Koninklijk Nederlands
Meteorologisch Instituut
Ministerie van Infrastructuur en Milieu

Multi-scale enhancement of climate prediction over land by increasing the model sensitivity to vegetation variability in EC-Earth

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WCRP Int. Conf. on S2D Prediction, Boulder, 18 September, 2018

http://projects.knmi.nl/proceed/

Outline

Motivation

The EC-Earth ESM, developed from the ECMWF prediction system, lacks sensitivity to vegetation variability

→ Introduction of an effective vegetation cover as a function of vegetation Leaf Area Index (LAI)

Multi-scale simulation/prediction enhancements in EC-Earth

- Effects on surface climatology and 20C climate change signal
- Effects on prediction skill at seasonal and weather time-scales
- Effects on potential predictability at decadal time-scale

Discussion

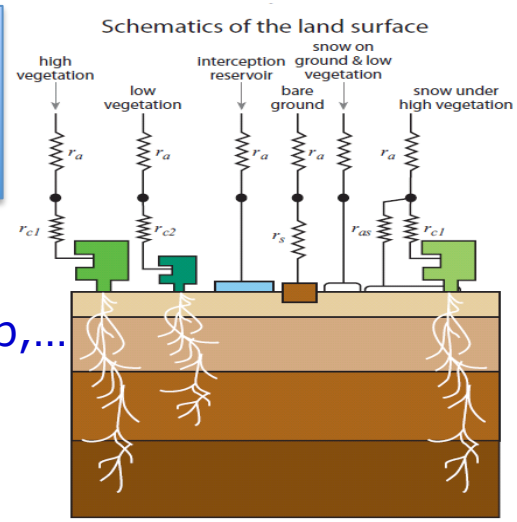
Motivation
Need to improve coupling of the modeled vegetation biophysical processes in EC-Earth

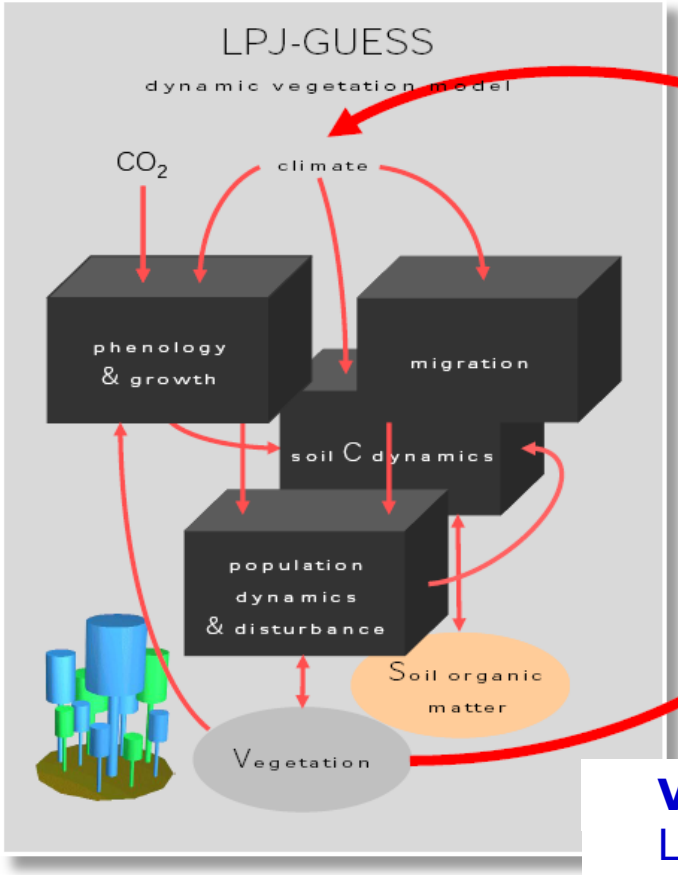
Coupling vegetation biophysics to EC-Earth

Coupling strategy

EC-Earth2.3

Atmosphere
IFS





Climate
radiation, temperature, precip,...

daily

Land
H-TESSEL

Vegetation affects coupling parameters:
albedo, roughness lenght, field capacity, effective cover on bare soils/snow

r_c Canopy resistance to evapotranspiration

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

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

Vegetation
LAI (High/Low veg.)
~~Vegetation cover (High/Low veg.)~~

Improved coupling of vegetation to EC-Earth: implementation of effective vegetation cover as a function of vegetation Leaf Area index

PAPER PUBLISHED:

A. Alessandri, F. Catalano, M. De Felice, B. Van Den Hurk, F. Doblas Reyes, S. Boussetta, G. Balsamo, and P. Miller, 2017: Multi-scale enhancement of climate prediction over land by increasing the model sensitivity to vegetation variability in EC-Earth, Clim. Dyn. doi:10.1007/s00382-016-3372-4

SPECS
Seasonal-to-decadal climate Prediction for the improvement of European Climate Services

Implementation of effective vegetation cover (Ceff) as a function of vegetation Leaf Area index

Effective fractional vegetation cover

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

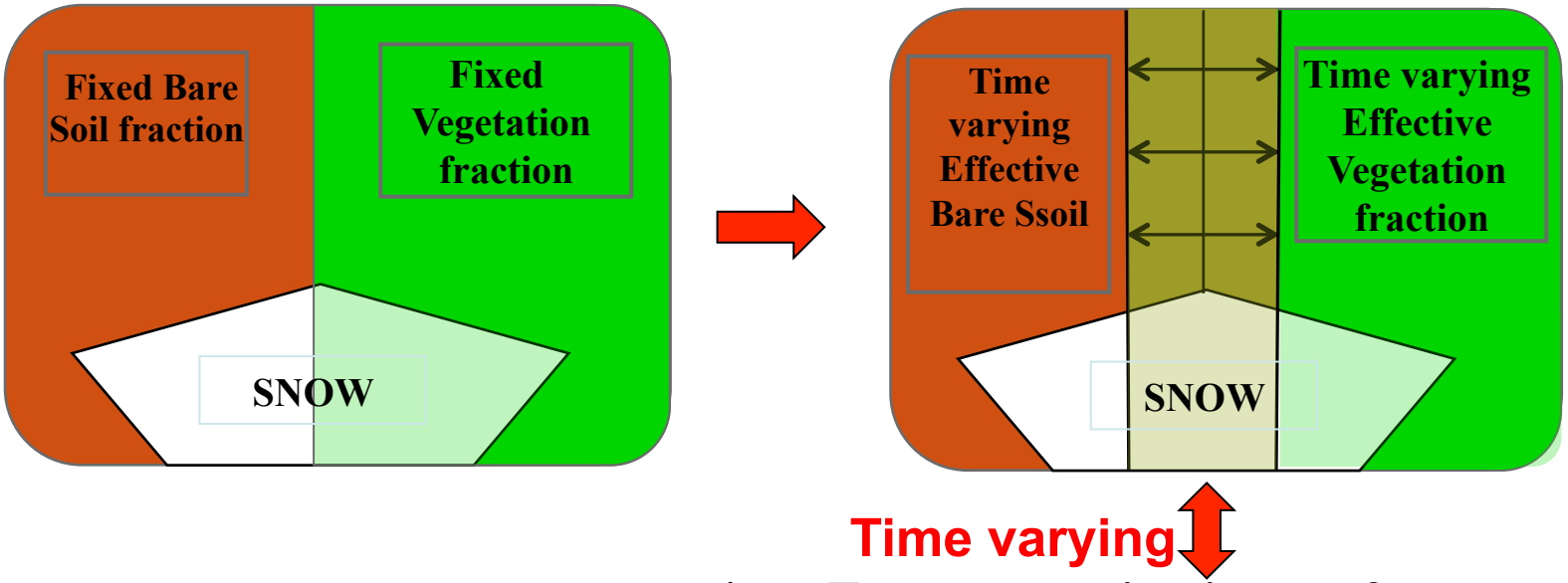
$_{L,H}$ low, high vegetation

A_L, A_H Max fractional coverages

C_L, C_H Vegetation density

Bare Soil fraction

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



Time varying

i. **Evapotranspirating surfaces**

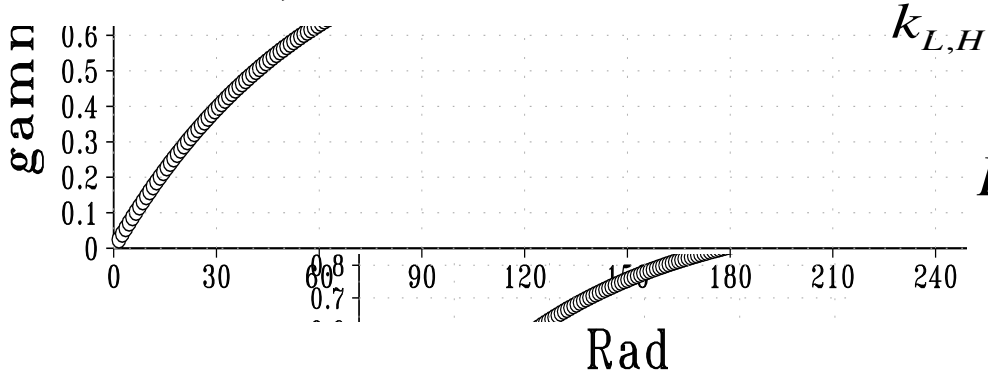
ii. **Roughness length**

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

vii. Surface **Albedo**

Implementation of effective vegetation cover as a function of vegetation Leaf Area Index

