Responses to reviewers' comments on "HIStory of LAND transformation by humans in South America (HISLAND-SA): annual and 1-km crop-specific gridded data (1950 - 2020)" (manuscript number essd-2024-527)

We sincerely thank the reviewers for their thoughtful and constructive comments. We have revised the manuscript accordingly. The detailed point-by-point responses are provided below (highlighted in blue), and the corresponding revisions in the manuscript are marked in red.

Responses to Reviewer 1:

The authors made an effort to map the long-term crop distribution in South America by synthesizing multiple sourced datasets. Their efforts should be acknowledged. Overall, the paper presents a clear storyline, which is divided into three sections.

Response: We thank the reviewer for the positive comments.

Unfortunately, I did not see the scientific question that the paper aims to address. Additionally, the intended application of the research is not clear, given the existence of several relevant datasets.

Response: We sincerely thank the reviewer for the thoughtful and valuable comment. While data papers in *Earth System Science Data* typically focus on dataset development, we fully agree that clarifying the scientific question and intended application for developing the HISLAND-SA dataset further improves the manuscript.

- **Scientific question:** The scientific question addressed by our dataset is to understand how agricultural land-use dynamics in South America have evolved over the past 70 years, with a focus on four major commodity crops: soybean, maize, wheat, and rice. We aim to analyze how the spatial-temporal patterns of these crops have shifted over time and how these shifts have influenced land-use transitions in South America. Our dataset fills a significant gap by providing long-term, high-resolution, and crop-specific information for South America — key attributes that are often missing from existing datasets.
- **Intended application:** The HISLAND-SA dataset serves multiple purposes, supporting research on agricultural land-use change, its ecological impacts, and the implications for food security. It is a valuable resource for assessing the impacts of agricultural expansion on deforestation, biodiversity loss, and greenhouse gas emissions. The dataset offers critical information for policymakers, researchers, and stakeholders involved in sustainable agriculture, climate change mitigation, and food security, helping to shape strategies that balance agricultural production with environmental conservation.

We have incorporated these points into the manuscript.

Revisions: Lines 26-32: While previous studies have documented land use and land cover changes in South America over recent decades, there is still a lack of spatially explicit, time series maps of crop types that capture shifts in crop distribution. Therefore, developing high-resolution, long-term, and crop-specific datasets is crucial for advancing our understanding of human-environment interactions and for assessing the impacts of agricultural activities on carbon and biogeochemical cycles, biodiversity, and climate.

Lines 132-140: This study focuses on understanding how the spatial-temporal patterns of these four commodity crops have evolved over the past seven decades and how these changes have influenced land-use transitions in South America. The dataset is designed to support research on agricultural land-use change, its ecological impacts, and food security, offering insights into the effects of agricultural expansion on deforestation, biodiversity loss, and greenhouse gas emissions. It provides critical information for policymakers, researchers, and stakeholders engaged in sustainable agriculture, thereby assisting in the development of strategies that balance agricultural production with environmental conservation.

It appears that the work is somewhat hobby-oriented, with the research area, spatial resolution, time scale, and targeted crop types being arbitrarily determined by the authors' interests. Furthermore, I have a few comments that are worth considering.

Response: We sincerely thank the reviewer for the thoughtful and valuable comment. We understand the concern regarding the selection of the research area, spatial resolution, time scale, and targeted crop types. We would like to clarify that these choices were based on solid scientific and practical considerations rather than personal interests. Below is an explanation of each selection:

- **Research area:** The focus on South America was driven by its critical role as both a global agricultural and deforestation hotspots. Agricultural expansion in this region has been a primary driver of land-use change, particularly through deforestation. The widespread increase in agricultural activities across South America makes it an ideal case for studying human-environment interactions, especially in the context of land-use change and its environmental consequences.
- **Spatial resolution:** The 1 km spatial resolution was selected to ensure sufficient detail for both regional and global assessments. This resolution meets the requirements of many ecosystem models and land-use change studies. Most long-term datasets for South America have a resolution greater than 10 km (Adalibieke et al., 2023; Klein Goldewijk et al., 2017), limiting their ability to capture fine-scale spatial patterns. Recent studies developing 1 km datasets also highlight the need for higher-resolution data (Cao et al., 2021; Li et al., 2023;

Ye et al., 2024), making 1 km resolution in this study essential for accurate analyses of land-use change and environmental impacts in South America

- **Time scale:** The choice of 1950 as the starting point reflects the significant shifts in agricultural practices and land-use dynamics that began in the mid-20th century. This period marks the onset of large-scale agricultural expansion, driven by technological advances, policy changes, and global demand. Additionally, the widespread conversion of natural vegetation into agricultural land makes the period from 1950 to 2020 critical for understanding the transformation of landscapes and ecosystems in South America.
- **Targeted crop types:** Soybean, maize, wheat, and rice were selected as focus crops because they are the primary staple crops in South America, driving large-scale production with significant economic and ecological impacts. These crops account for most agricultural land-use changes in South America, making them crucial for understanding broader environmental effects.

