Barcelona Supercomputing Center
Centro Nacional de Supercomputación

CMUG-CCI+ Science and Technical Highlights (**BSC**)

Pablo Ortega on behalf of colleagues from the Climate Variability and Change Group

24th-25th October 2022

ESA CMUG 2022 Integration Meeting (Frascati)

Importance of propagating observational uncertainties when assessing predictive skill (WP 3.4)

What is the impact of observational uncertainties in the estimated prediction skill of BSC's seasonal forecasts?

Task lead: **Aude Carreric**

CCI Involved: Sea Ice
SIC: CCI v2.0 VLF

Seasonal reforecasts
EC-Earth3 model
1993-2014 start dates
Initialized every 1st May
10 ensemble members

Propagation of uncertainties as in Belprat et al. (2017)

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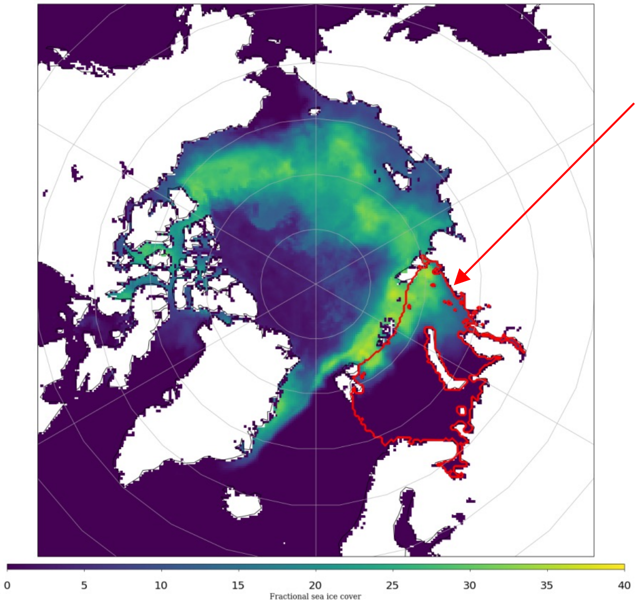
Standard Deviation of Aug-Sep SIC



Focus on: **Barents and Kara Seas**

A region and a season in which SIC has been linked with remote impacts:

- The North Atlantic Oscillation (Ruggieri et al, 2016)
- Extremes over Europe (Acosta Navarro et al, 2020)

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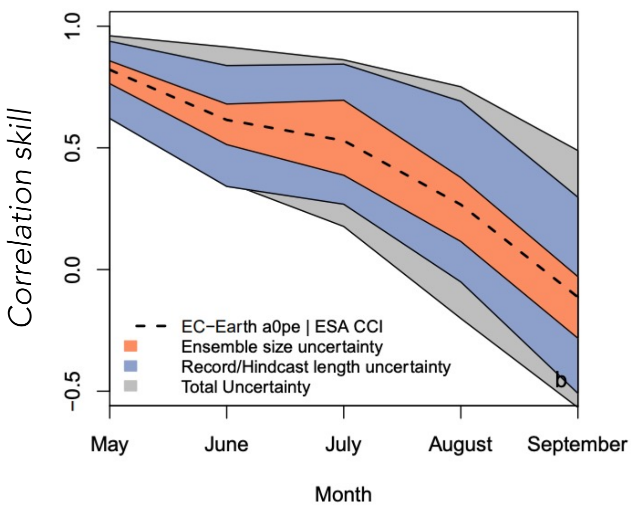
Sensitivity to Sampling Uncertainty



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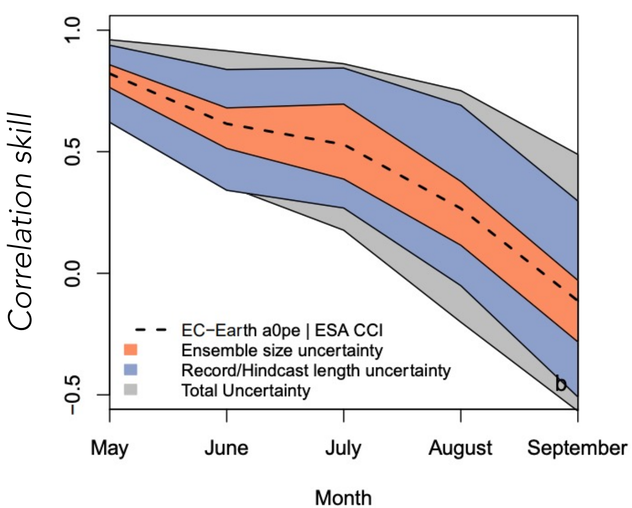

