



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

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16
17 **Abstract**

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

35
36 **1. Introduction**

37 Northern high latitudes experience pronounced warming due to Arctic
38 amplification (Serreze and Francis, 2006). Within the last decades, temperature
39 increase in the Arctic has been twice the amount of that in the tropics (Solomon
40 et al., 2007). The abrupt increase in Arctic temperatures threatens to destabilize
41 the global permafrost areas and can alter land surface structures, which can lead
42 to releasing considerable amounts of permafrost carbon as greenhouse gases to
43 the climate system (Schuur et al., 2008). The balance between CO₂ and CH₄
44 release from permafrost depends largely on the organic matter decomposition
45 pathway; larger inundated areas release more CH₄ than CO₂ using the anaerobic
46 pathway but overall release of greenhouse gases is greater under aerobic
47 conditions (Lee et al. 2014; Treat et al. 2015). The main natural sources of CH₄
48 emissions are from tropical wetlands, however the contributions from high
49 latitude wetlands are increasing each decade (Saunois et al., 2016) with further
50 thawing of permafrost.

51



1 With high percentage of surface wetland coverage (Grosse et al., 2013; Muster et
2 al., 2017), characterizing high latitude CH₄ emissions require detailed process
3 representations in models. However, Earth system models (ESMs) used in the
4 future climate projections struggle to represent the complex
5 physical/hydrological changes in the permafrost covered high latitude regions.
6 Therefore, it is necessary to improve model representation of surface hydrology
7 processes within the ESMs.

8
9 Permafrost processes have now been represented commonly within the land
10 surface models (Lawrence et al., 2008; Gouttevin et al., 2012; Ekici et al., 2014;
11 Chadburn et al., 2015), however, the complex hydrological feedbacks between
12 degrading permafrost and thermokarst lake formations have been a major
13 challenge. An extensive review of wetland modeling activities and an
14 intercomparison effort of evaluating methane-modeling approaches are given in
15 Wania et al. (2013) and Melton et al. (2013). These studies, however, do not
16 include permafrost specific features such as excess ice in frozen soils, therefore
17 they have tendency to under-represent key processes associated to permafrost
18 thaw. Excess ice melt within the frozen soils can lead to abrupt changes in the
19 surface topography, creating subsided ground levels, which can enhance pond
20 formation often recognized as thermokarst formation. Such changes in surface
21 microtopography can be very effective in altering the soil thermal and
22 hydrological conditions (Zona et al., 2011).

23
24 Lee et al. (2014) implemented surface subsidence processes in the Community
25 Land Model (CLM: Oleson et al., 2013; Lawrence et al., 2011; Swenson et al.,
26 2012) to overcome some of the limitations in representing processes associated
27 with permafrost thaw and subsequent land surface subsidence. The surface
28 conditions altered by the subsidence events change the microtopography of the
29 area, which can further modify the surface hydrological conditions in reality. Lee
30 et al. (2014) did not further couple the land surface subsidence with hydrological
31 processes to represent subsequent changes in local hydrology created under
32 permafrost thawing. Here we developed a conceptual coupling of excess ice
33 melting and subsequent land surface subsidence with hydrology and show how
34 implementing permafrost thaw induced subsidence affects surface
35 microtopography distribution and surface inundation in the CLM model.

36 37 **2. Methods**

38 Simulating the effects of permafrost thaw on surface water dynamics requires a
39 complex interaction of thermodynamics and hydrology within the model. Here
40 we use the 1° spatial resolution simulations of CLM5 (Lawrence et al., submitted
41 2018) to represent such dynamics. CLM is a complex, process based terrestrial
42 ecosystem model simulating biogeophysical and biogeochemical processes
43 within the soil and vegetation level. Lee et al. (2014) have presented the excess
44 ice implementation into CLM. The ground excess ice data from International
45 Circum-Arctic Map of Permafrost and Ground-Ice Conditions (Brown et al., 1997)
46 are used to create an initial soil ice dataset to be prescribed into the model. The
47 excess ice in the model undergoes physical phase change but most importantly
48 melting ice allows a first-order estimation of land surface subsidence under
49 permafrost thaw.



