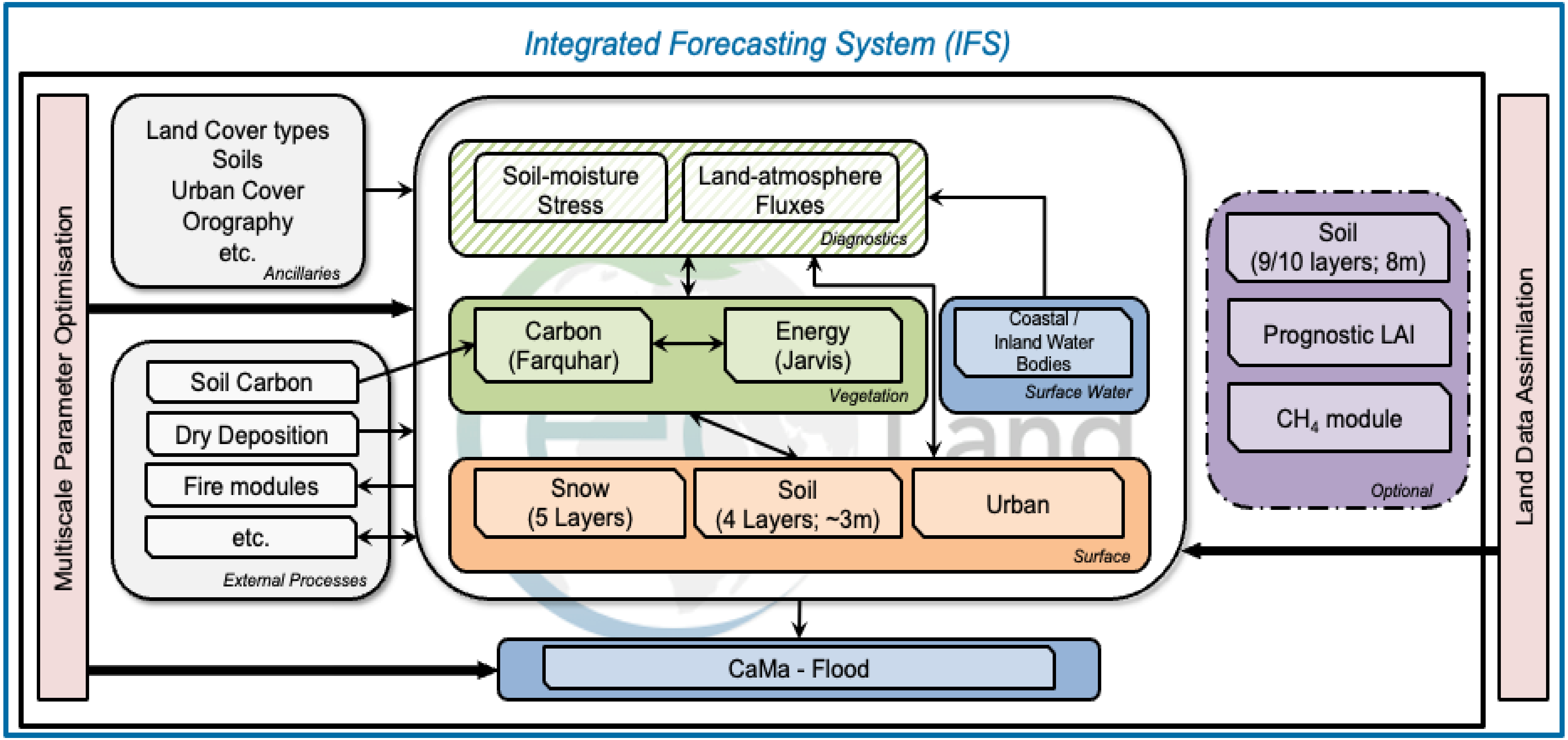
Ancillary data for land modelling within ecLand: status and perspectives

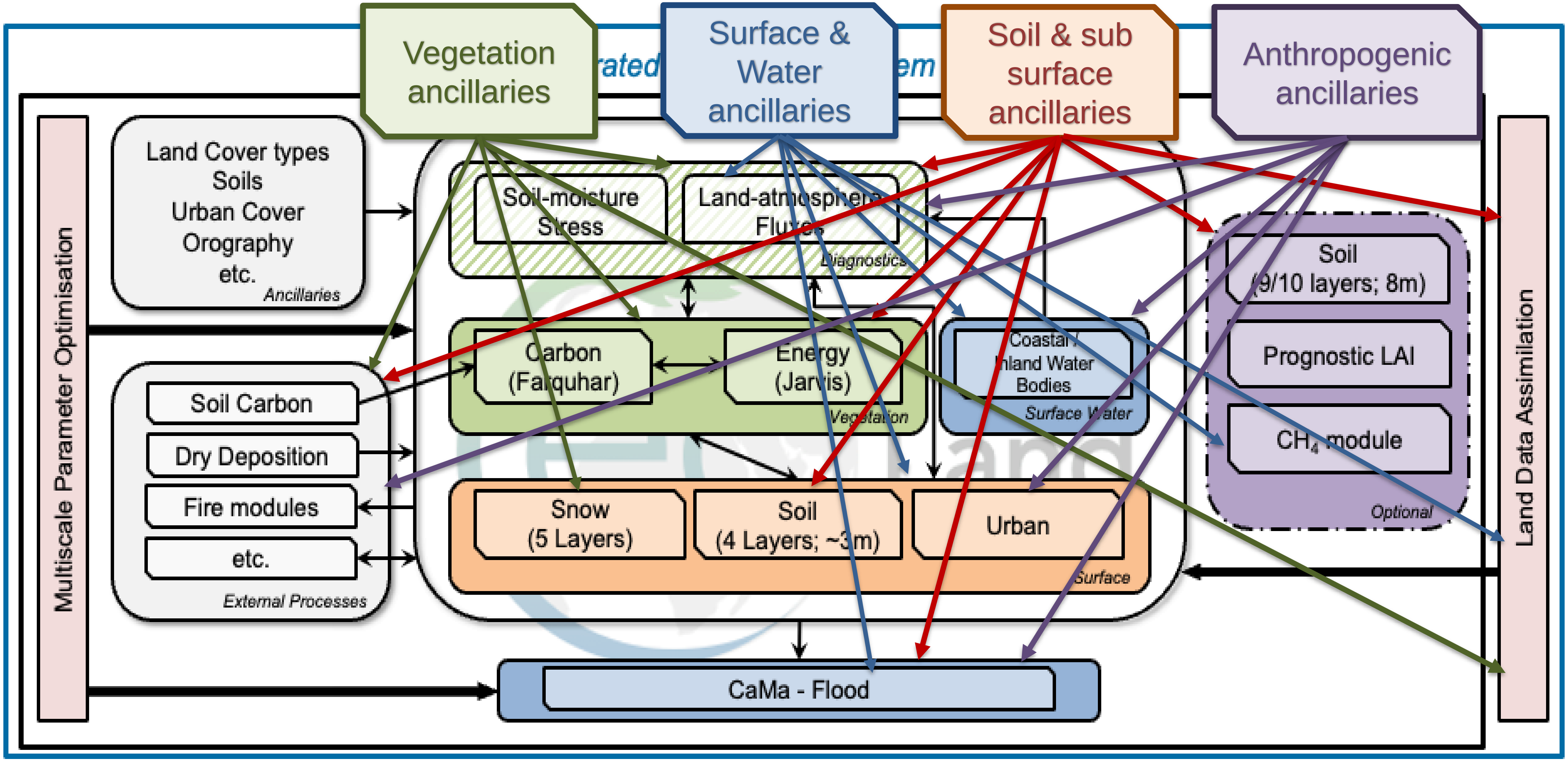
Souhail Boussetta

Thanks to:
Anna Agusti-Panareda, Annelize Van Niekerk, Anton Beljaars, Birgit Sützl, Christoph Rüdiger, Christoph Herbert, Cinzia Mazzetti, David Fairbairn, Emanuel Dutra, Ewan Pinnington, Gabriele Arduini, Gianpaolo Balsamo, Joe Mcnorton, Jasper Denissen, Magdalena Alonso Balmaseda, Margarita Choulga, Nils Wedi, Nina Raoult, Patricia de Rosnay, Pedro Maciel, Peter Dueben, Retish Senan, Peter Weston, Sebastien Garrigues, Xabier Pedruzo Bagazgoitia

ecLand – Current Structure



ecLand – Current Structure



Currently used in ecLand

Surface

Land sea mask & surface water fraction

Orographic and sub-grid orographic fields

Surface Albedo

Land use/Land cover

Leaf are index and photosynthetic pathway types (C3/C4)

Derived vegetation characteristics (global and LuTables)

Soil & subsurface

Soil texture

Derived water and heat related characteristics (global,LupTables, pdf)

Anthropogenic

Urban cover

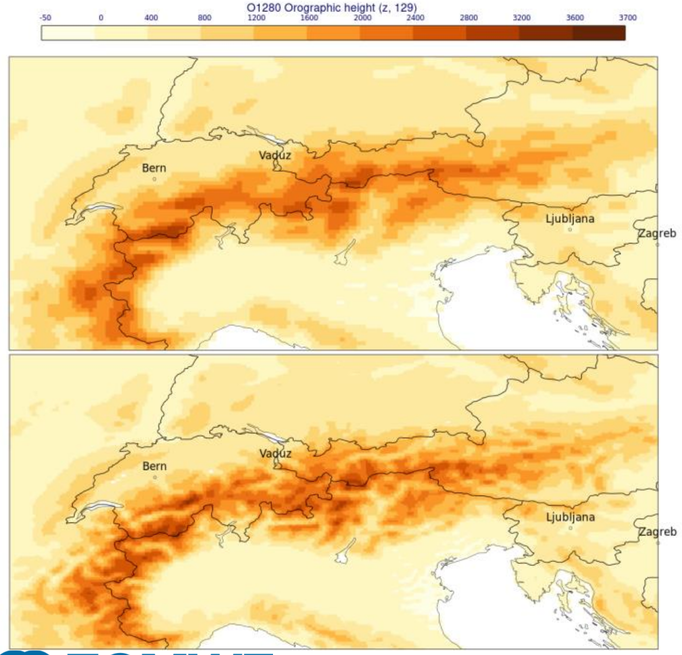
Important points:

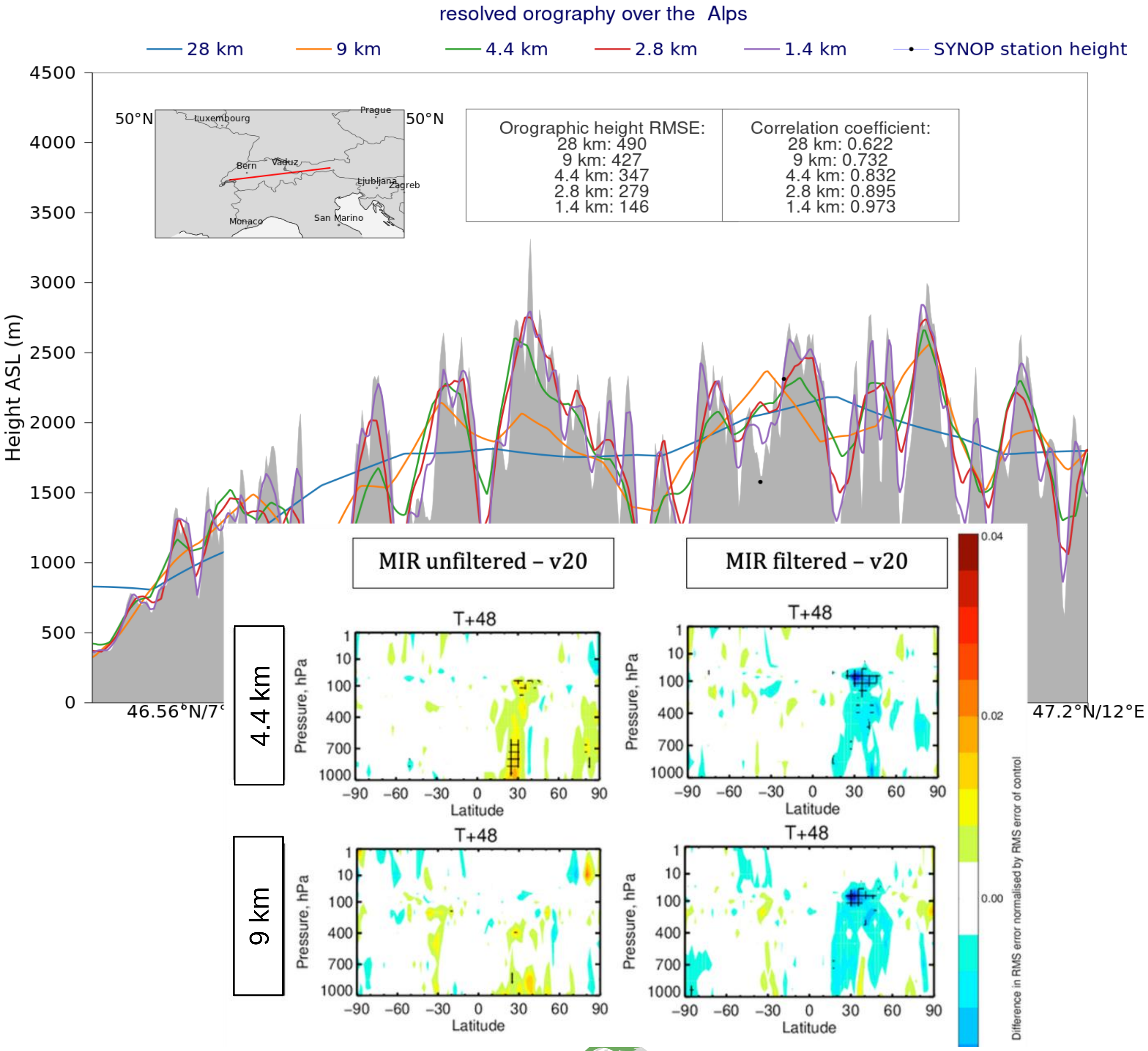
- Consistency of the ancillary with the model world (may be different between process).
- Consistency check between the ancillaries.
- The way to derive sub-ancillaries (Lup tables, pedotransfer functions, statistical methods ...)
- The interpolation from very high resolution to atmospheric model resolution.
- Is there a need to consider uncertainty as in DA procedures.

