

We would like to thank the editor and reviewers again for the valuable comments and suggestions that greatly helped us to improve the manuscript. Thank you very much for your time and efforts. In this major revision, we reworked the entire pipeline end-to-end: rebuilt the suitability masks following the reviewer's suggestion, retrained all species models, remapped the full 1961–2021 time series, and redid all validations and downstream analyses (multi-scale checks at county/city/province/state levels and independent comparisons to GLW products). To make limitations explicit, we also added a per-pixel, per-year uncertainty layer that integrates (i) temporal extrapolation with local sample support, (ii) feature completeness by species/year, and (iii) MESS-like environmental novelty. We encourage users to consult the accompanying uncertainty layers when interpreting historical results.

Comment 1. *(1) As the authors pointed out, one of the key steps of this work was that they generated municipal-level livestock data based on GLW4's grid data and FAOSTAT's national-scale livestock data, and then used it for modeling (Lines 117–119). This approach introduces significant spatial uncertainty: GLW4 only represents the global livestock distribution pattern in 2015, yet the study spans 1961–2021—a period marked by substantial shifts in livestock geography, such as China's livestock industry migrating notably northward between 1978 and 2014 (<https://doi.org/10.1016/j.agrformet.2019.03.022>). Consequently, relying on static 2015 data inherently fails to account for these dynamic spatial variations, conflicting with the study's aim to analyze temporal trends. This limitation is corroborated by Figure 6, where validating GLW4 (2015), GLW3 (2010), and GLW2 (2005) against the results reveals progressively declining correlation coefficients ($r = 0.84 \rightarrow 0.78 \rightarrow 0.73$), indicating a ~15% decrease in r -values over a decade—a clear signal of spatial reconfiguration that undermines extrapolating 2015 patterns to earlier decades, especially given the 60-year study span. (2) Additionally, how does the author prove the reliability of its earlier data such as those from the 1960s?*

Response: (1) We thank the reviewer for prompting this important refinement. We acknowledge the substantial difficulty of assembling globally consistent, fine-scale inputs for the 1990s and earlier decades. Consequently, we explicitly recognize that uncertainty is higher for early-period maps (1960s–1990s). Even so, at the global scale the maps still capture the major distributional patterns of different livestock types. To enable careful use of the dataset, this revision introduces a per-pixel, per-year uncertainty layer with the following method (Lines 180–188):

“For uncertainty quantification, we accompany each 5-km annual map with a per-pixel uncertainty index $U \in [0, 1]$, computed as the mean of three components: temporal extrapolation and sample support, feature completeness, and model applicability. First, temporal extrapolation and sample support combine the normalized distance from the reference year 2015 with a local sample-sparsity score (training points counted within a 5×5-pixel window); larger values indicate greater extrapolation and weaker local support. Second, feature completeness penalizes years/species with missing inputs—years with more available predictors receive lower uncertainty. Third, model applicability adopts a Multivariate Environmental Similarity Surfaces (MESS)

approach widely used in species distribution mapping: for each predictor we compare pixel values to the training 5th–95th percentile range, take the minimum similarity across predictors, and convert it to a 0–1 penalty. Higher U denotes higher uncertainty arising from larger temporal gaps, incomplete features, or extrapolation beyond the training domain.”

For uncertainty evaluation results, please kindly check Figure S1:

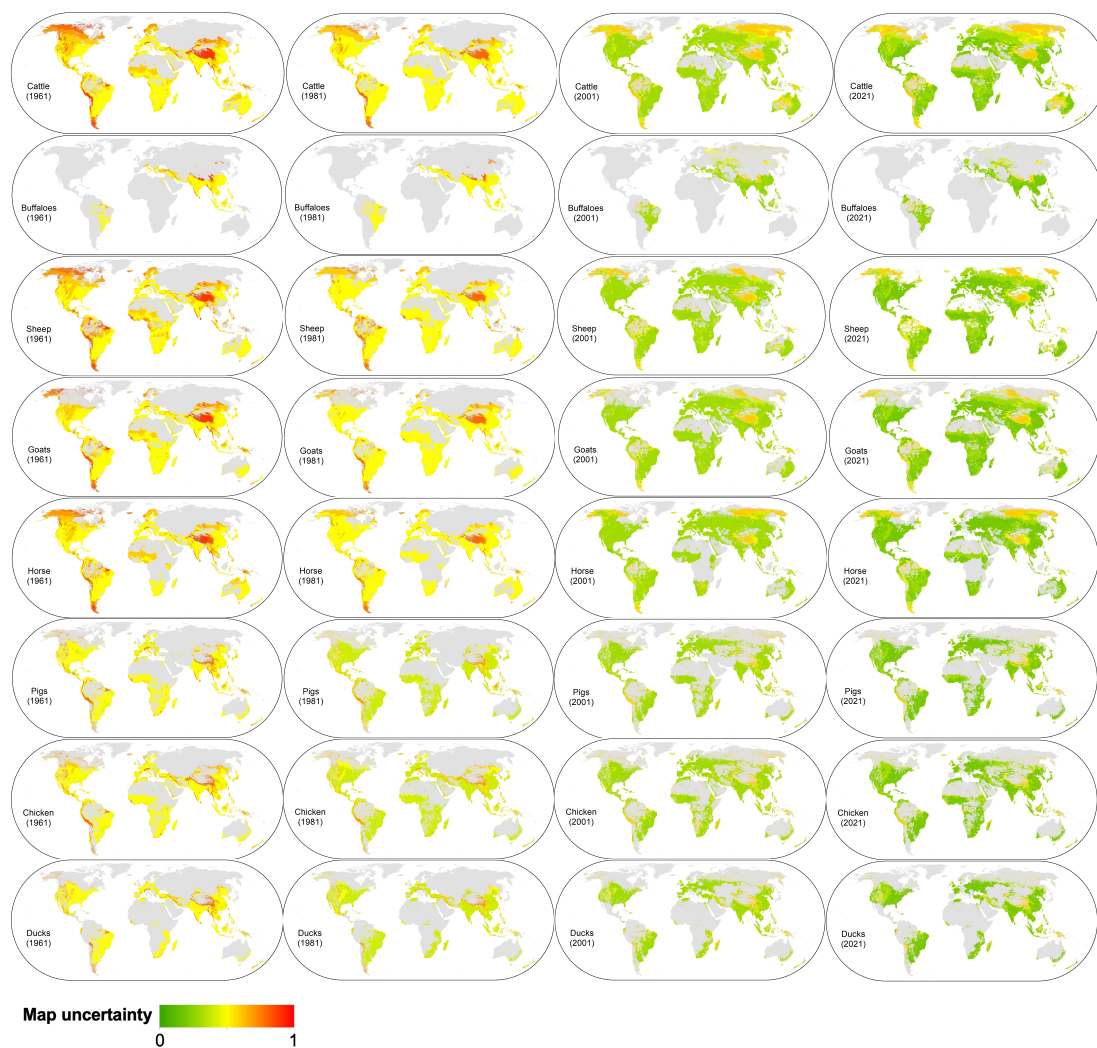


Figure S1. Livestock mapping uncertainty of AGLW dataset (take maps of 1961/1981/2001/2021 as examples).

In addition, it is important to note that our mapping framework did include time-varying environmental covariates in the Random Forest model. These covariates change over time and can drive some spatiotemporal shifts in the predicted distribution. This means our method is not completely “frozen” to 2015 patterns – it can adjust density based on suitability changes. However, we acknowledge that these indirect adjustments may not fully capture all historical shifts, especially those driven by management and policy. Therefore, we have further discussed this potential source of uncertainty in our previous response (Lines 326–330):

“To enable global-scale and long-term consistency, our study adopted a

proportion-based downscaling approach using the GLW4 dataset to redistribute FAOSTAT national totals at city level. While this method assumes relative stability in subnational livestock distributions across time, which may introduce uncertainty in dynamic regions, it is supported by previous large-scale studies (Theobald et al., 2020; Van Boeckel et al., 2019; Xu et al., 2019). Nevertheless, we recommend that users exercise caution when applying these data in regions with known subnational shifts in production systems.”

(2) Our mapping for the 1960s relies on FAOSTAT national livestock totals, which are the official statistics reported by countries. While these are the best available source and provide continuity back to 1960s, we acknowledge that the farther back in time, the more uncertainty may exist in some countries’ reported numbers. We assume FAOSTAT’s long-term time series is internally consistent and captures the broad trends, but there is an inherent limitation in verifying those 1960s figures on a fine scale. That said, at the country level, the data are as reliable as the FAO sources, and our maps will always match those national totals by construction. Thus, from a macro perspective, the early-year aggregate livestock counts are reliable in our dataset, it is the sub-national distribution of those animals that is uncertain.

For model performance and validation for early years, directly validating the spatial accuracy in the 1960s is extremely difficult, as detailed subnational livestock surveys or maps from that era are generally unavailable globally. However, we have performed several validations that give us confidence in our early-year results’ plausibility. Specifically, we chose 7 typical regions for each livestock, and compared our outputs against province- and state-level historical data for a few representative regions (as listed in Table 4 of the paper). Notably, this included cattle in Texas (United States) with data starting from 1969, pigs in Henan (China) from 1978, and buffaloes in Guangxi (China) from 1978. Our results showed a very high correlation ($r = 0.97$) with these province/state time series, indicating that the temporal fluctuations and general magnitude in those regions are well-captured even in the earlier decades. While this doesn’t guarantee pixel-level accuracy, it demonstrates that the overall trends from the 1960s–1970s in those areas are correctly represented by our model. In addition, we performed county-level validation in China from 1990 (the earliest available county data), finding good agreement ($r = 0.78$ at county scale). By extension, we expect maps of 1960s are not be wildly off in major patterns.

