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16. Abstract
Emissions from land use changes are relevant for environmental policy analysis. Since the late 1990s and early 2000s many of these analyses have examined induced land use changes (ILUC) from biofuel production and policy as well as their associated greenhouse gas (GHG) emissions. These studies have often used the Harmonized World Soil Data (HWSD) to evaluate the corresponding changes in soil organic carbon (SOC) as a part of their assessments. However, those modeling efforts that used this data set have not necessarily implemented its latest version, and therefore, their results may not represent the most recent available SOC data sources. As an example, the AEZ-EF model, which has been frequently used in assessing ILUC emissions, is using the oldest version of this data set. To improve the quality and accuracy of ILUC estimates, this paper creates a new global data set of SOC by combining the latest version of the HWSD(V.2.0) with newly available national soil maps for the USA and Australia. Using this new data set, we then calculate the average SOC for each land cover type (cropland, pasture, and forest) by country and by agro-ecological zones (AEZs). Furthermore, we revised AEZ-EF model to adopt the new SOC data by land types. Finally, the revised AEZ-EF model is used to assess ILUC emissions for a few biofuel pathways to demonstrate the extent to which the new SOC data may affect ILUC emissions. The results of this paper indicate that the newest version of the HWSD represents a lower level of SOC at the global scale compared to its older version. The results also show that the revised AEZ-EF model calculates relatively lower ILUC emissions for the examined pathways compared to its older version.

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Abstract

Emissions from land use changes are relevant for environmental policy analysis. Since the late 1990s and early 2000s many of these analyses have examined induced land use changes (ILUC) from biofuel production and policy as well as their associated greenhouse gas (GHG) emissions. These studies have often used the Harmonized World Soil Data (HWSD) to evaluate the corresponding changes in soil organic carbon (SOC) as a part of their assessments. However, those modeling efforts that used this data set have not necessarily implemented its latest version, and therefore, their results may not represent the most recent available SOC data sources. As an example, the AEZ-EF model, which has been frequently used in assessing ILUC emissions, is using the oldest version of this data set. To improve the quality and accuracy of ILUC estimates, this paper creates a new global data set of SOC by combining the latest version of the HWSD (V.2.0) with newly available national soil maps for the USA and Australia. Using this new data set, we then calculate the average SOC for each land cover type (cropland, pasture, and forest) by country and by agro-ecological zones (AEZs). Furthermore, we revised AEZ-EF model to adopt the new SOC data by land types. Finally, the revised AEZ-EF model is used to assess ILUC emissions for a few biofuel pathways to demonstrate the extent to which the new SOC data may affect ILUC emissions. The results of this paper indicate that the newest version of the HWSD represents a lower level of SOC at the global scale compared to its older version. The results also show that the revised AEZ-EF model calculates relatively lower ILUC emissions for the examined pathways compared to its older version.

1. Introduction

Over the past two decades, the scientific debate on biofuel policies has been focused on Induced Land Use Changes (ILUC) and their corresponding greenhouse gas (GHG) emissions. National Academies of Sciences, Engineering, and Medicine *et al* (2022) has provided an assessment of these studies. As recognized in this assessment, ILUC emissions are usually estimated using land-use changes obtained from economic models in combination with emission factors. These factors convert estimated ILUCs into GHG emissions using carbon data on soil and vegetation embedded in land. This paper aims at updating a set of these emissions factors that are used in the AEZ-EF model (Plevin *et al* 2014). This model has been widely used in ILUC assessment practices (California Air Resources Board 2015, Taheripour *et al* 2019, Prussi *et al* 2021, Zhao *et al* 2021) and in assessing land use change emissions associated with trade and climate change policies (Yao *et al* 2018, Haddad *et al* 2019, Peña-Lévano *et al* 2019, Villoria 2019, Richards *et al* 2020, Villoria *et al* 2022).

In a different but related research area, several efforts have been made to discuss, assess, and reconcile discrepancies between how global scientific models estimate anthropogenic land-use CO2 fluxes and how individual countries report these emissions in their National Greenhouse Gas Inventories (NGHGIs) (Hansis *et al* 2015, Gasser *et al* 2020, Gidden *et al* 2023; Grassi *et al* 2023, Houghton and Castanho 2023, Qin *et al* 2024). The difference between the NGHGI and modeling assessments of these emissions has been labeled as the Grassi gap. While these efforts and our paper tend to better assess the extent to which human activities affect carbon fluxes due to land-use and land-use changes, the goal and approach of our paper is entirely different from those papers that tend to assess or reduce the Grassi gap. In general, the goal of research assessing biofuels ILUC emissions is to estimate the marginal effects of these fuels on carbon fluxes in consequential life cycle analyses. To improve ILUC assessment, this paper concentrates on updating the AEZ-EF model.

The AEZ-EF model uses conversion and combustion factors published in the 2006 International Panel on Climate Change (IPCC) guidelines, biomass carbon data from several sources, and soil carbon information provided by (Gibbs *et al* 2014). Benavidez *et al* (2024: Forthcoming) have recently revised and updated the AEZ-EF model to follow the 2019 IPCC guidelines, updating litter data and forest combustion factors, among others. But the Soil Organic Carbon (SOC) data used in this carbon calculator has not been updated since its publication. Gibbs *et al* (2014) provided SOC data for selected land cover types (cropland, pasture, and forest) by AEZ and country/region using Harmonized World Soil Data V1.1 (HWSD). While various data sources provide SOC data (SoilGrids by Hengl *et al* (2017), and GSOCmap by FAO (2020))[4], as an internationally trustable data source, we use the most recent version of HWSD developed by the Food and Agricultural Organization (FAO) of the United Nations and the International Institute for Applied System Analysis (IIASA) to update the SOC component of the AEZ-EF model.

The early versions of HWSD (V1.0 and V1.1) were published in 2008 and 2009 by the FAO in collaboration with several international organizations (FAO *et al* 2009). Four main data sources were used in developing these two early versions of HWSD: Soil maps of the world by (FAO-UNESCO 1988), which last extension was made in 2003; Soil and terrain (SOTER) regional studies developed by various contributors between 1998 and 2008 (ISRIC 2016); The European soil database published in 2002 (ESB 2004), and the soil map of China published in 2004 (Shi *et al* 2004). In addition, various other data sources were used to determine the top and subsoil parameters.

