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D6.3 Report providing feedback on the impact of land data assimilation in reanalysis on seasonal forecasts

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1 Executive Summary

The new ECMWF offline land data assimilation system (LDAS) provides fast, cycle-consistent land-reanalysis that enable more frequent updates of land initial conditions for seasonal and subseasonal hindcasts and improves consistency with real-time forecast initialization. In this report it is used to initialise seasonal hindcasts with the ECMWF and Met Office prediction systems. Its introduction leads to a small overall improvement in 2-m temperature skill in hindcasts with the ECMWF system for both JJA and DJF, largely by improving the effective soil-moisture–atmosphere coupling, particularly in the Southern Hemisphere during DJF, indicating beneficial shifts in soil-moisture distribution. However, notable degradations are seen in some areas—for example, reduced DJF T2m skill over North America, likely related to snow-density errors, and degradations over Western Europe in JJA associated with increasing the effective soil-moisture atmosphere coupling strength. The Met Office JJA hindcasts show an overall negative T2m response, with causes still under investigation.

The use of LDAS initial conditions in ECMWF hindcasts improves atmospheric scores despite degrading soil-moisture hindcast skill, relative to GLEAMv3.8, and soil-moisture analysis fit to in-situ soil-moisture data. The LDAS also produces localized unrealistic soil-moisture trends, potentially due to variations in SYNOP data availability. These findings align with known behaviour in medium and short-range Numerical Weather Prediction systems: assimilating screen-level pseudo-observations can enhance lower-atmosphere forecast skill by improving surface fluxes, but often at the cost of soil-moisture realism. It highlights areas where the LDAS as well as the representation of coupled land-atmosphere processes in the ECMWF model can be improved.

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2 Introduction

The current set of contributions to the C3S Multi-model seasonal forecasting system do not currently utilise land data assimilation (DA) in the generation of initial conditions for their hindcasts, instead they are typically started from initial conditions generated by an “open-loop” land model forced by reanalysis meteorology. In the case of ECMWF the realtime forecasts with the current seasonal system SEAS5 use the operational Land DA system (LDAS) leading to potential inconsistency with the hindcasts, which may impact the quality of operational products.

A new "offline" LDAS has been developed at ECMWF specifically for this application. It allows land reanalyses to be run quickly with a new model cycle and also facilitates consistent land initial conditions between the hindcast and real-time forecasts.

In this report we evaluate the new LDAS system, and hindcasts initialised from it, and compare these to the open-loop and hindcasts initialised from the open-loop respectively.

2.1 Background

The scope of CERISE is to enhance the quality of the C3S reanalysis and seasonal forecast portfolio, with a focus on land-atmosphere coupling.

It will support the evolution of C3S, over the project’s 4 year timescale and beyond, by improving the C3S climate reanalysis and the seasonal prediction systems and products towards enhanced integrity and coherence of the C3S Earth system Essential Climate Variables.

CERISE will develop new and innovative ensemble-based coupled land-atmosphere data assimilation approaches and land surface initialisation techniques to pave the way for the next generations of the C3S reanalysis and seasonal prediction systems.

These developments will be combined with innovative work on observation operator developments integrating Artificial Intelligence (AI) to ensure optimal data fusion fully integrated in coupled assimilation systems. They will drastically enhance the exploitation of past, current, and future Earth system observations over land surfaces, including from the Copernicus Sentinels and from the European Space Agency (ESA) Earth Explorer missions, moving towards an all-sky and all-surface approach. For example, land observations can simultaneously improve the representation and prediction of land and atmosphere and provide additional benefits through the coupling feedback mechanisms. Using an ensemble-based approach will improve uncertainty estimates over land and lowest atmospheric levels.

By improving coupled land-atmosphere assimilation methods, land surface evolution, and satellite data exploitation, R&I inputs from CERISE will improve the representation of long-term trends and regional extremes in the C3S reanalysis and seasonal prediction systems.

In addition, CERISE will provide the proof of concept to demonstrate the feasibility of the integration of the developed approaches in the core C3S (operational Service), with the delivery of reanalysis prototype datasets (demonstrated in pre-operational environment), and seasonal prediction demonstrator datasets (demonstrated in relevant environment).

CERISE will improve the quality and consistency of the C3S reanalysis systems and of the components of the seasonal prediction multi-system, directly addressing the evolving user needs for improved and more consistent C3S Earth system products.

2.2 Scope of this deliverable

2.2.1 Objectives of this deliverable

The aim of this deliverable is to describe a scientific assessment of the ECMWF offline LDAS system and its impact on seasonal forecast quality. Currently, none of the seasonal forecasting systems contributing to the C3S multi-model seasonal system utilise land-data assimilation to constrain the land-surface state used for initial conditions. Instead, the systems run a version of their land-model in either "offline" mode (forced with atmospheric reanalysis, such as ERA5) or coupled to an atmospheric model that is being relaxed to reanalysis (see Day et al., 2025). Land DA has been shown to be beneficial at subseasonal timescales (Nair et al., 2024) and we investigate this question for the seasonal time scales with both the ECMWF and MetO forecasting systems.

2.2.2 Work performed in this deliverable

In this deliverable the work outlined in The Description of Action (WP6 T6.2): to assess the impact of developments in reanalysis methods, specifically the impact of land-DA, will be described.

2.2.3 Deviations and counter measures

No deviations have been encountered.

2.2.4 Reference Documents

[1] Project 101082139- CERISE-HORIZON-CL4-2021-SPACE-01 Grant Agreement

2.2.5 CERISE Project Partners:

ECMWF	European Centre for Medium-Range Weather Forecasts
Met Norway	Norwegian Meteorological Institute
SMHI	Swedish Meteorological and Hydrological Institute
MF	Météo-France
DWD	Deutscher Wetterdienst
CMCC	Euro-Mediterranean Center on Climate Change
BSC	Barcelona Supercomputing Centre
DMI	Danish Meteorological Institute
Estellus	Estellus
IPMA	Portuguese Institute for Sea and Atmosphere
NILU	Norwegian Institute for Air Research
MetO	Met Office

3 Summary of experiments and initial conditions

3.1 Offline land data assimilation system

As part of the Integrated Forecast System (IFS), an offline LDAS has been developed that replicates the primary characteristics of the operational coupled land DA system employed at ECMWF for soil moisture and snow cover. Other variables, such as lake fields, are freely evolving. Similar to the land assimilation in the operational IFS, the Simplified Ensemble Kalman Filter (SEKF) assimilates European Remote Sensing Satellite Scatterometer (ERS-SCAT; 1992–2006) and Advanced Scatterometer (ASCAT; 2007 onwards) surface soil moisture observations, as well as Interactive Multisensor Snow and Ice Mapping System (IMS) snow cover and pseudo screen-level observations, over 12-hour assimilation windows. Although the SEKF algorithm is similar to the IFS algorithm, the SEKF is implemented in 'offline' mode and is driven by atmospheric reanalysis (ERA5). For convenience, the 12-hour assimilation windows run from 00:00 to 12:00 UTC and from 12:00 to 24:00 UTC, i.e. three hours ahead of the long-window DA in the IFS. Soil moisture increments are added at the end of the assimilation window. While the SEKF algorithm is similar to that of the IFS, its implementation in "offline" mode means it is constrained by the atmospheric reanalysis ERA5.

