Reviewer #1 comments

The study explores short-term variability of the meteorological variables on the permafrost ground temperatures. The major finding is that short-term variability can slow down gradual permafrost warming predicted by many LSM type models. This is mainly true; however, resolution is another important factor that needs to mentioned in the study. For example, at fine scale resolution, topography and vegetation might intercept snow allowing warmer ground temperatures. This effect will not be captured at low resolution with global models. Overall, the manuscript is well written and requires some minor edition, which I list below.

We like to thank the reviewer for their time to carefully read the manuscript and prepare the review. Indeed, your comment on small-scale heterogeneity of soil properties, vegetation and snow depth is very relevant. Since thermal and hydrological processes are nonlinear and heterogeneity is large in these landscapes, we can expect biases when only assuming one average value for state variables, such as temperature or moisture. The interesting question here would be: How would the presented effects of short-term variability of meteorological variables on soil temperature change when also taking into account spatial heterogeneity? At first we can assume little differences: If temperature goes above freezing point more often, then snow will melt regardless of the actual spatial differences in snow melt. However, there can be nonlinear threshold effects: If a snowmelt event happens in autumn but there is no snow in some micro-sites, then there will be also no effect of melting. This is an interesting question for further studies. We extended the discussion section of the revised version of the manuscript, 5th paragraph by

"Future studies should clarify if these temporal variability effects of meteorological variables on snow depth are lower or higher when additionally taking into account lateral heterogeneity of soil properties (Beer, 2016) or snow, for instance due to snow intercept by topography or vegetation."

L151. Not sure what is reservoir initialization.

In transient runs using dynamical models we first need to estimate the state variables at the starting point, which is e.g. the period before the industrialization around 1860. This is done by forcing the dynamic model constantly with the same pre-industrial climate. After some time (decades for physical state variables or millennia for carbon reservoirs) the state variables will not change any more and are in equilibrium with the pre-industrial climate. Now, we can start the transient simulation e.g. until 2010 or into the future with changing climate. This is common practice in Earth system modelling, and here we wanted to explain that we did the full procedure with both climate datasets, CNTL and REDVAR. We however notice that the term "reservoir" is not correct in particular for soil temperature and replace it by "state variables" :

"Here, CNTL and REDVAR model runs are done exactly the same way including the spin-up approach for bringing state variables, such as soil temperature in equilibrium with pre-industrial climate."

REDVAR is introduced in L143 and explained only in L205. Need a better logical flow.

We agree with this comment and change the order of section 2 subsections such that model experiments are explained after the forcing data explanation.

L228. What is the resolution of the GIPL1.3 model? Why GIPL?

The idea was to find an independent soil temperature map for Alaska for evaluating the JSBACH model results. GIPL1.3 uses a semi-analytical solution for mean annual ground temperature following Kudryavtsev, et al., (1974). We believe that this map produced by Sergei Marchenko and Vladimir Romanovsky from the University of Alaska Fairbanks is able to represent large-scale soil temperature pattern in Alaska. The resolution is 2kmx2km which we have further aggregated to 0.5 deg in order to be comparable with JSBACH results. We extend the description of this dataset in the methods section in the following way:

"First, JSBACH model results are compared to model results from the GIPL 1.3 model (Sergei Marchenko, University of Alaska Fairbanks) over Alaska for the period 1980-1989. For this we downloaded GIPL model results at 2kmx2km grid cell size from http://arcticlcc.org/products/spatial-data/show/simulated-mean-annual-ground-temperature. Then, the map was reprojected to geographic lat/lon using a bilinear method and further aggreagated to 0.5 degrees grid cell size in order to be comparable with JSBACH outputs."

L230. Typically, permafrost ground temperature observation made at depth from 15 to 20 m. Why authors choose 38m as comparison depth for the model?

The observation-based map from the Melikov Permafrost Institute (Fedorov et al., 1989, 1991) presents permafrost temperature and we assume it represents mean annual ground temperature which is thought to be constant over time. In order to be comparable with this information, we chose the last soil layer of model results.

However, we notice a small mistake in the figure 2 and 3 captions and replace 49.5 by 38 m depth.

For the evaluation using borehole measurements (Fig 1), however, we were using particularly model results from the same depth as the measurements. This is now further clarified by extending the figure 1 caption by the sentence

"Model results are taken from the depth of observation for each point."

Figures 4 and 9. Since your colorbar include green, I suggest to make non-permafrost areas colorless.

We agree with this and in the revised version of the manuscript use white for non-land pixels and gray for non-permafrost land pixels. Please, also note all the changes in color bar and color scale in these plots according to the comments of reviewer 2.

Percentile on the figure introduced in L320, explained in L326. Better flow.

The information on percentiles used for minimum and maximum values is repeated at both locations in the text now.

L361. Not sure what authors are trying to say by bolded text.

In the results section we compare the reduced climate variability JSBACH results (REDVAR) with the control variability JSBACH results (CNTL) while in the discussion section we address the question on the effects of potentially increasing variability in future.

Reviewer #2 comments

The manuscript by Beer et al discusses the role of changes to variability in weather rather than mean climate in governing soil temperature change in the northern high latitudes. The result is that reduced variability is likely to lead to (a) increased snowpack via less frequent melting events, and (b) changed bryophyte thermal conductivity. The authors then take the inverse of this argument to argue that the response under warming is likely to be an increase in the variability, and thus a decrease in snow packs, and thus a reduction in the rate of soil to air warming.

The implication of this is that anomaly forcing methods may therefore lead to some biases in the response, although I am not totally clear after reading the paper how important this bias actually is. Nonetheless it is an important point to make and consider.

We thank the reviewer for their time to read and carefully evaluate this manuscript. First of all, we learn about a potential lower future soil warming due to increasing climate variability but you are right that a second implication is the importance of considering higher statistical moments in bias correction methods, as pointed out in the conclusion section. One additional conclusion from this study is that snow and near-surface vegetation functions are essential for the land-atmosphere heat flux and hence need to be represented in Earth System Models.

The article is interesting, well-written, and worth publishing. The basic outline of the argument makes sense, although it would seem simpler if the argument were streamlined to take as a reference case one where variability were held constant and mean values changed in the future transient, and this were compared to the case where both transient means and variabilities were taken from a GCM, as this would not require the change in signs that the current argument requires.

Thank you for this additional idea which indeed could be interesting to look at in a separate study. Following your suggestion, we would have two climate datasets that show a difference in short-term variability while long-term averages are conserved.

Beside long-term and annual-seasonal variability, there are also different characteristic patterns of inter-monthly, inter-weekly or inter-daily variability (Mahecha et al., 2010). These can also greatly differ between ecosystems and even in time. Even with carefully producing such dataset of constant short-term variability, still there is a risk of unintentionally producing unrealistic climate for the specific location, e.g. there is uncertainty in estimating the characteristic variabilities. It is also unclear if the characteristic short-term variabilities should be derived at annual or seasonal or monthly scale? This is an interesting idea for future studies but required a lot of more detailed and careful thinking and data preparation. With our method we keep as much as possible the characteristics the original dataset and just reduce the variability of residuals to the mean seasonal cycle. Our idea was to generate an as realistic as possible climate data for the period 1901-2010 also in the artificial REDVAR dataset in order to avoid additional indirect artificial effects on ecosystem states and functions (JSBACH results).

Still, it would be interesting to reduce the variability of future projections as is discussed below. We already did this for several individual grid cells, but we see a major limitation due to manpower, disk storage and CPU time for producing such dataset and running the JSBACH model at pan-Arctic scale.

I also don't understand why the transient cases were not run globally. This would allow us to more quantitatively estimate the magnitude of the bias as well, rather than having to use the qualitative comparison in the paragraph lines 409-423. So I'd suggest that the authors try to explain why they didn't follow such an approach here.

In a major effort we designed the global REDVAR dataset 1901-2010 with constantly reduced short-term variability of climate variables and performed the CNTL and REDVAR model runs. The assumption is that comparing the results from these two model experiments will provide the same insight as ncreasing the variability continuously from 2010 until 2100. To evaluate this assumption we repeated the whole procedure for 2 grid cells: 1) design the REDVARfut dataset with increasing variability during 2010-2100, and ii) perform the JSBACH runs. Indeed, results from these additional runs are very similar to the global runs using the constant difference in variability.

In general, one could also repeat the whole study and design a REDVAR climate dataset with increasing reduced variability until 2100 and again force JSBACH with that climate in addition to a CNTL. However, manpower, storage capacity and CPU time available at the moment are the *limiting factors. Please, keep in mind that if future projections are the focus of the study, the whole procedure including REDVAR data preparation is required for an ensemble of climate model results and different RCP scenarios. From the results at the two locations in Canada and Siberia, which were conducted in addition to the main modelling experiment at continental scale, we are however confident that our main conclusions would not change.*

Please, see our suggestion for extending the discussion in this respect as presented in the response to your question on permafrost extend and active-layer thickness below.

Minor/specific points:

What are the units in figure 4a ? if unitless, what scale are they relative to – i.e. (T_redvar - T_control) / T_control would be different if in K or C...

This is actually a very good point. All temperatures in this manuscript are in degree Celsius. We improve the figure captions in order to make underlying units clear. If it was Kelvin in Fig 4a, then the relative difference of these mean values would have been even much smaller when dividing the difference by several hundreds of Kelvin. We decided now to show the absolute difference of temperature averages in degree C as also done for the soil temperature results. The main point of that figure is to see that indeed, long-term averages are similar between the datasets. The color scale of Fig 4a is now adjusted to match that one of Fig 9 in order to address the next comment.

The colorbars are really confusing. The same yellow-green-blue colorbar is used throughout, even though each instance of it is being used for a different purpose. I.e. in figure 4, the colorbar is being used for a divergent quantity, but the zero point is in a different point of the colorbar in the two panels. Then in figure 5, the same colorbar is being used for a non-divergent scale, but with two very different gains. Then in figure 6, the same colorbar is used again, but now the zero is at the bottom of the colorscale rather than the top, etc. This sort of thing is really confusing for a reader who must recalibrate their expected color with each new figure. Please try to stick to a convention where you only use one colorbar for one purpose, different types of colorbars for divergent and nondivergent scales, and if you show something with different units, then please use a new and different colorbar. At an absolute minimum, please just keep zero in the same place for each figure.

Thank you very much for this comment. All color bars and color scales have been adjusted accordingly. With this we hope to improve the readability.

Our reasoning is as follows: A) Differences between mean temperatures are displayed using one constant color bar and color scale. (Fig 4a and Fig 9). B) Effects on snow (Fig 6) or moss (Fig 8) properties get another constant color bar and color scale each. For this purpose we swapped snow thermal diffusivity and snow melt result figures (Fig 6d and Fig 7) and carefully adjusted the figure references in the text. C) All other maps come with their own color bar and color scale. D) Exceptions are Fig 2 and 3 (model evaluation) for which we use the same color bar than for Fig 6 *but the maps are really different (region and projection). Therefore we assume that using the same color bar here will not confuse the reader. Still, color scales for Fig 3a and 3b are adjusted.*

Due to the standardized color scales according to purposes, we cannot see any spatial details in Fig 4a anymore. That is logical and reflects the whole message of the study: mean air temperature differences are negligible while mean annual ground temperature differ by up to 0.8 degree C due to the difference in climate variables standard deviation.

In figure 6, why isn't the land/ice mask consistent over greenland between the panels?

