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 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.

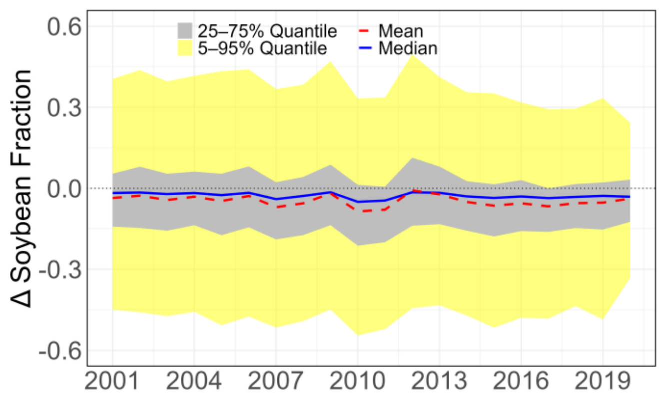

Figure 13. Temporal variation in soybean density difference between GLAD and this study (2001-2020).

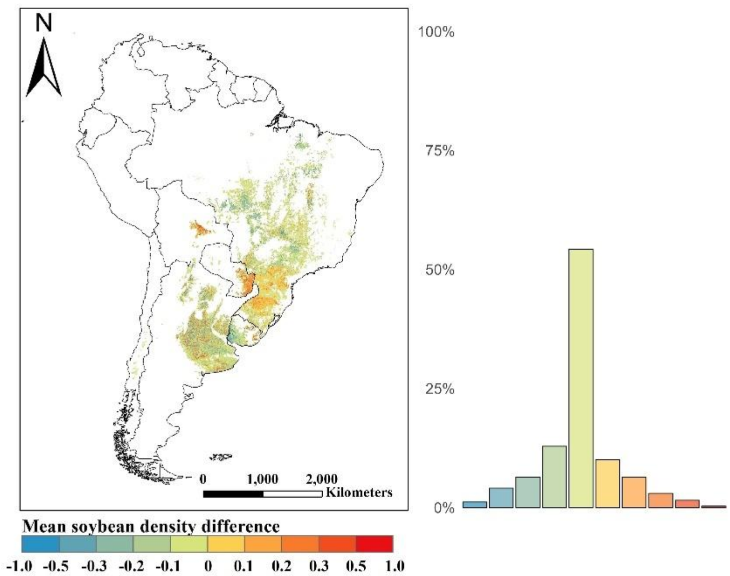

Figure S9. Spatial distribution (left) and frequency (right) of mean soybean density difference between GLAD and this study at the 1-km resolution from 2001 to 2020 for South America.

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.

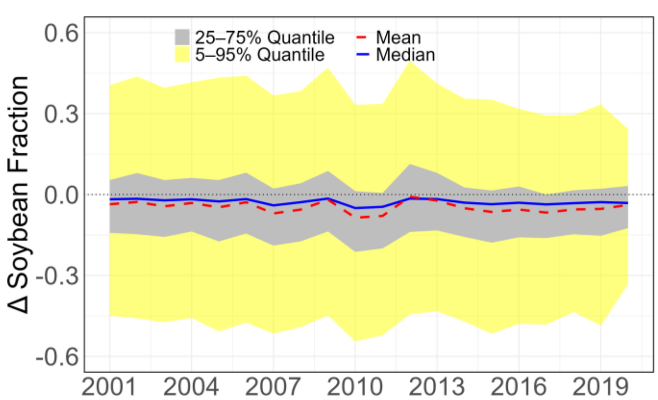

Figure 13. Temporal variation in soybean density difference between GLAD and this study (2001-2020).

