Response to Reviewer 1

General Comments:

This manuscript developed an annual grazing intensity dataset at 100-m spatial resolution for the Qinghai-Tibet Plateau (QTP) by integrating machine learning algorithms, census data, and multiple environmental and socio-economic data. Through comparisons with previous datasets, census data, and field observations, the GDGI data proved to be a good grazing intensity dataset with fine resolution. The data can be applied to quantify the impacts of grazing management on the ecosystem in the QTP. The authors have done good work in response to the comments from the reviewers and did lot of work on input data preparation, field-level validation, and discussion sections. However, some concerns about data uncertainties and a few minor points that could be addressed.

Response: Thank you very much for your overall positive words about our revised paper. We are delighted to hear that our manuscript received such feedback. We have improved the manuscript according to your suggestions, especially your concerns about data uncertainties. In the following sections, you will find our detail responses to each of your points and suggestions. We are grateful for the time and energy you expended on our behalf.

Major comments:

According to the methods, the ET model predicted mean grazing intensity at the county level was corrected in the final step, but it can't solve the problem of spatial uncertainty. Thus, the authors should also generate the uncertainty maps by using the ET model and provide to the data users.

Response: We appreciate your valuable suggestion and concur that the inclusion of uncertainty maps is essential. In response to your feedback, we have employed the ET model in conjunction with Monte Carlo simulation techniques to generate the uncertainty maps (refer to sections 2.5 and 3.2 in the revised version).

In addition, we have also provided the original simulation results from the ET model, along with the corresponding error maps (refer to Figure 4c).

Additionally, I found that the GDGI data (https://figshare.com/s/ad2bbc7117a56d4fd88d, https://zenodo.org/records/10851120) was not publicly available, and I couldn't download the data.

Response: We apologize for this inconvenience due to the expired link. Please check the updated link below. https://zenodo.org/records/13141090?preview=1&token=eyJhbGciOiJIUzUxMiJ

**9.eyJpZCI6ImVjMmEyNjFkLTVmOGYtNDA0NS05OWRhLTUyMTBhYzJlMz
VmZiIsImRhdGEiOnt9LCJyYW5kb20iOiIxMzMyMTc4YWUxM2NmNDYxNG
QxYWUxYTNjMGFjZDAwZSJ9.ESaMJvGyehZgrB6bI_CMCHym4SEKqddJ7
GsTOEoI9kxmpjWqaHRjubdzkb2qW_v1DTTDGRLrZyGLQcq85hNMOw**

Some minor comments:

Line 280: Is it ‘0123’? Please check it.

Response: Thanks for raising this point. We have corrected “0123” as “0.123” (see line 308 in the revised version).

Figure 5: Why do about half of the field observations in the Alpine Meadow ecosystem have the same grazing intensity (about 4 Su/ha)? Please add some short explanations.

Response: We are grateful for your insightful comment. In direct response to your concerns, we have conducted a meticulous review of all field observations. Our verification confirms that the grazing intensity in the alpine meadows predominantly falls within the range of 4 ± 0.5 SU/ha on the Qinghai-Tibet Plateau. This range is supported by findings from other peer-reviewed scholarly articles that are grounded in extensive, long-term observational studies (Cao et al., 2004; Li et al., 2018a; Wang et al., 2020; Zhuang et al., 2019). Consequently, we are confident that this data accurately represents the actual grazing conditions within the alpine meadows of the Plateau (refer to Table S3 for details).

Figure 7e should include a legend of linear trend value.

Response: We appreciate your observation. In Figure 7e, rather than presenting the linear trend values in isolation, we have chosen to depict them in conjunction with their statistical significance. Specifically, a linear trend with a value greater than zero and a p-value less than 0.01 is illustrated in dark purple, whereas a trend with a value less than zero and a p-value less than 0.01 is depicted in dark green (refer to Figure 8e in the revised version).

Response to Reviewer 2

General Comments：

Enriching the grid data on grazing intensity on the Qinghai-Tibet Plateau is significant for improving environmental impact assessments. While the paper has seen substantial improvements after several revisions, the data still shows considerable uncertainty.

