

Response to Editor's and reviewers' comments:

We have carefully revised the manuscripts by addressing the comments given by reviewers. The following describes how the paper is revised.

Response to Reviewer 1 Comments:

General comments:

This study by Lixin Lin and coworkers is focused on disentangling the soil organic carbon (SOC) stock from complex vegetation and water cover using fuzzy deep learning, employing satellite data (Landsat-8) and spectral indices, like NDVI and NDWI. The model modifies the spectral reflectance according to the vegetation and water cover so that it is optimized for SOC stock estimations.

The whole paper could benefit a lot from better writing and would improve content understanding. Work that has been done should be explained better and the scope of this work should be made clear:

Vegetation, and water can affect the spectral reflectance in satellite imagery, and a fuzzy formula to modify the reflectance according to vegetation and water indices is used. Models that use the fuzzified spectra perform better than the unfuzzified.

We would like to express our heartfelt gratitude to you for your help, best wishes for you and your family. And we had revised our manuscript according your comments carefully.

To make the scope of our work more clearly, we have revised our Introduction as follows:

Step 1: the sequence and description of the second paragraph was revised. First, we explained the implementation of SOC remote sensing depends on a SOC model; Second, we introduced the studies focused on optimal soil conditions, i.e., laboratory sieved and air-dried soil samples or small-area bare, dry, and smooth soils; Then, we introduced the SOC mapping at European scale and subsequently the scope of our study (reducing the effects of vegetation and water on the spectral reflectance in satellite imagery). And “The Land Use/Cover Area frame statistical Survey (LUCAS) topsoil database, which is the largest expandable topsoil dataset for the European region, has supported the development of measures intended to protect the soil and environment of the continent (Orgiazzi et al., 2018). The combination of LUCAS and satellite remote sensing provides tremendous potential for timely observation of SOC stock at the European scale (Ward et al., 2020). However, natural land surfaces comprise heterogenous mixtures of vegetation, water, and soil, and the effects of surfaces such as vegetation and water have marked impact on the SOC spectral response, making SOC stock estimation more difficult. Consequently, most previous studies on SOC determination from spectral reflectance focused on optimal soil conditions, i.e., laboratory sieved and air-dried soil samples or small-area bare, dry, and smooth soils (Hutengs et al., 2019; Mueller et al., 2021; Liu et al., 2022). In recent years, some studies have attempted to simulate SOC stock at the European scale. For example, Yigini and Panagos (2016) used the LUCAS topsoil database and multiple linear regression to study the topsoil (0–20 cm) SOC stock in Europe, and their results produced a coefficient of determination (R^2) value of 0.40. Lugato et al. (2014) used the CENTURY agroecosystem model to study the SOC stock in European agricultural topsoil (0–30 cm), and they reported a root mean square error (RMSE) of 52.2 and 30.0 t C ha⁻¹ for pasture land and permanent cropland, respectively. The low performance of models in such studies has been attributed to many factors but especially complex land cover.” was revised as

"The implementation of SOC remote sensing depends on a SOC model developed using field SOC data and their corresponding spectral pixels, then we can use this model to estimate the SOC for all pixels of images (Koparan et al., 2022). In recent years, many studies on SOC content/stock SOC determination from spectral reflectance focused on optimal soil conditions, i.e., laboratory sieved and air-dried soil samples or small-area bare, dry, and smooth soils have been reported (Mueller et al., 2021; Liu et al., 2022). For example, Ward et al. (2020) tested SOC models using airborne hyperspectral remote sensing data and simulated satellite Environmental Mapping and Analysis Programme (EnMAP) data as input. Hutengs et al. (2019) examined in-situ spectroscopy and SOC estimation models using in-situ Mid-Infrared (MIR) spectra. The Land Use/Cover Area frame statistical Survey (LUCAS) topsoil database, which is the largest expandable topsoil dataset for the European region (Orgiazzi et al., 2018), has supported several field SOC data for SOC spectroscopic modeling (Ward et al., 2020) and the combination of LUCAS and satellite data has provided tremendous potential for timely observation of SOC stock at the European scale. Based on LUCAS database, for example, Yigini and Panagos (2016) performed a digital soil mapping for European SOC, using climate, land cover, terrain, and soil covariates. Lugato et al. (2014) used an agro-ecosystem SOC model to calculate European SOC stocks using soil/climate/land-use/management drivers, among others. However, natural land surfaces comprise heterogenous mixtures of vegetation, water, and soil, and the effects of surfaces such as vegetation and water have marked impact on the SOC spectral response, resulting to the low performance of models in these previous studies." (L33-48 page 2)