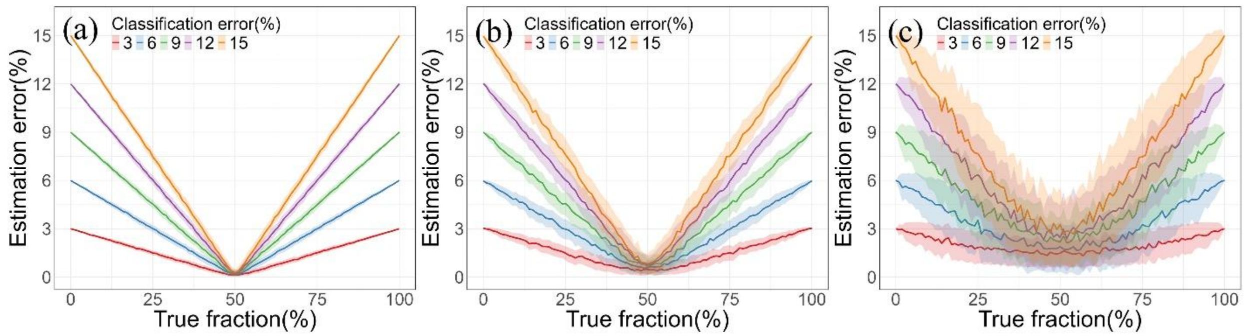

Figure S7. Monte Carlo simulation of aggregation-induced estimation error under varying classification error rates and spatial resolutions. (a), (b), and (c) represent the spatial resolution of 10 m, 30 m, and 100 m, respectively. The x-axis represents the true fraction (%) of the target class in a 1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

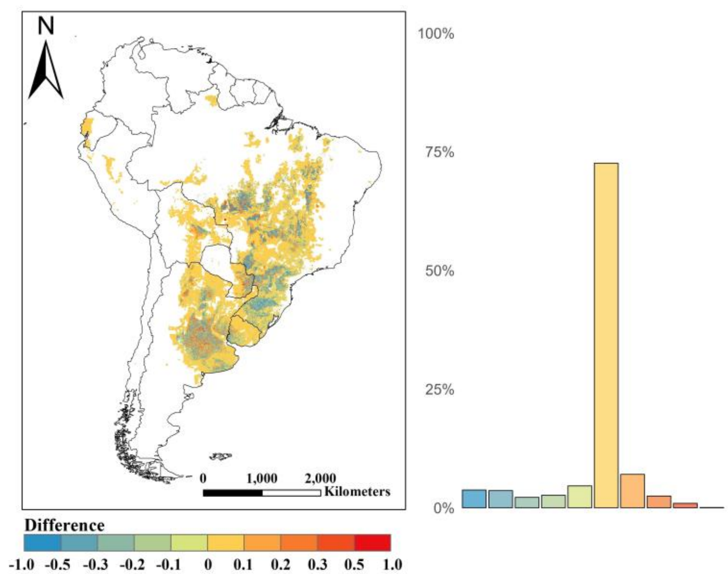

Figure S8. Mean soybean density difference (GLAD-this study) at 1-km resolution across South America (2001-2020): spatial pattern (left) and pixel-wise frequency (right).

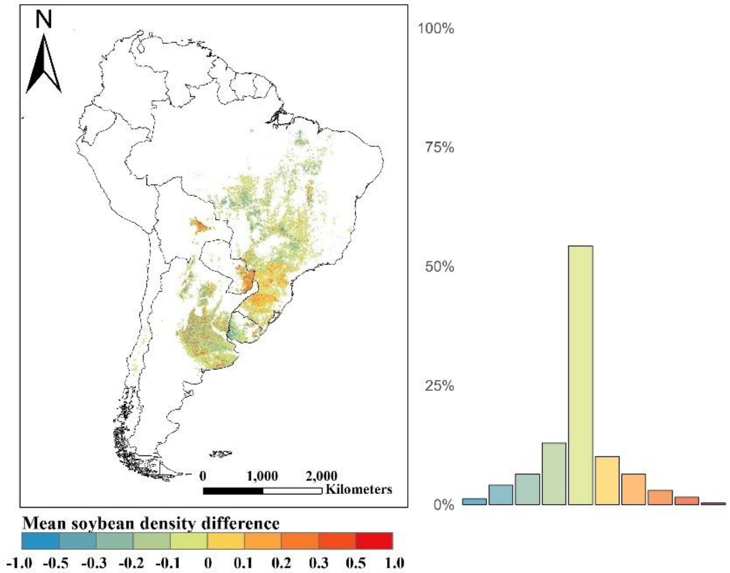

Figure S9. Spatial distribution (left) and frequency (right) of mean soybean density difference between GLAD and this study at the 1-km resolution from 2001 to 2020 for South America.

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.

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