)
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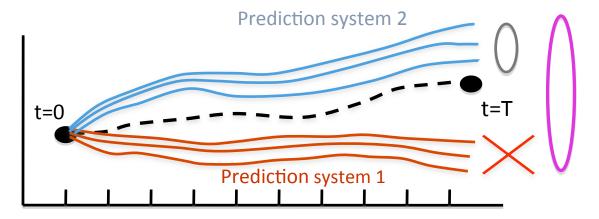


The rationale in using multi-models



The rationale behind use of Multi-Models





time

MME can improve by:

- Combining the skill from the single models
- Improve ensembles dispersion and uncertainty consideration

➢Independence of the Single models systems

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Degree of over-confidence

(Hagedorn et al., 2005; Weigel et al., 2009; Alessandri et al., 2011)











Grand ENSEMBLES-CliPAS/APCC Multi-Model by combining Asian-Pacific (CliPAS/APCC) and European (ENSEMBLES) MMEs



Performance and usefulness of CLImate predictions: Beyond current liMITationS (<u>http://tinyurl.com/fp7-iof-climits</u>)

Supported by European Union (FP7 programme) Marie Curie IOF

















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The Grand ENSEMBLES-CliPAS/APCC MME

Two independent MME:

11 Prediction Systems from **CliPAS/APCC** and **5** from EU

ENSEMBLES

CliPAS/APCC (Wang et al., 2009)

APCC Asia-Pacific Economic Cooperation Climate Center, S. Korea.

NCEP, National Center for Environmental Prediction, USA

BMRC, Bureau of Meteorology Research Center, Australia

PNU, Pusan National University, S. Korea.

MSC, Meteorological Service of Canada, Canada (CANCM3, CANCM4)

NASA, National Aeronautics and Space Administration, USA

SNU, Seoul National University, S. Korea

UH, University of Hawaii, USA

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GFDL, The Geophysical Fluid Dynamics Laboratory , USA

FRCGC, Frontier Research Center for Global Change, Japan

ENSEMBLES (Weisheimer et al, 2010; Alessandri et al, 2011)

ECMWF, European Centre for Medium-Range Weather Forecasts, United Kingdom

UKMO, UK-Met Office Met Office, United Kingdom

MF, Meteo France. France

INGV-CMCC, Centro Euro-Mediterraneo per i Cambiamenti Climatici, Italy

IFM-GEOMAR, Leibnitz Institute of Marine Sciences at Kiel University, Germany

ENSEMBLE-based predictions of climate changes and their impacts (**ENSEMBLES**) supported by **EU** FP6 programme

Climate Prediction and its Application to Society project (**CliPAS**; Wang et al., 2009) sponsored by **APCC**

common hindcast period 1983-2005

1 May and 1 Nov start dates



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The Added Value of Seas Forecasting for Integrated Ri



Maximization of probabilistic seasonal forecasts performance at each grid point by combining ENSEMBLES and CliPAS/APCC models



Performance and usefulness of CLImate predictions: Beyond current liMITationS (<u>http://tinyurl.com/fp7-iof-climits</u>)

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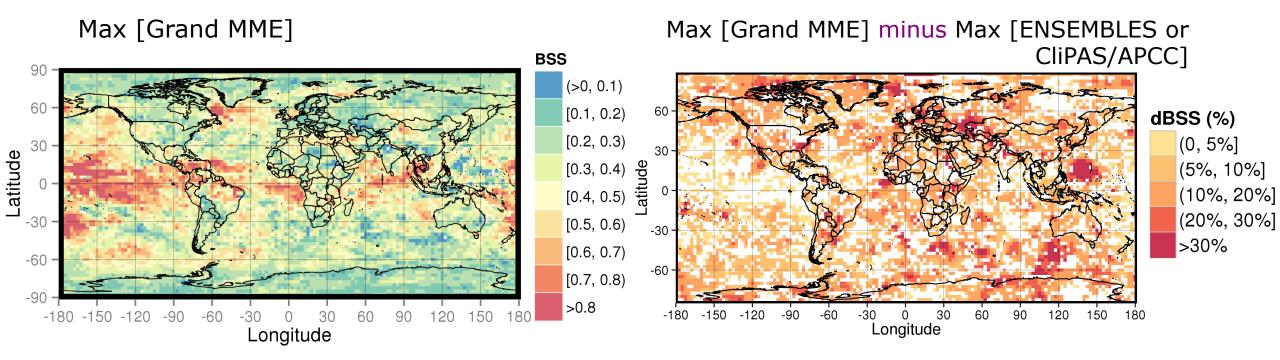