Newer global and national soil databases provide more accurate estimates of soil characteristics and could be used to update SOC data in ILUC emission calculators. The newer versions of HWSD (v1.2 and V2.0) released in 2012 and 2023 (FAO *et al* 2012, FAO & IIASA 2023) have better quality, reliability, and accuracy compared to earlier versions. These datasets have improved soil bulk density information and use the latest data on soil texture, organic matter, and porosity. Moreover, the HWSD V2.0 improves its reliability in soil attribute information by using the WISE30sec database that builds from the HWSD raster but corrects using climate covariates (Batjes 2016). However, as noted in the documentation of HWSD V2.0 (FAO & IIASA 2023), it does not use the latest national data for US, Canada and Australia. Thus, it is possible to improve HWSD V.2.0 by combining it with publicly available national soil maps for these selected countries.

The objective of this paper is to provide more accurate estimates of the emission factors used for ILUC calculations by updating the SOC data used in the AEZ-EF model using the latest available data sources. Specifically, we use the most recent version of HWSD (V2.0) as our core data source to obtain an updated SOC data set. We compare the results obtained from this data source with the results obtained from HWSD (V1.2)[5] to assess changes in SOC data between these two versions of HWSD. In general, various versions of HWSD have highlighted the need to increase the data sources' reliability for the US, Canada, and Australia (FAO *et al* 2012, FAO & IIASA 2023). To remove this deficiency, we reviewed and evaluated the latest available national soil maps for these three countries and created a new global SOC map which combines data from HWSD v2.0 and the new national soil maps for the US and Australia. For Canada, we decided to keep the data from HWSD (V2.0) due to outliers and inconsistencies in this national dataset. We then revised the emissions factors in the AEZ-EF model using SOC data from the new global SOC map and evaluated the sensitivity of these estimates using different land cover information and for different reference years. The outcomes of this paper could improve future ILUC assessments and help better policy decisions.

The remainder of the paper proceeds as follows: section 2 reviews the data available for soil properties, provides formulation for SOC calculation and describes methods to harmonize estimates and comparison; section 3 presents the results by showcasing the data comparison, the estimated SOC and using these new

[4] Developing a validation practice to compare the existing data sources on soil carbon data is an important research agenda, because alternative data sources are subject to various pros and cons. However, this practice is going beyond the scope of this paper.

[5] The early versions of HWSD (V1.0 and V1.1) are no longer publicly available, making it difficult to replicate the calculations done by Gibbs *et al* (2014). Thus, we rely on the SOC stocks values calculated using HWSD version 1.2 as a proxy estimates.

estimates into the AEZ-EF model to calculate ILUC emissions for selected biofuel pathways; section 4 discusses the findings; and section 5 concludes this paper.

2. Methodology and data

2.1. Data

We evaluated the SOC data of HWSD versions 1.2 and 2.0, at the global level. As previously mentioned, core soil properties in HWSD V2.0 are derived from WISE30sec database, rather than relying on the legacy HWSD, making this update of substantial improvement in terms of accuracy[6]. One caveat of both releases is their reliability in certain regions. From version 1.2 to version 2.0 there was an improvement in countries like Türkiye, Ghana and Afghanistan. However, concerns about its reliability I n North America and Australia were not addressed in the latest release. Therefore, we also evaluated six national databases for the US (STATSGO, SSURGO, Soil property maps, and SOLUS), Australia (CSIRO) and Canada (SLC). We qualitatively explored these databases and their documentation, including the nature of the data, methods and accuracy assessments made in the databases' documentation.

For the US, the STATSGO database generalizes more detailed survey maps and creates an inventory of soil and non-soil areas (Soil Survey Staff (n.d.)). SSURGO contains field soil sampling information with a greater sample than STATSGO (Soil Survey Staff (n.d.)). The Soil Properties Map (SPM) developed by UC-Davis and USDA-NCRS combines both databases using SSURGO as base and back-filling with STATSGO (Walkinshaw *et al* 2023). The Soil Landscapes of the United States (SOLUS) is constructed using models trained using national gridded soil surveys and a set of covariates including climate parameters, vegetation, and surface water (Nauman *et al* 2024). In the case of Canada, the Soil Landscapes of Canada (SLC) was constructed using machine learning models, soil profile data and climate and soil covariates (Agriculture and Agri-Food Canada 2025). Finally, for Australia, the Soil and Landscape Grid National Attribute Maps from CSIRO estimates properties using a quantile regression forest with national data and fifty-seven covariates (Wadoux *et al* 2022, 2023).

After analyzing the documentation, we identified certain limitations in each database. For example, STATSGO has various missing values. While SSURGO compensates for these missing values, its high resolution imposes a challenge to retrieve data for the continental US. On the other hand, SPM combines both. However, the SOC data in SPM are estimated using the horizon depth; therefore, topsoil estimates cannot be retrieved. For Canada, although the SLC presents a high R^2 in their technical validation, the data showed extreme values in SOC. Finally, for Australia, the only disadvantage is the data's lack of subsoil level estimates, which do not directly affect our SOC calculations.

2.2. Methods

Besides the qualitative aspects of the databases, we analyzed them quantitatively through two avenues. First, we evaluated the spatial differences in SOC values at the grid-cell level. We then calculated the aggregated stocks for each land cover type (cropland, pasture, forests) by AEZ and by country using land cover maps as area weights while excluding grid-cells under wetland and desert areas.

2.2.1. SOC estimation

Following the formulation provided by Guo and Gifford (2002)[7] and followed by Gibbs *et al* (2014), we estimated SOC from the soil properties data embedded in each database as shown equation (1):

$$SOC_{u,\,Di} = BD_{u,\,Di} \times OCC\%_{u,\,Di} \times D_i. \tag{1}$$

In this equation u denotes soil mapping unit, D_i shows depth of soil layer measured in centimeter, BD is soil bulk density measured in g cm^{-3}, and $OCC\%$ represents soil organic carbon concentration in percent. However, other formulations to calculate SOC are found in the literature including formulations that consider coarseness (Poeplau *et al* 2017). We continue to use equation (1) to follow the original work by Gibbs *et al* (2014). However, as an example, figure S4 in the supplement shows the sensitivity of SOC stocks to change in formulation for coarseness for cropland.

This equation is used in most of the databases. However, in the case of STATSGO, SSURGO and UC-Davis SPM, only data on soil organic matter is available, represented in concentration for STATSGO and SSURGO and in stocks for SPM. We convert soil organic matter to SOC by multiplying soil organic matter with a coefficient of 0.58 (Mann 1986).

[6] Dai *et al* (2019) explicitly validates improved accuracy of WISE30sec when compared to the legacy HWSD data.

[7] Guo and Gifford (2002)'s formulation was used by Gibbs *et al* (2014) drawing SOC from organic matter. However, the newer versions of HWSD do not provide organic matter, providing organic carbon concentration instead.

