ANONYMOUS REFEREE #2

This paper presents an important study integrating digital soil mapping (DSM) and CMIP6 climate projections to assess spatial–temporal SOC stock dynamics in two contrasting Taiwanese watersheds. The manuscript is generally well structured and provides a comprehensive analysis. However, some parts require improvement.

Response:

We thank the reviewer for their kind suggestions and constructive comments, which have improved the structure, clarity, and quality of our manuscript.

Comments:

1. **Line 102: Please explain why the 0–30 cm soil depth was selected. Soil changes due to temperature and rainfall are generally most pronounced within the top 10 cm.**

   Response: We thank the reviewer for bringing this to our attention. Although climate-induced (temperature and rainfall) changes often show the strongest effects in the 0–10 cm depth, the 0–30 cm depth was chosen based on the Intergovernmental Panel on Climate Change (IPCC) (2006, 2019) recommendation. The 0–30 cm depth represents the primary processes influencing SOC dynamics, such as root activity, litter incorporation, and microbial decomposition, where the majority of accumulation and loss of SOC occur (Food and Agriculture Organization (FAO), 2019). Therefore, to improve the clarity of the manuscript, we have added the citation from IPCC in section ***2.2 Soil samples and analyses.***

   Revised text: "A total of 901 topsoil samples (0–30 cm, based on IPCC (2006, 2019a) recommendation) were obtained **(Line 129-130)**."

   References:

   FAO. Measuring and modelling soil carbon stocks and stock changes in livestock production systems: Guidelines for assessment (Version 1). Livestock Environmental Assessment and Performance (LEAP) Partnership. Rome, FAO. 170 pp, 2019.

   IPCC. 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Agriculture, Forestry and Other Land Use. Volume 4, https://www.ipcc-nggip.iges.or.jp/public/2006gl/vol4.html (last access: October 22, 2025), 2006.

   IPCC. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Agriculture, Forestry and Other Land Use. Volume 4, https://www.ipcc-nggip.iges.or.jp/public/2019rf/vol4.html (last access: October 22, 2025), 2019.

2. **Line 124: In Figure S1a, the legend for the colours is missing.**

Response: We appreciate the reviewer's comment. The different colors in Figure S1a represent township boundaries. However, since the main purpose of this figure is to illustrate the spatial distribution of sampling points, we will remove the background colors to avoid distraction from the main focus of the figure **(Line 125)**.

Revised figure:

