Dear Drs Zha and Zhuang,

Thank you for responding to the referee reports. Work on the manuscript has addressed many of the concerns by referees, and I am content with these (e.g. the issue of equifinality). However, I am not convinced that you have managed to alleviate the main point of referee 1, which is that the uncertainty associated with both models compared here is so large that it is not possible to judge any potential improvement from incorporating dormancy. I would therefore like to ask you to revise the manuscript further to address the issue of modelling uncertainty. I include some further specific explanations below.

Response: We highly appreciate Dr. Subke’s constructive comments. Below we detail how we have revised the manuscript by specifically further addressing the model uncertainty. We have also addressed some other minor comments regarding figure quality.

I agree with referee 1 that model uncertainty is key for this comparison, and this is not well illustrated also in the revised paper. Figures 2, 4 and 5 show that in some instances the new model follows temporal dynamics better, but the improvement over the nondormancy model is not that clear, and in absence of explicit uncertainty associated with either model, the reader can not judge whether this is a significant improvement. This then leads to similar problems when making regional predictions – Are stated differences for the contrasting models within the model uncertainty?

Response: We used Fig. 2 to show dormancy model performance in comparison with observational data. We used different sets of observational data to verify both dormancy and nodormancy models in Figs. 4 and 5. While we acknowledge both models have various temporal dynamics in comparison with observational data, especially considering relatively large uncertainty associated with dormancy model (also for nodormancy model). However, we do see in general the dormancy model performs better. To confirm this, we plotted the linear model comparison with observational data for both models shown in Fig. 6. The comparison shows that the dormancy model MIC-TEM-Dormancy performs better with smaller intercepts and larger slopes that are closer to 1. For the simulated NEP of both models, we compared them with observational data in Table 5. In general, the dormancy model has relatively smaller intercepts while slopes and R values varying for various ecosystems. With recognition of these site-level uncertainties, we conducted ensemble simulations in the last revision to quantify the regional uncertainties for both models. Our results were presented with uncertainties in Figs. 11 and 12. Consequently, our conclusions were drawn by considering these uncertainties. In this revision, we revised the Abstract and Conclusion sections to reflect these changes concerning model differences and uncertain parameters and simulations by adding standard deviations.
You also don’t address fully the point that the dormancy model increases modelling uncertainty owing to the larger number of parameters. As no modelling uncertainty is quantified at present, I think that this fundamental limitation of constructing a more complex model (i.e. with more parameters) is not reflected appropriately. Figure 11 seems to show the wide band of uncertainty (but this is not clearly explained in the figure caption). Can the apparent difference/improvement of the model prediction be justified, given the considerable underlying uncertainty?

**Response:** Thanks for the comments. We agree that adding the dormancy effects makes the model more complex by increasing number of parameters, which might increase model uncertainty. This is a fundamental modeling dilemma, i.e., shall we use a simpler model (less processes considered) or a more adequate model (more essential processes considered). In this study, we believe, the dormancy dynamics are an important process to be considered to more adequately capture microbial decomposition. Two versions of the model simulations and observational data comparisons for dominant ecosystems in the region indicate that the dormancy model better captures the observation while there are uncertainties for both models. We agree this study has not fully addressed this problem – which is subject to a research community debate. Therefore, in this revision, we added a paragraph to discuss this modeling dilemma, quoted below “While our analysis suggests it is important to incorporate microbial dormancy dynamics into a process-based biogeochemistry model to more adequately simulate carbon dynamics in northern high latitudes, we do confront modeling dilemmas. First, our process-based models have a relatively large number of parameters, which unavoidably creates the “equifinality” problem as recognized in our previous studies for the model (e.g., Tang and Zhuang, 2008, 2009). To alleviate this problem in this analysis, we have conducted parameter ensemble simulations at both site and regional levels and presented our results with uncertainties, which could be a standard approach for process-based complex biogeochemistry modeling analyses. Second, incorporating more ecosystem processes increases the number of parameters in our model, inducing even larger uncertainties for both site level and regional simulations. On the one hand, the more complex model to a certain degree helps capture observations, on the other hand, the model uncertainty has not been constrained or even enlarged. We highlight the need to further investigate this trade-off within the modeling research community.”.

Some of the figures are still very hard to read. Axis labels and numbers are generally too small. Fig. 3, for example, is improved as far as resolution is concerned, but font size is far too small. The same applies to other figures.

**Response:** Thanks much for the suggestion. In this revision, we improved the quality of these figures.

Best regards, Jens-Arne Subke
Microbial dormancy and its impacts on Arctic terrestrial ecosystem carbon budget

Junrong Zha and Qianlai Zhuang

Department of Earth, Atmospheric, and Planetary Sciences and Department of Agronomy, Purdue University, West Lafayette, IN 47907 USA

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Correspondence to: qzhuang@purdue.edu
Abstract

A large amount of soil carbon in the Arctic terrestrial ecosystems could be emitted as greenhouse gases in a warming future. However, lacking detailed microbial processes such as microbial dormancy in current biogeochemistry models might have biased the quantification of the regional carbon dynamics. Here the effect of microbial dormancy was incorporated into a biogeochemistry model to improve the quantification for the last and this century. Compared with the previous model without considering the microbial dormancy, the new model estimated the regional soils stored 75.9 Pg more C in the terrestrial ecosystems during the last century, and will store 50.4 Pg and 125.2 Pg more C under the RCP 8.5 and RCP 2.6 scenarios, respectively, in this century. This study highlights the importance of the representation of microbial dormancy in earth system models to adequately quantify the carbon dynamics in the Arctic.
1. Introduction

The land ecosystems in northern high latitudes (>45 °N) occupy 22% of the global surface and store over 40% of the global soil organic carbon (SOC) (McGuire & Hobbie, 1997; Melillo et al., 1993; Tarnocai et al., 2009; Hugelius et al., 2014). During the past decades, a greening accompanying a warming in the region has been documented (Zhou et al., 2001; Lloyd et al., 2002; Stow et al., 2004; Callaghan et al., 2005; Tape et al., 2006). The regional carbon dynamics are expected to loom large in the global carbon cycle and exert large feedbacks to the global climate system (McGuire et al., 2009; Davidson & Janssens, 2006; Bond-Lamberty & Thomson, 2010).

To date, numerous ecosystem models have been developed to project the feedbacks between terrestrial ecosystem carbon cycling and climate (Raich et al., 1991; Zhuang et al., 2001, 2002, 2015; Parton et al., 1993; Knorr et al., 2005; Running & Coughlan, 1988), but they can bias their quantifications due to missing detailed microbial mechanisms in these models (Schmidt et al., 2011; Todd-Brown et al., 2013; Conant et al., 2011; Treseder et al., 2011).

Microorganisms play a central role in decomposition of litter and soil organic carbon, which further governs the global carbon cycling and climate change (Xu et al., 2014; Treseder et al., 2011; Wang et al., 2015). An emerging field of research has begun to incorporate microbial ecology into existing process-based models to represent decomposition in ways that include important microbial processes that were previously ignored (Zha & Zhuang, 2018; Schimel & Weintraub, 2003; Allison et al., 2010; German et al., 2012). These microbial-based models tend to better reproduce field and satellite observations than traditional ones that treat soil decomposition as a first-order decay process without considering microbial activities (Treseder et al., 2011; Wieder et al., 2013; Todd-Brown et al., 2011; Lawrence et al., 2009; Moorhead et
al., 2006). However, some vital microbial traits such as microbial dormancy and community shifts are still rarely explicitly considered in large-scale ecosystem models (Wieder et al., 2015), and this may introduce notable uncertainties (Graham et al., 2014, 2016; Wang et al., 2015; Bouskill et al., 2012; Kaiser et al., 2014).

Dormancy is broadly recognized as a strategy for microorganisms to cope with periodical environmental stresses (Harder & Dijkhuizen, 1983). When environmental conditions are unfavorable for growth, microbes switch to a dormant state, which is a reversible state of low to zero metabolic activity (Stolpovsky et al., 2011; Lennon & Jones, 2011). In this state, biogeochemical processes such as soil decomposition are slow (Blagodatskaya et al., 2013). At any given time, there is only a fraction of, likely below 50%, metabolically active microbes in natural soils (Wang et al., 2015; Stolpovsky et al., 2011). Soil decomposition and nutrient cycling mainly depend on these active microbes because only active ones can consume organic matter and replicate themselves (Wang et al., 2015; Blagodatskaya et al., 2014). To date, most existing biogeochemistry models use total rather than active microbial biomass as an indicator of microbial activities (Wieder et al., 2015), which could bias the estimates of soil decomposition and ecosystem carbon budget (Hagerty et al., 2014; He et al., 2015). Especially, the Arctic terrestrial ecosystems are nitrogen-limited, neglecting microbial dormancy will lead to incorrect estimates of nitrogen availability through soil decomposition, failing to capture nitrogen feedbacks to carbon dynamics (Wang et al., 2015; Stolpovsky et al., 2011; Thullner et al., 2005).

Furthermore, the Arctic has experienced a marked seasonality of active and dormant microbial cycles and the above-global-average warming, which might have increased the proportion of active microbes in soils (He et al., 2015). Thus, incorporating dormancy effects will improve model realism to provide a better projection of the Arctic carbon dynamics.
This study incorporated the effects of microbial dormancy trait into an extant process-based biogeochemistry model (MIC-TEM) (Zha & Zhuang, 2018; He et al., 2015). The dormant and active microbial physiology has been considered explicitly in the new version of model (MIC-TEM-dormancy). The revised model was parameterized, validated, and then applied to evaluate the carbon dynamics during the last and this centuries in the Arctic terrestrial ecosystems (north 45°N above). By comparing the results of MIC-TEM-dormancy and MIC-TEM, we can show that incorporating microbial dormancy may produce a much different prediction in historical and future carbon budget.

2. Methods

2.1 Overview

Due to the importance of microbial dormancy, some recent work has been done to consider the metabolic activation and deactivation of microbes in soil and its effects on soil carbon (C) dynamics and climate feedbacks. For example, Wang et al. (2015) has incorporated transformation processes between active and dormant states to develop two versions of MEND, that is, MEND with and without dormancy. The two versions of the model have been applied to quantify the carbon decomposition in laboratory incubations of four soils. Salazar et al. (2018) have also taken microbial dormancy into account to compare their predictions of microbial biomass and soil heterotrophic respiration ($R_H$) under simulated cycles of stressful (dryness) and favorable (wet pulses) conditions. Our study extends those modeling studies to the whole Arctic region by developing a more detailed biogeochemistry model considering the dormancy impacts. Below, we first describe how we developed the new model (MIC-TEM-dormancy) by incorporating the microbial dormancy trait into an existing microbial-based biogeochemistry model (MIC-TEM).
Second, we discuss how parameterization and validation of MIC-TEM-dormancy model were conducted using observed net ecosystem exchange data, and heterotrophic respiration data at representative sites. Third, we presented how the model was applied to northern high latitudes (above 45°N) for the 20th and 21st centuries and discussed the dormancy effects on regional carbon budget.