While the AEZ-EF model only considers SOC stocks at the topsoil level (30 cm), soil layer definitions and ranges are heterogeneous across each soil map (see table S1 in the appendix). Therefore, the estimates by soil depth layer were aggregated accordingly to allow comparable SOC across all databases. Following the literature, the aggregation is simply made by summing up estimates up to the 30 cm layer[8].

SOC is estimated for each soil mapping unit in HWSD and in SOLUS. For example, in HWSD v.2.0 there are around 29,538 soil mapping units (FAO & IIASA 2023). Note that other soil maps do not have explicit soil mapping units, so SOC is computed at the original resolution, later downscaled to raster maps with 0.5 × 0.5 degree resolution, and then converted into points. Note that grid cells which belong to the same soil mapping unit will also have the same stock values. The spatial level SOC were compared across each database by estimating the mean absolute error and root mean square error.

2.2.2. Land filters, land-cover imposition and aggregation

Following Gibbs *et al* (2014), global wetland and desert maps were first used as filters before mapping out the SOC estimates to the land cover maps. Wetlands are high carbon ecosystems and are often not associated with direct economic benefits (Withey and van Kooten 2014). Two wetland maps were utilized: the Global Lakes and Wetlands database (Lehner and Döll 2004) and (Reich 1997) wetland maps. In the case of deserts, we used the FAO's eco-floristic zones map (FAO 2000), filtering out subtropical deserts, temperate deserts, and tropical deserts.

After applying the wetland and desert map filters, aggregated SOC for each country and each AEZ were computed for agriculture lands (cropland and pasture) and forest lands using land cover areas as weights. To assess the sensitivity of these estimates to the underlying land cover data, this paper uses two land cover maps to represent cropland and pasture (Ramankutty *et al* 2008, Chen *et al* 2025). For forestry, we only use the MODIS (Moderate Resolution Imaging Spectroradiometer) forest land cover dataset by (Sulla-Menashee and Friedl 2022) and adapted by (Chen *et al* 2025). Note that identifying the optimal choice of land cover map for SOC stock estimation is out of the scope of this paper.

The area maps for pasture and cropland *circa* 2000 by (Ramankutty *et al* 2008) were developed by combining agricultural inventory data for land use and satellite land cover data from MODIS and Global Land Cover (GLC-2000) to create higher resolution maps for agricultural land. The maps identify cropland and pasture for the year 2000. (Gibbs *et al* 2014) used these maps to classify cropland and pastureland in the construction of soil carbon data embedded in the AEZ-EF model. While the *circa* 2000 layer aligns survey totals with spatial detail, there are newer satellite products which we used when updating SOC estimates for cropland and pastureland. Specifically, we rely on cropland, pasture and forestry cover from Chen *et al* (2025) which used MODIS land-cover products. The MODIS satellite data contains thirteen land-cover classifications according to the vegetation and humidity characteristics. To have a consistent classification of land, the authors used the FAO mapping equations to convert the MODIS classification into the FAO-reported land-covers. They then matched grassland, natural, herbaceous, woody croplands, and tree-covered FAO[9] areas to represent pastureland, cropland, and forests using their formulation. Additionally, they performed long-term evaluations of this database to understand the pattern of land-cover change and its drivers (Chen *et al* 2025).

Using (Ramankutty *et al* 2008), therefore provides direct continuity with the original AEZ-EF implementation and with the GTAP land-use database used in many global economic models. In turn, the MODIS-based product offers a harmonized, annually updated representation of the same broad land-cover categories (cropland, pasture and forest), allowing SOC stocks to be embedded consistently in more recent policy scenarios. Together, these two datasets provide reasonable land-cover products for harmonizing SOC stocks for the AEZ-EF while remaining aligned with standard GTAP/AEZ land-use classifications.

Each land cover dataset is paired independently with SOC maps to generate separate stock estimates. We then tested the sensitivity of those estimates to (a) the choice of land cover map and (b) the choice reference year (in MODIS case). Because the MODIS products start in 2001, the 2001 layer is used as the closest match to circa 2000. Most global economic models that evaluate land cover, and land use change due to policy use data for a single reference year. For example, the latest GTAP-BIO, which is a model to assess biofuels policy changes, uses data for 2017 reference year; this comparison therefore mirrors standard practice while highlighting the implications of using more recent satellite data.

Finally, another map is overlayed to classify the 18 AEZs and geographic regions in the GTAP model (Lee *et al* 2005) (see table S2 in the SI). Final SOC stocks[10] are aggregated to the AEZ level via area weighted average.

[8] In the case of HWSD version 2 in which layers cut at 20–40 cm, we took the first layer and half of the second layer to assess topsoil SOC as done in (European Commission. Joint Research Centre. Institute for Environment and Sustainability 2011).

[9] To detail on how the area in MODIS are classified and estimated see FAO documentation on land-cover (FAO 2024).

[10] We developed a tool to update the SOC estimates according to the most suitable soil database and the land-cover choice to update the AEZ-EF model.

