Reviewer 2

The title could be revised as: "Leveraging machine learning for quantitative precipitation estimation from Fengyun-4 geostationary observations and ground meteorological measurements"

RESPONSE: Thanks, it has been revised per your suggestion.

"Large-scale and high-quality precipitation products derived from satellite remote sensing spectral data have always been a challenging issue in satellite quantitative precipitation estimation (QPE) . Moreover, QPE research related to China's Fengyun-4A (FY-4A) geostationary satellite is still very limited." could be revised as: "Deriving large-scale and high-quality precipitation products from satellite remote sensing spectral data is always challenging in quantitative precipitation estimation (QPE), and limited studies have been conducted even using the China's latest Fengyun-4A (FY-4A) geostationary satellite."

RESPONSE: Thanks, it has been revised.

Line 156: "We constructed an RF model through the RF data package in R language, and established a relationship model of the satellite spectrum, cloud parameters and precipitation for the inversion and prediction of precipitation" could be changed to "A data-driven regression model was established between the observed precipitation and satellite spectrum as well as cloud parameters using the RF method."

RESPONSE: Thanks, it has been revised.

Figure 1: legend notations should be corrected, e.g., all_station should be automatic station?

RESPONSE: Thanks for pointing out, we have revised them in this revision.

Figure 4: the results indicate significant over-fitting issue of these two prediction models, what are possible reasons? Also, the high precipitation was underestimated, is there any possible way to address this?

RESPONSE: Thanks for your valuable comments. We think that the significant over-fitting issue could be attributable to the high complexity of the RF model. Reducing the number of predictors based on clustering thought is an effective way to reduce the complexity of the RF model, but different dimensionality reduction or feature optimization methods are suitable for different datasets and scenarios. The QPE algorithm established in this paper has high accuracy, so we will not discuss over-fitting in detail in this paper.

At the same time, the over-fitting of machine learning is mainly attributed to the inadequacy of the non-linear model in terms of data extension. Once the training data lacks representativeness, it will have a great impact on the prediction accuracy. Our research data is 48 hours of continuous precipitation, the number of the high precipitation samples in the dataset is relatively low. That is why it is underestimated.

Here we give a possible way to avoid the underestimation of the high precipitation. Based on past precipitation cases, a large number of high precipitation (heavy rain level and above) samples are selected for RF model training, and an algorithm suitable for estimating high precipitation is constructed by correcting model parameters and predictor dimensionality reduction. In actual application, the predictors are input into the universally applicable QPE algorithm established in this paper (which will underestimate high precipitation) and the

high precipitation estimation algorithm respectively. The estimation results of moderate rain level and below in the universally applicable QPE algorithm and the estimation results of heavy rain level and above in the high precipitation estimation algorithm is used as the final precipitation estimation results.

Figure 9: large biases were observed for stations located in mountain areas, maybe the inclusion of DEM as a predictor could account for such biases.

RESPONSE: Thanks for your constructive comments. By following your suggestion, we added DEM as a regressor in the model, and large biases over stations located in mountain areas were greatly reduced.