1 In CLM, surface inundated fraction (f_{h2osfc}) of each grid cell is calculated by using
2 the microtopography distribution (σ_{micro}) and the surface water level (d) of the
3 grid cell (Eq. 1 - 3).
4

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

5
6
7 Eq.1: Parameterization of surface inundated fraction ' f_{h2osfc} ' using an error function of
8 surface water level ' d ' (height in m relative to the gridcell mean elevation) and
9 microtopography distribution ' σ_{micro} ' (m).
10

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

11
12
13 Eq. 2: Microtopography distribution ' σ_{micro} ' as a function of slope, where β is the
14 prescribed topographic slope.
15

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

16
17
18 Eq. 3: Adjustable coefficient β_0 as a function of maximum topographical distribution
19 ' σ_{max} '. Original value for σ_{max} is 0.4 while η is -3.
20

21 This parameterization is similar to the TOPMODEL approach (Beven and Kirkby,
22 1979), where a hypsometric function is used to define the height of standing
23 water (d) within the gridbox by assuming a normal statistical distribution of
24 ground level microtopography. In this study, the subsidence levels from
25 permafrost thaw induced excess ice melt are coupled with σ_{micro} in order to
26 represent the naturally occurring subsided landscapes within the permafrost-
27 affected areas. With increasing excess ice melt, more subsidence occurs and the
28 amount of subsidence redefines the surface σ_{micro} , which is inversely related to
29 f_{h2osfc} (Eq. 1). Therefore, to represent increased f_{h2osfc} , σ_{micro} has to be decreased
30 in value. However, σ_{micro} is the statistical distribution of surface
31 microtopography, hence cannot be directly related to physical subsidence levels.
32 Therefore, a preliminary method of relating σ_{micro} to an order of magnitude lower
33 ground subsidence levels is used (Eq. 4).
34

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

35
36
37 Eq. 4: New microsigma parameterization ' σ'_{micro} ' where ' s ' is the subsidence in meters
38 and ' b ' is the adjustable parameter set to 10.
39

40 We implemented a conditional formulation regarding the severity of subsidence.
41 In general, the surface is forced to allow more ponding of water with moderate
42 levels of subsidence. However, advance levels of excess ice melt can degrade the
43 surface levels so much that the small troughs created from the initial degradation
44 can connect to create a drainage system that the grid box can no longer support



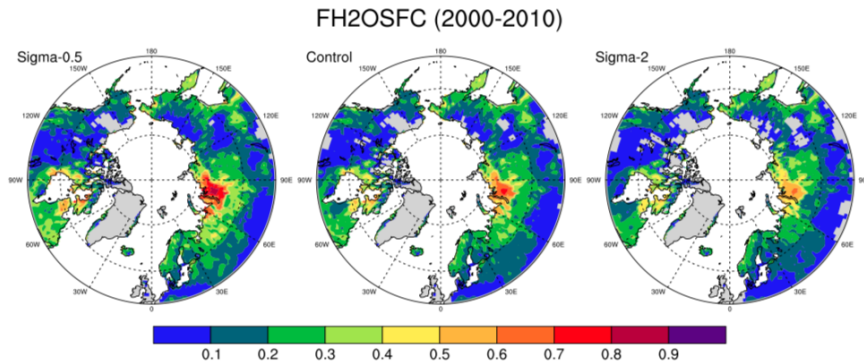
1 any ponding (Liljedahl et al., 2016). For this reason, the excess ice melt has a
2 reversed effect on σ_{micro} after a threshold value of 0.5 m (Eq.4). Choice of this
3 threshold value is discussed in the following section.

