How can climate prediction capabilities be advanced?

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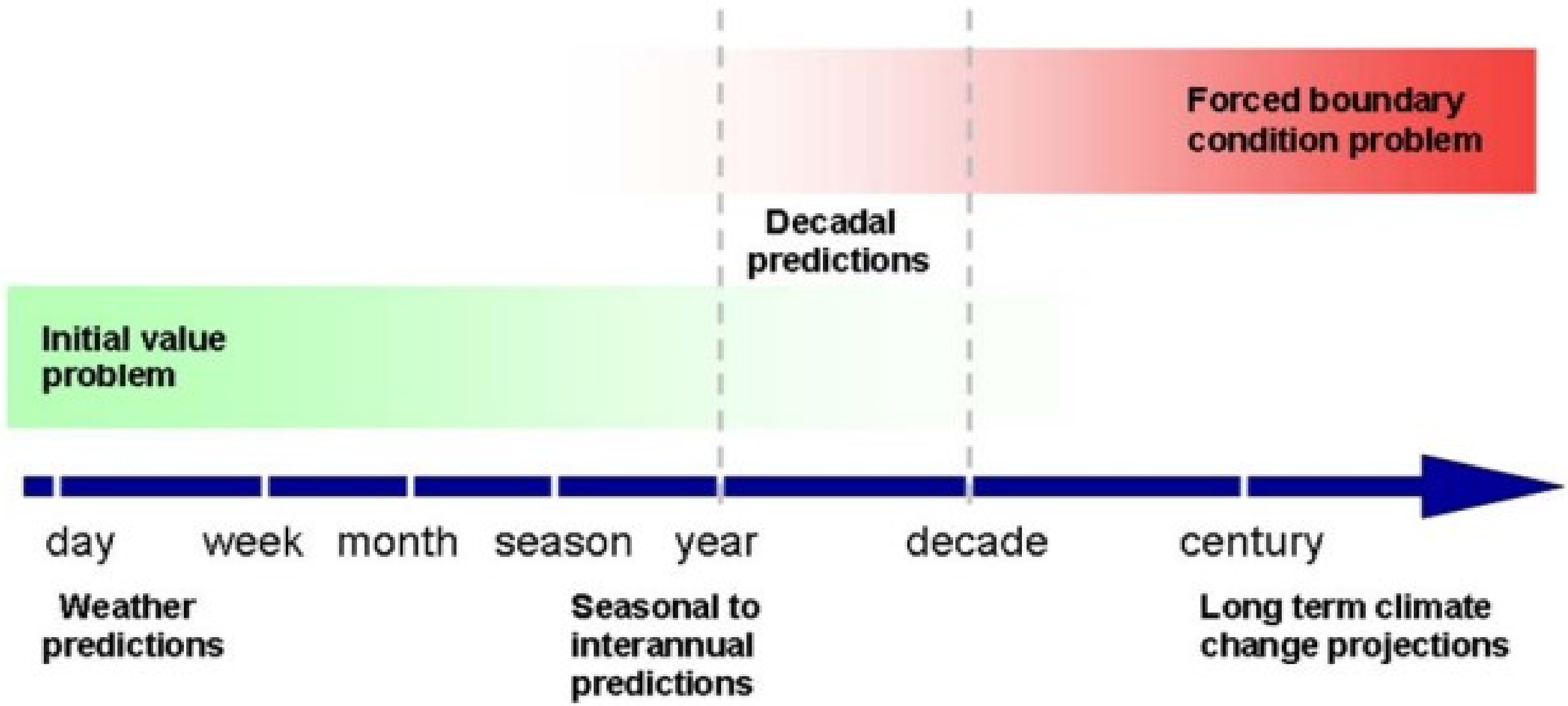
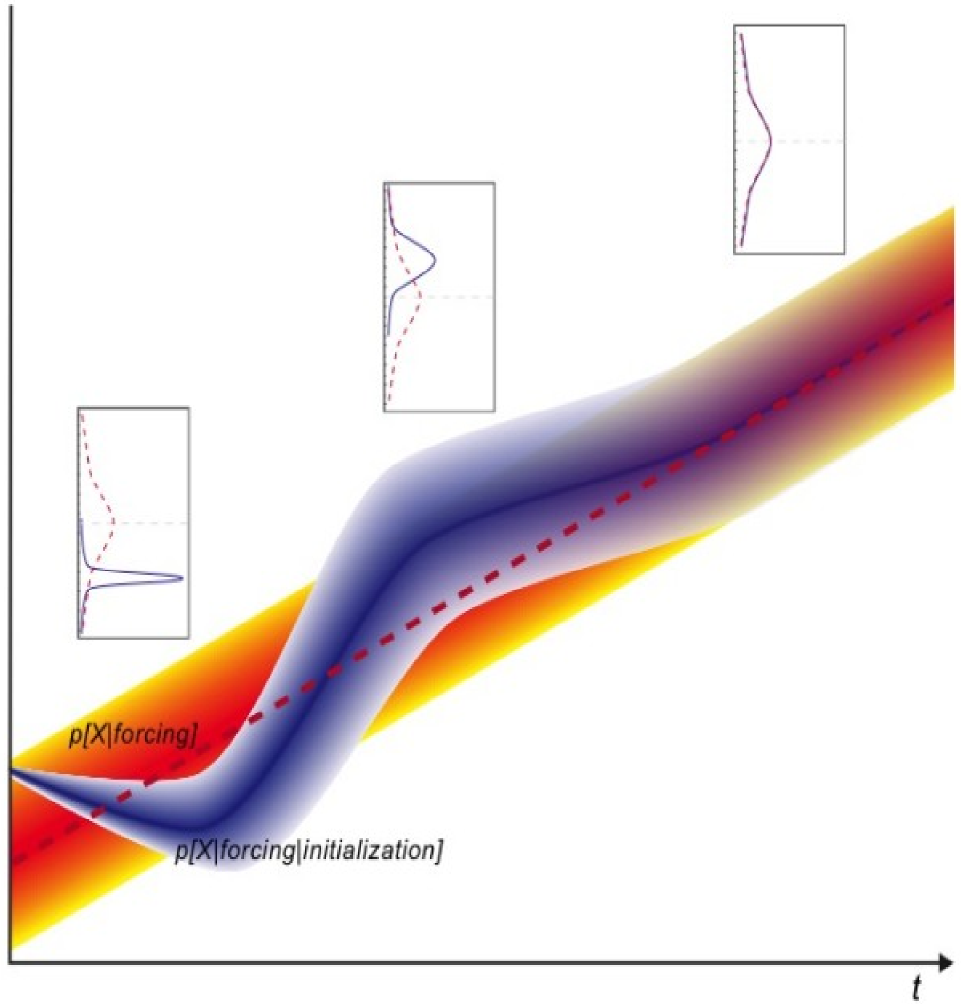
What is climate prediction?

- Forecast based on climate models, starting from observed conditions
- Often targeting average climate conditions and extremes of the coming seasons or years
- Goal:
  - To provide probabilities in addition to persistence and observed trends, suitable for actionable information and services for public and private stakeholders

Prediction vs projection



Box 11.1, Figure 2: A schematic illustrating the progression from an initial-value based prediction at short timescales to the forced boundary-value problem of climate projection at long timescales. Decadal prediction occupies the middle ground between the two (based on Meehl et al. (2009b)).



Box 11.1, Figure 3: A schematic representation of prediction in terms of probability. The probability distribution corresponding to a forced simulation is in red with the deeper shades indicating higher probability. The probabilistic forecast is in blue. The sharply peaked forecast distribution based on initial conditions broadens with time as the influence of the initial conditions fades until the probability distribution of the initialized prediction approaches that of an uninitialized projection (based on Branstator and Teng (2010)).

Can we actually live up to the potential?

