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METHODOLOGY FOR SPATIAL MODELING OF SOIL ORGANIC CARBON STOCKS IN THE NORTH OF EUROPEAN RUSSIA

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The paper provides accurate assessment of the spatial inhomogeneity of soil organic carbon (SOC) stocks in the permafrost-affected soils of the European Northeast, using mean values (standards based on samples) of SOC stocks for each of the soil taxa and other georeferenced factors. A very high correlation was observed between soil organic carbon stocks and environmental factors (combined soil taxa, mesotopography, climatic characteristics), which suggests that SOC stocks tend to be directly controlled by them. It has been demonstrated that, in conjunction with soil taxa, the absolute height, and the amount of precipitation in June and July play the most important role in SOC stocks dynamics, whereas the terrain dissection appears a less significant characteristic. When calculated using reference values, the amount of SOC stocks averaged 32.0 kg·m^{-2} for the region, while with such additional factors as climate and topography, the SOC stocks were estimated at 21.6 kg·m^{-2}. This model served as a basis for creation of the SOC stock map at a regional scale.

Soil organic carbon, spatial empirical-statistical modeling, mapping, permafrost soils, topography, climate

INTRODUCTION

Soil organic carbon (SOC) is one of the most important components of soil largely influencing the growth of plants and acting as source of energy and thereby improving soil structure. Potential impacts of climate changes on agricultural productivity and increased greenhouse gases emissions in the atmosphere have called for the growing interest in SOC studies due to the heightened need for estimation of its stocks, its stability and susceptibility to temperature changes, etc. [*Jobbagy and Jackson, 2000; Lal, 2004; Houghton, 2007; Schuur et al., 2009*].

Estimation of SOC stocks in the Arctic and Subarctic regions have become of particular concern due to the fact that most of soil organic carbon is conserved in the permafrost. According to the Intergovernmental Panel on Climate Change [*IPCC, 2007*] projections, temperatures in the high latitudes will increase significantly in the 21st century, therefore, in contrast to the temperate and tropical latitudes, the arctic and subarctic ecosystems will become particularly vulnerable components of the global carbon cycle [*Schuur et al., 2008; McGuire et al., 2009*]. Despite the significant differences and uncertainties in the calculations, most researchers estimate the SOC pool stored in the permafrost to be about double size of the atmospheric carbon stock [*Schuur et al., 2009; Tarnocai et al., 2009*]. Therefore, a more accurate assessment of spatial heterogeneity of SOC stocks in permafrost terrains is needed [*Johnson et al., 2011*]. Only few works provide region-specific calculations for spatial variability of SOC in the entire strata of the soil profile (O–B–C horizons), in the active layer and permafrost horizons [*Hugelius et al., 2011; Pastukhov and Kaverin, 2013*]. These papers yielded reference values for each of the soil types, and then, based on the generated large-scale soil maps, the SOC stocks were calculated in individual sites occupied by the tundra and forest-tundra. Soils were sampled according to two separate sampling methodologies, transect sampling and stratified random sampling. Transects were chosen so as to represent the main vegetation types and geomorphology of the landscape based on field reconnaissance and they measured 900 m in length at 100 m intervals. Nevertheless, these estimates (when applied to the entire region) appear quite rough, as the soil cover is exceedingly heterogeneous and its diversity and complexity increases at higher spatial resolution. Therefore, to improve the accuracy of SOC stocks estimates it is necessary to use the spatially georeferenced factors (physical and chemical properties of soil, climate, micro-organisms, relief, deposits, soil age and spatial coordinates). Some studies using a number of these factors have shown that this approach yields a more accurate representation of spatial variability in soil properties, thus lowering the prediction error [*Thompson and Kolka, 2005; Rasmussen, 2006; Meersmans et al., 2008*].

The simulation studies of the SOC stocks dynamics and spatial distribution included climate modeling, which demonstrated gradual degradation of permafrost and, as a consequence, increased SOC emissions in the form of greenhouse gases [*Lawrence et al., 2008; Koven et al., 2011; Schaefer et al., 2011*].

