MCIT
Modeling, control & information technologies

Modelling soil organic carbon turnover with assimilation of satellite soil moisture data

https://doi.org/10.31713/MCIT.2021.31

Olha Stepanchenko, Liubov Shostak, Olena Kozhushko, Viktor Moshynskyi, Petro Martyniuk[1]
Department of Computer Sciences and Applied Mathematics
National University of Water and Environmental Engineering
Rivne, Ukraine
ol.d.kozhushko@nuwm.edu.ua

Abstract — **The content of organic carbon is one of the essential factors that define soil quality. It is also notoriously challenging to model due to a multitude of biological and abiotic factors influencing the process. In this study, we investigate how decomposition of soil organic matter is affected by soil moisture and temperature. Soil organic carbon turnover is simulated by the CENTURY model. The accuracy of soil moisture data used is ensured by data assimilation approach, combing mathematical model and satellite retrievals. Numerical experiments demonstrate the influence of soil moisture regimes and climate on the quantity of soil humus stocks.**

***Keywords* — soil organic carbon; carbon turnover; CENTURY model; mathematical modelling; soil moisture; data assimilation.**

I. INTRODUCTION

Soil is one of the principal components for the existence of living organisms on the Earth. Intensive use of agricultural lands in recent decades has resulted in its exhaustion. To assure sustainable land use, an optimal set of indicators for production management has to be established.

A significant role in soil fertility is played by the soil organic matter. The content of organic matter depends on the soil's chemical composition, temperature, texture and moisture. Soil quality is defined largely by the organic carbon stock. Carbon plays a vital role in supporting soil ecological sustainability, since it absorbs pesticides and decomposes excess Nitrogen.

A number of approaches and indices has been developed to evaluate the soil carbon, taking into account land use practices. A few notable models for soil organic carbon (SOC) stock are CENTURY, RothC and PaSim [1].

PaSim is a model simulating the humus, nitrogen and water balance for grazing lands. It consists of five submodels that account for physical and biological properties of soil medium, vegetation type, livestock and microclimate.

RothC is used for evaluating SOC content in upper layers of the arable lands for arid climate territories. The model accounts for vegetation, soil type, temperature and moisture. The organic remains are classified into plant and resistant to decomposition remains.

The CENTURY models describes the carbon, nitrogen, sulfur and phosphorus dynamics. It divides organic remains into root and surface litter, which, in their turn, are separated into structural and metabolic remains. The model can also estimate soil state under different land use and irrigation scenarios [2].

II. SOIL ORGANIC CARBON MODEL

A. *Organic Matter Transformation*

After analyzing the principal models for SOC evaluation, we chose CENTURY as the basis of our model. The model keeps track of the input plant organic material from aboveground and root remains, which are divided into structural and metabolic litter. All soil organic matter is separated into active, slow and passive pools depending on their decomposition time. Soil active pool consists of organic remains and microbes that are easily decomposable; slow organic matter is biologically and physically resistant to transformation, and passive matter is physically protected and less susceptible to chemical turnover.

Essential role in organic matter transformation is played by the microbial mass, lignin content, soil texture, moisture and

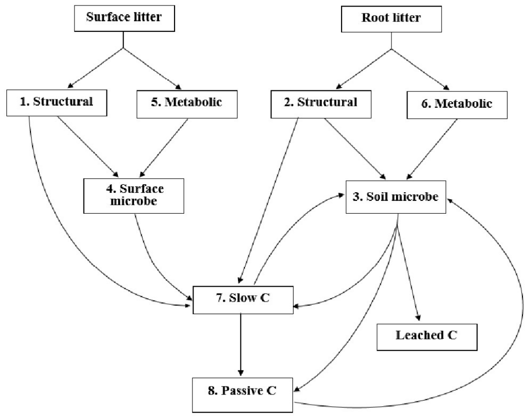

Figure 1. Structure of the CENTURY model

---

[1] The research is supported by EOS Data Analytics.

temperature. The model specifies the relations by which metabolic and structural litter are separated based on lignin to nitrogen ratio.