Depends on

- **Quality** of the model
- Existence of **sources** of predictability
  - in the real climate system and
  - in models
- The method of **initialization**

Sources of predictability = natural oscillations in solar forcing and climate system

Sources of predictability

- **Signal storage capacity**
- **Observable phenomena (oscillations, forcing, events) which can serve as predictor (i.e,. relate to a quantity to be predicted).**
- **Physical mechanisms linking predictors to predicted quantity (e.g. temperature over Europe and the Arctic)**
- Need to
  - understand physical mechanisms representation in models to gain confidence in forecasts
  - optimize
    - initialization methods
    - Ensemble building methods
    - Models

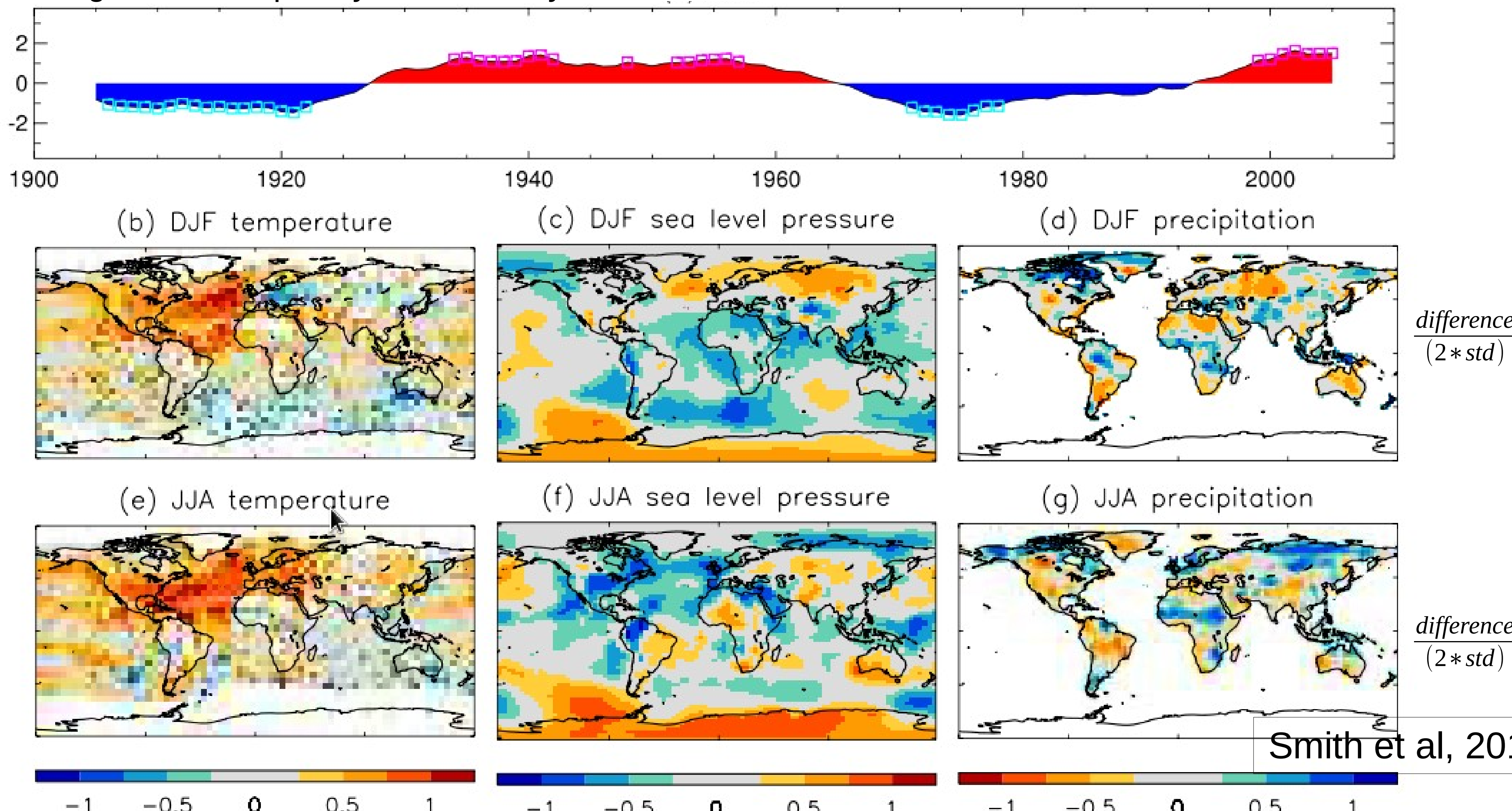
Example for a source of predictability:

Atlantic multi-decadal oscillation (AMO)

is characterized by a sharp rise and fall of the North Atlantic basin-wide sea surface temperatures (SST) on multi-decadal time scales.

AMO can be related to
- Air temperatures and rainfall anomalies of Northern Hemisphere,
- North American and European summer climate.
- frequency changes of droughts in North America
- Drying of Sahel in the 1960–70s
- change in the frequency and intensity of Atlantic hurricanes

AMO is predictable “a few years” ahead.