$$Cv_{L,H}(t) = f(LAI_{L,H}) = (1 - e^{-k \cdot LAI})$$



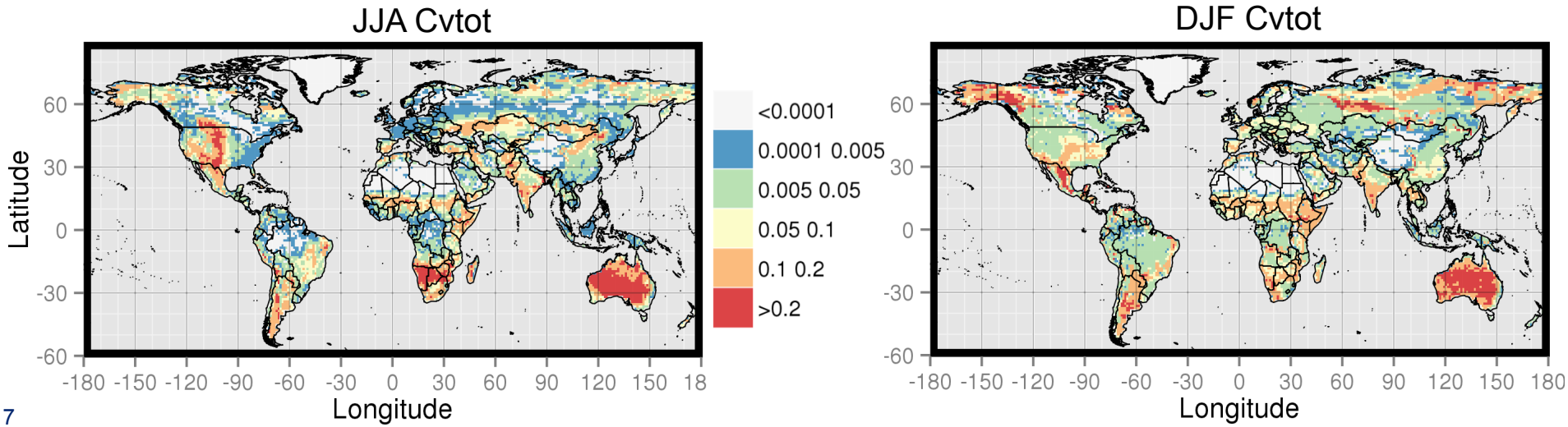
$k_{L,H}$

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

$$LAI_T = f(Cv_L + Cv_H)$$

$$Cv_{L,H} = f(LAI_{L,H})$$

Implemented effective cover interannual variability (std dev)



Effect on the temperature bias of EC-Earth

MODIF
vs.
CTRL

Alessandri et al., 2017, Clim Dyn

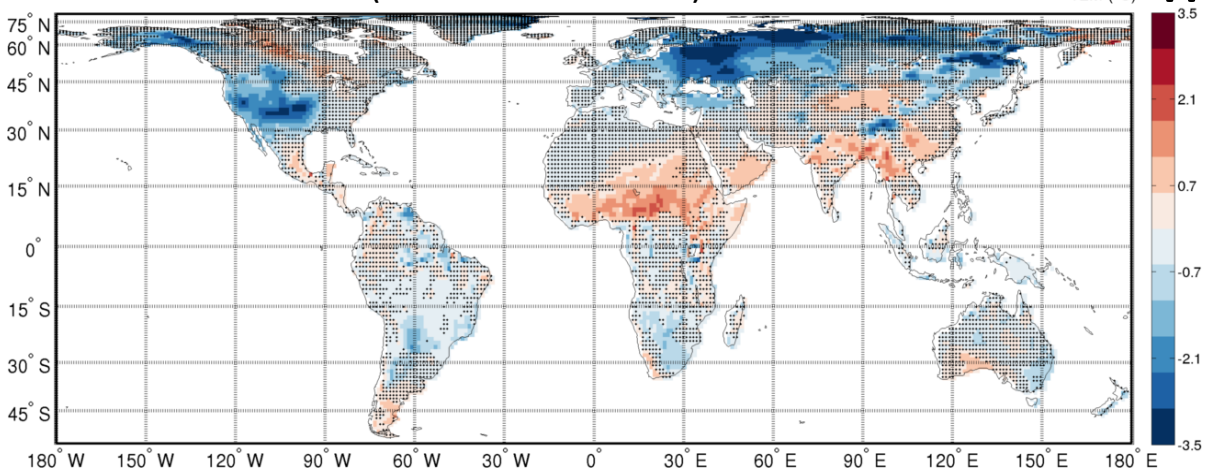
2m temperature: Sensitivity vs. BIAS DJF

1979-2009 historical simulations

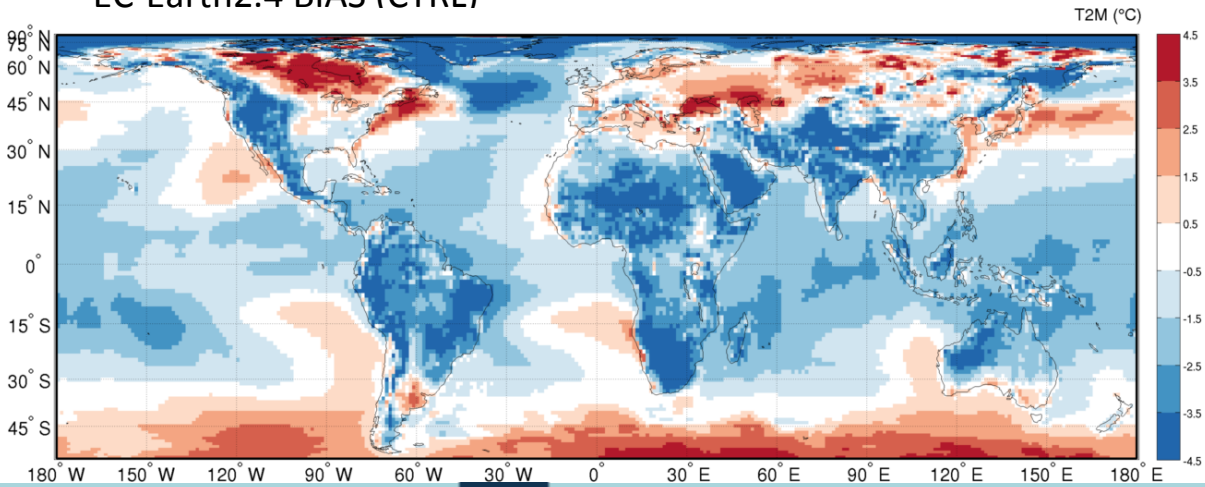
Dots: no significance of differences at 10% level

T2m SENSITIVITY (MODIF minus CTRL)

WINTER DJF



EC-Earth2.4 BIAS (CTRL)



