CONFESS

National Research Council of Italy

# The role of vegetation in climate predictability and prediction

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# Outline

- Background
  - Bio-physical effects of land cover-vegetation on climate

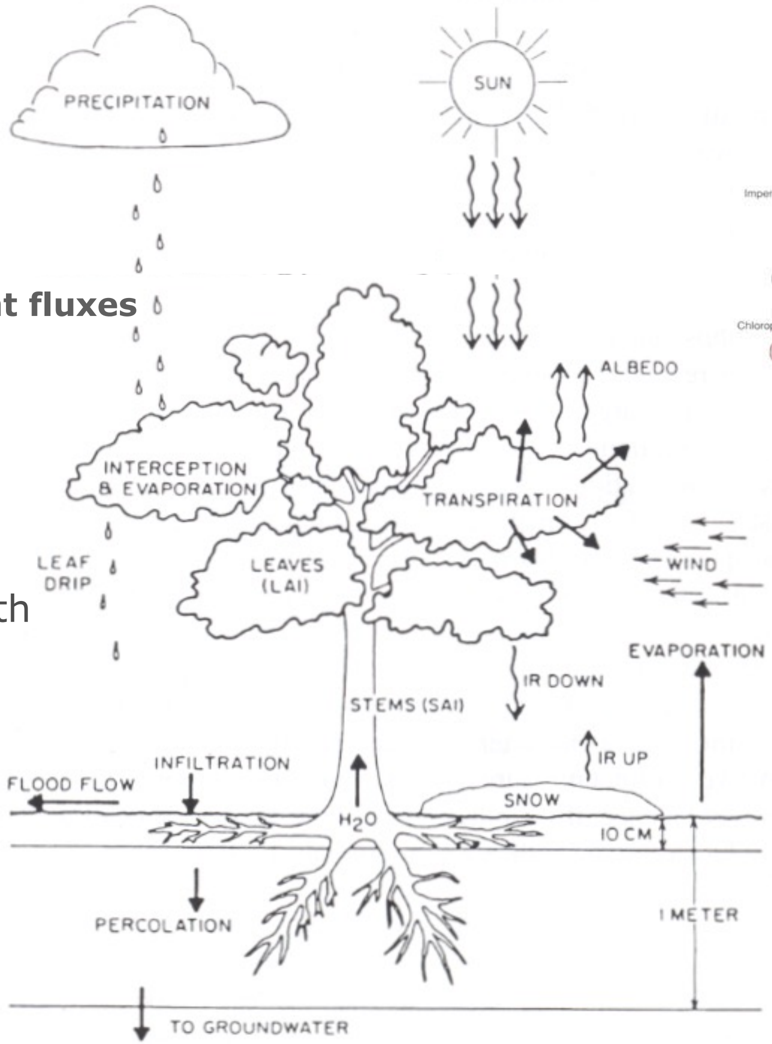
    Observations and models
- Vegetation effects at Seasonal timescale - realistic effective vegetation cover in SEAS5 (low res)
  - Sensitivity of surface climate prediction (ACC)
  - Relation with/effects on NAO prediction and signal to noise ratio
- Land cover/vegetation effects at Decadal timescale, DCPP-veg experiment
  - Sensitivity of climate climate prediction (Bias)
  - Sensitivity of surface climate prediction (ACC)
- Summary and Discussion

# Background

# Bio-physical effects of land cover-vegetation on climate

Turbulent fluxes

$Z_0$ = roughness length



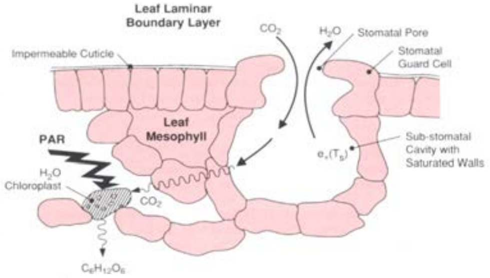



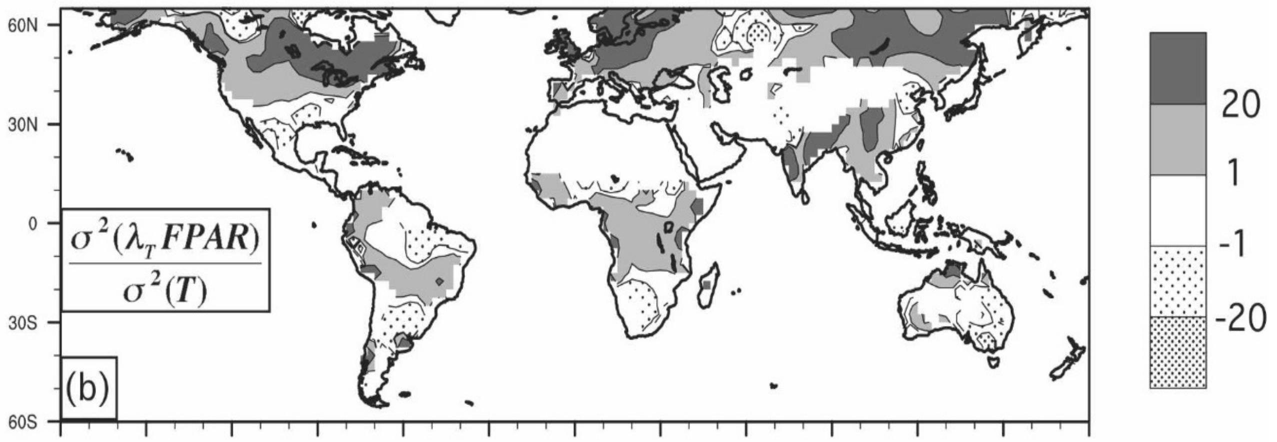

Fig. 5.5 Diagram showing the effects of the vegetation canopy on the water and energy fluxes. From Dickinson (1984). © American Geophysical Union.]

Leaf Area Index (LAI) characterizes the density of vegetation and is defined as the projected area of leaves per unit area of ground.

# Observational Evidence for vegetation-atmosphere interaction – Forced 2m Temperature variance

Forcing of Vegetation (satellite LAI proxy, FPAR) on Temperature (NCEP Reanalysis) monthly-mean interannual anomalies.

T2m variance forced by vegetation




*From Liu et al., (2005)*

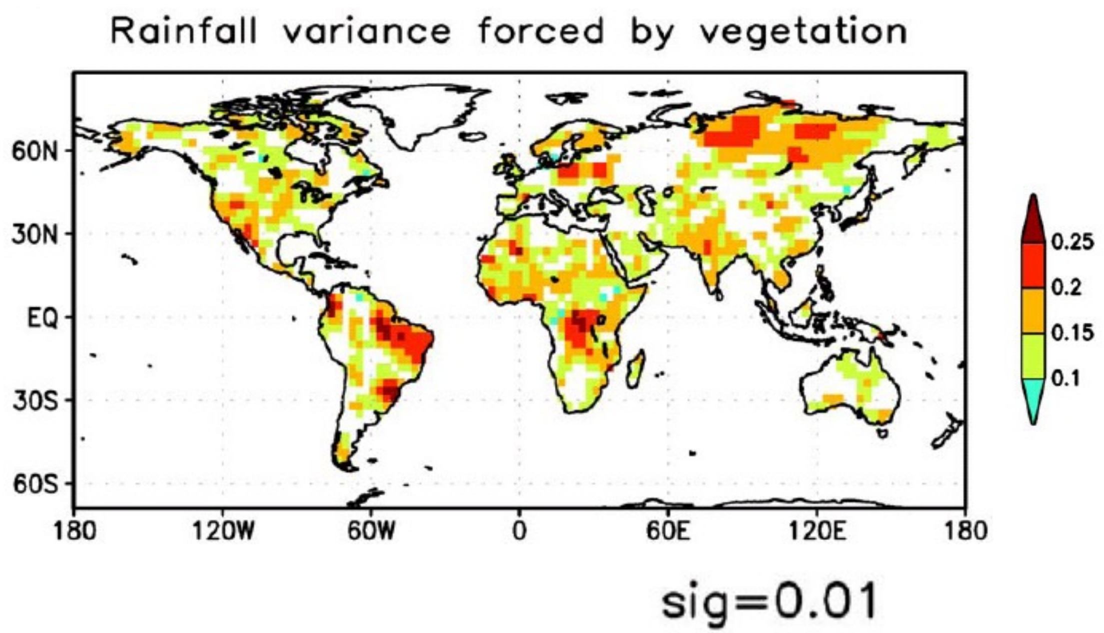
Linearized feedback analysis applied to monthly-mean interannual anomalies

# Observational Evidence for vegetation-atmosphere interaction – Forced Precipitation variance

The reciprocal forcing between rainfall and vegetation has been assessed at the 1% significance level using the Coupled Manifold technique

We used seasonal mean interannual anomalies of Rainfall (CMAP) and Vegetation (satellite LAI proxy, NDVI).

We estimated that 12% of the rainfall variability is forced by vegetation (period 1982-1998).



