Effects of variability of meteorological measures on soil temperature in permafrost regions

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Abstract. To clarify effects of the variability of meteorological measures and their extreme events on topsoil and subsoil temperature in permafrost regions, an artificially manipulated climate dataset has been used for process-oriented model experiments. Climate variability mainly impacts snow depth, and the cover and thermal diffusivity of lichens and bryophytes. The latter effect is of opposite

5   direction in summer and winter. These impacts of climate variability on insulating layers together substantially alter the heat exchange between atmosphere and soil. As a result, soil temperature is 0.2 to 1 K higher when climate variability is reduced under conserved long-term mean meteorological measures, depending on the location. Earth system models project warming of the Arctic region but also increasing variability of meteorological measures and extreme events. Therefore, our results

10   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 measures, and ii) when representing dynamic snow and lichen and bryophyte functions in land surface models.

1   Introduction

15   Soil temperature is an important physical measure 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). 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).

20   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

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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 re-

25 sponse 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 (Koven et al., 2015) potentially leading to a

30 positive climate-carbon cycle feedback (Zimov et al., 2006; Beer, 2008; Heimann and Reichstein, 2008).

Meteorological measures, 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

35 instance, for northern high-latitude regions, climate models project an increase of the annual maximum of the daily maximum temperature by 4 K until 2100 (Seneviratne et al., 2012) while annual maximal daily precipitation is projected to increase by 20% in these areas until 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 vari-

40 ability of meteorological measures on mean ecosystem functions can enhance or dampen the effects of gradual changes (Reichstein et al., 2013). That is why there is a strong need to understand these 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 permafrost environments have not been studied so far.

45 Due to the well-known dampening effects of soil insulating layers of snow and near-surface vegetation (Yershov, 1998, pages 361-369) (Goodrich, 1982; Zhang, 2005; Wang et al., 2016) and the dampening effect of the soil organic layer (Jafarov and Schaefer, 2016) and mineral soil (Campbell and Norman, 1998) itself one would expect no to little effects of changing air temperature fluctuations on soil temperature, in particular not on subsoil and permafrost temperature. However, air

50 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. The dependence of conductivity on water and ice content (Campbell and Norman, 1998) additionally complicates the picture because water and ice contents themselves are also temperature-dependent.

Lichens are symbiotic organisms consisting of a fungus and at least one green alga or cyanobac-

55 terium, 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 mosses 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). In addition, climate variability might impact gross productivity (Beer et al., 2014) and hence the cover of lichens and bryophytes itself, which ranges between 0 and 100 % depending on the environmental conditions.

Snow manipulation experiments have proven the large *spatial* heterogeneity of soil temperature in cold regions due to snow height heterogeneity (Wipf and Rixen, 2010). Here, we aim to investigate the effects of *temporal* variability of meteorological measures on snow and lichen and bryophyte insulating properties and hence soil temperature in permafrost regions. For this, a land surface model (LSM) has been run with two distinct climate forcing datasets, one control dataset and one that has identical long-term seasonal averages but reduced day-to-day variability. The LSM has recently been advanced by permafrost-specific processes, and in particular also by a dynamic snow representation (Ekici, 2015) and by a near-surface vegetation model (Porada et al., 2016a).

2 Methods

2.1 Permafrost advancement of the land surface model

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). 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 balance via latent heat of fusion and the effects of ice and water on thermal properties, and a snow model for soil insulation. The model simulates the heat balance, soil hydrology and carbon cycle in a 1-D vertical scheme. The version used in this study has been updated from the one used in Ekici et al. (2014) by two additional soil layers for thermal and hydrological processes of 13 and 30 m which lead to a total potential soil profile of 53 m which is constrained for soil hydrological processes 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 snow module that includes a *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 $\rho_{min} = 50 kg m^{-3}$. Then the compaction effect is included as a function of time and a maximum density ($\rho_{max} = 450 kg m^{-3}$) value (Eq. 1),

$$\rho_{snow}^{t+1} = \left(\rho_{snow}^{t} - \rho_{max} \right) \exp \frac{-0.001 \cdot \Delta t}{3600} + \rho_{max} \qquad (1)$$

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 transfer 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 $0.52 MJm^{-3}K^{-1}$ and λ_{snow} with $0.1 Wm^{-1}K^{-1}$,

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

where c_{ice} is the specific heat capacity of ice $\left(2106 Jkg^{-1}K^{-1}\right)$, 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 here is 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 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). 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. The coverage of the layer determines its influence on heat exchange between atmosphere and soil. The layer has a thickness of 4.5 cm and a porosity of 80 %.

