

Ground subsidence effects on simulating dynamic high latitude surface inundation under permafrost thaw using CLM5

Altug Ekici^{1,2,3}, Hanna Lee¹, David M Lawrence⁴, Sean C Swenson⁴, and Catherine Prigent⁵

¹NORCE Norwegian Research Centre, Bjerknes Centre for Climate Research, Bergen, Norway

²Climate and Environmental Physics, Physics Institute, University of Bern, Bern, Switzerland

³Oeschger Centre for Climate Change Research, University of Bern, Bern, Switzerland

⁴Climate and Global Dynamics Division, National Center for Atmospheric Research, Boulder, Colorado, USA

⁵LERMA, Observatoire de Paris, PSL Research University, CNRS, UMR 8112, F-75014, Paris, France

Correspondence to: ekici@climate.unibe.ch

Abstract

Simulating surface inundation is particularly challenging for the high latitude permafrost regions. Ice-rich permafrost thaw can create expanding thermokarst lakes as well as shrinking large wetlands. Such processes can have major biogeochemical implications and feedbacks to the climate system by altering the pathways and rates of permafrost carbon release. However, the processes associated with it have not yet been properly represented in Earth system models. We show a new model parameterization that allows direct representation of surface water dynamics in CLM (Community Land Model), the land surface model of several Earth System Models. Specifically, we coupled permafrost-thaw induced ground subsidence and surface microtopography distribution to represent surface water dynamics in the high latitudes. Our results show increased surface water fractions around western Siberian plains and northeastern territories of Canada. Additionally, localized drainage events correspond well to severe ground subsidence events. Our parameterization is one of the first steps towards a process-oriented representation of surface hydrology, which is crucial to assess the biogeochemical feedbacks between land and the atmosphere under changing climate.

1. Introduction

Northern high latitudes experience pronounced warming due to Arctic amplification (Serreze and Francis, 2006). Within the last decades, temperature increase in the Arctic has been twice the amount of that in the tropics (Solomon et al., 2007). The abrupt increase in Arctic temperatures threatens to destabilize the global permafrost areas and can alter land surface structures, which can lead to releasing considerable amounts of permafrost carbon as greenhouse gases to the climate system (Schuur et al., 2008). Similarly, increased precipitation can accelerate the release of permafrost carbon in high latitudes (Chang et al., 2019; Grant et al., 2017). The balance between CO₂ and CH₄ release from permafrost depends largely on the organic matter decomposition pathway; larger inundated areas release more CH₄ than CO₂ using the anaerobic pathway but overall release of greenhouse gases is greater under aerobic conditions (Lee et al. 2014; Treat et al. 2015). However, for a future model estimate, Knoblauch et al (2018) predicts twice as much permafrost carbon release in anoxic conditions (241±138 g CO₂ kgC-1) compared to oxic conditions (113±58 g CO₂ kgC-1) by 2100. The main

1 natural sources of CH₄ emissions are from tropical wetlands, however the
2 contributions from high latitude wetlands are increasing each decade (Saunio
3 et al., 2016) with further thawing of permafrost.

4
5 With high percentage of surface wetland coverage (Grosse et al., 2013; Muster et
6 al., 2017), characterizing high latitude CH₄ emissions require detailed process
7 representations in models. Besides surface wetland conditions, models should
8 also properly estimate permafrost thaw stage (Malhotra & Roulet, 2015),
9 changing surface topography (Olefeldt et al., 2013), and surface vegetation and
10 microbial conditions (Grant et al., 2017) in order to improve estimations of
11 surface CH₄ emissions.

12 However, Earth system models (ESMs) used in the future climate projections
13 struggle to represent the complex physical/hydrological changes in the
14 permafrost covered high latitude regions. Therefore, it is necessary to improve
15 model representation of surface hydrology processes within the ESMs.

16
17 Permafrost processes have now been represented commonly within the land
18 surface models (Lawrence et al., 2008; Gouttevin et al., 2012; Ekici et al., 2014;
19 Chadburn et al., 2015), however, the complex hydrological feedbacks between
20 degrading permafrost and thermokarst lake formations have been a major
21 challenge. An extensive review of wetland modeling activities and an
22 intercomparison effort of evaluating methane-modeling approaches are given in
23 Wania et al. (2013) and Melton et al. (2013). These studies, however, do not
24 include permafrost specific features such as excess ice in frozen soils, therefore
25 they have tendency to under-represent key processes associated to permafrost
26 thaw. Excess ice melt within the frozen soils can lead to abrupt changes in the
27 surface topography, creating subsided ground levels, which can enhance pond
28 formation often recognized as thermokarst formation. Such changes in surface
29 microtopography can be very effective in altering the soil thermal and
30 hydrological conditions (Zona et al., 2011).

31
32 Lee et al. (2014) implemented surface subsidence processes in the Community
33 Land Model (CLM: Oleson et al., 2013; Lawrence et al., 2011; Swenson et al.,
34 2012) to overcome some of the limitations in representing processes associated
35 with permafrost thaw and subsequent land surface subsidence. The surface
36 conditions altered by the subsidence events change the microtopography of the
37 area, which can further modify the surface hydrological conditions in reality. Lee
38 et al. (2014) did not further couple the land surface subsidence with hydrological
39 processes to represent subsequent changes in local hydrology created under
40 permafrost thawing. Here we developed a conceptual coupling of excess ice
41 melting and subsequent land surface subsidence with hydrology and show how
42 implementing permafrost thaw induced subsidence affects surface
43 microtopography distribution and surface inundation in the CLM model.

44 45 **2. Methods**

46 Simulating the effects of permafrost thaw on surface water dynamics requires a
47 complex interaction of thermodynamics and hydrology within the model. Here
48 we use the 1° spatial resolution simulations of CLM5 (Lawrence et al., submitted
49 2018) to represent such dynamics. CLM is a complex, process based terrestrial

ecosystem model simulating biogeophysical and biogeochemical processes within the soil and vegetation level. Lee et al. (2014) have presented the excess ice implementation into CLM. The ground excess ice data from International Circum-Arctic Map of Permafrost and Ground-Ice Conditions (Brown et al., 1997) are used to create an initial soil ice dataset to be prescribed into the model. This excess ice is added between 0.8 and 3.8 meters in CLM soil scheme where permafrost exists and increases the relevant soil layer thicknesses. The amount of excess ice for each gridcell is estimated by multiplying percent permafrost area with amount of excess ice from the Brown et al. (1997) dataset. The soil physical parameters (heat capacity and conductivity) are updated with the addition of excess ice. The excess ice in the model undergoes physical phase change but most importantly melting ice allows a first-order estimation of land surface subsidence under permafrost thaw. First the soil ice is allowed to melt and then the excess ice is subjected to phase change. Ice melt water is then added the soil hydrology scheme in CLM and can be directed as runoff if it exceeds saturation. The soil layer thicknesses are then updated with the disappearing amount of excess ice. Lee et al. (2014)'s scheme does not allow formation of excess ice after initialization.