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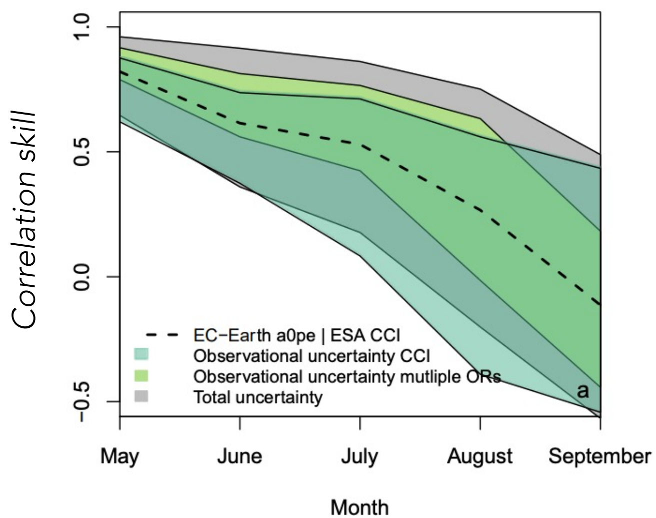

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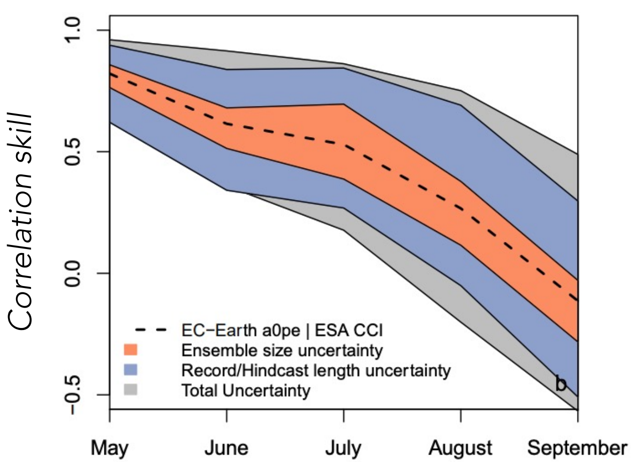

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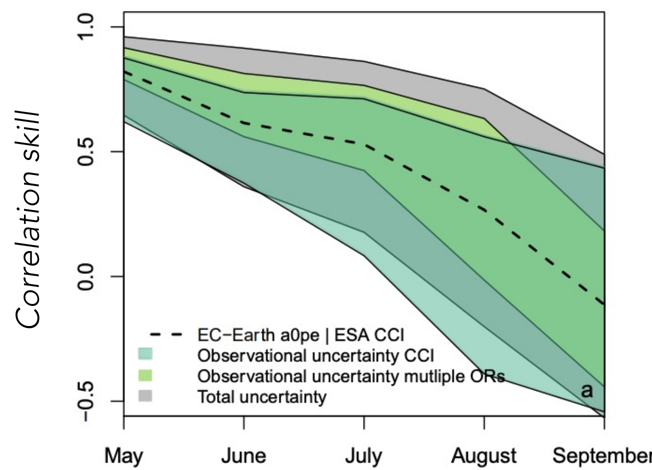

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Propagation of uncertainties as in Belprat et al. (2017)

Correlation skill metrics range from 0.7 (i.e. very good performance) to -0.4 (i.e. really poor performance)
This effect is comparable to the combined effect of the ensemble size and hindcast length uncertainty

Importance of propagating observational uncertainties when simulating wild fires (**WP 3.4**)

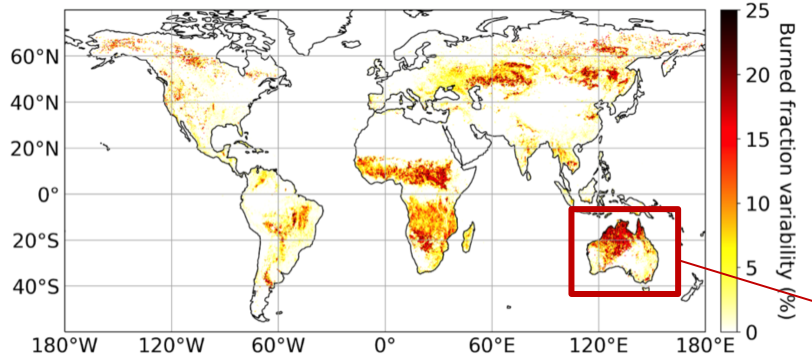
How well does the vegetation model in EC-Earth represent the observed climatology of burned area?

