Dear Editor-in-Chief of ECRS2023 Conference

First of all, on behalf of co-author, I would like to express our appreciations to the Editor-in-Chief and anonymous reviewers for valuable and constructive comments to this manuscript. We believe that these precious suggestions and comments have greatly strengthened our paper. We answer all reviewer comments point by point below. You will find the reviewer comment in ***bold*** *and our answer in italic letters. We have addressed all the comments as explained below (****Q#:*** **Question***, A#: Answer and highlight: The related revised text of the paper is reported). We have done many efforts to consider all reviewers' comments and suggestions to improve the paper. So I hope this version of paper could be acceptable for the reviewers.*
Please find enclosed the revised version of our paper ().

Thanks again for your help and support,
Best regards,

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16 January 2024
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REVIEWER #1

Q1: ***The paper compares the proposed method to bicubic interpolation but lacks comparisons with other state-of-the-art super-resolution techniques?***

A1: Thank you very much for your valuable comments, I appreciate your insightful feedback. As per your suggestion, we conducted a comparative analysis between EDSR and our proposed method and the result shown in table1.

Q2: ***The paper briefly mentions modifications to the SRResNet architecture but lacks a detailed explanation of the rationale behind these changes.***

A2: Done. We added this paragraph in the section "2.Method".
The modifications to the SRResNet architecture aim to address issues related to training convergence, perceptual quality, sensitivity to noise, and handling variations in illumination and color. The incorporation of a learning rate decay strategy and perceptual loss is motivated by the desire to improve the overall performance and visual quality of the super-resolution model. By using perceptual loss, the model is encouraged to generate outputs that not only match the ground truth at the pixel level but also capture higher-level features like textures, structures, and object semantics. This often leads to visually more pleasing and semantically meaningful results.

Q3: ***The paper mentions the use of the SEN2VENµS dataset but lacks details on its size, diversity, and any potential biases.***

A3: Thank you for your insightful comment, we added more details in the "3. Results and discussions" section.
We have harnessed the comprehensive SEN2VENµS dataset to enhance the depth and robustness of our findings. This dataset, detailed in the referenced paper, comprises an extensive collection of 132,955 patches, collectively amounting to 116 gigabytes of data. Spanning 29 distinct sites across various geographical locations, the dataset showcases a diverse array of landscapes, including natural, semi-natural, urban areas, forests, and shorelines. This diversity is observed over a two-year period, encapsulating different seasons and contributing valuable context to our study. Acknowledging an inherent imbalance in patch distribution across sites, it's crucial to recognize that this imbalance is distinctive in nature, focusing on capturing the inherent variability and equity among different landscape types rather than adhering to a conventional uniform distribution of patches per site. the SEN2VENµS dataset serves as a robust foundation for our research, providing both substantial size and a nuanced appreciation of its diversity.

Q4: ***The learning rate decay strategy is mentioned, but the paper lacks clarity on specific parameters, thresholds, and the reasoning behind choosing this strategy.***

A4: Thanks for your feedback. We added this paragraph in "2.1. Make improvements in SRResNet architecture" section.

In our experiments, we monitored the validation loss, and if it did not improve after two consecutive loops, we multiplied the learning rate by a decay factor of 0.9. Multiplying the learning rate by a decay factor of 0.9 reduces the step size during optimization, allowing the model to make smaller adjustments to its parameters and potentially escape local minima or plateaus in the loss landscape.This strategy encourages the model to fine-tune its parameters and make more precise adjustments, leading to improved performance.

Q5: ***The conclusion is brief and lacks a summary of key findings and potential future work***

A5: Done. We added this paragraph in "4. Conclusions and future work" section.
In this study, we have introduced a novel approach for achieving 2x super-resolution of Sentinel-2 RGB bands, enabling a resolution of 5m. Empirical results showcase the potential of our methodology in the domain of satellite image super-resolution, particularly in the context of Sentinel-2 imagery. Our proposed methodology opens avenues for future research and exploration and demonstrated notable success in enhancing the resolution of Sentinel-2 RGB bands, providing clear benefits for applications requiring finer spatial details. The incorporation of a learning rate decay strategy and perceptual loss in the SRResNet architecture contributed to improved convergence and perceptual quality in the generated images.

The authors would like thank again the academic editors and other reviewers for their comments that help us to improve the quality of this manuscript.