See poster from B. Suetzl et al.

Representation of Orography

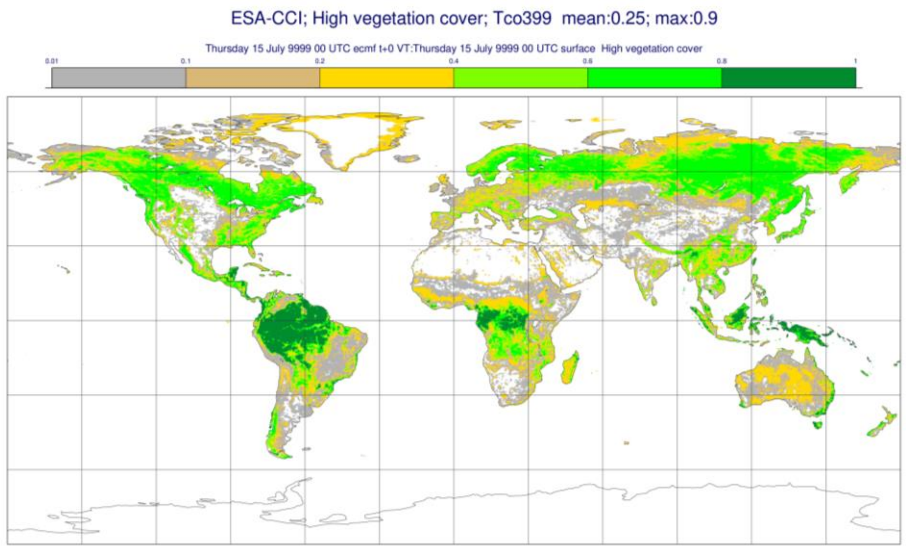
- Several pre-filtering steps replaced with conservative interpolation.
- Dampening of small scales reduces bias from high amplitude gravity waves (e.g. Tibet plateau).
- Spectral filtering improves large-scale circulation also at 9 km.
- Positive impact of new source data.



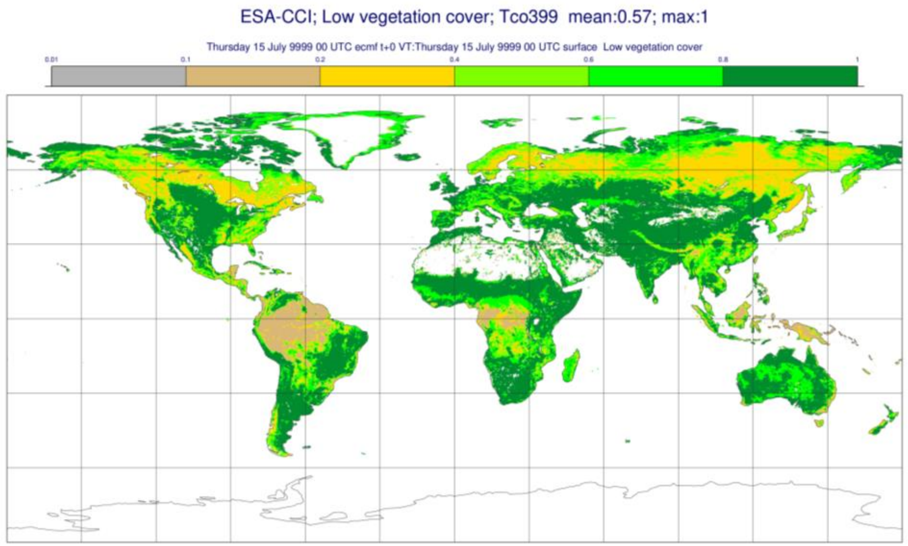


Updated vegetation LULC & LAI

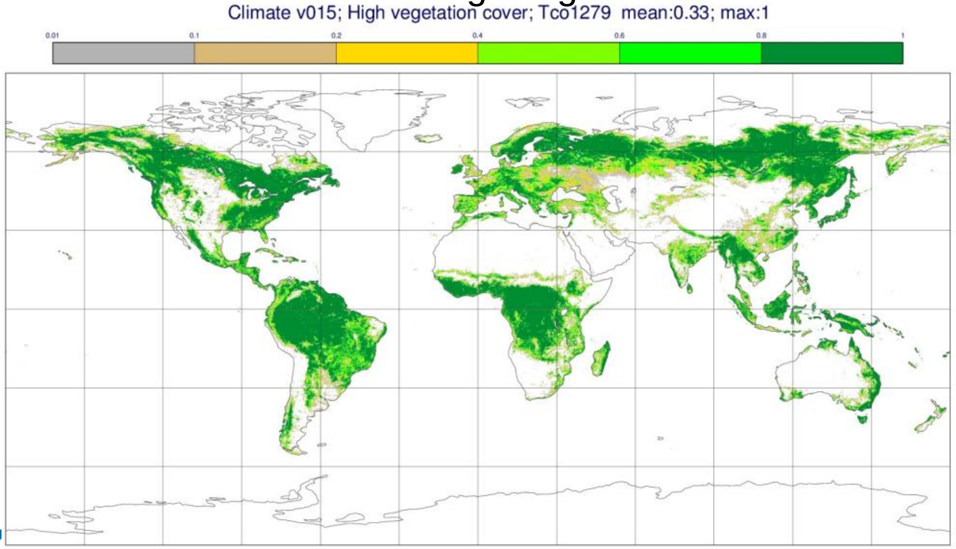
ESA-CCI high veg cover



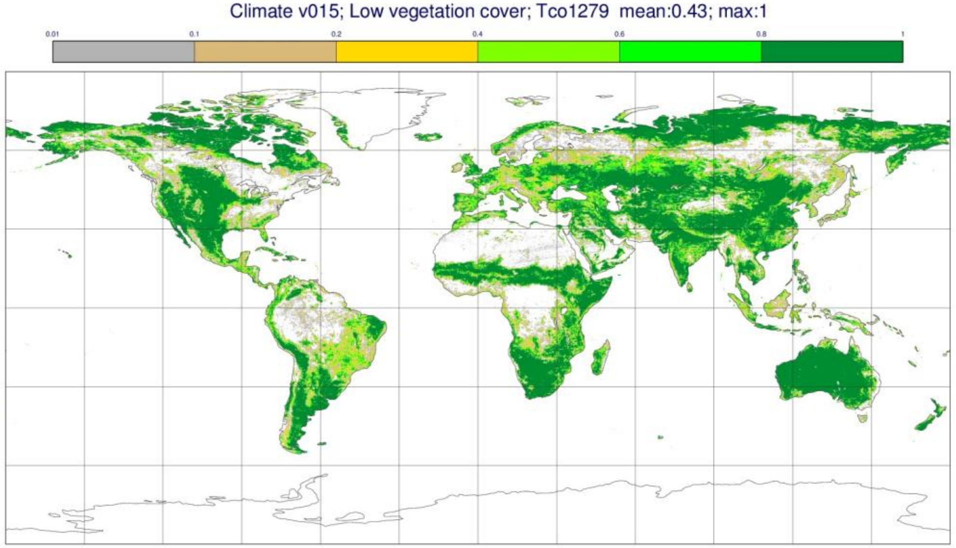
ESA-CCI low veg cover



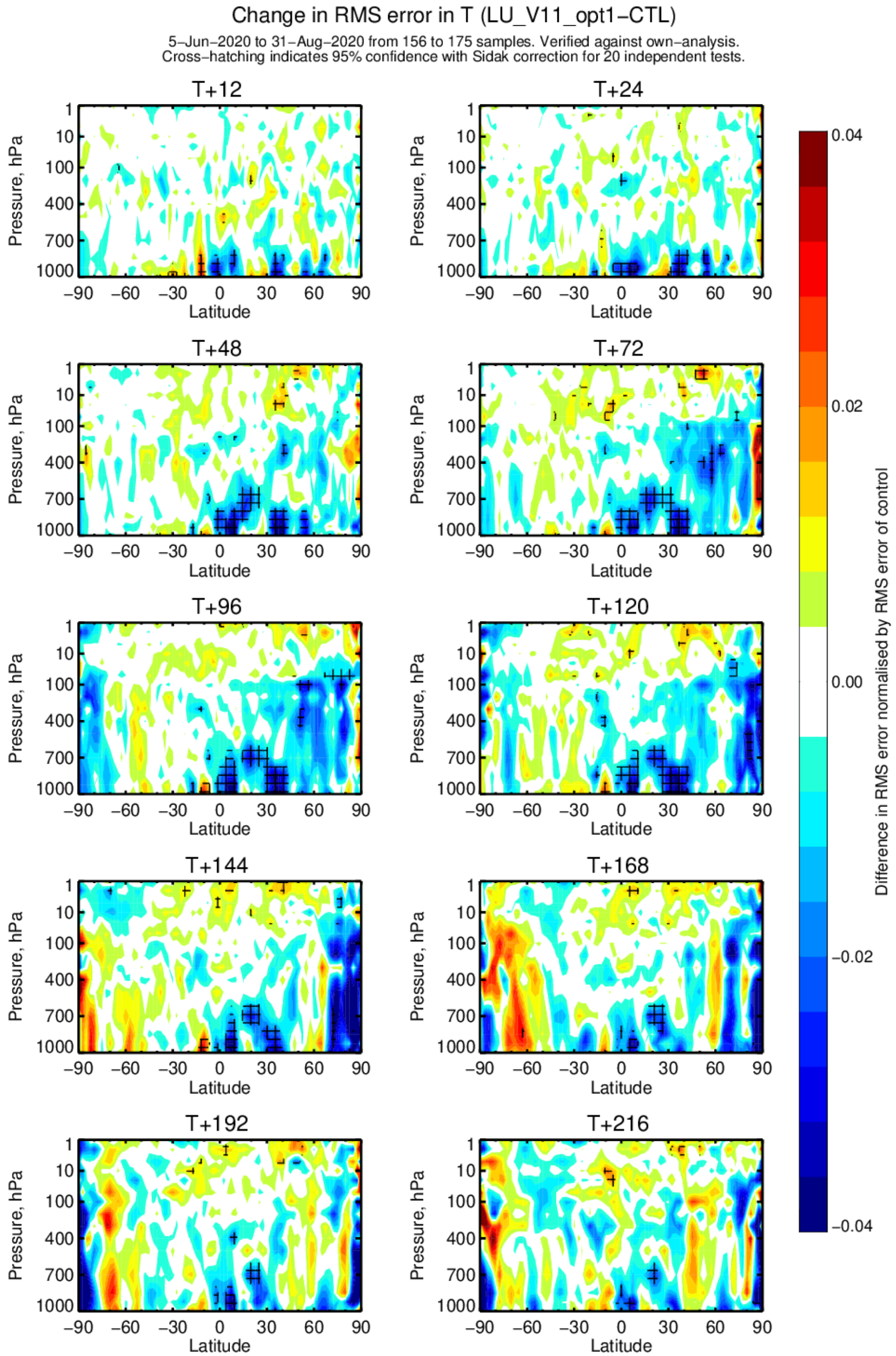
GLCC1.2 high veg cover



GLCC1.2 low veg cover



Model adjustments and Impact on L-A interaction

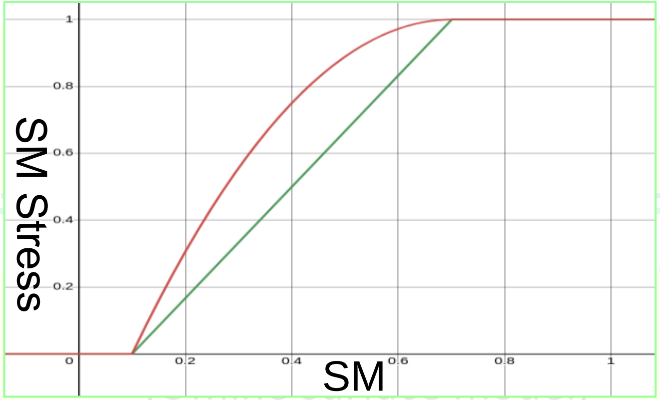


Updated Vegetation:
C3S LULC + CGLS LAI (+ **new disaggregation operator**)