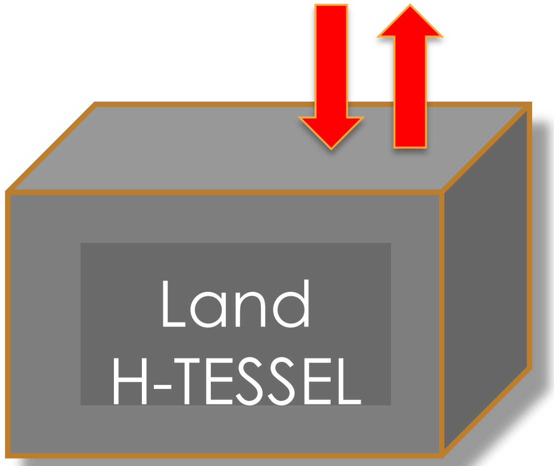

*From Alessandri and Navarra, 2008 (GRL)*

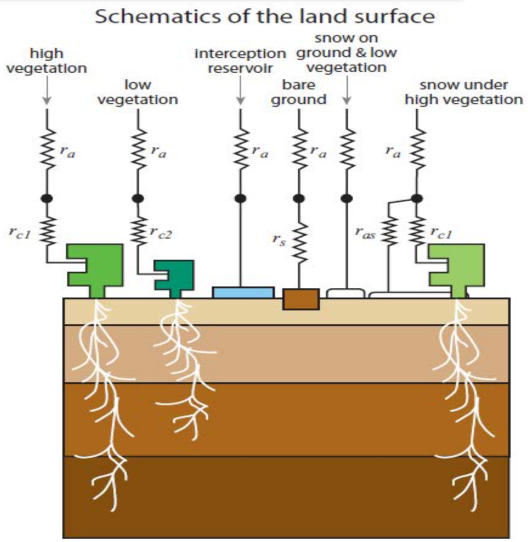
# Modeling land cover vegetation in EC-Earth/ECMWF Integrated Forecasting System

# Land surface coupling in IFS/EC-Earth

IFS

**Climate**
radiation, temperature, precip,…




$r_c$ Canopy resistance to transpiration

$$r_c(LAI) = \frac{r_{s,\min}}{LAI} f_1(Rs)\cdot f_2(\bar{\omega})\cdot f_3(D_a)$$

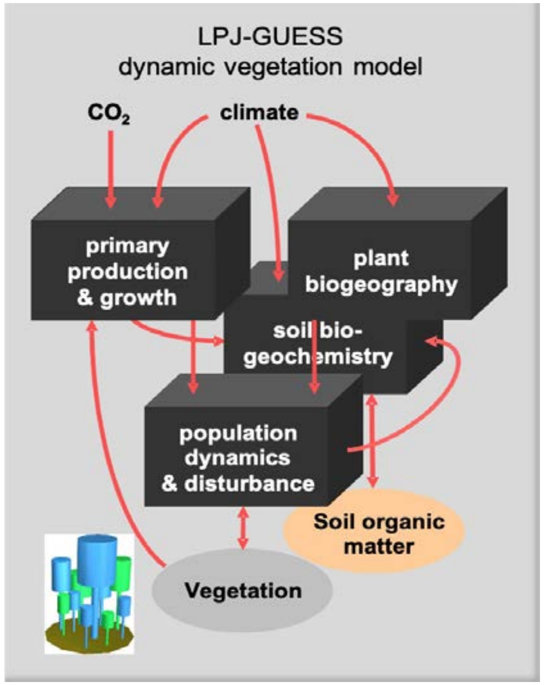
Rs downward shortwave radiation
ω soil moisture content
Da atmospheric water vapor deficit

Land cover-vegetation prescribed and not interannually varying

**Vegetation fixed**
LAI (High/Low veg.) – seasonal cycle
Land cover (High/Low veg) - constant

# Land surface coupling in IFS/EC-Earth

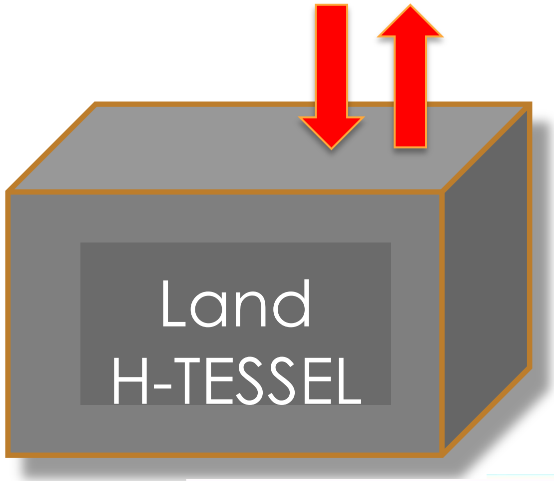
## Coupling biophysics




From Observations
or
LPJ-Guess

IFS

**Climate**
radiation, temperature, precip,…

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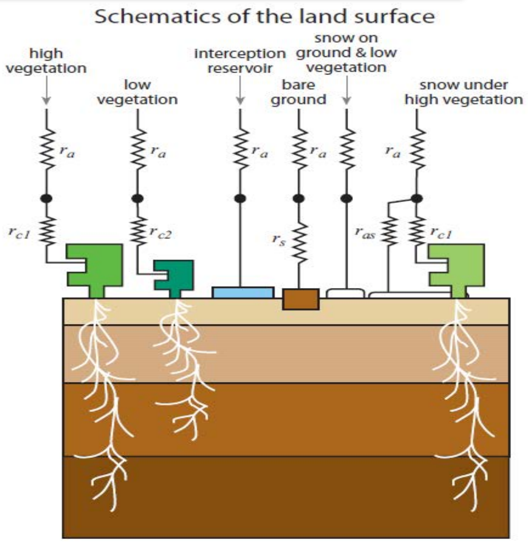



**Vegetation effective cover affects coupling parameters:**

- -roughness length,
- -albedo,
- -field capacity,
- -evapotranspiration resistance

**Vegetation dynamics**
LAI (High/Low veg.)
Land cover (High/Low veg)

# Effective vegetation cover (Ceff) parameterization as a function of vegetation Leaf Area index

**Effective fractional vegetation cover**

$$Ceff(t) = Cv_L(LAI[t]) \cdot A_L + Cv_H(LAI[t]) \cdot A_H$$

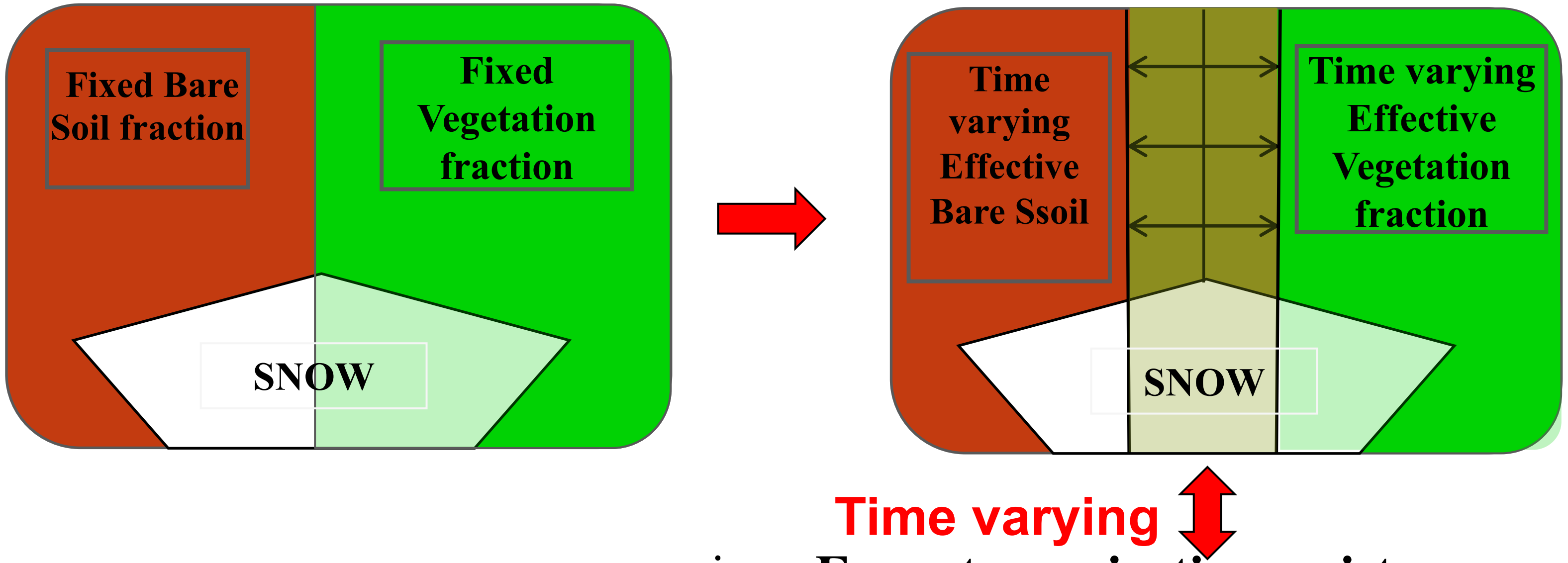
**Bare Soil fraction**

$$bareS = 1 - Ceff(t)$$

$_{L,H}$ low, high vegetation

$A_L, A_H$ Max fractional coverages

$C_L, C_H$ Vegetation density




**Time varying**

i. **Evapotranspiration resistance**

ii. **Roughness length**

iii. The contribution of root density of each vegetation-type to the **Field Capacity**

iv. Surface **Albedo**

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# Effective vegetation cover (Ceff) parameterization as a function of vegetation Leaf Area index

