An introduction to Earth system modelling and climate predictions

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Outline

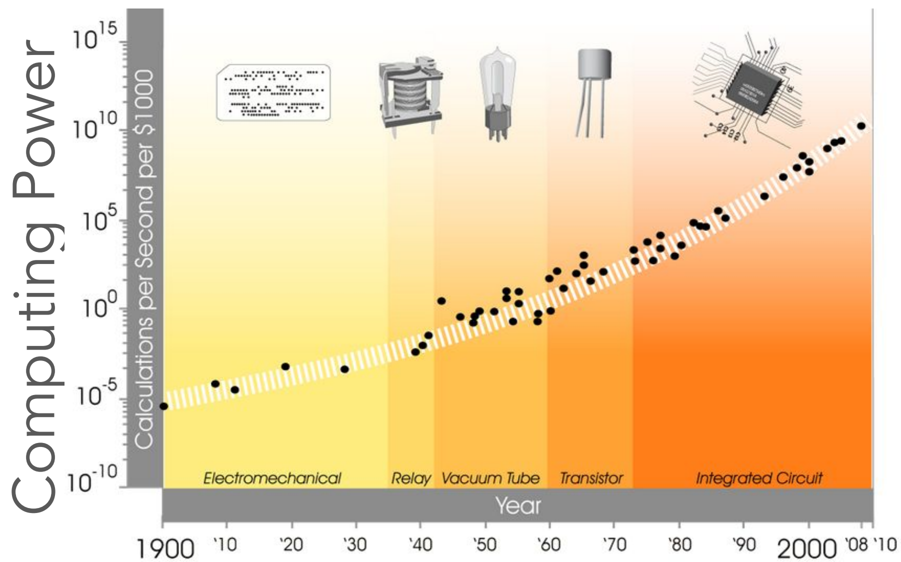
- Introduction to Earth System Models: introduce the basic definitions, give a brief history of global climate models and discuss their evolution from the basic radiative transfer models all the way up to the contemporary state-of-the-art Earth System Models.

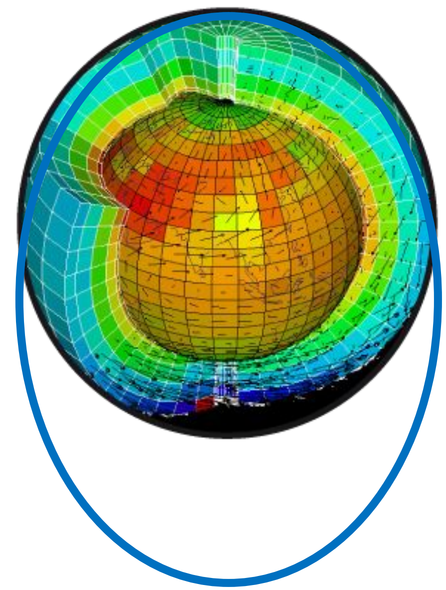
- Earth System Models for near term prediction: how we manage to live with the butterfly effect; what are the sources of predictability for the different time horizons of a climate forecast. methodology and introduction to evaluation tools for benchmarking these climate forecasts.

- Examples of climate predictions: modes of climatic variability that the state-of-the-art models can skillfully predict.

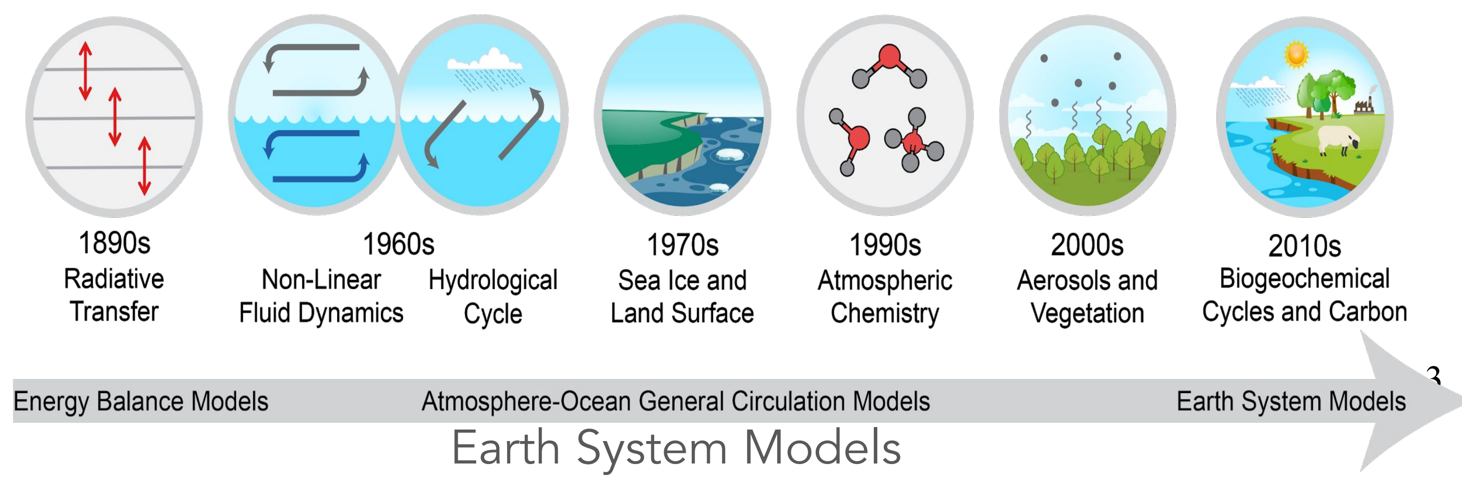
- Exercise: exercise with climate data using an R script, that includes the following post processing steps: calculation of climatology, anomalies, bias correction and some basic skill scores for evaluation of the climate prediction.

Earth System (and HPC) evolution

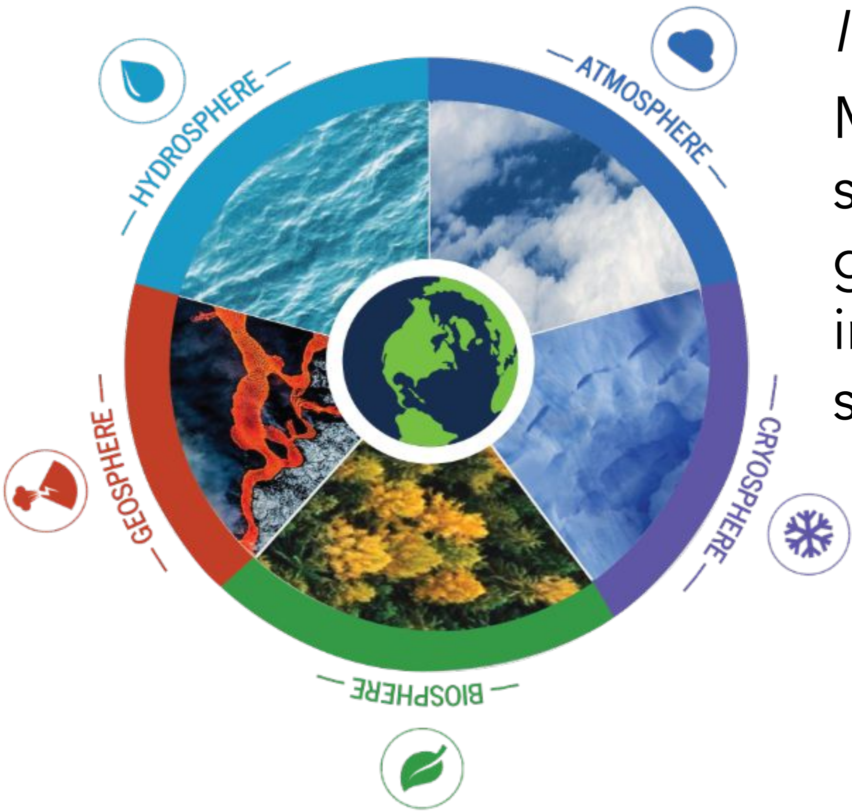




4th National Climate Assessment (US), Volume I



Earth System Models (as *experimentation labs*)



In essence

Mathematical representation of the Earth system through the fundamental laws governing the evolution within and interactions between the different Earth system components.

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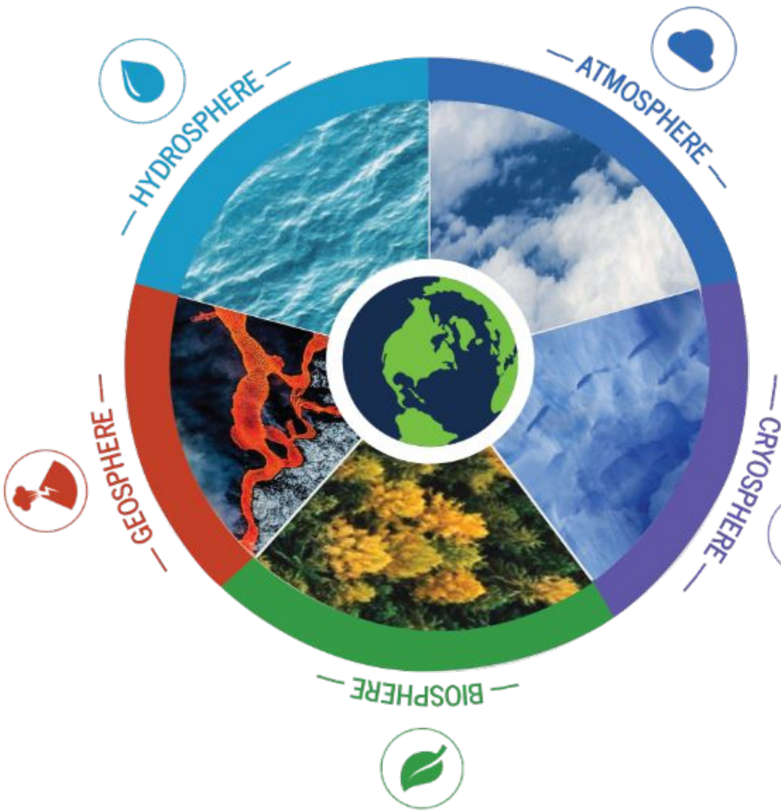

