RC1: 'Comment on essd-2024-588', Anonymous Referee #1, 16 Mar

Section 3.2. Could you give more explanation about the principles of selecting variables? For example, from Fig.2, the *R* between AH and SOCD is almost 0, why select this variable? And only 18 variables have been shown on Fig. 2 without CLCU, how to select CLCU as an input predictor?

We sincerely appreciate these insightful questions about our feature selection process. In our original methodology, the variable selection followed these principles:

The initial variable selection in our methodology followed a rigorous procedure. First, we established a comprehensive candidate pool comprising 19 environmental variables across four categories: climatic factors (e.g., temperature and precipitation), topographic attributes (elevation, slope, aspect), vegetation indices (NDVI, EVI), and soil properties (clay and sand content). Subsequently, correlation-based screening was applied to retain variables significantly associated with soil organic carbon density (SOCD) ($p < 0.05$) and exhibiting at least a minimal linear relationship (absolute Pearson's $r > 0.1$). Two exceptions were made, anthropogenic heat (AH) was retained due to its potential interactive effects in specific climatic regimes, and land cover type (CLCD) was included based on its well-established ecological relevance in prior literature, despite their weaker correlations with SOCD. Finally, to mitigate multicollinearity, variables with pairwise correlations exceeding 0.8 (absolute value) were eliminated, prioritizing those with clearer physical or mechanistic interpretations.

It is worth noting that, as the reviewer astutely observed, AH indeed exhibited a weak initial correlation with SOCD. Although AH and CLCD were considered based on the aforementioned reasons in the initial stages, during the final model construction and feature importance evaluation, these variables demonstrated low actual predictive contribution. Therefore, they were ultimately excluded from the core variable set used for modeling to ensure model parsimony and predictive efficacy.

Upon careful consideration of the reviewers' comments, we have significantly refined our feature selection approach. We implemented an enhanced feature selection methodology for SOCD prediction. The refined approach begins with initial screening through Pearson correlation analysis ($p < 0.05$ significance threshold), followed by Random Forest-based importance ranking to evaluate non-linear relationships. Subsequently, we conducted exhaustive combinatorial optimization of all possible feature combinations to maximize predictive performance (R^2). Key methodological improvements include: (1) removal of marginally contributing variables (AH, CLCD) with limited predictive value; (2) incorporation of spectral indices (SR, BSI) to better characterize vegetation-soil interactions; and (3) implementation of stricter redundancy thresholds ($|r| > 0.95$) to further minimize multicollinearity. The final optimized feature set comprises 'Tem', 'Elevation', 'NDVI', 'Clay', 'SR', 'BSI', and 'Slope', representing a balanced combination of climatic, topographic, vegetation, and soil properties. This rigorous multi-stage approach effectively integrates statistical correlation analysis with machine learning-based feature importance assessment, ensuring optimal variable selection while maintaining ecological interpretability.

The methodological refinements have been systematically incorporated throughout the manuscript. Section 3.2 Feature optimization for RF modelling has been comprehensively revised to detail the improved approach, with particular emphasis on the integration of machine learning-based importance assessment. Figure 2 has been updated to visually present the final selected feature set and their relative importance scores.