However, these studies based on the models with fairly rough extrapolation due to the limited number of field data contain significant drawbacks, and therefore resulted estimates of SOC often fail to reflect the actual spatial mosaic of the soil cover. These models are often used, though, to predict the SOC stocks balance rather than possible losses of SOC from the perennially frozen strata, which estimates range very widely, depending on the climate model scenario and parameters included in the model.

For example, for scenario with the most warming (representative concentration pathway (RCP) 8.5) the projected emissions of SOC confined in the permafrost are 19–45 Gt by 2040, 162–288 Gt by 2100 and to 381–616 Gt by 2300 out of 1700 Gt of total carbon held in the permafrost of the Northern Hemisphere [*Schuur et al., 2013*].

The purpose of this study is to analyze the SOC stocks dynamics affected by the environmental factors (soil, topography and climate) at a regional scale and to build the explicit generalized linear model of the spatial distribution of SOC stocks on the southern limit of the European permafrost zone, which includes: 1) real field data with spatially linked SOC stocks in major soil taxa; 2) climate data (air temperature and the amount of rainfall); 3) geomorphological data (quantitative characteristics of the relief). This approach can significantly increase the spatial resolution (up to 300 meters in 1 pixel) and reduce the prediction error.

The advanced planning includes building predictive models and maps of SOC stocks projected for 2050, 2100 and 2199 years, using various climate scenarios, such as for example E-GISS and HadCM3.[1]

STUDY AREA

The study area is located in the European Northeast with its latitude and longitude is 59°00′–63°10′ E and 66°42′–67°30′ N, respectively, and covers 18 132.55 km^2, comprising the middle portion of the Usa river (the main tributary to the Pechora) basin and – as it delimits the southern boundary of permafrost and is attributed to the “tundra–northern taiga” regional ecotone, i.e. the most susceptible to climatic and (or) human-induced changes – was selected to be the actual test site for this study. The focus region represents by itself the Russian Plain terminus gently sloping to the north, composed by Precambrian, Silurian, Devonian, Permian, Triassic, Jurassic, Cretaceous deposits which are covered by massive (averaging 80–100 m) Quaternary deposits with a complex facial structure [*Atlas..., 2010*]. Its geomorphology, besides the tectonic movements that had basically shaped the relief, also involved exogenous processes – the marine transgression, glaciations of the Quaternary and water erosion taking place in the interglacial.

Parent material that participated in soil-formation processes are moraine, fluvioglacial, eluvial-deluvial, lacustrine-alluvial, alluvial, lacustrine-boggy deposits, with the latter represented by sandy-clayey sediments and peatlands. The climate of the study area is moderately continental and moderately cold. The mean air annual temperature (MAAT) is about −5 °C, average annual amount of precipitation varies from 600 to 700 mm, two thirds of which falls on the warm period [*Atlas..., 1997*].

The extreme northeastern part of Europe is underlain by thick and extensive permafrost, with varied thicknesses (sometimes up to 50 m). However, recent warming of the Arctic and subarctic permafrost has significantly changed geocryological conditions in the study area. Given that permafrost underlying the beds of major watercourses are penetrated by a system of through taliks in watershed areas, the permafrost table has a complex configuration there. The areas of merging and non-merging permafrost tend to alternate, with the latter being predominant type [*Afanasiev, 1986*].

The vegetation cover of the study area is represented by combinations of dwarf birch tundra, raised bogs, patches of spruce and birch thin forests. For the most part, flora is broadly represented by subarctic species, which are pointedly remarkable in the compositions of plant communities. Poorly drained areas are occupied by peat plateaus, with the large-mound type (as termed in Russian literature) predominating.