4
5 We performed several experiments using CLM5 to assess the general response of
6 surface hydrology to changing microsigma parameter values. First, the
7 dependence of f_{h2osfc} to σ_{micro} is investigated by doubling σ_{micro} (experiment:
8 Sigma-2) and reducing it by half (experiment: Sigma-0.5). Afterwards, the new
9 σ_{micro} parameterization (experiment: Exice) is compared to the default model
10 version (experiment: Control), where subsidence does not alter σ_{micro} or f_{h2osfc}
11 and to a satellite driven data product (GIEMS, the Global Inundation Extent from
12 Multiple Satellites, Prigent et al., 2012). All experiments include 155-year
13 transient simulations following a spin up procedure of repeating 1901-1930
14 climate forcing for 100 years. The transient 155-year simulation represents the
15 time period from 1860 till 2015. CRU-NCEP (Viovy, 2009), a combined dataset of
16 Climate Research Unit (CRU) and National Center for Environmental Protection
17 (NCEP) reanalysis datasets, is used as the atmospheric forcing for these
18 experiments.

19
20 The GIEMS surface inundation dataset from Prigent et al. (2007, 2012) is used to
21 compare the simulated inundated fractions. GIEMS uses a combination of
22 satellite observations to derive the distribution and dynamics of the global
23 surface water extent. The inundated areas are calculated using passive
24 microwave observations from Special Sensor Microwave/Imager (SSM/I),
25 active microwave observations from the scatterometer on board the European
26 Remote Sensing (ERS) satellite and the normalized difference vegetation index
27 (NDVI) from the Advanced Very High resolution Radiometer (AVHRR). The
28 dataset provides monthly-mean values of surface water area from 1993 to
29 2007, with a spatial resolution of 0.25°. The dataset is spatially projected onto a
30 1° resolution grid for comparison with the model results.

31 32 **3. Results and Discussion**

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



1
2 Fig. 1: High latitude ($>50^{\circ}\text{N}$) maps of simulated surface water fractions (f_{h2osfc}) from
3 Control, Sigma-0.5, and Sigma-2.0 experiments with different microsigma distributions
4 averaged for the period 2000-2010.

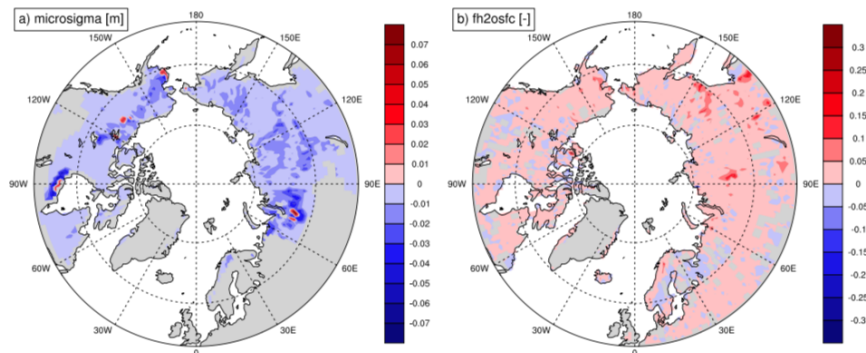
5
6 Our results illustrate the dependence of f_{h2osfc} on σ_{micro} and how certain range of
7 σ_{micro} values can result in very high f_{h2osfc} . This relation emphasize the need for a
8 dynamic circum-Arctic σ_{micro} value to capture the natural variability of surface
9 conditions when representing permafrost thaw associated hydrological changes.
10 In the Exice experiment, coupling excess ice melt induced ground subsidence to
11 σ_{micro} leads to significant changes in surface hydrology (Fig. 2). In our
12 simulations, σ_{micro} is consistently lower in Exice compared to Control at the end
13 of the 20th century (Fig. 2a). This is the model representation of increased
14 variability in surface microtopography due to uneven subsidence events within
15 the gridcell. Particularly larger inundated fractions are simulated around
16 western Siberia and northeast Canada, which conform well to the observational
17 datasets of peatland distribution (Tarnocai et al., 2007; 2009). Several other
18 observational estimates agree on the spatial distribution of high latitude
19 peatlands, where most of the wetland formations are expected in the future
20 (Melton et al., 2013). Therefore, the new parameterization of surface inundated
21 fraction is a stepping-stone towards a more realistic representation of surface
22 hydrology in permafrost-affected areas. Other modeling studies support these
23 results with similar spatial patterns of surface wetland distributions (Wania et
24 al., 2013; Melton et al., 2013). In the previous version of CLM, simulated
25 inundated area shows slightly different patterns (Riley et al., 2011), mainly due
26 to non-process based description of inundated fractions. We emphasize that
27 although our parameterization is only conceptual, this is the first attempt
28 towards coupling permafrost thaw associated land surface subsidence with
29 hydrological changes in a land surface model within an ESM.

