EARTH'S CRYOSPHERE

SCIENTIFIC JOURNAL

Earth`s Cryosphere, 2017, vol. XXI, No. 2, pp. 3–9 **http://earthcryosphere.ru/**

GEOCRYOLOGICAL MONITORING AND PREDICTION

DOI: 10.21782/EC2541-9994-2017-1(3-9)

RUSSIAN PERMAFROST IN THE 21st CENTURY: MODEL-BASED PROJECTIONS AND ANALYSIS OF UNCERTAINTIES

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The authors study model-based active layer thickness in permafrost regions of European and Asian Russia in terms of sensitivity to variations in its key controls: air temperature, snow depth, and vegetation patterns. The model has been used to estimate current changes of active layer thickness between two periods of 1961–1990 and 2004–2013. The calculations were performed using a scenario of coupled climatic and vegetation changes till the mid-21st century, with regard to input data uncertainty. According to the modeling results, the greatest permafrost loss relative to the mean of 1961–1990 (30 ± 14 cm) by the middle of the 21st century can be expected in the industrially developed Yamal-Nenets district of north-western Siberia. Over most of the East Siberian permafrost regions, the projected changes to the active layer thickness are 20 ± 10 cm.

Permafrost regions, modeling, active layer thickness, variability, stochastic projection

INTRODUCTION

In our recent publication [*Anisimov and Sherstyukov*, *2016*], we inferred the thermal dynamics of permafrost to depend mainly on snow depth and vegetation patterns, and predicted possible active layer thickness changes (permafrost thaw) during the 21st century. The applied modeling approach differed in three basic points from other more or less complex models which use several climate projections [*Arzhanov et al., 2013; Koven et al., 2013; Slater and Lawrence, 2013*]. The points of difference are, namely, (i) the use of an ensemble climate projection optimized for the permafrost zone based on advanced models of the Coupled Model Intercomparison Project, phase 5 (CMIP5), (ii) regard for vegetation changes, and (iii) uncertainty analysis.

There are three main types of uncertainty which are due, respectively, to imperfect permafrost models, incomplete data on soil properties and vegetation, and to errors in present and predicted climate estimates. Special efforts have been undertaken to reduce each uncertainty: (i) choosing a permafrost model scaled to the resolution of available input data coverage for the whole permafrost zone; (ii) re-interpreting input climate data used in a stationary permafrost model of a medium complexity; (iii) using the stochastic projection approach to modeling with regard to small-scale natural variations in permafrost parameters; (iv) testing climate projections using individual CMIP5 models based on regional criteria; (v) obtaining an ensemble of models optimal for the Russian permafrost zone for calculating the parameters and state of permafrost expected for the 21st century.

CHOICE OF PERMAFROST MODEL AND ASSESSMENT OF ITS SENSITIVITY TO GOVERN PARAMETERS

The existing permafrost models synthesized in our recent overview [*Anisimov et al., 2012*] are either stationary or dynamic. Dynamic modeling requires complete thermal and moisture datasets at all vertical levels, including the land cover, but they remain incomplete and do not cover some permafrost regions of Russia. Therefore, a simpler stationary model has been chosen, which stems from the assumption of the seasonal range of air temperature variations (amplitude) decaying exponentially with depth and from the balance of heat turnovers in warm and cold seasons. The classical algorithm of *Kudryavtsev et al.* [*1974*] was later updated to account for the effect of snow in the permafrost dynamics model of the Geophysical Institute Permafrost Lab (GIPL) [*Sazonova and Romanovsky, 2003*]) and the upper organic layer of soil [*Anisimov, 2009*]. Details of the formalism can be found in the cited publications and are omitted below. It consists in successive calculations of changes in the amplitude and mean annual values of ground temperature with corrections for the effects of snow depth, vegetation, and thermal offset due to thermal conductivity difference between frozen and unfrozen soils. Mean seasonal snow depth is calculated from total atmospheric precipitation while thermal properties averaged over the upper soil layer are input parameters; their values are found from semi-empirical parameterization and depend on soil composition and moisture.