In CLM, surface inundated fraction (f_{h2osfc}) of each grid cell is calculated by using the microtopography distribution (σ_{micro}) and the surface water level (d) of the grid cell (Eq. 1 - 3). Surface water is defined by a spatial scale elevation variation that is the microtopography. The microtopography is normally distributed around the grid cell mean elevation. The fractional area of the grid cell that is inundated (f_{h2osfc}) can be calculated with the standard deviation of this microtopographic distribution. The surface inundated fraction, in turn, affects the soil heat/water/carbon fluxes with the atmosphere.

$$f_{h2osfc} = \frac{1}{2} \left(1 + \operatorname{erf} \left(\frac{d}{\sigma_{micro} \sqrt{2}} \right) \right)$$

Eq.1: Parameterization of surface inundated fraction ' f_{h2osfc} ' using an error function of surface water level ' d ' (height in m relative to the gridcell mean elevation) and microtopography distribution ' σ_{micro} ' (m).

$$\sigma_{micro} = (\beta + \beta_0)^\eta$$

Eq. 2: Microtopography distribution ' σ_{micro} ' as a function of slope, where β is the prescribed topographic slope and " η " is an adjustable parameter.

$$\beta_0 = (\sigma_{max})^{\frac{1}{\eta}}$$

Eq. 3: Adjustable coefficient β_0 as a function of maximum topographical distribution ' σ_{max} '. Original value for σ_{max} is 0.4 while η is -3.

1 This parameterization is similar to the TOPMODEL approach (Beven and Kirkby,
2 1979), where a hypsometric function is used to define the height of standing
3 water (d) within the gridbox by assuming a normal statistical distribution of
4 ground level microtopography. In this study, the subsidence levels from
5 permafrost thaw induced excess ice melt are coupled with σ_{micro} in order to
6 represent the naturally occurring subsided landscapes within the permafrost-
7 affected areas. With increasing excess ice melt, more subsidence occurs and the
8 amount of subsidence redefines the surface σ_{micro} , which is inversely related to
9 f_{h2osfc} (Eq. 1). Therefore, to represent increased f_{h2osfc} , σ_{micro} has to be decreased
10 in value. However, σ_{micro} is the statistical distribution of surface
11 microtopography, hence cannot be directly related to physical subsidence levels.
12 Therefore, a conceptual method of relating σ_{micro} to an order of magnitude lower
13 ground subsidence levels is used (Eq. 4). This first step of conceptualization can
14 be improved with subgrid scale parameterization (Aas et al., 2019) in future
15 studies.

16

$$17 \quad \sigma'_{\text{micro}} = \begin{cases} \sigma_{\text{micro}} - s \div b, s < 0.5 \\ \sigma_{\text{micro}} + s \div b, s \geq 0.5 \end{cases}$$

18

19 Eq. 4: New microsigma parameterization ' σ'_{micro} ' where ' s ' is the accumulated
20 subsidence in meters and ' b ' is the adjustable parameter set to 10.

21

22 We implemented a conditional formulation regarding the severity of subsidence.
23 In general, the surface is forced to allow more ponding of water with moderate
24 levels of subsidence. However, advance levels of excess ice melt can degrade the
25 surface levels so much that the small troughs created from the initial degradation
26 can connect to create a drainage system that the grid box can no longer support
27 any ponding (Liljedahl et al., 2016). For this reason, the excess ice melt has a
28 reversed effect on σ_{micro} after a threshold value of 0.5 m (Eq.4). Choice of this
29 threshold value is discussed in the following section.

30

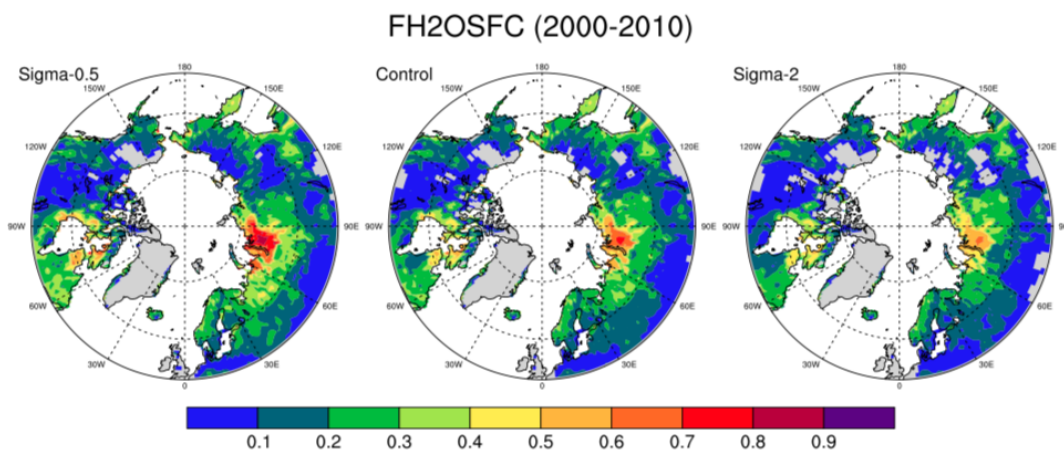
31 We performed several experiments using CLM5 to assess the general response of
32 surface hydrology to changing microsigma parameter values. First, the
33 dependence of f_{h2osfc} to σ_{micro} is investigated by doubling σ_{micro} (experiment:
34 Sigma-2) and reducing it by half (experiment: Sigma-0.5). Afterwards, initialized
35 with the default microsigma distribution (Fig. S1), results of the new σ_{micro}
36 parameterization (experiment: Exice) is compared to the default model version
37 (experiment: Control), where subsidence does not alter σ_{micro} or f_{h2osfc} and to a
38 satellite driven data product (GIEMS, the Global Inundation Extent from Multiple
39 Satellites, Prigent et al., 2012). All experiments include 155-year transient
40 simulations following a spin up procedure of repeating 1901-1930 climate
41 forcing for 100 years. The transient 155-year simulation represents the time
42 period from 1860 till 2015. CRU-NCEP (Viovy, 2009), a combined dataset of
43 Climate Research Unit (CRU) and National Center for Environmental Protection
44 (NCEP) reanalysis datasets, is used as the atmospheric forcing for these
45 experiments.

46

1 The GIEMS surface inundation dataset from Prigent et al. (2007, 2012) is used to
 2 compare the simulated inundated fractions. GIEMS uses a combination of
 3 satellite observations to derive the distribution and dynamics of the global
 4 surface water extent. The inundated areas are calculated using passive
 5 microwave observations from Special Sensor Microwave/Imager (SSM/I),
 6 active microwave observations from the scatterometer on board the European
 7 Remote Sensing (ERS) satellite and the normalized difference vegetation index
 8 (NDVI) from the Advanced Very High resolution Radiometer (AVHRR). The
 9 dataset provides monthly-mean values of surface water area from 1993 to
 10 2007, with a spatial resolution of 0.25°. The dataset is spatially projected onto a
 11 1° resolution grid for comparison with the model results.

13 3. Results and Discussion

14 In our experiments, surface inundation (f_{h2osfc}) increases where surface
 15 microtopography distribution (σ_{micro}) decreases (Fig. 1) as expected from the
 16 CLM parameterization. When σ_{micro} decreases (Sigma-0.5) compared to the
 17 original value (shown in Supplementary Figure S1), it results in very high f_{h2osfc}
 18 over western Siberia and Hudson Bay area, while increasing σ_{micro} (Sigma-2)
 19 results in lower f_{h2osfc} in general. In the original CLM parameterization, f_{h2osfc} is
 20 calculated with a static microtopography index (Fig. S1) derived from a
 21 prescribed topographic slope dataset (Oleson et al., 2013).



