Response to Reviewer 1

This study creates global maps of soil organic carbon turnover times (τ) at both topsoil and subsoil depths with observation-based datasets and machine learning methods. It addresses an important knowledge gap regarding the global maps related to the depth-dependent variations and environmental controls of soil carbon turnover, which is essential for understanding terrestrial carbon storage and dynamics, especially in the context of climate change. The methods used are well-suited to the scale and complexity of the question being addressed. The use of over ninety thousand geo-referenced soil profiles, satellite-derived environmental variables, and machine learning models, provides a robust framework for mapping and analyzing τ across a wide range of environmental conditions and different biomes. The authors' approach to quantify the uncertainty of their maps also adds considerable value, making their results more applicable to future carbon cycle modelling and land management efforts. In conclusion, I recommend the acceptance of this manuscript after revisions following several suggestions I listed below.

AC: Thank you for your kind words. We are delighted that you acknowledge the importance of our work and recognize that the findings in our work could bridge the gap and help producing a qualified τ map dataset.

(1) Organic carbon turnover times can be calculated from influencing factors, such as carbon allocation belowground, SOC stocks. Why not first generate the spatial distribution data of those factors based on sampling data with machine learning method, then calculate organic carbon turnover times with the physical equations.

AC: Our approach prioritizes direct estimation of τ using a combination of soil profile observations, root distribution data, and machine learning-based spatial predictions. However, we acknowledge the alternative approach suggested by the reviewer — first predicting the spatial distribution of influencing factors (e.g., carbon input and SOC stocks) and then computing τ using physical equations. We chose our approach for the following reasons:

1) Uncertainty propagation and data constraints: many of the influencing factors (e.g., belowground carbon allocation, root distribution) have limited global observations and high spatial variability. If we were to separately predict these variables before calculating τ, errors from each step would compound, potentially increasing overall uncertainty. By training the machine learning model directly at sample locations, we reduce the risk of error propagation from multiple independent modeling steps.
2) Machine learning model ability to capture complex relationships: The turnover time of SOC is influenced by nonlinear interactions between climate, soil properties, and vegetation. Machine learning can capture the feature importance and their interactions effectively from modelling τ–environment relationships at sample locations. In contrast, if using all grid values to fit a model and then analyze the driving mechanisms, attributing variations in τ to multiple environmental variables suffer from a circularity issue.

Therefore, we reckon that using the independent soil sample data to calculate τ at sample locations firstly, and then using a model to make the global τ maps should be a more reasonable choice from both mapping and driving analysis aspects.

(2) From the physical equations 1 to 8, the importance of different factors could be derived. Do the importance results of RF coincide with those equations?

AC: After using those equations to calculate τ at sample locations, we used RF model to analyze the driving factors (e.g., feature importance) on τ at global, biome, and local scales. The above two steps have different purpose. The RF model was not used to directly compute τ but rather assesses how various environmental factors (we focused on climate, soil physio-chemical properties, and topography) correlate with the observed spatial variation in τ.

(3) While the methods section is thorough, some readers may benefit from further clarification on the choice of specific methods, particularly regarding the machine learning model calibration. A more explicit discussion of how the model's hyper-parameters were tuned would help readers better appreciate the methodology's rigor.

AC: We appreciate the reviewer's suggestion to clarify the details of our machine learning model calibration, particularly regarding hyper-parameter selection. When using RF model, there are two important user-defined parameters in the RF. The first is the number of covariates that randomly selected for each tree building process. We used the rounded down square root of the total number of covariates as this parameter value by default (Breiman, 2001). The second parameter is *ntree*, which is defined as the number of trees to be learned in the forest. We set *ntree* = 200, for the previous soil mapping studies showed that it is sufficient to obtain stable results when the number of trees is larger than 150 (Lopes, 2015; Wadoux et al., 2019; Zhang et al., 2021). We added some sentences in Section 2.2 to describe above content.

References:

Lopes, M.E., 2015. Measuring the algorithmic convergence of random forests via bootstrap extrapolation. Technical Report. Department of Statistics. University of California, Davis CA.

Wadoux, A.M.J.C., Brus, D.J., Heuvelink, G.B.M., 2019. Sampling design optimization for soil mapping with random forest. Geoderma 355, 113913. https://doi.org/10.1016/j.geoderma.2019.113913.

Zhang, L., Yang, L., Ma, T., Shen, F., Cai, Y., Zhou, C., 2021. A self-training semi-supervised machine learning method for predictive mapping of soil classes with limited sample data. Geoderma 384, 114809. https://doi.org/10.1016/j.geoderma.2020.114809

(4) The cross-validation procedure is well-executed, but it would be helpful to provide more specific details on how the biome-specific samples were handled during the 10-fold validation process. Ensuring that the sample division properly accounts for the geographical and ecological variation across biomes could further strengthen the model's credibility.

AC: We appreciate the reviewer's request for further clarification on how biome-specific samples were handled during the 10-fold cross-validation process. To ensure that our validation approach accounted for geographical and ecological variation across biomes, we implemented a biome-stratified cross-validation strategy as follows: We stratified the dataset based on biome classifications before performing cross-validation. Each biome was treated as a separate category to ensure that the sample distribution was maintained across all folds. Instead of randomly splitting the entire dataset, we ensured that each fold contained a proportional representation of samples from

each biome. This approach prevented certain biomes (e.g., tundra, boreal forests) from being underrepresented in the validation sets, thereby improving model generalization across diverse ecosystems. When calibrating the model, the method of over-sampling was adopted to increase training data in biomes with smaller sample size, this way can alleviate the imbalance in data when training the model (Chawla, 2010). We clarified these details in the revised manuscript.

Reference:

Chawla, N.V., 2010. Data Mining for Imbalanced Datasets: An Overview, in: Maimon, O., Rokach, L. (Eds.), Data Mining and Knowledge Discovery Handbook. Springer US, Boston, MA, pp. 875–886. https://doi.org/10.1007/978-0-387-09823-4_45

(5) The paper requires careful attention to language for clarity and readability. I would recommend reviewing some descriptions for possible simplifications in sentence structure and corrections in grammar. Some examples are listed below.

18: "… is central to …" -> "… plays a crucial role in …".

AC: Corrected. Thank you.

19: "remain" -> "remains".

AC: Corrected. Thank you.

92: it is better to change the word "minimize" to "reduce".

AC: Corrected. Thank you.

103: "layers observations" -> "layer observations".

AC: Corrected. Thank you.

465: "insights of this study -> "insights from this study".

AC: Corrected. Thank you.

We further made a great effort in polishing the paper so that it is more explicit and clearer.