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

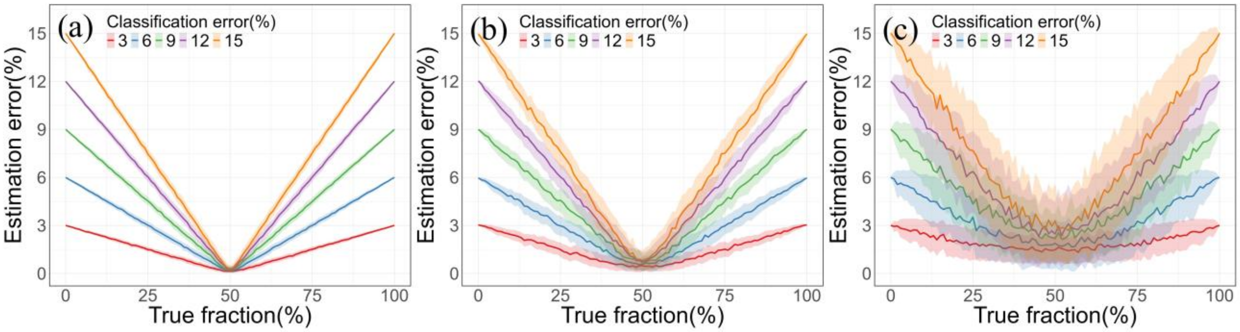

Figure S7. Monte Carlo simulation of aggregation-induced estimation error under varying classification error rates and spatial resolutions. (a), (b), and (c) represent the spatial resolution of 10 m, 30 m, and 100 m, respectively. The x-axis represents the true fraction (%) of the target class in a 1 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.

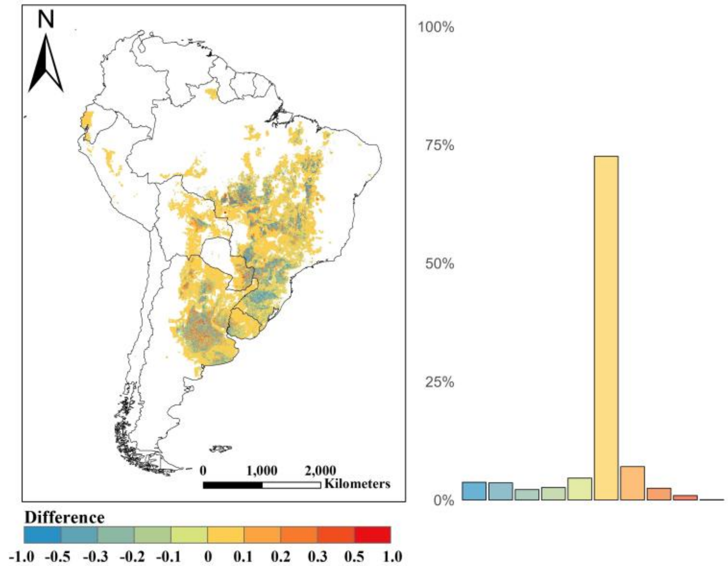

Figure S8. Spatial distribution (left) and frequency (right) of pixel-wise differences between SPAM (resampled to 1 km) and GLAD (aggregated to 1 km) soybean map in 2010 for South America.

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:

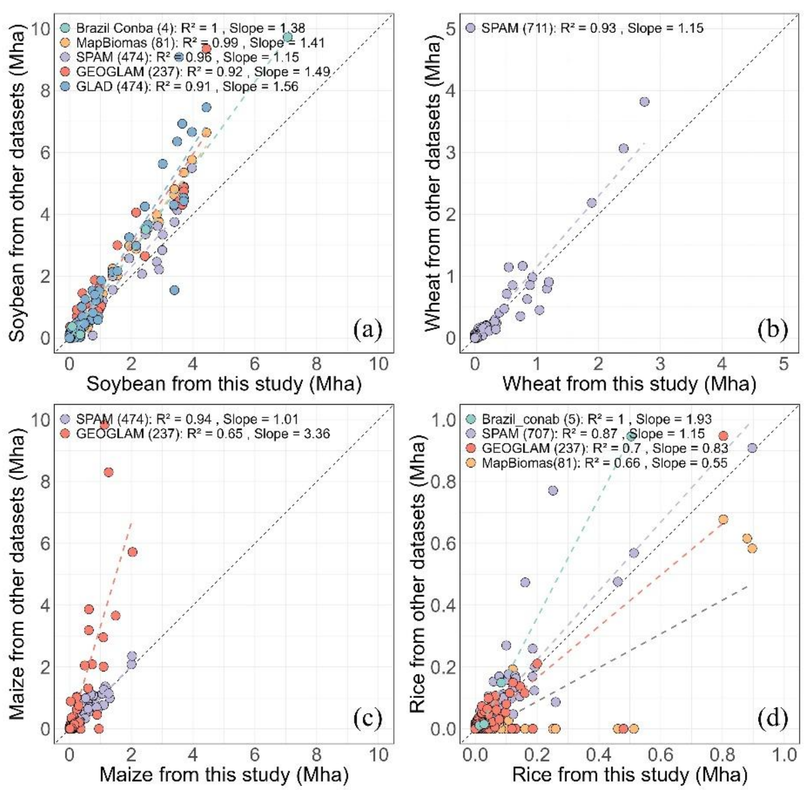

Figure 6. Comparison of crop type areas between this study and existing datasets (gridded datasets that were not involved in reconstruction process, i.e., MapBiomas (2000, 2005, 2010), SPAM (2000, 2005), GEOGLAM (2020),

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.

Responses to Reviewer 2:

The paper reconstructs the historical expansion of four major crops—soybean, maize, wheat, and rice—across South America at an annual time scale and high spatial resolution (1 km × 1 km). By integrating multiple data sources such as remote sensing, model-based reconstructions, and historical agricultural census data, the researchers aim to provide a comprehensive dataset that captures long-term trends in land use change. The study covers 13 South American countries and employs validation methods using existing datasets (FAO, GEOGLAM, SPAM, GLAD) and accuracy assessments at various administrative levels. The findings reveal a dramatic expansion of agricultural land, particularly for soybean and maize, mainly at the expense of natural vegetation. Soybean cultivation grew from almost zero in 1950 to 48.8 million hectares (Mha) in 2020, leading to the loss of 23.92 Mha of forests, pastures, and shrublands. Maize also saw significant growth, doubling from 12.7 Mha in 1950 to 26.9 Mha in 2020, with rapid acceleration after 2000. In contrast, wheat and rice areas remained relatively stable over the study period. The analysis of land use transitions shows that 24.49 Mha of forests and 13.82 Mha of pastures were converted into croplands, largely for soybean and maize production. The dataset developed in this study is valuable for assessing the environmental impacts of agricultural expansion, such as deforestation, carbon emissions, and biodiversity loss. It also has critical implications for policymakers looking to balance food security and environmental conservation in South America. By providing a long-term, high-resolution record of crop-specific land transformation, this dataset enhances our understanding of human-environment interactions and supports global efforts in sustainable agriculture and climate change mitigation. While this paper presents a significant contribution to historical land use mapping in South America, it has several notable weaknesses.

Response: We sincerely thank the reviewer for the thoughtful comments and for recognizing the significance of our contribution to historical land use mapping in South America. We have carefully considered all the comments and revised the manuscript accordingly. Below, we provide detailed point-by-point responses to each comment.

1. The authors spend little effort in collecting, processing raw data sources. Instead they overly rely on statistical interpolation and integration of existing datasets. For a data product, the most important and also most time-consuming task is to collect the original, raw data. In this HISLAND, it should be sub-national crop area (e.g. upto 2nd admin level) and production data from 1950-2020. Without a great effort to assemble such a long-time series (currently mostly at 1st admin (e.g. province) level), the study instead uses linear interpolation to fill gaps in crop-specific data, assuming constant trends between known data points. This approach can oversimplify non-linear trends in agricultural expansion, particularly in regions where crop cultivation was influenced by policy shifts, market dynamics, or environmental changes. In contrast, studies using machine learning or geostatistical modeling (e.g., SPAM series though the authors only used SPAM2010)

often produce more accurate reconstructions by focusing on the fundamental effort of collecting sub-national crop data and capturing complex relationships between variables.

Response: We sincerely thank the reviewer for the thoughtful comments. Our detailed responses to each point are provided below:

- **Data collection:** We agree that assembling agricultural census data at the municipality-level can provide more spatially detailed and accurate inputs for developing long-term, high-resolution land use datasets. However, municipality-level data in South America are extremely limited in terms of public availability — only for selected countries and specific years (Argentina: 1960, 2008, 2018; Bolivia: 1950; Brazil: 1995, 2006, 2017; Chile: 1960; Paraguay: 2008), leaving large temporal gaps without constraints. This lack of temporal continuity can lead to inconsistencies in the reconstructed time series if municipality-level data were used directly for interpretation or trend estimation. In contrast, provincial-level data provided more frequent observations over time (Table S1), which offer better temporal continuity and constraints for long-term series reconstruction. Therefore, we primarily used provincial-level data to reconstruct the long-term series of crop-specific harvested areas, while municipality-level data were used to validate the reliability of our datasets. While province-level data represents a coarser administrative granularity compared to municipalities, our disaggregation results demonstrate that the reconstructed crop-specific distributions align well with municipality-level statistics (Figure 7).
- **Interpolation:** We acknowledge that linear interpolation may not fully capture potential non-linear trends in crop-specific harvested areas caused by policy, market, or environmental drivers. However, this approach was chosen due to the temporal characteristics of available agricultural census data in South America, which are typically reported at intervals of 10 years or more. Given these data constraints, linear interpolation remains a widely used and practical method in historical land use reconstruction at the administrative level (Klein Goldewijk et al., 2017; Leite et al., 2011; Li et al., 2023; Liu and Tian, 2010; Ye et al., 2024). While it may introduce some uncertainty, the interpolation is bounded by observed data points at both ends, ensuring that the overall trends remain grounded in empirical data. It is also important to note that SPAM is designed for static allocation of crop production in selected benchmark years (e.g., 2000, 2005, 2010, and 2020) and does not provide continuous temporal information. In contrast, our reconstruction aims to generate a consistent annual time series of crop-specific harvested areas from 1950 to 2020, offering valuable temporal dynamics to support long-term land use and environmental analyses.

We have further discussed the limitations and future improvements of data collection and interpolation-based approach in the revised manuscript.

