Response to Reviewer 4 Comments

Thank you for your letter commenting on our manuscript entitled "*Innovative Cloud Quantification: Deep Learning Classification and Finite Sector Clustering for Ground-Based All Sky Imaging*" (MS No.: egusphere-2024-678). These comments are valuable and very helpful for the revision and improvement of our paper. We have carefully studied and made corrections, and hope to get your approval. The main changes of the paper and the responses to the review comments are as follows.

Comments 1: The description of the deep neural network architecture and the process of finite element segmentation and clustering is detailed and provides a clear understanding of the approach. However, the authors might consider including additional visual aids or flow diagrams that could further elucidate the step-by-step process, especially for readers who may not be as familiar with the technical aspects of neural networks and image segmentation.

Response 1: Dear reviewers, thank you very much for your careful review and valuable suggestions on our paper. We fully agree with you that the description of deep neural network architecture, finite element segmentation and clustering process can be made more intuitive and understandable by adding visual aids, especially for those readers who are not familiar with neural network technology and image segmentation, and we will take the following steps to make the changes:

Add a flowchart: an adaptive image segmentation flowchart (shown in Figure 1) is added to the paper, which clearly shows the whole cloud detection process from all-sky image preprocessing results, deep learning classification to finite sector segmentation with K-means clustering, which will help the readers to intuitively understand how the various steps are implemented in sequence and the logical relationship between them.

Hopefully, this revision will improve the readability and comprehension of the article and ensure that the technical details are transparent and easy to grasp for all readers. Thank you again for your feedback, it is crucial for us to improve the quality of our paper, and we look forward to your further guidance on our revised manuscript.



Figure 1. Adaptive image segmentation process. (a) Image after preprocessing; (b) Sector segmentation based on cloud type; (c) Sector K-means clustering recognition; (d) Cloud recognition result.

Comments 2: The authors have used an extensive dataset from the Yangbajing station in Tibet. It would be beneficial to discuss the representativeness of this dataset in the context of other geographic regions or climatic conditions. If the model's applicability is limited to regions similar to the dataset's origin, this limitation should be explicitly stated.

Response 2: Dear reviewers, thank you very much for your valuable comments on our paper. You pointed out that we should discuss the representativeness of the extensive dataset originating from the Yangbajing station in Tibet in other geographic regions of the globe or under different climatic conditions, as well as clarifying whether the scope of model application is limited by the similarity of the regions from which the dataset originates. We fully agree with you that this is essential for assessing the generalizability and usefulness of the model. We have made the following changes and additions to the corresponding section of the paper:

"Due to the limitations of single-site data in revealing broader patterns of cloud variability, we have decided to incorporate data from more diverse geographic locations and climate conditions in future research to enhance the model's applicability to various geographical environments and climate scenarios. We plan to establish a multi-site, cross-regional cloud cover and cloud type dataset, which, through integration and comparison of data from different locations, can not only validate and optimize the proposed cloud cover quantification method but also assess its applicability and accuracy in different climatic backgrounds. While this study only conducted instance verification at the Yangbajing station in Tibet, the method proposed exhibits strong scalability and universality."

It is worth noting that we have designed our cloud quantization methods, including adaptive segmentation strategies, finite sector clustering, and illumination invariant image enhancement algorithms, to be flexible and scalable. Theoretically, with proper tuning and targeted training, these methods can be adapted to accommodate more diverse cloud cover and illumination conditions. However, the current research phase does have dataset geographical limitations, which we have explicitly pointed out in the paper to ensure scientific rigor in the interpretation and application of the results. We hope that the above additions express both a clear understanding of the limitations of the current study and a vision of the direction of future research.

Comments 3: The paper presents impressive classification accuracy rates. However, it would be advantageous for the authors to include additional validation, possibly through a comparison with other state-of-the-art methods or by applying the framework to an independent dataset to verify its generalizability.