Thus, in CENTURY soil organic carbon is divided into eight SOC pools, as shown in Fig. 1. Decomposition of each carbon pool is calculated by the following set of equations:

$$\begin{aligned} &\frac{dC_i}{dt} = K_i L_c A C_i, && i = 1,2, \\ &\frac{dC_i}{dt} = K_i A T_m C_i, && i = 3, \\ &\frac{dC_i}{dt} = K_i A C_i, && i = 4,5,6,7,8, \\ &T_m = (1-0.75T), \quad L_c = e^{-3L_s} && \end{aligned} \tag{1}$$

where C_i is the quantity of organic carbon in the i-th pool (pools are numbered as in Fig. 1), K_i is maximum decomposition rate for the i-th pool, A is a combined abiotic impact of soil moisture and soil temperature on decomposition, T_m is effect of soil texture on active SOC turnover, where T is equal to the sum of silt and clay fraction, L_C is the impact of lignin content of structural material (L_s) on structural decomposition [3].

CENTURY considers that turnover of organic matter in above and belowground layers is tied to microbial biomass and microbial respiration. Each carbon transformation involves loss of fixed fraction of carbon due to respiration. For instance, organic carbon that leaves soil active pool is divided between microbial respiration, slow and passive pools and loss due to leaching.

B. Abiotic Stress

Soil moisture and temperature have significant effect on the carbon turnover cycle. It has been show by a number of studies that biological processes leading to carbon decomposition require certain temperature and moisture regimes. If either is not met, the decomposition processes are slowed down or even stopped completely. This effect is called abiotic stress.

We chose the expolinear relation for calculating temperature stress, following original CENTURY papers [3]:

$$\begin{gathered} \mathrm{A}_t = t_1^{0.2} \cdot t_2, \\ t_1 = (45 - T_s)/(45-35), \quad t_2 = \exp\left(0.076\left(1 - t_1^{2.63}\right)\right), \end{gathered} \tag{2}$$

where T_s is soil temperature, and 45 and 35 are maximum and optimal temperatures for decomposition, respectively.

For water stress, we make use of an empirical function used in [4] (retrieved from their Github repository)

$$\mathrm{A}_w = -1.1 \cdot S_{rel}^2 + 2.4 S_{rel} - 0.29, \tag{3}$$

where S_{rel}, in its own turn, is defined as absolute soil moisture θ linearly scaled between wilting point θ_{wp} and field capacity θ_{fc}:

$$S_{rel} = \left(\theta - \theta_{wp}\right) / \left(\theta_{fc} - \theta_{wp}\right). \tag{4}$$

Both stress function and relative moisture values are limited to the interval [0, 1]. The resulting abiotic stress function is then a product of temperature stress A_t and water stress A_w.

III. Soil Moisture Model

The soil moisture data are generated by a separate model that is based on the Richards equation with Mualem–van Genuchten model for soil parameters. The model is one-dimensional and calculates moisture profile for the soil layer at a given point.

To improve the accuracy of model results and update it to the real world state, we add satellite moisture estimates to the model. Since neither the model nor the estimates can be considered absolutely truthful, various data assimilation algorithms can be used to combine them and thus improve estimates. We use Newtonian nudging assimilation for the moisture equation, which is one of the 4DDA methods family. Basically, Newtonian nudging is realized by adding a special nudging term to the governing equation, which can be view as an external force pulling the result closer towards observations. The implementation and validation of the model and assimilation are described in our previous work [5].