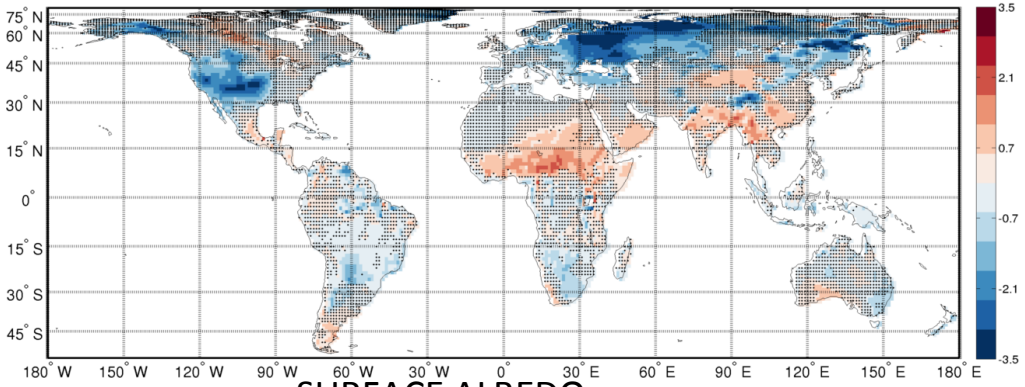
Alessandri et al., 2017, Clim Dyn

Sensitivity: 2m Temperature, Albedo and Bowen Ratio DJF

SENSITIVITY (MODIF minus CTRL)

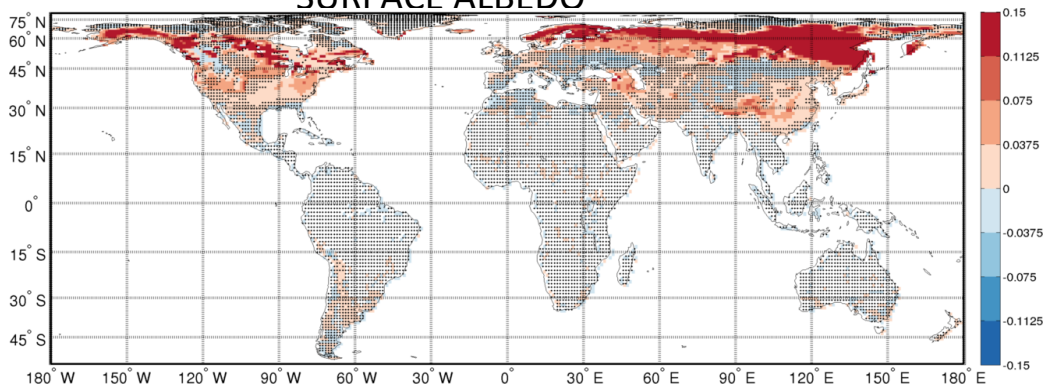
Dots: no significance of differences at 10% level

TEMPERATURE 2 Meters

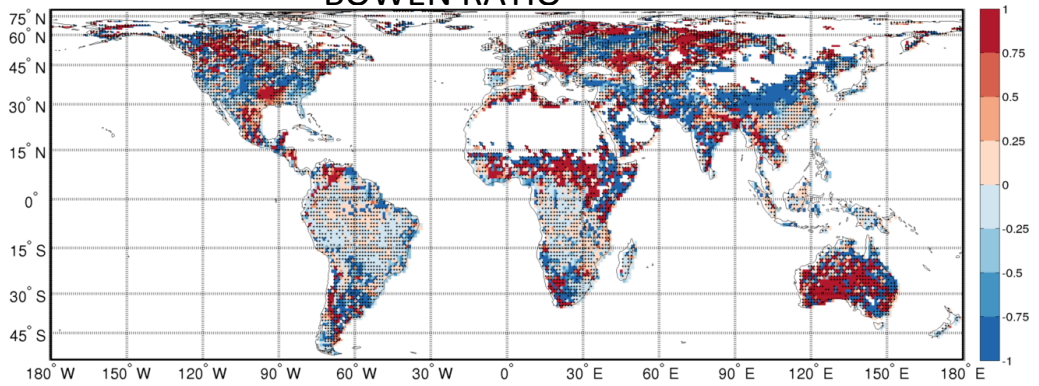


WINTER DJF

SURFACE ALBEDO



BOWEN RATIO



Effect on Surface Air Temperature change in historical 20C simulations
[1980-2009] minus [1910-1939]

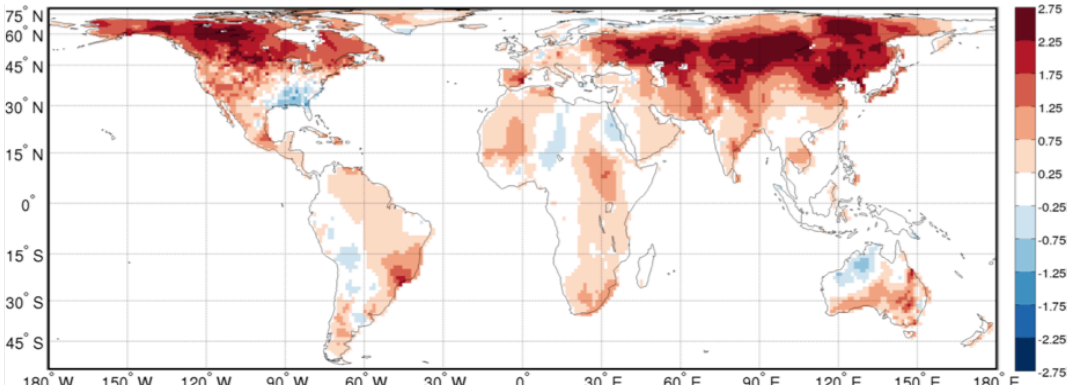
Alessandri et al., 2017, Clim Dyn

SPECS
Seasonal-to-decadal climate Prediction for the improvement of European Climate Services

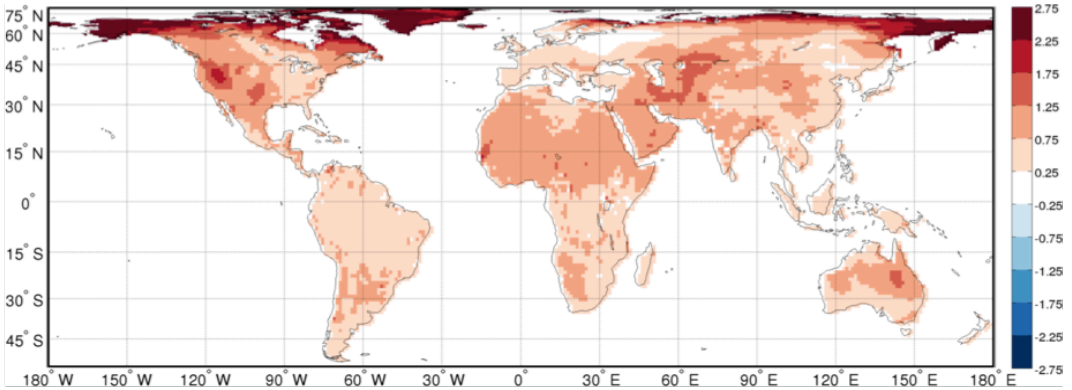
Surface air temperature change: (2009-1980) minus (1939-1910)