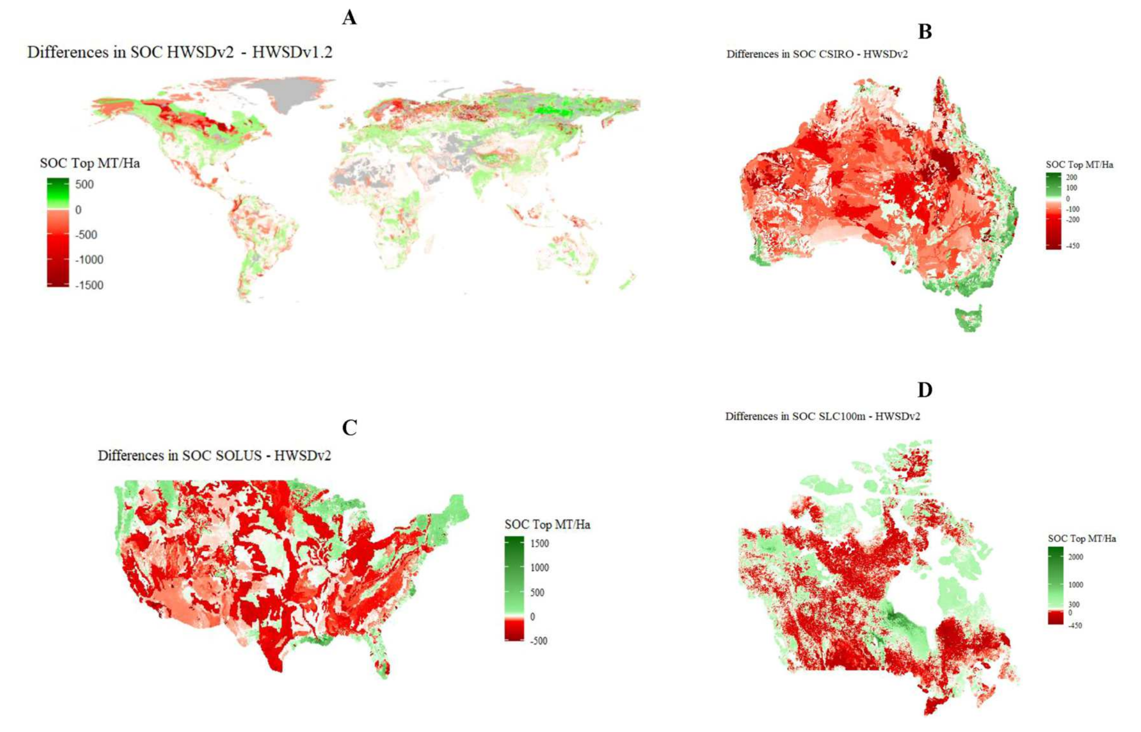

Figure 1. Spatial distribution of differences in SOC across databases (HWSD V2.0—Version 1.2 and Country data - HWSDv2).

The grid overlay, filter maps, AEZ-region imposition, and area-weighting procedure are applied to both land-cover map scenarios and to all SOC maps.

2.2.3. Comparing ILUC emissions using different SOC stocks

We calculate emission factors across diverse land conversions embedded into the AEZ-EF model and compare the ILUC emissions at the global level from a few different biofuel pathways given the original AEZ-EF model and its revised version which includes the updated SOC data. Specifically, we examine the ILUC emissions from three biofuels pathways namely U.S. Soybean HEFA (USSOY), Brazilian Soybean HEFA (BRSOY), and a Global Blend Soybean HEFA (GLBSOY). The estimates of land use changes for these pathways are taken from the GTAP-BIO simulations outlined in by Zhao *et al* (2021).

3. Results

3.1. Evaluating SOC across different databases

We estimated SOC data at the grid-cell level and calculated differences across the databases (figure 1). Panel A in figure 1 shows the differences between HWSD v2.0 and HWSD v1.2. Note that we used HWSD v1.2 as a proxy[11] for HWSD v1.1, which is the original spatial data used in (Gibbs *et al* 2014) but is no longer publicly available. We retain HWSD v2.0 as the reference global database[12] in this assessment as it is the benchmark considered in the older AEZ-EF. Pronounced negative differences (in red) were found in the Northern Hemisphere, South America and Southeast Asia, indicating that the stock estimates from HWSD v2.0 are smaller than those found in v1.2 for these regions. Overall, the global area weighed average SOC in v2.0 is 36.5% lower than in v1.2 (48.05 MT Ha^{-1} compared to 75.69 MT Ha^{-1}, respectively). The newest version of HWSD has more than double the number of soil mapping units than its predecessor, which partially drives an area-weighted average SOC down as soil mapping units are smaller. At the same time, since HWSD V2.0 is based on a newer soil properties database (WISE30sec) the soil properties magnitudes are partially different. In the case of A side-to-side comparison in the soil mapping units that are present in both versions, organic carbon concentration is 10.7% higher in version 2.0, but bulk density is 3.7% smaller. However, in the overall

[11] We continue using HWSD version 1.2 as a proxy for estimates coming from HWSD version 1.1. through the results section.

[12] We briefly evaluated SoilGrids, as a reference for additional global databases using one of the land cover products evaluated in this paper (circa2000) and aggregated them at the AEZ level. At the global level, the area weighed average SOC in SoilGrids is smaller than HWSD V2.0, and these differences are negligible (48.05 MT/Ha in HWSD V2.0 and 46.59 MT/Ha in SoilGrids). However, we acknowledge the possible regional differences.

Table 1. Comparative measures of country databases and HWSD version 2.0.

Country	Mean average error (MAE) (MT C/Ha)	Root mean square error (RMSE) (MT C/Ha)
United States	104.3	141.1
Australia	101.2	133.9
Canada	142.7	235.4

comparison where all soil mapping units of each version are considered, differences in organic concentrations are smaller (0.3% lower in HWSD V2.0.), whereas average bulk density is higher in HWSDV1.2 (by 6.9%). Therefore, as the overall comparison indicates, average soil properties magnitude is smaller in HWSD V2.0, this combined with smaller areas by soil mapping units drives the average SOC stocks down. The mean absolute error (MAE) shows that the average difference between the databases is around 50.17 MT Ha^{-1}. However, a root mean square error (RMSE) of 104.49 MT Ha^{-1} suggests the presence of outliers, increasing the average error.

The spatial distribution of differences for selected countries[13] (Panels B through D in figure 1) denotes a trend in which SOC from the official country data sources are generally smaller than in HWSD v2 (red areas). However, across coastlines, islands, and areas close to or in water bodies[14], the stocks from national data are smaller in HWSD v2.0 (green areas). The largest differences are found in Canada with zones in which SOC is 2,000 MT Ha^{-1} higher in the SLC data than in HWSD v.2.0. Table 1 presents statistical measures comparing the databases. In all cases the mean absolute errors and root mean square errors are high. For the case of MAE, these large values indicate a large disagreement between the national data and the HWSD. For Canada the RMSE is 65% higher, indicating an elevated presence of outliers as this measure penalizes large differences found when comparing the databases.

As mentioned before, we filtered wetlands and desert categories prior to calculating the aggregated SOC for each AEZ, region and land cover type. Appendix figure S1 displays the effects of the variations in filtering wetlands and deserts when calculating aggregated SOC by AEZ at the global level for croplands. Overall, there are small variations in the estimated stocks when these filters are applied across AEZs.

We analyzed the global SOC for each AEZ using two reference years and using land cover data from MODIS. Specifically, we compared cropland, forest, and pasture global average SOC stocks from the HWSD v2.0 for 2001 (the year used for comparison in this paper) and for 2017 (current reference year for GTAP-BIO database). Overall, global average SOC for all land cover are not sensitive to the selected reference years, as the changes fall mostly between the range of +20% and −20% (See appendix, figure S2). The stability of the global average SOC from HWSD v2.0 is observed when comparing multiyear estimates. Figure S3 in the appendix shows small differences in the global average SOC stock for Cropland between 2015 to 2020. This shows that for the 6-year period the choice of reference year for the land-cover map has relatively small impacts on SOC estimated at the global level.