Revisions: Lines 682-703:

4.3.1 Spatial and temporal gaps in census data

A key consideration in reconstructing historical land use dynamics is the availability of agricultural census data. Ideally, sub-national level (e.g., municipality, county, or district) agricultural statistics would allow for more detailed spatial allocation of crop-specific harvested areas. However, their availability across South America is highly limited and temporally inconsistent. Most countries provide only a few isolated years of data at the municipal level (i.e., Argentina: 1960, 2008, 2018; Bolivia: 1950; Brazil: 1995, 2006, 2017; Chile: 1960; Paraguay: 2008), which creates large temporal gaps and hampers their direct use in annual time series reconstruction. In contrast, provincial level data are more consistently reported over time, typically at 10-year intervals. These more frequent observations enable more robust interpolation and better constrain the temporal evolution of harvested areas. While these provincial units represent a coarser administrative granularity, we combined them with a high-resolution crop-specific base map and temporal cropland density maps to spatially disaggregate the data across all years. This approach allows us to preserve long-term trends while capturing spatial variability. To address the temporal discontinuities between census years, we applied linear interpolation to construct continuous annual times series of harvested areas at the administrative level. While we acknowledge that the use of linear interpolation may not fully reflect potential non-linear trends driven by policy, market, or environmental drivers, it remains a practical and widely used method under the constraints of sparse historical data(Klein Goldewijk et al., 2017; Leite et al., 2011; Li et al., 2023; Liu and Tian, 2010; Ye et al., 2024). Additionally, linear interpolation in this study is always bounded by observed census points, which help to preserve long-term trends and prevent fluctuations.

2. One of the great strengths of this long-term, high-resolution maps is to compare and contrast the crop area/production changes from year to year and to show the crop switches and crop pattern changes at a spatially granular level of gridcells. Figure 2(The flow chart in this study) shows the methodology, and I could hardly see how crop type transition from year to year is handled, or how is the cropland intensity comparable from year to year. For example, if I compare the maize area in one gridcell from Year 1 to Year 2, the change of maize area between these two years are the REAL maize area change or simply the error from the modelling/allocation?

Response: Thank you for your thoughtful comments. To address the concern regarding the temporal comparability and reliability of interannual crop-type changes at the grid cell level, we conducted an evaluation using the 1-km GLAD soybean dataset from 2001 to 2020. Specifically, we analyzed the pixel-wise annual differences between our reconstructed soybean fraction and the GLAD data to assess whether year-to-year changes in crop distribution represent actual dynamics or modeling artifacts. Figure 13 presents the temporal variation of the soybean fraction difference (Model − GLAD) across years. The median and mean differences remain close to zero throughout the study period, with narrow interquartile ranges (25–75%) and relatively stable 5–95% quantile envelopes. This indicates that the model's interannual fluctuations are consistent and not driven by random noise or allocation instability. Figure S9 shows the spatial distribution and frequency histogram of the 20-year average difference. The majority of pixels fall within ±0.1, and the histogram is tightly centered around zero, suggesting no systematic spatial bias in model estimates over time. These results together support the temporal consistency of our crop-type maps and suggest that the observed interannual changes are not dominated by allocation error but rather reflect meaningful shifts in crop distribution. While some uncertainty remains inherent to crop mapping, the strong agreement with independent GLAD observations indicates that year-to-year comparisons and crop-switching signals in our dataset are reliable at the 1-km grid cell level.

Revisions: Lines 747-771: To assess the spatial and temporal consistency of our reconstructed crop type maps, we conducted an uncertainties analysis using the resampled GLAD 1-km soybean density dataset from 2001 to 2020 as an independent benchmark. This analysis focuses on evaluating whether the interannual variation in soybean density reflects actual crop dynamics. Figure 13 illustrates the annual difference in soybean density at the pixel level across South America. The results show that the median and mean differences remain close to zero over time, with narrow interquartile ranges (25%-75%) and relatively stable 5%-95% quantile envelopes. These findings suggest that the year-to-year fluctuations in our dataset are not random but follow a consistent trend with GLAD data, indicating reliable temporal comparability. In addition, Figure S9 presents the spatial distribution of the mean soybean density difference averaged over the 20-year period, along with a histogram of its pixel-wise distribution. Most regions exhibit minimal bias, with more than 50% of grids falling within ±0.1. The distribution is systematically centred around zero, and areas of substantial over- or underestimation are spatially limited. These two evaluations together evidence that our data maintains robust agreement with independent observations (i.e., GLAD) both spatially and temporally. While similar high-resolution and long-term crop-specific datasets are currently unavailable for maize, wheat, and rice across South America, and thus prevent a comparable validation. However, the consistency observed in the soybean evaluation provides indirect support for the robustness of our spatial allocation framework. Given that the same methodological approach and harmonized inventory inputs were applied across all four crops, we expect the reconstructed patterns for other crop types to similarly reflect plausible spatial and temporal dynamics. Nonetheless, further evaluation using future regional datasets will be essential to assess the reliability of crop-specific maps beyond soybean.

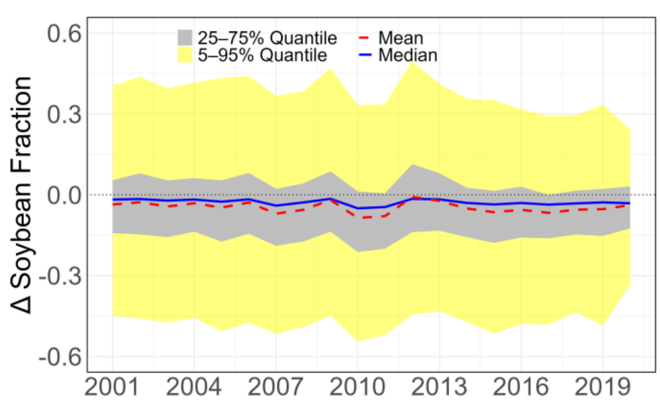

Figure 13. Temporal variation in soybean density difference between GLAD and this study (2001-2020).

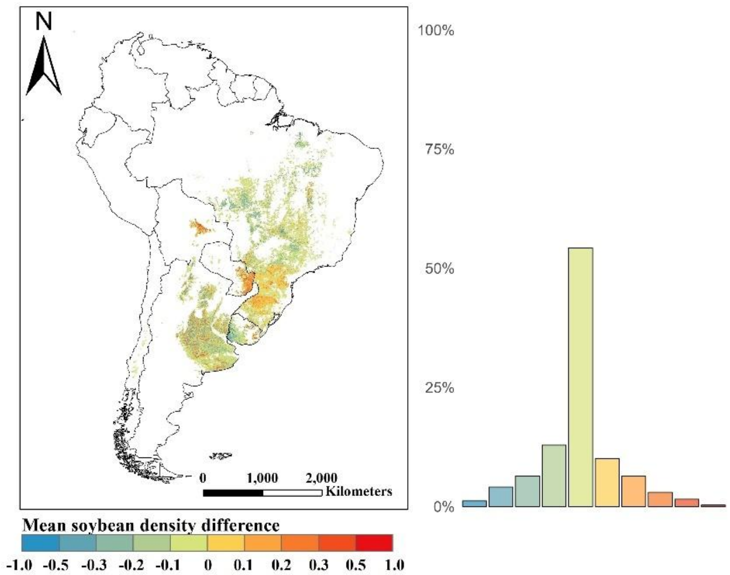

Figure S9. Spatial distribution (left) and frequency (right) of mean soybean density difference between GLAD and this study at the 1-km resolution from 2001 to 2020 for South America.

3. Uncertainty and Validation Issues. While the study integrates multiple datasets and performs validation at different administrative levels, it lacks a comprehensive uncertainty analysis. Unlike datasets such as HYDE or MapBiomas, which provide detailed error estimates and confidence intervals for their reconstructions, this study does not explicitly quantify the uncertainties in its spatial allocation methods or crop-specific data modeling. Additionally, validation is largely dependent on comparisons with existing datasets, some of which have their own biases. A more robust ground-truth validation (e.g., field data or higher-resolution satellite imagery) would strengthen the dataset's reliability.

Response: Thank you for your thoughtful comments. Given the temporal sparsity of historical inventories, varying spatial resolutions of input datasets, and the necessity of interpolations and resampling, a formal uncertainty assessment is indeed essential to ensure the reliability and interpretability of our results. Therefore, we conducted a structured uncertainty analysis targeting three key aspects:

- The temporal limitations and spatial granularity of historical census data.
- The effects of spatial aggregation and resampling.
- The overall spatiotemporal consistency of the final product.

Then, we implemented a Monte Carlo simulation framework to quantify aggregation-induced uncertainty under varying classification error rates and resolutions (Section 4.3.2). We further evaluated the consistency of crop dynamics through comparison with independent remote sensing-derived crop maps (Section 4.3.3), and explicitly discussed the constraints associated with subnational inventory availability and interpolation-based time series reconstruction (Section

4.3.1). These components were newly introduced in Section 4.3 to provide a more transparent and systematic quantification of uncertainty in both the input data and final outputs.

Revisions: Lines 681-771:

4.3 Uncertainty analysis

4.3.1 Spatial and temporal gaps in census data

A key consideration in reconstructing historical land use dynamics is the availability of agricultural census data. Ideally, sub-national level (e.g., municipality, county, or district) agricultural statistics would allow for more detailed spatial allocation of crop-specific harvested areas. However, their availability across South America is highly limited and temporally inconsistent. Most countries provide only a few isolated years of data at the municipal level (i.e., Argentina: 1960, 2008, 2018; Bolivia: 1950; Brazil: 1995, 2006, 2017; Chile: 1960; Paraguay: 2008), which creates large temporal gaps and hampers their direct use in annual time series reconstruction. In contrast, provincial level data are more consistently reported over time, typically at 10-year intervals. These more frequent observations enable more robust interpolation and better constrain the temporal evolution of harvested area. While these provincial units represent a coarser administrative granularity, we combined them with a high-resolution crop-specific base map and temporal cropland density maps to spatially disaggregate the data across all years. This approach allows us to preserve long-term trends while capturing spatial variability. To address the temporal discontinuities between census years, we applied linear interpolation to construct continuous annual times series of harvested areas at the administrative level. While we acknowledge that the use of linear interpolation may not fully reflect potential non-linear trends driven by policy, market, or environmental drivers, it remains a practical and widely used method under the constraints of sparse historical data (Klein Goldewijk et al., 2017; Leite et al., 2011; Li et al., 2023; Liu and Tian, 2010; Ye et al., 2024). Additionally, linear interpolation in this study is always bounded by observed census points, which help to preserve long-term trends and prevent fluctuations.

4.3.2 Resampling-related spatial uncertainty

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 5. 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

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 unsampled 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 (R2) 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.