30
31 By introducing the effects of ground subsidence on σ_{micro} , a dynamic inundated
32 fraction is calculated. However, there is no observed dataset to evaluate the
33 relation between subsidence and ground topography, therefore an assumption
34 had to be made regarding this coupling. In this study, changes in σ_{micro} are
35 proportional to the changes in ground subsidence with the difference in an order
36 of magnitude. This assumption is put to test by doubling and halving the initial
37 σ_{micro} values and the results show 10 to 20 % change in surface inundated
38 fractions (Fig. 1). The difference in dynamic parameterization (Fig. 2b) stays in



1 between these values and on average shows a 10 – 15 % increase, thus
2 supporting the coupling assumption.

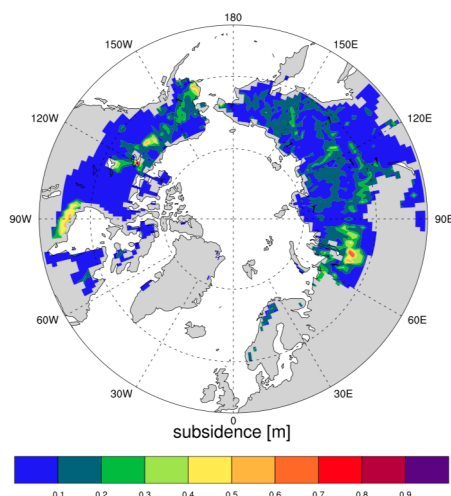
Exice-Control (2000-2010)



3
4 Fig. 2: Effects of coupled subsidence-microsigma parameterization on ' σ_{micro} ' and ' f_{h2osfc} '
5 from $>50^\circ\text{N}$ difference maps of Exice-Control experiments for the period 2000-2010.
6

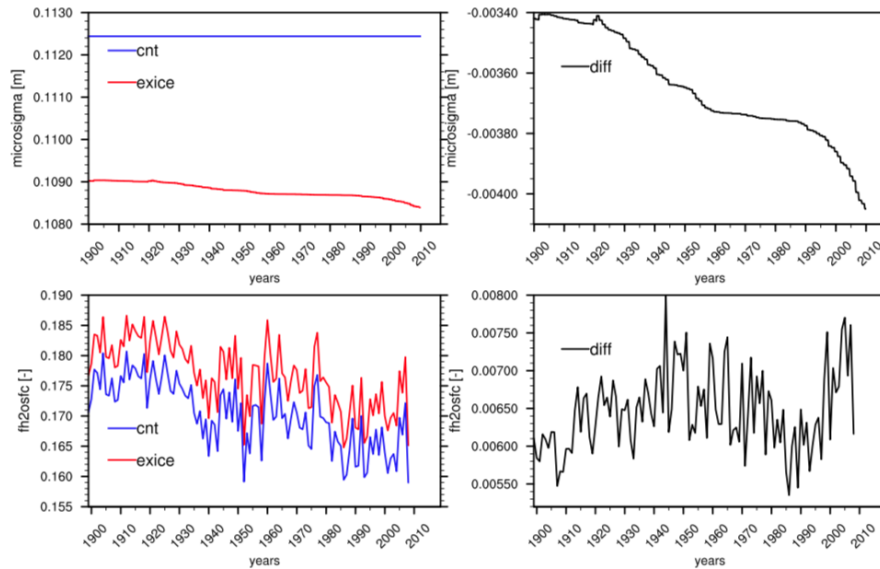
7 As expected, the f_{h2osfc} and σ_{micro} changes are directly related to the ground
8 subsidence processes in most cases. Exice experiment produces land surface
9 subsidence in some gridcells (Fig. 3) similar to the spatial patterns exhibited in
10 σ_{micro} and f_{h2osfc} in Fig. 2, suggesting that melting of excess ice directly affects
11 changes in surface hydrology. This is most pronounced around western Siberia,
12 south of Hudson Bay and around northwestern Canada and central Alaska,
13 where initial excess ice was large (Lee et al. 2014). Simulated ground subsidence
14 is directly associated to changes in surface inundated fraction (f_{h2osfc}) described
15 in Fig. 2.
16

