Author’s Response

We thank all the Anonymous Referees for their comments about our research and we are pleased to find that our manuscript was carefully reviewed. All the comments are valuable and helpful for our manuscript improving. We have studied these comments carefully and have made corrections which we hope to meet with approval. Here are the specific responses to each Referee comment and the detailed modifications of the manuscript. Since the Anonymous Referees#1 agreed with the previous revisions of this manuscript and did not propose more revision requirements, we mainly response to the comments of the other two Referees.

Report #2

Point 1: The article is lack of systematic analysis to the application research progress of this model in crop drought assessment field.

Response 1: Thanks to referee for pointing out the above issues. We have revised and supplemented the analysis on the application research progress of the EPIC model (Please refer to page 5, line 3-22). We first review its simulation performance under different water stress environments, which shows that the model has good crop yield simulation capabilities (Bryant et al., 1992;Ko et al., 2009). On this basis, we further introduced its application in crop drought assessment field, including irrigation management (Rinaldi, 2001), drought impact prediction (Webber et al., 2018;Leng and Hall, 2019) and drought vulnerability assessment (Wang et al., 2013;Kamali et al., 2018c). It is found that the model can effectively provide fine yield loss data for drought assessment by inputting drought scenario data, which means it can be a good technical support for our research.

Point 2: The author should state how to choose the curve of vulernability assessment, rather than a straight line.

Response 2: We are very grateful to the referee for his/her valuable comments. The vulnerability curve describes the functional relationship between drought intensity and loss. As drought intensify, disaster losses begin to appear and gradually increase until the end of the disaster. That is regarded as an interactive process of energy accumulation and resisting effect (Chen et al., 2015;Chen et al., 2017). Drought intensification brings about energy accumulation, which will be released when it reaches a certain level; meanwhile, resistance, such as system adjustment ability, always exists. In the initial stage, it appears as a slow development of drought due to insufficient energy storage and the existence of resistance. And if the driving force is stopped or weakened, the energy accumulation basically ends. Otherwise, energy will continue to accumulate, then break through the resistance and release, resulting in explosive development. Finally, the drought event gradually subsided with energy attenuation and resistance influence.

The linear trend cannot well describe the above-mentioned beginning and end of disaster changes, and it tends to mean that the disaster growth will not end. Therefore, we argue that the relationship between drought intensity and loss is a non-linear, monotonically increasing function, and has at least two critical points representing the initial, development and attenuation stages change. These characteristics are consistent with the S-shaped curve. So we select the typical logistics model in the S-shaped curves for vulnerability curve construction (Skrobacki, 2007). We have modified the Section 2.1 of the manuscript to better illustrate this point (Page 3, line 21-Page 4, line6).

Point 3: The author needs to explain what is the improvement over previous research about the drought index method. If there is no further improvement, the author needs to state the innovative content of the article.

Response 3: We thank the referee for putting forward the constructive comment. The vulnerability assessment methods over previous research can be divided into three categories: the index method based on selected relevant indicators, the statistical method based on historical disaster data, and the vulnerability curve method based on based on field experiments and crop model simulations. However, the index method can only express the relative level of vulnerability between regions, but cannot quantitatively predict the loss(Wilhelmi and Wilhite, 2002;Simelton et al., 2009;Wu et al., 2010); the statistical method is easily affected by the availability and quality of disaster loss data, and is difficult to apply to high-resolution spatial analysis(Lobell and Burke, 2008;Hlavinka et al., 2009;Rowhani et al., 2011); the vulnerability curve belongs to infinite dimensional data and is difficult to conduct spatial analysis directly, mainly used in risk assessment field with insufficient vulnerability information mining (Kamali et al., 2018a;Yin et al., 2014).

In this context, the main innovative content of this article is to putting forward the vulnerability curve feature extraction and spatial difference analysis method, which improves the quantitative degree of vulnerability spatial analysis. In order to highlight such innovation, we emphasize the limitations of previous research in the introduction. Please refer to line 18 at page 2 to line 24 at page 3.

Point 4: The study needs to explain how to ensure classification method of drought index.

Response 4: Thanks for giving us this effective suggestion. Actually, the vulnerability curve contains indicators in two dimensions: drought index and loss rate when performing spatial analysis. We classify the vulnerability curve according to the attributes of these two dimensions. We referred to the idea of general curve clustering when clustering the vulnerability curve (James and Sugar, 2003). The first step is to filter the infinite dimensional curve data to a finite set of representative parameters. In order to represent the loss and loss change characteristics of the S-shaped vulnerability curve comprehensively, we choose the loss rate and the growth rate of loss rate under fixed drought index as representative parameters.

The second step is to select an appropriate clustering tool for the representative parameters. K-means is a clustering algorithm which based on partition. It has the characteristics of faster calculation speed and good clustering effect; moreover, it has been widely used in clustering analysis (Sun et al., 2008). We utilized the Euclidean distance to compare the similarity of vulnerability curve among grid cells (Jacques et al., 2014). The smaller the distance, the more similar the vulnerability curves. The selection of optimal K value is the key to K-means clustering, which was determined by the elbow method and the density of each cluster comprehensively (Nainggolan et al., 2019;Wang et al., 2019). We add more details in the section 2.3.2. (Page 9, line 22- Page 10, line 26) and section 3.3 (Page 13, line 5-10).

Point 5: The evaluation unit of national statistical yield data and drought index grid data(0.5°×0.5°) is not matched. So, the credibility of the article is lack.