4.3.3 Spatial-temporal consistency assessment

To assess the spatial and temporal consistency of our reconstructed crop type maps, we conducted an uncertainties analysis using the resampled GLAD 1-km soybean density dataset from 2001 to 2020 as an independent benchmark. This analysis focuses on evaluating whether the interannual variation in soybean density reflects actual crop dynamics. Figure 13 illustrates the annual difference in soybean density at the pixel level across South America. The results show that the median and mean differences remain close to zero over time, with narrow interquartile ranges (25%-75%) and relatively stable 5%-95% quantile envelopes. These findings suggest that the year-to-year fluctuations in our dataset are not random but follow a consistent trend with GLAD data, indicating reliable temporal comparability. In addition, Figure S9 presents the spatial distribution of the mean soybean density difference averaged over the 20-year period, along with a histogram of its pixel-wise distribution. Most regions exhibit minimal bias, with more than 50% of grids falling within ±0.1. The distribution is systematically centred around zero, and areas of substantial over- or underestimation are spatially limited. These two evaluations together evidence that our data maintains robust agreement with independent observations (i.e., GLAD) both spatially and temporally. While similar high-resolution and long-term crop-specific datasets are currently unavailable for maize, wheat, and rice across South America, and thus prevent a comparable validation. However, the consistency observed in the soybean evaluation provides indirect support for the robustness of our spatial allocation framework. Given that the same methodological approach and harmonized inventory inputs were applied across all four crops, we expect the reconstructed patterns for other crop types to similarly reflect plausible spatial and temporal dynamics. Nonetheless, further evaluation using future regional datasets will be essential to assess the reliability of crop-specific maps beyond soybean.

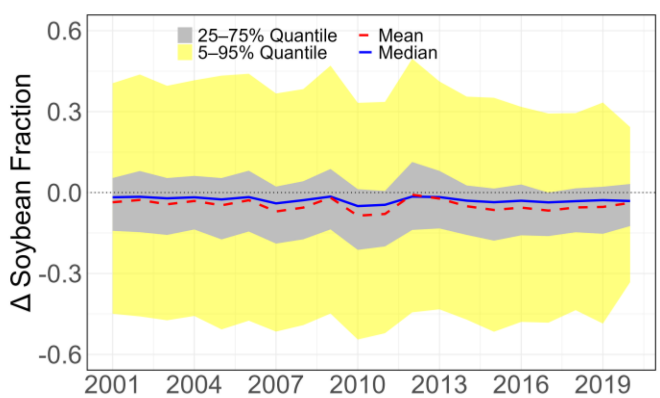

Figure 13. Temporal variation in soybean density difference between GLAD and this study (2001-2020).

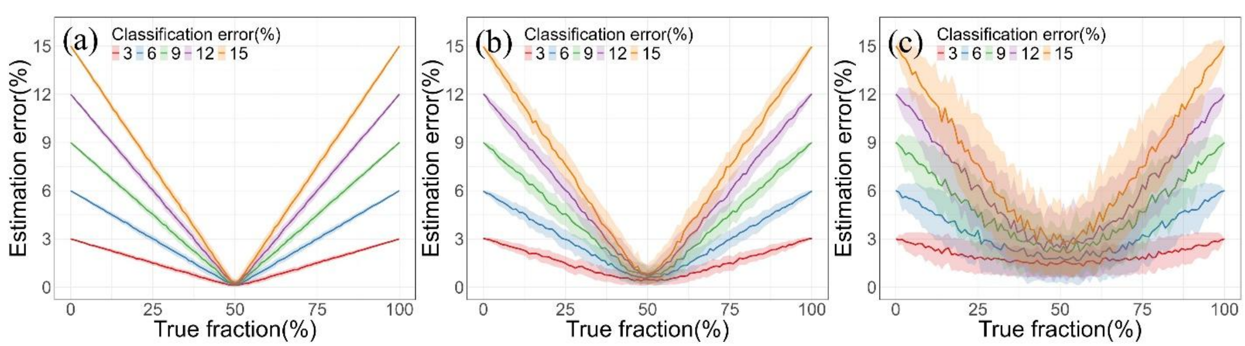

Figure S7. Monte Carlo simulation of aggregation-induced estimation error under varying classification error rates and spatial resolutions. (a), (b), and (c) represent the spatial resolution of 10 m, 30 m, and 100 m, respectively. The x-axis represents the true fraction (%) of the target class in a 1 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.

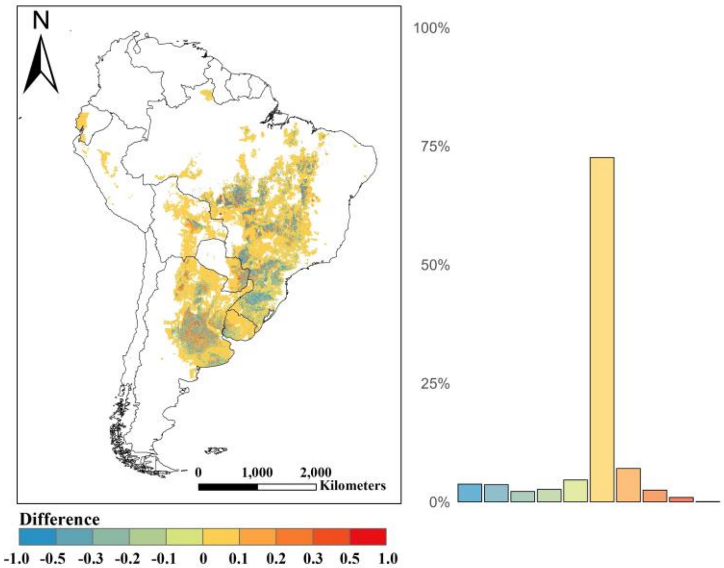

Figure S8. Mean soybean density difference (GLAD-this study) at 1-km resolution across South America (2001-2020): spatial pattern (left) and pixel-wise frequency (right).

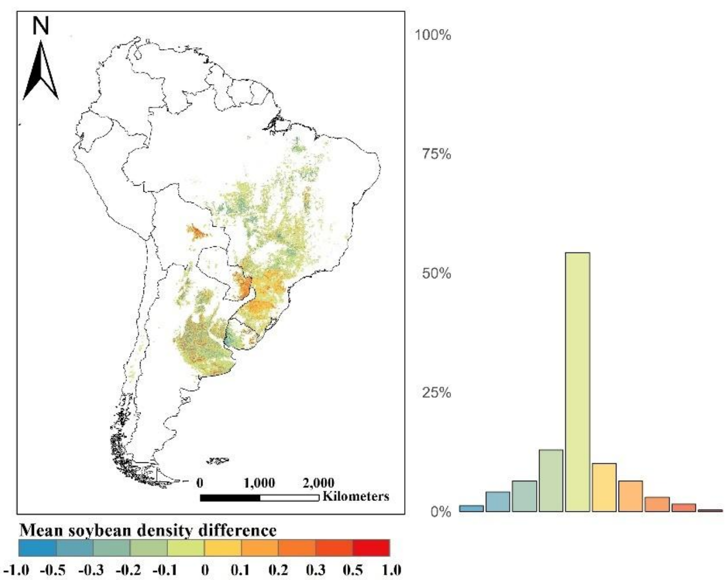

Figure S9. Spatial distribution (left) and frequency (right) of mean soybean density difference between GLAD and this study at the 1-km resolution from 2001 to 2020 for South America.

4. Lack of Socioeconomic and Policy Considerations. Although the study acknowledges the role of economic and policy drivers (e.g., subsidies, trade policies, and neoliberal reforms), it does not quantitatively integrate these factors into the model. Other land-use datasets, such as those from GFSAD (Global Food Security-support Analysis Data) and EarthStat, incorporate economic and climate factors to model cropland changes more dynamically. Without this integration, the dataset may overestimate or underestimate cropland expansion in response to policy shifts and market fluctuations.

Response: Thank you for your thoughtful comments. We fully agree that socioeconomic and policy factors have played a critical role in shaping cropland dynamic in South America. However, unlike products such as GFSAD or EarthStat, which focus on either remote sensing-based classification or static allocation using production statistics and suitability layers (e.g., cropping systems, economic and climate factors), our dataset reconstructs long-term crop-specific harvested areas directly from historical census records, prioritizing consistency and continuity across decades. Incorporating such factors into annually resolved, multi-decadal reconstructions face several key challenges. First, long-term, sub-national policy and economic data are often unavailable or inconsistently reported across countries. Second, the impacts of these drivers are typically region-specific, non-linear, and time-lagged, posing challenges for systematic modeling. Third, coupling them with harvested area data would require strong assumptions, which may introduce additional uncertainties and compromise the robustness of the reconstruction. Nevertheless, we acknowledge that this may reduce the model's sensitivity to abrupt shifts in cropland patterns. We have discussed this limitation in the revised manuscript.

Revisions: **Line 824-838:** Limitations in representing socioeconomic and environmental drivers. While our data provides long-term, annually resolved reconstructions of crop-specific harvested areas, we did not consider the explicit socioeconomic and environmental drivers such as soil conditions, management practices, or market access. However, incorporating such factors into a harmonized reconstruction presents considerable challenges. First, long-term, high-resolution data on these drivers are unavailable or inconsistently reported across countries. Second, the effects of these drivers are typically region-specific, non-linear, and time-lagged, which poses challenges for systematic modelling. Third, integrating them would require strong assumptions, potentially introducing additional uncertainties into the reconstruction. As a result, our current framework relies on observed statistical records to ensure internal consistency over time but may be less responsive to abrupt cropland shifts induced by major policy or market events. Future improvements could explore the integration of these factors into a hybrid modelling framework (e.g., machine learning or statistical downscaling models such as the GAEZ crop suitability layers) to improve the spatial and temporal realism of crop allocation patterns.

5. Crop yield is not mapped. A critical component for such mappings is the crop yield, which has great spatial heterogeneity and much more critical for food security. Admittedly mapping crop

yields is more challenging as cropping system (e.g. rainfed vs irrigated, smallholder vs large estate farming), management is far difficult to map. And yet missing this critical component severely limits the value and usefulness of this product.

Response: Thank you for your thoughtful comments. We agree that crop yield is a critical variable for understanding food production dynamics and food security. However, the focus of this study is specifically on reconstructing historical patterns of crop-specific harvested areas rather than production or yield. Accurately mapping yield would require integrating additional factors — such as cropping systems (e.g., rainfed or irrigated), input use, farm scale, and climate variability — which are currently unavailable or inconsistent at long-term, sub-national scales across South America. We acknowledge that the absence of crop yield data limits the applicability of our dataset for certain application scenarios. We have added a statement in the revised manuscript to acknowledge this limitation and to outline our intention to explore historical yield reconstruction in future versions of the dataset.