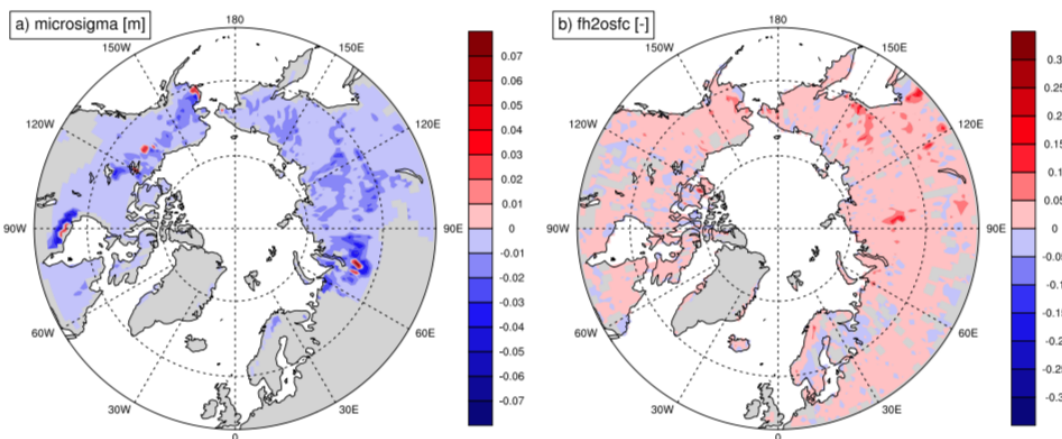
22
 23 Fig. 1: High latitude (>50°N) maps of simulated surface water fractions (f_{h2osfc}) from
 24 Control, Sigma-0.5, and Sigma-2.0 experiments with different microsigma distributions
 25 averaged for the period 2000-2010.

26
 27 Our results illustrate the dependence of f_{h2osfc} on σ_{micro} and how certain range of
 28 σ_{micro} values can result in very high f_{h2osfc} , and differences in f_{h2osfc} can be quite
 29 regional (Fig. S2). This relation emphasize the need for a dynamic circum-Arctic
 30 σ_{micro} value to capture the natural variability of surface conditions when
 31 representing permafrost thaw associated hydrological changes. In the Exice
 32 experiment, coupling excess ice melt induced ground subsidence to σ_{micro} leads
 33 to significant changes in surface hydrology (Fig. 2). In our simulations, σ_{micro} is
 34 consistently lower in Exice compared to Control at the end of the 20th century
 35 (Fig. 2a). This is the model representation of increased variability in surface
 36 microtopography due to uneven subsidence events within the gridcell.
 37 Particularly larger inundated fractions are simulated around western Siberia and
 38 northeast Canada, which conform well to the observational datasets of peatland

1 distribution (Tarnocai et al., 2007; 2009). Several other observational estimates
 2 agree on the spatial distribution of high latitude peatlands, where most of the
 3 wetland formations are expected in the future (Melton et al., 2013). Therefore,
 4 the new parameterization of surface inundated fraction is a stepping-stone
 5 towards a more realistic representation of surface hydrology in permafrost-
 6 affected areas. Other modeling studies support these results with similar spatial
 7 patterns of surface wetland distributions (Wania et al., 2013; Melton et al., 2013).
 8 In the previous version of CLM, simulated inundated area shows slightly
 9 different patterns (Riley et al., 2011), mainly due to non-process based
 10 description of inundated fractions. We emphasize that although our
 11 parameterization is only conceptual, this is the first attempt towards coupling
 12 permafrost thaw associated land surface subsidence with hydrological changes
 13 in a land surface model within an ESM.

14
 15 By introducing the effects of ground subsidence on σ_{micro} , a dynamic inundated
 16 fraction is calculated. However, there is no observed dataset to evaluate the
 17 relation between subsidence and ground topography, therefore an assumption
 18 had to be made regarding this coupling. In this study, changes in σ_{micro} are
 19 proportional to the changes in ground subsidence with the difference in an order
 20 of magnitude. This assumption is put to test by doubling and halving the initial
 21 σ_{micro} values and the results show 10 to 20 % change in surface inundated
 22 fractions (Fig. 1). The difference in dynamic parameterization (Fig. 2b) stays in
 23 between these values and on average shows a 10 – 15 % increase, thus
 24 supporting the coupling assumption.

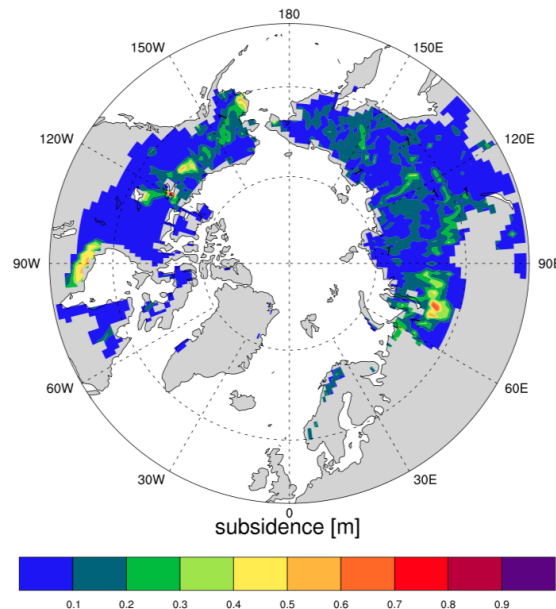
Exice-Control (2000-2010)



25
 26 Fig. 2: Effects of coupled subsidence-microsigma parameterization on ' σ_{micro} ' and ' f_{h2osfc} '
 27 from $>50^{\circ}\text{N}$ difference maps of Exice-Control experiments for the period 2000-2010.

28
 29 As expected, the f_{h2osfc} and σ_{micro} changes are related to the ground subsidence
 30 processes in most cases. Exice experiment produces land surface subsidence in
 31 some gridcells (Fig. 3) similar to the spatial patterns exhibited in σ_{micro} and f_{h2osfc}
 32 in Fig. 2, suggesting that melting of excess ice affects changes in surface
 33 hydrology. This is most pronounced around western Siberia, south of Hudson
 34 Bay and around northwestern Canada and central Alaska, where initial excess ice
 35 was large (Lee et al. 2014). Simulated ground subsidence is associated to
 36 changes in surface inundated fraction (f_{h2osfc}) described in Fig. 2.

1
2 As a result of subsidence threshold parameterization (see Methods), reversed
3 effect of excess ice melting is shown in the σ_{micro} plots (Fig. 2a), where red points
4 are directly related to the severe ground subsidence locations (Fig. 3). These
5 areas consistently exhibit abrupt melting of excess ice leading to increased σ_{micro} .
6 Larger negative deviations of σ_{micro} from the original values were observed in
7 central Alaska, northwestern Canada, south of Hudson Bay, southwest Russia,
8 central Siberia, and northern Yakutia regions of Russia (areas with dark blue in
9 Fig2a). In reality, different landscapes should have a different threshold value,
10 yet our work is aimed to capture the overall changes and general patterns rather
11 than local conditions, so a preliminary choice of a single threshold value is used.
12 Same areas show increased f_{h2osfc} compared to Control (Fig. 2b). The largest
13 increases in f_{h2osfc} are observed in central Siberia and southeastern Russia, while
14 some minor decreases in f_{h2osfc} values are present in an unevenly distributed
15 pattern. It is important to add that the choice of 0.5 m threshold is arbitrary and
16 can be modified according to the surface dataset of excess ice.