Task lead: **Aude Carreric**

CCI Involved: Fire
GFED4

EC-Earth Simulation
Historical period (2001-2017) Forced with ERA5 surface fluxes

Standard deviation of burned area annual fraction



Focus on: **Australia** (most wild-fires are climate driven)

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esa

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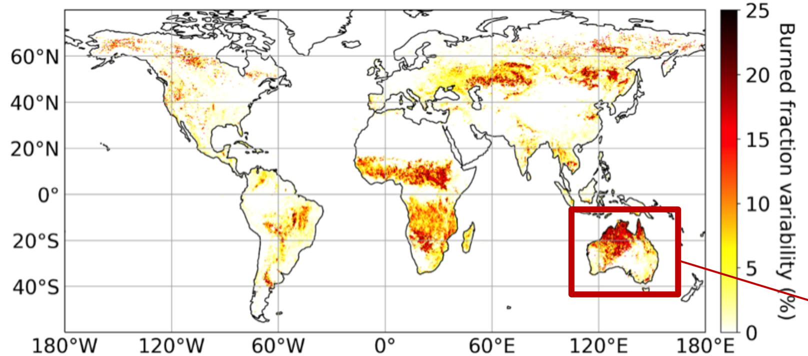

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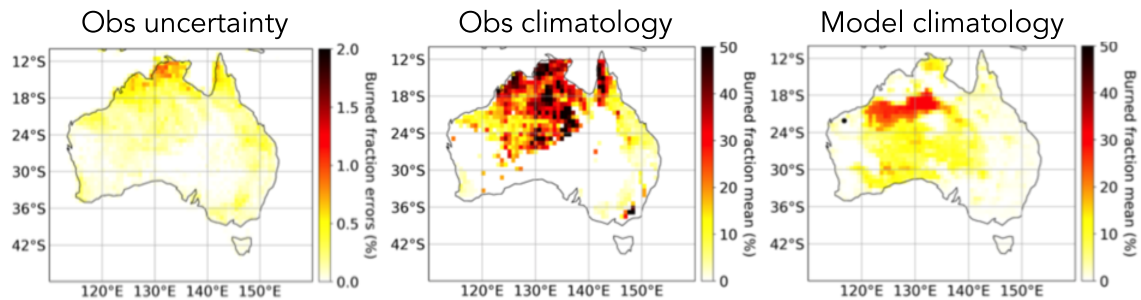

Propagation of uncertainties as in Belprat et al. (2017)

Impact of an enhanced Sea Ice reanalysis on the initialization of seasonal predictions (**WP 3.8**)

What is the added value of assimilating SIC data on the seasonal skill in the Arctic and beyond?

Task lead: **Juan Acosta Navarro**

CCI Involved: **Sea Ice**

OSISAF v2

Seasonal reforecasts
EC-Earth3 model
1992-2018 start dates
Initialized every 1st May
30 ensemble members
2 sets w/wo assimilation

Three different SIC products assimilated

Ocean/Atmos	Sea Ice
ORA5 / ERA5	OSISAFv2
	CERSAT
	ORAS5

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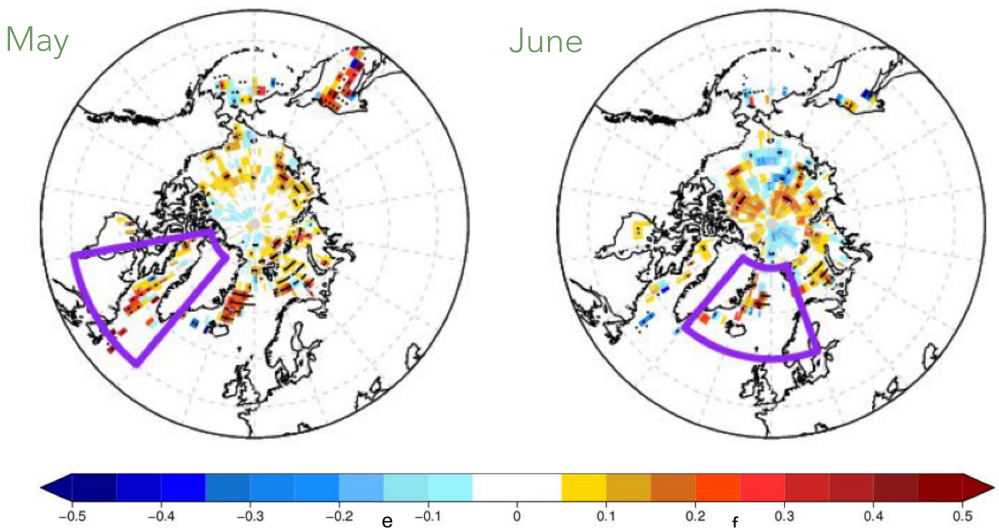
Added value of SIC assimilation for predicting Arctic Sea Ice (ACC differences)