Revisions: **Lines 814-824:** Crop yield was not considered in this version of dataset. While harvested areas provide valuable insights into land use patterns, crop yield remains a critical variable for assessing agricultural production and food security. Accurately reconstructing historical crop yields would require multiple additional factors, including cropping systems (e.g., rainfed or irrigated), input use, farm scale, climate and weather data. However, such data are generally unavailable or lack consistency across long-term and sub-national scales in South America, particularly before the 2000s. As a result, this version of the dataset focuses exclusively on harvested areas. Future developments could explore the integration of satellite-derived biophysical indicators (e.g., NDVI, LAI), historical production statistics, and climatic data to support the reconstruction of spatial-temporal yield dynamics.

Responses to Reviewer 3:

This study presents a long-term, high-resolution spatial dataset of four major crops across South America. The topic is timely, and the dataset has clear potential for impactful use in agricultural, environmental, and economic research. The manuscript is generally well-written and logically structured.

Response: We thank the reviewer for the positive comments.

However, significant methodological simplifications and a lack of uncertainty quantification weaken confidence in the reliability and robustness of the dataset. My concerns are detailed below.

Response: Thank you for your thoughtful comments. We acknowledge the importance of methodological transparency and uncertainty assessment in enhancing the credibility of our dataset. A point-by-point response is provided below to address the specific concerns raised.

1. Methodological Uncertainty in Reconstructing Historical Maps (Section 2.4.3)

This section is the methodological core of the dataset, reconstructing 70 years of crop-specific spatial maps. However, the approach introduces several sources of uncertainty that compromise the robustness of the dataset:

- Temporal Anchoring to 2020:

The spatial allocation relies heavily on crop distribution circa 2020. Although cropland density based on inventory is used to constrain the extent, this approach assumes that spatial distribution patterns have remained relatively stable over seven decades, which is unlikely. For example, Figure 12 shows clear cropland expansion in GLAD data from 2001 to 2020, whereas the developed maps reflect more intensification than expansion—an inconsistency that may misrepresent true land use change.

Response: Thank you for your thoughtful comments. We agree that using 2020 crop distribution as a baseline assumes spatial stability that may not fully hold over seven decades, especially in dynamic regions like Mato Grosso. This is a known limitation in long-term crop reconstructions due to the lack of historical high-resolution crop maps. To address this, we constrained spatial allocation with annual cropland density maps derived from multi-source datasets which ensure that total cropland expansion is preserved even if crop type shifts are smoothed. In Figure 12, GLAD shows more pronounced expansion, while our maps emphasize intensification. This difference likely reflects methodological limitations in our reconstruction approach. While GLAD can directly detect recent frontier expansion using high-resolution satellite imagery, our method—relying on harmonized census data and constrained by historical cropland density—does not fully capture abrupt spatial shifts, especially in newly cultivated frontiers. Nevertheless, our maps maintain broad consistency with high-resolution products in terms of spatial patterns and offer a unique, long-term perspective from 1950 to 2020 that complements satellite-based datasets.

Revisions: **Lines 616-625:** GLAD maps show clear signals of frontier expansion, while our results emphasize more gradual intensification. This difference may be attributed to the fact that our reconstruction is based on harmonized census data and historical cropland density, which may limit its ability to capture abrupt shifts as precisely as satellite-based maps. Nevertheless, our results remain broadly consistent with high-resolution products in terms of spatial patterns. Importantly, our dataset provides long-term, annually resolved crop-specific maps from 1950 to 2020, filling key temporal gaps that satellite-only datasets cannot address. Thus, despite limitations in detecting fine-scale expansion, the HISLAND-SA dataset complements existing remote-sensing products by offering a coherent and historically extended view of crop type dynamics in South America.

- Shared Temporal Trends Across Crops

The temporal variation of crop-specific area is derived from cropland density of ratios between years. As a result, all four crops follow the same temporal trend within each pixel, which oversimplifies the complexity of crop dynamics and ignores crop substitution or rotation over time.

Response: Thank you for your thoughtful comments. We acknowledge that deriving temporal trends using the same ratio-based approach across all crop types within a pixel may oversimplify crop dynamics and does not capture crop rotation or substitution. This simplification was necessary due to the limited availability of long-term, crop-specific spatial data at high resolution. We recognize that this assumption may introduce some uncertainty into the temporal allocation of individual crops. However, as more high-resolution, crop-specific datasets become available in the future, particularly those with annual coverage, our framework can be refined to better reflect true crop transitions and improve the reliability of the reconstructed time series.

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.

- Order of Allocation:

The order of crop allocation (soybean → maize → wheat → rice) could significantly affect the final spatial distribution. The rationale behind this sequence should be clearly justified, or alternative orders tested to assess sensitivity.

Response: Thank you for your thoughtful comments. Thank you for your thoughtful comments. The allocation order was chosen primarily based on the availability and quality of spatial data. Specifically, high-resolution remote sensing datasets such as GLAD and Argentina MNC provide the most accurate and validated spatial information for soybean and maize, particularly around the baseline year (2020). By assigning these crops first, we are able to leverage the strongest spatial signals available to anchor the allocation process. This approach helps ensure that the most reliable crop-specific distributions are preserved, especially in areas where multiple crops compete for limited cropland. We acknowledge that this choice may not fully reflect historical dominance patterns, but it reflects a practical trade-off based on data confidence. We have clarified this point in the revised manuscript.

Revisions: **Lines 371-376:** This allocation was performed sequentially for soybean, maize, wheat, and rice, based on the availability and reliability of high-resolution crop-specific datasets. In particular, soybean and maize were prioritized because they are supported by well-validated spatial products (e.g., GLAD and Argentina MNC), which offer a reliable basis for anchoring the allocation and maintaining spatial consistency with observed crop distributions.

Suggestions to Reduce Uncertainty:

- Incorporate higher-resolution statistical data (e.g., Admin 2 or subnational data) where available to improve spatial representativeness.

Response: Thank you for your thoughtful suggestion. We agree that assembling agricultural census data at the municipality-level can provide more spatially detailed and accurate inputs for developing long-term, high-resolution land use datasets. However, municipality-level data in South America are extremely limited in terms of public availability — only for selected countries and specific years (Argentina: 1960, 2008, 2018; Bolivia: 1950; Brazil: 1995, 2006, 2017; Chile: 1960; Paraguay: 2008), leaving large temporal gaps without constraints. This lack of temporal continuity can lead to inconsistencies in the reconstructed time series if municipality-level data were used directly for interpretation or trend estimation. In contrast, provincial-level data provided more frequent observations over time (Table S1), which offer better temporal continuity and constraints for long-term series reconstruction. Therefore, we primarily used provincial-level data to reconstruct the long-term series of crop-specific harvested areas, while municipality-level data were used to validate the reliability of our datasets. While province-level data represents a coarser administrative granularity compared to municipalities, our disaggregation results demonstrate that the reconstructed crop-specific distributions align well with municipality-level statistics (Figure 7). We have further discussed the limitations and future improvements of data collection in the revised manuscript.

Revisions: Lines 682-703:

4.3.1 Spatial and temporal gaps in census data

A key consideration in reconstructing historical land use dynamics is the availability of agricultural census data. Ideally, sub-national level (e.g., municipality, county, or district) agricultural statistics would allow for more detailed spatial allocation of crop-specific harvested areas. However, their availability across South America is highly limited and temporally inconsistent. Most countries provide only a few isolated years of data at the municipal level (i.e., Argentina: 1960, 2008, 2018; Bolivia: 1950; Brazil: 1995, 2006, 2017; Chile: 1960; Paraguay: 2008), which creates large temporal gaps and hampers their direct use in annual time series reconstruction. In contrast, provincial level data are more consistently reported over time, typically at 10-year intervals. These more frequent observations enable more robust interpolation and better constrain the temporal evolution of harvested areas. While these provincial units represent a coarser administrative granularity, we combined them with a high-resolution crop-specific base map and temporal cropland density maps to spatially disaggregate the data across all years. This approach allows us to preserve long-term trends while capturing spatial variability. To address the temporal discontinuities between census years, we applied linear interpolation to construct continuous annual times series of harvested areas at the administrative level. While we acknowledge that the use of linear interpolation may not fully reflect potential non-linear trends driven by policy, market, or environmental drivers, it remains a practical and widely used method under the constraints of sparse historical data(Klein Goldewijk et al., 2017; Leite et al., 2011; Li et al., 2023; Liu and Tian, 2010; Ye et al., 2024). Additionally, linear interpolation in this study is always bounded by observed census points, which help to preserve long-term trends and prevent fluctuations.

Lines 788-797: In some countries, historical agricultural census data are limited. Adequate historical agricultural census data is the basis for the reconstruction of historical spatial data. Although provincial-level data are available in every country, only a few years of data are accessible in some countries due to inconsistencies in national policies and agricultural census years. Even though this data can be reconstructed in various ways (i.e., interpolation) (Li et al., 2023; Mao et al., 2023), some uncertainties remain. Additionally, national-level trends and interpolation methods were used to reconstruct provincial-level data, which to some extent may miss internal trends of some provinces. Interannual variability at the provincial level is generally not fully consistent with that at the national level, and such reconstruction methods may introduce some overestimation or underestimation of the results.

- Integrate additional spatial products across the time series (e.g., SPAM maps for 2000, 2005, 2010, and 2020) as anchor points or for calibration.

Response: Thank you for your thoughtful comments. We fully agree that incorporating additional spatial datasets across the time series is a valuable strategy to improve temporal consistency and support spatial calibration. However, as shown in Figure S10, SPAM 2000 exhibits relatively coarse resolution and spatial fragmentation that do not align well with either our reconstructed data or high-resolution references such as GLAD 2001. These limitations make SPAM less suitable as a spatial anchor. That said, we did incorporate SPAM 2010 into the construction of our crop-specific base map for 2020, but only in regions where high-resolution remote sensing products (e.g., GLAD, MapBiomas, Argentina MNC) were unavailable. In those areas, SPAM served as a supplementary data source to ensure full spatial coverage, despite its limitations. This selective integration strategy helped balance spatial completeness with data quality.

Revisions: Lines 776-788: The base maps of cropland density and crop types are crucial for constraining the spatial patterns of crops. In general, reconstructing historical crop type distributions requires using the present crop type distribution as a benchmark to project back into the past. In this study, we used several high-resolution remote sensing products (i.e., Argentina MNC, MapBiomas, and Uruguay LC) to construct a base map. However, these datasets do not provide full spatial coverage of South America and are limited to specific years, which introduces spatial gaps and temporal inconsistencies across the region. As a result, we selectively supplemented the base map with SPAM 2010 in areas where high-resolution products were unavailable, despite its coarser resolution. This highlights the pressing need to develop long-term and high-resolution crop type datasets with consistent spatial and temporal coverage at the regional or global scales. Such datasets would greatly enhance the accuracy and reliability of historical crop-specific reconstructions.

