Author's Response

We thank 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 (marked in red).

Response to Anonymous Referee #1

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

Response A-1: We are very sorry for the understanding difficulties caused by our English writing. In order to solve this problem, we first carefully checked the full text and modified some paragraphs or sentences that may not be clear, especially the ones mentioned in the comments. On this basis, we asked a professional institute, American Journal Experts (AJE), for further English editing (verification code: A86C-32AC-F0EB-B41A-7FB9). All revision details can be found in the following marked-up manuscript.

Point A-2: In addition, the definition of drought index is not clear. More explanation should be added.

Response A-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 A-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 (see Revision A-2-1 and A-2-2).

Revision A-2-1 (section2.2, page 4, line 21-24 in the separate manuscript):
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, <u>where the water stress (WS) factor is computed as the ratio of soil water use over potential plant water use.</u>

Revision A-2-2 (section 2.3.2, page 7, line34-38):

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 A-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 A-3: Thank you very much for your suggestions. We have added a reference (Wang et al., 2013) to the Drought Index method in the manuscript (see section 2.3.2, page 7, line38).

Wang, X. C., Li, J., Tahir, M. N., and Hao, M. D.: Validation of the EPIC model using a long-term experimental data on the semi-arid Loess Plateau of China, Mathematical and Computer Modelling, 54, 976-986,doi:10.1016/j.mcm.2010.11.025, 2011.

Point A-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 A-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 A-4-1), the crop yield simulation research on the EPIC model in different water conditions (see Revision A-4-2), and the input and output data of the EPIC model in this manuscript (see Revision A-4-3). 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 A-4-1 (section 2.2, page 4, line17-26):

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 A-4-2 (section 2.2, page 4, line27-page 5, line 6):

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 A-4-3 (section 2.2, page 5, line 12-27):

Inputs to EPIC include topography, soil, meteorological, and field management data. …

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

Response A-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 A-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 A-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 A-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 A-5-3).

Revision A-5-1: Supplementary validation time series in data and method sections

section 2.2, page 5, line 23-24:

We use statistical yields of 2000 for model localization, and yields of other years between 1974 and 2004 for validation.

section 2.3.1, page 7, line 18-22:

To validate the parameterization results, we generate the simulated grid yields of 1974-2004 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 A-5-2: Updated verification results (section 3.1, page 9, line 11-18)

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.

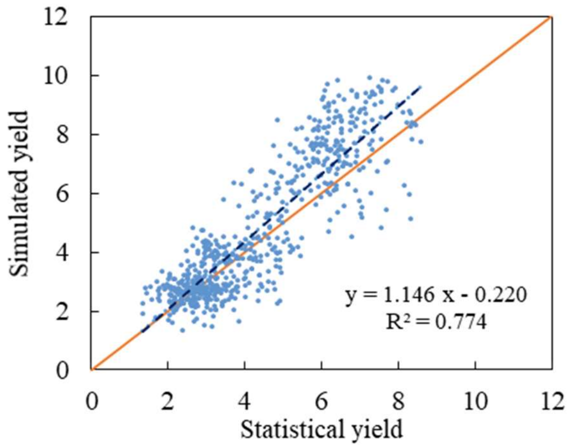

Figure 1: Comparison of national winter wheat yield reported by FAO and simulated by calibrated EPIC during the period from 1974-2004 (excluding calibration year of 2000).

Revision A-5-3: Simulation of physical vulnerability (**section 2.3.2, page 7, line 28-32**)

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 A-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 A-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 A-6-1) and added to the discussion of model uncertainty to improve the explanation of limitations (see Revision A-6-2).

Revision A-6-1 (section 2.3.1, page7, line 7-22):

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 1974-2004 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 A-6-2 (section 4.1, page 13, line14-20):

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 A-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 A-7: Thanks for the 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 valuable 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 A-7).

Revision A-7 (section 4.1, page 13, line 6-page 14, line 23):

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.

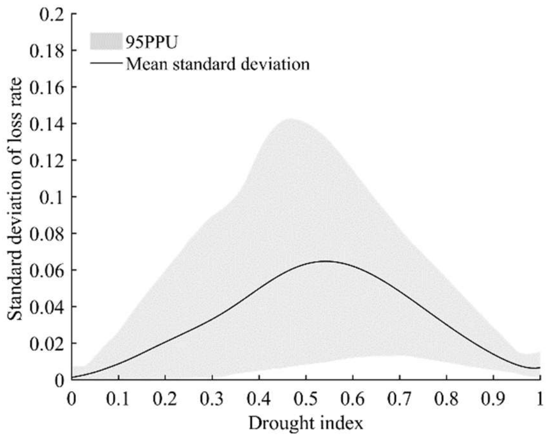

Figure 7: Distribution of standard deviation of loss rate under different drought index. The mean standard deviation and 95 % prediction uncertainty band (95PPU) are calculated by the standard deviations of sample grids, which are randomly selected from the five vulnerability curves at a proportion of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

Point A-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 A-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 A-8).

Revision A-8 (section 1, page 2, line 2-page3, line 21)**:**

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.

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

Response A-a: 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, where the third derivative of the vulnerability curve is equal to zero) and the turning point of the loss growth rate (P2, where the second derivative of the vulnerability curve equals zero) 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."

Minor comment A-b: Figure 2: Symbols should be explained in the legend.

Response A-b: Thanks for the suggestion. We have supplemented the explanation of the symbols in Figure 2:

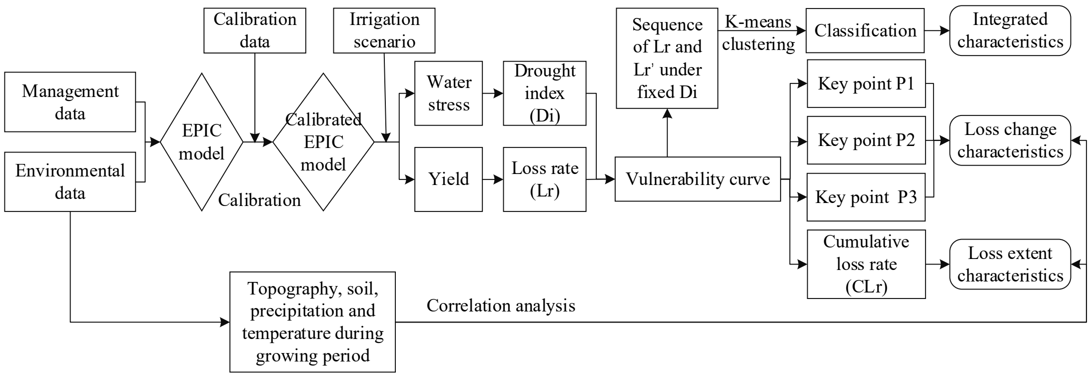

Figure 2: Basic research framework. **First, we input relevant data into the EPIC model and perform model calibration. Next, we obtain a series of water stress and yield data based on the calibrated EPIC model by setting different irrigation scenarios, which are converted into drought index (Di) and 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 growth 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.**

Minor comment A-c: Equation 2: How drought index is defined? Reference should be added.