2.2 Model description

A non-dormancy version of biogeochemistry model (MIC-TEM) has been developed by incorporating a microbial module (Allison et al., 2010) into an extant large-scale biogeochemical model (TEM) to explicitly (Zhuang et al., 2003) consider the effects of microbial dynamics and enzyme kinetics on carbon dynamics (Zha & Zhuang, 2018). Here we further advanced the MIC-TEM by incorporating algorithms that describe the effects of microbial dormancy dynamics based on He et al. (2015). Different from He et al. (2015), in which microbial module was driven with existing data of carbon stocks and fluxes, our study incorporated the microbial module into an extant MIC-TEM that simulates carbon data dynamically. This coupling enables us to extrapolate our model to whole northern high-latitudes region, rather than only for temperate forest region in He et al. (2015). In our new model (MIC-TEM-dormancy), microbial biomass pool was divided into two fractions, including the dormant and active microbial biomass pools. The two microbial biomass pools and the reversible transition between them have been considered explicitly in the new model (Figure 1), which was ignored in MIC-TEM. In previous MIC-TEM, heterotrophic respiration \( R_H \) is calculated as:

\[
R_H = \text{ASSIM} \times \left( \sqrt[2]{1-CUE} \right) \tag{1}
\]
Where ASSIM and CUE represent microbial assimilation and carbon use efficiency, respectively.

For detailed carbon dynamics in MIC-TEM, see Zha & Zhuang (2018).

Here we revised MIC-TEM by incorporating microbial dormancy dynamics according to He et al. (2015). In MIC-TEM-dormancy, the soil heterotrophic respiration $R_H$ is comprised of three parts: the maintenance respiration from the active and dormant microorganisms and the CO$_2$ production through the process of microbial assimilation (He et al., 2015):

$$R_H = m_R Q_{10mic}^{\text{temp}-15} B_a + \beta m_R Q_{10mic}^{\text{temp}-15} B_d + \text{CO}_2$$

(2)

where the first two terms are maintenance respiration from the active and dormant microorganisms, respectively. The last term is the CO$_2$ produced during the process of microbial assimilation.

For first two terms, $B_a$ and $B_d$ represents the active and dormant microbial biomass pool, respectively. The parameter $m_R$ denotes the specific maintenance rate at active state (h$^{-1}$), and $\beta$ is the ratio of dormant maintenance rate to active maintenance rate. Thus, $\beta m_R$ denotes the maximum specific maintenance rate at dormant state. Temperature sensitivity was expressed as the $Q_{10}$ function ($Q_{10}^{\text{temp}-15}$), where temp is soil temperature at top 20 cm (units: °C).

For the third term, the CO$_2$ produced through microbial assimilation is calculated as in He et al. (2015) and Allison et al. (2010):

$$\text{CO}_2 = \text{ASSIM} \times \Phi (1 - Y_g)$$

(3)

Where ASSIM represents the microbial assimilation and the parameter $Y_g$ represents carbon use efficiency. Microbial assimilation (ASSIM) is calculated as in He et al. (2015):

$$\text{ASSIM} = \frac{1}{Y_g} \frac{\Phi}{\alpha} m_R Q_{10enz}^{\text{temp}-15} B_a \left( \frac{CN_{soil}}{CN_{mic}} \right)^{0.6}$$

(4)
Here parameter $\alpha$ is maintenance weight (h$^{-1}$), $CN_{soil}$ and $CN_{mic}$ denotes the C:N ratios of soil and that of microbial biomass. Besides, $\Phi$ is the substrate saturation level and defined as in He et al. (2015) and Wang et al. (2014):

$$\Phi = \frac{S}{K_s+S}$$  \hspace{1cm} (5)

Where $K_s$ is the half saturation constant for substrate uptake as indicated by the Michaelis–Menten kinetic, and $S$ is soluble C substrates that are directly accessible for microbial assimilation (Wang et al., 2014). Here we quantified concentration of soluble C substrates that are directly accessible for microbial assimilation by using conceptual framework from Davidson et al. (2012):

$$S = \text{Soluble C} \times D_{liq} \times \theta^3$$  \hspace{1cm} (6)

The term ‘Soluble C’ denotes the state variable of soluble carbon pool. $D_{liq}$ is the diffusion coefficient of the substrate in the liquid phase, and is formulated as:

$$D_{liq} = \frac{1}{(1-BD/PD)^3}$$  \hspace{1cm} (7)

Where BD is the bulk density and PD is the soil particle density. $\theta$ is the volumetric soil moisture.

Different from MIC-TEM, the transitions between active and dormant microbial biomass are included in MIC-TEM-dormancy.

$$B_{a\to d} = (1-\Phi) m_R Q_{10mic}^{temp-15} B_a$$  \hspace{1cm} (8)

$$B_{d\to a} = \Phi m_R Q_{10mic}^{temp-15} B_d$$  \hspace{1cm} (9)

Where $B_{a\to d}$ and $B_{d\to a}$ denote the transition from the active to dormant microbe and from the dormant to active microbe, respectively (He et al., 2015; Wang et al., 2014). Thus, dormancy rate is affected by active and dormant biomass, soil temperature (temp) and soil moisture ($\theta$ in $\Phi$).

The active microbial biomass ($B_a$) is modeled as (He et al., 2015; Wang et al., 2014):

$$\frac{dB_a}{dt} = \text{ASSIM} \times Y_g - m_R Q_{10mic}^{temp-15} B_a - B_{a\to d} + B_{d\to a} - \text{DEATH} - \text{EPROD}$$  \hspace{1cm} (10)
Where DEATH and EPROD denotes microbial biomass death and enzyme production, which are modeled as proportional to active microbial biomass with constant rates \( r_{\text{death}} \) and \( r_{\text{EnzProd}} \) (Allison et al., 2010):

\[
\text{DEATH} = r_{\text{death}} \times \rightarrow \text{Ba} \\
\text{EPROD} = r_{\text{EnzProd}} \times \rightarrow \text{Ba}
\]

Where \( r_{\text{death}} \) and \( r_{\text{EnzProd}} \) are the rate constants of microbial death and enzyme production, respectively.

The dormant microbial biomass (\( B_d \)) is modeled as (He et al., 2015; Wang et al., 2014):

\[
\frac{dB_d}{dt} = -\beta m_R Q_{10}^{\text{temp}-15} \left( B_d + B_a \rightarrow d - B_d \rightarrow a \right)
\]

The Soluble C pool is modeled as (He et al., 2015; Allison et al., 2010):

\[
\frac{d \text{Soluble C}}{dt} = \text{DECAY} - \text{ASSIM} + \text{ELoss} + \text{DEATH}
\]

Where DECAY represents the enzymatic decay of soil organic carbon (SOC), and ELOSS represents the loss of enzyme.

DECAY is regulated by enzyme biomass (ENZ), soil organic carbon (SOC), soil temperature, and substrate quality (He et al., 2015):

\[
\text{DECAY} = V_{\text{max}} \times \left( Q_{10}^{\text{temp}-15} \times \text{ENZ} \times \frac{\text{SOC}}{K_{\text{uuptake}} + \text{SOC}} \right) \times (120 - CN_{\text{soil}})
\]

Where \( V_{\text{max}} \) is the maximum SOC decay rate, \( K_{\text{uuptake}} \) is half saturation constant for enzymatic decay.

ELOSS is modeled as a first-order process (Allison et al., 2010) to represent enzyme turnover:

\[
\text{ELOSS} = r_{\text{enzloss}} \times \rightarrow \text{ENZ}
\]

Where \( r_{\text{enzloss}} \) is the rate constant of enzyme loss.

The soil organic carbon pool (SOC) is modeled as:
\[
\frac{d \text{SOC}}{dt} = \text{Litterfall} - \text{DECAY}
\]

(17)

Where Litterfall is estimated as a function of vegetation carbon (Zhuang et al., 2010).

Last, enzyme pool (ENZ) is modeled as:

\[
\frac{d \text{ENZ}}{dt} = \text{EPROD} - \text{ELOSS}
\]

(18)

With the modification of microbial carbon dynamics by considering microbial life-history trait, soil decomposition is changed since it is controlled by microbes. When microbial dormancy is considered, the number of active microbes that participate in soil decomposition is much less. The changes in soil decomposition directly influence the amount of soil respiration, and further influence soil nitrogen (N) mineralization that determines soil N availability for plants, affecting gross primary production (GPP). Since both GPP and R_H can be affected by microbial dormancy, net ecosystem production (NEP) will also be affected.

2.3 Model parameterization and validation

The detailed description of parameters that are related to microbial dormancy can be found in He et al. (2015) (Table 1). Here we calibrated the MIC-TEM-dormancy at six representative sites with gap-filled monthly net ecosystem productivity (NEP, gCm^{-2}mon^{-1}) data in northern high latitudes (Table 2). Site-level climatic data and soil texture data were organized for driving model. All sites information can be found on AmeriFlux network (Davidson et al., 2000). The results for model parameterization were presented in Figure 2. We conducted the parameterization using a global optimization algorithm known as SCE-UA (Shuffled complex evolution) method (Duan et al., 1994). An ensemble of 50 independent sets of parameters were performed based on prior ranges from literature (Table 1) to minimize the difference between the monthly simulated and measured NEP at the chosen sites. The cost function of the minimization is:
\[
\text{Obj} = \sum_{i=1}^{k} (\text{NEP}_{\text{obs},i} - \text{NEP}_{\text{sim},i})^2
\]  
(17)

Where \( \text{NEP}_{\text{obs},i} \) and \( \text{NEP}_{\text{sim},i} \) are the observed and simulated NEP, respectively. \( k \) is the number of data pairs for comparison. Except for the parameters of microbial dormancy, other parameters are derived directly from MIC-TEM (Zha & Zhuang, 2018). The optimized parameters were used for model validation and regional simulations.

