Dear Referee:

Thanks very much for your great support and constructive suggestions with regard to our manuscript. These 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 made our best efforts to improve our paper very carefully following your comments and suggestions. Our point by point response to the comments are given below. We hope the revised manuscript will be acceptable to your requirements. If still there are concerns, we will be happy to take care once we hear from you.

Comment 1: In the simulated dataset at section 3.1.1. For component V1, do negative values affect the result? The distance resolution is set as 0.5, why? Why not 1 or 2..?

[Response]: Thanks for your comment.

In our simulated case, V1 will not be negative according to our setting. Even if V1 is negative, it will not affect the performance of the GSARNN model. This is because the training process is driven by the loss (MSE in our experiments), and the loss represents the deviation of the interpolated value from the real value, which is equivalent for positive V1 and negative V1.

Setting distance resolution as 0.5, 1 or 2 is equivalent. Different distance resolutions are only different in global magnification, but the relative positions of sample points and the spatial distribution characteristics of element values are the same.

Comment 2: In Section 3.1.2 authors experiment on "1,555 data points in the training set and 173 data points in the validation set". Does the number of data points affect the performance of the algorithm? How?

[Response]: Thanks for your very helpful comment. We use the 10-fold cross-validation method for model training, which is a common strategy. The 10-fold cross-validation randomly divides the dataset into 10 equal portions, among which nine portions serve as the training set, and the remaining portion is used as the validation set in turn. This ensures that each sampled point is used as training data and

validation data, avoids the impact of data division on results, and fully verifies the performance of interpolation methods. A big fold number will lead to a long training time; a small fold number will cause the training set to be too small to fully learn the data characteristics.

Comment 3: For section 3.1.3, what is the settings for OK method?

[Response]: Thanks for your very helpful comment. In OK method, we adopt the gaussian model to fit the functional relationship between the semi-variogram and the spatial distance, which turns out to be the optimal variation function model among linear, gaussian, spherical and exponential models. Some explanations have been added in Section 3.1.2, Paragraph 2.

"Besides, the power parameter of IDW method is 4, and in Kriging method, we adopt the gaussian model to fit the functional relationship between the semi-variogram and the spatial distance, which turns out to be the optimal variation function model among linear, gaussian, spherical and exponential models."

Comment 4: What are limitations and challenges of your algorithm?

[Response]: Thanks for your provident comment. In GSARNN model, as the number of sampled points increases, the number of input neurons and output neurons of the GSARNN will also increase, resulting in the expansion of network parameters and the extension of training time inevitably. This limits the application of the model in scenarios with large amounts of data. How to maintain a stable and acceptable training time given different sample data volumes is a challenge to be tackle in further researches. Some discussions have been added in Section 5 Conclusion.

"In addition, as the number of sampled points increases, the number of input neurons and output neurons of the GSARNN will also increase, resulting in the expansion of network parameters and the extension of training time inevitably. Therefore, how to maintain a stable and acceptable training time given different sample data volumes is an important problem to be tackled in further researches."