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Earth System Dynamics Discussions

Interactive comment on "Life time of soil moisture perturbations in a coupled land-atmosphere simulation" *by* T. Stacke and S. Hagemann

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Reply to Prof. Dirmeyer We very much thank Prof. Dirmeyer for the constructive review of our manuscript. In the following we will repeat the comments before answering them.

Comment: [. . .] Throughout: Correlations in particular should be accompanied with results of significance tests. For spatial correlations some estimate of the reduced numbers of degrees of freedom need to be used, based either on estimates of the spatial autodecorrelation distance for the variable, or a count of extrema. Explained variance alone is not enough. When correlations through 9 members are discussed (e.g., Fig 10), the 2-tailed 95% confidence is at r=0.67, for 1-tailed 0.58.

Reply: We thank very much for this advice, which we now have implemented in our

study. Of course, we need to consider the spatial autocorrelation for the individual variables prior to give a valid estimate on the correlation significance. In order to cancel the effect of autocorrelation on our analysis, we take random samples (n « N) from our data and compute the correlation and significance for those until the whole dataset is considered. As the sample size is much smaller than the population, one can assume that the locations within the randomly chosen samples are not autocorrelated any more. The whole procedure is repeated several times to minimize the possibility that autocorrelated locations are sampled by chance. Indeed, only few spatial correlation are judged significant (below 5%) using this method and we accordingly revised Fig. 8. Also, we added a description of our correction at the end of experiment setup section:

"Furthermore, the spatial correlation between variables are affected by the spatial autocorrelation within the individual variables, resulting in a too significance correlation coefficients. We account for this effect using a sub-sampling technique, where consecutively only a small, randomly chosen sample of locations is analysed at a time until eventually the full field is sampled. As the size of these samples is much smaller than the full field, we assume that the selection of autocorrelated locations within an individual sample is very improbable. Nonetheless, we repeat this analysis up to 10000 times or until the variation in the resulting significance is smaller than 5%."

However, as Fig 10. is mentioned we want to stress that we did not compute correlations for this figure, but only show the relation between the seasonal mean initial memory and the respective seasonal mean (ensemble mean) initial perturbation as well as the seasonal mean full memory and the seasonal mean (ensemble mean) extreme perturbation. We want to demonstrate that for some variables the latter relation is larger than the first, while for others there is not much of a change. Correlation coefficients are not computed because we do not expect a linear correlation anyway.

Comment: A small caveat: by design the extreme perturbations in soil moisture initial conditions are synchronized everywhere (i.e., the most extreme value at each grid point at the same initial date), whereas in the free-running model (REF) and reality there would be a spatial distribution of wet, dry and normal. Thus, remote or large scale effects in INI tend away from reasonable - it's not that different than a Shukla & Mintz (1982; Science) type of simulation in this regard. This design may amplify local responses via regional-continental scale changes that would not arise in the "normal" evolution of climate. This should be noted somewhere, perhaps in Sec 6.

Reply: We agree with this statement and added a note to our discussion: "[. . .] Second, as we initialize all simulations with extreme states, we artificially synchronize extreme events in terms of their temporal occurrence. This could affect soil moisture memory via remote effects between extremes. In order to avoid such interactions it would be necessary to preserve a natural pattern of extremes. However, this would require a much larger number of simulations beyond the computational capacities available for this study."

Comment: Couldn't it be also that there would be memory "stored" in other states as well, such as the snow cover or vegetation state, that would emerge later? Vegetation might be a negative feedback, thinking about it, as a green vegetation (say in a semi-arid zone) would transpire more, reducing memory. This could be mentioned in the discussion section.

Reply: As we understand this, it would be quite close to our first hypothesis about memory recurrence in soil moisture due to interaction with memory in other variables (3rd paragraph in Sec. 5), except you assume stored memory in variables already before we perturb the soil moisture, right? This is an interesting extension of the hypothesis. However, we already searched for this behaviour assuming that SNR curves between variables should exhibit temporal correlation in such cases. We found this for a very small sample of grid cells, which were too few and unsystematically distributed to serve as evidence for this interaction. Nonetheless, we added this idea to our first hypothesis:

"Additionally, stored memory might already exist in other land surface variables like snow cover or vegetation prior to the soil moisture perturbation and could amplify or mitigate the initial soil moisture memory using the same process chain."

