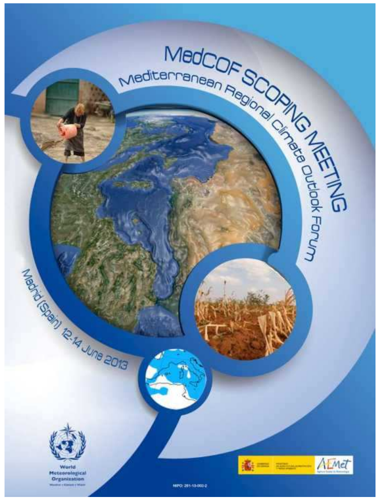


Operational seasonal forecast constrained by low predictability

E. Rodríguez-Camino, AEMET

Outline

- Introduction: need to respond to society demands!
- Many sources of information
- Best practices
- Sources of predictability
- Predictability issue → windows of opportunity
- Conclusions

Seasonal forecasting

- Increasing demand of seasonal prediction products by many sectors→ NMHSs need to respond → critical place in weather and climate services
- Balance btw
  - meeting demands
  - predictability issues
  - credibility of the organization
  - commercial issues

3 categories of seasonal predictability

- Variables that exhibit **INERTIA** or memory:
  ocean heat content, sea-ice, Sn, SM

- Dominant **PATTERNS** of atmospheric and
  ocean variability: ENSO, NAO, etc

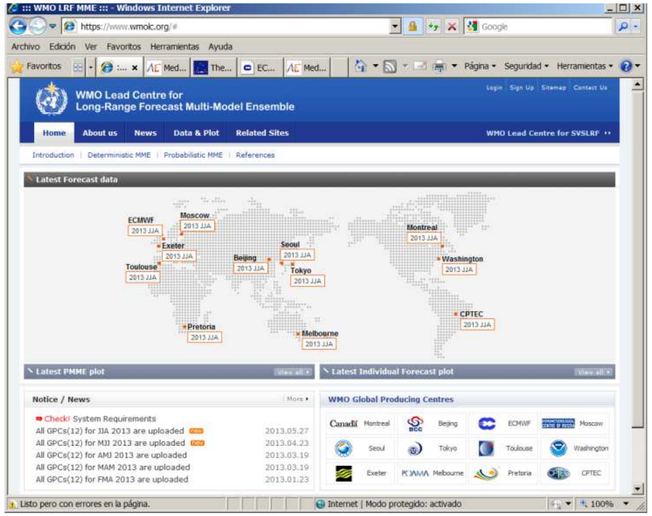
- External **FORCING**: volcanic eruptions,
  changes in solar activity

Many sources of information

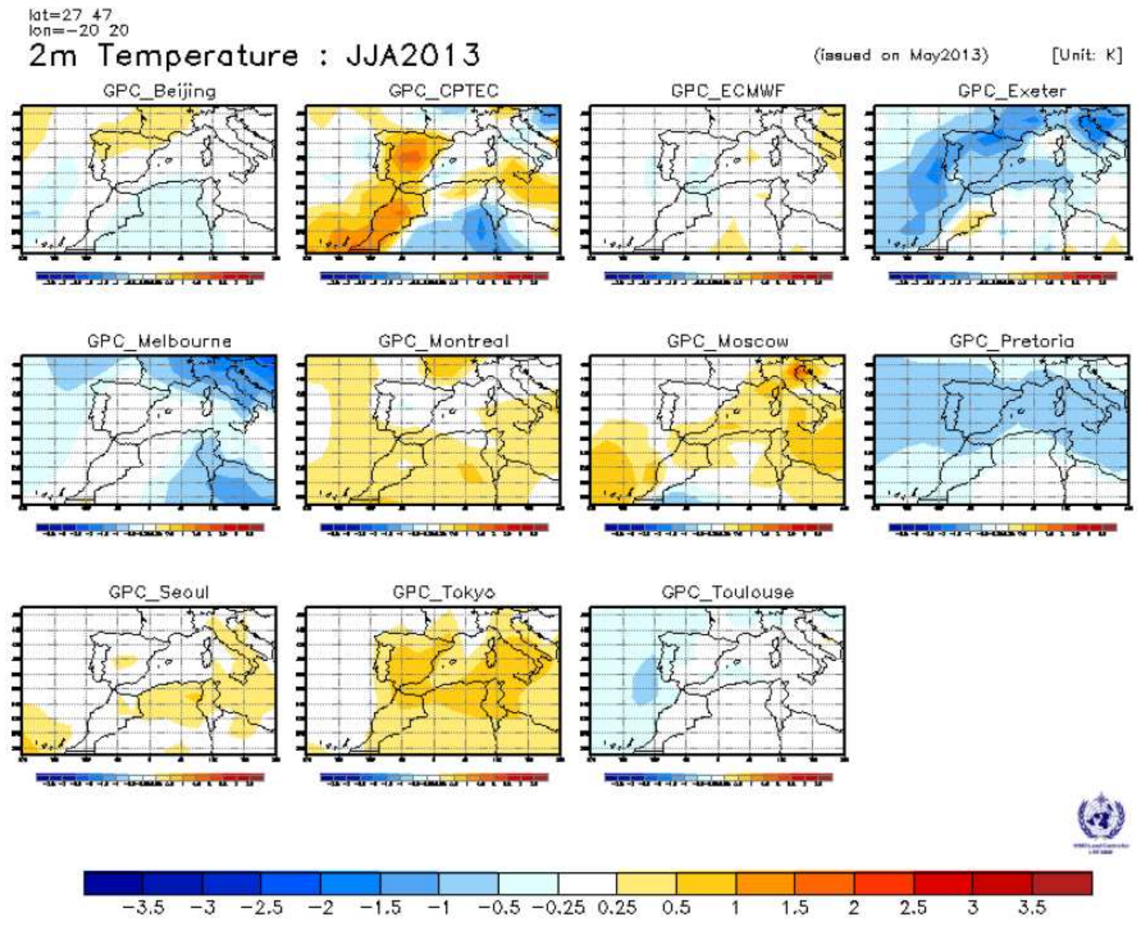
- Model Systems based on ensembles (e.g., ECMWF, MF, NCEP,…)
- Multi-Model Systems (e.g., EUROSIP, LC-LRFMME, IRI, APCC, …)

WMO Lead Centre for Long-Range Forecast Multi-Model Ensemble

(https://www.wmolc.org/)



4.2 Temperatura



5.1 Temperatura

MODELOS	NW	SW	NE	SE	CANARIAS	BALEARES
IRI						
EUROSIP						
BEIJING						
ECMWF						
CPTEC						
EXETER						
MELBOURNE						
MONTREAL						
MOSCOW						
PRETORIA						
SEOUL						
TOKYO						
TOULOUSE						
WASHINGTON	sin datos	sin datos	sin datos	sin datos	sin datos	sin datos

	Débil anomalía positiva
	Moderada anomalía positiva
	Débil anomalía negativa
	Moderada anomalía negativa

CONCLUSIÓN: No hay anomalías significativas de temperatura para JJA del 2013 con respecto a los valores normales en toda España

