Response to Anonymous Referee #1

Dear Anonymous Referee:

Thank you for your comments concerning our manuscript entitled "Establishment and characteristics analysis of a crop-drought vulnerability curve: a case study of European winter wheat" (MS No.: nhess-2019-175). Those comments are all valuable and helpful for our manuscript improving. We have studied the comments carefully and have made corrections which we hope meet with approval. The responses to your comments are structured in the sequence: (1) **Point X:** comments from Referees, (2) **Response X:** author's response, (3) **Revision X:** author's changes in manuscript (highlighted in red fonts). Here are our responses to your 13 comments (including 5 minor comments).

Point 1: *The English writing of the manuscript should be improved. Some sentences are hard to understand.*

Response 1: Thank you for your comments. We are very sorry for the understanding difficulties caused by English writing. In order to solve this problem as much as possible, we first carefully reviewed and revised the writing of the entire manuscript, especially the sentences mentioned in the comments. On this basis, we asked a professional institute, American Journal Experts (AJE), for further English editing (editing certificate can be found in supplement). Some of revision details can be found in the following responses.

Point 2: *In addition, the definition of drought index is not clear. More explanation should be added. Therefore, the following questions should be modified before publication.*

Response 2: Thank you very much for your comments. We have elaborated on the definition of drought index as relative cumulative water stress during the crop growth period, which can reflect both water stress intensity and stress duration, and have added the reference for the calculation method (see Revision 2-2). We have further supplemented the explanation of water stress in the manuscript, which is an output element of the EPIC model, reflecting the relationship between daily water supply and water demand (Williams et al., 1989) (see Revision 2-1 and 2-2).

Revision 2-1: Introduction to Water Stress in the basic information of the EPIC model

In the process of simulation, intercepted photosynthetic active radiation is converted into potential biomass, which is adjusted by five daily stress factors (water, nitrogen, phosphorus, temperature, and aeration) to predict actual biomass growth, where the water stress (WS) factor is computed as the ratio of soil water use over potential plant water use.

Revision 2-2: Explanation of water stress and drought index (changes in page 6, line 16-19 in original manuscript)

As an output factor of the EPIC model, WS reflects the relationship between daily water supply and crop water demand. WS ranges from 0-1; the larger the value, the more serious the water shortage will be. To characterize integrated drought intensity affecting yield, drought intensity index (Di) is defined as relative cumulative water stress during the crop growth period, which can reflect both WS intensity and stress duration (Eq. (1), (2)) (Wang et al., 2013):

$$Di_i = \frac{HI_i}{\max(HI)} \ , \tag{1}$$

$$HI_i = \sum_{d=1}^{n}(WS_k) \ , \tag{2}$$

Point 3: *The drought index method based on the crop model has been proposed and applied in many papers. The author needs to explain the improvement of the method in the paper. If there is no further improvement, it is necessary to mention the citation references.*

Response 3: Thank you very much for your suggestion. We have added a reference (Wang et al., 2013) to the Drought Index method in the manuscript (see Revision 2-2).

Point 4: *There is no systematic introduction to the basic information of the Erosion-productivity Impact Calculator (EPIC) model or the research progress of this model in crop drought field.*

Response 4: Thank you very much for your valuable comments. We have supplemented and improved the introduction to the basic information of the EPIC model (including the basic simulation mechanism) (see Revision 4-1), the crop yield simulation research on the EPIC model in different water conditions (see Revision 4-2), and the input and output data of the EPIC model in this manuscript (see Revision 4-2). The above content shows that the EPIC model has good performance in yield simulation in a water stress environment, which supports our research well.

Revision 4-1: Introduction to the basic information of the EPIC model (changes in page 3, line 31- page 4, line 2 in original manuscript)

The EPIC model, published by the United States in 1984 (Williams et al., 1984), is selected to simulate the growth process of winter wheat. It can simulate soil erosion and productivity for hundreds of years on a daily step under a variety of climatic, environmental and management conditions. It simulates all crops with one model framework based on crop's physiological commonality and uses unique crop parameters for each crop. In the process of simulation, intercepted photosynthetic active radiation is converted into potential biomass, which is adjusted by five daily stress factors (water, nitrogen, phosphorus, temperature, and aeration) to predict actual biomass growth, where the water stress (WS) factor is computed as the ratio of soil water use over potential plant water use. Crop yields are estimated as the product of the actual above ground biomass and a harvest index (economic yield/above ground biomass) (Williams et al., 1989).