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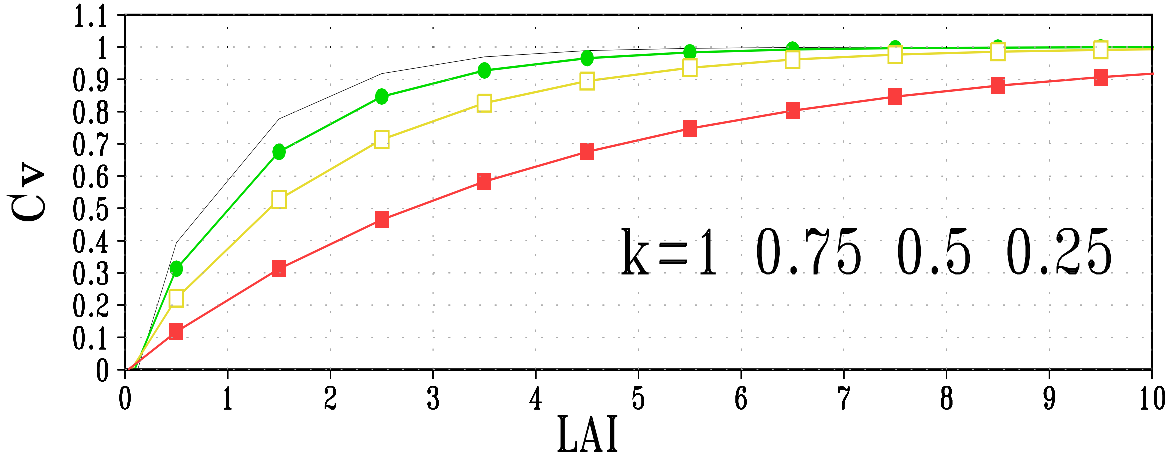
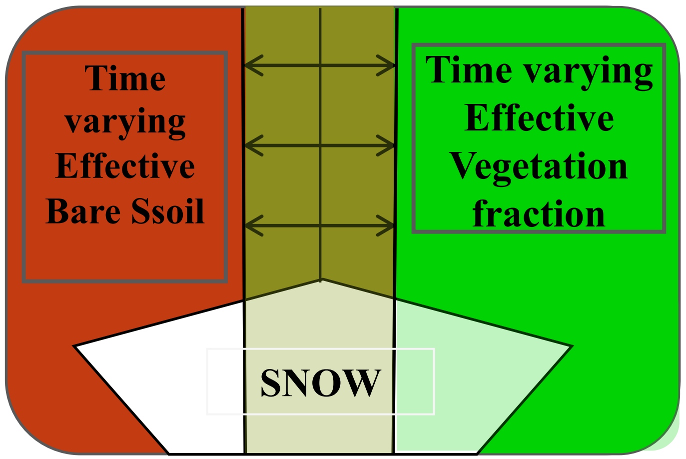



**LAI and vegetation density (Cv) Time varying & interactively coupled**

$$Cv_{L,H}(t) = f\left(LAI_{L,H}\right) = \left(1 - e^{-K_{L,H} \cdot LAI_{L,H}}\right)$$

$_{L,H}$ low, high vegetation

$A_L, A_H$ *Max fractional Land Cover*

$C_L, C_H$ Vegetation density

$k_{L,H} = 0.5$

**Time varying**

i. **Evapotranspiration resistance**

ii. **Roughness length**

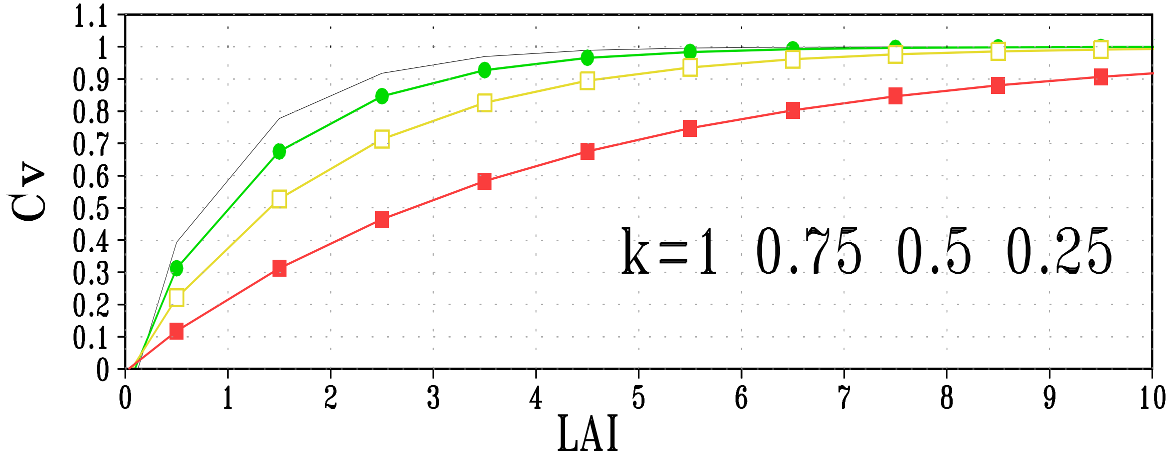
iii. The contribution of root density of each vegetation-type to the **Field Capacity**

iv. Surface **Albedo**

Alessandri et al 2017

# Effective vegetation cover (Ceff) parameterization as a function of vegetation Leaf Area index

$$Ceff(t) = Cv_L(LAI[t]) \cdot A_L + Cv_H(LAI[t]) \cdot A_H$$




In CONFESS we estimated $K_{L,H}$ for each of the vegetation types in the land model (ESA-CCI land cover) using inverse modelling and based on available *Fraction of Green Vegetation Cover* (**FCover**) observational data from **Copernicus**:

$$K_{H.L} = f\left(D_{H,L}\right) = \text{minimization problem}$$

$$D_{H,L} = dominant\ vegetation\ type$$

for High and Low vegetation

**LAI and vegetation density (Cv) Time varying & interactively coupled**

$$Cv_{L,H}(t) = f\left(LAI_{L,H}\right) = \left(1 - e^{-K_{L,H} \cdot LAI_{L,H}}\right)$$

$_{L,H}$ low, high vegetation

$A_L, A_H$ *Max fractional Land cover*

$C_L, C_H$ Vegetation density



van Oorschot et al 2023, under Submission

# Constrain Effective vegetation cover parameterization using observational FCover data

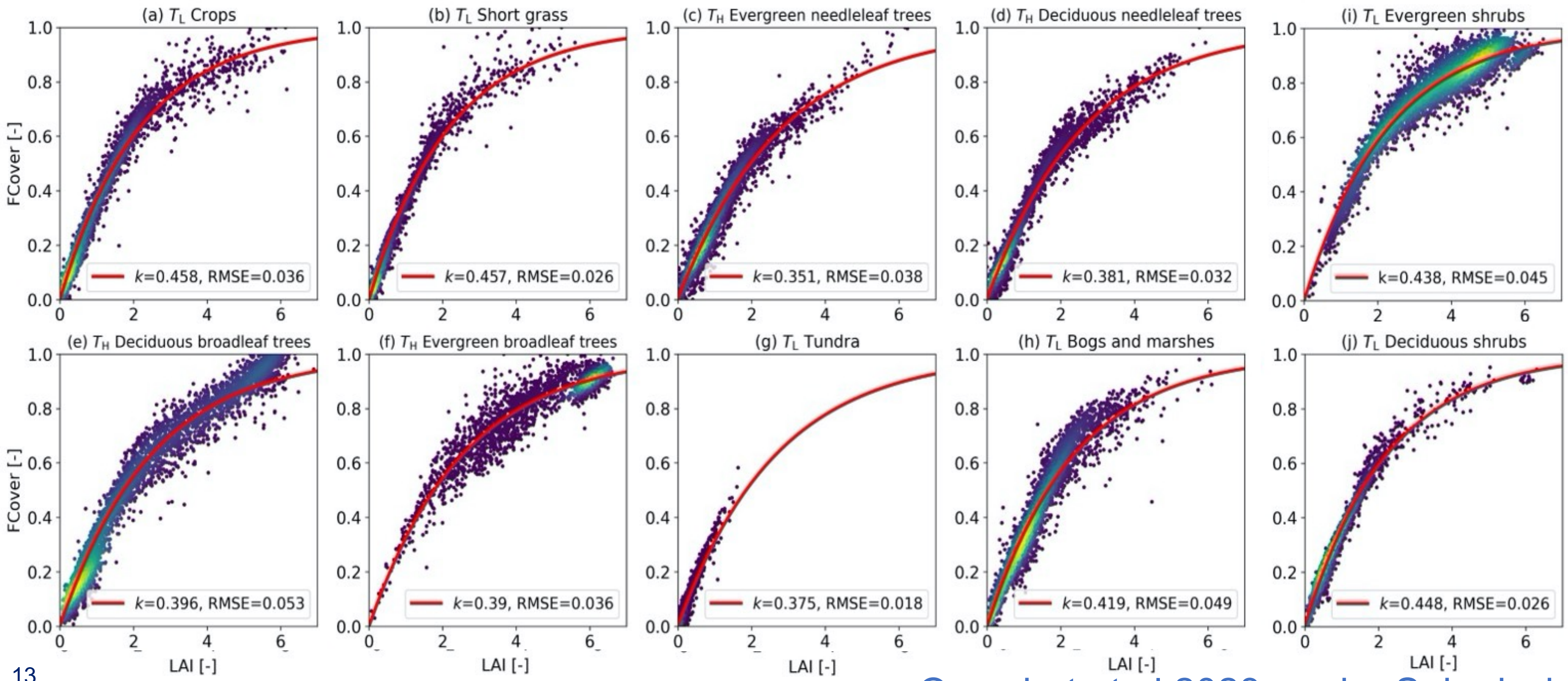
<u>Data</u> [~1km grid; 1999-2019]

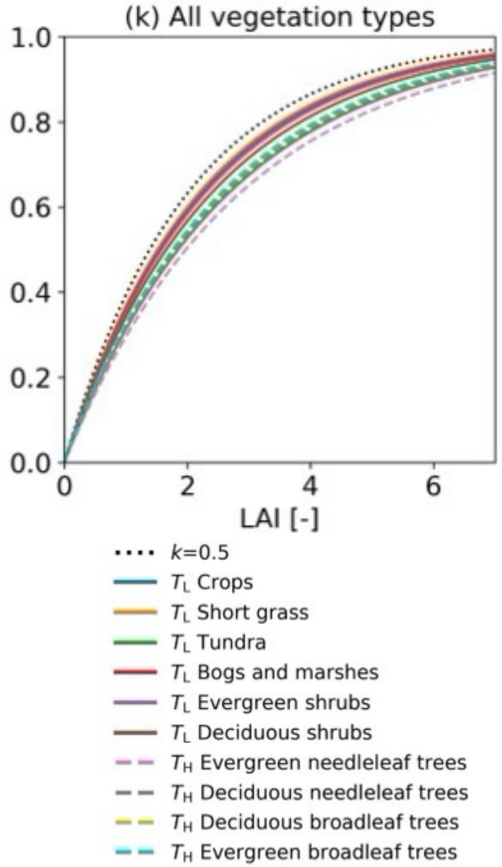
Copernicus FCOVER [10-daily]
Copernicus LAI [10-daily]
ESA-CCI land cover [yearly]

$$\rightarrow Cv_{L/H} = FCover = 1 - e^{-k_{L/H,iveg} * LAI_{L/H}}$$

*Non-linear least-squares minimization of $\boldsymbol{k}$ for each vegetation type following Chambers (1992)*