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In Practice

ESMs are our major tool to generate scientific understanding via hypothesis testing on topics as diverse as:

Attribution of past climate changes

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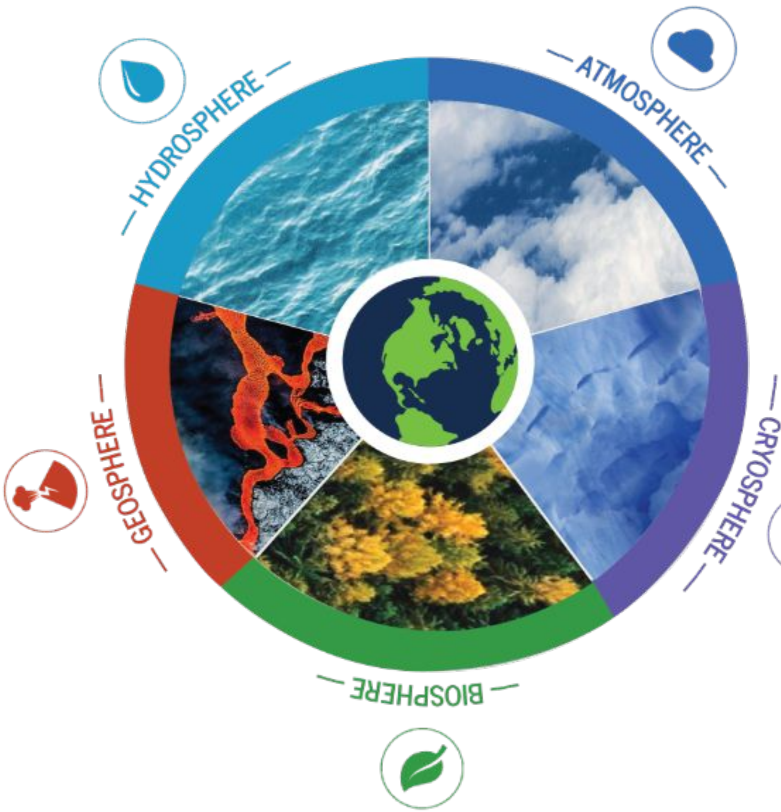

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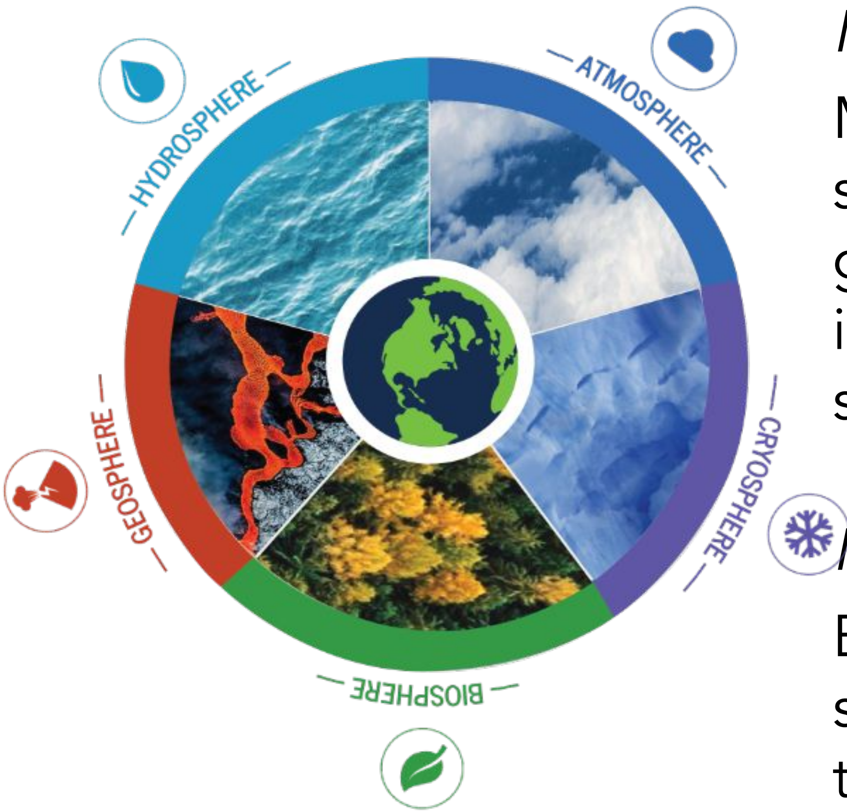

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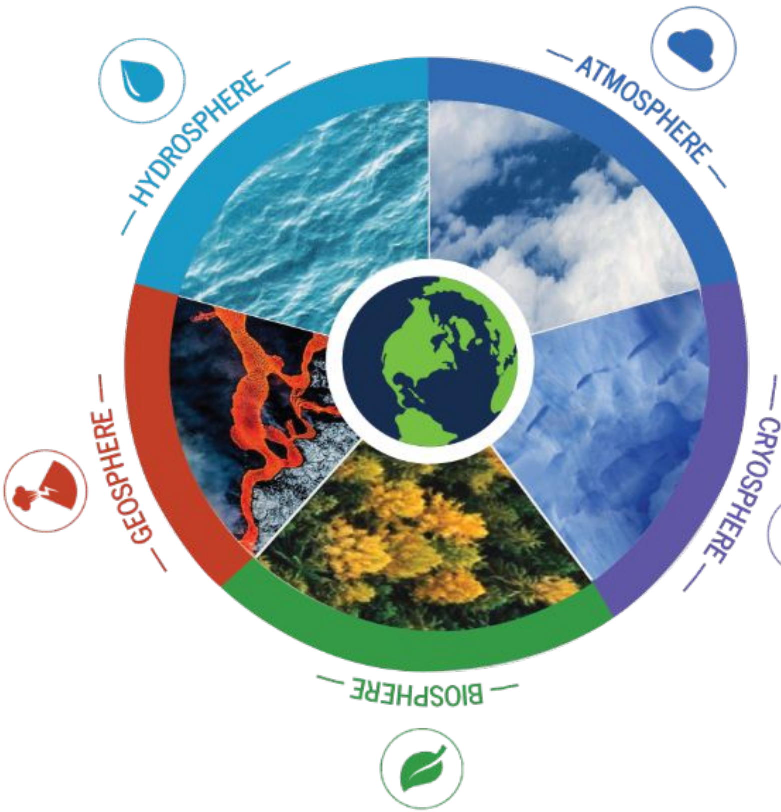

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Near-term climate prediction

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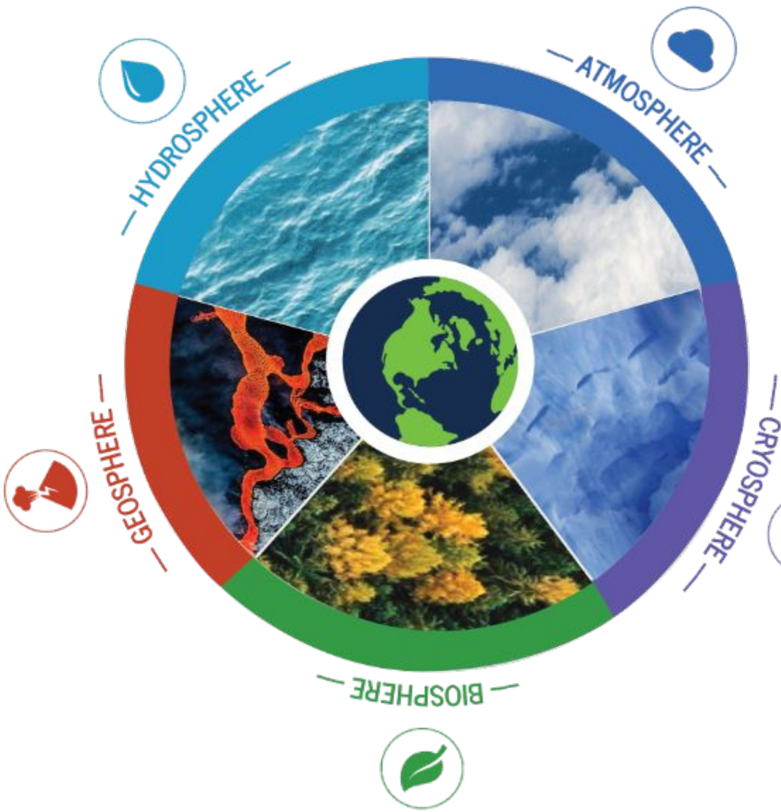

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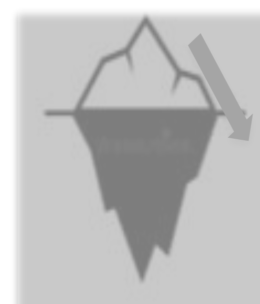


Near-term climate prediction

Near-term
climate prediction

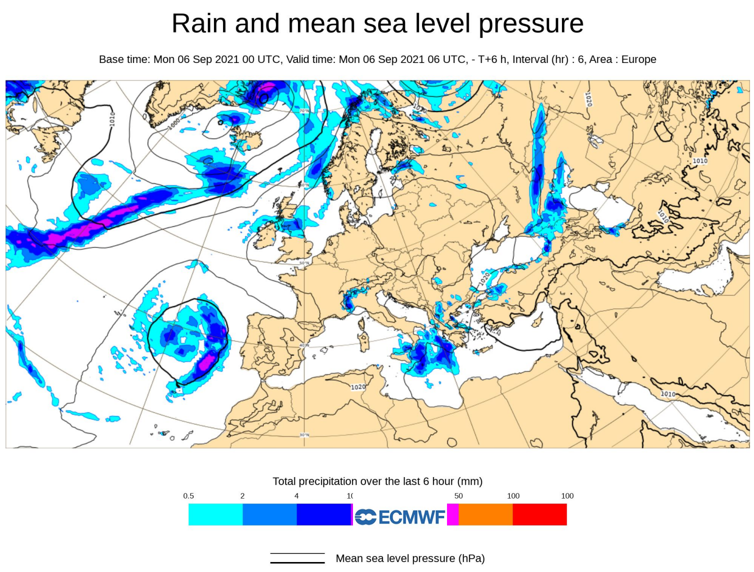
Earth System Models for near-term climate prediction