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Max [Grand MME] vs Max [ENSEMBLES or CliPAS/APCC] Brier Skill score - above upper tercile T2m JJA









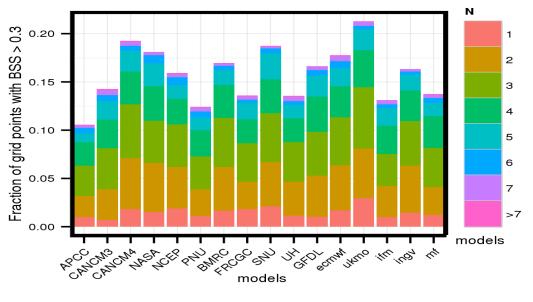
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Usefulness of the contributing models

Brier Skill score - above upper tercile T2m JJA



All models contribute to the improved performance of the Grand MME



The improvements are larger when adding independent models to the MMEs



Fraction of grid-points each model is needed to maximize performance

Normalized marginal contribution of adding APCC or ENSEMBLES models to combinations of APCC only, ENSEMBLES only and mixed MMEs



Prediction of Electricity demand over Italy using seasonal climate forecasts



•Forecasting of anomalous summer Temperature at the seasonal time-scale over "hot-spot" land areas such as Euro-Mediterranean has been recently shown to have the potential to drive predictions of electricity demand anomalies due to increased summer refrigeration and air conditioning.

De Felice, Alessandri and Catalano, 2015 (Appl. Energy)



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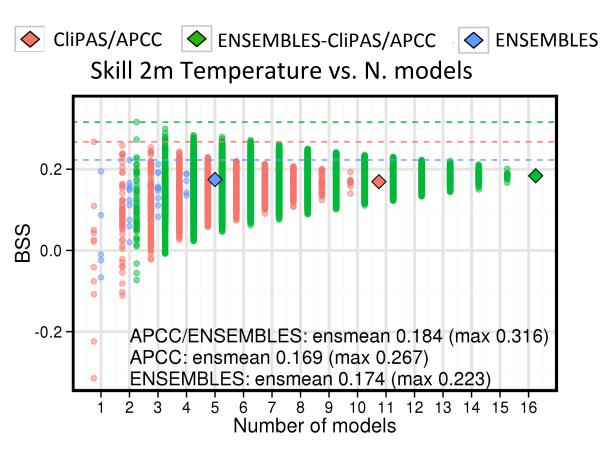