Response A-c: Thank you 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.

Minor comment A-d: Page 7 Line 7-8: How are five levels of CLr defined? There is no detailed numbers.

Response A-d: Thank you 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)."

Minor comment A-e: Page 8 Line 13-14: This sentence is not clear.

Response A-e: Thanks for your comment and sorry for our negligence on the English writing. We have modified this sentence and its related context to make it clear:

"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.”

Response to Anonymous Referee #2

Point B-1: Other than an English proofing that prevented me from understanding some sentences properly, …

Response B-1: We are very sorry for the understanding difficulties caused by English writing and have tried our best to improve them. We first carefully reviewed and revised the writing of the entire manuscript, and then we asked a professional institute, American Journal Experts (AJE), for further English editing (verification code: A86C-32AC-F0EB-B41A-7FB9). All revision details can be found in the following marked-up manuscript.

Point B-2: …, my main concerns rely on the lack of an uncertainty analysis enabling the reliability of the estimates to be assessed quantitatively.

Response B-2: Thank you very much for your valuable suggestions. We have supplemented the uncertainty analysis as the first section of discussion, which includes 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. For better quantitative evaluation of calibration results, we have extended the time series of simulated and statistical yield data for comparison, that is, from 2001-2004 to 1974-2004 (see Revision B-2-1). According to new comparison results, the R^2 of the two has reached 0.77, indicating a high reliability in the calibrated EPIC model (see Revision B-2-2 and B-2-3).

(2) Uncertainties related to the vulnerability assessment results. For assessing quantitatively, we reiterate the vulnerability simulation and vulnerability curve constructions 20 times at randomly selected grids, the standard deviation of loss rate in 20 repeated vulnerability curves of each sample grid is obtained to characterize the grid uncertainties, and the mean standard deviation and 95 % prediction uncertainty band (95PPU) of loss rate of total are calculated characterize overall uncertainties. The results show that the mean standard deviation of loss rate is between 0 and 0.065; the width of PPU95 is between 0.007 and 0.135; and the two indicators reach the peak when the drought index is between 0.4 and 0.7. 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, so it has little effect on the distribution pattern of vulnerability. In summary, the vulnerability assessment results of this paper are credible (see Revision B-2-3).

Revision B-2-1: Supplementary validation time series in data and method sections

section 2.2, page 5, line 23-24:

We use statistical yields of 2000 for model localization, and yields of other years between 1974 and 2004 for validation.

section 2.3.1, page 7, line 18-22:

To validate the parameterization results, we generate the simulated grid yields of 1974-2004 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 B-2-2: Updated verification results (**section 3.1, page 7, line 11-18**)

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.

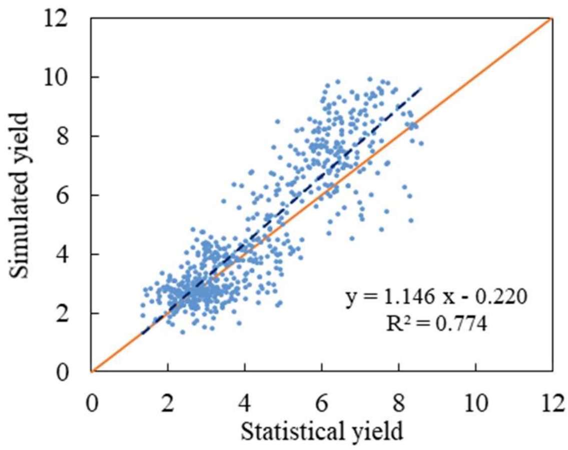

Figure 3: Comparison of national winter wheat yield reported by FAO and simulated by calibrated EPIC during the period from 1974-2004 (excluding calibration year of 2000).

Revision B-2-3: Supplement as the first section of the discussion (section 4.1, page 13, line 6-page 14, line 23)

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.

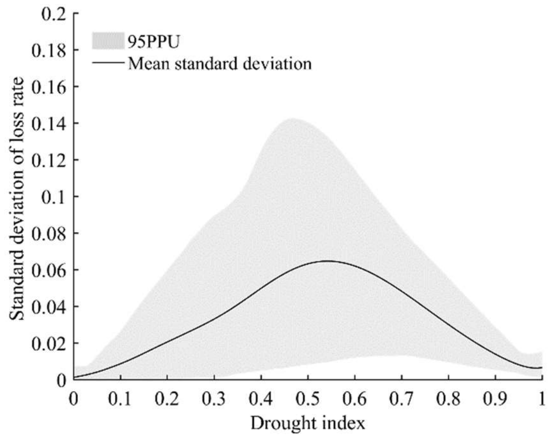

Figure 7: Distribution of standard deviation of loss rate under different drought index. The mean standard deviation and 95 % prediction uncertainty band (95PPU) are calculated by the standard deviations of sample grids, which are randomly selected from the five vulnerability curves at a proportion of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

Point B-3: Furthermore, no details at all have been reported by the authors on the EPIC model, neither in the literature experiences available to date.

Response B-3*:* Thank you very much for your valuable comments. We have make supplements and modifications to Section 2.2 in the manuscript, which elaborate the basic information of the EPIC model and the crop yield simulation researches of the EPIC model in different water conditions. The above content shows that the EPIC model has good performance in yield simulation under water stress environment, which supports our research well (see Revision B-3).

Revision B-3 (section 2.2, page 4, line17- page 5, line 6):

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).

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.

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List of all relevant changes made in the manuscript

- The affiliations of co-authors were updated.
- Some sentences were modified to be clearer.
- The research progress in the introduction was expanded and rewritten.
- The basic information and the related applied researches of the EPIC model were supplemented.
- Table1: The description of administrative boundary data was supplemented, and the years of historical daily meteorological data and statistical yield data were updated.
- Figure 2: The explanation of the symbols was supplemented.
- The calibration and validation methods of the EPIC model were modified.
- More explanation on the definition of drought index and the related citation reference were supplemented.
- Section 3: The validation results of the EPIC model (including Figure 3 and text) were updated.
- Uncertainty analysis of the EPIC model and vulnerability simulation results was added to the discussion.
- The references were updated.