METHODS

1. Soil survey profiles study in determinations of carbon stocks

Most of the field determinations and samples of SOC stocks conducted in 2007–2008 were subsequently complemented by the results of further field seasons. During the soil studies, the 153 soil profiles were sampled, which was followed by manual drilling to a depth of 1.5–2.0 m in non-permafrost soils, and 30–50 cm into the permafrost in case of shallow (in the range of 1 meter) occurrence of the permafrost table. On peat plateaus, the samples were taken from the outcrops exposed by thermokarst processes during thermokarst lakes formation, and from mounds tapped by manual drilling of wells to a depth of 1.5–2.5 m. Part of the soil profiles were sampled using transects with a length of 900 m at 100 m interval, comprising a variety of vegetation types and landscape geomorphology. Soil samples were collected into the graduated cylinder sequentially from each horizon with vertical resolution 5–10 cm, for determinations of their volume weight and subsequent estimation of SOC stocks. Chemical analysis of soil samples were carried out at “Ekoanalit”, the accredited eco-analytical laboratory of Institute of Biology

[1] Two climate scenarios – moderate and extremely high – will be used for calculations of the projected SOC stocks changes. E-GISS, the moderate model of Goddard Institute for Space Research, NASA. HadCM3 (Hadley Centre Coupled Model, version 3) – extremely high model of Hadley Center, UK, built on the basis of atmospheric-ocean general circulation model (AOGCM). This is also one of the basic models used in the 2001 IPCC Third Assessment Report.

of Komi Science Centre. The bulk volume of carbon content was determined on EA-1100 analyzer, whereas acid-soluble organic carbon – employing the Tyurin's method with a photometric ending. The laboratory tests were performed following the standards in the manual [*Procedures for Soil Analyses, 2002*].

SOC stocks were estimated for each profile by summing up carbon stocks in each of the horizons, from the surface downwards to the depth of occurrence of parent material, by the following formula:

$$\mathrm{SOC} = \sum_{j=1}^{n} C_j \rho_j D_j \left(1 - L_j/100\right) \div 100,$$

where SOC – carbon total reserves in each soil profile, kg·m^{-2}; j = 1, 2, 3, ..., n – number of soil horizon; C_j – bulk volume of carbon, %; ρ_j – soil density, kg·m^{-3}; D_j – thickness of each horizon, m; L_j – fraction of soil matrix and ice, %.

Ice fraction in the permafrost was determined as a difference between the sample mass under field conditions and after drying at room temperature.

2. Cartographic works

Satellite multispectral imaging system Landsat 7 ETM+ in combination of channels 5, 4, 3, georeferenced topographic and soil maps, QuickBird high-resolution images of individual areas and soil data served as a basis for creation of a soil map. Imagery processing was performed in the Erdas Imagine 2014 software environment using supervised classification, while those for soil polygons analysis – on the basis of ArcGIS 10.2.

Final adjustment of soil polygons not supported by soil profiles was performed using digital elevation models (DEM) SRTM with a resolution of 90 m, topographic maps and maps of Quaternary deposits.

Classification definition of soils and indexing of genetic horizons were given according to the World Reference Base for soil resources [*IUSS Working Group WRB, 2014*], since more formalized criteria are thereby applied for assignment of soil to a particular taxon in comparison with the 2004 "Classification and Diagnostics of Soils of Russia" and officially recognized by the Russian soil scientists "Classification and diagnostics of Soils of the USSR", published in 1977. There were allocated 15 taxonomic units at the WRB subgroups level.

Average values of SOC [kg·m^{-2}] for each subgroup of soils were calculated as the mean arithmetic value of the SOC content in the studied soil profiles for each group and subgroup of soils indicated on the map.

3. Spatial modeling and prediction error

The priority was given to the methodology for determining and creating a database of current SOC stocks in the context of the study region. The relationship between the studied soil characteristics (in this case, SOC stocks) and environmental factors (quantitative parameters of climate and relief) usually is statistical in nature, since it is impossible to incorporate infinite number of the environmental factors. However, if the considered soil characteristic correlates well with the environmental factors, it can be predicted directly from them.