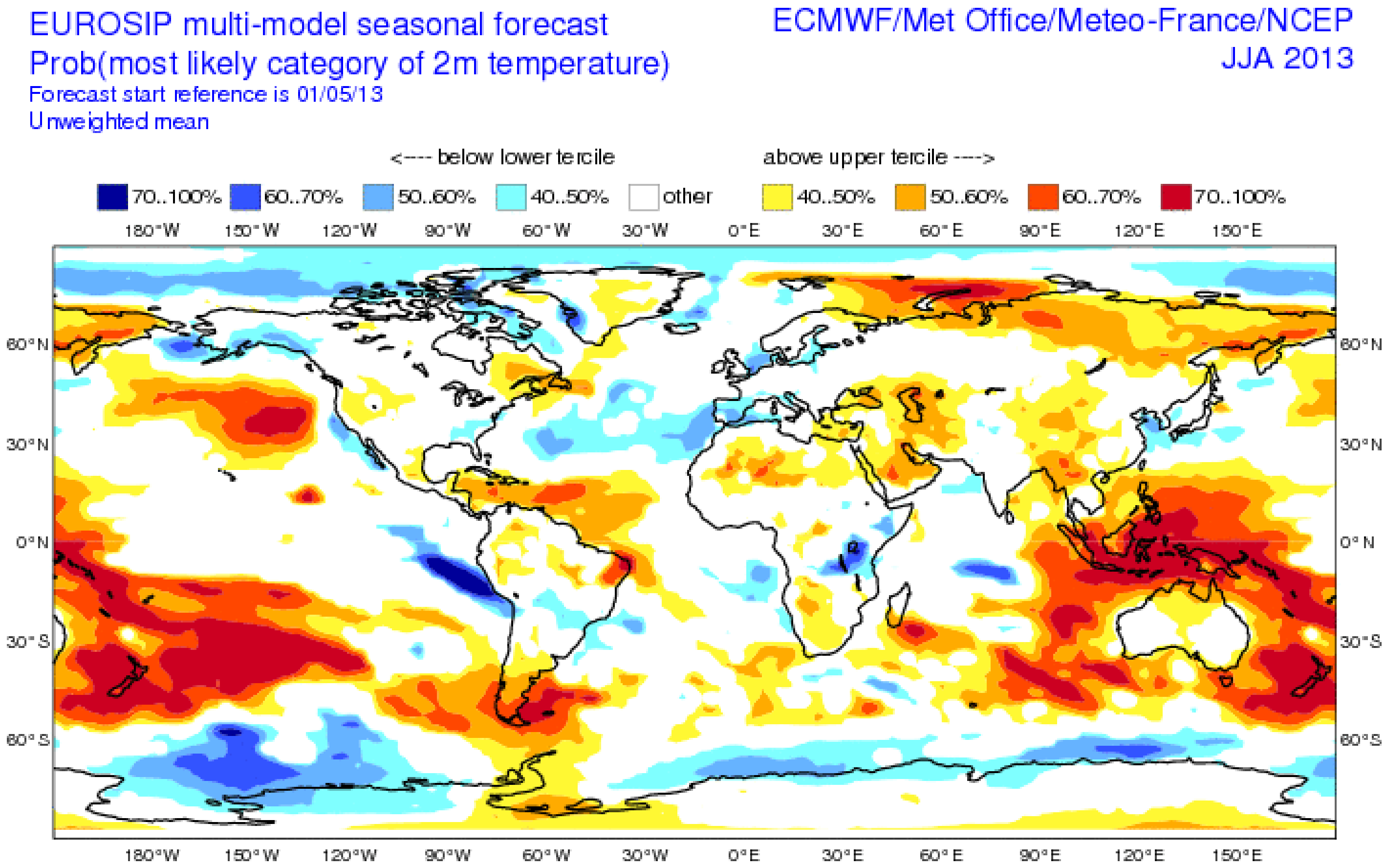
	Ausencia de anomalía
	Débil anomalía positiva
	Moderada anomalía positiva
	Débil anomalía negativa
	Moderada anomalía negativa

Multi-Model APCC

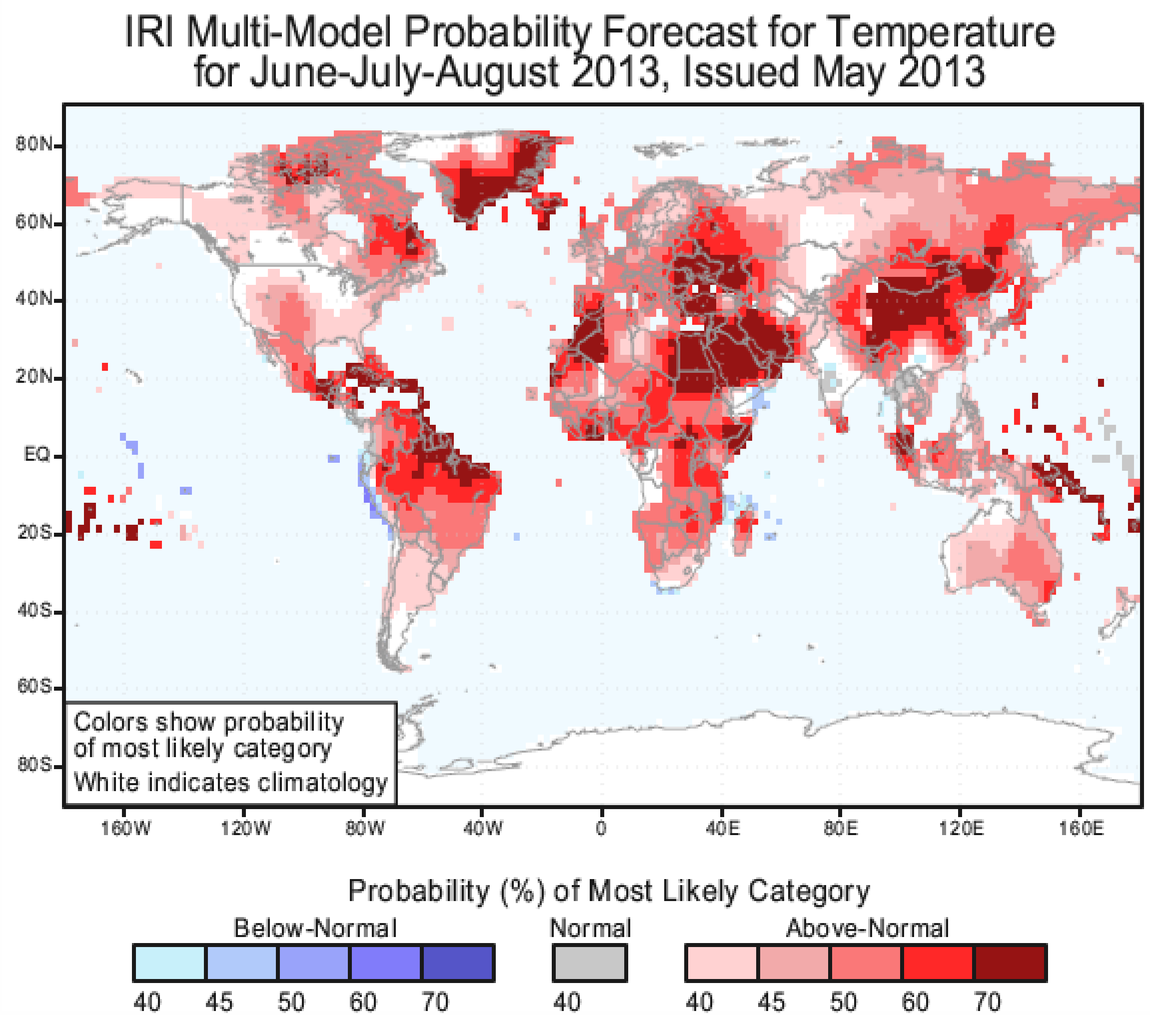
(http://www.apcc21.net)