Establishment and characteristics analysis of a crop-drought vulnerability curve: a case study of European winter wheat

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Abstract. As an essential component of drought risk, crop-drought vulnerability refers to the degree of the adverse response of a crop to a drought event. Different drought intensities and environments can cause significant differences in crop yield losses. Therefore, quantifying ~~the~~ drought vulnerability and then identifying its spatial distribution pattern will contribute to understanding vulnerability and the development of risk-reduction strategies. We select the European winter wheat growing area as the study area and 0.5°×0.5° grids as the basic assessment units. Winter wheat drought vulnerability curves are established based on the Erosion-Productivity Impact Calculator model simulation. Their loss ~~transmutation~~ change and loss extent characteristics are quantitatively analysed by the key points and cumulative loss rate, respectively, and are then synthetically identified VIA K-means clustering. The results show the following. (1) The regional yield loss rate starts to rapidly increase from 0.13 when the drought index reaches 0.18 and then converts to a relatively stable stage with the value of 0.74 when the drought index reaches 0.66. (2) The stage transitions of the vulnerability curve lags behind in the southern mountain area~~,~~; only when the drought index is higher, indicating a stronger tolerance to drought in the system, in contrast to the Pod Plain. (3) According to the loss characteristics during the initial, development and attenuation stages, the vulnerability curves can be divided into five clusters, namely, Low-Low-Low, Low-Low-Medium, Medium-Medium-Medium, High-High-High and Low-Medium-High loss types, corresponding to the spatial distribution from low latitude to high latitude and from mountain to plain. ~~It is recommended to improve the integrated mitigation capability in the Medium-Medium-Medium and High-High-High loss type areas and to develop the ability to mitigate droughts in the 0.3-0.6 intensity range, as non-engineering measures for the droughts greater than 0.6 intensity in Low-Medium-High loss type areas.~~ The results provide ideas for the study of the environment's impact on vulnerability and as well as guidance for drought risk management.

1 Introduction

Drought is a widespread natural disaster causing the largest agricultural losses in the world. More than one-half of the earth is susceptible to drought, including nearly all of the major agricultural areas (Kogan, 1997). Under the context of climate change and ~~globalisation~~ globalization, drought will pose a threat to future food security. How to assess and manage agricultural drought risks has become a focus of the world (Reid et al., 2006;Li et al., 2009;Mishra and Singh, 2010). As vulnerability is a key factor in determining risk, drought vulnerability assessment is an important foundation for drought risk assessment and management (Zhang et al., 2015;Knutson C, 1998).

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. ~~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 their characteristics can help identify the vulnerability distribution and local mitigation-oriented drought management (Wilhelmi and Wilhite, 2002).~~

~~The commonly used crop drought vulnerability assessment methods mainly include the vulnerability index and vulnerability curve methods (Yuan-yuan et al., 2014;Jayanthi et al., 2014). The vulnerability index method identifies vulnerability indicators, determines their weights and then calculates a comprehensive value, visualising through thematic maps (Jain et al., 2014;Huang et al., 2012;Pandey et al., 2010). The indicators commonly include climate, topography, watershed location, soil, and water resource accessibility (Tánago et al., 2015). This method can express the relative vulnerability level and the relative contribution of indicators in different regions, providing decision makers with potential means to reduce disasters (Wilhelmi and Wilhite, 2002). However, the exploration of the disaster-causing mechanism is not sufficiently comprehensive, and it is impossible to quantitatively predict losses. In addition, indicator selection and weight determination during the evaluation process have a certain subjectivity and uncertainty (Jianjun et al., 2010;Simelton et al., 2009).~~

~~The vulnerability curve method aims to quantify the crop yield response to different drought intensities. Rainfall anomalies, Standardized Precipitation Index, water stress and other indicators are often used to characterise drought intensity, yield or yield loss rate to characterise crop yield response (Yao and Jing'ai, 2012;Todisco et al., 2012;Yuan-yuan et al., 2014). The data are mainly from observation, statistics or crop model simulation. Crop model simulations are based on the crop growth and development mechanism, using mathematical physics methods and computer technology to quantitatively describe the crop growth and yield formation process in specific environments, which can solve the problem of insufficient samples or limited precision in observational or statistical data to some extent (Palosuo et al., 2011;Challinor et al., 2009). This method can provide ideas for the study of disaster-causing mechanisms and help to improve risk prediction (Papathoma-Köhle, 2016). However, because the curve is infinite dimensional data (James and Sugar, 2003), it is difficult to directly express the vulnerability and analyse the regional differences. Therefore, exploring the methods of key information mining and spatial analysis for the crop drought vulnerability curve is beneficial to improve the existing research deficiencies, 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 visualisation perspective.~~

(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 Erosion-Productivity Impact Calculator (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 ~~Erosion-Productivity Impact Calculator model (~~EPIC~~)~~ simulation. Then, the loss extent and loss ~~variation~~ 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.

2 Data and methods

2.1 Basic concept

Crop drought vulnerability curve is a function of the relationship between drought intensity and loss. ~~In theory~~ Theoretically, this function is monotonously increasing and non-linear, that is, the loss gradually increases with the ~~increase in~~ drought intensity~~ (the first derivative of the curve is always greater than 0)~~, and the growth rate of loss is phased, which may increase or decrease. Restricted by ecosystem resistance, drought usually begins during the invisible accumulation period, then enters a rapid development period, and, finally, a stable end period (Chen et al., 2015). Therefore, the drought vulnerability curve should be S-shaped and can be divided into three stages as follows (Wang et al., 2013;Kucharavy and De Guio, 2011): (1) initial stage, corresponding to low drought intensity and slight loss, during which there is slow loss growth acceleration; (2) development stage, corresponding to moderate drought intensity and a rapid increase in loss, during which the loss growth rate continues to increase to reach a peak and then quickly falls; and (3) attenuation stage, corresponding to high drought intensity and stable high loss, during which the loss growth rate slowly decays (Fig. 1).

In different environments, the drought vulnerability curve presents different shapes (Yue et al., 2015;Guo et al., 2016;Wang et al., 2013) and the core lies in the difference in loss extent and loss ~~variation~~ change

(Wang et al., 2013;Hu et al., 2012;Gottschalk and Dunn, 2005). Therefore, the key points of the vulnerability curve—the ~~turning~~ transition point of the stages (~~the third order is 0~~ P1 and P3, where the third derivative of the vulnerability curve is equal to zero) and the turning point of the ~~increasing speed (the second order is 0)~~ loss growth rate (P2, where the second derivative of the vulnerability curve equals zero) are used to describe the loss ~~variation~~ change characteristics, the cumulative loss to the loss extent characteristics, and the morphological classification ~~to~~ of the integrated description.