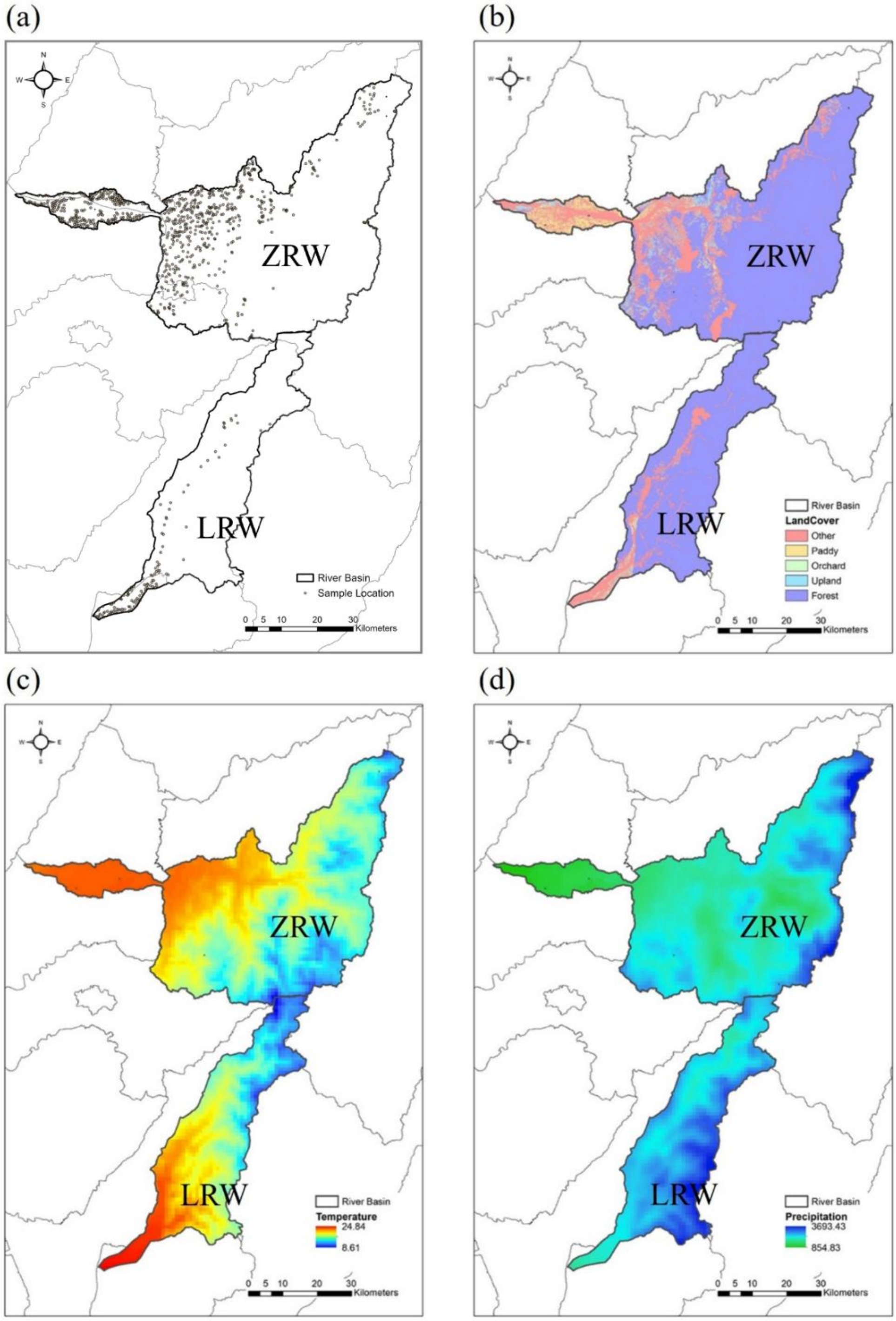


Fig. S1. The sampling sites (a), land cover (b), mean annual temperature (c), and total annual precipitation (d) of the Zhuoshui River watershed (ZRW) and the Laonong River watershed (LRW). **(Supplementary file Line 1-4)**

3. **Line 130: It would be helpful to indicate size in millimetres (mm).**

   Response: We appreciate the reviewer's helpful suggestion. We have revised the sentence and included the 35-mesh screen soil sieve opening in mm (0.5 mm).

   Revised text: "After the samples had been air-dried at room temperature, they were sieved through a 35-mesh screen (0.5 mm sieve opening) and stored in plastic containers **(Line 125-126)**."

4. **Line 134: Please provide the full name for the abbreviation TOC**.

   Response: We appreciate the reviewer's helpful suggestion. We have revised the sentence and included the abbreviation of TOC (Total Organic Carbon).

   Revised text: "Because the LOI method typically overestimates SOC (Li et al., 2021), a correction function was applied to adjust SOC content from LOI values to those obtained using a total organic carbon (TOC) analyzer (solid TOC cube, Elementar) **(Line 128-130)**."

5. **Line 170:** More information is needed on how the **resolution was changed from 1 km to 20 m**.

   Response: We appreciate the reviewer's attention to this matter. The climatic variables, including mean annual temperature and total annual precipitation, were originally at a spatial resolution of 1 km. To match the spatial scale of other covariates, these raster layers were resampled to 20 m resolution using the resample function from the raster package in R (Hijmans, 2022), with bilinear interpolation (method = "bilinear"). **(Line 169-169)**

   Reference:
   Hijmans, R. J. raster: Geographic data analysis and modeling. https://doi.org/10.32614/CRAN.package.raster, 2022.

6. **Line 171:** The **land-cover class** and **soil order** variables are categorical. Were these treated as **factors or numeric data**?

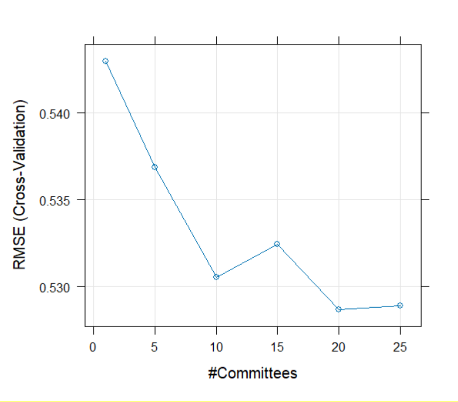
   Response: We thank the reviewer for bringing this to our attention. The variables for land-cover class and soil order are categorical and were treated as factors in the analysis. This approach ensures precise management of qualitative differences in the modeling process.