Revisions: **Lines 50-71 (Research area):** South America is of critical importance due to its substantial contribution to global agriculture, which is essential for meeting the world's growing food demand (Ceddia et al., 2014; Hoang et al., 2023). Cropland expansion in this region has been a significant driver of land-use transformation, particularly through deforestation, with profound effects on ecosystems and biogeochemical processes (Song et al., 2021; Zalles et al., 2021). As one of the main types of land use and land cover (LULC), cropland plays a crucial role in supporting human nutritional needs and ensuring food security (He et al., 2017; Yu and Lu, 2017). However, to meet the growing demand for food and fiber driven by population growth and consumption patterns, cropland has increasingly encroached on natural vegetation (Winkler et al., 2021). Additionally, economic and policy factors have reshaped crop cultivation structures across the region (Cheng et al., 2023; Mueller and Mueller, 2010; Song et al., 2021). These changes are driven by a combination of trade dynamics, investment flows, and market concentration (Boyd, 2023; Clapp, 2021). As a result, the transformation of crop types has occurred, weakening the resilience of agroecosystems and contributing to biodiversity loss (Frison et al., 2011; Renard and Tilman, 2019). In response to these challenges, the international community has increasingly emphasized the need to align agricultural systems with climate mitigation and food security goals (ICJ, 2025). Therefore, an improved understanding of the spatial distribution and historical dynamics of crop types is urgently needed to assess the impacts of cropland expansion and crop pattern shifts across South America. Such insights are crucial for evaluating the environmental and socio-economic consequences of cropland expansion, particularly in terms of its impact on climate, ecosystems, and food security.

Lines 72-106 (Time scale and targeted crop types): Agriculture in South America has experienced significant changes driven by agricultural policies, socio-economic shifts, and technological innovations after the 1950s (Altieri, 1992; Ceddia et al., 2014; Zalles et al., 2021). These changes have not only reshaped regional economies, as in other historical periods of agrarian reform, but have also been justified by global food security goals, alongside such other important drivers as trade relationships, investors, subsidies, and debt serving goals (Boyd, 2023; OAS, 2024). In this context, crop cultivation has shifted from traditional crops to high-yield and high-demand commodity crops, reflecting both the increasing global demand for food and fuel, as well as the urgent need to enhance agricultural efficiency and yields (Garrett et al., 2013; Meyfroidt et al., 2014). Specifically, the major commodity crops (i.e., maize, soybean, wheat, and rice) have become the core of agricultural production in South America (FAO, 2020). The cultivation of these crops has not only significantly boosted food production in the region but also secured a strong position for many producers in the global food market. After the 1950s, countries in South America (e.g., Bolivia, Brazil, Chile, Colombia, Ecuador, and Peru) undertook land reforms to reduce land concentration and promote agricultural production (De Janvry et al., 1998), which significantly affected land use outputs and efficiency and laid a substantial foundation for the development of agriculture (De Janvry et al., 1998; Munoz and Lavadenz, 1997). After the 1980s, neoliberal economic reforms were further carried out in South America, accelerating the ongoing agricultural modernization (Chonchol, 1990) and greatly facilitating the cultivation of soybeans by eliminating price controls and export restrictions on agricultural products (Campos Matos, 2013). Since the 2000s, soybeans have continued to grow dramatically due to global demand, technological advances, economic subsidies and other supportive policies (de LT Oliveira, 2017; Song et al., 2021). This growth has further bolstered the expansion of maize cultivation, driven by the promotion of maize-soybean cropping systems and the adoption of direct seeding, no-tillage practices, and double cropping (Klein and Luna, 2022). In comparison, the area under wheat and rice cultivation has remained relatively stable. Although there is a growing demand for wheat, its market price is less fluctuating, leading farmers, farm managers, and investors to prefer crops with higher market returns (Erenstein et al., 2022). Meanwhile, rice primarily serves domestic demand rather than being export-oriented (Dawe et al., 2010). Despite government reports and documents that have recorded changes in the dynamics of agriculture in South America over the past few decades, there is still a lack of spatially explicit and time-series maps of historical crop types that reflect changes in crop distribution. This deficiency makes it difficult to fully understand the spatial and temporal evolution of major commodity crops and hinders understanding of their impacts on environmental changes.

Lines 107-129 (Spatial resolution): Many efforts have produced commodity crop maps at regional or global scales. For example, datasets such as the Spatial Production Allocation Model (SPAM) (Yu et al., 2020), M3 (Monfreda et al., 2008), and CROPGRIDS (Tang et al., 2023) offer valuable solutions by providing detailed crop type information based on the census data and spatial allocation algorithms. SPAM, for instance, provides data on crop area, yield, and production for 42 major crops at a spatial resolution of 5 arcmin under four farming systems. However, these datasets have a coarse spatial resolution and are available for only a few years, which makes it challenging to accurately characterize the spatial-temporal distribution of crop types at finer scales (Becker-Reshef et al., 2023; Ye et al., 2024). In contrast, with the continuous evolution of remote sensing technologies, high-resolution data were increasingly being used to develop fine-scale crop type maps. For example, Song et al., (2021) developed annually updated soybean maps with a 30 m resolution for South America from 2000 to 2023 using all Landsat and MODIS images and a probability sample of continental field observations. MapBiomas also provides high-resolution crop type maps for Argentina, Brazil, and Uruguay, covering the period from 1985 to the present (De Abelleyra et al., 2020; Petraglia et al., 2019; Souza and Azevedo, 2017). However, these existing datasets are available only at partial national or local scales, cover only a single crop type, or lack rigorous validation. Furthermore, most remote sensing data dates back only to 1985, making it challenging to depict crop dynamics further back. Therefore, it is imperative to develop high-resolution and time-series crop type data for driving terrestrial ecosystem models to quantify the impact of crop dynamics on ecosystems and climate. Such an dataset will draw on innovations in earth science and data use to contribute to related fields that address the “advance of the agricultural frontier” in South America, and its implications for human-environmental interactions (OAS, 2024).