1st revision of Canopy resistance and momentum parameters (rsmin, cveg)

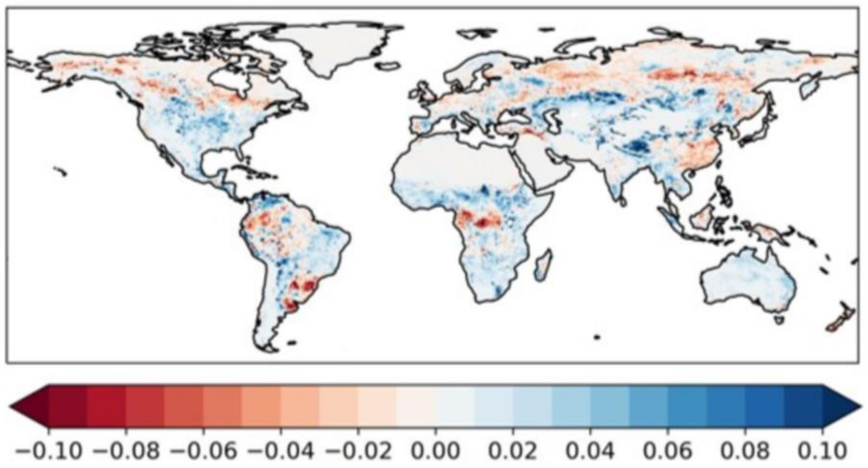
Updated Soil moisture stress

2nd revision of Canopy resistance parameters and momentum (rsmin, cveg)



* Physically consistent with the soil matric potential
* Allow higher evapotranspiration under drier conditions

Time-varying vegetation in ECLand



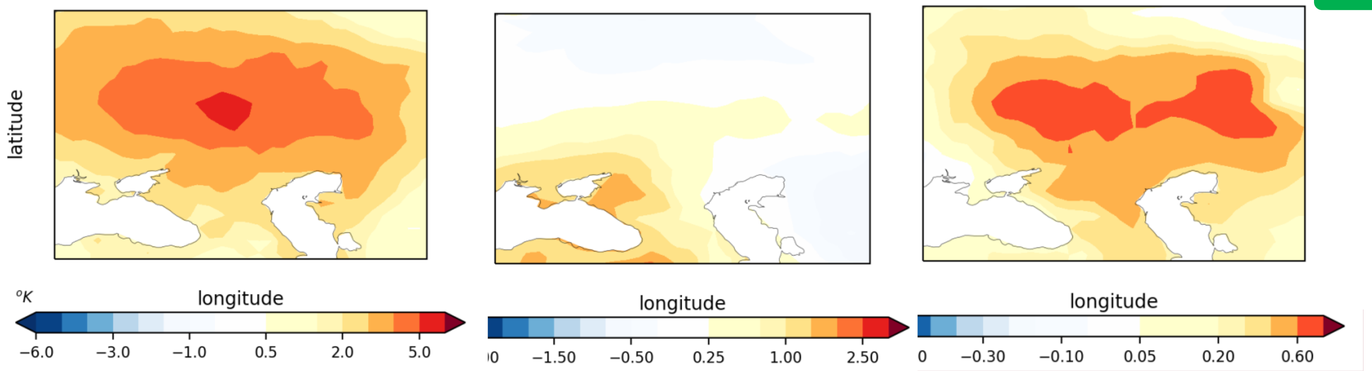
Anolmaly correlation diffrence of the Evaporation (Time varying LAI – static LAI) for 1993-2019

Coupled seasonal forecast

49R1

Consistent impact on extreme 2T seasonal forecasts

ERA5 | Static LULC+LAI | Time-varying Veg



Summer 2010Russian heat wave

Updated Vegetation:
C3S LULC + CGLS LAI (+ **new disaggregation operator**)

1st revision of Canopy resistance and momentum parameters (rsmin, cveg)

Updated Soil moisture stress

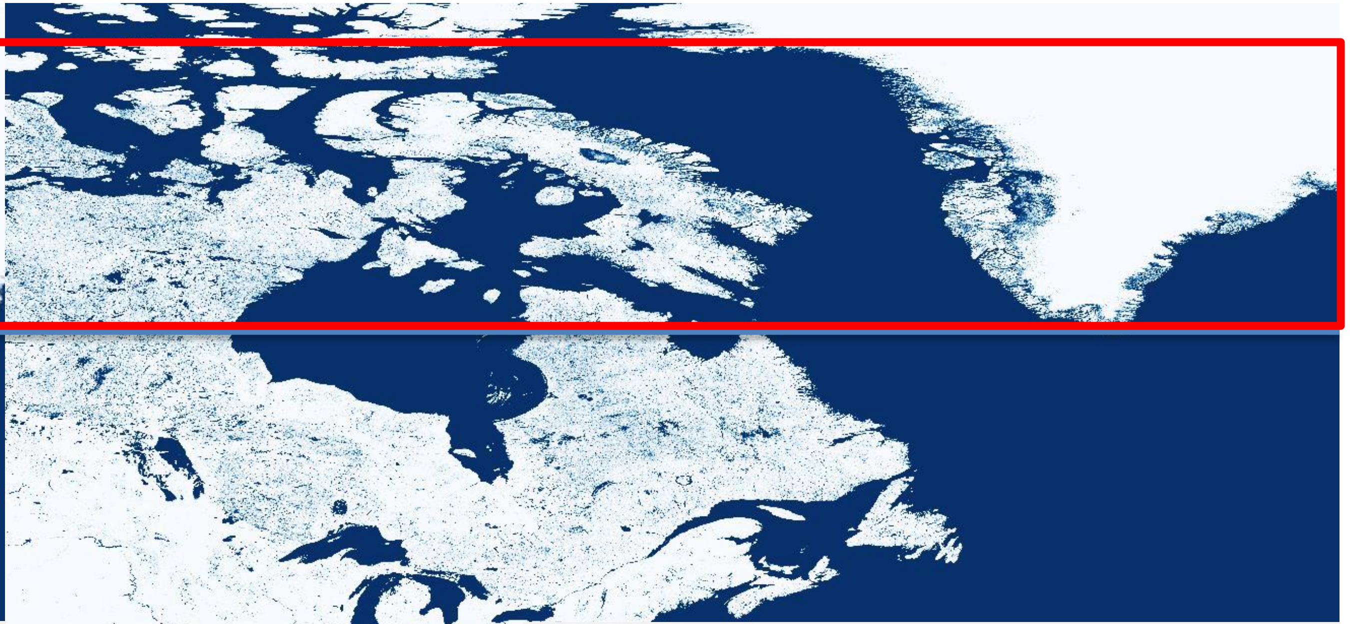
2nd revision of Canopy resistance parameters and momentum (rsmin, cveg)

Time-varying LULC &/or LAI
(Offline surface model)
+
Updated Climate field suite for Climate.v021

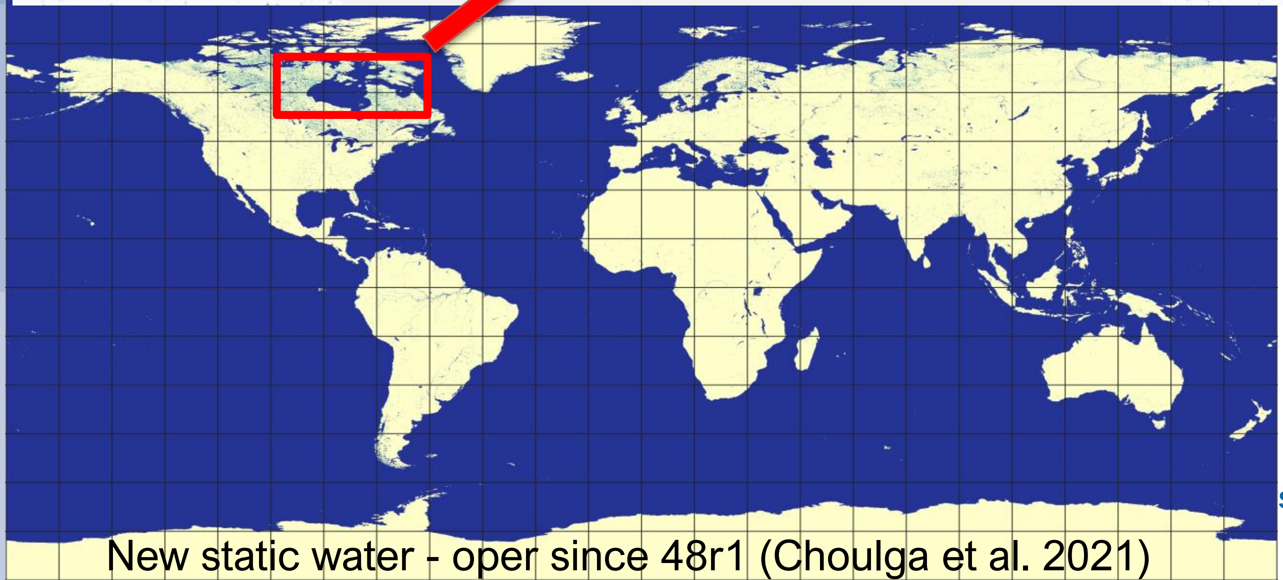
Foreseen implementation in ERA6Land and ERA7/SEAS7

Improved representation of Water Surfaces

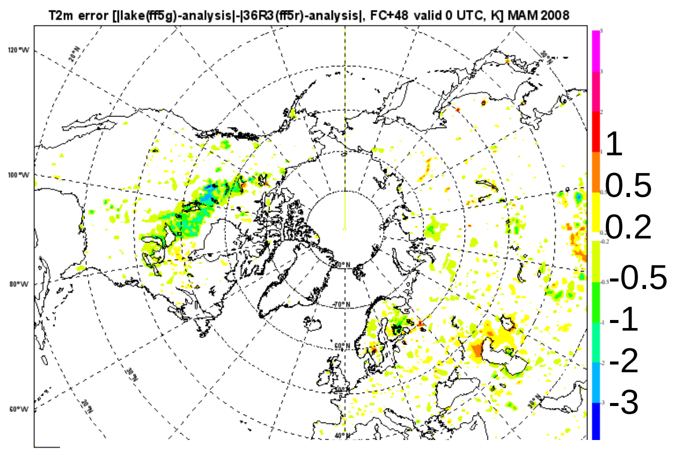
VHRES 1 km – Previous Land-Sea Mask



VHRES 1 km – New Land-Sea Mask (GSWE)



New static water - oper since 48r1 (Choulga et al. 2021)