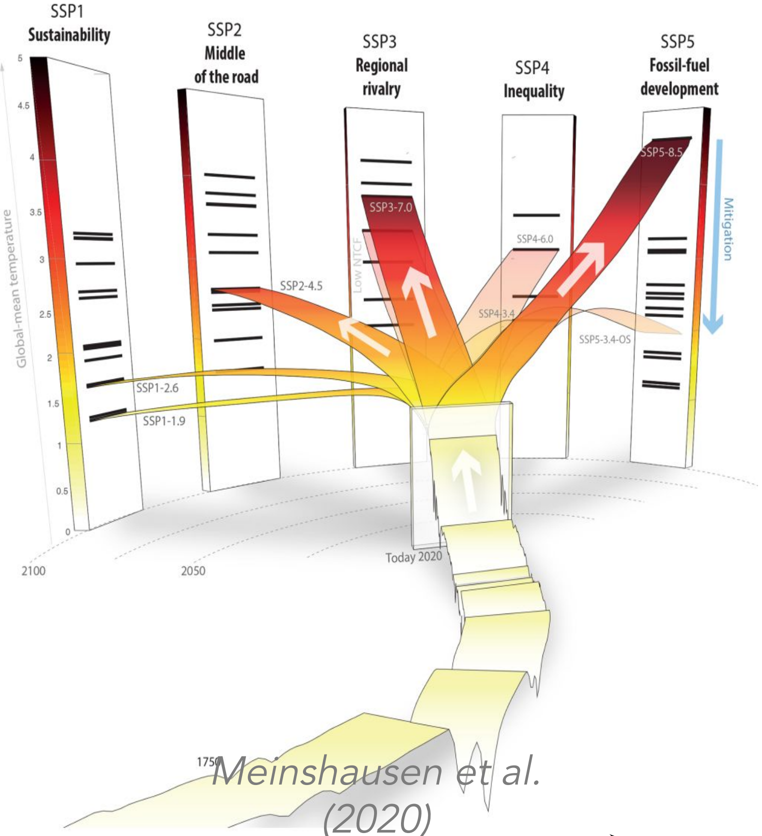
Earth System Models for near-term climate prediction

Climate projections

Fundamentals of climate prediction

Weather forecasts





Meinshausen et al. (2020)

Days Weeks Months Seasons Years Decades Centuries

Earth System Models for near-term climate prediction

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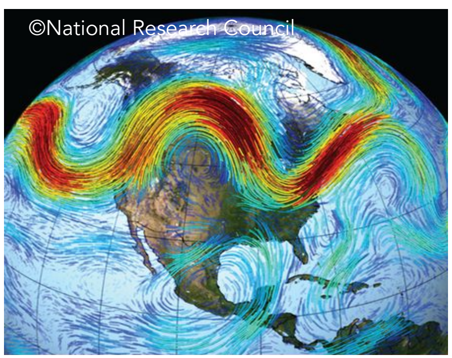
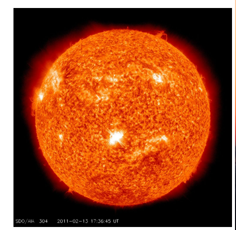
Fundamentals of climate prediction

Weather forecasts



Accurate constraint of the current meteorological state
[INITIAL VALUE PROBLEM]



Good guess of future changes in the forcing factors
[BOUNDARY CONDITION PROBLEM]

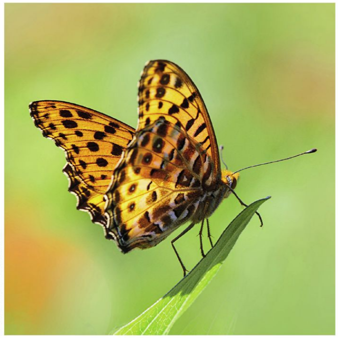
Days Weeks Months Seasons Years Decades Centuries

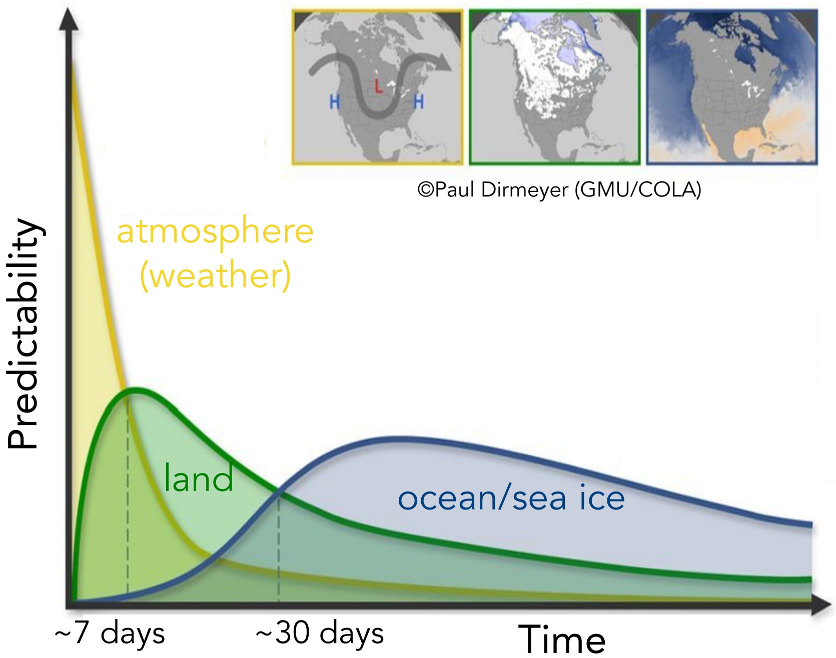
Earth System Models for near-term climate prediction

Fundamentals of climate prediction

In seasonal to decadal prediction both contributions matter !!

Living with the butterfly effect: sources of predictability

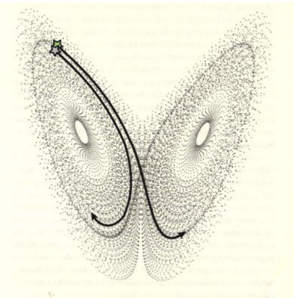




Mariotti et al (2018)

Weather prediction → ~ 10 days

Due to the chaotic nature of atmospheric variability (butterfly effect)



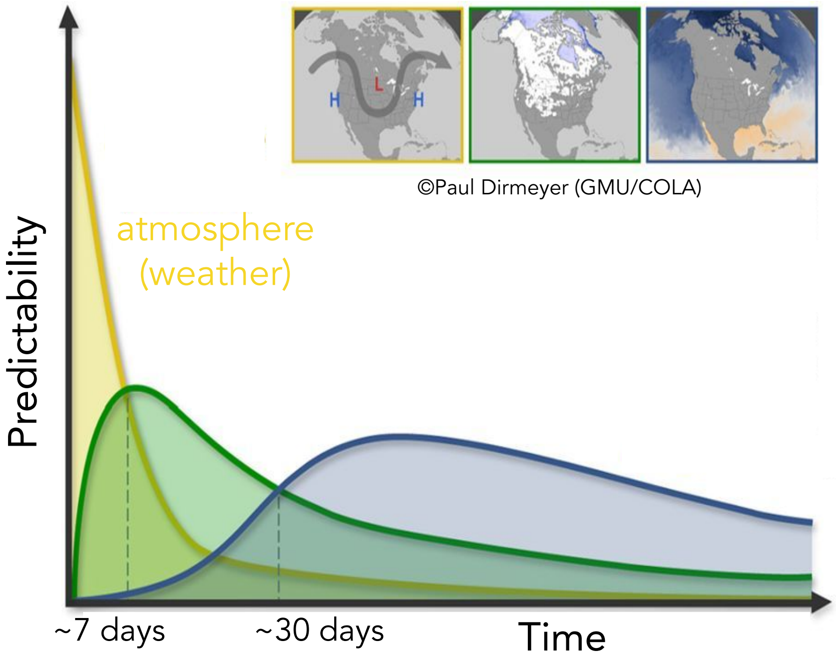
Climate prediction → weeks to decades

ocean

sea ice

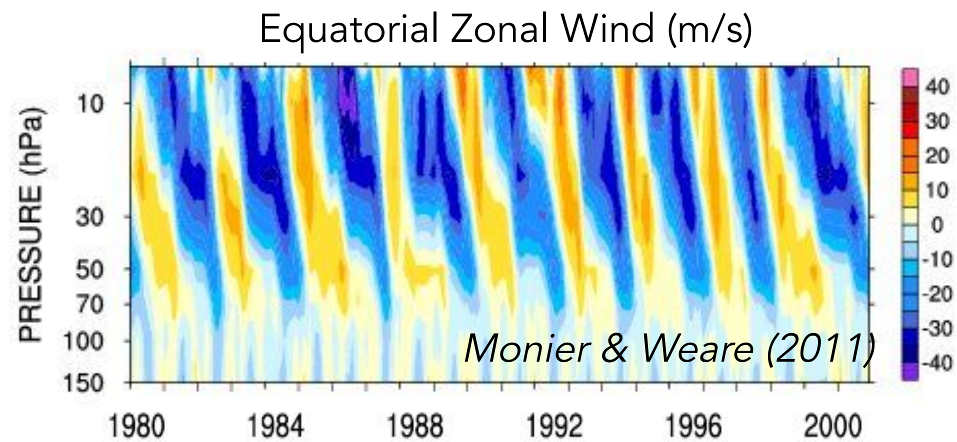
soil moisture

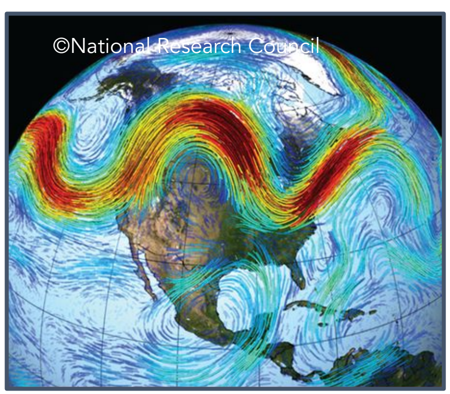
Living with the butterfly effect: sources of predictability