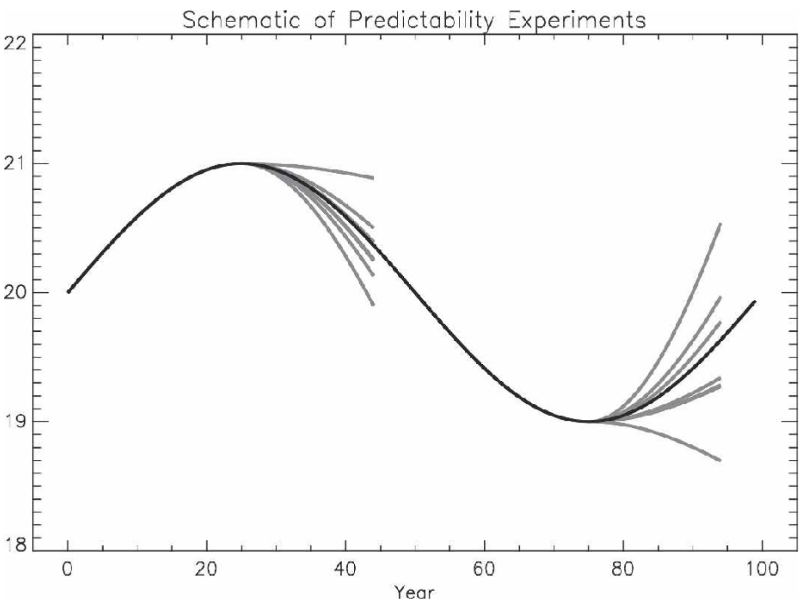
Smith et al, 2012

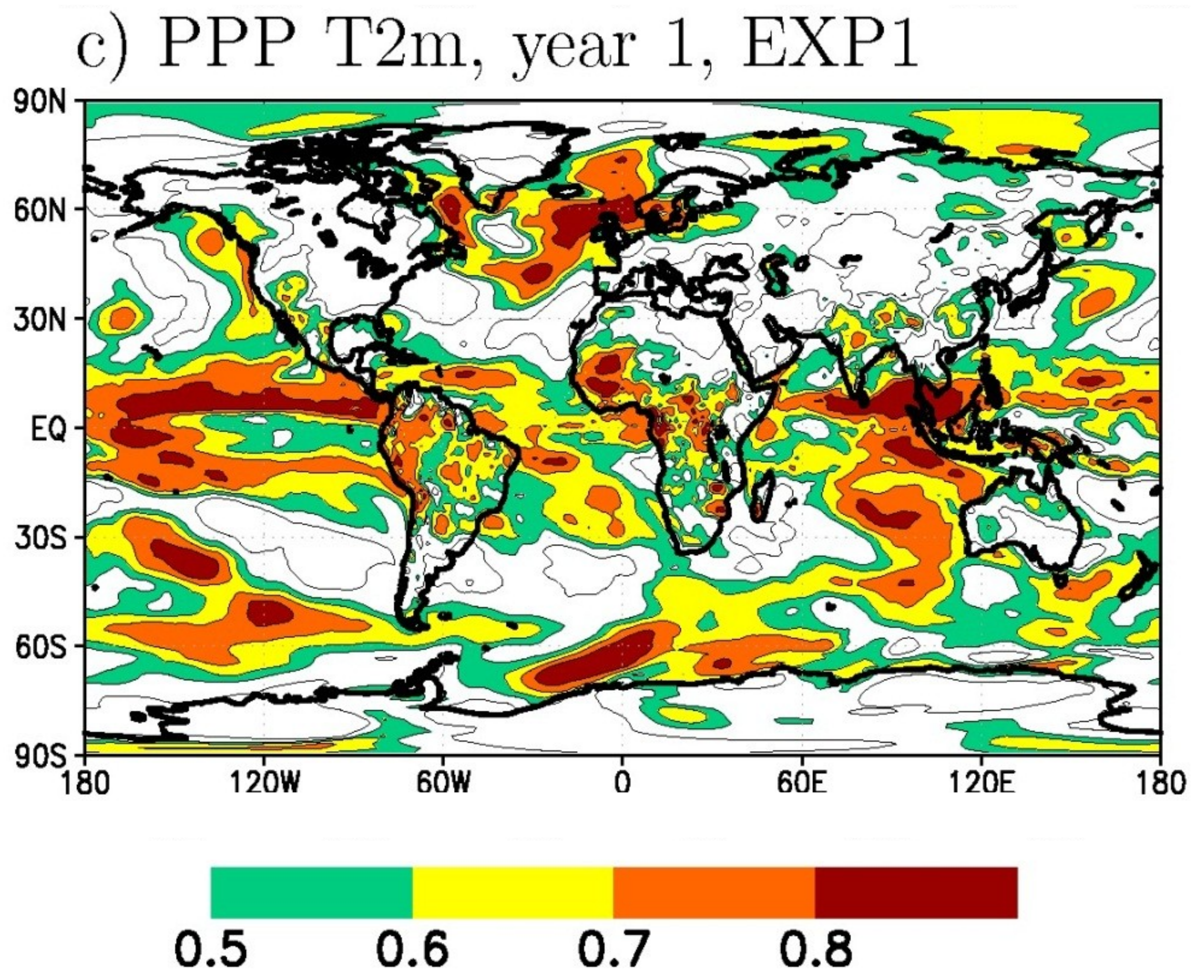
More sources of predictability

- **Solar cycle** (Ineson et al. 2011)
- **North Atlantic Oscillation** (NAO)
- Arctic **sea ice** extent (SIE)
- **El Nino** (Ineson and Scaife, 2009) and La Nina variability (Fereday et al, 2008)
- **Snow cover** (e.g. Cohen and Jones 2011)
- **Vegetation** (Weiss et al. 2012)
- Sea surface temperature (SST) variability in the North Atlantic (Rodwell and Folland 2002)
- Quasi-biennial oscillation (**QBO**) in the tropical stratosphere (e.g. Marshall and Scaife 2009)
- Major tropical **volcanic eruptions** that cause warming of the Nordic regions sometimes for more than one winter (Jones et al. 2003; Marshall et al 2009). Remote influences on Atlantic hurricanes and sahel precipitation.
- Madden-Julian Oscillation (**MJO**)
- The role of resolution and ensemble technique
- Pacific decadal variability (**PDV**)
- Atlantic multi-decadal variability (**AMV**)
- North Atlantic ocean currents are potentially predictable on decadal timescales. “Some skill” in initialised (real live) predictions
- Increased **aerosols** => cool N. Atlantic => anomalous Hadley circulation => ITCZ shifts south => fewer storms
- Aggressive aerosol mitigation in RCP2.6 => reduced cooling (more warming) in N. Atlantic) => stronger anomalous Hadley circulation => ITCZ shifts north => more storms
- skill from the climate change signal
- Emerging importance of external factors: aerosols, volcanoes, solar, greenhouse gases via sea ice?

Interannual potential predictability

PPP = prognostic potential predictability





Koenigk et al. 2012, SMHI

- Potential predictability = Approximation of upper limit predictability, under the assumption that the climate model represents the real world.
- That upper limit can be further enhanced by improving the model (more realistic descriptions of the sources of predictability)

Region	PPP CTRL
North Atlantic (10-60W,30-60N)	**0.85**
Europe (0-60E,30-60N)	**0.72**
Africa (10W-40E, -30S–30N)	**0.57**
S. Asia (60-130E, 10-40N)	**0.71**
N Asia (60-150E, 40-70N)	0.39
N America (70-150W, 30-70N)	0.42
S America (40-80W, 50S-10N)	0.11
Australia (110-155E, 40S-10S)	0.27
Antarctic (0-360E, 90S-70S)	0.35
Arctic (0-360E, 70-90N)	**0.77**
Labrador Sea (48-65W,45-65N)	**0.87**
global	**0.85**

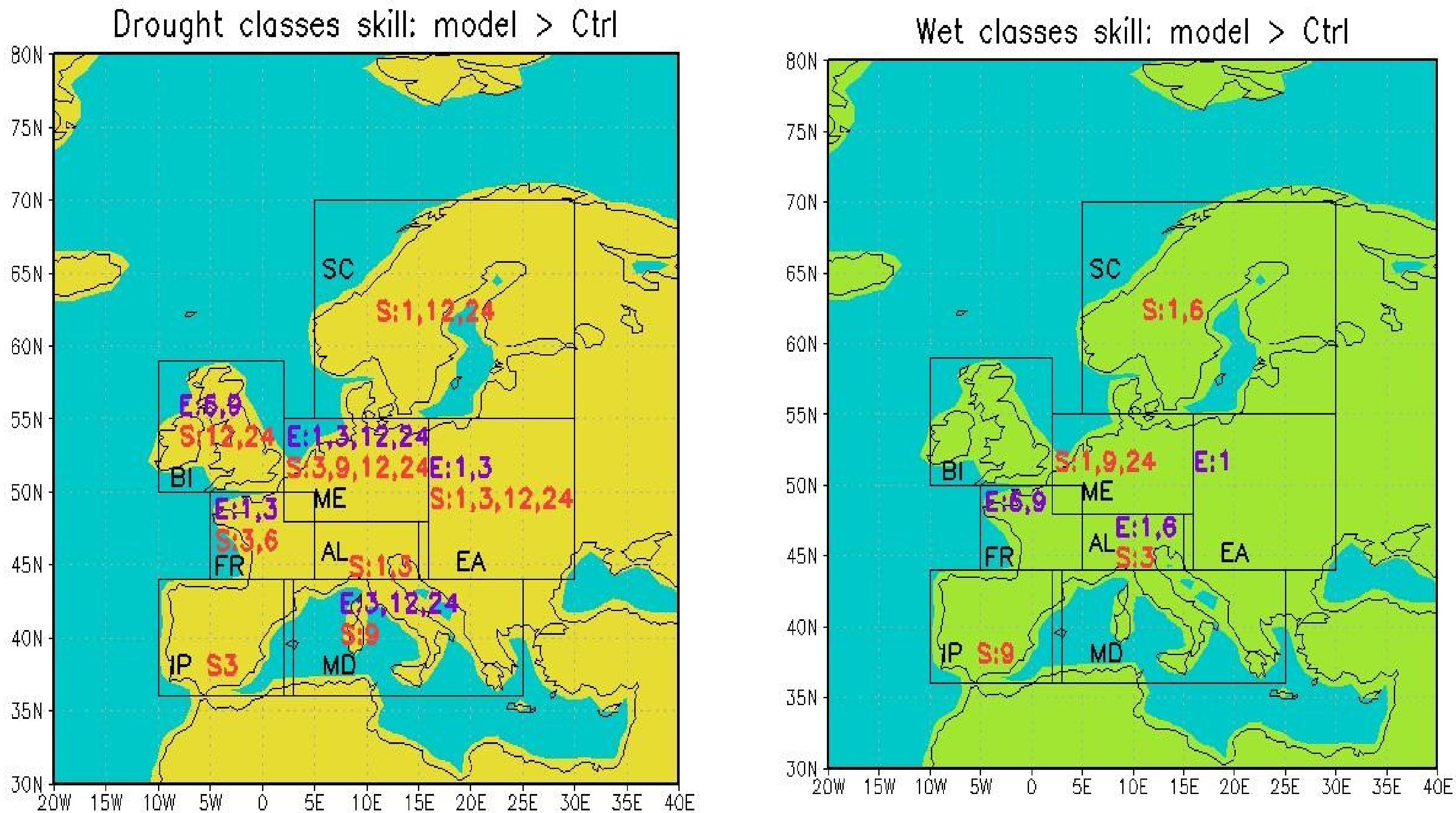
Potential predictability for regions

PPP for regional means, T2m, y1-10, PPP increases with enlarging regions.