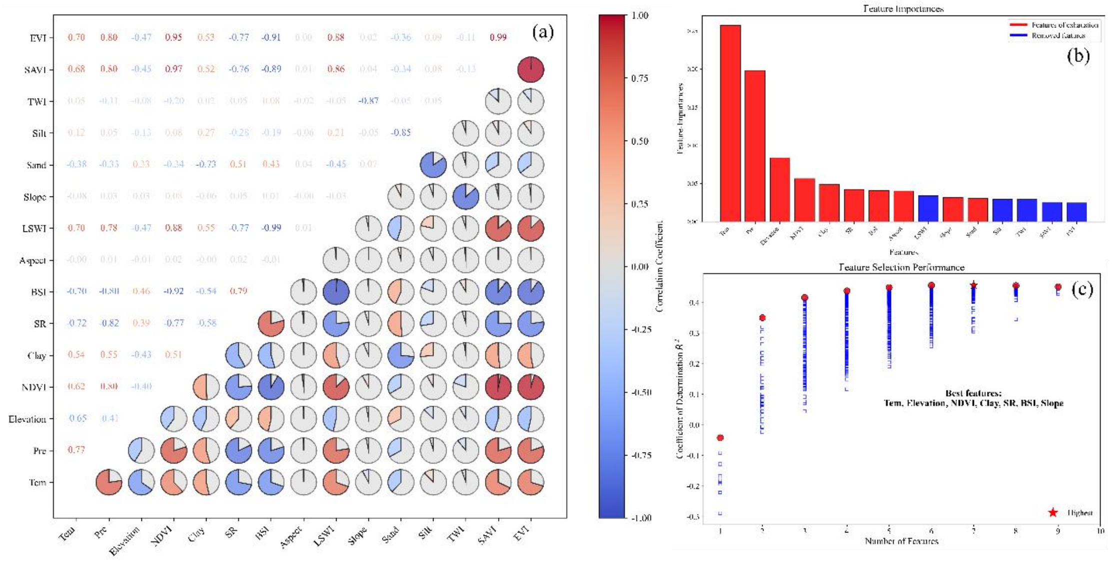
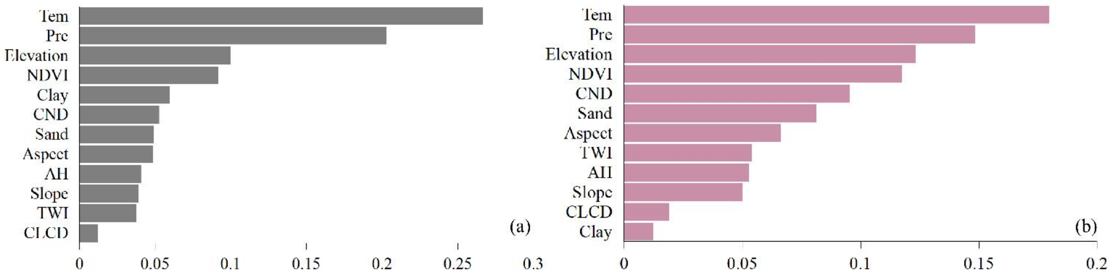


Figure 2. Feature selection process for predicting soil organic carbon density (SOCD). (a) Pearson correlation matrix of top environmental covariates (upper triangle shows correlation coefficients; red=positive, blue=negative), with boxed features indicating the final selected variables. (b) Hierarchical feature importance evaluation combining correlation filtering (removing |r| > 0.95), random forest-based ranking (Gini importance), and combinatorial optimization. The optimal feature set (highlighted in bold) comprised seven variables: mean annual temperature (Tem), elevation, NDVI, clay content (Clay), simple ratio index (SR), bare soil index (BS1), and slope, which collectively maximize prediction accuracy (R^2) while maintaining ecological interpretability.

Section 4.2. Fig. 8 and Line 250: The discussion of different features for SOCD estimations is comprehensive, which can help us to understand the important factors of SOCD variations. But it's very interesting to find that the features have different important values in the two depth models. Please try to discuss more about these differences.



We greatly appreciate the reviewer's valuable observations regarding the distinct patterns of feature importance between our 0-20 cm and 0-100 cm depth models. These differences provide important insights into the depth-dependent mechanisms controlling soil organic carbon (SOC) distribution and accumulation.

The comparative analysis reveals fundamental differences in how environmental factors influence SOC at different soil depths. In the surface layer (0-20 cm), climate variables (temperature and precipitation) demonstrate particularly strong predictive power, reflecting their direct control over biological processes that govern surface carbon cycling. The vegetation index (NDVI) also shows greater importance in this shallow layer, consistent with its role as a proxy for organic matter inputs through plant litter and root exudates. These patterns collectively highlight the dominance of contemporary biological processes in surface SOC dynamics.