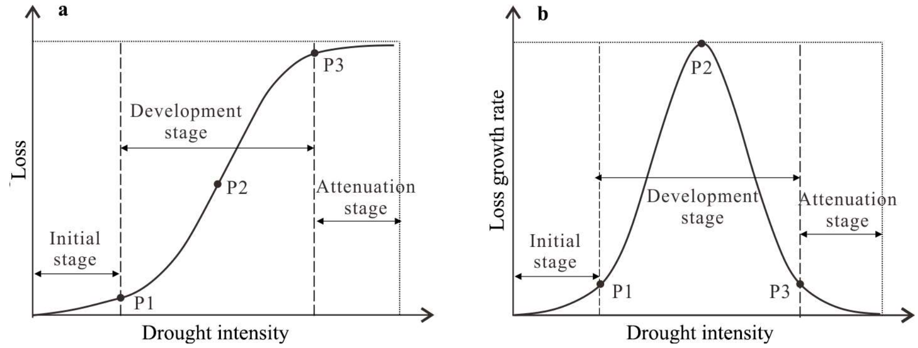


Figure 1: The relationship between drought intensity and (a) loss and (b) loss growth rate as shown by the S-shape drought vulnerability curve. P1, P2, P3 represent the starting point, inflection point and end point of the rapid loss growth, respectively.

2.2 EPIC model and database construction

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).

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.

The study area is the European wheat harvested area provided by the Center for Sustainability and the Global Environment, University of Wisconsin-Madison (Monfreda et al., 2008), and further screened by the wheat planting habit distribution map of CIMMYT (Lantican et al., 2005) for winter wheat distribution. Distributed in the range of 10° W-50° E and 42° N-59° N, this area is one of the world's major wheat-producing areas.

~~The EPIC model is used to simulate the growth process of winter wheat, which can simulate the crop growth process and crop yield in a variety of climatic, environmental and management conditions with high precision, being widely used in many countries and regions (Zhi-qiang et al., 2008;Williams et al., 1984). It's inputs~~ Inputs to EPIC include topography, soil, meteorological, and field management data (Table 1). 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 ~~properties~~ 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 ~~2000~~ 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.

Table 1: Basic database

Category	Name	Source	Spatial resolution
Distribution range data	Harvested area of wheat	Sustainability and the Global Environment, University of Wisconsin-Madison (Monfreda et al., 2008)	5′×5′
	Distribution of wheat planting habit	CIMMYT (Lantican et al., 2005)	Site unit
	Administrative boundary	Eurostat (https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data)	1: 10 Million
Environmental data	DEM	United States Geological Survey (1996)	0.5′×0.5′
	Slope	Food and Agriculture Organization of the United Nations/International Institute for Applied Systems Analysis (2000)	5′×5′

	Soil	International Soil Reference and Information Centre (Batjes, 2012)	5′×5′
	Historical daily meteorological data (1974-2004)	German Federal Ministry of Education and Research: the ISIMIP Fast Track project (Hempel et al., 2013)	0.5°×0.5°
Management data	Growth period of winter wheat	University of Wisconsin-Madison Sustainability and the Global Environment (Sacks et al., 2010)	0.5°×0.5°
	Irrigation	OKI Laboratory, University of Tokyo (Oki, 2002)	0.5°×0.5°
	Fertilizer	Land Use and the Global Environment (Potter et al., 2010)	0.5°×0.5°
Statistical yield data	Statistical yield for calibration (2000)	Food and Agriculture Organization of the United Nations (http://faostat.fao.org)	National（regional）unit
	Statistical yield for validation (1974-2004)		

~~The statistical yield data are not required for EPIC model input but for the localisation of crop parameters in the model and accuracy verification 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 localisation, and yields of 2001-2004 for accuracy verification, to match with the years of meteorological data.~~

2.3 Research method

This study consists of the following three parts. (1) ~~Calibrate~~ Calibration and validation the EPIC model. ~~localise~~ Critical crop parameters in the model are localized to improve the simulation accuracy ~~at~~ in different ~~locations~~ regions. Then the calibrated model performance is validated by comparing simulated and statistical yields. (2)~~Construct the~~ Construction of winter wheat drought vulnerability curves based on the calibrated EPIC model simulation. ~~For each grid unit, define series water supply scenario data and input them into the calibrated EPIC model to generate water stress and yield scenario values, thereby calculating the disaster intensity and yield loss rate, and construct a vulnerability curve.~~ A set of WS and yields are simulated for each grid unit by setting series of irrigation scenarios, which are converted into drought index and yield loss rate for the construction of the vulnerability curve. (3) ~~Analyse the characteristics of the vulnerability curves. Extract their loss extent and loss variation characteristics and cluster morphologically similar curves, and then perform spatial analysis~~ Vulnerability curve characteristics analysis. Key points and cumulative loss rate of vulnerability curves are calculated for the spatial analysis of loss change and loss extent characteristics, and the vulnerability curves are clustered for the integrated spatial analysis (Fig. 2).

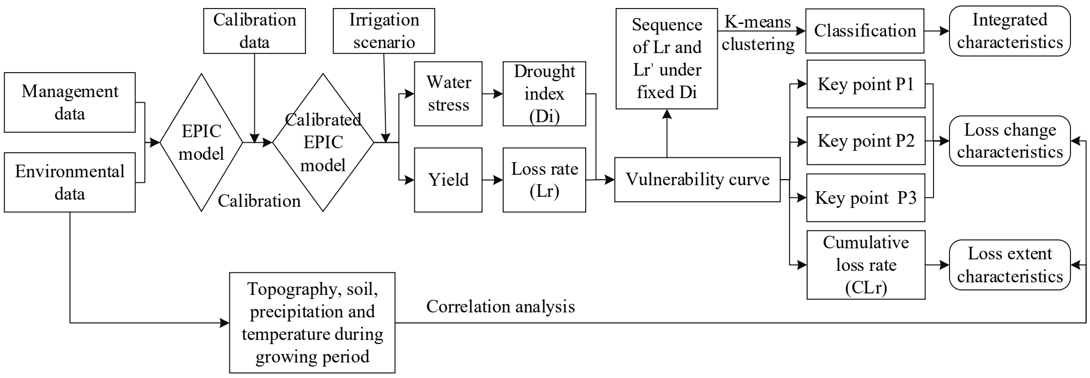


Figure 2: Basic research framework. First, we input relevant data into the EPIC model and perform model calibration. Next, we obtain a series of water stress and yield data based on the calibrated EPIC model by setting different irrigation scenarios, which are converted into drought index (Di) and yield 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 growth 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.

2.3.1 Calibration and ~~accuracy verification~~ validation of the EPIC model

The calibration method refers to the research of Guo et al. (2016). Four key parameters of WA (biomass-energy ratio), HI (harvest index), DLMA (maximum potential leaf area index), and DLAI (fraction of the growing season when the leaf area decreases) are selected for calibration (Barros et al., 2005;Wang and Li, 2010;Wang et al., 2011). 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.