The basic assumption is that the annual temperature cycle is harmonic, and the model is thus sensitive

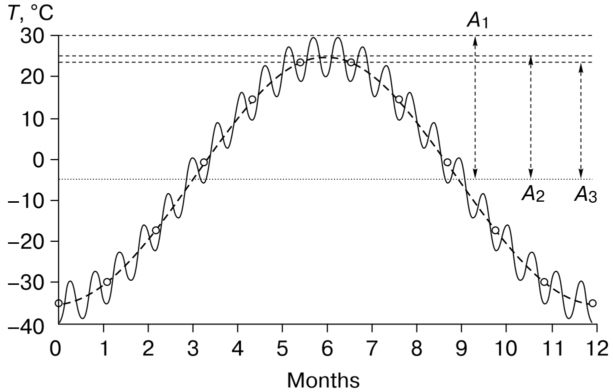

Fig. 1. Amplitudes of the annual temperature cycle calculated using monthly (A_3) and daily (A_2) means and maximum and minimum (A_1) air temperatures.

to the air temperature amplitude found as half-difference between the annual maximum and minimum temperatures. The calculated amplitudes decrease as input temperature data become less discrete (are averaged over longer periods) because the absolute maximum and minimum values inevitably become smoother (Fig. 1). The calculations give the smallest amplitude (A_3) when monthly means are used (temperatures for each month are shown as open dots in Fig. 1) and higher amplitudes (A_2, A_1) with daily means or with maximum and minimum temperatures, respectively (smooth dash line and curve oscillating about it).

Thus, the most often used mean monthly air temperatures lead to underestimation of temperature amplitudes and active layer thickness (ALT). This systematic error is evident upon comparison of measured and calculated (see, for instance [*Sazonova and Romanovsky, 2003*]) values. Correction is possible with less discrete input air temperatures.

The ranges of annual air temperature variations based on maximum and minimum values for each month were compared with those calculated using updated gridded climate datasets of monthly means (CRU TS 3.10) [*Harris et al., 2014*] averaged over 1961–1990. The relative difference (Fig. 2, *A*) decreases from west to east and from south to north. The ratio of the amplitudes is the lowest in West Siberia and Yakutia (<1.2) and is within 1.2–1.3 elsewhere in the permafrost zone.

To estimate the magnitude of error due to choice of averaging period (discreteness of input data), we calculated the respective ALT difference (Fig. 2, *B*). Comparison of panels *A* and *B* in Fig. 2 shows that the ALT difference is of the same order of magnitude as that of temperature amplitudes but the two parameters have different spatial patterns. The ratios (Fig. 2, *A* and *B*) are very similar in northern European Russia but differ ever more strongly eastward, especially in the Chukchi Peninsula and in eastern Yakutia (though being again similar in central and western Yakutia).

The spatial patterns observed in Fig. 2, *A* and *B* are consistent with sensitivity of permafrost temperature to air temperature we estimated earlier [*Anisimov and Sherstyukov, 2016*]. In that study sensitivity was expressed via the ratio K_{pmf} of mean annual ground and air temperatures based on observations. The K_{pmf} ratio was shown (Fig. 4 in [*Anisimov and Sherstyukov, 2016*]) to be small (0.1–0.3) in northern European Russia and in central and western Yakutia but twice as high (0.3–0.6) in the Chukchi and eastern Yakutia regions. The areas of high K_{pmf} correspond to those of largest difference between the ratios mapped in panels *A* and *B* of Fig. 2, because permafrost is highly sensitive to even minor changes in air temperature amplitude, which may change ALT to a degree exceeding the original disturbance.

The accuracy of input data as a source of uncertainty can be assessed more generally by considering the permafrost model as a mathematical operator that converts space-time variations in climate controls (vegetation, snow and soil) to ALT variations. The