Response: We are deeply grateful for your acknowledgment of the significance of our work. In the updated manuscript, we have carefully incorporated your valuable feedback. In particular, to address your concerns about data uncertainty, we have added new sections (please refer to sections 2.5 and 3.2 for details in the revised version) that utilize an ET model in conjunction with a Monte Carlo simulation to evaluate the uncertainty within the annual grazing intensity maps. In the subsequent sections, we provide a detailed response to each of your perceptive comments. It is our earnest hope that these revisions meet your expectations.

Major comments:

Firstly, in Section 3.1, the performance metrics of the validation set are excellent. However, in Section 3.2, the validation results of the calibrated grazing data are worse. Why is this? Is it related to the choice of the model's test set, or are there other factors? Moreover, the data for township validation points is very sparse. Is it reasonable to increase samples through a temporal dimension?

Response: Thanks for raising this important point. We appreciate your insight regarding the potential impact of test set selection on model performance. To address this concern, we conducted additional verification. Specifically, we employed Python's train_test_split function from the sklearn. Model_selection library to randomly allocate 30% of the data as the test set. To assess the influence of test set selection on model performance, we varied the random_state parameter from 1 to 20 and executed the model 20 times. Consistently, the range of R^2 values was between 0.92 and 0.97, suggesting that the choice of test set does not substantially affect the model's performance in this study.

Regarding the variance in model performance which you mentioned, we attribute the primary cause to the scale effect. In Section 3.1, we demonstrate the model's performance on a county-scale test set comprising 30% of the total, with 1499 samples, yielding an R^2 value of 0.955. In Section 3.3 of the revised version

(formerly Section 3.2), the model's performance on the township scale, involving 18 townships, resulted in an R^2 value of 0.867; on the pixel scale, with 112 points, the R^2 value was 0.804. This indicates a decline in model performance as the scale becomes more refined. The primary reason for this may be the resolution of the input data. Since the census data in model training is county-level, the input environmental variables also correspond to county-level, which to some extent, smooths spatial details and thus limits the model's expressiveness at finer scales.

We acknowledge the scarcity of township-scale validation data in our study. As you know, collecting livestock census at the township level in the Tibetan Plateau is indeed challenging. We have highlighted this limitation in the discussion section of the revised version (see lines 577~581). To address the issue of insufficient validation data from the same year, we independently verified the data across different years on a temporal scale. In fact, in cases of limited validation data, scholars frequently increase samples through a temporal dimension. For instance, Meng et al. (2023) validated their grazing data using livestock data from 2001 to 2021(Meng et al., 2023), and Venter et al. (2016) used satellite imagery data from 1999 to 2015 to validate their human footprint data. We hope you find these revisions rise to your expectations (Venter et al., 2016).

Secondly, in Figure 7, there is a sharp decline in the data from 1990 to 2000. What is the cause? Given this significant decline, does it contradict the common understanding that China implemented large-scale ecological projects in the new century? I suggest starting the data development from the year 2000.

Response: This is another good point. Yes, Figure 7 (Figure 8 in the revised version) illustrates a sharp decline in grazing intensity on the Qinghai-Tibet Plateau from 1997 to 2001. This downward trend is corroborated by official livestock census from governments, which indicate a reduction of 1,889,400 livestock during this period. Furthermore, this trend also aligns with findings from other researches. For instance, Sun et al. (2021) noted a decrease in grazing intensity of 43 sheep units per hectare from 1995 to 2000. The precipitous drop in grazing intensity between 1997 and 2001 is likely predominantly associated with natural disasters. Take Naqu alone as an example, Ye et al. (2020) demonstrated that the severe snow disaster of 1997–1998 has led to the loss of more than 820,000 livestock (Ye et al., 2020).

Figure 7 (Figure 8 in the revised version) also delineates a significant increase in grazing intensity on the Qinghai-Tibet Plateau from 2000 to 2010. This

observation is congruent with the results reported by Sun et al. (2021) and Li et al. (2021) (Li et al., 2021; Sun et al., 2021). This increase in grazing intensity is likely a rebound effect following the natural disasters. Additionally, Figure 7 (Figure 8 in the revised version) indicates a consistent decline in grazing intensity across the plateau post-2010, which is largely attributed to the implementation of extensive ecological projects. To address any potential reader misconceptions about this phenomenon, it has been thoroughly discussed in the revised draft's discussion section (refer to lines 461-473).