Comment: A few small language issues are present, e.g., P1748 L7: "only few information exist" should be "little information exists". Careful proofreading would solve them.

Reply: Thank you. We corrected this mistake and try to hunt down the others.

Comment: P1747 L12: say "methods" not "tools" - different methodologies yield different estimates of soil moisture memory (e.g., if daily vs. pentad or monthly data are used, lagged autocorrelations vs. variance ratios (e.g., SNR), etc.)

Reply: Corrected, thanks.

Comment: Sec 2: Since soil moisture is so strongly controlled by precipitation, it would be good to know about the precipitation biases in this model. Do the local features in extremes (later in Fig 4) correspond to precipitation biases, or are they believable?

Reply: For this model, several precipitation biases are known. Dry biases occur in the tropics and in the low precipitation regions in the southern subtropics. Wet biases are evident around 50° S, in the northern high latitudes during boreal spring and summer and along steep mountain slopes. Further details about precipitation biases of ECHAM6/JSBACH can be found in Hagemann et al. (2013). There is no systematic relation visible between our memory distribution (Fig. 4 and 5) and those biases.

Comment: Eq 1: Is this SNR calculated separately for every season, so that j=9? Thus, the sample size is quite small - is this correct?

Reply: Yes, if the SNR is computed for a single season and initialization the sample size equals 9. We agree that this sample size would be quite small. For this reason we combined our results into seasonal and similarly initialized ensembles with sample sizes of 18 (wet and dry initialized simulations for a given season) and 36 (all four seasons for a given initialization). In order to make this more obvious to the reader we added the following paragraph to the description of our analysis:

"As the ensemble size of j = 9 for a given season and initialization is rather small, our analyses are usually based on combined ensembles where either all seasons for a given initialization are merged (j = 36) or both initializations for a given season (j = 18)."

Comment: Fig 3: Please give more details for Fig 3. Are these all of the land points or just ice-free? Every grid box goes into the distribution? All seasons together? What is meant by "seasonal ensembles"; is that from REF climatology or the wet and dry INI cases combined?

Reply: All figures showing distribution analysis include all land surface grid cells. We added this information to the captions of the figures 3, 7, 8, 9, 10, 11 and 14. Explanation for seasonal and initialization ensembles are added (see previous question).

Comment: Fig 4: The mean is much different than the median soil moisture for many points in the very dry and wet regimes. Could that skewness contribute to the low apparent memory regions in Fig 4 when there are dry anomalies in dry regions, and wet anomalies in wet regions: it causes a weak signal relative to noise (which is calculated by the conventional RMSE approach in Eq 1that implicitly assumes a normal distribution)? Or asked another way, does the weak memory in those regions emerge in the tau_lag term or the tau-0 term? Do you consider this a bug or a feature of this approach, as typically memory is thought to be very high in arid regions in general (cf. Orlowsky and Seneviratne 2010; J Climate).

Reply: Yes, the skewness contributes to the short memory in very wet or dry regimes. It is intentional and we consider it a feature. Our study investigates to what extent soil moisture memory can be exploited to improve short-term climate predictions. In this respect, memory in those regions is short because even extreme perturbations quickly decay in the noise, very much limiting the value of a good initialization (after a correct spin-up to end up in this regime)

Comment: P1755 L5-20: It would be good here to refer to relevant previous work that describes these processes, like Koster and Suarez (2001 JHM; fig 5), or Seneviratne and Koster (2012; JHM).

Reply: Thank you, we added references to these studies to this paragraph.

Comment: Fig 7: Please put a tick for the mean and median on each red and blue side.

Reply: Done.

Comment: Fig 8: This needs more description - what exactly is shown?