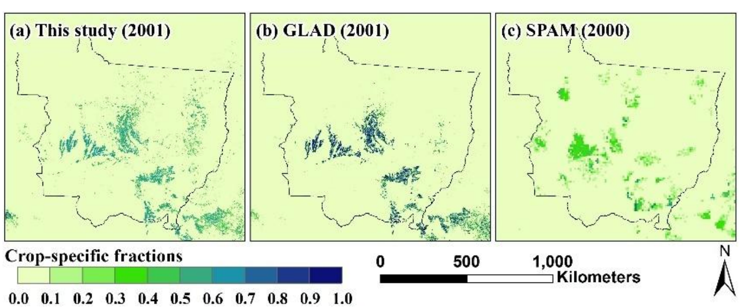

Figure S10. Spatial comparison of soybean fraction maps in Mato Grosso: (a) this study (2001), (b) GLAD (2001), and (c) SPAM (2000).

- Employ machine learning or statistical downscaling models (e.g., GAEZ crop suitability layers) to guide spatial allocation based on biophysical, socioeconomic, and historical drivers.

Response: Thank you for your thoughtful comments. Integrating machine learning or statistical downscaling approaches with biophysical or socioeconomic drivers could indeed enhance the realism of crop spatial allocation, especially in regions or periods where high-resolution crop maps are unavailable or incomplete. However, the implementation of such approaches is currently constrained by the limited availability of consistent long-term gridded datasets on key variables (e.g., soil conditions, management practices, market access), particularly across South America over multiple decades. Nevertheless, this is still a promising direction for future work and we have acknowledged it in the revised manuscript.

Revisions: Lines 824-838: Limitations in representing socioeconomic and environmental drivers. While our data provides long-term, annually resolved reconstructions of crop-specific harvested areas, we did not consider the explicit socioeconomic and environmental drivers such as soil conditions, management practices, or market access. However, incorporating such factors into a harmonized reconstruction presents considerable challenges. First, long-term, high-resolution data on these drivers are unavailable or inconsistently reported across countries. Second, the effects of these drivers are typically region-specific, non-linear, and time-lagged, which poses challenges for systematic modelling. Third, integrating them would require strong assumptions, potentially introducing additional uncertainties into the reconstruction. As a result, our current framework relies on observed statistical records to ensure internal consistency over time but may be less responsive to abrupt cropland shifts induced by major policy or market events. Future improvements could explore the integration of these factors into a hybrid modelling framework (e.g., machine learning or statistical downscaling models such as the GAEZ crop suitability layers) to improve the spatial and temporal realism of crop allocation patterns.

2. Crop-to-Land Use Transition Methodology

The paper does not clearly explain how changes in crop-specific areas are reconciled with changes in land use categories. Given the reliance on different products (e.g., HILDA+, inventory data), it is unclear:

- How were increases or decreases in crop area assigned to different land use classes?
- In cases where crop-specific changes exceed the corresponding land use change within a pixel, how was the conflict resolved?
- How was consistency maintained when both datasets carry uncertainties—particularly in earlier decades?

This aspect is critical to validate transitions over time and should be supported with additional evidence, such as inventories, case studies, or literature-based benchmarks.

Response: Thank you for your thoughtful comments. First, our study did not impose hard constraints linking crop expansion to specific land use types. Instead, transitions were assessed by overlaying annual crop type maps with HILDA+ land use data to infer original land use classes. Second, there is no conflict at the pixel level between crop-specific areas and land use capacity, as crop type data was derived directly from reconstructed annual crop-specific density maps. However, we acknowledge that uncertainty does exist. This uncertainty stems primarily from the inherent limitations and discrepancies between our reconstructed data and HILDA+, rather than from the land use transition method itself. To clarify, we have reorganized the method for land use transition details to improve clarity and traceability.

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, wheat, and rice, based on the availability and reliability of high-resolution crop-specific datasets. In particular, soybean and maize were prioritized because they are supported by well-validated spatial products (e.g., GLAD and Argentina MNC), which offer a reliable basis for anchoring the allocation and maintaining spatial consistency with observed crop distributions. 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 land 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.

3. Uncertainty Analysis is Essential

Given the simplified methodology and the integration of disparate datasets, a formal uncertainty analysis is essential to strengthen the reliability of the product. Discrepancies visible in Figure 6 and Table 4, as well as known limitations in source datasets (e.g., inventories), point to substantial uncertainty that needs to be acknowledged and quantified.

Consider approaches such as:

- Sensitivity analysis to test different assumptions (e.g., crop order, data source weights).
- Comparison against independent datasets or national statistics (where available).
- Monte Carlo simulations or bootstrapping to evaluate variability in key assumptions.

Response: Thank you for your thoughtful comments. We acknowledge that the integration of heterogeneous datasets and the use of simplified allocation assumptions inevitably introduce uncertainty into our reconstructed crop type maps. Given the temporal sparsity of historical inventories, varying spatial resolutions of input datasets, and the necessity of interpolations and resampling, a formal uncertainty assessment is indeed essential to ensure the reliability and interpretability of our results. Therefore, we conducted a structured uncertainty analysis targeting three key aspects:

- The temporal limitations and spatial granularity of historical census data.
- The effects of spatial aggregation and resampling.
- The overall spatiotemporal consistency of the final product.

Then, we implemented a Monte Carlo simulation framework to quantify aggregation-induced uncertainty under varying classification error rates and resolutions (Section 4.3.2). We further evaluated the consistency of crop dynamics through comparison with independent remote sensing-derived crop maps (Section 4.3.3), and explicitly discussed the constraints associated with subnational inventory availability and interpolation-based time series reconstruction (Section 4.3.1). These components were newly introduced in Section 4.3 to provide a more transparent and systematic quantification of uncertainty in both the input data and final outputs.

Revisions: Lines 681-771:

4.3 Uncertainty analysis

4.3.1 Spatial and temporal gaps in census data

A key consideration in reconstructing historical land use dynamics is the availability of agricultural census data. Ideally, sub-national level (e.g., municipality, county, or district) agricultural statistics would allow for more detailed spatial allocation of crop-specific harvested areas. However, their availability across South America is highly limited and temporally inconsistent. Most countries provide only a few isolated years of data at the municipal level (i.e., Argentina: 1960, 2008, 2018; Bolivia: 1950; Brazil: 1995, 2006, 2017; Chile: 1960; Paraguay: 2008), which creates large temporal gaps and hampers their direct use in annual time series reconstruction. In contrast, provincial level data are more consistently reported over time, typically at 10-year intervals. These more frequent observations enable more robust interpolation and better constrain the temporal evolution of harvested area. While these provincial units represent a coarser administrative granularity, we combined them with a high-resolution crop-specific base map and temporal cropland density maps to spatially disaggregate the data across all years. This approach allows us to preserve long-term trends while capturing spatial variability. To address the temporal discontinuities between census years, we applied linear interpolation to construct continuous annual times series of harvested areas at the administrative level. While we acknowledge that the use of linear interpolation may not fully reflect potential non-linear trends driven by policy, market, or environmental drivers, it remains a practical and widely used method under the constraints of sparse historical data (Klein Goldewijk et al., 2017; Leite et al., 2011; Li et al., 2023; Liu and Tian, 2010; Ye et al., 2024). Additionally, linear interpolation in this study is always bounded by observed census points, which help to preserve long-term trends and prevent fluctuations.

4.3.2 Resampling-related spatial uncertainty

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 5. 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

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 unsampled 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 (R2) 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.

4.3.3 Spatial-temporal consistency assessment

To assess the spatial and temporal consistency of our reconstructed crop type maps, we conducted an uncertainties analysis using the resampled GLAD 1-km soybean density dataset from 2001 to 2020 as an independent benchmark. This analysis focuses on evaluating whether the interannual variation in soybean density reflects actual crop dynamics. Figure 13 illustrates the annual difference in soybean density at the pixel level across South America. The results show that the median and mean differences remain close to zero over time, with narrow interquartile ranges (25%-75%) and relatively stable 5%-95% quantile envelopes. These findings suggest that the year-to-year fluctuations in our dataset are not random but follow a consistent trend with GLAD data, indicating reliable temporal comparability. In addition, Figure S9 presents the spatial distribution of the mean soybean density difference averaged over the 20-year period, along with a histogram of its pixel-wise distribution. Most regions exhibit minimal bias, with more than 50% of grids falling within ±0.1. The distribution is systematically centred around zero, and areas of substantial over- or underestimation are spatially limited. These two evaluations together evidence that our data maintains robust agreement with independent observations (i.e., GLAD) both spatially and temporally. While similar high-resolution and long-term crop-specific datasets are currently unavailable for maize, wheat, and rice across South America, and thus prevent a comparable validation. However, the consistency observed in the soybean evaluation provides indirect support for the robustness of our spatial allocation framework. Given that the same methodological approach and harmonized inventory inputs were applied across all four crops, we expect the reconstructed patterns for other crop types to similarly reflect plausible spatial and temporal dynamics. Nonetheless, further evaluation using future regional datasets will be essential to assess the reliability of crop-specific maps beyond soybean.

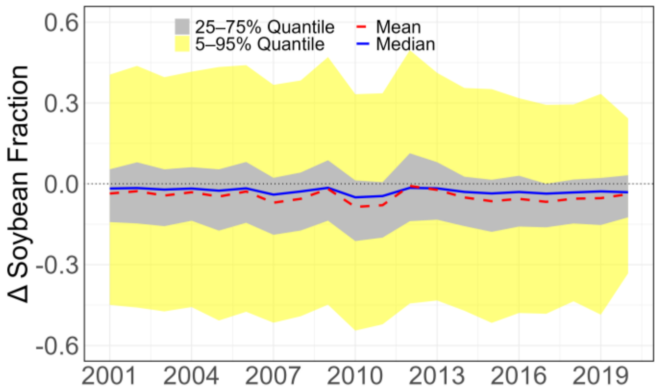

Figure 13. Temporal variation in soybean density difference between GLAD and this study (2001-2020).