Thirdly, while the authors emphasize the high spatial resolution of the developed data, only the elevation, slope, and population data among the auxiliary data have a comparable resolution. Furthermore, the evaluation of the population data shows that its accuracy on the plateau is not high. In this context, higher spatial resolution may lead to greater uncertainty. Do the authors need such a high resolution?

Response: We appreciate your raising this crucial point. We are well aware of the formidable challenge in generating a 100-meter resolution map of grazing intensity across the Tibetan Plateau. Our pursuit is underpinned by three key motivations. Firstly, we firmly believe that high-resolution grazing maps will substantially improve grassland management and guide pertinent decision-making on the plateau. Secondly, the successful publication of several global-scale 100-meter resolution maps by other scholars has underscored the feasibility and reliability of this resolution in practical applications. For example, studies on population distribution, forest management, and land cover have adeptly utilized this resolution, as evidenced by the works of Lloyd et al. (2017, Lesiv et al. (2022), and Masiliūnas et al. (2021) (Lesiv et al., 2022; Lloyd et al., 2017; Masiliūnas et al., 2021). Lastly, the key input data for our grazing dataset, though generated by ourselves, have demonstrated their efficacy through stringent accuracy validation (refer to lines 49-112 in the supplementary file). These results reinforce our confidence in producing a 100-meter resolution grazing map that promises to be both precise and valuable.

Regarding the accuracy of the population distribution data for the Qinghai-Tibet Plateau, which you highlighted, we selected the 100-meter resolution data from Worldpop, primarily informed by the research of Li et al. (2020). Their comparative analysis of WorldPop (100m), GPW (1000m), and the Chinese datasets CnPop1, CnPop2, and CnPop3 (all at 1000m resolution, except CnPop3 at 100m) within the Qinghai-Tibet Plateau revealed that the WorldPop data at 100m resolution offers the highest degree of accuracy, with an R^2 value in

relation to county-level census data that can even approach 0.90(Li et al., 2020). That is to say, WorldPop data has a good performance in the Tibetan Plateau, which is also the reason why we use it as the data source of population distribution.

Regarding the constraints, why are areas with a population density greater than 50 people/km² designated as non-grazing areas? Grazing areas often overlap with rural residential areas, and livestock often graze around these settlements in the mornings and evenings, leading to higher grazing intensity. Additionally, in the Qinghai-Tibet Plateau, there are many uninhabited areas where animals often live. Also, how is slope related to grazing areas? What is the basis for the 40° threshold?

Response: We appreciate this valuable comment. In this study, we define areas with a population density exceeding 50 people/km² as non-grazing areas, primarily drawing on the research conducted by Li et al. (2018). In their study, areas with a population density above 50 people/km² were categorized as urban built-up areas on the Qinghai-Tibet Plateau (Li et al., 2018b). We consider it logical to extend this definition to classify urban areas as non-grazing zones. In our research, all regions falling below this population density were designated as potential grazing areas, including the uninhabited areas you mentioned, ensuring that the distribution of rural settlements is fully accounted for and the continuity of grazing practices is maintained.

The rationale for designating 40% of the area as non-grazing is largely informed by the findings of Robinson et al. (2014). In their work on the Gridded Livestock of the World (GLW2), they suggested that areas with slopes exceeding 40% were unsuitable for grazing activities due to topographic constraints and issues of accessibility (Robinson et al., 2014). We have adopted this criterion to ensure that our model incorporates the impact of topographic factors on the feasibility of grazing activities in our assessments of grazing suitability. We hope you find these explanations rise to your expectations.

In Figure 4, the readability of the image details is insufficient.

Response: We appreciate your observation. In response, we have revised Figure 4 to enhance its clarity and improve readability for readers (see Figure 4).

Finally, as a data-centric paper, I recommend including the selection and description of auxiliary variables in the main text.