Provider	Economy	Variables	Model Designation	SST Specification (Hindcast/Forecast)	Ensemble
BCC	China	PREC T850 Z500	NCC CGCM T63L16	Predicted SST/ Predicted SST	8
COLA	U.S.A.	T2M PREC SLP T850 U850 V850 U200 V200 Z500 OLR	COLA AGCM v2.2.5 T63L18	OISSTv2/ IRI SST Forecast	10
CWB	Chinese Taipei	T2M PREC SLP T850 U850 V850 U200 V200 Z500	CWB T42L18	OPG SST from CWB/ OPG SST from CWB	10
GCPS	Republic of Korea	T2M PREC SLP T850 U850 V850 U200 V200 Z500	GCPS T63T21	KMA/SNU SST Forecast/ KMA/SNU SST Forecast	4
GDAPS_F	Repulic of Korea	T2M PREC SLP T850 U850 V850 U200 V200 Z500	GDAPS T106L21	KMA/SNU SST Forecast/ KMA/SNU SST Forecast	20
HMC	Russia	T2M PREC SLP T850 Z500	SL-AV 1.125 x 1.406, L28	Persistent SST/ Persistent SST	10
IRIF	U.S.A.	T2M SST PREC SLP T850 U850 V850 U200 V200 Z500 OLR	ECHAM4.5 T42L19	Observed SST/ Predicted SST	24
MGO	Russia	T2M SST PREC SLP T850 U850 V850 Z500 OLR	MGOAM2 T42L14	Observed SST/ Persistent SST	10
MSC_GEM	Canada	PREC T850 Z500 T2M SLP U850 V850 U200 V200	RPN GEMCLIM v3.2.1 2.0 x 2.0, L50	Persistent ERA40 SST/ Persistent CMC SST	10
MSC_GM2	Canada	PREC T850 Z500 T2M SLP U850 V850 U200 V200	CCCma AGCM2 T32, L10	Persistent ERA40 SST/ Persistent CMC SST	10
MSC_GM3	Canada	PREC T850 Z500 T2M SLP U850 V850 U200 V200	CCCma AGCM2 T63, L32	Persistent ERA40 SST/ Persistent CMC SST	10
MSC_SEF	Canada	PREC T850 Z500 T2M SLP U850 V850 U200 V200	RPN SEF T95, L27	Persistent ERA40 SST/ Persistent CMC SST	10
NASA	U.S.A.	T2M SST PREC SLP T850 U850 V850 U200 V200 Z500 OLR	NASA-GSFC 2.5 x 2.0, L34	Perdicted SST/ Predicted SST	8
NCEP	U.S.A.	T2M SST PREC SLP T850 U850 V850 U200 V200 Z500 OLR	NCEP CFS T62L64	Predicted SST/ Predicted SST	15
NIMR	Repulic of Korea	PREC SLP T850 U850 V850 U200 V200 Z500	METRI AGCM 5.0 x 4.0, L17	Persistent OISST/ Persistent OISST	10
POAMA	Australia	T2M SST PREC SLP T850 U850 V850 U200 V200 Z500 OLR	POAMA 1.5 T47L17	Predicted SST/ Predicted SST	15

Multi-Model EUROSIP:
ECMWF/MetOffice/MF/NCEP



Multi-Model IRI

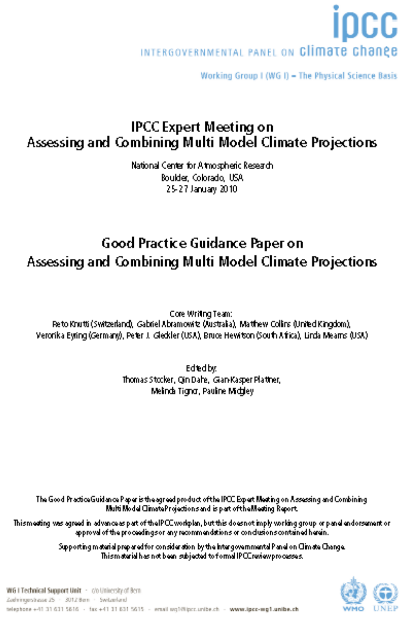


Many sources of information

- Model Systems based on ensembles (e.g., ECMWF, MF, NCEP,…)
- Multi-Model Systems (e.g., EUROSIP, LC-LRFMME, IRI, APCC, …)
- Operational empirical systems (e.g. IBIMET, …)
- Combination of systems (e.g., EUROBRISA)
- Compilation/Expert judgement (e.g., RCC- LRF AR VI by MF)
- Local usage of different downscaling methods, CPT, …
- Many studies focused on windows of opportunity
- …

Recommendations for Model Selection, Averaging and Weighting (best practices)

- A multi-model average often out-performs any individual model compared to observations.
- Document results from all models
- Range spanned by the models
- Weighting models in an ensemble is not an appropriate strategy for some studies.
- Rankings or weightings could be used to select subsets of models
- Model agreement is not necessarily an indication of likelihood.


ipcc
INTERGOVERNMENTAL PANEL ON climate change
Working Group I (WG I) – The Physical Science Basis

IPCC Expert Meeting on
Assessing and Combining Multi Model Climate Projections

National Center for Atmospheric Research
Boulder, Colorado, USA
25-27 January 2010

Good Practice Guidance Paper on
Assessing and Combining Multi Model Climate Projections

Core Writing Team:
Reto Knutti (Switzerland), Gabriel Abramowitz (Australia), Matthew Collins (United Kingdom), Veronika Eyring (Germany), Peter J. Gleckler (USA), Bruce Hewitson (South Africa), Linda Mearns (USA)

Edited by:
Thomas Stocker, Qin Dahe, Gian-Kasper Plattner, Melinda Tignor, Pauline Midgley

The Good Practice Guidance Paper is the agreed product of the IPCC Expert Meeting on Assessing and Combining Multi Model Climate Projections and is part of the Meeting Report.

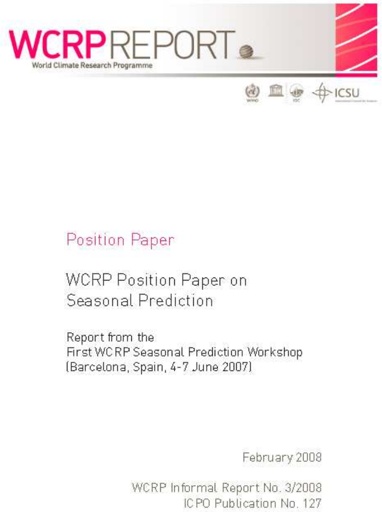
This meeting was agreed in advance as part of the IPCC workplan, but this does not imply working group or panel endorsement or approval of the proceedings or any recommendations or conclusions contained herein.

Supporting material prepared for consideration by the Intergovernmental Panel on Climate Change. This material has not been subjected to formal IPCC review processes.