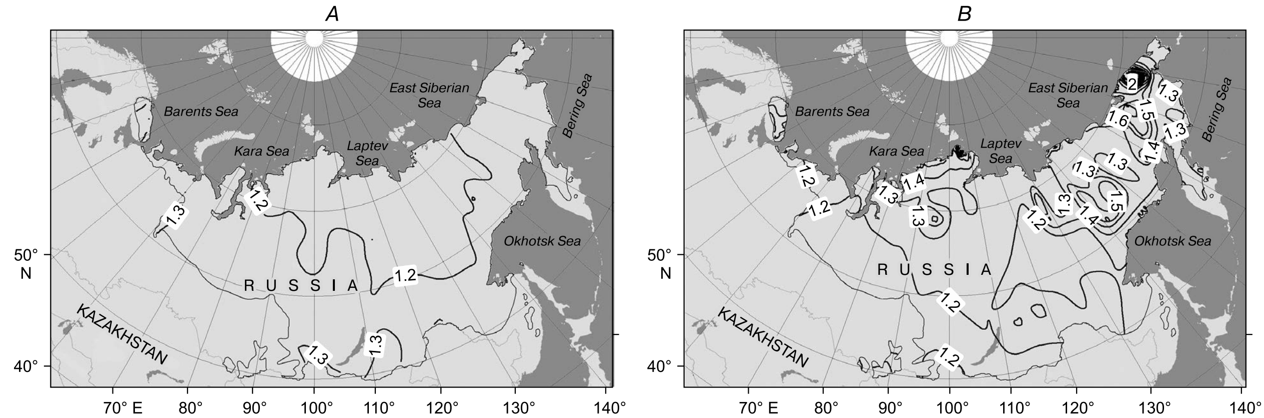

Fig. 2. Ratios of annual air temperature (*A*) and ALT (*B*) amplitudes based on maximum and minimum monthly values averaged over 1961–1990.

Table 1. **Sensitivity of ALT to variations in govern parameters calculated using the standard model**

Permafrost	Snow depth (±50 % of background)	Height of lower plants (5–50 cm)	Thickness of organic layer (0–20 cm)	Thermal conductivity (±40 % of background)	Temperature amplitude (±20 % of background)
European Russia					
Continuous	0.11	0.16	0.17	0.47	0.38
Discontinuous and sporadic	0.05	0.18	0.13	0.46	0.15
Siberia, Chukchi Peninsula					
Continuous	0.07	0.20	0.19	0.45	0.74
Discontinuous	0.09	0.18	0.13	0.45	0.22
Sporadic	0.09	0.19	0.12	0.46	0.14

properties of this operator were studied in numerical experiments in which one parameter was allowed to vary while all others were locked, and the sensitivity of calculated ALT to these variations was estimated as

$$\frac{\Delta Z_i}{\bar{Z}} = k_i \frac{\Delta \Pi_i}{\bar{\Pi}_i}, \quad (1)$$

where $\Delta\Pi_i$ and ΔZ_i are, respectively, the error in the parameter i and the related ALT deviation from the means $\bar{\Pi}_i$ and $\bar{Z}$ ($\bar{\Pi}_i / \bar{Z}$ ratio is normalized variation); k_i is the ALT sensitivity to the parameter Π_i. The model operator is shrinking with respect to the given parameter at $k_i < 1$, neutral at $k_i \approx 1$, and extending at $k_i > 1$. The coefficient k_i refers to the contribution of relative error in the given input parameter to uncertainty. Note that two things have to be taken into account: (i) thus obtained estimates represent sensitivity restricted to a certain permafrost model and (ii) k_i depends on variation ranges of parameters due to nonlinearity. Therefore, it is important to keep the model variations within the ranges of observed values.

The sensitivity (k_i) of ALT to different input variables is presented in Table 1 for continuous, discontinuous, and sporadic permafrost; discontinuous and sporadic permafrost are shown as a single category for the European territory where the two permafrost subzones have no distinct boundary in the existing maps. The calculations were at nodes of a regular grid, with 0.5° spacing in latitude and longitude, from monthly means of the CRU TS 3.10 datasets [*Harris et al., 2014*] averaged over the 1961–1990 period; the seasonal air temperature variation ranges (amplitudes) were corrected according to data of Fig. 2; k_i were averaged over each permafrost subzone. Note that comparison in Fig. 2 is between ratios of temperature amplitude and ALT pairs whereas Table 1 compares variations of parameters normalized to their means.

Table 1 confirms the known fact that soil thermal conductivity causes the greatest effect on ALT. The dependence of ALT on soil type, moisture content and frozen/unfrozen state has been quite well investigated and is included into the models via the respective parameterizations. Among other parameters, ALT is highly sensitive to air temperature. Note that the contribution of errors in variables that characterize vegetation and soil organic layer to uncertainty is two or three times smaller in areas of continuous permafrost than in those of discontinuous and sporadic permafrost. ALT is the least sensitive to snow depth variations in all regions.