Response 5: Thanks to the referee for putting forward this valuable comment, which is worthy of discussion. The drought index data and simulated yield data (grid unite, 0.5°×0.5°) were obtained through the EPIC model simulation. In the process, muti-year statistical and simulated yield data is needed to calibrate crop parameters and validate simulate results. However, unlike studies under site and field scale(Wang et al., 2011;Wang and Li, 2010;Ko et al., 2009;Sun et al., 2015;Cavero et al., 2000), it is difficult to obtain the observational yield data of all grid units for many years on continent scale. Therefore, **limited by the availability of data, the inconsistence between the spatial resolution of crop statistical yield data and the spatial resolution of the simulation evaluation unit on a large scale is a common problem.**

In response to the lack of data, some studies directly apply the default values in the EPIC model or relevant values in publications, assuming that the crop parameters in the region are homogeneous and then avoiding using statistical yield for calibration (Balkovič et al., 2013;Liu et al., 2007;Wriedt et al., 2009). Some studies perform partition calibration based on the natural environmental or administrative division, based on the assumption that the crop parameters in a sub-region are homogeneous, and identify the unique crop parameters of each sub-region (Abbaspour et al., 2015;Angulo et al., 2013). Then, they assign national statistical yield data to each grid within the country. When simulated yield of grids are generally closest to the country statistical yield, the optimal crop parameters are obtained (Kamali et al., 2018b). In terms of model validation, it is common to aggregate the simulated grid yields to the national-scale level for comparison(Xiong et al., 2014;Abbaspour et al., 2015;Kamali et al., 2018b) . **In short, national statistical yield is a commonly used data source in larger-scale studies** (Ittersum et al., 2013). So we applied the above-mentioned partition calibration and up-scaling validation method.

We acknowledge that the spatial resolution unconsistency between the two types of data will bring certain uncertainty to the crop parameters localization and validation, **and we have raised**

this point in the discussion section (page 17, line 9-13). However, it is acceptable under current situation with limited data. When more multi-year and higher-resolution statistical yield data is available in the future, the calibration and validation of model will be further improved.

Point 6: This paper needs to analyze the shortcomings of this study and the research direction of the next step.

Response 6: We appreciate and agree with this constructive suggestion. We have revised the section of discussion as follows. The section 4.2 mainly discusses the uncertainty and limitations of two aspects, the EPIC model calibration and the vulnerability simulation assessment. The uncertainty and limitations of the calibration mainly include the selection of calibrated crop parameters and the accuracy of the statistical yield data; whereas the uncertainty in the simulation evaluation process may mainly come from the experimental design. So we conducted quantitative analysis by changing the irrigation scenario settings and repeating the experiment.

On the basis of introducing the application value of the vulnerability curve, Section 4.3 further proposed two major directions for future research. One is to conduct a comprehensive vulnerability assessment combined with social vulnerability, and the other is to develop dynamic vulnerability evaluation through considering climate change and socio-economic changes. Please refer to page 16, line 31-page 19, line 8 for more details.

Report #3

Point 7: ***I have some concerns about the model that they are applying but it is one way to do it. However, in the vulnerability curve fit there are very few information and they should detail a little more.***

Response 7: We really appreciate these constructive comments. We further explained the reasons why we chose the S-shaped curve for fitting from the perspective of the interaction between energy accumulation and resisting effect. Please refer to the **Response 2.**

Regarding the effect of vulnerability curve fit, we use coefficient of determination (R^2) and Root Mean square error (RMSE) to measure(Quiring and Papakryiakou, 2003). We emphasized this part in the method, referring to page 8, line 29-33. Then we analyse these two indicators from the grid and regional scale at page 1, line 9-16.

Point 8: ***About the clustering, the authors claim they applied k-means clustering but even in this point you have several options to chose and they don't specify which options and why the have chosen it. Part of the appendix should be included in the text. Just realise that the k-means is based in several parameters. Which is the number of clusters? how do you chose that number? This is an important point as it is the core of this research.***

Response 8: Thanks for the valuable suggestions and we fully agree. We have added explanation of clustering analysis methods and K-means clustering algorithm in the section of method, including the principle of K-means clustering algorithm and the selection of K value. Please refer to line 22 at page 9 to line 26 at page 10. K-means is a clustering method which based on partition. The classical form usually uses Euclidean distance to compare the similarity of data points, and classifies data through multiple iterations. It has the characteristics of faster calculation speed and excellent clustering effect, and it is the most widely method of clustering analysis (Han et al., 2012;Sun et al., 2008). Based on such reasons, we decided to choose it as the clustering tool.

K-means clustering needs to set up the number of clusters in advance. In order to obtain the optimal cluster number, we combined the elbow method and the density of each cluster, which have commonly used in the research. This part was originally expressed by Appendix B, and it has now been modified into the text to better support the research results. Please refer to line 5-10 at page 13.

Point 9: ***Some details. The legends for graphs and tables should be improved.***

Response 9: We are sorry for the imperfections in details. We have re-checked all the graphs and tables in this article, and made the corresponding modifications to improve them as much as possible, such as adding coordinates and legends (fig.3, Table 4), modifying legend symbols and text size (fig.4, fig.5, fig.6, fig 8), standardizing serial numbers (fig.1, fig.4, fig.5, fig.6, fig 8) and so on.

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List of all relevant changes made in the manuscript

- The affiliations of co-authors were updated.
- The introduction is revised to highlight the innovation.
- The related applied researches of the EPIC model are supplemented.
- The reasons for choosing the S-shaped vulnerability curve are further supplemented.
- Application research progress of EPIC model in crop drought assessment field are supplemented.
- The fitting result of the vulnerability curves is supplemented.
- More explanations on K-means clustering method are added.
- Research limitations and prospects are supplemented.
- The calibration and validation methods of the EPIC model were modified.
- Some figures, tables and appendix are modified.
- Some references are supplemented.