In recent decades, this methodology has been widely used in ecology [*Guisan and Zimmermann, 2000*], soil science [*Scull et al., 2003*] and agriculture [*Shary et al., 2011*] and is known as predictive modeling. In this simulation, the matrix for soil characteristics is calculated from measurements in the dozens or hundreds of monitoring points, on the basis of close relationship with environmental factors, and serves as a basis for creation of a predictive map. The environmental factors are represented by matrices, each describing one environmental factor and capable of comprising hundreds of thousands of elements.

The data on SOC stock in the study site were collected in 153 georeferenced points. Matrix resolution of the environmental factors equaled 300 meters, with all the matrices transformed to Kavrayskiy projection for the European part of Russia.

Given that at this resolution some observation points fell into the same matrix element (as was discussed earlier, that part of the key soil profiles were laid as transects with a 100 m grid step), the data were aggregated by averaging in each element of the matrix at 110 observation points (A110 set of samples). The global multi-resolution terrain elevation data GMTED2010 [*Danielson and Gesch, 2011*] at 15″ resolution (i.e. approximately 464 m on the equator and 182 m at the region located 67° N) served as a reference matrix for the environmental factors. As many as 18 basic morphometric variables (MVs) used for the topography description [*Shary et al., 2002*]. Matrices for precipitation, as well as the mean, maximum and minimum temperatures for each month with the 30″ resolution sourced from [*Hijmans et al., 2005*], were also used for calculating the mean annual and average temperatures, and cumulative amounts of precipitation during the winter, spring, summer and autumn periods.

In order to proceed with SOC reserves spatial modeling and predictive mapping, our data on SOC stocks coupled with the GMTED2010 digital terrain matrix with derived MVs [*Shary et al., 2002*], and the average temperatures and amounts of precipitation matrices [*Hijmans et al., 2005*] were pooled to form statistical data. Calculations of topographic attributes and statistical analyzes were performed using the "Analytical GIS Eco" and "R2" software packages [*Shary et al., 2011*].

RESULTS

Modern digital soil map is essentially a spatial database of soil properties compiled from statistical

Table 1. **Mean SOC content in the studied profiles**

Soils	Area		OH depth, cm (±SD)	Permafrost depth, cm (±SD)	SOC_{tot}	SOC_{perm}	SOC_{org}	N
	km^2	%			kg·m^{-2} (±SD)			
Cryic Histosols	3138.54	17.6	173 ± 94	84 ± 24	101.6 ± 42.5	54.5 ± 48.4	92.3 ± 42.7	33
Cryic Fibric Histosols	102.07	0.6	77 ± 34	142 ± 77	28.3 ± 11.9	2.8 ± 5.3	20.3 ± 10.6	5
Fibric Histosols	97.62	0.5	80 ± 14	71 ± 19	40.8 ± 4.3	9.6 ± 12.0	35.7 ± 5.6	7
Cryosols	1389.97	7.8	9 ± 5	89 ± 21	11.4 ± 2.4	1.7 ± 1.7	2.9 ± 1.4	14
Histic Cryosols	4687.74	26.5	22 ± 10	55 ± 24	24.8 ± 10.6	8.4 ± 8.8	7.7 ± 4.6	25
Fluvisols	21.11	0.1	4 ± 2	–	13.2 ± 1.3	0.0	1.5 ± 0.6	10
Histic Fluvisols	16.56	0.1	6 ± 1	–	20.6 ± 2.7	0.0	2.0 ± 0.6	4
Gleysols	481.96	2.7	14 ± 5	–	8.0 ± 3.2	0.0	3.1 ± 2.4	3
Histic Gleysols	3042.64	17.1	15 ± 8	–	19.0 ± 3.8	0.0	5.9 ± 4.8	9
Podzols	160.94	0.9	10 ± 5	–	7.4 ± 2.2	0.0	3.2 ± 1.1	2
Histic Podzols	1073.51	6.0	11 ± 3	–	12.7 ± 3.6	0.0	2.5 ± 1.5	4
Stagnosols	2161.48	12.2	9 ± 4	–	12.8 ± 3.8	0.0	2.7 ± 1.1	30
Retisols	964.29	5.4	8 ± 3	–	11.5 ± 1.3	0.0	3.0 ± 1.2	3
Histic Retisols	342.89	1.9	17 ± 5	–	16.1 ± 1.2	0.0	9.0 ± 2.2	3
Regosols*	102.25	0.6	0	–	3.6	0.0	0.0	1
Total	17 783.57	100	86 ± 113	–	39.5	–	–	153
Water surface	348.98							

