

# ҐРУНТОЗНАВСТВО

## SOIL SCIENCE

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### Digital mapping of soil organic carbon stocks in Ukraine

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ARTICLE INFO	ABSTRACT
<p>Received 02.07.2019 Received in revised form 22.07.2019 Accepted 19.08.2019 Available online 01.09.2019</p> <hr/> <p><b>Keywords:</b></p> <p><i>digital soil mapping; Global Soil Organic Carbon Map; GSOCmap; organic carbon; soil cover of Ukraine.</i></p>	<p><b>Aim.</b> Create a digital map of organic carbon stocks in the soils of Ukraine using digital soil mapping technologies. <b>Methods.</b> To create a digital map, spatial prediction methods were applied using R programming language. <b>Results.</b> Based on information on the organic carbon content in soil of Ukraine, legacy soil maps, remote sensing materials and additional topographic and climatic characteristics using the digital mapping technology, a national digital map of soil organic carbon stocks in a 0-30 cm layer with a resolution of 1x1 km was created. Modelling of the spatial distribution of organic carbon stocks in mineral soils was performed using the Random Forest algorithm, in peatlands – using the kriging method. The most significant predictors for spatial distribution of soil organic carbon stocks in the country's soil cover were soil type, climate variables, spectral reflectance of bare soil in the near infrared range of the spectrum. <b>Conclusions.</b> The digital map of organic carbon stocks in Ukraine's soils was developed in accordance with the specifications of the Global Soil Partnership of the United Nation Food and Agriculture Organization (FAO) and integrated into the FAO Global Soil Organic Carbon Map (GSOCmap). The created national digital map of carbon stocks in the soils of Ukraine can be used as a basis for further monitoring of organic carbon stocks, however, this task can be achieved only if a unified national soil information system is created, in which information on field surveys is accumulated and updated.</p>

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## 1. Introduction

Soil organic carbon (SOC) is one of the fundamental components of the soil that is crucial for food production as well as for soil health and its ability to provide ecosystem services [1]. The importance of soil carbon for food security and resilience against climate change has been widely recognized on the international level, thus SOC became of the sub-indicators for Sustainable Development Goals (SDG) target 15.3.1 (Proportion of land that is degraded over total land area) contained in the United Nations Resolution A/RES/70/1 of 25 September 2015. According to the Status of the World's Soil Resources (SWSR) report [2], around 33 % of the world soils are in currently in degraded state, which means significant loss of soil organic carbon around the world. This creates the necessity of estimation and monitoring of SOC stocks and their spatial distribution on the global, regional and nation levels. Several global maps of SOC stocks have been created to date which show the overall spatial distribution of carbon on Earth [3], however, they lack the precision to be applicable on the national level. In order to improve the knowledge of SOC in the world, FAO's Global Soil Partnership (GSP) launched an initiative to create a global soil organic map based on the distributed approach where each country would create its own map according to the GSP methodology and using the best available local data and knowledge. As a member of the GSP, and taking into account the importance of Ukrainian chernozem soils for food security, Ukraine participated in this global process by creating the national map of soil organic carbon stocks. The creation of the national soil organic carbon map of Ukraine was conducted according to the agreement between FAO/GSP and National Scientific Center «Institute for Soil Science and Agrochemistry Research named after O.N. Sokolovsky» (NSC ISSAR). The methodology was applied according to the GSP Guidelines for sharing national data/information to compile a Global Soil Organic Carbon map [4] and the Cookbook [5].

## 2. Materials and methods

### 2.1. Collection of SOC Database

**SOC content.** Since the beginning of the Project, a total number of 4134 points of SOC data have been collected. The major method for determining of soil organic carbon content in Ukraine is method of wet oxidation by Tyurin. Soil organic matter (SOM) content is derived from applying a conversion factor - the classic conversion factor is 1.724 for mineral soils.