Revision 4-2: Crop yield simulation research on the EPIC model in different water conditions (changes in page 3, line 31- page 4, line 2 in original manuscript)

EPIC model has been successfully applied in yield simulation for different crops and water input conditions in many parts of the world (Roloff et al., 1998;Gassman et al., 2005). Williams et al. (1989) described the EPIC model simulation results of 6 crop species throughout the U.S. and in European and Asian countries and concluded that the average simulated yields were always within 7% of the average measured yields. Bryant et al. (1992) used the EPIC model to duplicate 38 irrigation stress experiments in the Texas High Plains during 1975-1977 and found that simulated corn yields explained 83, 86, and 72 % of the variance in 3-year measured yields separately. Rinaldi (2001) simulated 66 irrigation scenarios for sunflower grown in Southern Italy, involving a combination of irrigation times, seasonal irrigation amounts and irrigation frequency, and obtained optimized irrigation scheduling without carrying out long and expensive field experiments. Ko et al. (2009) calibrated the EPIC model based on field studies in South Texas, and demonstrated that under full and deficient irrigation and rainfall conditions, EPIC-simulated yields of maize and cotton were in agreement with the measured yields according to a paired t-test. With good performance in water stress tests, EPIC model supports our research well.

Revision 4-3: Input and output data of the EPIC model (changes in page 4, line 3- page 5, line 4 in original manuscript)

Inputs to EPIC include topography, soil, meteorological, and field management data. The soil data in this study are provided by the International Soil Reference and Information Centre (Batjes, 2012), including soil type distribution raster maps and soil physical and chemical property lookup tables (soil bulk density, soil water content, grit content, clay content, organic carbon content, pH, etc.). The daily meteorological data are derived from HadGEM2-ES model data (Hempel et al., 2013) from 1974 to 2004, which are based on meteorological observations including solar radiation, maximum temperature, minimum temperature, average temperature, precipitation, relative humidity and average wind speed. All the original input data are processed onto 0.5° × 0.5° grids, which are the basic units for the yield simulation and vulnerability assessment.

The statistical yield data are not required for EPIC model input but for the localization of crop parameters in the model and validation of simulated yields. They are derived from the Food and Agriculture Organization (FAO) and are country-based statistics. We use statistical yields of 2000 for model localization, and yields of other years between 1974 and 2004 for validation. Outputs from the EPIC model include daily stress factors (water, nitrogen, phosphorus, temperature, and aeration) and annual yield value. The WS and yield can be further processed into sample for the construction of vulnerability curve.

Point 5: *The time series of meteorological data is too short to prove the credibility of the vulnerability simulation results.*

Response 5: Thank you very much for your valuable comments. These sections now describe meteorological data, including EPIC model calibration, model validation, and simulation of water stress-scenario yield samples for vulnerability curve construction.

In terms of EPIC model calibration and validation, we originally used the meteorological data of 2000 for EPIC model calibration and the meteorological data of 2001-2004 for calibrated EPIC model validation. The time series of meteorological data was indeed relatively short, which could not adequately prove the credibility of the calibrated EPIC model in yield simulation. Therefore, we have supplemented the meteorological data of 1974-1999 (the meteorological data during this period is also processed based on the actual meteorological observation data) and obtained supplementary simulated yields based on calibrated EPIC to fully prove its credibility (see Revision 5-1).

We re-compared the national-scale EPIC simulated yields and FAO statistical yields of 1974-2004 (excluding 2000 used for calibration). For national statistical yields with significant trends, linear de-trending transformations are applied to remove the impacts of technology progress (Xiong et al., 2014;Kamali et al., 2018a) (see Revision 5-1). The R-square between the simulated and the statistical yields is 0.77, showing high consistency on a long-term scale and indicating reliable performance of EPIC for yield simulation. We have modified the data and methods sections and updated the results in Section 3.1 (see Revision 5-2).