Mariotti et al (2018)

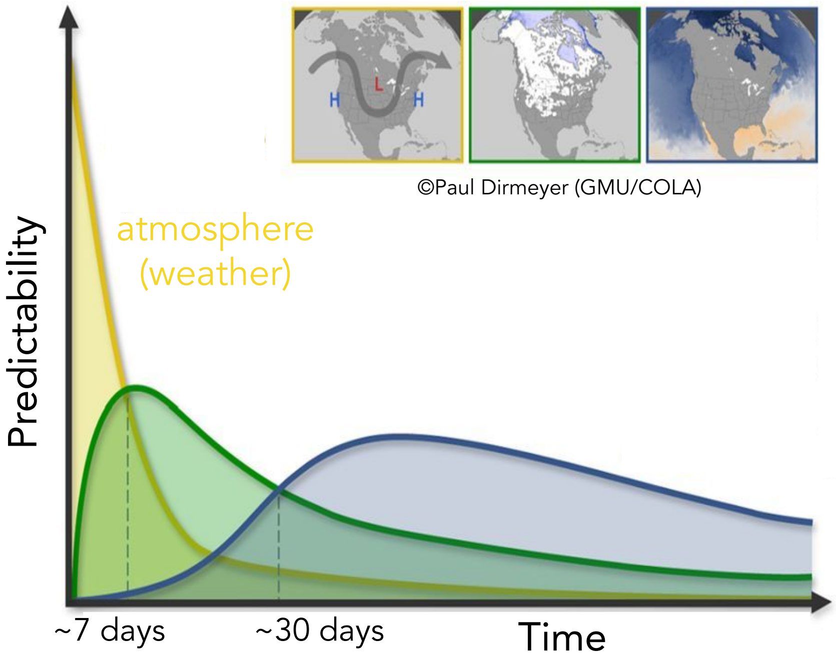
The atmosphere can also provide memory beyond a month:
The Quasi-Biennial Oscillation (QBO)





Through a modulating effect on wave propagation, the QBO can impact the polar vortex strength and contribute to Northern Hemisphere predictability at seasonal and interannual scales.

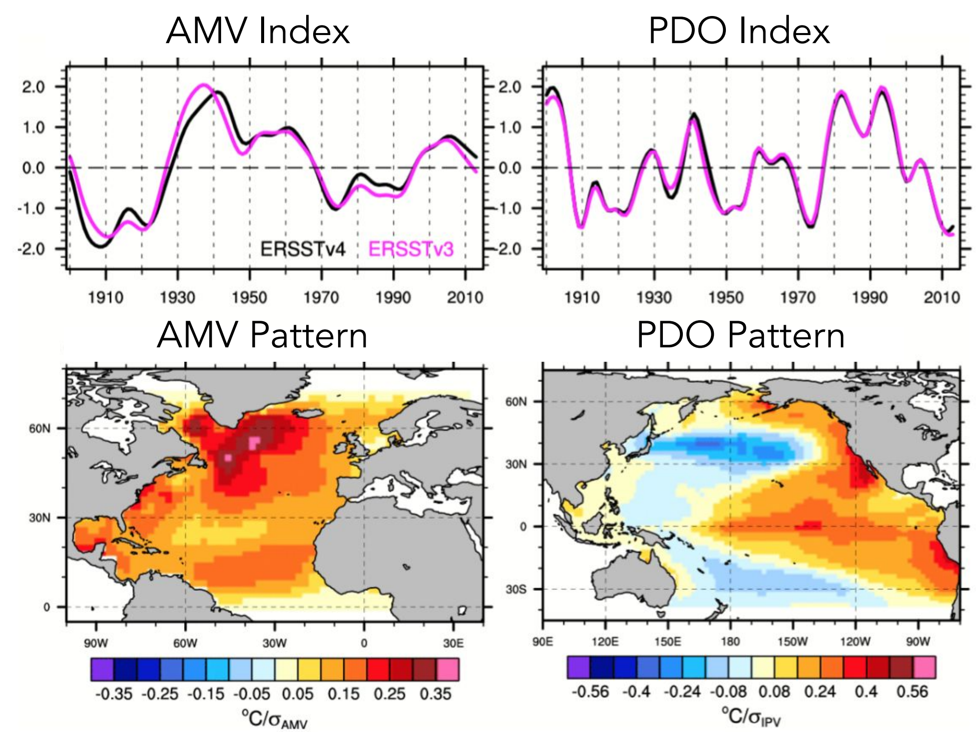
Living with the butterfly effect: sources of predictability



Mariotti et al (2018)

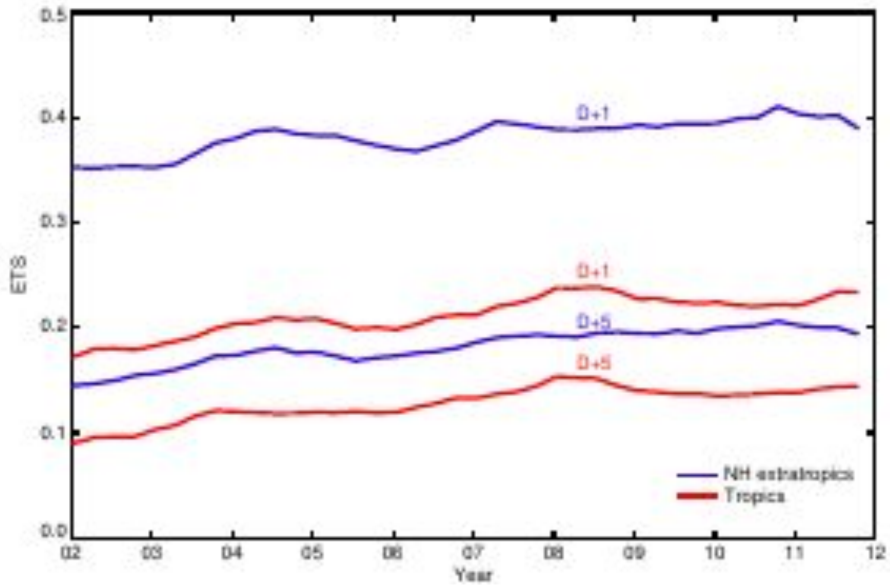
ocean

The ocean exhibits **modes of decadal variability** both in the **Atlantic and Pacific basins**



Living with the butterfly effect: other sources of predictability

- model improvements, such as better convection schemes (see, e.g., Bechtold et al., 2012)



Time-series of 24 hours precipitation forecast skill of the ECMWF model as measured by the Equitable Threat Score (ETS) for precipitation events > 5 mm for forecast lead times day+1 and day+5. A one-year running average has been applied to filter out seasonal variations. Perfect forecasts have an ETS of 1. (Bechtold et al., 2012)

Living with the butterfly effect: other sources of predictability

- model improvements, such as better convection schemes (see, e.g., Bechtold et al., 2012)
- the inclusion of more relevant processes, for example relating to the ocean

> In the last 5 years, the prediction systems of global and regional ocean forecasting were significantly improved from several points of view. The global systems have sensibly increased their resolution while the regional systems were applied on new areas. The complexity of the models has been increased: the models are now able to resolve more processes such as tides and waves, and are associated with more accurate data-assimilation schemes. Product services have been developed, and now the products of almost all the systems are available in near real time.

Tonani et al., 2015

Living with the butterfly effect: other sources of predictability

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  et al., 2012)

