



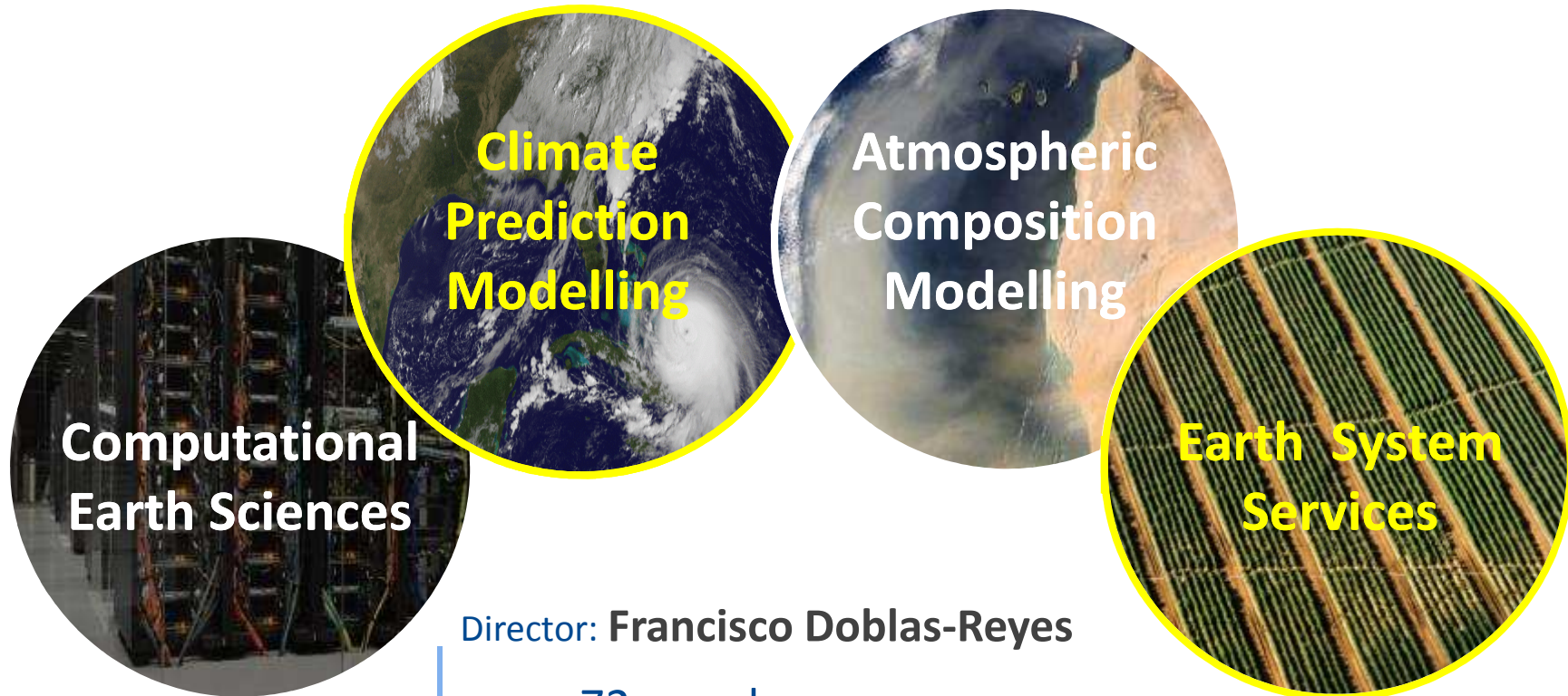
Predicción Climática Decadal Global con el modelo Ec-Earth*:

Avanzando hacia una predicción Operativa en Tiempo Real

P. Ortega, R. Bilbao, L-P. Caron, F. Doblas-Reyes,
M. Menegoz, D. Verfaillie, S. Wild

Earth Science Department

Environmental modelling and forecasting, with a particular focus on weather, climate and air quality



Director: **Francisco Doblas-Reyes**

- 72 people
- Leading: H2020 projects, COPERNICUS contracts, ERC Consolidator Grant and hosts an AXA Chair