** Statistical significance of parameters tested (5%; using T-value statistics)*




van Oorschot et al 2023, under Submission

# Seasonal hindcast experiment

# Setup

# Experimental Setup

We use SEAS5 i.e. version 5 of ECMWF seasonal prediction system (SEAS5; Johnson et al 2019) at low-resolution configuration (Tco199Orca1_Z75)

Two ensemble re-forecasts are performed using (1) standard (CTRL) and (2) modified (SENS) versions of the SEAS5 lowres with the same configuration, resolution and initial conditions in both CTRL and SENS but land surface.

| | CTRL | SENS - potential predictability |
|---|---|---|
| Period | 1982-2014 | 1982-2014 |
| Stard Dates | 1 November | 1 November |
| Members\Lenght | 25\7 months | 25\7 months |
| Atmospheric IC | ERA-Interim | ERA-Interim |
| Ocean IC | ORAS5 | ORAS5 |
| LAI | Seasonal Climatology (MODIS) | Prescribed interannually Varying (LAI3g) |
| Vegetation Cover | Fixed in time | Effective cover parameterization function of LAI (K=0.5) |
| Land IC | ERA-Interim Land | ERA-Interim Land (rerun) |

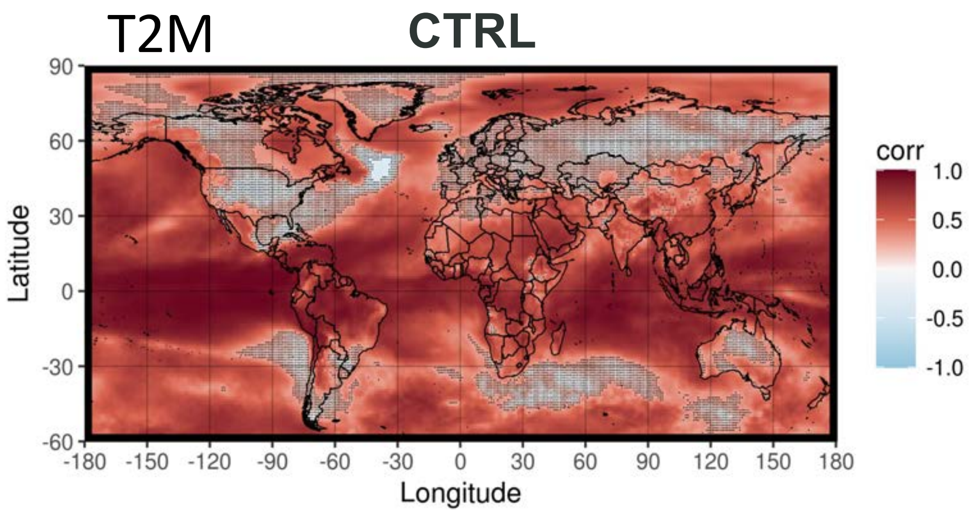
# Seasonal hindcast experiment

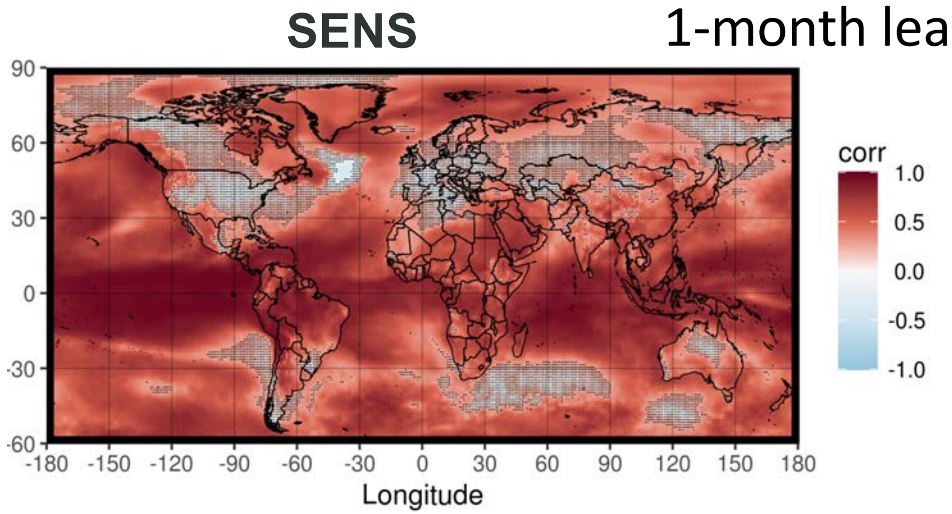
## Sensitivity of surface climate
## Correlations vs. OBS/ERA5

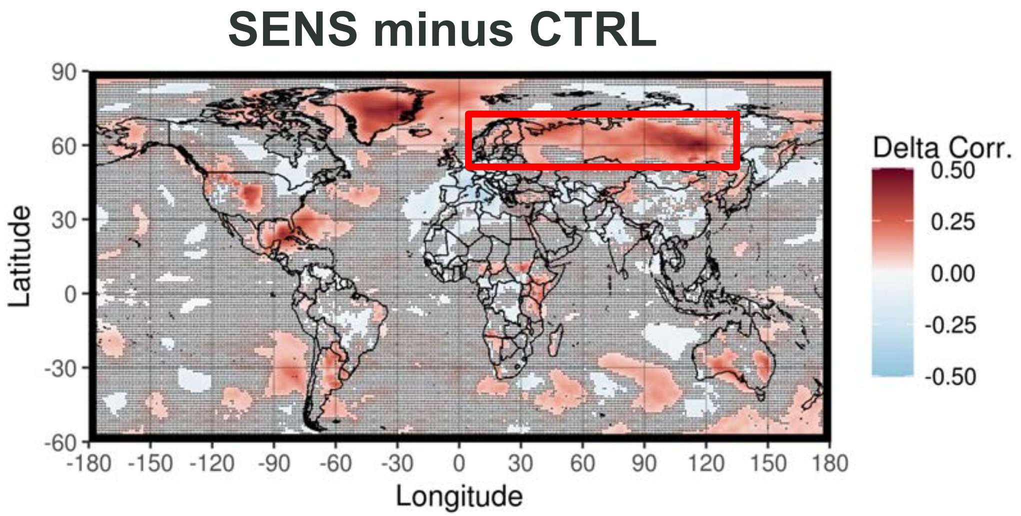
# Effect on 2m-Temperature correlation (vs. ERA5)

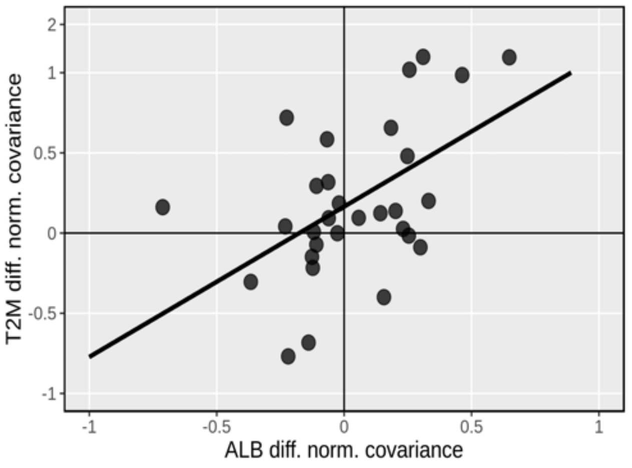
WINTER T2M DJF
1-month lead

T2M




$$\Delta \frac{\left(X^{i}_{\text{mod}} - \overline{X}_{\text{mod}}\right)\left(X^{i}_{obs} - \overline{X}_{obs}\right)}{\sigma^{X}_{\text{mod}} \cdot \sigma^{X}_{obs}}$$