**Bulk density.** In the collected database, 3775 samples (91 % of all data) had the information about bulk density of soil based on field measurements according to ISO 11272:1998. For the samples in which bulk density was not determined in the field, the following methods were used to derive density parameters:

- 196 samples – calculated from humus (SOM) content and physical clay (granulometric fractions <0,01 mm) content using the pedotransfer function, developed by the scientists of NSC ISSAR for Ukrainian soils [6] with the formula:

$$BD = 1,6929 - 0,0103 * FG - 0,0645 * Humus + 0,0001 * FG^2 - 0,0001 * FG * Humus + 0,0006 * Humus^2, \quad (1)$$

where  $BD$  - bulk density,  $g/cm^3$ ;  $Humus$  - humus (SOM) content, %;  $FG$  - physical clay (granulometric fractions < 0.01 mm) content, %;

- 24 samples – derived from literature data [7];
- 139 samples – calculated with Truskavetsky method (for peat soils) [8].

**Coarse fragments.** Stoniness is not a common characteristic for soil in most of regions of Ukraine, therefore, estimation of coarse fragments content is not a part of a standard soil survey. Out of 4134 samples in the database, only 11 had indication of stoniness estimated visually. Because of the lack of data on this parameter, correction coefficient for stoniness was not included in the calculation of SOC stocks.

**SOC stocks.** For the calculation of SOC stocks the basic formula was used [4]:

$$SOC = d * BD * (C_{tot} - C_{min}) * CF_{st} \quad (2)$$

where  $SOC$  – soil organic carbon ( $kg/m^2$ );  $C_{tot}$  and  $C_{min}$  – total and mineral (or inorganic) carbon ( $g \cdot g^{-1}$ ), to be considered for calcareous soils, and if dry combustion is used with typically high temperatures (otherwise:  $C_{tot}$  equals  $C_{min}$ );  $d$  – depth of horizon/depth class (m);  $BD$  – bulk density ( $kg/m^3$ );  $CF_{st}$  – correction factor for stoniness and gravel content:

$$CF_{st} = 1 - \frac{gravel(\%) + stones(\%)}{100} \quad (3)$$

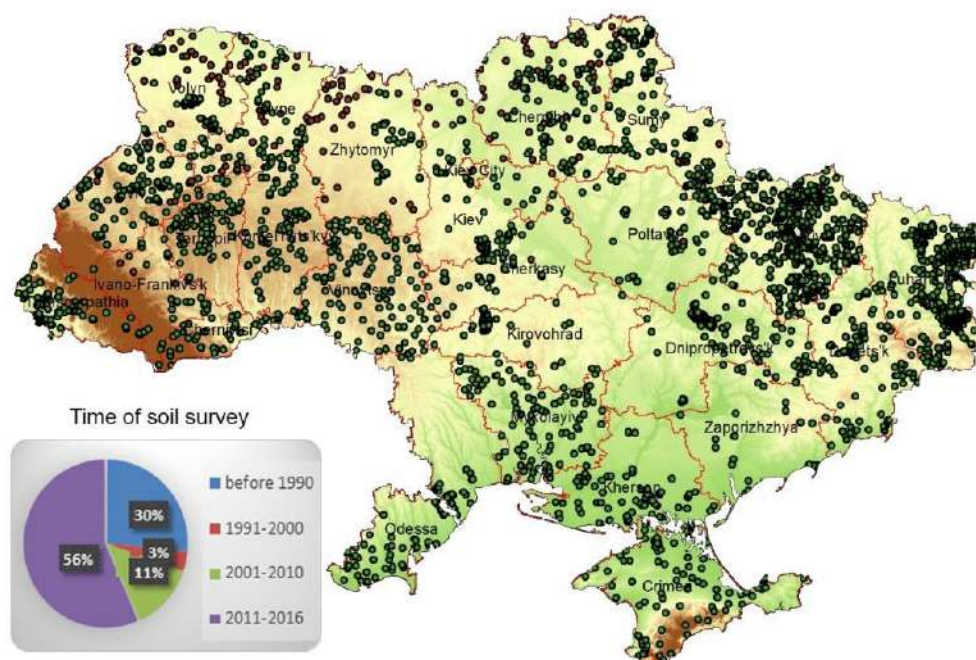
However, since Tyurin method of wet oxidation determines only organic carbon, and there is no sufficient stoniness data, the formula was reduced to the following:

$$SOC_{stock} = SOC * d * BD \quad (4)$$

**Soil types.** The collected data covers most of the major Ukrainian soil types according to the national classification. The majority of samples represent Chernozems and Podzolized soils, which corresponds to the structure of Ukrainian soil cover. The Cinnamonic soils that are not represented in the database are a rare soil type for Ukraine, which form only under specific conditions on the south coast of Crimea. Other underrepresented soil types correspond to specific forms of gleyed and salinity.

The majority of samples were taken within last two decades with 56 % from 2011 until 2016; 30 % of samples were taken before 1990 starting from 1960s. Because of the gaps in coverage, a lot of archive data were used, resulting in significant percentage of outdated points. The spatial distribution of SOC data points covers all regions and climate zones of Ukraine (Fig. 1).

However, a significant amount of points come from archive data with time of sampling prior to 1991. The use of archive data allowed to cover most of the "white spots", however it means that the resulting model is based on the mixed data originating from different decades, thus it does not fully represent the current status of SOC stocks in Ukrainian soils. The fact that almost all peat data is outdated means that it does not have accurate georeferencing which significantly reduces the accuracy of the model. Therefore, more up-to-date soil surveys need to be conducted all over the country, especially on the peat soils, to improve the accuracy of assessment of current status of SOC stocks in Ukraine.



**Fig. 1.** SOC point data spatial distribution

## 2.2. Digital Soil Mapping Methods

In accordance with digital soil mapping methodology [9] the rasters of environmental covariates have been created. The main parameters to be included based on S.C.O.R.P.A.N model are: soil, climate, organisms and land cover, relief, parent material, age, spatial or geographic position.

To include these parameters in the model a number of rasters were created by means of digitization of a soil map, processing of satellite imagery and relief data.

To derive soil properties a soil map of Ukraine at scale 1:750 000 was digitized. The original map was produced by NSC ISSAR under supervision of prof. M.K. Krupsky in 1975 based on soil survey of 1961-1963. The map consists of 7026 polygons each of them containing the attributes such as soil type and subtype, soil texture class, parent material, type of gley, complexes with salinized soils, type of salinization, stoniness. According to soil texture class, average physical clay content (*FG*) was assigned to each polygon.

As a source of elevation data, tiles of USGS product GMTED2010 were downloaded at 7.5 arcsec resolution. From this DEM the following relief parameters were derived using SAGA GIS 3.0 [10]: slope, aspect, longitudinal curvature, cross-sectional curvature, topographic wetness index, relative slope position, closed depressions, topographic position index.

The European Space Agency's CCI land cover product at 300 m resolution [11] was chosen as a baseline land cover layer. Land cover classes were aggregated into 8 categories: arable land, grassland and shrubs, broadleaf forest, needle leaf (coniferous) forest, mixed forest, artificial (urban) areas, bare land and water bodies. The water bodies and artificial areas were used to mask out corresponding pixels from all raster data.

### *Satellite imagery.*

MODIS imagery was chosen as a main source of satellite data. 2 MODIS products were used for NIR reflectance mosaic raster, NDVI and EVI rasters and for Primary Productivity raster.

Previous researches showed that NIR reflectance of bare soil has strong correlation with organic carbon content [12]. To acquire a continuous layer of bare soil reflectance it was necessary to make a mosaic of multi-temporal images. April was chosen as the best month for bare soil observation. Typical crop rotation in Ukraine is a 5-year cycle, so images from last 5 years 2012-2016 were taken for mosaicing. Considering MOD13Q1 product is a 16-days composite, there were 2 April images for each year, 10 images for each tile, 40 images for the whole Ukraine.