1. A lot of work relates to raster data resampling. How can we assess the uncertainty and sensitivity of cross-scale data resampling?

Response: Thank you for your thoughtful comments. In our study, we employed two resampling strategies to achieve a consistent 1 km resolution: (1) aggregation of high-resolution remote sensing products, and (2) upsampling of the SPAM dataset.

- **Aggregation:** This process does not introduce additional spatial uncertainty, aside from inherent classification errors in the high-resolution input data. To quantify the uncertainty resulting from classification errors during aggregation, we performed a Monte Carlo simulation. We assumed a range of classification error rates (i.e., 3-15%) and introduced symmetric noise by randomly flipping a proportion of target (e.g., cropland or crop types) and non-target pixels in simulated high-resolution raster data. For each classification error rate and true fraction, we aggregated the modified high-resolution raster to 1 km resolution and computed the aggregated fraction. This process was repeated 100 times per fraction to estimate the mean and deviation of the aggregated fraction, allowing us to assess the magnitude and variability of the estimation error of aggregation under different classification error rates (Figure S1). Given a specific spatial resolution and classification error rate, the overall uncertainty was quantified as the expected absolute estimation error across the full range of possible true fractions (i.e., 0-100%). This was calculated by averaging the absolute difference between the aggregated and true fractions across all simulated fractions. Therefore, we separately quantified the potential aggregation-induced uncertainty for each dataset, including Uruguay LC (spatial resolution: 10 m, classification error: 11.5%, total uncertainty: 5.81%), MapBiomas (30 m, 14.2%, 7.36%), Argentina MNC (30 m, 9%, 4.59%), GLAD (30 m, 4%, 2.08%), and CGLS-LC100 (100 m, 20%, 10.49%). It is evident that aggregation is influenced not only by classification errors but also by sensitivity to spatial resolution. We have added this part in the revised manuscript.

Revisions: Lines 705-732: To ensure spatial consistency across input datasets, we employed two resampling strategies to achieve a standardized 1 km resolution: (1) aggregation of high-resolution remote sensing products, and (2) upsampling of lower-resolution datasets, such as SPAM. While resampling is essential for harmonizing spatial scales, it introduces varying degrees of uncertainty depending on the original resolution and classification accuracy of the source data.

Aggregation of high-resolution datasets does not introduce additional spatial uncertainty beyond the inherent classification errors present in the original data. However, these classification errors can propagate into aggregated outputs and finally affect spatial statistics. To quantify this aggregation-induced uncertainty, we conducted a Monte Carlo simulation by introducing symmetric random noise at various classification error rates (i.e., 3% to 15%), whereby a proportion of target and non-target pixels were randomly flipped. For each combination of classification error rate and true fraction, we aggregated the modified raster to 1 km resolution and calculated the resulting aggregated fraction. This process was repeated 100 times per fraction to obtain stable estimates of the mean and standard deviation of the aggregated values (Figure S7). We then computed the uncertainty as a function of both classification error and spatial resolution. Specifically, total uncertainty was defined as the average absolute deviation between aggregated and true values across the full range of possible true fractions (i.e., 0% to 100%). This allowed us to isolate the magnitude of uncertainty attributable to aggregation process. This simulation framework was applied to each of the aggregation datasets, yielding the acceptable uncertainties (Table 5). These results demonstrated that total uncertainty increases with both classification error and coarser input resolution. Datasets with higher native resolution (e.g., Uruguay LC) tend to exhibit lower aggregation uncertainty, even when classification error is moderate. This underscores that aggregation-induced uncertainty is not solely a function of accuracy, but also of the granularity of the input data. This uncertainty component must be explicitly considered when integrating heterogeneous land cover datasets for spatial modelling or policy-relevant assessments.

Table 4. Aggregation-induced uncertainty under varying classification errors and spatial resolutions.

Dataset	Spatial resolution (m)	Classification error (%)	Total uncertainty (%)
Uruguay LC	10	11.5	5.81
MapBiomas	30	14.2	7.36
Argentia MNC	30	9.0	4.59
GLAD	30	4.0	2.08
CGLS-LC100	100	20.0	10.49