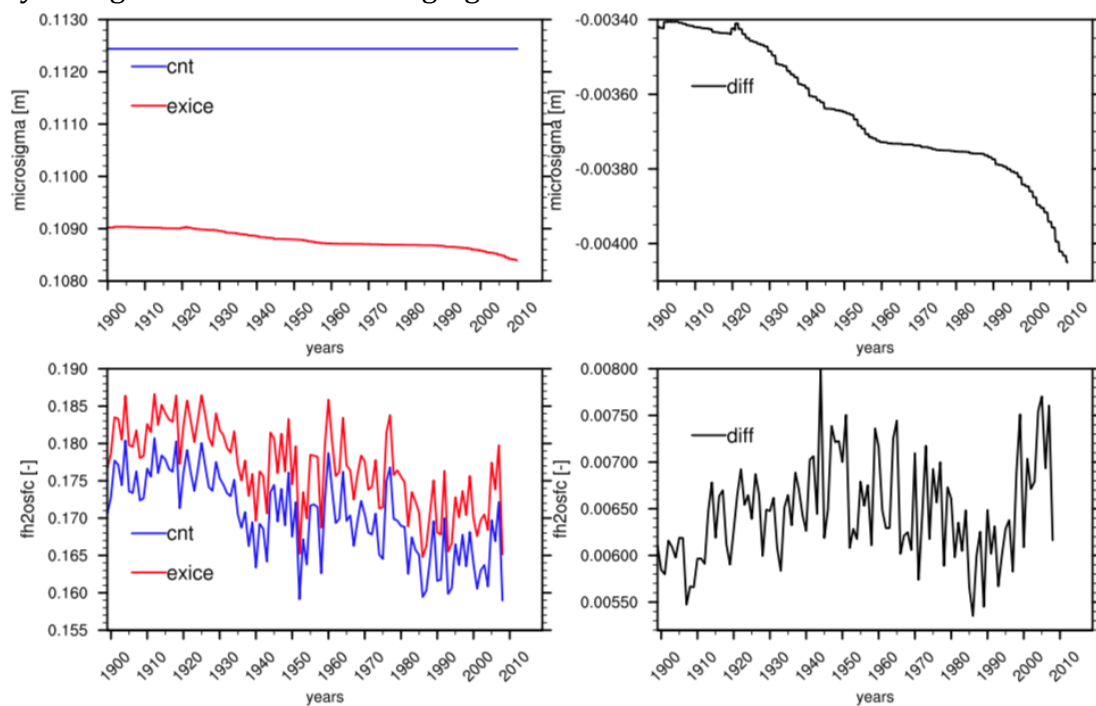
17
18 Fig. 3: High latitude ($>50^{\circ}\text{N}$) map of ground subsidence simulated from the Exice
19 experiment averaged for the period 2000-2010.
20

21 Spatially averaged timeseries of σ_{micro} and f_{h2osfc} show that in the Exice
22 experiment σ_{micro} decreases over time and f_{h2osfc} shows a more dynamic change
23 during the simulation (Fig. 4). The discrepancy in σ_{micro} between Exice and
24 Control in the beginning of the simulation is due to prior excess ice melting
25 during the spin-up period (Fig. S3) and the values continue to decrease
26 throughout the 20th century, while the decrease halts temporarily during 1960-
27 1990 (microsigma-diff plot in Fig. 4).
28

29 Model results show that f_{h2osfc} is quite sensitive to the σ_{micro} parameter. With the
30 current knowledge, there is no perfect way to optimize the σ_{micro} parameter for
31 each gridbox in global simulations, this is why we tried to estimate σ_{micro} by
32 coupling to other well-known physical processes like excess ice melt. Since there
33 is no global dataset to directly compare with our model results, one should be
34 cautious interpreting our model's contemporary and future estimates. One

1 avenue to constrain our parameterization will be to use the terrestrial
 2 greenhouse gas fluxes in future studies.

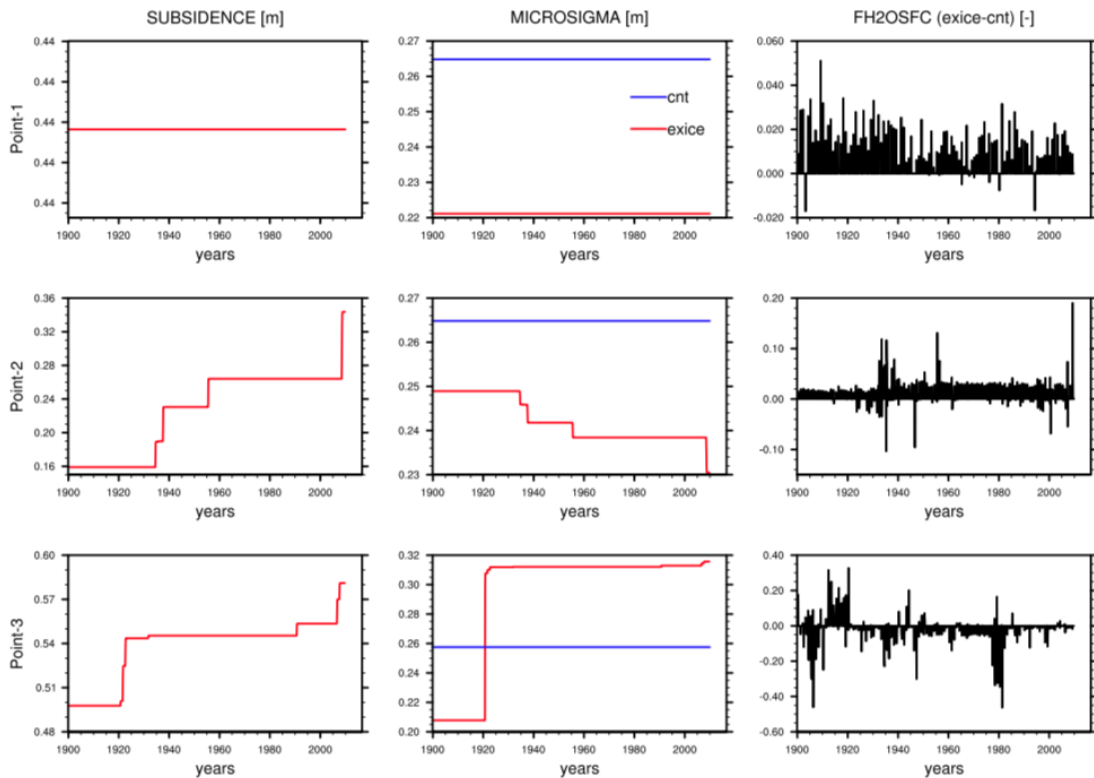
3
 4 Higher f_{h2osfc} are observed in Exice experiment, however, the differences
 5 between Exice and Control show a general increase throughout the simulation
 6 except the period between 1960-1990. The spatially averaged f_{h2osfc} values
 7 exhibit a non-linear progression during the 20th century (Fig. 4). Mainly the
 8 change in climate forcing contributes to this trend. Analyzing the CRUNCEP
 9 atmospheric forcing data suggests that the precipitation pattern over the
 10 experiment domain shows a sudden reduction at the beginning of 1960s (Fig.
 11 S4). Even though the average precipitation starts increasing again, the lower
 12 values contribute to the reduced f_{h2osfc} values. Similar changes occur with the
 13 patterns in atmospheric temperatures (Fig. S4), which is a direct forcing for
 14 permafrost thaw and ground subsidence. A process-based representation of
 15 f_{h2osfc} allows the model to naturally represent the temporal changes in climate.
 16 Hence, our representation of f_{h2osfc} will improve the estimation of future surface
 17 hydrological states under changing climatic conditions.



18
 19 Fig. 4: Timeseries of spatially averaged high latitude (>50°N) σ_{micro} and annual
 20 maximum f_{h2osfc} variables from Exice and Control experiments together with the
 21 timeseries of Exice-Control difference (diff) for the period 1900-2010.