The lichen and bryophyte water balance is integrated into the scheme of hydrological fluxes in JSBACH. Most importantly, 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. The simulated relations between thermal properties of the lichen and bryophyte layer and water content agree well with field observations. Porada et al. (2016a) provides a more detailed description of the dynamic model version used in this study.

2.2 Forcing data

The driver of the JSBACH model 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 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 WATCH forcing data as described in Beer et al. (2014) (Piani et al., 2010).

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). Specifically, results following the representative concentration pathway (RCP) 8.5 have been used. Data of a region of 4x4 grid cells around 70N/100E were cut out and then 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 plant functional types of this grid cell (Ekici et al., 2014). This 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 sptial 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 similar to the method described by Beer et al. (2014). Subsequently, the dataset with reduced variability is called REDVAR dataset. In that data set, the variability of daily values is reduced by a variance factor of $k = 0.25$ (see Beer et al. (2014) for details), but the seasonal variability is still 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, the bias-corrected future climate data has been manipulated such that the short-term variability of meteorological measures *is dynamically reduced* 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. .

2.4 Model experiments

JSBACH has been run for the northern hemisphere during 1901-2010. Prior to this period, state variables have been brought into equilibrium using a spin-up approach. 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 climate. This is followed by another 100 years spin-up with the same climate data 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.

For addressing the research question about effects of climate variability on soil 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 the artificial climate dataset that represents a reduced short-term (day-to-day) variability while the long-term (30-a) averages are conserved (section 2.3). Then, differences in long-term (seasonal) averages of simulated snow and lichen and bryophyte properties and ultimately soil temperature can be interpreted due to a difference in variability of meteorological measures.

In addition to the general question about the effects of reduced variability of meteorological measures on ecosystem states and functions (REDVAR experiment described above), 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 measures. 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? In order to address this specific question, another artificial experiment has been conducted for a selected region around 70N/100E. The CNTL simulation has been extended from 2011 until 2100. Then, the additional REDVARfut experiment has been conducted for the same period using the additionally produced REDVARfut forcing dataset with dynamic difference in short-term variability of meteorological measures.

3 Results

3.1 Climate forcing data comparison

The long-term (30-a) averages of air temperature differ by 0.01 K at maximum (Fig. 1a) or 0.004 % between CNTL and REDVAR. Long-term precipitation averages differ between the datasets by only

195 2e-8 kg m-2 s-1 at maximum (Fig. 1b) which translates into 0.2 %. In other words, these long-term averages are similar between both datasets.

In contrast, the variability of meteorological measures at daily resolution in both datasets is substantially different. Although the statistical transformation of measures has been performed at residuals to the mean seasonal cycle (Beer et al. (2014), cf. section 2.3), still the standard deviation of
200 air temperature is up to 1 K lower in the REDVAR dataset (Fig. 2a), or 10 %. Interestingly, there are spatial pattern of variability differences with lower standard deviation differences towards colder regions, such as East Siberia and the Canadian High Arctic. REDVAR precipitation results are up to 2e-6 kg m-2 s-2 (6 %) lower than the CNTL precipitation data (Fig. 2b).

In the reduced variability climate dataset, high air temperature values (percentile 99) are 1 to 3.5
205 K lower (Fig. 3a) in permafrost regions compared to CNTL. The percentile 99 of precipitation is 1 to 7 % lower in REDVAR (Fig. 3b).

3.2 Effects on snow depth and thermal diffusivity

Fig. 4a shows that snow depth is generally higher under reduced climate variability conditions. In fact, the snow depth difference can be explained by differences in snow water equivalents in the
210 same direction (Fig. 4b). In contrast, a possible lower snow density under these conditions cannot explain the difference in snow depth (Fig. 4c). Snow melt flux differences in autumn between both model experiments (Fig. 5) 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. Interestingly, there is a spatial gradient of snow water equivalent differences between
215 REDVAR and CNTL experiments along with air temperature, e.g. along a longitudinal gradient in Eurasia and from Quebec to Alaska (Fig. 4b). The same longitudinal gradient can be also seen with snow melt flux differences (Fig. 5). The reason for this gradient is that in the higher continental climate in Siberia there are less often melting events during the beginning of the snow season than in Europe. Hence, a reduction in air temperature variability hardly reduces such events further in
220 Siberia compared to Europe.

3.3 Effects on cover and thermal diffusivity of lichens and bryophytes

Under reduced climate variability JSBACH simulates about 2 to 3 percent higher cover of lichens and bryophytes in some boreal and temperate forest regions in Europe and Northern America (Fig. 6a). Differences are however negligible in most of Siberia and tundra. Due to the effects of climate vari-
225 ability on water and ice saturation, lichen and bryophyte thermal diffusivity differs between the experiments by up to 4 percent in summer and 10 percent in winter (Fig. 6). Clear regional differences are visible. In European Russia, South Alaska and the US West Coast, thermal diffusivity is larger during the summer but smaller during the winter under reduced climate variability. In Siberia, differences in winter are negligible while in summer thermal diffusivity is larger under reduced variability.