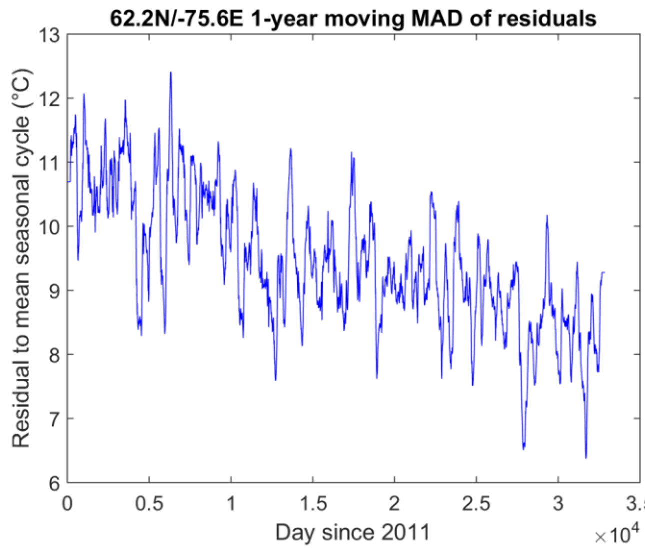
These differences were just due to the fact that the model assumes constant glacier cover in these areas but the way snow and soil processes are treated differ between glacier and land areas in JSBACH. Since glaciers are not the focus of this study, plotting glacier regions is therefore not useful and in the improved plots all glacier area results are removed.

During that work we also recognized that for a few locations for which we do have borehole measurements from GTN-P the model grid cell assumes glacier cover. Therefore, these locations are also not useful for the Fig 1 model evaluation exercise and hence removed in this updated version of the manuscript. The model-data mismatch is now further reduced and the whole conclusion from the evaluation exercise remains.

For figure 10, it looks like the range of variability is reducing quite a bit in the control case. this is clearly the case with temperature, and most likely the case with precip if expressed relative to the mean value (which, it should be pointed out given the motivation on line 160, is how anomaly forcing for precipitation is applied). and the same appears to be true in figure 11. if this is generally the case, doesn't this undercut the whole argument of the discussion section, which starts out by positing that variability will increase rather than decrease?

Thank you very much for this comment which let us recognize that the applied percentiles were not an ideal metric for the purpose of characterizing the difference in the data. We are not interested in the 1-2 most extreme days during the year and if their temperature or precipitation changed in time, but in the day-to-day and inter-weekly variability of meteorological variables. Therefore, we now compute the mean absolute difference (MAD) between daily data of both datasets during each year and show 10-year running means of these annual time series in the insets of Fig 10 and 11 a and b. Here, we can see that this difference in the daily data between the datasets is increasing with time while the mean annual data remains similar. The MAD definition has been added to the methods section 2.6, equation 5.

Still, your comment on the variability of the control dataset is valid. To address this question, the following plot shows the mean absolute deviation (difference of daily data to the mean) using a 1-year moving window approach. However, the mean seasonal cycle has been removed from the daily data before in that analysis because we are only interested in the short-term variability and not in changing mean seasonal cycles. One can see that this short-term variability is decreasing at *the one example location in Canada. (Still, the REDARfut data would decrease even more according to the inset of Fig 10a).*



Therefore, you are right and there will be grid cells of decreasing climate variability in Arctic regions in our CNTL dataset. Your question was if that will undercut the motivation of the study. That is clearly not the case. In our study we are using one specific climate dataset (bias-corrected MPI-ESM output from the CMIP5 archive, see section 2.2) which is not representative for an ensemble of climate model results as e.g. used in Seneviratne et al., (2012). We are just using this dataset as CNTL in order to compare JSBACH model results to the artificially reduced variability dataset (REDVARfut) from which we then learn about the effects of climate variability on mean soil temperature. These additional model runs into the future at two grid cells are also only complementing the main experiment presented in this paper at a continental scale for the period until 2010, and the results in Fig 10 and 11 confirm the continental scale results in Fig 9. We therefore do not expect a different result if the CNTL dataset showed an increasing short-term variability instead.

For figure 10, how do you compute the 1st and 99th percentiles of annual mean data when you only have a single timeseries that spans a 100-year transient run?

We calculated percentiles of daily data for each year but as stated in the above response these percentiles have not been a useful measure for the change in variability and we replaced them by the mean absolute difference between daily data during a year, see comment above, equation 5 and Fig 10 and 11.

One thing that is missing here that would help the reader assess the importance of the problem is how large is the change in permafrost area, or active layer thickness within permafrost area? Such figures would have required a transient, global reduced variability run. Why couldn't such a run have been produced?

We fully agree with the reviewer in this is indeed a very interesting question. One could address this question with new pan-Arctic scale model experiments until 2100 or 2300 for which we would also need to process new climate forcing data of reduced variability. Please, see our response above to this point. The main limitation here is CPU time and disk storage; it would be a whole project in its own over the next year.

Actually, a 0.2 to 0.8 °C cooler soil due to increasing climate variability can have a significant effect on future permafrost area extend. This can be seen when looking into recent pan-Arctic projections of soil temperature under different warming scenarios. For instance in Schaphoff et a. (2013) future soil temperature at 38 cm depth is projected to reach -1 to +1 °C over the major part of the current permafrost area depending on the warming scenario. For a mean annual ground temperature close to the freezing point, a difference of 0.5 °C will matter.

We extend the discussion section, second last paragraph by

"Soil temperature is projected to arrive at values around the freezing point in 38 cm depth over the major part of the current permafrost area (Schaphoff et al., 2013). Therefore, differences of soil temperature of 0.1 to 0.8 °C due to changing climate variability would have an effect on active-layer thickness and permafrost extent, too. It would be interesting to generate an additional artificial REDVARfut dataset with pan-Arctic cover and investigate in detail the impacts of climate variability on active-layer thickness and permafrost extend at the end of the century in a future project."

I don't follow the argument on line 436 at all.

This sentence was isolated within the manuscript and not useful. It has been removed it in the revised version of the manuscript.

References

Fedorov, A. N., Botulu, T. A., and Varlamov, S. P.: Permafrost Landscape of Yakutia (in Russian), Novosibirsk: GUGK, 1989.

Fedorov, A. N., Botulu, T. A., and Varlamov, S. P.: Permafrost Landscape Map of Yakutia ASSR, Scale 1:2500000, Moscow: GUGK, 1991.

Kudryavtsev VA, Garagulya LS, Kondrat'yeva KA, Melamed VG (1974) *Fundamentals of Frost Forecasting in Geological Engineering Investigations (in Russian)*. Nauka, Moscow.

Mahecha, M. D., et al. (2010) Comparing observations and process-based simulations of biosphere-atmosphere exchanges on multiple timescales, J. Geophys. Res., 115, G02003, doi:10.1029/2009JG001016.

Schaphoff, S., Heyder, U., Ostberg, S., Gerten, D., Heinke, J., and Lucht,W.: Contribution of permafrost soils to the global carbon budget, Environmental Research Letters, 8, 014 026, http://iopscience.iop.org/1748-9326/8/1/014026, 2013

Seneviratne, 630 S., Nicholls, N., Easterling, D., Goodess, C., Kanae, S., Kossin, J., Luo, Y., Marengo, J., McInnes, K., Rahimi, M., Reichstein, M., Sorteberg, A., Vera, C., and Zhang, X.: Changes in climate extremes and their impacts on the natural physical environment, in: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation, edited by Field, C., Barros, V., Stocker, T., Qin, D., Dokken, D., Ebi, K., Mastrandrea, M., Mach, K., Plattner, G., Allen, S., Tignor, M., and Midgley, P., pp. 109–230, A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK, and New York, NY, USA, 2012.

Manuscript prepared for The Cryosphere
with version 2014/09/16 7.15 Copernicus papers of the LaTeX class copernicus.cls.
Date: 21 December 2017

Effects of short-term variability of meteorological variables on soil temperature in permafrost regions

Christian Beer[1,2], Philipp Porada[1,2], Altug Ekici[1,3], and Matthias Brakebusch[1,2]

[1]Department of Environmental Science and Analytical Chemistry (ACES), Stockholm University, 10691 Stockholm, Sweden
[2]Bolin Centre for Climate Research, Stockholm University, 10691 Stockholm, Sweden
[3]Uni Research Climate, Bjerknes Centre for Climate Research, Bergen, Norway

Correspondence to: Christian Beer (christian.beer@aces.su.se)

Abstract. Effects of the short-term temporal variability of meteorological variables on soil temperature in northern high latitude regions have been investigated. For this, a process-oriented land surface model has been driven using an artificially manipulated climate dataset. Short-term climate variability mainly impacts snow depth, and the thermal diffusivity of lichens and bryophytes. ~~This latter effect is of opposite direction in summer and winter in most regions.~~ These impacts of climate variability on insulating surface layers together substantially alter the heat exchange between atmosphere and soil. As a result, soil temperature is 0.1 to 0.8 °C higher when climate variability is reduced. Earth system models project warming of the Arctic region but also increasing variability of meteorological variables and more often extreme meteorological events. Therefore, our results show that projected future increases in permafrost temperature and active-layer thickness in response to climate change will be lower i) when taking into account future changes in short-term variability of meteorological variables, and ii) when representing dynamic snow and lichen and bryophyte functions in land surface models.

1 Introduction

Soil temperature is an important physical variable of a terrestrial ecosystem since it controls many functions of microbes and plants. In permafrost regions, soil temperature also defines the biologically active part of the soil that is thawing in summer (active layer). Therefore, impacts of future warming on soil temperature have been investigated in numerous experimental and modelling studies during the past decades. Large-scale soil temperature is mainly determined by vertical heat conduction. Therefore, soil temperature usually follows an annual sinusoidal cycle of air temperature with a damped oscillation (Campbell and Norman, 1998). That is why the projected large increase in air temperature in the Arctic region over the next 100 years (Ciais et al., 2013) is raising large concerns about the response of soil temperature and hence permafrost thawing in the Arctic. Indeed, measurements during the last decades already show an increasing permafrost temperature (Romanovsky et al., 2010) and active-layer thickness (Callaghan et al., 2010) in response to global warming. Also, first modelling results confirm such simple response of increasing future soil temperature and active-layer thickness (Schaefer et al., 2011; Koven et al., 2011; Lawrence et al., 2012; Peng et al., 2016). As a result of increasing soil temperature and active-layer thickness, heterotrophic respiration is suggested to increase because of the temperature-response of biochemical functions (Arrhenius, 1889; van't Hoff, 1896; Lloyd and Taylor, 1994) and the additional availability of decomposable substrate (Schaphoff et al., 2013; Koven et al., 2015) potentially leading to a positive climate-carbon cycle feedback (Zimov et al., 2006; Beer, 2008; Heimann and Reichstein, 2008).

Meteorological variables, such as air temperature and precipitation will not only change gradually into the future but also their short-term variability and frequency of extreme events is projected to change (Easterling et al., 2000; Rahmstorf and Coumou, 2011; Seneviratne et al., 2012). For instance, for northern high-latitude regions, climate models project an increase of the annual maximum of the daily maximum temperature by 4 °C by 2100 (Seneviratne et al., 2012) while annual maximal daily precipitation is projected to increase by 20% in these areas by 2100. At the same time, many ecosystem functions respond non-linearly to environmental factors, cf. for instance the temperature-dependence of biochemical functions (Arrhenius, 1889). Therefore, effects of the short-term (daily to weekly) variability of meteorological variables on the long-term (decadal) mean ecosystem functions can enhance or dampen the effect of a general gradual warming (Reichstein et al., 2013; Schwalm et al., 2017). That is why there is a strong need to understand such effects of climate variability on ecosystem states and functions in addition to gradual changes in order to reliably project future ecosystem state dynamics and climate. In this context, effects of climate variability on soil temperature in northern high latitude environments have not been studied so far: In addition to a gradual warming of Arctic air and soil temperature, what are the specific effects of changing short-term variability of meteorological variables on the long-term mean annual or seasonal soil temperature? Will a short-term variability change have the capability to enhance or dampen the anticipated soil warming?