WG I Technical Support Unit · c/o University of Bern
www.ipcc-wg1.unibe.ch
WMO UNEP

Best practices

(WCRP Position Paper on Seasonal Prediction Report. 1st WCRP Seasonal Prediction Workshop (Barcelona, Spain, 4-7 June 2007)


WCRP REPORT
World Climate Research Programme

Position Paper

WCRP Position Paper on Seasonal Prediction

Report from the First WCRP Seasonal Prediction Workshop (Barcelona, Spain, 4-7 June 2007)

February 2008

WCRP Informal Report No. 3/2008
ICPO Publication No. 127

- Address forecast error by appropriately quantifying dynamical model uncertainty;
- Recalibrate model output based on historical model performance;
- Issue probabilistic forecast information;
- Provide description of forecast process (including post-processing methodologies);
- Provide forecast quality information including several metrics of quality;
- Regional climate service providers need to work with both the forecasting and application communities to develop tailored downscaled products All the ensemble members should be used;
- Web based tools need to be developed to allow users of the prediction information to tailor the underlying climate information more easily to their needs (e.g. climate range/thresholds, spatial scale(s)).
- Use regional mechanisms like RCOFs to develop consensus based regional climate outlooks based on a scientific assessment of multiple prediction outcomes
- Actively promote user liaison to understand their climate information needs in decision making and also raise their awareness of the uncertainty aspects of seasonal forecasting
- Promote regional/national ownership of seasonal forecasts through effective and sustained capacity building and infrastructural support

A RCOF should have a protocol for producing consensus seasonal forecast based on a code of best practices →

Some kind of decalogue strictly followed during the process of forecast producion

Sources of predictability

- Variables that exhibit INERTIA or memory: ocean heat content, sea-ice, Sn, SM

- Dominant PATTERNS of atmospheric and ocean variability: ENSO, NAO, etc

- External FORCING: volcanic eruptions, changes in solar activity

e.g., IBIMET

Monthly large scale predictors indexes:		Lead Time [months]
Atmosphere		
SV – NAM		*6*
Mod. Zonal Index		*3*
Multi ENSO Index		*4*
SSTA		
Atl. Tripole		*6*
1st EOF Guinea		*3*

Comprehensive list of good predictors → many papers focused on certain windows of opportunity (season, region, …)

Are processed well represented by models?

Are simple empirical methods an alternative or a complement to dynamical seasonal forecasts?

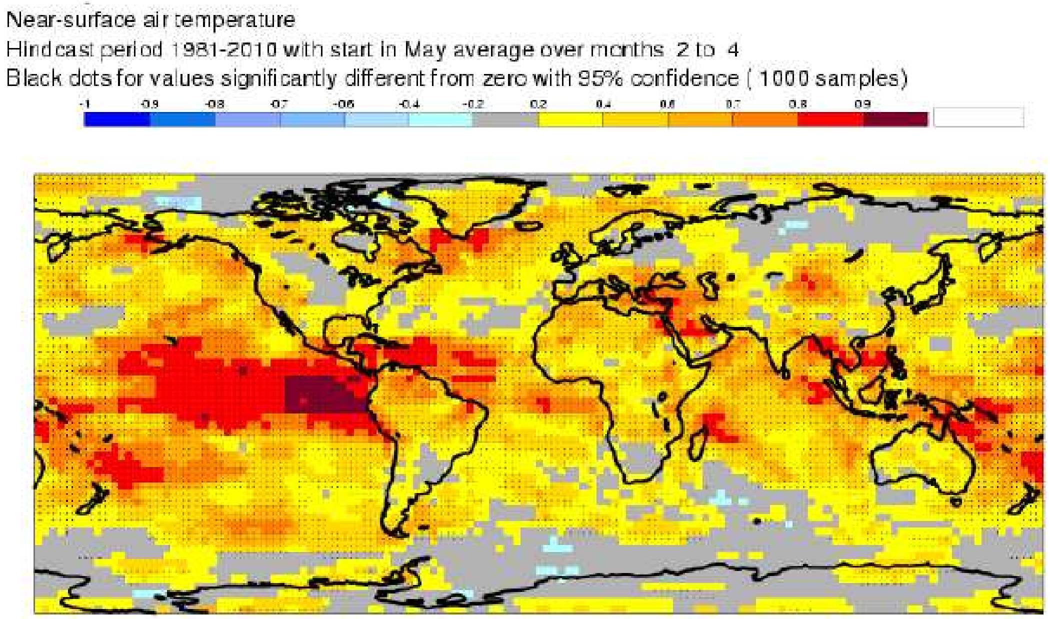
DYNAMICAL

- Non-linear interactions → YES
- Cond. of non-stationarity → YES
- INITIALISATION → crucial
- Some processes/phenomena are not properly simulated [e.g., stratosphere, snow–atmosphere coupling, land surface-atmosphere coupling, strong SST gradients, etc]
- They always produce some prediction although frequently useless

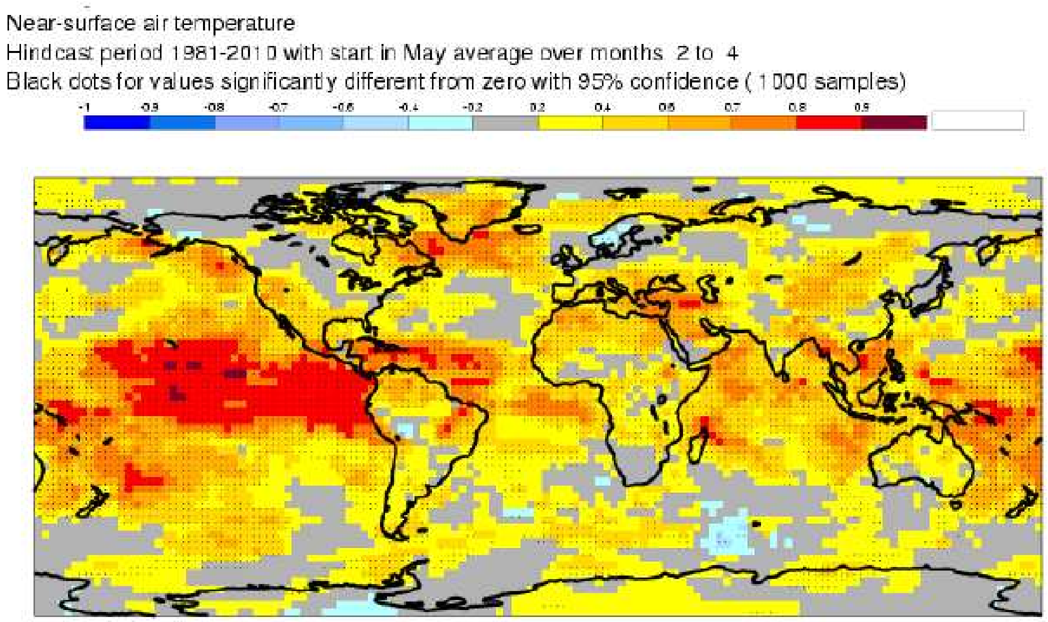
EMPIRICAL METHODS

- Non-linear interactions → NO
- Cond. of non-stationarity → NO
- USEFUL until dynamical forecast systems improve
- Simple linear methods go directly to correlate those processes/ phenomena not properly simulated by models
- Predictors used by empirical methods are constrained to certain seasons, regions, variables □
- Need to identify the most adequate predictors for each season, region, variable.