The SEKF configuration described in de Rosnay et al. (2013) is used, with finite differences rather than ERA5-EDA Jacobians, as the former was found to perform better for land reanalysis applications. An SEKF snow analysis has also been implemented that assimilates Cryoclim (from 1987-2010) and IMS (from 2010 onwards) snow cover observations.

3.2 Seasonal hindcast description

Here we compare pairs of seasonal hindcast experiments with and without land DA run using the ECMWF and Met Office seasonal forecast systems. The same ECMWF analysis outputs are used to initialise each system. The experiments in each pair differ only by the choice of land initial conditions. One hindcast set was initialised with the ECMWF Offline Land Data Assimilation System (LDAS) and the other was initialised with an open-loop run with the ECMWF land-surface model ecLand.

The hindcast experiments were run with CY49R1 of the Integrated Forecasting System, in the case of ECMWF (see ECMWF (2025a) and ECMWF (2025b) for a description) and GloSea6-GC3.2 (Kettleborough et al., *in review*) in the case of the Met Office. The ensemble size for each hindcast is 51 for ECMWF, and 20 for the Met Office. The hindcasts were initialised on 1st May 1993-2022 for both ECMWF and the Met Office and run over the June to August (JJA) season, when the impact on the northern hemisphere atmospheric skill is expected to be more significant. Further to the core intercomparison, ECMWF additionally produced a hindcast initialised on the 1st November to examine the December to February (DJF) season

The Met Office experiments were run coupled to an ocean model, whereas the ECMWF experiments were run in atmosphere only mode, with prescribed sea surface temperatures. This difference will promote higher scores in the ECMWF hindcasts than the MetO but is unlikely to strongly affect the overall difference between the LDAS and open-loop initialised runs, which is the principal aspect that is addressed by this analysis.

4 Results

4.1 Evaluation of ECMWF land analysis experiments

In this section we evaluate two versions of the ECMWF offline LDAS experiment compared to an open-loop (no DA) offline simulation with ecLand. Note that these experiments are used to initialise subsequent hindcasts by both ECMWF and MetO.

4.1.1 Soil-moisture: evaluation against in-situ

In order to demonstrate the impacts of the soil moisture and snow data assimilation in ecLand, it was necessary to run three experiments. Two LDAS experiments were run, the first with snow data assimilation only (ies2) and the second with both the soil and snow data assimilation (iene). These were compared against a control open-loop experiment (ieo7). The three experiments are listed in Table 1.

The validation was performed using in situ soil moisture (SM) and temperature (ST) data over networks in the United States (SCAN, USCRN, SNOTEL), France (SMOSMANIA), Spain (REMEDHUS), Germany (TORENO), Australia (OZNET) and Brazil (CEMADON ACQUA and CEMADON AGRO). The data was collected from the International Soil Moisture Network (ISMN, Dorigo et al., 2011; 2013). Since 2022 it has been hosted and managed by the International Centre for Water Resources and Global Change (ICWRGC) and the Federal Institute of Hydrology (BfG) in Germany. The analysis focusses on the period between January 2010 to December 2019, when the ISMN data coverage is highest.

Experiment	Soil Moisture analysis	Snow analysis
ieo7 (control)	No	No
ies2	No	Yes
iene	Yes	Yes

Table 1: List of offline land reanalysis experiments.

For Soil Moisture (SM), a total of 837 stations were used for the surface (5 cm depth) and 724 stations for the root-zone (0-1 m depth) after the quality control. The following Taylor diagrams in Fig. 1 measure the dataset's skill based on the correlation coefficient and the variability. In these diagrams the perfect performance would be at the position of the star (i.e. corr=1, normalised standard deviation=1). The surface soil moisture performance is slightly., but significantly, degraded for iene (full LDAS) compared to the other experiments on average. The root-zone SM performance is also slightly degraded for iene compared to the other experiments on average. In terms of the anomaly correlation coefficients, 27.8% of the stations for the root-zone SM were significantly degraded and 1.4% were significantly improved (see Table 2).

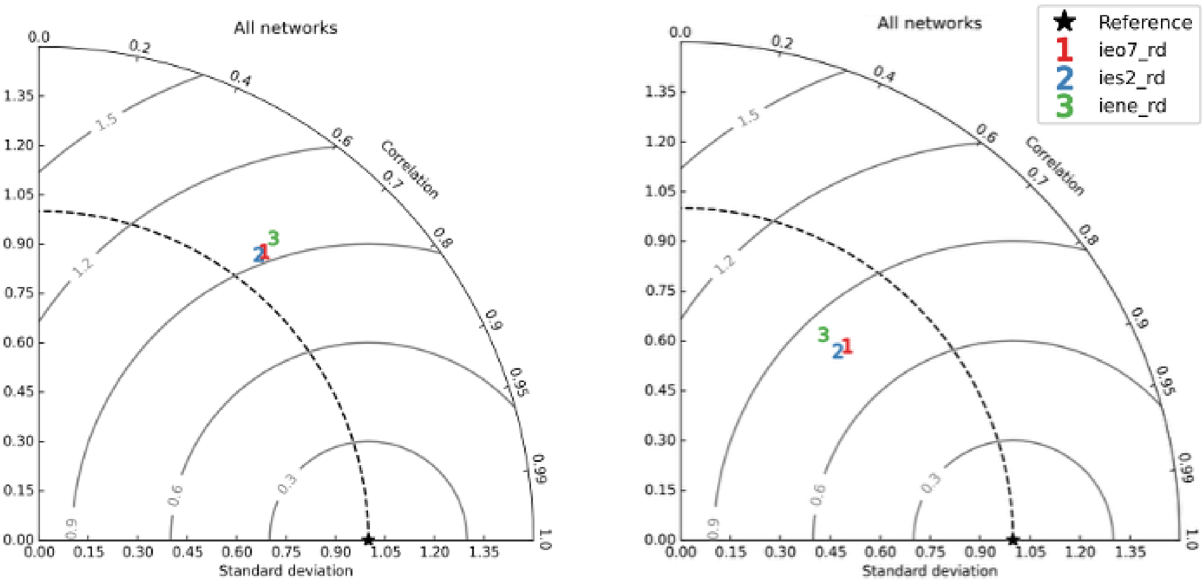

Fig 1: Taylor diagrams showing the surface (left) and root-zone (right) SM performance for the experiments in Table 1, averaged over 2010-2019.

For Soil Temperature (ST), a total of 701 stations were used for the surface, and 673 stations were used for the root-zone validation after the quality control. From the Taylor diagrams (Fig 2), the performance is similar for the surface and root-zone ST for all the experiments. However, in terms of the anomaly correlation coefficients, about 10% of the stations are significantly degraded for the surface and root-zone ST in both LDAS experiments (iene and ies2; see Table 2).