- the inclusion of more relevant proce
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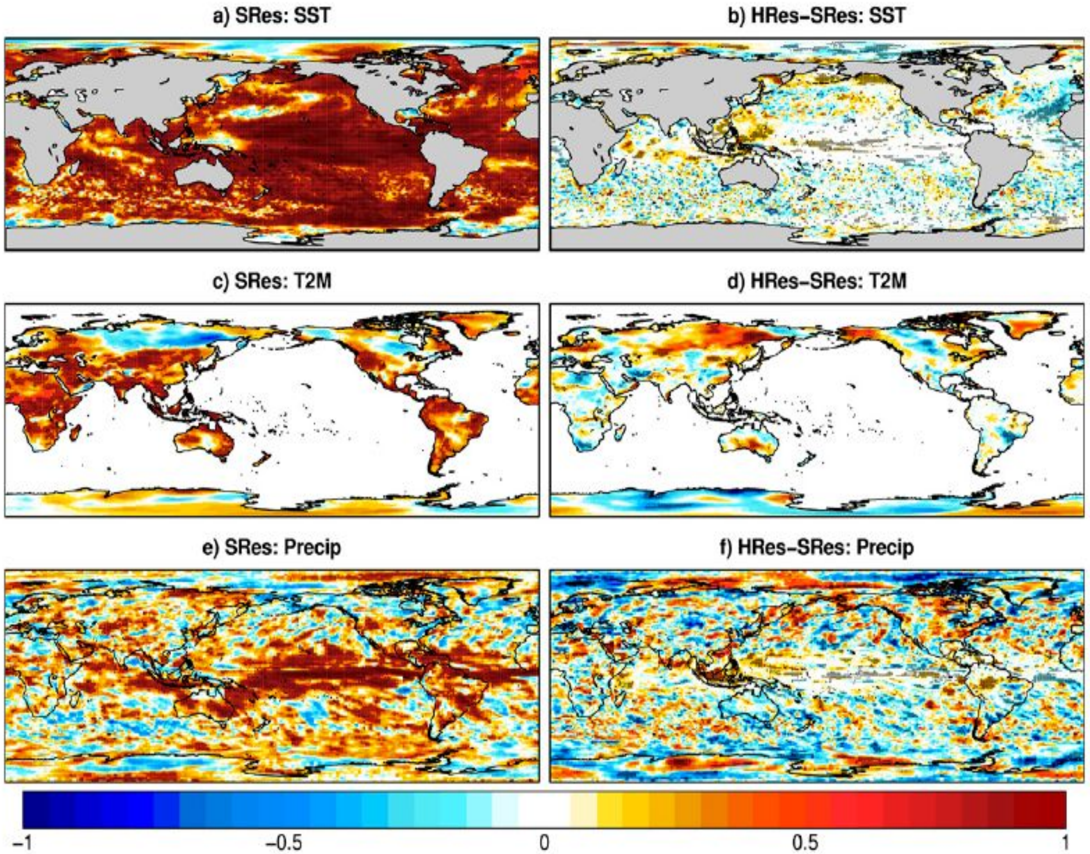
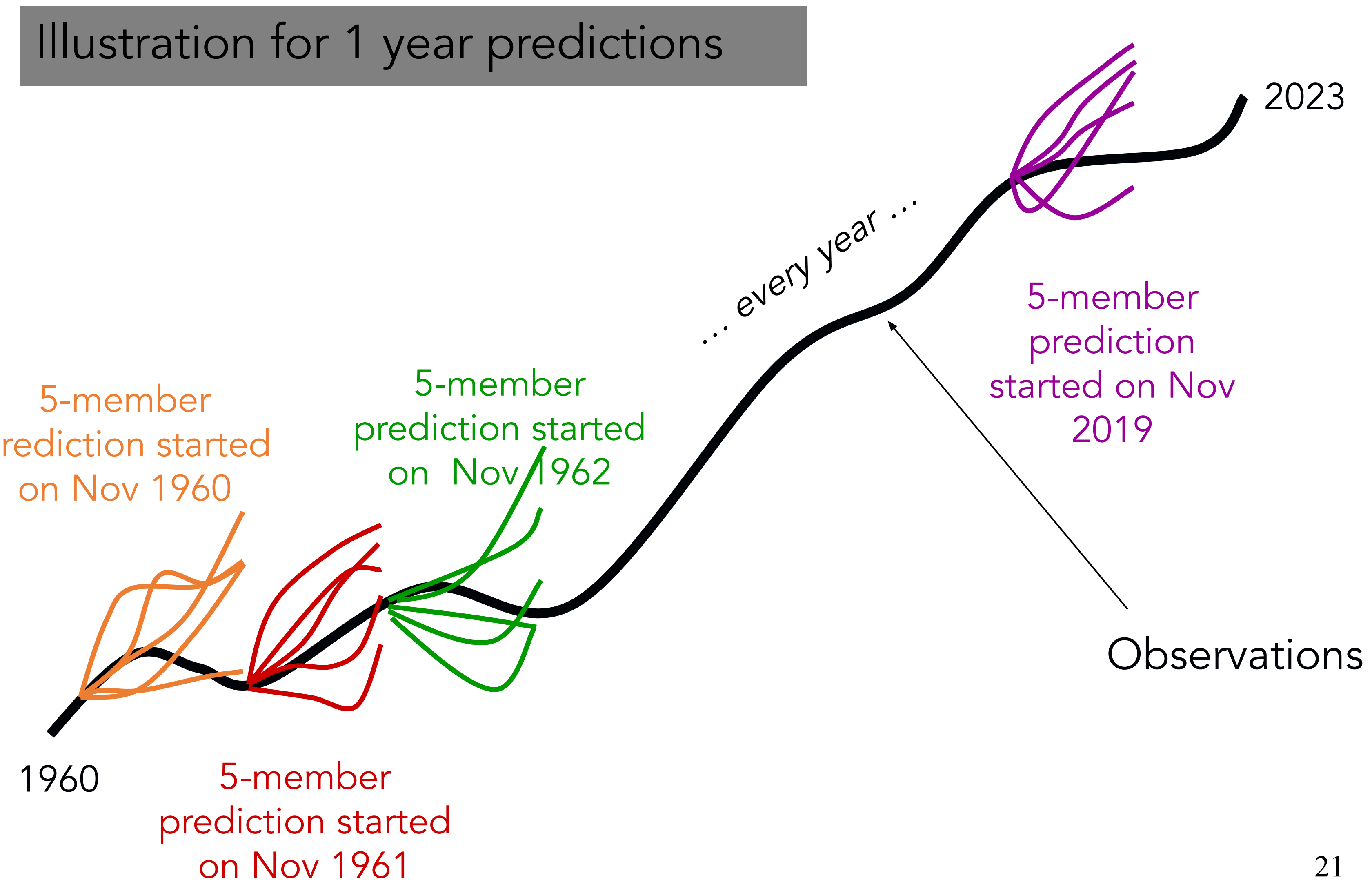


Prodhomme et al., 2016

Living with the butterfly effect: other sources of predictability

- model improvements, such as better convection schemes (see, e.g., Bechtold et al., 2012)
- the inclusion of more relevant processes, for example relating to the ocean
- higher model grid resolutions thanks to much faster supercomputers
- more accurate estimates of the initial conditions thanks to advances in the global observing system and data assimilation methods.

Earth System Models for near-term climate prediction



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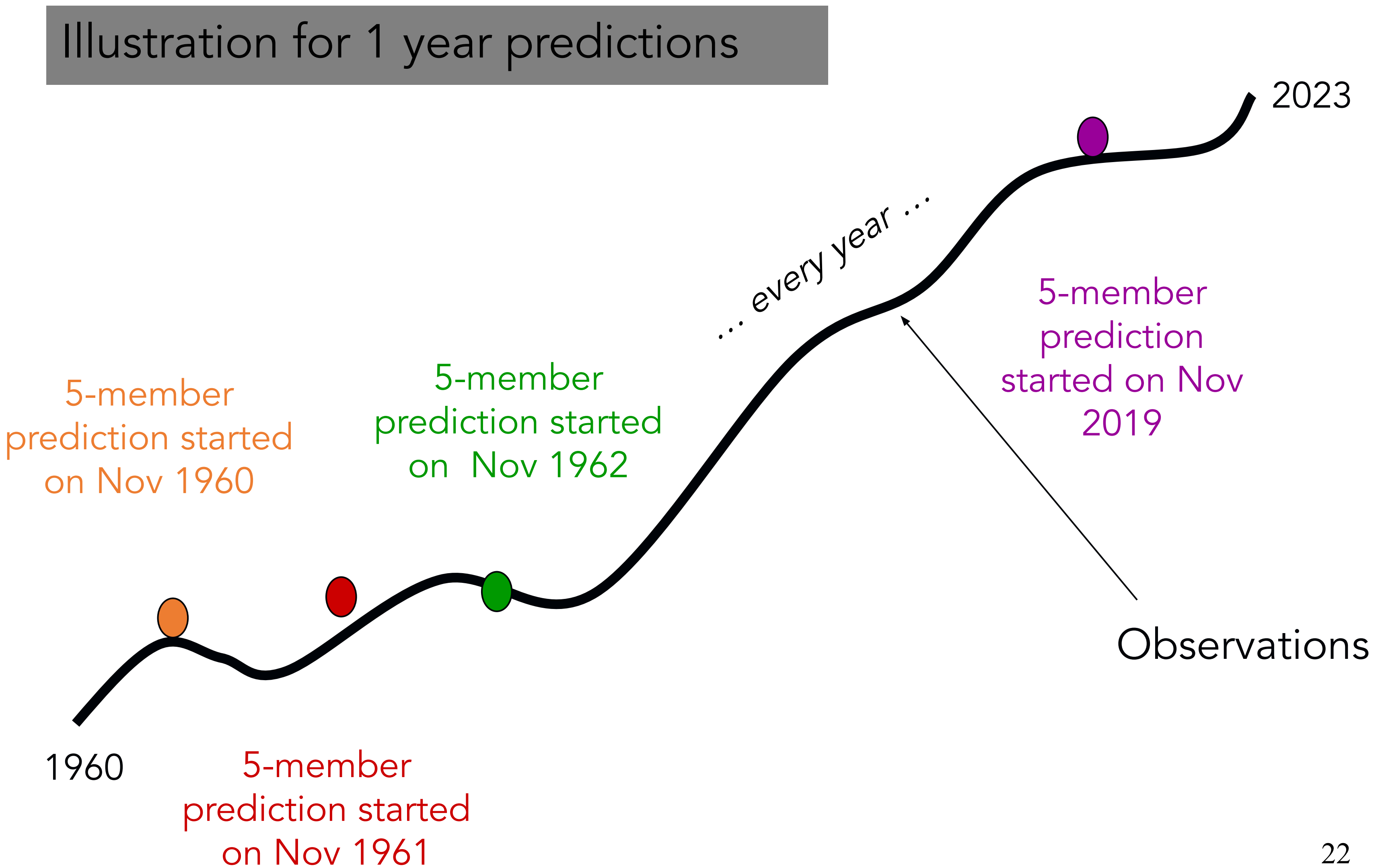