Comment 2. *(1) Another key step of this work is that authors categorize animals into “grazing livestock” (e.g., buffalo, cattle, goats, horses, sheep) and “captive livestock” (e.g., chickens, ducks, pigs), and assume grazing species inhabit grasslands while captive species are confined to impervious surfaces (Lines 83-85). This simplification is problematic, as intensively raised livestock (e.g., pigs) frequently occupy peri-urban or rural agricultural lands rather than impermeable surfaces alone (<https://doi.org/10.1016/j.oneear.2023.08.012>). (2) In the reply letter, the authors cited Jiangsu pig farms to validate this classification, but subsequent checks revealed the mapped “impermeable surfaces” correspond to industrial calcium production facilities (name: 晶诚钙业 Jingcheng Calcium Industry 晶诚钙业 - 百度地图) rather than*

pig farms. Given the global prevalence of industrial sites, such misclassifications risk severely compromising data product accuracy.

Response: (1) Thanks for the comment. In the revised manuscript, we have updated our suitability mask for all livestock to include agricultural lands, not only grassland and impervious surfaces. Thanks again for the recommended research, and we have now included this paper for better explanation. We have added a description of this improved method in Lines 128-129 of the paper and adjusted all the following result outputs, accuracy assessment and analysis accordingly (Figure 2-7). The model now better reflects real-world patterns, and the validation results also showed higher correlation coefficients as highlighted in the abstract. We believe this revision addresses the reviewer's concern, and we thank the reviewer for helping us improve the robustness of our approach.

(2) We appreciate the reviewer's careful check. We fully acknowledge the concern regarding the specific example cited in our previous reply. The coordinate we provided was based on a location labeled as a pig farm in a peer-reviewed publication focused on livestock facility detection in Jiangsu Province, as shown below:

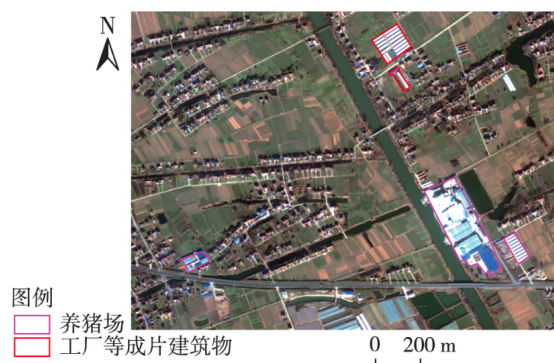


Figure R1. Representative pig farm and industrial areas.

(The purple boundary denotes identified pig farms, while the red boundary indicates large-scale industrial facilities such as factories.)

This paper was published in 2020 (<https://doi.org/10.19741/j.issn.1673-4831.2019.0764>). We now understand that the current appearance of this location may correspond to a calcium industry facility. Nevertheless, we would like to emphasize that our study, much like the GLW (Gridded Livestock of the World) series developed by FAO and collaborators, does not aim to pinpoint the exact location of individual farms or facilities. Rather, our goal is to produce spatially and temporally continuous livestock density maps that reflect broader spatial patterns and temporal dynamics in livestock distribution at global scale. This distinction is crucial: the GLW products also rely on land use suitability and proxy variables (such as population density, land cover, and topography) rather than exact farm locations, due to the infeasibility of acquiring ground-truth farm locations globally, especially retrospectively over a multi-decade timespan. In this context, our methodology aligns with established livestock mapping practices. While individual mismatches (as the reviewer kindly pointed out) can occur, our model was validated against multiple GLW versions, along with county-level, city-level, provincial, and national statistics. The core objective of our suitability mask is to

guide probabilistic allocation of livestock within subnational units using ecological and socio-environmental proxies, not to directly geolocate farms.

Finally, we greatly appreciate the reviewer's feedback, which pushed us to re-examine and strengthen the core methodological framework of our study. Your input has played a critical role in enhancing the scientific quality and credibility of this work. Given the limited revision timeline, we have deposited an initial subset of the revised products (selected species/years together with the matching uncertainty layers) to our Zenodo repository (see Data Availability). We will continue to expand this record on a rolling basis to include the full set of maps and uncertainty layers, with clear versioning and a changelog to document updates. We believe that the revised manuscript and the new dataset will now meet your expectations.