The procedure of creating bare soil NIR raster was performed in several steps, including the following: extract NIR, NDVI and Pixel Reliability rasters, create and apply NDVI values mask, normalize NIR raster, calculate mean values of all NIR rasters, apply water and urban area masks from land cover data and fill-in the gaps in coverage using natural neighbor

interpolation. This procedure was performed using R programming language.

For modeling vegetation effect on SOC, mean values of vegetation indices NDVI and EVI from all 16-day composites March-October 2012-2016 (300 images) were calculated taking into account pixel reliability of each image. Also, a layer of mean Primary Productivity throughout 15 years (2000-2014) was derived from MOD17A3H product.

As for the climate data, it has been shown by Ukrainian scientists [13] the key factor determining soil characteristics in Ukraine is the Hydro-Thermal Coefficient (HTC) which is the ratio of precipitation (P) in mm during the period with average air temperatures above 10 °C to the sum of temperatures ( $\Sigma t$ ) over the same time reduced 10 times:

$$HTC = \frac{P * 10}{\Sigma t}, \quad (5)$$

To assess this parameter the data from 137 meteorological stations throughout Ukraine was collected and average yearly values from 100 years of observations (1890-1990) were calculated for precipitation during the year, precipitation during warm period (May-September), sum of temperatures during warm period (May-September). From these values, HTC was calculated for each meteorological station. Then raster layers for precipitation, temperatures and HTC were created by interpolating point values with inverse distance weighting method.

Additionally, World Climate Data grids [14] at resolution of 1 km with mean monthly temperature and precipitation for the years 1960-1990 were downloaded. The rasters like sum of temperatures and mean precipitation of warm/cold period and hydro-thermal coefficient (HTC) were created from these layers.

As a next step, it appears necessary to combine meteorological stations derived data with World Climate derived data for better quality of climate layers.

ISRIC World Soil Information (Wageningen, the Netherlands) provided 3 stacks of rasters representing different environmental variables for all countries participating in the GSP's GSOCmap project. Out of this data, 48 rasters were selected and added to the data prepared by NSC ISSAR to be used in modeling.

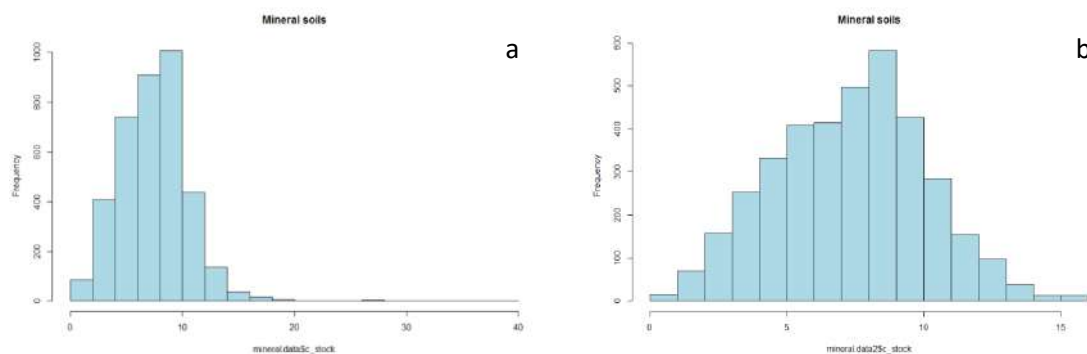
Since relief and satellite data has resolution of 250 m or better it was decided to use 250 m template for all layers.

#### *Spatial modelling.*

The work was done with the R script using R studio software [15]. First, point data were loaded into the program and tested for duplicates and missing values. As a result, 203 points out of 4134 were removed as duplicates.