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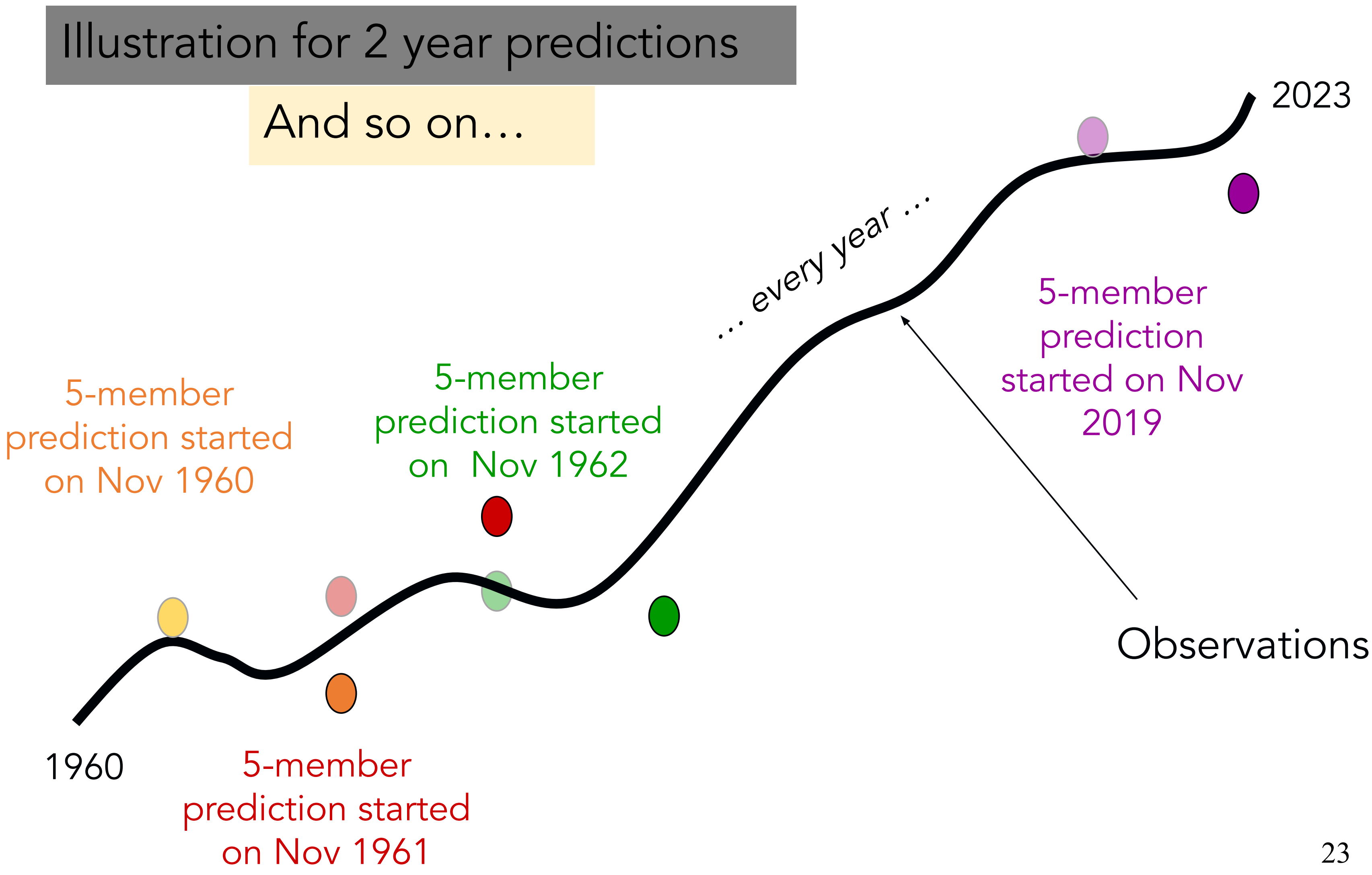
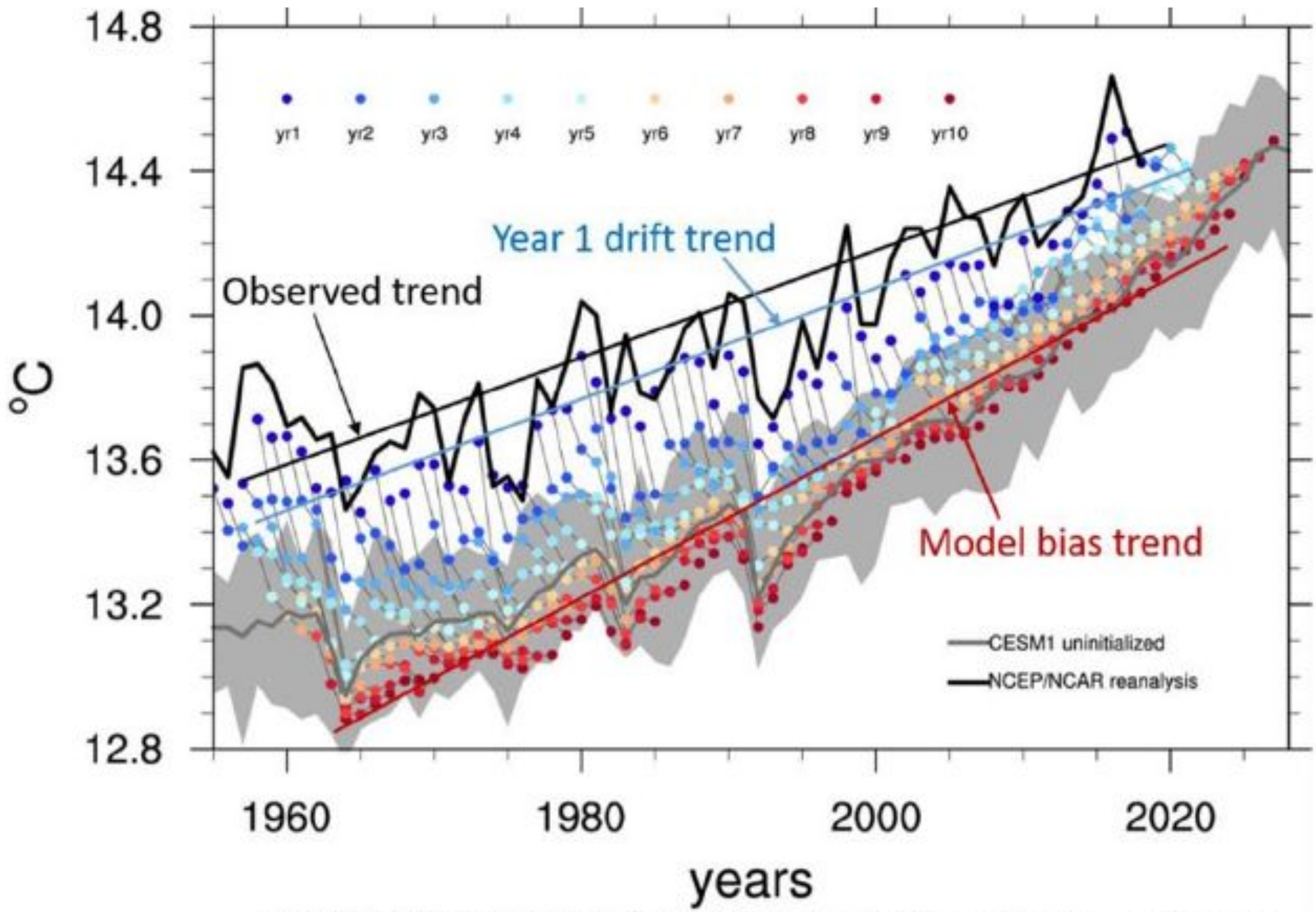


Earth System Models for near-term climate prediction

Model error, bias and drift



Global Annual Surface Air Temperature

Meehl et al, 2022

Earth System Models for near-term climate prediction

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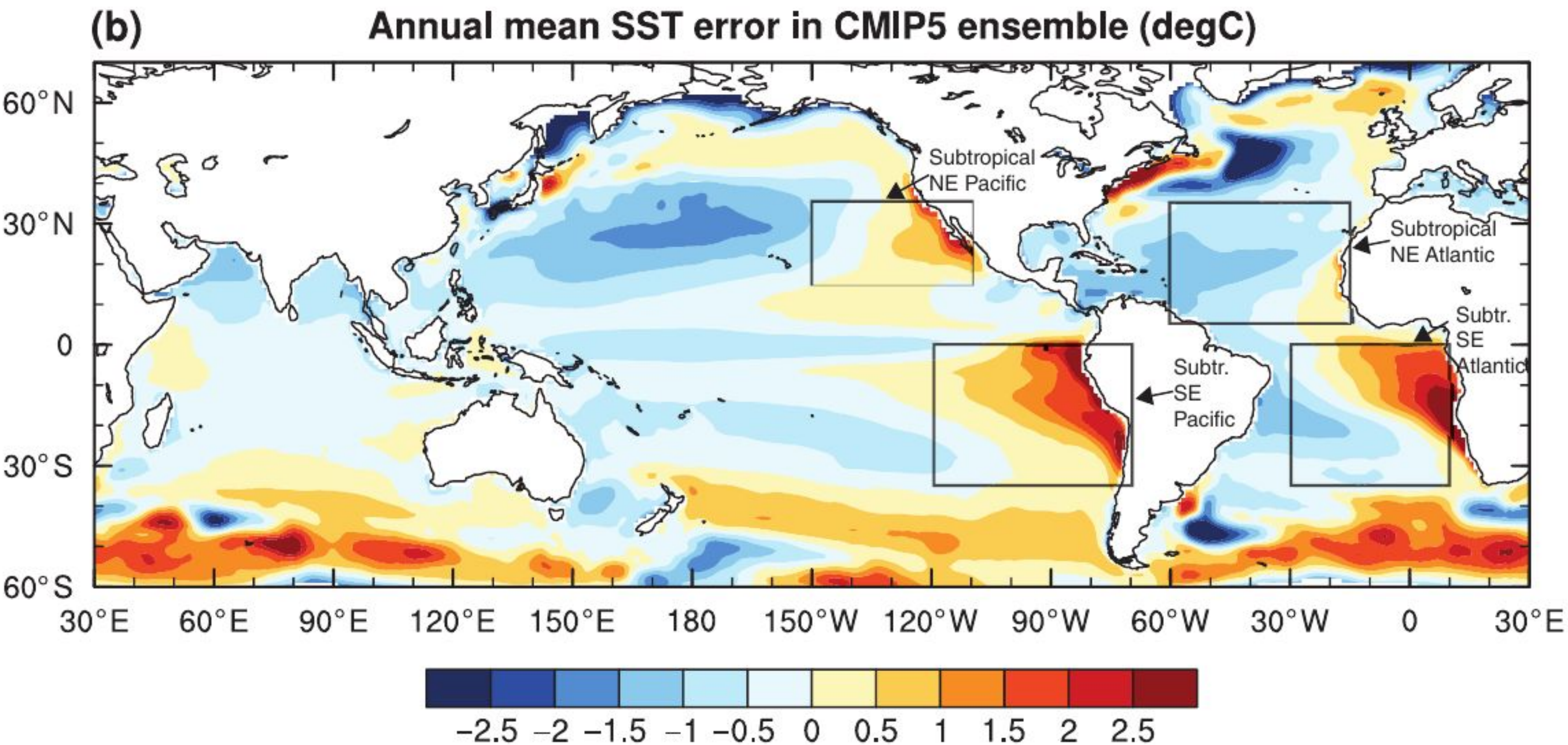