ENSEMBLE CLIMATE PROJECTION OPTIMAL FOR RUSSIAN PERMAFROST

Earth system models of thermal dynamics provide a non-competitive source of knowledge on possible climate change in the 21st century. An exhaustive overview of such models in the context of Russian permafrost studies can be found in [*Kokorev and Anisimov, 2013; Kokorev and Sherstyukov, 2015*]. The modeling includes data of greenhouse gas (GHG) emission which has been the principal manmade climate forcing, specifically, measured concentrations for the period 1850 through 2005 and projected emission scenarios for different conditions of future world economy development [*Meinshausen et al., 2011*]. The scenarios, or representative concentration pathways (RCP), were coded according to radiative forcing (W/m^2) by 2100 caused by the respective emissions: RCP8.5 [*Riahi et al., 2011*], RCP6 [*Masui et al., 2011*], RCP4.5 [*Thomson et al., 2011*], and RCP2.6 [*van Vuuren et al., 2011*]). The results of modeling with the emission scenarios are called *climate projections* to highlight their projective rather than predictive character. According to the emission scenario of maximum radiative forcing RCP8.5, the global temperature may become about 1 °C and up to 2.7 °C warmer than at present (average over the 2004–2013 period) by the middle and end of the century, respectively, or 2.0 and 3.7 °C warmer relative to the preindustrial level of 1850. Projections with less aggressive radiative forcing scenarios give smaller warming, correspondingly. All RCP-based projections show global warming within 0.2 °C before 2030, which is twice lower than the difference between estimates according to different models in any RCP scenario (0.4 °C) [*Stocker et al., 2013*].

The regional difference of air temperature and precipitation projections, both between assessment models and RCP scenarios, is the greatest in permafrost regions [*Collins et al., 2013*]. This is largely due to complexity of surface processes which are not always properly accounted for in the models. The uncertainty of climate projections can be reduced by rejecting the models that lead to large errors in historic variations of permafrost forcing variables and by joining the models that provide higher-quality results into groups of best projections (regionally optimal ensembles). This approach was applied earlier to projections based on variables that refer to dynamics of glaciers in the Northern Hemisphere [*Anisimov and Kokorev, 2013*] and Arctic socio-economic systems [*Anisimov and Kokorev, 2016*].

Forty six CMIP5 models were checked for reproducibility of degree-day totals of the warm season and the air temperature amplitude in the Russian permafrost of 1981–2005, using calculation results for the historic period. The climate models of the CMIP5 generation and the quality checking method, as applied to the Russian territory, were discussed in our previous publications [*Anisimov and Kokorev, 2013, 2016; Kokorev and Anisimov, 2013; Kokorev and Sherstyukov, 2015*]. Finally, we chose fifteen models that gave errors in the trends of the variables within the average over all models. The fifteen models of the ensemble optimal for the Russian permafrost are characterized in detail at www.permafrost.su/gcm and are beyond this consideration.

COUPLED CLIMATE AND VEGETATION PROJECTIONS FOR THE 21st CENTURY

Several issues relevant to vegetation-climate coupling were discussed in previous publications: the mechanism of vegetation effect on permafrost [*Anisimov and Sherstyukov, 2016*], empirical statistical modeling of climate-induced changes to the boundaries of Arctic biomes in the 21st century [*Zhiltsova and Anisimov, 2013*]; regression analysis of biomass variations in vegetation zones as related to temperature and moisture, based on spaceborne data of Normalized Difference Vegetation Index (*NDVI*) [*Anisimov et al., 2015; Zhiltsova and Anisimov, 2015*]. The methods and results of these studies were used for obtaining coupled climate and vegetation projections for the 21st century with regard to decadal changes in vegetation zones and in biomass controlled by local conditions within each zone.

The modeling was for several periods: 1961–1990 (background), 2004 to 2013 (present), and 2036 to 2065 (future). Average air temperature and atmospheric precipitation monthly means were calculated for each period at all nodes of the spatial grid covering the permafrost zone. The input data were generated using the CRU TS 3.10 datasets for the historic periods; for the future periods increments to these values were calculated additionally using the ensemble climate projections optimal for the Russian permafrost based on the RCP8.5 scenario. Besides being input data for the permafrost model (with corrected air temperature amplitudes) and the empirical statistical model of vegetation zones [*Anisimov et al., 2011*], the data were used to calculate deviations of thermal (heat insulation) properties of vegetation from background values in each zone.