Analysis of data distribution showed that organic carbon stock values for mineral soils and peat soils were incomparable. High concentrations of SOC in the peat soils was in bright contrast with low concentrations of the nearby mineral soil because of different process of carbon accumulation and different factors influencing it. Furthermore, the available SOC stocks data for peat soils had the values for the full depth of peat, while for the mineral soils the standard depth was 30 cm of topsoil. As a result, it was decided to split the data in 2 groups: mineral soils and peat soils, and make separate models for each. The splitting was done based on the soil type, indicated in the database. After splitting, 3792 points were classified as mineral soils, and 139 points - as peat soils. Thereafter, the mineral soil data and peat soil data were analyzed separately.

Analysis of the histogram of SOC stocks in mineral soils allowed to identify outliers with extremely high values which were subsequently removed (Fig. 2.)



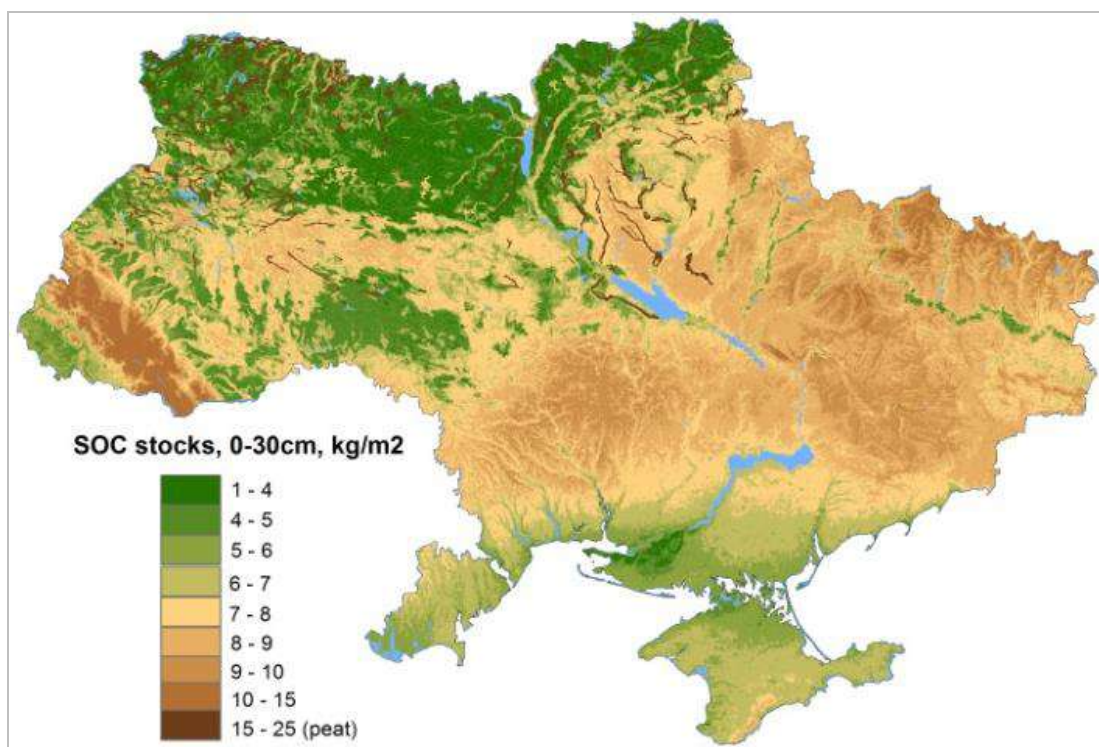
**Fig.2.** Histograms of distribution of SOC stocks in mineral soils: a) before removing outliers; b) after removing outliers

Then the auxiliary rasters were loaded into the program and their values were extracted to the points with SOC data, thus creating a regression matrix. In the situation when soil class extracted from the map did not coincide with the soil class indicated in the point database, the preference was given to point data observations due to possible inaccuracy and generalized nature of the soil map. The categorical variables in the matrix: soil class, parent material and land cover class were transformed from numeric to factor data type.