~~In view of the model calibration cost, we consider that the grid units in the same country are homogeneous in the winter wheat variety, that is, they have the same set of crop parameters, which is acceptable for European countries with not large national land areas. Therefore, for all grid units within each country, the default value of the crop parameters in the EPIC model is taken as the initial value, and the actual geographical environmental, field management and meteorological data of 2000 are input to obtain the simulated yields of 2000. Then, the root mean square error (RMSE) between them and the statistical yields of 2000 are calculated. Next, we adjust the four key parameters on these grid units for another round of yield simulation and RMSE calculation. The smaller of the two RMSE values determines the following parameters adjustment direction. The parameters adjustment, yield simulation and RMSE calculation will continue in this manner until the last RMSE is less than the threshold or the number of~~

~~simulations exceeds the threshold, then the adjustment work is completed.~~

~~The goal of EPIC model calibration is to make the simulation yield as near as possible to the statistical yield, which is also the criterion for the model accuracy. Thus, to evaluate model calibration results, we generate the simulated yields for 2001-2004 based on the calibrated EPIC model and calculate the national average simulated yields to compare to the statistical yields.~~

To validate the parameterization results, we generate the simulated grid yields of 1974-2004 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.

2.3.2 Vulnerability curve construction based on the calibrated EPIC model

(1) Generation of ~~water stress~~ WS and yields under different irrigation scenarios

After parameter ~~localisation~~ localization, the EPIC model can be used to simulate WS and the winter wheat yields under different drought scenarios, providing samples ~~of water stress (WS) and yields~~ for the construction of vulnerability curves to drought.

To focus on physical drought vulnerability and eliminate the impact of other stress factors on yields, we ~~maintain the meteorological data, growth period and fertiliser addition rate constant~~ use meteorological data with suitable temperature and no precipitation, and control the water supply condition by setting 20 irrigation scenarios ~~for each grid evaluation unit~~, in which the irrigation amount uniformly increases from 0 to the optimum (the maximum irrigation amount without ~~water stress~~ 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.

(2) Calculation of drought index and yield loss rate index

As an output factor of the EPIC model, WS ~~is an index in the EPIC model that~~ reflects the relationship between daily water supply and crop water demand. WS ranges from 0-1; ~~The~~ the larger the value ~~is~~, the more serious the water shortage will be. ~~We normalise it to obtain the drought index (Di) as follows (Eq. (1), (2)),~~ 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 water stress intensity and stress duration (Eq. (1), (2)) (Wang et al., 2013):

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

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

where Di_i is the drought index of a grid unit under the irrigation scenario i, ranging from 0-1; HI_i is the cumulative value of ~~water stress~~ WS during the growth period under this scenario; max(HI) is the maximum value of HI_i under all irrigation scenarios; WS_k is the ~~water stress~~ WS value on day k of the growth period; and n is the number of days affected by ~~water stress~~ WS during the growth period.

The yield loss rate (Lr) is used to express the response of the yield to drought effects, calculated following Eq. (3):

$$Lr_i = \frac{\max(y) - y_i}{\max(y)} \quad , \tag{3}$$

where Lr_i is the yield loss rate of a grid unit under irrigation scenario i, y_i is the yield under this scenario and max(y) is the maximum yield under the optimal irrigation scenario.

(3) Fitting of drought vulnerability curves

The aforementioned Di - Lr samples were fitted by a logistical curve to obtain the vulnerability curve on each grid unit as follows (Eq. (4)):

$$\mathrm{Lr} = \frac{\mathrm{a}}{1+\mathrm{b}\times e^{c\times Di}} + d \quad , \tag{4}$$

where a, b, c, and d are constant parameters.

2.3.3 Feature extraction and spatial analysis of the vulnerability curves

(1) Identification of key points

According to the analysis in Section 2.1, taking the derivative of Eq. (4), and setting the second and third derivatives equal to 0, the coordinates of the key points can be obtained to ~~characterise~~ characterize the phase change ~~of~~ in the vulnerability curve (Table 2).

Table 2: Key point coordinates of the vulnerability curve

	The starting point of rapid loss growth (P1)	The inflection point of rapid loss growth (P2)	The end point of rapid loss growth (P3)
Di	$-\frac{\ln(2-\sqrt{3})b}{c}$	$-\frac{\ln b}{c}$	$-\frac{\ln(2+\sqrt{3})b}{c}$
Lr	$\frac{(3-\sqrt{3})a}{6}+d$	$\frac{a}{2}+d$	$\frac{(3+\sqrt{3})a}{6}+d$

(2) Calculation of the cumulative loss rate

The cumulative loss rate (CLr) is obtained by the integral of Equation 4 on the Di interval of [0,1] ~~for describing~~ to describe the overall vulnerability. All CLr values are divided into five levels by 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).

(3) Clustering of the vulnerability curves

To identify the morphological characteristics of the vulnerability curves, the curves are divided into some categories by clustering. The first step is to filter the infinite dimensional curve data to a finite set of representative parameters (James and Sugar, 2003). A set of Lr and growth rate of Lr (Lr') under the fixed Di ~~value is~~ are selected to preserve both the loss extent and variation characteristics (Di=0.2, 0.4, 0.6, and 0.8, when Di=0 or 1, there is little difference in the value of Lr and Lr' between the curves). The 8 elements are separately normalised following Eq. (5) for the second step of clustering. We use the K-means clustering method to compare the distance or dissimilarity between the curves (Jacques and Preda, 2014). After clustering, the further category vulnerability curves are fitted by the Di-Lr samples of the corresponding grid vulnerability curves.

$$N(Lr_{Di=x})_t = \frac{(Lr_{Di=x})_t}{\mathrm{SD}(Lr_{Di=x})} \quad , \tag{5}$$

where $(\mathrm{Lr}_{\mathrm{Di=x}})_{\mathrm{t}}$ is the value of Lr (Lr') when Di=x for the vulnerability curve t, and x=0.2, 0.4, 0.6, and 0.8; $\mathrm{SD}(\mathrm{Lr}_{\mathrm{Di=x}})$ is the standard deviation of Lr (Lr') when Di=x for all vulnerability curves; and $\mathrm{N}(\mathrm{Lr}_{\mathrm{Di=x}})_{\mathrm{t}}$ is the normalised value.

3 Results and analysis

3.1 ~~Verification~~ Validation of the EPIC model simulation results

From the ~~simulation~~ national comparison results ~~of the country (region) winter wheat yield~~ from ~~2001~~ 1974 to 2004 (excluding calibration year of 2000), though the simulated yields are slightly lower than the statistical yields~~. However~~, there is a high ~~degree of consistency~~ agreement between the two (Fig. 3). The regression equation has an R^2 ~~between 0.89 and 0.93~~ of 0.77 and passes the test with a confidence of 0.01, indicating ~~that the EPIC model works well~~ a reliable performance of the calibrated EPIC model for yields simulation in various regions and ~~during~~ various years.