WINTER DJF

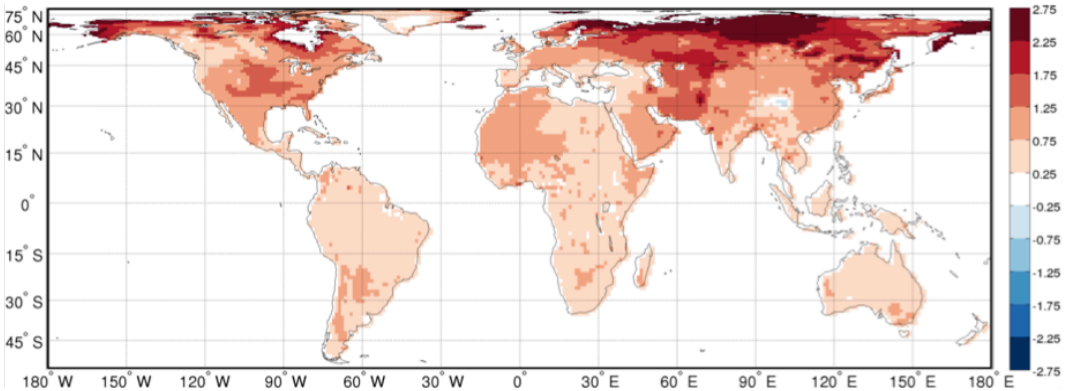
OBSERVATION CRU
2m Temperature



CTRL
2m Temperature



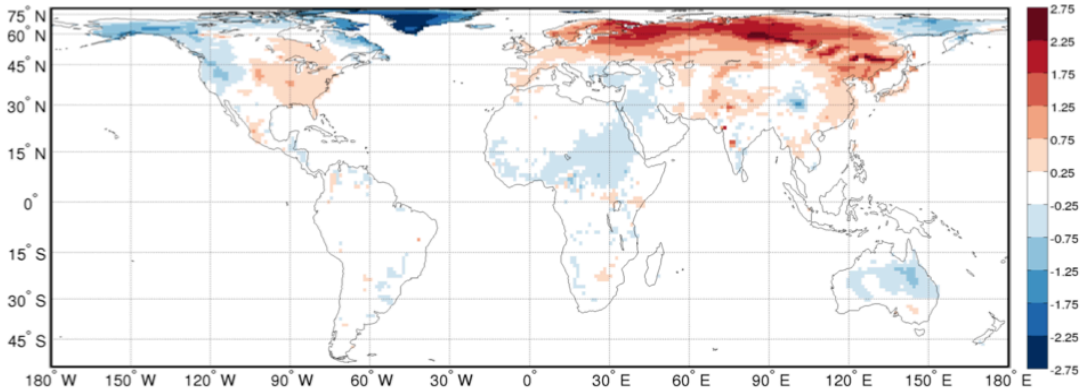
MODIF
2m Temperature



Surface air temperature change: (2009-1980) minus (1939-1910) MODIF minus Control

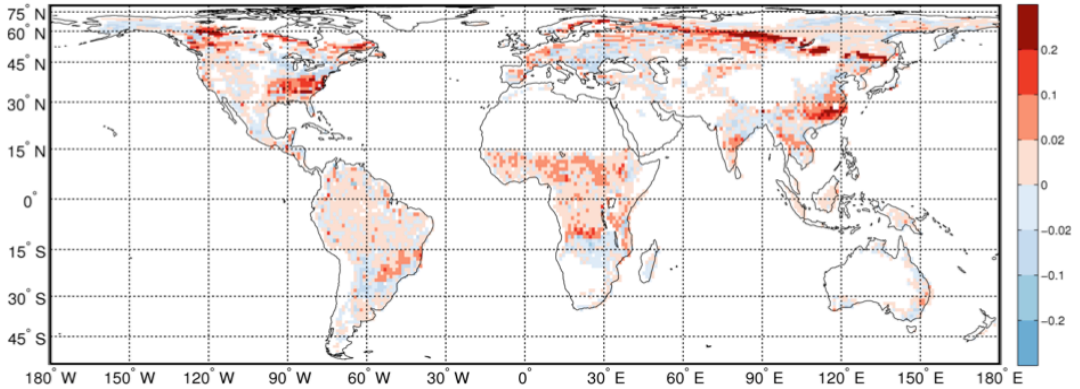
MODIF minus CTRL

2m Temperature

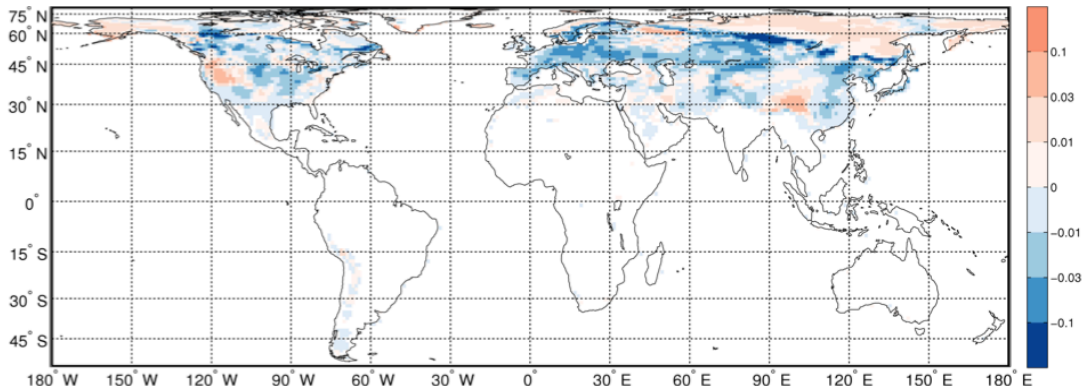


WINTER DJF

High vegetation cover change



albedo



Sensitivity of seasonal climate forecasts to modified parameterization

MODIF
vs.
CTRL

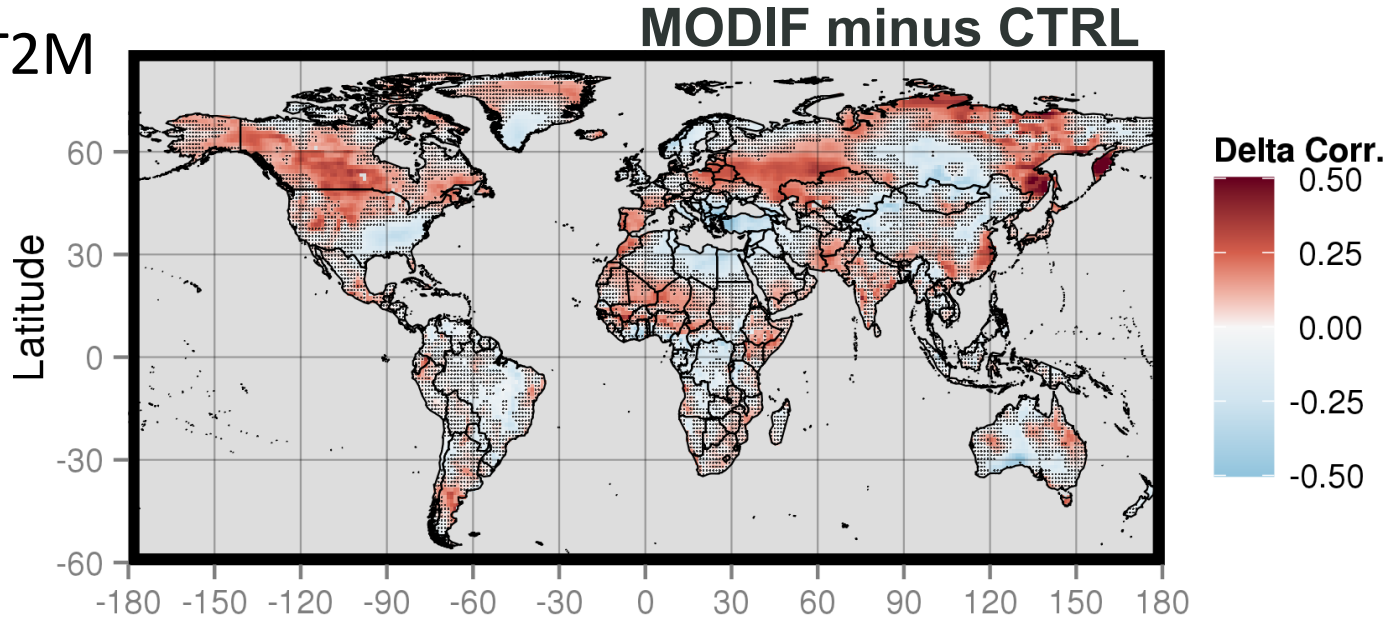
LAI prescribed from observations (LAI3g, Zhu et al, 2013)
[1982-2009, 10members, 7months hindcasts, 1st May and 1st November]

Alessandri et al., 2017, Clim Dyn.