22
 23 The direct effects of the new model parameterization are better analyzed while
 24 inspecting point scale changes as shown in Fig. 5. The three selected points show
 25 a range of scenarios to observe the effects of subsidence on microsigma and
 26 f_{h2osfc} . Point 1 has no change in subsidence during the simulation and with lower
 27 microsigma values in Exice (due to prior subsidence in spinup), the difference in
 28 f_{h2osfc} compared to Control simulation is always positive, meaning higher surface
 29 inundated fractions. In Point 2, Exice microsigma decreases due to the increase
 30 in subsidence during the simulation. These gradual changes are reflected in
 31 f_{h2osfc} , where sudden increases are shown around 1935 and 1955, exactly when

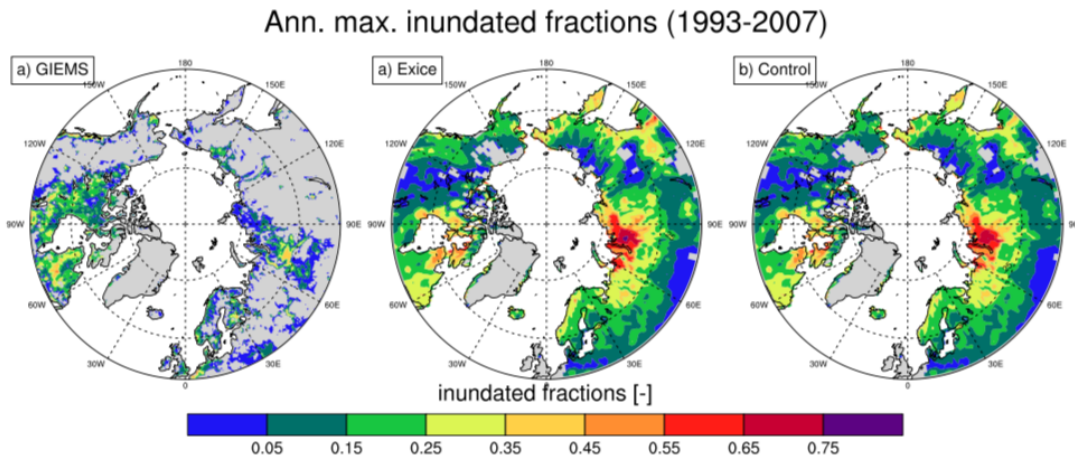
1 the subsidence changes occur. Similarly in Point 3, subsidence causes a lower
 2 microsigma in the beginning of the simulation; however the subsidence values
 3 surpass the 0.5m threshold around 1920s, which causes the reversed effect on
 4 microsigma by increasing it compared to the Control experiment. Severe
 5 subsidence causing more drainage is represented in this way within our
 6 parameterization. The f_{h2osfc} values show this drainage with a sudden decrease
 7 at 1920 and continuing with mostly negative values throughout the simulation.
 8 These scenarios support the validity of our new parameterization that can be
 9 used for any future climate scenario for a better representation of surface
 10 hydrology and subsidence coupling.



11
 12 Fig. 5: Timeseries of subsidence, σ_{micro} , and f_{h2osfc} variables from Exice and Control
 13 experiments at three selected sites. Point 1: lat 54 N lon 272 E, Point 2: lat 64 N lon 80 E,
 14 Point 3: lat 65 N lon 70 E.

15
 16 GIEMS dataset (Prigent et al., 2012) provides the surface area of wetlands for each
 17 gridbox. Fraction of wetland-covered gridbox is calculated to compare with the model
 18 results (Fig. 6). The range of estimated surface wetland fraction is different in the
 19 satellite dataset and model outputs; however, spatial distribution of surface inundated
 20 area is fairly comparable between the model and the satellite dataset. They both
 21 exhibit larger inundated fractions in western Siberia and around Hudson Bay. The
 22 ranges of estimated surface wetland fraction between the satellite dataset and
 23 model outputs are different due to differences in the definitions of inundated
 24 areas. However, spatial distribution of surface inundated area is comparable
 25 between the model and the satellite dataset, where both exhibit larger inundated
 26 fractions in western Siberia and Hudson Bay. Since our model provides the
 27 fraction of gridbox that is inundated, the satellite dataset had to be converted
 28 from actual wetland area to fractions. The GIEMS dataset assumes 773 km²
 29 gridboxes all over the globe (Prigent et al., 2007), which creates grid-size

1 problems comparing to model gridbox area. Another issue with such
 2 comparison stems from the differences in the definition of inundated fraction.
 3 GIEMS dataset uses satellite observations at different wavelengths to derive the
 4 wetland area, while the CLM creates the surface inundation with the topography
 5 index and water inputs to the gridbox. Within the model parameterization, the
 6 height of the surface water level is calculated by a hypsometric function and the
 7 gridbox fraction is further derived from the grid size. This allows an ever-
 8 existing surface inundated fraction even in very dry gridboxes, whereas the
 9 GIEMS method underestimates the small wetlands comprising less than 10% of
 10 the gridbox area (Prigent et al., 2007); hence a model overestimation of satellite
 11 dataset is expected. Definition of modelled and satellite derived inundated
 12 fraction is not the same. Unfortunately there is no standard definition
 13 (Reichhardt, 1995), which produces the struggle to find a proper observational
 14 dataset to evaluate model results. What we emphasize from our findings is,
 15 nevertheless, the spatial patterns of higher inundated fractions occurring at
 16 similar locations in model and satellite dataset (Fig. 6).
 17



18
 19 Fig. 6: Surface water fraction comparison from high latitude ($>50^{\circ}\text{N}$) maps of annual
 20 maximum surface wetlands from GIEMS dataset (Prigent et al., 2012) and annual
 21 maximum f_{h2osfc} values of Exice and Control experiments for the period 1993-2007.
 22

23 **4. Conclusion**

24 A warming climate affects the Arctic more severely than the rest of the globe.
 25 Increasing surface temperatures pose an important threat to the vulnerable high
 26 latitude ecosystems. Degradation of Arctic permafrost due to increased soil
 27 temperatures leads to the release of permafrost carbon to the atmosphere and
 28 further strengthens the greenhouse warming (IPCC, 2013; Schuur et al., 2008).
 29 For future climate predictions, it is necessary to properly simulate the Arctic
 30 surface inundated areas due to their physical and biogeochemical coupling with
 31 the atmosphere.
 32

33 This study summarizes a new parameterization within the CLM to represent
 34 prognostic surface inundated fractions under permafrost thawing using a
 35 conceptual approach that can lead to implementation of a physical process-based
 36 parameterization. Coupling ground subsidence to surface microtopography
 37 distribution, hence allowing a natural link between surface hydrological

1 conditions and soil thermodynamics, resulted in generally increased surface
2 inundated fractions over the northern high latitudes, with larger surface
3 inundated fractions around western and far-east Siberian plains and
4 northeastern Canada. Projected increase in global temperatures will inevitably
5 cause more excess ice melting and subsequent ground subsidence, therefore, it
6 will be necessary to incorporate a process-based parameterization to accurately
7 account for future ground subsidence effects on surface hydrological states.

8
9 Our results confirm the enhancements of coupling ground subsidence and
10 surface inundation to represent the temporal changes in surface hydrology
11 reflected by soil physical states and the atmospheric forcing, which is much
12 needed for a future scenario experiment. Here we conclude that our new
13 parameterization is implemented successfully and functions globally for the CLM
14 model, that the inundated areas exist at the same areas as the observational data.
15 It can be used for future climate scenarios such as shown in Lee et al. (2014)
16 with major subsidence events during the 21st century under a high warming
17 scenario.