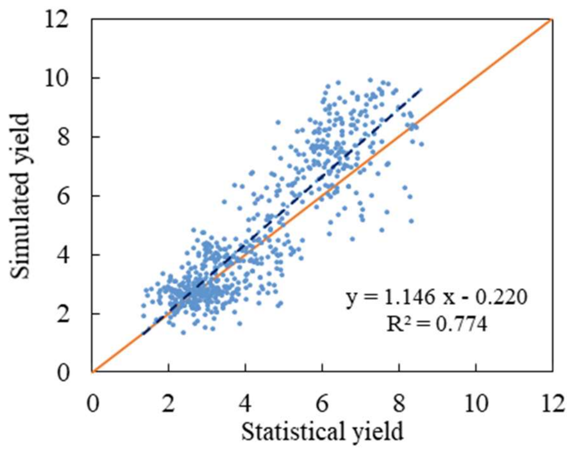


Figure 3: ~~Regression relationship between statistical winter wheat yield and simulated yield based on country units during (a) 2001; (b) 2002; (c) 2003; and (d) 2004.~~ Comparison of national winter wheat yield reported by FAO and simulated by calibrated EPIC during the period from 1974-2004 (excluding calibration year of 2000).

3.2 European winter wheat drought vulnerability curves and characteristics analysis

3.2.1 Winter wheat drought vulnerability curves

Figure 4a shows the winter wheat drought vulnerability curves of the 2010 grid assessment unit in Europe. Their R^2 values are greater than 0.94, indicating a high overall goodness of fit. They are quite different in morphology and can be classified into several types via curve clustering (Appendix A).

The regional starting point, inflection point and end point of the rapid ~~loss~~ growth of loss ~~is~~ correspond~~ing~~ to ~~a~~ Di values of 0.27, 0.47 and 0.68 and ~~a~~ Lr values of 0.17, 0.43 and 0.75 (Fig. 4b), respectively. For most grids, the Di values at the three key points is mainly distributed ~~between~~ from 0.15-0.55, 0.35-0.7 and 0.4-0.8, while ~~and~~ the Lr values have a relatively small distribution, from ~~between~~ 0.1-0.2, 0.4-0.5 and 0.7-0.8~~, respectively, with a relatively insignificant difference~~. Therefore, ~~the Di of key points can be used to compare the difference in the stage transitions of the vulnerability curve~~ 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 later the qualitative change of Lr, and~~ 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 the tolerance to drought disturbance.

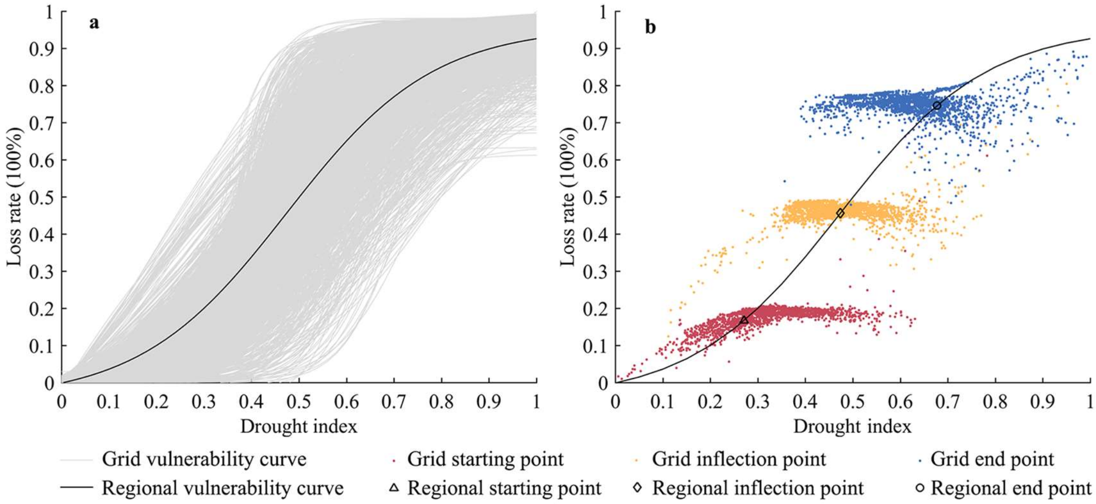


Figure 4: Distribution of (a) regional and grid vulnerability curves and (b) their three key points. The regional vulnerability curve (the black curve) is fitted by all drought index -loss rate sample data in the region.

3.2.2 Spatial distribution of the characteristic value

In terms of spatial distribution, the Di values at key points ~~to~~ in the south are higher than ~~that to~~ those in the north (Fig. 5). In the southern areas, the Di values at the starting ~~points~~, inflection ~~points~~ and end points~~, respectively, reach~~ are concentrated in 0.4-0.5, 0.5-0.7 and greater than 0.7, while in north-central areas, they are less than 0.2, 0.3-0.5, and 0.5-0.7, respectively. Therefore, the stage transitions of ~~Lr are lagging~~ in the southern areas lag behind, indicating a higher tolerance to drought disturbance ~~and the tolerance to drought disturbance is higher~~. ~~In the north-central areas, the Di are respectively concentrated at less than 0.2, 0.3-0.5 and 0.5-0.7, respectively, the stages of Lr change earlier and the tolerance to drought disturbance is weaker.~~ In the northeast, the Di values at the start and end points ~~is~~ are within the range of 0.2-0.4 and 0.4-0.6, respectively, indicating that the Lr ~~has~~ changes drastically ~~changed~~ during short development stages, ~~when the~~ during which these areas are particularly ~~susceptive~~ susceptible to drought.

The CLr ~~representing~~ represents the ~~total~~ overall vulnerability, which is contrary to the meaning of Di at key points, and naturally shows an opposite distribution of low in the south and high in the north. Though both the north-central areas and the northeast areas have extremely high CLr values, ~~the loss rate stages~~ stage transition characteristics in the two areas are different. The CLr integrates the characteristics of the key points, but shows information loss in the characteristics of ~~the~~ loss ~~rate transitions~~ change.