Due to the well-known dampening effects of snow, near-surface vegetation, and the organic layer (Yershov, 1998, pages 361-369) (Goodrich, 1982; Zhang, 2005; Wang et al., 2016; Jafarov and Schaefer, 2016), one would expect no to little additional effects of changing air temperature fluctuations on soil temperature, in particular not on subsoil and permafrost temperature. However, air temperature variability will have an impact on snow height indirectly through snow density (Abels, 1892) and also directly when temperature is periodically rising above the melting point. In addition, the dependence of soil and near-surface vegetation conductivity on water and ice content (Campbell and Norman, 1998) complicates the picture because water and ice contents themselves are also temperature-dependent. Snow manipulation experiments have proven the large *spatial* heterogeneity of soil temperature in cold regions due to snow height heterogeneity (Wipf and Rixen, 2010). The temporal variability of insulating layers and their properties should be of similar importance for soil temperature.

At high latitudes, near-surface vegetation consists to a large part of lichens and bryophytes, which often form a continuous layer on the ground. Lichens are symbiotic organisms consisting of a fungus and at least one green alga or cyanobacterium, while bryophytes are non-vascular plants which have no specialised tissue such as roots or stems. Both groups cannot actively control their water uptake and loss, but they tolerate drying and are able to reactivate their metabolism on rewetting. Typical species of upland regions at high latitudes are feather bryophytes such as *Hylocomium splendens* and *Pleurozium schreberi* or the lichen *Cladonia stellaris*. This near-surface vegetation is growing on top of any organic horizon and hence important for heat fluxes between land and atmosphere. In particular also for this layer, thermal and hydrological properties depend highly on water and ice content. Hence, lichens and bryophytes dynamically influence the vertical heat conduction (Porada et al., 2016a).

This study investigates the effects of *temporal* variability of meteorological variables on snow and lichen/bryophyte insulating properties and hence soil temperature in permafrost regions. For this, a recently advanced land surface model (LSM) has been used that also represents permafrost-specific processes, and in particular a dynamic snow representation and a dynamic near-surface vegetation model (Porada et al., 2016a). While the model has been evaluated against several types of observations in other studies (Ekici et al., 2014, 2015; Porada et al., 2016a; Chadburn et al., 2017), here mean annual ground temperature (MAGT) is evaluated again against different observations or other modelling studies. Then, the model is run with two distinct climate forcing datasets, one control dataset and one that has identical long-term averages but reduced day-to-day variability of meteorological variables, such as air temperature and precipitation. The differences in long-term average results from these two model runs will therefore demonstrate the exclusive effects of temporal variability of climate variables and extreme meteorological events on MAGT in high latitude permafrost regions.

2 Methods

2.1 The land surface model JSBACH

The Jena Scheme for Biosphere-Atmosphere Coupling in Hamburg (JSBACH) is the land surface scheme for the Max Planck Institute Earth System Model (MPI-ESM) (Raddatz et al., 2007; Reick et al., 2013). It runs coupled to the atmosphere inside the ESM or offline forced by observation-based or projected climate input data. This model has recently been advanced by several processes which are particularly important in cold regions (Ekici et al., 2014): coupling of soil hydrology and heat conduction via latent heat of fusion and the effects of soil ice and water content on thermal properties, and a snow model for soil insulation. The model simulates heat conduction and soil hydrology in a 1-D vertical scheme using several layers (Hagemann and Stacke, 2015). The version used in this study has been updated from the one used in Ekici et al. (2014) by two additional deep soil layers for thermal and hydrological processes of 13 and 30 m, respectively, which lead to a total potential soil profile of 53 m. However, soil hydrological processes are constrained by the depth to the bedrock. Another constraint on soil hydrological processes is the potentially available pore volume which is reduced by ice content.

In contrast to the model version described in Ekici et al. (2014), here we use a further advanced snow module that includes *dynamic* snow density and snow thermal properties (Ekici, 2015). In this approach, the snow density (ρ_{snow}) follows a similar representation as in Verseghy (1991). It is initialized with a minimum value of $\rho_{min} = 50kgm^{-3}$. Then the compaction effect is included as a function of time and a maximum density ($\rho_{max} = 300kgm^{-3}$) value (Eq. 1),

$$\rho_{snow}^{t+1} = \left(\rho_{snow}^{t} - \rho_{max}\right) \exp \frac{-0.002 \cdot \Delta t}{3600} + \rho_{max} \tag{1}$$

where Δt is the timestep length of model simulation. Additionally, when there is new snowfall, snow density is updated by taking a weighted average of fresh snow density (ρ_{min}) and the calculated snow density value of the previous timestep.

Snow density controls snow heat conduction parameters. Eq. 2 and Eq. 3 show the relationships of volumetric snow heat capacity (c_{snow}) and snow heat conductivity (λ_{snow}) to snow density following the approach of Abels (1892) and Goodrich (1982). With no previous snow layers, c_{snow} is initialized with an average value of $0.52MJm^{-3}K^{-1}$ and λ_{snow} with $0.1Wm^{-1}K^{-1}$,

$$c_{snow} = c_{ice} \cdot \rho_{snow} \tag{2}$$

where c_{ice} is the specific heat capacity of ice $\left(2106Jkg^{-1}K^{-1}\right)$, and

$$\lambda_{snow} = 2.9 \cdot 10^{-6} \cdot \left(\rho_{snow}\right)^2 \tag{3}$$

Another important advancement of the JSBACH model version used in this study is the inclusion of a dynamic lichen and bryophyte model (Porada et al., 2013, 2016a). This model is designed to predict lichen and bryophyte net primary productivity (NPP) in a process-based way from available light, surface temperature, atmospheric carbon dioxide concentration, and water content of lichens and bryophytes. Furthermore, it is applicable to estimate various impacts of lichens and bryophytes on biogeochemical cycles (Porada et al., 2016b; Lenton et al., 2016; Porada et al., 2017). The model includes a dynamic representation of the surface cover which depends on the balance of growth due to NPP and reduction by disturbance, such as fire (Porada et al., 2016a). The coverage of the layer determines its influence on heat exchange between atmosphere and soil. The layer thickness and porosity is set to 4.5 cm and 80%, respectively.

The lichen and bryophyte water balance is integrated into the scheme of hydrological fluxes in JSBACH. In addition, the lichen and bryophyte layer is fully integrated into the heat conduction scheme and hence also functions as a soil insulating layer (Porada et al., 2016a). Soil insulation depends on the fractional grid cell coverage of the lichen and bryophyte layer as well as on its hydrological status. Thereby, thermal diffusivity of this layer is computed as a function of water, ice and air content in the lichen and bryophyte layer (Porada et al., 2016a). The simulated relations between thermal properties of the lichen and bryophyte layer and water content agree well with field observations. Porada et al. (2016a) provide a complete description of the dynamic lichen and bryophyte model in JSBACH. The model version used here differs from Porada et al. (2016a) only with respect to the parametrisation of the snow layer, which has a slightly longer compression time, and a few bug fixes. This updated version is also used in Chadburn et al. (2017), where it shows good agreement with site level soil temperature observations.

2.2 Forcing data

The JSBACH model driver estimates half-hourly climate forcing data using daily data of maximum and minimum air temperature, precipitation, short-wave and long-wave radiation, specific humidity and surface pressure. We are using global data at 0.5 degree spatial resolution which has been produced following the description in (Beer et al., 2014). The historical data from 1901-1978 came from the WATCH forcing dataset (Weedon et al., 2011), and for the period 1979-2010 ECMWF ERA-Interim reanalysis data (Dee et al., 2011) has been bias-corrected against the WATCH forcing data following Piani et al. (2010) as described in Beer et al. (2014).

For a specific additional projection into the future (REDVARfut, section 2.4), meteorological data during 2011-2100 have been obtained from the CMIP5 output of the Max-Planck-Institute Earth System Model (Giorgetta et al., 2012) following the representative concentration pathway (RCP) 8.5. Meteorological data of the two grid cells representing the Canadian and Russian sites were cut out and then also bias corrected to the observation-based period following Piani et al. (2010) as described in Beer et al. (2014).

Grid cells are divided into four tiles according to the four most dominant vascular plant functional types of this grid cell (Ekici et al., 2014). This vascular vegetation coverage is assumed to stay constant over the time of simulation. In the model simulations used in this study, we apply new soil parameters. Hydrological parameters have been assigned to each soil texture class following Hagemann and Stacke (2015) according to the percentage of sand, silt and clay at 1 km spatial resolution as indicated by the Harmonized World Soil Database (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012). Thermal parameters have been estimated as in (Ekici et al., 2014) at the 1 km spatial resolution. Then, averages of 0.5-degree grid cells have been calculated. Soil depth until bedrock follows the map used in Carvalhais et al. (2014) based on Webb et al. (2000).

2.3 Meteorological forcing data with manipulated variability

Based on the climate data described above (subsequently called CNTL dataset), an additional climate dataset has been developed. This dataset shows reduced day-to-day variability but conserved long-term mean values when comparing to CNTL, as described in detail in Beer et al. (2014). The dataset with reduced variability is called REDVAR. In that dataset, the variability of daily values is reduced by a variance factor of $k = 0.25$ (see Beer et al. (2014) for details), but the mean seasonal cycle is conserved. The seasonal variability is represented by an 11-year running average across same dates. Differently from Beer et al. (2014), seasonal means in the REDVAR dataset were exactly preserved by normalization with respect to the CNTL dataset for the annual quarters December-January-February, March-April-May, June-July-August, and September-October-November for each year individually.

For the specific additional projection until 2100 at site-level scale, bias-corrected future climate data has been manipulated such that the short-term variability of meteorological variables *is dynamically* reducing during 2011-2100, in contrast to the REDVAR dataset for which a constant reduction factor has been applied. This additional artificial dataset is called REDVARfut in the following. For REDVARfut, the variance factor k is set to change linearly from 1 to 0.1 over these 90 years following Eq. 4:

$$k = 1 - \left(2.7^{-5} \cdot d\right) \tag{4}$$

where d is the day relative to 1 Jan 2011. This has been done for two grid cells representing one location in Canada (medium recent MAGT) and one location in East Siberia (cold recent MAGT) (cf. section 2.4). The CNTL and REDVARfut datasets are identical for the time period before 2011.

2.4 Model experiments

For addressing the research question about effects of climate variability on mean annual ground temperature in permafrost regions (cf. section 1), artificial model experiments are conducted in this study. In addition to the control model run (CNTL), in one model experiment called REDVAR the land surface model has been driven by an artificial climate dataset that represents a reduced short-term (day-to-day) climate variability while the decadal averages are conserved (section 2.3). Then, differences in decadal averages of simulated snow and lichen and bryophyte properties and ultimately soil temperature can be interpreted exclusively due to a difference in variability of meteorological variables.

Two different kinds of such experiments are presented in this study. The main experiments are conducted at the pan-Arctic scale over historical to recent time periods (1901-2010). Here, CNTL and REDVAR model runs are done exactly the same way including the spin-up approach for bringing state variables, such as soil temperature in equilibrium with pre-industrial climate. At the end, results are compared from "two different worlds" with the same average climate, one with a constantly lower variability of meteorological variables than the other.

The second kind of experiments has been performed at site-level scale. Here, JSBACH has been run over the period 1901-2100 (CNTL) and a second model run with constantly *increasing* reduction of climate variability (REDVARfut, see section 2.3) has been performed for the period 2011-2100. This experiment additionally clarifies the effects of changing future climate variability on permafrost temperature. The REDVARfut experiment additionally contributes to the question on how climate data should be prepared in order to perform so called offline model experiments into the future. Of particular concern are potential biases in future projections of ecosystems states using LSMs because in these projections anomalies of raw ESM output is usually added to recent short-term variability of meteorological variables. Even if that is the most reliable approach of conducting such future projections at the moment, still we need to address the question, how high could be the bias just because a change in short-term variability has been neglected? The REDVARfut experiment has been conducted for two grid cells representing two sites, one Canadian site at about 62.2N, -75.6E with MAGT of about -5 deg C, and one East Siberian site at about 72.2N, 147E with MAGT of about -10 deg C. At these sites, JSBACH results differed by only 0.7 and 0.2 deg C from the borehole measurements.