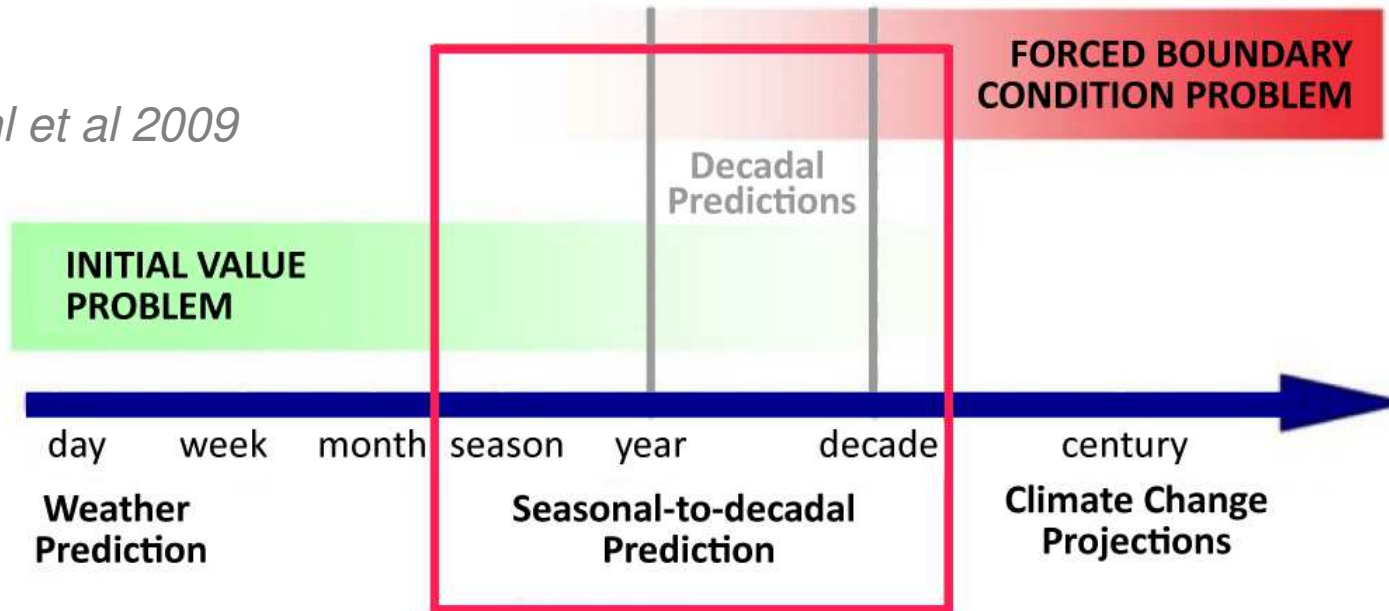
Cornerstones of Climate Prediction



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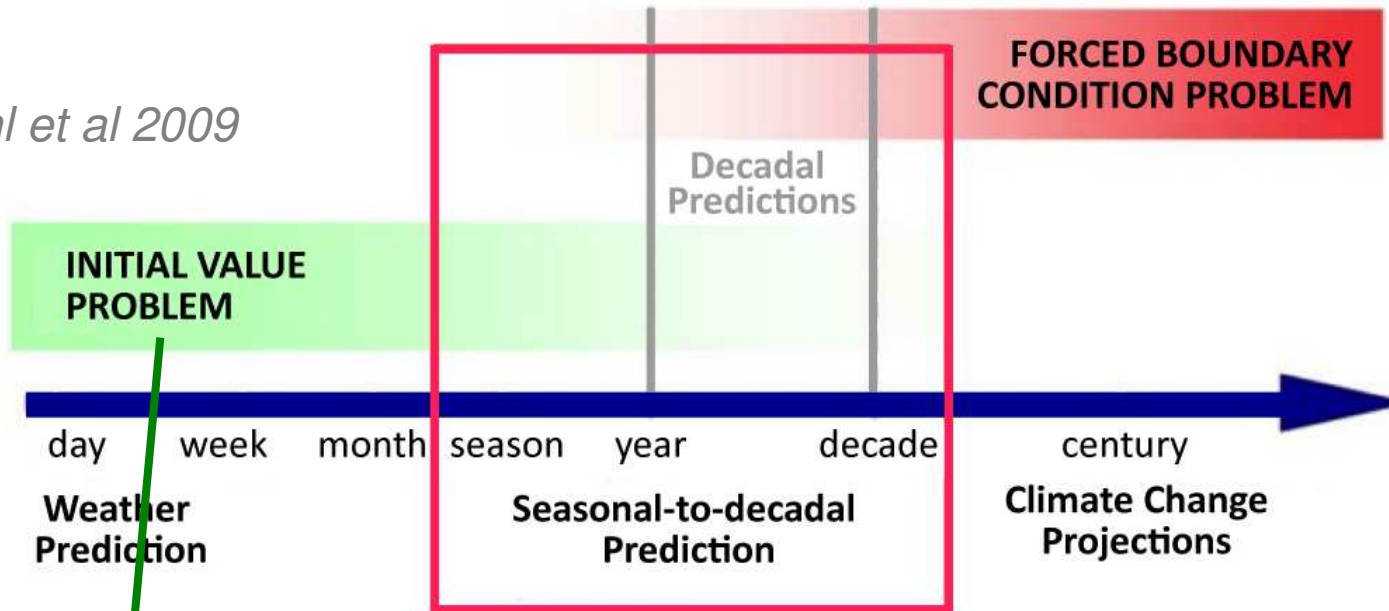
Meehl et al 2009



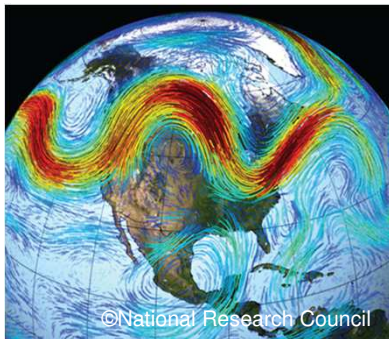
Cornerstones of Climate Prediction



Meehl et al 2009



Current Meteorological state



Correct Initialization of internal sources of predictability

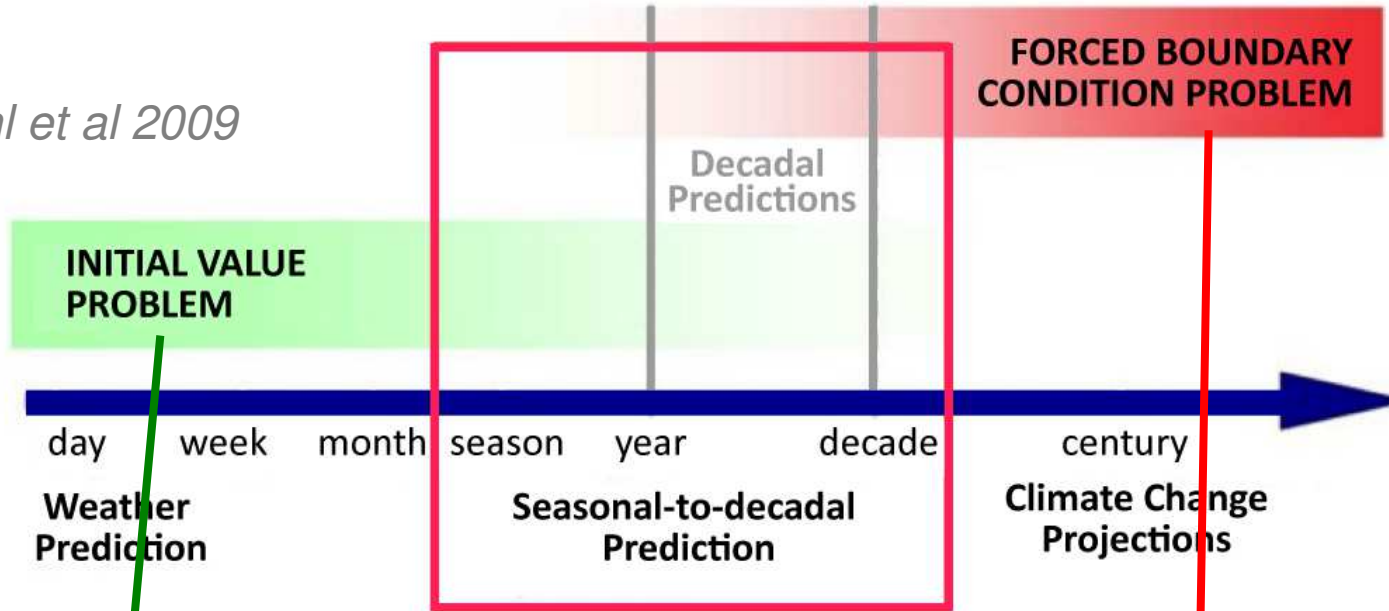
Cornerstones of Climate Prediction



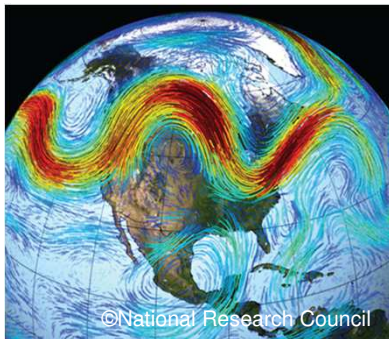
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Meehl et al 2009

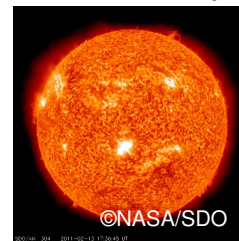


Current Meteorological state



Correct Initialization of internal sources of predictability

Solar Activity



GHGs



Volcanic Aerosols



Good guess of future changes in the forcing

Internal sources of Climate Predictability



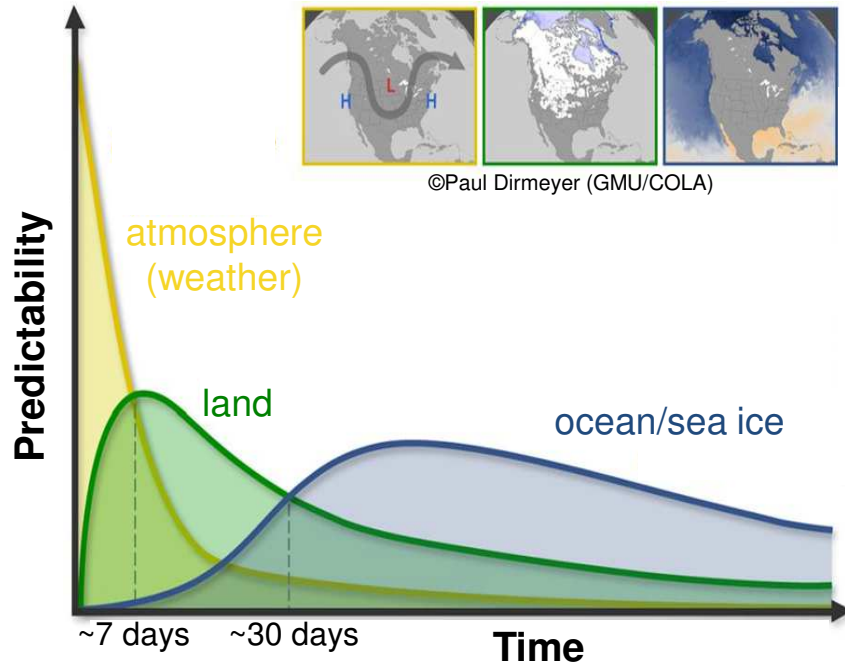
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Mariotti et al 2018