Note. OH – organogenic horizon; SD – standard deviation; SOC_{tot} – total soil organic carbon stocks; SOC_{perm} – SOC stocks in permafrost; SOC_{org} – SOC stocks in organogenic horizons; N – number of the studied profiles.

* In the Regosols there may occur soils without surface cover, which represent primarily soils of beaches, etc. Given that human-induced disturbances in this particular area are insignificant, they are not delineated on this map.

samples (profiles) from landscapes, rather than just a set of traditional polygons. Field descriptions of profiles are commonly applied to determinations of spatial distribution of various soil properties, with their accurate measurements performed in the laboratory. The data are subsequently applied for approximations and predictions of soil properties in the unexplored areas. Digital soil maps fill these prediction uncertainties, and as these are continuously updated data (e.g. monitoring), provide most recent information on the dynamic soil processes [*Hartemink et al., 2008*]. The modern advanced digital soil mapping techniques thus provide open systems for new input soil data (e.g. SOC stocks) into predictive models of landscape transformations as a response to global climate and anthropogenic changes [*Sanchez et al., 2009*].

Digital soil mapping for the study area includes information on soil taxa, their geo-referencing and areas (Table 1). In the structure of soil cover, 73.4 % of the area falls into four soil subgroups: Cryic Histosols (Peat Permafrost-affected soils)[2], Histic Cryosols (Peat Permafrost-affected Gleyzems), Histic Gleysols (Peat-Gleyzems) and Stagnosols (Cryometamorphic soils). Cryic Histosols, which occupy just 17.6 % of the area, make the largest contribution to SOC stocks, which accounts for 45.7 % of the entire reserves.

Given that SOC stocks differ significantly between the allocated soil taxa, this will require high precision soil mapping, properly complemented by automated classification techniques. The Landsat imagery contain information about the vegetation cover in vast areas, with large peatland complexes documented remarkably only throughout the ledum-cloudberry tundra distributions.

However, the satellite images can be used to extract information about peatlands with varying thicknesses, where both soils of peat plateaus – Cryic Histosols (with peat cover exceeding 40 cm in thickness) and mineral peat-gleyzems (Histic Cryosols), 10–40 cm thick, are developed. Differentiation of the geographical ranges of these groups of soils usually additionally requires a significant amount of sections and reconnaissance pits.

The mapping processes included SRTM DEM with a 90 m resolution [*The Shuttle Radar..., 2014*]. Their product is freely available on the Internet (http://glcf.umd.edu/) and represents by itself a combination of relief exceedances attributed to points of fairly fine regular grid, and is a digital expression of high-altitude terrain characteristics on a topographic map. The topographic variables (slope steepness, slope exposure, absolute elevation) in combination with spectral characteristics of the satellite images were used for spatial modeling of the predominant

[2] Here and elsewhere, names of soils are given after [*Shishov et al., 2004*].

vegetation cover, enabling thereby the boundaries detection between the vegetation classes.

The generated soil map of SOC stocks for the region is wholly digital, rather than digitized (as, for example, the existing electronic version of the State soil map at 1:1 million scale), providing a comparison of all types of spatial information with GIS. Therefore, the non-mapped areas can be easily extrapolated on the basis of the existing map. This map, however, remains static, nor allowing projecting the existing soil map ahead by calculating, for example, SOC stocks for all points and starting a new SOC layer employing the predictive function.