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230 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 3.2).

3.4 Effects on soil temperature

In contrast to the climate forcing data, the long-term average of both topsoil and subsoil temperature differs between REDVAR and CNTL experiments (Fig. 7a,Fig. 7b). In most regions, soil is warmer

235 when climate variability is reduced, most pronounced in West Siberia, European Russia, and Quebec. In these regions, differences can be up to 1 K. These results and also the spatial pattern are similar between topsoil and subsoil values (Fig. 7a,Fig. 7b). The pattern of topsoil temperature differences between the model experiments varies between winter and summer season (Fig. 7c,Fig. 7d). In doing so, the winter topsoil temperature pattern is similar to the annual soil temperature pattern shown in

240 Fig. 7a and Fig. 7b. REDVAR summer temperature results are now, in contrast to winter or annual values, lower than results from the CNTL experiment in many permafrost regions, e.g. in Northern Canada or Northwest Siberia, while in many other places still the topsoil is simulated to be warmer when climate variability is reduced, e.g. in Northern Central and East Siberia, European Russian tundra or Alaska (Fig. 7d).

245 ### 3.5 Effects of future changes of climate variability on soil temperature

In order to analyze effects of changing variability of meteorological measures in time until 2100, the results of the specific model runs into the future at 70N/100E are displayed as time series in Fig. 8.

The bias-corrected MPI-ESM CMIP5 model output following RCP8.5 shows increasing air temperature (Fig. 8a) and increasing precipitation (Fig. 8b). This positive trend is also seen by the an-

250 nual minimum (percentile 1) and maximum (percentile 99) temperature (Fig. 8a) and precipitation (Fig. 8b). Meteorological forcing data of the REDVARfut dataset shows similar long-term averages to the CNTL dataset (Fig. 8a,Fig. 8b). Hence, REDVARfut variables follow the general positive trend. However, as the short-term variability is designed to being increasingly reduced, the differences in the minima and maxima air temperature are increasing during 2011-2100 (Fig. 8a). The

255 increasing precipitation at the high end of the distribution in the CNTL dataset has been reversed in REDVARfut where the amount of precipitation at percentile 99 is decreasing in time (Fig. 8b).

These time-varying changes in the variability of meteorological measures under conserved long-term average have effects on topsoil temperature of up to 0.9 K (Fig. 8c), i.e. the overall increasing topsoil temperature due to increasing air temperature is a bit higher in case of reduced climate vari-

260 ability. We even see some small effect in 38 m depth (Fig. 8d) even though short-term atmospheric data fluctuations should be most filtered at this depth.

4   Discussion

Climate model projections show increasing variability of meteorological measures and hence increasing frequency of extreme meteorological events (Seneviratne et al., 2012) along with a gradu-
ally changing climate (change of long-term mean values) (Ciais et al., 2013). Because of the non-
linearity of ecosystem response functions, changing extreme events and climate variability generally
can have a higher impact on ecosystem state and function than a gradual change of mean meteo-
rological measures (Reichstein et al., 2013). This study contributes to this overall question from a
theoretical point of view with two LSM experiments for which artificially manipulated climate forc-
ing datasets have been employed. These climate datasets practically do not differ in their long-term
(30-a) averages while they show a substantial difference in the short-term (daily) variability (section
3.1). Therefore, differences in simulated state variables and fluxes over 30-year periods will be only
due to differences in *variability* of meteorological measures. This contributes to our understanding
of the effect of climate variability on soil temperature in permafrost regions. The CNTL experiment
shows *higher* climate variability than the artificial experimental dataset (REDVAR). In section 3
the difference of the manipulated climate experiment (REDVAR) to CNTL is therefore described.
However, for interpreting the results in terms of future ecosystem responses to *increasing* climate
variability, we carefully invert the direction of the conclusions in this discussion section.

For land-atmosphere heat conduction the thermal properties of snow, near-surface vegetation
(e.g. mosses and lichens), and the soil organic layer, and their spatial extent and height are of major
importance (Yershov, 1998; Gouttevin et al., 2012; Wang et al., 2016; Jafarov and Schaefer, 2016).
Therefore, in this study we first analyze effects of climate variability on these soil insulating layers
for a later explanation of the ultimate effects on soil temperature. 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 ice-rich winter time.