In terms of simulation of vulnerability samples, since the manuscript focuses on physical vulnerability, that is, the physical response of winter wheat to water shortage, we control the water supply condition using the meteorological data with suitable temperature and no precipitation and by setting a series of irrigation scenarios. Therefore, the reliability of the simulation results is not affected by the length of the processed ideal meteorological data. We have strengthened this description in the methods section of the article (see Revision 5-3).

Revision 5-1: Supplementary validation time series in the section of data and method

The statistical yield data are not required for EPIC model input but for the localization of crop parameters in the model and validation of simulated yields. They are derived from the Food and Agriculture Organization (FAO) and are country-based statistics. We use statistical yields of 2000 for model localization, and yields of other years between 1974 and 2004 for validation (changes in page 5, line 1-4 in original manuscript).

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To validate the parameterization results, we generate the simulated grid yields of 1974-1999 and 2001-2004 based on the calibrated EPIC model, and aggregate to the nation level by averaging. For FAO national statistical yields of 1974-2004 with significant trends, linear de-trending transformations are applied to remove the impacts of technology progress (Xiong et al., 2014;Kamali et al., 2018a). Then we compare national simulated yields with the statistical yields across all European countries (changes in page 6, line 1-4 in original manuscript).

Revision 5-2: Updated verification results (changes in page 7, line 4-page 5, line 3 in original manuscript)

From the national comparison results from 1974 to 2004 (excluding calibration year of 2000), though the simulated yields are slightly higher than the statistical yields, there is high agreement between the two (Fig. 3). The regression equation has an R^2 of 0.77 and passes the test with a confidence of 0.01, indicating a reliable performance of the calibrated EPIC model for yields simulation in various regions and various years.

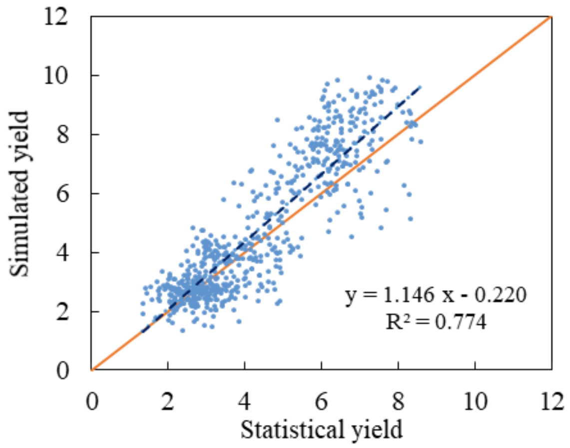

Figure 1: Comparison of national winter wheat yield reported by FAO and simulated by calibrated EPIC during the period from 1974-2004 (excluding calibration year of 2000).

Revision 5-3: Simulation of physical vulnerability (page 6, line 10-14 in original manuscript) To focus on physical drought vulnerability and eliminate the impact of other stress factors on yields, we use meteorological data with suitable temperature and no precipitation, and control the water supply condition by setting 20 irrigation scenarios, in which the irrigation amount uniformly increases from 0 to the optimum (the maximum irrigation amount without WS). The optimal value is determined by pre-testing. Consequently, we obtain the outputs of 20 groups of WS and yield for each grid evaluation unit.

Point 6: *The spatial resolution of crop yield data is inconsistent with the spatial resolution of the simulation evaluation unit. It brings uncertainties to the validation of the model and the localization of crop parameters, which affects the credibility of the research results and needs to be further improved.*

Response 6: Thank you very much for pointing out this issue, which is worthy of further discussion.

There are types of simulated evaluation units such as fields, sites, grids and countries, and the selection of them is usually related to the scale of the study area. For different types of simulation evaluation units, the available observed yield data will vary, resulting in different model calibration and validation methods (Wang et al., 2012), which can be roughly divided into the following two categories.

(1) Field or site-based simulation evaluation units are commonly used in small or medium-scale studies, where crop parameters usually apply the default values in the model, or relevant values in the literature or field experiments. Simulation evaluation units usually have the same

parameters due to a small study area. Additionally, the model validation generally uses the field or site yield data obtained through field observation (Wang et al., 2011;Wang and Li, 2010;Ko et al., 2009;Sun et al., 2015;Cavero et al., 2000). Therefore, this type of study more easily achieves consistency between the spatial resolution of the observed yield data and the spatial resolution of the simulation evaluation unit.