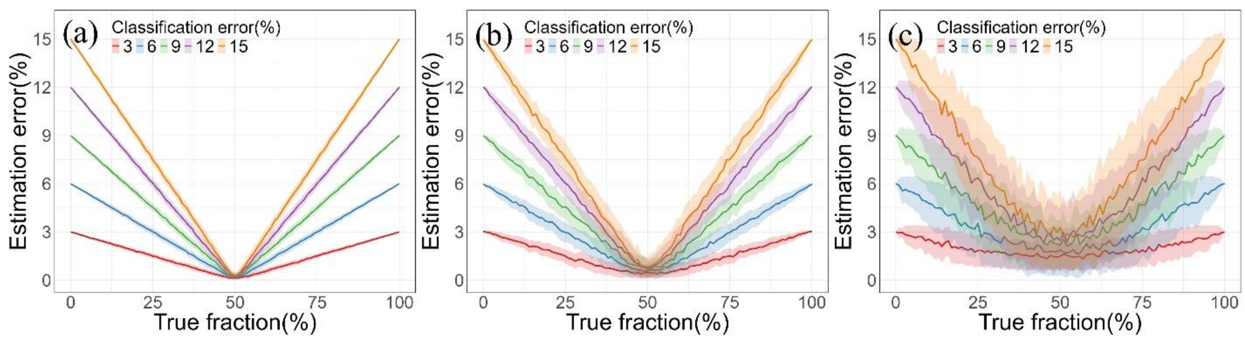

Figure S7. Monte Carlo simulation of aggregation-induced estimation error under varying classification error rates and spatial resolutions. (a), (b), and (c) represent the spatial resolution of 10 m, 30 m, and 100 m, respectively. The x-axis represents the true fraction (%) of the target class in a 1 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.

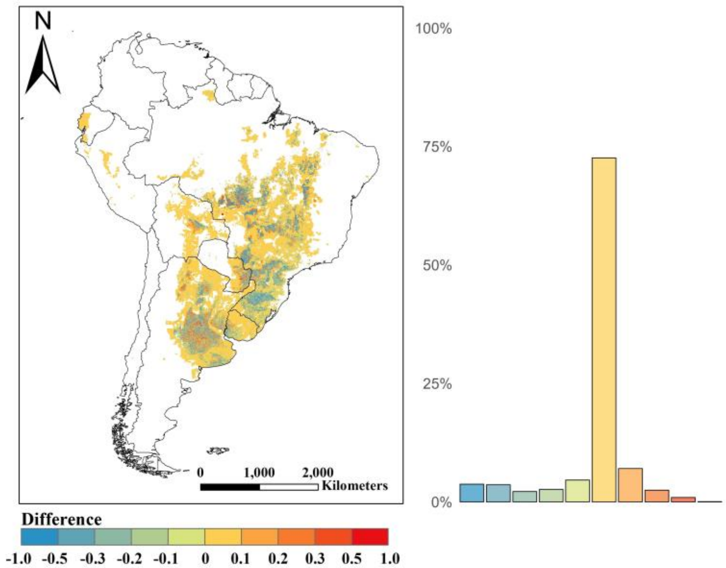

Figure S8. Mean soybean density difference (GLAD-this study) at 1-km resolution across South America (2001-2020): spatial pattern (left) and pixel-wise frequency (right).

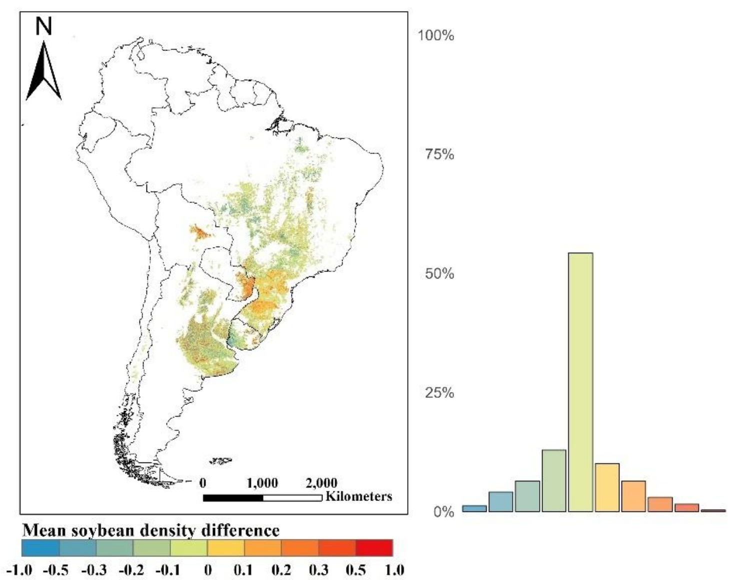

Figure S9. Spatial distribution (left) and frequency (right) of mean soybean density difference between GLAD and this study at the 1-km resolution from 2001 to 2020 for South America.

4. Clarification on Presentation of Results

- Figure 6: Since spatial data were adjusted at the provincial level using inventory data (Eq. 2), comparisons shown are essentially against data already used for calibration. This limits the independence of the validation and should be acknowledged.

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 Figure 6, 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. 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:

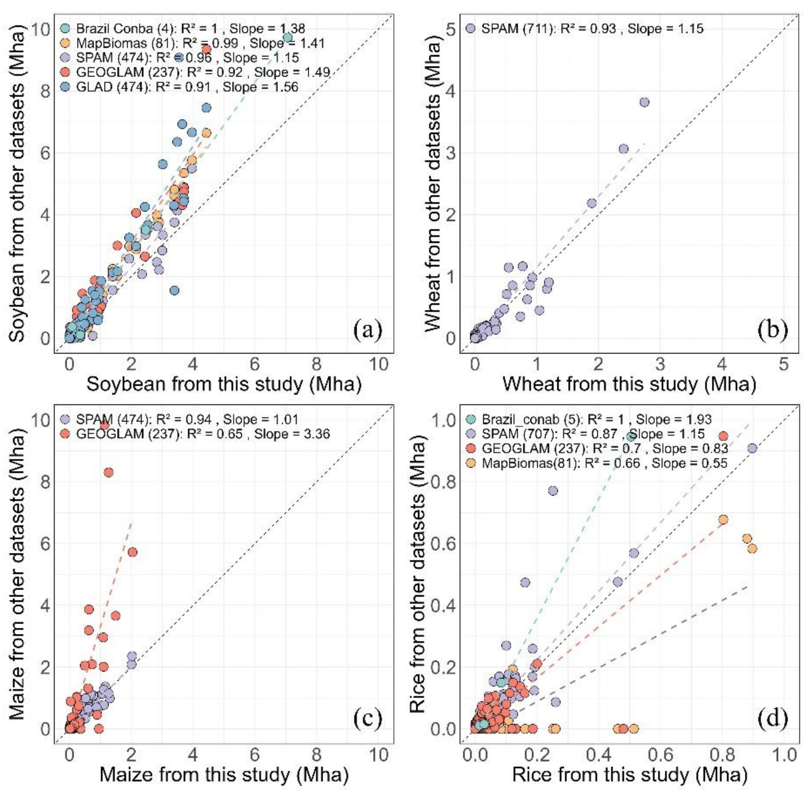

Figure 6. Comparison of crop type areas between this study and existing datasets (gridded datasets that were not involved in reconstruction process, i.e., MapBiomas (2000, 2005, 2010), SPAM

(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.

- Figure 11: Please clarify whether these 2020 maps are derived from existing products or developed as part of this study. If they are pre-existing, the comparisons do not reflect the added value of the developed dataset.

Response: Thank you for your thoughtful comments. The 2020 maps in the first column are derived from existing products, but we calibrated using provincial-level inventory data to ensure consistency with reported statistics (refer to section 2.4.1). Figure 11 aims to evaluate the spatial consistency between our reconstructed dataset and high-resolution crop maps. However, due to the lack of comparable remote sensing-based crop dataset (i.e., maize, wheat, and rice) for earlier years, we used 2020 as a benchmark year for visual comparison. We acknowledge that some of the reference datasets (i.e., panels b, e, h, and l) were also used in constructing the 2020 base map, which may partially contribute to the high agreement. To further assess the temporal robustness of our reconstructed data, we compared our annual soybean maps with the GLAD product in Figure 12, which shows good spatial consistency across multiple years and supports the reliability of our long-term reconstruction. We have clarified it in the revised manuscript.

Revisions: Line 608-625: Although Figure 11 demonstrates strong spatial agreement between our reconstructed data and existing high-resolution crop maps for 2020, some of these maps were also used to construct the base map, which may partially account for the high levels of consistency. To further evaluate the temporal reliability of our dataset, GLAD, being the only soybean distribution maps in South America with a high-resolution and long-time series and validation accuracy, allows us to compare spatial distributions of reconstructed data over time (Song et al., 2021). As shown in Figure 12, we selected the Brazilian state of Mato Grosso, one of the most significant regions for soybean expansion since 2000, as an example to present comparative results. GLAD maps show clear signals of frontier expansion, while our results emphasize more gradual intensification. This difference may be attributed to the fact that our reconstruction is based on harmonized census data and historical cropland density, which may limit its ability to capture abrupt shifts as precisely as the high-resolution satellite-based maps. Nevertheless, our results remain broadly consistent with high-resolution products in terms of spatial patterns. Importantly, our dataset provides long-term, annually resolved crop-specific maps from 1950 to 2020, filling key temporal gaps that satellite-only datasets cannot address. Thus, despite limitations in detecting fine-scale expansion, the HISLAND-SA dataset complements existing remote-sensing products by offering a coherent and historically extended view of crop type dynamics in South America.

Line 627-629: Figure 11. Visual comparison of crop-specific maps between this study and other datasets. The left column shows the crop-specific maps in this study, with high-resolution data in the middle and coarse-resolution data on the right. Panels b, e, h, and l were also used as input layers in generating the 2020 base map.

Specific Comments

- Title: Consider specifying the focus on four major commodity crops for clarity.

Response: Thank you for your suggestion. We have revised the title to explicitly include the four major commodity crops — soybean, maize, wheat, and rice — for improved clarity.

Revisions:

Title: HIStory of LAND transformation by humans in South America (HISLAND-SA): annual and 1-km gridded data for soybean, maize, wheat, and rice (1950-2020)

- Line 33: Replace "cropland" with the names of the four crops to avoid confusion.

Response: Thank you for your suggestion. We have replaced "cropland" with the specific crop names (i.e., soybean, maize, wheat, and rice) in Line 33 to avoid confusion.

Revisions: Lines 35-38: The results showed that soybean and maize cultivation expanded rapidly in South America by encroaching on other vegetation (i.e., forest, pasture/rangeland, and unmanaged grass/shrubland) over the past 70 years, whereas wheat and rice areas remained relatively stable.

- Line 36: If "other vegetation" in Line 36 matches the scope in Line 34, merge or clarify the definitions.

Response: Thank you for your suggestion. We have clarified the definition of "other vegetation" upon its first use to avoid confusion.