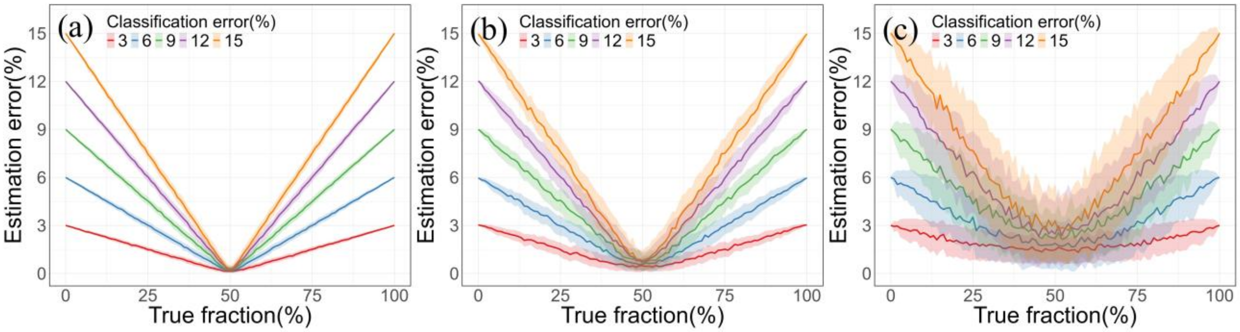

Figure S7. Monte Carlo simulation of aggregation-induced estimation error under varying classification error rates and spatial resolutions. (a), (b), and (c) represent the spatial resolution of 10 m, 30 m, and 100 m, respectively. The x-axis represents the true fraction (%) of the target class in a 1 km grid, while the y-axis shows the absolute estimation error (%) after aggregating the modified high-resolution raster. Each line corresponds to different simulated classification error rates (i.e., 3%, 6%, 9%, 12%, and 15%). Shaded areas represent the standard deviation across 100 Monte Carlo iterations.

- **Upsampling:** To assess the uncertainty introduced by upsampling, we conducted a spatial comparison using soybean as a case — the only crop for which SPAM (10 km) and high-resolution crop map (i.e., GLAD, 30 m) are available for South America. We first upsampled the SPAM soybean layer in 2010 to 1 km using bilinear interpolation. To evaluate spatial consistency, we aggregated the 30 m GLAD soybean in 2010 to 1 km as the "ground truth" and compared the two datasets on a pixel-by-pixel basis across the continent. Then, we conducted two complementary assessments. First, a pixel-wise comparison at the 1 km resolution yielded a coefficient of determination (*R^2*) of 0.50, indicating a moderate level of agreement. Second, the distribution of pixel-wise differences showed that over 70% of the values fell within ±0.1, where larger discrepancies (greater than ±0.3) were mainly concentrated in fragmented or heterogeneous cropping regions (Figure S1). Despite the presence of local structure uncertainty, these results suggest that the resampled 1 km SPAM data retain broad-scale spatial patterns that are reasonably consistent with reference data. This supports its application as a baseline crop distribution map at regional and continental scales. We have incorporated this part into the revised manuscript.

  Revisions: Lines 733-745: To evaluate the spatial uncertainty introduced by the upsampling process, we conducted a quantitative comparison between SPAM and GLAD soybean maps for 2010 in South America. The original SPAM data were upsampled to 1 km using bilinear interpolation, while the GLAD soybean layer was aggregated to 1 km resolution and treated as reference. A pixel-by-pixel comparison was performed between the two datasets across the continent. First, the pixel-wise comparison yielded a coefficient of determination (R^2) of 0.50, indicating moderate agreement between resampled SPAM and GLAD data. Second, the distribution and frequency of pixel-level differences revealed that over 70% of the pixels fell within a ±0.1 range, while larger deviations (greater than ±0.3) were mainly observed in fragmented and heterogeneous cropping regions (Figure

S8). Although the resampling process introduced local structure uncertainty and smoothed fine-scale heterogeneity, these results suggest that the unsampled 1 km SPAM data retain meaningful broad-scale spatial patterns. Therefore, the resampled dataset in this study remains suitable for use as a baseline crop distribution map at continental scale.

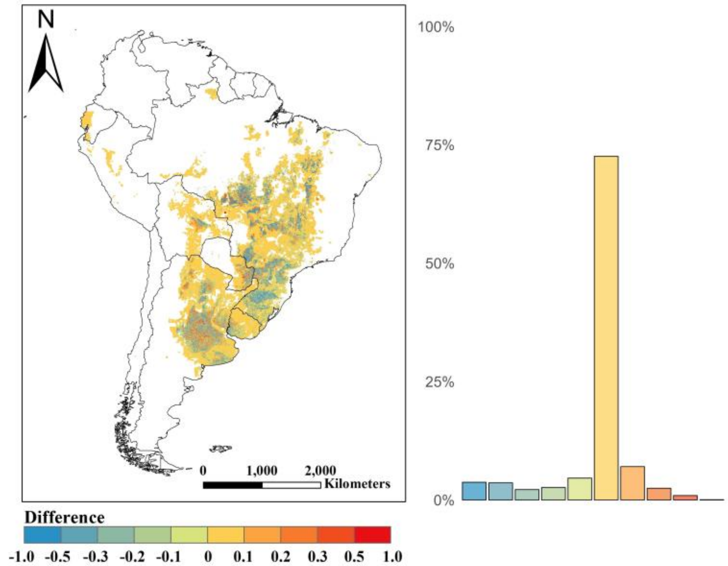

Figure S8. Spatial distribution (left) and frequency (right) of pixel-wise differences between SPAM (resampled to 1 km) and GLAD (aggregated to 1 km) soybean map in 2010 for South America.

2. Figure 3 presents the spatial distribution of crop-specific density. I find it somewhat difficult to understand. Does it represent the proportion of a given crop in a 1x1 km grid, or does it indicate the fraction of a given crop in the total cropland area within a 1x1 km grid? This is a bit confusing.

Response: Thank you for your thoughtful comments. We appreciate your feedback and apologize for any confusion caused by the presentation of crop-specific density in Figure 3. To clarify, Figure 3 represents the proportion of a given crop within each 1 × 1 km grid, rather than the proportion of the crop in the total cropland area within the grid. We have revised the caption of Figure 3 to improve clarity.