State variables have been brought into equilibrium using a spin-up approach prior to the transient model runs (1901-2010 or 1901-2100). We assume the time period 1901-1930 to be a representative for pre-industrial climatology following (Cramer et al., 1999; McGuire et al., 2001). Therefore, randomly selected years from that period have been used. For a proper spin-up of soil physical state variables in permafrost regions, we suggest a 2-step procedure. First, a 50-year model run with the above described randomly selected climate from the period 1901-1930 has been done without considering any freezing and thawing. This first spin-up will bring the soil temperature and water pools in a first equilibrium with pre-industrial climate. In a second step, another 100 years spin-up with the same climate data is performed but now freezing and thawing is switched on in order to have all pools including soil ice and water content, and soil temperature in equilibrium with climate.

2.5 Mean annual ground temperature evaluation

The frost-enhanced JSBACH model has been intensively evaluated elsewhere (Ekici et al., 2014, 2015; Porada et al., 2016a). The model version used here has also been recently extensively evaluated against site-level observations (Chadburn et al., 2017). In this paper, the simulated mean annual ground temperature (MAGT) is again evaluated against various other datasets at different spatial scales. First, JSBACH model results are compared to model results from the GIPL 1.3 model (Sergei Marchenko, University of Alaska Fairbanks) over Alaska for the period 1980-1989. For this we downloaded GIPL model results at 2kmx2km grid cell size from http://arcticlcc.org/products/spatial-data/show/simulated-mean-annual-ground-temperature. Then, the map was reprojected to geographic lat/lon using a bilinear method and further aggreagated to 0.5 degrees grid cell size in order to be comparable with JSBACH outputs. For this comparison we used JSBACH mean soil temperature results from layer 7 (38 m depth) and during 1980-1989. Then, spatial details of MAGT are compared to the information from the Geocryological Map of Yakutia (Beer et al., 2013) using also model results from layer 7 but a mean value during 1960-1989. The depth of 38 m ensures that temperature variation is negligible and hence comparable to the information in the observation-based map. The time period 1960-1989 represents observations used to create this map (Beer et al., 2013). Last, JSBACH subsoil temperature is compared to pan-Arctic borehole measurements collected by the GTN-P initiative (Romanovsky et al., 2010; Christiansen et al., 2010; Smith et al., 2010) using model results from the layer corresponding to the measurement depth and from year 2008. The respective GTN-P Thermal State of Permafrost (TSP) snapshot data has been dowloaded from the National Snow and Ice Data Center (NSIDC).

2.6 Analysis

In order to analyse effects of variability of meteorological variables on snow and near-surface vegetation properties and hence soil temperature, model results have been averaged during the period 1980-2009. As the averages of climate forcing data is similar between both experiments REDVAR and CNTL, (relative) differences in long-term average model results, such as snow depth or soil temperature, show the effects of short-term variability of climate forcing data on ecosystem states and functions. Usually, differences are calculated as REDVAR minus CNTL, and relative differences accordingly as (REDVAR-CNTL)/CNTL. Therefore, relative differences are displayed as a fraction (no unit). In Fig. 4 to Fig. 9 the gray area represents all land outside the (sporadic) permafrost zone which is masked by applying a long-term mean air temperature threshold of -3 °C.

In order to evaluate the short-term variability of the REDVARfut and CNTL time series in section 3.6 the mean absolute difference (MAD) of both daily time series is computed for each year as

$$MAD(x,y) = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i|. \quad (5)$$

Here, i denotes the day of the year and $n = 365$ or $n = 366$.

3 Results

3.1 Mean annual ground temperature evaluation

When comparing against a global dataset of mean annual ground temperature (MAGT) at depth ranging usually from 1 to 20 m (GTN-P initiative) JSBACH shows almost no bias (-0.4 °C) and a root mean square error of 3 °C Fig. 1. JSBACH represents the spatial variation in mean annual ground temperature (MAGT) reasonably well with a coefficient of determination of 0.5. Fig. 1 shows that for a number of measurements between 0 and -1 °C, JSBACH simulates a larger variation ranging from 2 to -8 °C. In addition, JSBACH clearly underestimates MAGT at three borehole sites in the Canadian High Arctic (data about -10 °C, model about -22 °C) which requires further evaluation, e.g. about the representativeness of these data points or about the validity of snowfall input data to the model.

When looking at alternative estimates of spatial details of MAGT, JSBACH both underestimate or overestimate MAGT by about 2 to 4 °C depending on the location (Fig. 2,Fig. 3). The JSBACH results for Alaska are compared to another model output. JSBACH overestimates MAGT in many areas in Alaska by several °C while also underestimates MAGT at the southern end of the North Slope (Fig. 2). In East Siberia (Yakutia), the model usually underestimates MAGT by 2 to 6 °C (Fig. 3) when comparing to an observation-based map (Beer et al., 2013). However, the cold bias is largely reduced when taking the uncertainty (standard deviation) in the original geocryological map into account (Fig. 3). Then, the difference is negligible in many regions. Still, there is a very strong cold bias in the mountainous regions of East Siberia. When taking the map uncertainty into account (Fig. 3) the model still underestimates MAGT by about 6 to 8 °C here. This bias can also not be explained by the general warm bias of very low MAGT in the geocryological map when comparing to GTN-P observations (Beer et al., 2013). In fact, very low snow depth model results in these areas of about 15 cm on average (data not shown) seem to be the reason for a too low insulation of soil during a very cold winter.

3.2 Climate forcing data comparison

The long-term (1980-2010) averages of air temperature differ by only 0.015 °C at maximum or 0.004 % between CNTL and REDVAR in permafrost regions (Fig. 4a). Also long-term precipitation averages are similar between the datasets, with differences of -0.2 to 0.1 % (Fig. 4b).

In contrast, the difference in short-term variability of meteorological variables at daily resolution between both datasets is remarkable. Although the statistical transformation of variables has been performed at residuals to the mean seasonal cycle (section 2.3), still the standard deviation of air temperature at daily resolution is usually 0.2 to 1 °C lower in the REDVAR dataset compared to CNTL, or 2 to 10 % (Fig. 5a). That means that temperature of warmer days have been reduced while air temperature of colder days have been increased such that the overal mean air temperature is similar. Interestingly, the amount of variability difference between the two datasets also depends on the location. For example, lower standard deviation differences are visible towards colder regions, such as East Siberia and the Canadian High Arctic. One explanation for this pattern is the higher mean seasonal cycle in continental climate, which has not been manipulated (section 2.3), and which therefore dominates stronger the overall variability, which is analyzed in Fig. 5a. Also REDVAR precipitation standard deviation is usually 2 to 6 % lower than precipitation standard deviation of the

CNTL dataset (Fig. 5b).Hence, in this artificial climate dataset, extremely heavy rainfall or snowfall is reduced while small precipitation amounts have been increased.

3.3 Climate variability effects on snow properties

Importantly, snow depth is up to 20 percent higher under reduced climate variability conditions (Fig. 6a). In fact, the snow depth difference can be explained by differences in snow water equivalents of same magnitude (Fig. 6b). In contrast, the slightly higher snow density under reduced climate variability (Fig. 6c) is not able to explain the difference in snow depth. Snow melt flux differences in autumn between both model experiments of 10 to 40 percent (Fig. 7) demonstrate clearly that under reduced air temperature variability during the beginning of the snow season, individual snow melt events and hence the total snow melt flux are reduced. Besides snow depth, the thermal diffusivity of snow controls the overall heat conduction. Fig. 6d shows that under reduced climate variability conditions, thermal diffusivity of snow is 0.5 to 2.5 percent higher in high latitude regions.

3.4 Climate variability effects on thermal diffusivity of lichens and bryophytes

Thermal diffusivity of lichens and bryophytes differs only marginally between the REDVAR and CNTL model experiments over most of the northern high latitude permafrost regions (Fig. 8a). In western Siberia and Quebec, winter thermal diffusivity of bryophytes and lichens is up to 12 percent lower under reduced climate variability conditions (Fig. 8a). In contrast, summer diffusivity of bryophytes and lichens is usually higher under reduced variability of meteorological variables (Fig. 8b). Under these climate conditions, it is raining more often a little bit and air temperature are not extreme resulting in more moist conditions for lichens and bryophytes, hence higher thermal diffusivity. In tundra the difference is about 2 percent while in the boreal forest it can be up to 6 percent (Fig. 8b).

3.5 Ultimate climate variability effects on soil temperature

The estimated long-term average of both topsoil and subsoil temperature differs between REDVAR and CNTL experiments (Fig. 9a,Fig. 9b). Soil is 0.1 to 0.8 °C warmer when climate variability is reduced (Fig. 9a,Fig. 9b). These results and also the spatial pattern are similar between topsoil and subsoil values (Fig. 9a,Fig. 9b) with a bit larger effect on topsoil temperature. Soil temperature differences are larger in winter with values up to 1.5 °C compared to the summer when differences are typically 0.2-0.5 °C (Fig. 9c,Fig. 9d).

3.6 Effects of future changes of climate variability on soil temperature

In order to analyze effects of *changing variability* of meteorological variables *into the future*, the results of the respective additional future projections at two sites are displayed as time series in Fig. 10 and Fig. 11. In contrast to the continental model experiments, in these additional point simulations the variability of meteorological variables is *increasingly reduced* during 2011-2100 in the REDVARfut input dataset while the historical climate until 2010 is identical (section 2.3).

The bias-corrected MPI-ESM CMIP5 model output following RCP8.5 shows increasing air temperature in both locations (solid blue line in Fig. 10a and Fig. 11a). Precipitation is also increasing but not constantly (solid blue line in Fig. 10b and Fig. 11b). ~~This positive trend is also seen by the annual minimum (1-percentile and maximum (99-percentile) temperature, and maximum precipitation (dashed blue lines in Fig. 10 and Fig. 11).~~ Meteorological forcing data of the REDVARfut dataset (red lines) shows similar long-term averages to the CNTL dataset (Fig. 10a, Fig. 10b, Fig. 11a, Fig. 11b). Hence, REDVARfut meteorological variables follow the general positive trend. ~~However, as the short-term variability is designed to being increasingly reduced,the differences in the minimum (1-percentile) and maximum (99-percentile) air temperature are increasing during 2011-2100. The increasing maximum daily precipitation in the CNTL dataset has been reversed in REDVARfut where the amount of precipitation at percentile 99 is even decreasing in time (Fig. 10b, Fig. 11b).~~ However, the two time series increasingly differ in their day-to-day and week-to-week variability by design. This is shown by the mean absolute difference of daily data (cf. equation 5) in the insets of Fig. 10a and Fig. 10b as well as Fig. 11a and Fig. 11b.

These CNTL and REDVARfut climate datasets have been used as forcing data for JSBACH in the additional point-scale model runs. The respective soil temperature results are compared to each other in Fig. 10c and Fig. 10d as well as Fig. 11c and Fig. 11d. The increasing differences in the variability of meteorological variables under conserved long-term averages leads to an increasing difference in topsoil temperature (Fig. 10c, Fig. 11c), i.e. the overall increasing topsoil temperature due to increasing air temperature is a bit higher in case of reduced climate variability. This effect is also visible in 38 m depth (Fig. 10d, Fig. 11d) even though short-term atmospheric data fluctuations in general should be most filtered at this soil depth.