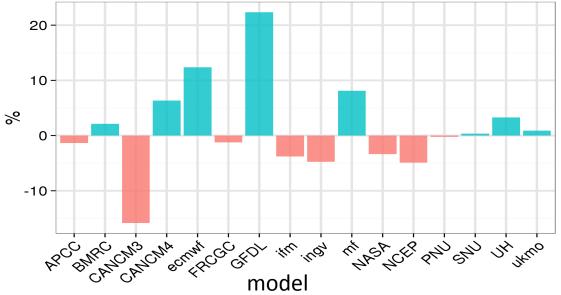




Seasonal forecast skill for Temperature prediction over Italy

Brier Skill score - above upper tercile T2m JJA





Avg. marginal skill contribution of each model



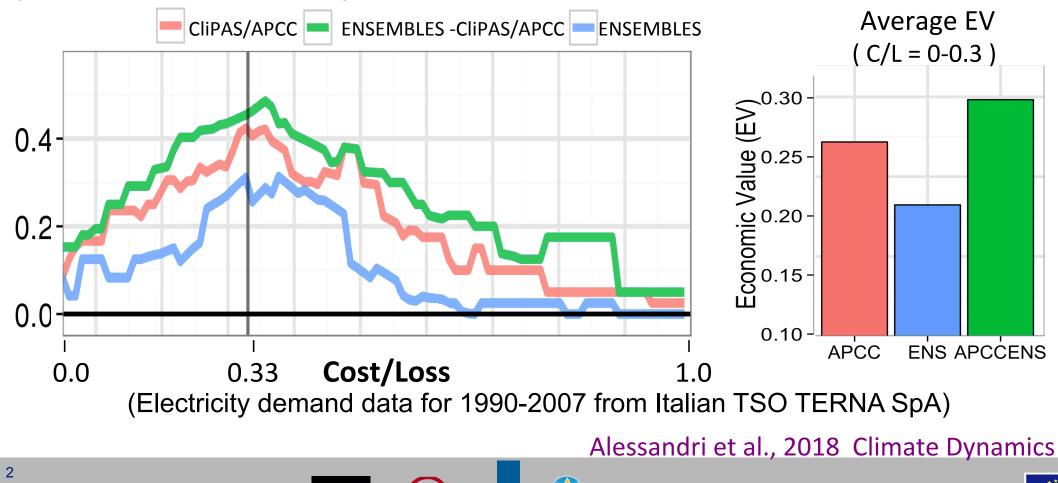


Potential Economic Value (Cost-Loss decision model; Richardson, 2003)



[E+] implies financial **Loss** if no preventive action is taken at a financial **Cost**

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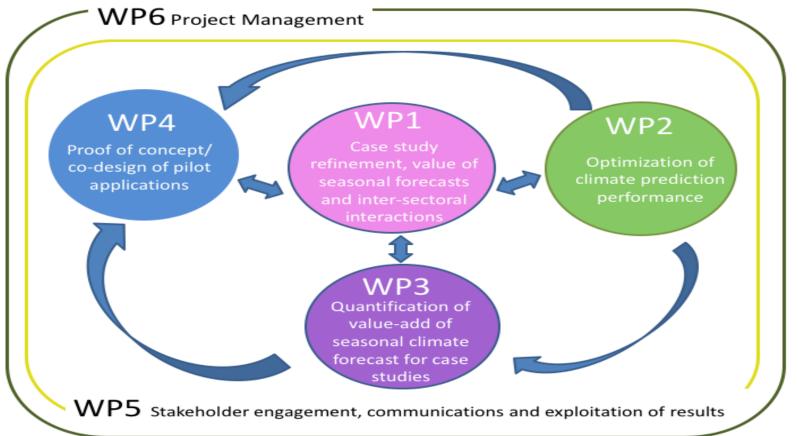


Optimization of Seasonal Climate prediction in SECLI-FIRM (WP2)



SECLI-FIRM WP2





Objective to optimize and exploit maximum seasonal climate prediction performance for the key climate variables considered in the case studies identified in WP1 by the industrial co-designers