For model validation, we chose another six sites that containing monthly NEP data from AmeriFlux network (Table 3). Moreover, we also conducted site-level validations with monthly soil respiration data from AmeriFlux network and Fluxnet dataset. The site information was provided in Table 4. For these sites, we assumed 50% of soil respiration was heterotrophic respiration (\( R_H \)) for forest (Hanson et al., 2000), 60% and 70% of that was \( R_H \) for grassland (Wang et al., 2009) and tundra (Billings et al., 1977). Because there is a limited amount of available \( R_H \) data, we could not conduct a regional validation for all pixels in northern high latitudes. Instead, we extracted 61 sites providing data of average annual heterotrophic respiration from ORNL global Soil Respiration Dataset (https://daac.ornl.gov/SOILS/guides/SRDB_V4.html, Bond-Lamberty et al., 2018) for model validation. The site-level observed average annual \( R_H \) was used to compare with simulated annual \( R_H \) by MIC-TEM-dormancy and MIC-TEM. The MIC-TEM-dormancy was run at monthly time step to keep consistent with the time step of MIC-TEM. Although microbial dynamics occur at fine temporal scales (Tang & Riley, 2014), we can still quantify the cumulative impacts of microbial dynamics on carbon and nitrogen cycling at monthly time by not changing the model structure.

### 2.4 Spatial extrapolation
For historical simulations during the 20th century, two sets of regional simulations using MIC-TEM-dormancy and MIC-TEM at a spatial resolution of 0.5° latitude × 0.5° longitude were conducted. Our model simulation contains two parts: spin-up and transient simulation. A typical spin-up was conducted to get the model to a steady state for each spatial location, which will be used as initial conditions for transient simulations (McGuire et al., 1992). During spin-up procedure, cyclic forcing data was used to force the model run, and repeated continuously until dynamic equilibrium was achieved at which the modeled state variables show a cyclic pattern or become constant. Specifically, this study used the monthly historical climate data from 1900 to 1940 to repeatedly drive the model for the spin-up. Before spin-up procedure, the model was initialized with default built-in carbon stocks (Raich et al., 1991). During transient simulations, the calibrated ecosystem-specific parameters were used for regional simulations. The previous dynamic equilibrium was used as initial value for transient simulation. The historical climatic forcing data, including the monthly air temperature, precipitation, cloudiness, and atmospheric CO2 concentrations, were organized from the Climatic Research Unit (CRU TS3.1) from the University of East Anglia (Harris et al., 2014). We also used gridded data of soil texture (Zhuang et al., 2003), elevation (Zhuang et al., 2015), and potential natural vegetation (Melillo et al., 1993) from literatures. In our model, we assumed that soil texture, elevation, and potential natural vegetation data only vary spatially, not vary over time (Zhuang et al., 2015).

In addition, regional simulations over the 21st century were conducted under two Intergovernmental Panel on Climate Change (IPCC) climate scenarios (RCP 2.6 and RCP 8.5). The future climatic forcing data under these two climate change scenarios were derived from the HadGEM2-ESmodel, which is a member of CMIP5project (https://esgf-node.llnl.gov/search/c mip5/). Then the regional estimations were obtained by summing up the
gridded outputs for our study region. The positive simulated NEP represents a CO\textsubscript{2} sink from the atmosphere to terrestrial ecosystems, while a negative value represents a source of CO\textsubscript{2} from terrestrial ecosystems to the atmosphere.

### 2.5 Parameter equifinality effects

Our previous studies using TEM has demonstrated that equifinality derived from site-level parameterization will affect the uncertainty in the estimation of regional carbon dynamics (Tang and Zhuang, 2008, 2009). Here equifinality refers to that a number of sets of parameters result in model simulations that all match the data similarly well. To quantify this effect on our simulation uncertainty, we conducted ensemble regional simulations with 50 sets of parameters for both historical and future studies. The 50 sets of parameters were obtained according to the method in Tang and Zhuang (2008).

### 3. Results

#### 3.1 Inversed Model Parameters and model validation

Using SCE-UA ensemble method, 50 independent sets of parameters were converged to minimize the objective function. Then the optimized parameters are calculated as the mean of these 50 sets of inversed parameters. The boxplot of parameter posterior distributions reflects different ecosystem properties at these sites (Figure 3). For instance, growth yield was higher in tundra types than in forests, meaning microorganisms in environment with higher energy limitation tend to enhance the efficiency of energy transportation. Besides, alpha, the maintenance weight, was also higher in tundra types than in forests. From the plot for parameter beta, the ratio of dormant maintenance rate to specific maintenance rate for active biomass in tundra types is lower than that in forest types. Other microbial related parameters did not differentiate much among different vegetation types.
After parameterization, the MIC-TEM-dormancy was validated with monthly NEP data for six representative ecosystems, and the comparisons between monthly observed NEP and simulated NEP were presented in Figure 4. With the optimized parameters, the dormancy-based model was used to reproduce NEP to compare with the measured NEP (Table 5). The $R^2$ ranges from 0.67 for Atqasuk to 0.93 for Bartlett Experimental Forest (Table 5). Generally, our new model performs better for forest ecosystems than for tundra ecosystems. Compared with MIC-TEM, dormancy model performs better for alpine tundra, temperate coniferous forest, and grassland. For other sites, both models show similar performance (Table 5). Besides, a set of monthly soil respiration data were selected to evaluate the estimated $R_H$. The comparisons between monthly observed $R_H$ and simulated $R_H$ from two contrasting models were conducted (Figure 5). MIC-TEM-dormancy has higher $R^2$ and lower root mean square error (RMSE) (Table 6). Sixty-one sites with average annual $R_H$ in northern high-latitude regions were used to further evaluate the new model performance. The dormancy model has lower intercept and slope with $R^2$ of 0.45, while $R^2$ of MIC-TEM is 0.3 (Figure 6). These analyses indicate that new model is more realistic in representing $R_H$ by considering microbial dormancy. This difference in $R_H$ further affects soil available nitrogen dynamics, influencing nitrogen uptake by plants, the rate of photosynthesis and NPP (Zhuang et al., 2015; Zha et al., 2018; Thullner et al., 2005).

3.2 Regional carbon dynamics during the 20th century

Regional extrapolation with both models estimated a regional carbon sink but with different magnitudes (Figure 7c). With optimized parameters, MIC-TEM estimated a regional carbon sink of 77.6 Pg with the interannual standard deviation of 0.21 Pg C yr$^{-1}$ during the 20th century. However, MIC-TEM-dormancy nearly doubles the sink at 153.5 Pg with the interannual standard
deviation of 0.12 Pg C yr\(^{-1}\) during the last century (Figure 7c). At the end of the century, MIC-TEM estimated that NEP reaches 1.0 Pg C yr\(^{-1}\) in comparison with MIC-TEM-dormancy estimates of 1.5 Pg C yr\(^{-1}\) (Figure 7c). Both models simulated similar trends for regional NPP, R\(_H\) and NEP (Figure 7). Generally, they show an increasing trend in the 20th century (Figure 7). Meanwhile, with optimized parameters, MIC-TEM-dormancy estimated NPP and R\(_H\) at 7.94 Pg C yr\(^{-1}\) and 6.4 Pg C yr\(^{-1}\), which are 5.8% and 16.3% less than the estimations from MIC-TEM, respectively (Figures 7a and 7b). This pronounced difference of NEP between two models comes from the disparity between the simulated NPP and R\(_H\) with them since NEP is calculated as the difference between NPP and R\(_H\). Without considering dormancy, MIC-TEM estimates more active microbial biomass since it assumes the whole microbial biomass pool will participate in soil decomposition. The fact is only active part of microbial biomass can affect organic matter decomposition, meaning MIC-TEM overestimates R\(_H\). On the other hand, overestimation of R\(_H\) can induce higher nitrogen uptake by plants, which will accelerate rate of photosynthesis and further enhance NPP projection. Although MIC-TEM estimates higher NPP and R\(_H\) than MIC-TEM-dormancy does, NEP estimated from MIC-TEM is actually lower.

The average annual seasonal patterns of NPP, R\(_H\) and NEP during the 1990s were also organized from regional simulations with two models (Figure 8). Temporally, both models projected higher NPP and R\(_H\) in summer than in winter (Figures 8a and 8b) due to higher soil temperature and moisture (McGuire et al., 1992). Setting the R\(_H\) projection from MIC-TEM as a baseline, MIC-TEM-dormancy averagely projected 33% less R\(_H\) in summer (May to September), and 30% more in winter (other months) (Figure 8b), which indicates that without dormancy, model tends to estimate lower soil respiration compared to dormancy model due to ignorance of dormant respiration in winter but estimate higher soil respiration due to higher estimation of
active biomass in summer. In the meantime, seasonal cycle of NPP with MIC-TEM-dormancy shows a relative flattening pattern compared with MIC-TEM, which is similar to seasonal cycle of $R_{hf}$ (Figure 8a). Though $R_{hf}$ and NPP show the similar seasonal patterns, NEP can still show different pattern. Here seasonal cycles of NEP with models are close to each other (Figure 8c), but dormancy model projected slightly higher NEP in summer.

3.3 Regional carbon dynamics during the 21st century

Under the RCP 8.5 scenario, both models estimated the region acts as a carbon sink (Figure 9). The MIC-TEM-dormancy predicted a C accumulation of 129.9 Pg by the end of this century with the interannual standard deviation of 0.13 Pg C yr$^{-1}$, whereas MIC-TEM estimates a C accumulation of 79.5 Pg with the interannual standard deviation of 0.37 Pg C yr$^{-1}$ during the 21st century (Figure 9). Thus, MIC-TEM-dormancy estimates an increase of 50.4 Pg regional carbon sequestration relative to MIC-TEM, with less interannual variation (Figure 9). Under this scenario, both models predict similar temporal trends for NEP, namely increasing from the 2000s and then decreasing from the 2070s onward (Figure 9). MIC-TEM-dormancy predicts that carbon sink reaches 1.36 Pg C yr$^{-1}$ in the 2090s, which is 0.26 Pg C yr$^{-1}$ more than projection of MIC-TEM. Moreover, MIC-TEM-dormancy estimated NPP and $R_H$ at 10.2 Pg C yr$^{-1}$ and 8.9 Pg C yr$^{-1}$, which are 1.3 Pg C yr$^{-1}$ and 1.8 Pg C yr$^{-1}$ less than the estimations from MIC-TEM, respectively (Figure 9).