Response: We appreciate this valuable suggestion. In the revised version, we have added the selection and description of auxiliary variables in the main text (see section 2.2).

Response to Reviewer 3

General Comments：

This study provides a high-resolution grazing intensity dataset on the Qinghai-Tibet Plateau using machine learning algorithms based on county-level data. The dataset could be a potential interest to other researchers who focus on the Tibet Plateau. Authors also compare and validate their datasets with other comparable datasets as well as their own monitoring data. The dataset is also accessible. I still found more clarifications/corrections needed before it can be considered for publication.

Response: Thank you for these overall positive words. We have thoroughly addressed all of your comments and suggestions in the revised version. Please see our detail responses to the individual comments in the following sections. We are grateful for the time and energy you expended on our behalf.

Major concerns:

1. Clarify the reason for 100 m. Though 100m spatial resolution is appealing, the authors didn't clarify why they chose this spatial resolution for the final dataset. Actually, if I understood correctly, the authors trained and validated the model at the county level and then applied the model to 100m spatial resolution. (a) What is the reason for this? Do the authors have a reliable input at the 100m spatial resolution?

Response: Thanks for raising this important point. We recognize the immense challenge of creating a 100-meter resolution map depicting grazing intensity across the Tibetan Plateau. Our endeavor is driven by three principal motivations. Firstly, we are convinced that high-resolution grazing maps will significantly enhance grassland management and inform related decision-making processes on the plateau. Secondly, the successful publication of several global-scale 100-meter resolution maps by other researchers have demonstrated the feasibility and reliability of this resolution in practical applications. For instance, studies on population distribution (Lloyd et al., 2017), forest management (Lesiv et al., 2022), and land cover (Masiliūnas et al., 2021) have all utilized this scale effectively (Lesiv et al., 2022; Lloyd et al., 2017; Masiliūnas et al., 2021). Lastly, the key input data for our grazing dataset, although generated by ourselves, have proven their efficacy through rigorous accuracy validation (see lines 49-112 in the supplement for details). These results bolster our confidence in producing a 100-meter resolution grazing map that will be both accurate and useful.

(b) Actually, I also think that an overview table of all the input data is helpful, which shows the temporal and spatial resolution of each input data (for county-level model training and 100m application respectively).

Response: We appreciate this valuable comment. In the revised version, we have provided an overview table of each input data (see Table 1 and Table 2 in the revised version).

(c) I also find it would be helpful to add a data use note on how users can use the data at different spatial resolutions and how to avoid potential misuse.

Response: Thank you very much for your valuable suggestion. In the revised version, we have provided the data use notes for users, and uploaded it together with the GDGI dataset (see notes in the meta-data file).

2. Lines 357-390 and figure 8, the discussion is not convincing. Yes, the authors' dataset shows a better alignment with observations. This could be the result of a better algorithm or selective factors, but also could simply be due to the grazing map correction based on county-level data. For a fair comparison, the authors should also correct other datasets using the county-level data and compare again.

Response: We greatly appreciate this insightful comment. Our decision not to compare all grazing datasets after the county-level livestock census correction stems from three main considerations. Firstly, it is an objective reality that discrepancies between different grazing map products are inevitable due to differences in the methodologies used, environmental factors selected, and livestock census data employed. Because all the four grazing data products compared in this paper have been refined using control method, further corrections would alter the intrinsic values of these maps, potentially compromising their original integrity. Thus, preserving the original data values is crucial to maintaining the authenticity and scientific merit of each dataset.

Secondly, maintaining the original data values can ensure that comparative analyses accurately reflect the distinctions between various grazing intensity products, enhancing the transparency and reproducibility of these datasets. This approach allows readers and peers to directly assess the comparative strengths and limitations of each product through unaltered comparative results.

Thirdly, extensive literature review indicates that direct comparison of different data products is a normal practice. For instance, Meng et al. (2023) directly compared their grazing intensity maps with ALCC and GLW datasets. Similarly, Li et al. (2021) made a direct comparison of their grazing maps to

GLW data(Li et al., 2021). This method is also prevalent in the analysis of other data types, as evidenced by Mu et al. (2022) who compared their human footprint data directly with three published datasets, and Li et al. (2020) who directly compared their 2010 population distribution data with five other published datasets (Li et al., 2020; Mu et al., 2022).

