Reply to the reviews for our manuscript “Life time of soil moisture perturbations in a coupled land-atmosphere simulation” in ESDD

Reply to Referee #1

We thank the referee for the positive review of our manuscript. In the following we will repeat the referee comments before answering them.

1. The experimental setup implies that the atmospheric model is coupled only with the land surface model not the ocean or other earth system components. However the introduction appears to suggest that this study aims to address the issues related to the use of ESMs for decadal and seasonal predictions. Please reword the first paragraph of the introduction suitably. Please provide a description of the prescribed SSTs in the experiment setup and replace “AMIP-type” in the abstract with “prescribed ocean” or appropriate words.

Indeed, we used a coupled land-surface model with prescribed ocean and thus focus on a limited aspect of the full Earth System. While we acknowledge there might be some impact of an interactive ocean on land surface memory, we expect the major process interactions to take part between land and atmosphere. Thus, we omitted the ocean simulation thereby significantly reducing the computation costs for the ensembles.

In order to make readers aware of this, we used the phrase “prescribed ocean” in the abstract and repeated this fact in the experiment setup section together with the references (Taylor et al., 2000) for the ocean fields.

2. The authors find that the strength of soil moisture memory depend on dynamically changing land atmosphere interactions rather than static soil or land cover properties. However the analyses only focus on the bringing out the interactions of soil moisture with land surface state variables. The analyses of the induced anomaly and memory statistics in near surface air temperature and humidity would have added more insight to how the favorable climate states contribute to persistent soil moisture anomalies.

In terms of our experiment setup and method, we don't expect to gain much additional information by analysing induced anomaly and memory in the atmospheric fields. Already at the surface, the variability of humidity is very high and much more ensemble members are probably required to derive a significant signal in the lower atmosphere. With increasing height variability likely increases e.g. due to advection. Thus, a more physical approach like a tracking scheme would be needed to explicitly follow the pathways of soil memory – atmosphere interaction.

3. Please include a discussion on how much the conclusion that the ‘soil moisture initialization has potential for decadal and seasonal predictions using ESMs’ will be dependent on the atmosphere-land coupled modelling framework used in this study.

We agree that our results are, of course, model dependent. However, we cannot quantitatively conclude on how much our results would change in a different model framework, without actually testing it. However, we expect that a framework including the most critical parametrization, namely the existence of a root zone soil layer and a deep zone soil layer below, would show similar memory characteristics. We added to following paragraph to the discussion:

“Furthermore, it has to be noted that the results are, of course, model dependent and the exact numbers will differ for individual modelling frameworks. Nonetheless, as long as critical land surface parametrizations are existent, namely the separation of the soil column into several layers containing a root zone and a deep soil layer, we expect similar soil moisture memory characteristics to emerge. Thus, the potential for improved climate predictions should exist for all state of the art modelling frameworks.”

4. Please describe all the acronyms used in the manuscript e.g. ECHAM6, JSBACH etc.

In the very beginning, the acronym ECHAM was combined from the ECMWF (where the model originated from) and Hamburg, the place where its parametrization was developed. JSBACH stood as acronym for “Jena Scheme for Biosphere-Atmosphere Coupling in Hamburg”. However, both acronyms became obsolete and the terms ECHAM and JSBACH are used as individual names by now. Thus, no description of the name will be provided in the manuscript.

The explanations for the remaining acronyms, MiKlip (Mittelfristige Klimaprognosen), SPECS (Seasonal-to-decadal climate Prediction for the improvement of European Climate Services), and CMIP5 (Coupled Model Intercomparison Project Phase 5) have been added to the manuscript.

Reply to Referee #2

We thank the referee for the positive review of our manuscript. In the following we will repeat the referee comments before answering them.

The manuscript “Life time of soil moisture perturbations in a coupled land-atmosphere simulation” by T. Stacke and S. Hagemann evaluates the memory of initial soil moisture perturbations using a global coupled land-atmosphere-ocean model.

No, the ocean is not part of our modeling framework but prescribed using AMIP2 boundary conditions for sea surface temperature and sea ice concentration of the respective time periods. We put more emphasize on this fact by adapting the abstract and adding the reference to the AMIP2 data to the experiment setup section.

However, it is not clear how realistic are the results, particularly re-occurrence of soil moisture memory. The results are purely model based and no observational data are used in order to support any of the findings, which is the weakest point of the manuscript. […]

1) Use of observed soil moisture or other land surface parameter (available for some European and north American stations), will make the results more acceptable to the research community rather than relying only on the model simulation.

We fully agree with the referee that study is purely model based. However, this is done on purpose, for two reasons. First, we are interested in the potential of soil moisture initialization to improve predictions done by models. For this task it is actually not critical whether the concept of soil moisture memory is realistic or not. Instead, we want to demonstrate that it exists in our modelling framework in a way that could ultimately be utilized to improve its predictive skill. Nonetheless, soil moisture memory in general is found in observations (see Vinnikov and Yeserkepova, 1991 already cited in our manuscript and Shinoda and Nandintsetseg, 2011, now added to the introduction) although such studies are very rare. Second, there are no observations available that are directly comparable with our experiment. We actively perturb the soil and analyse the temporal characteristics of its response to an ensemble of extreme events by comparing to the undisturbed case. This cannot be derived from time series of observed soil moisture as there is naturally no unperturbed reference data for the same climate conditions available. Thus, we did use the discussion for a general comparison of soil moisture patterns and length found by other studies. But rather than comparing our results against observations that in the best case could be a vague proxy for our definition of soil moisture memory, we hope to motivate others to set up a comparable laboratory or field-site experiment to verify our findings.

2) Figure 12, 13 suggests that initial soil moisture perturbation is too strong, perhaps far away from the real level? I am wondering if the perturbations are too strong in some regions, despite authors have chosen a good method to do so. Is there any particular region (climatic condition), where re-occurrence of memory, as evident in leaf carbon content (Fig. 12) is very large? This appears to me the middle and high latitude region, where strong seasonal effect persists. Any observational evidence/reference of previous observation finding?

We cannot follow the referee here. How do figures 12 and 13 suggest perturbations are too strong? While perturbations might be unrealistic compared to reality, they are extreme but fully realistic in terms of model variability as they are based on the statistics of our reference simulation. Concerning leaf carbon memory recurrence, it is strongest for the transitional soil moisture regime (see Fig. 14). We explain this with the combined effect of seasonality and soil moisture sensitivity (see 2nd paragraph in Sec. 5). Actually, a connection between soil moisture and vegetation memory is also proposed by an observation based study (Shinoda and Nandintsetseg, 2011), which we now added to the discussion.

3) In section 4. "The largest impact of soil moisture perturbation is expected for surface and soil moisture .... " Figure 9: this is simplified assumption. There are strong non-linearity in the atmospheric state variable, which is evident in the spread of surface air temperature anomaly. Are the found anomalies are statistically significant?

In fact, we stated that we expect the largest effect on surface and soil temperature, not moisture. Anyway, the referee raises a very valid point about whether the observed spread is due to soil moisture perturbation or atmospheric interactions. Indeed, all anomaly data Fig. 9 comes from those points where at least 1 day of memory is evident, which also is the vast majority of points. This demonstrates a strong control of soil moisture over surface temperature in the model. However, the memory is usually quite short, which we attribute to compensating effects via atmospheric states. We added a short note to the discussion:

"Likewise, for most other surface variables, like humidity and pressure, only short memory is diagnosed. Soil moisture control seems strong enough to induced some anomalies, however their memory is quickly dissipated by strongly non-linear processes in the interacting atmospheric states."

4) As mentioned, this model does not have freezing/thawing of soil moisture, how reliable are the found memory over high latitude/permafrost region? Some discussion is required.

We assume the general pattern won't change too much when melting and freezing processes are considered. Especially permafrost regions are dominated by long periods of frozen conditions where memory would be similar in both soil schemes, and only during the relatively short periods of melting and freezing soil memory might be affected due to the water and energy coupling. As we already stated we need to test whether or not this additional process would significantly effect memory.

5) Many coupled model show drift, which last for several years/decade. As this experiment used only two years of spin-up, the results may be affected by the model drift.

Thanks for making us aware of our quite misleading statement. As with most land surface models, spin up especially of soil moisture can regionally take up to 30 years and more. For this reason, our model was not started from scratch but all state where taken from similar simulation running over several decades. We just added the two more years of spin-up to allow the model to adapt to small differences in the forcing. We added this information in our draft:

“The first set consists of one reference simulation (REF) for the period 1995-2008. It's initial states were taken from an earlier spin-up simulation running over several decades. […] No INI are started prior to December 1996 as this time is regarded as additional spin-up for the model to adapt to minor differences in the forcing between the REF and the spin-up simulation.”

Reply to Prof. Dirmeyer

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

[…] 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.

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.

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.

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."

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.

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."

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.

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

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.)

Corrected, thanks.

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?

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 50º 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.

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

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 ($j = 18$)."

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?

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).

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).

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)

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).

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

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

Done.

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

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.”

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.

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)

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

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'.

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?*

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.

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.

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. “

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?

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.

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.*

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.

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.

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.”

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

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

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.

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.”

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?

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.”

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.

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.”

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)?

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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Figures

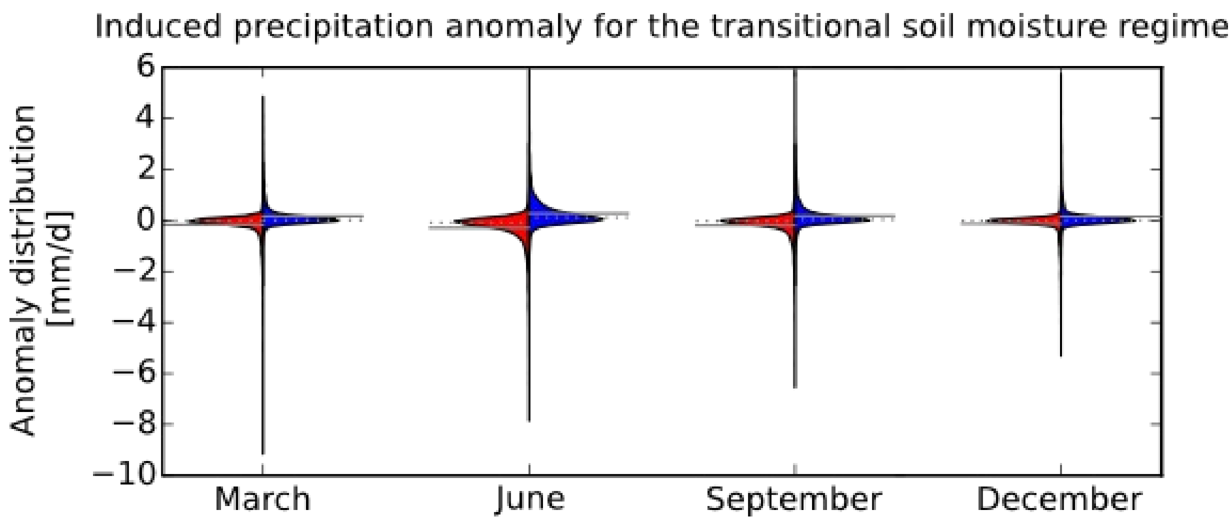

Fig. 1

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Life time of soil moisture perturbations in a coupled land-atmosphere simulation

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Abstract. In order to evaluate whether the initialization of soil moisture has the potential to improve the prediction skill of ~~coupled climate models~~ Earth System Models (ESMs) at seasonal to decadal time scales, an elaborated ~~AMIP-type~~ experiment was conducted. For this task a coupled land-atmosphere model with prescribed ocean was utilized. The experiment design considered soil moisture initialization in different seasons and years, and yields information about the life-time (memory) of extreme yet realistic soil moisture perturbations. Our analyses were focused on root zone soil moisture (RootSM) as it comprises the part of the soil that directly interacts with the atmosphere via bare soil evaporation and transpiration. We found that RootSM memory differs not only spatially but also depends on the time of initialization. Long memory up to one year is evident mostly for dry soil moisture regimes, after heavy precipitation periods or prior to snow covered conditions. Short memory below two weeks prevails in wet soil moisture regimes and prior to distinct precipitation periods or snow melt. Furthermore, RootSM perturbations affect other land surface states, e.g. soil temperature and leaf carbon content, and even induce anomalies with specific memory in these variables. Especially for deep layer soil temperature these anomalies can last up to several years. As long as RootSM memory is evident, we found that anomalies occur periodically in other land surface states whenever climate conditions allow for interactions between that state and RootSM. Additionally, anomaly recurrence is visible for RootSM itself. This recurrence is related to the thickness of the soil layer below the root zone and can affect RootSM for several years. From our findings we conclude that soil moisture initialization has the potential to improve the predictive skill of climate models on seasonal scales and beyond. However, a sophisticated, multi-layered soil hydrology scheme is necessary, to allow for the interactions between RootSM and the deep soil layer reservoir.