In contrast, the full profile model (0-100 cm) shows relatively reduced importance of climatic and vegetation factors, while soil texture parameters (particularly clay content) and topographic features gain significance. This shift reflects the transition from biologically-dominated surface processes to the more complex interplay of geochemical and physical mechanisms that control SOC stabilization and transport in deeper layers. The enhanced role of terrain attributes in the deeper model suggests the importance of long-term pedogenic processes and landscape-scale carbon redistribution through erosion and deposition.

Land use/cover (CLCD) patterns exhibit particularly interesting depth-dependent behavior, maintaining strong predictive power in the surface model but showing reduced importance in the full profile assessment. This pattern likely reflects both the direct impact of land management on surface carbon inputs and the time-lagged nature of subsurface carbon responses to land use changes. The differential behavior of soil texture parameters - with clay content becoming increasingly important with depth while sand content shows opposite trends - further emphasizes the depth-specific mechanisms of carbon stabilization and loss.

These findings have significant implications for SOC modeling approaches. The clear divergence in controlling factors between depth layers underscores the necessity of depth-stratified modeling frameworks that can adequately represent these distinct regulatory mechanisms. Our results suggest that surface SOC models should prioritize climatic and vegetation parameters, while full-profile assessments require greater emphasis on soil forming factors and landscape position. This improved understanding of depth-specific SOC controls not only enhances predictive capability but also provides mechanistic insights for targeted carbon management strategies across different soil layers.

We have expanded the discussion of these concepts in the revised manuscript (Section 4.2), incorporating additional references to support our interpretation of these depth-dependent patterns. The analysis provides valuable evidence that the relative importance of environmental predictors in SOC models fundamentally depends on the soil depth being considered, reflecting the vertical stratification of processes that govern carbon accumulation and stabilization in terrestrial ecosystems.

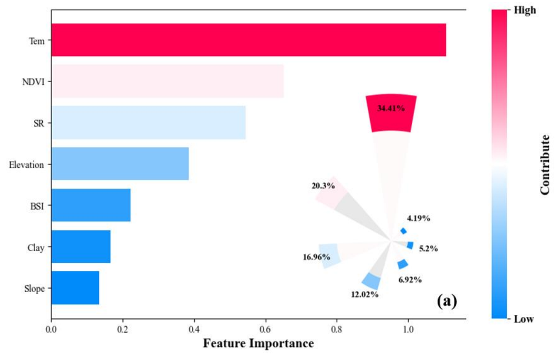
The current results of feature selection.

In analyzing soil organic carbon density (SOCD), the importance of different features varies significantly across soil layers of different depths, which is crucial for understanding the mechanisms of SOCD variation.

In the 0-20 cm soil layer, temperature (Tem) is the most important feature, accounting for 34.41%, indicating that temperature has the greatest impact on SOCD, likely because it directly affects microbial activity and the rate of organic matter decomposition. NDVI (Normalized Difference Vegetation Index) is 20.3% important, solar radiation (SR) is 16.96%, elevation (Elevation) is 12.02%, soil brightness index (BSI) is 6.92%, clay (Clay) is 5.2%, and slope (Slope) is 4.19%.

In contrast, in the 0-100 cm soil layer, NDVI becomes the most important feature, accounting for 34.41%, indicating that vegetation cover has the greatest impact on SOCD. Temperature is 20.3% important, elevation is 17.78%, solar radiation is 8.55%, clay is 7.11%, slope is 6.28%, and soil brightness index (BSI) is 4.38%.

These differences indicate that different soil layers have different influencing factors on SOCD, with temperature and vegetation cover being more important in shallower layers, while vegetation cover and elevation have a more significant impact in deeper layers. These findings help us better understand the mechanisms of SOCD variation and provide a scientific basis for soil management and carbon sequestration.