Catalano et al., 2017, In Preparation

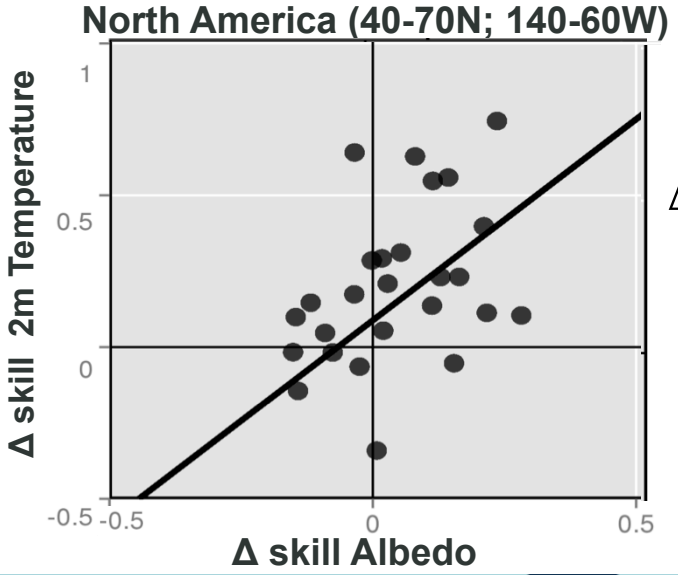
Seasonal hindcasts - 1st Nov start date - 2m Temperature
Correlation differences (MODIF minus CTRL) vs. ERA-Interim

T2M



WINTER DJF
1-month lead

(dotted non significant 10% level)



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

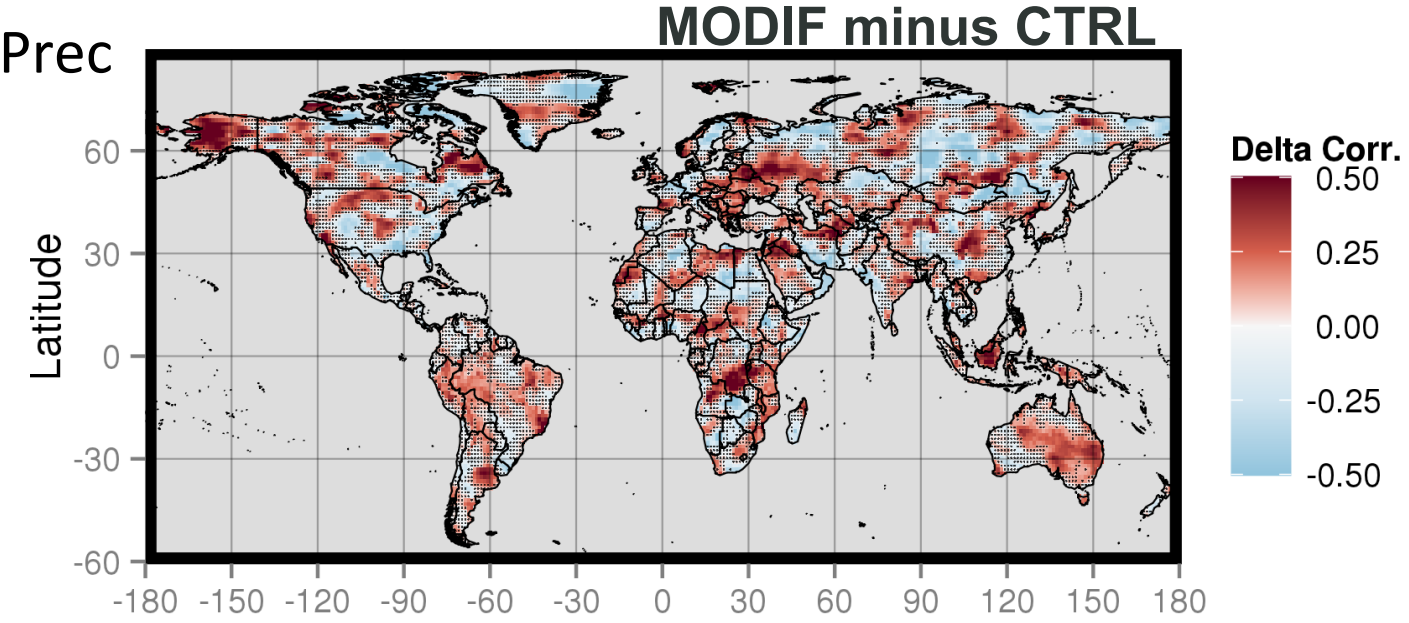
Δ MODIF minus CTRL

i = each single year

Regression line (coefficient significant at 5% level)

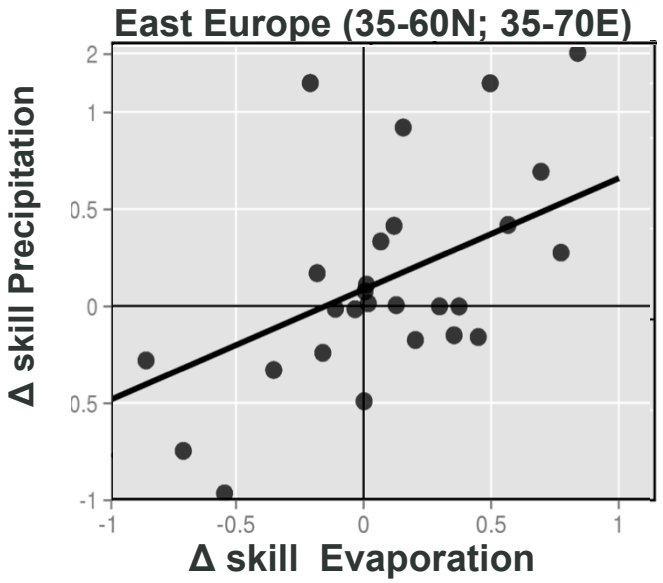
Seasonal hindcasts - 1st May start date - Precipitation
Correlation differences (MODIF minus CTRL) vs. ERA-Interim

Prec



SUMMER JJA
1-month lead

(dotted non significant 10% level)



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

Δ MODIF minus CTRL

i = each single year

Regression line (coefficient significant at 5% level)

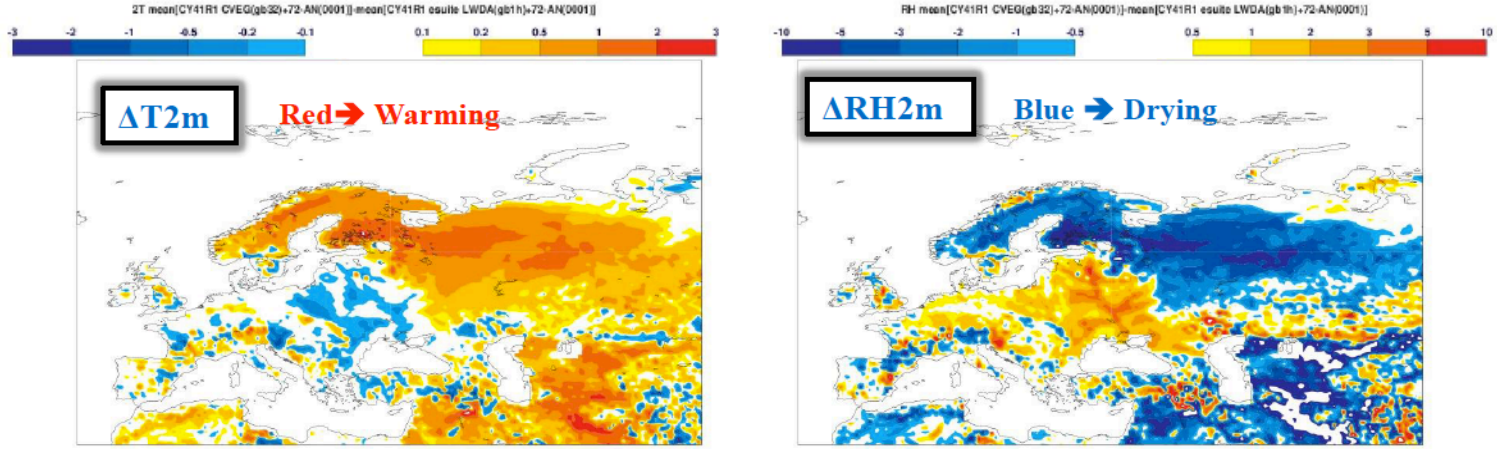
Sensitivity of Numerical Weather Forecasts
Case study for 4-days ECMWF NWPs in March 2015