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Weather prediction $\xrightarrow[\text{horizon}]{\text{time}}$ ~ 10 days

Because of the chaotic nature of atmospheric variability

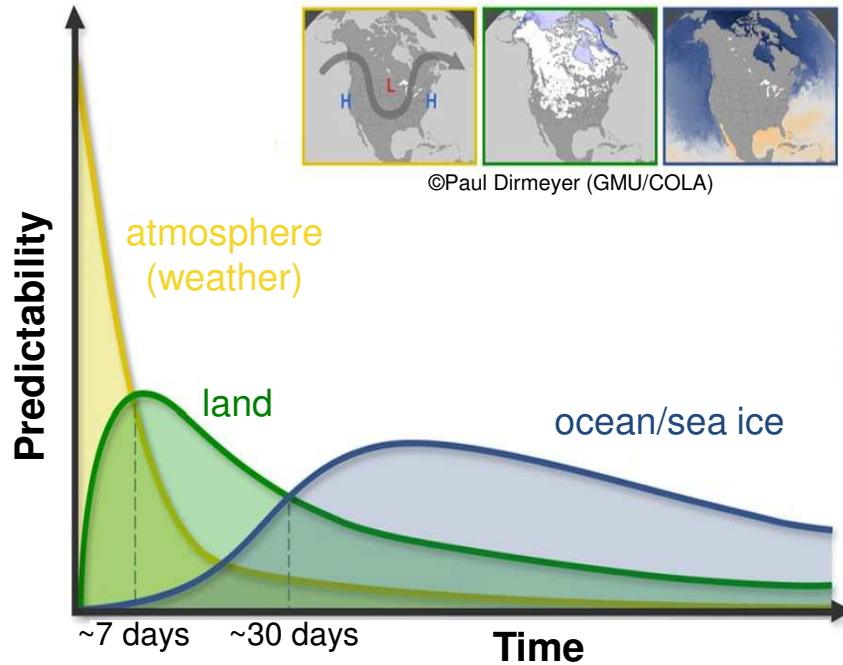
Internal sources of Climate Predictability



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Weather prediction $\xrightarrow[\text{horizon}]{\text{time}}$ **~ 10 days**

Because of the chaotic nature of atmospheric variability

Climate prediction $\xrightarrow[\text{horizon}]{\text{time}}$ **Weeks Decades**

It relies on the longer memory of other elements of the climate system

ocean



sea ice



soil moisture



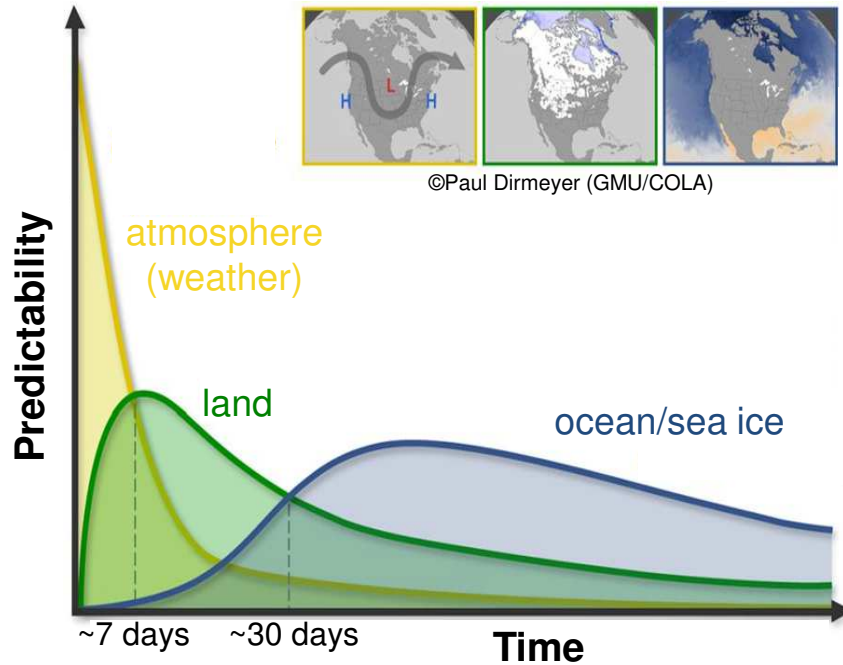
Internal sources of Climate Predictability



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Mariotti et al 2018

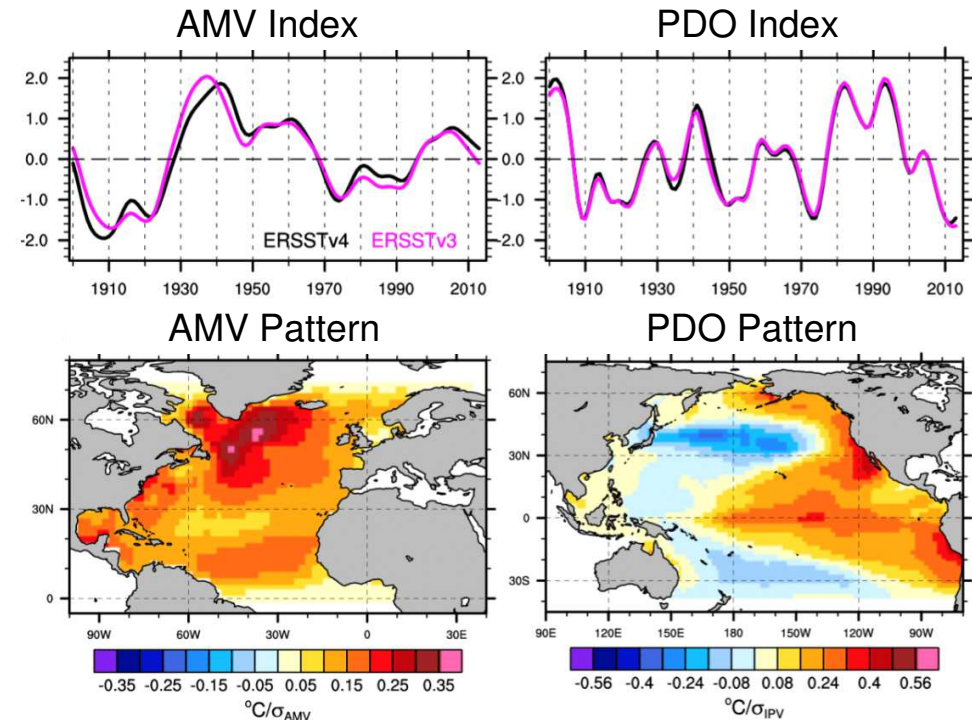


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ocean



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



Cassou et al,
Technical Note for DCPD-Component C

Introducing our main prediction tool



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Model Components

IFS (Atmospheric Model):

T255 (0.75°) ~80km

L91 (top 0.01hPa) ~mesosphere

IFS-HTESSEL (Land Model)

NEMO (Ocean Model):

Nominal 1° Resolution

L75 levels (thousands km deep)

PISCES (Biogeochemistry Model)

LIM (Sea-ice Model):

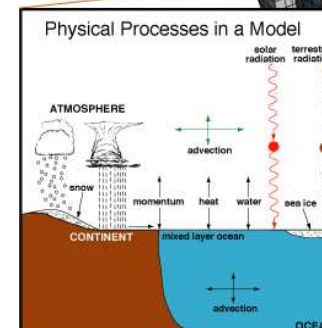
Multiple (5) ice category



EC-EARTH Global Coupled model

Horizontal Grid
(Latitude-Longitude)

Vertical Grid
(Height or Pressure)



Introducing our main prediction tool



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EC-EARTH Global Coupled model