1 Introduction

Until recently, the main application for Earth System Models (ESMs) was the reproduction or projection of long term climate statistics over periods of 30 years or longer (Taylor et al., 2012b). However, during the last decade this focus was expanded towards decadal (Meehl et al., 2009) and seasonal predictions (Palmer et al., 2004). On such time scales, not only the quality of model physics and the external forcing play a major role, but also an appropriate initialization of state variables (Pohlmann et al., 2009; Müller et al., 2014). In the climate community, the potential of initialization is investigated focusing mostly on decadal predictions and the state of the ocean (e.g. Keenlyside et al., 2008; Pohlmann et al., 2009; Matei et al., 2012). But especially for short-term simulations like numerical weather forecasts or reanalysis, the land surface has also been identified as interesting target for initializations. Initialization experiments focusing on snow cover (Douville and Royer, 1996; Jeong et al., 2013) and soil moisture (Atlas et al., 1993; Betts, 2004; Fischer et al., 2007; Beljaars et al., 1996; Small, 2001; Kim and Hong, 2007; Koster and Suarez, 2003) are shown to affect the climate state and therefore their initialization can be expected to enhance the predictive skill of an ESM.

The reason for the importance of initialization is the interaction between land surface and atmospheric states, which are rather complex and result in a number of feedbacks (e.g. Bony et al., 2006). Of those, one of the most investigated processes are soil moisture feedbacks (e.g. Dirmeyer and Shukla, 1993; Eltahir, 1998; Seneviratne et al., 2010). They rely on the important role that soil moisture plays in both, the terrestrial water balance as well as the energy balance. On the one hand, soil moisture determines the separation of incoming water fluxes into surface runoff and infiltration. Surface runoff is transported into rivers and leaves a given region. Infiltrated water adds to the soil moisture and might be available for evapotranspiration, again. Thus, soil moisture strongly effects the regional water balance. On the other hand, both energy and water balance, can be effected simultaneously via the evapotranspiration flux. Depending on the state of soil moisture, incoming short wave radiation is separated into latent and sensible heat flux. This effects both, the water and the energy balance as the latent heat flux transports not only energy but also water to the atmosphere. From this two major soil moisture feedbacks arise. The first feedback is between soil moisture and temperature. Wet or dry soil moisture anomalies directly affect the partition between latent and sensible heat flux. Wetter (drier) soils lead to increased (decreased) latent heat flux and evapotranspiration, therefore extracting more (less) water from the soil, which might result in compensating the soil moisture anomaly and thus form a negative feedback loop. However, the associated changes in sensible heat flux and latent cooling lower (increase) surface temperature and thus also decrease (increase) evaporative demand. In case the effect of changes in evaporative demand on evapotranspiration is stronger than the direct effect of the changed soil moisture state, the soil moisture-temperature coupling can result in a positive feedback. Thus, the soil moisture anomaly can be stabilized or even enhanced. A second feedback is based on the coupling between soil moisture and precipitation. Here precipitation anomalies result in subsequent anomalies in soil moisture which then affect evapotranspiration. At this point, the feedback loop can be already interrupted if the precipitation anomaly is smaller than the change in evapotranspiration and cannot sustain the anomaly in the soil. Otherwise, the evapotranspiration anomaly can effect precipitation either locally or in downwind regions. Alternative to the direct recycling of evaporated water as precipitation, it was also proposed that the effect on precipitation happens rather because anomalous soil surfaces impact the distribution of boundary layer moist static energy (Eltahir, 1998). More detailed information about soil moisture interactions and feedbacks can be found in Seneviratne et al. (2010, and references therein).

A large number of studies exist which investigate the impact of soil moisture anomalies on the terrestrial climate on different temporal and spatial scales. One objective of those studies is the reproduction of specific seasonal climate conditions and the analysis of its dependence on soil moisture states (Atlas et al., 1993; Ferranti and Viterbo, 2006; Fischer et al., 2007). Those studies demonstrate that extreme climate conditions are more likely to occur if extensive soil moisture anomalies exist in the past season. Additionally, there are several sensitivity studies investigating the effect of soil moisture anomalies on different regions like the North American (Beljaars et al., 1996; Small, 2001; Betts, 2004), African and/or Asian Monsoon regions (Douville et al., 2001; Kim and Hong, 2007) and Europe (Rowntree and Bolton, 1983; Jaeger and Seneviratne, 2011). Often, but not always, prescribing positive soil moisture anomalies is correlated with the simulation of enhanced precipitation in the following season and vice versa. Also the persistence of soil moisture anomalies is investigated in several studies, e.g. Manabe and Delworth (1990); Huang et al. (1996); Koster and Suarez (2001); Betts (2004); Wu and Dickinson (2004); Seneviratne et al. (2006); Dirmeyer et al. (2009); Hagemann and Stacke (2015). Estimates for soil moisture memory range between 1 to 6 months but differ based on the ~~tools~~ methods and models used to investigate it. Manabe and Delworth (1990) found short memory of 1 to 2 months for low latitudes with increases up to 5 months in high latitudes, peaking in memory up to 10 months in northern Siberia. For Europe they found memory of 2 to 3 months, which agrees well with Ferranti and Viterbo (2006). Some similarities exists also with the results of Hagemann and Stacke (2015), especially for regions with short memory. However, they found less memory for northern Siberia and memory longer than one year for desert regions. Most studies, however, do not explicitly compute the soil moisture memory but rather estimate its length based on a prescribed decay function of the soil moisture autocorrelation coefficient for a given lag (often one month) (Huang et al., 1996; Koster and Suarez, 2001; Betts, 2004; Wu and Dickinson, 2004; Seneviratne et al., 2006). The resulting soil moisture memory ranges between 1 to 10 months and shows spatial pattern with long memory in arid regions and high latitudes and short memory for Monsoon influenced regions. Seasonal variations in soil moisture memory were analysed by Dirmeyer et al. (2009). Looking at daily statistics they found considerably less memory, which exceeds one season only for desert or energy limited regions during the respective seasons. Soil moisture memory estimates based on observations are extremely rare, but range roughly in the same order of magnitude as most modelling studies. Based on 50 measurement sites across the former USSR, Vinnikov and Yeserkepova (1991) computed soil moisture memory ranging from 1 to 5 months, while Shinoda and Nandintsetseg (2011) found seasonally varying memory between 1.5 and 8 months for 24 stations in Mongolia.

Most of those studies have in common that they investigated the effect of soil moisture perturbations or soil moisture memory for a very limited time period usually focusing on the next season. Although the results indicate that soil moisture memory might be much longer for several regions, only ~~few~~ little information exist about the maximum time period to which soil moisture perturbations can be expected to affect climate simulations. Considering recent projects focusing on seasonal to decadal prediction systems (see MiKlip (Mittelfristige Klimaprognosen) http://www.fona-miklip.de/en/ and SPECS (Seasonal-to-decadal climate Prediction for the improvement of European Climate Services) http://www.specs-fp7.eu/), it would be valuable to learn more about the potential of soil moisture initialization. Particularly, information about the persistence of soil moisture perturbations in ESMs can contribute to decisions about the necessity to initialize soil moisture in short or even long-term predictions.

For this reason we set up an experiment to investigate the life-time of soil moisture perturbations for different seasons. In contrast to previous work by Hagemann and Stacke (2015) the focus is not on the general impact of soil representation on soil moisture autocorrelation length. Instead we analyse the impact of root zone soil moisture (RootSM) initialization for different seasons and regions. In our paper we first describe the model characteristics, experiment setup and the applied analysis methods. Following this we present the distribution of soil moisture memory and its variance throughout the year. Next, the origin of soil moisture memory is investigated, and its relation to different soil properties and climate variables is discussed. Finally, we contrast our findings against knowledge gained from previous studies and give directions for further research.

2 Experiment setup and analysis methods

The soil moisture initialization experiment uses the coupled atmosphere/land model ECHAM6/JSBACH (Stevens et al., 2013; Raddatz et al., 2007) with prescribed ocean fields (PCMDI AMIP2) of sea surface temperature and sea ice concentration for the appropriate time periods (Taylor et al., 2000). All simulations are conducted with a horizontal resolution of T63 ($\approx 1.8°$) and 47 vertical levels for the atmosphere. While most of the setup is identical to the CMIP5 (Coupled Model Intercomparison Project Phase 5) setup (Giorgetta et al., 2013), the standard JSBACH soil module is replaced with the new 5-layer soil hydrology scheme (Hagemann and Stacke, 2015). In contrast to the former bucket scheme, this scheme separates the soil into 5 distinct layers to a maximum depth of about 10m or the bedrock. The top soil layer is the reservoir for bare soil evaporation. The accumulated moisture in the upper layers within the rooting depth is defined as RootSM and is subject to transpiration. The layers below are associated with the deep zone soil moisture (DeepSM). As the latter is not directly accessible by plants, it can loose water only by drainage or diffusion into upper soil layers. Thus, the deep layers are often equivalent to a long term water storage and were shown to improve the representation of soil moisture memory in JSBACH compared to the standard bucket scheme (Hagemann and Stacke, 2015). It is important to note that the applied version of JSBACH does not consider any melting and freezing processes within the soil. Thus, there is no interaction between water and energy states within the soil column, and soil moisture anomalies can effect soil temperature only via the pathway of evapotranspiration and surface temperature.

The soil moisture initialization experiment is composed of two sets of simulations. The first set consists of one reference simulation (REF) for the period 1995–2008. It's initial states were taken from an earlier spin-up simulation running over several decades. For every year and month, restart data is generated by the model and six hourly averages of the RootSM and of the soil moisture for the individual soil layers (LaySM) are stored. From these data, extreme wet and dry soil moisture states are extracted as initial conditions for the second set of initialized simulations (INI). The INI are restarted at the start of every season for the years between December 1996 and September 2005, running freely for three years (see Fig 1). No INI are started prior to December 1996 as this time is regarded as additional spin-up for the model to adapt to minor differences in the forcing between the REF and the spin-up simulation. Thus, this experiment yields ensembles consisting of 9 members (one for each year) per restart month (4) and initialization state (2), respectively, accumulating to $9 \times 4 \times 2$ simulations resulting in a dataset of 216 simulation years.