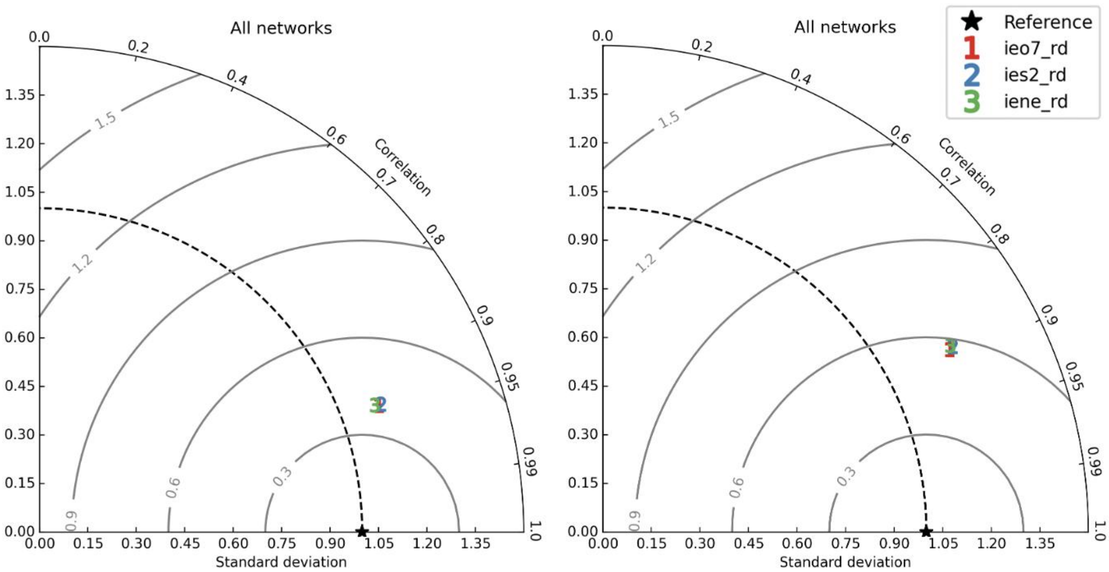

Fig 2: Taylor diagrams showing the surface (left) and root-zone (right) ST performance for the experiments in Table 1, averaged over 2010-2019.

Variable	Number of stations	ies2 vs control		iene vs control	
		%sig improved	%sig degraded	%sig improved	%sig degraded
Surface SM	837	0	0.1	2.3	4.4
Root-zone SM	724	0	0.3	1.4	27.8
Surface ST	668	0.3	9.7	0.6	11.1
Root-zone ST	670	1.0	9.2	4.0	11.6

Table 2: Table showing the % of ISMN stations where the anomaly correlation of SM and ST is improved in each experiment relative to the control over the period 2010-2019.

The degradations in the fit to in-situ soil temperature and soil-moisture data observations are not unexpected and are consistent with what has been seen before with the use assimilation of screen level 2m temperature and relative humidity for soil-moisture assimilation (Draper et al., 2011). Draper et al., (2011) showed that while the assimilation of screen level “pseudo-observations” generally improved the skill of low-level atmospheric forecasts it often leads to unrealistic model soil-moisture. As a result, it is not expected that the procedure will improve the soil-moisture analysis, but it will rather improve the skill of atmospheric forecasts initialised from the resulting analysis as has been shown for the medium-range (e.g. Drusch et al., 2009). However, the impacts of this procedure for seasonal timescales, where soil-moisture anomalies are a source of predictability, has not been investigated.

4.1.2 Snow: evaluation against in-situ

A database of in-situ snow course observations developed for the SNOWPEX project (Mudryk et al., 2025) provides an independent source of verification data to compare the LDAS (iene) and open-loop (ieo7) experiments (Fig. 3).

The LDAS has somewhat higher mean absolute errors than the open-loop, partly, but not entirely, related to the 3m maximum bound applied to the snow water equivalent for land reanalysis applications, resulting in the open-loop having a better fit in areas with very deep snow (see Fig 4). It is difficult to estimate the number of independent observations in the SNOWPEX dataset, but assuming they are independent makes the lower fit to observations in the LDAS significant at the 1% level. Subsetting for just the less deep snowpacks, less than 1.5m results in the LDAS being a better fit for SWE, but still a poorer fit for density and depth.

In the snow assimilation, only snowcover fraction is assimilated, as a result one would not expect much divergence in the interior of the snowpack, since for locations away from the snow edge there shouldn't be any increments to explain this divergence between the two experiments. Further investigation into this has revealed that the density bounds, which for the physical model were set between 50 and 500kg m^{-3}, were set to 100 and 450kg m^{-3} in the version of the LDAS used in this report. This was consistent with an older version of the EC-land model and will be corrected for future land-reanalysis runs. Additional testing to see if this will explain the statistically significant degradation described in the paragraph above is ongoing.

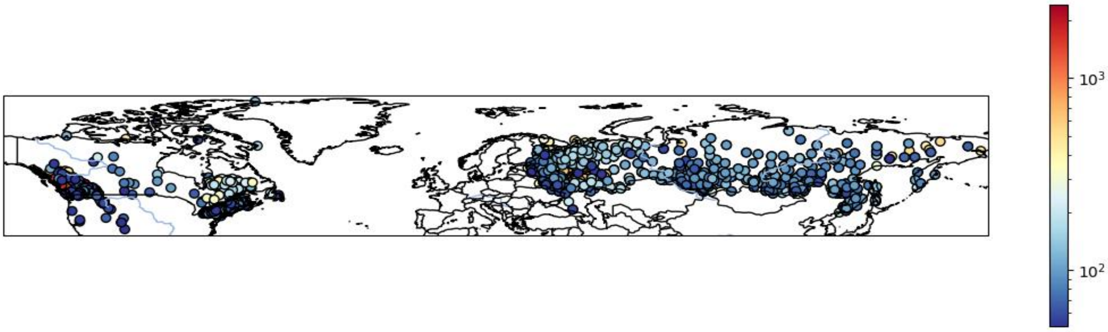

Fig 3: Locations of snow surveys contained in the SNOWPEX dataset, coloured by the total number of surveys during the period 1980-2021.