Revisions: Lines 442-444: Figure 3. The spatial pattern of soybean, maize, rice, and wheat from 1950 to 2020. The first, second, third, and fourth rows represent the crop-specific density of soybean, maize, rice, and wheat. Crop-specific density represents the proportion of a given crop within each 1 × 1 km grid.

3. From Figure 3, it is also difficult to interpret the areas of multiple cropping, assuming multiple cropping significantly exists in this region.

Response: Thank you for your thoughtful comments. We agree that multiple cropping, including double and even triple cropping in certain regions and/or years, plays an important role in shaping agriculture landscapes. However, the primary focus of our study is on the spatial and temporal distribution of four major commodity crops (i.e., soybean, maize, wheat, and rice) at an annual scale, and the current analysis does not explicitly distinguish between single- and multi-season cropping systems. We acknowledge that this may limit the interpretability of some regions where intensive cropping practices are present. To address this, we have revised the manuscript to acknowledge the existence of multiple cropping systems and to discuss this limitation and potential extensions of our method in future work.

Revisions: **Lines 797-814:** Cropping practices complexity (e.g., crop rotation and multiple cropping) poses a significant challenge for accurate crop distribution mapping. These practices can substantially influence both the spatial patterns and intensity of agriculture land use. Crop rotation, the practice of growing different crops in the same field across multiple years, contributes to soil health, pest control, and long-term cropland management. Ye et al., (2024) considered crop rotation to reconstruct the historical crop distribution maps for the United States, relying on Cropland Data Layer (CDL) data for crop rotation information; however, similar high-resolution products are lacking for South America. In addition, Pott et al., (2023) visualized crop rotation information for soybean, maize, and rice in Rio Grande do Sul, southern Brazil, but it did not sufficiently represent the overall rotation patterns across South America. In contrast, multiple cropping involves the cultivation of more than one crop within the same year in the same field. This practice is common in regions with favorable climate conditions and contributes significantly to agricultural intensity. However, our current method does not differentiate between single- and multi-season cropping systems, which limits its ability to reflect cropping intensity in areas with prevalent double and triple cropping. Therefore, future research should focus on crop type mapping in South America to obtain crop rotation and multiple cropping patterns, enabling the generation of more accurate historical crop-specific maps in subsequent versions.

4. The purpose of presenting Figure 4 is unclear. This figure could simply be produced when statistics on harvested areas are available.

Response: Thank you for your thoughtful comments. We agree that the data presented in Figure 4 could indeed be derived from statistics on the harvested area. However, the main purpose of Figure 4 is to show the temporal changes in the total harvested area of different crops in South America from 1950 to 2020, highlighting trends in agricultural expansion and shifts in crop dominance. We thought this information was important for readers to know, especially for those who are unfamiliar with the crop change patterns in South America.

5. If Figure 3 represents the proportion of crop-specific density, then Figure 5 is hard to understand. By what method can this proportion be allocated to a specific land change process?

Response: Thank you for your thoughtful comments. To assess the transitions between land use and specific crop types, we first converted the annual crop-specific density maps into Boolean crop-type maps for each year from 1950 to 2020, following the method described by Li et al., (2023). For each crop and each year, grid cells were ranked in descending order by crop-specific density. Boolean values (presence = 1, absence = 0) were then assigned to the top-ranked grid cells until the total area assigned to each crop matched the reconstructed provincial-level harvested area within a 100-hectare margin. Second, we overlaid the annual Boolean crop-type maps with the annual land use maps (i.e., the Historic Land Dynamics Assessment +) (Winkler et al., 2021) to identify crop-specific land-use change processes. We have added additional methodological details to the revised manuscript to clarify how crop-specific land-use changes were identified.

Revisions: Lines 365-384:

2.5.4 Analyzing crop-specific land-use transitions

To assess the transitions between land use and specific crop types, we first converted the annual crop-specific density maps into Boolean crop-type maps for each year from 1950 to 2020, following the method described by Li et al., (2023). For each crop and year, grid cells were ranked in descending order based on crop-specific density. Boolean values (presence = 1, absence = 0) were then assigned to the top-ranked grid cells until the cumulative area matched the reconstructed provincial-level harvested area within a 100-hectare margin. This allocation was performed sequentially for soybean, maize, and rice in that order. To identify land-use transitions associated with specific crops, we overlaid the annual Boolean crop-type maps with the annual land-use maps from the Historic Land Dynamics Assessment + (HILDA +) (Winkler et al., 2021). This spatial overlay allowed us to determine which crop types occupied areas that had been newly converted cropland in a given year. It is important to note that this approach assumes that the spatial allocation based on crop-specific density rankings reflects the dominant crop type established after cropland conversion. While this process introduces some uncertainty, the method offers a consistent and spatially explicit framework for attributing land-use change processes to specific crops in the absence of pixel-level crop rotation data.

6. The validation scheme is unclear and lacks a systematic approach. Given that existing datasets have been used for modeling, it is difficult to understand why they are also used for evaluation. For example, Section 3.3.1, "Evaluation Against Existing Datasets at the Provincial Level," is puzzling, as in many cases $R^2 = 1$.