(2) Grid-based simulation evaluation units are commonly used in large-scale studies, especially in continent or global-scale studies. When localizing crop parameters, some studies directly apply the default values in the model or relevant values in publications without considering spatial variability, due to the lack of crop variety distribution data on a large scale (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. Each sub-region identifies a unique set of crop parameters, and all simulated evaluation units in one sub-region have the same crop parameters (Abbaspour et al., 2015;Angulo et al., 2013). For example, Kamali et al. (2018a) localized the crop parameters for each Sub-Saharan African country. They reiterated the simulation of maize yield on a grid at a spatial resolution of 0.5 °, aggregated to the national scale, and then compared to the FAO national statistical yields to obtain the optimal parameters. Xiong et al. (2014) divided the world into 433 homogenous units, selected 10 grids as calibration and validation units from each homogenous unit, and reiterated model simulations by incrementally changing the crop parameters and then compared them to the downscaled rice yield at 5' grid level resolution in International Food Policy Research Institute databases. Least Root Mean Square Error (RMSE) was chosen for the homogeneous unit. When validating the calibrated model, despite the method of calibration, large-scale studies generally aggregate the simulated grid yields to the administrative unit level to compare with the statistical yields (Balkovič et al., 2013;Liu et al., 2007;Kamali et al., 2018a;Xiong et al., 2014). Statistical yields used to estimate yield gap are generally based on yields reported in FAOSTAT and the Agro-MAPS project, a collaboration between FAO, IFPRI (International Food Policy Research Institute), SAGE (Centre for Sustainability and the Global Environment) and CIAT (The International Centre for Tropical Agriculture) (Ittersum et al., 2013).

In short, given the limited amount of data available, it is hard to ensure consistency between the spatial resolution of crop statistical yield data and the spatial resolution of the simulation evaluation unit on a large scale. To achieve model calibration and validation, it is necessary to aggregate the simulated grid yields to the statistical unit level or disaggregate statistical yields to the grid level.

This manuscript selects the European region as the study area and the 0.5 ° grid as the simulation evaluation unit. Therefore, we localize the parameters for each country based on the idea of large-scale partition calibration. That is, we assume that all the grids in one country have the same winter wheat and then have the same set of crop parameters. We simply assign an FAO national statistical yield to the grids within a country, and this allocation method is consistent with Monfreda et al. (2008). The crop parameters are the optimal values for a country that minimize the RMSE between the simulated and assigned statistical grid yields. When validating the calibrated model, we aggregate the simulated grid yields to the country level by averaging and then compare the simulated and statistical yields across all countries.

Using such country-scale statistical yield data does bring some uncertainty to the localization of crop parameters and the validation of the model, but it is acceptable given the current situation with limited data. When more multi-year and higher-resolution statistical yield data is available in the future, the credibility of the results will be further improved. The above calibration and validation methods are further elaborated in the manuscript to avoid any unclear interpretation (see Revision 6-1) and added to the discussion of model uncertainty to improve the explanation of limitations (see Revision 6-2).

Revision 6-1 (page 5, line 21-page 6, line 4 in original manuscript)**:**

Considering the limitation of statistical yields on a grid scale, we localize the four key parameters at the country level based on the idea of partition calibration (Liu et al., 2007;Balkovič et al., 2013;Kamali et al., 2018a). That is, each country has a unique set of crop parameters, and all the grids within one country are the same. The default values of the crop parameters in the EPIC model are taken as the initial value, and the geographical environmental, field management and meteorological data are entered to obtain simulated grid yields of 2000. We simply assign a FAO national statistical yield to the grids within a country. Then the root mean square error (RMSE) between the simulated and statistical grid yields are calculated. We reiterate the yield simulations and RMSE calculations by incrementally adjusting the four key parameters to minimize RMSE. The calibration will be finished when the least RMSE is below the threshold or the number of reiterations is above the threshold.

To validate the parameterization results, we generate the simulated grid yields of 1974-1999 and 2001-2004 based on the calibrated EPIC model, and aggregate to the nation level by averaging. For FAO national statistical yields of 1974-2004 with significant trends, linear de-trending transformations are applied to remove the impacts of technology progress (Xiong et al., 2014;Kamali et al., 2018a). Then we compare national simulated yields with the statistical yields across all European countries.