Random Forest [16] algorithm was applied to model the spatial distribution of SOC stocks in mineral soils. For peat data regression models did not show any ability to describe the variation using the auxiliary parameters, resulting in  $R^2$  around 0.1. Yet, the SOC stock values showed some spatial correlation, therefore it was decided to use ordinary kriging to model the SOC spatial distribution for peat soils. To generate the final layer, SOC stocks predictions for mineral soils and peat soils were combined to produce the final map. To comply with the GSOCmap specifications, the map was resampled from 250m to 1km resolution.

### 3. Results and Discussion

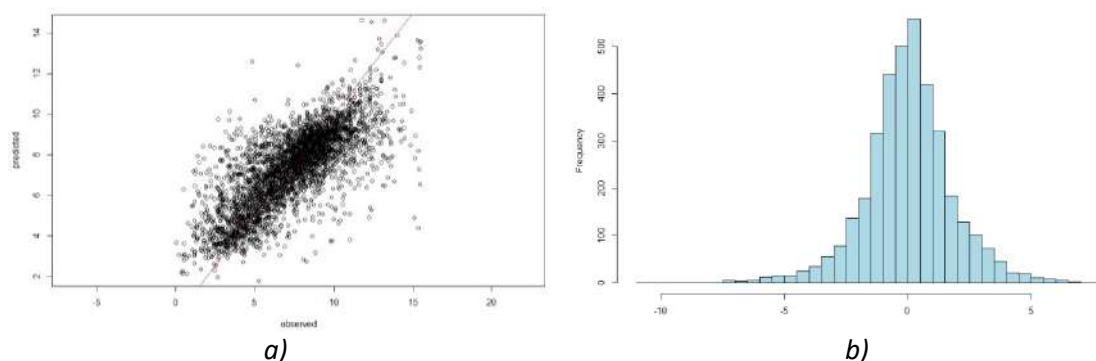
The final map (Fig. 3) shows the predicted values of SOC stocks in Ukrainian soils at 1 km resolution. The rich in carbon Chernozem zone is clearly distinguishable on the map, the lowest values correspond to sandy podzolic soils of Northern Ukraine as well as the arid area in the South. The effect of relief is also clearly visible. Overall, the model's output is consistent with the expectations of soil organic carbon distribution. However, the Carpathian Mountains show rather high values of SOC stock, which could be due to the features of soil genesis in these conditions and indeed high humus content (up to 15 % in the upper horizon) and, consequently, organic carbon.



**Fig. 3.** SOC stocks map of Ukraine

The uncertainty of the model was assessed using such parameters as determination coefficient ( $R^2$ ) and root mean squared error (RMSE), which were obtained through cross-validation. The result showed reasonably good model fit with  $R^2=0.56$  and  $RMSE=1.82$  for mineral soils (Fig. 4, a). Analysis of residuals showed their normal distribution which proves that the model is not biased (Fig. 5, b).

To assess the importance of the predictors in the model, the Random Forest's IncMSE and IncNodePurity parameters were used. IncMSE is the increase in mean squared errors of predictions as a result of a certain variable being permuted (randomly shuffled). IncNodePurity measures how many the splits of Random Forest decision trees with a certain parameter reduce node impurity (difference of mean squared errors before and after split).



**Fig. 4.** a) Random Forest model goodness of fit; b) distribution of residuals

Based on IncMSE, the most important parameters in the model were the following:

- soil type 4 (Soddy-podzolic soils);
- soil type 5 (Gray forest soils);
- temperature seasonality
- near-infrared reflectance of the bare soil
- precipitation of the cold period (December-February)

Based on IncNodePurity, the most important predictors were:

- temperature seasonality;
- near-infrared reflectance of bare soil;
- soil type 4 (Soddy-podzolic soils);
- hydro-thermal coefficient;
- soil type 1 (Chernozem).

Summing up, we can say that soil type, climate and infrared reflectance of soil were the most important predictors in the model.

After the completion of the National Soil Organic Carbon map of Ukraine it was integrated into the Global Soil Organic Carbon map by the Global Soil Partnership Secretariat along with the contributions from other countries [17].