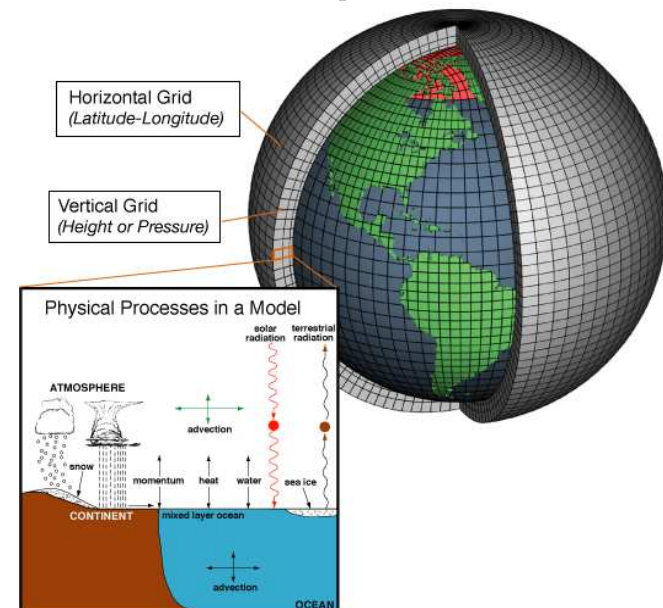
Initial Conditions produced in-house

Atmosphere
reanalysis
(ERA-Interim)

Sea Ice
reanalysis
(IC3/BSC)

Land reanalysis
(ERA-Land)

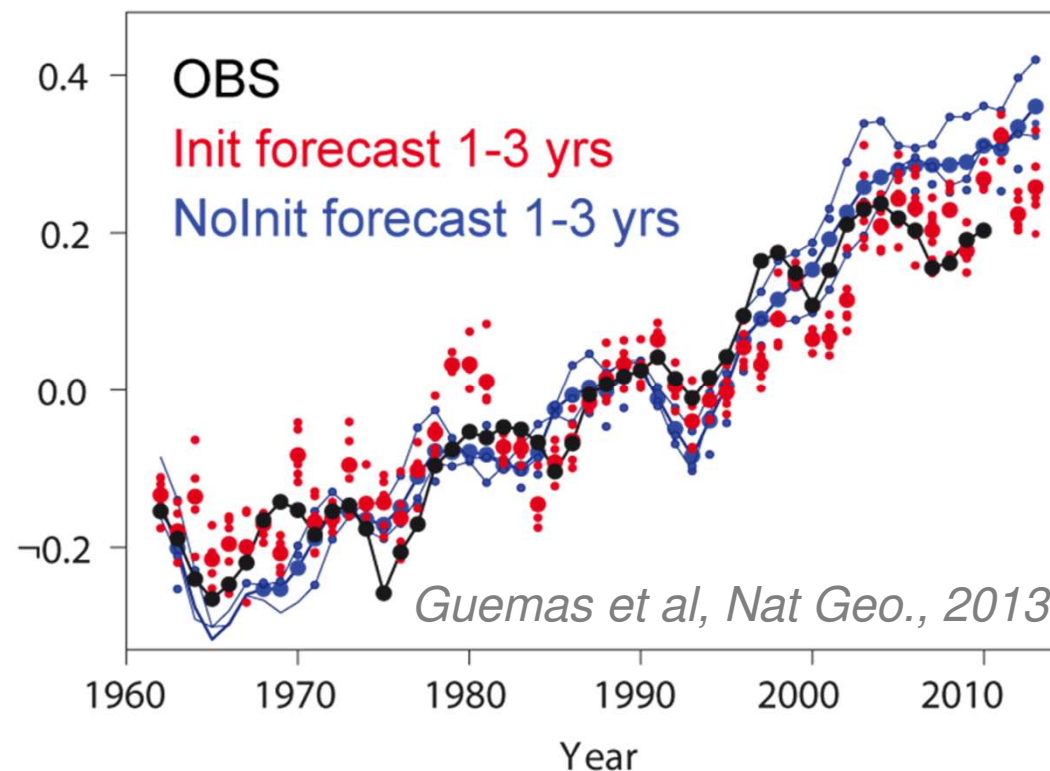
Ocean reanalysis
(ORAS4)



Two examples in decadal prediction (II)



Predictive skill of **global mean surface-air temperature** (Ec-Earth2.3)

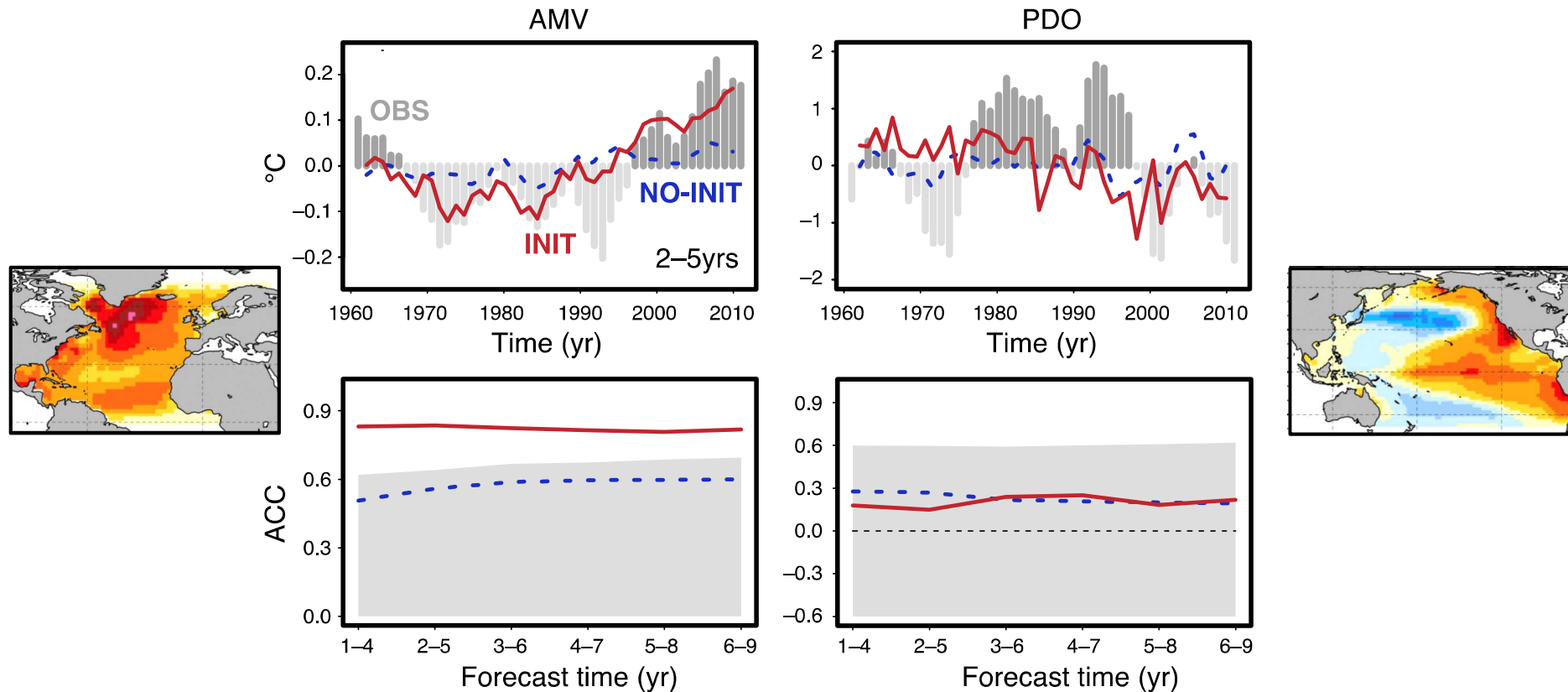


Initialised forecasts with EC-Earth reproduce the global temperature, and **describe more accurately** than the non-initialized ones the recent **HIATUS** period, which suggests a **key contribution of internal climate variability**

Two examples in decadal prediction (II)



Predictive skill of modes of multi-annual climate variability (in CMIP5)



Doblas-Reyes et al, Nat. Comm., 2013

Only in the **Atlantic Ocean**, the **initialized forecasts** show significant **predictive skill** and beat persistence, for forecast times of **up to 10 yrs**

Towards Real Time Decadal Climate Prediction



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Multi-model decadal forecast exchange

The Met Office coordinates an informal exchange of near-real time decadal predictions. Many institutions around the world are developing decadal prediction capability and this informal exchange is intended to facilitate research and collaboration on the topic.