$\Delta$ MODIF minus CTRL

$i$ = each single year

Regression line (coefficient significant at 5% level)

non dotted: 10% significance level
montecarlo method

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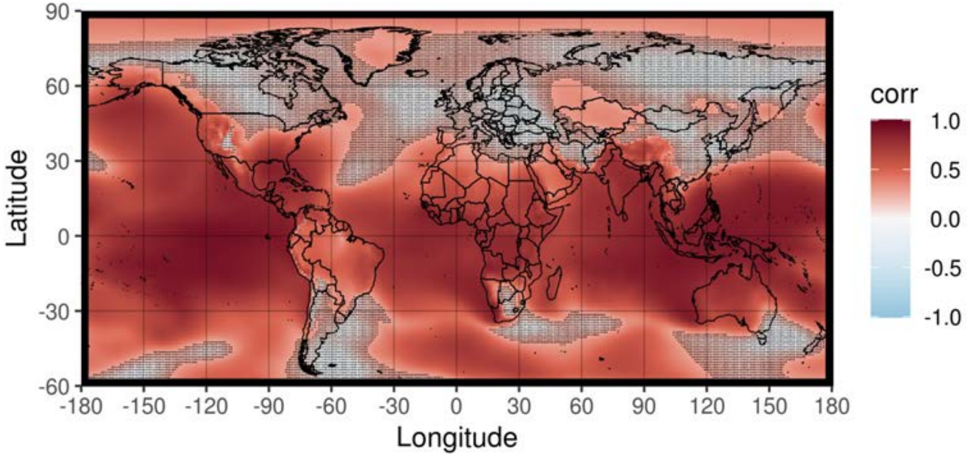
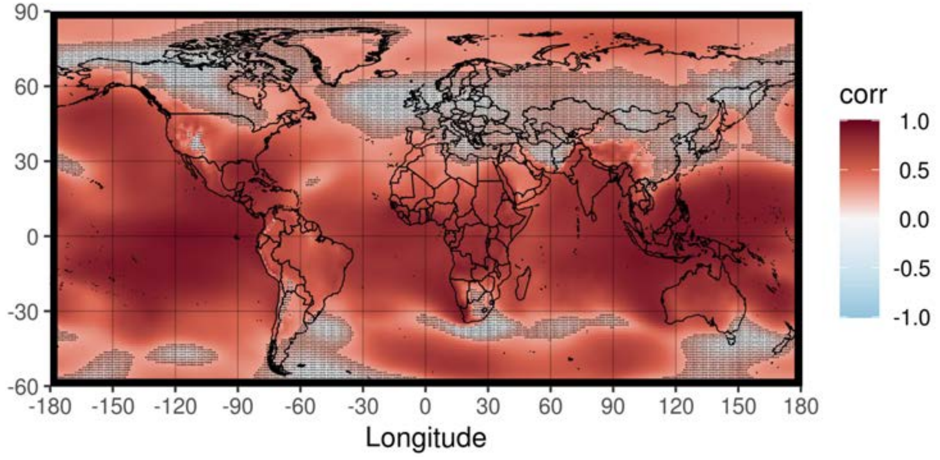
# Effect on MSLP correlation (vs. ERA5)

WINTER MSLP DJF
1-month lead

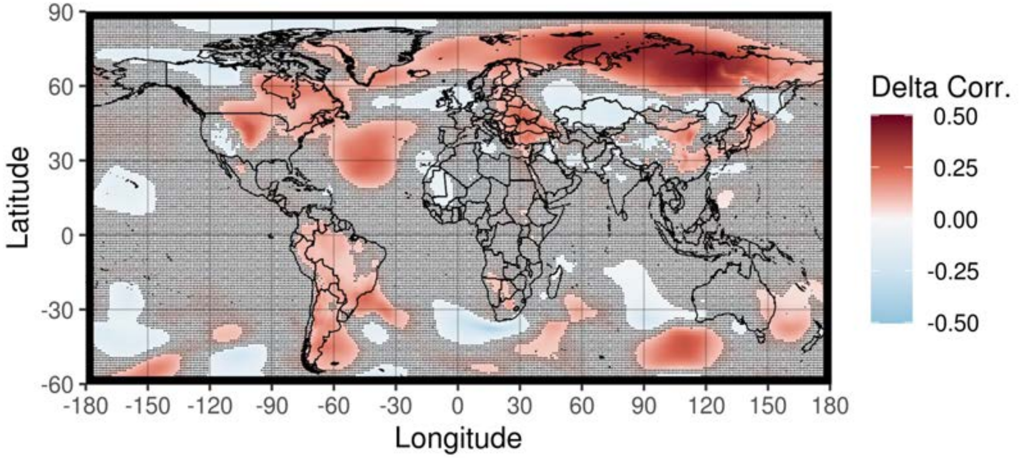
MSLP **CTRL**




**SENS**




**SENS minus CTRL**




non dotted: 10% significance level
montecarlo method

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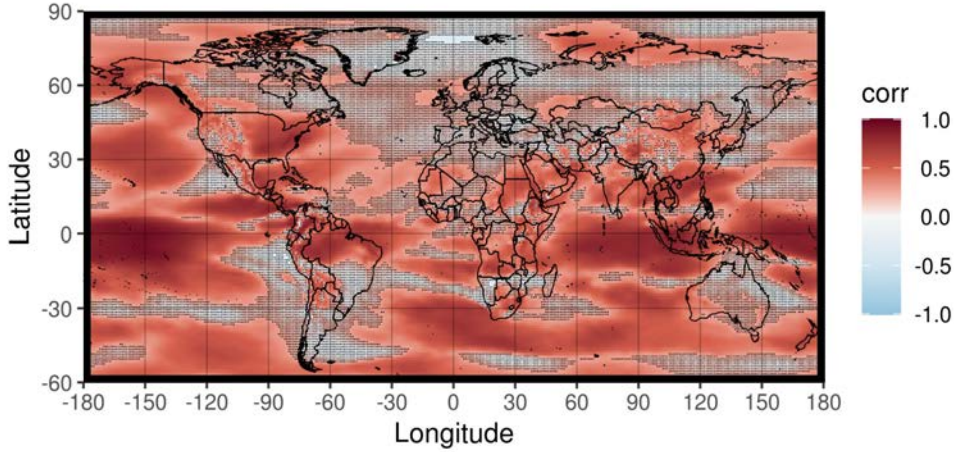
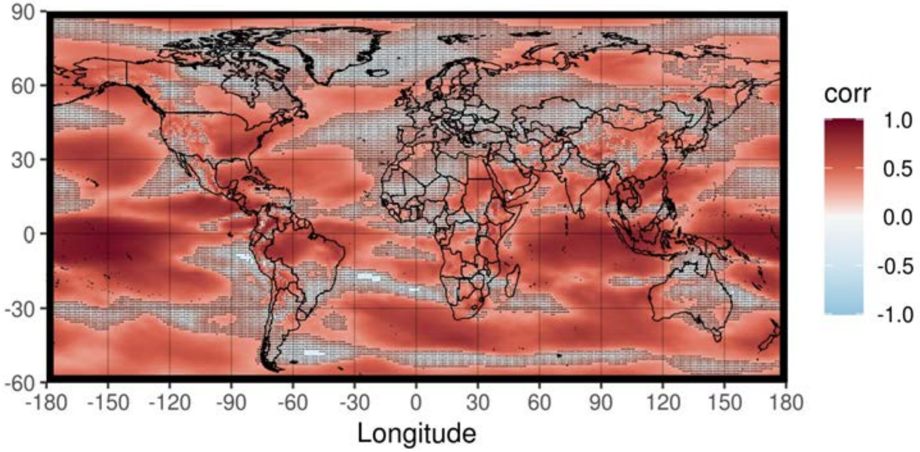
# Effect on U850 correlation (vs. ERA5)

WINTER U850 DJF
1-month lead

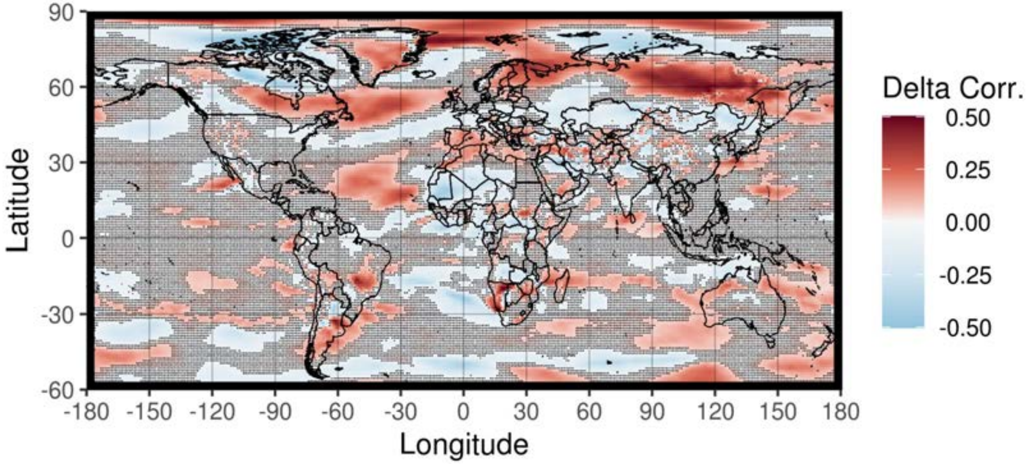
U850 **CTRL**




**SENS**




**SENS minus CTRL**




non dotted: 10% significance level
montecarlo method

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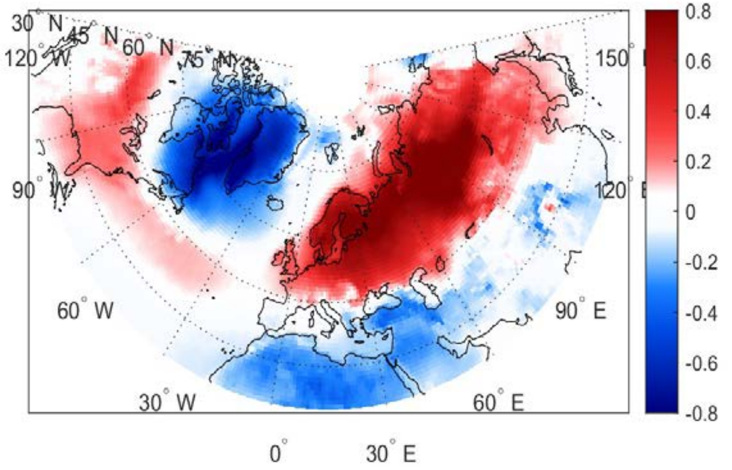
# Seasonal hindcast experiment