Revisions: Lines 35-41: The results showed that soybean and maize cultivation expanded rapidly in South America by encroaching on other vegetation (i.e., forest, pasture/rangeland, and unmanaged grass/shrubland) over the past 70 years, whereas wheat and rice areas remained relatively stable. Specifically, soybean is one of the most dramatically expanded crops, increasing from essentially zero in 1950 to 48.8 Mha in 2020, resulting in a total loss of 23.92 Mha of other vegetation.

- Line 50–53: Specify whether this refers to global patterns or South America only.

Response: Thank you for your thoughtful comment. The original sentence referred to global land-use patterns, which did not align with the South America-focused theme of the study. Therefore, we removed the sentence and revised the first paragraph of Introduction to better emphasize the regional context.

Revisions: Lines 50-71: 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.

- Figure 1: Recommend adding GADM Admin 1 boundaries for better spatial context.

Response: Thank you for your suggestion. We have revised Figure 1 to include GADM Level 1 administrative boundaries for better geographic reference.

Revisions: Lines 158-159:

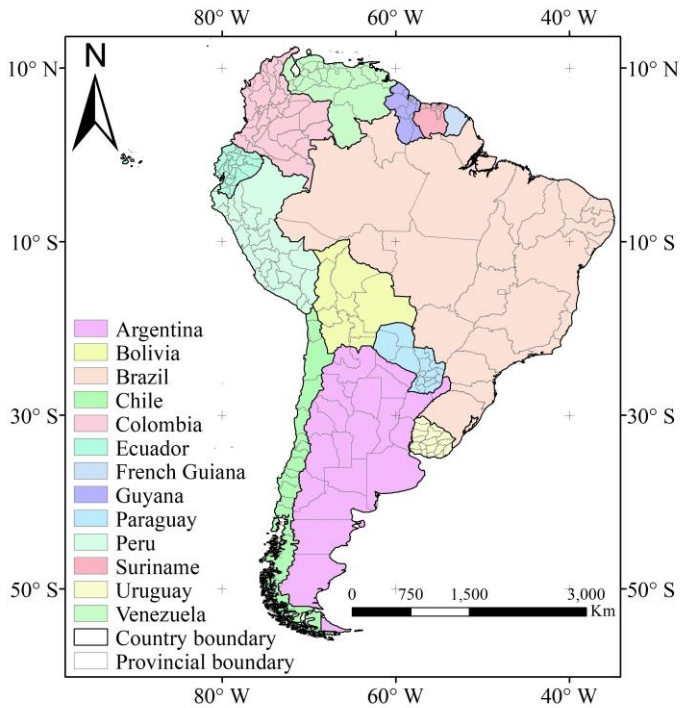

Figure 1. Geopolitical and administrative divisions of South America.

- Lines 248–253 (Step 1): The interpolation process between missing years is unclear. While Equation 1 is mentioned, how is this different from linear interpolation? Clarify the assumptions behind using national trends versus pixel-level trends.

Response: Thank you for your thoughtful comment. The first step aims to reconstruct the total cropland area at the provincial level, using two complementary interpolation approaches: ratio-based interpolation and standard linear interpolation. When provincial-level cropland area was missing but national-level cropland area was available, we estimated the missing value by scaling the closest available provincial-level cropland area according to the relative change in national-level cropland area (as defined in Equation 1). This approach assumes that changes in the cropland area at the provincial-level follow the same relative trend as those observed at the national scale. In cases where national-level cropland area was unavailable, we applied standard linear interpolation between known provincial-level cropland areas to interpolate missing values. We have clarified this process in the revised manuscript.

Revisions: **Lines 267-279:** The reconstruction of a total cropland area at the provincial level covers the period from 1950 to 2020. In this step, we mainly used two complementary interpolation approaches: ratio-based interpolation and linear interpolation. For years with available national-level cropland area but missing provincial-level cropland area, we estimated provincial-level cropland area by scaling the nearest known provincial-level cropland area according to the relative change in national-level cropland area (Equation 1). This assumes that provincial-level changes follow the same relative trend as those observed on the national scale. From 1961 to 2020, national cropland areas from FAO were used to calculate annual change rates. For years prior to 1961, we relied on agricultural census records or HYDE data. In cases where neither provincial nor national cropland areas were available, we applied linear interpolation between known provincial cropland areas. Since data availability and reference years differ across countries, the reconstruction was performed separately for each country.

- Line 260–269 (Step 2): Clarify how mismatches were handled when one product had spatial coverage but the other did not. How did interpolation behave near transition years (e.g., 1984, 2014)? Were there artificial spatial jumps in coverage? Given HILDA+ provides annual maps, why wasn't it used for interpolation?

Response: Thank you for your thoughtful and detailed comments. We appreciate your attention to the spatial and temporal consistency of our cropland reconstruction methodology. Please find our point-by-point responses and revisions below:

- **Spatial coverage mismatches:** To extend cropland density maps prior to the availability of CGLS-LC100 (2015-2019), we employed a backward projection method using GLC_FCS30D (1985-2022) and HYDE (1950-1990). Specifically, we selected CGLS-LC100 in 2015 as the base map for GLC_FCS30D, and 1990 as the base year for HYDE due to its decadal resolution. We then projected cropland density backward by applying annual or decadal fractional changes from these two datasets to their respective base maps. Accordingly, we applied the following rules to handle dataset integration:
    - **GLC_FCS30D > 0, CGLS_LC100 > 0:** The relative change in cropland density between the years (e.g., 2014 to 2015 from GLC_FCS30D) was applied directly to the corresponding CGLS-LC100 grid cell.
    - **GLC_FCS30D > 0, CGLS-LC100 = 0:** The product of any change rate and zero yields zero; thus, the cropland density for that year and grid cell remained zero.
    - **GLC_FCS30D = 0, CGLS-LC100 > 0:** This implies no recorded change in cropland presence; thus, the CGLS-LC100 value was retained without adjustment.

  A similar method was applied when using HYDE to reconstruct pre-1985 cropland density maps.

  Revisions: **Lines 285-299:** To extend cropland density maps prior to the availability of CGLS-LC100, we employed a backward projection method using GLC_FCS30D and HYDE. Specifically, we selected CGLS-LC100 in 2015 as the base map for GLC_FCS30D, and 1990 as the base year for HYDE due to its decadal resolution. We then projected cropland density backward by applying annual or decadal fractional changes from these two datasets to their respective base maps. Accordingly, we applied the following rules to handle dataset integration: (a) GLC_FCS30D > 0, CGLS_LC100 > 0: The relative change in cropland density between the years (e.g., 2014 to 2015 from GLC_FCS30D) was applied directly to the corresponding CGLS-LC100 grid cell; (b) GLC_FCS30D > 0, CGLS-LC100 = 0: The product of any change rate and zero yields zero; thus, the cropland density for that year and grid cell remained zero; (c) GLC_FCS30D = 0, CGLS-LC100 > 0: This implies no recorded change in cropland presence; thus, the CGLS-LC100 value was retained without adjustment. A similar method was applied when using HYDE to reconstruct cropland density maps prior to 1985, with decadal change rates applied to the 1990 baseline.

- **Interpolation:** To ensure spatial consistency, all datasets were processed at a 1km resolution. Specifically, we did not directly stitch CGLS-LC100, GLC_FCS30D, or HYDE. Instead, we used the cropland density of CGLS-LC100 in 2015 as a structural baseline and generated a temporally continuous set of potential cropland density maps from 1950 to 2014. This was achieved by applying backward trends from GLC_FCS30D (1985-2014) and HYDE (1950-1990) to generate "CGLS-like" cropland density. Since HYDE provides data at decadal intervals, we applied linear interpolation to fill in the annual gaps between 1950 and 1985. As a result, transitions between these datasets were inherently smoothed, and no abrupt spatial jumps were observed. As for HILDA+, although it provides annual land use/cover information in a Boolean format (i.e., presence or absence of cropland). This format is not suitable for constructing continuous cropland density maps.

  Revisions: **Lines 263-266:** All gridded datasets used in this section were first aggregated to a common spatial resolution of 1km. All subsequent operations, including trend operation, interpolation, and cropland density adjustment, were performed at this resolution to ensure spatial consistency.

  Lines 299-300: Since HYDE provides data at decadal intervals, we applied linear interpolation to fill in the annual gaps between 1950 and 1985 on a grid-by-grid basis.

- Figure 2: Suggest moving this figure earlier (e.g., at the beginning of Section 2) to help readers follow the workflow.

Response: Thank you for your suggestion. We have moved Figure 2 to the beginning of the Section 2 to help readers better understand the overall workflow of this study.

Revisions: **Lines 161-168:** The structure of this paper includes three main sections. The first section provides a detailed description of the input data and methods. The second section performs a comprehensive analysis of the spatial and temporal characteristics of four major commodity crops over the past seven decades. The third section compares the results of this study with other existing datasets and analyses the driving forces and uncertainties associated with the reconstructed data.

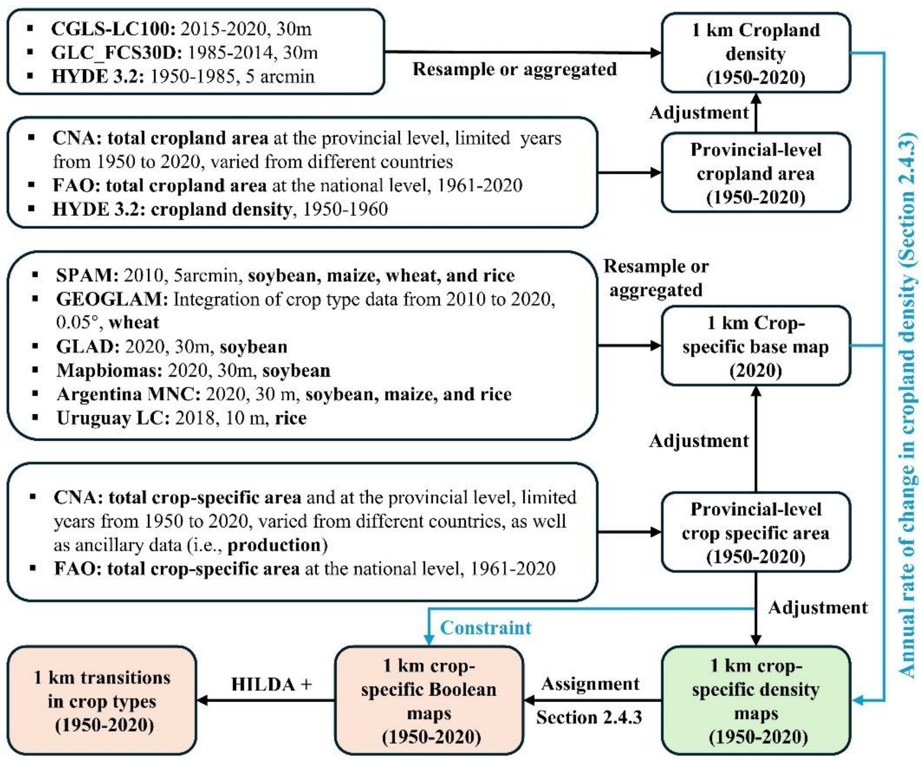

Figure 2. The flow chart of this study. CNA refers to Census National Agriculture.