The deviations of vegetation heat insulation from the background were calculated taking into account features of lower and higher plants, which differ as follows. The moss-lichen cover provides similar insulation as peat and can be considered as an additional upper organic layer of soil with its properties depending on its thickness, moisture, and taxonomy of plants. Few published data allow approximate estimates for the thermal properties of the frozen and unfrozen moss-lichen-peat cover for different moisture conditions. The density and biomass of lower plants which control the insulation capacity of the layer depend on heat availability estimated from air temperature data. Modeling for zones that lack higher plants (polar desert or northern tundra) used regression analysis relating the thickness of the upper organic layer with both air temperatures and total precipitation for the warm season and thermal parameters with total precipitation. Surface vegetation and peat, which have similar properties, are joined into a single layer.

Higher vascular plants (graminoids, low shrubs and shrubs) respond more strongly to climate change, especially to temperature, by changing their phytomass which is responsible for the heat insulation of soil. These responses are interpreted as changes in canopy density or effective heights of plants at constant specific heat and thermal conductivity, and are estimated via regression relationships. Thus calculated height is specified explicitly as a variable in the permafrost model. The obtained estimates of ALT sensitivity to variations in lower (part of the organic soil layer) and higher plants (height variations) are listed in Table 1.

PRESENT AND FUTURE CHANGES IN ACTIVE LAYER THICKNESS

There are no rigorous time limits for the background period in the literature on climate-induced permafrost changes. Many geocryological maps are based on data of the 1960–1970s, when the climate was more stable. The broadly used digital mapping of permafrost based on model assimilation of observations and subsequent extrapolation uses later periods when permafrost became subject to warming effects. In order to compare geocryological data for different periods, we calculated active layer thickness for

2004–2013 relative to the background of 1961–1990 (Fig. 3). The current permafrost changes have a distinct sector-like pattern, with two zones (Gydan Peninsula and eastern Kolyma basin) of high permafrost loss (15–20 cm) standing against general changes within 10 cm.

The model, checked and calibrated against modern data [*Anisimov, 2009*], was applied to calculate ALT changes by the middle of the 21st century, using the RCP8.5 scenario and the related coupled climate and vegetation projections. Uncertainty was estimated using the stochastic approach [*Anisimov, 2009*]. Without repeating the considerations from the cited publication, we only note that the approach was used for different combinations of variables characterizing snow, vegetation, and climate which varied about the average at each grid cell. The calculation sets were obtained separately for each of fifteen climate projections in the optimal ensemble and then processed by standard statistical procedures to find means, standard deviations, variance, and distribution density.

In this study we took into account that input climate data affect strongly the uncertainty in modeling results. Therefore, only climate projections were varied in a series of numerical experiments. Statistical samples consisted of fifteen calculations at each point with varied climate data at locked values of other thermal, soil, and vegetation variables.

The assumptions for continuous and discontinuous permafrost were as follows: 10 and 15 cm thicknesses of the upper organic layer, respectively; 20 and 50 cm heights of above-ground vegetation (grasses and shrubs), respectively; thermal properties of the mineral soil component corresponding to silt at moisture contents typical of permafrost. In order to reduce the effect of possible errors in non-climatic input parameters, we analyzed ALT changes relative to the long-term average background for each grid cell rather than the calculated thickness values. Prognostic estimates of these changes (average values) and their

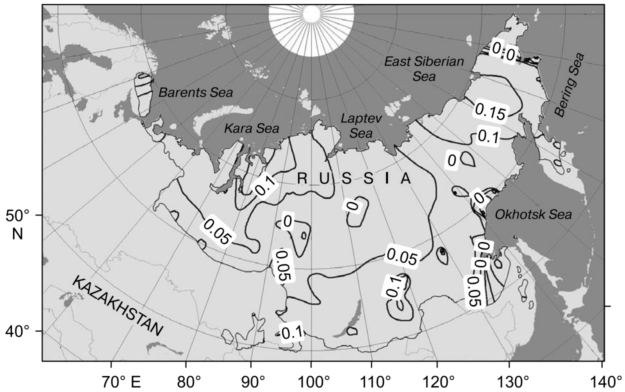

Fig. 3. Calculated anomalies of long-term average ALT (m) for the period 2004–2013 relative to the background of 1961–1990.

standard deviations are given in Fig. 4, *A* and *B*, respectively. All these data together allow estimating the confidence interval of the values which refers to uncertainty.