The above discussed largely determines the use of spatial predictive modeling methods, represented inter alia by *scorpan*-SSPFe (soil spatial prediction function with spatially autocorrelated errors) [*McBratney et al., 2003*]. This method benefits largely the predictive soil mapping and is described by the following formula proposed by Hans Jenny in 1941 (state equation for soil formation):

$$Sa = f(s,c,o,r,p,a,n),$$

where *Sa* – quantitative characteristic of soil taxonomic unit; *s* – soil (other soil properties); *c* – climate (local climatic characteristics); *o* – organisms, vegetation, fauna, human; *r* – relief (morphometric data); *p* – parent material, lithology; *a* – age, time; *n* – spatial position. This method is based on the famous soil formula pioneered by V.V. Dokuchaev back in 1886 and refined by S.A. Zakharov in 1932 [*Florinskii, 2012*].

The *scorpan* model has seven factors or sets of input variables, and, ideally, each needs to be depicted. Given that the model accuracy diminishes (digital estimation of soil resources) as the factors' values grow (variables, or predictors), many models involve predictors selection procedures, e.g. using stepwise regression based on maximum criterion for the so called "tuned" coefficient of determination [*Montgomery and Peck, 1982; Guisan and Zimmermann, 2000*]. In practice, four to six predictors often prove sufficient, since the rest are already statistically insignificant in the model [*Shary et al., 2011*], which means that when they are applied the statistical hypothesis about the regression coefficients being other than zero is rejected at the 5 % level.

McBratney et al. [*2003*] relying on the analysis of published data highlighted key prediction factors most frequently used in the studies, with each having the following application frequency: *r* – 80 % of incidences, *s* – 35 %, *o* – 25 %, *p* – 25 %, *n* – 20 % and *c* – 5 %, whereas *a* was probably not used as a factor. One out of seven possible factors was employed in 40 % of research; two, three and four factors – in 40 %, 10 and 2 %, respectively. Possibility of application of five or more factors has not thus far been considered. The most common combination involves *r* and *s* factors. Most studies used DEM as the main source of auxiliary data, followed by the remote sensing of images and pre-existing soil covers.

This study involves the four factors: *r*, *s*, *o*, *n* (which is only 2 % of the research as of 2003), with generalized linear models (GLM) in the form of multiple regression type acting as the tool for analysis:

$$f(W) = aA + bB + cC + dD + e + \varepsilon,$$

where *W* – response (in our case, SOC stock); *A*, *B*, *C*, *D* – predictors; *a*, *b*, *c*, *d*, *e* – regression coefficients; ε – error; *f*(*W*) – link function, adjusting error distribution, is to be satisfactory for normal distribution.

Verification of the correlation ratio (the strength of link) between individual predictors used in GLM, as well as evaluation of predictors independence were carried out using the technique proposed P.A. Shary [*Shary et al., 2011*][3]. The 18 basic morphometric indices and climate data were used as quantitative characteristics in the model [*Shary et al., 2002; Shary, 2008*], as was mentioned above.

Non-quantitative environmental factors such as soil taxa were described by indicator variables, or indicators. Given that the indicator takes two different numerical values, therefore *N* – 1 indicator is required for the description of *N* soil taxa [*Montgomery and Peck, 1982*]. In case the data from Table 1 are generalized, the three major taxa of soil can be discriminated, which will differ greatly in SOC stocks (Table 2). Documentation of the allocated three major soil taxa will require two indicators (Table 2).

The SOC stocks in the observation points of the A110 set of samples (the remaining samples used in the models counted 110 points, since the points were in part aggregated, without allowing for the Regosols and water surface data) ranged from 5.8 to 188.7 $kg{\cdot}m^{-2}$ averaging (39.9 ± 42.6) $kg{\cdot}m^{-2}$ and K_{var} = 107 % (coefficient of variation)[4].

