SPECIAL PROJECT PROGRESS REPORT

All the following mandatory information needs to be provided. The length should *reflect the complexity and duration* of the project.

Reporting year	………………2022……………………………….……
Project Title:	Exploit observations to constrain land cover, vegetation and hydrology processes for improved near-term climate predictions over land
Computer Project Account:	……spitales…………………………….……
Principal Investigator(s):	…… Andrea Alessandri ……………………….……
	……………………………………………….……
Affiliation:	…… ISAC-CNR ………………………….……
Name of ECMWF scientist(s) collaborating to the project (if applicable)	G. Balsamo (ECMWF), S. Boussetta, T. Stockdale and M. Balmaseda
Start date of the project:	…2022…………………………………….……
Expected end date:	…2023………………………………………….……

Computer resources allocated/used for the current year and the previous one

(if applicable)

Please answer for all project resources

		Previous year		Current year	
		Allocated	Used	Allocated	Used
High Performance Computing Facility	(units)			8000000	316012
Data storage capacity	(Gbytes)			40000	1976

Summary of project objectives (10 lines max)

The objective of this special project is to exploit the latest available observational data over land to improve the representation of processes related to land cover, vegetation and hydrology that can positively contribute to skillful near-term climate predictions. Parameter-fitting and/or inverse modelling techniques will be employed to better constrain the land surface parameterizations to the available observations followed by careful verification that will be first conducted off-line through ERA-5 forced land-only simulations. Finally, a set of decadal predictions with enhanced representation of land cover, vegetation and hydrology processes will be performed to assess the improvement of the predictions.

Summary of problems encountered (10 lines max)

The porting of the decadal prediction system (DCPP framework) on Atos is still under discussion and the version(s) of EC-Earth to be included in the next decadal prediction system to be used there is still to be decided within the modelling consortium. However, the delayed switch-off of cca may allow to run a sensitivity DCPP experiment already in 2022. According to this we are working to speed up the whole setup in order to run as much as possible during summer 2022. Depending on these outcomes, we may need to apply for additional HPC resources to be spent during 2022 to complete the simulations using cca.

Summary of plans for the continuation of the project (10 lines max)

A careful evaluation of the off-line simulations will permit to decide the better land cover/vegetation configuration for the coupled prediction experiment. Accordingly, a set of retrospective decadal predictions (DCPP-sens) with the improved representation of land cover and vegetation will be performed. DCPP-sens will cover a subset of the tier-1 (Component A1) decadal hindcasts already performed in the framework of DCPP (DCPP-ctrl) at BSC (DCPP-ctrl), as a sensitivity experiment. The comparison between DCPP-sens and DCPP-ctrl will allow to assess the effect of the improved representation of land cover and vegetation on the decadal hindcasts. The usefulness of the improved decadal predictions will be evaluated with respect to the surface-climate and hydrological variables (e.g. evapotranspiration, runoff, …) comparing with available observations.

List of publications/reports from the project with complete references

Van Oorschot, F., van der Ent, R.J., Hrachowitz, M., Catalano, F., Boussetta, S., di Carlo, E., Cherchi, A., Alessandri, A., Improving the vegetation variability in land surface models based on satellite observations, in preparation

Summary of results

If submitted **during the first project year**, please summarise the results achieved during the period from the project start to June of the current year. A few paragraphs might be sufficient. If submitted **during the second project year**, this summary should be more detailed and cover the period from the project start. The length, at most 8 pages, should reflect the complexity of the project. Alternatively, it could be replaced by a short summary plus an existing scientific report on the project attached to this document. If submitted **during the third project year**, please summarise the results achieved during the period from July of the previous year to June of the current year. A few paragraphs might be sufficient.

Exploitation of available observational data to improve land cover, vegetation and hydrology processes