MODIF
vs.
CTRL

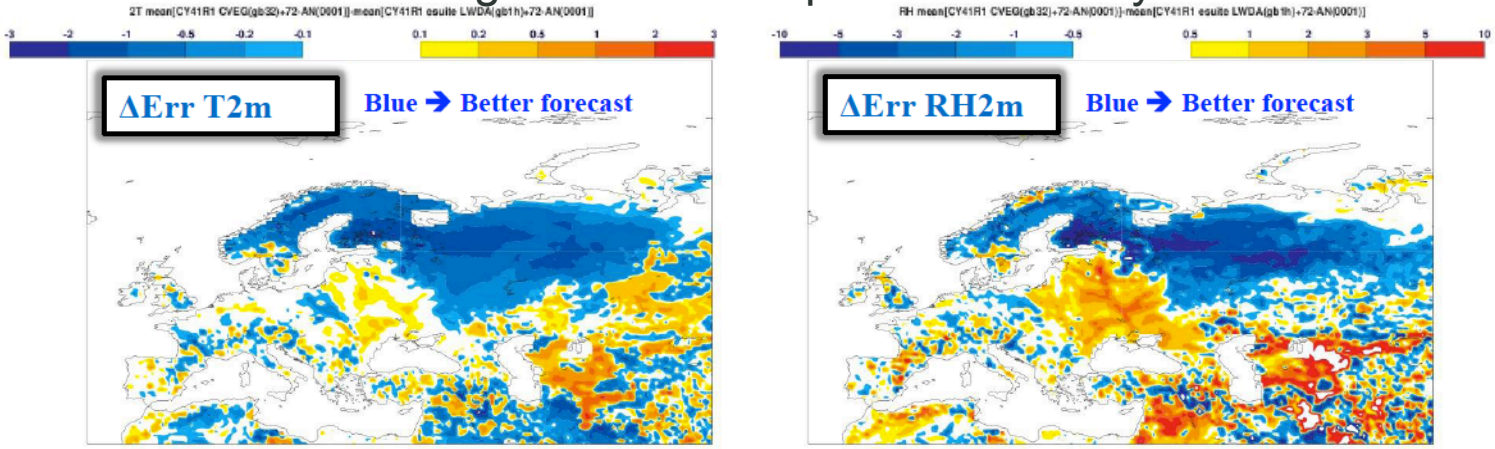
Alessandri et al., 2017, Clim Dyn

Case study for 4-days ECMWF Weather forecasts in March 2015
MODIF minus **CTRL** (FC +72hr) & comparison with analysis

Modified minus Control

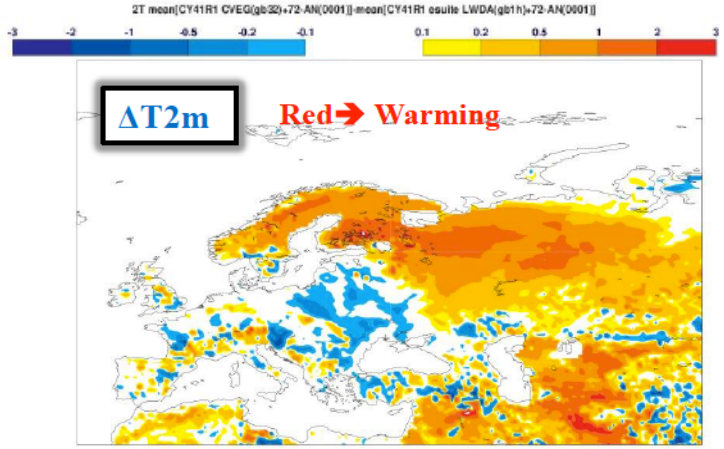


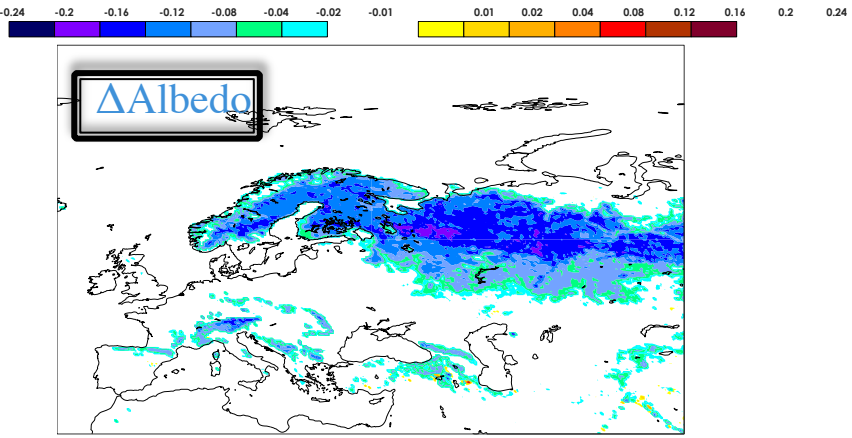
Change of Error compared with analysis



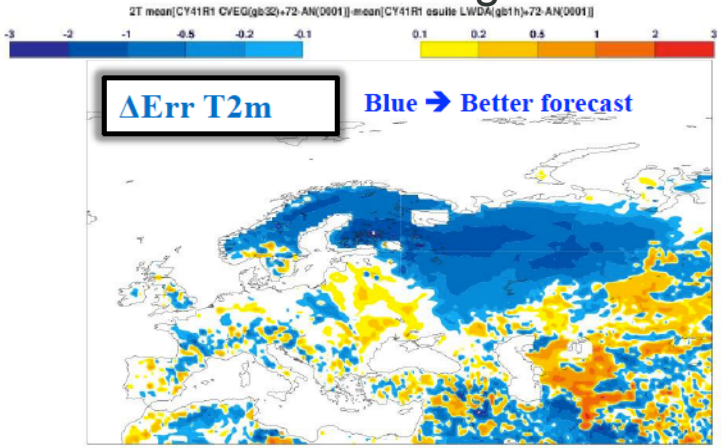
Case study for 4-days ECMWF Weather forecasts in March 2015
MODIF minus **CTRL** (FC +72hr) & comparison with analysis

Modified minus Control





Change of Error compared with analysis



Potential predictability at decadal time scale due to vegetation effective cover change

MODIF

vs.

CTRL

Potential predictability: “model world” (MODIF) assumed as “real world”

[1960-2005, 7 members, 5yrs hindcasts, every 5 yrs]

Alessandri et al., 2017, Clim Dyn.

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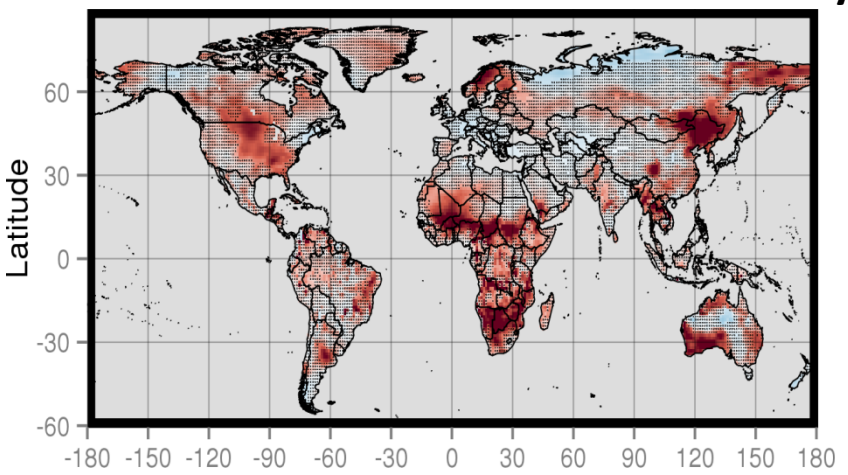
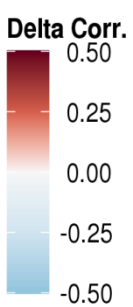
Decadal potential predictability (MODIF minus CTRL)
Correlation differences vs. historical simulation (real world)