The spatial model was thus built for SOC stocks in the southern tundra – forest-tundra in the middle portion of the Usa basin, accounting for climate and

[3] In this case, the SOC stocks are considered, which function on the test site as a response controlled by the environmental factors being *per se* independent variables (of soils, climate characteristics, relief and spatial position). This allows to raise the question as to what percentage of the SOC stocks spatial variability is accounted for by these factors. At the same time, such an approach makes it possible to avoid using "reference" values of SOC stocks for soil taxa, and to elucidate on to what extent those same "reference" values depend on climate and relief characteristics. To this end, GLM with multiple regression is used, which theory appears best developed at present moment [*Montgomery and Peck, 1982; McCullagh and Nelder, 1989*].

[4] Coefficient of variation is defined as the ratio of the standard deviation, or root mean square (RMS), to the mean, in percentage terms. It measures relative dispersion of the variables in statistical aggregate.

Table 2. **Mean SOC content in the studied soil profiles**

I_1	I_2	Soil taxa	Area		OH depth, cm	SOC_{tot}	SOC_{perm}	SOC_{org}	N
			km^2	%		kg·m^{-2} (±SD)			
2	1	Organogenic	3338.23	18.8	40–430	89.0 ± 43.7	41.7 ± 46.6	75.2 ± 48.0	35
1	1	Peaty-mineral	9163.34	51.5	18 ± 9	20.3 ± 13.6	–	6.4 ± 4.5	43
1	2	Mineral	5179.75	29.1	8.3 ± 4.4	12.5 ± 3.8	–	2.6 ± 1.2	32
		Regosols	102.25	0.6	0	3.6	–	0	1
		Total	17 783.57	100	–	–	–	–	111
		Water surface	348.98						

Note. I_1, I_2 – indicators 1 and 2; SD – standard deviation.

terrain characteristics besides the soil taxa. The equation takes the form:

$$\ln(\mathrm{SOC})_{A110} = 0.02626 \cdot I_1 P_{jul+16.92} - 0.1617 \cdot P_{jun-5.29} - 0.00369 \cdot I_2 Z_{-4.17} + 0.04225 \cdot I_2\, rot^{P}_{+2.66} + 8.487, \quad (1)$$

coefficient of determination $R^2 = 0.840$ ($Degr = 1.5$ %)[5]; significant probability $p < 10^{-6}$.

Here, A110 is a set of samples consisting of 110 averaged observation points, in which the SOC stocks have been estimated; 0.02626, –0.1617, –0.00369, 0.04225 are the regression coefficients; I_1, I_2 are predictors indicating organogenic and mineral soils with the organogenic horizon at depths 0–10 cm, respectively (Table 2); subscripts +16.92, –5.29, –4.17, +2.66 are the *t*-statistics values[6]; P_{jul}, P_{jun} – the amount of precipitation in July and June; Z – absolute elevation; rot^P – one of the converted (superscript "P") morphometric values[7], designating terrain dissection.

This model shows that 84 % of the spatial distribution of carbon stocks ln (SOC) depends on soil taxa, climatic (rainfall in P_{jun} and P_{jul}) and relief characteristics (height Z, terrain dissection *rot*). All predictors appear significant in the model, i.e. the difference between the peatlands and other soil taxa (by I_1 indicator organogenic soils are differentiated from other soil taxa).

Equation (1) is logarithmic, as it provides for a significant deviation of the SOC statistical distribution from normal, which is associated with the specific role of soil taxa in the context of this region. The model was validated by the Allen cross-validation using *Degr* degradation criterion, which value equals 1.5 %, at 50 % acceptable in ecology and soil science [*Shary et al., 2011*].

It is shown that, along with soil taxa the relief elevations and summer rainfall play the most important role for SOC stocks occurrence in the region, while the terrain dissection appears less important. Thus, the estimated by reference values average SOC stocks totaled 32.0 kg·m^{-2} for the soil, and when complemented by the climate and relief characteristics, carbon stocks averaged 21.6 kg·m^{-2} (Fig. 1).