Our theoretical study shows that one major effect of higher climate variability on cold region
environments is a lower snow water equivalent (section 3.2) which directly translates into lower
snow depth values. The potential alternative explanation for lower snow depth would be a higher
snow density. However, the results show exactly the opposite (Fig. 4c). 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. Therefore, the
net *snow-related* effects of climate variability on soil temperature (section 3.4) are explained by
snow depth differences alone.

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 3.2). 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 3.2 when combining temporal climate variability effects on snow water equivalent results (Fig. 4) and snow melt flux results (Fig. 5) 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, our findings show that projected higher climate variability in future can lead to lower snow depth which will reduce the soil warming in response to air warming.

In addition to the insulating effect of snow, lichens and bryophytes growing on the ground have a high effect on heat conduction. First, higher climate variability can lead to lower cover of lichens and bryophytes (Fig. 6a). The concave light-response curve of photosynthesis is the main reason for a decreasing productivity under increasing climate variability (Beer et al., 2014). However, highest differences in the cover of lichens and bryophytes between REDVAR and CNTL experiments are about 2 % (Fig. 6a) which is in fact not very large. In contrast, it is interesting to note that when climate variability is higher, moss thermal diffusivity can be substantially *higher in winter* and *lower in summer* in the same region. This fact points to an important role of near-surface vegetation: it will less insulate from air temperature during winter and more insulate 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 3.2). Ultimately, the effects of climate variability on moss thermal diffusivity will reduce the soil warming effect of climate change in future.

Recent modelling studies suggest a soil temperature increase of 0.02 K per year since 1960 (McGuire et al., 2016) which translates into 2 K 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 K (Ekici, 2015). Soil temperature differences due to climate variability differences alone (section 3.4) of the same order of magnitude (0.5-1 K) demonstrate that under increasing variability of meteorological measures 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 *substantially dampened*. Our results are conservative here because the 99 percentiles of air temperature and precipitation from the artificial dataset (REDVAR) differ by only 2-3.5 K (temperature) and 1-7 % (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). Such soil temperature dampening will also reduce the otherwise positive biogeochemical feedback to climate (Zimov et al., 2006; Beer, 2008; Heimann and Reichstein, 2008).

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335   To address this question of validity of future soil temperature projections, for one point we additionally extended the CNTL model simulation until 2100 following the RCP 8.5. Then, in the additional experiment REDVARfut the variability of meteorological measures has been reduced continuously from 2011 until 2100 while the long-term average is still conserved. The resulting topsoil temperature difference of 0.8 K in 2100 agrees in direction and magnitude with the findings from
340   the (spatially explicit) REDVAR experiment (see above). The subsoil temperature difference is much smaller in this experiment compared to REDVAR because more time were required until the surface signal is also seen in 38 m depth.

The presented effects of short-term variability of meteorological measures on ecosystem states and functions, such as soil temperature, are also important from a methodological point of view. To
345   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). As a result, the climate forcing shows the same trend signal as the raw ESM output but the monthly
350   mean and daily variability is corrected towards the data from the observation-based period (Piani et al., 2010; Hempel et al., 2013). Such climate forcing data can be used in general to quantify the general effects of climate change on e.g. soil temperature and permafrost thawing (Schaefer et al., 2011; Schaphoff et al., 2013; Koven et al., 2015). However, the results of the presented REDVAR and REDVARfut experiments demonstrate that using current short-term variability of climate data
355   as a proxy for future atmospheric conditions might introduce a soil temperature bias of up to 1 K.

Our findings have three major implications for future permafrost science:

1. Insulation characteristics of both snow and near-surface vegetation are responsible for a difference in soil temperature due to differences in climate variability. Therefore, future developments of LSMs should include a dynamic lichens and bryophyte model.

360   2. 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.

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

365   In summary, projected future increases in permafrost temperature and active-layer thickness will be *less pronounced* in response to climate change than what current state-of-the-art modelling results suggest because i) current models usually do not consider dynamic functions of snow and lichens and bryophytes and ii) future changes of short-term variability of meteorological measures are not mapped to the applied bias-corrected forcing data. A first run of the MPI-ESM with the permafrost-
370   advanced land surface scheme JSBACH coupled to the atmosphere model showed a remarkable

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bias in 2m air temperature of 1-4 K in permafrost regions compared to the standard model version without freezing and thawing (Hagemann et al., 2016). Our results also suggest that this bias could be potentially reduced when implementing representations of dynamic snow and of dynamic lichens and bryophytes.

375 ## 5 Conclusions

Artificial model experiments quantify the impact of the variability of meteorological measures and their extreme events on the long-term mean of soil temperature in permafrost-affected terrestrial ecosystems. This impact is mainly due to temperature variability effects on snow melt hence snow depth as well as climate variability effects on the cover and (seasonally different) thermal diffusivity

380 of lichens and bryophytes. Overall, the soil temperature response to increasing climate variability and extreme events (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

385 to represent changes in short-term variability of meteorological measures in bias-corrected climate data of future periods.