Response 3: Thank you very much for recognizing our research and for your valuable suggestions. You mentioned that our paper demonstrated impressive classification accuracy, and also suggested that we further strengthen the validation, such as by comparing with other cutting-edge methods or applying the framework to independent datasets to verify its generalization ability. We fully agree with you that this will significantly enhance the persuasiveness and usefulness of our research results. Based on your suggestions, we plan to take the following steps to make additions and modifications:

In our paper, indeed, we employed a comparative analysis using the YOLOv8 model against the BoMS[1] method from 2016 on the TCI dataset, which evidenced substantial improvements. We are acutely aware of the dynamism and rapid pace of technological advancements within the field, as exemplified by a recent study where a streamlined convolutional neural network based on MobileNet[2] architecture achieved an overall accuracy of up to 97.45% on comparable public datasets. Additionally, other state-of-the-art cloud classification networks such as CloudNet [3], Transformer-based models [4], and Combined convolutional network [5] have also shown commendable results. However, due to the fact that this current work has not yet directly applied or conducted comprehensive comparative experiments with these cutting-edge algorithms on the same dataset, we were unable to provide a direct quantitative comparison in the present paper. Nonetheless, we wholeheartedly agree with your perspective and commit to incorporating these recent advancements in our future research agenda, thereby enabling a more thorough evaluation of the robustness and generalization capabilities of our YOLOv8 model architecture under complex meteorological conditions. To better convey this information, we have included an additional table (See Table 1 below; this is Table 4 from Chapter 5 of the thesis) in the revised version, which presents a comparative overview of our model's performance against the latest techniques reported in the literature concerning cloud quantification metrics. This visual representation serves to clearly illustrate the relative strengths and weaknesses of various methods, thus validating the efficacy of our model and contributing to the provision of more accurate and efficient cloud quantification solutions for climate science research. Once again, we thank you for your expert guidance and assure you that we will diligently incorporate your recommendations into the enhancement and refinement of our article's content.

Article	Dataset	Year	Model/Method	Accuracy(%)
Li et al. (2016)	TCI	2016	BoMS	93.80
Zhang et al. (2018)	CCSN	2018	CloudNet	88.0
Li et al. (2022)	ASGC	2022	Transformer	94.2
	CCSN			92.7
	GCD			93.5
Zhu et al. (2022)	MGCD	2022	Combined	90.0
	NRELCD		convolutional network	95.6
Fabel et al. (2022)	All sky images (Owned)	2022	Self-supervised learning	95.2
Gyasi et al. (2023)	CCSN	2023	Cloud-MobiNet	97.45
Ours	All sky images	2023	YOLOv8	98.19
	TCI			98.31

Table 1. Comparison of this study with the latest technological approaches in the literature.

 Li, Q.; Zhang, Z.; Lu, W.; Yang, J.; Ma, Y.; Yao, W. From pixels to patches: a cloud classification method based on a bag of micro-structures. Atmos. Meas. Tech. 2016, 9, 753-764. [CrossRef]

[2] Gyasi, E.K.; Swarnalatha, P. Cloud-MobiNet: An Abridged Mobile-Net Convolutional Neural Network Model for Ground-Based Cloud Classification. Atmosphere. 2023, 14. [CrossRef]

[3] Zhang, J.; Liu, P.; Zhang, F.; Song, Q. CloudNet: Ground-Based Cloud Classification With Deep Convolutional Neural Network. Geophys. Res. Lett. 2018, 45, 8665-8672. [CrossRef]

- [4] Li, X.; Qiu, B.; Cao, G.; Wu, C.; Zhang, L. A Novel Method for Ground-Based Cloud Image Classification Using Transformer. Remote Sens. 2022, 14. [CrossRef]
- [5] Zhu, W.; Chen, T.; Hou, B.; Bian, C.; Yu, A.; Chen, L.; Tang, M.; Zhu, Y. Classification of Ground-Based Cloud Images by Improved Combined Convolutional Network. Applied Sciences. 2022, 12. [CrossRef]

Comments 4: While the paper addresses illumination dynamics and their impact on cloud quantification, it would be interesting to see a more in-depth analysis of how different lighting conditions, such as those during sunrise and sunset, affect the accuracy of cloud detection.

Response 4: You mentioned that you would like to see a more in-depth analysis of the impact of different lighting conditions, especially the special lighting conditions at sunrise and sunset, on the accuracy of cloud detection, which is a very valuable research direction. We do notice that image recognition outside of these two time points becomes more difficult and prone to misclassification. At sunrise and sunset, the sun's angle is low and the light is oblique, resulting in a large change in the contrast between the light intensity on the ground and in the clouds, a change that may make the edges of the clouds blurry and increase the difficulty of distinguishing clouds from the background sky. For example, thin cloud layers and high altitude cirrus clouds may be difficult to recognize at dusk or dawn due to light scattering, affecting the accurate quantification of cloud cover. Due to sensor limitations, blue skies and clouds at night cannot be captured directly by visible light and need to be detected with other data. We have shown individual example recognition images for sunrise and night in Figure 2 below:



Figure 2 Cloud detection results at sunrise and night. (a) Example of full sky image at sunrise (b) Cloud recognition result in Figure a (c) Example of sky image at night (d) Cloud recognition result in Figure c

Comments 5: The discussion on the scalability and versatility of the approach is promising. To bolster these claims, a section on potential modifications or adaptations required to apply this framework to different meteorological stations would be beneficial.