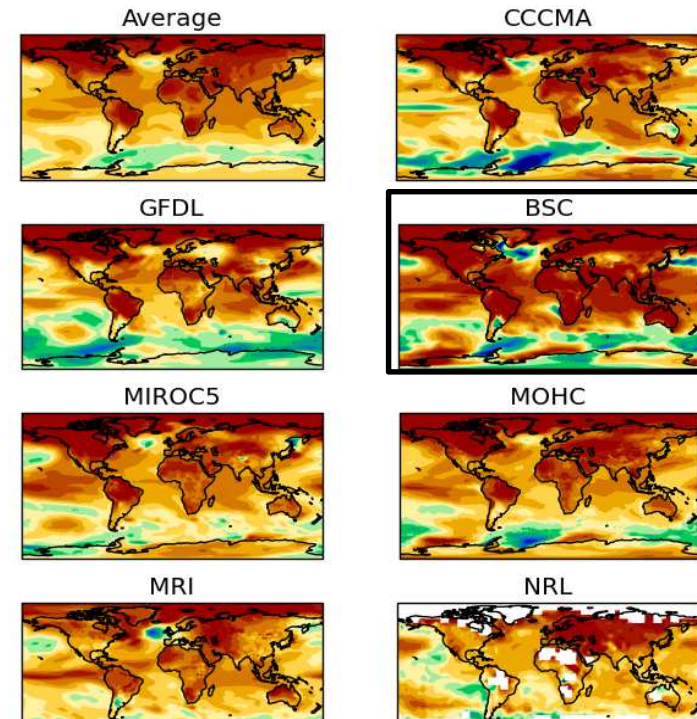
[The contributing prediction systems](#) are a mixture of dynamical and statistical methods. The prediction from each institute is shown below, alongside an average of all the models. When possible, observations for the period of the forecast are also shown. Currently three variables are included: surface air temperature, sea-level pressure and precipitation. These are shown as differences from the 1971-2000 baseline. More diagnostics, including ocean variables are planned for the future. Please use the drop-down menus below to explore the data collected to date.

This work is supported by the European Commission SPECS project.



Smith et al. (2013, ClimDyn)

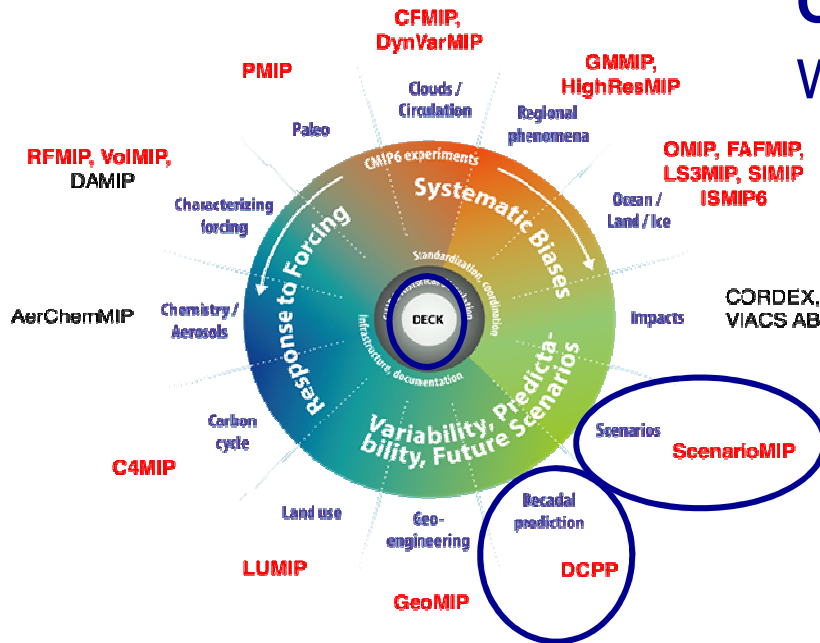
2015 predictions for 2016 SAT



15 centers will contribute to Annual Decadal Climate Prediction Exchange
4 applied for WMO-designation (**BSC** the only non meteorological center)



Simpkins (2017)



Contributions to CMIP6

With EC-Earth 3.2 in standard resolution ($\sim 1^\circ$)

DCPP Component A:

Retrospective Predictions [1960-2017]

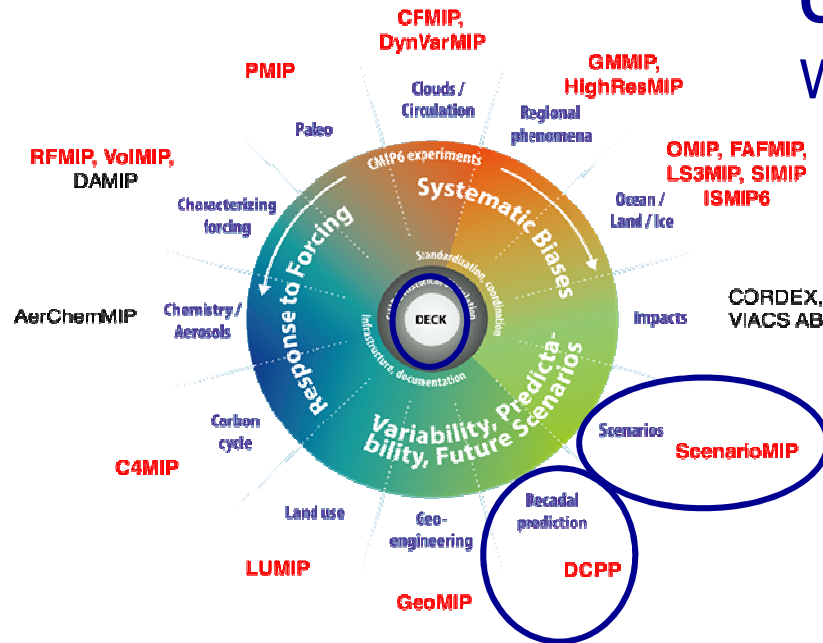
DCPP Component B:

Near-real time Forecasts [2018 onwards]

DECK+ScenarioMIP:

Historical+SPSS2-4.5 [1850-2100]

Simpkins (2017)



Contributions to CMIP6

With EC-Earth 3.2 in standard resolution ($\sim 1^\circ$)

DCPP Component A:

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DECK+ScenarioMIP:

Historical+SPSS2-4.5 [1850-2100]



Other H2020 activities

With EC-Earth 3.2 in high resolution ($\sim 0.25^\circ$)



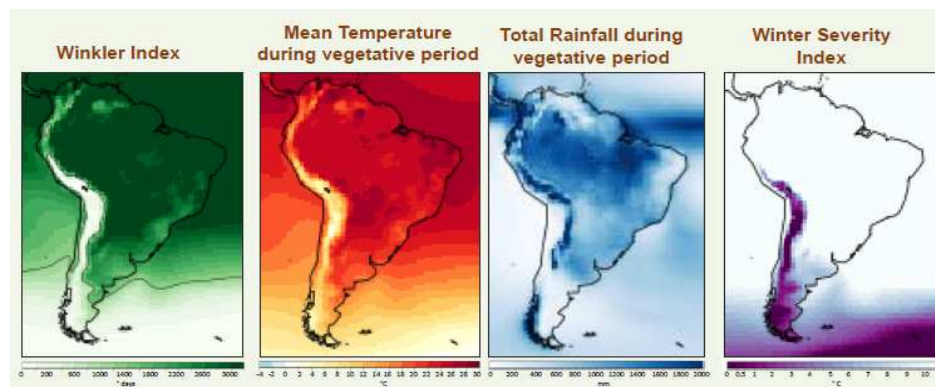
DCPP Component A-like:

Retrospective Predictions [1960-2017]

Bodegas Torres (and other wineries) are looking for **new vineyard locations**

They have purchased high elevation terrains near the Pyrenees

They are considering South America, in areas with no current wine production



Bodegas Torres is thus requesting **local climate information** (with uncertainty assessments) relevant for the **vegetative cycle of grapes**.