We present results for the aggregated SOC by AEZ for the regions in which we analyzed their national databases. For this paper's purpose, we focus on the results for cropland SOC only (figures 2 to 4). Results for pasture and forest are found in the appendix figures S6 through S11. We compare several estimates of AEZ-level SOC calculated from the national soil maps, global soil maps using circa 2000 land cover data as well as MODIS land cover data for year 2001. We also compare these to the original SOC values in the AEZ-EF model from (Gibbs *et al* 2014).

For the US, we focus on two national sourced databases namely SOLUS and SPM. The rest of US databases presented major disadvantages, specifically, the technical disadvantages of SSURGO and STATSGO as mentioned in the data section of the paper. Although SPM also presents estimation bias, we showcase the aggregated estimates for comparison. We addressed the bias of SOLUS versus raw databases like SSURGO by extracting a substantial portion of raw observations (95.2% of the continental US counties) from SSURGO and comparing them with SOLUS. The differences at the aggregated level for these two sources were less than 5% in the majority of AEZs (See appendix figure S5).

We can observe high heterogeneity in US SOC across databases and cropland cover data. Cropland SOC stocks calculated under circa 2000 land cover data (figure 2, left panel) shows very large values for AEZ 14 to 16 under SOLUS soil map while for AEZ 9 to 12, the estimates are largest under HWSD v.2.0. Note that the

[13] In the case of the US, we estimated spatial differences only for SOLUS database, aggregated comparison is made for all databases when possible.
[14] Recall water bodies are not considered in the final estimates.

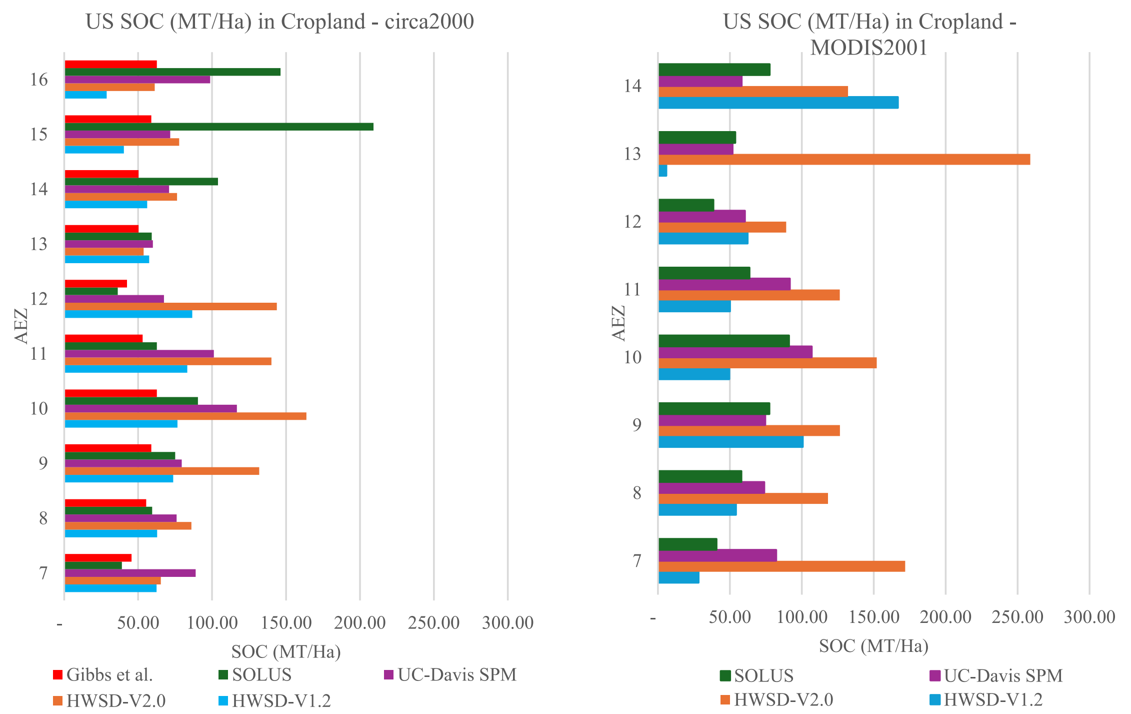

Figure 2. Estimates of cropland SOC (MT/Ha) for the United States by AEZ under circa 2000 (left) and MODIS 2001 (right) land cover data sets.

original values of US cropland SOC in the AEZ-EF model from (Gibbs *et al* 2014) are generally lower than other estimates which are based on more recent soil map data. Therefore, revising the US SOC stocks in AEZ-EF model with those calculated from HWSD v2.0 would likely result in a moderate increase in ILUC emission factors. Under circa 2000 land cover data (figure 2, right panel), the computed SOC from HWSD version 2 are relatively larger than estimates from other databases. This pattern is also observed for pasture and forest (see appendix figures S6-S7).

In a previous analysis based on USDA data, the estimated ranges of US SOC stocks are between 52.2 to 121.3 MT Ha^{-1} for cropland, between 60.1 to 136.0 MT Ha^{-1} for pasture and between 51.6 to 202.1 MT Ha^{-1} for forest (Loecke and Soil Survey Staff 2016). Based on our results under MODIS land-cover maps, the stocks from HWSD v2 surpass these ranges in five AEZs, while estimates from SOLUS exceed these ranges in two AEZs under circa2000 cropland and pasture. For forest, only one of the estimates from SOLUS falls below the range identifies in previous work (37.95 MT Ha^{-1}).

Figure 3 shows the cropland SOC for Australia. In general, we see that the estimates computed from HWSD v.2 and v.1.2 are larger than those calculated from CSIRO national data. Under circa 2000 land cover (figure 3, left panel), SOC in AEZs 3, 4 and 8 to 10 are largest under HWSD v1.2 while for AEZs 1, 2, 5 and 6 values for HWSD v.2.0 are highest. Note that the cropland SOC from Gibbs *et al* (2014) are smallest across all AEZs. Comparing circa 2000 and MODIS 2001, we see less heterogeneity in cropland SOC for Australia unlike in the US estimates. However, we do see the absence of cropland SOC estimate in AEZ 17 under circa 2001 land cover using the MODIS data. The original SOC estimates in the AEZ-EF model are closer to the official CSIRO database. This is especially true in the case of pasture (appendix, figure S8).

Previous studies which estimated SOC data for Australia have found lower SOC values on average compared to US and Canada. Viscarra Rossel *et al* (2014) estimated average SOC values between 22.6 to 37.9 MT Ha^{-1} for Australia. An updated estimation using data collection from five thousand sites assessing carbon sequestration potential revealed a baseline average SOC value of 49.6 MT Ha^{-1}. These papers reported averages match the CSIRO estimates. The range of estimates from HWSD v2 across all land types is greater than most estimates found in literature.