Response 5: We strongly agree with the importance of your reference to the scalability and generalizability of the methodology in this paper, and your suggestion to add a discussion of potential adaptations or modifications needed to adapt the framework to different weather stations. With this in mind, we would like to add the following to the "5.2 Model scalability" section of the paper to strengthen our argument:

"In this study, although the example validation is only carried out at the Yangbajing station in Tibet, the method is highly scalable and universal, and the constructed end-to-end cloud recognition framework has the ability of generalization, and can be adapted to the cloud morphology characteristics of other geographic locations after appropriate model fine-tuning in the following ways:

(a) The climate characteristics of weather stations in different geographic locations are very different, such as high humidity in the tropics, extreme low temperature in the polar regions, and complex terrain in mountainous regions, for which the image preprocessing module needs to be adjusted as follows, (1) Climate-adapted image preprocessing: introduce region-specific light models and adjust the atmospheric light parameter A value in the image enhancement algorithm to adapt to the changes in the light under different climatic conditions, e.g., for the high latitude regions, the processing intensity of the defogging algorithm is strengthened to cope with the frequent fog and low-light conditions in winter; (2) terrain influence compensation: for mountainous or urban environments, the original zenith angle cropping range is modified to ensure that cloud identification is not interfered by surrounding environmental factors.

(b) Differences in all-sky camera models, resolutions and installation locations used by weather stations require the following adjustments to the reading module, (1) Modify the lens parameters in the algorithm configuration file, such as the image cropping range, the image suffix (e.g., jpg, png, etc.), and the image resolution standard. (2) Adjust the common data interface to ensure that the system can seamlessly access different brands and models of cloud cameras and data recording equipment to achieve automatic loading and standardized processing of data.

(c) Considering the specific needs of different weather stations, the system can provide highly personalized configuration options: (1) Parameter number configuration template: Provide preset parameter templates to set the optimal identification parameters and algorithm configurations for different climatic regions (e.g., tropical rainforests, deserts, and poles) and the frequency of occurrence of cloud types. (2) Dynamic adjustment mechanism: Dynamically adjust the algorithm parameters, such as the K value of K-Means clustering and the threshold value of cloud type identification, according to the system operation status and identification accuracy, in order to optimize the identification effect."

Thank you again for your review and guidance; we have made substantial improvements in the revised manuscript as suggested here and will fully reflect these improvements in future revisions of the paper. **Comments 6:** *Ensure consistency in terminology, especially when referring to the various neural network components and cloud types, to avoid confusion.*

Response 6: Thank you very much for your valuable feedback, your correction on the consistency of terminology plays a key role in improving the quality of the paper. In response to your suggestion, we have carefully revised the terminology to ensure that all references to neural network components and cloud types are consistent throughout the paper, so as to avoid potential confusion, some of the changes are as follows:

(1) The nomenclature of the four cloud types has been standardized, and the terms "cirrus", "clear sky", and "cumulus" are strictly used in the text, figures, and references. cumulus", and "stratus" are strictly used to ensure the accuracy and consistency of the terminology.

(2) For the adopted deep learning framework, we have clarified YOLOv8 as the unified title of the core algorithm in this paper, and maintained the consistency of this expression in all related discussions and descriptions, avoiding abbreviations or other variants that may cause confusion.

(3) The description of the internal structure of the YOLOv8 framework has been further calibrated to ensure that network components such as Darknet-53 and C2f modules are referred to with precise expressions that match the actual structure of the framework.

We are confident that these revisions not only enhance the clarity and professionalism of the paper, but also enhance the reader's comprehension experience. Thank you again for your careful review and constructive comments, which have greatly contributed to the rigor of our research and the accuracy of our presentation. We look forward to your further guidance on the revised manuscript, and we are willing to make continuous improvements to meet the high standards of academic publication.

Comments 7: The use of precision, recall, and F1-score is appropriate. Including additional statistical analyses, such as a confusion matrix, would provide a more comprehensive overview of the model's performance across all classes.