## Relation with/Effects on NAO prediction

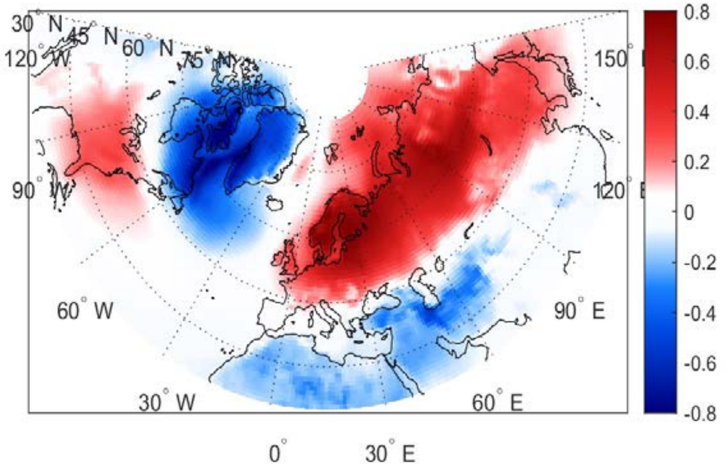
# Sensitivity of the prediction of NAO in ECMWF SEAS5 - regression on 2m temperature (T2m) and vegetation cover (Ceff) – 1month lead

T2m DJF

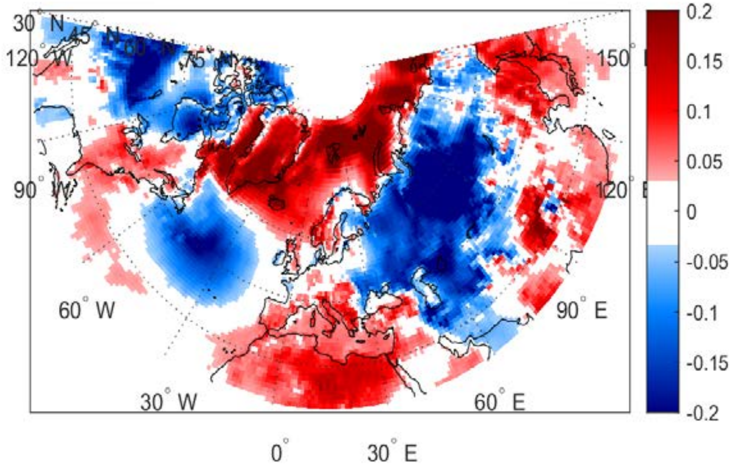
ERA5



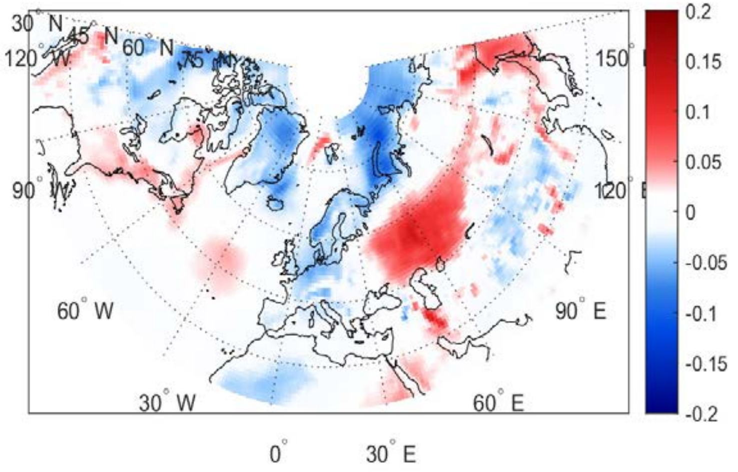

CTRL



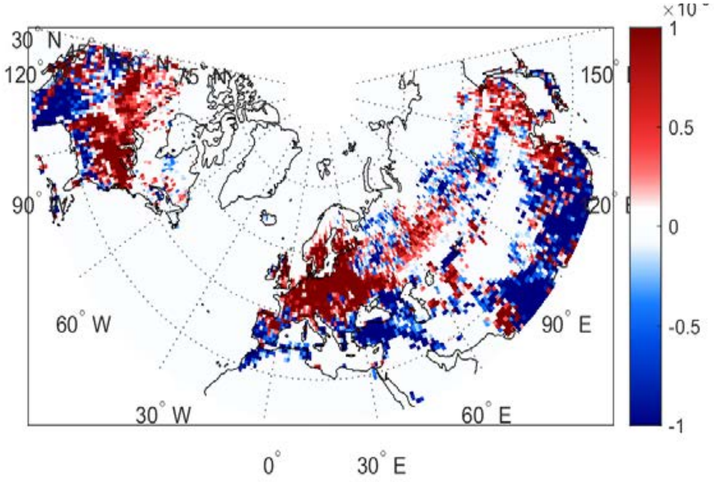

CTRL minus ERA5




SENS minus CTRL




Ceff DJF OBS

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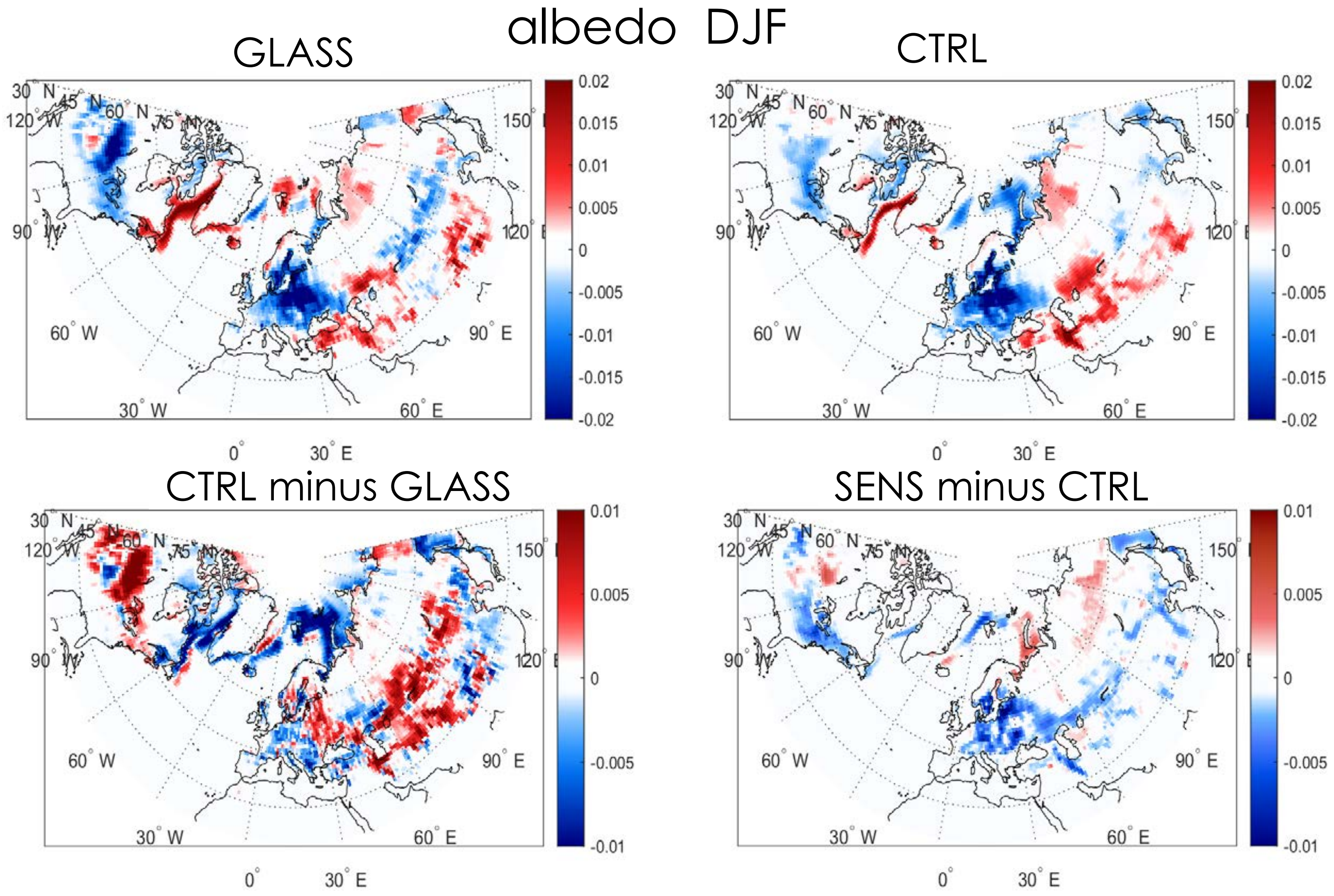
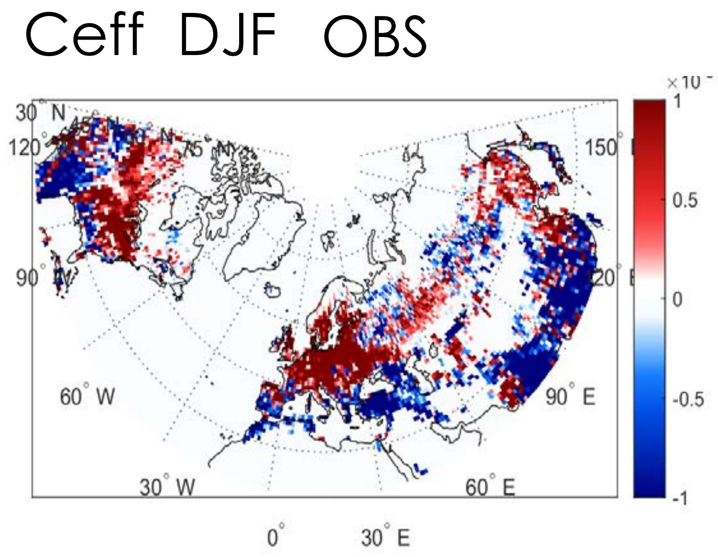
# Sensitivity of the prediction of NAO in ECMWF SEAS5 - regression on surface albedo and vegetation cover (Ceff) – 1month lead




GLASS satellite surface albedo product (Liu et al., 2013)

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# Decadal hindcast experiment

# Setup

# Experimental Setup

We use EC-Earth 3.3.3.1 at standard resolution (T255L91, ORCA1L75)

The ensemble hindcasts (DCPP-SENS) is performed using the same configuration and initial conditions of the standard DCPP-A (as performed at BSC), but more realistic vegetation.