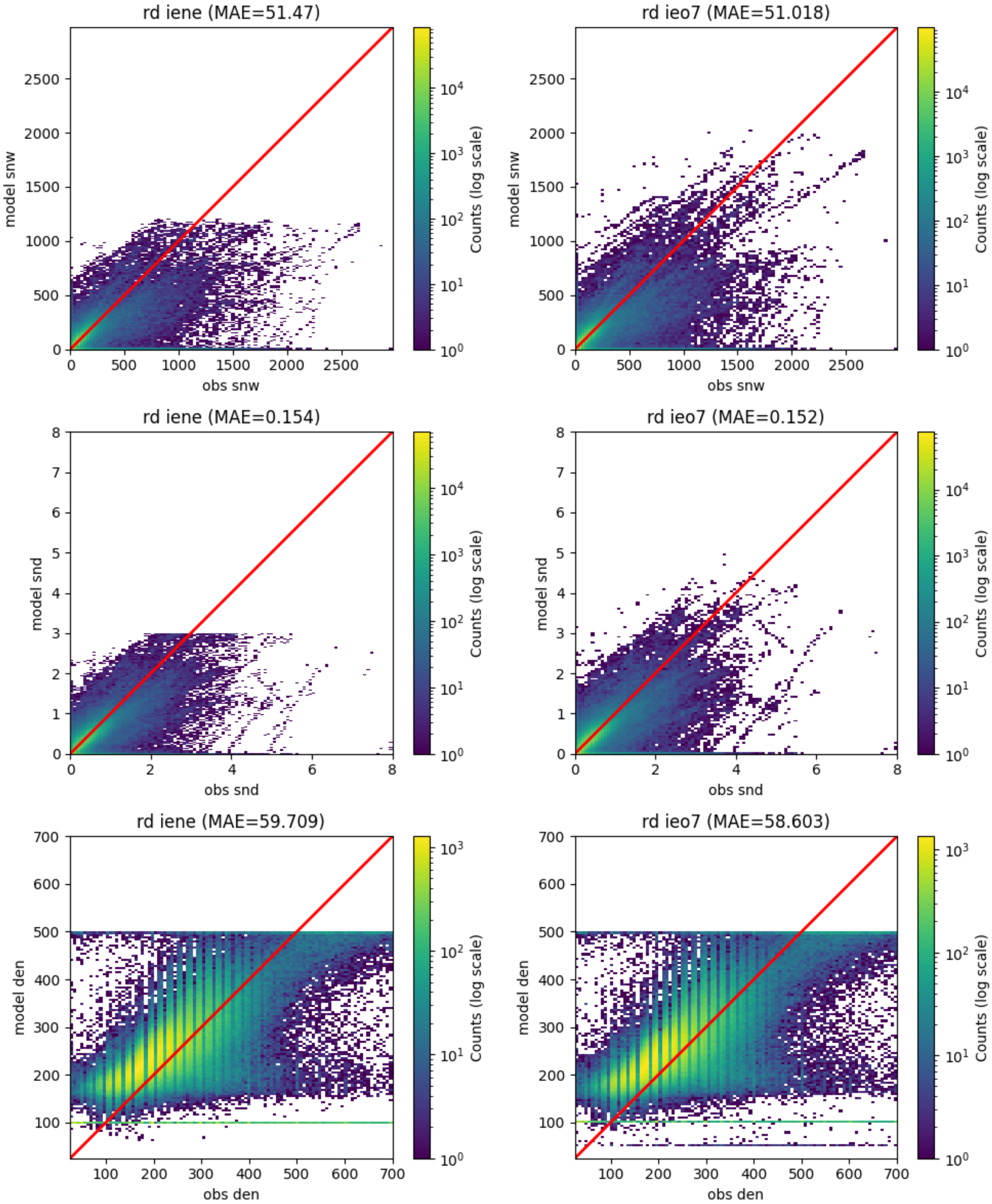

Fig 4: Histograms of observations vs open-loop (left column) and observations vs LDAS (right column) for snow water equivalent (in kg m^{-2}; top row), snow depth (in m; middle row) and snow density (in kg m^{-3}; bottom row).

4.1.3 Soil-moisture trends

Trends in root-zone soil moisture are broadly consistent between the GLEAMv3.8, LDAS and Open-loop experiments with drying trends over SW North America, South America, Central Africa and Western Eurasia, and wetting over India, parts of Southern Africa and high latitudes of North America and Eurasia (Fig. 5).

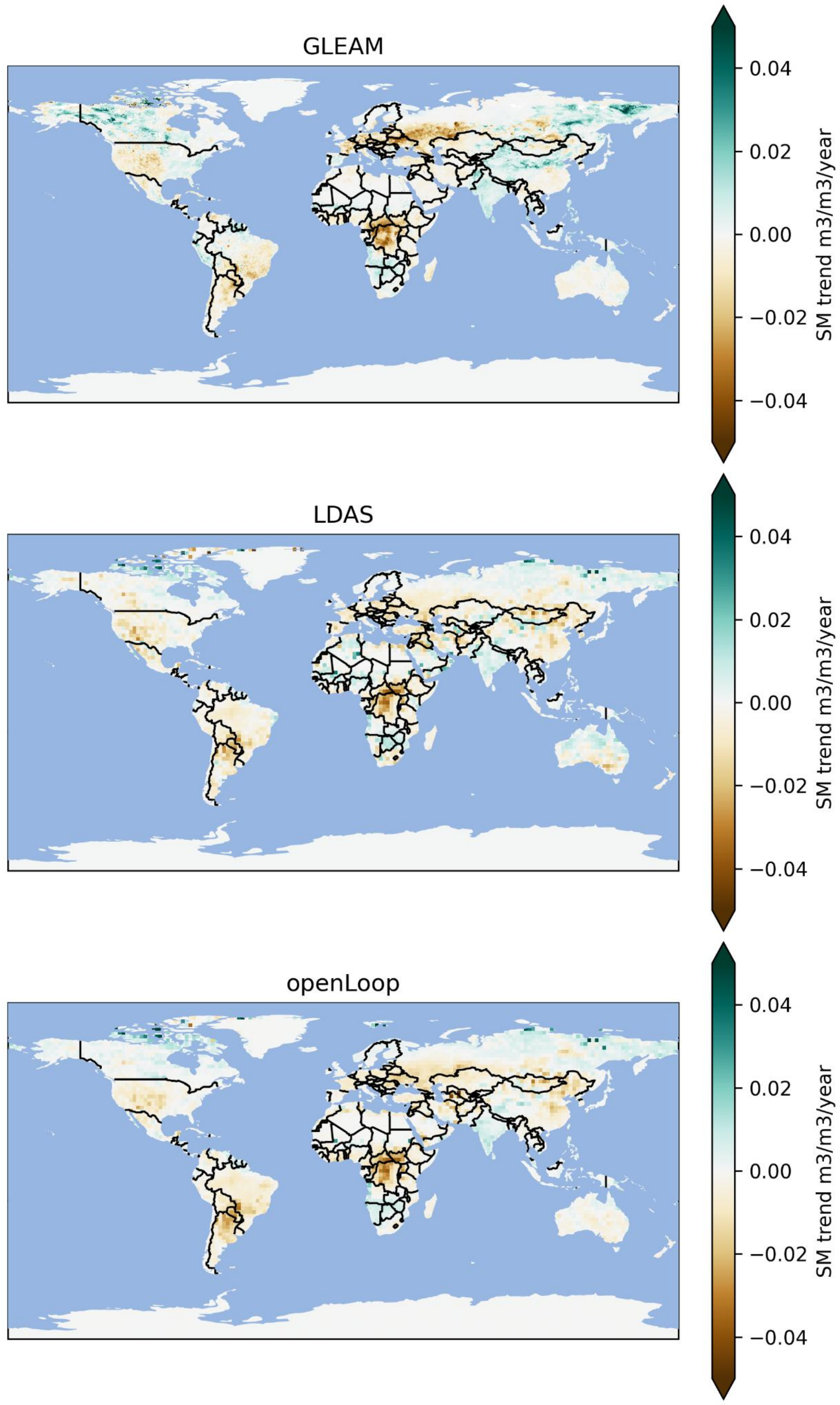

Fig 5: Trend in annual mean root-zone soil moisture from 1990-2022 using least squares regression from GLEAMv3.8, LDAS and Open-loop experiments.

Focussing on Eurasia and North Africa we highlight some points with trends in the LDAS that are not common with GLEAMv3.8 or the ecLand open-loop and do not look physically realistic (Fig. 6). For example, time-series for two locations in Algeria are shown. In the first of these there is close agreement with the open-loop until about 2005 at which point a strongly positive trend develops that is not seen in the other timeseries (similar behaviour can also be seen at a point in Iran). In the timeseries shown in the bottom right panel there is a negative trend during the initial first few decades shown, with soil-moisture initially higher, but then reducing sharply before rapidly increasing again in the last few years. It may be that such behaviour is caused by inconsistency in the available SYNOP T2m or RH2m data, which is used to infer soil-moisture increments, for example, a station only being present for part of the reanalysis period.

In other locations the year-to-year variations and long-term trends are consistent with the other experiments, suggesting the trends are a response to variations in the ERA5 forcing data which is common to both analyses.