Moreover, the soil temperature is also modelled since it often differs from the air temperature. This submodel is governed by the heat transfer equation based on Fourier’s law. We also take into account the interrelations between water and heat flow. The model overall consists of the following equations:

$$\begin{aligned} \frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x}\left(k(h)\frac{\partial h}{\partial x} - k(h)\right) - S(h,x,t) + \\ + G \cdot W(x,\mathrm{t})\varepsilon(x)\left(\theta_{obs} - \theta\right), \end{aligned} \tag{5}$$

$$\left.\left(-k(h)\frac{\partial h}{\partial x} + k(h)\right)\right|_{x=0} = \mathrm{Q}(t) - \mathrm{E}_s(t), \mathrm{t} > 0, \tag{6}$$

$$\left.\frac{\partial h}{\partial x}\right|_{x=l} = 0, \mathrm{t} > 0,\ h(x,0) = h_0(x),\ x \in [0;l]. \tag{7}$$

$$c_T \frac{\partial T(x,t)}{\partial t} = \frac{\partial}{\partial x}\left(\lambda(h)\frac{\partial T}{\partial x}\right) - \rho c_w u(h)\frac{\partial T(x,t)}{\partial t}, \tag{9}$$

$$\left.T(x,t)\right|_{x=0} = T_1(t),\ t \ge 0, \tag{10}$$

$$\left.T(x,t)\right|_{x=l} = T_2(t),\ t \ge 0, \tag{11}$$

$$T(x,0) = T_0(x),\ x \in [0;l]. \tag{12}$$

IV. Experiment setting and data

In this paper, we aim to highlight the effect of soil moisture and temperature on the organic carbon cycle. For this purpose, we chose three agricultural sites within Ukraine with different climates and soils, located in Rivne (near Stepan’), Zakarpattia (Vynogradiv) and Kherson (Novopavlivka) regions.

Soil classes and parameters are derived from SoilGrids dataset [6]. The data used for sites are summarized in Table 1.

Soil carbon stock values, which are used as initial condition for the SOC model, are distributed between carbon pools according to the statistics presented in [7].

TABLE II. EXPERIMENT SITES AND DATA

Location, Region	**Soil type**	**Organic carbon stock (kg/m^2)**	**Average moisture**[a]	**Field capacity**	**Wilting point**
Stepan', Rivne	Sandy Loam	4.4	0.319	0.21	0.09
Vynogradiv, Zakarpattia	Clay Loam	5.1	0.209	0.33	0.16
Novopavliv-ka, Kherson	Clay	4.9	0.182	0.44	0.2

a. Average soil moisture based on the satellite estimates

The average moisture column in Table 1 demonstrates a variety of moisture regimes on the experimental sites. For the first site, moisture is mostly above field capacity, whereas for the third site the average moisture is below wilting point in case no irrigation is applied. Thus, the three sites represent different moisture conditions.

As carbon turnover processes are known to be slow, we intended to cover at least a few decades with modelling data. Weather data for temperature and moisture modelling are assumed as for the nearest weather station, provided by the LaMetSy service (https://lametsy.pp.ua). Satellite soil moisture estimates are taken from the Copernicus database [8]. The simulation is carried out for the period from 1990 to 2020, since the period before 1990 is lacking coverage with satellite imagery.

Litter incomes are assumed at 60 and 140 $g/(m^2 \cdot year)$ of aboveground and root litter, respectively. These average yearly values are then distributed on a sine curve for the growing season (March – September).

V. DISCUSSION OF RESULTS

The results of 30 years modelling of carbon turnover with described input data are presented in Fig. 2. The first plot shows the amount of carbon in slow SOC pool, which is the largest pool and is commonly associated with humus. As seen from the plot, results are quite similar for wetter sites in Zakarpattia and Rivne region, with slowly decreasing amount of humus in the soil. However, for the arid site in Kherson the quantity of humus is growing quite rapidly over the simulation period. It might be concluded then that higher moisture, while increasing overall turnover rate, results in higher leaching and respiration losses, and, therefore, decreased carbon stocks. Slower turnover in dryer soils, on the other hand, provides a more sustainable system. This assumption is also supported by the fact that soils in the south of Ukraine are much more fertile than in the other regions.