Reply: In figure 8 it is investigated whether a given grid cell in a given season is always susceptible for perturbations and whether the size of the perturbation determines the memory length. To this end, we compute the spatial correlation between the seasonal ensemble wet and dry memory fields for the different soil moisture regimes (upper plot). Here, we find the fields are weakly correlated with a maximum rank coefficient up to 0.4 for the DJF ensemble in the transitional regime. Only for this season and region the correlation is significant ($p < 5\%$). For the lower plot, we investigate the correlation between seasonal fields of memory length and the respective initial perturbation. Here, the rank correlation is stronger, demonstrating that the perturbation size has a pronounced impact on memory. However, the maximum correlation coefficient is 0.7 indicating that there is still a large part of spatial variance in memory that cannot be explained by the initial perturbation alone. For the wet and dry regime no significant correlations are found. Here, the memory length is dominated by factors other than initial perturbation size. We changed the caption into a hopefully more complete description of the plot:

"Bar plot for different soil moisture regimes and seasons indicating correlation coefficients for spatial rank correlations. The upper panel shows the correlation between the pattern of wet tau and dry tau. The lower panel shows the correlation between the pattern of wet and dry tau and the respective initial perturbation. Significant correlations below the 5% level are indicated by solid bars."

Comment: P1757: Most of the discussion of correlations here should be accompanied by "not shown", or the complete set of correlations for each season could be presented in a table.

Reply: We decided to add the requested table to provide a thorough documentation of our results. However, we did not add it directly to the manuscript, but to the supplements. We also move the former tables 1 and 2 into the supplements as the data should be documented for interested readers but are not necessary in such detail to follow our discussion. For this analysis, taking into account the spatial autocorrelation (see reply to first comment) yielded quite different results. Thus, we rewrote the whole paragraph on the correlation between soil moisture memory and static soil properties (last paragraphs in Sect. 3)

Comment: P1759 L15-16: "...does not seem to be correlated..." - please quantify the correlations for each.

Reply: Thanks for making us aware of our poor choice of words. We are actually not looking at the correlation, but only at the general relation between memory and perturbation in this plot. In particular, whether any change in this relation is visible between the initial case and the full time series. The single data points represent the mean value for a given season and soil moisture regime, additionally subdivided into northern and southern hemisphere to minimize counteracting seasonal effects. That means we have only 8 data points for a given perturbation of which half are based on a different area (due to hemisphere separation). In our opinion, this database is not robust enough to make qualitative statements about changes in correlation, but only to consider whether or not a change in relation might be visible, which is later on (Fig. 12 and 13) investigated in more detail at the point scale. Thus, we just changed 'correlated' to 'related'.

Comment: Fig 10: tau_max is a bit of a dubious quantity to me: as a summation, it

should be mainly a quadratic of the linear tau_0 term, with (usually) a little randomness added at longer time scales, no? Shouldn't tau_max >= tau_0*(tau_0+1)/2? Then how to explain the carbon panel where tau_0 is close to tau_max? Am I missing something?

Reply: We don't see how this relation follows from our definition of the memory terms. Tau_0 is the length of the first consecutive memory period after the perturbation while tau_max is the overall amount of (not necessarily consecutive) periods of memory. Thus, tau_max = tau_0 + recurring memory +- some random variation as we use only one standard deviation to define the SNR. There is no fixed relation between tau_max and tau_0 (except tau_max >= tau_0) that would hold for all grid cells and variables. If tau_max is close to tau_0 it simply means that after the initial perturbation the signal stays within the natural variation of the system while tau_max > tau_0 indicates that memory re-emerge later on. The latter happens due to interactions between two variables (e.g. soil moisture and leaf carbon or root zone moisture and deep zone soil moisture). The strength of those interactions is time and region dependent, and does not follow a quadratic equation.

Comment: P1760 L6-20: I cannot follow how this discussion comes from Fig 11. This seems to be a key result but I really cannot understand how it comes from this figure. If you are actually comparing Fig 11 to features of Figs 3 and 9, please state clearly. It may be clearer to show the differences also in another set of panels.

Reply: We apologize for the confusion. Indeed all the discussion is based on comparing Fig. 11 to the figures 3 and 9. We modified the paragraph accordingly:

"More details for the overall memory and anomalies in soil moisture and temperature are displayed in Fig. 11 and are compared to the statistics of the initial perturbation and memory (see Fig. 3 for soil moisture and Fig. 9 for soil temperature) in the following discussion. "

Comment: Fig 11: What's the difference between "extreme anomalies" vs. INI initial perturbations in the case of soil moisture? The text uses thetas and the figures do not.

