Response to Reviewer 2 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 review of existing traditional cloud detection methods is not comprehensive enough, and a more systematic evaluation of their strengths and limitations is needed.*

Response 1: Thank you very much for your valuable suggestions on the review section of traditional cloud detection methods. In the original manuscript, we indeed did not provide a comprehensive and systematic assessment of the existing traditional cloud detection methods, especially failing to fully elaborate on the advantages and limitations of each method. To improve this, we will deepen and expand this section in the revised manuscript to ensure that readers can gain a more complete and in-depth understanding.

In the "Introduction" chapter of the new revised version, we will introduce the application of traditional image processing techniques in cloud detection, including threshold segmentation and texture analysis, compare their performance in different scenarios, and analyze their adaptations in dealing with complex lighting conditions, cloud diversity, and ground object occlusion, etc., and analyze their adaptability and limitations when dealing with complex lighting conditions, cloud type diversity, and ground occlusion. At the same time, we will cite more related research literature to reflect the comprehensiveness and objectivity of the evaluation of existing methods.

In addition, we will especially emphasize the characteristics of traditional methods in data processing and real-time, such as the advantages of cloud radar in vertical structure detection and satellite remote sensing in large-area coverage, while pointing out their deficiencies in resolution, local small-scale cloud detection, and light sensitivity. Through such comparative analysis, we will be able to highlight more clearly the innovation and necessity of adopting deep learning and adaptive segmentation strategies in this research.

Once again, we thank you for your professional guidance in this research direction, and we will fully incorporate your comments in the upcoming revisions, with a view to making this paper a stronger demonstration of the advancement and practicability of our proposed method based on evaluating and comparing traditional cloud detection methods.

Comments 2: *Although data from the Tibetan Plateau site was used, the spatial representativeness is still limited due to the use of a single site. Future work should consider incorporating data from multiple regions to enhance the model's broad applicability.*

Response 2: Dear reviewer, you have pointed out that this study only uses data from the Yangbajing station on the Tibetan Plateau, so there are some limitations in spatial representativeness, which is a direction we should focus on when further improving and expanding our research work in the future. We also recognize the limitations of single-site data in revealing the pattern of cloud cover change over a larger region, and we have decided to incorporate more data from meteorological stations with different geographic locations and climatic conditions into our future studies to enhance the generalizability of the model to a wide range of geographic environments and climatic scenarios. *We plan to build a dataset containing multi-site, cross-geographic cloud amount and cloud type data. By integrating and comparing data from different locations, we can not only validate and optimize the currently proposed cloud quantification method, but also assess its applicability and accuracy in different climatic contexts.*

In the next iteration of the study, we intend to actively collaborate with other meteorological observatories to share and integrate all-sky imaging data from multiple meteorological stations around the globe, with the aim of creating a large dataset that is more reflective of the diversity of global climatic features and cloud variability. The purpose of doing so is to further enhance the value and credibility of the application of automatic cloud identification and quantification techniques in global climate research.

We thank you again for your review and guidance, and we have made substantial improvements in the "Discussion" section of the revised manuscript in response to this suggestion, and will fully reflect these improvements in future revisions of the paper.

Comments 3: *While the association between cloud amount and solar radiation is mentioned, no in-depth discussion is provided. It is recommended to further analyze the influence of different cloud types on solar radiation characteristics.*

Response 3: Your valuable suggestions on this study are sincerely appreciated. You have pointed out that although the correlation between cloudiness and solar radiation is mentioned in the paper, the extent to which the relationship between the two is explored in depth is not yet sufficient, in particular the lack of a specific analysis of the effect of different types of cloud cover on the solar radiation characteristics. We fully recognize your comments and set out for you in this response how we plan to improve this section.

In the Discussion section of the revised manuscript, we plan to discuss the effects of different types of clouds on solar radiation characteristics, analyzing in detail how cirrus, cumulus, stratocumulus, and clear-sky conditions can alter the Earth's energy balance through their different absorption, scattering, and reflection characteristics of shortwave and longwave radiation. We will analyze a large amount of satellite image data to construct a solar radiation model using machine learning techniques such as XGBoost, CNN-LSTM, etc., in conjunction with the research results of Rocha and Santos (2022), in order to deeply investigate the *mechanism of the various types of clouds affecting the solar radiation in the temporal and spatial dimensions. Meanwhile, the cloud detection technique proposed in this study is utilized to more precisely quantify the blocking and greenhouse effects of different types of clouds on solar radiation flux, especially how different types of clouds affect surface temperature and energy balance in different seasonal and regional contexts. In addition, we will draw on the research ideas of Matsunobu et al. (2021) to visualize the specific effects of different cloud amounts on the solar radiation balance by analyzing the unique visual characteristics of cloud cover in remote sensing images.*

We will practically implement your suggestions in the subsequent revisions to enhance the overall academic value and impact of the paper.

Comments 4: *Although the methodology is clearly presented, some details regarding equations, parameters, and symbols are not comprehensively explained, requiring further elaboration and clarification to ensure the reproducibility and transparency of the research work. Specifically: An explanation of the variables TP, FP, TN, and FN used in the evaluation metrics such as precision, recall, and F1-score, along with their calculation methods, should be provided to facilitate better understanding of the evaluation system.*

Response 4: Thank you very much for your valuable suggestions on the calculation methods of cloud classification performance evaluation metrics in this paper. Based on your review comments, we will further clearly explain the three core variables used in the evaluation metrics, TP, FP, and FN, as well as their specific calculation methods in the revised paper to enhance readers' understanding of the whole evaluation system.

In the context of cloud classification tasks, we define the following:

True Positive (TP): The actual number of positive samples correctly predicted by the model (i.e., cloud category), representing the number of true cloud images identified by the model.