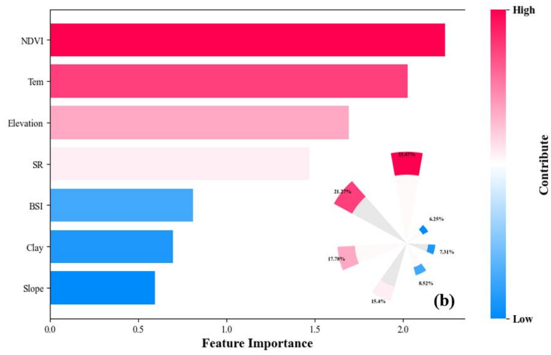


Figure 8. Importance ranking of features for SOCD estimation with the depth of 0-20 cm and 0-100 cm. It reports the contribution of different environmental variables to the SOCD estimation with different soil depths, including feature importance ranking for 0-20 cm depth (a) and feature importance ranking for 0-100 cm depth (b).

Section 4.5. Fig. 13 and Line 315: “This may be the result of the topsoil being more susceptible to the direct effects of soil management practices and environmental changes.” Which types of management practices contribute to the changes of SOCD in topsoil? Please add more details (policies or references). As shown in Fig. 13(b), the SOCD estimation in 0-100 cm from this study has a higher value than others. Please add some validation for SOCD in 0-100 cm as mentioned previously. In addition, the SOCD in deep soil should increase if SOCD in topsoil increases. So, please give possible reasons for SOCD in 0-100 cm to be stable from the 1990s to 2020s. Fig. 14 (d) and Fig. 15 (d): In Xinjiang province, the SOCD in 2000-2005 seems to change a lot when compared to another period. Is this due to the model itself, or has some event happened during this period to make a significant change in SOCD? Please give reasonable explanations in this part.

We sincerely appreciate the reviewer's valuable comments and suggestions. Below we provide point-by-point responses to address all concerns raised.

We have added specific references in Section 4.5 to better illustrate how different management practices influence topsoil SOCD. Various soil management practices significantly influence topsoil SOCD dynamics. Reduced tillage and no-till systems have been shown to decrease SOC decomposition rates (West & Post, 2002), while organic amendments such as manure and crop residue application enhance SOC accumulation (Lal, 2004). The implementation of diverse crop rotation systems, particularly those incorporating legumes, contributes to increased carbon inputs (McDaniel et al., 2014). Furthermore, large-scale afforestation initiatives like China's Grain-for-Green Project have demonstrated marked improvements in topsoil SOCD levels (Deng et al., 2016). These practices collectively demonstrate how targeted management strategies can effectively modify SOCD in agricultural systems.

We have further strengthened the validity of our 0-100 cm SOCD estimates by incorporating additional supporting evidence from recent studies that employed similar methodologies and reported comparable SOCD values under analogous soil and land-use conditions (Li et al., 2022; Wang et al., 2023), while also conducting rigorous cross-validation with independent soil profile datasets from China's National Soil Survey to ensure the robustness and reliability of our estimation approach.