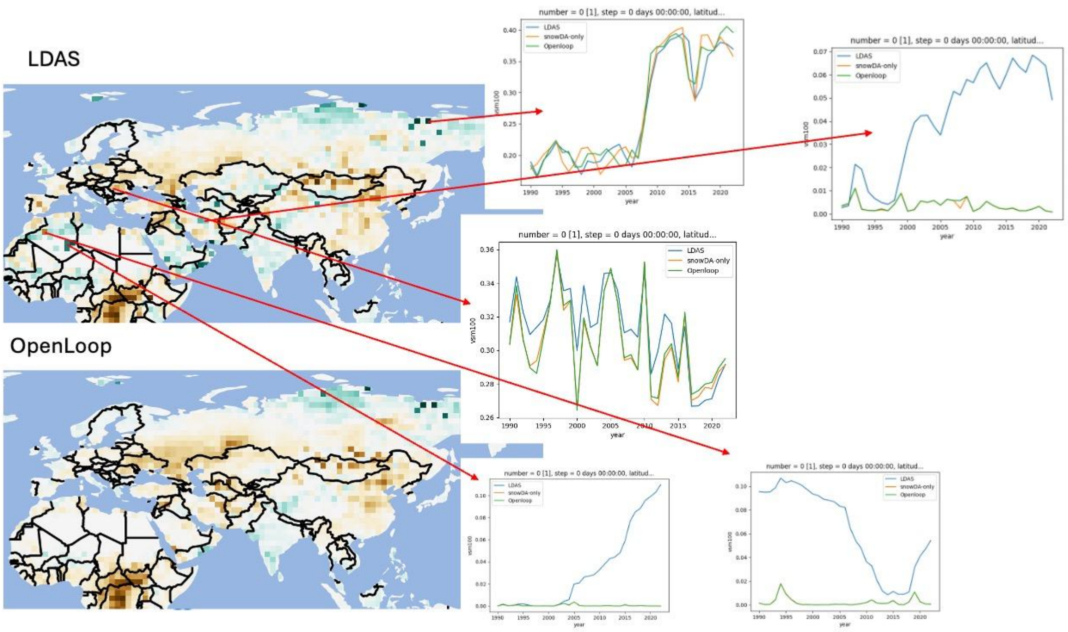

Fig. 6: Zoomed in version of the previous figure with timeseries for various points.

4.2 Impact of land DA in seasonal hindcasts

4.2.1 Soil-moisture

Although the mean state of soil-moisture is highly model dependent and hard to assess (e.g. Koster et al., 2009), seasonal hindcasts tend to do well at predicting seasonal soil-moisture anomalies (see Day et al., 2025) due to its long persistence timescale.

Soil-moisture anomalies correlation, verified against GLEAM, are somewhat reduced overall in the LDAS initialised ECMWF and MetO hindcasts, compared to the open-loop run, and highly reduced in some locations (Figs 7, 8). This is potentially the impact of the issues with trends mentioned above in Section 4.1.3.

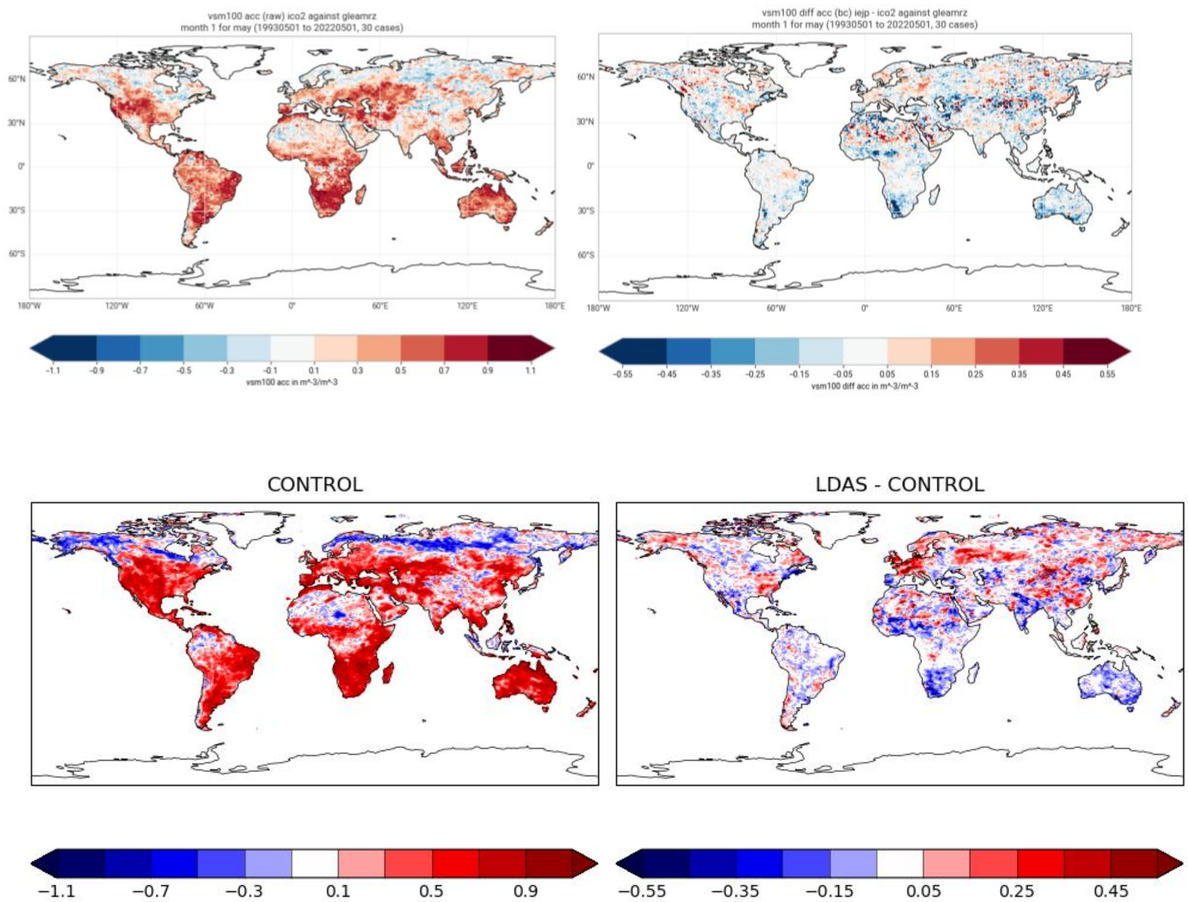

Fig 7 Anomaly correlation between JJA top 1m soil moisture (in m3/m3) in the ECMWF (top) and MetO (bottom) control hindcast set and observed root-zone soil moisture (left) and the difference between the corresponging LDAS initialised hindcasts and the control hindcasts (right). The ECMWF analysis is for 1993-2022 using theGLEAMv3.8 dataset, while the MetO analysis is for 1993-2016 using GLEAMv4.2.