Therefore, in light of these precedents, we deem it more appropriate to directly compare the different grazing datasets without altering their original map product values.

To bolster the fairness and rigor of our study, in the revised version, we have standardized the verification of the GDGI products and other grazing intensity maps against livestock census data at the township level. Specifically, we have chosen livestock census data from ten townships in 2015 as the validation baseline (refer to lines 393-397 and Figure 9c in the revised version). The selection of data from 2015 is due to the availability of the GLW data product for that year only. The township-level validation results underscore that the GDGI products not only excel in spatial and temporal resolution but also exhibit the lowest error rates (see lines 396-397 in the revised version), suggesting that their superior performance attributable to a more refined algorithm and the selection of more pertinent environmental factors.

Nevertheless, we acknowledge that the livestock census from the ten townships may be limited. This limitation is addressed and discussed in the revised paper (refer to lines 578-581). We hope that our responses and revisions adequately address your concerns.

Minor concerns:

1. Even though the authors described the meta-data in the manuscript, I expected that the meta-data should also be included in the dataset, including the unit, coverage, and projected coordinate system.

Response: Thank you for this great suggestion. In the revised version, we have provided a meta-data file in the GDGI dataset, which contains all specific information you mentioned (see the meta data file for details).

2. Line 216, why chose 50 as a threshold?

Response: Thanks for raising this point. The determination of this threshold is based on the research results of Li et al. (2018), who regard the population

density greater than 50 people/km^2 as the urban building area (Li et Al., 2018). We consider it logical to extend this definition to classify urban areas as non-grazing zones.

3. Line 243, can the authors provide L_CCensus/L_Cgrid for each county and year in the supplement or their dataset?

Response: We appreciate your raising this significant point. However, due to confidentiality agreements we've established with the pertinent government departments when procuring the livestock census data, we are constrained from disclosing the original livestock data. As an alternative, in compliance with your suggestion, the revised manuscript now includes the converted grazing intensity grid data spanning the years 1990 to 2020 (see table 4S in the supplementary file).

4. How did the authors tune the parameters of each machine learning algorithm?

Response: Thanks for raising this point. The tuning of the optimal parameters of each machine learning algorithm were done in python using Randomized Search CV functions.

5. Line 228, the authors used 70% of the samples for training and the remaining for testing for the algorithm selection. After selecting the Extra Trees regression as the best algorithm, did you train the model with all the samples (100%) again before applying it to 100m spatial resolution?

Response: This is indeed another critical point. Following the selection of the Extra Trees regression model as the optimal algorithm, we did not retrain the model using all samples. This decision was based on the testing results, which showed an R-squared (R^2) value as high as 0.955, indicating that the ET model performs exceptionally well. However, we fully concur with your view that the reliability of the ET model should be validated before its application at a 100-meter resolution. To this end, in the revised manuscript, we have conducted 100 random simulations using the Monte Carlo method at the 100-meter spatial scale to further ascertain the robustness of the ET model at this resolution. The Mean Relative Error (MRE) and Standard Deviation (STD) of the simulation outcomes are also found to be satisfactory, thereby further substantiating the model's reliability at the 100-meter spatial resolution (refer to lines 314-326). We hope that these revisions will meet your expectations.

6. The authors may consider including the sample data from the supplement to their dataset to increase the accessibility.

Response: Thank you for your good suggestion. In the revised version, we have included the sample data to the GDGI database.

7. Supplement, line 28, disaggregate?

Response: Done. Thank you (see line 28 in the supplement).

References

Cao, G. M., Tang, Y. H., Mo, W. H., Wang, Y. S., Li, Y. N., and Zhao, X. Q., 2004. Grazing intensity alters soil respiration in an alpine meadow on the Tibetan plateau. Soil Biol Biochem. 36, 237-243.