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



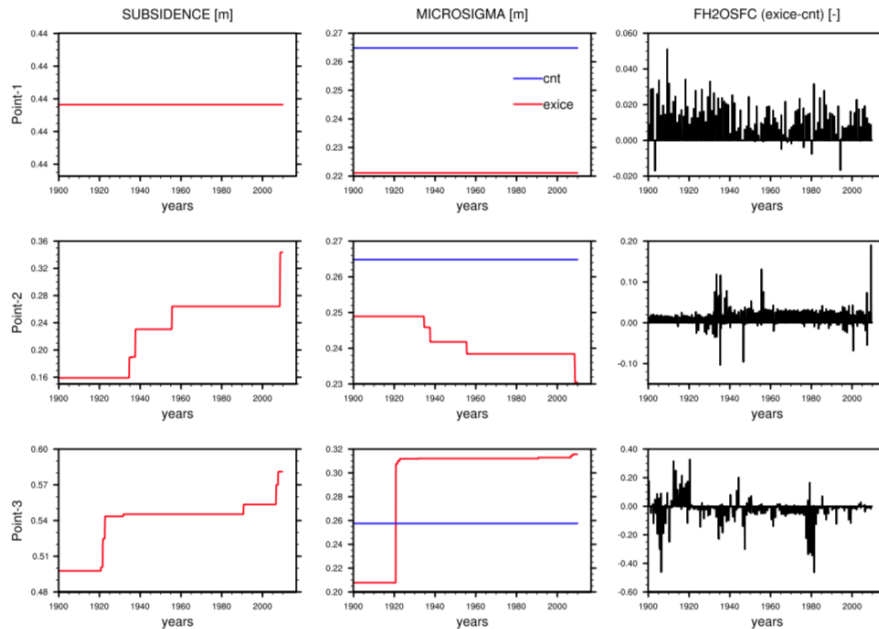
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2 Fig. 3: High latitude (>50°N) map of ground subsidence simulated from the Exice
3 experiment averaged for the period 2000-2010.
4

5 Spatially averaged timeseries of σ_{micro} and f_{h2osfc} show that in the Exice
6 experiment σ_{micro} decreases over time and f_{h2osfc} shows a more dynamic change
7 during the simulation (Fig. 4). The discrepancy in σ_{micro} between Exice and
8 Control in the beginning of the simulation is due to prior excess ice melting
9 during the spin-up period and the values continue to decrease throughout the
10 20th century, while the decrease halts temporarily during 1960- 1990
11 (microsigma-diff plot in Fig. 4). Higher f_{h2osfc} are observed in Exice experiment,
12 however, the differences between Exice and Control show a general increase
13 throughout the simulation except the period between 1960-1990. The spatially
14 averaged f_{h2osfc} values exhibit a non-linear progression during the 20th century
15 (Fig. 4). Mainly the change in climate forcing contributes to this trend. Analyzing
16 the CRUNCEP atmospheric forcing data suggests that the precipitation pattern
17 over the experiment domain shows a sudden reduction at the beginning of 1960s
18 (Fig. S2). Even though the average precipitation starts increasing again, the
19 lower values contribute to the reduced f_{h2osfc} values. Similar changes occur with
20 the patterns in atmospheric temperatures (Fig. S2), which is a direct forcing for
21 permafrost thaw and ground subsidence. A process-based representation of
22 f_{h2osfc} allows the model to naturally represent the temporal changes in climate.
23 Hence, our representation of f_{h2osfc} will improve the estimation of future surface
24 hydrological states under changing climatic conditions.