Concluding remarks

Decadal Climate Prediction relies on the **proper initialization** of regions with internal multi-annual climate variability, usually associated with the ocean

Multi-model decadal predictions within DCPP will be a **key contribution to CMIP6**, helping to:

- identify the **regions/variables robustly predictable**
- better **understanding** the origin of **systematic errors**

Decadal Climate Predictions provide important **strategic information** to guide future decisions by **stakeholders and policymakers**

Real-time decadal prediction exchange will continue and will be **enhanced** if the BSC is finally recognised by the WMO as a **global producing center**

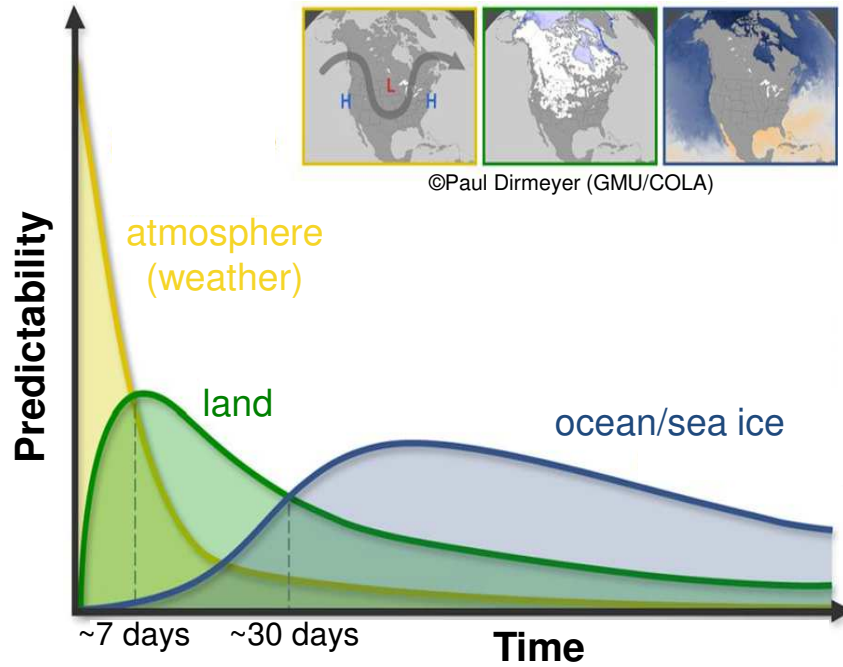
Thank you!

pablo.ortega@bsc.es



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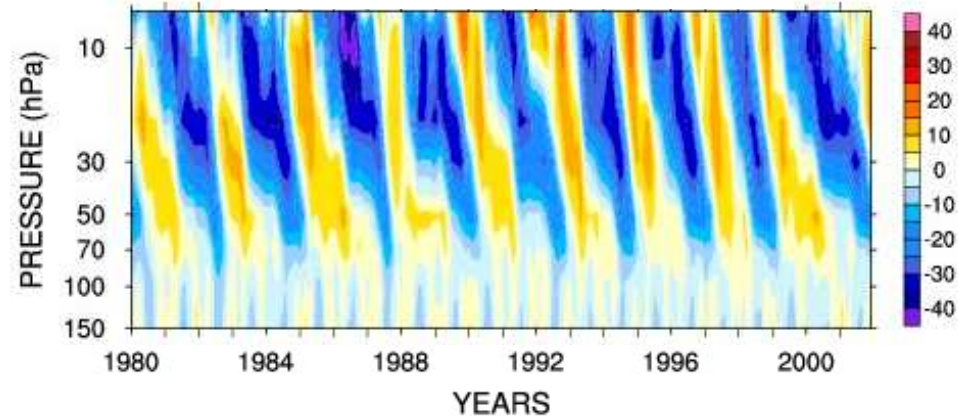
Mariotti et al 2018



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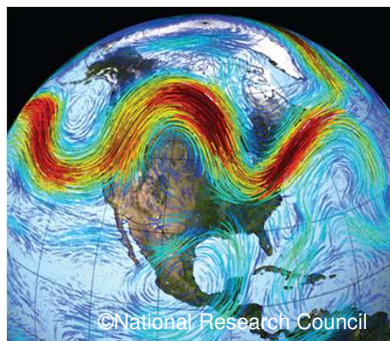
The **atmosphere** can also provide **memory** beyond monthly timescales

Equatorial Zonal Wind (m/s)



Monier & Weare (2011)

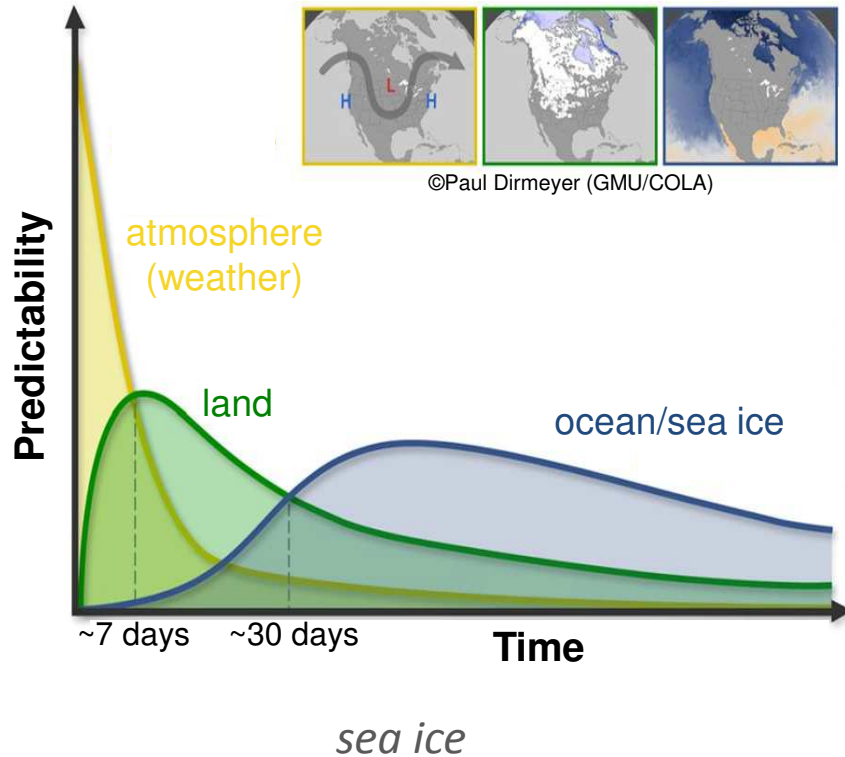
atmosphere



©National Research Council

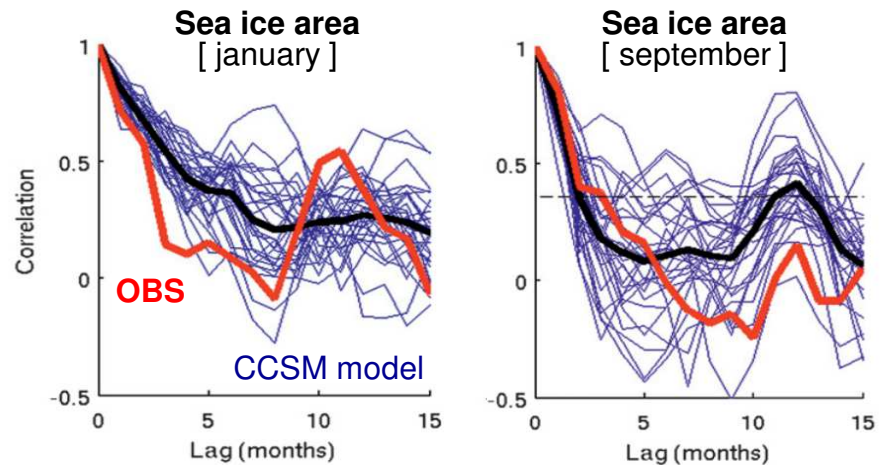
Through its key role on wave propagation that can further impact the polar vortex strength, the **Quasi-biennial Oscillation** can contribute to Northern Hemisphere predictability at seasonal and interannual timescales.