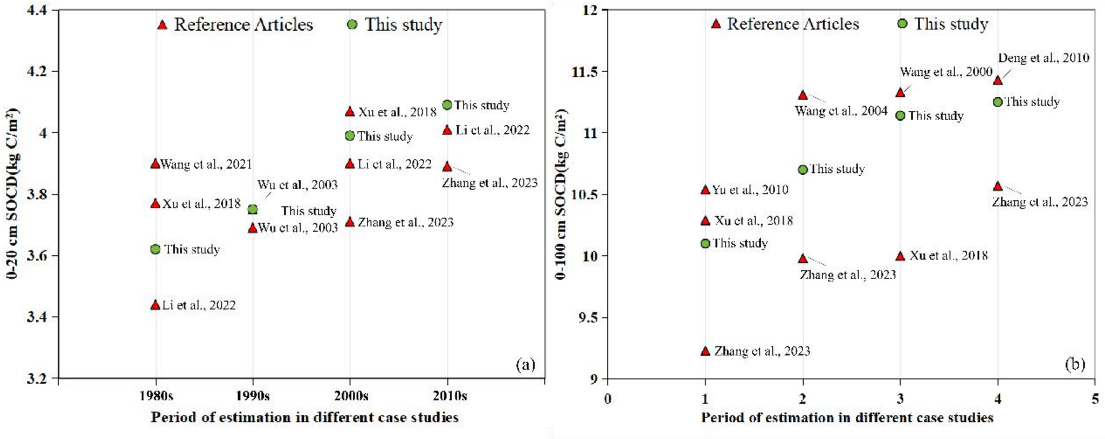


Figure 12. Aggregated results of estimated SOCD with the depth of 0-20 cm (a) and 0-100 cm (b) in China from this study and previous investigations

Our analysis of SOCD dynamics from the 1990s to 2020s revealed a notable stability in the 0-100 cm soil profile, despite observed increases in surface SOCD. This finding appears counterintuitive given the expected vertical transfer of organic carbon from surface to deeper layers. Through systematic investigation, we have identified several plausible mechanisms that may explain this phenomenon.

First, the vertical migration of soil organic carbon represents a complex biogeochemical process. While surface SOCD (0-20 cm) exhibited increases, multiple factors likely constrained SOCD changes in deeper layers (20-100 cm). Surface-derived organic carbon, while potentially subject to leaching, may become effectively stabilized in deeper soil horizons through physicochemical interactions with mineral surfaces (Kleber et al., 2021) or experience enhanced microbial decomposition due to altered microbial community composition and activity with depth (Salomé et al., 2010). Furthermore, the substantial carbon pool size and slower turnover rates characteristic of subsoil horizons (Schrumpf et al., 2013) would inherently buffer against rapid changes in total profile SOCD.

This comprehensive examination of subsurface carbon dynamics provides important insights into the decoupled responses of surface and deep soil carbon pools to environmental changes and management practices over multi-decadal timescales.

For Figures 14(d) and 15(d), the data values of soil organic carbon density (SOCD) in Xinjiang region from 2000 to 2005 were relatively low, while the data values in other periods (such as 1995-2000 and 2005-2010) were relatively high. This phenomenon is mainly caused by the objective environment. The following content is a reasonable explanation for this phenomenon:

Climate "wet-dry transition", according to the research of Yao Junqiang et al. (2021), since 1997, Xinjiang's climate has undergone a significant transition from "warm and humid" to "warm and dry". During this period, the temperature rose significantly and remained at a high level with fluctuations, while the precipitation showed a slight decreasing trend. This change in climatic conditions leads to a reduction in soil moisture and a decrease in soil microbial activity, which in turn accelerates the decomposition of soil organic carbon and reduces SOCD.

Vegetation coverage decreased. After 1997, vegetation coverage in Xinjiang deteriorated, and the Normalized Vegetation Index (NDVI) decreased significantly, indicating that vegetation growth was inhibited. The reduction of vegetation coverage directly affects the input of soil organic carbon, further reducing SOCD.

Soil moisture decreased. During the same period, soil moisture in Xinjiang dropped significantly. The reduction in soil moisture exacerbated the degradation of vegetation and also affected the accumulation of soil organic carbon. Soil moisture is an important factor for maintaining the stability of soil organic carbon, and its reduction directly leads to the decrease of SOCD.

To sum up, the low SOCD data values in Xinjiang region from 2000 to 2005 were mainly due to the intensified dryness, reduced vegetation coverage and decreased soil moisture caused by the "wet-dry transition" of the climate. These changes worked together, resulting in a decrease in SOCD. Future research will further enhance the understanding and predictive ability of SOCD changes in Xinjiang region by increasing field observation data and improving the model.