- Line 309: How were the upward/downward trends and anomaly values identified? Over what period was the trend computed? Again, clarify the role of Equation 1 versus linear interpolation.

Response: Thank you for your thoughtful comments. The identification of upward/downward trends and anomalies was based on visual inspection. No statistical method was applied to detect anomalies. Instead, we assumed that harvested area should generally follow a gradual trend over time. Years showing abrupt increases or drops inconsistent with adjacent years were manually flagged as potential data issues. This screening was necessary due to the heterogeneous nature of input data sources. Regarding Equation 1, we used two complementary approaches to reconstruct the total cropland area at the provincial level: ratio-based interpolation and standard linear interpolation. When provincial-level cropland area was missing but national-level cropland area was available, we estimated the missing value by scaling the closest available provincial-level cropland area according to the relative change in national-level cropland area (as defined in Equation 1). This approach assumes that changes in the cropland area at the provincial-level follow the same relative trend as those observed at the national scale. In cases where national-level cropland area was unavailable, we applied standard linear interpolation between known provincial-level cropland areas to interpolate missing values. We have clarified this process in the revised manuscript.

Revisions: Lines 335-338: Second, anomaly values in the time-series of crop-specific harvested area were identified and removed through visual inspection, based on the assumption that harvested area typically follows a gradual upward or downward trend over time. Years with abrupt deviations inconsistent with adjacent values were flagged as potential anomalies.

Lines 267-279: The reconstruction of a total cropland area at the provincial level covers the period from 1950 to 2020. In this step, we mainly used two complementary interpolation approaches: ratio-based interpolation and linear interpolation. For years with available national-level cropland area but missing provincial-level cropland area, we estimated provincial-level cropland area by scaling the nearest known provincial-level cropland area according to the relative change in national-level cropland area (Equation 1). This assumes that provincial-level changes follow the same relative trend as those observed on the national scale. From 1961 to 2020, national cropland areas from FAO were used to calculate annual change rates. For years prior to 1961, we relied on agricultural census records or HYDE data. In cases where neither provincial nor national cropland areas were available, we applied linear interpolation between known provincial cropland areas. Since data availability and reference years differ across countries, the reconstruction was performed separately for each country.

- Equation 3: The model does not appear to account for long-term productivity changes due to technological or genetic improvements. Consider integrating literature-based estimates or assumptions for these factors.

Response: Thank you for your thoughtful comments. The current model does not incorporate long-term productivity improvements due to technological or genetic advances. However, we would like to clarify that crop production data were used only to fill gaps in Brazil from 1950 to 1970, where harvested area statistics were unavailable. Equation 3 is applied only in this limited context. Moreover, during this early period, the influence of technological and genetic improvements on productivity was relatively modest, especially compared to post-1980 developments. We have clarified this point in the revised manuscript.

Revisions: Lines 339-344: Fourth, in countries where harvested area statistics were unavailable, crop-specific harvested areas were reconstructed using production data, based on the strong correlation between production and harvested area (R2 = 0.92, Equation 3). Specifically, in Brazil from 1950 to 1970, provincial-level crop production data were used to estimate harvested areas, as no public statistics data were available during this period.

- Line 335: Define “top N grids”—how were they selected, and why?

Response: Thank you for your thoughtful comments. Cropland density maps might be treated as a proxy for the probability of the presence of cropland. Thus, prioritizing high-density grid cells in the Boolean conversion process helps maximize the spatial accuracy and reflects the most likely cropland distribution (Li et al., 2023). We have revised the text to clarify the definition of "top N grids".

Revisions: Lines 366-371: 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.

- Section 2.4.3: Clarify how crop-specific harvested areas were adjusted when provincial totals and pixel-level cropland constraints conflicted. What happens if the sum of crop areas exceeds the available cropland in a pixel?

Response: Thank you for your thoughtful comments. In the current version of our dataset, crop-specific harvested areas were adjusted independently for each crop to match provincial-level statistical totals. As a result, in some pixels, particularly in regions with intensive crop activity, the total sum of all crops may exceed the available cropland area or even exceed 1.0. This is a known limitation of the current method. We chose not to implement a pixel-level normalization step in order to avoid introducing artificial proportions without reliable rotation or coexistence data. As a related but distinct point, crop rotation was not considered due to the lack of consistent, high-resolution, time-series crop-type datasets. Thus, crop allocation was performed on a per-crop, per-year basis. We have acknowledged this limitation in the revised manuscript.

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 favourable 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.

- Figure 3: Use a background color to distinguish zero-value grids more clearly.

Response: Thank you for your thoughtful comments. We have revised the Figure 3 with a background color.

Revisions: Lines 441-444:

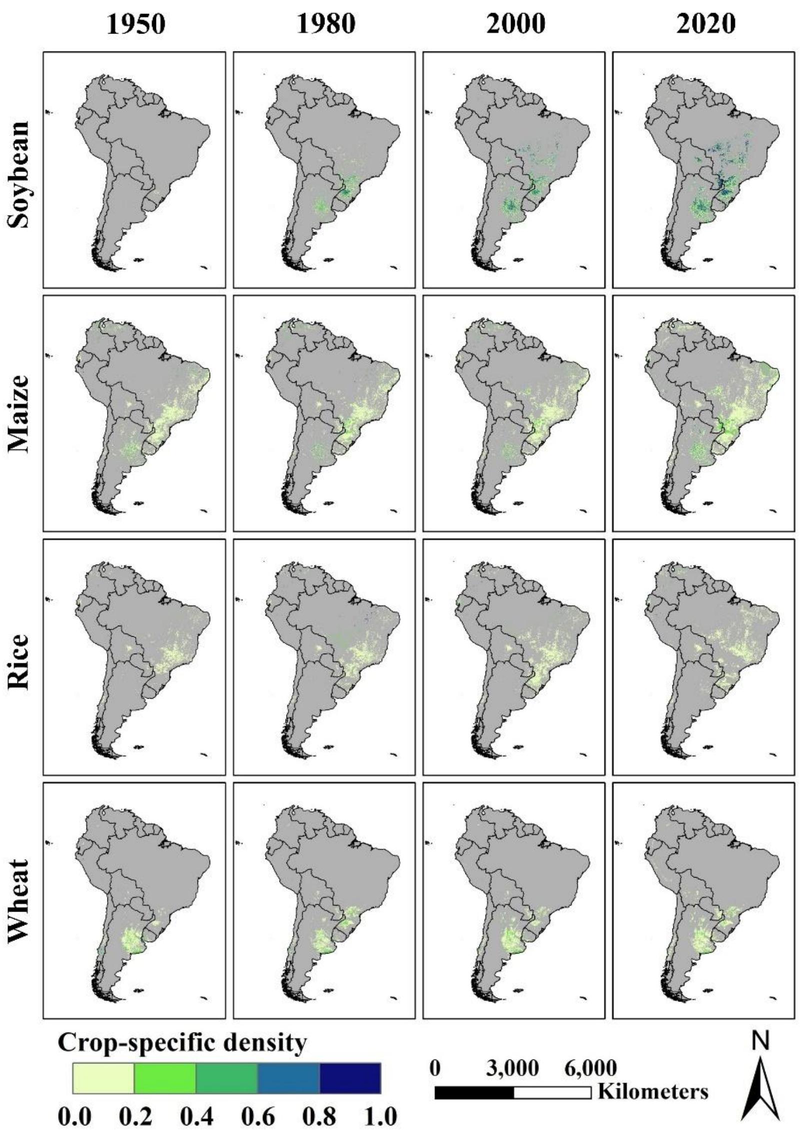

Figure 3. The spatial pattern of soybean, maize, rice, and wheat from 1950 to 2020. The first, second, third, and fourth rows represent the crop-specific fraction of soybean, maize, rice, and wheat. Crop-specific density represents the proportion of a given crop within each 1 × 1 km grid.

- Figure 6: The slope values >1 suggest lower crop estimates in the developed dataset. Cross-validate these values as the discrepancies are significant.

Response: Thank you for your thoughtful comments. We agree that slope values greater than 1 suggest that, in some regions, our reconstructed estimates may appear to be lower than the reference datasets. However, our reconstruction is fundamentally constrained by official provincial level statistics. Importantly, when compared with SPAM — a dataset that also relies on statistical inputs — the slope values fall largely within the range of 0.90 to 1.21, indicating strong agreement and supporting the reliability of our results. In contrast, greater variability appears when compared with remote sensing-based datasets. These discrepancies are expected due to differences in data sources and classification uncertainties. We have clarified this in the revised manuscript.

Revisions: **Lines 590-596:** Additionally, the comparison with multiple reference datasets shows that slope values between our reconstructed cropland area at the provincial level vary across sources (Figure 6). When compared to SPAM — a dataset that also incorporates official statistics — the slope values are largely within the range of 0.90 to 1.21 across crop types, indicating strong agreement and suggesting that our product is reliable in representing provincial-scale cropland distribution. In contrast, comparisons with remote sensing-based datasets exhibit larger deviations. These discrepancies are expected due to differences in data sources and classification uncertainties.

- Figure 8: Explain how spatial proportions from census data were allocated to grid cells. If all grids within a municipal boundary received the same value, state this in the caption.

Response: Thank you for your thoughtful comments. We clarify that Figure 8 presents a comparison at the municipal level rather than at the grid-cell level. Specifically, we first allocated provincial level crop-type data to 1 km grids using the method described in Section 2.5.3. These gridded values were then aggregated to the municipal level and compared with official municipal statistics. Both the gridded aggregated values and the statistical data were divided by the corresponding municipal area to obtain crop-type proportions. This standardized comparison allowed us to evaluate the spatial consistency of the allocation method we developed. We have clarified this in the figure caption.

Revisions: **Lines 533-538:** Figure 8. Spatial comparison of the soybean proportion (i.e., soybean area/municipal area) between this study and census data at the municipal level in Argentina (2008 and 2018) and Brazil (1995, 2006, and 2017). Proportions were calculated by aggregating gridded crop-type data (allocated from provincial level statistics) and dividing by municipal area. These were compared with official municipal statistics processed in the same way. Left column: soybean proportion from this study; Middle column: soybean proportion from census data; Right column: the difference in soybean proportion between this study and census data.

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