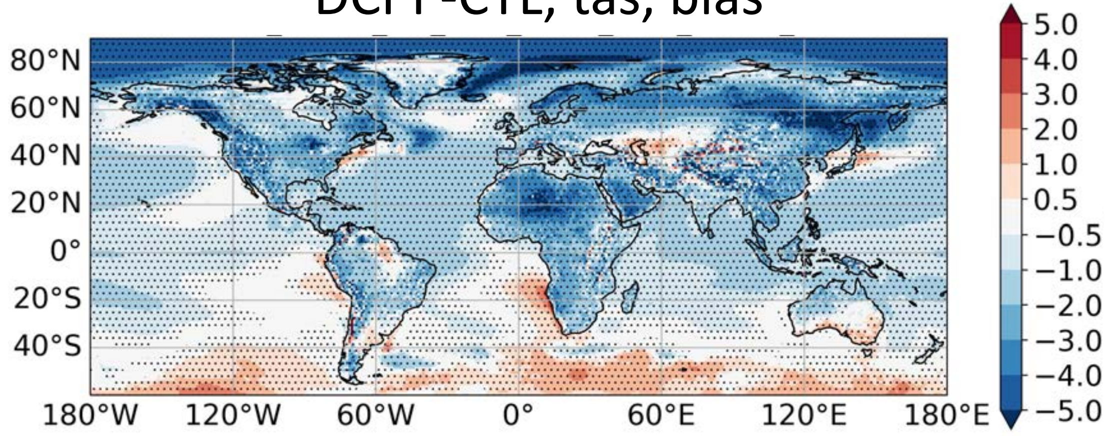
| | DCPP-CTRL | DCPP-SENS - potential predictability |
|---|---|---|
| Period | 1993-2014 | 1993-2014 |
| Start Dates | 1 November | 1 November |
| Members\Lenght | 10\5 years | 10\5 years |
| Atmospheric IC | ERA-Interim | ERA-Interim |
| Ocean IC | ORAS4 | ORAS4 |
| LAI and Land Cover | prescribed and derived from an EC-Earth historical simulation coupled with the LPJ-GUESS | Prescribed interannually Varying LAI (CGLS-C3S) and land cover (CGLS/ESA-CCI) |
| Effective vegetation cover parameterization | prescribed and derived from an EC-Earth historical simulation coupled with the LPJ-GUESS | Effective cover parameterization as a function of LAI (K for each vegetation type) |
| Land IC | Offline ERA-Interim/Land type | Offline ERA5/Land type |

# Decadal hindcast experiment

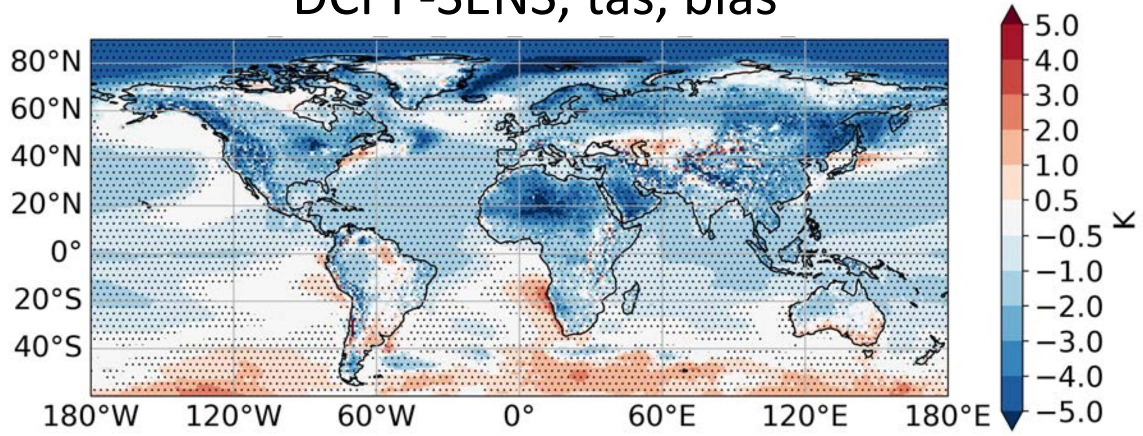
# Sensitivity of surface climate
# Bias vs. ERA5