Step 2: "Therefore, the focus of this study..." has been revised as a new paragraph according to your comments. (L51 page 2)

Step 3: to explain the rationale for this study, "In this study, the two indexes including normalized difference vegetation index (NDVI) and normalized difference water index (NDWI) were used in our spectral fuzzy learning. Based on a series of fuzzy disentangling processes, the SOC model was developed, which produced better performance than the unfuzzified model." was revised as "Take vegetation for example, the effects of vegetation on spectral reflectance can take on only three situations, namely increasing, unchanging and decreasing. Assuming that we can modify the spectral reflectance according to these situations, the effect of vegetation will be disentangled. In this study, we attempted to modify the spectral reflectance of satellite imagery using our spectral fuzzy learning. This spectral fuzzy learning approach can disentangle the effects from vegetation and water through a series of fuzzy disentangling processes, based on the two indexes including normalized difference vegetation index (NDVI) and normalized difference water index (NDWI). Based on the fuzzified spectra, the SOC model was developed, which produced better performance than the model using unfuzzified spectra." (L59-64 page 2)

Step 4: Moreover, "Vegetation and water can affect the spectral reflectance in satellite imagery. In this study, the fuzzy formula (Eq. (2)) was used to modify the reflectance according to the two vegetation and water indices, and the SOC model based on the fuzzified spectra was developed for the satellite observations of SOC stocks." was also added in our Results and discussion. (L159-161 page 7)

Step 5: the all "the unfuzzified model" was revised as "the model using unfuzzified spectra" (L18, 219, 220, 231 pages 18, 219, 220, 231)

Specific comments and Technical Corrections:

Line 33 - 38: The references and their description from line 33 to line 38 should be made clearer:

Apologize for our unclear description and thanks for your help, and we have revised the sequence and description of this paragraph. And “The Land Use/Cover Area frame statistical Survey (LUCAS) topsoil database, which is the largest expandable topsoil dataset for the European region, has supported the development of measures intended to protect the soil and environment of the continent (Orgiazzi et al., 2018). The combination of LUCAS and satellite remote sensing provides tremendous potential for timely observation of SOC stock at the European scale (Ward et al., 2020). However, natural land surfaces comprise heterogenous mixtures of vegetation, water, and soil, and the effects of surfaces such as vegetation and water have marked impact on the SOC spectral response, making SOC stock estimation more difficult. Consequently, most previous studies on SOC determination from spectral reflectance focused on optimal soil conditions, i.e., laboratory sieved and air-dried soil samples or small-area bare, dry, and smooth soils (Hutengs et al., 2019; Mueller et al., 2021; Liu et al., 2022). In recent years, some studies have attempted to simulate SOC stock at the European scale. For example, Yigini and Panagos (2016) used the LUCAS topsoil database and multiple linear regression to study the topsoil (0–20 cm) SOC stock in Europe, and their results produced a coefficient of determination (R^2) value of 0.40. Lugato et al. (2014) used the CENTURY agroecosystem model to study the SOC stock in European agricultural topsoil (0–30 cm), and they reported a root mean square error (RMSE) of 52.2 and 30.0 t C ha⁻¹ for pasture land and permanent cropland, respectively. The low performance of models in such studies has been attributed to many factors but especially complex land cover.” was revised as “The implementation of SOC remote sensing depends on a SOC model developed using field SOC data and their corresponding spectral pixels, then we can use this model to estimate the SOC for all pixels of images (Koparan et al., 2022). In recent years, many studies on SOC content/stock SOC determination from spectral reflectance focused on optimal soil conditions, i.e., laboratory sieved and air-dried soil samples or small-area bare, dry, and smooth soils have been reported (Mueller et al., 2021; Liu et al., 2022). For example, Ward et al. (2020) tested SOC models using airborne hyperspectral remote sensing data and simulated satellite Environmental Mapping and Analysis Programme (EnMAP) data as input. Hutengs et al. (2019) examined in-situ spectroscopy and SOC estimation models using in-situ Mid-Infrared (MIR) spectra. The Land Use/Cover Area frame statistical Survey (LUCAS) topsoil database, which is the largest expandable topsoil dataset for the European region (Orgiazzi et al., 2018), has supported several field SOC data for SOC spectroscopic modeling (Ward et al., 2020) and the combination of LUCAS and satellite data has provided tremendous potential for timely observation of SOC stock at the European scale. Based on LUCAS database, for example, Yigini and Panagos (2016) performed a digital soil mapping for European SOC, using climate, land cover, terrain, and soil covariates. Lugato et al. (2014) used an agro-ecosystem SOC model to calculate European SOC stocks using soil/climate/land-use/management drivers, among others. However, natural land surfaces comprise heterogenous mixtures of vegetation, water, and soil, and the effects of surfaces such as vegetation and water have marked impact on the SOC spectral response, resulting to the low performance of models in these previous studies.” (L33-48 page 2)