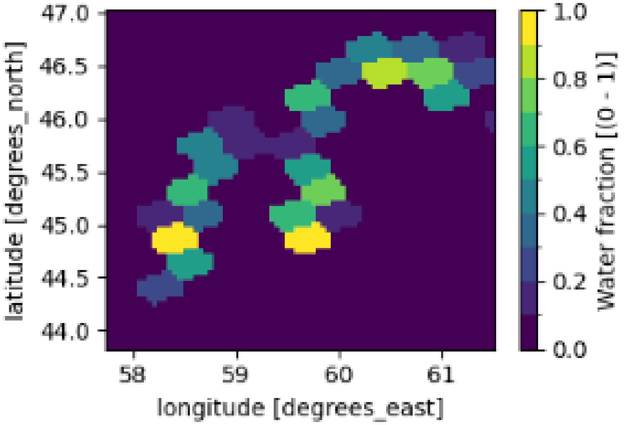
Improves 2m temperature

Degrades 2m temperature

Improving the representation of the water surface and have better impact for L-A interaction

Time-Varying Water Surfaces

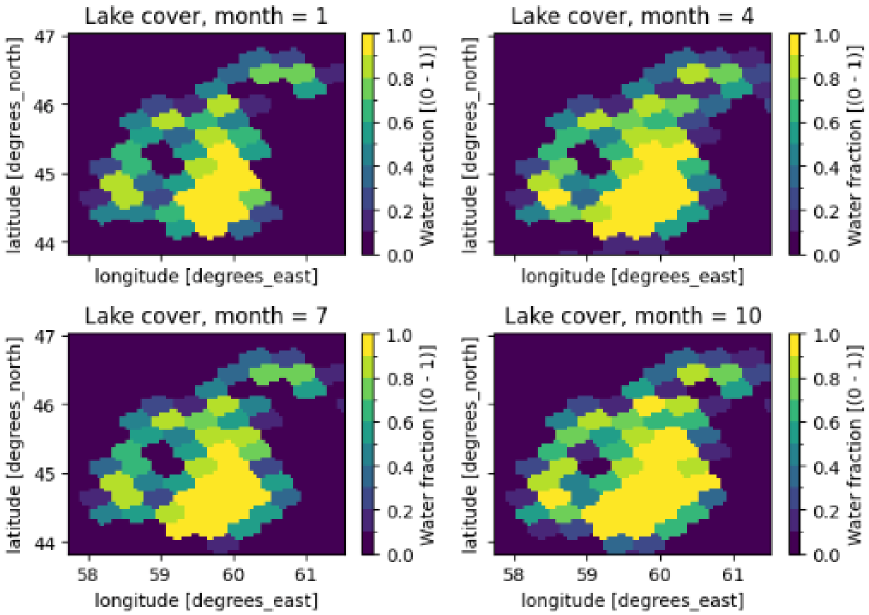
Static lake cover

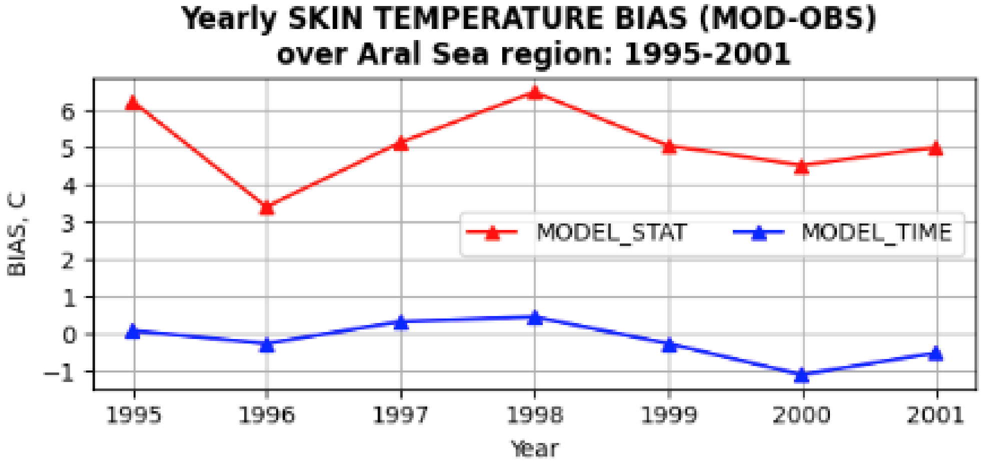


Kazakhstan/Uzbekistan

Ex. for the Aral sea

Time-varying lake cover: 1995-2001

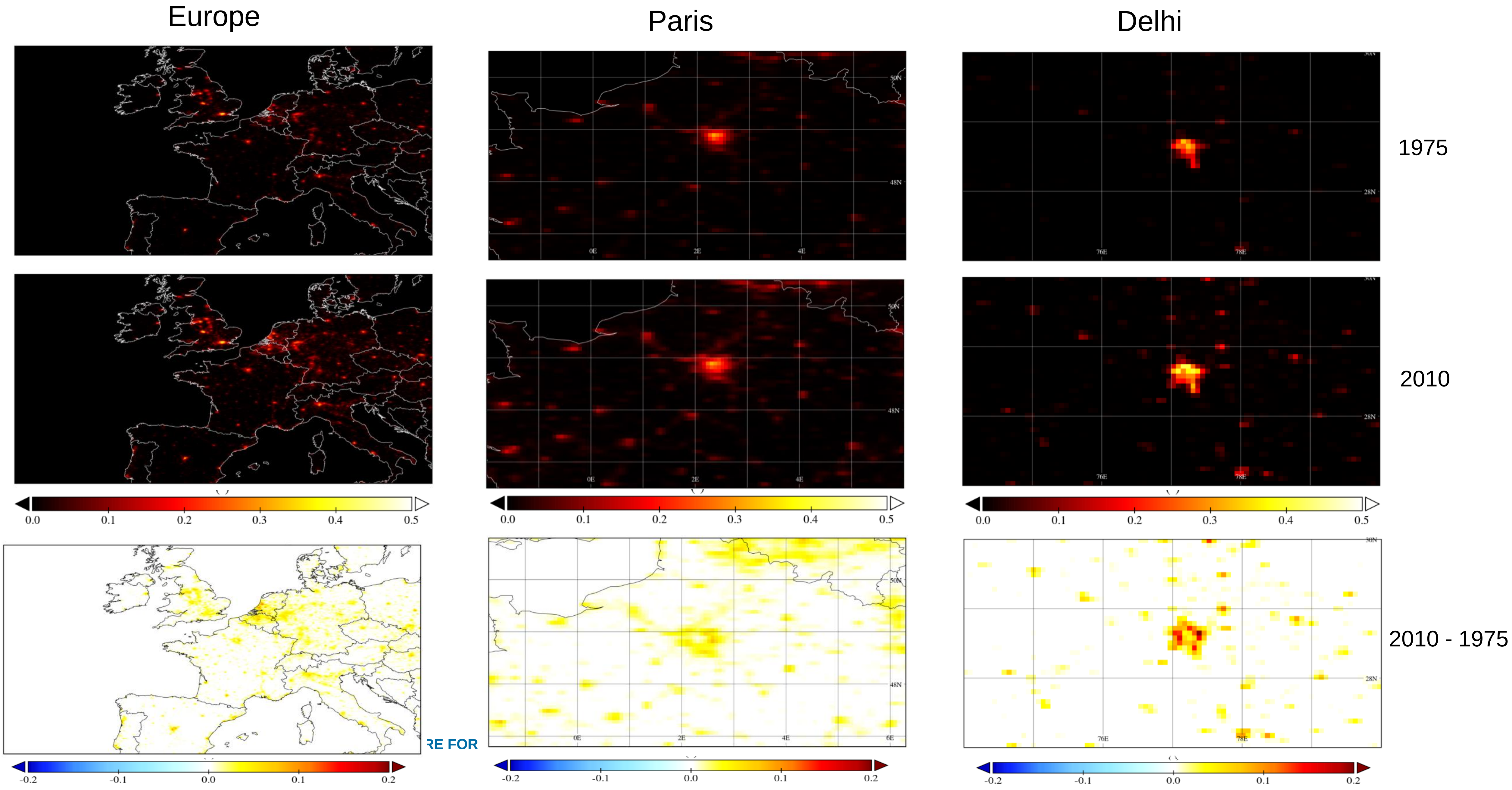




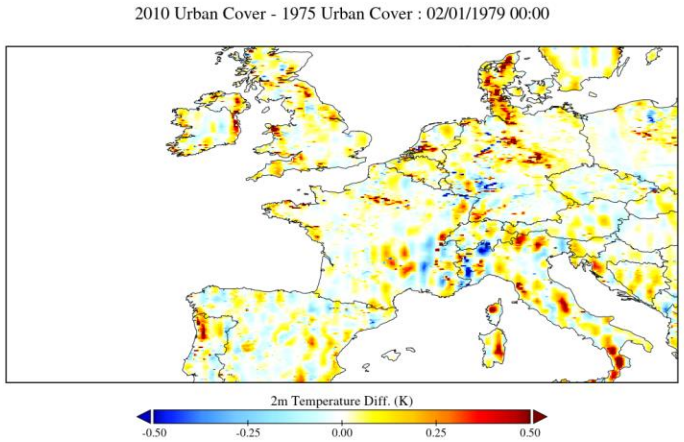
Substantial decrease in skin temperature BIAS when considering time-varying lakes for previous decades.

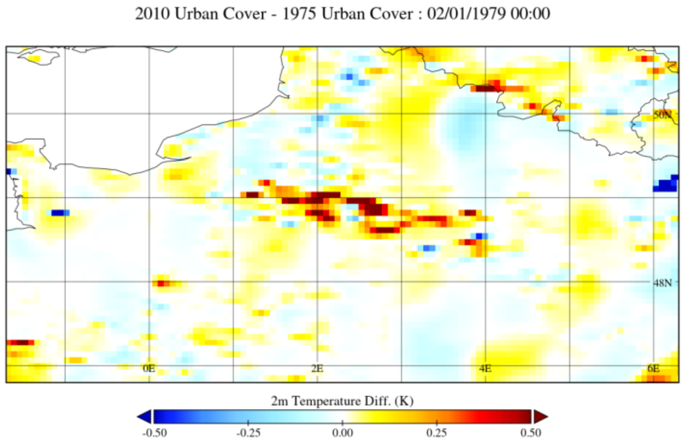
See poster from M. Choulga et al.