Lesiv, M., Schepaschenko, D., Buchhorn, M., See, L., Dürauer, M., Georgieva, I., Jung, M., Hofhansl, F., Schulze, K., and Bilous, A., 2022. Global forest management data for 2015 at a 100 m resolution. Sci Data. 9, 199.

Li, G., Zhang, Z., Shi, L. L., Zhou, Y., Yang, M., Cao, J. X., Wu, S. H., and Lei, G. C., 2018a. Effects of Different Grazing Intensities on Soil C, N, and P in an Alpine Meadow on the Qinghai—Tibetan Plateau, China. Int J Env Res Pub He. 15, 2584.

Li, L., Zhang, Y., Liu, L., Wang, Z., Zhang, H., Li, S., and Ding, M., 2020. Mapping Changing Population Distribution on the Qinghai–Tibet Plateau since 2000 with Multi-Temporal Remote Sensing and Point-of-Interest Data. Remote Sens., 4059.

Li, S., Wu, J., Gong, J., and Li, S., 2018b. Human footprint in Tibet: Assessing the spatial layout and effectiveness of nature reserves. Sci Total Environ 621, 18-29.

Li, X. H., Hou, J. L., and Huang, C. L., 2021. High-Resolution Gridded Livestock Projection for Western China Based on Machine Learning. Remote Sens. 13, 5038.

Lloyd, C. T., Sorichetta, A., and Tatem, A. J., 2017. High resolution global gridded data for use in population studies. Sci Data. 4, 1-17.

Masiliūnas, D., Tsendbazar, N.-E., Herold, M., Lesiv, M., Buchhorn, M., and Verbesselt, J., 2021. Global land characterisation using land cover fractions at 100 m resolution. Remote Sens Environ. 259, 112409.

Meng, N., Wang, L. J., Qi, W. C., Dai, X. H., Li, Z. Z., Yang, Y. Z., Li, R. N., Ma, J. F., and Zheng, H., 2023. A high-resolution gridded grazing dataset of grassland ecosystem on the Qinghai-Tibet Plateau in 1982-2015. Sci Data. 10, 68.

Mu, H., Li, X., Wen, Y., Huang, J., Du, P., Su, W., Miao, S., and Geng, M., 2022. A global record of annual terrestrial Human Footprint dataset from 2000 to 2018. Sci Data 9, 176.

Robinson, T. P., Wint, G. R., Conchedda, G., Van Boeckel, T. P., Ercoli, V., Palamara, E., Cinardi, G., D'Aietti, L., Hay, S. I., and Gilbert, M., 2014. Mapping the global distribution of livestock. Plos One. 9, e96084.

Sun, Y. X., Liu, S. L., Liu, Y. X., Dong, Y. H., Li, M. Q., An, Y., and Shi, F. N., 2021. Grazing intensity and human activity intensity data sets on the Qinghai-Tibetan Plateau during 1990–2015. Geosci

Data J. 9, 140-153.
Venter, O., Sanderson, E. W., Magrach, A., Allan, J. R., Beher, J., Jones, K. R., Possingham, H. P., Laurance, W. F., Wood, P., Fekete, B. M., Levy, M. A., and Watson, J. E., 2016. Global terrestrial Human Footprint maps for 1993 and 2009. Sci Data 3, 160067.
Wang, J. L., Liu, Y. Z., Cao, W. X., Li, W., Wang, X. J., Zhang, D. G., Shi, S. L., Pan, D. F., and Liu, W. L., 2020. Effects of grazing exclusion on soil respiration components in an alpine meadow on the north-eastern Qinghai-Tibet Plateau. Catena. 194, 104750.
Ye, T., Liu, W. H., Mu, Q. Y., Zong, S., Li, Y. J., and Shi, P. J., 2020. Quantifying livestock vulnerability to snow disasters in the Tibetan Plateau: Comparing different modeling techniques for prediction. International Journal of Disaster Risk Reduction 48.
Zhuang, M. H., Gongbuzeren, Zhang, J., and Li, W. J., 2019. Community-based seasonal movement grazing maintains lower greenhouse gas emission intensity on Qinghai-Tibet Plateau of China. Land Use Policy. 85, 155-160.