Richter 2015

Earth System Models for near-term climate prediction

Bias correction, calibration

$T_{\mathrm{REF}}(t)$ Model variable for a reference period

$O_{\mathrm{REF}}(t)$ Observed variable for the same reference period

$T_{\mathrm{RAW}}(t)$. Model variable for the future period

Earth System Models for near-term climate prediction

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Hawkins et al, 2012

$$T_{\mathrm{SH}}(t) = T_{\mathrm{RAW}}(t) + (\overline{O_{\mathrm{REF}}} - \overline{T_{\mathrm{REF}}}).$$

The variability in observations and model is assumed to be the same; the daily data is shifted by the mean bias in the reference period

Earth System Models for near-term climate prediction

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$$T_{\mathrm{BC}}(t) = \overline{O_{\mathrm{REF}}} + \frac{\sigma_{O,\mathrm{REF}}}{\sigma_{T,\mathrm{REF}}}(T_{\mathrm{RAW}}(t) - \overline{T_{\mathrm{REF}}}).$$

Additionally the variability is corrected, by taking into account the standard deviations of observations and model output in the reference period

Earth System Models for near-term climate prediction

Forecast verification

D: deterministic

P: probabilistic

(non-exhaustive list)

D Anomaly Correlation Coefficient (ACC)

D Root mean squared error skill score (RMSS)

P Ranked probability skill score (RPSS)

P Brier Skill Score

P Rate of return

P Reliability analysis

Earth System Models for near-term climate prediction

Forecast verification (D)

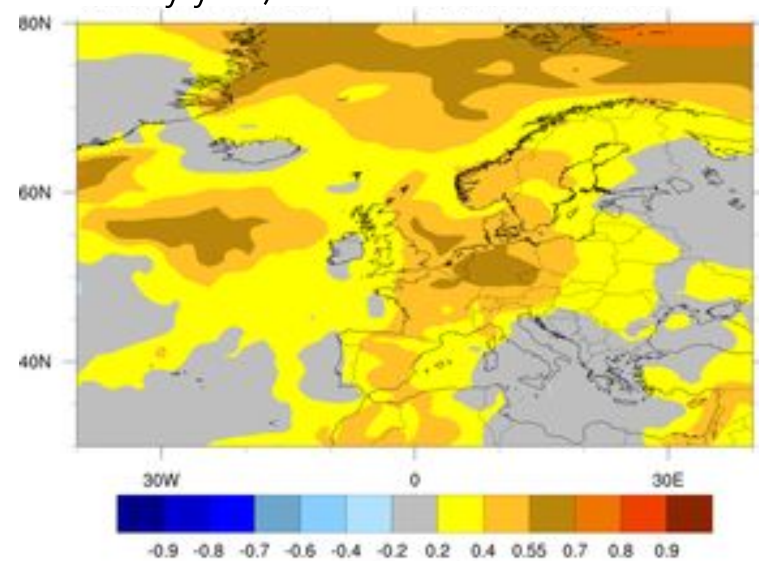
Anomaly Correlation Coefficient (ACC): Measuring the strength of linear relationship between forecasts and their corresponding observations (or reanalysis, such as ERA5).

To remove the model drift, the lead-time dependent model climatology is removed to obtain the forecast anomalies (f-c).

The ACC is computed on the ensemble-mean of the forecast anomalies (f-c) and observational anomalies (a-c).

$$ACC = \frac{\overline{(f-c)(a-c)}}{\sqrt{\overline{(f-c)^2}\ \overline{(a-c)^2}}}$$

GCFS2 forecasts 1990-2017, October, November December (initialized 01/09 every year)



Anomaly correlation for 2m air temperature (reference: ERA-Interim)

Earth System Models for near-term climate prediction

Forecast verification (D)

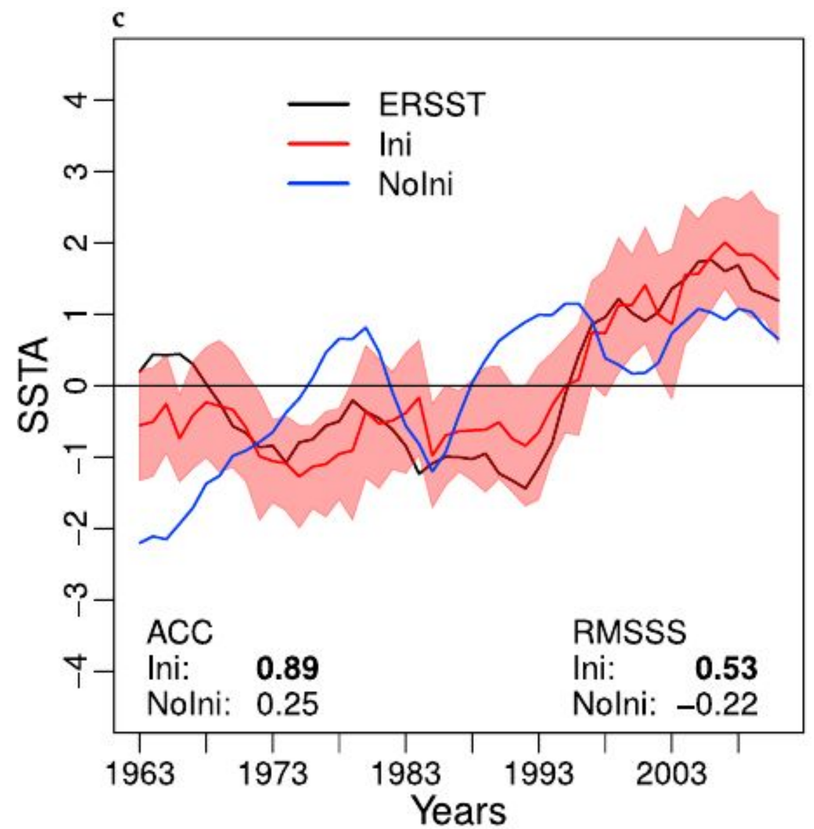
Root Mean Square Skill Score (RMSSS)

$$\mathrm{RMSSS} = 1 - \frac{\mathrm{RMSE}_{for}}{\mathrm{RMSE}_{clim}}$$

With RMSE_{for} and RMSE_{clim} the root-mean-square error of the forecast and of a climatological forecast.

- RMSSS = 1 for perfect forecast
- RMSSS ≤ 0 for a forecast with no improvement over the climatological forecast.

Five year mean standardized SSTA from observations (black), Ini Multi-model Ensemble Mean (MME, red) and NoIni MME (blue).



Caron et al, 2015

Earth System Models for near-term climate prediction

Forecast verification (P)

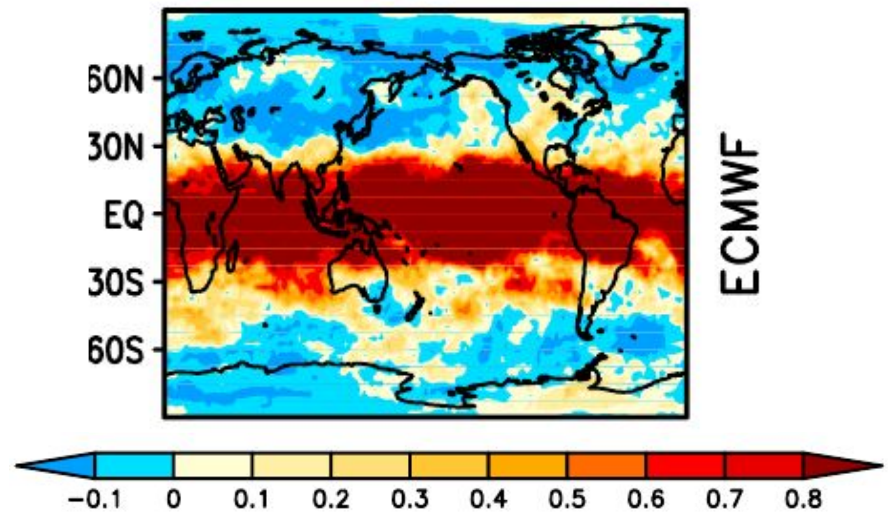
Brier Skill Score (BSS): is based on the squared probability error for the given forecast category, such as above normal temperature. Thus, in a 3-category system there are three Brier scores—one for each of the three categories. The squared probability error is the squared difference between the categorical forecast probability y_k and the corresponding observed "probability" o_k

$$BSS = 1 - \frac{BS_{for}}{BS_{ref}} \quad BS = \frac{1}{n}\sum_{k=1}^{n}(y_k - o_k)^2$$

BS_{for} and BS_{ref} Brier scores of the actual and reference forecast.

- BSS = 1 for perfect forecast
- BSS ≤ 0 for a forecast with no improvement over the climatological forecast.