Under the RCP 2.6 scenario, the cumulative NEP from two models diverged by 125.2 Pg C by 2100. The trajectory of inter-annual NEP estimated with the two models also diverged. The MIC-TEM predicted the region fluctuates between carbon sinks and sources, and totally acts as a carbon source of 1.6 Pg C with the interannual standard deviation of 0.24 Pg C yr$^{-1}$ during the 21st century. In contrast, MIC-TEM-dormancy projected the region acts as a carbon sink of 123.6
Pg C with an interannual standard deviation of 0.1 Pg C yr$^{-1}$ (Figure 9). MIC-TEM-dormancy estimates NPP and $R_H$ at 9.9 Pg C yr$^{-1}$ and 8.7 Pg C yr$^{-1}$, which are 0.5 Pg C yr$^{-1}$ and 1.7 Pg C yr$^{-1}$ less than the estimations from MIC-TEM, respectively (Figure 9). Moreover, simulations under the two contrasting climate scenarios (RCP 2.6 and RCP 8.5) exhibit a large difference of 81.1 Pg C of cumulative NEP during the 21st century by MIC-TEM, but only 6.3 Pg C of that by MIC-TEM-dormancy. This difference indicates microbes provide a resistant response to climate change due to dormancy to some extent (Treseder et al., 2011).

The average annual seasonal patterns of NPP, $R_H$ and NEP during the 2990s by two models were also presented (Figure 10). MIC-TEM-dormancy estimated higher $R_H$ in winter, but lower $R_H$ in summer under both future scenarios (Figure 10). NPP is the same in winter with or without dormancy, and in the late summer is higher than that without dormancy, especially in the RCP 8.5 scenario. The combined flattening patterns of NPP and $R_H$ result in different patterns for NEP. Under the RCP 2.6 scenario, MIC-TEM-dormancy predicts higher NEP from June to October, but lower NEP from January to April compared to MIC-TEM (Figure 10). Under the RCP 8.5 scenario, MIC-TEM-dormancy predicts higher NEP from June to September, but much lower NEP in other months than MIC-TEM (Figure 10).

3.4 Regional uncertainty considering equifinality effects during 20th and 21st centuries

The ensemble simulations for the 20th century is shown in Figure 11. Given the uncertainty in parameters, MIC-TEM-dormancy predicted that the regional cumulative carbon ranges from a carbon loss of 28.2 Pg to a carbon sink of 362.1 Pg by different ensemble members, with a mean of 71.2±54.8 Pg (Figure 11). For the 21st century, MIC-TEM-dormancy predicted that the region acts from a carbon source of 49.3 Pg C to a carbon sink of 296.5 Pg C, with a mean of 112.7±116.5 Pg under the RCP 2.6 scenario (Figure 12). Under the RCP 8.5
scenario, MIC-TEM-dormancy predicted that the region acts from a carbon source of 27.1 Pg C to a carbon sink of 401.3 Pg C, with a mean of 143.1±162.5 Pg (Figure 12).

4. Discussion

Soils are the largest carbon repository in the terrestrial biosphere and hold 2.5 times more carbon than the atmosphere (Frey et al., 2013; Schlesinger & Andrews, 2000). Especially, a significant portion of soil organic carbon stored in northern high latitudes (Tarnocai et al., 2009). Besides, the magnitude of the warming in these regions is larger, almost twice, that of the global average (Serreze & Francis, 2006) and the changing climate is expected to alter the carbon cycle through influencing the activities of microorganisms in controlling soil decomposition (Manzoni et al., 2012; Melillo et al., 2011). Therefore, explicit consideration of microbial traits and functions in large-scale biogeochemistry models is necessary for better quantification of carbon-climate feedbacks (Thullner et al., 2005; Wang et al., 2015). Our regional simulations with two contrasting models (MIC-TEM, MIC-TEM-dormancy) indicate the region was a carbon sink in past decades, which is consistent with results from other process-based models (White et al., 2000; Houghton et al., 2007; McGuire et al., 2009; Schimel, 2013). However, the magnitudes of this sink are quite different in two models. Moreover, MIC-TEM-dormancy predicts the sink will decrease under both RCP 8.5 and RCP 2.6 scenarios during the 21st century, while MIC-TEM projects that the sink will increase under the RCP 8.5 but change to carbon source under the RCP 2.6 scenario. Estimations based on models without dormancy could fit observations of $R_H$ as well as estimations with dormancy, but at the cost of underestimating microbial biomass (Wang et al., 2014). Differences in predicted $R_H$ with and without dormancy increase with temperature and with the length of the dry periods between wetting events (Salazar et al., 2018). The large difference in two models suggests the importance of incorporating microbial dormancy effects.
The large bias between dormancy and non-dormancy models mainly comes from two parts. First, many important microbial activities such as soil organic carbon decomposition and nutrient cycling largely depend on the active fraction of microbial communities, not total microbial biomass (Wang et al., 2014; Blagodatsky et al., 2000). However, only a small part (about 0.1-2%, seldom exceed 5%) of the total soil microbial biomass is recognized to be active under natural conditions (Blagodatsky et al., 2011; Werf & Verstraete, 1987). Thus, dormancy could be a prominent feature in soil systems (Wang et al., 2014). Without considering dormancy, the “effective” microbial biomass for soil decomposition could be overestimated, resulting in overestimation of heterotrophic respiration (He et al., 2015). He et al. (2015) predicted total soil $R_H$ of all temperate forests (25°N-50°N) from the dormancy model amounted to 7.28 Pg C yr$^{-1}$ and 8.83 Pg C yr$^{-1}$ from a no-dormancy model, which is 21.3% higher than the dormancy model. Although their study region and simulation period are different from our study, the results can still be comparable. Both studies indicated that the magnitude of $R_H$ from no-dormancy model are higher than dormancy models. Second, high soil respiration stimulates N mineralization in soils (Zhuang et al., 2001, 2002), making more nutrients for photosynthesis of plants (Raich et al., 1991; McGuire et al., 1995). Therefore, NPP will be higher due to the N enrichment from higher $R_H$. However, how NEP will change is still unclear. Our estimates of the northern extratropical NEP in the 1980s (1.61 Pg C yr$^{-1}$ with MIC-TEM-dormancy and 0.84 Pg C yr$^{-1}$ with MIC-TEM) are within ranges (0.6 to 2.3 PgC yr$^{-1}$) reported in the literature for northern regions (Schimel et al., 2001). Moreover, our predicted time trajectory of NEP in the 21st century under the RCP 2.6 scenario is very similar to the finding of White et al. (2000), indicating that NEP increases from the 2000s to the 2070s, and then decreases in the 2090s. Although our dormancy model can project reasonable carbon fluxes and indicate the importance
of incorporating microbial dormancy when compared with MIC-TEM (Zha & Zhuang et al., 2018), there are some other microbial traits have not yet been considered in our model. For instance, one vital common evolutionary trait of microbe is the community shift (Wang et al., 2015) with changing environment, including warming, N fertilization and precipitation (Treseder et al., 2011; Frey et al., 2013; Allison et al., 2009; Evans & Wallenstein, 2011). Community shift will influence microbial physiology, temperature sensitivity and growth rates (Classen et al., 2015), which will further affect the rate of soil decomposition and other carbon dynamics (Treseder et al., 2011; Schimel & Schaeffer, 2012; Todd-Brown et al., 2011). Besides, microbial community composition was ignored in our model. We didn’t separate among functional microbial groups, but gather microbes into one “box”. However, microbial community composition could influence ecosystem functioning, and their variance in responses to environmental conditions could alter the prediction of the rates of decomposition of organic material (Balser et al. 2002; Fierer et al. 2007). Especially, some narrowly-distributed functions can be more sensitive to microbial community composition, and these might benefit most from explicit consideration of distinguishing functional groups in ecosystem models (McGuire & Treseder, 2010; Schimel 1995). Thus, functional dissimilarity in microbial communities can be considered in next step for model development (Strickland et al., 2009; Moorhead et al., 2006). Moreover, microbial acclimation, a mechanism of adaption to a new temperature regime, is another important trait to affect soil decomposition. Recent studies have found that the warming-induced elevated respiration of the microbial community could decrease over time because of acclimation (Melillo et al. 1993; Todd-Brown et al., 2011). This mechanism shall be factored into future soil decomposition analysis.
Except for model limitations mentioned above, additional uncertainties may come from inadequate model parameterization and model assumptions. For example, a critical microbial parameter, carbon use efficiency (CUE), is a primary control to soil CO$_2$ efflux. Higher CUE indicates more microbial growth and more carbon uptake by plants, while lower CUE indicates higher soil decomposition (Manzoni et al., 2012). Theoretical and empirical studies have suggested that CUE depends on both temperature and substrate quality (Frey et al., 2013) and decreases as temperature increases and nutrient availability decreases (Manzoni et al., 2012). Our study considered the CUE sensitivity to temperature, but not nutrient availability. On the other hand, some model assumptions can also cause uncertainties. For example, we assumed that vegetation will not change during the transient simulation. However, over the past few decades in northern high latitudes, temperature increases have led to vegetation shift from one type to another (Hansen et al., 2006; White et al., 2000). The vegetation changes will affect carbon cycling in these ecosystems.

While our analysis suggests it is important to incorporate microbial dormancy dynamics into a process-based biogeochemistry model to more adequately simulate carbon dynamics in northern high latitudes, we do confront modeling dilemmas. First, our process-based models have a relatively large number of parameters, which unavoidably creates the “equifinality” problem as recognized in our previous studies for the model (e.g., Tang and Zhuang, 2008, 2009). To alleviate this problem in this analysis, we have conducted parameter ensemble simulations at both site and regional levels and presented our results with uncertainties, which could be a standard approach for process-based complex biogeochemistry modeling analyses. Second, incorporating more ecosystem processes increases the number of parameters in our model, inducing even larger uncertainties for both site level and regional simulations. On the
one hand, the more complex model to a certain degree helps capture observations, on the other hand, the model uncertainty has not been constrained or even enlarged. We highlight the need to further investigate this trade-off within the modeling research community.