ECMWF S4



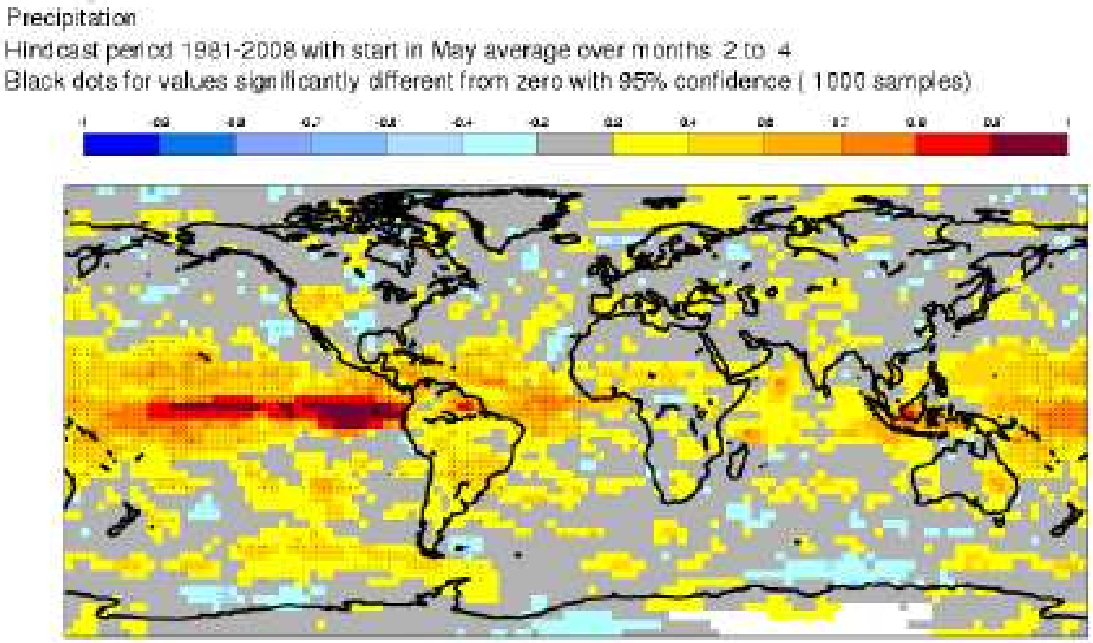
ECMWF S3



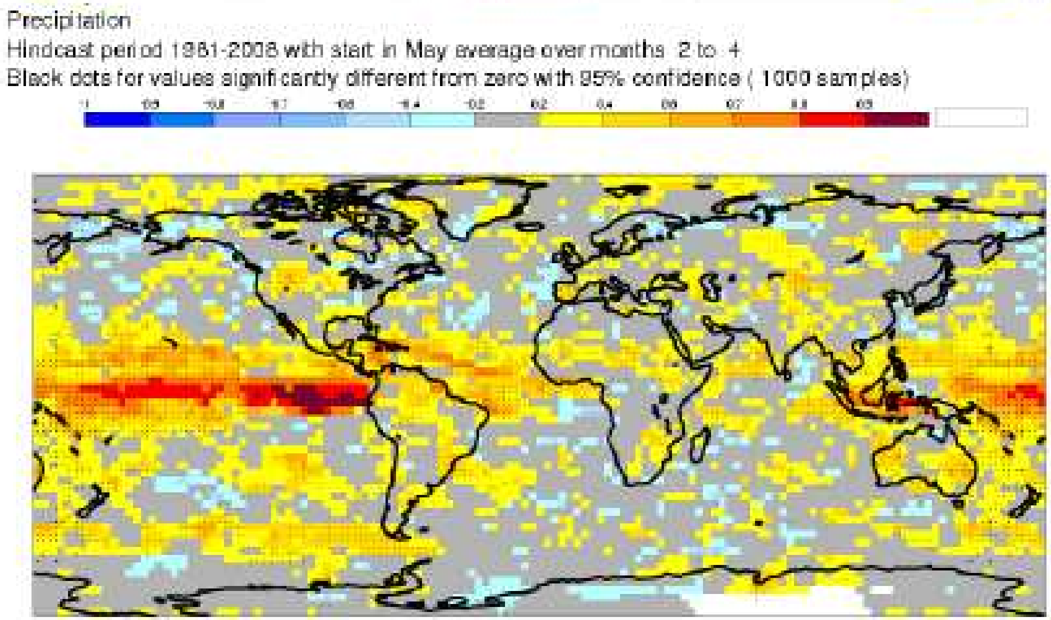
(Molteni et al. 2011)

Ensemble-mean anomaly correlation for 2m_T in JJA: S4 (top), S3 (bottom).

ECMWF S4



ECMWF S3



(Molteni et al. 2011)

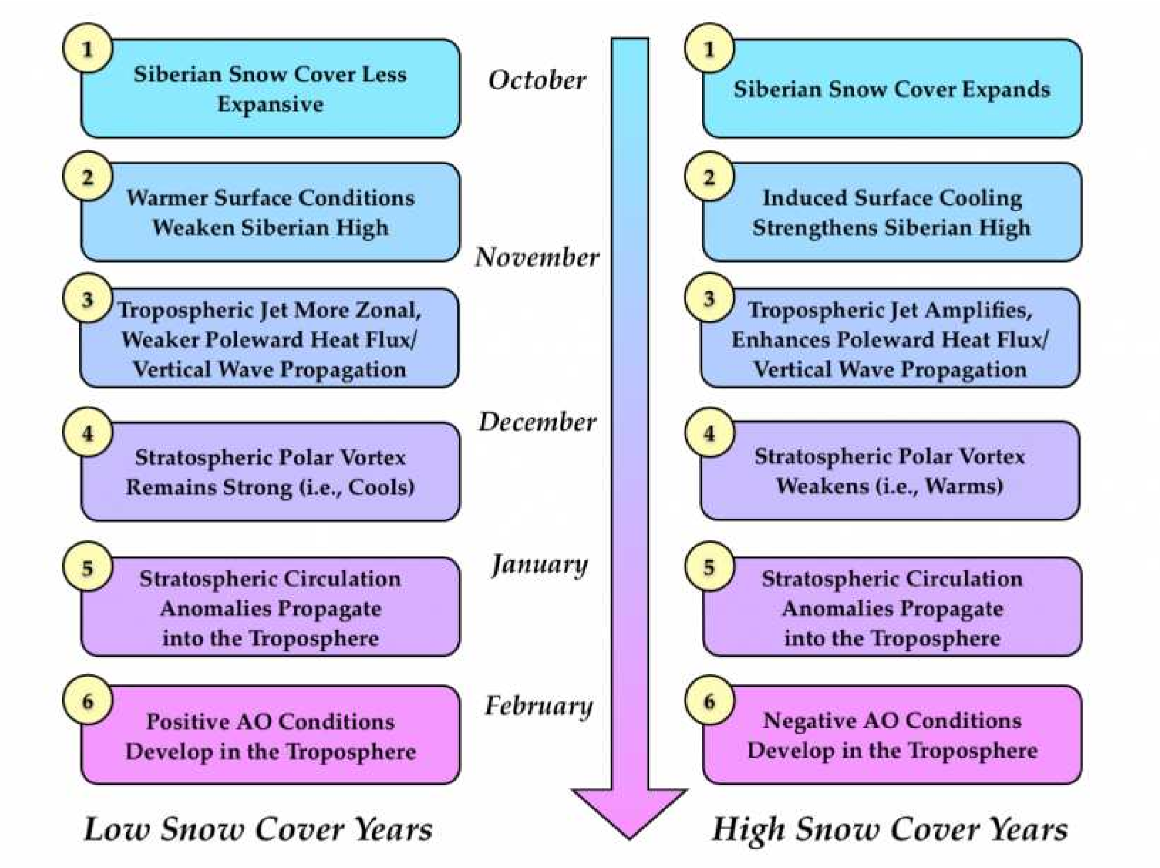
Ensemble-mean anomaly correlation for precipitation in JJA: S4 (top), S3 (botto

- Predictors used by empirical methods are constrained to certain seasons, regions, variables →
- Need to identify the most adequate predictors for each season, region, variable.