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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., 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., ?u, M., Saatchi, S., Santoro, M., Thurner, M., Weber, U., Ahrens, B., Beer, C., Cescatti, A., Randerson, J., and Reichstein, M.: Global covariation of carbon turnover times with climate in terrestrial ecosystems, Nature, 514, 213–217, doi:10.1038/nature13731, http://www.nature.com/nature/journal/v514/n7521/full/nature13731.html, 2014.

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.

13

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., Mikolajew- icz, 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, n/a–n/a, 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.

Hagemann, S., Blome, T., Ekici, A., and Beer, C.: Soil-frost-enabled soil-moisture–precipitation feedback over northern high latitudes, Earth System Dynamics, 7, 611–625, doi:10.5194/esd-7-611-2016, http://www. earth-syst-dynam.net/7/611/2016/, 2016.

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., Schuur, E. A. G., Schädel, C., Bohn, T. J., Burke, E. J., Chen, G., Chen, X., Ciais, P., Grosse, G., Harden, J. W., and et al.: A simplified, data-constrained approach to estimate the permafrost carbon-climate feedback, Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sci- ences, 373, 20140 423, doi:10.1098/rsta.2014.0423, http://dx.doi.org/10.1098/rsta.2014.0423, 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.

470   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.

475   McGuire, A. D., Sitch, S., Clein, J. S., Dargaville, R., Esser, G., Foley, J., Heimann, M., Joos, F., Ka-
          plan, J., Kicklighter, D. W., Meier, R. A., Melillo, J. M., Moore, B., Prentice, I. C., Ramankutty, N., Re-
          ichenau, 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:
480   //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,
485   K., Schuur, E. A., Smith, B., Sueyoshi, T., and Zhuang, Q.: Variability in the sensitivity among model simu-
          lations of permafrost and carbon dynamics in the permafrost region between 1960 and 2009, Global Biogeo-
          chemical 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.,
490   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.

495   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,
500   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,
505   A.: High potential for weathering and climate effects of non-vascular vegetation in the Late Ordovician,
          NATURE COMMUNICATIONS, 7, doi:10.1038/ncomms12113, 2016b.

       Raddatz, T., Reick, C., Knorr, W., Kattge, J., Roeckner, E., Schnur, R., Schnitzler, K.-G., Wetzel, P., and Jung-
          claus, 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, PNAS, 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.

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.

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.

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.

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

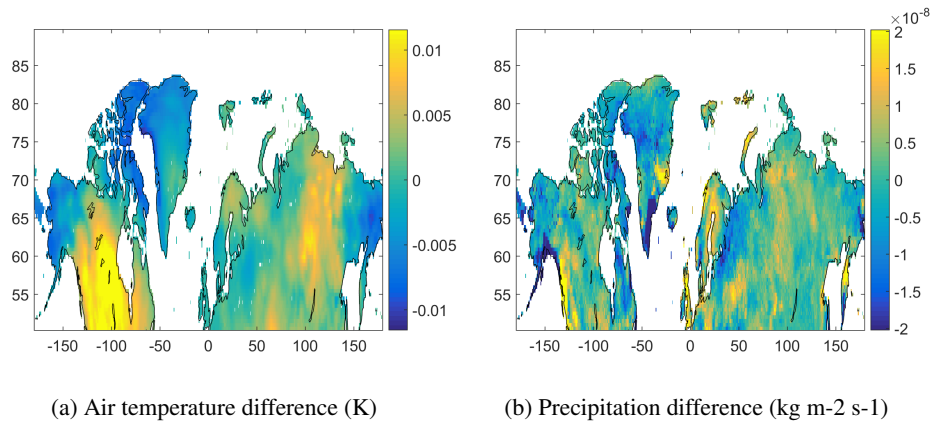Zimov, S. A., Schuur, E. A. G., and Chapin, 3rd, F. S.: Climate change. Permafrost and the global carbon budget., Science, 312, 1612–1613, doi:10.1126/science.1128908, http://dx.doi.org/10.1126/science.1128908, 2006.

(a) Air temperature difference (K)   (b) Precipitation difference (kg m-2 s-1)

Figure 1: Comparison of 1980-2009 averages of meteorological measures (REDVAR versus CNTL).