4 Discussion

Climate model projections show increasing variability of meteorological variables and hence increasing frequency of extreme meteorological events (Seneviratne et al., 2012) along with a gradually changing climate (change of long-term mean values) (Ciais et al., 2013). Because of the nonlinearity of ecosystem response functions, changing extreme event frequency and changing variability of meteorological variables can have a higher impact on ecosystem state and function than a gradual change of mean meteorological variables (Reichstein et al., 2013; Beer et al., 2014). This study contributes to this overall question from a theoretical point of view with LSM experiments for which artificially manipulated climate forcing datasets have been employed. These climate datasets practically do not differ in their decadal averages (section 3.2) while they are showing a substantial difference in the short-term (daily) variability (section 3.2). Therefore, differences in simulated state variables and fluxes over 30-year periods (soil temperature in this case) will be only due to differences in *temporal variability* of meteorological variables. This study addresses particularly the question about the effect of climate variability on soil temperature in northern high latitude regions. The CNTL experiment shows *higher* climate variability than the artificial experimental REDVAR dataset (sections 2.3 and 3.2), and respective model result differences between experiments using the manipulated climate REDVAR and the CNTL dataset are shown in section 3. Methodologically, it is important to artificially design a climate dataset with *reduced* temporal variability because otherwise there is a high risk for producing a physically unrealistic climate conditions. However, for interpreting the results in terms of future ecosystem responses to *increasing* climate variability (Seneviratne et al., 2012), **the direction of the conclusions are carefully inverted in this discussion section**.

In contrast to the climate forcing data, the long-term average of both topsoil and subsoil temperature differs between REDVAR and CNTL experiments (Fig. 9a,Fig. 9b). The same is true for respective future projections (Fig. 10, Fig. 11). In fact, under higher variability of meteorological variables and higher frequency of extreme events (CNTL versus REDVAR experiments) soil will be cooler (Fig. 9c,Fig. 9d,Fig. 10, Fig. 11) given all other environmental factors are similar. That means that the projected increase in future variability of meteorological variables (Seneviratne et al., 2012) has the potential to dampen soil warming occurring as a function of increasing mean air temperature. To further understand the underlying processes, individual effects of climate variability on snow and near-surface vegetation properties are discussed in the following paragraphs.

For land-atmosphere heat conduction the thermal properties of snow, near-surface vegetation (e.g. bryophytes and lichens), the soil organic layer, and their spatial extent and heights are of major importance (Yershov, 1998; Gouttevin et al., 2012; Wang et al., 2016; Jafarov and Schaefer, 2016). Snow generally insulates the soil from changing atmospheric temperature. However, effects are smaller during the melting period in spring because the snow is wet and conductivity therefore higher, and more importantly, the soil-to-air gradient in temperature is small. The insulation effect of near-surface vegetation also differs among the seasons because of the high dependence of thermal properties on water and ice contents of lichens and bryophytes. Usually, dry lichens and bryophytes during a continental summer should insulate much more than during wet spring or autumn, or during the ice-rich winter time.

This theoretical study shows that one major effect of higher climate variability on cold region environments is a lower snow water equivalent (section 3.3) which directly translates into lower snow depth values. The potential alternative explanation for a lower snow depth would be a higher snow density. However, the results show exactly the opposite (Fig. 6c). In addition to snow depth, snow thermal properties are also an important factor for heat conduction. However, winter snow thermal diffusivity is some percent lower under higher climate variability conditions (CNTL-REDVAR). Therefore, the net *snow-related* effect of higher climate variability on soil temperature, that is a cooler soil (section 3.5) is explained by snow depth differences alone, i.e. a lower snow depth under higher climate variability.

The reason for these snow water equivalent differences are more often circumstances of melting snow during the beginning of the snow season when day-to-day variability of air temperature is higher (section 3.3). These results also point to an interesting combination of impacts of both changing variability *and* gradually changing mean values on ecosystem states because both changes can lead to pass a threshold value (melting point in this case). These impacts can be seen in section 3.3 when combining temporal climate variability effects on snow water equivalent results (Fig. 6) and snow melt flux results (Fig. 7) with longitudinal pattern of these results towards a continental climate, which can be interpreted in terms of gradual climate change when substituting space for time. Overall, these findings show that projected higher climate variability in future can lead to lower snow depth which will reduce a soil warming in response to air warming. Future studies should clarify if these temporal variability effects of meteorological variables on snow depth are lower or higher when taking into account lateral heterogeneity of soil properties (Beer, 2016) or snow, for instance due to snow intercept by topography or vegetation.

In addition to the insulating effect of snow, lichens and bryophytes growing on the ground influence heat conduction (Porada et al., 2016a). ~~First, higher climate variability leads to lower cover of lichens and bryophytes). The concave light-response curve of photosynthesis is the main reason for a decreasing productivity under increasing climate variability~~ It is interesting to note that when climate variability is higher (CNTL conditions), bryophyte and lichen thermal diffusivity can be substantially *higher in winter* and *lower in summer* in the same region (section 3.4). This fact points to an important role of near-surface vegetation: it will insulate less from air temperature during winter and insulate more during summer with increasing climate variability in future. These effects of climate variability on thermal diffusivity of lichens and bryophytes and hence soil temperature are in the same direction as snow effects (section 3.3), again reducing the soil warming effect of future climate change.

Effects of climate variability on both snow and bryophyte and lichen properties are in the same direction (sections 3.3 and 3.4). As a result, soil will be cooler under higher climate variability (section 3.5). Recent modelling studies suggest a soil temperature increase of 0.02 °C per year since 1960 (McGuire et al., 2016) which translates into 2 °C in 100 years. Such soil temperature increase has also been projected using the JSBACH model under the RCP4.5 scenario (Ekici, 2015) while under the strong warming scenario RCP8.5, the soil temperature increase might be up to 6 to 8 °C (Ekici, 2015). Lower soil temperature under higher climate variability in the range 0.1 to 0.8 °C (section 3.5) demonstrate that under increasing variability of meteorological variables and increasing extreme events in the Arctic (Seneviratne et al., 2012), the effect of gradual air temperature increase on soil temperature and hence active-layer thickness will be *dampened*. Such dampening of future soil warming will also reduce the otherwise positive biogeochemical feedback to climate (Zimov et al., 2006; Beer, 2008; Heimann and Reichstein, 2008). Our results are conservative here because the 99 percentiles of air temperature and precipitation from the artificial dataset (REDVAR) differ by only 1-4 °C (temperature) and 1-10 % (precipitation). These values are at the lower end of the range of climate model projections for the Arctic region until 2100 (Seneviratne et al., 2012).

The presented effects of short-term variability of meteorological variables on ecosystem states and functions, such as soil temperature, are also important from a methodological point of view. To study the effects of environmental change on ecosystems, LSMs are usually forced by historical and reanalysis climate data for the past and present periods, and by future climate results from Earth system models. Since ESM results usually show biases, the ESM outputs cannot be used directly to drive the LSM offline model runs but first need to be bias-corrected (Hempel et al., 2013). The results of the presented REDVAR and REDVARfut experiments demonstrate that such bias-correction methods should account for the projected change in short-term (daily) variability in addition to general trends.

Soil temperature is projected to arrive at values around the freezing point in 38 cm depth over the major part of the current permafrost area (Schaphoff et al., 2013). Therefore, differences of soil temperature of 0.1 to 0.8 °C due to changing climate variability would have an effect on active-layer thickness and permafrost extent, too. It would be interesting to generate an additional artificial REDVARfut dataset with pan-Arctic cover and investigate in detail the impacts of climate variability on active-layer thickness and permafrost extend at the end of the century in a future project.

~~As a result, the climate forcing shows the same trend signal as the raw ESM output but the monthly mean is corrected towards the data from the observation-based period. Such climate forcing data can be used in general to quantify the effects of climate change on e.g. soil temperature and permafrost thawing. However, the results of the presented REDVAR and REDVARfut experiments demonstrate that using current short-term variability of climate data as a proxy for future variability of atmospheric conditions might introduce a soil temperature bias of up to 0.8 °C.~~

~~In addition, a first run of the MPI-ESM with the permafrost-advanced land surface scheme JSBACH coupled to the atmosphere model showed a remarkable bias in 2m air temperature of 1-4 °C in permafrost regions compared to the standard model version without freezing and thawing. Our results suggest that this bias could be potentially reduced when implementing representations of dynamic snow and of dynamic lichens and bryophytes.~~

Our findings have three major implications for future permafrost science:

1. New highly controlled laboratory and field experiments are required in order to confirm modelling results about climate variability effects on permafrost soil temperature.

2. Future developments of land surface models should include dynamic models of snow, and lichens and bryophytes.

3. Statistical methods need to be developed such that future forcing data for climate change impact studies can be prepared in a way that a potential change in short-term variability and frequency of extreme events is preserved.

5 Conclusions

Artificial model experiments have been used in order to quantify the impact of the variability of meteorological variables on the long-term mean of mean annual ground temperature in permafrost-affected terrestrial ecosystems. This impact is mainly due to temperature variability effects on snow melt and snow depth as well as climate variability effects on the (seasonally different) thermal diffusivity of lichens and bryophytes. Overall, the soil temperature response to increasing climate variability and extreme event frequency (soil cooling) will be opposite to the response of soil temperature to gradually increasing air temperature (soil warming). This shows the importance of representing dynamically snow and lichen and bryophyte functions in Earth system models for projecting future permafrost soil states and land-atmosphere interactions, hence future climate. Our findings also point to the need to represent changes in short-term variability of meteorological variables in bias-corrected climate data of future periods.

Acknowledgements. Financial support came from the European Union FP7-ENV project PAGE21 under contract number GA282700. Model simulations were performed on resources provided by the Swedish National Infrastructure for Computing (SNIC) at Linköping University. We acknowledge the Land Department, Max Planck Institute for Meteorology, Hamburg, Germany for JSBACH code maintenance. Special thanks to Ulrich Weber at the Max Planck Institute for Biogeochemistry, Jena, Germany for climate data processing. We thank Charles Koven and two anonymous reviewers for constructive reviews that helped to improve a previous version of the manuscript. We further acknowledge the borehole temperature dataset "IPA-IPY Thermal State of Permafrost (TSP) Snapshot Borehole Inventory, Version 1.0" downloaded from NSIDC.

References

Abels, H.: Beobachtungen der täglichen Periode der Temperatur im Schnee und Bestimmung des Wärmeleitungsvermögens des Schnees als Funktion seiner Dichtigkeit, Repertorium für Meteorologie, 16, 1–53, 1892.

Arrhenius, S.: Über die Reaktionsgeschwindigkeit bei der Inversion von Rohrzucker durch Säuren, Z. Phys. Chem., 4, 226–248, 1889.

Beer, C.: Soil science: The Arctic carbon count, Nature Geoscience, 1, 569–570, http://www.nature.com/ngeo/journal/v1/n9/abs/ngeo292.html, 2008.

Beer, C.: Permafrost Sub-grid Heterogeneity of Soil Properties Key for 3-D Soil Processes and Future Climate Projections, Frontiers in Earth Science, 4:81, doi:10.3389/feart.2016.00081, http://journal.frontiersin.org/article/10.3389/feart.2016.00081/full, 2016.

Beer, C., Fedorov, A. N., and Torgovkin, Y.: Permafrost temperature and active-layer thickness of Yakutia with 0.5-degree spatial resolution for model evaluation, Earth System Science Data, 5, 305–310, doi:10.5194/essd-5-305-2013, http://www.earth-syst-sci-data.net/5/305/2013/, 2013.

Beer, C., Weber, U., Tomelleri, E., Carvalhais, N., Mahecha, M. D., and Reichstein, M.: Harmonized European Long-Term Climate Data for Assessing the Effect of Changing Temporal Variability on Land-Atmosphere CO2 Fluxes, Journal of Climate, 27, 4815–4834, doi:10.1175/JCLI-D-13-00543.1, http://journals.ametsoc.org/doi/pdf/10.1175/JCLI-D-13-00543.1, 2014.

Callaghan, T. V., Bergholm, F., Christensen, T. R., Jonasson, C., Kokfelt, U., and Johansson, M.: A new climate era in the sub-Arctic: Accelerating climate changes and multiple impacts, Geophys. Res. Lett., 37, L14 705, doi:10.1029/2009GL042064, 2010.