18
19 This new parameterization represents the first step into a process-based
20 representation of such hydrological processes in CLM. Using this
21 parameterization, further work can proceed to investigate the biogeochemical
22 feedbacks of permafrost greenhouse gas fluxes between land and atmosphere.

23 24 **Code and data availability**

25 The code modifications to CLM model in accordance to this paper are accessible
26 through the Zenodo archive with the following link:

27 <https://zenodo.org/badge/latestdoi/183611414>

28 The overall CLM model code can be obtained from the NCAR archives, the
29 instructions on accessing the model code is given through this website:

30 <http://www.cesm.ucar.edu/models/cesm2/land/>

31 The full set of model data will be made publicly available through the Norwegian
32 Research Data Archive at <https://archive.norstore.no> upon publication.

33 34 **Author contribution**

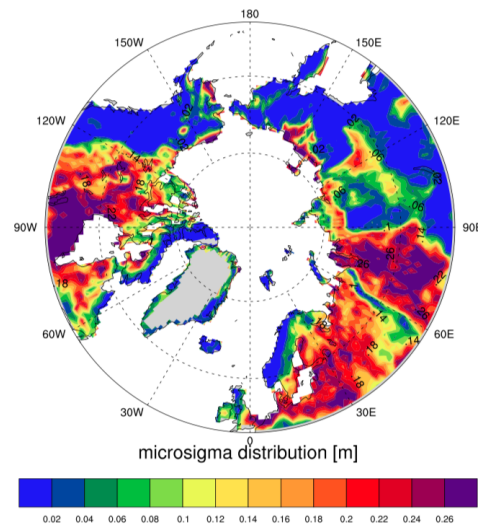
35 AE and HL designed the experiments and AE carried them out. DML and SCS
36 developed the main CLM model code and HL developed the previous version this
37 model is based on. CP has provided the GIEMS dataset. AE performed the
38 simulations and prepared the manuscript with contributions from all co-authors.

39 40 **Acknowledgements**

41 This work was supported by the Research Council of Norway projects
42 PERMANOR (255331) and MOCABORS (255061) and NSF EaSM-L02170157. The
43 simulations were performed on resources provided by UNINETT Sigma2-the
44 National Infrastructure for High Performance Computing and Data Storage in
45 Norway, accounts NS2345K and NN2345K.

1 **Supplementary**

2

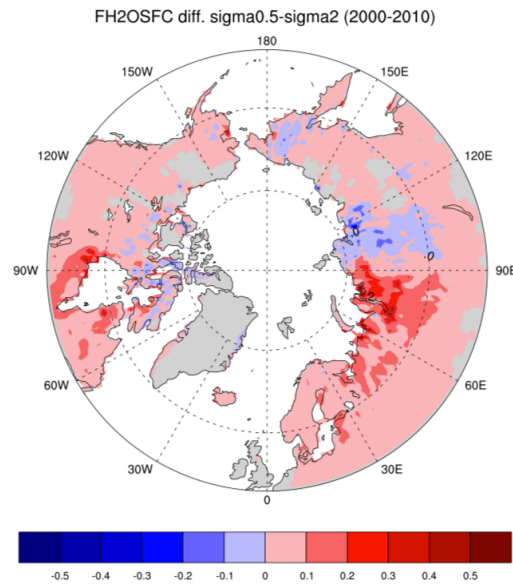


3

4

5

Fig. S1: High latitude ($>50^{\circ}\text{N}$) map of default microsigma distribution.

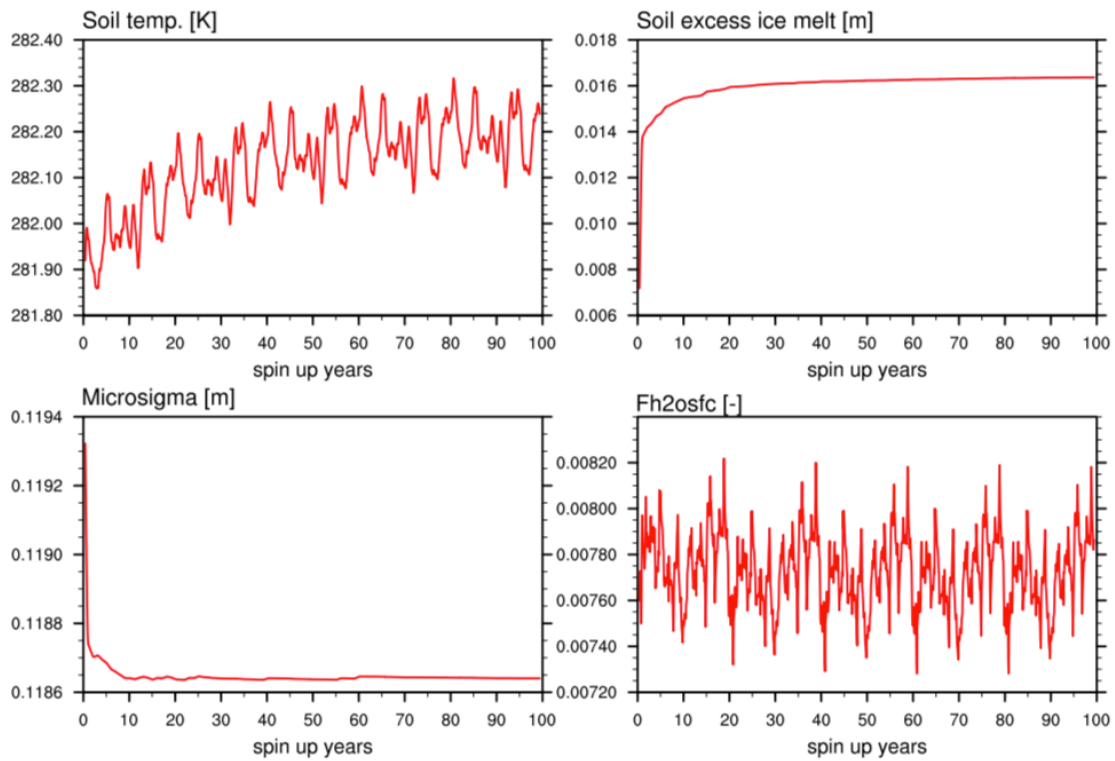


6

7

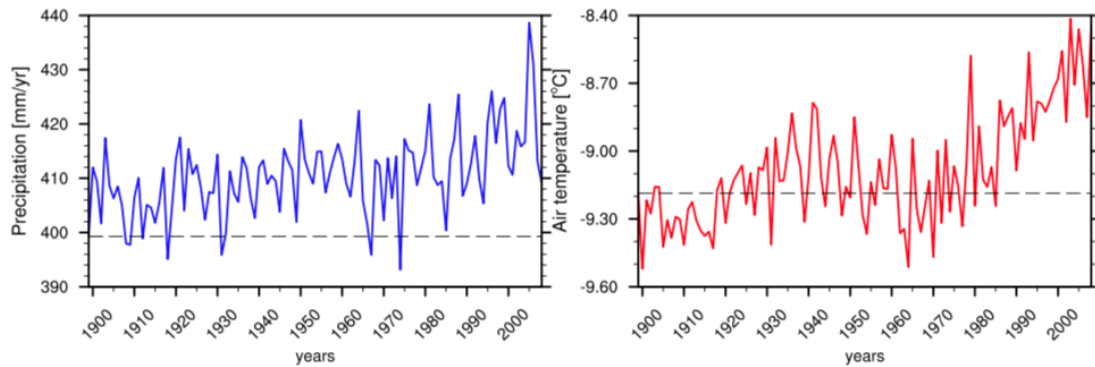
Fig. S2: Fh2osfc difference between Sigma-0.5 and Sigma-2 experiments.