(a) Air temperature standard deviation difference (b) Precipitation standard deviation difference (kg
(K)   m-2 s-1)
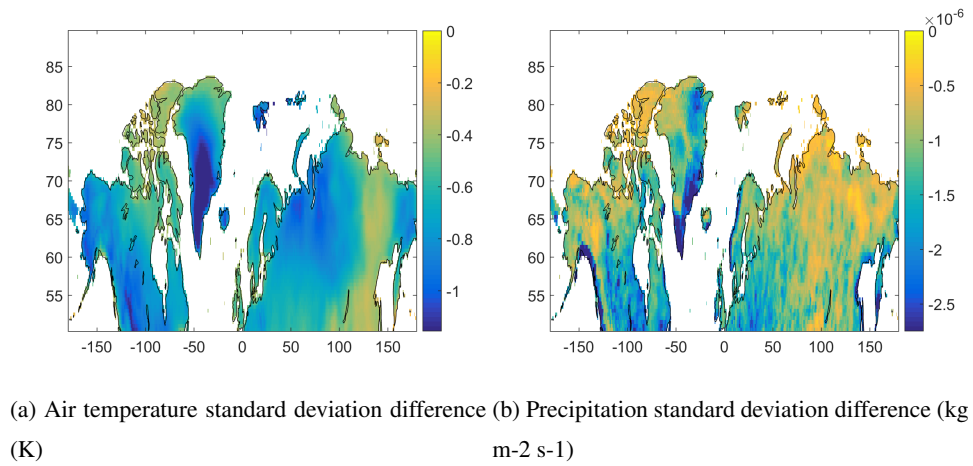
Figure 2: Comparison of 1980-2009 standard deviations of meteorological measures (REDVAR versus CNTL).
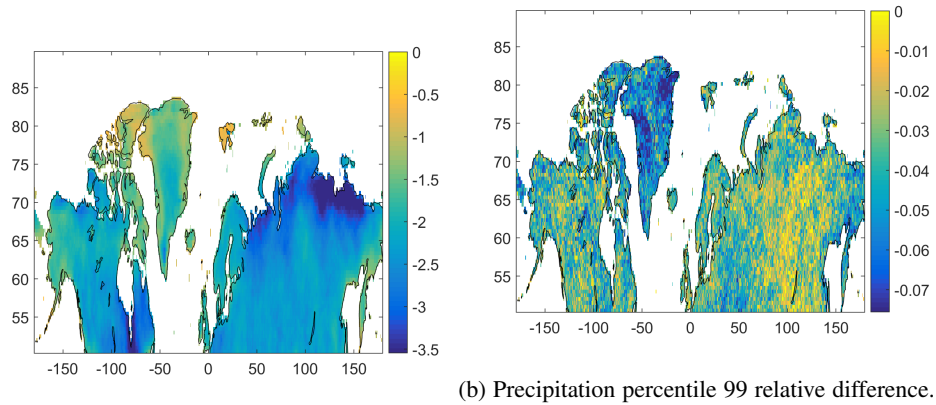
(a) Air temperature percentile 99 difference (K)

(b) Precipitation percentile 99 relative difference.
Numbers are expressed as a fraction.

Figure 3: Comparison of 1980-2009 maximum (percentile 99) meteorological measures (REDVAR versus CNTL).

(a) Snow depth relative difference.

(b) Snow water equivalent relative difference.
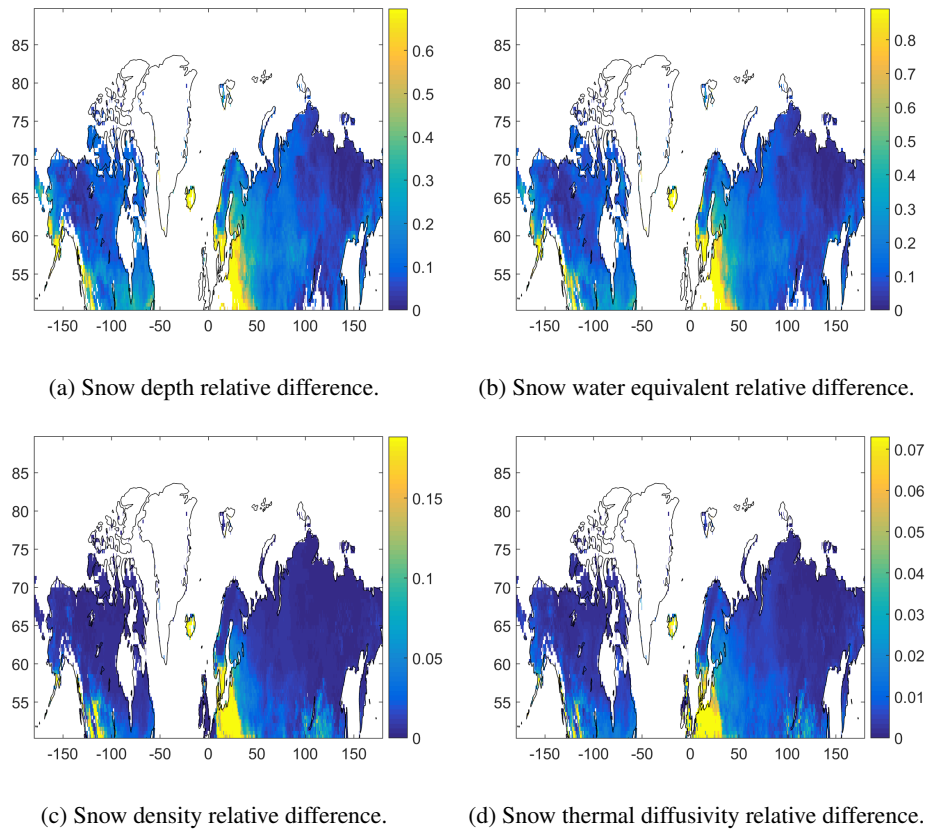
(c) Snow density relative difference.