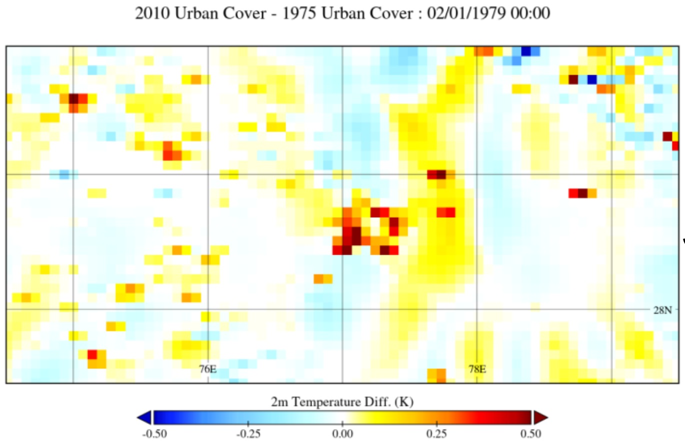
Considering Change in Urban cover



Impact on 2m Temperature





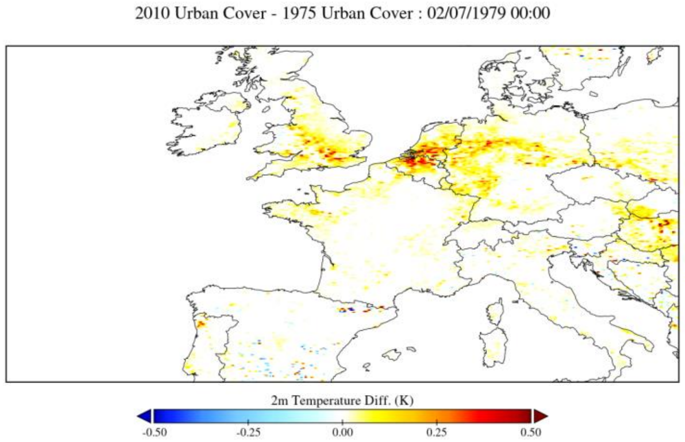


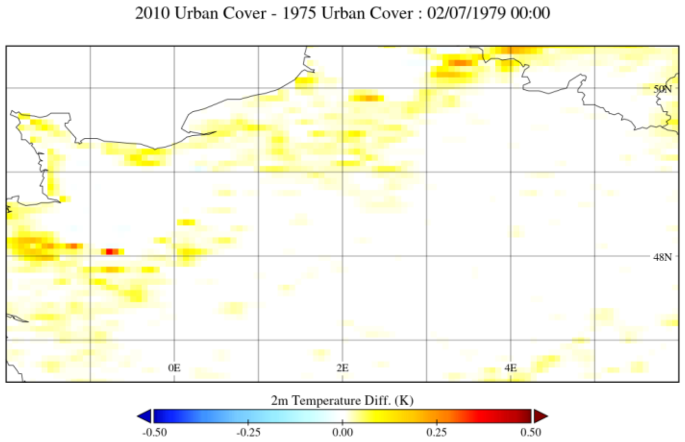
January

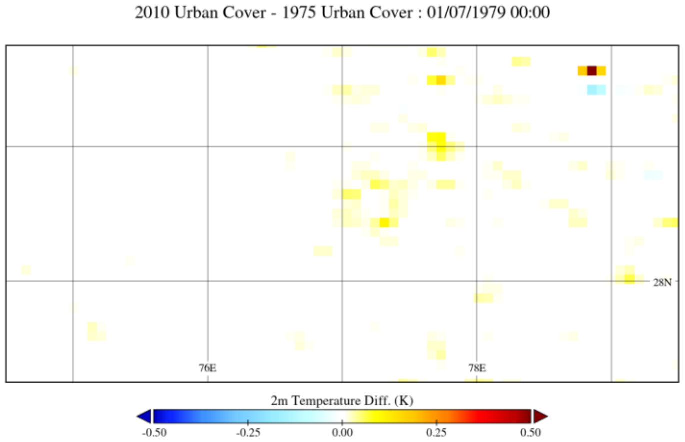
Europe

Paris

Delhi



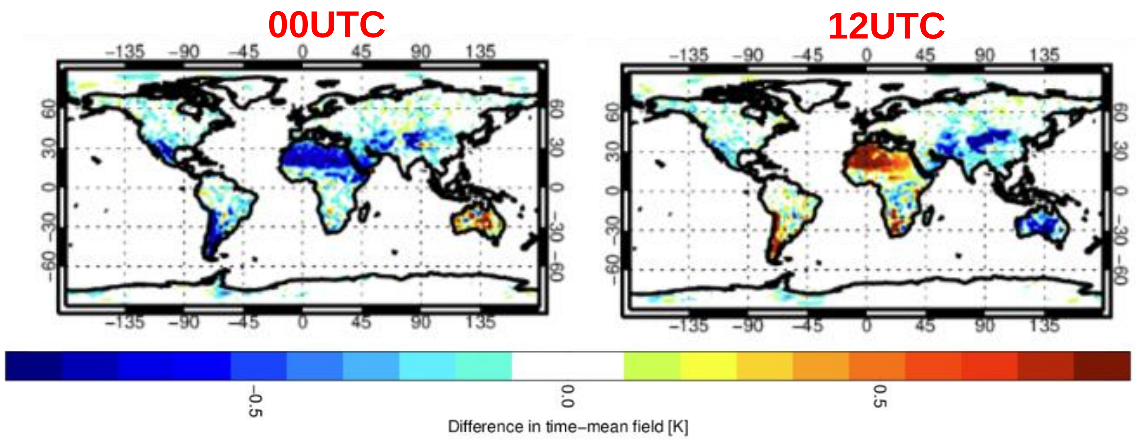




July

T. Joe McNorton

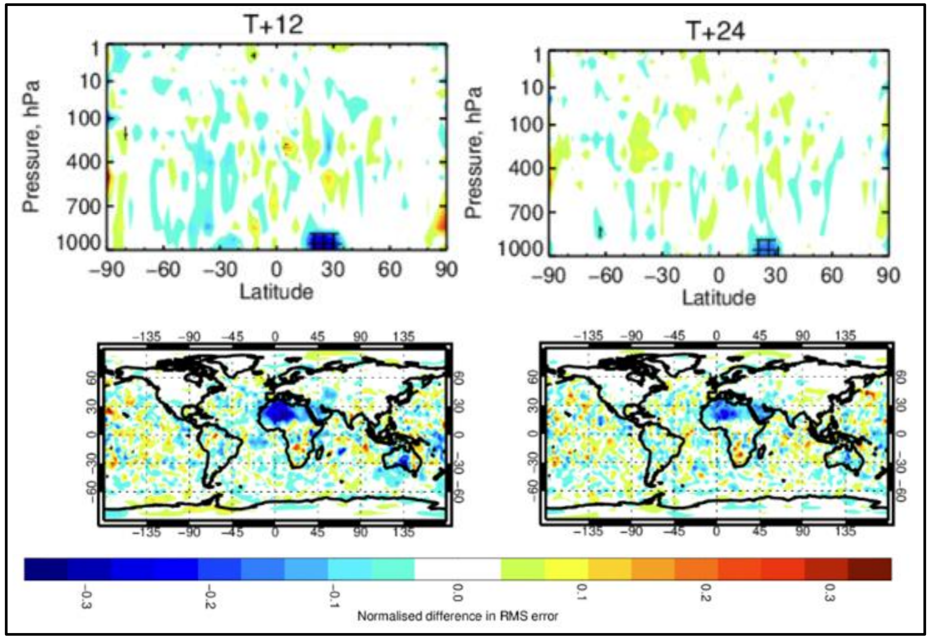
Non observable ancillaries: skin thermal conductivity as ex.



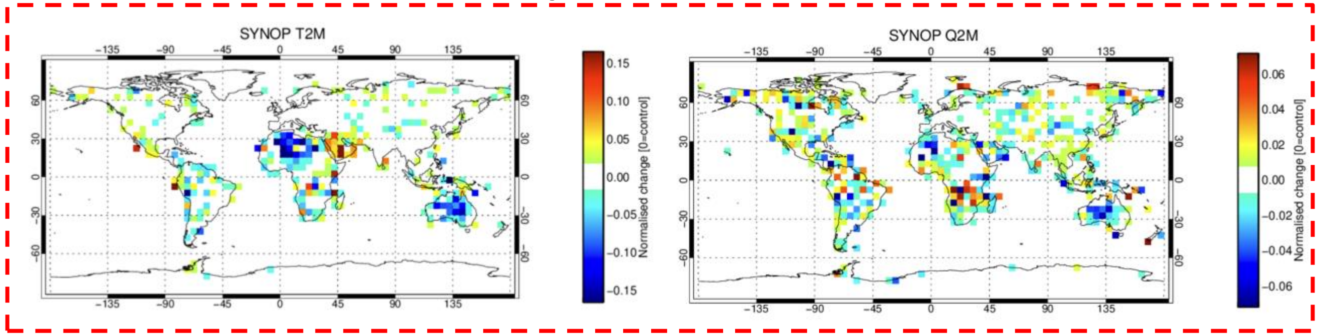
***Change in mean** SKT forecast field at different analysis times*

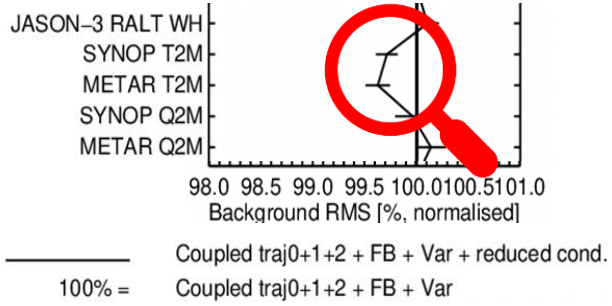
- Reducing the skin thermal conductivity for bare soil leads to an **increase in diurnal cycle** ✓

T at 1000hPa for 12 UTC analysis time



T2m/RH2m for 12 UTC analysis

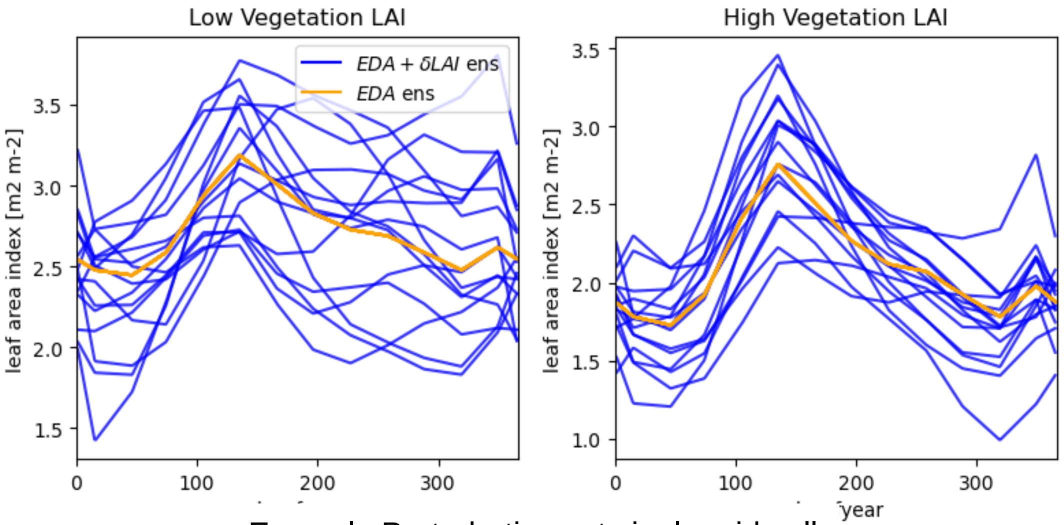




Impact of Perturbing Land ancillary Parameters

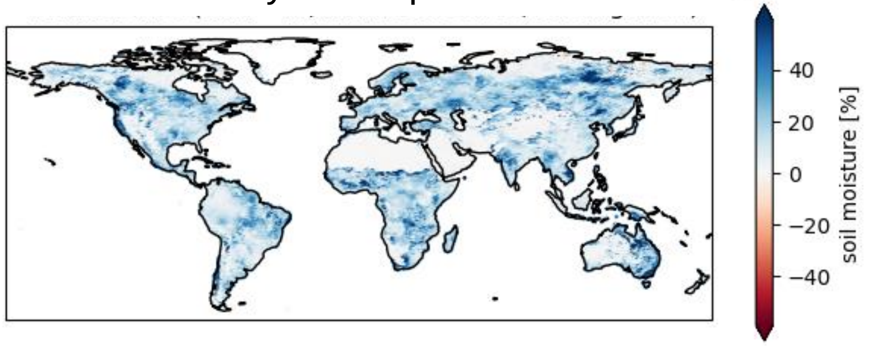
- The ECMWF Ensemble of Data Assimilations (EDA) is under-spread at the surface
- Stochastic Parameter Perturbation (SPP) approach for land surface parameters was applied on LAI and vegetation fraction to see if this can increase spread at the surface in a set of "offline" experiments (similar approach was investigated by Draper 2021).