Campbell, G. S. and Norman, J. M.: An introduction to environmental biophysics, Springer, New York, 2. ed. edn., 1998.

Carvalhais, N., Forkel, M., Khomik, M., Bellarby, J., Jung, M., Migliavacca, M., Mu, M., Saatchi, S., Santoro, M., Thurner, M., Weber, U., Ahrens, B., Beer, C., Cescatti, A., Randerson, J. T., and Reichstein, M.: Global covariation of carbon turnover times with climate in terrestrial ecosystems, Nature, 514, 213–217, doi:10.1038/nature13731, http://dx.doi.org/10.1038/nature13731, 2014.

Chadburn, S. E., Krinner, G., Porada, P., Bartsch, A., Beer, C., Belelli Marchesini, L., Boike, J., Ekici, A., Elberling, B., Friborg, T., Hugelius, G., Johansson, M., Kuhry, P., Kutzbach, L., Langer, M., Lund, M., Parmentier, F.-J. W., Peng, S., Van Huissteden, K., Wang, T., Westermann, S., Zhu, D., and Burke, E. J.: Carbon stocks and fluxes in the high latitudes: using site-level data to evaluate Earth system models, Biogeosciences, 14, 5143–5169, doi:10.5194/bg-14-5143-2017, https://www.biogeosciences.net/14/5143/2017/, 2017.

Christiansen, H. H., Etzelmüller, B., Isaksen, K., Juliussen, H., Farbrot, H., Humlum, O., Johansson, M., Ingeman-Nielsen, T., Kristensen, L., Hjort, J., Holmlund, P., Sannel, A. B. K., Sigsgaard, C., Åkerman, H. J., Foged, N., Blikra, L. H., Pernosky, M. A., and Ødegård, R. S.: The thermal state of permafrost in the nordic area during the international polar year 2007-2009, Permafrost and Periglacial Processes, 21, 156–181, doi:10.1002/ppp.687, http://dx.doi.org/10.1002/ppp.687, 2010.

Ciais, P., Sabine, C., Bala, G., Bopp, L., Brovkin, V., Canadell, J., Chhabra, A., DeFries, R., Galloway, J., Heimann, M., Jones, C., Le Quéré, C., Myneni, R., Piao, S., and Thornton, P.: Carbon and Other Biogeochemical Cycles, in: Climate change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, pp. 465–570, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2013.

Cramer, W., Kicklighter, D., Bondeau, A., Iii, B. M., Churkina, G., Nemry, B., Ruimy, A., Schloss, A., et al.: Comparing global models of terrestrial net primary productivity (NPP): overview and key results, Global Change Biology, 5, 1–15, http://onlinelibrary.wiley.com/doi/10.1046/j.1365-2486.1999.00009.x/full, 1999.

Dee, D., Uppala, S., Simmons, A., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M., Balsamo, G., Bauer, P., et al.: The ERA-Interim reanalysis: configuration and performance of the data assimilation system, Quarterly Journal of the Royal Meteorological Society, 137, 553–597, http://onlinelibrary.wiley.com/doi/10.1002/qj.828/full, 2011.

Easterling, D., Meehl, G., Parmesan, C., Changnon, S., Karl, T., and Mearns, L.: Climate Extremes: Observations, Modeling, and Impacts, Science, 289, 2068–2074, 2000.

Ekici, A.: Process-oriented representation of permafrost soil thermal dynamics in Earth System Models, Dissertation, University Fribourg, 2015.

Ekici, A., Beer, C., Hagemann, S., Boike, J., Langer, M., and Hauck, C.: Simulating high-latitude permafrost regions by the JSBACH terrestrial ecosystem model, Geosci. Model Dev., 7, 631–647, doi:10.5194/gmd-7-631-2014, http://dx.doi.org/10.5194/gmd-7-631-2014, 2014.

Ekici, A., Chadburn, S., Chaudhary, N., Hajdu, L. H., Marmy, A., Peng, S., Boike, J., Burke, E., Friend, A. D., Hauck, C., Krinner, G., Langer, M., Miller, P. A., and Beer, C.: Site-level model intercomparison of high latitude and high altitude soil thermal dynamics in tundra and barren landscapes, The Cryosphere, 9, 1343–1361, doi:10.5194/tc-9-1343-2015, http://www.the-cryosphere.net/9/1343/2015/, 2015.

FAO/IIASA/ISRIC/ISSCAS/JRC: Harmonized World Soil Database (version 1.2), FAO, Rome, Italy and IIASA, Laxenburg, Austria, 2012.

Giorgetta, M., Jungclaus, J., Reick, C., Legutke, S., Brovkin, V., Crueger, T., Esch, M., Fieg, K., Glushak, K., Gayler, V., Haak, H., Hollweg, H.-D., Kinne, S., Kornblueh, L., Matei, D., Mauritsen, T., Mikolajewicz, U., Müller, W., Notz, D., Raddatz, T., Rast, S., Roeckner, E., Salzmann, M., Schmidt, H., Schnur, R., Segschneider, J., Six, K., Stockhause, M., Wegner, J., Widmann, H., Wieners, K.-H., Claussen, M., Marotzke, J., and Stevens, B.: CMIP5 simulations of the Max Planck Institute for Meteorology (MPI-M) based on the MPI-ESM-LR model: The rcp85 experiment, served by ESGF, doi:10.1594/WDCC/CMIP5.MXELr8, https://doi.org/10.1594/WDCC/CMIP5.MXELr8, 2012.

Goodrich, L. E.: The influence of snow cover on the ground thermal regime, Canadian Geotechnical Journal, 19, 421–432, 1982.

Gouttevin, I., Menegoz, M., Dominé, F., Krinner, G., Koven, C., Ciais, P., Tarnocai, C., and Boike, J.: How the insulating properties of snow affect soil carbon distribution in the continental pan-Arctic area, Journal of Geophysical Research: Biogeosciences, 117, doi:10.1029/2011JG001916, http://dx.doi.org/10.1029/2011JG001916, g02020, 2012.

Hagemann, S. and Stacke, T.: Impact of the soil hydrology scheme on simulated soil moisture memory, Climate Dynamics, 44, 1731–1750, http://link.springer.com/article/10.1007%2Fs00382-014-2221-6, 2015.

Heimann, M. and Reichstein, M.: Terrestrial ecosystem carbon dynamics and climate feedbacks, Nature, 451, 289–292, 2008.

Hempel, S., Frieler, K., Warszawski, L., Schewe, J., and Piontek, F.: A trend-preserving bias correction – the ISI-MIP approach, Earth System Dynamics, 4, 219–236, doi:10.5194/esd-4-219-2013, http://www.earth-syst-dynam.net/4/219/2013/, 2013.

Jafarov, E. and Schaefer, K.: The importance of a surface organic layer in simulating permafrost thermal and carbon dynamics, The Cryosphere, 10, 465–475, doi:10.5194/tc-10-465-2016, http://www.the-cryosphere.net/10/465/2016/, 2016.

Koven, C. D., Ringeval, B., Friedlingstein, P., Ciais, P., Cadule, P., Khvorostyanov, D., Krinner, G., and Tarnocai, C.: Permafrost carbon-climate feedbacks accelerate global warming, Proceedings of the National Academy of Sciences, 108, 14 769–14 774, http://www.pnas.org/content/108/36/14769.short, 2011.

Koven, C. D., Lawrence, D. M., and Riley, W. J.: Permafrost carbon-climate feedback is sensitive to deep soil carbon decomposability but not deep soil nitrogen dynamics, Proceedings of the National Academy of Sciences, 112, 3752–3757, doi:10.1073/pnas.1415123112, http://www.pnas.org/content/112/12/3752.abstract, 2015.

Lawrence, D. M., Slater, A. G., and Swenson, S. C.: Simulation of Present-Day and Future Permafrost and Seasonally Frozen Ground Conditions in CCSM4, Journal of Climate, 25, 2207–2225, doi:10.1175/JCLI-D-11-00334.1, http://dx.doi.org/10.1175/JCLI-D-11-00334.1, 2012.

Lenton, T. M., Dahl, T. W., Daines, S. J., Mills, B. J. W., Ozaki, K., Saltzman, M. R., and Porada, P.: Earliest land plants created modern levels of atmospheric oxygen, Proceedings of the National Academy of Sciences, 113, 9704–9709, doi:10.1073/pnas.1604787113, http://www.pnas.org/content/113/35/9704.abstract, 2016.

Lloyd, J. and Taylor, J. A.: On the temperature dependence of soil respiration, Functional Ecology, 8, 315–323, 1994.

McGuire, A. D., Sitch, S., Clein, J. S., Dargaville, R., Esser, G., Foley, J., Heimann, M., Joos, F., Kaplan, J., Kicklighter, D. W., Meier, R. A., Melillo, J. M., Moore, B., Prentice, I. C., Ramankutty, N., Reichenau, T., Schloss, A., Tian, H., Williams, L. J., and Wittenberg, U.: Carbon balance of the terrestrial biosphere in the Twentieth Century: Analyses of CO2, climate and land use effects with four process-based ecosystem models, Global Biogeochemical Cycles, 15, 183–206, doi:10.1029/2000GB001298, http://dx.doi.org/10.1029/2000GB001298, 2001.

McGuire, A. D., Koven, C., Lawrence, D. M., Clein, J. S., Xia, J., Beer, C., Burke, E., Chen, G., Chen, X., Delire, C., Jafarov, E., MacDougall, A. H., Marchenko, S., Nicolsky, D., Peng, S., Rinke, A., Saito, K., Zhang, W., Alkama, R., Bohn, T. J., Ciais, P., Decharme, B., Ekici, A., Gouttevin, I., Hajima, T., Hayes, D. J., Ji, D., Krinner, G., Lettenmaier, D. P., Luo, Y., Miller, P. A., Moore, J. C., Romanovsky, V., Schädel, C., Schaefer, K., Schuur, E. A., Smith, B., Sueyoshi, T., and Zhuang, Q.: Variability in the sensitivity among model simulations of permafrost and carbon dynamics in the permafrost region between 1960 and 2009, Global Biogeochemical Cycles, 30, 1015–1037, doi:10.1002/2016GB005405, http://dx.doi.org/10.1002/2016GB005405, 2016GB005405, 2016.

Peng, S., Ciais, P., Krinner, G., Wang, T., Gouttevin, I., McGuire, A. D., Lawrence, D., Burke, E., Chen, X., Decharme, B., Koven, C., MacDougall, A., Rinke, A., Saito, K., Zhang, W., Alkama, R., Bohn, T. J., Delire, C., Hajima, T., Ji, D., Lettenmaier, D. P., Miller, P. A., Moore, J. C., Smith, B., and Sueyoshi, T.: Simulated high-latitude soil thermal dynamics during the past 4 decades, The Cryosphere, 10, 179–192, doi:10.5194/tc-10-179-2016, http://www.the-cryosphere.net/10/179/2016/, 2016.

Piani, C., Weedon, G., Best, M., Gomes, S., Viterbo, P., Hagemann, S., and Haerter, J.: Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models, Journal of Hydrology, 395, 199–215, http://www.sciencedirect.com/science/article/pii/S0022169410006475, 2010.

Porada, P., Weber, B., Elbert, W., Pöschl, U., and Kleidon, A.: Estimating global carbon uptake by lichens and bryophytes with a process-based model, Biogeosciences, 10, 6989–7033, doi:10.5194/bg-10-6989-2013, http://www.biogeosciences.net/10/6989/2013/, 2013.

Porada, P., Ekici, A., and Beer, C.: Effects of bryophyte and lichen cover on permafrost soil temperature at large scale, The Cryosphere, 10, 2291–2315, doi:10.5194/tc-10-2291-2016, http://www.the-cryosphere.net/10/2291/2016/, 2016a.