The second plot shows the amount of plant litter that has not been decomposed. It includes four SOC pools, both above and belowground, structural and metabolic. The visible waves are caused by the cropping cycle, since we assumed non-uniform vegetation cycle. As suggested above, plant litter on the two wetter sites is decomposed rather quickly after it enters the system due to fast turnover rate. On the other hand, plant litter on Kherson site is accumulated during the growing season, and decomposes in larger amounts in winter.

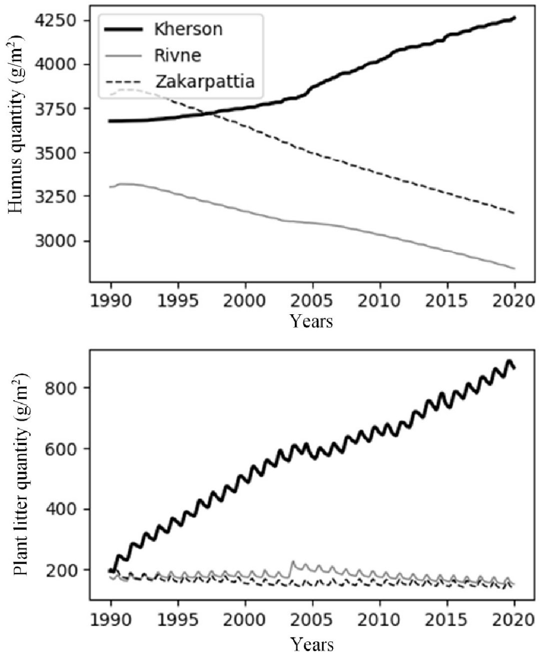

Figure 2. The modelled quantity of humus (top) and uncomposrd litter (bottom) after 30 years

REFERENCES

[1] K. A. Byrne and G. Kiely, "Evaluation of Models (PaSim, RothC, CENTURY and DNDC) for Simulation of Grassland Carbon Cycling at Plot, Field and Regional Scale," STRIVE Report Series no. 20, 2008.

[2] L. Shostak, M. Boiko, O. Stepanchenko, and O.Kozhushko, "Analysis of Soil Organic Matter Transformation Dynamics Models," Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska, 2019, vol. 9, no. 3, pp. 40–45.

[3] W. J. Parton, D. S. Ojima, C. V. Cole, and D. S. Schimel, "A General Model for Soil Organic Matter Dynamics: Sensitivity to Litter Chemistry, Texture and Management," in Quantitative Modeling of Soil Forming Processes, R. Bryant and R. Arnold, Eds. Madison: Soil Science Society of America, 1994, pp. 147–167.

[4] L. Zhu, Z. Deng, Y. Xie et al., "Factors controlling Carex brevicuspis leaf litter decomposition and its contribution to surface soil organic carbon pool at different water levels," Biogeosciences, 2021, vol. 18, pp. 1–11.

[5] O. Kozhushko, M. Boiko, M. Kovbasa, P. Martyniuk, O. Stepanchenko, and M. Uvarov, "Evaluation of the soil moisture model with data assimilation by the triple collocation method," Modeling, Control and Information Technologies: Proceedings of International Scientific and Practical Conference, 2020, vol. 4, pp. 35–38.

[6] L. Poggio, L. de Sousa, N. Batjes et al., "SoilGrids 2.0 : Producing soil information for the globe with quantified spatial uncertainty," SOIL, 2021, vol. 7, pp. 217–240.

[7] O. Bashir, T. Ali, Z. A. Baba et al., "Soil Organic Matter and Its Impact on Soil Properties and Nutrient Status," in Microbiota and Biofertilizers, G. H. Dar, R. A. Bhat, M. A. Mehmood, and Kh. R. Hakeem, Eds. Cham: Springer, 2021, vol. 2, pp. 129–160.

[8] R. Kidd, "Product User Guide and Specification. Land Service: Soil Moisture ECV," ECMWF Copernicus Report, v.3.0. Reading: ECMWF, 2021.