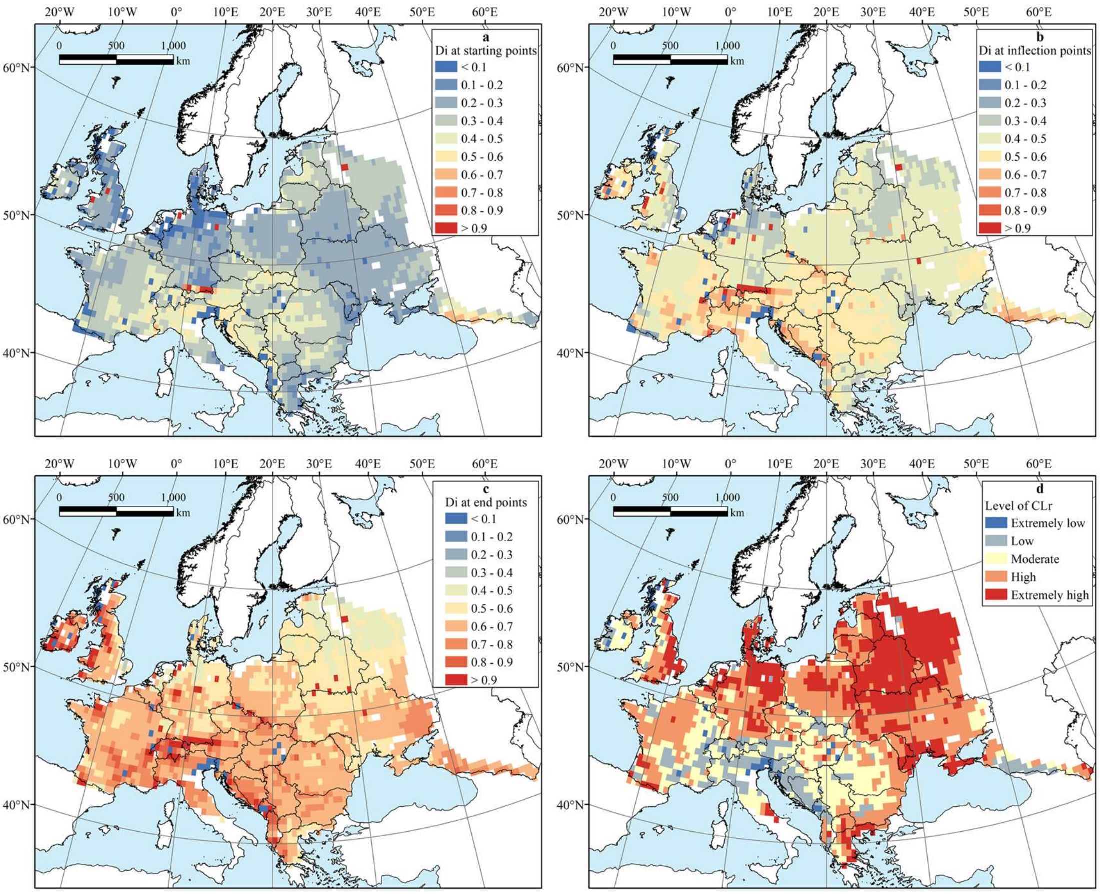


Figure 5: Spatial distributions of drought index (Di) at the (a) starting points, (b) inflection points and (c) end points, and (d) spatial distribution of the level of the cumulative loss rate (CLr) of vulnerability curves.

3.3 Categories of winter wheat drought vulnerability curves

Based on the characteristics of loss extent and ~~variation~~ change, the winter wheat vulnerability curves to drought in Europe can be divided into five types for a relatively uniform distribution, ~~such that the results are not over-concentrated or over-classified~~ so as not to be over-concentration or over-classification (Appendix B). ~~Comparing~~ Compared to the regional loss characteristics ~~during~~ at the initial, development and attenuation stages, these types of vulnerability curves are defined as Low-Low-Low (L-L-L), Low-Low-Medium (L-L-M), Medium-Medium-Medium (M-M-M), High-High-High (H-H-H) and Low-Medium-High (L-M-H) loss-type vulnerability curves (Fig. 6). Five category vulnerability curves are fitted based on the Di-Lr samples of related vulnerability curves for a comprehensive characterization.

The Lr of the L-L-L loss-type vulnerability curves ~~is~~ are lower than the regional level under the same Di, and the category CLr is only 0.33 (calculated by the category vulnerability curve), which is the lowest value of the five ~~category vulnerability curves~~ categories (Appendix C). ~~This type of~~ These vulnerability curves ~~is~~ are mainly distributed in mountain areas such as the Alps and the Dinara and Caucasus mountains, accounting for 10.0 % of the winter wheat planting area in Europe.

The L-L-M loss-type vulnerability curves have a relatively low loss rate and are susceptible to drought within the range of 0.4-0.7. When the Di values reach~~es~~ approximately 0.4, the loss rates begin to rapidly increase; when the Di values are greater than 0.6-0.7, the loss rates are near the regional level. The category CLr is 0.42. It is mainly found in the Danube river basins, including hilly areas and plains, accounting for 20.4 % of the winter wheat planting area in Europe.

The M-M-M loss-type vulnerability curves are near the regional vulnerability curve with a category CLr of 0.50, and mainly occur in the Western European Plains, the Pod Plains, Donets Ridge and surrounding highlands and lowlands. They have the widest distribution accounting for 33.9 % of the winter wheat planting area in Europe.

The Lr values of the H-H-H loss-type vulnerability curves ~~is~~ are higher than the regional level, and the category CLr reaches ~~up to~~ 0.57. ~~This loss type is~~ These vulnerability curves are concentrated in patches on the Pod Plain, Polesi and in lowland areas along the Black Sea and Eastern Great Britain, at approximately the same latitude zone as that of the M-M-M loss-type, ~~and it accounts~~ accounting for 23.4 % of the winter wheat planting area in Europe.

The L-M-H loss-type vulnerability curves show high susceptibility to drought in the range of 0.3-0.6, where the loss rate rapidly increases and reaches the regional level with the increase in Di. When Di values are greater than 0.6 and continue to increase, the loss rates maintain relatively stable high values; when Di values are less than 0.3, the yield losses are slight. The category CLr is 0.53. These curves are mainly distributed on the east European plain, accounting for 12.2 % of the winter wheat planting area in Europe.

~~On the whole~~ Overall, the spatial distributions of the five types of vulnerability curves are obviously latitudinal and consistent with the geographical pattern of Europe, where plains and mountains mostly extend from the east to the west in the mainland and extend from north to south in the British Isles. From south to north, and from mountain to plain, the vulnerability curves transition from concave to convex, and the CLrs show an upward trend, indicating increasing vulnerability. The heat difference at different latitudes and the water and heat difference at different altitudes may be the root cause of the type distribution.