Yang et al, 2018



BSS for the DJF 200-hPa geopotential height anomaly over the period of 1960–2005, for an average over the above-normal (AN) and below-normal (BN) events

Earth System Models for near-term climate prediction

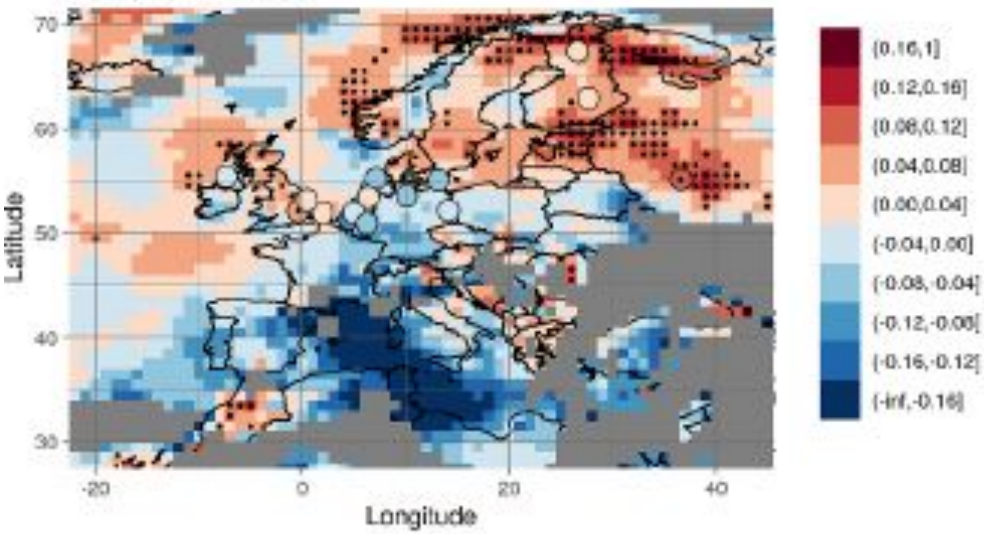
Forecast verification (P)

Continuous Ranked Probability Skill Score (CRPSS): is a measure of how good forecasts are in matching observed outcomes. It is calculated by comparing the Cumulative Distribution Functions (CDF) for the forecast against observations (or analyses) over a given period and compare it with the climatological forecast

CRPSS = 1 – CRPSforecast / CRPSclimat

- CRPSS = 1 perfect skill compared to climatology
- CRPSS = 0 no skill compared to climatology
- CRPSS <0 the forecast is less accurate than climatology

Ramon et al, 2021

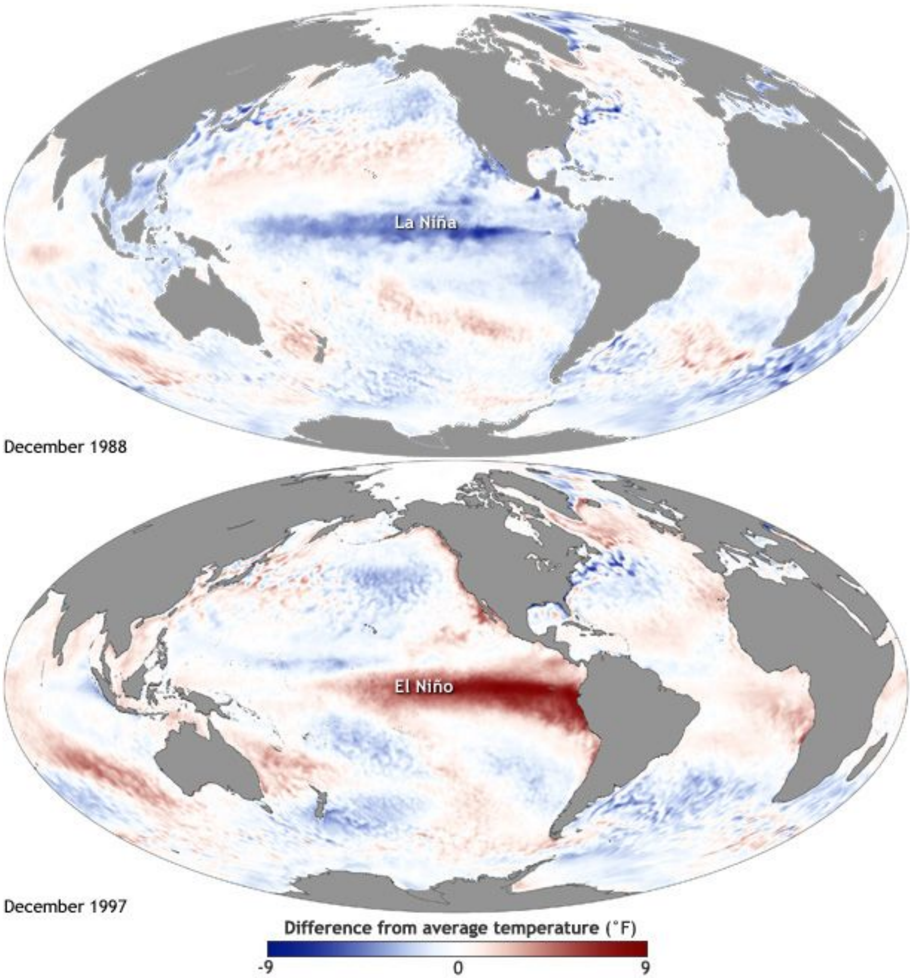


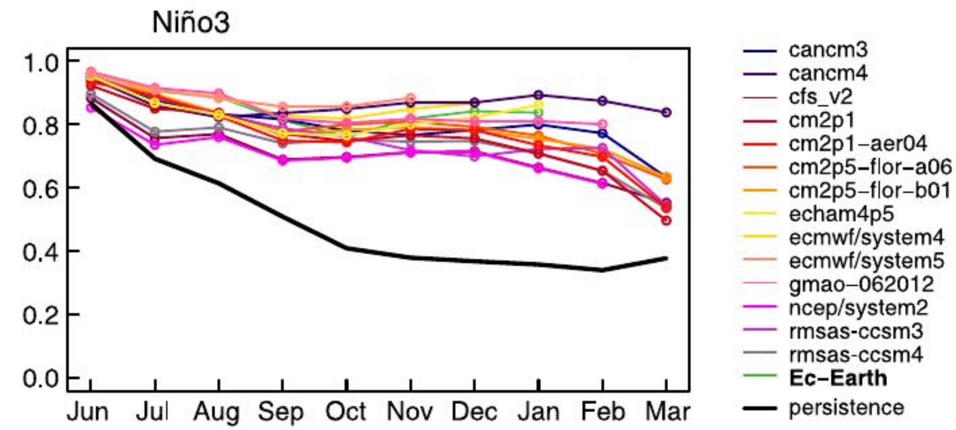
CRPSS of the multi-system near-surface wind speed predictions over Europe for DJF.

Earth System Models for near-term climate prediction

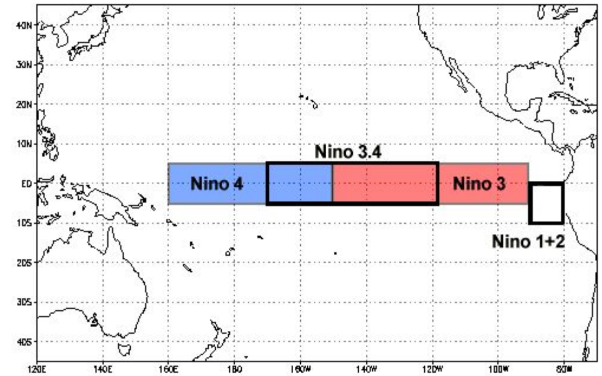
An example of seasonal climate prediction

Exarchou et al (2021)





nino3 Index

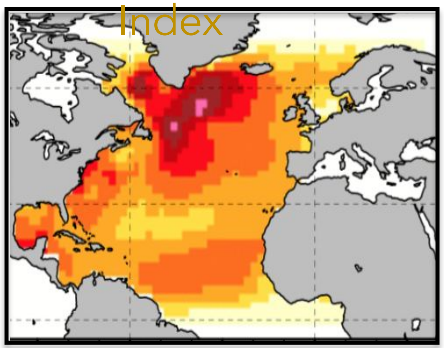


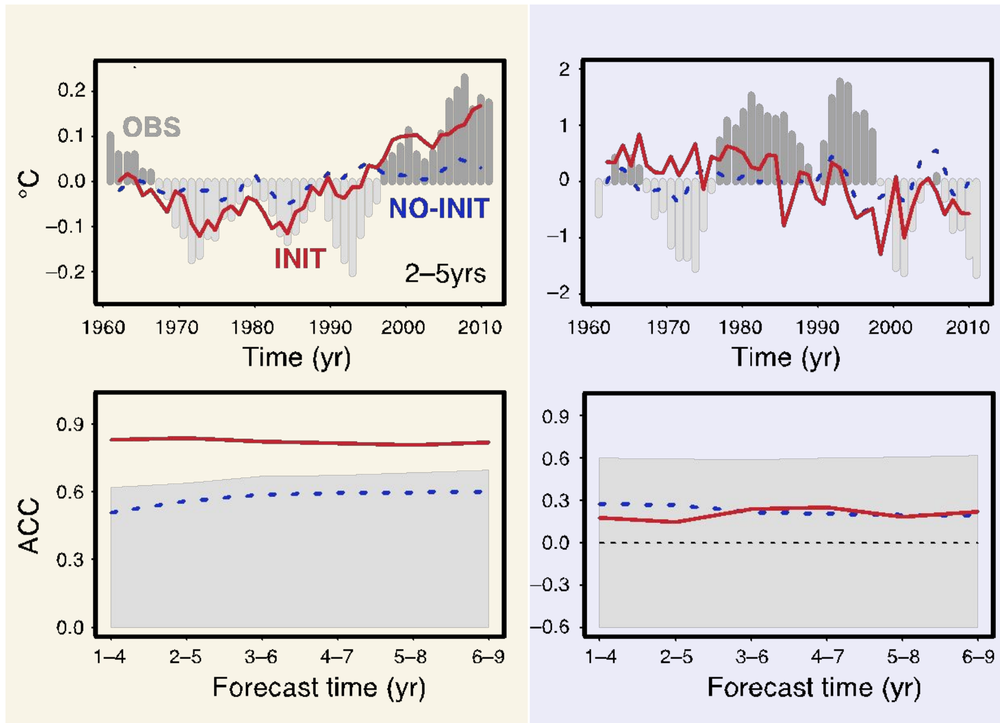
Initialised seasonal prediction forecasts show significant predictive skill for ENSO up to 10 months ahead

Earth System Models for near-term climate prediction

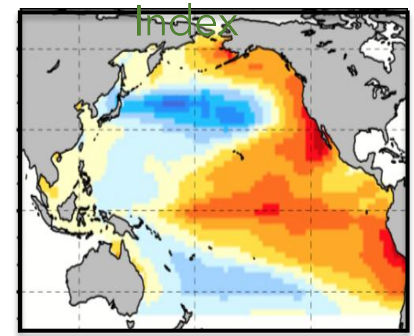
An example of decadal climate prediction

AMV Index





PDO Index



Doblas Reyes et al (2013)

Only for the AMV the initialised forecasts show significant predictive skill and beat persistence for predictive horizons of up to 9 years

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Thank you for your attention!!!