2-years mean

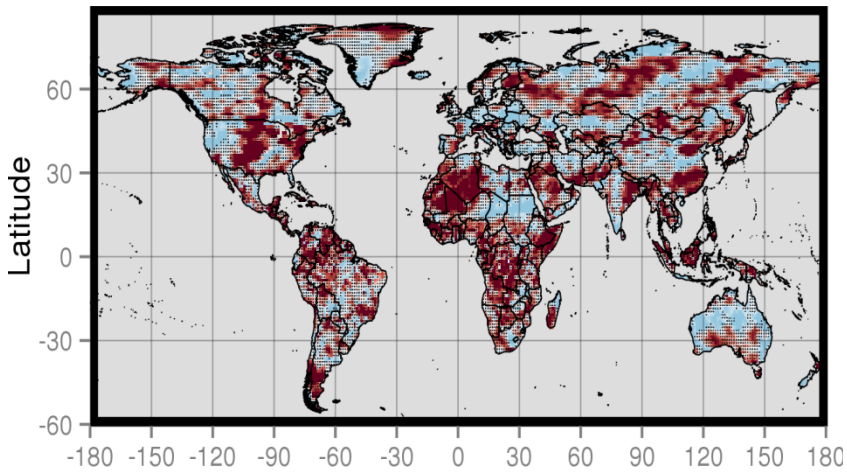
3 years lead time

T2M



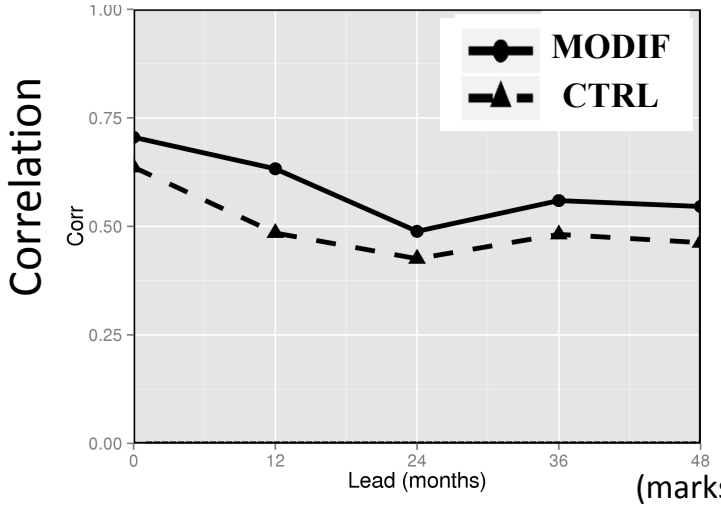


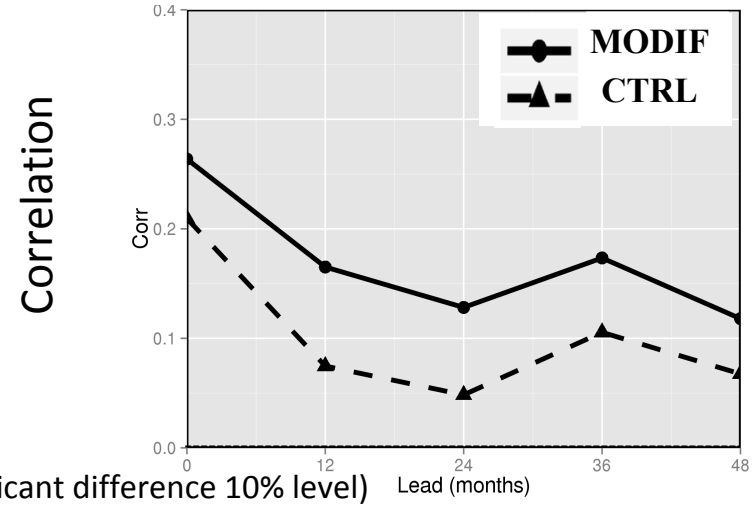
PRE



(dotted non significant 10% level)

Global annual mean correlation





(marks are for significant difference 10% level)

Alessandri et al., 2017, Clim Dyn.

Conclusions and Plans

A realistic representation of vegetation biophysical processes can improve Earth system simulation/prediction at multiple time-scales.

The inclusion of a realistic effective vegetation cover parameterization in EC-Earth leads to:

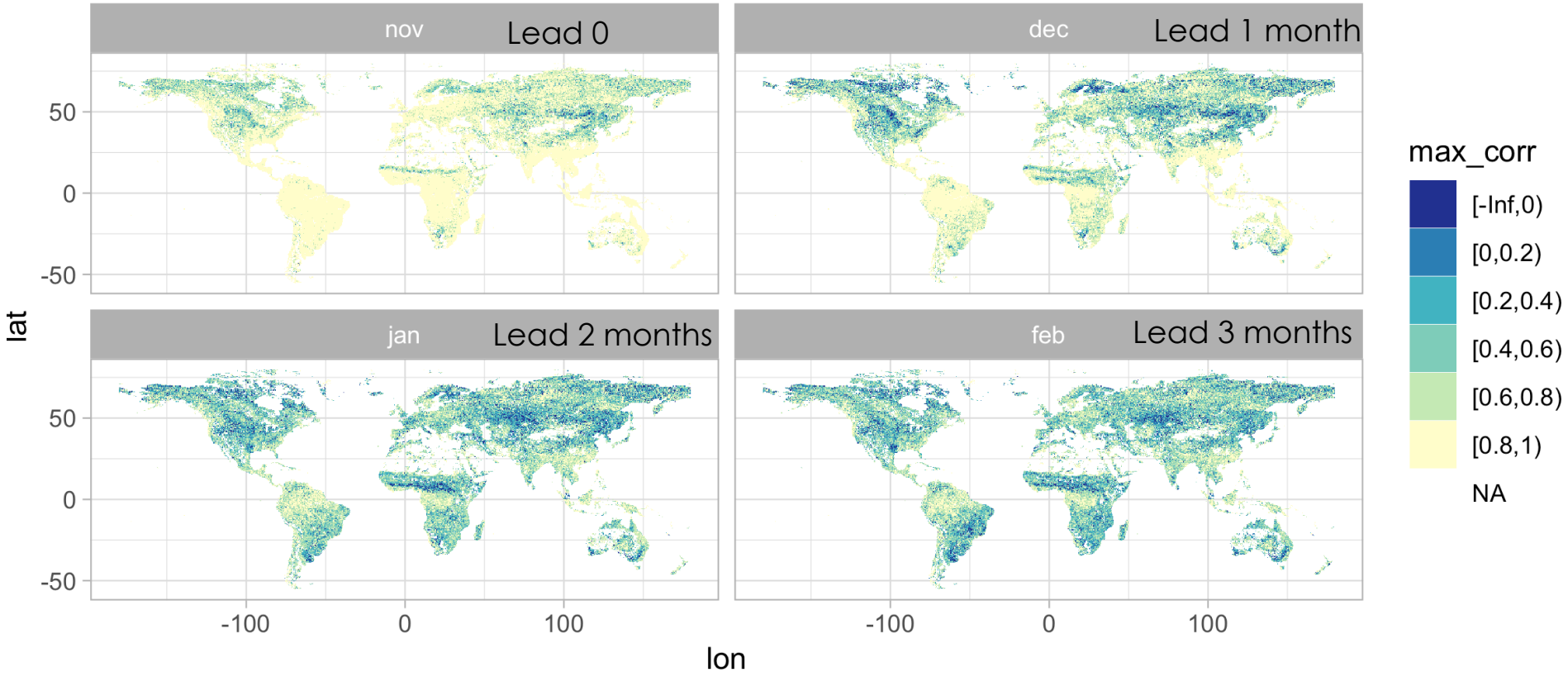
- Considerable improvement of surface climate bias, variability and response to 20C climate-change forcing
- Significant multi-scale enhancement of seasonal and weather « real » predictions (hindcasts) and of decadal potential predictability.

Above results motivate further research and enhancements in land/ vegetation representation.

- EU H2020 MSCA grant "PROCEED" http://projects.knmi.nl/proceed
- Proposal for MME project aimed at quantifying the impact of land Earth system processes and feedbacks on seasonal climate forecasts (GLACE-ESM) [Poster P-B6-01 19 Sept. Foothills Lab]

LAI memory:predictability of monthly LAI interannual anomalies using SARIMA model (10 years training).