Mariotti et al 2018



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Re-emergence mechanisms in Arctic sea ice can provide memory and thus predictability at seasonal scales



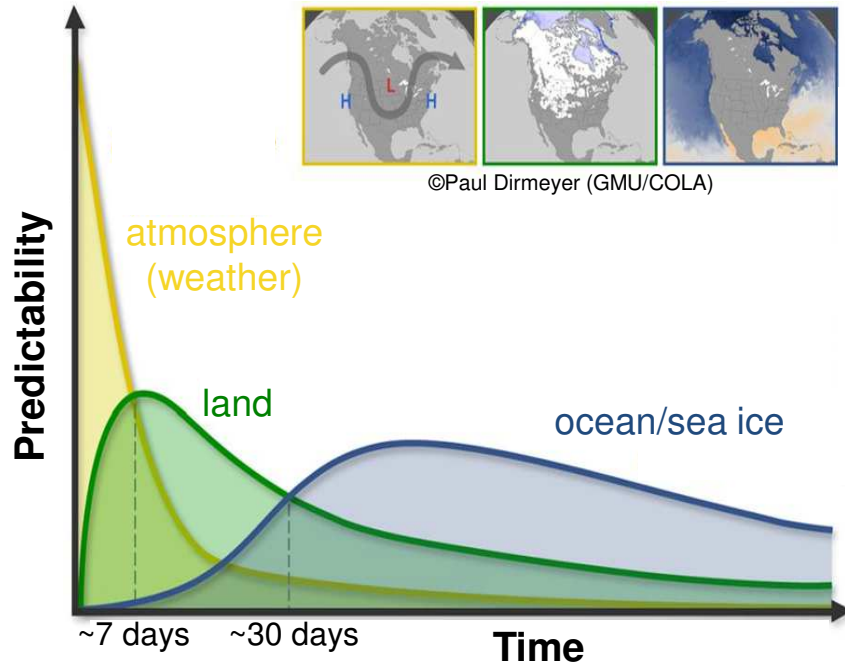
Blanchard-Wrigglesworth et al 2011



Mariotti et al 2018



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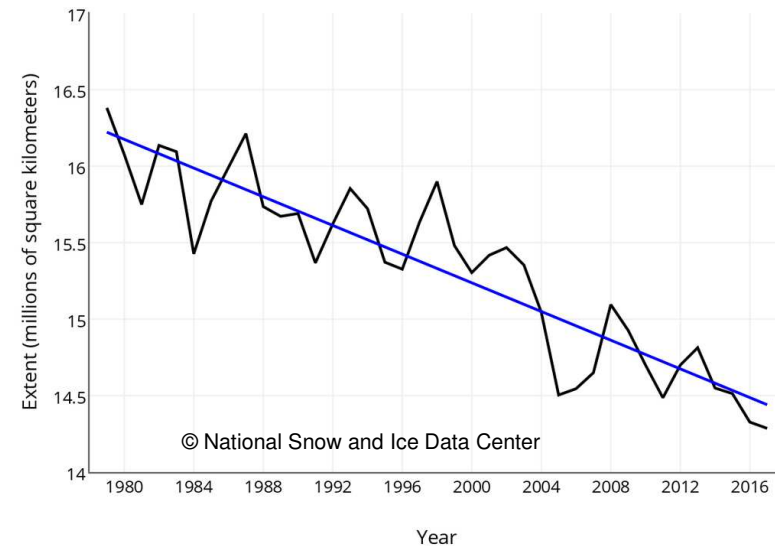


sea ice



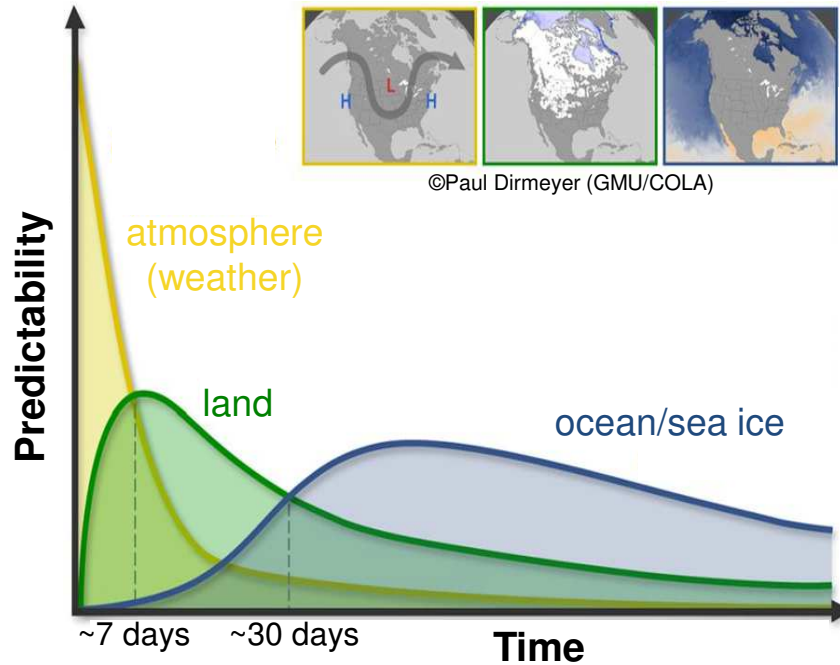
And at longer time-scales Arctic sea ice is experiencing long-term decline

Average Arctic Sea Ice extent
[February 1979-2017]



© National Snow and Ice Data Center

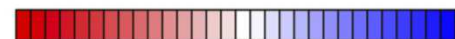
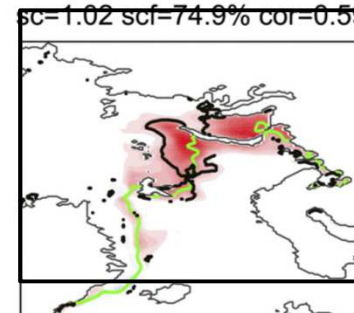
Mariotti et al 2018



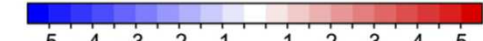
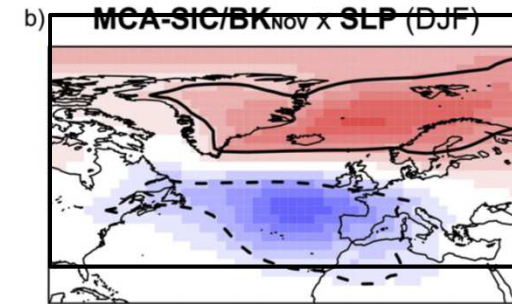
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While many studies report **important impacts of Arctic sea on the climate of the mid-latitudes**

1st EOF of November
Sea Ice Cover (SIC)