7. **Line 177:** It would be clearer to **move Section 2.4 ("Climate data in various emission scenarios and with extreme climate indices")** to the end of the **Methods** section.

   Response: We appreciate the reviewer's helpful suggestion. We have moved original Section 2.4 to the end of the Methods as Section 2.7. **(Line 252-269).**

8. **Line 214:** Please clarify why **20 committees** were used for the **Cubist model**.

   Response: We thank the reviewer for pointing this out. We have added a paragraph to clarify the reason 20 committees were used for the Cubist model. For further understanding, please refer to the attached figure below.



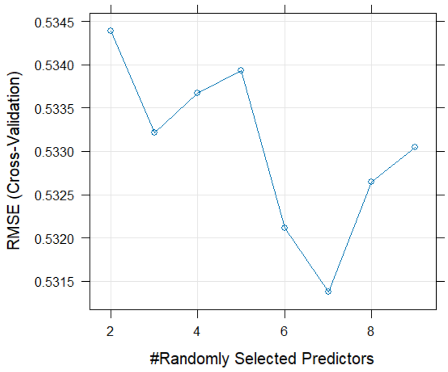
   Revised text: "We used the caret package (Kuhn, 2008) to perform hyperparameter tuning for the Cubist model, testing committee values of 1, 5, 10, 15, 20, and 25. Using 5-fold cross-validation, caret automatically evaluated the performance of each hyperparameter setting based on the root mean square error (RMSE). The tuning results indicated that setting committees = 20 produced the lowest cross-validation RMSE, suggesting that this configuration achieved the highest predictive accuracy. Therefore, committees = 20 was selected as the final model parameter." **(Line 194-200)**

   Reference:

   Kuhn, M.: Building Predictive Models in R Using the caret Package. Journal of Statistical Software, 28(5), 1–26. https://doi.org/10.18637/jss.v028.i05, 2008.

9. **Line 224:** Please explain the rationale for using **mtry = 7** and **ntree = 500** in the **Random Forest model**.

   Response: We thank the reviewer for bringing this to our attention. We have added a further explanation to the rationale for using mtry = 7 and ntree = 500 in the Random Forest model. Please refer to the revised text in the revised manuscript as well as the attached figure below for further understanding.



Revised text: "We used the *caret* package (Kuhn, 2008) to perform hyperparameter tuning for the Random Forest model. The parameter *mtry* was tested with values ranging from 2 to 9. Using 5-fold cross-validation, *caret* automatically evaluated the performance of each hyperparameter setting based on the root mean square error (RMSE). The tuning results indicated that the model achieved the lowest cross-validation RMSE when *mtry* = 7. The number of trees (*ntree*) was kept at the default value of 500, which is generally sufficient to ensure model stability (Peng et al., 2025). Therefore, the final Random Forest model was trained using *mtry* = 7 and *ntree* = 500." **(Line 209-216)**

Reference:

Peng, Y., Zhou, W., Xiao, J., Liu, H., Wang, T., & Wang, K.: Comparison of Soil Organic Carbon Prediction Accuracy Under Different Habitat Patches Division Methods on the Tibetan Plateau. *Land Degradation & Development*. https://doi.org/10.1002/ldr.70184, 2008.

10. **Line 230:** The sentence "The distribution of the two data sets is depicted in Fig. 2." should be moved to the **Results** section.

Response: We appreciate the reviewer's helpful suggestion. We have revised the sentence and moved it to the Results section to clarify the distribution of the training data set and validation data set described in Section 3.2.

Revised text:

"***3.2 Model performance in SOC stock prediction***

This study constructed SOC stock predictive models using the Cubist, RF, and regression kriging with the training data set and environmental covariates. The performance of these models was evaluated using R2 and RMSE values. Among the evaluated models, the RF model demonstrated the highest predictive performance in the training data set. The distribution of the training data set (calibration set) and validation data set is depicted in Fig. 2. Therefore, we focused on model performance in the prediction of validation data set prior to model selection. In this respect, the performance indicators of the Cubist model were R2

= 0.43 and RMSE = 0.45 kg m-2, while those of the RF model were R2 = 0.46 and RMSE = 0.43. After incorporating regression kriging, the indicators improved to R^2 = 0.48 and RMSE = 0.42 for the Cubist model, and remained at R^2 = 0.46 and RMSE = 0.43 for the RF model (Fig. 2).” **(Line 282-291)**

11. **Line 272:** Replace “Coefficient of determination (R^2)” with simply **R^2**.