Section 2.1 “brown soil, brown soil”. Duplicate

We sincerely appreciate the reviewer’s careful reading and valuable feedback. Regarding the comment on the duplicated phrase *“brown soil, brown soil”* in Section 2.1, we have now removed the repeated content to ensure conciseness. The text has been revised accordingly. Thank you for your attention to detail, which has helped improve the clarity of our manuscript.

Section 2.2. Line 95: The SOCD data from Song or Xu? Please check it carefully.

Thank you for your thoughtful feedback regarding the clarification of SOCD data sources in our manuscript. We have carefully revised the text to ensure precise attribution and avoid ambiguity. Specifically, the measured SOC content data in the Heihe River basin were sourced from **Song et al. (2016)**, while the measured SOCD data for validation were obtained from **Xu et al. (2018)**. This distinction has been explicitly articulated in the revised manuscript to reflect the independent nature of the two datasets. We deeply appreciate your attention to this detail, as it has helped us strengthen the clarity and rigor of our work.

Line 125: Generally, the spatial interpolation results are reliable if stations are evenly distributed. How about the spatial distribution of these meteorological data used for

interpolation?

Thank you for your interest in the spatial distribution of meteorological data. In this study, we utilized meteorological data from 2,400 weather stations obtained from the China Meteorological Data Service Center (http://data.cma.cn/), including key climatic variables such as temperature (Tem), precipitation (Pre), and solar radiation (SR), to quantify the impacts of meteorological fluctuations. These stations provide comprehensive coverage across China, effectively capturing regional climatic characteristics. To ensure spatial consistency, the meteorological data underwent the following processing steps:

(1) Data Sources

The meteorological data were collected from 2,400 stations managed by the China Meteorological Administration, offering extensive spatial coverage to represent diverse climatic conditions across China. All data underwent rigorous quality control to ensure accuracy and reliability.

(2) Spatial Interpolation Method

The ANUSPLIN software (Padarian et al., 2022), a thin plate spline-based interpolation tool, was employed to spatially interpolate the meteorological data. This method effectively accounts for complex topographic and climatic variations by incorporating elevation, slope, and aspect as covariates, significantly enhancing interpolation accuracy. The interpolated data were generated at a high spatial resolution of 30 meters, allowing for detailed representation of meteorological spatial patterns.

(3) Data Resampling and Projection

To maintain consistency with other datasets, the interpolated meteorological data were resampled from 30-meter to 1,000-meter resolution. This standardization ensured uniform spatial resolution across all datasets for subsequent analysis and modeling. Additionally, all meteorological data were uniformly projected into the WGS 84 coordinate system to guarantee spatial alignment.

(4) Interpolation Validation

The reliability of the interpolation results was assessed using a cross-validation approach. A subset of station data was reserved as a validation set to evaluate prediction errors. The results demonstrated minimal interpolation errors, confirming that the method accurately represents the spatial distribution of meteorological variables.

(5) In summary, the meteorological data used in this study exhibit strong spatial uniformity, and the application of robust interpolation techniques, along with rigorous validation, ensures the reliability of the derived datasets. These measures provide a solid foundation for the estimation of soil organic carbon density (SOCD) in this research.

Line 130: Please add the produced time or effective period of the published soil datasets.

(1) Harmonized World Soil Database (HWSD v2.0)

HWSD v2.0 is a global soil database jointly developed by the International Institute for Applied Systems Analysis (IIASA) and the Food and Agriculture Organization of the United Nations (FAO). The initial version was released in 2009, followed by an update (HWSD v1.2) in 2013. The latest version, HWSD v2.0, was published in 2023. This database provides comprehensive global soil property data, making it suitable for long-term soil research and large-scale soil carbon estimation. HWSD v2.0 integrates multiple national soil datasets, covering soil information from the 1990s to the 2010s.