We used observational data of Leaf Area Index (LAI), fraction of green vegetation cover (FCover) and land cover to introduce realistic variability representation in the model vegetation, and thereby improving the variability in modeled land water and energy fluxes. Moreover, we develop an improved model parameterization of the effective vegetation cover based on the observational data. Here LAI-data at 1 km spatial and 10-daily resolution was obtained from the Copernicus Global Land Service (CLGS) for 1999-2019, and from the C3S AVHRR-based data for 1993-1999 (Verger et al., 2014; Vermote, 2019). The different products were homogenized using a cumulative distribution function matching approach. The FCover describes the fraction of green vegetation per unit ground area. Similar to the LAI, the FCover is dynamic in time both seasonally and inter-annually. FCover was also obtained at a 1km spatial and 10-daily temporal resolution from CLGS for 1999-2019 (Baret et al., 2013).
Here the land cover describes vegetation type and areal coverage. We used the yearly ESA-CCI land cover data at a 300m spatial and yearly temporal resolution for the time period 1993-2019 (ESA, 2017).
The model effective vegetation cover represents the fraction of vegetation that effectively transpires. This fraction is described by a function of LAI trough an exponential relation (1-exp(-k*LAI)), with k the canopy light extinction coefficient. In previous modelling studies, k was set to a constant value of 0.5 (Alessandri et al., 2017; Krinner et al., 2005). However, the shape of this relation is different for different vegetation types (Chen et al., 2005). Therefore we used the FCover and LAI data (10-daily resolution) together with the ESA-CCI land cover (yearly resolution) to suitably estimate the shape of this exponential relation for different vegetation types by a non-linear least squares optimization. Figure 1 shows that the k=0.5 overestimates the variability in effective vegetation cover, especially for high vegetation types. The results of the fitting with the different values of k for each vegetation type has been implemented in the HTESSEL model.

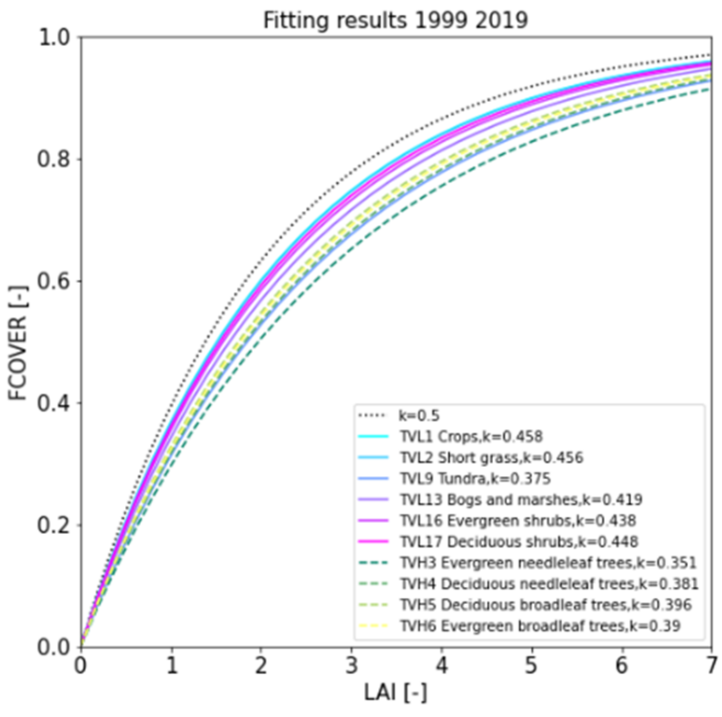

Figure 1. Results of nonlinear least squares fitting of LAI and FCover data for 1 km spatial and 10-daily temporal resolution for 1999-2019 for different vegetation types (based on ESA-CCI land cover data).

Off-line land-only simulations forced by ERA-5

We performed a first set of offline simulations (1980-2019 period, hourly forcing) to evaluate the effects of the vegetation variability introduced by using the observational data (LAI, land cover and effective cover). The model evapotranspiration was evaluated by comparing to evapotranspiration from the DOLCE v3 dataset, in which an optimal linear combination of different evaporation products is derived (Hobeichi et al., 2021). Here we evaluate the combined effect when implementing inter-annually varying LAI, inter-annually varying land cover and the vegetation specific exponential relation for effective vegetation cover (Fig. 1) (LAI_LC_EC experiment) compared to seasonally varying LAI, fixed land cover and the original (k=0.5) exponential relation for effective vegetation cover (CTR experiment). In Figure 2 we observe that the correlation of the model inter-annual anomalies of evaporation and the DOLCE data improves for the LAI_LC_EC experiment in most regions. However, we see a correlation reduction in some regions of the boreal forests. This effect may be attributed to errors in the inter-annually varying LAI in those regions. On the other hand, we observe a considerable reduction in model evaporation bias in the boreal forests when introducing the vegetation variability (not shown).

