Dear Editor and Reviewers:

Thanks for your comments concerning our manuscript entitled “GloUTCI-M: A Global Monthly 1 km Universal Thermal Climate Index Dataset from 2000 to 2022”. (No.: essd-2023-379). Those comments are all valuable and very helpful for revising and improving our paper, as well as the important guiding significance to our researches. We have studied comments carefully and have made correction which we hope meet with approval. The main corrections in the paper and the response to your comments are as follows:

Reviewer #1:

Thanks for your comments on our paper. We have revised our paper according to your comments:

This manuscript generated a global monthly 1 km universal thermal climate index dataset from 2000 to 2022. This work is meaningful and the result is basically satisfactory. However, some other problems in the manuscript are still concerned in the following:

Response:

Thank you for your nice comments on this research. We have revised the manuscript based on your comments and suggestions. These comments are valuable and helpful in revising and improving our paper, as well as providing important guidance for our research.

01. The authors applied XGBoost series methods to generate the dataset. Why not use deep learning models?

Response:

Thanks for your insightful question regarding our choice of using XGBoost series methods to generate the dataset instead of deep learning models. The decision to employ XGBoost series methods was based on several considerations specific to our research context.

Firstly, the nature of our dataset and the characteristics of the features make XGBoost series methods particularly well-suited. XGBoost series methods is known for its efficiency in handling tabular data, especially when dealing with a moderate-sized dataset with a relatively large number of features. It often outperforms deep learning models in such scenarios. Furthermore, the training time and computational resources required for deep learning models can be substantial, especially considering the scale of our dataset. XGBoost series methods offer a good balance between model performance and computational efficiency, which is essential for our research objectives.

It's worth noting that we acknowledge the potential of deep learning models and their success in various domains. However, for the specific tasks addressed in our study, we found that XGBoost series methods align better with our objectives and constraints. Following your suggestion, we have elaborated in the manuscript the reasons for choosing to use machine learning models rather than deep learning models to generate the dataset.

The following is the revised version:

(Lines 180-182) We apply machine learning models to produce the UTCI dataset because they are more suitable for handling tabular data and provide a good balance between model performance and computational efficiency compared to methods such as deep learning models.

02. More information on XGBoost, LightGBM and CatBoost should be exposed.

Response:

Thanks for your request for more detailed information on XGBoost, LightGBM, and CatBoost. Below, I provide an expanded overview of each algorithm:

XGBoost: Known for its high performance and accuracy, XGBoost is particularly effective for tabular data. It excels in capturing complex relationships within the data and provides robust predictions. The regularization techniques in XGBoost help prevent overfitting, making it suitable for our dataset.

LightGBM: LightGBM is designed for efficiency and scalability. It uses a histogram-based approach for tree construction, which accelerates the training process and makes it well-suited for large datasets. Its ability to handle categorical features efficiently is advantageous for our diverse feature set.

CatBoost: CatBoost is specifically designed to handle categorical features without the need for extensive preprocessing. This makes it convenient for our dataset, which contain a mix of categorical and numerical features. CatBoost's categorical boosting approach contributes to its robust performance.

All three algorithms (XGBoost, LightGBM, and CatBoost) are well-documented, widely used, and supported by a large community. This ensures ease of implementation and troubleshooting, facilitating a smoother integration into our research.

The following is the revised version:

(Lines 188-191) XGBoost is particularly effective for tabular data. It excels in capturing complex relationships within the data and provides robust predictions. It excels as a tool for massively parallel boosting trees and is characterized by its efficiency, flexibility, and portability.

(Lines 203-206) It uses a histogram-based approach for tree construction, which accelerates the training process and makes it well-suited for large datasets. Its ability to handle categorical features efficiently is advantageous for diverse feature set. LightGBM utilizes a leaf-wise tree growth strategy to select the leaf node with the highest gain at each split, enabling faster, deeper tree growth and improving model accuracy.

(Lines 213-216) CatBoost is specifically designed to handle categorical features without the need for extensive pre-processing. It computes statistics on categorical features, such as category frequency, and uses hyperparameters to generate new numerical features. CatBoost's categorical boosting approach contributes to its robust performance.

03. As stated in "Making the Earth clear at night: a high-resolution nighttime light image deblooming network", NTL data are subject to degraded issues. Did the authors preprocess NTL data?

Response:

Thank you for bringing attention to the potential degraded issues in the NTL data. We selected the NPP-VIIRS-like NTL data as the NTL data used. NPP-VIIRS-like NTL data have an excellent spatial pattern and temporal consistency which are similar to the composited NPP-VIIRS NTL data.

The proposed cross-sensor calibration is unique due to the image enhancement by using a vegetation index and an auto-encoder model. The production process of the NPP-VIIRS-like NTL data has implemented a series of preprocessing steps (Noise Reduction, Radiometric Calibration, Spatial Resolution Enhancement, Temporal Filtering), which can improve the resolution of potential degradation issues in NTL data. We have supplemented the revised manuscript with a more detailed description of the NPP-VIIRS-like NTL data.

The following is the revised version:

(Lines 114-118) NTL is indicative of human activities and urbanization. We utilized NPP-VIIRS-like NTL data, available at a spatial resolution of 500 m. This dataset effectively combines data from two NTL sources (DMSP-OLS and NPP-VIIRS), extending the temporal range of NTL observations (Chen et al., 2021). In response to the potential degradation of NTL data (Bai et al., 2023), a series of pre-processing steps in the production of NPP-VIIRS-like NTL data and the proposed cross-sensor calibration can effectively improve the problem.

04. More recent works are suggested to be included

Response:

Thanks for your valuable suggestion to include more recent works in our manuscript. In response to your suggestion, we have conducted a literature review to identify and incorporate relevant and recent works that contribute to the advancements in our research topic.