In contrast to previous soil moisture initialization experiments (e.g. Betts, 2004; Ferranti and Viterbo, 2006; Fischer et al., 2007; Jaeger and Seneviratne, 2011), the initial soil fields are not defined as a fixed percentage of the reference value nor set to a known critical state like wilting point or maximum soil water holding capacity. Instead the 6 hourly output for the period of $\pm$ 15 days around a given restart time were extracted for every year from REF and merged into one time series. From the time series, the 99^{th} and 1^{st} percentiles of RootSM were identified. These percentile fields serve as extreme wet and dry RootSM initializations, respectively. For LaySM initialization, data from the same time steps were used to be consistent with the RootSM fields. Following this procedure, restart fields were computed for the 1^{st} of December, March, June and September. While the absolute values of the initialization data are identical for the respective months for every year, it has to be noted that their differences to the reference state vary from year to year. Instead of constant soil moisture perturbations, a distribution of perturbations is generated with minimum perturbation in the year where the reference state is close to the respective percentile and maximum perturbation when the reference climate conditions are opposite to the initial state. In this way, the ensemble does not only consider the internal variability within the model, but additionally takes inter-annual climate variations into account. Furthermore, the perturbations range within model-realistic bounds because they are based on model data. Thus we avoid unrealistic perturbations that would result in causing spin-up behaviour (large model drifts) rather than triggering soil moisture memory.

The analysis is focused on the evaluation of soil moisture memory. In our study we diagnose memory for those time steps where the ensemble mean anomaly (EnsMean) – originating from the initial perturbation – exceeds the ensemble standard deviation (EnsStd). This is determined by the signal to noise ratio (SNR) for a given time step i as:

$$\mathrm{SNR}(i) = \frac{E\left[\Delta\theta_j(i)\right]}{\sqrt{E\left[\left(\Delta\theta_j(i) - E\left[\Delta\theta_j(i)\right]\right)^2\right]}} \tag{1}$$

where $\Delta\theta_j$ is the difference in the respective target variable between daily means of INI and REF for an ensemble member j and $E[]$ indicates the mean over all ensemble members. From this, two different memory quantities are derived. First, the initial perturbation length (τ_0) which we define as the period between the first occurrence of memory until the time step at which the initial perturbation is forgotten and the INI ensemble mean state cannot be distinguished from the REF state any more. Some variables like DeepSM may have a time lag (τ_{lag}) before the perturbation reaches the layer and memory occurs. This has to be accounted for in the definition of τ_0. Second, the overall memory ($\tau_{\max}$) which is the sum of all time steps showing memory. Those memory quantities are given as:

$$\tau_{lag} = \min_{i=1..n}\left(i : \mathrm{SNR}(i) > 1\right), \tag{2}$$

$$\tau_0 = \min_{i=1..n}\left(i : \mathrm{SNR}(i) \leq 1 \cap i \geq \tau_{lag}\right) - \tau_{lag}, \text{ and} \tag{3}$$

$$\tau_{max} = \sum_{i=1}^{n} k(i), \text{ where } k(i) := \begin{cases} 1 \text{ if } \mathrm{SNR}(i) > 1 \\ 0 \text{ if } \mathrm{SNR}(i) \leq 1 \end{cases} \tag{4}$$

where $n = 1095$ is the maximum number of time steps being equivalent to the 3 years simulation period. Further important metrics are the initial perturbation ($\Delta\theta_0$) and extreme anomaly ($\Delta\theta_{\max}$) of a time series. The former is the peak anomaly in the initial memory period and for RootSM usually evident at the first time step. The latter is the 99^{th} percentile in the anomaly time series during all memory periods. 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 ($j = 18$).

~~This~~ The memory analysis is demonstrated in Fig. 2 for ~~the~~ RootSM in an arbitrary grid cell and seasonal ensemble. In this example τ_0 for the extreme wet initialization is almost 1 month while the dry perturbation lasts distinctively longer up to about 2.5 months.

Several analyses in this study are based on the spatial correlation between τ_0 and other quantities, e.g. $\Delta\theta_0$. As τ_0 is usually not normally distributed, neither spatially nor temporally, we apply the Spearman's rank correlation for those analyses, computed as:

$$\rho = \frac{\sum_i \left(R(x_i) - \overline{R_x}\right)\left(R(y_i) - \overline{R_y}\right)}{\sqrt{\sum_i \left(R(x_i) - \overline{R_x}\right)^2}\sqrt{\sum_i \left(R(y_i) - \overline{R_y}\right)^2}} \tag{5}$$

Furthermore, the spatial correlation between variables is affected by the spatial autocorrelation within the individual variables, resulting in a too significant 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%.

3 Soil moisture memory

The evaluation of the soil moisture initialization experiment is focused on a global analysis of memory distribution as well as a comparison of its characteristics for different regions and seasons. Additionally, relations between memory and anomalies are investigated.

Figure 3 displays statistics for soil moisture $\Delta\theta_0$ and τ_0. The wet and dry initial perturbations are of similar magnitude for the respective soil moisture layers with no strong variations among the seasons. The initial ensemble mean perturbations for RootSM reach almost $\pm 0.2\mathrm{m}$. Variations are smallest ($\pm 0.01\mathrm{m}$) for the uppermost layer, which also has the smallest thickness ($0.07\mathrm{m}$). The $\Delta\theta_0$ increase with increasing soil depth and layer thickness and reach a maximum of $\pm 0.25\mathrm{m}$ in the fourth layer. They decrease again for the fifth layer because this layer is often cut off by the bedrock and thus its global average is less thick than that of the third and fourth layer. In many cases, the lowest layers are often not perturbed directly, as they can lie below the root depth and, thus, are not necessarily in a similarly extreme state. Consequently, only for the RootSM the wet and dry initialized simulations correspond perfectly to wet and dry initial perturbations while the single layers show much more variance for this. Already for the top soil layer, a small number of grid cells exist with initially wet perturbations for an overall dry root zone and vice versa. This effect increases with depth to about 20% of grid cells in the fifth layer which show the opposite perturbation signal than the RootSM. Analysis of memory time series show that in such cases the initial RootSM perturbations need some time to propagate into the deeper layers. This effect is negligible for layers within the root zone, but results in a perturbation delay of over 30 (10) days for 25% of fifth layer cells for wet (dry) initialization.

The life times τ_0 of these perturbations vary strongly depending on the respective soil layer, initialization season and state. For RootSM the interquartile range of τ_0 varies between 0.5 to 2 months for March and 0.65 to 3.5 months for December. Single grid cells (99^{th} percentile) for all seasons show memory up to 10 months. The memory for soil layer moisture increases with depth. The top layer only reaches median values of about one week although for individual grid cells the perturbation signal can be visible for up to 4 months (June and December). The median τ_0 increases to about 5 months in the fifth layer while the interquartile range increases exponentially. Thus, a large ratio of grid cells is still affected by the perturbation after three seasons in the fourth layer and even after two years in the fifth layer. Down to the third layer, the longest τ_0 is found for December initialization shifting to September for deeper layers. For the RootSM and the upper three layers wet initializations correspond to a slightly longer τ_0 than dry ones but for lower layers dry perturbations become much more persistent.

The spatial pattern of the RootSM τ_0 are investigated first by dividing the simulations into two, dry and wet initialized, ensembles (see Fig. 4) including all different seasons. Similar large-scale pattern can be found for both initialization states indicating a generally higher sensitivity for soil moisture perturbations in some parts of the world. Short memory between 2 to 4 weeks is evident for larger parts of Asia, Central Australia and northwestern North America. Regions with medium memory between 1 to 6 months are found for the eastern US, central and eastern South America, the larger part of Europe, Central Africa and southeastern Asia. However, there are distinct difference for the more extreme values. Long memory of up to one year and more is found for wet initialization in the Congo region and Eastern US while it is much more sparse for dry initialization with two spots south of the Amazon catchment and in northeastern China. In return, areas without any memory are more common for dry than for wet initializations. While wet initialization shows no memory for parts of the high northern latitudes as well as the Amazon basin, dry anomalies cannot persist for the southwestern US, the Sahel zone, South Africa, the Arabian peninsula, southeastern Asia, and western Australia. These regions very well coincide with dry conditions. There, dry perturbations have the lowest impact as the soils are usually in a dry state anyway. Thus the perturbations are relatively small and fall within the climate variability. Wet perturbations are much larger and can result in τ_0 of several months.

In a second step, the simulations were sorted with respect to the initialization season but not separated between wet and dry initial perturbations. As already indicated by Fig. 3, the resulting τ_0 distributions show much more variance between seasons than between wet and dry initialization (see Fig. 5). The most prominent features are found for the northern hemisphere. For most parts of the high northern latitudes and central Asia, τ_0 is shorter than one month for March to September initializations. However, with the onset of the boreal winter, τ_0 becomes much more persistent and reaches values up to six months and more. This pattern seems to be related to the regional climate conditions. For March to September, the initialization often precedes periods of higher soil moisture variability. Thus, the computed initial states for the simulations are relatively small compared to variability of the following season, and the perturbation signal decays fast. In contrast, the initial December states are still impacted by the summer soil moisture variability resulting in a large perturbation which by far exceeds the moisture variability during winter. This perturbation is then conserved by the snow cover on top of the soil which hampers the exchange of water and energy between land and atmosphere. Thus, the initial perturbations can persist until next years' snow melt. Another prominent feature are some regions along a band reaching from the African west coast towards India and then following the Asian coast in north-easterly direction. In the September ensemble they show memory up to one year. Almost the same regions are associated with three and six months less memory in the December and March ensembles, respectively, and shorten to less than two weeks in the June ensemble. A similar behaviour is visible for South Africa starting with the March ensemble and South America starting with the June ensemble, although the latter shows shorter memory of $\tau_0 \leq 6$ months. Most of those regions very well resemble areas impacted by monsoon circulation as outlined by Lin et al. (2014). Monsoon periods are characterized by heavy precipitation during one season which amounts to over 50% of the annual precipitation. Such precipitation results in a very high soil moisture content that completely removes all memory of previous wet or dry anomalies. However, in the seasons after monsoon, precipitation is much lower resulting in low soil moisture variability and longer persistence of anomalies. This is well reflected in the derived memory distribution. For the northern hemisphere, monsoon usually occurs during the summer season thus almost no memory is seen in the June ensemble for western Africa and India. The next season (September ensemble) shows the longest memory of about nine months that lasts until the next monsoon period, while every following seasonal ensemble has memory of three months less, respectively. The same reasoning holds for the southern hemisphere. There the South African monsoon lasts from November till March, resulting in no memory for the December ensemble. The South American Monsoon often lasts even longer until April resulting in short memory for the December and March ensemble as well as a respective cut on the long memory evident in the June ensemble. This analysis reveals that not only the initialization state (e.g. wet versus dry) but also the time of initialization has a large impact on the resulting memory. In more generalized form, this connection between precipitation variability and soil moisture memory is also described in Koster and Suarez (2001); Seneviratne and Koster (2012).

In order to identify more general systematics behind the spatial τ_0 distribution, regions of similar soil moisture regimes were defined using the classification described in Seneviratne et al. (2010). The regimes are computed from REF climatology for all four seasons based on the state of soil moisture θ in relation to the wilting point θ_{wilt}, below which no transpiration may occur, and the critical soil moisture θ_{crit}, above which transpiration occurs at the potential rate and is not limited by soil moisture anymore. The regimes are classified into dry ($\theta <= \theta_{wilt}$), wet ($\theta >= \theta_{crit}$) and transitional ($\theta_{wilt} < \theta < \theta_{crit}$) regimes (see Fig. 6). The grid cells are not distributed equally between the regimes. Instead grid cells in transitional regimes exceed those in others by a factor of 5 (wet cells) to 20 (dry cells).