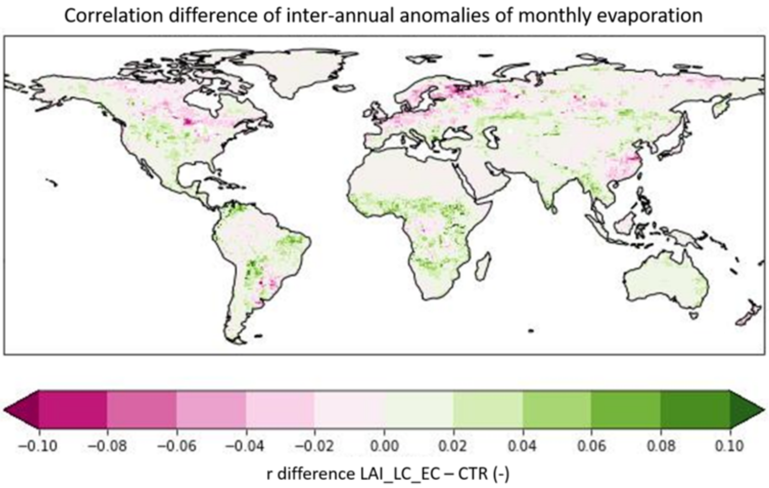

Figure 2. Pearson correlation difference between experiments LAI_LC_EC and CTR for inter-annual anomalies of evaporation compared to the DOLCE v3 evaporation dataset. Green is improvement, pink is reduction in correlation.

This preliminary analysis will be extended to include the comparison of more off-line sensitivity simulations and the outcomes will be discussed in a peer-reviewed paper for the scientific community that is currently in preparation:

Van Oorschot, F., van der Ent, R.J., Hrachowitz, M., Catalano, F., Boussetta, S., di Carlo, E., Cherchi, A., Alessandri, A., Improving the vegetation variability in land surface models based on satellite observations, in preparation

Workflow manager configuration and setup

In collaboration with the colleagues at Barcelona Supercomputing Centre (BSC), the Autosubmit workflow manager has been employed to set-up a semi-automated procedure for the production of retrospective decadal forecasts. The EC-Earth runtime scripts are being modified in order to perform parallel scheduling of the decadal predictions and post-processing and by setting up the required running environment including preparation and transfer in the working directory of the initial and boundary conditions required by the model.

References:

Alessandri, A., Catalano, F., De Felice, M. et al. Multi-scale enhancement of climate prediction over land by increasing the model sensitivity to vegetation variability in EC-Earth. Clim Dyn 49, 1215–1237 (2017). https://doi.org/10.1007/s00382-016-3372-4

Baret, F., Weiss, M., Lacaze, R., Camacho, F., Makhmara, H., Pacholczyk, P., Smets, B., 2013: GEOV1: LAI, FAPAR Essential Climate Variables and FCover global times series capitalizing over existing products. Part1: Principles of development and production. Remote Sensing of Environment 2013, vol. 137, 299–309.

Chen, J.M., C.H. Menges, S.G. Leblanc, 2005: Global mapping of foliage clumping index using multi-angular satellite data, Remote Sensing of Environment, 97(4), 447-457. https://doi.org/10.1016/j.rse.2005.05.003

ESA. Land Cover CCI product User Guide Version 2. tech. Rep. (2017). Available at: maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-Ph2-PUGv2_2.0.pdf

Hobeichi, S., Abramowitz, G., and Evans, J. P.: Robust historical evapotranspiration trends across climate regimes, Hydrol. Earth Syst. Sci., 25, 3855–3874, https://doi.org/10.5194/hess-25-3855-2021, 2021.

Krinner, G., Viovy, N., de Noblet-Ducoudré, N., Ogée, J., Polcher, J., Friedlingstein, P., Ciais, P., Sitch, S., and Prentice, I. C. (2005), A dynamic global vegetation model for studies of the coupled atmosphere-biosphere system, Global Biogeochem. Cycles, 19, GB1015, doi:10.1029/2003GB002199.

Verger, A., Baret, F., Weiss, M., 2014: Near real-time vegetation monitoring at global scale. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 2014, 7, 3473-3481. doi:10.1109/JSTARS.2014.2328632

Vermote, Eric; NOAA CDR Program. (2019): NOAA Climate Data Record (CDR) of AVHRR Leaf Area Index (LAI) and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), Version 5. [indicate subset used]. NOAA National Centers for Environmental Information. https://doi.org/10.7289/V5TT4P69.