Response 7: Thank you very much for your in-depth review of our study and your valuable suggestions. Your proposal to include a confusion matrix to complement the existing precision, recall, and F1 score evaluations is one that we fully agree with. Confusion matrix, as a powerful visualization tool, can indeed provide a comprehensive and nuanced view of the model's performance on all the categories, which helps to gain a deeper understanding of the classification correctness and error patterns among the categories, as shown in Figure 3 below for the validation set:



Figure 3. Confusion matrix results of the model on the validation set

Although we have not yet directly included the confusion matrix in the current submission, we value this constructive feedback from you and in the future, in further studies or extended versions of the paper, we plan to integrate the confusion matrix analysis to enhance the comprehensiveness of our model performance evaluation. This will not only help readers intuitively identify the strengths and weaknesses of the model across categories, but also facilitate effective comparisons with other research efforts, and we thank you again for your guidance in enhancing the rigor and transparency of our research.

Comments 8: The authors have briefly mentioned future work in improving the model's adaptability to overexposed regions. Elaborating on potential avenues for future research, such as incorporating additional atmospheric parameters or exploring the effects of climate change on cloud dynamics, would be insightful.

Response 8: Your insights about future work are pertinent and we deeply agree with them and have decided to further expand the discussion of future research directions by making the following additions and modifications to the Discussion section of the paper's conclusion:

For overexposed regions: (1) plan to incorporate additional meteorological data, such as temperature, humidity, and wind speed, into our predictive models by combining these parameters with image data to refine our understanding of cloud formation dynamics and improve model accuracy under variable atmospheric conditions; (2) explore the temporal evolution of cloud patterns and their response to global warming trends, analyze historical and projected climate data to quantify how changes in temperature gradients, precipitation patterns, and atmospheric stability affect cloud morphology and distribution, and to develop models that can predict long-term changes in cloudiness, thereby contributing to climate prediction models; (3) To address the challenge of overexposure, we plan to investigate and implement state-of-the-art exposure correction algorithms, such as adaptive histogram equalization or high dynamic range (HDR) imaging, that can mitigate the effects of overexposure and thereby improve the accuracy of models under bright conditions.

effects, thereby improving the model's ability to accurately identify cloud features under bright illumination conditions; (4) combining ground-based imagery with satellite data and potentially other remote sensing techniques can provide complementary perspectives on cloud cover and dynamics, and integrating these different data sources may enhance our ability to comprehensively model cloud systems, especially in regions where ground-based observations alone may not be sufficient.

Comments 9: The cited literature it is currently poor, I suggest to the authors to cite relevant studies on cirrus clouds and their importance.

Response 9: Thank you for your valuable comments on our paper, especially on the literature citation, we plan to enhance the literature support of the paper by including the following references:

[1] Gouveia, D. A., Barja, B., Barbosa, H. M. J., Seifert, P., Baars, H., Pauliquevis, T., and Artaxo, P.: Optical and geometrical properties of cirrus clouds in Amazonia derived from 1 year of ground-based lidar measurements, Atmos. Chem. Phys., 17, 3619-3636, 10.5194/acp-17-3619-2017, 2017. This study provides the one year of observational data on the optical and geometric properties of cirrus clouds in the Amazon region, which provides important information for understanding the role of cirrus clouds in the tropics.

[2] Marsing, A., Meerkötter, R., Heller, R., Kaufmann, S., Jurkat-Witschas, T., Krämer, M., Rolf, C., and Voigt, C.: Investigating the radiative effect of Arctic cirrus measured in situ during the winter 2015-2016, Atmos. Chem. Phys., 23, 587-609, 10.5194/acp-23-587-2023, 2023. The paper explores in detail the winter 2015-2016 field measurements of Arctic cirrus clouds, revealing their radiative effects, which are important for understanding the impact of polar cirrus clouds on the global energy balance.

[3] Shi, X. and Liu, X.: Effect of cloud-scale vertical velocity on the contribution of homogeneous nucleation to cirrus formation and radiative forcing, Geophys. Res. Lett., 43, 6588-6595, 10.1002/2016GL069531, 2016. This study focuses on the homogeneous nucleation process of cirrus cloud formation, especially the effect of intracloud vertical velocity on this process and the potential impact on radiative forcing, which provides a new perspective on the microphysical mechanism of cirrus cloud formation.

By citing this literature, we not only strengthen the scientific basis of the paper, but also enrich the discussion on the physical properties of cirrus clouds, their radiative effects, and their behavior under different regional and climatic conditions. We believe that these additions will significantly enhance the comprehensiveness and depth of the paper, and we look forward to your further review of the revised manuscript and welcome any additional feedback and suggestions.