In spite of the strong differences in sample size, the partition into the three soil moisture regimes appears to be reasonable as they show distinctively different characteristics of soil moisture τ_0 (see Fig. 7). For all seasons, the longest τ_0 is found in dry regimes and the shortest τ_0 in wet regimes. While the dry and wet distributions within the regimes are quite symmetric for the March ensemble, the other ensembles show longer memory for wet perturbations in dry regimes, a symmetric shape for the transitional regime and longer memory for dry perturbations in wet regimes. In contrast to the memory distribution, the $\Delta\theta_0$ distributions show a different relation to the soil moisture regimes. There, the smallest perturbations are evident for dry regimes and the largest for the transitional regime for all seasons (not shown). This already indicates that the size of the initial perturbation cannot be the dominant driver for the initial soil moisture memory. This is confirmed by analysing the spatial correlation between soil moisture τ_0 and $\Delta\theta_0$ for the different regimes and seasons as shown in Fig. 8 (lower panel). The correlations differ for the regimes as well as for seasons and show highest values of up to ± 0.7 for June and September in the transitional ~~and wet regime. However, even there the Spearman's rank correlation coefficient does not exceed 0.7~~regime. Similarly high values are found for June and September in the wet regime, although there they are not significant ($p > 5\%$). Thus, at most 50% of the spatial variance in memory pattern can be explained by the size of the initial perturbations. Furthermore, correlations between wet and dry memory are even lower with maximum values of 0.4 in the December ensemble for the transitional regime and ~~almost~~ no significant correlations for the ~~dry regime~~ other seasons and regimes at all (Fig. 8 upper panel). This indicates that for a given time step and grid cell, the soil might be susceptible for either wet or dry perturbations but rarely for both. Thus, the strength of soil moisture memory seems to depend ~~on~~ about equally on the initial soil moisture perturbation as well as on dynamically changing land atmosphere interactions ~~rather than~~ and static soil or land cover properties.

~~This statement is supported by~~ In order to verify whether the next largest impact is due to static soil and land properties or due to seasonal climate dynamics, the spatial correlations between soil moisture τ_0 and ~~static land surface properties . For most soil parameters (~~surface properties are computed (see Tab. 1 – 4). The investigated parameters are related to surface properties (forest fraction, orographic standard deviation, maximum vegetation fraction), soil moisture state thresholds (maximum soil water capacity, rooting depth, soil depth until bedrock) and parameters determining water movement within the soil column (Clapp and Hornberger exponent, saturated hydraulic conductivity, ~~porosity, pore size index, wilting point,~~ saturated matrix potential, soil pore size distribution index, volumetric soil field capacity, ~~matrix potential, vegetation fraction, forest fraction and orographic standard deviation)~~volumetric soil porosity, volumetric wilting point). For most parameters correlations are low, varying between -0.25 to 0.25 during most seasons ~~or are even insignificant. However, for hydraulic conductivity a low anti-correlation down to -0.36 indicates a longer for regions where hydraulic conductivity is low. This effect occurs for transitional and wet regimes and preferably for dry initialization. Rather than just reducing drainage and thus sustaining wet anomalies, the low conductivity also reduces diffusivity and thus limits the ability of the soil to compensate dry anomalies via upward diffusion of moisture from deep and wet layers. Stronger correlations are only found for rooting depth and soil depth down to the bedrock. Rooting depth plays a role mostly in transitional regimes with correlation coefficients up to 0.57 in the June and~~ and are rarely significant. In particular for wet and dry soil moisture regimes as well as for the December ensemble in all regimes, no significant spatial correlations exist at all.

For the transitional regime, the strongest correlations are found for maximum soil water capacity and rooting depth ranging between 0.4 to 0.6 in the March to September ensembles. Since these seasons coincide with the seasons of high memory – perturbation correlation (see Fig. 8), it can be assumed that the higher rooting depth ~~allows~~ and maximum soil water capacity allow for larger perturbations that cause longer memory. ~~In contrast, anti-correlation between~~ For the June ensemble, weak but significant correlations are also seen for the soil depth until bedrock. This is probably related to the rooting depth and ~~memory~~ soil water capacity correlations, as deep soils are often associated with thicker root zone. Furthermore, significant correlation is found for ~~wet perturbations in December and March ensemble for the wet regime with values down to -0.34. During this season, large areas in the wet regime are covered by snow and therefore wet perturbations cannot be easily compensated via transpiration but relying on drainage instead. However, being located in the wet regime it can be expected that the deep soil layers are close to saturation and retain the drainage flux. This effect strengthens with increasing soil layer thickness. Since the overall soil depth is limited, a thicker root zone is likely related to a thinner deep soil zone, leading to the simulated anti-correlation. Correlations with total soil depth are only important for wet perturbations. They are mostly positive (up to 0.45) because deep soils provide a stable reservoir from which water can rise upwards via diffusion to sustain the wet anomaly. Of course, this is only possible for those grid cells where the wet perturbations exist in all layers and not just in the root zone. Consequently, this correlation is only observed in seasons and regions where no strong anti-correlations with hydraulic conductivity exist~~the forest fraction (0.35) with dry initialization and the maximum vegetation fraction (0.41 to 0.46) with both initializations. The forest fraction correlation is related to the generally deeper roots of trees compared to other plant types. The deep roots transpire water from a larger fraction of the soil column effectively sustaining dry anomalies which in other grid cells are quickly compensated by percolating water. In contrast, the correlation with the maximum vegetation fraction is significant for both, wet and dry, initializations. Here, the higher vegetation cover results in higher transpiration. We assume that depending on the location of the grid cells within the transitional soil moisture regime, increased transpiration can either sustain dry anomalies as it removes water from the soil column. Alternatively, for regions where relative humidity is already high, the additional transpiration may trigger convection, resulting in additional precipitation and therefore sustain the wet anomalies. However, it should be noted that positive soil moisture – precipitation feedback is considered to be rare in reality on the local scale (Taylor et al., 2012a) 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).

Together with the observed seasonal dynamics in soil moisture memory, these correlations demonstrate the limitations in explaining soil moisture memory with static soil properties alone. Instead, the contribution of favourable climate states ~~appears to be equally~~ together with the size of the initial perturbation appear to be much more important to form persistent anomalies.

4 Interaction of perturbations between soil moisture and other state variables

As already pointed out by earlier studies (Seneviratne et al., 2006; Rowntree and Bolton, 1983, and others), soil moisture anomalies also lead to alterations in other – originally not perturbed – state variables due to feedback mechanisms (see Sect. 1). However, it is not yet clear to what extent the memory within a state variable is affected by such feedbacks. While assuming that memory is a specific characteristic for a given state, the overall memory of a coupled system of interacting states might differ distinctly from the sum of its parts. For this reason, the induced anomaly and memory statistics in other land surface states are analysed in the following.

The largest impact of soil moisture perturbations is expected for surface and soil temperatures due to the tight coupling of water and energy fluxes via the latent heat / evapotranspiration flux. Indeed, induced perturbations are evident there (Fig. 9, left). The $\Delta\theta_0$ are largest for the surface and top layer with median values of $1.1\mathrm{K}$ ($-1.4\mathrm{K}$) for dry (wet) initialization which decrease towards zero in the deepest layer. The extremes range between -10 to $9.5\mathrm{K}$ for the surface and still reach $\pm 0.5\mathrm{K}$ near the bottom of the soil column. While the interquartile range of the anomaly is consistent with the initial soil moisture perturbation for all layers, e.g. warm anomalies for dry initialization and cold anomalies for wet initialization, extreme values with opposite anomalies exist. The memory in soil layer temperature is much shorter than for moisture. Starting from few a days at the surface, the median τ_0 and its interquartile range increase with increasing depth towards a median of about 0.5 months in the fourth layer (Fig. 9, right). In the fifth layer, the value decreases again as a large fraction of the grid cells does not show any initial memory. The extremes, however, increase exponentially from three weeks at the surface to over two years in the lowest layer. Wet and dry initialized ensembles behave similar to each other, however the interquartile range for the 4^{th} and 5^{th} layer is respectively about 0.5 months and 1 months longer for wet initializations than for dry.

Induced perturbations are not only evident for surface and soil temperature, but do also occur in other land surface variables. Concerning the initial memory period (see Fig. 10, line symbols) induced perturbations result in anomalies in the range of $\pm 1\mathrm{hPa}$ for surface pressure, $\pm 0.005\mathrm{m}$ for snow water equivalent, -0.001 to $0.002\mathrm{kgm}^{-2}$ for specific surface humidity, -2.5 to $9.5\mathrm{kgm}^{-2}$ for vertically integrated water vapour and $\pm 0.003\mathrm{kgm}^{-2}$ for the leaf carbon content (see Tab. 5 for details). However, the τ_0 associated with these anomalies is rather short for all states but leaf carbon content where τ_0 lasts up to 4 months (see Tab. 6). In order to identify a systematic behaviour in these effects, the anomaly-memory relations are divided into wet and dry initializations. It becomes visible that the dry and wet perturbations in dry and transitional soil moisture regimes mostly result in either positive or negative anomalies. For the wet soil moisture regime, however, positive as well as negative anomalies are visible for any perturbation. The τ_0 does not seem to be ~~correlated~~ related with the $\Delta\theta_0$ for any state but leaf carbon content. Here the largest anomalies correspond to the longest memory and occur in the transitional regime, while both, dry and wet regimes show shorter memory and smaller anomalies. For the dry regime this is probably due to the low amount of plant cover whereas in the wet regime there is no water limitation and therefore leaf carbon content becomes insensitive to variations in soil moisture.

Taking into account the full time series (Fig. 10, filled symbols), the change in memory indicates that there are not only initial, induced perturbations with an associated memory, but anomalies recur again at later time steps. For some variables, these anomalies show even larger magnitudes than the initial ones. The accumulated memory τ_{max} for most variables rises from a few days to about one month, and the memory for leaf carbon content doubles to 6 months. Snow water equivalent τ_{max} stays low around one week for all regime–initialization combinations as does the leaf carbon content τ_{max} for dry perturbations in the dry soil moisture regime. While the sign of the anomalies corresponds to the expectations for some variables, e.g. wet initialization resulting in positive anomalies for leaf carbon content and negative anomalies for surface temperature and vice versa, other variables (snow cover, surface pressure) react with anomalies in both directions. 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. For soil moisture, there are almost no differences between the magnitudes of $\Delta\theta_0$ and $\Delta\theta_{\text{max}}$. Thus, anomalies during later memory periods are usually smaller than at the beginning, indicating that no positive feedbacks or new equilibria are triggered by the initial perturbations. However, τ_{max} for all layers is increased by 1 to 1.5 months for the median and up to 4 months for the 75^{th} percentile. The largest increase is visible for the upper extreme of RootSM memory with 15 months. Extreme anomalies for soil temperature behave similarly to initial anomalies and become smaller for deeper soil layers. Changes in magnitude range between -5 to 3K for the surface and vary around $\pm$0.3K in the deep layers. The separation between positive and negative anomalies in response to the initial soil moisture perturbation is not as distinct anymore for the upper three layers. The accumulated median memory is at least 1 month for all layers and interquartile range as well as extremes increase even stronger than for the initial memory. For the 75^{th} percentile, τ_{max} exceeds τ_0 by 1 (8) month for the first (fifth) layer. The differences between wet and dry initialization are less extreme compared to τ_0 statistics but still a slightly longer memory is found for wet initialization in the lowest layer.

These analyses demonstrate that memory occurrence and anomaly recurrence are not limited to soil moisture and the closely linked soil temperature. Instead, the soil moisture perturbations affect most of the land surface system although to a different extent. However, the mechanism responsible for the recurrence of anomalies in the different variables cannot be identified from these analyses.