CONCLUSIONS

The reported results allow several inferences on the accuracy of model projections for the Russian permafrost and its responses to climate change. First, the broadly used climate projections based on CMIP5 generation models make the greatest contribution to uncertainty in permafrost regions. The uncertainty can be reduced by excluding models leading to poor reproducibility of permafrost temperature and precipitation patterns. The algorithm designed for this purpose was described in a number of publications and the results obtained with the ensemble of models optimal for Russian permafrost are available at www.permafrost.su/gcm.

Another inference concerns possible long-term ALT changes (permafrost loss) which are expected to

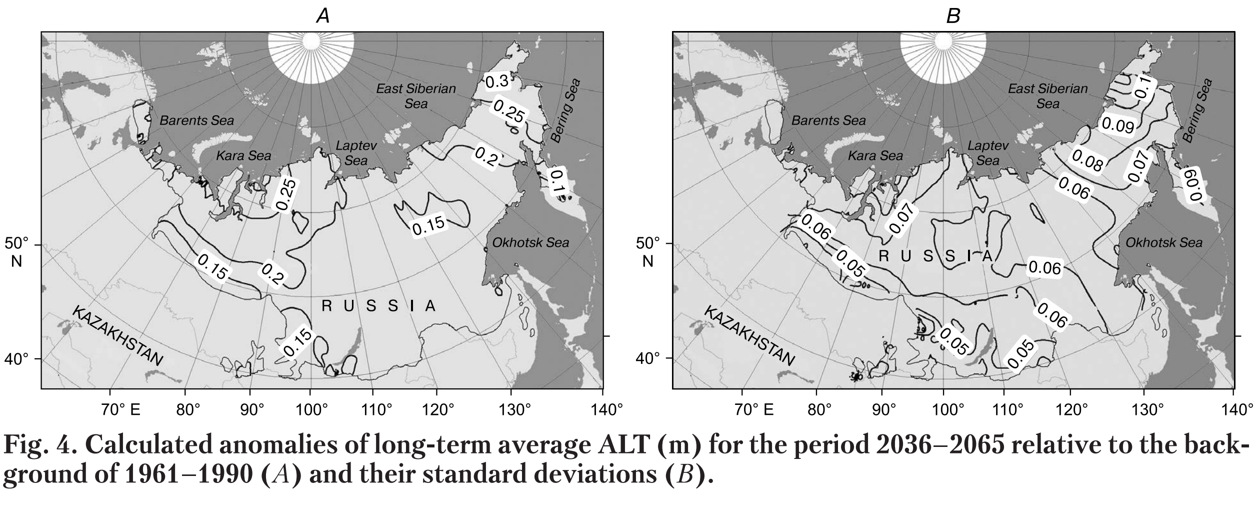

Fig. 4. Calculated anomalies of long-term average ALT (m) for the period 2036–2065 relative to the background of 1961–1990 (*A*) and their standard deviations (*B*).

be within (20 ± 10) cm by the middle of the 21st century over the greatest part of East Siberia (the data are quoted at 95 % confidence interval obtained by combining data in panels *A* and *B* of Fig. 4). The permafrost loss may be as high as (30 ± 14) cm in northern West Siberia and in the Yamal-Nenets district, i.e., in rapidly developed petroleum provinces with growing infrastructure. Projections for these regions are challenging because of numerous engineering construction problems, which will only increase in the coming decades. More difficulty comes from the presence of cold saline soils and brine lenses (cryopegs) which was neglected in the calculations.

Finally, the main conclusion is that permafrost models of different resolutions can provide significant prognostic estimates of future changes in permafrost parameters in the 21st century. Their uncertainty now reaches ~50 % but will reduce with improving quality of climate models.

The study was supported by grant 14-17-00037 from the Russian Science Foundation.

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Received December 9, 2015