Ward et al. tested SOC ML models using airborne hyperspectral remote sensing data and simulated satellite EnMAP data as input.

Has been revised. (L37-38 page 2)

Hutengs et al. examined in-situ spectroscopy and SOC estimation models using in-situ MIR spectra.

Has been revised. (L38-39 page 2)

Yigini and Panagos performed a digital soil mapping for SOC, using climate, land cover, terrain, and soil covariates.

Has been revised. (L43-44 page 2)

Lugato et al. used an agro-ecosystem SOC model to calculate SOC stocks using soil/climate/land-use/management drivers, among others.

Has been revised. (L44-45 page 2)

The sequence should also make sense to the reader and address the challenges related to vegetation and water faced by SOC estimation models using satellite remote sensing data. Subsequently, the rationale for this study should be elaborated.

We are very thankful to your help, and we have revised the sequence and description of this paragraph. (L33-48 page 2)

Line 36: Such studies usually predict SOC content, that can be used as a proxy for SOC stock, but not stock directly.

Thanks for your help, and we have revised "(Ward et al., 2020)." as "In recent years, many studies on SOC content/stock determination from spectral reflectance focused on optimal soil conditions, i.e., laboratory sieved and air-dried soil samples or small-area bare, dry, and smooth soils have been reported (Mueller et al., 2021; Liu et al., 2022). For example, Ward et al. (2020) tested SOC models using airborne hyperspectral remote sensing data and simulated satellite Environmental Mapping and Analysis Programme (EnMAP) data as input." (L35-38 page 2)

Line 48: The following should be a new paragraph "Therefore, the focus of this study..."

Has been revised. (L51 page 2)

Line 109: "inverse" does not seem to be the correct word: "modify", for example, seems more appropriate.

Has been revised. We have revised the all "inverse" as "modify" in our manuscript (L60, 61, 115, 160, pages 2, 4, 7)

Line 180: Please check whether they used satellite imagery in this study.

Thanks for your help and apologize for our fault, and we have revised the "satellite imagery" as "environmental predictors" and added one more reference which used SOC model and satellite imagery for deriving the regions with elevation of > 1000 m, and "instead, the SOC stock was derived using the SOC model and satellite imagery, as in the study by Yigini and Panagos (2016)." was revised as "instead, the SOC stocks were derived by combining the SOC models with environmental predictors (Yigini and Panagos, 2016) or satellite images (Zhou et al., 2021), as in previous studies." (L189-190 page 8)

And also the literature from Zhou et al. (2021) was added. (L311-313 page 14)

We would like to express our heartfelt gratitude to you. Thanks again for your constructive and valuable comments, which help a lot in revising our manuscript. Best wishes for you and your family!

Best regards,

The authors