

Response to Reviewer 2

The authors have responded to the feedback, but there is a lack of substantial revisions. In the next round of revisions, it is recommended to address the data uncertainties, particularly for the data prior to the year 2000, in the abstract or conclusion section. Additionally, the results presented in Table 3 and Figure 3 are log-transformed, which could potentially mislead readers.

Response: We are grateful for the time and energy you expended on our behalf. Regarding the issue of data uncertainty you raised, we have provided additional statements in the conclusion section of the revised manuscript (refer to lines 598-601). However, we do not concur that the data uncertainty is higher prior to the year 2000. In fact, as depicted in Figure 5a, the results from the Monte Carlo simulations indicate that the MRE for the period 1990-2000 ranges between 6.84% and 7.62%, whereas for the period 2001-2020, the MRE ranges between 7.33% and 9.08%. Furthermore, as we stated in our response to the previous revision, the conclusion that grazing intensity on the Qinghai-Tibet Plateau decreased between 1990 and 2000 is consistent with the findings of other scholars.

Additionally, Table 3 already contains the actual values, with the exponentials of the log-transformed numbers. Figure 3 does display the log-transformed results, and it is well annotated on the axes. In the revised version, to clarify any potential confusion, we have provided explanations in the text (refer to lines 295-296 and lines 298-299). We hope you find these revisions rise to your expectations.

Response to Reviewer 3

First, I cannot access the latest dataset. So, I cannot conclude on the data updates. Please make sure to update the dataset link for reviewers after each update and test if the link works. Also, please attach the link to the responses as the link in the manuscript does not work.

Response: We apologize for this inconvenience due to the expired link. Please check the updated link below.

https://zenodo.org/records/13701486?token=eyJhbGciOiJIUzUxMiJ9.eyJpZCI6IjA4YzVkM2FkLTA2NzktNDczYi05ZDA4LTk3ZGNjYmViYjRjZSI6ImRhdGEiOnt9LCJyZW5kb20iOiJIYTIwZTg5ODIxM2M0M2E1N2UzNzQ0ZmMzMGNiNzFiMSJ9.Oqcf7bqs_Yd_u0PEBQw2e1_w-JEpP-P00qP7yRjoVb9mUof7ATdeBaXl2cIw6Tqw71QSEhDH5yrkfe1fyjK7mw

Regarding my major comment #1 (reviewer 3 in your responses): The responses are still unconvincing. The authors trained and validated the model at the county level and then applied it to 100m resolution. Will there be some problem in this resolution transition? Did the authors assume the impacting factors at the county level are the same as the 100m level?

Response: We appreciate your insightful comments and the feedback provided. We apologize for any lack of clarity in our previous responses. Indeed, in this study, we have adopted the assumption made by the Food and Agriculture Organization (FAO) when creating global livestock grid maps—that the relationship between grazing intensity and environmental factors is similar across both administrative and pixel scales (refer to lines 214-215). This assumption underpins the creation of the majority of current grazing intensity maps (Robinson et al., 2014; Li et al., 2021; Liu, 2021; Zhan et al., 2023). We acknowledge that this approach to scale conversion may introduce certain limitations, as it inevitably smooths spatial details, thereby constraining the model's expression at the pixel scale. In recognition of this limitation, we have provided a detailed discussion in the discussion section (refer to lines 552-556). We hope you find these explanations rise to your expectations.

Regarding my major comment #2: What I meant is that the authors should weaken their statement on using a better algorithm and better factor selection as the comparisons are not the direct evidence to support their argument.

Response: We appreciate your important observation and concur with your suggestion. In the revised manuscript, we have moderated our assertion regarding the employment of a superior algorithm and the selection of more effective factors. Furthermore, we have expanded our discussion to consider that the choice of algorithm and factors might indeed be contributing factors to the discrepancies observed between the maps (refer to lines 421-427).

Regarding my minor comment #5: Would the easiest way to address this issue is to train the model with 100% samples rather than run the model 100 times to see the variance?

Response: We appreciate your recurring inquiry on this matter. The decision not to utilize 100% of the samples for training the ET model was deliberate and based on several methodological considerations. Firstly, the practice of partitioning samples into training and testing sets is a well-established approach in both machine learning and spatial analysis. This method ensures an unbiased assessment of model performance and generalizability using separate datasets (Chong et al., 2019; Oukawa et al., 2022).

Secondly, employing 100% samples for model training would preclude the availability of independent data for model validation, thereby increasing the risk of model overfitting. Moreover, a model trained with 100% samples would essentially be memorizing the training data rather than generalizing from it, thus compromising its predictive capabilities (Zhang and Yang, 2020).

Furthermore, models trained with the entire sampling dataset may not be robust, as they lack the rigor of validation against unseen data. In fact, the use of partitioned datasets for training and testing is widely adopted because it strikes an optimal balance between model accuracy and generalization (Verikas et al., 2011; Javeed et al., 2019; Yilmazer and Kocaman, 2020; Li et al., 2021; Meng et al., 2023; Zhan et al., 2023). Our analysis also corroborates this, demonstrating that a model trained with 70% of the samples has already achieved commendable performance, with an R-squared value of 0.955.

We hope you find these explanations rise to your expectations.

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