For Canada[15], cropland SOC derived from HWSD v2 and SLC are close to the original values in the AEZ-EF model in AEZs 9, 15 and 16 under circa 2000 land cover (figure 4, left panel). When circa 2001 land cover map is used, we see that computed SOC based on HWSD v2 relatively similar to SLC estimates in AEZs 9, 10, 15 and

[15] Several AEZs (AEZ 13 for cropland and pasture, AEZs 7 and 8 for forest) are absent when we map the new databases, explaining their zero values in the compared estimates.

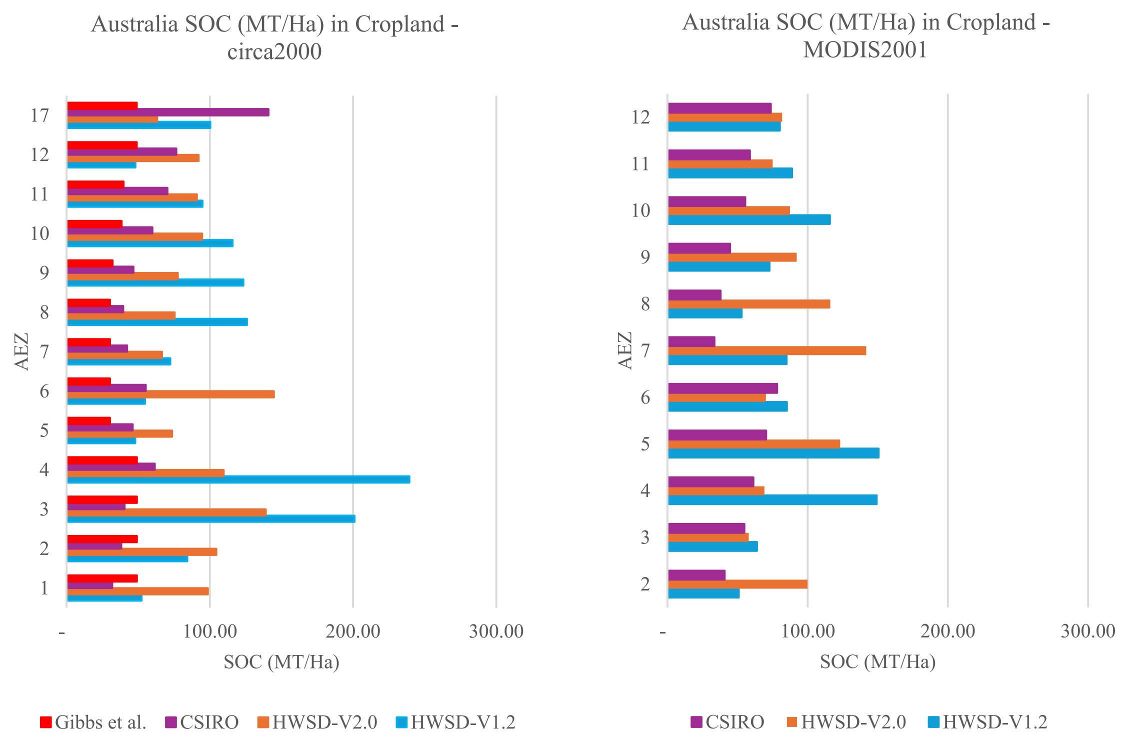

Figure 3. Estimates of cropland SOC (MT/Ha) for Australia by AEZ under circa 2000 (left) and MODIS 2001 (right) land cover data sets.

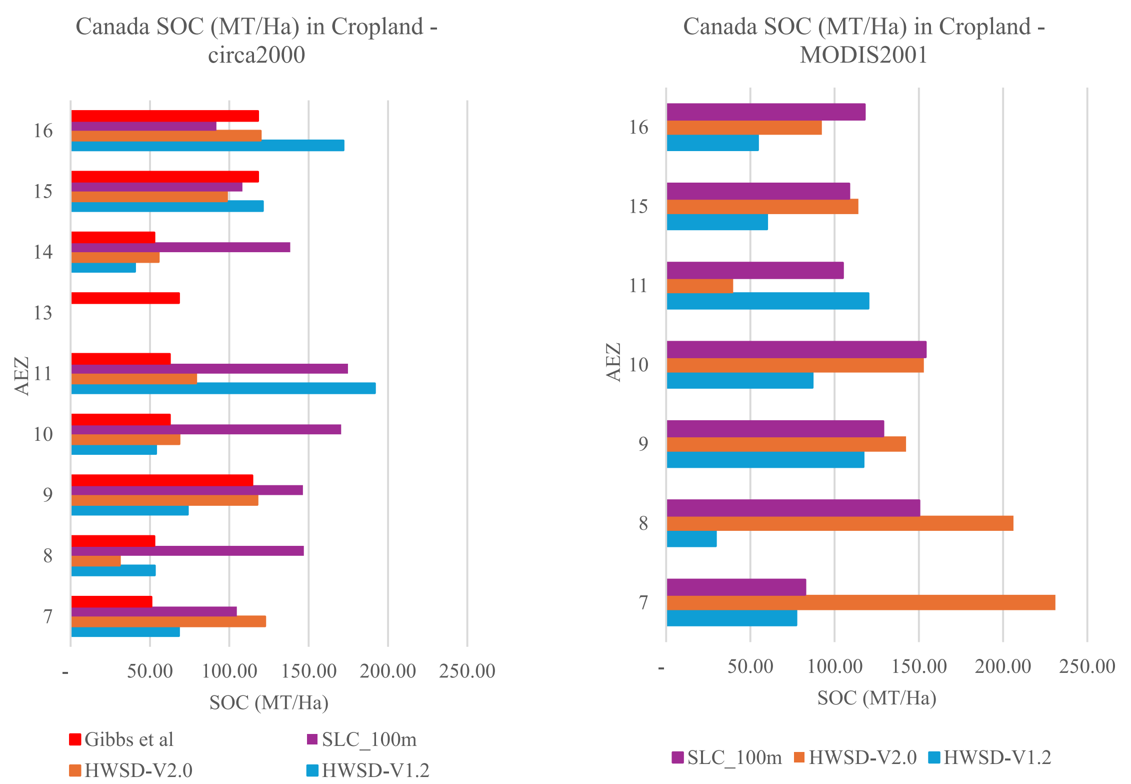

Figure 4. Estimates of Cropland SOC (MT/Ha) for Canada by AEZ under circa 2000 (left) and MODIS 2001 (right) land cover data sets.