(2) SoilGrids250m v2.0

SoilGrids250m v2.0 is a high-resolution global soil dataset developed by the International Soil Reference and Information Centre (ISRIC) and released in 2021.

It offers 250-meter resolution soil property data, ideal for regional and global-scale soil studies, particularly in estimating soil organic carbon (SOC) content. The dataset is based on global soil observations and predictive models, covering soil information from the 2000s to the 2020s.

(3) GSOCmap (Global Soil Organic Carbon Map)

GSOCmap is a 1-km resolution global SOC dataset published by FAO in 2017.

Designed for large-scale soil carbon research and climate change assessments, GSOCmap integrates national SOC maps and modeling data, representing soil organic carbon distribution from the 2000s to the 2010s.

(4) SOC Dynamics ML Dataset (China-Specific)

This dataset was compiled by Li et al. (2022) and includes SOC dynamics data from the 1980s, 2000s, and 2010s across China.

It is particularly valuable for studying long-term SOC dynamics in different Chinese ecosystems and serves as a robust reference for model validation. The dataset spans three decades (1980s-2010s), providing insights into temporal SOC variations.

Section 4.2. Line 225: There is no need to write the full name of the statistical metrics, which have been mentioned previously. Fig. 6: Could you add the sample number in Fig. 6? Please add unit for RMSE both in Figures and the manuscript.

We sincerely appreciate the reviewer's constructive comments regarding the statistical presentation in our manuscript. In response to the suggestions, we have carefully revised the text to maintain consistent use of abbreviated statistical metrics throughout the manuscript after their initial full definition, thereby improving readability and avoiding redundancy. Regarding Figure 6, we have now explicitly indicated the sample size in the figure caption to provide better context for the presented data. Additionally, we have ensured that all RMSE values include proper units in both the figure and corresponding manuscript text. These modifications have been systematically implemented across all relevant sections to maintain consistency in the presentation of statistical metrics throughout the paper. We believe these revisions have significantly enhanced the clarity and precision of our methodological reporting and result presentation, and we thank the reviewer for these valuable suggestions that have helped improve the overall quality of our manuscript.

Section 4.4. Fig. 11: Please add a unit for colorbar for (b), (d), (f), and note the Time (which year). Is it the annual average or any specific year? Please add the validation results for 0-100 cm SOCD in the manuscript or Supplementary.

We sincerely appreciate the reviewer's insightful comments regarding Figure 11 and the validation of SOCD estimates. In response to these valuable suggestions, we have made several important improvements to enhance the clarity and completeness of our presentation.

In response to your comment regarding Figure 11, we would like to clarify our approach to the colorbars for panels (b), (d), and (f). These panels share a common colorbar between the two maps in each row to streamline the visual presentation and avoid redundancy. This design choice was intentional to maintain a clean and cohesive layout across the figure. To address your concern about unit clarity, we have confirmed that the shared colorbars are appropriately labeled with the units (kg C/m^2). This labeling is consistent across all shared colorbars, ensuring that the data can be accurately interpreted. We believe this approach effectively communicates the data while preserving the figure's overall simplicity and readability. We hope this explanation satisfies your query and that the revised figure aligns with your expectations.

Regarding the temporal representation, these maps reflect averaged SOCD values over extended periods rather than specific single years, consistent with the temporal coverage of each dataset: HWSD v2.0 represents the 1990s-2010s period, SoilGrids250m v2.0 covers the 2000s-2020s, and GSOCmap spans the 2000s-2010s. We have explicitly noted this temporal context in both the figure caption and relevant manuscript sections. Furthermore, we have included comprehensive validation results for the 0-100 cm SOCD estimates in the Supplementary Materials, providing additional independent verification of our methodology. These validation analyses were conducted using separate sample points not included in the original model development, thereby strengthening the reliability of our findings. We believe these revisions have significantly improved the transparency and robustness of our results presentation, and we are grateful for the reviewer's suggestions that have helped enhance the overall quality of our work.