Revision 6-2 (see Revision 7 for more details)**:**

The calibration and validation are carried out on the country level because of the limitation of available statistical yield data, which may cause some uncertainties for the input data. When more multi-year and higher-resolution statistical yield data are available in the future, the results will be further improved. However, from the current comparison results of the national statistical yields and the simulated yields of the period from 1974-2004, the R2 of the two has reached 0.77, indicating a high reliability of the calibrated EPIC model.

Point 7: *The manuscript lacks uncertainty analysis of this model and vulnerability assessment results, which reduces the credibility of the manuscript and needs further improvement.*

Response 7: Thank you very much for your valuable suggestions. We have supplemented the uncertainty analysis of the model and vulnerability assessment results as the first section of the discussion according to your suggestions. We discuss the uncertainties in two parts: (1) Uncertainties related to the EPIC model input parameters, including the selection of sensitive crop parameters, the limitation of available statistical yield data used for parameters calibration and validation. (2) Uncertainties related to the vulnerability assessment results that may be caused by vulnerability simulations and vulnerability curve constructions. The two types of uncertainties are evaluated quantitatively by comparing the national statistical and simulated yields of a relatively long period from 1974-2004, and by evaluating the standard deviations of reiterated vulnerability simulation results at sample grids selected randomly, respectively, by which the credibility of the manuscript are proved (see Revision 7).

Revision 7: Supplement as the first section of the discussion

4.1 Uncertainty analysis

The EPIC model default crop parameters may deviate from the actual growth in different regions, so we localize and verify the crop parameters to minimize these uncertainties. There are 56 crop parameters in the EPIC model, and different input parameters have different degrees of influence on the EPIC model in different simulation environments (Zhang et al., 2017). The main method to reduce the uncertainties of input parameters is to carry out sensitivity analysis in the basic evaluation unit and calibrate the sensitivity parameters one by one. However, this requires multiple calculations and does not completely eliminate the uncertainties of the input parameters(Yue et al., 2018). Therefore, with reference to previous research, we focus on the calibration and validation of the above four main sensitive parameters. The calibration and validation are carried out on the country level because of the limitation of available statistical yield data, which may cause some uncertainties for the input data. When more multi-year and higher-resolution statistical yield data are available in the future, the results will be further improved. However, from the current comparison results of the national statistical yields and simulated yields of the period from 1974-2004, the R2 of the two has reached 0.77, indicating a high reliability of the calibrated EPIC model.

To quantify the uncertainties of the vulnerability assessment results, we reiterate the vulnerability simulation and assessment 20 times and evaluate the standard deviation distribution of the results. First, we randomly select 10 % of samples from the five types of vulnerability curves based on the principle of stratified sampling, and obtain a total of 201 sample grids. Next, according to the method in Section 2.3.1, we reiterate the vulnerability simulation and vulnerability curve construction process 20 times by changing the irrigation scenario settings, that is, keeping the non-irrigation and optimal irrigation scenarios unchanged and then randomly setting 18 irrigation scenarios between the two. From this, 20 reiterated vulnerability curves can be obtained for each sample grid. Then, by calculating the standard deviation of the loss rate for 20 reiterated vulnerability curves at the drought index interval of 0.1, the standard deviation of loss rate for each sample grid can be obtained to characterize the grid uncertainties. The mean standard deviation and 95 % prediction uncertainty band (95PPU) of total sample grids are finally calculated to characterize overall uncertainties. 95PPU is the range from 2.5 % to 97.5 % of the cumulative distribution function (Abbaspour et al., 2007). The results show that the mean standard deviation of loss rate is between 0 and 0.065, and the average is 0.033; the width of PPU95 is between 0.007 and 0.135, and the average is 0.067; the two indicators reach the peak when the drought index is between 0.4 and 0.7 (Fig. 7). Although the prediction uncertainty of loss rate is relatively large in such range, it is still significantly smaller than the difference in loss rate between regions (which can reach more than 0.5), so it has little effect on the distribution pattern of vulnerability. In summary, the vulnerability assessment results of this paper are credible.