16. The estimates from SLC are higher across cropland, pasture and forest (see appendix Figures S10 and S11), a result consistent with its elevated RMSE and outlier influence detected in our spatial differences analysis.

(Liang *et al* 2023) reports large ranges of SOC in grassland (70.4–121.2 MT Ha^{-1}) and agricultural land (54.9–116.6 MT Ha^{-1}). Comparing our estimates, both SLC and HWSDv2 estimates fall within reported

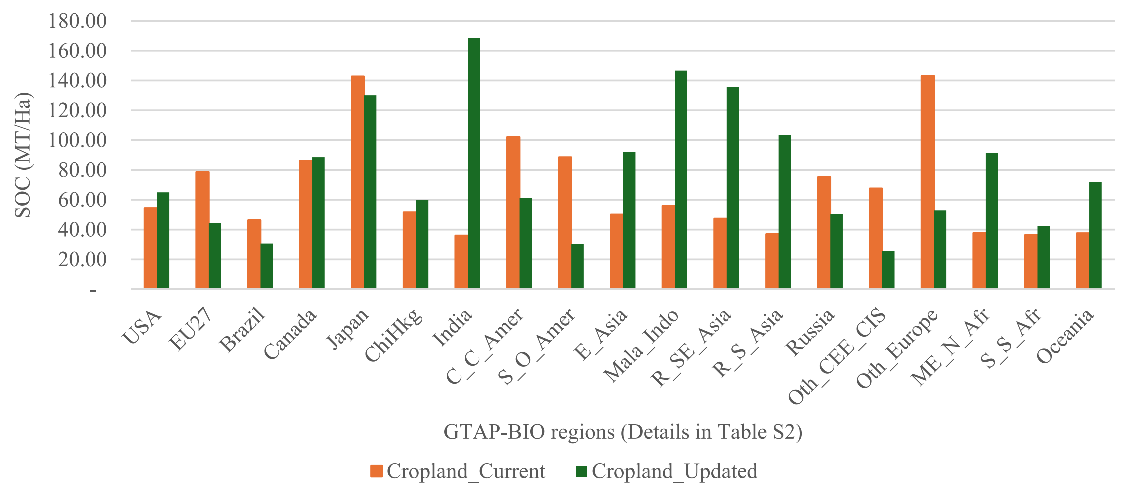

Figure 5. Cropland topsoil SOC estimates (MT/Ha) by region: Current values vs updated values.

ranges under circa2000 map. However, using MODIS cropland increases the average SOC, especially for AEZs 7 through 9 in cropland and AEZ 10 in pasture.

3.2. Updated SOC estimates and ILUC emission factors in the AEZ-EF model

The final SOC estimates for cropland, pasture and forest calculated in this paper were aggregated across nineteen regions[16] and 18 AEZs to match the aggregation in the AEZ-EF model. To update the AEZ-EF model, we used estimates from HWSD version 2, CSIRO, and SOLUS, leaving the update for Canadian data for future review. More explanation is provided in the discussion section. Figure 5 shows the original and updated SOC for cropland for each region in the AEZ-EF model (see appendix figures S12 and S13 for pasture and forest, respectively). We used estimates calculated using circa2000 land cover maps to make them more consistent with the original values in the AEZ-EF model.

In general, the new SOC estimates in cropland and pasture (appendix figure S12) are higher than those originally imbedded in the AEZ-EF model. Although the data for the US was updated using SOLUS data, the difference of topsoil SOC estimates is not as pronounced as in other regions. The largest difference between SOC stocks is found in India, where the new estimates are around 336% larger than the original. Other pronounced changes are found on the rest of Southeast Asia, and Malaysia and Indonesia regions. We see a similar pattern in the case of forest (appendix figure S13) wherein the updated SOC stocks are larger than the original values for these regions. For China-Hong Kong, the updated SOC stocks are almost the same as the original values for cropland, pasture and forest.

We introduced our new SOC data into the AEZ-EF model to recalculate emission factors for multiple land conversion pathways. Figure 6 shows ILUC emissions factors for the US when forests are converted to annuals (left) and when annuals are converted to pasture (right). The updated databases increase the estimated emissions for forest-to-crop (annuals) conversion in the majority of AEZ, except for AEZ 12. This reflects the fact that newer data shows higher soil carbon losses for this type of land conversion.

The pattern is different in conversion from annuals to pasture, this transition often results in negative emissions (i.e., net carbon sequestration), particularly in regions where pastureland holds more SOC than cropland. For the US, the variation is larger, especially on temperate AEZs (AEZs 7 to 12). This showcases larger sequestration with the updated data, at least under the circa2000 land representation across all AEZs.

The AEZ-EF model generates emission factors for each land-use transition simulated by the economic model. The mechanism in which AEZ-EF generates emission factors depends on the underlying data in SOC, biomass and stock change fractions that are derived from IPCC. For each transition, the soil carbon component is calculated using the SOC stock of the land being converted, the SOC stock of the final land use, and the IPCC stock-change factors for those land uses. Holding the stock change factors (SCF) constant, an increase in the initial SOC stock leads to an almost proportional increase in the calculated soil carbon loss per hectare. For example, to convert from forest to annuals, the SOC losses are calculated using the formulation below, indicating how our updated SOC stocks directly translate into changes in overall SOC and therefore in emission factors changes.

[16] The region's definition can be found on the appendix section, table S2.