Response: Thank you for your thoughtful comments. We apologize for the lack of clarity in the original manuscript. We would like to clarify that we did not use any datasets involved in the modeling process for evaluation purposes. In the modeling process, we primarily used two types of data: (1) gridded datasets for base map generation, including Argentina MNC (2020), MapBiomas (2020), GLAD (2020), GEOGLAM (2020, only for wheat), Uruguay LC (2018, only for rice), and SPAM (2010); and (2) historical inventory statistics. In Section 3.3.1, the gridded data used for evaluation come from years that were not involved in the base map generation, including Brazil Conab (2017-2020), MapBiomas (2000, 2005, 2010), GEOGLAM (2020, for soybean, maize, and rice), GLAD (2005, 2010), SPAM (2000, 2005). Therefore, these datasets serve as independent references for assessing the consistency of our reconstruction across time.

In the case of Brazil Conab data, although the R^2 =1, the slope deviates from 1, indicating a decrease of underestimation in our reconstructed dataset. Moreover, the Brazil Conab dataset only reports provincial-level statistics for 9 records over the period of 2017-2020, which is insufficient in both spatial and temporal coverage to serve as an input data for long-term model development. We have clarified it in the revised manuscript.

Revisions: **Lines 484-488:** We used gridded datasets that were not involved in the base map generation to ensure independence form the reconstruction process, including MapBiomas (soybean and rice in 2000, 2005, and 2010), SPAM (soybean, wheat, maize, and rice in 2000 and 2005), GEOGLAM (soybean, maize, and rice), GLAD (soybean in 2005 and 2010), and Brazil Conab (soybean and rice from 2017 to 2020).

Lines 503-507:

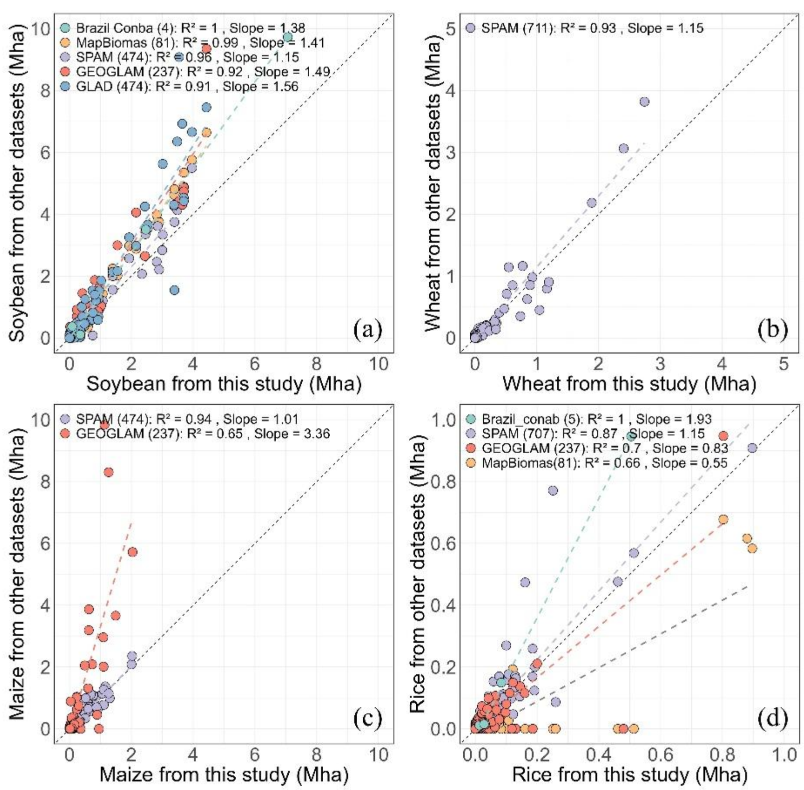

Figure 6. Comparison of crop type areas between this study and existing datasets (gridded datasets that were not involved in reconstruction process, i.e., MapBiomas (2000, 2005, 2010), SPAM (2000, 2005), GEOGLAM (2020),

GLAD (2005, 2010) at the provincial level. (a) Soybean; (b) Wheat; (c) Maize; (d) Rice. The numbers in parentheses represent the total number of samples.

7. Figure 7 presents the comparison of the crop-specific areas between this study and census data at the municipal level. However, it is not clear why to present Argentina (1960, 2008, and 2018), Bolivia (1950), Brazil (1995, 2006, and 2017), Chile (2017), Colombia (1960), and Paraguay (2008)? Rather than other regions in other years? Similar question to Figure 8, 9, and 10.

Response: Thank you for your thoughtful comments. The selected regions and years reflect the limited availability of publicly released municipal-level statistical data and high-resolution crop-specific maps. We included all accessible datasets that align with our reconstruction period.

References

Adalibieke, W., Cui, X., Cai, H., You, L., and Zhou, F.: Global crop-specific nitrogen fertilization dataset in 1961-2020, *Sci Data, 10*, 617, https://doi.org/10.1038/s41597-023-02526-z, 2023.

Altieri, M.A.: Sustainable agricultural development in Latin America: exploring the possibilities, *Agriculture, ecosystems & environment, 39*, 1-21, https://doi.org/doi.org/10.1016/0167-8809(92)90202-M, 1992.

Becker-Reshef, I., Barker, B., Whitcraft, A., Oliva, P., Mobley, K., Justice, C., and Sahajpal, R.: Crop Type Maps for Operational Global Agricultural Monitoring, *Sci Data, 10*, 172, https://doi.org/10.1038/s41597-023-02047-9, 2023.