(d) Snow thermal diffusivity relative difference.

Figure 4: Comparison of mean winter (DJF) season snow properties during 1980-2009 (REDVAR versus CNTL). Numbers are expressed as a fraction.
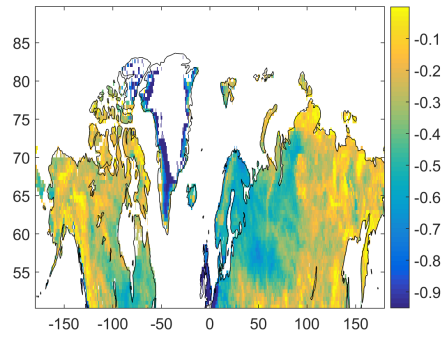
Figure 5: Autumn (SON) 1980-2009 average snow melt relative difference (REDVAR versus CNTL). Numbers are expressed as a fraction.
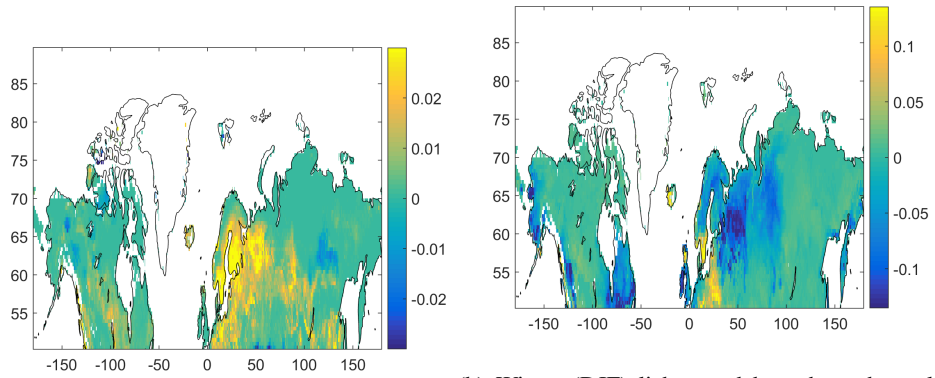
(a) Annual lichen and bryophyte cover.

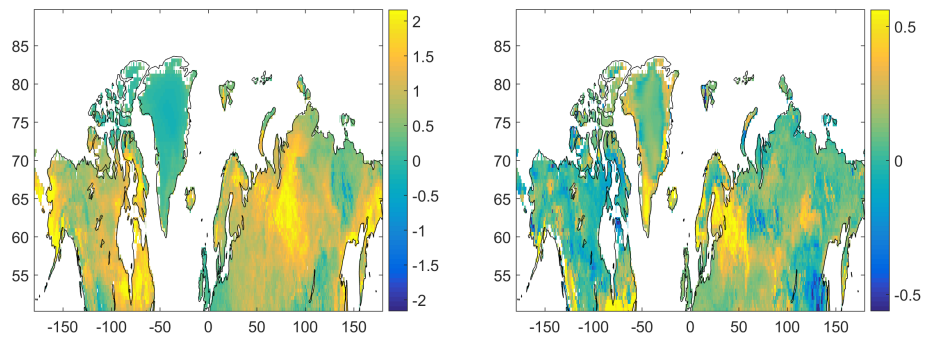(b) Winter (DJF) lichen and bryophyte thermal diffusivity.
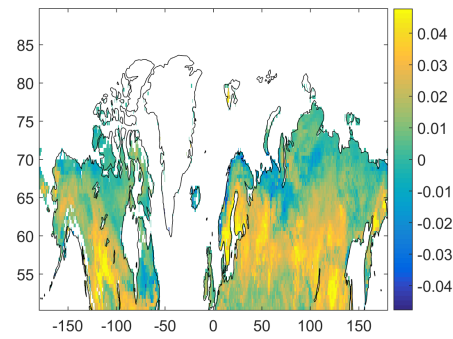
(c) Summer (JJA) lichen and bryophyte thermal diffusivity.