Spin up timeseries of soil variables



1
2
3
4
5

Fig. S3: 100 year spin up timeseries of spatially averaged soil physical variables related to the new parameterization.



6
7
8
9

Fig. S4: Timeseries of high latitude (>50°N average -land only) CRUNCEP precipitation and air temperature forcing for the period 1900-2010. Dotted lines show 1900 value.

References

11 Aas, Kjetil S., et al. "Thaw processes in ice-rich permafrost landscapes represented with
12 laterally coupled tiles in a land surface model." *The Cryosphere* 13.2 (2019): 591-609.
13
14 Beven, K. and Kirkby, M.: A physically based, variable contributing area model of basin
15 hydrology, *Hydrol. Sci. Bull. Sci. Hydrol.*, 24, 43–69, 1979.
16
17 Brown J, Ferrians, O. J. Jr., Heginbottom, J. A., and Melnikov, E. S.: Circum-Arctic Map
18 of Permafrost and Ground-Ice Conditions version 2 (Boulder, CO: National Snow and Ice
19 Data Center), 1997.
20

1 Chadburn, S., Burke, E., Essery, R., Boike, J., Langer, M., Heikenfeld, M., Cox, P., and
2 Friedlingstein, P.: An improved representation of physical permafrost dynamics in the
3 JULES land-surface model, *Geosci. Model Dev.*, 8, 1493-1508,
4 <https://doi.org/10.5194/gmd-8-1493-2015>, 2015.
5
6 Chang, K.-Y., Riley, W. J., Crill, P. M., Grant, R. F., Rich, V. I., & Saleska, S. R. (2019). Large
7 carbon cycle sensitivities to climate across a permafrost thaw gradient in subarctic
8 Sweden. *The Cryosphere*, 13(2), 647–663. <https://doi.org/10.5194/tc-13-647-2019>
9
10 Ekici, A., Beer, C., Hagemann, S., Boike, J., Langer, M., and Hauck, C.: Simulating high-
11 latitude permafrost regions by the JSBACH terrestrial ecosystem model, *Geosci. Model*
12 *Dev.*, 7, 631–647, doi:10.5194/gmd-7-631-2014, 2014.
13
14 Gouttevin, I., Krinner, G., Ciais, P., Polcher, J., and Legout, C.: Multi-scale validation of a
15 new soil freezing scheme for a land- surface model with physically-based hydrology, *The*
16 *Cryosphere*, 6, 407–430, doi:10.5194/tc-6-407-2012, 2012
17
18 Grant, R. F., Mekonnen, Z. A., Riley, W. J., Arora, B., & Torn, M. S. (2017). Mathematical
19 Modelling of Arctic Polygonal Tundra with Ecosys: 2. Microtopography Determines How
20 CO₂ and CH₄ Exchange Responds to Changes in Temperature and Precipitation. *Journal*
21 *of Geophysical Research: Biogeosciences*, 122(12), 3174–3187.
22 <https://doi.org/10.1002/2017JG004037>
23
24 Grosse, G., Jones, B., Arp, C.: *Thermokarst Lakes, Drainage, and Drained Basins*,
25 Elsevier: Amsterdam, The Netherlands, 2013.
26
27 IPCC: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group*
28 *I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*
29 [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y.
30 Xia, V. Bex and P.M. Midgley (eds.)], Cambridge University Press, Cambridge, United
31 Kingdom and New York, NY, USA, 1535 pp, doi:10.1017/CBO9781107415324, 2013.
32
33 Knoblauch, C., Beer, C., Liebner, S., Grigoriev, M. N., & Pfeiffer, E. M. (2018). Methane
34 production as key to the greenhouse gas budget of thawing permafrost. *Nature Climate*
35 *Change*, pp. 1–4. <https://doi.org/10.1038/s41558-018-0095-z>
36
37 Lawrence, D. M., Slater, A. G., Romanovsky, V. E., and Nicolsky, D. J.: Sensitivity of a
38 model projection of near-surface permafrost degradation to soil column depth and
39 representation of soil organic matter, *J. Geophys. Res.*, 113, 1–14, 2008.
40
41 Lawrence, D. M., Oleson, K. W., Flanner, M. G., Thornton, P. E., Swenson, S. C.,
42 Lawrence, P. J., Zeng, X., Yang, Z. L., Levis, S., Sakaguchi, K., and Bonan, G. B.:
43 Parameterization improvements and functional and structural advances in version 4 of
44 the Community Land Model, *Journal of Advances in Modeling Earth Systems*, 3(1), 2011.
45
46 Lawrence, D.M. R.A., Fisher, C.D. Koven, K.W. Oleson, S.C. Swenson, G. Bonan, N.
47 Collier, B. Ghimire, L. van Kampenhout, D. Kennedy, E. Kluzek, P.J. Lawrence, F. Li, H.
48 Li, D. Lombardozzi, W.J. Riley, W.J. Sacks, M. Shi, M. Vertenstein, W.R. Wieder,, C. Xu,
49 A.A. Ali, A.M. Badger, G. Bisht, M.A. Brunke, S.P. Burns,, J. Buzan, M. Clark, A. Craig,
50 K. Dahlin, B. Drewniak, J.B. Fisher, M. Flanner, A.M. Fox, P. Gentine, F.Hoffman, G.
51 Keppel-Aleks, R., Knox, S. Kumar, J. Lenaerts, L.R. Leung, W.H. Lipscomb, Y. Lu, A.,
52 Pandey, J.D. Pelletier, J. Perket,, J.T. Randerson, D.M. Ricciuto, B.M., Sanderson, A.
53 Slater, Z.M. Subin, J. Tang, R.Q. Thomas, M. Val Martin, and X. Zeng: The Community
54 Land Model version 5: Description of new features, benchmarking, and impact of forcing
55 uncertainty. *Submitted to J. Adv. Model. Earth Syst.*, 2018.
56