Boyd, W.: Food law's agrarian question: capital, global farmland, and food security in an age of climate disruption, *Research Handbook on International Food Law* (pp. 29-62): Edward Elgar Publishing, 2023.

Campos Matos, C.C.: Economic impact of agriculture trade liberalization in Argentina (Doctoral dissertation, KDI School)2013.

Cao, B., Yu, L., Li, X., Chen, M., Li, X., Hao, P., and Gong, P.: A 1 km global cropland dataset from 10 000 BCE to 2100 CE, *Earth System Science Data, 13*, 5403-5421, https://doi.org/10.5194/essd-13-5403-2021, 2021.

Ceddia, M.G., Bardsley, N.O., Gomez-y-Paloma, S., and Sedlacek, S.: Governance, agricultural intensification, and land sparing in tropical South America, *Proc Natl Acad Sci U S A, 111*, 7242-7247, https://doi.org/10.1073/pnas.1317967111, 2014.

Cheng, N.F.L., Hasanov, A.S., Poon, W.C., and Bouri, E.: The US-China trade war and the volatility linkages between energy and agricultural commodities, *Energy Economics, 120*https://doi.org/10.1016/j.eneco.2023.106605, 2023.

Chonchol, J.: Agricultural modernization and peasant strategies in Latin America, *International Social Science Journal, 42*https://doi.org/unesdoc.unesco.org/ark:/48223/pf0000088259, 1990.

Clapp, J.: The problem with growing corporate concentration and power in the global food system, *Nature Food, 2*, 404-408, https://doi.org/doi.org/10.1038/s43016-021-00297-7, 2021.

Dawe, D., Block, S., Gulati, A., Huang, J., and Ito, S.: Domestic rice price, trade, and marketing policies, *Rice in the global economy: strategic research and policy issues for food security. Los Baños, Philippines, International Rice Research Institute. 477p*2010.

INTA: Mapa Nacional De Cultivos. Campaña 2019/2020. Versión 1 Publicación No. 2, 2020.

De Janvry, A., Sadoulet, E., and Wolford, W.: The changing role of the state in Latin American land reforms.https://doi.org/doi.org/10.1093/acprof:oso/9780199242177.003.0011, 1998.

de LT Oliveira, G.: The geopolitics of Brazilian soybeans, *Soy, Globalization, and Environmental Politics in South America* (pp. 98-122): Routledge, 2017.

Erenstein, O., Jaleta, M., Mottaleb, K.A., Sonder, K., Donovan, J., and Braun, H.-J.: Global trends in wheat production, consumption and trade, *Wheat improvement: food security in a changing climate* (pp. 47-66): Springer International Publishing Cham, 2022.

FAO (2020). Food and Agriculture Organization of the United Nations. In: FAOSTAT Statistical Database. Retrieved from http://www.fao.org/faostat/en/.

Frison, E.A., Cherfas, J., and Hodgkin, T.: Agricultural biodiversity is essential for a sustainable improvement in food and nutrition security, *Sustainability, 3*, 238-253, https://doi.org/doi.org/10.3390/su3010238, 2011.

Garrett, R.D., Rueda, X., and Lambin, E.F.: Globalization's unexpected impact on soybean production in South America: linkages between preferences for non-genetically modified crops, eco-certifications, and land use, *Environmental Research Letters, 8*, 044055, https://doi.org/10.1088/1748-9326/8/4/044055, 2013.

He, C., Liu, Z., Xu, M., Ma, Q., and Dou, Y.: Urban expansion brought stress to food security in China: Evidence from decreased cropland net primary productivity, *Sci Total Environ, 576*, 660-670, https://doi.org/10.1016/j.scitotenv.2016.10.107, 2017.

Hoang, N.T., Taherzadeh, O., Ohashi, H., Yonekura, Y., Nishijima, S., Yamabe, M., Matsui, T., Matsuda, H., Moran, D., and Kanemoto, K.: Mapping potential conflicts between global agriculture and terrestrial conservation, *Proc Natl Acad Sci U S A, 120*, e2208376120, https://doi.org/10.1073/pnas.2208376120, 2023.

International Court of Justice (ICJ): Obligations of states in respect of climate change (Advisory opinion), 2025.

Klein Goldewijk, K., Beusen, A., Doelman, J., and Stehfest, E.: Anthropogenic land use estimates for the Holocene – HYDE 3.2, *Earth System Science Data, 9*, 927-953, https://doi.org/10.5194/essd-9-927-2017, 2017.

Klein, H.S., and Luna, F.V.: The impact of the rise of modern maize production in Brazil and Argentina, *Historia agraria: Revista de agricultura e historia rural*, 273-310, https://doi.org/10.26882/histagrar.086e09k, 2022.

Leite, C.C., Costa, M.H., de Lima, C.A., Ribeiro, C.A.A.S., and Sediyama, G.C.: Historical reconstruction of land use in the Brazilian Amazon (1940–1995), *Journal of Land Use Science, 6*, 33-52, https://doi.org/10.1080/1747423x.2010.501157, 2011.

Li, X., Tian, H., Lu, C., and Pan, S.: Four-century history of land transformation by humans in the United States (1630–2020): annual and 1 km grid data for the HIStory of LAND changes (HISLAND-US), *Earth System Science Data, 15*, 1005-1035, https://doi.org/10.5194/essd-15-1005-2023, 2023.