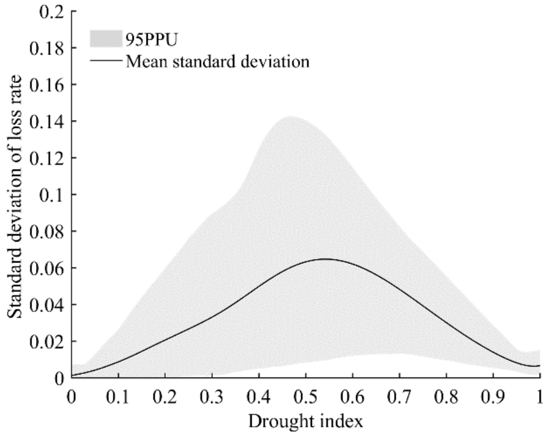

Figure 7: Distribution of standard deviation of loss rate under different drought index. The mean standard deviation and 95 % prediction uncertainty band (95PPU) are calculated by the standard deviations of sample grids, which are randomly selected from the five vulnerability curves at a proportion of 10 %.

Point 8: *The exposition of the theory and practice progress regarding crop drought vulnerability is insufficient in this research. It needs to be supplemented with a large amount of literature, especially those in the past 15 years, to discuss the historical research process of vulnerability assessment, which is from the single index to the linear index, and then to the curve index.*

Response 8: Thank you very much for your valuable comments. We have supplemented some recent literature and relevant research cases and made key revisions to the introduction based on your comments. According to the definition of vulnerability of the United Nations International Strategy for Disaster Reduction (UNISDR), vulnerability is the characteristics and circumstances of an affected body that make it susceptible to the damaging effects of a hazard (UNISDR, 2009). We have reclassified vulnerability research into three categories in the manuscript on the basis of different research methods. (1) Calculation of the vulnerability index based on selected relevant indicators. The characteristic of this method is to establish the evaluation index system and weight system based on meteorological, hydrogeological and other factors to form a vulnerability evaluation (Wilhelmi and Wilhite, 2002;Pandey et al., 2010;Simelton et al., 2009). (2) Quantitative research on vulnerability based on historical statistics and meteorological observations. This method mainly uses meteorological observation data, historical statistical data and so on to establish the quantitative relationship between disaster intensity and historical disaster loss through a regression model (Xu et al., 2013;Jayanthi et al., 2014;Fishman, 2016). (3) Quantitative research on vulnerability curves based on field experiments and crop model simulations. The method is characterized by conducting field control experiments or crop growth model simulations through artificially setting up different disaster intensity scenarios and then fitting vulnerability curves from the perspective of the crop disaster-causing mechanism (Wang et al., 2013;Yin et al., 2014;Kamali et al., 2018b). The above three aspects, vulnerability assessment by index construction and by regression model, and vulnerability curve construction based on the disaster-causing mechanism, have been expanded in the manuscript (see Revision 8).

Revision 8 (changes in page 2, line 2-page 3, line 1 in original manuscript)**:**

Crop drought vulnerability assessment focuses on crops, particularly the biophysical factors closely related to crop growth processes (Wu et al., 2017;Tánago et al., 2015), describing the damage to crops caused by different intensity hits. At present, crop drought vulnerability assessment methods mainly include the following three aspects.

(1) Calculation of the comprehensive vulnerability index based on selected relevant indicators. Some of these studies encompass recognition of the factors influencing drought vulnerability, construction of vulnerability indicators from physiographic, climatic and hydrologic aspects, assignment of their weights and calculation of a comprehensive index (Wilhelmi and Wilhite, 2002;Shahid and Behrawan, 2008;Jain et al., 2014). For example, Pandey et al.(2010) identify seven influence indicators, such as watershed geography, soil types, water availability and so on, grade each of them and then add them up to obtain the drought vulnerability index of the Sonar basin in the Madhya Pradesh. Some of these studies are based on the components of vulnerability, construct sensitivity and exposure indicators, and combine them to form a vulnerability index (O'Brien et al., 2004;Antwi-Agyei et al., 2012;Tánago et al., 2015) . For example, Simelton et al. (2009) use the crop failure index to characterize sensitivity, the drought index to characterize exposure, and the ratio of the two to characterize crop drought vulnerability and to further explore the correlation between drought vulnerability and socioeconomic characteristics in China. This method can express the relative vulnerability level and the relative contribution of indicators in different regions, providing potential means to reduce disasters for decision makers, and providing a strong reference for the establishment of quantitative vulnerability relationships.