Northwestern Europe is the populated area where decadal predictions might have the highest potential for improvement compared to traditional scenario simulations. Compared to previous studies, results indicate a slightly higher predictability over land regions. If the relatively high resolution in EC-Earth compared to the models used in most previous studies contribute to this fact remains to be analyzed. The predictability of air temperature averaged over continental-size regions increases particularly for northern hemispheric regions compared to the predictability on the grid size scale.

Koenigk et al. 2012, SMHI

Predicted regional extremes



Regions and their forecast skill for extreme (E) or severe (S) events. The numbers in the figure indicate the length of extreme periods (in months) with skill. (blue for extreme events, red for severe events,)

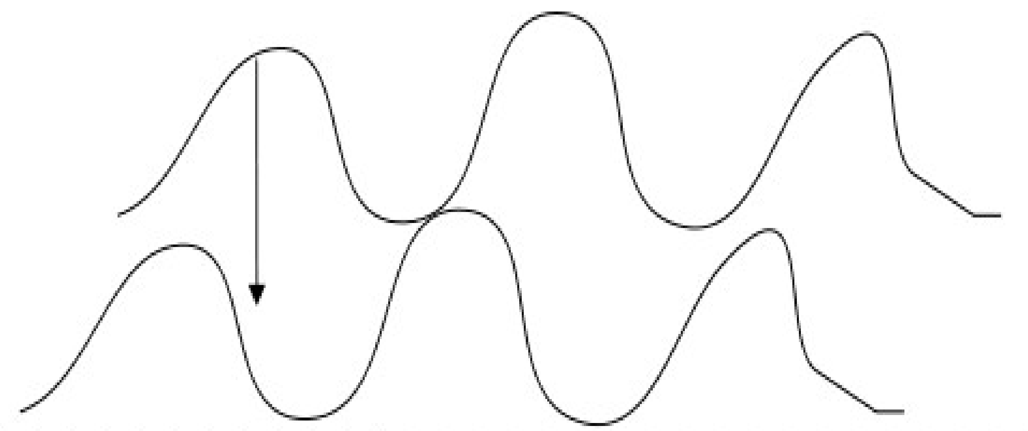
The model is able to give the probability of extreme or severe events for specific regions

(Skill is measured by means of the Standardized Precipitation Index (SPEI, Edwards and McKee, 1997). The forecast was an initialized climate prediction run with EC-Earth v2. Skill is shown in the figure only if it outperforms the non-initialized model and if the skill has statistically significant values.)

Caian, Rossby Centre, SMHI

Example for improvement of skill:
Phase anomaly initialization

Phasing ("process" projections):



EOF decomposition of observations and model.

Observation fields are recomposed with modified amplitude and phase, derived from the model signal, and then used for initialization.

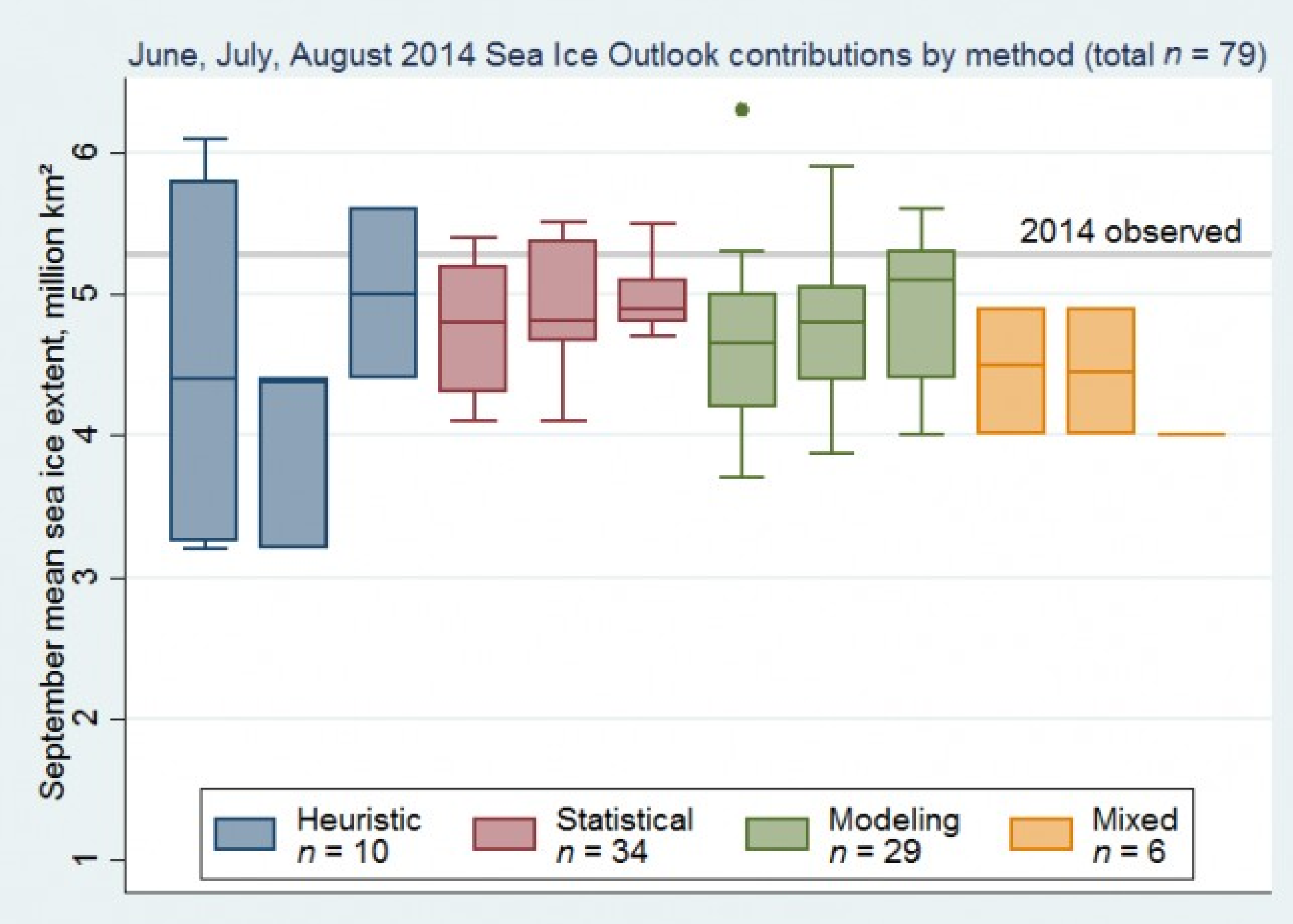
Anomaly correlation skill:

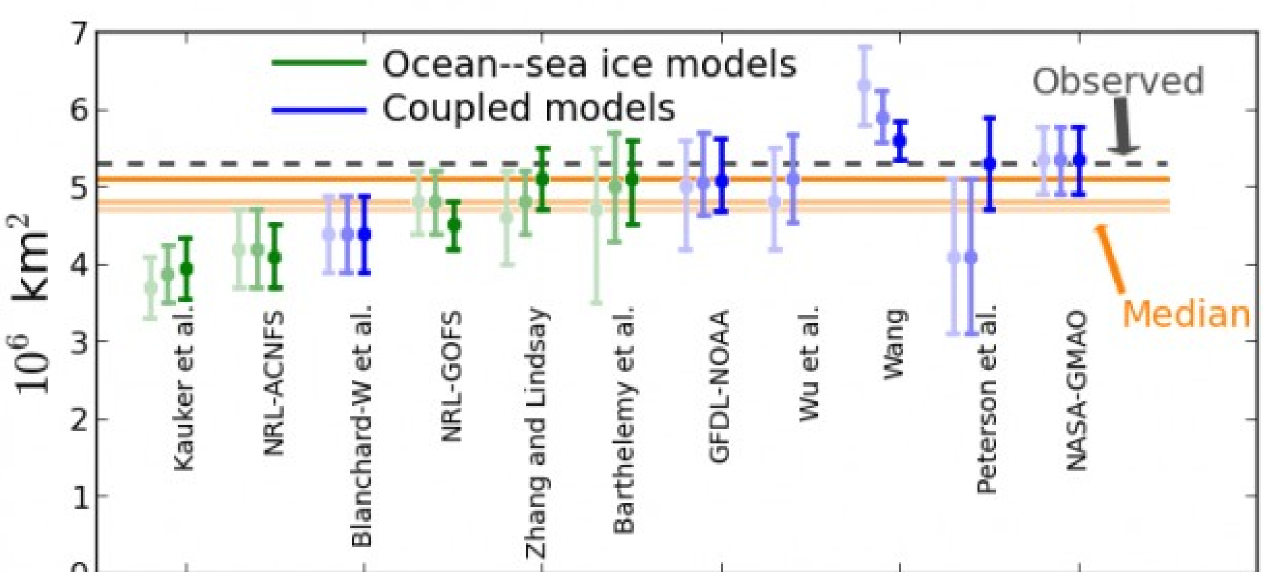
AN 95	0.35 (p1)	0.22 (p2)	0.35 (p3)	0.62 (p4)	0.56 (t)	**0.71 (ts)**	0.47 (tsuv)	0.41 (anaice)

Best skill for T and S
phase initialization
at all levels. (Robust finding,
Tested for several decades)

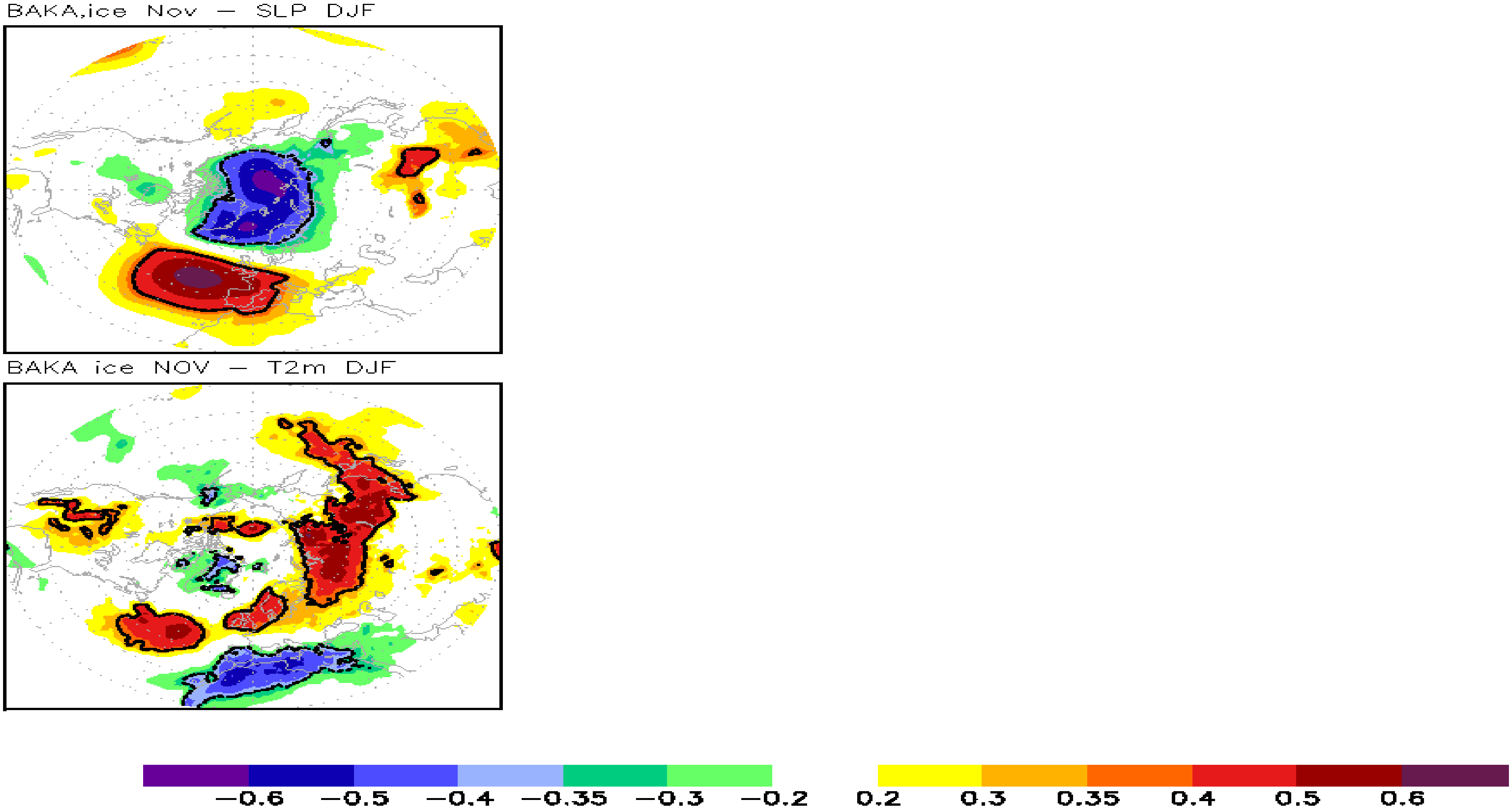
Caian et al., in prep, SMHI

Arctic Sea ice outlook 2014





Arctic winter atmosphere is conditioned by autumn sea ice



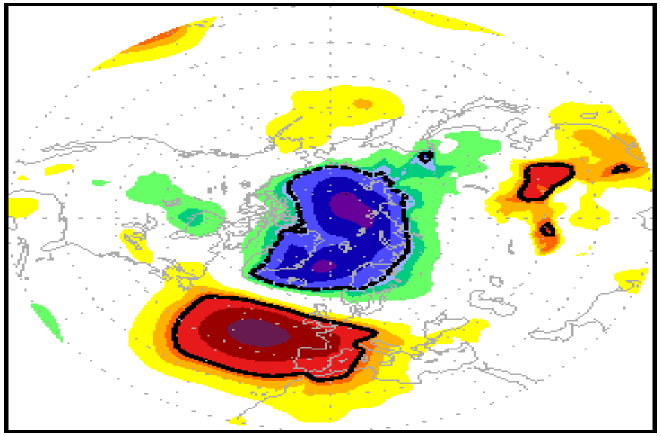
Correlation of **November sea-ice area in Barents/Kara Sea**,
with **winter (DJF)**

SLP-Variationen (upper panel) und T2m (lower panel). All Data detrended; 1982-2013; sea ice area from OSISAF; SLP, T2m ERAinterim; black lines indicate significance limits 95%.