5. Conclusions

This study incorporated microbial dormancy into a detailed microbial-based soil decomposition biogeochemistry model to examine the fate of large Arctic soil carbon under changing climate conditions. Regional simulations using MIC-TEM-dormancy indicated that, over the 20th century, the region is a carbon sink of $166.8 \pm 97.7 \pm 53.5$ Pg. This sink could decrease to $175.9 \pm 105.4 \pm 29.9$ Pg under the RCP 8.5 scenario or $125.4 \pm 85.5 \pm 23.6$ Pg under the RCP 2.6 scenario during the 21st century. Whether considering microbial dormancy or not can cause large differences in soil decomposition estimation between two models. Meanwhile, due to available nitrogen affected by soil decomposition, net primary production is consequently influenced in these two centuries. The combined changes in soil decomposition and net primary production led to large differences in carbon budget estimation between two models. Compared with MIC-TEM, MIC-TEM-dormancy projected 75.9 Pg more C stored in the terrestrial ecosystems over the last century, 50.4 Pg and 125.2 Pg more C under the RCP 8.5 and RCP 2.6 scenarios, respectively. This study highlights the importance of the representation of microbial dormancy in earth system models in order to adequately quantify the carbon dynamics in northern high latitudes.
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References:

Allison, E. H., Perry, A. L., Badjeck, M.-C., Neil Adger, W., Brown, K., Conway, D., Halls, A. S., Pilling, G. M., Reynolds, J. D., Andrew, N. L., and Dulvy, N. K.: Vulnerability of national economies to the impacts of climate change on fisheries, Fish and Fisheries, 10, 173-196, 10.1111/j.1467-2979.2008.00310.x, 2009.

Allison, S. D., Wallenstein, M. D., and Bradford, M. A.: Soil-carbon response to warming dependent on microbial physiology, Nature Geoscience, 3, 336-340, 10.1038/ngeo846, 2010.

Balser, T. C., Kinzig, A. P., and Firestone, M. K.: Linking soil microbial communities and ecosystem functioning, The functional consequences of biodiversity: Empirical progress and theoretical extensions, 265-293, 2002.

Blagodatskaya, E., and Kuzyakov, Y.: Active microorganisms in soil: Critical review of estimation criteria and approaches, Soil Biology and Biochemistry, 67, 192-211, 10.1016/j.soilbio.2013.08.024, 2013.

Blagodatskaya, E., Khomyakov, N., Myachina, O., Bogomolova, I., Blagodatsky, S., and Kuzyakov, Y.: Microbial interactions affect sources of priming induced by cellulose, Soil Biology and Biochemistry, 74, 39-49, 10.1016/j.soilbio.2014.02.017, 2014.

Blagodatsky, S., Grote, R., Kiese, R., Werner, C., and Butterbach-Bahl, K.: Modelling of microbial carbon and nitrogen turnover in soil with special emphasis on N-trace gases emission, Plant and soil, 346, 297-330, 10.1007/s11104-011-0821-z, 2011.

Blagodatsky, S. A., Heinemeyer, O., and Richter, J.: Estimating the active and total soil microbial biomass by kinetic respiration analysis, Biol Fertil Soils, 32, 73-81, 2000.

Bond-Lamberty, B., and Thomson, A.: Temperature-associated increases in the global soil respiration record, Nature, 464, 579-582, 10.1038/nature08930, 2010.
Bond-Lamberty, B., Bailey, V. L., Chen, M., Gough, C. M., and Vargas, R.: Globally rising soil heterotrophic respiration over recent decades, Nature, 560, 80-83, 10.1038/s41586-018-0358-x, 2018.

Bouskill, N. J., Tang, J., Riley, W. J., and Brodie, E. L.: Trait-based representation of biological nitrification: model development, testing, and predicted community composition, Frontiers in microbiology, 3, 364, 10.3389/fmicb.2012.00364, 2012.

Callaghan, T., Björn, L. O., Chernov, Y., Chapin, T., Christensen, T. R., Huntley, B., Ims, R., Jolly, D., Jonasson, S., Matveyeva, N., Panikov, N., Oechel, W., and Shaver, G.: Arctic tundra and polar desert ecosystems, Arctic climate impact assessment, 243-352, 2005.

Carney, K. M., and Matson, P. A.: The influence of tropical plant diversity and composition on soil microbial communities, Microbial ecology, 52, 226-238, 10.1007/s00248-006-9115-z, 2006.

Chmielewski, R. A. N., and Frank, J. F.: Formation of viable but nonculturable Salmonella during starvation in chemically defined solutions, Letters in Applied Microbiology, 20, 380-384, 1995.

Classen, A. T., Sundqvist, M. K., Henning, J. A., Newman, G. S., Moore, J. A. M., Cregger, M. A., Moorhead, L. C., and Patterson, C. M.: Direct and indirect effects of climate change on soil microbial and soil microbial-plant interactions: What lies ahead?, Ecosphere, 6, art130, 10.1890/es15-00217.1, 2015.

Conant, R. T., Ryan, M. G., Ågren, G. I., Birge, H. E., Davidson, E. A., Eliasson, P. E., Evans, S. E., Frey, S. D., Giardina, C. P., Hopkins, F. M., Hyvönen, R., Kirschbaum, M. U. F., Lavalle, J. M., Leifeld, J., Parton, W. J., Megan Steinweg, J., Wallenstein, M. D., Martin Wetterstedt, J. Å., and Bradford, M. A.: Temperature and soil organic matter decomposition rates - synthesis of current knowledge and a way forward, Global change biology, 17, 3392-3404, 10.1111/j.1365-2486.2011.02496.x, 2011.

Coursolle, C., Margolis, H. A., Barr, A. G., Black, T. A., Amiro, B. D., McCaughey, J. H., Flanagan, L. B., Lafleur, P. M., Roulet, N. T., Bourque, C. P. A., Arain, M. A., Wofsy, S. C., Dunn, A., Morgenstern, K., Orchansky, A. L., Bernier, P. Y., Chen, J. M., Kidston, J., Saigusa, N., and Hedstrom, N.: Late-summer carbon fluxes from Canadian forests and peatlands along an east–west continental transect, Canadian Journal of Forest Research, 36, 783-800, 10.1139/x05-270, 2006.

Davidson, E. A., Trumbore, S. E., and Amundson, R.: Biogeochemistry: soil warming and organic carbon content, Nature, 408, 2000.

Davidson, E. A., and Janssens, I. A.: Temperature sensitivity of soil carbon decomposition and feedbacks to climate change, Nature, 440, 165-173, 10.1038/nature04514, 2006.

Davidson, E. A., Janssens, I. A., and Luo, Y.: On the variability of respiration in terrestrial ecosystems: moving beyond Q10, Global change biology, 12, 154-164, 10.1111/j.1365-2486.2005.01065.x, 2006.

Duan, Q., Sorooshian, S., and Gupta, V. K.: Optimal use of the SCE-UA global optimization method for calibrating watershed models, Journal of Hydrology, 158, 265-284, 1994.

Evans, S. E., and Wallenstein, M. D.: Soil microbial community response to drying and rewetting stress: does historical precipitation regime matter?, Biogeochemistry, 109, 101-116, 10.1007/s10533-011-9638-3, 2011.
Fierer, N., Morse, J. L., Berthrong, S. T., Bernhardt, E. S., and Jackson, R. B.: Environmental controls on the landscape-scale biogeography of stream bacterial communities, Ecology, 88, 2162-2173, 2007.

Frey, S. D., Lee, J., Melillo, J. M., and Six, J.: The temperature response of soil microbial efficiency and its feedback to climate, Nature Climate Change, 3, 395-398, 10.1038/nclimate1796, 2013.

German, D. P., Marcelo, K. R. B., Stone, M. M., and Allison, S. D.: The Michaelis-Menten kinetics of soil extracellular enzymes in response to temperature: a cross-latitudinal study, Global change biology, 18, 1468-1479, 10.1111/j.1365-2486.2011.02615.x, 2012.

Gilmanov, T. G., Tieszen, L. L., Wylie, B. K., Flanagan, L. B., Frank, A. B., Haferkamp, M. R., Meyers, T. P., and Morgan, J. A.: Integration of CO2 flux and remotely-sensed data for primary production and ecosystem respiration analyses in the Northern Great Plains: potential for quantitative spatial extrapolation, Global Ecology and Biogeography, 14, 271-292, 10.1111/j.1466-822X.2005.00151.x, 2005.

Gough, C. M., Hardiman, B. S., Nave, L. E., Bohrer, G., Maurer, K. D., Vogel, C. S., Nadelhoffer, K. J., and Curtis, P. S.: Sustained carbon uptake and storage following moderate disturbance in a Great Lakes forest, Ecological Applications, 23, 1202-1215, 2013.

Goulden, M. L., Winston, G. C., McMillan, A. M. S., Litvak, M. E., Read, E. L., Rocha, A. V., and Rob Elliot, J.: An eddy covariance mesonet to measure the effect of forest age on land-atmosphere exchange, Global change biology, 12, 2146-2162, 10.1111/j.1365-2486.2006.01251.x, 2006.

Graham, E. B., Wieder, W. R., Leff, J. W., Weintraub, S. R., Townsend, A. R., Cleveland, C. C., Philippot, L., and Nemergut, D. R.: Do we need to understand microbial communities to predict ecosystem function? A comparison of statistical models of nitrogen cycling processes, Soil Biology and Biochemistry, 68, 279-282, 10.1016/j.soilbio.2013.08.023, 2014.

Graham, E. B., Knemelia, J. E., Schindlbacher, A., Siciliano, S., Breulmann, M., Yannarello, A., Beman, J. M., Abell, G., Philippot, L., Prossec, J., Foulquier, A., Yuste, J. C., Glanville, H. C., Jones, D. L., Angel, R., Salminen, J., Newton, R. J., Burgmann, H., Ingram, L. J., Hamer, U., Siljanen, H. M., Peltoniemi, K., Potthast, K., Baneras, L., Hartmann, M., Banerjee, S., Yu, R. Q., Nogaro, G., Richter, A., Koranda, M., Castle, S. C., Gobena, M., Song, B., Chatterjee, A., Nunes, O. C., Lopes, A. R., Cao, Y., Kaisermann, A., Hallin, S., Strickland, M. S., Garcia-Pausas, J., Barba, J., Kang, H., Isobe, K., Papaspyrou, S., Pastorelli, R., Lagomarsino, A., Lindstrom, E. S., Basiliko, N., and Nemergut, D. R.: Microbes as Engines of Ecosystem Function: When Does Community Structure Enhance Predictions of Ecosystem Processes?, Frontiers in microbiology, 7, 214, 10.3389/fmicb.2016.00214, 2016.

Griffis, T. J., Lee, X., Baker, J. M., Billmark, K., Schultz, N., Erickson, M., Zhang, X., Fassbinder, J., Xiao, W., and Hu, N.: Oxygen isotope composition of evapotranspiration and its relation to C4 photosynthetic discrimination, Journal of Geophysical Research, 116, 10.1029/2010jg001514, 2011.