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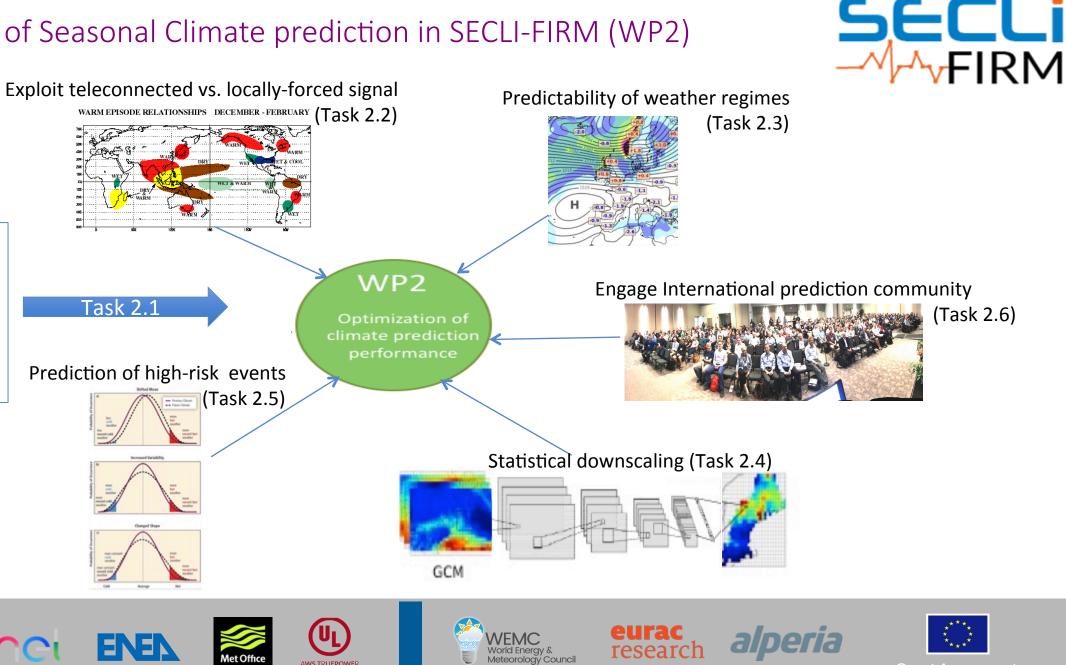
Optimization of Seasonal Climate prediction in SECLI-FIRM (WP2)

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MME



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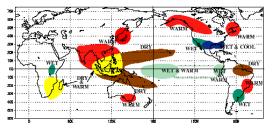
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Optimization of Seasonal Climate prediction in SECLI-FIRM (WP2)

Task 2.2: Exploit teleconnected vs. locally-forced signal

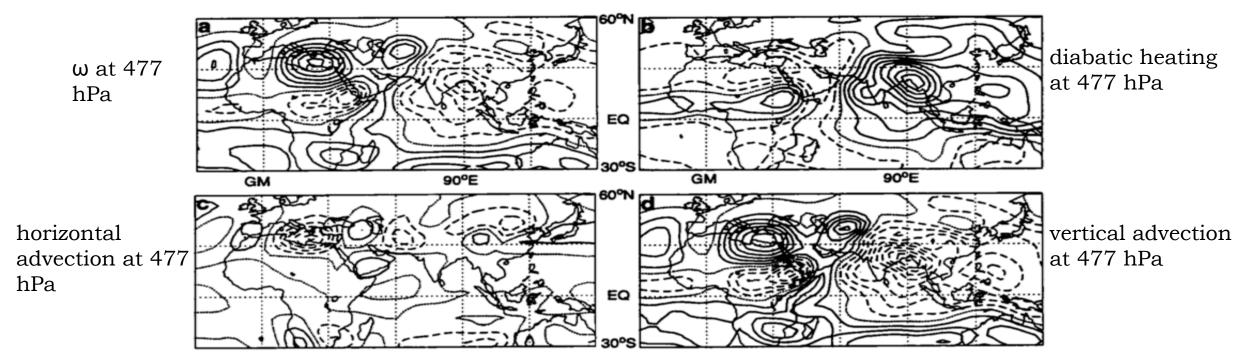
WARM EPISODE RELATIONSHIPS DECEMBER - FEBRUARY





Monsoon-desert mechanism (Rodwell and Hoskins, 1996; 2001)

descent over the Mediterranean region is a consequence of the interaction between westward propagating Rossby waves (generated by diabatic heating over the Asian monsoon sector) and mean westerly flow north of it



Thermodynamic energy equation:

$$\frac{Q}{c_p} = v \cdot \nabla_p T + (\frac{p}{p_0})^k \omega \frac{\partial \theta}{\partial p}$$

horizontal temperature advection to balance temperature equation in mid-latitudes