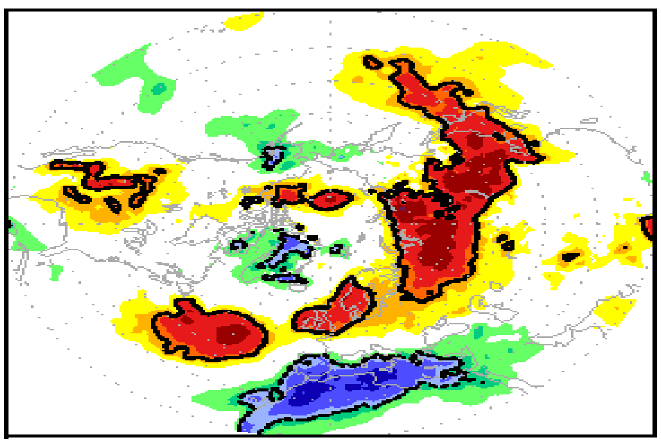
Koenigk et al., submitted

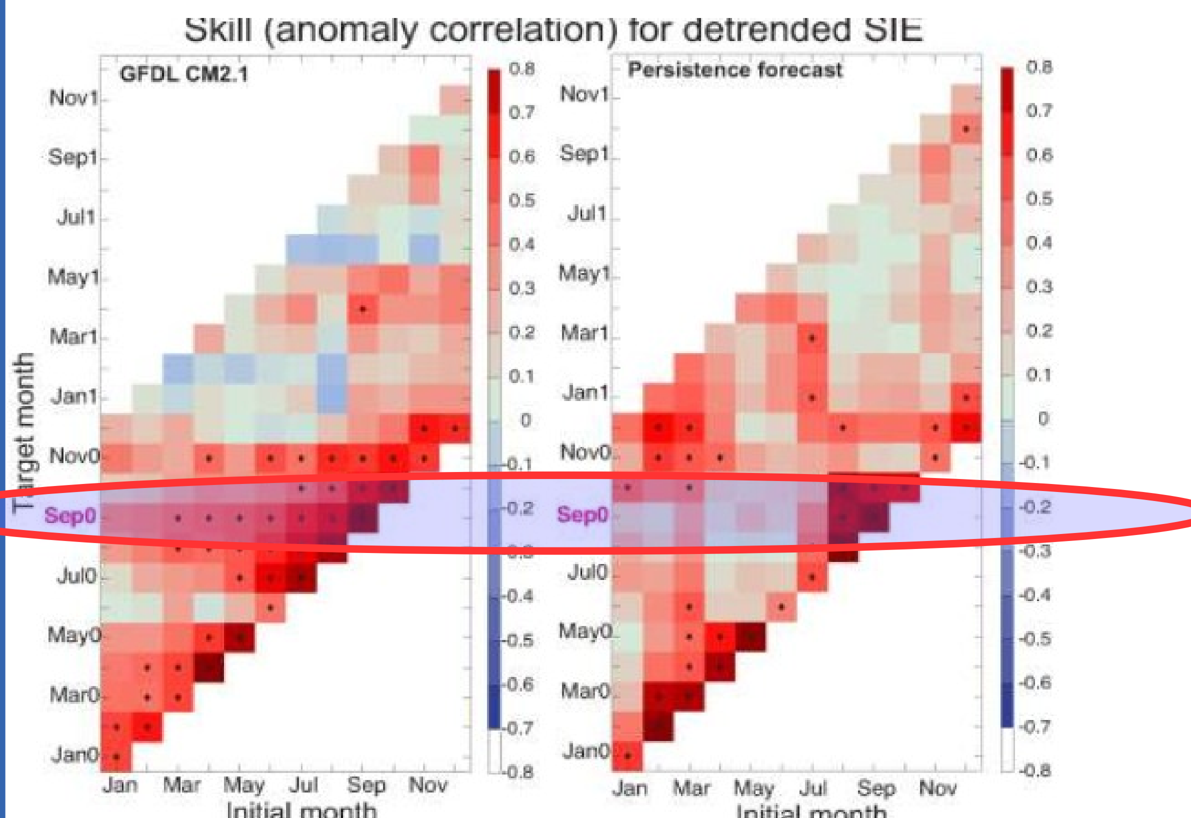
Arctic winter atmosphere is conditioned by autumn sea ice

BAKA,ice Nov — SLP DJF



BAKA ice NOV — T2m DJF





Msadek, GFDL: Overall better skill than persistence, significant up to 7 months ahead during summer.

Correlation of **November sea-ice area in Barents/Kara Sea**, with **winter (DJF)**

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Koenigk et al., submitted

Lessons from Arctic Sea ice prediction
(Sea ice outlook, SPECS, ...)

- **Better initialization of sea ice conditions**, i.e., incorporating more observational data in the sea ice and the ocean models with consistent ocean and sea ice states;
- Tailored **anomaly initialization** methods to minimize the drift that would account for the bounded nature of the sea ice variables;
- More advanced **model physics** (melt ponds, surface scheme in general);
- **Ensemble generation methods** that better account for initial condition uncertainties and model physics uncertainties;
- Encourage groups to **provide information on what they consider as the greatest source of uncertainty** in their simulations.

What can we expect from climate prediction?

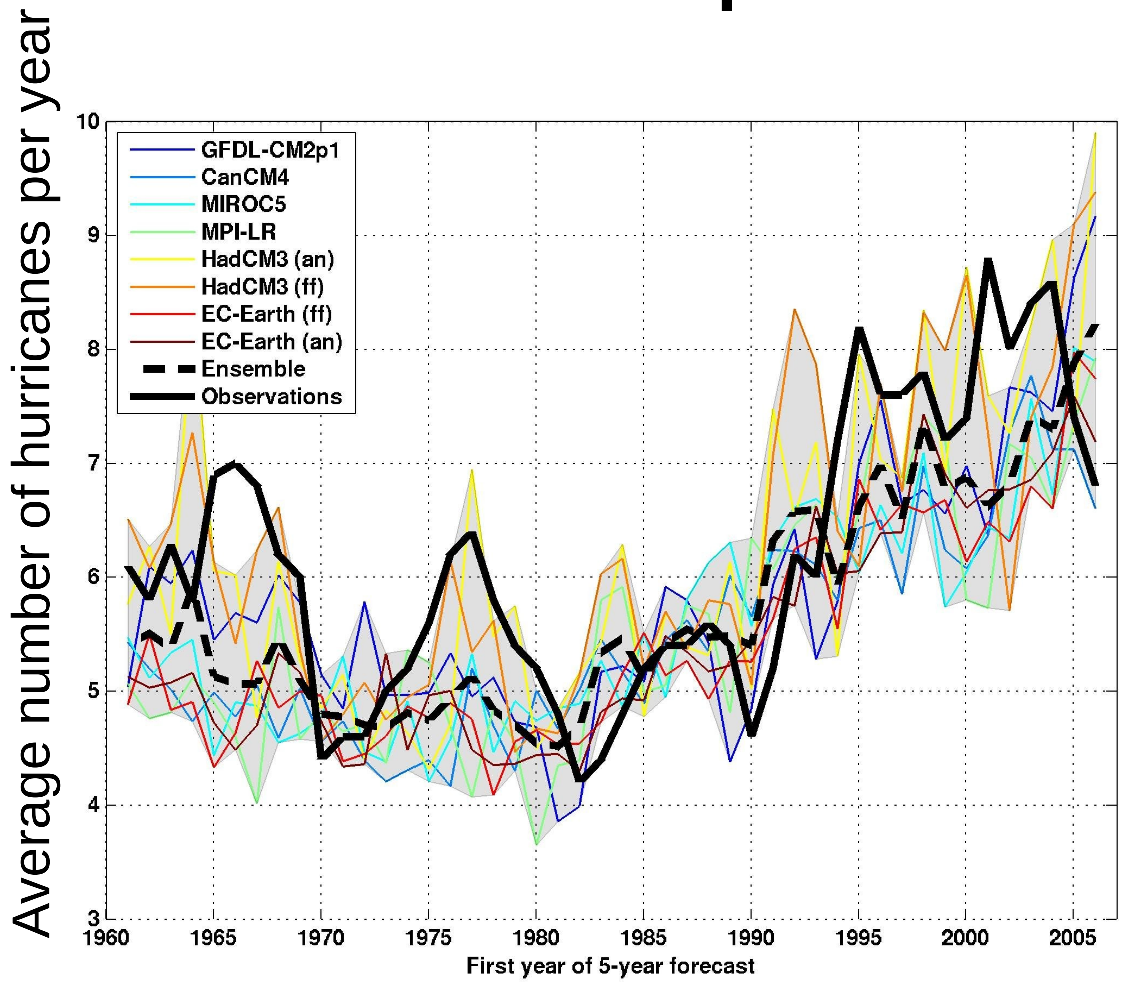
- Provision of **probability information**, better than persistence and observed trends
- There is **potential decadal predictability for Northern Europe and parts of the Arctic**, and other regions, sources of predictability exist
  - Skill exists today **for specific regions**
- Real-world multi-annual forecasts exist in an experimental state (SPECS, ...)
  - **Different skills in average conditions and extreme events**
- Specific applications (e.g. hurricane prediction) has good prospects in the future
- **Improvements** expected from
  - Better models / more complete process description / signal storage / atmospheric composition / higher resolution
  - More sophisticated initialization / assimilation methods / coupled initialization / ensemble building / Arctic: sea ice thickness
- Climate prediction has established a research base with initialized GCMs, which likely will be able to answer the current major questions on its potential during the coming years. (SPECS)
- The demand of action-relevant climate information on multi-annual time scales is growing. Forecaster and users need to learn how to make use of probability information.