Hagerty, S. B., van Groenigen, K. J., Allison, S. D., Hungate, B. A., Schwartz, E., Koch, G. W., Kolka, R. K., and Dijkstra, P.: Accelerated microbial turnover but constant growth efficiency with warming in soil, Nature Climate Change, 4, 903-906, 10.1038/nclimate2361, 2014.

Hansen, J., Sato, M., Ruedy, R., Lo, K., Lea, D. W., and Medina-Elizade, M.: Global temperature change, Proceedings of the National Academy of Sciences of the United States of America, 103, 14288-14293, 10.1073/pnas.0606291103, 2006.
Harder, w., and Dijkhuizen, L.: Physiological responses to nutrient limitation, Annual Review of Microbiology, 37, 1983.

Harris, I., Jones, P. D., Osborn, T. J., and Lister, D. H.: Updated high-resolution grids of monthly climatic observations - the CRU TS3.10 Dataset, International Journal of Climatology, 34, 623-642, 10.1002/joc.3711, 2014.

He, Y., Yang, J., Zhuang, Q., Harden, J. W., McGuire, A. D., Liu, Y., Wang, G., and Gu, L.: Incorporating microbial dormancy dynamics into soil decomposition models to improve quantification of soil carbon dynamics of northern temperate forests, Journal of Geophysical Research: Biogeosciences, 120, 2596-2611, 10.1002/2015jg003130, 2015.

Hugelius, G., Strauss, J., Zubrzycki, S., Harden, J. W., Schuur, E. A. G., Ping, C. L., Schirrmeister, L., Grosse, G., Michaelson, G. J., Koven, C. D., amp, apos, Donnell, J. A., Elberling, B., Mishra, U., Camill, P., Yu, Z., Palmtag, J., and Kuhry, P.: Estimated stocks of circumpolar permafrost carbon with quantified uncertainty ranges and identified data gaps, Biogeosciences, 11, 6573-6593, 10.5194/bg-11-6573-2014, 2014.

Jenkins, J. P., Richardson, A. D., Braswell, B. H., Ollinger, S. V., Hollinger, D. Y., and Smith, M. L.: Refining light-use efficiency calculations for a deciduous forest canopy using simultaneous tower-based carbon flux and radiometric measurements, Agricultural and Forest Meteorology, 143, 64-79, 10.1016/j.agrformet.2006.11.008, 2007.

Kaiser, C., Franklin, O., Dieckmann, U., and Richter, A.: Microbial community dynamics alleviate stoichiometric constraints during litter decay, Ecology letters, 17, 680-690, 10.1111/ele.12269, 2014.

Knorr, W., Prentice, I. C., House, J. I., and Holland, E. A.: Long-term sensitivity of soil carbon turnover to warming, Nature, 433, 2005.

Lawrence, C. R., Neff, J. C., and Schimel, J. P.: Does adding microbial mechanisms of decomposition improve soil organic matter models? A comparison of four models using data from a pulsed rewetting experiment, Soil Biology and Biochemistry, 41, 1923-1934, 10.1016/j.soilbio.2009.06.016, 2009.

Lennon, J. T., and Jones, S. E.: Microbial seed banks: the ecological and evolutionary implications of dormancy, Nature reviews. Microbiology, 9, 119-130, 10.1038/nrmicro2504, 2011.

Lloyd, A. H., Rupp, T. S., Fastie, C. L., and Starfield, A. M.: Patterns and dynamics of treeline advance on the Seward Peninsula, Alaska, Journal of Geophysical Research, 108, 10.1029/2001jd000852, 2002.

Manzoni, S., Taylor, P., Richter, A., Porporato, A., and Agren, G. I.: Environmental and stoichiometric controls on microbial carbon-use efficiency in soils, The New phytologist, 196, 79-91, 10.1111/j.1469-8137.2012.04225.x, 2012.

McEwing, K. R., Fisher, J. P., and Zona, D.: Environmental and vegetation controls on the spatial variability of CH4 emission from wet-sedge and tussock tundra ecosystems in the Arctic, Plant and soil, 388, 37-52, 10.1007/s11104-014-2377-1, 2015.

McGuire, A. D., Melillo, J. M., Joyce, L. A., Kicklighter, D. W., Grace, A. L., III, B. M., and Vorosmarty, C. J.: Interactions between carbon and nitrogen dynamics in estimating net primary
productivity for potential vegetation in North America, Global Biogeochemical Cycles, 6, 101-124, 1992.

McGuire, A. D., Melillo, J. M., Kicklighter, D. W., and Joyce, L. A.: Equilibrium responses of soil carbon to climate change: Empirical and process-based estimates, Journal of Biogeography, 22, 785-796, 1995.

McGuire, A. D., and Hobbie, J. E.: Global climate change and the equilibrium responses of carbon storage in arctic and subarctic regions, In Modeling the Arctic system: A workshop report on the state of modeling in the Arctic System Science program, 53-54, 1997.

McGuire, A. D., Anderson, L. G., Christensen, T. R., Dallimore, S., Guo, L., Hayes, D. J., Heimann, M., Lorenson, T. D., Macdonald, R. W., and Roulet, N.: Sensitivity of the carbon cycle in the Arctic to climate change, Ecological Monographs, 79, 523-555, 2009.

McGuire, K. L., and Treseder, K. K.: Microbial communities and their relevance for ecosystem models: Decomposition as a case study, Soil Biology and Biochemistry, 42, 529-535, 10.1016/j.soilbio.2009.11.016, 2010.

Me´tris, A., Gerrard, A. M., Cumming, R. H., Weigner, P., and Paca, J.: Modelling shock loadings and starvation in the biofiltration of toluene and xylene, Journal of Chemical Technology and Biotechnology, 76, 565-572, 2001.

Melillo, J. M., McGuire, A. D., Kicklighter, D. W., III, B. M., Vorosmarty, C. J., and Schloss, A. L.: Global climate change and terrestrial net primary production, Nature, 363, 1993.

Melillo, J. M., Butler, S., Johnson, J., Mohan, J., Steudler, P., Lux, H., Burrows, E., Bowles, F., Smith, R., Scott, L., Vario, C., Hill, T., Burton, A., Zhou, Y.-M., and Tang, J.: Soil warming, carbon - nitrogen interactions, and forest carbon budgets, PNAS, 108, 9508-9512, 2011.

Merbold, L., Kutsch, W. L., Corradi, C., Kolle, O., Rebmann, C., Stoy, P. C., Zimov, S. A., and Schulze, E. D.: Artificial drainage and associated carbon fluxes (CO2/CH4) in a tundra ecosystem, Global change biology, 15, 2599-2614, 10.1111/j.1365-2486.2009.01962.x, 2009.

Moorhead, D. L., and Sinsabaugh, R. L.: A theoretical model of litter decay and microbial interaction, Ecological Monographs, 76, 151-174, 2006.

Oechel, W. C., Laskowski, C. A., Burba, G., Gioli, B., and Kalhori, A. A. M.: Annual patterns and budget of CO2flux in an Arctic tussock tundra ecosystem, Journal of Geophysical Research: Biogeosciences, 119, 323-339, 10.1002/2013jg002431, 2014.

P.J. Hanson, N. T. E., C.T. Garten, J.A. Andrews: Separating root and soil microbial contributions to soil respiration: A review of methods and observations, Biochemistry, 48, 115-146, 2000.

Parton, W. J., Scurlock, J. M. O., Ojima, D. S., Gilmanov, T. G., Scholes, R. J., Schimel, D. S., Kirchner, T., Menaut, J. C., Seastedt, T., Moya, E. G., Kamnalrut, A., and Kinyamario, J. I.: Observations and modeling of biomass and soil organic matter dynamics for the grassland biome worldwide, Global Biogeochemical Cycles, 7, 785-809, 1993.

Raich, J. W., Rastetter, E. B., Melillo, J. M., Kicklighter, D. W., Steudler, P. A., Peterson, B. J., Grace, A. L., III, B. M., and Vorosmarty, C. J.: Potential net primary productivity in South America: application of a global model, Ecological Applications, 1, 399-429, 1991.

Richardson, A. D., Jenkins, J. P., Braswell, B. H., Hollinger, D. Y., Ollinger, S. V., and Smith, M. L.: Use of digital webcam images to track spring green-up in a deciduous broadleaf forest, Oecologia, 152, 323-334, 10.1007/s00442-006-0657-z, 2007.

Running, S. W., and Coughlan, J. C.: A general model of forest ecosystem processes for regional applications I. Hydrologic balance, canopy gas exchange and primary production processes., Ecological Modelling, 42, 125-154, 1988.
Schimel, D. S.: Terrestrial ecosystems and the carbon cycle, Global change biology, 1, 77-91, 1995.

Schimel, D. S., House, J. I., Hibbard, K. A., Bousquet, P., Ciais, P., Peylin, P., Braswell, B. H., Apps, M. J., Baker, D., Bondeau, A., Canadell, J., Churkina, G., Cramer, W., Denning, A. S., Field, C. B., Friedlingstein, P., Goodale, C., Heimann, M., Houghton, R. A., Melillo, J. M., III, B. M., Murdiyarso, D., Noble, I., Pacala, S. W., Prentice, I. C., Raupach, M. R., Rayner, P. J., Scholes, R. J., Steffen, W. L., and Wirth, C.: Recent patterns and mechanisms of carbon exchange by terrestrial ecosystems, Nature, 414, 2001.

Schimel, J.: Microbes and global carbon, Nature Climate Change, 3, 867-868, 10.1038/nclimate2015, 2013.

Schimel, J. P., and Weintraub, M. N.: The implications of exoenzyme activity on microbial carbon and nitrogen limitation in soil: a theoretical model, Soil Biology and Biochemistry, 35, 549-563, 10.1016/s0038-0717(03)00015-4, 2003.

Schimel, J. P., and Schaeffer, S. M.: Microbial control over carbon cycling in soil, Frontiers in microbiology, 3, 348, 10.3389/fmicb.2012.00348, 2012.

Schlesinger, W. H., and Andrews, J. A.: Soil respiration and the global carbon cycle, Biogeochemistry, 48, 7-20, 2000.

Schmidt, M. W., Torn, M. S., Abiven, S., Dittmar, T., Guggenberger, G., Janssens, I. A., Kleber, M., Kogel-Knabner, I., Lehmann, J., Manning, D. A., Nannipieri, P., Rasse, D. P., Weiner, S., and Trumbore, S. E.: Persistence of soil organic matter as an ecosystem property, Nature, 478, 49-56, 10.1038/nature10386, 2011.

Serreze, M. C., and Francis, J. A.: The Arctic on the fast track of change, Weather, 61, 65-69, 2006.