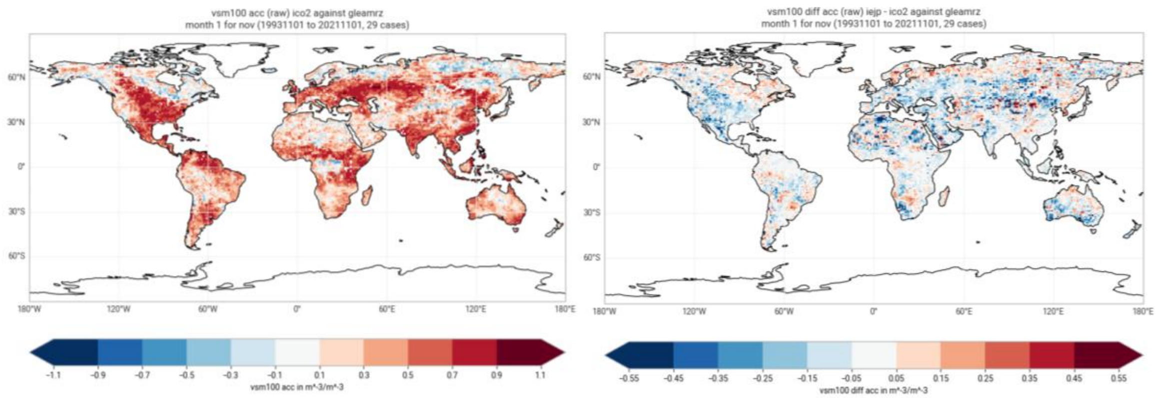

Fig 8: As fig 7 above but for DJF with the ECMWF hindcasts.

4.2.2 Snow

Snow reliability assessment is performed for the two ECMWF hindcasts iejp (with LDAS initial conditions) and ico2 (with open-loop initial conditions) in years 1993 – 2022. Analyzed are winter-mean (DJF) snow water equivalent (SWE) in comparison with ESA Snow-CCI SWE dataset, which provides coverage in the Northern Hemisphere excluding mountainous regions, glaciers and Greenland. Two binary events based on terciles of the long-term distribution are considered i) low - and ii) high snow accumulation winters, that correspond to i) lower tercile and ii) upper tercile. In order to quantify the reliability of forecasts, we apply categorization based on the slope of the best-fit reliability line and its uncertainty following Weisheimer and Palmer (2014). The uncertainty around the best-fit reliability line is assessed as 90 percent confidence interval obtained from 1000 bootstrap resamples with replacement.

Fig 9 shows the results. In all cases, snow hindcasts are indicated as reliable in the Northern Hemisphere. For low snow accumulation winters, both experiments indicate marginally useful reliability. Despite that, the slopes of best-fit reliability lines have slightly improved in the iejp experiment. For high snow accumulation winters, the experiment iejp shows a significant improvement in regions Central North Asia (CNAS) and Eastern North Asia (ENAS) in terms of snow reliability. This indicates that LDAS initial conditions contribute positively to the snow amount in winter, especially over central and eastern Eurasia.

One should keep in mind that snow reliability assessment here is performed over the non-mountainous terrain due to ESA Snow-CCI data availability. Performing similar assessment against reanalysis-type products that include mountains, may result in slightly changed reliability categories.

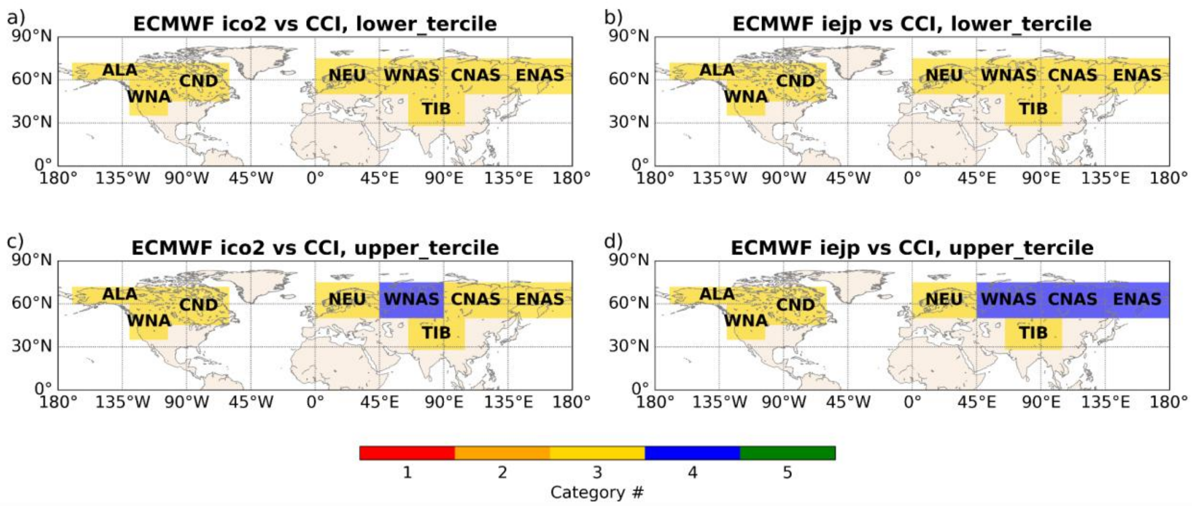

Fig 9. Reliability of the ECMWF snow re-forecasts in DJF 1993-2022 for (a) ico2 experiment in low snow winters, (b) iejp experiments in low snow winters, (c) ico2 experiment in high snow winters, and (d) iejp experiments in high snow winters. Reliability categories are color-coded following Weisheimer and Palmer (2014) and are 5 – perfect, 4 – useful, 3 – marginally useful, 2 – not useful and 1 – dangerous.

4.2.3 Atmospheric fields and coupling

The continuous ranked probability skill score (CRPSS) of T2m in the ECMWF an MetO control hindcasts is generally positive or zero over land in DJF (in the case of ECMWF) and JJA (for both) except for in some regions where the strength of soil-moisture-atmosphere coupling is too strong (regions surrounded by green contours in Figs 10 and 12) as seen in Day et al. (2025). The metric used to assess the soil-moisture atmosphere coupling is the I_{SM-}

$_{T2m}=\sigma(T2m)\rho(SM,E)\rho(E,T2m)$. This approach was initially proposed by Dirmeyer et al., (2014) and used by Day et al. (2025) to interpret forecast errors related to soil-moisture feedback strength.

Control experiments for both centres show similar T2m CRPSS values over land compared to the operational hindcast sets shown in Day et al. (2025) (see their Fig 8).

It should be noted that the higher CRPSS values in the ECMWF compared to MetO, over the ocean, are due to the fact that the ECMWF experiments are run with prescribed, time varying SSTs and the MetO experiments are coupled to an ocean model. This difference may also promote higher scores over land in the control run. In terms of the difference between the LDAS and open-loop initialised runs, it is unlikely to make this biased, but may make it more noisy.

The change in CRPSS in the ECMWF (Fig. 10) and MetO JJA hindcasts (Fig. 11) show some common changes, such as the improvement over central Asia and reduced skill over Western Europe and the US Midwest. However, the impact in the ECMWF model is on average positive (i.e. an increase in CRPSS) whereas it is negative on average in the MetO system. Nevertheless, the changes in both systems are relatively small on average globally.

In both Europe and the US Midwest during JJA the reduction in CRPSS goes hand in hand with the coupling strength getting worse, i.e. stronger coupling although it is already too strong. Note that we wouldn't expect the response to be exactly the same in both experiments. The response of a shift in the soil-moisture distribution on land-atmosphere coupling will be highly model dependent. Similarly, soil moisture-atmosphere coupling can only be a source of skill when soil moisture anomalies are sufficiently well forecast.