1
 2 Fig. 4: Timeseries of spatially averaged high latitude ($>50^{\circ}\text{N}$) σ_{micro} and annual
 3 maximum f_{h2osfc} variables from Exice and Control experiments together with the
 4 timeseries of Exice-Control difference (diff) for the period 1900-2010.

5
 6 The direct effects of new model parameterization can better analyzed while
 7 inspecting point scale changes as shown in Fig. 5. The three selected points show
 8 a range of scenarios to observe the effects of subsidence on microsigma and
 9 f_{h2osfc} . Point 1 has no change in subsidence during the simulation and with
 10 higher microsigma values in Exice (due to prior subsidence in spinup), the
 11 difference in f_{h2osfc} compared to Control simulation is always positive, meaning
 12 higher surface inundated fractions. In Point 2, Exice microsigma decreases due to
 13 the increase in subsidence during the simulation. These gradual changes are
 14 reflected in f_{h2osfc} , where sudden increases are shown around 1935 and 1955,
 15 exactly when the subsidence changes occur. Similarly in Point 3, subsidence
 16 causes a lower microsigma in the beginning of the simulation; however the
 17 subsidence values surpass the 0.5m threshold around 1920s, which causes the
 18 reversed effect on microsigma by increasing it compared to the Control
 19 experiment. Severe subsidence causing more drainage is represented in this way
 20 within our parameterization. The f_{h2osfc} values show this drainage with a sudden
 21 decrease at 1920 and continuing with mostly negative values throughout the
 22 simulation. These scenarios support the validity of our new parameterization
 23 that can be used for any future climate scenario for a better representation of
 24 surface hydrology and subsidence coupling.

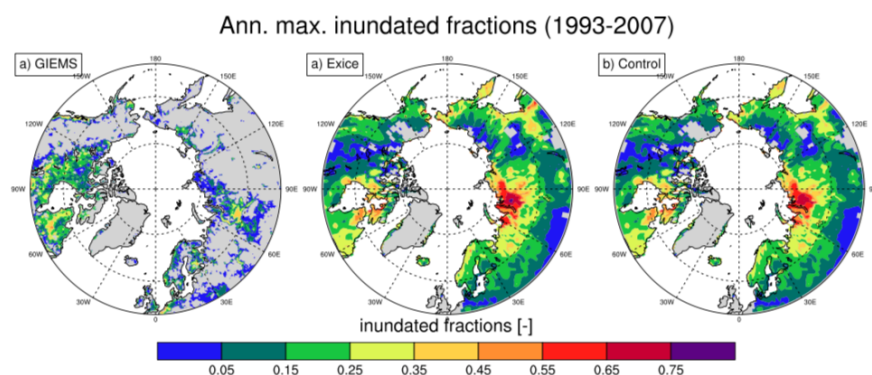


1
 2 Fig. 5: Timeseries of subsidence, σ_{micro} , and f_{h2osfc} variables from Exice and Control
 3 experiments at three selected sites. Point 1: lat 54 N lon 272 E, Point 2: lat 64 N lon 80 E,
 4 Point 3: lat 65 N lon 70 E.
 5