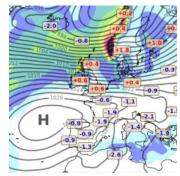


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Optimization of Seasonal Climate prediction in SECLI-FIRM (WP2)

Task 2.3: Predictability of weather regimes



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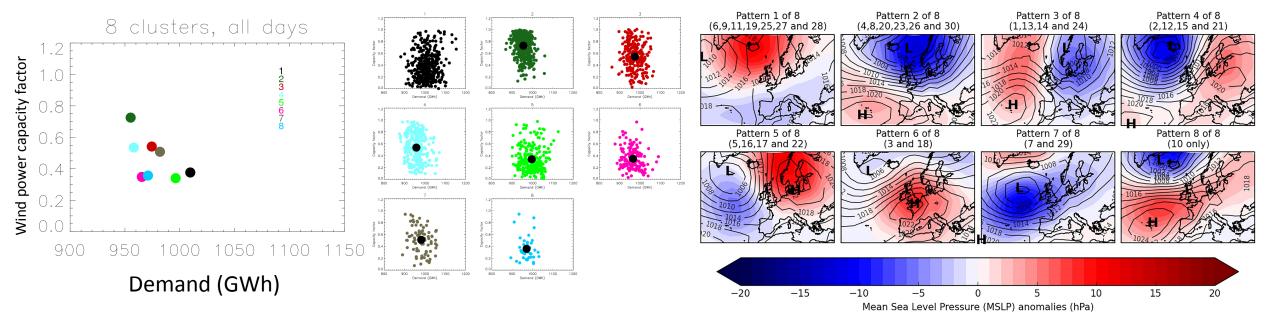


Predictability of weather regimes



The Neal et al. (2016) Weather Types

Early exploration from Hazel Thornton, relating wind power, demand, and WTs:

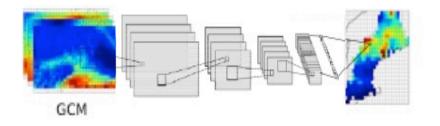






Optimization of Seasonal Climate prediction in SECLI-FIRM (WP2)

Task 2.4: Statistical downscaling





Downscaling of snow depth (sdp) / snow water equivalent

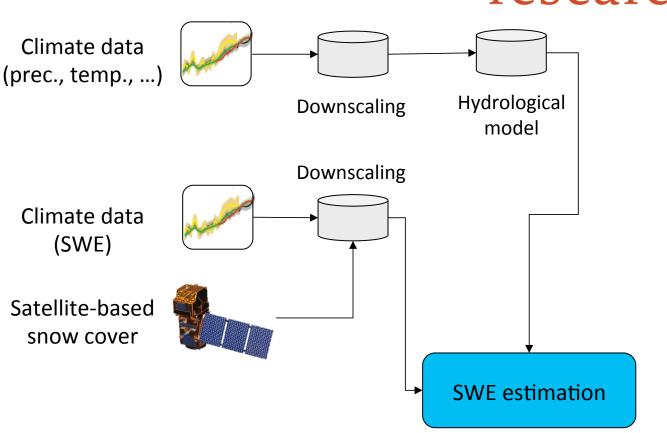
We are working on two approaches

- Combination of downscaled climate forecasts and hydrological modelling to derive snow
- 2. Exploiting remotely sensed snow cover fraction for the downscaling of the snow variables of the seasonal climate forecast
- 3. Combination of approach 1 and 2

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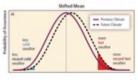
Task 2.5: Prediction of high-risk events