Please be clear and consistent. Also, what are the offset colored horizontal ticks in a few places in the panels?

Reply: For soil moisture the initial anomalies are the extreme anomalies. While most other variables experience larger anomalies at later periods in the time series, the initial soil moisture perturbations are always the maximum anomaly.

We added the symbols to the caption of the figure now being consistent with Figs. 9, and 3. Thanks for pointing us to the additional ticks. These are artefacts from another plot. Fig. 11 was replotted to remove them.

Comment: P1761 L9-12: In the set of criteria, what about a minimum duration of the later periods after the anomaly rebounds? A minimum duration (much more than 1 or 2 days) might weed out some noise like that which is apparent in the example Figure 2.

Reply: Thank you, a minimum duration would be a good criteria, too. However, the tau_max – tau_0 > 600d criteria already yielded a number of grid cells with pronounced memory recurrence where this criteria is implicitly fulfilled. Thus, there is no need to repeat the analysis but we'll keep it in mind in case of later studies.

Comment: P1762 L16: Regarding the "temporally hidden" memory, please see Guo et al. (2011; GRL, 2012; J Climate) for another related example of this hidden and rebounding predictability from state anomalies.

Reply: Thank you for making us aware of these interesting studies. We included them in our discussion of recurring memory:

"A related example for memory recurrence is presented by Guo et al (2011, 2012) who found that the predictability of atmospheric states due to realistic land surface initialization can recover from a decrease even after one season. This is caused by the existence of persistent land surface anomalies whose impact on the atmosphere increases due to an increase in land-atmosphere coupling strength."

Comment: Fig 13: Place a vertical black line at 12 and 24 months so it is easy to reckon the duration of the annual cycle in all plots

Reply: Done for all plots showing time series (Fig. 2, 12, and 13)

Comment: Fig 14: This is not clear to me - so is there memory recurrence at every grid cell, just at different frequencies (where the CDF approaches 1)? Or is this only for a subset of points where recurrence is present? Or is the X axis "memory" and not "memory recurrence"? Please explain the figure in more detail.

Reply: Sorry for the confusion. The x-axis shows memory occurrence (tau_max – tau_0) for all grid cells of a given soil moisture regime. The soil moisture regime is further subdivided depending on the thickness of the deep zone soil layer. Indeed, there is only a small number of grid cell without any memory recurrence (between 0% to 20%). The CDF shows the ratio of grid cells with a given memory recurrence. We rephrased the caption as:

"Normalized cumulative frequency of grid cells with recurring memory (tau_max - tau_0) for different soil moisture regimes (upper, middle and lower panels). The regimes are further subdivided depending on the thickness of the deep soil zone below the root zone (orange, green and blue colours). Wet (dashed lines) and dry (solid lines) initial states and seasons are merged into the panels."

Comment: Sec 6: Please state how these results fit with C. Taylor's evidence (several papers) that locally positive soil moisture-precipitation feedbacks are rare, and Guillod et al. (2015; Nature Comm) that shows there are spatial as well as temporal dimensions to the land-atmosphere feedback issue?

Reply: We do see positive soil moisture – precipitation feedback in our model, however, the induced perturbations are rather small with means varing around ± 0.3mm/d (Fig 1 in this reply). Another indication for positive soil moisture – precipitation feedback in our results is a positive correlation between maximum vegetation fraction and soil moisture memory (now discussed in the last paragraphs of Sect. 3) which implies that more vegetation fraction together with a positive soil moisture anomaly results in more transpiration which increases local recycling thus sustaining the wet anomaly. However, we see this in a quite coarse model with parametrized convection. Thus, we do not feel that we can add much to the discussion whether the feedback exists in reality based on our model results. We added a remark to Sect. 3:

"However, it should be noted that positive soil moisture - precipitation feedback on the local scale is considered to be rare in reality (Taylor et al., 2012) and also Guillod et al. (2015) found that precipitation events tend to be located over drier patches. Still, those patches generally need to be surrounded by wet conditions (Guillod et al., 2015) so that positive temporal and spatial soil moisture–precipitation relationships are driven by large-scale soil moisture distribution. Additionally, positive soil moisture – precipitation feedback might be overestimated in the model due to its coarse resolution and the parametrization of convection (Hohenegger et al., 2009)."