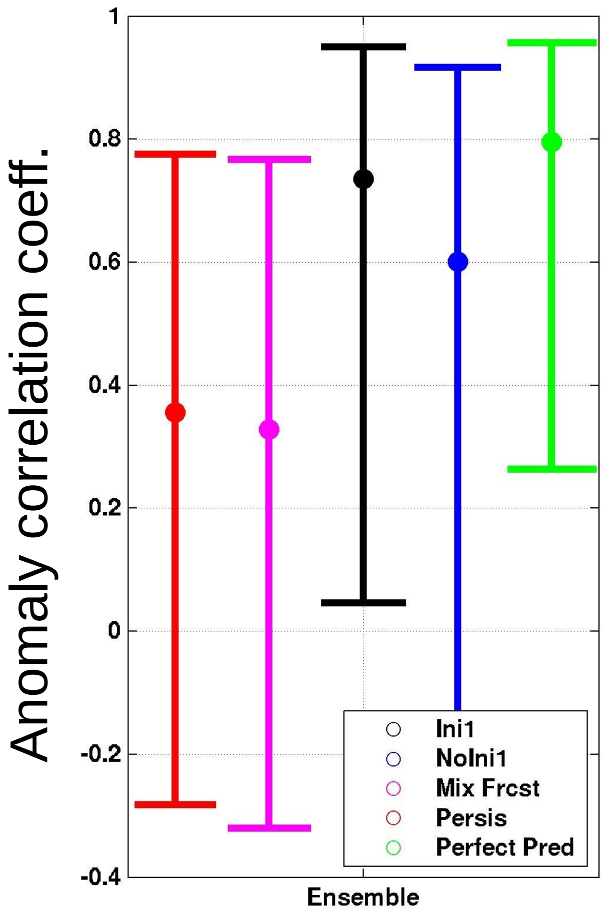
ECRA
European Climate Research Alliance

SMHI

End

Example: Hurricanes





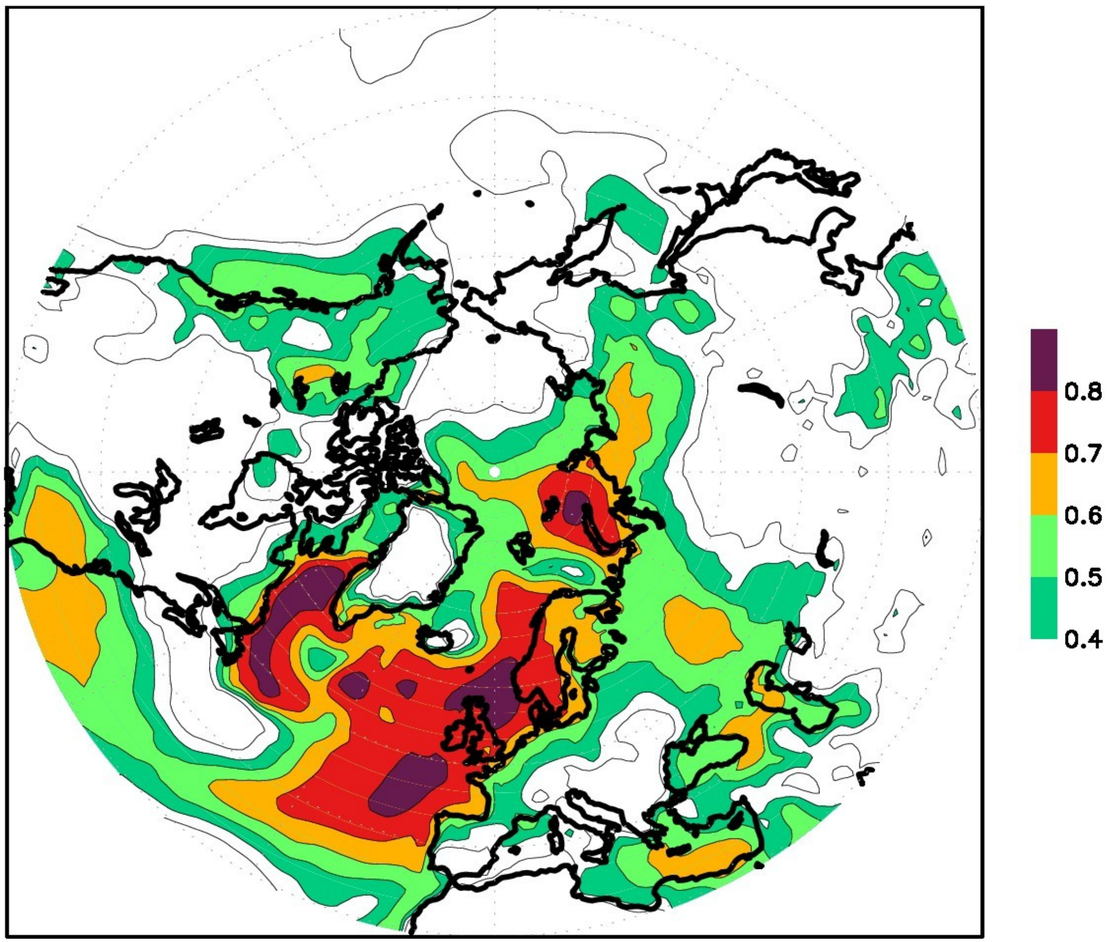
Caron et al. (2014), IC3, SMHI

Average number of hurricanes per year estimated from observations and from the CMIP5 multi-model decadal prediction ensemble (forecast years 1-5).

The correlation of the ensemble mean for the initialized, uninitialized and statistical predictions are shown with the 95% confidence intervals.