5 Anomaly interaction pathways between state variables

In technical terms, the recurrence of state variable anomalies indicates that the anomaly mean and the anomaly standard deviation for a given location are not just two steadily decreasing and increasing curves at whose intersection the memory ends. Instead one or both of them show temporal variations which result in the anomaly becoming visible (SNR ≥ 1) again. In the following, this possible recurrence is explored on grid cell level by investigating the relation of SNR time series (see Eq. 1) between different state variables. Here, we focus on leaf carbon content and (deep layer) soil temperature as longest accumulated memory was computed for these variables. In order to find suitable grid cells for the analysis, we applied a number of conditions, namely the difference between τ_{max} and τ_0 being > 600 days and the amount of recurring memory periods ≥ 3. Only such grid cells were analysed that comply with these conditions. Additionally, they were ranked according to the similarity between the length of their memory periods as we expect more robust results for regularly recurring anomalies.

For all state variables except soil moisture, the anomaly recurrence is simple to explain. For example, soil moisture perturbations affect leaf carbon content and can result in anomalies with a distinct memory (see Sect. 4). However, leaf carbon content follows a yearly cycle and can become insensitive to soil moisture anomalies during certain time periods, i.e. when soil moisture is below the wilting point or above the critical soil moisture. The latter case occurs ~~in the example for~~ for the leaf carbon content shown in Fig. 12 (right). Here, the anomaly vanishes during periods of maximum leaf carbon in the reference simulation. In case the soil moisture perturbation still exists after the peak, a new anomaly is triggered and leaf carbon memory recurs. A connection between the memory pattern of soil moisture and vegetation is also proposed by an observation based study by Shinoda and Nandintsetseg (2011). Similarly, soil temperature anomalies do not depend on soil moisture anomalies alone, but also on evapotranspiration anomalies. These are only triggered when several climate conditions (e.g. downward radiation, surface humidity) are favourable (not shown). Thus, temperature anomalies emerge as long as these conditions apply but, as surface temperature memory is short, are interrupted whenever the favourable conditions fade. In both cases, the recurrence of state memory is possible only because soil moisture memory lasts long enough until conditions for anomalies become favourable again.

As there is no state variable that demonstrated longer memory than soil moisture, another explanation is needed for its memory recurrence. Still, there are several possible explanations for this phenomenon: The first hypothesis is based on feedbacks between different state variables. As shown in the previous section soil moisture perturbations induce anomalies in other variables. However, the induction may have a certain lag time and furthermore the memory of the anomalies differs between the various states. Thus, it would be possible that a soil moisture anomaly induces a temporally lagged anomaly in another state with a different memory. While the soil moisture anomaly is already decayed, the induced state anomaly might still exist and – in case there is a feedback loop between both – induces a secondary anomaly in soil moisture. This effect would be visible as wave-like variations in the ensemble anomaly mean. ~~Secondly,~~ 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. Second, the soil moisture anomalies might be stable over long time periods, but its memory could be temporally hidden during periods with pronounced variability in interacting variables. This would become visible as a rather steady and slow decline of the anomaly mean curve which would be overlain by periodical increases in the ensemble anomaly standard deviation.

For soil moisture, the best example is found for a grid cell at -2.8°N and 13.12°E (West Africa, Republic of Congo) during wet initialization in September. Its ensemble mean anomaly and SNR timeseries are shown in Fig. 13 for soil moisture and soil temperature in the different soil layers. At this location the depth of the bedrock is prescribed with $5.6\mathrm{m}$ while root depth extents down to $2.8\mathrm{m}$. This means that the water content of the lowest soil moisture layer as well as about 50% of the fourth layer is not directly accessible to plants for transpiration. Consequently, the SNR soil moisture curves (Fig. 13, right) exhibit very different temporal dynamics for the soil layers. In the upper three layers, which are within the root zone, the initialized perturbation decays within 1 (2) months for the first (third) layer. It recurs at yearly intervals for a three months period, although only the recurrence after 12 months shows memory for all three layers while for later recurrences SNR stays below 1. In between those intervals the SNR curves are subject to high-frequency variations. The increasing length of memory and less variable SNR signal reflect the increasing soil layer thickness with depth in these layers. The root zone moisture as a whole also reflects the yearly intervals of increased SNR, but shows much less high-frequency variability. The SNR is above 1 for most of the time series. In contrast to the upper layers, the fourth and fifth layer, which represent the water reservoir below the root zone, show the slowly decaying SNR signal of the initial perturbation without any short-term variability. Comparing the SNR curves to the anomaly time series (Fig. 13, left), the same slow decay is visible for the anomalies in the two lowest layers. Above, distinct wet anomalies mark the annual recurrence of memory while in between small wet and dry anomalies are visible. The intra-annual anomalies usually show a small time lag for deeper layers indicating that the anomaly is migrating from the top layer into the deeper layers. However, the annual anomalies are already visible in the third layer before they start in the second or first one. Therefore, the wet anomalies could be related to water percolating downwards from above that is retained here due to the higher water content of the lower layers. Alternatively, it is even possible that water is migrating upwards via diffusion due to the positive water anomaly in the lower layers leading to an strengthened gradient between those layers. For the actual grid cell, the second case is more probable as the wet anomalies coincide with the minima of the REF precipitation climatology. Thus, the anomaly and memory recurrence within the RootSM results from interactions with the uninterrupted period of memory in the deep moisture layers below the root zone.

Additionally, the vertical profile of soil temperature memory is analysed for the same grid cell (Fig. 13, bottom). Similar to soil moisture memory, variability for soil temperature is higher for the thin top layers and lower for the thick, deep layers. Three events of increased memory are visible that correspond to the memory recurrence in soil moisture. Even though variability in the top layer is very high, a distinct downward movement of the memory signal is visible, starting with short periods of a few days in the top soil layer. The downward movement shows a short time lag in memory occurrence for every layer together with a longer memory of the single events due to the increasing layer thickness. Additionally, the accumulation of anomaly and memory is visible in the lower two layers. Here, the vertical structure of the signal reflects the migration of the induced temperature anomalies from the top layer downwards. As the memory increases with depth and layer thickness, the rather short-lived anomalies of the top layer accumulate to a distinct and steady anomaly in the lower two layers. This top-down movement is not only supported by the pattern of the anomaly time series (Fig. 13, left), but follows from the model physics. In this version of JSBACH, phase changes of moisture within the ground are not considered and there is no interaction between moisture and temperature within the soil column. The only existing link between both is the latent heat flux / evapotranspiration at the soil surface. Thus, the first part of the hypothesized anomaly and memory transport between variables is realized here, as changes in RootSM induce anomalies and memory in the deep layer soil temperatures. However, there is no feedback evident from the temperatures to the moisture state. Thus, in this experiment the recurring soil temperature anomalies are most likely caused by recurring soil moisture memory but not vice versa.

The grid cell analysis demonstrates the possibility of memory interactions between variables although no indication was found for a closed memory interaction loop that feeds back into soil moisture again. Instead, anomaly recurrence in RootSM seems to depend on the existences of deep soil layers below the root zone. In order to conclude whether this is true for the model in general or just for the one grid cell, we divided all grid cells in three groups depending on the thickness of the soil column below the root zone. For these groups, the frequency distribution of memory recurrence was calculated for every soil moisture regime and is displayed in Fig. 14. Indeed the curves differ distinctively between grid cells without any deep soil layers and grid cells with either thin ($\leq 1\mathrm{m}$) or thick deep soil layers. It can be seen, that memory recurrence is generally more frequent for dry soil moisture regimes than for wet ones. Additionally, the impact of the deep soil thickness is strongest for dry regimes and almost not visible for the wet regimes. The figure also shows the impact of different seasons and initializations on the memory recurrence. The seasonal variations are mostly not distinguishable, but the wet initialization shows systematically less memory recurrence than the dry initialization. For the transitional regime, the major part of the impact is seen for the recurrence range of 5 to 200 days where all three sets of deep layer thickness are well separated. In the dry regime there are no differences between thin or thick deep soil layers, but a large offset to the cells without any deep soil layers. Consequently, the deep soil moisture storage seems to play a prominent role for the memory characteristics within the RootSM in all but the wet soil moisture regime. Still, there is a significant part of the land surface where memory recurrence is caused by other processes, e.g. in the wet soil moisture regimes and all the grid cells without any deep soil layers. There are indications, that the second hypothesis, the steadily declining anomalies interrupted by periods of high variability, is realized as well. An example on grid cell scale is shown in Fig. 12 (left). Here the anomaly is above the mean level of ensemble standard deviation over the whole three years. It even increases periodically due to recharge from the deep soil layer. However, during the rainy seasons, the ensemble standard deviation increases strongly and overlays the mean, thus, dividing the memory signal into several separate periods. However, a more comprehensive analysis of this effect and other possible reasons for memory recurrence on global scale is beyond the scope of this study as it would need a different experiment setup.

6 Summary

The presented soil moisture initialization experiment was designed to reveal information about the life-time of extreme – yet realistic – soil moisture perturbations in a coupled climate model. For the root zone, those lifetimes range from days up to one year and, thus, are consistent with the range of memory found by other studies (e.g. Manabe and Delworth, 1990; Hagemann and Stacke, 2015; Ferranti and Viterbo, 2006).

The distribution of memory shows a systematic relation with soil moisture regimes and is consistent with large-scale physical characteristics. A prominent example is the soil moisture memory for monsoon regions, which is extremely low during the monsoon period as any soil moisture perturbations are negligible in face of the heavy precipitation. A similar result was reported by Seneviratne et al. (2006) who computed the global soil moisture autocorrelation pattern based on an ensemble of eight atmospheric general circulation models. Their simulations started in June and lead to a memory pattern very similar to the pattern of the June ensemble in our study. However, memory in the period after the monsoon is among the longest found globally and lasts until the next years' monsoon season starts again. Thus, monsoon regions are actually regions of significant memory if considered after the main precipitation period. Similarly, we see long memory in the high-northern latitudes in the December ensemble as perturbations are preserved because land atmosphere interactions are hampered by snow cover. These regions coincide with the long memory regions identified by Manabe and Delworth (1990). But again, the date of initialization is critical, since snowmelt and summer precipitation reduce the memory after the winter period, as seen in the other seasonal ensembles. Only limited agreement can be found between our memory pattern and the soil moisture autocorrelation length shown by Hagemann and Stacke (2015), although the same Earth System Model (ESM) was used. While for South America and the high northern latitudes some similarities are visible, the extremely long memory exceeding one year for most arid regions cannot be confirmed. This might be due to their use of autocorrelation diagnostics which the authors themselves report to be problematic in very dry and very wet regions. On average, longest memory is visible for dry soil moisture regimes and shortest for wet regimes. Within these regions it shows only low dependency on the type (dry/wet) of the initial perturbation. In terms of temporal variance, long memory is more common in dry periods following distinct rainy seasons and during extensive periods with snow cover.

Although soil moisture memory is often associated with static soil properties like soil depth (e.g. Asharaf and Ahrens, 2013; Hagemann and Stacke, 2015) we find that soil moisture memory is a dynamical feature which strongly depends not only on the size of a given anomaly, but also on favourable climate conditions. ~~Even the~~ The size of the initial perturbations can ~~only~~ explain up to 50% of the spatial pattern of memory while static parameters like ~~soil depth~~maximum soil water capacity, rooting depth or ~~hydraulic conductivity display even weaker correlations.~~ forest fraction 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.