    Response: We thank the reviewer for bringing this to our attention. We have rephrased the sentence and replaced “Coefficient of determination (R^2)” with **R^2**.

    Revised text: “The performance of these models was evaluated using R^2 and RMSE values **(Line 283-284)**.”

12. **Lines 294–296:** This section requires further explanation, as it is currently difficult to understand.

    Response: We appreciate the reviewer's helpful suggestion. We have revised the structure of the sentence to help the reader understand it better.

    Revised text: “The results of the Cubist model indicated that the importance of aspect, curvature, and flow accumulation was relatively low, thus they exhibited either no usage or very low usage frequency (Fig. 3a). Among the covariates included, more than half of the data incorporated covariates such as elevation (98%), annual mean temperature (62%), NDVI (59%), TRI (54%), K-value (53%), and slope (52%). These results indicated that climatic and topographic factors strongly contributed to model performances. In summary, the RF and Cubist models identified soil order, elevation, and annual mean temperature as the factors representing the influence of soil, topography, and climate, respectively, on the SOC stock in the study areas. **(Line 301-309)**.”

13. **Line 301:** When creating the **SOC map**, did you use only the **70% training data** or the **entire dataset (100%)**?

    Response: We thank the reviewer for pointing this out. The SOC map was created using 70% of the training data set. The remaining 301 samples (30%) were used as the validation data set (validation set) to determine the model’s predictive performance. We have also described that in **Line 219-221.**

14. **Lines 335–345:** This section should be moved to **“3.7** Extreme climate index parameter estimates in three emission scenarios**.”**

    Response: We thank the reviewer for the helpful suggestion. We have moved the paragraph to Section 3.7 to better emphasize the results under three emission scenarios and facilitate better understanding by the reader.

    Revised text: “In all emission scenarios, major spatial heterogeneity and temporal increases were found in SOC stocks (Table 3, Figs. 6 and 7), particularly under high-emission conditions. These findings underscore the importance of modifying the management practices of land use in the future, especially if climate change is severe. In forested areas in both watersheds, significant SOC accumulation was predicted. Areas with an SOC accumulation value of >15 Mg C ha^{-1} were expected to exhibit an increase in SOC accumulation from <5% (2020, baseline) to more than 25% by 2100 in scenario SSP5-8.5. By contrast, lowland agricultural zones are expected to maintain relatively low SOC stocks (<9 Mg C ha^{-1}), with minor gains across scenarios. Scenario SSP5-8.5 was found to result in the greatest projected increase in SOC stocks as a result of elevated CO2 and potential biomass input, although spatial disparities are expected to increase, particularly in erosion-prone or intensively cultivated lands (Fig. S3)." **(Line 353-363).**

15. **Line 481:** It would strengthen the discussion to **compare the SOC maps** produced in this study with **existing SOC maps** from other publications.

    Response: We thank the reviewer for the helpful suggestion. On the Section **4.2 *Effects of environmental covariates on SOC stocks***, we have included citations from previous studies regarding SOC maps to compare and support the results of our study. Therefore, this section remained as it was **(Line 493-517).**

16. **Figure 3:** there are two "fig 3", so remove one. Most samples appear concentrated in **croplands**, and future work could include a more balanced sampling across different **land types (e.g., forest)**.

    Response: We thank the reviewer for bringing this to our attention. We have deleted one of the "Fig. 3" in the figure caption **(Line 890-892).** We also appreciate the reviewer's suggestion regarding future work. We believe that including a more balanced sampling across different land types will provide more comprehensive results. We will take this suggestion into consideration for our future study.

17. **Figure 6:** Please specify **which climate scenario** (e.g., **CWD**) is displayed.

    Response: We thank the reviewer for bringing this to our attention. The Figure 6 shows the spatiotemporal predictions of SOC stocks (kg m^{-2}) and SOC sequestration rates (kg m^{-2} per year) relative to the 2020s under three emission scenarios. The climate scenarios were list on the top of the figure.