SPP Perturbations

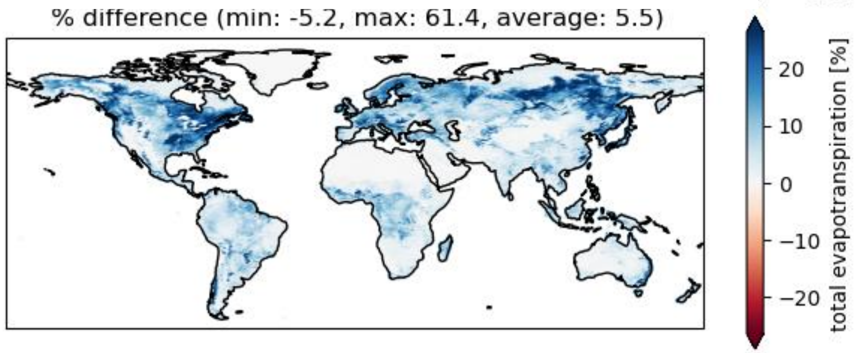


Example Perturbations at single grid cell
for Leaf Area Index

Soil Moisture Layer 1 – spread increase



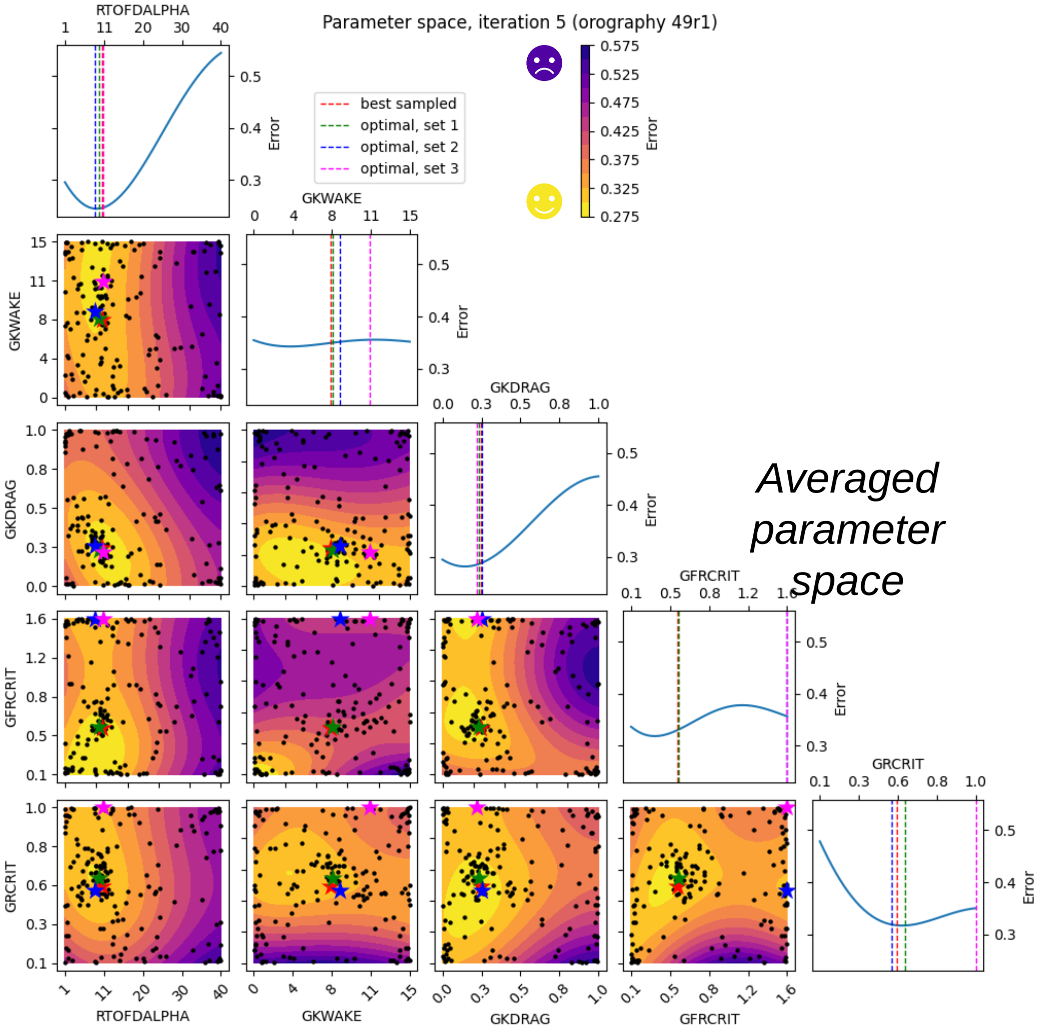
Evapotranspiration – spread increase



- Maps: differences in spread between the EDA offline surface ensemble with and without perturbations.
- Blue corresponds to an increase in spread
- Further increase expected in the coupled EDA

(See poster by E. Pinnington P. Weston et al.)

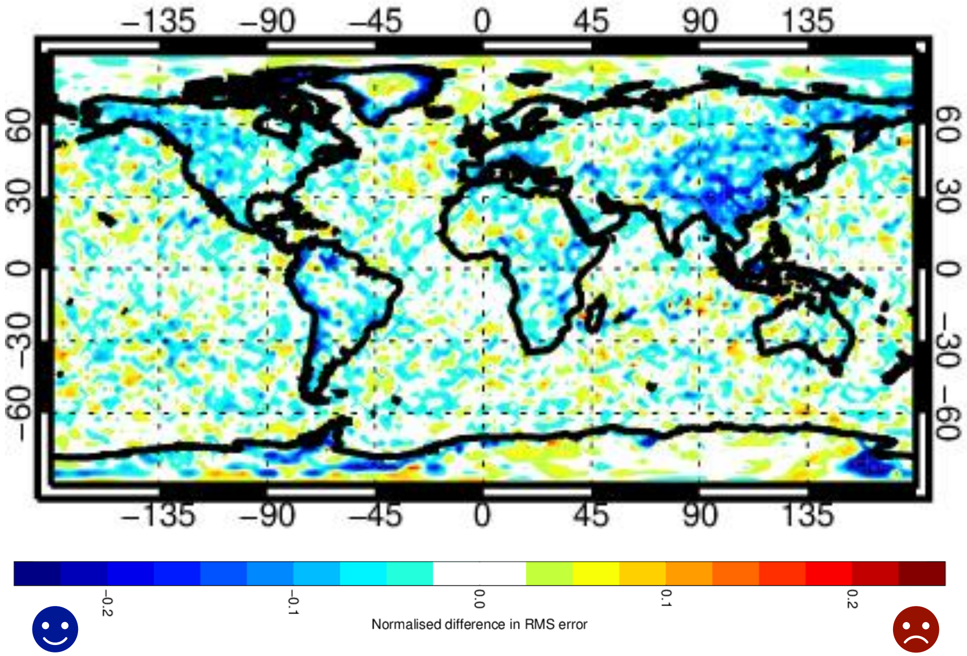
Representation of the sub-grid orography



Averaged parameter space

Parameters partial dependence

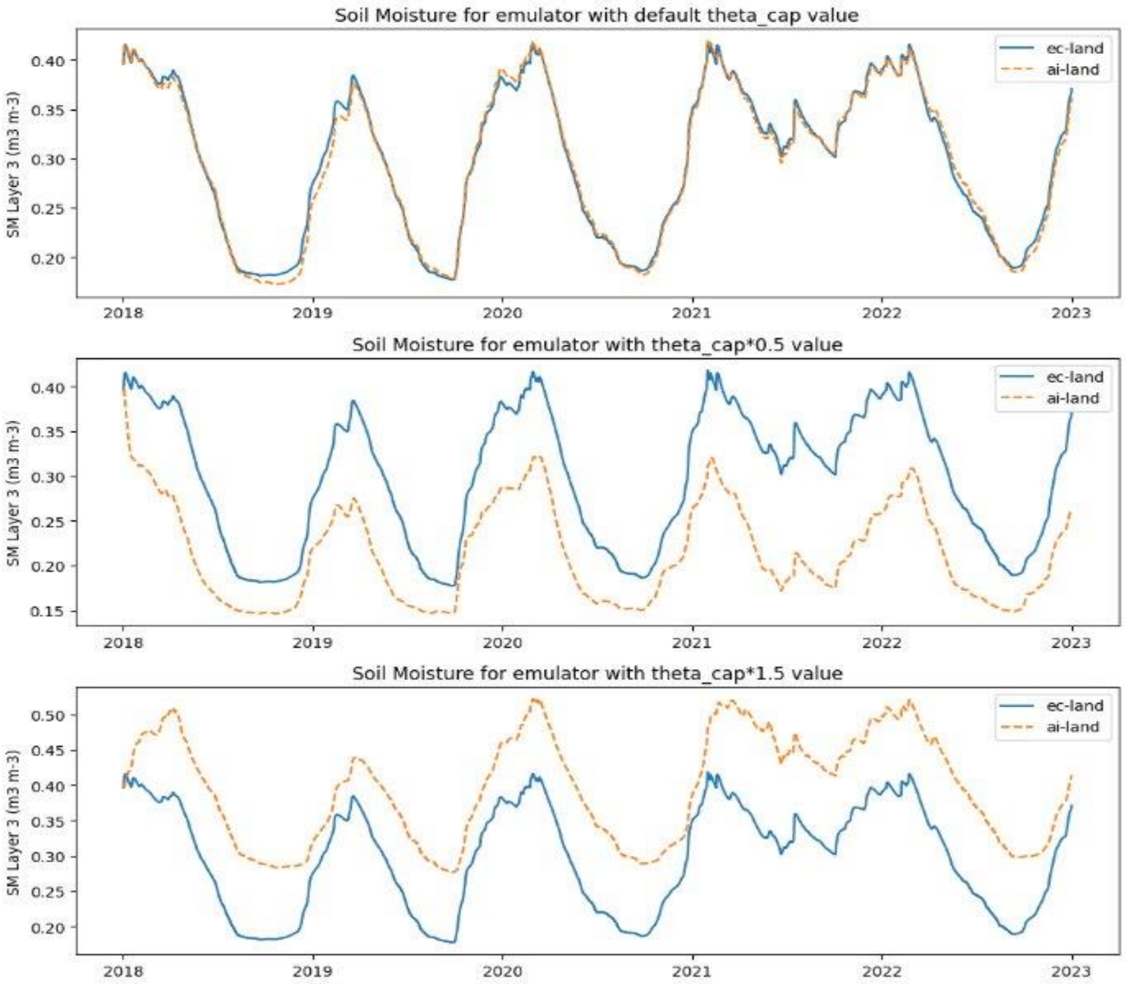
- Multi-parameter optimisation for 5 parameters in the sub-grid orographic parameterisations.
- Using verification scores for different variables as forecast error metric.
- New parameters improve wind, particularly at lower levels.



New vs. old orography: change in RMSE of 10m zonal winds, T+72, 28 km resolution

See poster from B. Suetzl et al.

Use of ML for Model Parameterisations



	By fine tuning against **observations**, can we **learn biases** in the model?
	With more information on parameter sensitivities, can we use the emulator for **parameter estimation**?
	Can we exploit the **differentiability** of aiLand for land model **data assimilation**?
	How do we **couple** aiLand with the other **Earth System components** (physical or machine learnt)?

(T. E. Pinnington and N. Raoult)

Outlook and remarks

Ancillaries could be also classified as

- Basic / derived
- Observable / Non observable
- Physically defined / Non-physical or Empirical

Considering:

- Very High resolution and limit to representativity
- Time evolution
- Uncertainty quantification

Perturbation & perspectives for ML

But also

- Not to neglect the technical side and the assumptions made in the processing/preprocessing (interpolation, filtering,…)

Could Parameters Optimization be an alternative with careful consideration of the parameters space (also with ML perspectives):

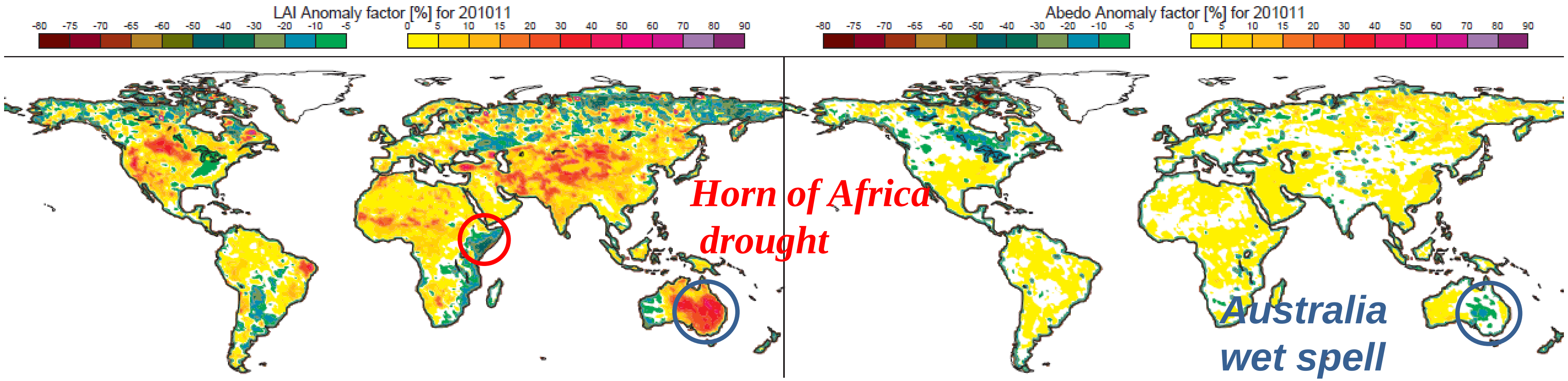
- solely based on final impact
- under observation constraints
- under physical/theoretical constraints