Although SOC stocks in organogenic soils (peatlands) are largely independent of climate and topography, in the mineral soil taxa they are essentially linked to the climate and terrain properties, which has diminished average estimates of the SOC stocks, when besides the soil taxa, climate and topography are also considered. Therefore, both the currently existing SOC stocks and those speculated in the literature need to be adjusted, and it is critical that the average carbon stocks of soil taxa to be included in the calculations in conjunction with the climate and terrain characteristics.

DISCUSSIONS

The construction of spatial models has given rise to many questions critical for their correctness and accuracy: How realistic are the data on SOC stocks derived from the constructed model? Are there other factors affecting soil formation? etc. However, this approach has been widely used in science. The undoubted advantages are its low price compared to traditional methods, and that most of the software and the required massifs of the already selected and analyzed data are available. One of the most essential conditions for the model is the quality and quantity of the actual soil profiles data required for model calibration. Ideally, the best option would be Latin hy-

[5] The degradation index $Degr = 100 \cdot \left(R^2 / R^2_{\mathrm{Pred}} - 1\right)$ can be used to assess quality of the model's predictions in new observation points. The empirical criterion $Degr < 50$ % is applied as verification success criterion using Allen's method for not too large sample sizes (<120) in the field of ecology, soil science and agriculture, rather than in the technology-related disciplines, where the strength of the link between response and predictors may be much higher [*Shary et al., 2011*].

[6] *t*-statistics depend on the level of significance (everywhere, lower than $p = 0.05$) and the number of degrees of freedom $n - k - 1$, which is always less than 105 (n – size of sampling: 110, k – the number of predictors: 4).

[7] For statistical analysis, the morphometric measurements were transformed according to the formulas after P. Shary [*Shary et al., 2002*], to normalize their distribution.

Fig. 1. Map of the model-derived carbon stocks for the study region (1).

percube sampling [*McKay et al., 2000*], the constrained Monte Carlo sampling scheme. This permits to trace the data and detect the positions taxonomically most comparable with the combination of selected values, or to find positions that correspond to the intervals of different variables. In either case, a set of spatial coordinates (positions) is obtained, in which soil attribute (s) can be easily observed.

In real cases, applicable to the high northern latitudes and other remote areas it is possible, practically, to collect field data (in this context, SOC stocks) from only a few small key sites, whereasit is necessary to assess, as a rule, SOC stocks in more extensive areas, where these sites resemble mere spots in appearance. Specifically, climatic characteristics can not be accountable in these key sites (10–15 km^2 in size)[8], however, given a set of sites located in different areas is used, climatic factors become tangible already in the regression.

Accordingly, extrapolation methods were introduced [*Lagacherie et al., 2001*], to define the reference area (key site) [*Favrot, 1989*], which, when assisted by using the spatial data layers, extrapolates well to a larger area. Sampling of the reference area can be either purposive, or systematic (the model is adjusted and extrapolated for the rest of the area). In this study, the approach employing the reference sites and extrapolation is critical, with the high strength of link (correlation ratio) (R^2 = 0.84) and low degradation index of the model (*Degr* = 1.5 %) indicating a satisfactory quality of the extrapolation.

CONCLUSIONS

The use of modern digital cartographic methods, such as *scorpan*-SSPF, in soil science allows to accurately calculate and model the SOC stocks spatial heterogeneity in permafrost soils of the European Northeast.

The results and findings may be presented in the form of raster maps for current SOC stocks and predictive maps (with possibility of space-time prediction) using the existing predictive climate scenarios (E-GISS, HadCM3 et al.).

The high correlation between spatial variability of SOC stocks and environmental factors (the combined soil taxa, topography, mesorelief, climatic char-

[8] As was discussed above, climatic matrices from [*Hijmans et al., 2005*] with the 30″, or 364 m resolution at 67° N of the study region were further used for average annual mean and meant temperatures and sums of the amounts of precipitations for winter, spring, summer, and autumn periods. Within a small site, 10–15 km^2 in size, climatic factors vary insignificantly, with no observable influence on the model response.

acteristics) ($R^2 = 0.840$, $p < 10^{-6}$) suggests that the SOC stocks distribution is directly controlled by these factors.

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