Porada, P., Lenton, T. M., Pohl, A., Weber, B., Mander, L., Donnadieu, Y., Beer, C., Poeschl, U., and Kleidon, A.: High potential for weathering and climate effects of non-vascular vegetation in the Late Ordovician, NATURE COMMUNICATIONS, 7:12113, doi:10.1038/ncomms12113, 2016b.

Porada, P., Pöschl, U., Kleidon, A., Beer, C., and Weber, B.: Estimating global nitrous oxide emissions by lichens and bryophytes with a process-based productivity model, Biogeosciences, 14, 1593–1602, doi:10.5194/bg-14-1593-2017, http://www.biogeosciences.net/14/1593/2017/, 2017.

Raddatz, T., Reick, C., Knorr, W., Kattge, J., Roeckner, E., Schnur, R., Schnitzler, K.-G., Wetzel, P., and Jungclaus, J.: Will the tropical land biosphere dominate the climate–carbon cycle feedback during the twenty-first century?, Climate Dynamics, 29, 565–574, http://link.springer.com/article/10.1007/s00382-007-0247-8, 2007.

Rahmstorf, S. and Coumou, D.: Increase of extreme events in a warming world, Proceedings of the National Academy of Sciences, 108, 17 905–17 909, doi:10.1073/pnas.1101766108, 2011.

Reichstein, M., Bahn, M., Ciais, P., Frank, D., Mahecha, M. D., Seneviratne, S. I., Zscheischler, J., Beer, C., Buchmann, N., Frank, D. C., Papale, D., Rammig, A., Smith, P., Thonicke, K., van der Velde, M., Vicca, S., Walz, A., and Wattenbach, M.: Climate extremes and the carbon cycle, Nature, 500, 287–295, doi:10.1038/nature12350, http://dx.doi.org/10.1038/nature12350, 2013.

Reick, C. H., Raddatz, T., Brovkin, V., and Gayler, V.: Representation of natural and anthropogenic land cover change in MPI-ESM, Journal of Advances in Modeling Earth Systems, 5, 459–482, doi:10.1002/jame.20022, http://dx.doi.org/10.1002/jame.20022, 2013.

Romanovsky, V., Smith, S., and Christiansen, H.: Permafrost thermal state in the polar Northern Hemisphere during the international polar year 2007–2009: A synthesis, Permafrost and Periglacial Processes, 21, 106–116, http://onlinelibrary.wiley.com/doi/10.1002/ppp.689/full, 2010.

Schaefer, K., Zhang, T., Bruhwiler, L., and Barrett, A. P.: Amount and timing of permafrost carbon release in response to climate warming, Tellus B, 63, 165–180, 2011.

Schaphoff, S., Heyder, U., Ostberg, S., Gerten, D., Heinke, J., and Lucht, W.: Contribution of permafrost soils to the global carbon budget, Environmental Research Letters, 8, 014 026, http://iopscience.iop.org/1748-9326/8/1/014026, 2013.

Schwalm, C. R., Anderegg, W. R. L., Michalak, A. M., Fisher, J. B., Biondi, F., Koch, G., Litvak, M., Ogle, K., Shaw, J. D., Wolf, A., Huntzinger, D. N., Schaefer, K., Cook, R., Wei, Y., Fang, Y., Hayes, D., Huang, M., Jain, A., and Tian, H.: Global patterns of drought recovery, Nature, 548, 202–205, http://dx.doi.org/10.1038/nature23021, 2017.

Seneviratne, S., Nicholls, N., Easterling, D., Goodess, C., Kanae, S., Kossin, J., Luo, Y., Marengo, J., McInnes, K., Rahimi, M., Reichstein, M., Sorteberg, A., Vera, C., , and Zhang, X.: Changes in climate extremes and their impacts on the natural physical environment, in: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation, edited by Field, C., Barros, V., Stocker, T., Qin, D., Dokken, D., Ebi, K., Mastrandrea, M., Mach, K., Plattner, G., Allen, S., Tignor, M., and Midgley, P., pp. 109–230, A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, Cambridge, UK, and New York, NY, USA, 2012.

Smith, S., Romanovsky, V., Lewkowicz, A., Burn, C., Allard, M., Clow, G., Yoshikawa, K., and Throop, J.: Thermal state of permafrost in North America: a contribution to the international polar year, Permafrost and Periglacial Processes, 21, 117–135, doi:10.1002/ppp.690, http://dx.doi.org/10.1002/ppp.690, 2010.

van't Hoff, J. H.: Studien zur chemischen Dynamik, W. Engelmann, Leipzig, 1896.

Verseghy, D. L.: Class-A Canadian land surface scheme for GCMS. I. Soil model, International Journal of Climatology, 11, 111–133, doi:10.1002/joc.3370110202, http://dx.doi.org/10.1002/joc.3370110202, 1991.

Wang, W., Rinke, A., Moore, J. C., Ji, D., Cui, X., Peng, S., Lawrence, D. M., McGuire, A. D., Burke, E. J., Chen, X., Decharme, B., Koven, C., MacDougall, A., Saito, K., Zhang, W., Alkama, R., Bohn, T. J., Ciais, P., Delire, C., Gouttevin, I., Hajima, T., Krinner, G., Lettenmaier, D. P., Miller, P. A., Smith, B., Sueyoshi, T., and Sherstiukov, A. B.: Evaluation of air–soil temperature relationships simulated by land surface models during winter across the permafrost region, The Cryosphere, 10, 1721–1737, doi:10.5194/tc-10-1721-2016, http://www.the-cryosphere.net/10/1721/2016/, 2016.

Webb, R. W., Rosenzweig, C. E., and Levine, E. R.: Global Soil Texture and Derived Water-Holding Capacities (Webb et al.), doi:10.3334/ORNLDAAC/548, https://doi.org/10.3334/ORNLDAAC/548, 2000.

Weedon, G., Gomes, S., Viterbo, P., Shuttleworth, W., Blyth, E., Österle, H., Adam, J., Bellouin, N., Boucher, O., and Best, M.: Creation of the WATCH Forcing Data and its use to assess global and regional reference crop evaporation over land during the twentieth century, Journal of Hydrometeorology, 12, 823–848, http://journals.ametsoc.org/doi/abs/10.1175/2011JHM1369.1, 2011.

Wipf, S. and Rixen, C.: A review of snow manipulation experiments in Arctic and alpine tundra ecosystems, Polar Research, 29, 95–109, doi:10.1111/j.1751-8369.2010.00153.x, 2010.

Yershov, E. D.: General geocryology, Cambridge University Press, Cambridge, UK., 1998.

Zhang, T.: Influence of the seasonal snow cover on the ground thermal regime: An overview, Reviews of Geophysics, 43, n/a–n/a, doi:10.1029/2004RG000157, http://dx.doi.org/10.1029/2004RG000157, rG4002, 2005.

Zimov, S. A., Schuur, E. A. G., and Chapin, 3rd, F. S.: Climate change. Permafrost and the global carbon budget., Science, 312, 1612–1613, doi:10.1126/science.1128908, http://dx.doi.org/10.1126/science.1128908, 2006.

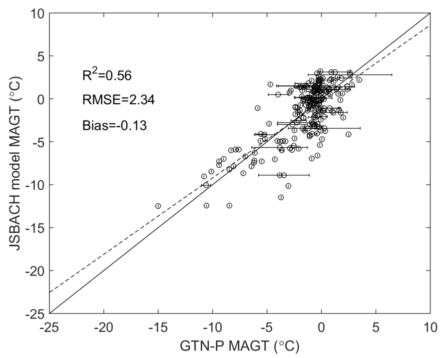


Figure 1: Evaluation of mean annual ground temperature against GTN-P borehole measurements. Model results are taken from the depth of observation for each point.

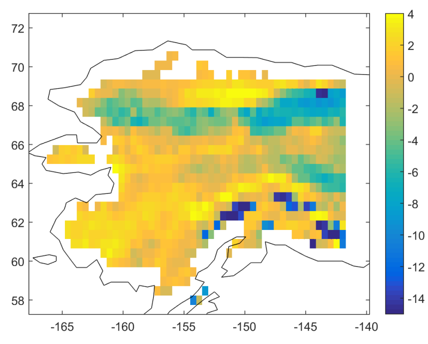


Figure 2: Difference in subsoil temperature (°C) between the models JSBACH and GIPL1.3 from the University of Alaska Fairbanks (1980-1989 average). JSBACH results from 38 m depth.

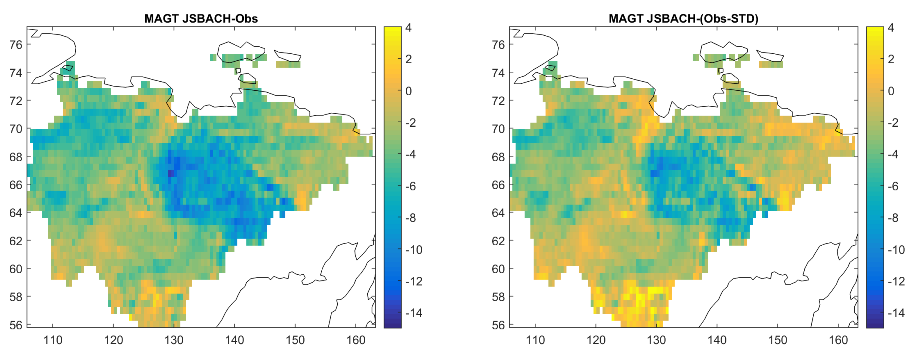
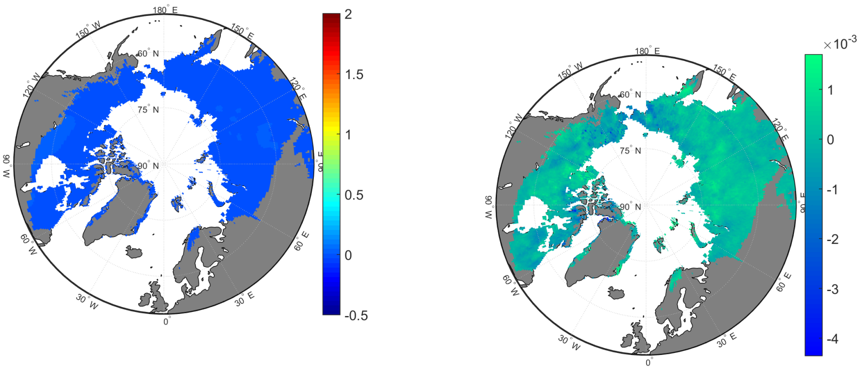


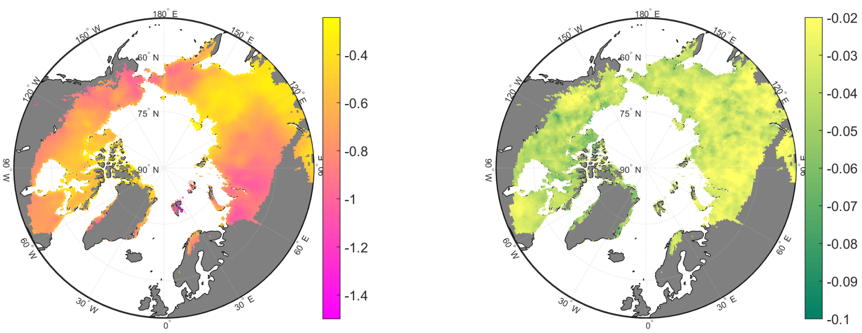
Figure 3: Difference in subsoil temperature (°C) between the JSBACH model (1960-1990 average) and the geocryological map of Yakutia (Beer et al., 2013). JSBACH results from 38 m depth. The right-hand side figure shows the difference to MAGT mean minus standard deviation (spatial uncertainty) from the geocryological map of Yakutia.



(a) Air temperature difference (°C). Color scale adjusted to Fig. 9.