Stolpovsky, K., Martinez-Lavanchy, P., Heipieper, H. J., Van Cappellen, P., and Thullner, M.: Incorporating dormancy in dynamic microbial community models, Ecological Modelling, 222, 3092-3102, 10.1016/j.ecolmodel.2011.07.006, 2011.

Stow, D. A., Hope, A., McGuire, D., Verbyla, D., Gamon, J., Huemmrich, F., Houston, S., Racine, C., Sturm, M., Tape, K., Hinzman, L., Yoshikawa, K., Tweedie, C., Noyle, B., Silapaswan, C., Douglas, D., Griffith, B., Jia, G., Epstein, H., Walker, D., Daeschner, S., Petersen, A., Zhou, L., and Myneni, R.: Remote sensing of vegetation and land-cover change in Arctic Tundra Ecosystems, Remote Sensing of Environment, 89, 281-308, 10.1016/j.rse.2003.10.018, 2004.

Strickland, M. S., Lauber, C., Fierer, N., and Bradford, M. A.: Testing the functional significance of microbial community composition, Ecology, 90, 441-451, 2009.

Tang, J., Q. Zhuang (2009) A global sensitivity analysis and Bayesian inference framework for improving the parameter estimation and prediction of a process-based Terrestrial Ecosystem Model J. Geophys. Res., 114, D15303, doi:10.1029/2009JD011724., 2009.

Tang, J., Q. Zhuang (2008) Equifinality in parameterization of process-based biogeochemistry models: A significant uncertainty source to the estimation of regional carbon dynamics J. Geophys. Res., 113, G04010, doi:10.1029/2008JG000757, 2008.

Tang, J., and Riley, W. J.: Weaker soil carbon–climate feedbacks resulting from microbial and abiotic interactions, Nature Climate Change, 5, 56-60, 10.1038/nclimate2438, 2014.

Tape, K. E. N., Sturm, M., and Racine, C.: The evidence for shrub expansion in Northern Alaska and the Pan-Arctic, Global change biology, 12, 686-702, 10.1111/j.1365-2486.2006.01128.x, 2006.
Tarnocai, C., Canadell, J. G., Schuur, E. A. G., Kuhry, P., Mazhitova, G., and Zimov, S.: Soil organic carbon pools in the northern circumpolar permafrost region, Global Biogeochemical Cycles, 23, n/a-n/a, 10.1029/2008gb003327, 2009.

Thullner, M., Van Cappellen, P., and Regnier, P.: Modeling the impact of microbial activity on redox dynamics in porous media, Geochimica et Cosmochimica Acta, 69, 5005-5019, 10.1016/j.gca.2005.04.026, 2005.

Todd-Brown, K. E. O., Hopkins, F. M., Kivlin, S. N., Talbot, J. M., and Allison, S. D.: A framework for representing microbial decomposition in coupled climate models, Biogeochemistry, 109, 19-33, 10.1007/s10533-011-9635-6, 2011.

Wang, G., Jagadamma, S., Mayes, M. A., Schadt, C. W., Steinweg, J. M., Gu, L., and Post, W. M.: Microbial dormancy improves development and experimental validation of ecosystem model, The ISME journal, 9, 226-237, 10.1038/ismej.2014.120, 2015.

Zha, J., and Zhuang, Q.: Microbial decomposition processes and vulnerable arctic soil organic carbon in the 21st century, Biogeosciences, 15, 5621-5634, 10.5194/bg-15-5621-2018, 2018a.

Zha, J., and Zhuang, Q.: Microbial decomposition processes and vulnerable Arctic soil organic carbon in the 21st century, Biogeosciences Discussions, 1-34, 10.5194/bg-2018-241, 2018b.

Zhou, L., Tucker, C. J., Kaufmann, R. K., Slayback, D., Shabanov, N. V., and Myneni, R. B.: Variations in northern vegetation activity inferred from satellite data of vegetation index during
Zhuang, Q., Romanovsky, V. E., and McGuire, A. D.: Incorporation of a permafrost model into a large-scale ecosystem model: Evaluation of temporal and spatial scaling issues in simulating soil thermal dynamics, Journal of Geophysical Research: Atmospheres, 106, 33649-33670, 10.1029/2001jd001244, 2002.

Zhuang, Q., He, J., Lu, Y., Ji, L., Xiao, J., and Luo, T.: Carbon dynamics of terrestrial ecosystems on the Tibetan Plateau during the 20th century: an analysis with a process-based biogeochemical model, Global Ecology and Biogeography, 19, 649-662, 10.1111/j.1466-8238.2010.00559.x, 2010.

Zhuang, Q., Zhu, X., He, Y., Prigent, C., Melillo, J. M., David McGuire, A., Prinn, R. G., and Kicklighter, D. W.: Influence of changes in wetland inundation extent on net fluxes of carbon dioxide and methane in northern high latitudes from 1993 to 2004, Environmental Research Letters, 10, 095009, 10.1088/1748-9326/10/9/095009, 2015.

Zhuang, Q., McGuire, A. D., Melillo, J. M., Clein, J. S., Dargaville, R. J., Kicklighter, D. W., Myneni, R. B., Dong, J., Romanovsky, V. E., Harden, J., and Hobbie, J. E.: Carbon cycling in extratropical terrestrial ecosystems of the Northern Hemisphere during the 20th century: a modeling analysis of the influences of soil thermal dynamics, Tellus B: Chemical and Physical Meteorology, 55, 751-776, 10.3402/tellusb.v55i3.16368, 2016.

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Materials & Correspondence. Correspondence and material requests should be addressed to qzhuang@purdue.edu.
Figure 1. Framework of the dormancy model: microbial biomass is split into two parts, active microbial biomass and dormant microbial biomass (shown in the green dashed circle). Maintenance respiration from these two parts, and the CO₂ production through microbial assimilation contributes to heterotrophic respiration. The model was revised based on Zha & Zhuang (2018).
Figure 2. Comparison between observed and simulated NEP (gC m$^{-2}$mon$^{-1}$) at: (a) Ivotuk (alpine tundra), (b) UCI-1964 burn site (boreal forest), (c) Howland Forest (main tower) (temperate coniferous forest), (d) Univ. of Mich. Biological Station (Temperate deciduous forest), (e) KUOM Turfgrass Field (Grassland), and (f) Atqasuk (Wet tundra). Note: scales are different. Error bars represent standard errors among daily measure data in one month.
Figure 3. Boxplot of parameter posterior distribution that are obtained after ensemble inverse modeling for MIC-TEM-dormancy all six sites: US-Ivo: Iivotuk (alpine tundra), CA-NS3: UCI-1964 burn site (boreal forest), US-Ho1: Howland Forest (temperate coniferous forest), US-UMB: Univ. of Mich. Biological Station (temperate deciduous forest), US-KUT: KUOM Turfgrass Field (grassland), US-Atq: Atqasuk (wet tundra).
Figure 4. Comparison between observed and simulated NEP (gC m$^{-2}$mon$^{-1}$) at: (a) Ivotuk (alpine tundra), (b) UCI-1964 burn site (boreal forest), (c) Howland Forest (main tower) (temperate coniferous forest), (d) Bartlett Experimental Forest (Temperate deciduous forest), (e) Brookings (Grassland), and (f) Atqasuk (Wet tundra). Note: scales are different.
Figure 5. Comparison between observed and simulated $R_H$ (gC m$^{-2}$mon$^{-1}$) at: (a) US-EML (alpine tundra), (b) CA-SJ2 (boreal forest), (c) US-Ho2 (temperate coniferous forest), (d) US-UMB (Temperate deciduous forest), (e) US-Ro4 (Grassland), and (f) RU-Che (Wet tundra). Note: scales are different.
Figure 6. Linear regression between simulated and observed annual $R_H$ (gC m$^{-2}$ yr$^{-1}$) for: (a) MIC-TEM-dormancy, and (b) MIC-TEM.
Figure 7. Simulated annual net primary production (NPP, top panel), heterotrophic respiration ($R_H$, center panel) and net ecosystem production (NEP, bottom panel) during the 20th century by dormancy model and MIC-TEM, respectively.
Figure 8. Annual seasonal pattern of simulated (a) net primary production (NPP, top panel), (b) heterotrophic respiration ($R_{H}$, center panel) and (c) net ecosystem production (NEP, bottom panel) during the 1990s from dormancy model and MIC-TEM.
Figure 9. Predicted changes in carbon fluxes: (i) NPP, (ii) $R_h$, and (iii) NEP for all land areas north of 45°N in response to transient climate change under the RCP 8.5 scenario (left panel) and RCP 2.6 scenario (right panel) with dormancy model and MIC-TEM, respectively. The decadal running mean is applied.
(a)

(b)
Figure 10. Annual seasonal pattern of simulated net primary production (NPP, top panel), heterotrophic respiration ($R_H$, center panel) and net ecosystem production (NEP, bottom panel) during the 2090s from dormancy model and MIC-TEM under: (a) RCP 2.6 scenario (top panel) and (b) RCP 8.5 scenario (bottom panel).
Figure 11. Simulated annual net primary production (NPP, top panel), heterotrophic respiration ($R_H$, center panel) and net ecosystem production (NEP, bottom panel) by MIC-TEM-dormancy with ensemble of parameters.
Figure 12. Simulated annual net primary production (NPP, top panel), heterotrophic respiration ($R_H$, center panel) and net ecosystem production (NEP, bottom panel) under RCP 8.5 scenario (left panel) and RCP 2.6 scenario (right panel) by MIC-TEM-dormancy with ensemble of parameters. The decadal running mean is applied. The grey area represents the upper and lower bounds of simulations.
Table 1. Parameters associated with detailed microbial dormancy in MIC-TEM-dormancy