Thank you

Souhail Boussetta
Souhail.Boussetta@ecmwf.int

https://github.com/ecmwf-ifs/ecland

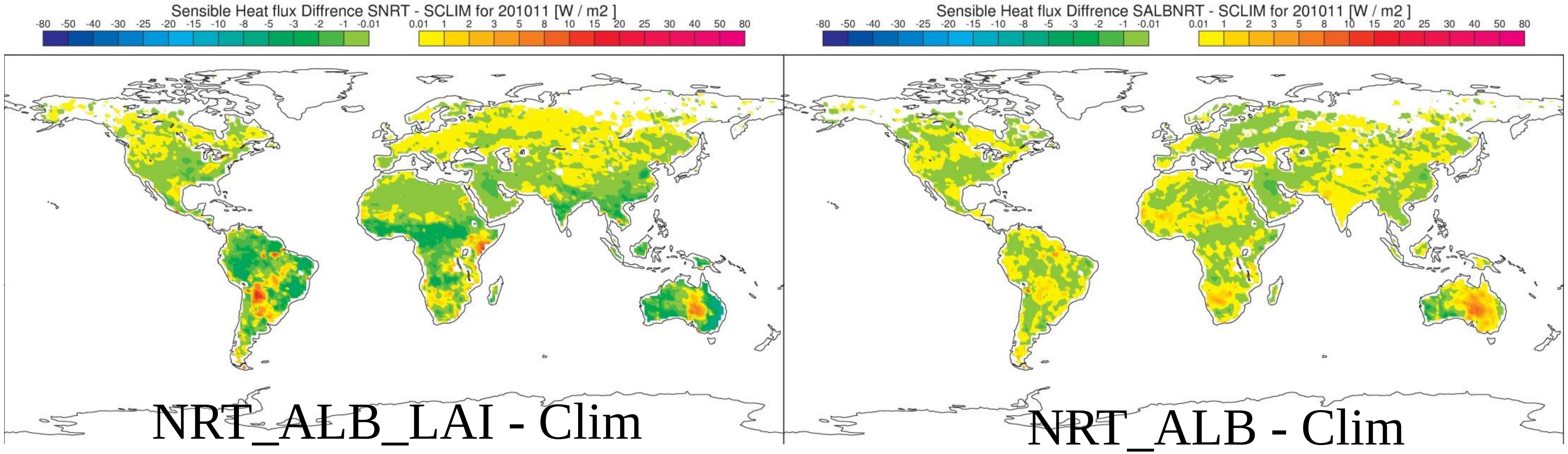
Time varying LAI & albedo



LAI anomaly

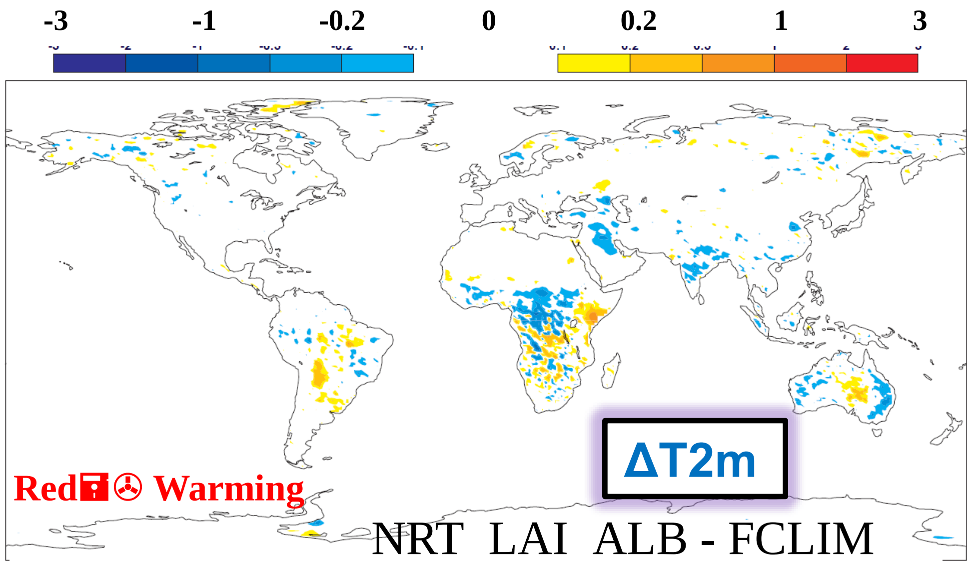
Albedo anomaly

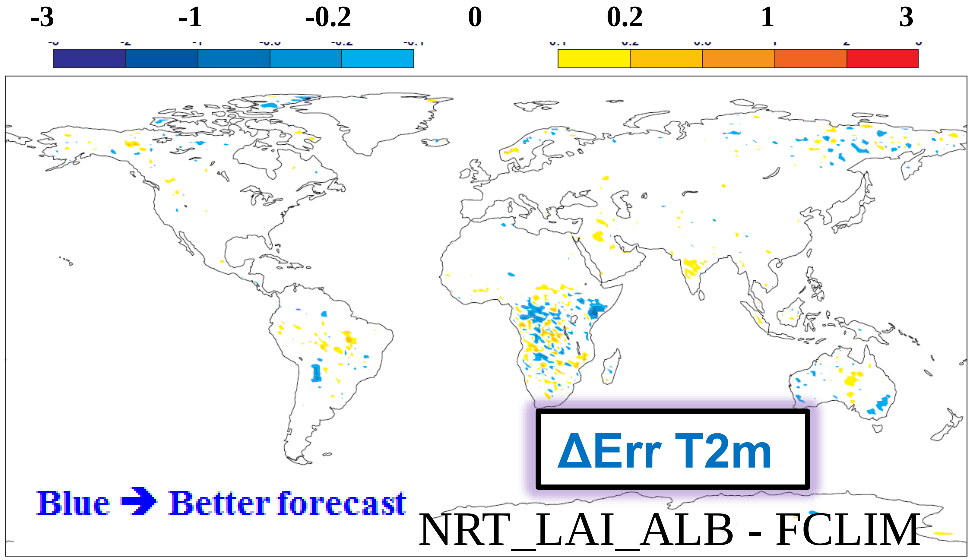
Sensible Heat flux



=> NRT LAI is able to fairly detect/monitor anomalous year
=> NRT albedo and LAI signals are covariant mainly during wet episodes.

2m temperature sensitivity in coupled run



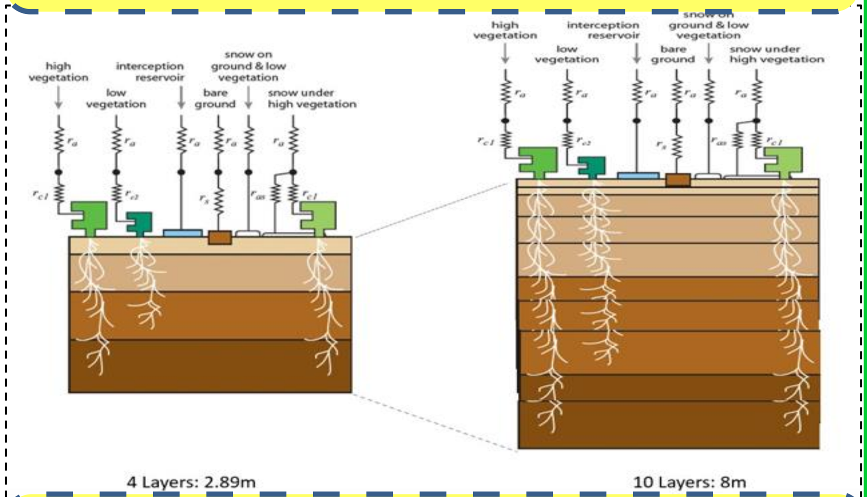


Ongoing/Perspectives

Process–oriented ECLand global parameters optimization

Time-varying vegetation
LULC &/or LAI

Improving the soil vertical discretisation



Coupled water, energy and CO2
Farquhar (LE,CO2)

Dynamic LAI

Hydrological coupling

A step wise approach:
- Independent optimization for process-related parameters in offline mode (mitigate surface model biases).
- Adaptive parameter tuning for residual errors and coupling related parameters (focus on non-observable ones)

Collaborative framework

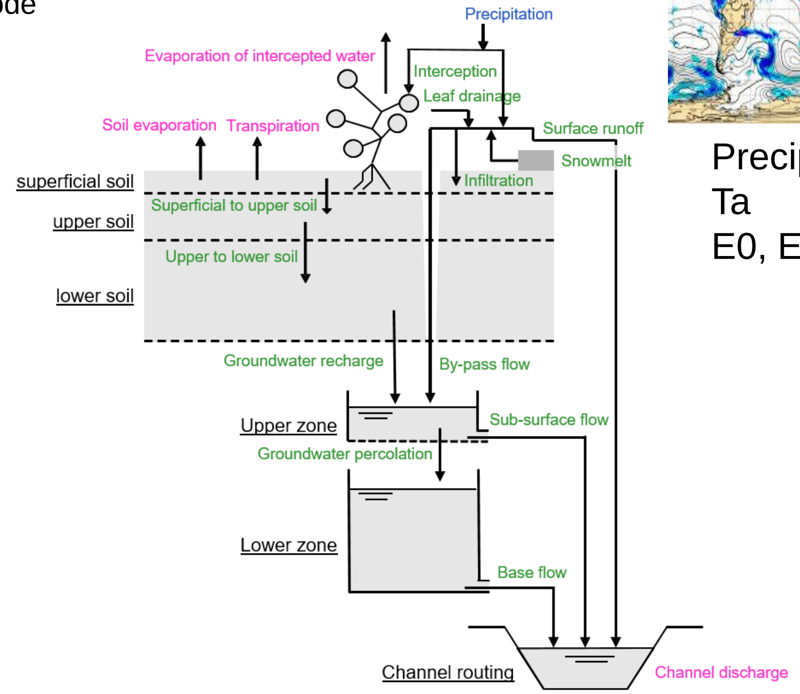
- CERISE (w. ESP and CA) : to support the vegetation dynamic and assimilation developments.
- CORSO(w. CAMS): to support the vegetation developments and coupling LE-CO2.
- DestineE to support km scale land modelling and climate fields update.
- IFS-IFSRI (w. BSC,Hydro team): to support soil hydrology and MPR developments.
- CONTROL (w. IPMA): Collaboration on vegetation developments.
- PLUMBER2 + Urban PLUMBER under the GEWEX-GLASS framework.