Predicted DJF
Sea Level Pressure



García-Serrano et al 2014

sea ice



For example, on Europe at **seasonal timescales** through an influence of Barents-Kara Sea SIC changes on the **North Atlantic Oscillation**

Example of climate service for the agriculture sector: wine yields

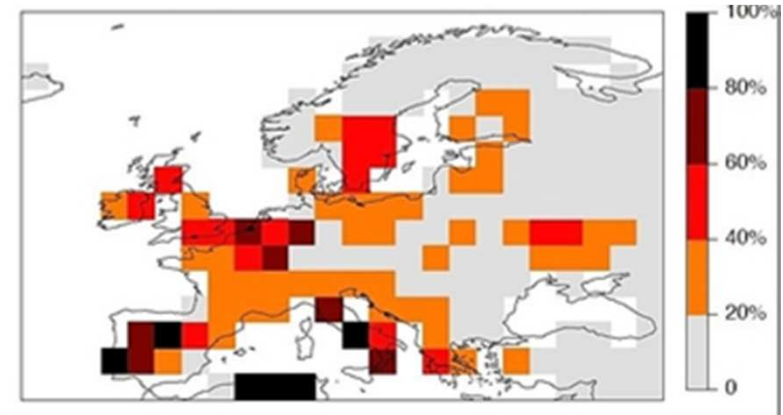
Engaging with the users to understand their needs



Developing a Climate Service

Scientific research and development of tailored indicators

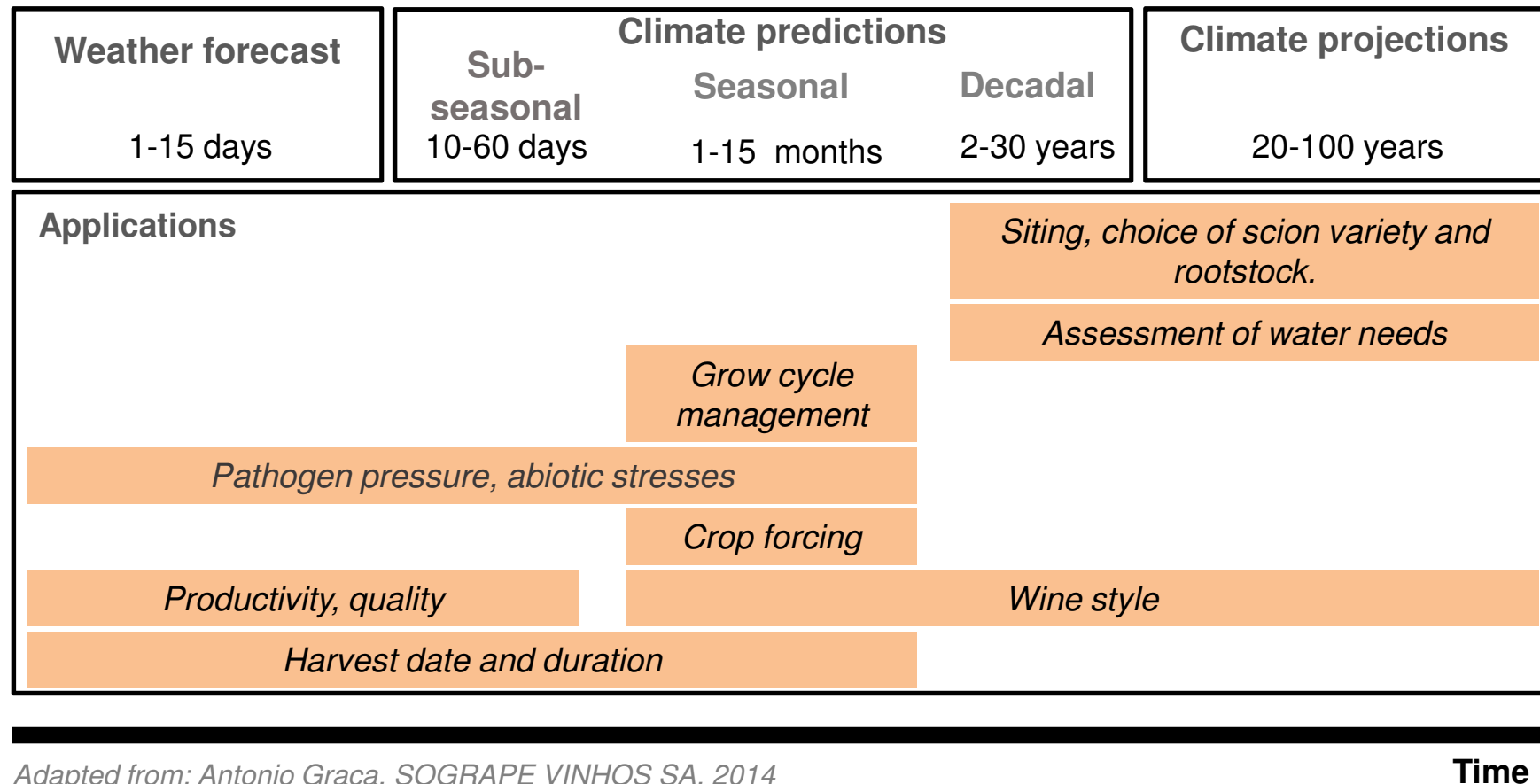
Prediction of extreme drought (August 2017)



Tools and assessment of decision making processes

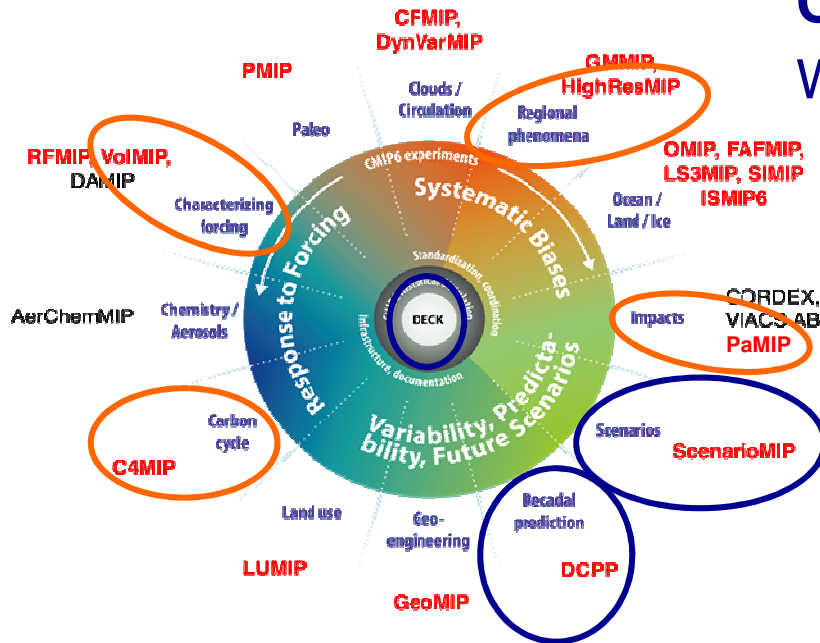
Terrado, M., I. Christel, D. Bojovic, A. Soret and F. Doblaz-Reyes (2017) "Climate change communication and user engagement: a tool to anticipate climate change". Published in Handbook of Climate Change Communication

Example of **climate service** for the agriculture sector: **wine yields**



Adapted from: Antonio Graça, SOGRAPE VINHOS SA, 2014

Simpkins (2017)



Contributions to CMIP6

With EC-Earth 3.2 in standard resolution ($\sim 1^\circ$)

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Near-real time Forecasts [2018 onwards]

DECK+ScenarioMIP:

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Other CMIP6 contributions

VoIMIP: Evaluating the predictability associated to volcanoes

C4MIP: Investigating the predictability of the carbon cycle

HiResMIP: Determining the advantages of super high resolution ($1/12^\circ$)

PaMIP: Constraining the long-term impacts due to Arctic Sea Ice decline