Example: index for winter predictions

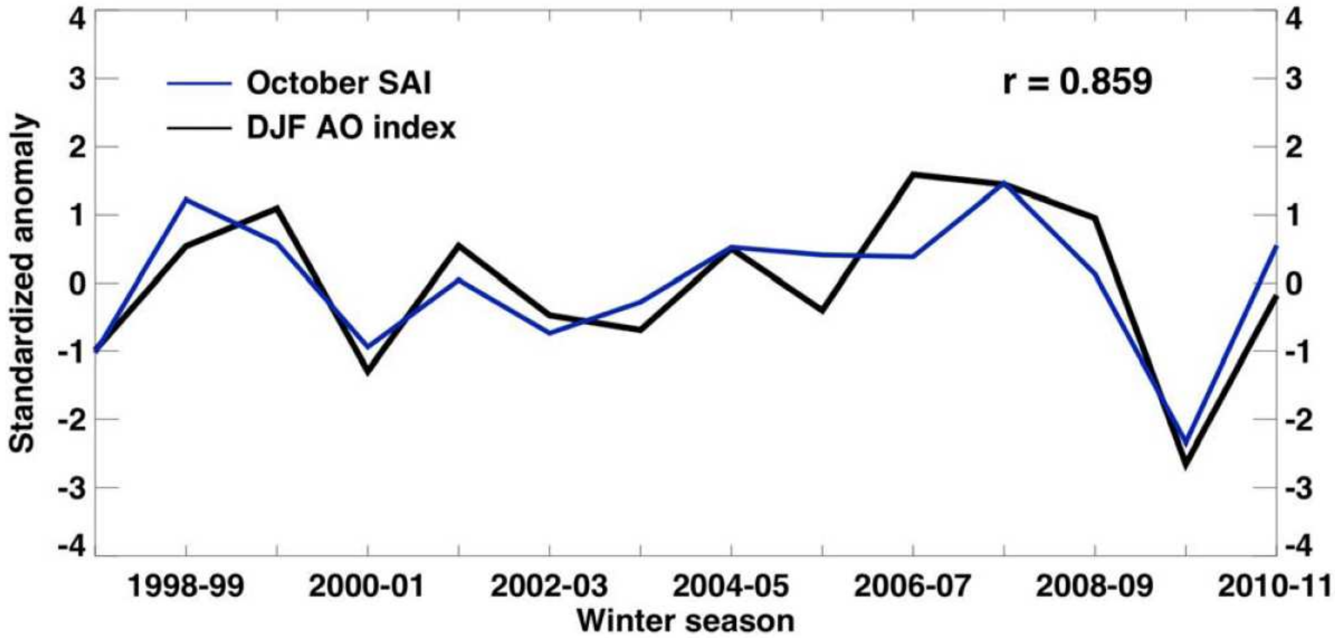
(Cohen & Jones 2011)

- Arctic Oscillation (AO) explains the largest fraction of temperature variance for NH winter.
- AO results from intrinsic atmospheric dynamics or chaotic behavior and therefore is unpredictable.
- Snow advance index (SAI) derived from antecedent observed snow cover that explains a large fraction of the variance of the winter AO.
- High correlation between SAI and the winter AO => AO is most likely predictable => Skillful seasonal climate predictions.



SAI definition

- Rate of increase of Eurasian snow cover in October, as described b the regression coefficier of the least squares fit o the daily/weekly Eurasia snow cover extension in geographical domain covering 25º–60ºN, 0º–180ºE. [Units: million km2/day]
- Daily SAI → Interactive Multisensor Snow and IceMapping System (IMS), which are availat on a resolution of 24 km for each day from 1997 onward (Ramsay 1998).
- Weekly SAI → NOAA satellite-sensed observations, offering a much longer time series (from 1972 onward) at the expense of a lower temporal and spatial resolution (Robinson et al. 1993).



- SAI Index is the regression coefficient of the least square fit of the daily Eurasian SCE equatorward of 60°N calculate d for the month of October. Units: million km2/day. Only snow cover for Eurasia (25–85°N and 0–180°E) is computed.

Pearson corr. btw October SAI and DJF precipitation

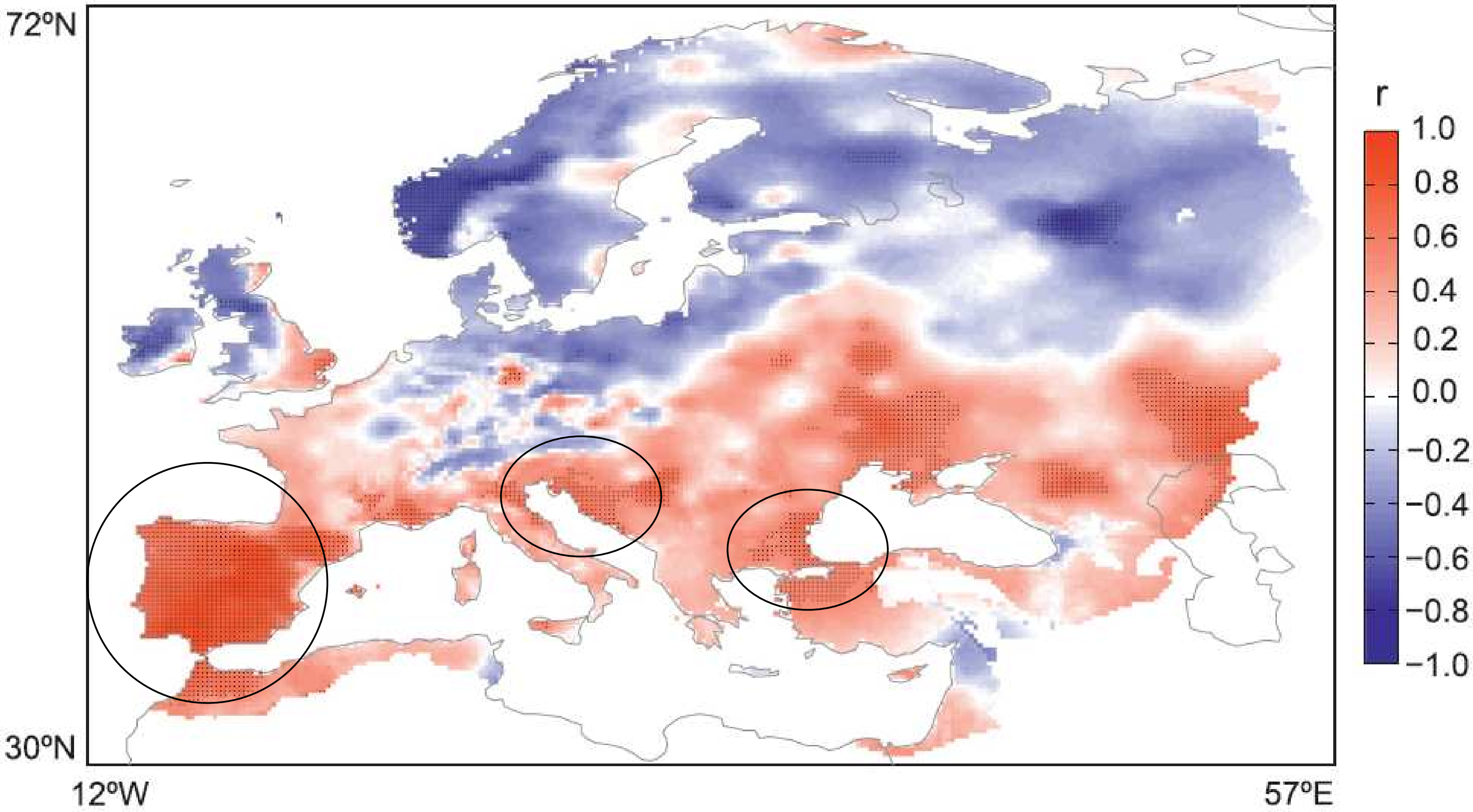
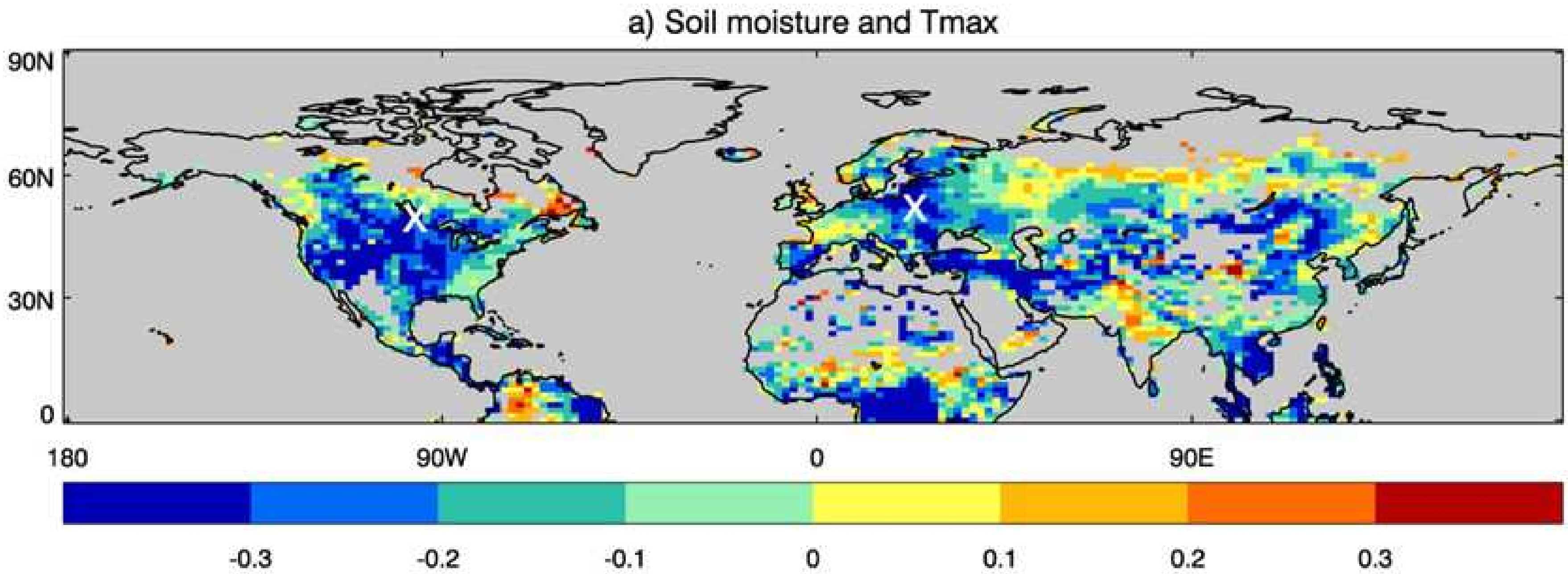