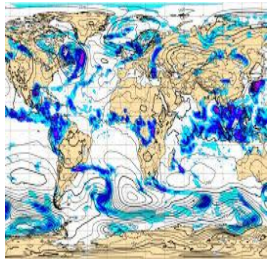
CEMS FLOODS HYDROLOGY

Emergency Management

LISFLOOD

https://github.com/ec-jrc/lisflood-code



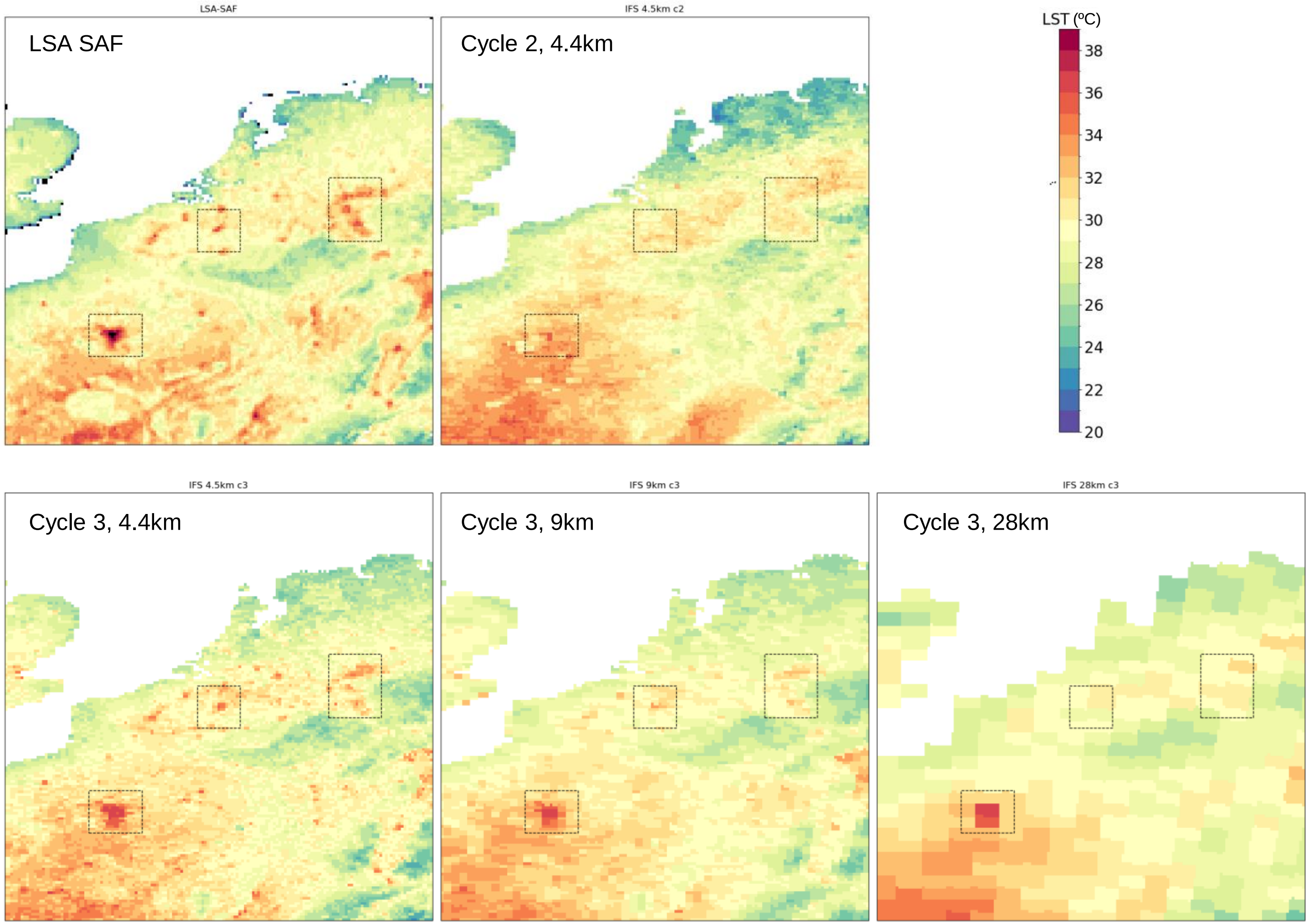


Precipitation
Ta
E0, Es, ET

Category	Description	Source
Topography	Drainage network Slope Elevation	• MERIT DEM • MERIT HYDRO
Land use fractions Crop coefficients Mannings' coeff.	Water, sealed, forest, irrigated crops, rice, other	• Copernicus Global Land Cover Layers: CGLS-LC100 collection 2 • Spatial Production Allocation Model (SPAM) - Global Spatially-Disaggregated Crop Production Statistics Data for 2010 (V 1.0) • CORINE Land Cover 2018 CLC2018
Soil properties	Soil depth, saturated/residual volumetric soil moisture, pore size index, Van Genuchten parameter (α), saturated conductivity	• ISRIC World Soil Information • PTFs proposed by Toth et al. (2015)
Vegetation	LAI for forest, irrigated crops and other	• Copernicus Global Land Cover Layers: CGLS-LC100 collection 2
Rivers	Slope, channels length, roughness, width, depth	• MERIT DEM: Multi-Error-Removed Improved-Terrain DEM • CaMa-Flood

Distributed physically-based hydrological model
Rainfall-runoff and river routing (including lakes and dams)
3 soil layers with variable soil depth
Km-scale regional and global applications

Km-scale modeling for improved realism + high-res features at surface



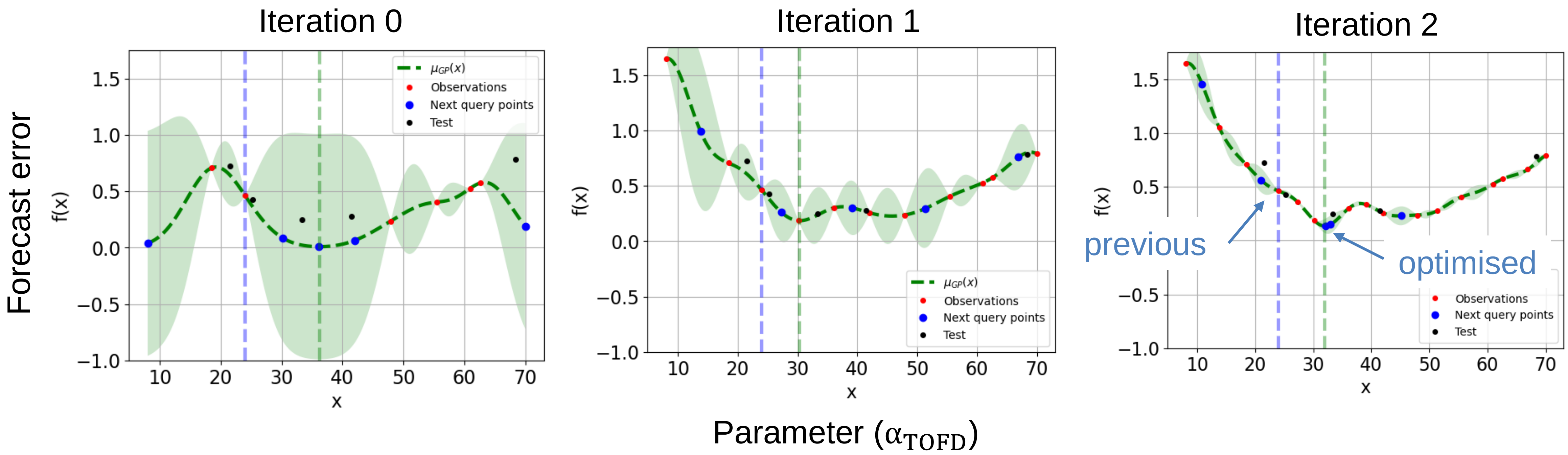
Clear benefit with resolution increase down to 4.4km

Improvements due to Land Use/Land cover over vegetated areas across cycles

New LU/LC + urban scheme shows urban imprints

T. Xabier Pedruzo Bagazgoitia

Bayesian Multi-Parameter Optimisation



Bayesian optimisation 1D example

Gaussian process emulator estimates forecast error as a function of the parameter space.

Emulator is trained with simulations sampling the parameter space.

Land Surface Emulator

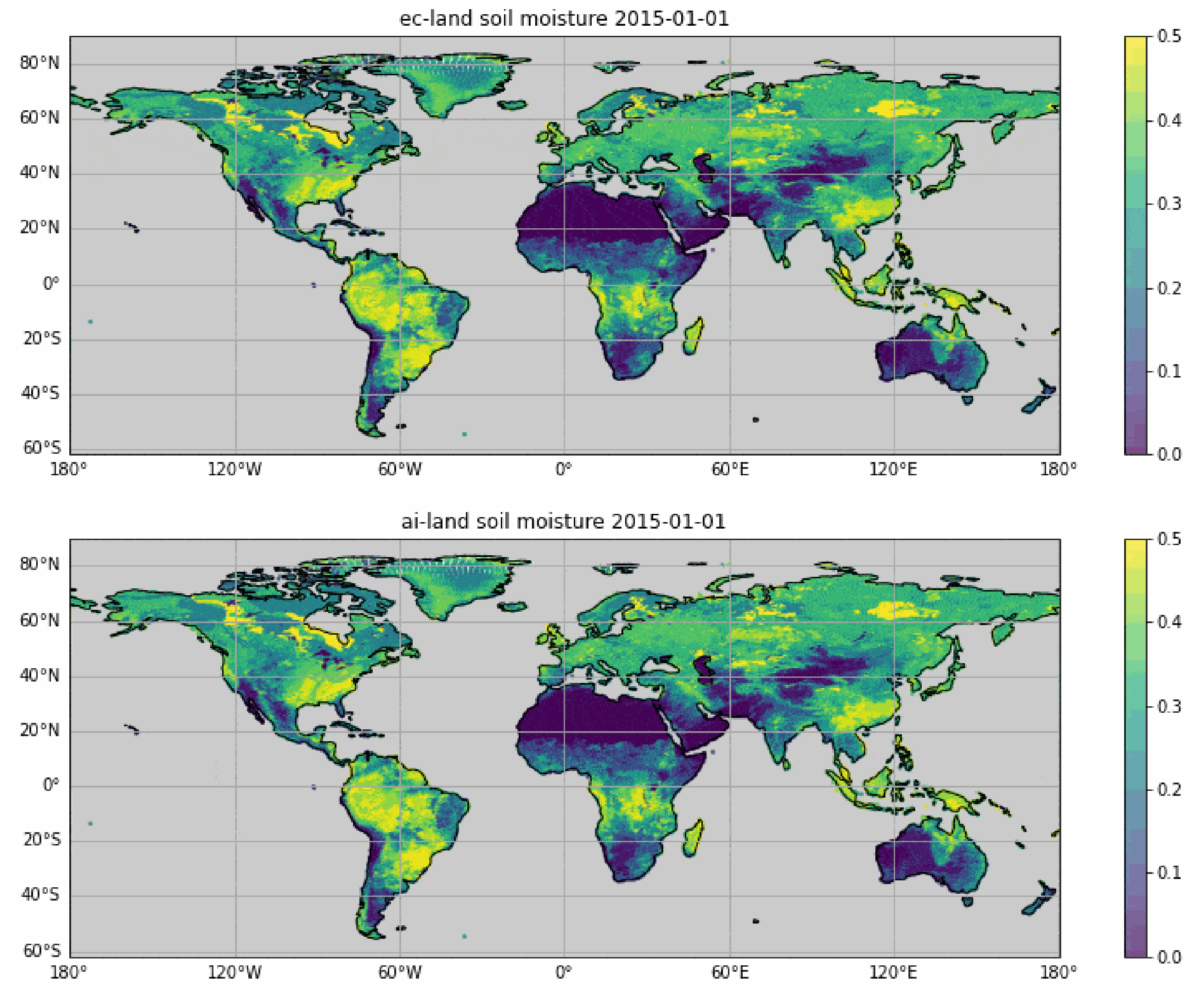
Small MLP prototype developed

Next steps:

Include more data in the **training**
- fluxes; e.g., photosynthesis & latent heat
- observations; e.g., SMAP soil moisture

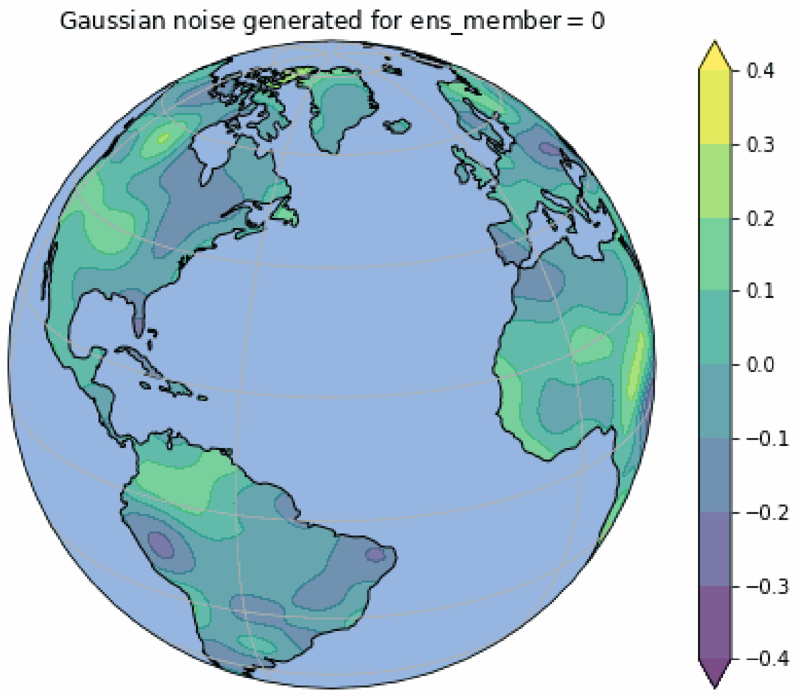
Use to improve **physical model**
- validate with observations
- parameter estimation
- replace uncertain parts of the model

Couple with AIFS
- compare with trained together version
- work towards fully coupled system



Perturbing Land ancillary Parameters

- The ECMWF Ensemble of Data Assimilations (EDA) is under-spread at the surface
- Stochastic Parameter Perturbation (SPP) approach for land surface parameters was applied on LAI and vegetation fraction to see if this can increase spread at the surface in a set of "offline" experiments (similar approach was investigated by Draper 2021).



Perturbations generated with spatial and temporal correlation length scale