| parameter  | unit      | description                                                                 | Parameter range | references         |
|------------|-----------|------------------------------------------------------------------------------|-----------------|--------------------|
| m<sub>R</sub> | h<sup>-1</sup> | Specific maintenance rate at active state                                    | [0.001, 0.08]   | Wang et al. (2014) |
| Q<sub>10mic</sub> | -         | Temperature effects on microbial metabolic activity (rate change per 10 °C increase in temperature). Based on 0.65 eV activation energy for soils | [1.5, 3.5]      | He et al. (2015)   |
| Q<sub>10enz</sub> | -         | Temperature effects on enzyme activity (rate change per 10 °C increase in temperature). Based on 6% rate increase per degree Celsius | 1.79            | He et al. (2015)   |
| α          | -         | the ratio of m<sub>R</sub> to the sum of maximum specific growth rate         | [0.01, 0.5]     | Wang et al. (2014) |
| β          | -         | Ratio of dormant microbial maintenance rate to m<sub>R</sub>                  | [0.0005, 0.005]  | Wang et al. (2014) |
| Y<sub>g</sub> | -         | carbon use efficiency                                                        | [0.3, 0.7]      | He et al. (2015)   |
| K<sub>s</sub> | mgC cm<sup>-2</sup> | Half-saturation constant for directly accessible substrate                  | [0.01, 10]      | Wang et al. (2014) |
| K<sub>m</sub><sub>uptake</sub> | mgC cm<sup>-2</sup> | Half-saturation constant for enzymatic decay of SOC                  | [200, 1000]     | He et al. (2015)   |
| r<sub>death</sub> | h<sup>-1</sup> | Potential rate of microbial death                                            | [2e<sup>-4</sup>, 2e<sup>-3</sup>] | Allison et al. (2010) |
| r<sub>EnzProd</sub> | h<sup>-1</sup> | Enzyme production rate of microbe                                             | [1e<sup>-4</sup>, 8e<sup>-4</sup>] | He et al. (2015)   |
| r<sub>enzloss</sub> | h<sup>-1</sup> | Enzyme loss rate                                                             | [0.0005, 0.002]  | Allison et al. (2010) |
| V<sub>max</sub> | mgC cm<sup>-2</sup> h<sup>-1</sup> | Maximum SOC decay rate                                                      | [1e<sup>-4</sup>, 5e<sup>-3</sup>] | He et al. (2015)   |
Table 2. Site description and measured NEP data used to calibrate MIC-TEM-dormancy

| Site Name               | Location (Longitude (degrees)/Latitude (degrees)) | Elevation (m) | Vegetation type | Description                                                                 | Data range      | Citations                  |
|------------------------|-----------------------------------------------|--------------|----------------|-----------------------------------------------------------------------------|-----------------|---------------------------|
| Univ. of Mich. Biological Station | 84.71W 45.56 N | 234 | Temperate deciduous forest | Located within a protected forest owned by the University of Michigan. Mean annual temperature is 5.83°C with mean annual precipitation of 803mm | 01/2005-12/2006 | Gough et al. (2013) |
| Howland Forest (main tower) | 68.74W 45.20N | 60 | Temperate coniferous forest | Closed coniferous forest, minimal disturbance. | 01/2004-12/2004 | Davidson et al. (2006) |
| UCI-1964 burn site | 98.38W 55.91N | 260 | Boreal forest | Located in a continental boreal forest, dominated by black spruce trees, within the BOREAS northern study area in central Manitoba, Canada. | 01/2004-10/2005 | Goulden et al. (2006) |
| KUOM Turfgrass Field | 93.19W 45.0N | 301 | Grassland | A low-maintenance lawn consisting of cool-season turfgrasses. | 01/2006-12/2008 | Hiller et al. (2011) |
| Atqasuk | 157.41W 70.47N | 15 | Wet tundra | 100 km south of Barrow, Alaska. Variety of moist-wet coastal sedge tundra, and moist-tussock tundra surfaces in the more well-drained upland. | 01/2005-12/2006 | Oechel et al. (2014); |
| Ivotuk | 155.75W 68.49N | 568 | Alpine tundra | 300 km south of Barrow and is located at the foothill of the Brooks Range and is classified as tussock sedge, dwarf-shrub, moss tundra. | 01/2004-12/2004 | McEwing et al. (2015) |
### Table 3. Site description and measured NEP data used to validate MIC-TEM-dormancy

| Site Name               | Location (Longitude /Latitude) | Elevation (m) | Vegetation type          | Description                                                                                                                                                                                                 | Data range       | Citations                                      |
|-------------------------|--------------------------------|---------------|--------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------|------------------------------------------------|
| Bartlett Experimental Forest | 71.29W/44.06N                 | 272           | Temperate deciduous forest | Located within the White Mountains National Forest in north-central New Hampshire, USA, with mean annual temperature of 5.61 °C and mean annual precipitation of 1246mm.                                      | 01/2005-12/2006  | Jenkins et al. (2007); Richardson et al. (2007); |
| Howland Forest (main tower) | 68.74W/45.20N                 | 60            | Temperate coniferous forest | Closed coniferous forest, minimal disturbance.                                                                                                                                                               | 01/2003-12/2003  | Davidson et al. (2006)                         |
| UCI-1964 burn site       | 98.38W/55.91N                 | 260           | Boreal forest            | Located in a continental boreal forest, dominated by black spruce trees, within the BOREAS northern study area in central Manitoba, Canada.                                                             | 01/2002-12/2003  | Goulden et al. (2006)                          |
| Brookings               | 96.84W/44.35N                 | 510           | Grassland                | Located in a private pasture, belonging to the Northern Great Plains Rangelands, the grassland is representative of many in the north central United States, with seasonal winter conditions and a wet growing season. | 01/2005-12/2006  | Gilmanov et al. (2005)                         |
| Atqasuk                 | 157.41W/70.47N                | 15            | Wet tundra               | 100 km south of Barrow, Alaska. Variety of moist-wet coastal sedge tundra, and moist-tussock tundra surfaces in the more well-drained upland.                                                                | 01/2003-12/2004  | Oechel et al. (2014);                          |
| Ivotuk                  | 155.75W/68.49N                | 568           | Alpine tundra            | 300 km south of Barrow and is located at the foothill of the Brooks Range and is classified as tussock sedge, dwarf-shrub, moss tundra.                                                                     | 01/2005-12/2005  | McEwing et al. (2015)                          |
Table 4. Site description and measured $R_H$ data used to validate MIC-TEM-dormancy model

| Site   | Location (Longitude (degrees) /Latitude (degrees)) | Elevation (m) | Vegetation type       | Data range           | Citations            |
|--------|---------------------------------------------------|---------------|-----------------------|----------------------|----------------------|
| US-EML | 149.25W/63.88N                                     | 700           | Alpine tundra         | 01/2009-12/2013      | Belshe et al. (2012) |
| CA-SJ2 | 104.65W/53.95N                                     | 580           | Boreal forest         | 01/2004-12/2008      | Coursolle et al. (2006) |
| US-Ho2 | 68.75W/45.21N                                      | 91            | Temperate coniferous forest | 01/2000-12/2004 | Davidson et al. (2006) |
| US-UMB | 84.71W/45.56N                                      | 234           | Temperate deciduous forest | 01/2005-12/2006 | Gough et al. (2013) |
| US-Ro4 | 93.07W/44.68N                                      | 274           | Grasslands            | 01/2016-12/2017      | Griffis et al. (2011) |
| RU-Che | 161.34E/68.61N                                     | 6             | Wet tundra            | 01/2002-12/2005      | Merbold et al. (2009) |
| Site Name             | Vegetation type         | Models     | Intercept | Slope  | R-square | Adjusted R-square | p-value |
|----------------------|-------------------------|------------|-----------|--------|----------|-------------------|---------|
| Ivotuk               | Alpine tundra           | MIC-TEM    | 0.85      | 0.83   | 0.70     | 0.67              | <0.001  |
|                      |                         | Dormancy   | -0.51     | 1.09   | 0.75     | 0.73              | <0.001  |
| UCI-1964 burn site   | Boreal forest           | MIC-TEM    | 0.18      | 1.03   | 0.912    | 0.9080            | <0.001  |
|                      |                         | Dormancy   | -0.21     | 0.96   | 0.90     | 0.894             | <0.001  |
| Howland Forest       | Temperate coniferous    | MIC-TEM    | 7.29      | 0.72   | 0.85     | 0.83              | <0.001  |
| (main tower)         |                         | Dormancy   | 0.27      | 1.05   | 0.89     | 0.88              | <0.001  |
| Bartlett Experimental| Temperate deciduous     | MIC-TEM    | -6.05     | 0.91   | 0.944    | 0.941             | <0.001  |
| Forest               |                         | Dormancy   | -2.34     | 1.13   | 0.93     | 0.924             | <0.001  |
| Brookings            | Grassland               | MIC-TEM    | 3.05      | 0.71   | 0.84     | 0.83              | <0.001  |
|                      |                         | Dormancy   | 0.17      | 0.95   | 0.90     | 0.898             | <0.001  |
| Atqasuk              | Wet tundra              | MIC-TEM    | 7.22      | 1.85   | 0.71     | 0.70              | <0.001  |
|                      |                         | Dormancy   | 0.19      | 0.82   | 0.67     | 0.66              | <0.001  |
Table 6. Model validation statistics for Dormancy model and MIC-TEM at six sites with RH data

| Site ID | Vegetation type          | Models          | Intercept | Slope | R-square | Adjusted R-square | RMSE  | p-value |
|---------|--------------------------|-----------------|-----------|-------|----------|-------------------|-------|---------|
| US-EML  | Alpine tundra            | MIC-TEM         | 2.90      | 0.91  | 0.79     | 0.78              | 3.55  | <0.001  |
|         |                          | Dormancy        | 1.81      | 0.74  | 0.87     | 0.85              | 2.69  | <0.001  |
| CA-SJ2  | Boreal forest            | MIC-TEM         | 7.59      | 1.12  | 0.84     | 0.83              | 9.8   | <0.001  |
|         |                          | Dormancy        | 2.6       | 0.74  | 0.86     | 0.85              | 3.97  | <0.001  |
| US-Ho2  | Temperate coniferous forest | MIC-TEM         | 4.07      | 0.89  | 0.86     | 0.84              | 12.39 | <0.001  |
|         |                          | Dormancy        | 6.59      | 0.71  | 0.91     | 0.89              | 11.83 | <0.001  |
| US-UMB  | Temperate deciduous forest | MIC-TEM         | -4.73     | 1.32  | 0.81     | 0.8              | 20.05 | <0.001  |
|         |                          | Dormancy        | 13.6      | 0.67  | 0.85     | 0.84              | 12.94 | <0.001  |
| US-Ro4  | Grassland                | MIC-TEM         | 9.34      | 0.87  | 0.81     | 0.79              | 11.25 | <0.001  |
|         |                          | Dormancy        | 4.81      | 0.65  | 0.86     | 0.84              | 9.21  | <0.001  |
| RU-Che  | Wet tundra               | MIC-TEM         | 2.5       | 0.67  | 0.72     | 0.71              | 6.24  | <0.001  |
|         |                          | Dormancy        | 1.96      | 0.77  | 0.81     | 0.79              | 5.95  | <0.001  |