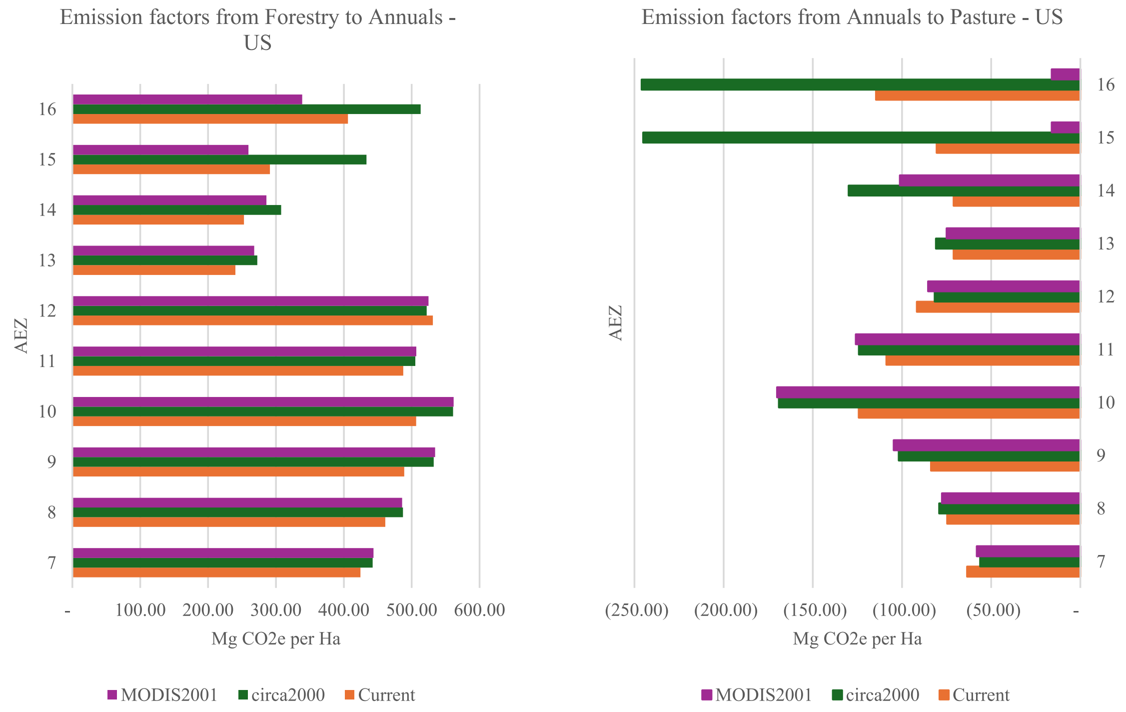

Figure 6. Emission factors from two land conversions in the US.

Table 2. Comparison of ILUC emissions by pathways in g CO2e MJ-1.

ILUC pathway	Current	Circa2000	MODIS2001
USSOY	18.03	17.64	17.68
BRSOY	16.25	13.91	13.80
GLBSOY	18.01	15.95	15.89

$$SOC_{losses} = SOC_{forest}{}^{*}\left(\frac{SCF_{forest}}{SCF_{cropland}}\right)$$

3.3. Implications for ILUC emissions

As previously noted in the paper, emission factors (including SOC data) are used in the assessment of ILUC emissions from biofuel production and policy. Table 2 presents ILUC emissions for three soybean pathways: U.S. Soy (USSOY), Brazilian Soy (BRSOY), and a Global Blend Soy (GLBSOY) expressed in grams of CO_2 equivalent per megajoule (g CO_2e/MJ). The estimates of land use changes for these pathways are taken from the GTAP-BIO simulations outlined in by Zhao *et al* (2021). ILUC for each pathway is evaluated under three scenarios: using the current AEZ-EF emission factors as well as updated emission factors computed using circa 2000 and circa 2001 MODIS land cover maps. The results show small to moderate reductions in ILUC estimates when shifting from current to updated emission factors which are based on more recent global and regional soil maps. For example, under the USSOY pathway the ILUC emissions are around 2% lower compared to the emissions based on current AEZ-EF emission factors (18.03 vs 17.64 and 17.68 g CO2e MJ-1). The range of reductions in ILUC emissions are larger under the BRSOY pathway at around 14% to 15% less than the emissions calculated from the current emission factors (16.25 vs 13.91 and 13.80 g CO2e MJ-1). These results highlight the importance of using the latest publicly available soil maps in calculating SOC stocks and emission factors in carbon calculators used in ILUC emission assessments.

4. Discussion

This paper provides a comprehensive qualitative and quantitative assessment of global and regional soil properties databases to improve estimates of SOC and emission factors and to enhance policy making regarding ILUC emissions.

For the US databases, most of the national databases analyzed present advantages over the global HWSD soil map. USDA sources are constructed by experts in digital soil mapping (STATSGO) and laboratory samples (SSURGO). SPM databases combine both STATSGO and SSURGO while SOLUS provides information at a higher resolution using machine learning modeling. However, these national maps also have disadvantages. The SPM lack information about the depth levels used for SOC stock calculation which limits its functionality to replace the SOC estimates in the AEZ-EF model. Due to the size of the data, it is difficult to obtain full spatial representation of SOC with the SSURGO map. Although SOLUS also presents challenges such as its lower accuracy in the cross-validation assessment. It provides the advantage of having a fully reproducible map of SOC estimates for the US, and their estimates closely mirror those obtained from the raw SSURGO database.

For Australia, the national data analyzed was constructed with data from soil sample sites compiled from official institutions and covariates that help improve the accuracy of the estimates. Moreover, the extensive accuracy assessment made by the authors for both soil properties strengthen its reliability. The aggregated estimates mirror those in literature, minimizing risks of over-estimation of SOC stocks that could lead to biases in the estimation of ILUC emissions factors.

Finally for Canada, the database is provided by a reputable institution, was developed using machine learning methods and its estimates are close in range to those found in literature. However, it relies on legacy surveys and clustered samples means and it may not fully capture country-level SOC (Geng *et al* 2025). The spatial analysis shows presence of outliers. In depth analysis reveals that the Soil Landscapes of Canada produces much higher and SOC stocks in a considerable number of grid-cells. Moreover, the Canadian Soil Information Services advice the products are still under evaluation. This highlights the need for further refinement before this database can be considered fully reliable to be introduced in the AEZ-EF model.

Soil organic carbon, and vegetation biomass carbon are key elements in calculating emission factors and ILUC values; therefore, updating them reflects a moderate change across emission factors across different land conversions in all regions that are later translated into our policy exercise with reduced ILUC values. Recently Taheripour *et al* (2024) analyzed uncertainties in land-use emission factors and their effect on ILUC values, focusing on two carbon calculators, including the AEZ-EF model, finding significant differences across sources. This paper provides further insights by exploring one of the sources of variation in emission factors and after assessing them, harmonize the databases deemed as the most fit to provide improved emission factors to be used in policy analysis.

5. Conclusions

This paper aimed to evaluate the reliability and relevance of official soil property databases for the United States, Australia, and Canada, and assess their potential use in the AEZ-EF model compared to the HWSD v2. Based on the analysis, we updated the model using the national databases for US and Australia and made no revision for Canada, keeping HWSD v2 as base map.

The updated emission factors derived from revised SOC databases reveal that prior estimates used in ILUC modeling may have overstated emissions. Incorporating high-resolution, country-specific SOC data leads to lower carbon loss estimates, particularly for forest-to-cropland conversions. When these updated SOC values are combined with improved land-cover maps and reintroduced in the AEZ-EF model. The results from the newly calibrated model show relatively lower ILUC emissions for the examined pathways compared. Overall, these results emphasize the critical role of accurate SOC and land-use data in generating relevant ILUC assessments.

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Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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