# Effect on 2m-Temperature, lead 3, 2-year mean bias (vs. ERA5)

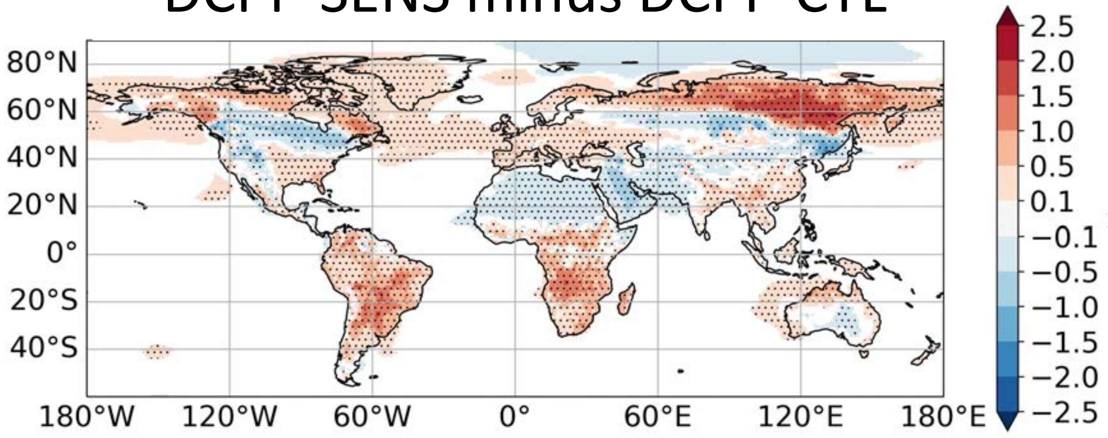
DCPP-CTL, tas, bias




DCPP-SENS, tas, bias



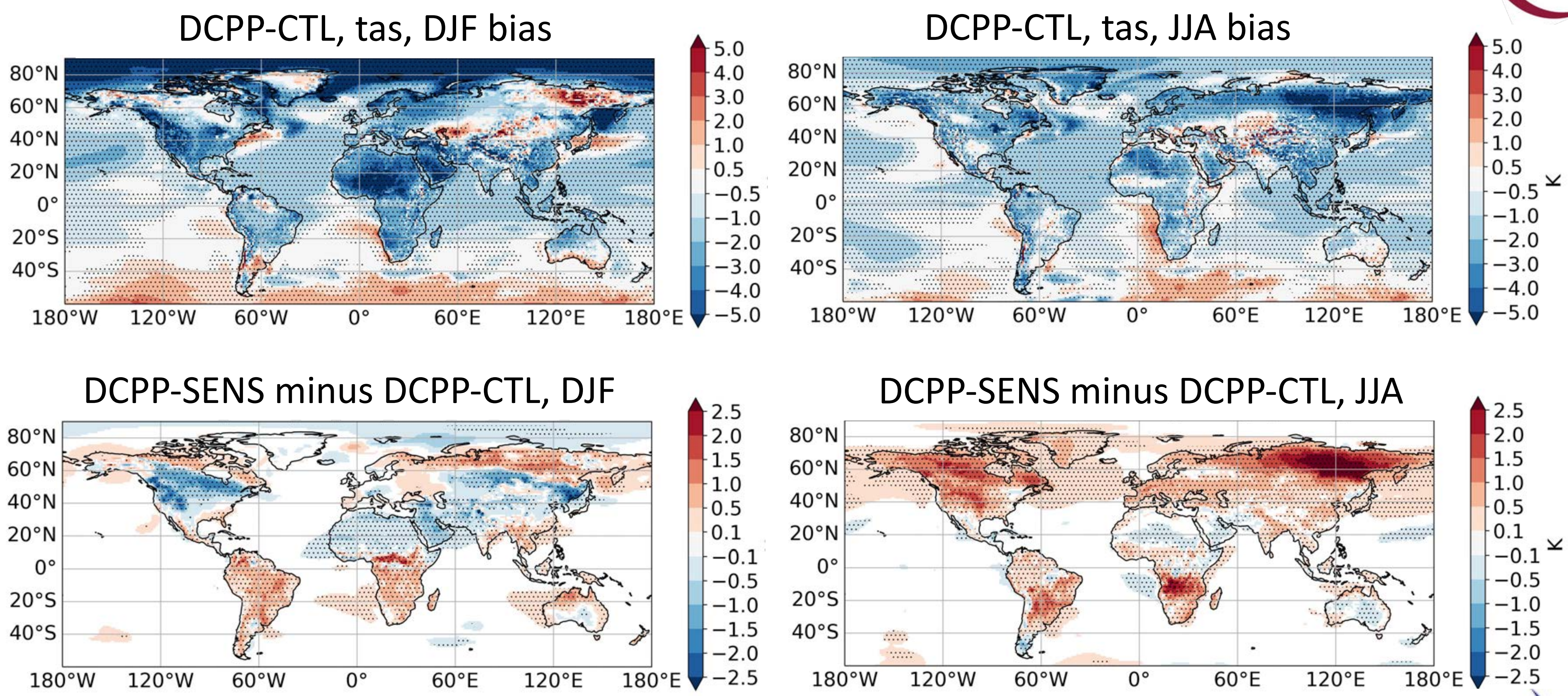

DCPP-SENS minus DCPP-CTL




dotted: 5% significance level
Montecarlo method

Di Carlo et al., 2023, in preparation

# Effect on 2m-Temperature, lead 3, 2-year mean bias (vs. ERA5)




dotted: 5% significance level
Montecarlo method

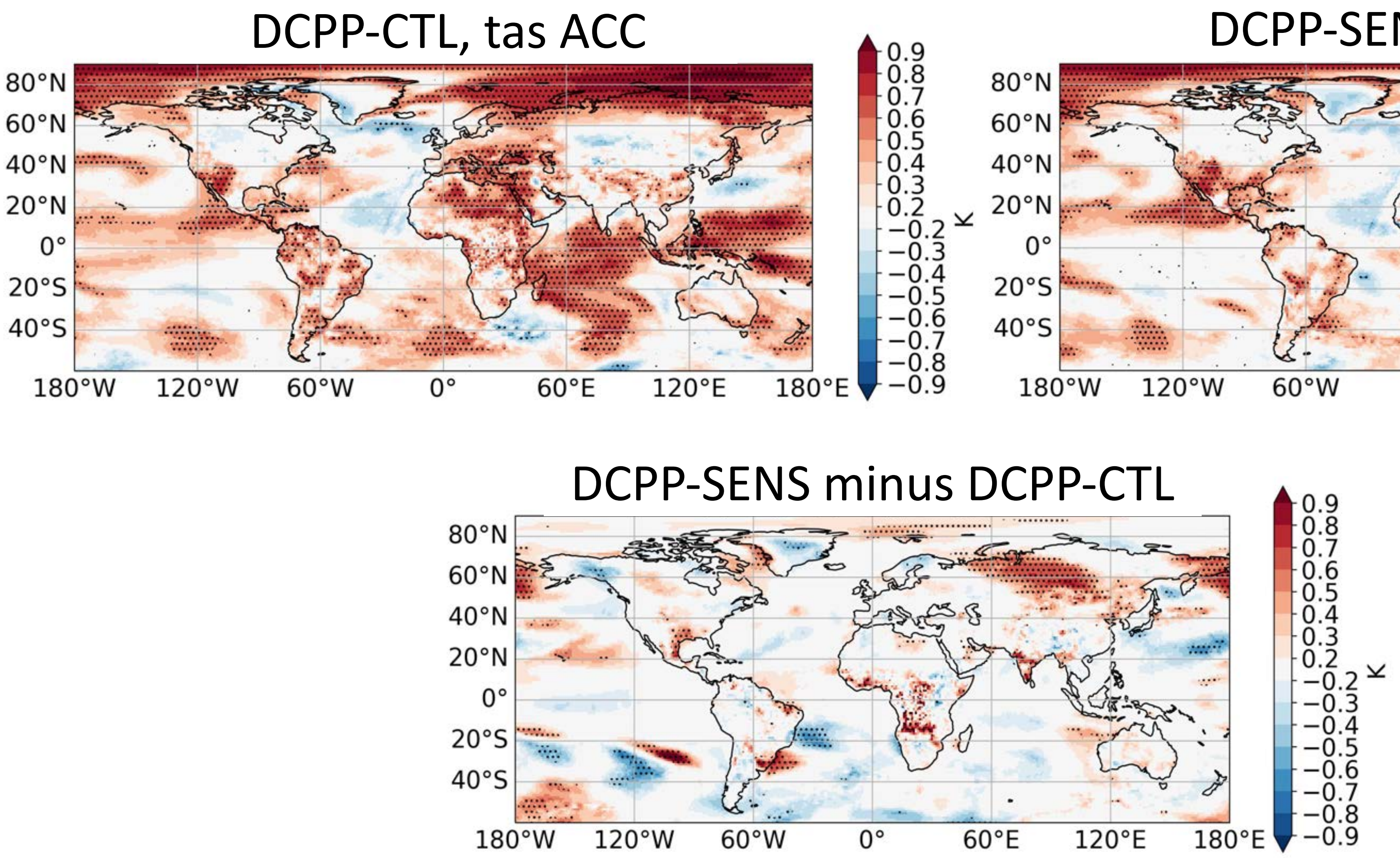
Di Carlo et al., 2023, in preparation

Decadal hindcast experiment

Sensitivity of surface climate
Correlations vs. ERA5

Preliminary results

# Effect on 2m-Temperature, lead 3, 2-year mean ACC (vs. ERA5)




dotted: 5% significance level
Montecarlo method

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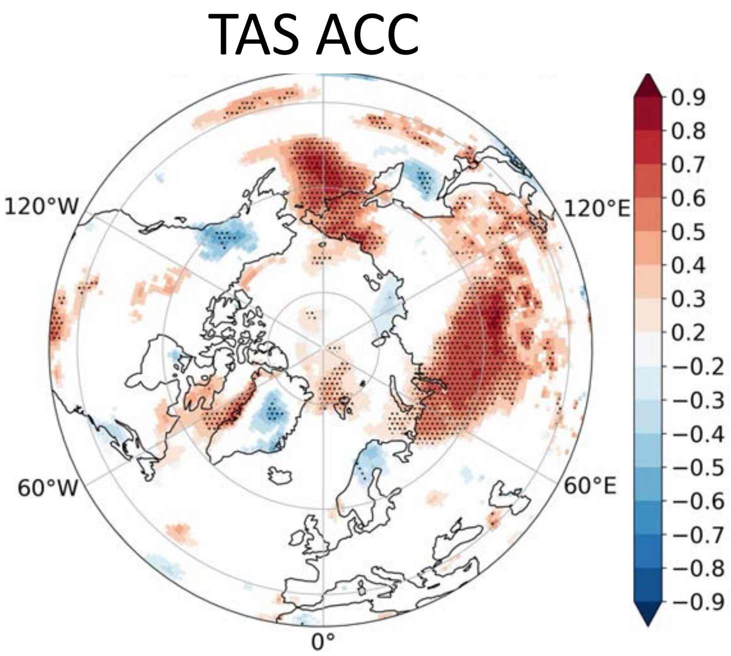
# Effect on surface climate (T2m, MSLP, U850) lead 3, 2-year mean ACC (vs. ERA5)

**DCPP-SENS minus DCPP-CTL**




dotted: 5% significance level
Montecarlo method

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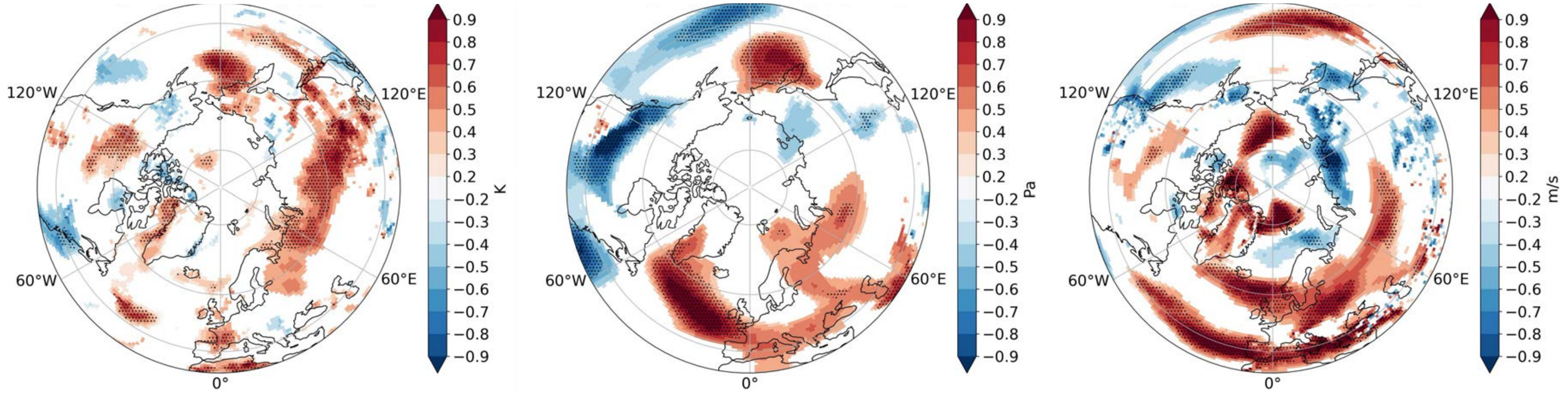
# Effect on surface climate (T2m, MSLP, U850) lead 3, 2-year **DJF** mean ACC (vs. ERA5)

**DCPP-SENS minus DCPP-CTL**

TAS ACC | MSLP ACC | U850 ACC




dotted: 5% significance level
Montecarlo method

Di Carlo et al., 2023, in preparation

# Summary and Discussion

A realistic representation of land cover-vegetation has significant –potential– effects on S2D prediction skill esp. over boreal forests and include large-scale circulation effects:

- The effective vegetation cover variability has a considerable effect on SEAS5 prediction for boreal winter (lead-1 DJF):
  - The T2M improvements over Euro-Asian boreal forests is connected to a large-scale circulation effect connecting Siberia to North Atlantic (MSLP, U850)
  - It is suggested that vegetation dynamics may be a missing process that could explain (in part) the signal-to-noise paradox in Euro-Asian land and North Atlantic.

- The representation of land cover-vegetation variability has considerable effects on DCPP predictions using EC-Earth (lead-3yr 2-yr mean)
  - T2M bias and ACC is improved in particular over middle-to-high latitudes boreal forests and tundra.
  - The ACC improvements (T2M, MSLP, U850) over Euro-Asian boreal forests extend towards N. Atlantic resembling results for DJF seasonal forecasts.



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# Future steps

- How does vegetation variability affect large-scale circulation?
  - Could the Atlantic jet stream variability be affected by Land-cover vegetation?
- Results indicate that vegetation effects on albedo variability improve prediction skill. What about the effects on roughness length? (not in output to be re-computed offline)
- <u>To what extent could vegetation effect on climate predictions be model-dependent?</u> Planning multi-model coordinated intercomparison at the seasonal time-scale.