(2) Quantitative research on vulnerability based on historical statistics and meteorological observations. This method mainly uses meteorological observation data and historical statistical data to establish the quantitative relationship between disaster intensity and historical disaster loss (Lobell and Burke, 2008;Hlavinka et al., 2009;Rowhani et al., 2011). Fishman (2016) uses Indian daily rainfall and statistical yield data from 1970 to 2003 to analyse the relationship

between precipitation variability and major crop yields. Jayanthi et al. (2014) use satellite rainfall based-water requirement satisfaction index and historical yield loss rate as regression indicators to develop a maize drought vulnerability model in Kenya, Malawi and Mozambique. Xu et al. (2013) select consecutive rainless days as the drought intensity index, convert drought affected area into the drought-induced yield loss rate, and then establish vulnerability curves of corn, wheat and rice in the monsoon region of east China using the daily precipitation data and historical disaster data. Such a method generally builds a linear model between drought intensity and crop yield through regression analysis based on a large amount of data, exploring how crop yield loss varies with disaster intensity.

(3) Quantitative research on vulnerability curves based on field experiments and crop model simulations. This method generally conducts field experiments or crop growth model simulations by artificially setting up different disaster intensity scenarios, and then fitting cooperative vulnerability curves from the perspective of a crop disaster-causing mechanism. Pan et al. (2017) conduct field experiments by artificially controlling soil water content at the Huanghua experimental site in Hebei, China. Based on the experimental data showing the effects of drought intensity and biomass loss on maize growth, the physical drought vulnerability curves of the five growth stages are constructed. Yin et al. (2014) use the Environmental Policy Integrated Climate (EPIC) model to obtain drought index and yield loss rates, and construct a drought vulnerability curve for maize in 35 regions of the world. Kamali et al. (2018b) use the precipitation and EPIC simulated maize yield to fit the cumulative distribution function to describe the crop sensitivity and exposure indexes to drought, respectively, and link the two indexes using a power curve fitted to describe the physical vulnerability of sub-Saharan African countries. This method provides a new research idea and perspectives for vulnerability quantitative assessment based on the crop growth mechanism. Additionally, the crop model can quantitatively describe and predict the crop growth and yield formation process in a specific environment, with lower cost than the field experiments and fewer limitations in historical disaster statistical sample or spatial accuracy, which is conducive to high-precision quantitative research on crop vulnerability (Palosuo et al., 2011;Challinor et al., 2009).

Affected by factors such as the natural environment and crop variety, there are regional differences in crop drought vulnerability (IPCC, 2012, 2014). Therefore, based on a quantitative assessment, analysing and mapping these characteristics can help identify the vulnerability distribution and local mitigation-oriented drought management (Wilhelmi and Wilhite, 2002). However, since the vulnerability curve is infinite dimensional data and does not include the environmental dimension (James and Sugar, 2003), it is difficult to directly express the vulnerability-like vulnerability index, which is not conducive to providing references and guidance for reducing regional vulnerability for different regions. Therefore, exploring the methods of key information mining and spatial analysis for the crop drought vulnerability curve is beneficial to improve the deficiencies in the evaluation and analysis of the vulnerability curve, which can not only quantify regional drought vulnerability based on the disaster-causing mechanism but also convey vulnerability information to decision makers from a risk visualization perspective.

This paper aims to develop a new crop drought vulnerability analysis method. As wheat is one of the three major grain crops in the world, we select the main wheat producing area, the European winter wheat growing area, as the research area, using the 0.5°×0.5° grid as the basic assessment unit. The vulnerability curve of winter wheat drought was established based on EPIC simulation. Then, the loss extent and loss change characteristics of the vulnerability curve are extracted to analyse the vulnerability characteristics to drought in various areas. By clustering the curve shapes, areas with similar vulnerability characteristics are identified for exploring their environment and providing scientific guidance regarding the development of regional drought mitigation strategies.