Liu, M., and Tian, H.: China's land cover and land use change from 1700 to 2005: Estimations from high-resolution satellite data and historical archives, *Global Biogeochemical Cycles, 24* https://doi.org/10.1029/2009GB003687, 2010.

Mao, F., Li, X., Zhou, G., Huang, Z., Xu, Y., Chen, Q., Yan, M., Sun, J., Xu, C., and Du, H.: Land use and cover in subtropical East Asia and Southeast Asia from 1700 to 2018, *Global and Planetary Change, 226*https://doi.org/10.1016/j.gloplacha.2023.104157, 2023.

Meyfroidt, P., Carlson, K.M., Fagan, M.E., Gutiérrez-Vélez, V.H., Macedo, M.N., Curran, L.M., DeFries, R.S., Dyer, G.A., Gibbs, H.K., and Lambin, E.F.: Multiple pathways of commodity crop expansion in tropical forest landscapes, *Environmental Research Letters, 9*, 074012, https://doi.org/10.1088/1748-9326/9/7/074012, 2014.

Monfreda, C., Ramankutty, N., and Foley, J.A.: Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000, *Global Biogeochemical Cycles, 22*https://doi.org/10.1029/2007gb002947, 2008.

Mueller, C., and Mueller, B.: The evolution of agriculture and land reform in Brazil, 1960–2006, *Economic Development in Latin America: Essay in Honor of Werner Baer* (pp. 133-162): Springer, 2010.

Munoz, J., and Lavadenz, I.: Reforming the agrarian reform in Bolivia.https://doi.org/10.22004/ag.econ.294410, 1997.

OAS: Organization of American States: Special Rapporteurship on Economic, Social, Cultural and Environmental Rights, A hemispheric agenda for ESCER: Work plan 2024-2026, Javier Palummo Lantes, 2024.

Petraglia, C., Dell'Acqua, M., Pereira, G., and Yussim, E.: Mapa integrado de cobertura/uso del suelo del Uruguay, año 2018, *Anuario OPYPA, 27,* 2019.

Pott, L.P., Amado, T.J.C., Schwalbert, R.A., Corassa, G.M., and Ciampitti, I.A.: Mapping crop rotation by satellite-based data fusion in Southern Brazil, *Computers and Electronics in Agriculture, 211*https://doi.org/10.1016/j.compag.2023.107958, 2023.

Renard, D., and Tilman, D.: National food production stabilized by crop diversity, *Nature, 571*, 257-260, https://doi.org/doi.org/10.1038/s41586-019-1316-y, 2019.

Song, X.P., Hansen, M.C., Potapov, P., Adusei, B., Pickering, J., Adami, M., Lima, A., Zalles, V., Stehman, S.V., Di Bella, C.M., Conde, M.C., Copati, E.J., Fernandes, L.B., Hernandez-Serna, A., Jantz, S.M., Pickens, A.H., Turubanova, S., and Tyukavina, A.: Massive soybean expansion in South America since 2000 and implications for conservation, *Nat Sustain, 2021*https://doi.org/doi.org/10.1038/s41586-018-0411-9, 2021.

Souza, C., and Azevedo, T.: MapBiomas general handbook, *MapBiomas: São Paulo, Brazil*, 1-23, https://doi.org/10.13140/RG.2.2.31958.88644, 2017.

Tang, F.H.M., Nguyen, T.H., Conchedda, G., Casse, L., Tubiello, F.N., and Maggi, F.: CROPGRIDS: A global geo-referenced dataset of 173 crops circa 2020, *Earth Syst. Sci. Data Discuss., 2023*, 1-22, https://doi.org/10.5194/essd-2023-130, 2023.

Winkler, K., Fuchs, R., Rounsevell, M., and Herold, M.: Global land use changes are four times greater than previously estimated, *Nature Communications, 12*https://doi.org/10.1038/s41467-021-22702-2, 2021.

Ye, S., Cao, P., and Lu, C.: Annual time-series 1 km maps of crop area and types in the conterminous US (CropAT-US): cropping diversity changes during 1850–2021, *Earth System Science Data, 16*, 3453-3470, https://doi.org/doi.org/10.5194/essd-16-3453-2024, 2024.

Yu, Q., You, L., Wood-Sichra, U., Ru, Y., Joglekar, A.K.B., Fritz, S., Xiong, W., Lu, M., Wu, W., and Yang, P.: A cultivated planet in 2010 – Part 2: The global gridded agricultural-production maps, *Earth System Science Data, 12*, 3545-3572, https://doi.org/10.5194/essd-12-3545-2020, 2020.

Yu, Z., and Lu, C.: Historical cropland expansion and abandonment in the continental U.S. during 1850 to 2016, *Global Ecology and Biogeography, 27*, 322-333, https://doi.org/10.1111/geb.12697, 2017.

Zalles, V., Hansen, M.C., Potapov, P.V., Parker, D., Stehman, S.V., Pickens, A.H., Parente, L.L., Ferreira, L.G., Song, X.-P., and Hernandez-Serna, A.: Rapid expansion of human impact on natural land in South America since 1985, *Science Advances, 7*, eabg1620, https://doi.org/10.1126/sciadv.abg1620, 2021.