Furthermore, soil moisture perturbations affect other land surface states due to different interactions. Strongest impacts are seen for leaf carbon content whose anomalies are associated with a memory of up to 6 months in transitional soil moisture regimes. While the effect on surface temperature is very short-lived and shows much high-frequency variation, the respective anomalies migrate through the soil column into deeper layers and there accumulate to considerable memory that can even exceed the simulation period of three years. Likewise, for most other surface variables, such as humidity and pressure, only short memory is diagnosed. Soil moisture control seems strong enough to induce some anomalies, however their memory is quickly dissipated by strongly non-linear processes in the interacting atmospheric states. 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.

~~However, we~~ 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.

We also find that root zone soil moisture (RootSM) memory itself can emerge again after the initial memory was already lost. In most cases this is related to the existence of a deep soil moisture storage below the root zone. As all soil layers interact with each other, anomalies which were already faded in upper layers might recur. This is caused by anomalies still existing in lower layers that either modify percolation or – in case of wet anomalies – can even migrate wet anomalies via upward diffusion. This effect is most common in dry and transitional soil moisture regimes but quite insensitive to the initialization date and type.

From ~~this~~our study, we can conclude that memory is not just a property of a single variable but it is modified by the interactions of states in a coupled system. Between different states, only one interaction direction is clearly visible in our simulation, going from soil moisture towards soil temperature and leaf carbon content, respectively. However, we do see two-sided interactions between soil moisture in different layers, namely root zone and deep soil. As deep soil memory exists for the full three year simulation period for some regions and feeds back to root zone memory, the predictive potential of soil moisture initialization might be much longer than previously expected. Thus, soil moisture has the potential to play an important role in seasonal predictions. However, ~~it has to be noted that~~ there a some limitations to our study which have to be noted. First, in the current version of JSBACH, phase changes within the soil column are not yet considered and, thus, water and energy balances are not connected. However, this process is implemented in the next version (Ekici et al., 2014). It leads to a tight moisture-temperature coupling and might result in significant two-sided memory interactions within the two long-memory states. Whether this will result in long-term stabilization or rather in a quick compensation of anomalies is difficult to predict and needs to be tested. 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. Finally, it has to be noted that the results are, of course, model dependent and the exact numbers will differ for individual modelling frameworks. Nonetheless, as long as critical land surface parametrizations are existent, namely the separation of the soil column into several layers containing a root zone and a deep soil layer, we expect similar soil moisture memory characteristics to emerge. Thus, the potential for improved climate predictions should exist for all state of the art modelling frameworks.

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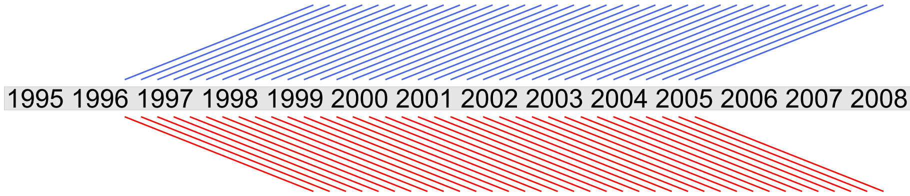

Figure 1. Schematic of the soil moisture initialization experiment setup. The grey bar indicates the time line of reference simulation (REF) while the blue and red lines indicate the extreme wet and dry initialized simulations (INI), respectively.

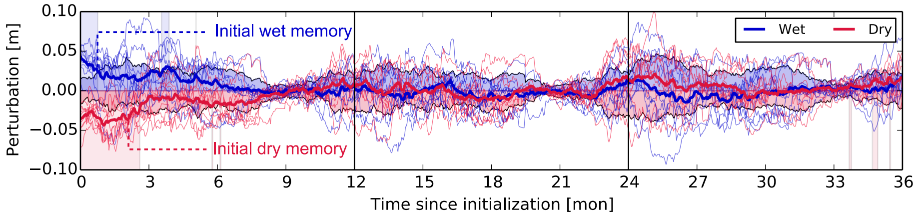

Figure 2. Example for soil moisture perturbation at grid cell scale (June ensemble, grid cell near Hamburg, Germany). The thick blue and red lines indicate the ensemble mean wet and dry perturbation, respectively. The thin lines are single ensemble members and the filled area displays the ensemble standard deviation.

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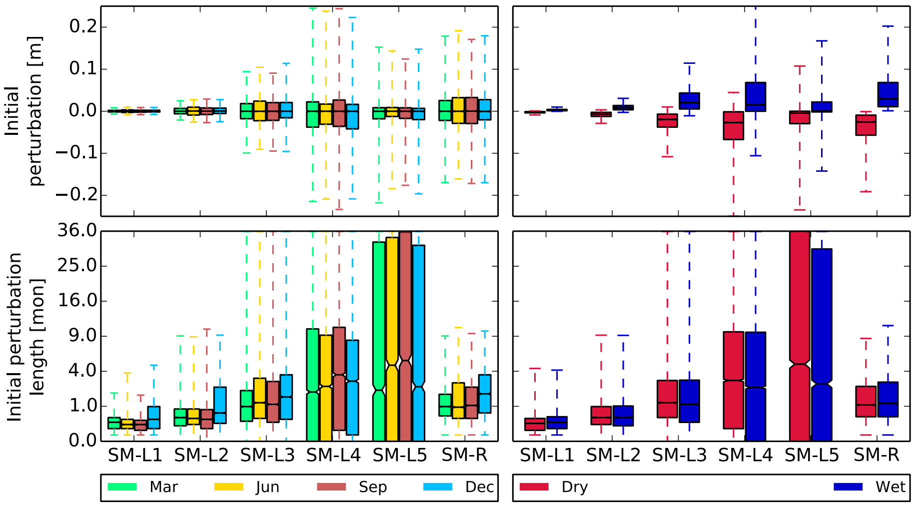

Figure 3. Initial perturbation initial perturbation ($\Delta\theta_0$) (upper panels) and perturbation length initial perturbation length (τ_0) (lower panels) statistics subdivided into seasonal ensembles (left) as well as into wet and dry initialized ensembles (right). Metrics are shown for soil layer moisture (SM-L[1-5]) and the root zone soil moisture (SM-R) for all land surface grid cells. The whiskers indicate the 1^{st} and 99^{th} percentiles respectively, the box indicates the interquartile range and the notch indicates the median. Note the exponential axis for τ_0.

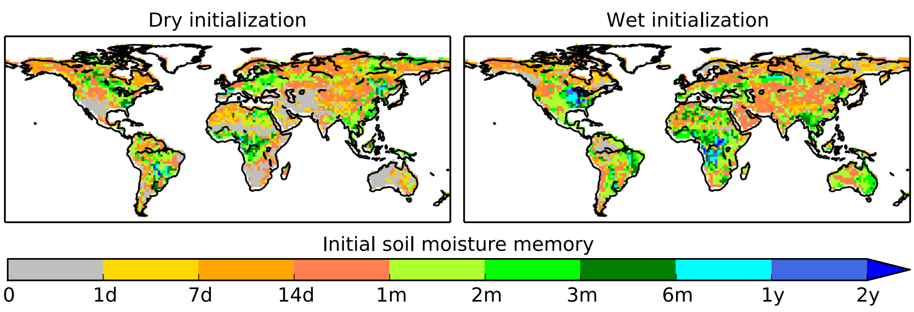

Figure 4. Initial perturbation length for root zone soil moisture in dry (left) and wet (right) initialized simulations. The letters d, m and y indicate days, months and years, respectively.

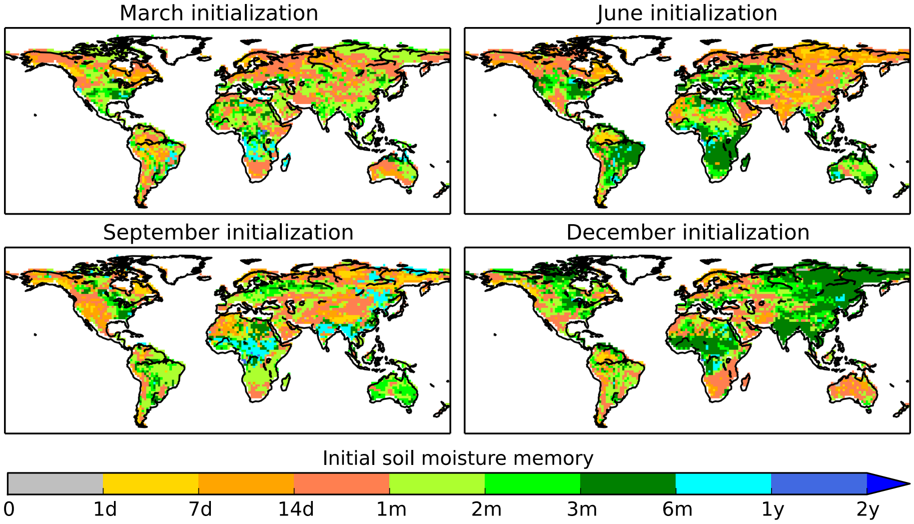

Figure 5. Ensemble mean τ_0 for all (dry and wet) simulations initialized in a given season.

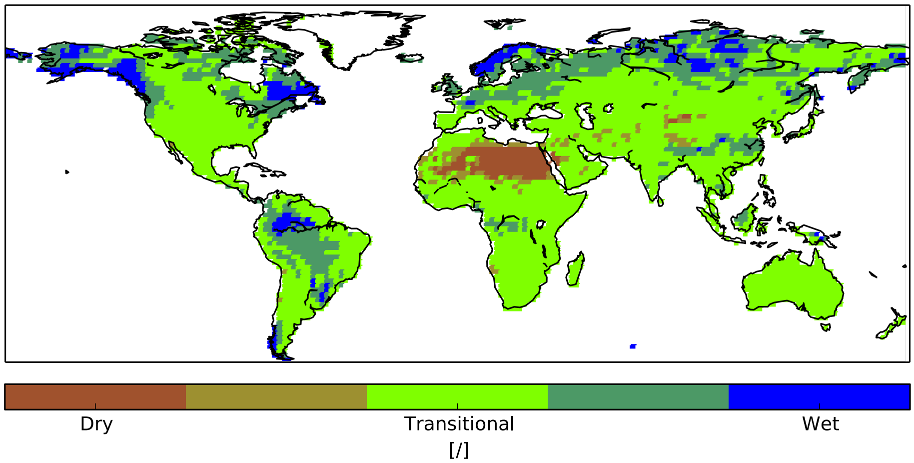

Figure 6. Soil moisture regimes based on REF climatology. Transient colors mark grid cells switching between the transitional and wet/dry regimes seasonally while the others remain in their category for the whole year.

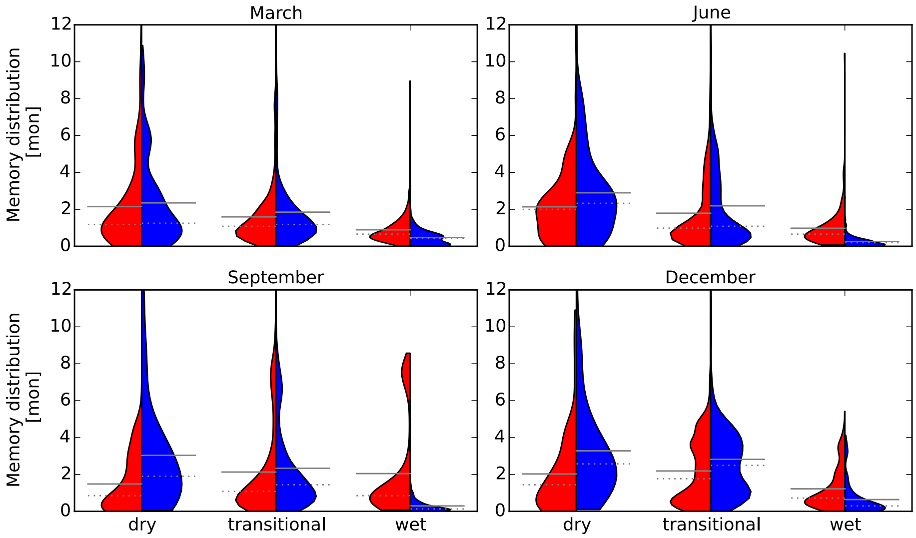

Figure 7. Violin plots of τ_0 distribution for dry (red) and wet (blue) initialization in the three soil moisture regimes for the four seasonal ensembles. The horizontal gray lines indicate the mean (solid) and the median (dashed) of the distributions. All land surface grid cells of a given regime are included.