Minor comments:

A: *Page 3 Line 19-20: more explanation should be added for 'the third order' and 'the second order'.*

Response A: Thank you so much for your suggestion. We are sorry for the unclear expression before and we correct 'the second/third order' to 'the second/third derivative of the vulnerability curve':

Therefore, the key points of the vulnerability curve—the transition points of three stages (P1 and P3, <u>where the third derivative of the vulnerability curve is equal to zero</u>) and the turning point of the loss growth rate (P2, <u>where the second derivative of the vulnerability curve equals zero</u>) are used to describe the loss change characteristics, the cumulative loss to the loss extent characteristics, and the morphological classification to of the integrated description.

B: *Figure 2: Symbols should be explained in the legend.*

Response B: Thank you so much for your suggestion. We have supplemented the explanation of the symbols in Figure 2:

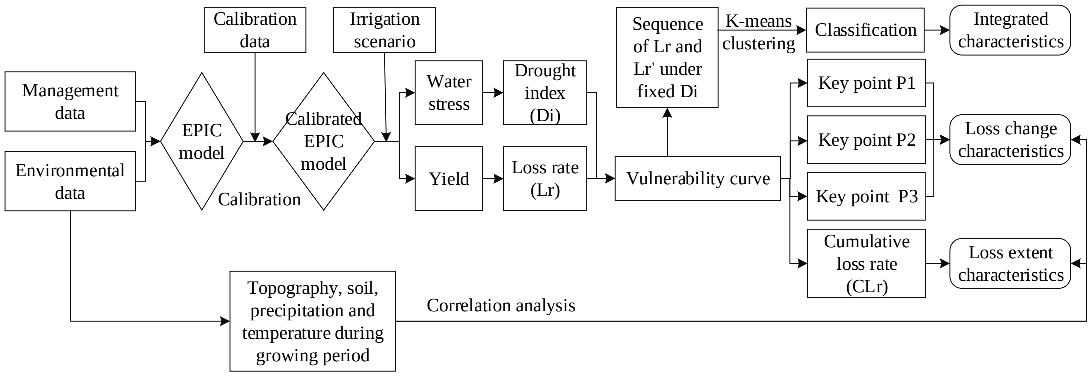

Figure 2: Basic research framework. First, we input relevant data into the EPIC model and perform model calibration. Next, we obtain a series of water stress and yield data based on the calibrated EPIC model by setting different irrigation scenarios, which are converted into drought index (Di) and yield loss rate (Lr) for the construction of vulnerability curves. Then, we extract three key points and calculate the cumulative loss rate of vulnerability curves for the spatial analysis of loss change and loss extent characteristics. Finally, we calculate the Lr and the change rate of Lr (Lr') under a set of fixed Di to transform the vulnerability curves into a finite data set for clustering, and the classification of vulnerability curves can be used for the integrated spatial analysis.

C: *Equation 2: How drought index is defined? Reference should be added.*

Response C: Thank you very much for your comments. We have supplemented the definition of drought index with references to its calculation formulas. More details can be found in Responses 2 and 3 above.

D: *Page 7 Line 7-8: How are five levels of CLr defined? There is no detailed numbers.*

Response D: Thank you very much for your suggestion. We have supplemented detailed numbers of five levels of CLr:

All CLr values are divided into five levels by the natural breakpoint method: extremely low (0.22-0.34), low (0.34-0.42), moderate (0.42-0.49), high (0.49-0.55), and extremely high (0.55-0.69).

F: *Page 8 Line 13-14: This sentence is not clear.*

Response F: Thank you very much for your comment and sorry for our negligence on the English writing. We have modified this sentence and its related context to make it as clear as possible:

For most grids, the Di values at the three key points are mainly distributed from 0.15-0.55, 0.35-0.7 and 0.4-0.8, while the Lr values have a relatively small distribution, from 0.1-0.2, 0.4-0.5 and 0.7-0.8. Therefore, the characteristics of stage transitions of grid vulnerability curves can be simplified by only using the Di at key points instead of two coordinates. The larger the Di is at key points, the more severe the drought must be to cause a similar loss rate; this is reflected in the lag in the stage transitions of vulnerability curve, indicating a greater tolerance to drought disturbance.

We appreciate for your warm work earnestly, and hope that the correction will meet with approval.

Once again, thank you very much for your comments and suggestions.

Yours sincerely,

Jing'ai Wang

References

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