The investigation of spatial feedbacks was omitted in our analysis as it would require to rerun our simulations with major model modifications to track lateral transport of anomalies. We added a short comment to Sect. 6:

"Alternatively, it might be possible that anomalies are transported by the atmosphere and might influence the memory in downwind grid cells. Recently, a combination of spatial and temporal feedbacks between soil moisture and precipitation was proposed by Guillod et al. (2015), however this effect cannot be captured by our analysis and its potential influence on soil moisture memory remains open for further study."

Comment: P1756 L18 and P1767 L7: up to 50% of the variance is not small - I think the authors are understating the impact of initial soil moisture anomalies.

Reply: Yes, we agree. We wrote it this way because we actually expected an even larger correlation between initial perturbation and memory. Additionally we wanted to emphasize that at least 50% of the variance in soil moisture memory pattern cannot be

explained just by the initial anomaly but is determined by dynamical interactions. We rephrased both sentences accordingly:

"Thus, the strength of soil moisture memory seems to depend about equally on the initial soil moisture perturbation as well as on dynamically changing land atmosphere interactions and static soil or land cover properties."

And

"The size of the initial perturbations can explain up to 50% of the spatial pattern of memory while static parameters like soil depth, rooting depth or hydraulic conductivity are only important for some regions and seasons. Thus, a large part of pattern variance remains and can be assumed to be related to seasonal climate conditions."

Comment: L1767 P10-16: Does this model allow for organic carbon (leaf litter) to interact with soil properties and alter soil structure over time? Could that act as another delayed effect (perhaps more on decadal time scales)?

Reply: No, these processes are not implemented. Currently all soil properties in the model are fixed in time. Given the low correlation we found between soil moisture memory and soil properties, we do not expect a large impact.

Added References:

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Guo, Z., Dirmeyer, P. A., DelSole, T., and Koster, R. D.: Rebound in Atmospheric Predictability and the Role of the Land Surface, J. Climate, 25, 4744–4749, doi:10.1175/jcli-d-11-00651.1, 2012.

Hagemann, S.; Loew, A. & Andersson, A. Combined evaluation of MPI-ESM land surface water and energy fluxes, JAMES, 2013, 5, 259-286

Hohenegger, C., Brockhaus, P., Bretherton, C. S., and Schär, C.: The Soil Moisture-Precipitation Feedback in Simulations with Explicit and Parameterized Convection, J. Climate, 22, 5003–5020, doi:10.1175/2009jcli2604.1, 2009.

Taylor, C. M., de Jeu, R. A. M., Guichard, F., Harris, P. P., and Dorigo, W. A.: Afternoon rain more likely over drier soils, Nature, 489, 423–426, doi:10.1038/nature11377, 2012.

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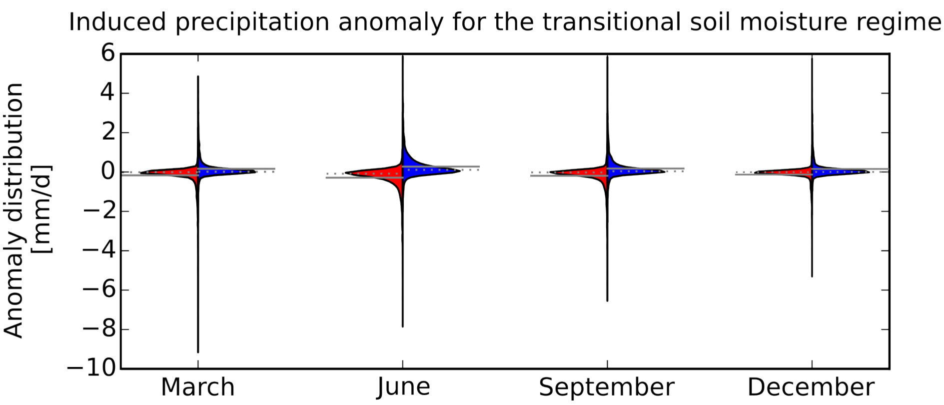

Fig. 1.