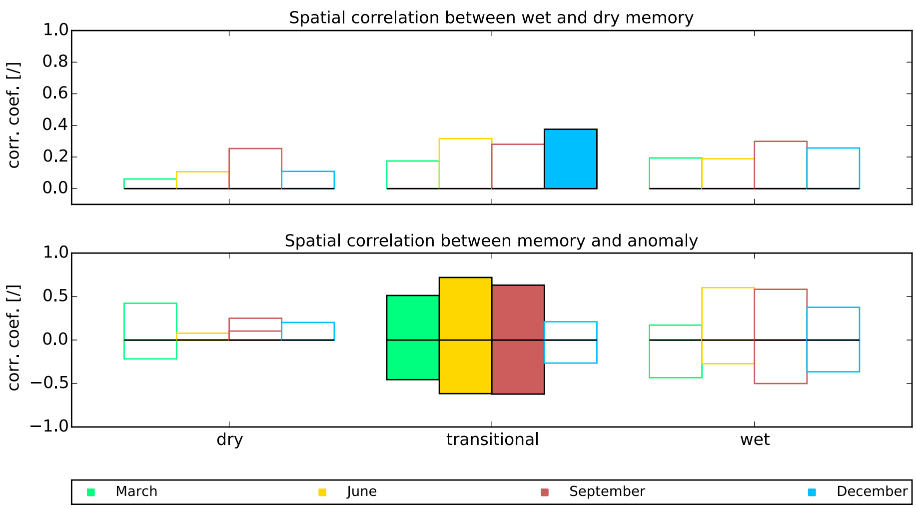

Figure 8. ~~Spearman rank correlation coefficient~~ Bar plot for different soil moisture regimes and seasons indicating correlation coefficients for spatial rank correlations. The upper panel shows the ~~spatial~~ correlation between the pattern of wet τ_0 and dry τ_0. The lower panel shows the ~~spatial~~ correlation between the pattern of wet and dry τ_0 and the respective $\Delta\theta_0$. ~~Only significant~~ Significant correlations below the 5% level are ~~included~~indicated by solid bars.

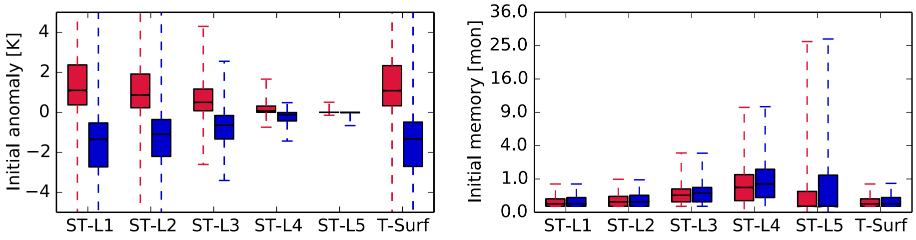

Figure 9. Global statistics for $\Delta\theta_0$ (left) and τ_0 (right) in soil layer (ST-L[1-5]) and surface temperatures (T-Surf) in the wet (blue) and dry (red) initialized ensemble simulations for all land surface grid cells. The whiskers indicate the 1^{st} and 99^{th} percentiles respectively, the box indicates the interquartile range and the notch indicates the median. Note the exponential axis for the memory statistics.

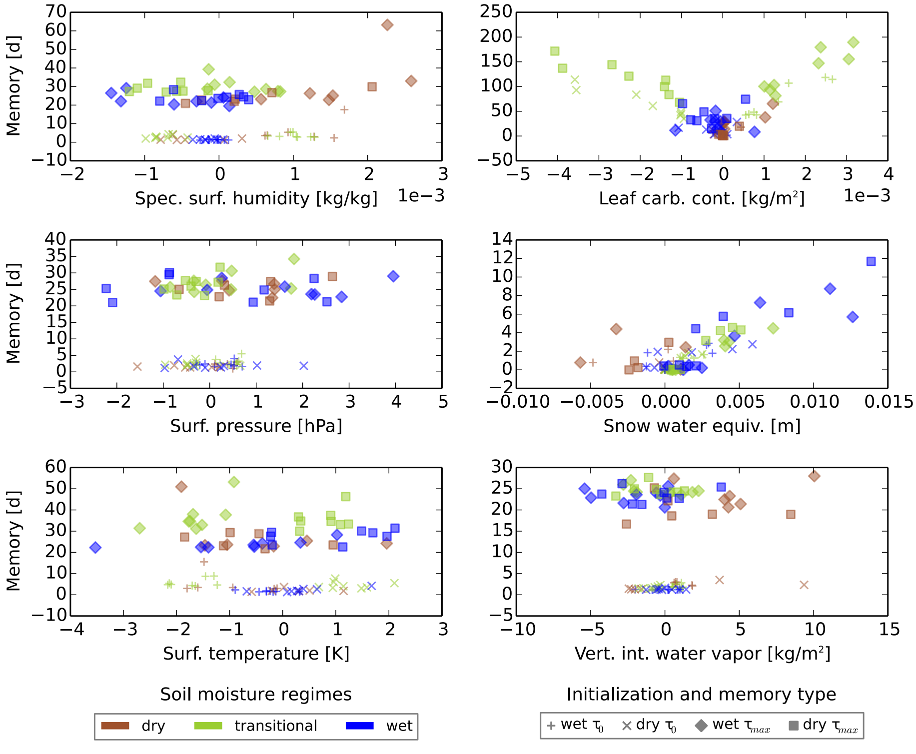

Figure 10. Scatter plots of induced anomaly – memory relation in surface states for all land surface grid cells. The colours indicate the soil moisture regime. The marker symbols refer to the soil moisture initialization state and the memory metric.

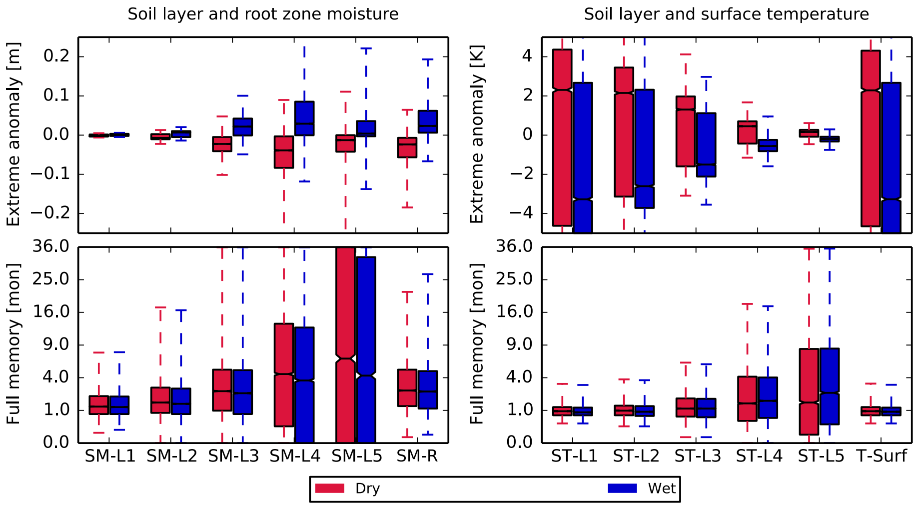

Figure 11. Global statistics for extreme anomalies extreme anomaly ($\Delta\theta_{\max}$) during the full time series (top panels) and accumulated memory overall memory ($\tau_{\max}$) (bottom panels) in soil layer moisture (left side) and temperature (right side) in the wet (blue) and dry (red) initialized ensemble simulations. All land surface grid cells are included.

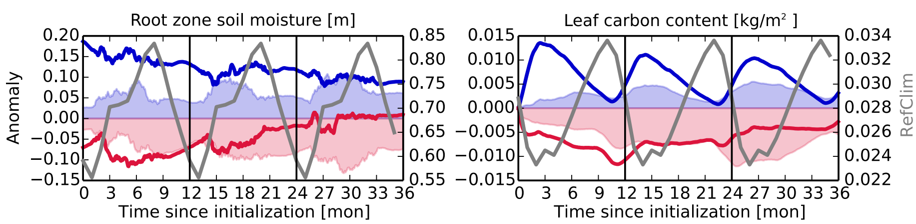

Figure 12. Ensemble mean anomaly (coloured lines) and standard deviation (shaded area) for root zone soil moisture (left) and carbon content in leafs (right) with the respective climatologies (grey) from the reference simulation. Blue colours indicate wet initialization and red colours indicate dry initialization. Time series are from a grid cell at -2.8°N and 13.12°E.

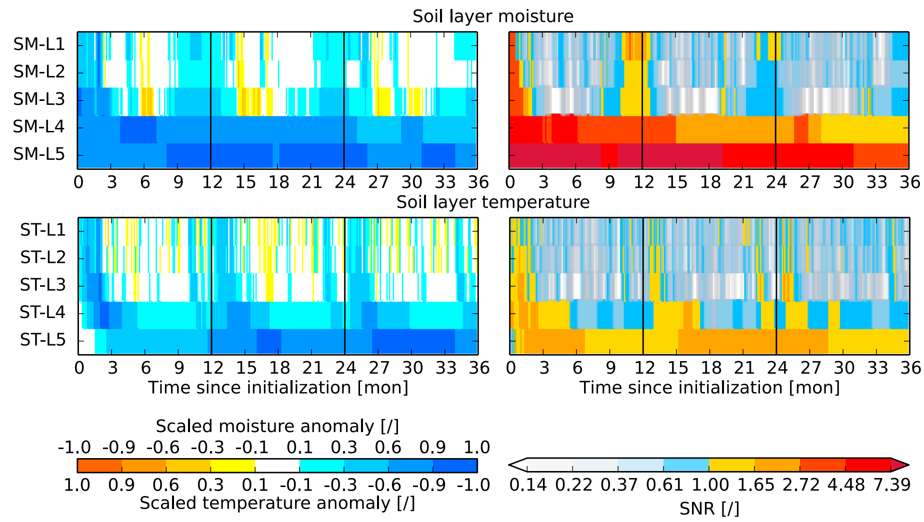

Figure 13. Time series of ensemble mean $\Delta\theta_0$ and SNR for a grid cell at -2.8°N and 13.12°E (Republic of Congo) of the wet initialization September ensemble. The upper and lower panels show soil moisture and soil temperature, respectively, for all soil layers. The anomaly notation is mirrored for the soil temperature. Note, that the SNR color spacing is logarithmic in order to display the ratio similar to a normal distribution. All yellow and red patches in the right panels indicate time periods defined as memory.