False Positive (FP): The number of samples incorrectly predicted as positive but actually belonging to the negative class (non-cloud category), indicating the number of cloud images erroneously classified by the model.

False Negative (FN): The number of samples incorrectly predicted as negative but actually belonging to the positive class, representing the number of cloud images missed by the model.

We have explained these concepts and their calculations in detail in the "Cloud Classification Evaluation Indicators" section of the revised draft so that readers can better grasp the performance evaluation criteria of the model in cloud classification tasks.

Comments 5: *Although the methodology is clearly presented, some details regarding equations, parameters, and symbols are not comprehensively explained, requiring further elaboration and clarification to ensure the reproducibility and transparency of the research work. Specifically: The details of the image enhancement algorithm for dehazing need to be thoroughly described, especially the processes for obtaining the key parameters, atmospheric light A and transmission rate t, to ensure the reproducibility of the image enhancement step.*

Response 5: Thank you for your attention and valuable suggestions on the details of image enhancement algorithm de-fogging in this paper. In the revised paper, we have fully responded to your request by describing in detail the key steps of the de-fogging process and the parameter acquisition method to ensure the reproducibility of the image enhancement session. Our image enhancement algorithm adopts the dark channel prior algorithm, and its main process is as follows:

(a) Computing the dark channel image: For each pixel in the input image, the dark channel image is computed by selecting the minimum value among its RGB channels. The dark channel image reflects the minimum brightness within pixel regions, where low brightness regions typically correspond to areas containing haze, providing us with clues for estimating haze information.

(b) Estimating the global atmospheric light A: The global atmospheric light intensity A is estimated using the minimum non-zero value in the dark channel image. Atmospheric light serves as the background light source that affects the overall scene brightness, playing a crucial role in the haze scattering model.

(c) Obtaining the transmission rate t: Based on the atmospheric scattering model, the transmission rate t is calculated for each pixel in the image, representing the visibility of the pixel. The transmission rate reflects the extent of haze's impact on light propagation.

(d) Applying the dehazing formula: The dehazed enhanced image $J(x) = I(x) * (1 - A)t + A$ *is applied, where J represents the dehazed image, and I is the original input image. Through this dehazing algorithm, haze in the image can be effectively removed, making cloud layers and the boundary of the blue sky more distinct, which is beneficial for generating high-quality cloud cover data.*

In particular, when dealing with different types of cloud layers, we have devised adaptive enhancement strategies for varying cloud thicknesses. For instance, for thin stratocumulus clouds, to avoid excessive enhancement and filter out cloud layer details, a smaller atmospheric light value A is chosen. In contrast, for thicker cumulus, stratocumulus, and clear sky images, a larger atmospheric light value A is used to enhance the removal of overexposed areas and achieve a more uniform sky distribution.

Thank you again for your review and guidance, and we believe that the requirement of ensuring the reproducibility of the image enhancement steps has been fulfilled by the above detailed description. If necessary, we can also provide more detailed algorithm implementation steps and parameter adjustment basis for peer scholars' reference and verification.

Comments 6: *Although the methodology is clearly presented, some details regarding equations, parameters, and symbols are not comprehensively explained, requiring further elaboration and clarification to ensure the reproducibility and transparency of the research work. Specifically: The finite sector K-means clustering segmentation strategy employs different numbers of sectors for different cloud types, but the rationale and basis for this setting are not explained. The authors should clarify the reasons behind the chosen sector numbers for each cloud type.*

Response 6: Thank you for your valuable comments on the paper, particularly regarding the rationale and basis for setting different numbers of sectors for different cloud types in the finite sector K-means clustering segmentation strategy. Based on your feedback, we recognize the need for a more detailed explanation of this key design decision. In the study in this paper, we have designed different sectorization schemes for each of the four typical cloud patterns - cirrus, clear sky, cumulus, and stratocumulus. This differentiated setup is based on the following rationale:

(a) Cirrus clouds, due to their weak shape and color similarity to the sky, pose significant identification challenges. To capture cirrus cloud features more finely, we segment the entire sky image into 72 sector areas. More sectors aid in extracting subtler color and texture variations, thereby enhancing the clustering algorithm's accuracy in distinguishing cirrus clouds from other celestial elements.

(b) Clear sky images, containing fewer elements, require only 4 sectors for effective differentiation. This avoids unnecessary subdivisions, reducing computational complexity and enhancing algorithmic execution efficiency and classification accuracy in simple scenes.

(c) Cumulus clouds exhibit distinct edges, but uneven lighting may cause visual disturbances. To balance edge information capture and internal structure consistency, we divide them into 36 sector areas. This ensures both cloud boundary recognition and adaptation to potential lighting differences within cumulus clouds.

(d) Stratocumulus images consist of relatively few and evenly distributed elements. Therefore, they are also divided into 4 sectors to meet the clustering analysis requirements, maintaining necessary spatial resolution while avoiding noise and redundant calculations resulting from excessive sectorization.

The selection of these sectors is based on a large amount of measured data and an in-depth understanding of cloud morphology, and we experimentally verified that these adaptive segmentation strategies significantly improve the accuracy of the clustering algorithm in identifying different types of cloud cover. In the "3.4 Finite Sector Segmentation and K-means Clustering" section of the revised paper, we will further clarify the theoretical basis for choosing a specific number of sectors for each cloud type, in order to let the readers understand and agree with our methodological foundation more comprehensively. We hope that readers will more fully understand and agree with the basis of our methodology. Thank you again for your review and suggestions, and we look forward to answering your questions and improving the quality and scientific value of the paper in the revised manuscript.