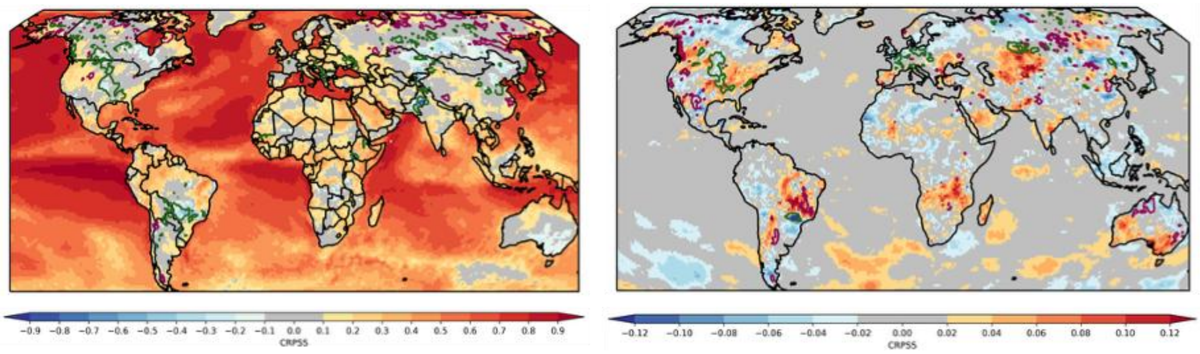

Fig 10: Left: CRPSS of JJA (1993-2022) T2m of the control hindcast compared to ERA5 (filled contours) and bias in coupling strength, $I_{SM\text{-}T2m}$ where Green contours are areas where the SM-T2m coupling is too strong and purple too weak. Right: difference in CRPSS and $I_{SM\text{-}T2m}$ between the LDAS initialised hindcast and the open-loop initialised hindcast.

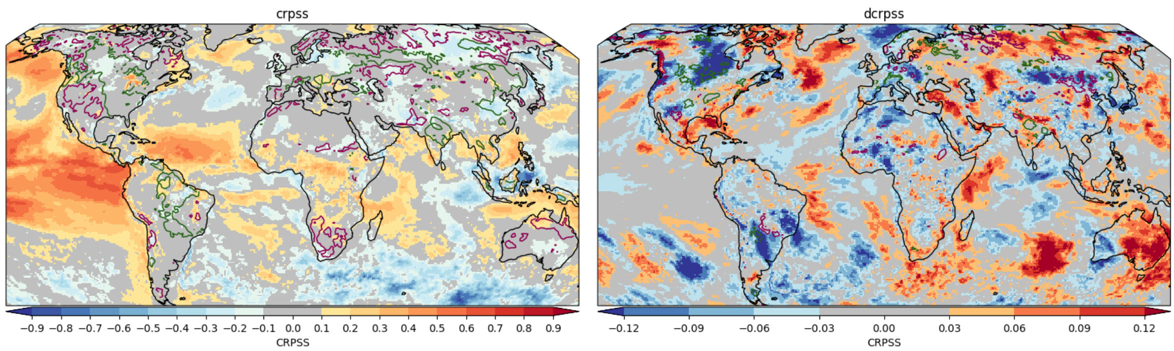

Fig 11: As Fig 10 but for the MetO experiments.

In DJF the ECMWF hindcasts with LDAS initial conditions show a positive impact on average (Fig 12), with increased skill in some regions (such as parts of South America, Africa and Australia) in the southern hemisphere where the coupling strength is getting better (inside the purple contours) with the LDAS. However, in North America and parts of North Africa, where skill gets significantly worse (see Figs A1 and A2 for CRPSS difference with significance).

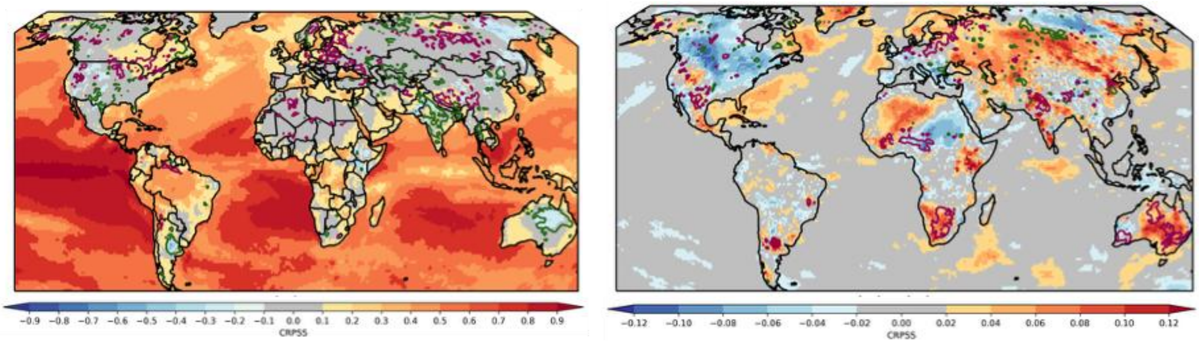

Fig 12: As Fig 10 but for DJF.

To investigate deeper the impact of the LDAS in the ECMWF hindcasts in western Europe we show a scatter plot of Evapotranspiration (ET) and Soil-moisture. It shows that the LDAS has a wider distribution of soil-moisture values and tends to be dryer in dry years. As a result, the dry years tend to have a lower ET in the LDAS initialised hindcast. This will have the result of increasing T2m anomalies in those years.

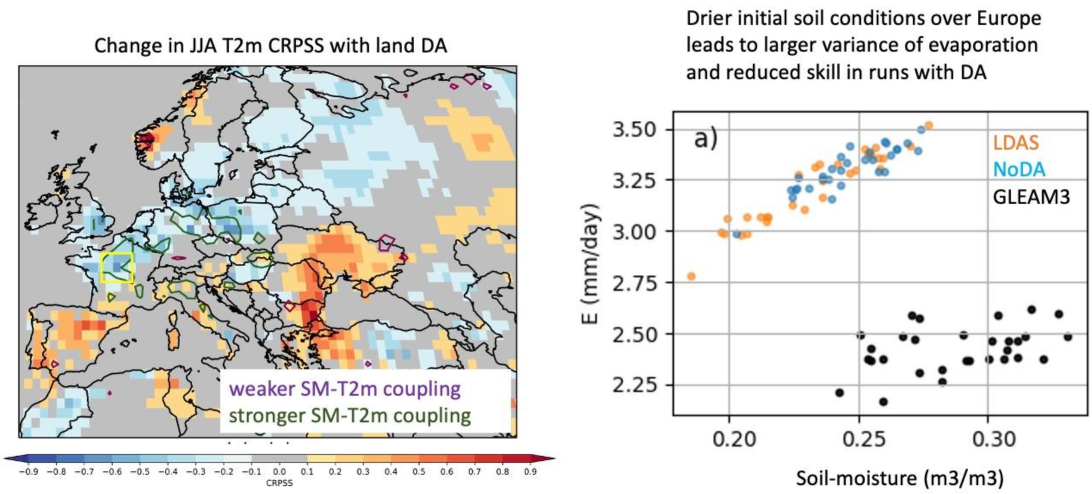

Fig 13: Difference in JJA (1993-2022) T2m CRPSS (using ERA5 reference) between ECMWF hindcasts using the LDAS and open-loop (left) and a scatter plot of evapotranspiration vs root-zone (or 1m) soil moisture for a region in northern France.

5 Conclusions

The ECMWF land data assimilation system provides a method for producing reanalysis initial conditions consistent with each model cycle quickly, allowing for more frequent updates of land initial conditions for seasonal and subseasonal hindcasts, and improved consistency between hindcast and realtime forecast land initial conditions.