Figure 6: Comparison of lichen and bryophyte 1980-2009 average properties (REDVAR versus CNTL). Numbers are expressed as a fraction.
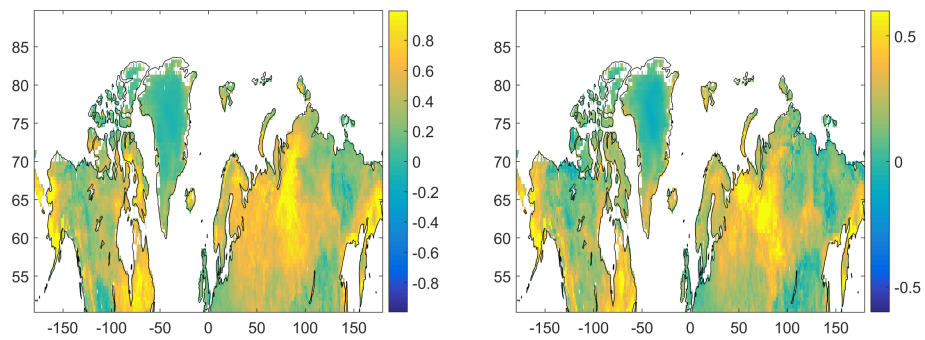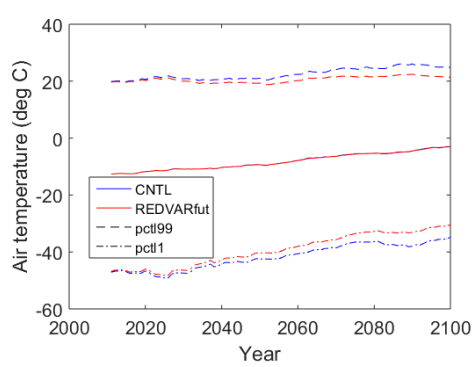
(a) Annual topsoil temperature difference (K).
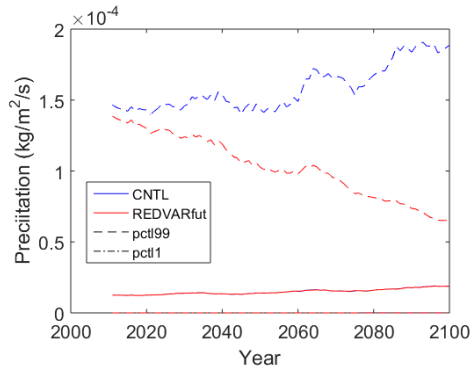
(b) Annual subsoil temperature difference (K).

(c) Winter (DJF) topsoil temperature difference (K).

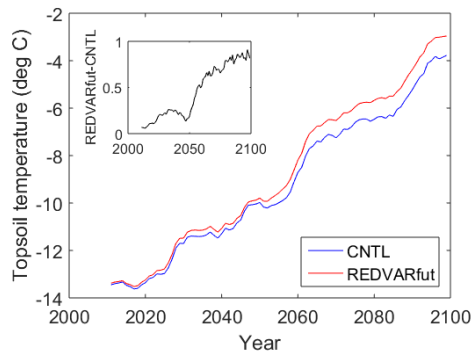(d) Summer (JJA) topsoil temperature difference (K).

Figure 7: Comparison of 1980-2009 average soil temperature (REDVAR versus CNTL). Topsoil and subsoil refer to depths of 3 cm and 38 m, respectively.
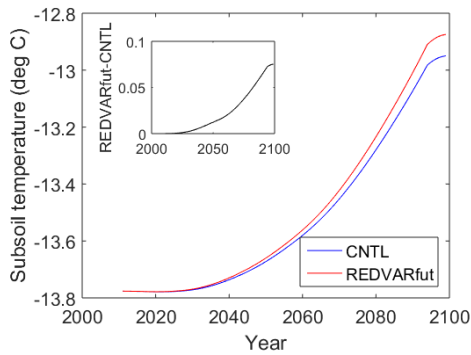
(a) Air temperature (deg C) annual mean, per-
centile 1 and percentile 99.

(b) Precipitation (kg/m2/s) annual mean, per-
centile 1 and percentile 99.

(c) Annual topsoil (3 cm) temperature time series
(deg C). Inset shows difference time series.

(d) Annual subsoil (38 m) temperature time series
(deg C). Inset shows difference time series.

Figure 8: REDVARfut experiment results at 70N/100E during 2011-2100 showing the effects of
changing climate variability in future on soil temperature. 10-year running means are shown.