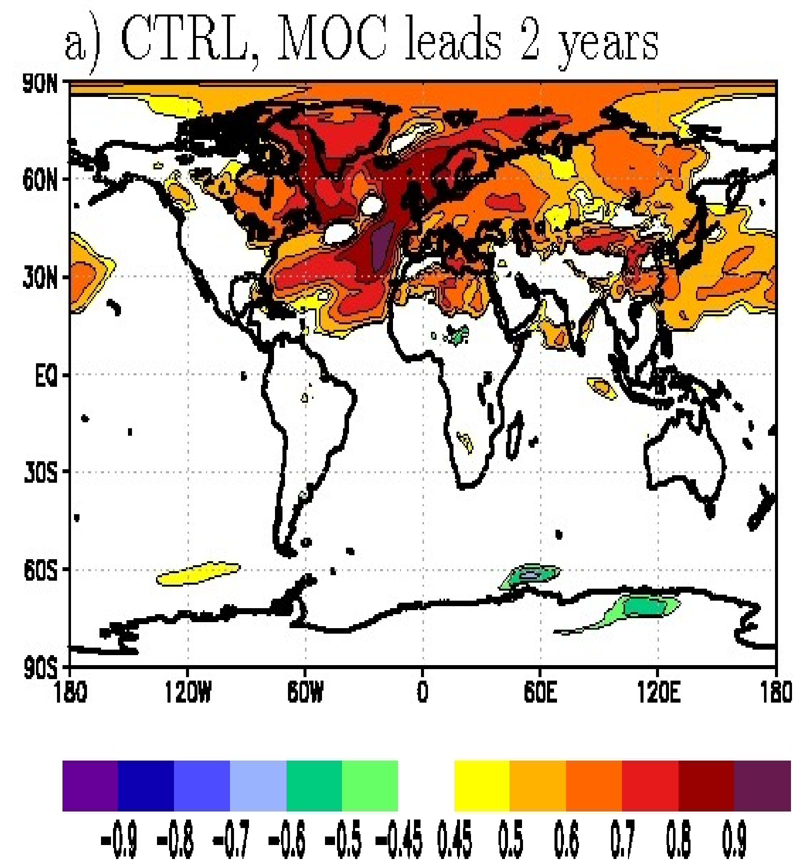
Uncertainty with respect to model complexity

Decadal Prognostic Potential Predictability for surface air temperature



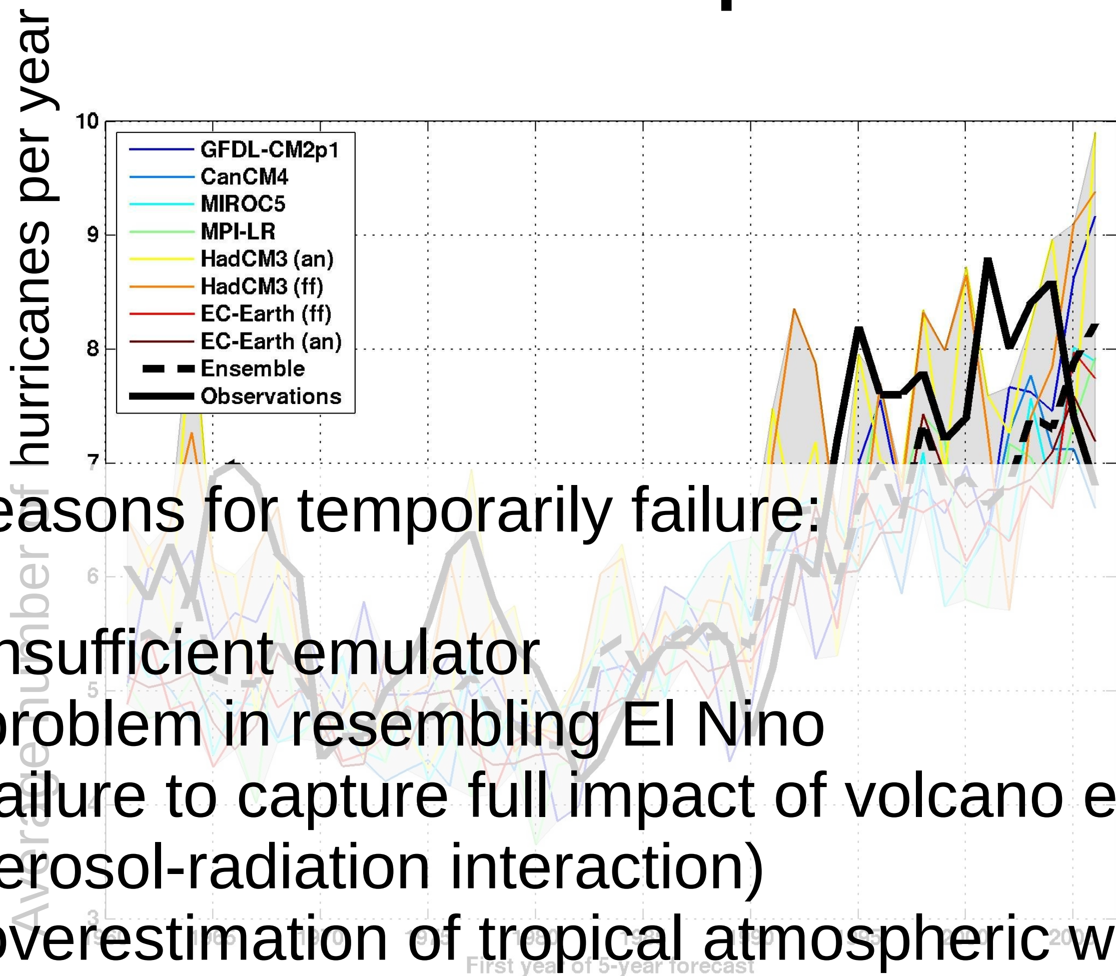
Prognostic potential predictability for surface air temperature in perfect ensemble experiments with EC-Earth 2.1 using present day climate conditions. Values between 0.4 and 0.9 display the scale from low to high predictability. Shown is the potential predictability of the mean of the first 10 years after initialization. The figure is based on <u>Koenigk et al. 2012</u> (their Fig. 11). Note that all values have been detrended before calculating the predictability. The potential predictability of local decadal mean surface air temperature is significant over entire Europe with exception of the South and South-west.

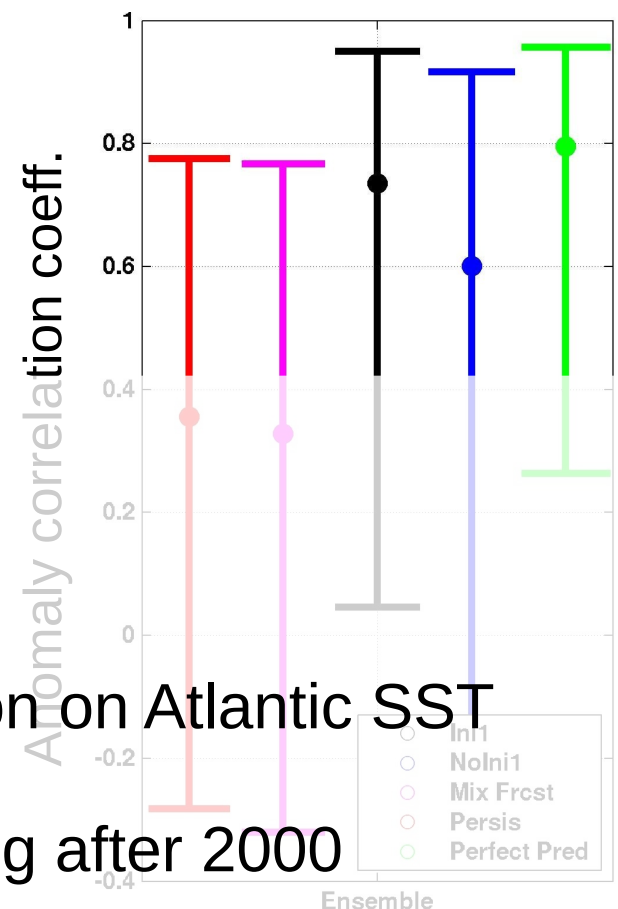
Reason for high predictability over Europe:



Decadal correlation between the ocean overturning circulation (MOC) and surface air temperature

Example: Hurricanes





Reasons for temporarily failure:

- insufficient emulator
- problem in resembling El Nino
- failure to capture full impact of volcano eruption on Atlantic SST (aerosol-radiation interaction)
- overestimation of tropical atmospheric warming after 2000

Caron et al. (2014), IC3, SMHI

The models need

- a better representation of ocean-atm heat exchange and circulation

Average number of hurricanes per year estimated from observations and from the CMIP5 multi-model decadal prediction ensemble (forecast years 1-5).

The correlation of the ensemble mean for the initialized, uninitialized and statistical predictions are shown with the 95% confidence intervals.