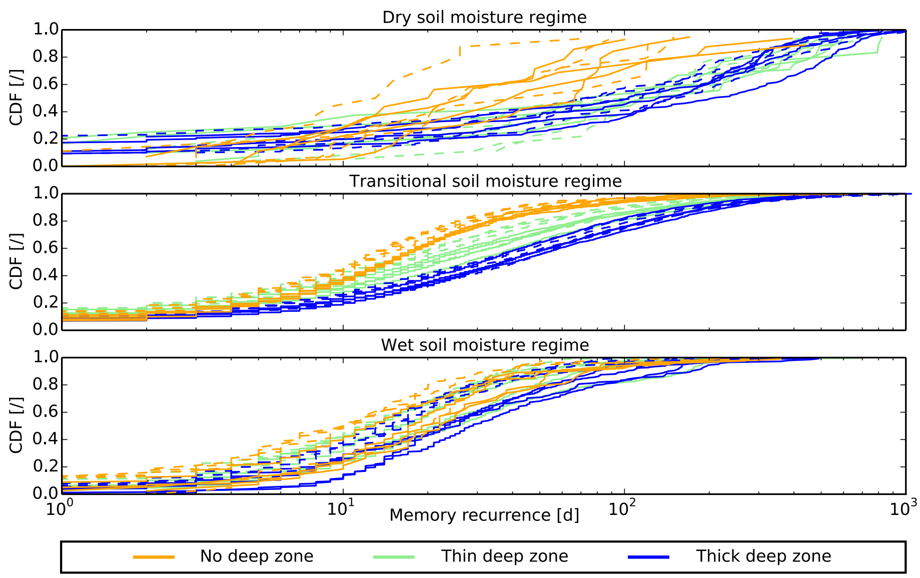

Figure 14. ~~Cumulative density functions~~ Normalized cumulative frequency of ~~recurring memory for~~ grid cells with recurring memory (τ_{max} - τ_0) for different soil moisture regimes (upper, middle and lower panels). The regimes are further subdivided depending on the thickness of the deep soil zone ~~thickness~~ below the root zone ~~soil moisture~~ (orange, green and blue colours)~~in all soil moisture regimes~~. ~~Different initial states~~ Wet (~~wet~~ dashed lines) and dry (solid lines) initial states and seasons are merged into the ~~plot where wet and dry initializations are indicated with dashed and solid lines, respectively~~panels.

Table 1. Spatial March ensemble rank correlation coefficients between soil moisture τ_0 and static soil properties for different soil moisture regimes and initializations. Gray font indicates insignificant correlation (p > 5%).

	Dry initialization			Wet initialization		
	dry	trans	wet	dry	trans	wet
Clapp and Hornberger exponent b	-0.08	0.23	0.2	-0.05	0.16	0.1
Forest fraction	nan	0.16	0.03	nan	0.11	-0.3
Saturated hydraulic conductivity	0.13	-0.11	-0.26	0.19	0.06	-0.13
Maximum soil water capacity	0.08	0.26	0.23	0.16	0.4	-0.23
Saturated matrix potential	-0.13	0.17	0.25	-0.18	0.03	0.11
Orographic standard deviation	-0.14	-0.01	-0.06	0.06	0.02	0.1
Soil pore size distribution index	0.1	-0.22	-0.24	0.16	-0.12	-0.11
Rooting depth	0.15	0.27	0.09	0.2	0.44	-0.32
Soil depth until bedrock	0.1	0.06	-0.04	-0.03	0.14	-0.15
Volumetric soil field capacity	-0.11	0.07	0.23	-0.16	-0.05	0.12
Volumetric soil porosity	-0.13	0.04	0.22	-0.18	-0.1	0.17
Maximum vegetation fraction	-0.1	0.18	0.13	0.0	0.29	-0.21
Volumetric wilting point	-0.1	0.14	0.23	-0.14	0.02	0.12

Table 2. Spatial June ensemble rank correlation coefficients between soil moisture τ_0 and static soil properties for different soil moisture regimes and initializations. Gray font indicates insignificant correlation (p > 5%).

	Dry initialization			Wet initialization		
	dry	trans	wet	dry	trans	wet
Clapp and Hornberger exponent b	-0.13	0.19	0.11	-0.17	0.12	0.06
Forest fraction	nan	0.36	-0.02	nan	0.07	0.05
Saturated hydraulic conductivity	-0.11	-0.07	-0.1	-0.08	0.08	-0.04
Maximum soil water capacity	0.15	0.47	0.06	0.04	0.55	0.12
Saturated matrix potential	0.05	0.12	0.05	0.03	-0.02	0.05
Orographic standard deviation	-0.04	-0.1	-0.07	-0.09	-0.02	0.23
Soil pore size distribution index	-0.08	-0.16	-0.09	-0.07	-0.06	-0.05
Rooting depth	0.14	0.46	-0.08	0.02	0.57	0.09
Soil depth until bedrock	0.27	0.34	0.03	0.23	0.44	0.24
Volumetric soil field capacity	0.06	0.1	0.08	0.08	-0.05	0.07
Volumetric soil porosity	0.07	0.05	0.09	0.05	-0.13	0.05
Maximum vegetation fraction	0.04	0.41	-0.08	-0.07	0.46	0.15
Volumetric wilting point	0.03	0.13	0.11	0.05	0.0	0.05

Table 3. Spatial September ensemble rank correlation coefficients between soil moisture τ_0 and static soil properties for different soil moisture regimes and initializations. Gray font indicates insignificant correlation (p > 5%).

	Dry initialization			Wet initialization		
	dry	trans	wet	dry	trans	wet
Clapp and Hornberger exponent b	-0.04	0.18	0.18	-0.16	0.07	0.09
Forest fraction	nan	0.35	0.07	nan	0.23	0.04
Saturated hydraulic conductivity	-0.05	-0.12	-0.13	0.18	0.05	-0.15
Maximum soil water capacity	0.1	0.44	0.22	0.02	0.51	0.28
Saturated matrix potential	-0.0	0.13	0.07	-0.17	-0.01	0.11
Orographic standard deviation	0.1	-0.22	-0.27	-0.02	-0.24	-0.05
Soil pore size distribution index	-0.05	-0.15	-0.16	0.19	-0.04	-0.09
Rooting depth	0.13	0.42	0.08	0.14	0.53	0.15
Soil depth until bedrock	0.09	0.17	0.05	0.07	0.31	0.26
Volumetric soil field capacity	0.03	0.15	0.13	-0.17	-0.04	0.18
Volumetric soil porosity	0.04	0.12	0.12	-0.19	-0.08	0.17
Maximum vegetation fraction	-0.01	0.28	-0.0	-0.1	0.39	0.14
Volumetric wilting point	0.01	0.17	0.21	-0.16	-0.01	0.15

Table 4. Spatial December ensemble rank correlation coefficients between soil moisture τ_0 and static soil properties for different soil moisture regimes and initializations. Gray font indicates insignificant correlation (p > 5%).

	Dry initialization			Wet initialization		
	dry	trans	wet	dry	trans	wet
Clapp and Hornberger exponent b	-0.15	0.18	0.13	0.04	0.15	0.27
Forest fraction	nan	0.18	0.18	nan	0.04	-0.3
Saturated hydraulic conductivity	-0.04	-0.27	-0.1	-0.02	-0.12	-0.34
Maximum soil water capacity	0.06	0.02	0.24	0.09	0.17	0.02
Saturated matrix potential	0.03	0.24	0.07	0.03	0.14	0.33
Orographic standard deviation	-0.14	-0.07	-0.13	-0.06	0.01	0.02
Soil pore size distribution index	-0.03	-0.22	-0.1	-0.01	-0.15	-0.3
Rooting depth	0.07	-0.02	0.08	0.13	0.16	-0.24
Soil depth until bedrock	0.1	-0.2	0.07	-0.03	-0.1	-0.02
Volumetric soil field capacity	0.02	0.21	0.13	0.02	0.1	0.29
Volumetric soil porosity	0.04	0.24	0.14	0.02	0.1	0.32
Maximum vegetation fraction	-0.06	0.01	0.18	0.07	0.17	-0.0
Volumetric wilting point	nan	0.22	0.14	0.04	0.11	0.3

Table 5. Area-weighted mean values of $\Delta\theta_0$ (upper part) and $\Delta\theta_{\max}$ (lower part) for different soil moisture regimes and initializations.

	Dry regime		Transitional regime		Wet regime	
	Dry	Wet	Dry	Wet	Dry	Wet
leafmass [kg/m**2]	-2.5e-04;1.8e-05	8.7e-06;4.5e-04	-3.6e-03;-9.4e-04	5.6e-04;2.7e-03	-1.1e-03;3.4e-04	-2.5e-04;9.4e-05
prsurf [hPa]	-1.56;0.21	0.11;0.59	-0.96;0.66	-0.29;0.69	-0.97;2.03	-0.30;0.70
snow [m]	-3.9e-04;0.0e+00	-4.8e-03;5.7e-04	-2.9e-05;2.5e-03	0.0;2.6e-03	-1.3e-03;5.9e-03	-1.2e-03;3.2e-03
humidityspec [kg/kg]	-7.9e-04;3.1e-04	6.2e-04;1.7e-03	-9.9e-04;-4.2e-04	6.6e-04;1.3e-03	-3.5e-04;5.1e-05	-2.5e-04;1.3e-04
watervapor [kg/m**2]	-2.43;9.36	0.62;1.85	-1.77;-0.23	0.48;1.23	-1.27;1.43	-1.99;1.01
leafmass [kg/m**2]	-9.3e-05;4.0e-04	2.4e-05;1.2e-03	-4.1e-03;-1.0e-03	1.0e-03;3.2e-03	-9.7e-04;5.5e-04	-1.1e-03;7.7e-04
prsurf [hPa]	-0.66;2.64	-1.17;1.40	-0.98;0.22	-0.85;1.81	-2.23;2.52	-1.06;3.95
snow [m]	-2.4e-03;2.6e-04	-5.7e-03;1.4e-03	4.0e-04;5.1e-03	3.4e-04;7.3e-03	-7.6e-05;0.01	2.3e-04;0.01
humidityspec [kg/kg]	-4.5e-04;2.1e-03	5.7e-04;2.6e-03	-1.2e-03;-1.5e-04	-1.6e-04;8.2e-04	-8.0e-04;4.0e-04	-1.5e-03;1.4e-04
watervapor [kg/m**2]	-2.59;8.47	0.60;10.05	-3.30;1.31	-2.79;2.26	-4.25;3.79	-5.40;0.22

Table 6. Area-weighted mean values of τ_0 (upper part) and τ_{max} (lower part) in months for different soil moisture regimes and initializations.

	Dry regime		Transitional regime		Wet regime	
	Dry	Wet	Dry	Wet	Dry	Wet
leafmass	0.02;0.42	0.05;0.76	1.14;3.74	1.39;3.88	0.12;0.93	0.06;0.41
prsurf	0.04;0.07	0.03;0.10	0.06;0.13	0.07;0.18	0.04;0.12	0.05;0.13
snow	0.0;0.03	1.6e-03;0.07	0.0;0.06	0.0;0.05	7.0e-03;0.09	0.0;0.09
humidityspec	0.04;0.13	0.08;0.57	0.06;0.14	0.09;0.18	0.04;0.07	0.04;0.05
watervapor	0.04;0.11	0.07;0.10	0.05;0.08	0.05;0.09	0.04;0.05	0.04;0.04
leafmass	0.02;0.65	0.47;2.14	2.23;5.63	2.67;6.21	0.50;2.44	0.28;1.67
prsurf	0.71;0.95	0.74;0.91	0.76;1.04	0.79;1.12	0.69;0.99	0.75;0.95
snow	0.0;0.10	1.6e-03;0.14	0.0;0.15	0.0;0.15	0.01;0.38	0.0;0.29
humidityspec	0.69;0.98	0.75;2.07	0.89;1.06	0.89;1.29	0.73;0.93	0.64;0.96
watervapor	0.55;0.83	0.68;0.92	0.76;0.91	0.77;0.88	0.70;0.86	0.68;0.84