1 Lee, H., Swenson, S. C., Slater, A. G., and Lawrence, D. M.: Effects of excess ground ice
2 on projections of permafrost in a warming climate, *Environmental Research*
3 *Letters*, 9(12), p.124006, 2014.
4
5 Liljedahl, A. K., Boike, J., Daanen, R. P., Fedorov, A. N., Frost, G. V., Grosse, G.,
6 Hinzman, L. D., Iijima, Y., Jorgenson, J. C., Matveyeva, N., and Necsoiu, M.: Pan-Arctic
7 ice-wedge degradation in warming permafrost and its influence on tundra
8 hydrology, *Nature Geoscience*, 9(4), pp.312-318, 2016.
9
10 Malhotra, A., & Roulet, N. T. (2015). Environmental correlates of peatland carbon fluxes
11 in a thawing landscape: Do transitional thaw stages matter? *Biogeosciences*, 12(10),
12 3119–3130. <https://doi.org/10.5194/bg-12-3119-2015>
13
14 McCalley, C. K., Woodcroft, B. J., Hodgkins, S. B., Wehr, R. A., Kim, E.-H., Mondav, R., et al.
15 (2014). Methane dynamics regulated by microbial community response to permafrost
16 thaw. *Nature*, 514(7523), 478–481. <https://doi.org/10.1038/nature13798>
17
18 Melton, J. R., Wania, R., Hodson, E. L., Poulter, B., Ringeval, B., Spahni, R., Bohn, T.,
19 Avis, C. A., Beerling, D. J., Chen, G., Eliseev, A. V., Denisov, S. N., Hopcroft, P. O.,
20 Lettenmaier, D. P., Riley, W. J., Singarayer, J. S., Subin, Z. M., Tian, H., Zürcher, S.,
21 Brovkin, V., van Bodegom, P. M., Kleinen, T., Yu, Z. C., and Kaplan, J. O.: Present state
22 of global wetland extent and wetland methane modelling: conclusions from a model inter-
23 comparison project (WETCHIMP), *Biogeosciences*, 10, 753-788,
24 <https://doi.org/10.5194/bg-10-753-2013>, 2013.
25
26 Muster, S., Roth, K., Langer, M., Lange, S., Aleina, F.C., Bartsch, A., Morgenstern, A.,
27 Grosse, G., Jones, B., Sannel, A. B. K., and Sjöberg, Y.: PeRL: A Circum-Arctic
28 Permafrost Region Pond and Lake Database, *Earth Syst. Sci. Data*, 9, 317–348, 2017.
29
30 Olefeldt, D., Turetsky, M. R., Crill, P. M., & McGuire, A. D. (2013). Environmental and
31 physical controls on northern terrestrial methane emissions across permafrost zones.
32 *Global Change Biology*, 19(2), 589–603. <https://doi.org/10.1111/gcb.12071>
33
34 Oleson, K. W., Lawrence, D. M., Bonan, G. B., Drewniak, B., Huang, M., Koven, C. D.,
35 Levis, S., Li, F., Riley, W. J., Subin, Z. M., Swenson, S. C., Thornton, P. E., Bozbiyik, A.,
36 Fisher, R., Kluzek, E., Lamarque, J. -F., Lawrence, P. J., Leung, L. R., Lipscomb, W.,
37 Muszala, S., Ricciuto, D. M., Sacks, W., Sun, Y., Tang, J., and Yang, Z. -L: Technical
38 Description of version 4.5 of the Community Land Model (CLM), Ncar Technical Note
39 NCAR/TN-503+STR, National Center for Atmospheric Research, Boulder, CO, 422 pp,
40 DOI: 10.5065/D6RR1W7M, 2013.
41
42 Prigent, C., Papa, F., Aires, F., Rossow, W. B., and Matthews, E.: Global inundation
43 dynamics inferred from multiple satellite observations, 1993–2000, *Journal of*
44 *Geophysical Research: Atmospheres*, 112(D12), 2007.
45
46 Prigent, C., Papa, F., Aires, F., Jimenez, C., Rossow, W. B., and Matthews, E.: Changes
47 in land surface water dynamics since the 1990s and relation to population
48 pressure, *Geophysical Research Letters*, 39(8), 2012.
49
50 Reichhardt, T.: Academy under fire on “wetlands” definition, *Nature*, 375, 171, 1995.
51
52 Riley, W. J., Subin, Z. M., Lawrence, D. M., Swenson, S. C., Torn, M. S., Meng, L.,
53 Mahowald, N. M., and Hess, P.: Barriers to predicting changes in global terrestrial
54 methane fluxes: analyses using CLM4Me, a methane biogeochemistry model integrated
55 in CESM, *Biogeosciences*, 8, 1925-1953, <https://doi.org/10.5194/bg-8-1925-2011>, 2011.
56

1 Saunois, M., Bousquet, P., Poulter, B., Peregon, A., Ciais, P., Canadell, J. G.,
2 Dlugokencky, E. J., Etiope, G., Bastviken, D., Houweling, S. and Janssens-Maenhout,
3 G.: The global methane budget 2000-2012, *Earth System Science Data*, 8(2), p.697,
4 2016.
5
6 Schuur, E. A., Bockheim, J., Canadell, J. G., Euskirchen, E., Field, C. B., Goryachkin, S.
7 V., Hagemann, S., Kuhry, P., Lafleur, P.M., Lee, H., and Mazhitova, G.: Vulnerability of
8 permafrost carbon to climate change: Implications for the global carbon cycle, *AIBS*
9 *Bulletin*, 58(8), pp.701-714, 2008.
10
11 Serreze, M. C. and Francis, J. A.: The Arctic amplification debate, *Clim. Change* 76, 241–
12 264 (2006), 2006.
13
14 Solomon, S., Qin, D., Manning, M., Averyt, K., and Marquis, M. eds.: Climate change
15 2007-the physical science basis: Working group I contribution to the fourth assessment
16 report of the IPCC (Vol. 4), Cambridge university press, 2007.
17
18 Swenson, S. C., Lawrence, D. M. and Lee, H.: Improved simulation of the terrestrial
19 hydrological cycle in permafrost regions by the Community Land Model, *Journal of*
20 *Advances in Modeling Earth Systems*, 4(3), 2012.
21
22 Tarnocai, C., Swanson, D., Kimble, J., and Broll, J.: Northern Circumpolar Soil Carbon
23 Database, Tech. Rep. Version 1, Research Branch, Agriculture and Agri-Food Canada,,
24 available at: <http://wms1.agr.gc.ca/NortherCircumpolar/nothercircumpolar.zip> (last
25 access: 1 October 2012), 2007.
26
27 Tarnocai, C., Canadell, J. G., Schuur, E. A. G., Kuhry, P., Mazhitova, G., and Zimov, S.:
28 Soil organic carbon pools in the northern circumpolar permafrost region, *Global*
29 *Biogeochem. Cy.*, 23, GB2023, doi:10.1029/2008GB003327, 2009.
30
31 Treat, C.C., Natali, S.M., Ernakovich, J., Iversen, C.M., Lupascu, M., McGuire, A.D.,
32 Norby, R.J., Roy Chowdhury, T., Richter, A., Šantrůčková, H., and Schädel, C.: A
33 pan-Arctic synthesis of CH₄ and CO₂ production from anoxic soil incubations, *Global*
34 *change biology*, 21(7), pp.2787-2803, 2015.
35
36 Viovy, N. CRUNCEP data set.
37 ftp://nacp.ornl.gov/synthesis/2009/frescati/temp/land_use_change/original/readme.htm,
38 last access: 11.12.2017.
39
40 Wania, R., Melton, J. R., Hodson, E. L., Poulter, B., Ringeval, B., Spahni, R., Bohn, T.,
41 Avis, C. A., Chen, G., Eliseev, A. V., Hopcroft, P. O., Riley, W. J., Subin, Z. M., Tian, H.,
42 van Bodegom, P. M., Kleinen, T., Yu, Z. C., Singarayer, J. S., Zürcher, S., Lettenmaier,
43 D. P., Beerling, D. J., Denisov, S. N., Prigent, C., Papa, F., and Kaplan, J. O.: Present
44 state of global wetland extent and wetland methane modelling: methodology of a model
45 inter-comparison project (WETCHIMP), *Geosci. Model Dev.*, 6, 617-641,
46 <https://doi.org/10.5194/gmd-6-617-2013>, 2013.
47
48 Zona, D., Lipson, D. A., Zulueta, R. C., Oberbauer, S.F., and Oechel, W. C.:
49 Microtopographic controls on ecosystem functioning in the Arctic Coastal Plain, *Journal*
50 *of Geophysical Research: Biogeosciences*, 116(G4), 2011.
51