Results published in Acosta Navarro et al. (2022)

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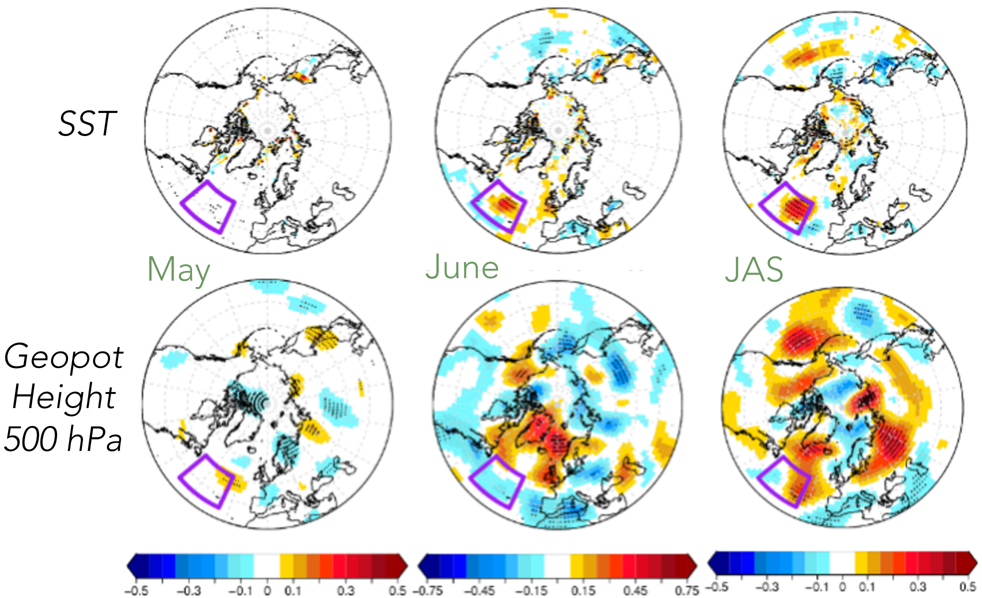
Added value of SIC assimilation for predicting mid-latitude climate



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CCI data for a skill assessment of decadal climate predictions (WP 4.7)

What is the spatio-temporal consistency between the different observational products?

Task lead: **Jaume Ruiz de Morales**

CCIs Involved
Cloud cover, SL, SST

Variable (units)	Product	Time Period	Original resolution
Cloud cover (%)	EUMETSAT ESA AVHRR-PM v3.0	01/1982-05/2019 01/1982-12/2016	0.25° 0.5°
Sea Surface Height Anomaly (in m)	C3S CMEMS	01/1993-10/2019 01/1993-02/2020	0.25°x0.25° 0.25°x0.25°
Sea Surface Temperature (in °C)	ESA L4 HadISSTv1.1 ERSST	01/1982-12/2020 01/1870-12/2020 01/1854-12/2020	0.05° 1°x1° 2°x2°

Decadal Predictions
EC-Earth3 model
1960-2020 start dates
Initialized every 1st Nov
10 ensemble members

Initial conditions derived from

Ocean/Sea ice	Atmosphere
ORAS4	ERA40
	ERA-Interim

EC-Earth decadal predictions largely analysed in Bilbao et al. (2021)

CCI data for a skill assessment of decadal climate predictions (WP 4.7)

esa

What is the spatio-temporal consistency between the different observational products?

Task lead: **Jaume Ruiz de Morales**

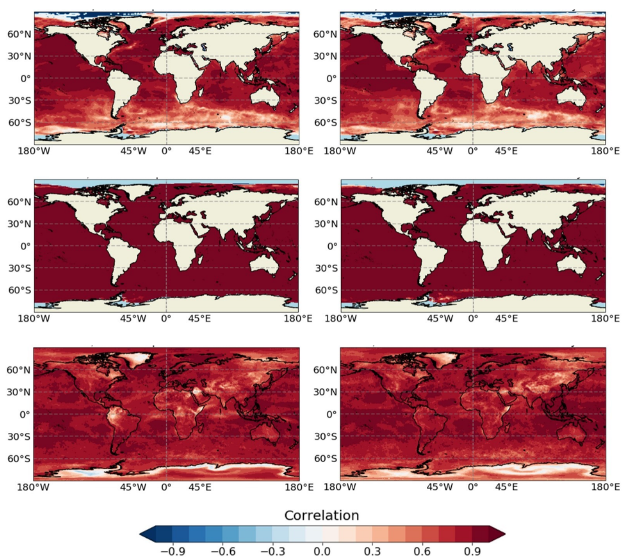
Minimum correlation inter-products

undetrended *detrended*

SST

SSH

Cloud Cover



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Is prediction skill similar for sea surface height and dynamical sea level?