FIG. 1. Pearson correlation coefficients between the October daily SAI and the precipitation sums of the following DJF ($n = 14$; critical value $= +0.53$). Locally significant correlations ($\alpha_{local} = 0.05$) are shaded in black. Global significance was obtained ($\alpha_{global} = 0.05$); all calculations are based on E-OBS.

(Brands et al. 2012)

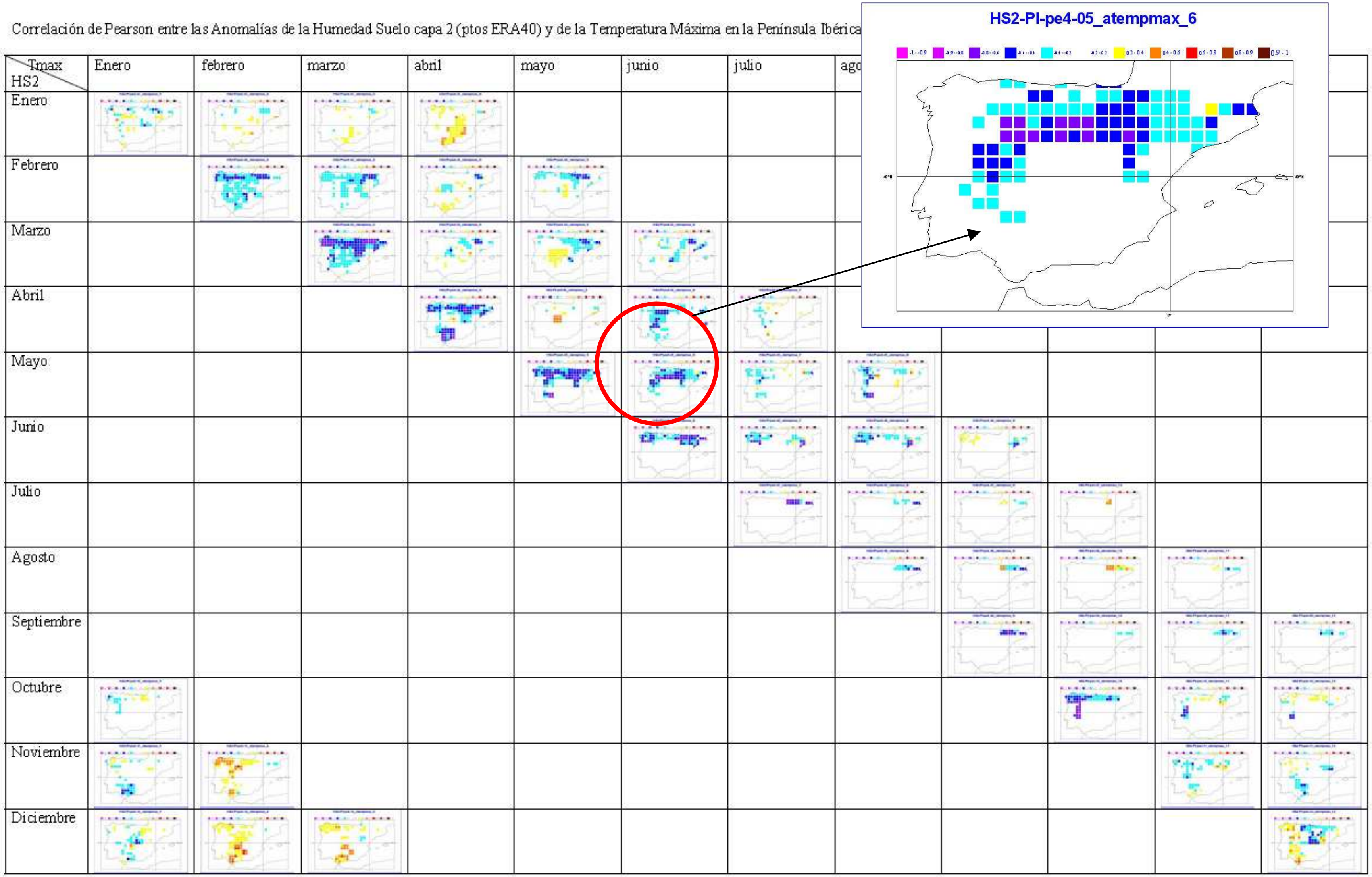
Another example:

Correlation coefficient for **May soil moisture anomaly (top 2m, from ERA-I) vs Forecast Mean JJA Tmax in 21 years of GLOSEA4 May hindcasts**