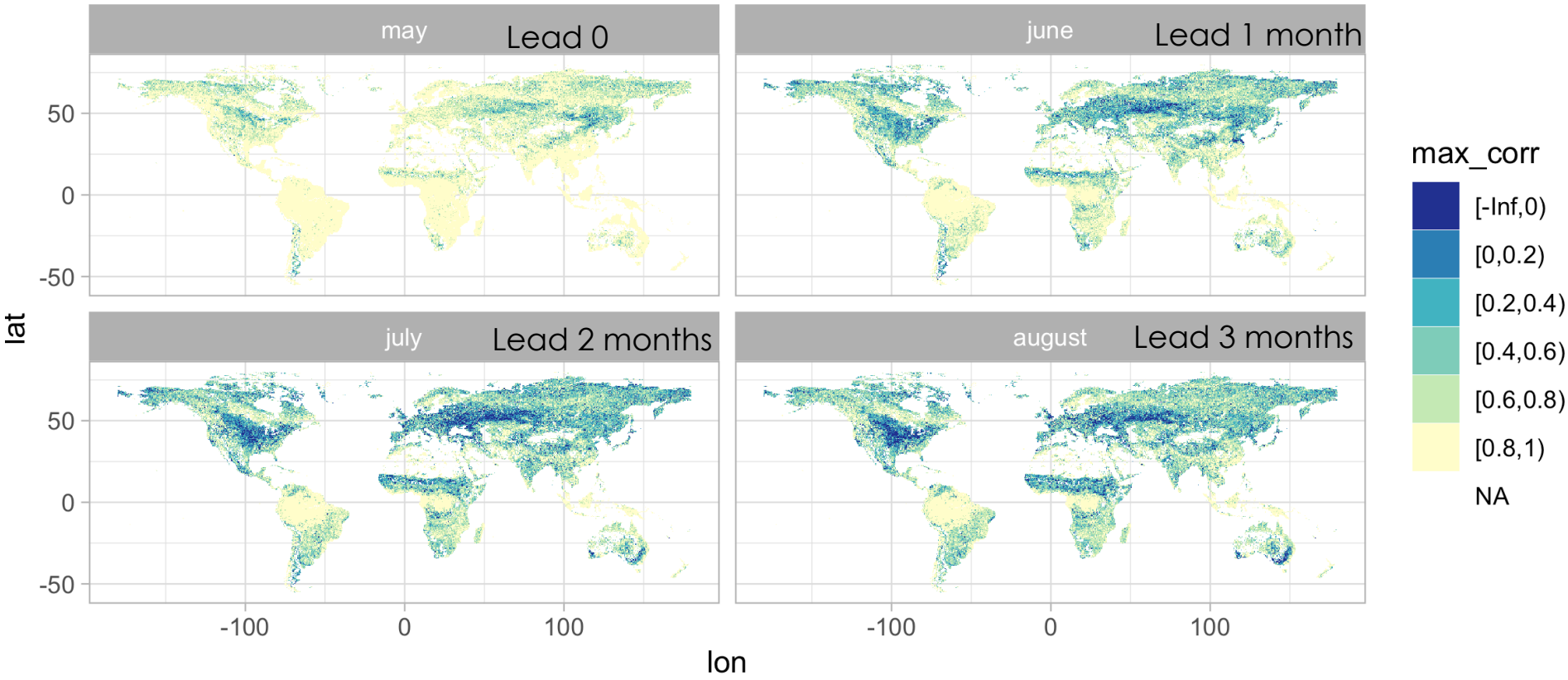
1st November start date



LAI monthly data [1982-2014] *(GLCF GLASS http://glcf.umd.edu/data/lai/ Xiao Z., et al., 2013)*

LAI memory:predictability of monthly LAI interannual anomalies using SARIMA model (10 years training).

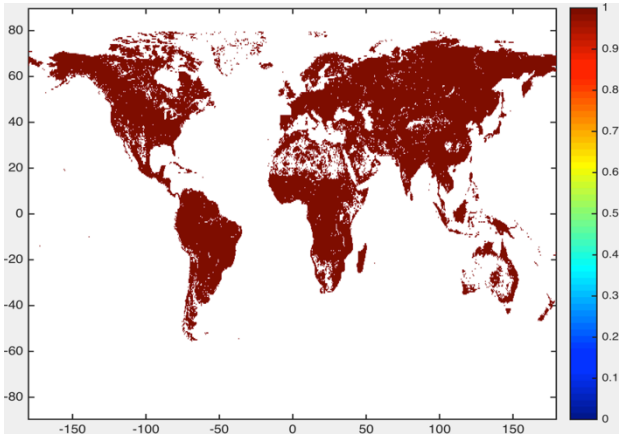
1st May start date



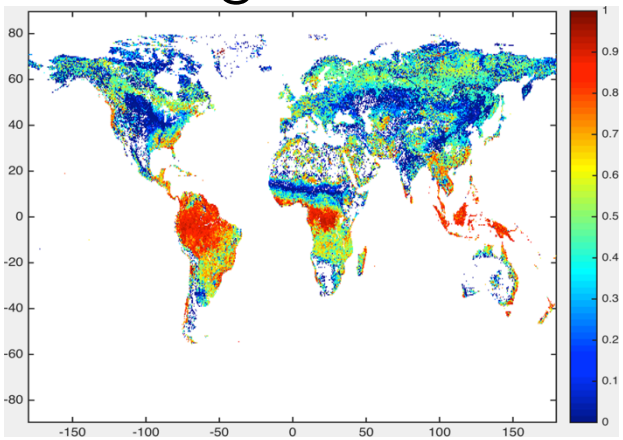
LAI monthly data [1982-2014] *(GLCF GLASS http://glcf.umd.edu/data/lai/ Xiao Z., et al., 2013)*

LAI memory: autocorrelations of seasonal-mean interannual anomalies

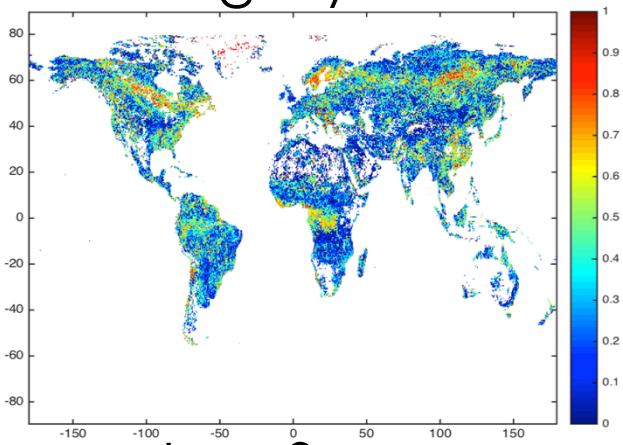
Lag 0 seas



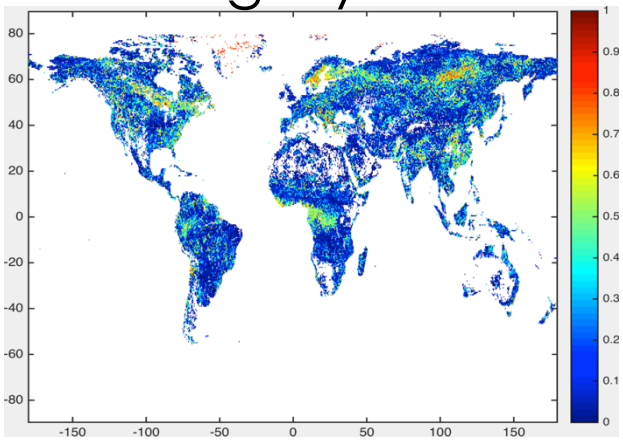
Lag 1 seas



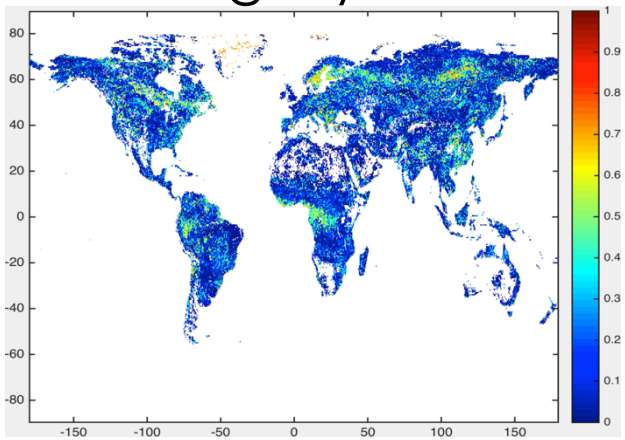
Lag 1 year



Lag 2 years



Lag 3 years



LAI DATA [1982-2014] *(GLCF GLASS http://glcf.umd.edu/data/lai/ Xiao Z., et al., 2013)*.