(b) Precipitation relative difference (-).

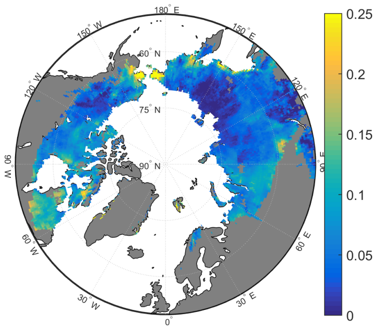
Figure 4: Comparison of 1980-2009 averages of meteorological variables (REDVAR-CNTL) or (REDVAR-CNTL)/CNTL.



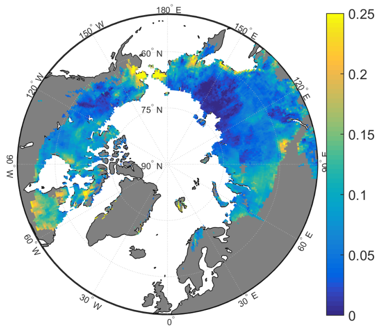
(a) Air temperature standard deviation difference (°C).

(b) Precipitation standard deviation relative difference (-).

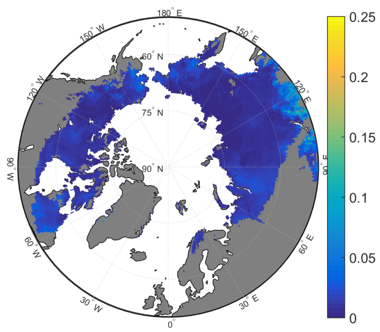
Figure 5: Comparison of 1980-2009 standard deviations of meteorological variables (REDVAR-CNTL) or (REDVAR-CNTL)/CNTL.



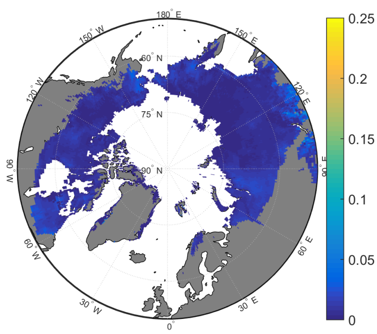
(a) Snow depth relative difference (-).



(b) Snow water equivalent relative difference (-).



(c) Snow density relative difference (-).



(d) Snow thermal diffusivity relative difference (-).

Figure 6: Comparison of mean winter (DJF) season snow properties during 1980-2009. Relative difference (REDVAR-CNTL)/CNTL expressed as a fraction.

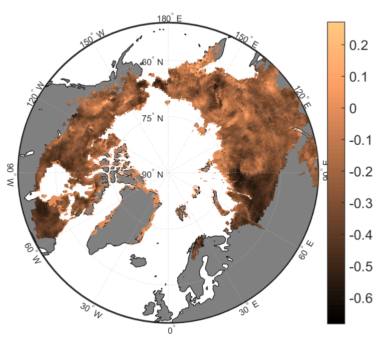
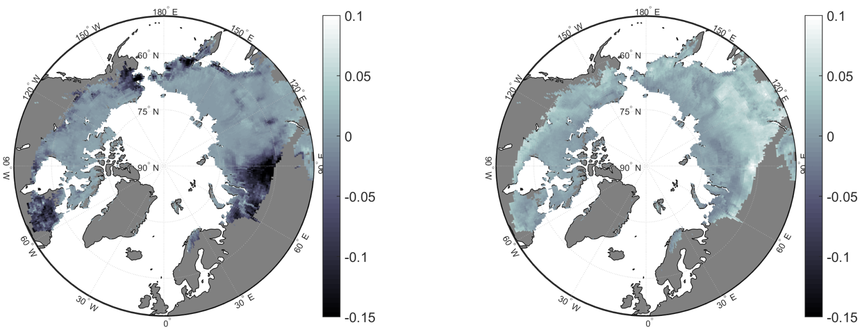


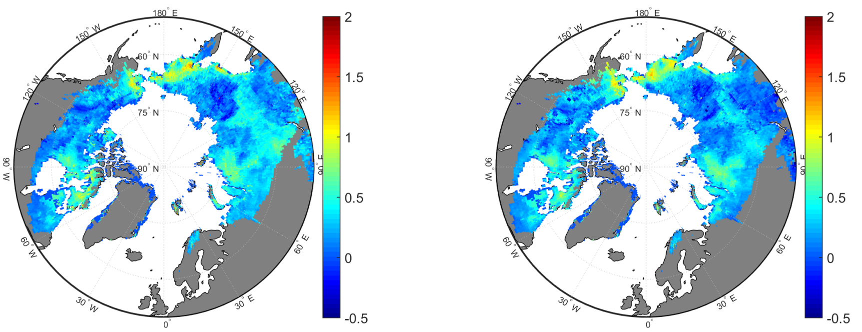
Figure 7: Autumn (SON) 1980-2009 average snow melt relative difference. Relative difference (REDVAR-CNTL)/CNTL expressed as a fraction.



(a) Winter (DJF) lichen and bryophyte thermal diffusivity relative difference.

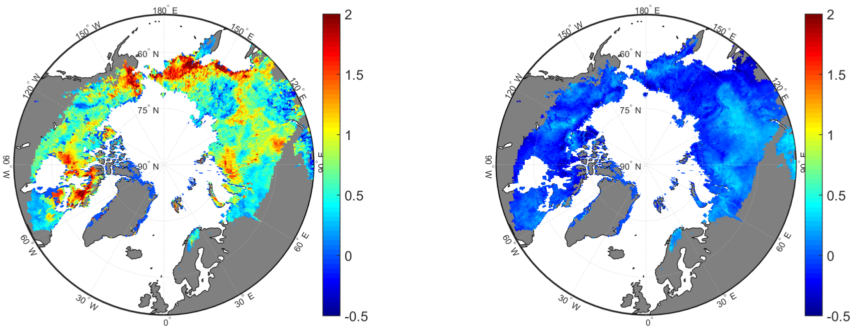
(b) Summer (JJA) lichen and bryophyte thermal diffusivity relative difference.

Figure 8: Comparison of lichen and bryophyte 1980-2009 average properties. Relative difference (REDVAR-CNTL)/CNTL expressed as a fraction.



(a) Annual topsoil temperature difference (°C).

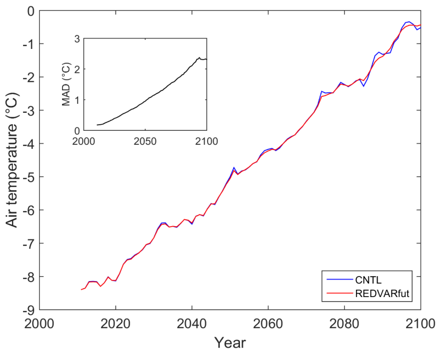
(b) Annual subsoil temperature difference (°C).



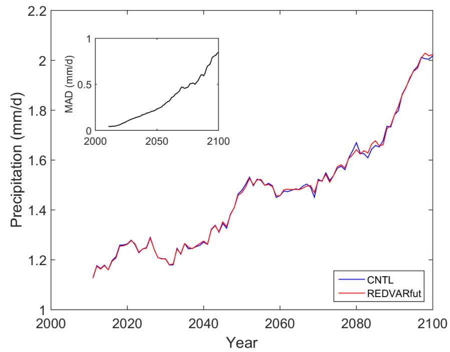
(c) Winter (DJF) topsoil temperature difference (°C).

(d) Summer (JJA) topsoil temperature difference (°C).

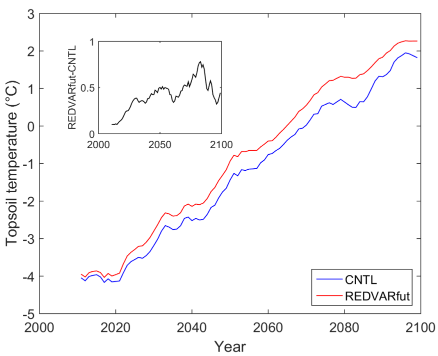
Figure 9: Comparison of 1980-2009 average soil temperature (REDVAR minus CNTL). Topsoil and subsoil refer to depths of 3 cm and 38 m, respectively.



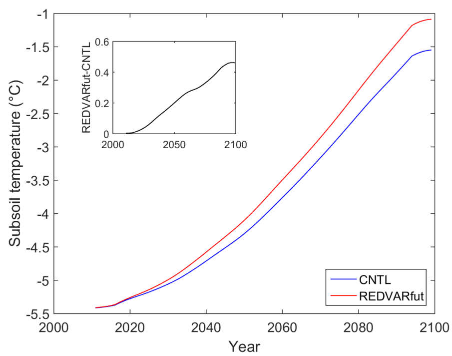
(a) Air temperature (°C) annual mean. Inset shows mean absolute daily differences.



(b) Precipitation (mm/d) annual mean. redInset shows mean absolute daily differences.

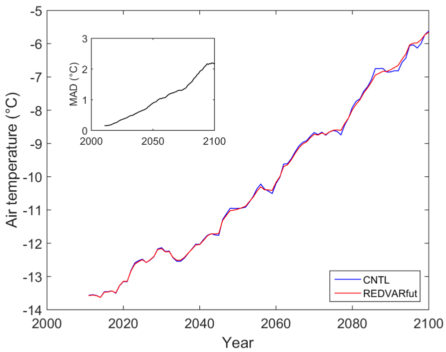


(c) Annual topsoil (3 cm) temperature (°C). redInset shows mean annual differences.

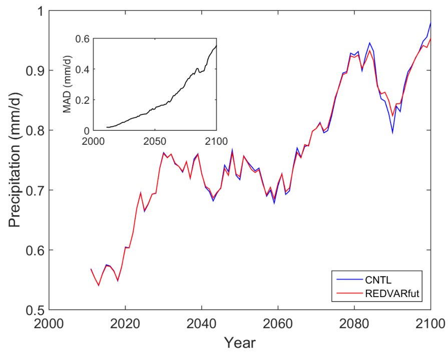


(d) Annual subsoil (38 m) temperature (°C). redInset shows mean annual differences.

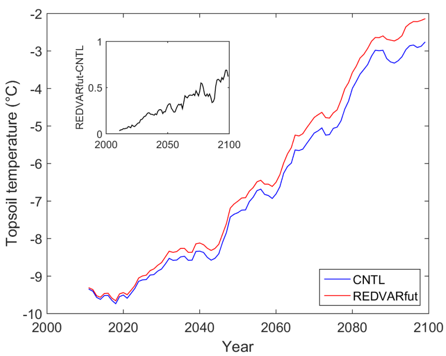
Figure 10: REDVARfut experiment results at a Canadian site (62.2N/-75.6E) during 2011-2100 showing the effects of changing climate variability on future soil temperature. 10-year moving means are shown.



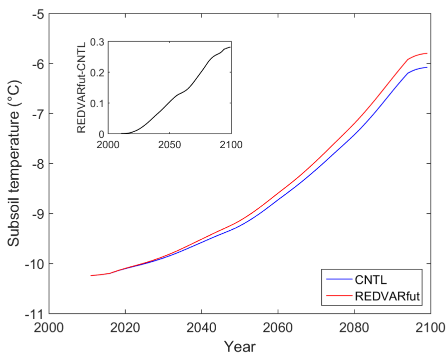
(a) Air temperature (°C) annual mean. redInset shows mean absolute daily differences.



(b) Precipitation (mm/d) annual mean. redInset shows mean absolute daily differences.



(c) Annual topsoil (3 cm) temperature (°C). redInset shows mean annual differences.



(d) Annual subsoil (38 m) temperature (°C). redInset shows mean annual differences.

Figure 11: REDVARfut experiment results at a Siberian site (72.2N/147E) during 2011-2100 showing the effects of changing climate variability on future soil temperature. 10-year moving means are shown.