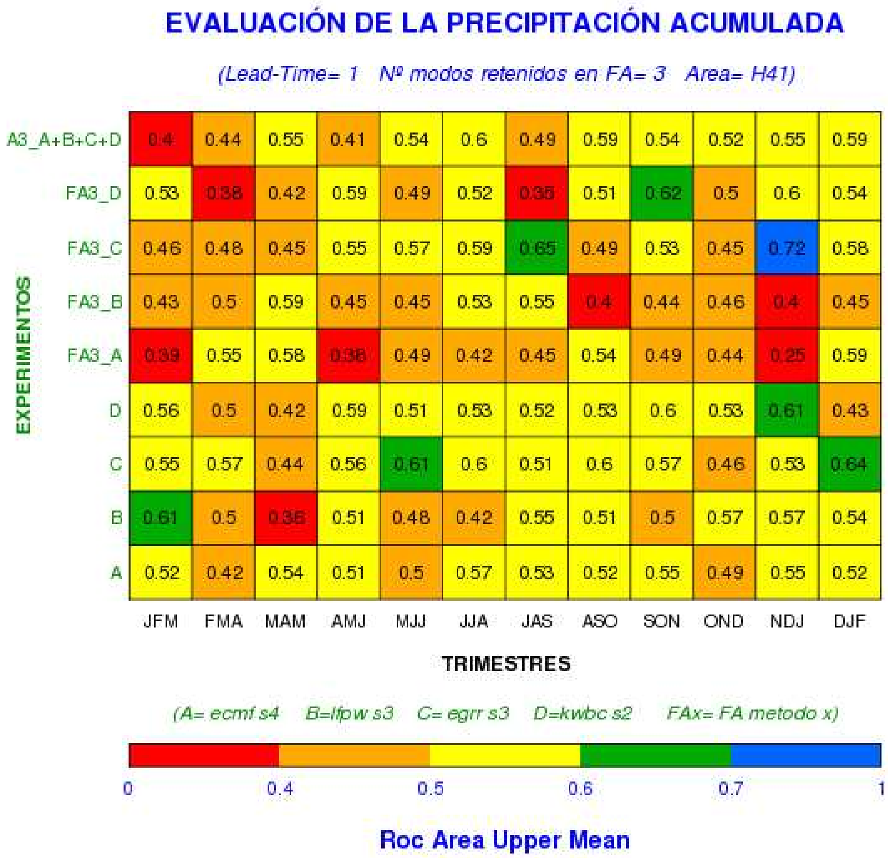
(Hewson 2011)

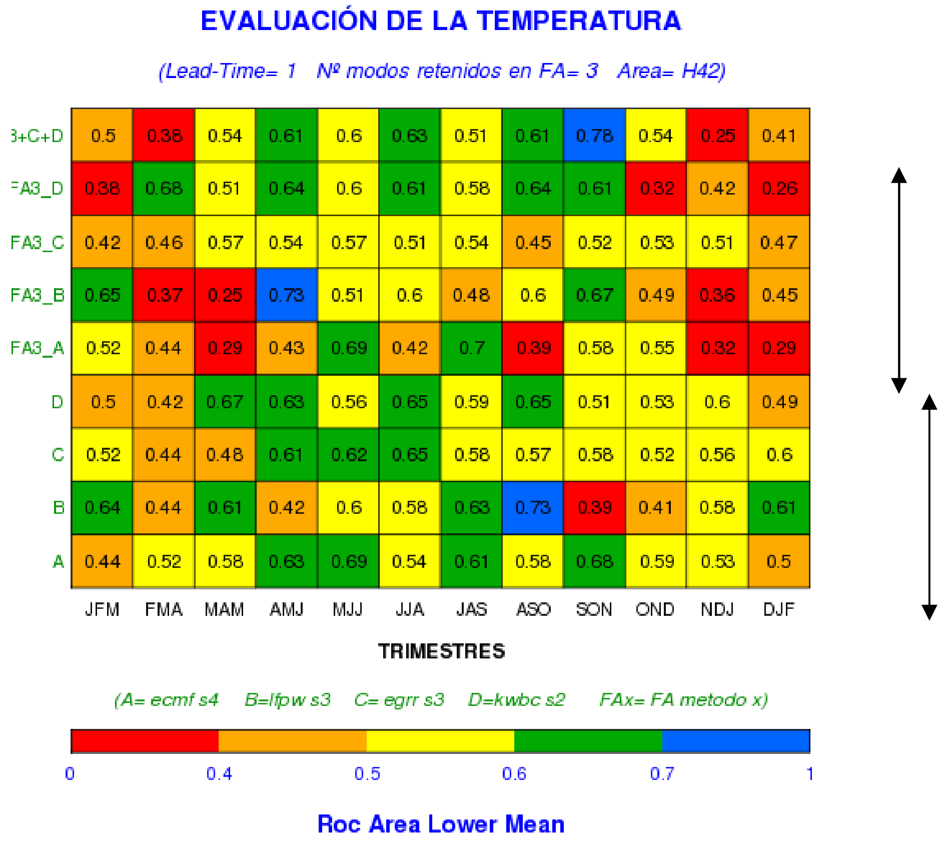
Pearson corr. SM (ERA40) vs Tmax



(Diez 2011)

Need of predictability estimation for every prediction system using a variety of metrics





(Sanchez 2013)

Better with downscaling!

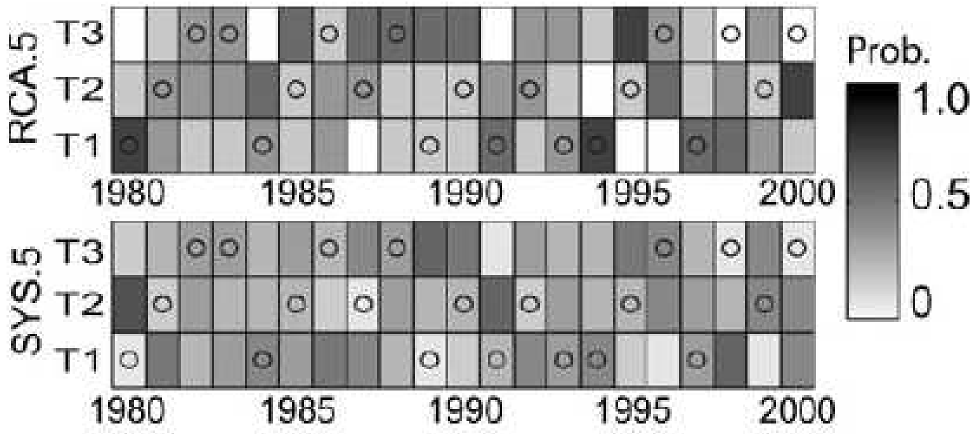


Fig. 2. Probability forecasts of the three terciles (dry/normal/wet) for an illustrative grid point shown in Figs 3(c) and (d) for the period 1981–2001 as resulting from the RCA.5 and the SYS.5 predictions. The circles show the corresponding observed terciles for each of the years.

Tellus 63A (2011), 4

In mid-latitudes, significant predictability is only found for particular seasons (SON), areas (mostly over the Iberian Peninsula) and events (dry). However, the regions where the regional downscaled forecasts are skillful differ from those of the global ensemble.

(Diez et al. 2011)

SUBSEASONAL TO SEASONAL PREDICTION

RESEARCH IMPLEMENTATION PLAN

22 June 2012

- Common methodologies and metrics to validate models, estimate skill and to evaluate model performance in simulating and predicting teleconnections.
- Identify potential sources of predictability and their representation in models
- Identify, represent and convey the conditional skill of forecasts during 'windows of opportunity' when predictability is enhanced
- Modelling issues: initialization, resolution, coupling oc/at, spred/skill relationship, ensemble generation, ……

Conclusions/recommendations

- Seasonal forecasting over Europe/Med. region would benefit from a coordinated effort to improve the forecast systems and to combine climate information from different sources (Doblas-Reyes 2010)
- Seasonal forecasting over Europe/Med. region would probably be feasible only restricted to certain windows of opportunity (variability patterns, seasons, variables, regions, systems,…). But exactly what these are or how to recognise them is still unclear!
- Never disregard any source of predictability! Use all sources of available information (models and empirical) and mix them in an “intelligent” way
- Provide probabilistics products meeting users needs → EUPORIAS project approach
- Verify, verify and verify