Task lead: **Jaume Ruiz de Morales**

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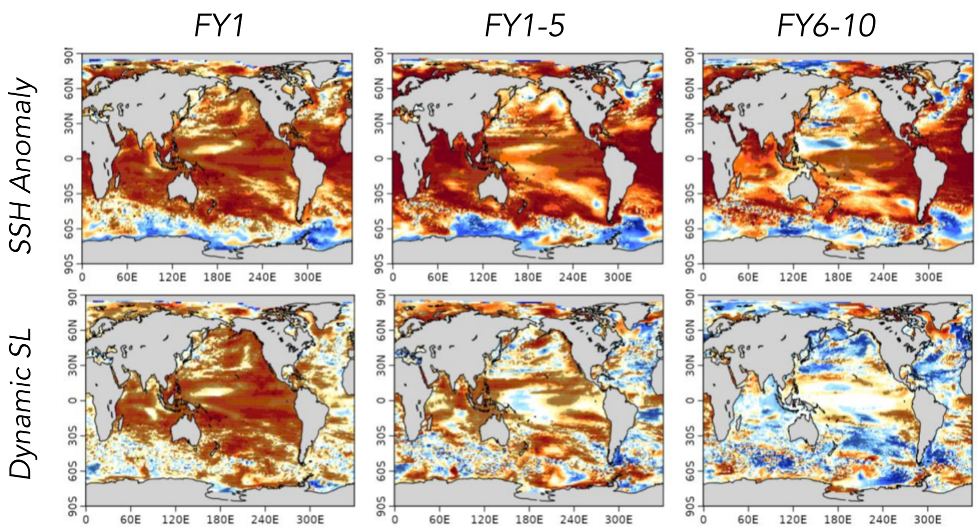
Decadal Prediction skill



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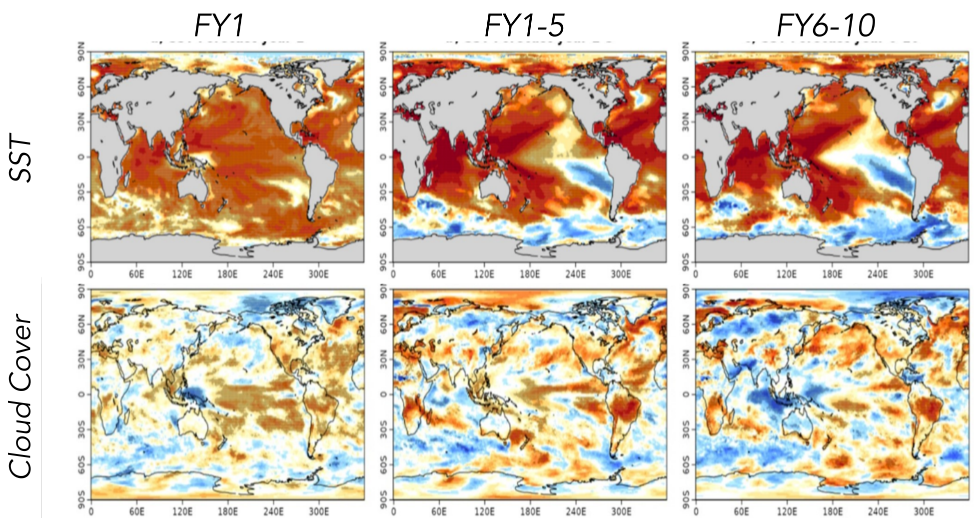
CCI data for a skill assessment of decadal climate predictions (WP 4.7)

Can we identify areas with significant predictive skill for both SST and cloud cover?

Task lead: **Jaume Ruiz de Morales**

Decadal Prediction skill



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Main advances and lessons learned in CMUG-CCI+

- Demonstrated importance of including observational uncertainties in several modeling applications
- New capabilities to assimilate observations (sea ice concentrations) proved of great value for seasonal prediction. To be further exploited in new case study on predictability of marine biogeochemistry
- Observational uncertainties can translate into differences in the temporal evolution which can be particularly important for some variables and regions (e.g., southern ocean SSTs)
- Prediction skill of sea level can largely vary depending on the specific variable that is evaluated (sea surface height vs dynamical sea level), mostly due to their different sensitivity to the external forcings