6 GIEMS dataset (Prigent et al., 2012) provides the surface area of wetlands for each
 7 gridbox. Fraction of wetland-covered gridbox is calculated to compare with the model
 8 results (Fig. 6). The range of estimated surface wetland fraction is different in the
 9 satellite dataset and model outputs; however, spatial distribution of surface inundated
 10 area is fairly comparable between the model and the satellite dataset. They both
 11 exhibit larger inundated fractions in western Siberia and around Hudson Bay. The
 12 ranges of estimated surface wetland fraction between the satellite dataset and
 13 model outputs are different due to differences in the definitions of inundated
 14 areas. However, spatial distribution of surface inundated area is comparable
 15 between the model and the satellite dataset, where both exhibit larger inundated
 16 fractions in western Siberia and Hudson Bay. Since our model provides the
 17 fraction of gridbox that is inundated, the satellite dataset had to be converted
 18 from actual wetland area to fractions. The GIEMS dataset assumes 773 km²
 19 gridboxes all over the globe (Prigent et al., 2007), which creates grid-size
 20 problems comparing to model gridbox area. Another issue with such
 21 comparison stems from the differences in the definition of inundated fraction.
 22 GIEMS dataset uses satellite observations at different wavelengths to derive the
 23 wetland area, while the CLM creates the surface inundation with the topography
 24 index and water inputs to the gridbox. Within the model parameterization, the
 25 height of the surface water level is calculated by a hypsometric function and the
 26 gridbox fraction is further derived from the grid size. This allows an ever-
 27 existing surface inundated fraction even in very dry gridboxes, whereas the
 28 GIEMS method underestimates the small wetlands comprising less than 10% of
 29 the gridbox area (Prigent et al., 2007); hence a model overestimation of satellite



1 dataset is expected. Definition of modelled and satellite derived inundated
2 fraction is not the same. Unfortunately there is no standard definition
3 (Reichhardt, 1995), which produces the struggle to find a proper observational
4 dataset to evaluate model results. What we emphasize from our findings is,
5 nevertheless, the spatial patterns of higher inundated fractions occurring at
6 similar locations in model and satellite dataset (Fig. 6).
7



8
9 Fig. 6: Surface water fraction comparison from high latitude ($>50^{\circ}\text{N}$) maps of annual
10 maximum surface wetlands from GIEMS dataset (Prigent et al., 2012) and annual
11 maximum f_{h2osfc} values of Exice and Control experiments for the period 1993-2007.
12

13 4. Conclusion

14 A warming climate affects the Arctic more severely than the rest of the globe.
15 Increasing surface temperatures pose an important threat to the vulnerable high
16 latitude ecosystems. Degradation of Arctic permafrost due to increased soil
17 temperatures leads to the release of permafrost carbon to the atmosphere and
18 further strengthens the greenhouse warming (IPCC, 2013; Schuur et al., 2008).
19 For future climate predictions, it is necessary to properly simulate the Arctic
20 surface inundated areas due to their physical and biogeochemical coupling with
21 the atmosphere.
22

23 This study summarizes a new parameterization within the CLM to represent
24 prognostic surface inundated fractions under permafrost thawing using a
25 conceptual approach that can lead to implementation of a physical process-based
26 parameterization. Coupling ground subsidence to surface microtopography
27 distribution, hence allowing a natural link between surface hydrological
28 conditions and soil thermodynamics, resulted in generally increased surface
29 inundated fractions over the northern high latitudes, with larger surface
30 inundated fractions around western and far-east Siberian plains and
31 northeastern Canada. Projected increase in global temperatures will inevitably
32 cause more excess ice melting and subsequent ground subsidence, therefore, it
33 will be necessary to incorporate a process-based parameterization to accurately
34 account for future ground subsidence effects on surface hydrological states.
35

36 Our results confirm the enhancements of coupling ground subsidence and
37 surface inundation to represent the temporal changes in surface hydrology



1 reflected by soil physical states and the atmospheric forcing, which is much
2 needed for a future scenario experiment. Here we conclude that our new
3 parameterization is implemented successfully and can be used for future climate
4 scenarios such as shown in Lee et al. (2014) with major subsidence events
5 during the 21st century under a high warming scenario.

6
7 This new parameterization represents the first step into a process-based
8 representation of such hydrological processes in CLM. Using this
9 parameterization, further work can proceed to investigate the biogeochemical
10 feedbacks of permafrost greenhouse gas fluxes between land and atmosphere.

11

12 **Code and data availability**

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

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

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

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

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

21

22 **Author contribution**

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

27

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31 simulations were performed on resources provided by UNINETT Sigma2-the
32 National Infrastructure for High Performance Computing and Data Storage in
33 Norway, accounts NS2345K and NN2345K.

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