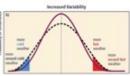
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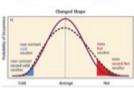
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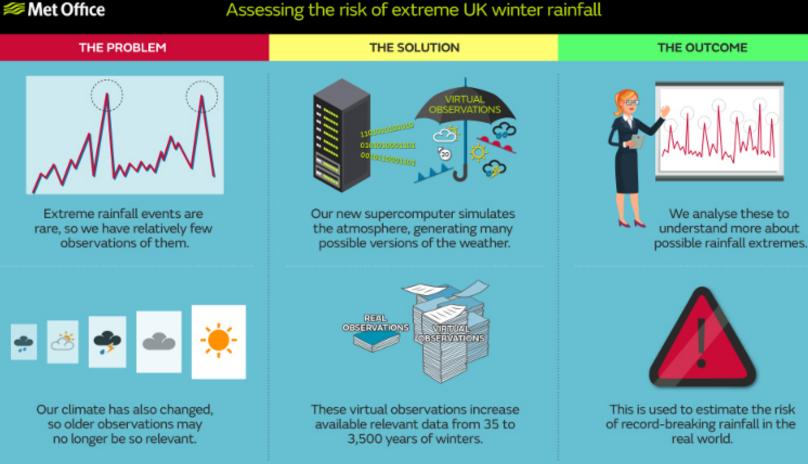
Meteorology Council



Following the methodology of Thompson et al., 2017*



Using an ensemble of hindcasts from the Met Office's DePreSys3 prediction system (based on GloSea5)



* High risk of unprecedented UK rainfall in the current climate. Thompson et al., 2017. Nature Communications.



















Optimization of Seasonal Climate prediction in SECLI-FIRM (WP2) –

Task 2.6: Engage International prediction community





Task 2.6 – Engagement and feedback with international prediction community (Lead KNMI)

Organized Sessions in 2018 at EGU and AOGS:

-EGU2018, Earth System Prediction and Applications -AOGS 2018, Earth System Prediction Predictability and Applications

-Participation at the WMO/WCRP "Sub-seasonal to decadal (S2D)" conference (17-21 September 2018, Boulder, CO, USA)

Proposed session for 2019

-EGU2019, "Challenges in climate prediction: multiple time-scales and the Earth system dimensions".

D2.6: Report on the capability of the very latest advancements in the prediction systems from the ongoing international efforts to overcome limitations in forecasting the key predictands [Lead KNMI; Month 36]











Performance and limitations of ECMWF prediction system over land Preliminary analysis of SYS5 vs. SYS4

Potential for improvement over Land -> link to other EU H2020 projects (e.g. PROCEED)



Seasonal hindcasts - 1st Nov start date - 2m Temperature Correlations vs. ERA-Interim

corr

corr

1.0

0.5

0.0

-1.0

1.0

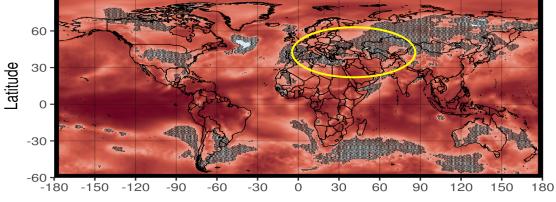
0.5 0.0

-0.5

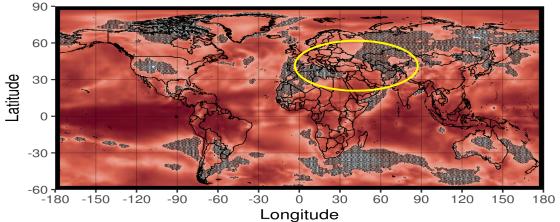


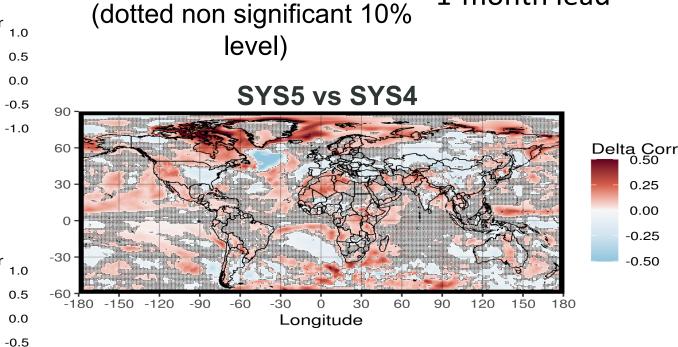
SYS5

T2M























Discussion: Q & A