Here, the output of land surface assimilation is analysed, alongside results from seasonal hindcast simulations initialised using these analyses and analyses without land data assimilation. The evaluation of soil and snow fields against independent in-situ data shows small but statistically significant degradations compared to the EC-land open-loop for all snow and soil variables. In the case of the soil-moisture this is consistent with previous studies looking at the impact of the assimilation of screen-level “pseudo-observations” (see Draper et al., 2011 for further discussion). In the case of the snow, this may be related to incorrect density bounds being used in the LDAS (which will be updated in the future).

The impact on T2m scores is slightly positive on average in the ECMWF hindcasts in both JJA and DJF. The impact of the LDAS on the Met Office JJA hindcasts T2m skill is on average slightly negative, but the causes of this need to be investigated more fully to understand these differences.

In both the ECMWF and MetO hindcasts, the regions with the most positive improvements tend to go hand-in-hand with reduced biases in coupling strength metric ($I_{SM\text{-}T2m}$). This is most clear in the southern hemisphere in the ECMWF DJF (austral summer) simulations. This is telling us that there has been a shift in the initial soil-moisture distribution that improves the effective coupling strength later in the forecasts. However, the impact is not positive everywhere and in particular there is a large degradation in T2m CRPSS over North America in DJF (possibly due to the snow density issue in the initial conditions). There are also some regions where the $I_{SM\text{-}T2m}$ gets worse and as a result CRPSS is reduced, such as Western Europe in JJA. There is also a positive impact on SWE reliability in DJF hindcasts is positive, (particularly in NE Eurasia).Whilst overall atmospheric skill in the ECMWF hindcasts is increased with the use of LDAS initial conditions, the anomaly correlation of soil-moisture, with respect to GLEAM, is on average degraded in both DJF and JJA. This is consistent with the evaluation of soil moisture initial conditions against independent in-situ ISMN soil-moisture and temperature data which shows small but statistically significant degradation compared to the EC-land open-loop for all variables.

The impact on SWE reliability in DJF hindcasts is positive, (particularly in NE Eurasia).

The annual mean soil-moisture trends in the LDAS are broadly similar to the open-loop and the GLEAMv3.8 dataset, however numerous points are identified where trends/timeseries do not look physically realistic, possibly relating to differences in the availability of SYNOP T2m and RH2m data.

Overall, this perspective is similar to what has been seen at medium-range timescales: assimilation of screen-level “pseudo-observations” for soil-moisture assimilation improves lower-atmospheric forecast skill, as a result of improving turbulent fluxes, but this is achieved at the expense of the realism of the soil-moisture fields. See Draper et al., (2011) and Drusch et al., (2009) for more discussion of the impacts on medium-range forecasts.

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Appendix 1

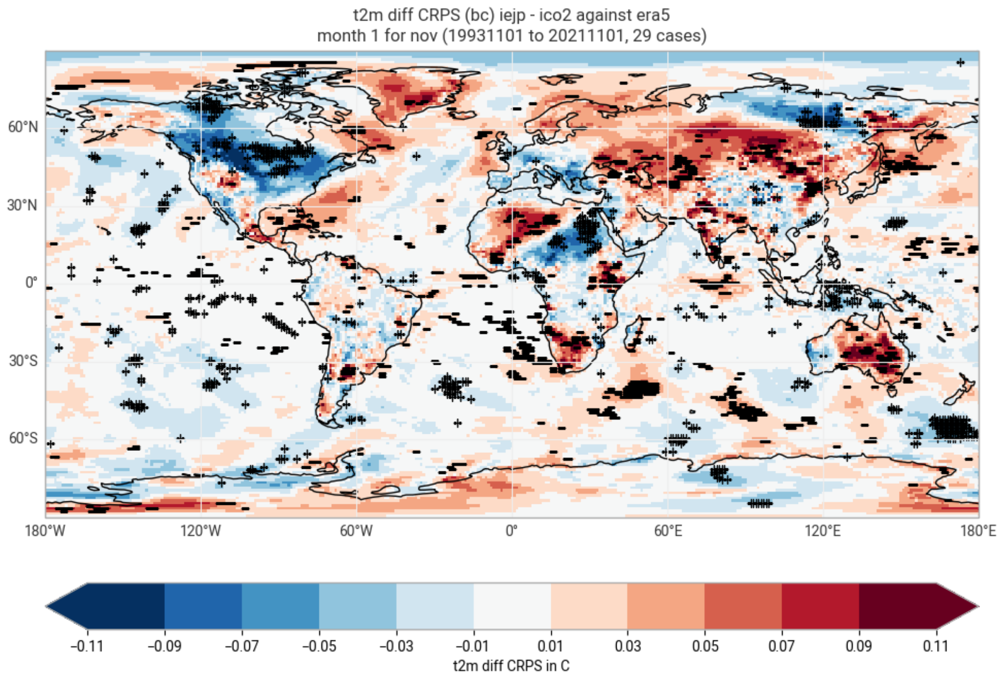

Fig A1: Change in T2m CRPSS between LDAS hindcast and open-loop hindcast, with 5% significance according random walk test (DelSol and Tippet, 2016), stippled.

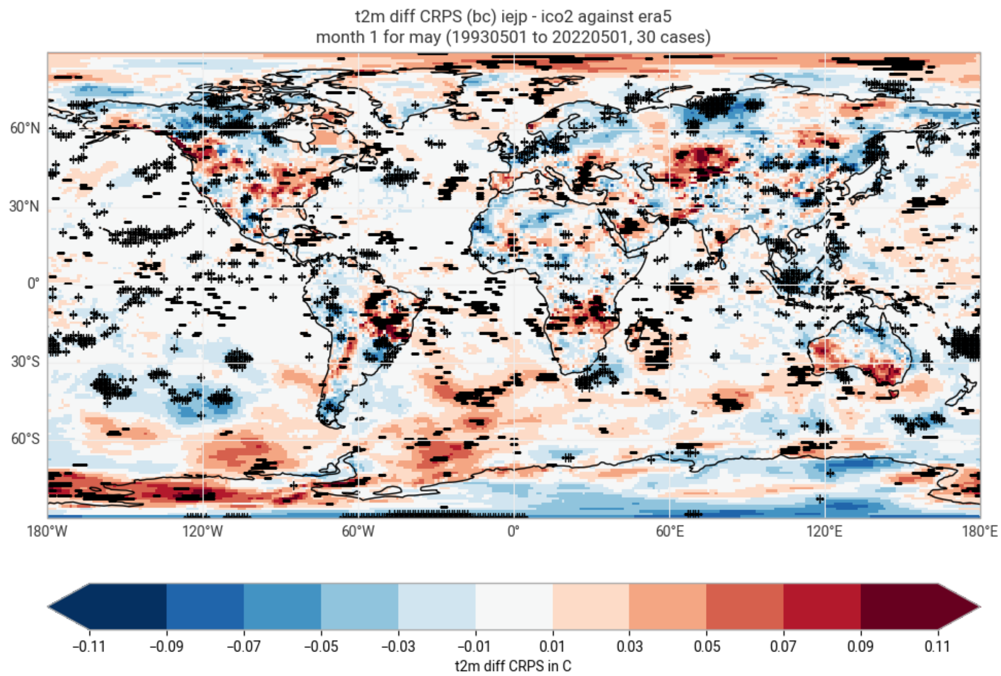

Fig A2: As Fig A1 but for JJA.

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