CMUG-CCI+ Science and Technical Highlights (BSC)

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

Propagation of uncertainties as in Belprat et al. (2017)
Importance of propagating observational uncertainties when assessing predictive skill (WP 3.4)

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Propagation of uncertainties as in Belprat et al. (2017)
What is the impact of observational uncertainties in the estimated prediction skill of BSC’s seasonal forecasts?

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?

Standard deviation of burned area annual fraction

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

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

Task lead: Aude Carreric

CCI Involved: Fire

GFED4

EC-Earth Simulation
Historical period (2001-2017)
Forced with ERA5 surface fluxes
Importance of propagating observational uncertainties when simulating wild fires (WP 3.4)

Task lead: Aude Carreric

CCI Involved: Fire

GFED4

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

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

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)

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

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

Three different SIC products assimilated

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

Task lead: Juan Acosta Navarro

CCI Involved: Sea Ice

OSISAF v2

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

May

June

Results published in Acosta Navarro et al. (2022)
Impact of an enhanced Sea Ice reanalysis on the initialization of seasonal predictions (WP 3.8)

Task lead: Juan Acosta Navarro

CCI Involved: Sea Ice

OSISAF v2

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

Added value of SIC assimilation for predicting mid-latitude climate

SST

May  June  JAS

Geopot Height 500 hPa

Results published in Acosta Navarro et al. (2022)

Three different SIC products assimilated

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

Task lead: Jaume Ruiz de Morales

CCIs Involved

Cloud cover, SL, SST

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<td>Sea Surface Anomaly (in m)</td>
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<td>Sea Surface Temperature (in °C)</td>
<td>ESA_L4, HadISSTv1.1, ERSST</td>
<td>01/1982-12/2020, 01/1984-12/2020</td>
<td>0.05°, 1°x1°, 2°x2°</td>
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Decadal Predictions

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

Initial conditions derived from

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EC-Earth decadal predictions largely analysed in Bilbao et al. (2021)
CCI data for a skill assessment of decadal climate predictions (WP 4.7)

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

Minimum correlation inter-products

- undetrended
- detrended

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

Task lead: Jaume Ruiz de Morales

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

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

Decadal Prediction skill

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<td>SSH Anomaly</td>
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<td>Sea Surface Height Anomaly (m)</td>
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EC-Earth decadal predictions largely analysed in Bilbao et al. (2021)

Task lead: Jaume Ruiz de Morales

CCIs Involved

Cloud cover, SL, SST

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

**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