#### 4. Conclusions

The National Soil Organic Carbon map of Ukraine is Ukrainian contribution to the Global Soil Organic Carbon map (GSOC map). It is the first map of Ukrainian soil properties that was created using state-of-the-art digital soil mapping techniques.

The map of SOC stocks in Ukraine is representative for the SOC spatial distribution and is the most accurate assessment of SOC stocks available to date. However, it is based on the dataset, 30% of which comes from before the year 1991. This means that to establish a baseline for SOC monitoring in Ukraine, further research and additional data is required. The model for SOC stocks in peat soils has a high uncertainty due to insufficient amount and quality of data. Addition study of Ukrainian peat soils is required to have an accurate estimation of their present status.

The map of SOC stocks in Ukraine should be constantly updated and improved upon acquiring new data. The most effective way of organizing this process would be through establishing a digital soil information system in Ukraine, which would allow processing the incoming data and transforming it for digital soil mapping procedures.

#### 5. Acknowledgements

We acknowledge financial and methodological support from the Global Soil Partnership. We acknowledge ISRIC for implementing the training on digital soil mapping and preparing the covariate layers for spatial modelling. We acknowledge authors of Ukrainian scientific and educational institutions which contributed their data for the project, namely: National Scientific Center «Institute for Soil Science and Agrochemistry Research named after O.N. Sokolovsky» and its Polisska Experimental Station; National Scientific Center "Institute of Agriculture of NAAS"; Cherkasy State Agricultural Experimental Station of NSC "Institute of Agriculture of NAAS"; Rice Research Institute; Institute of Agricultural Microbiology and Agroindustrial Production NAAS; Institute of Agriculture of Carpathian Region NAAS; Volyn State Agricultural Experimental Station of the Institute of Agriculture of Western Polissya; Kirovograd State Agricultural Experimental Station; Luhansk Institute of Agroindustrial Production NAAS;

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## Цифрове картографування запасів органічного вуглецю у ґрунтах України

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Метою роботи було створення цифрової карти запасів органічного вуглецю в ґрунтах України із застосуванням технологій цифрового картографування ґрунтів. Для створення цифрової карти були застосовані методи просторового прогнозування із використанням мови програмування R. Результати. На основі інформації про вміст у ґрунтах України органічного вуглецю, архівних ґрунтових карт, матеріалів дистанційного зондування та додаткових топографічних і кліматичних характеристик із використанням технологій цифрового картографування була створена національна цифрова карта запасів ґрунтового органічного вуглецю у шарі 0-30 см із роздільною здатністю 1x1 км. Моделювання просторового розподілу запасів органічного вуглецю в мінеральних ґрунтах було виконано з використанням алгоритму Random Forest, торфовищах – методом крігінга. Найбільш вагомими предикторами для прогнозування просторового розподілу запасів органічного вуглецю у ґрунтовому покриві країни є тип ґрунту, кліматичні зміни, спектральний коефіцієнт відбиття відкритого ґрунту у ближньому інфрачервоному діапазоні спектра. Висновки. Цифрова карта запасів органічного вуглецю в ґрунтах України була розроблена відповідно до специфікацій Глобального ґрунтового партнерства Продовольчої і сільськогосподарської Організації Об'єднаних Націй (ФАО) і інтегрована в Глобальну карту ґрунтового органічного вуглецю ФАО (GSOCстар). Створена національна цифрова карта запасів вуглецю у ґрунтах України може бути використана, як базова для подальшого моніторингу запасів органічного вуглецю, однак реалізація цього завдання, можлива лише за умови створення єдиної національної ґрунтової інформаційної системи, у якій буде акумулюватись та оновлюватись інформація щодо польових обстежень ґрунтів.

**Ключові слова:** Глобальна карта запасів ґрунтового органічного вуглецю; GSOCстар; ґрунтовий покрив України; органічний вуглець; цифрове картографування ґрунтів.

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