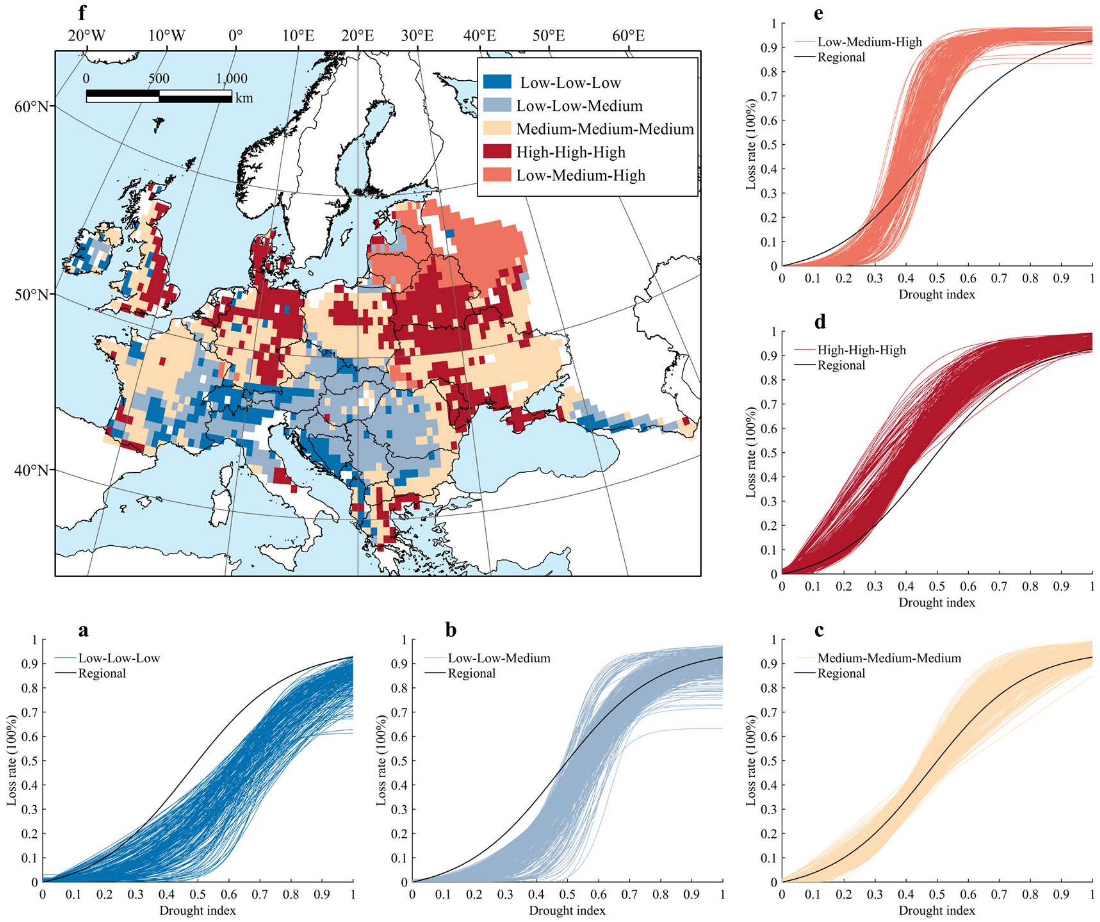


Figure 6: Five types of European winter wheat vulnerability curves to drought: (a) Low-Low-Low, (b) Low-Low-Medium, (c) Medium-Medium-Medium, (d) High-High-High and (e) Low-Medium-High loss-type vulnerability curves, and (f) their spatial distributions.

4 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 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.

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.

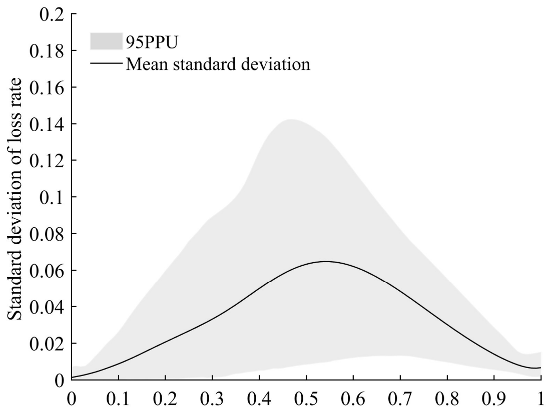


Figure 7: Distribution of standard deviation of loss rate under different drought index. The mean standard deviation and 95 % prediction uncertainty band (95PPU) are calculated by the standard deviations of sample grids, which are randomly selected from the five vulnerability curves at a proportion of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

4.~~1~~2 Relationship between vulnerability characteristics and environmental variables

To further explore the relationship between the vulnerability characteristics ~~parameter~~ distribution and environmental variables, Spearman correlation analysis is performed between the vulnerability characteristics parameters (Di_1, Di_2, Di_3, and CLr) and environmental variables (elevation, slope, soil sand content, precipitation during growth period, average temperature during growth period, and relative humidity during growth period). The results all passed the significance test at the level of 0.01 (Table 3). The Di_1 value is positively correlated with relative humidity and elevation, and the correlation coefficients ~~is~~ are 0.41 and 0.40, respectively. That is, in areas with high relative humidity or altitude, only when the drought develops to a rather serious extent does it begin to have a significant impact on winter wheat yield. Additionally, the ~~The~~ L-L-L, L-L-M and L-M-H loss-type areas with high Di_1 values have the characteristics of high elevation or high relative humidity (Appendix D).

The four characteristic parameters are highly correlated with the environmental variables with latitudinal zonality, such as elevation, slope, temperature and soil sand content and the environmental variables with latitudinal zonality, which ~~This~~ verifies the inference of the distribution ~~law~~ of characteristic parameters ~~previously mentioned~~ above. The Di_1, Di_2 and Di_3 values characterising drought tolerance are positively correlated with elevation, slope and temperature, and negatively correlated with soil sandy content, while the CLr value ~~characterising~~ characterizing the comprehensive vulnerability ~~is~~ shows the opposite trend. The H-H-H loss-type areas with high vulnerability have typical characteristics of low elevation, slope, temperature and high soil sandy content.

From the perspective of an influencing mechanism, when the soil sandy content is high, the soil drainage ability is high, and the crop is more vulnerable to drought, exhibiting low Di_1, Di_2, and Di_3 values and a high CLr value in the vulnerability curve (Reid et al., 2006;Papathoma-Köhle, 2016). The cause-effect relationship between the temperature and the characteristic parameters cannot be defined, although the spatial distributions of the two have a certain correlation. Because temperature stress is removed from the drought scenarios, the temperature variable has no direct influence on the results of yield loss rate to drought and the characteristic parameters. It may have an indirect influence by affecting the crop parameters of winter wheat during the previous calibration process. Similarly, elevation does not directly affect the values of the characteristic parameters. Simulation experiments based on the EPIC model found that changing the input of elevation has little effect on the simulated yield (Thomson et al., 2002). Thus, the elevation may indirectly affect yield and drought vulnerability by acting on other environmental variables such as temperature, precipitation and soil. The aforementioned can provide ideas for ~~the study of~~ studying the impact of the environment on vulnerability.

Table 3: Correlation between vulnerability characteristic parameters and environmental variables (P≤0.01)

	Di_1	$Di_{\cancel{m}2}$	$Di_{\cancel{2}3}$	CLr
Elevation	0.40	0.43	0.37	-0.44
Slope	0.31	0.44	0.45	-0.48
Soil sand content	-0.10	-0.35	-0.44	0.38
Average temperature during growth period	0.32	0.34	0.30	-0.38
Precipitation during growth period	-0.09	0.19	0.33	-0.26
Relative humidity during growth period	0.41	0.23	0.09	-0.27

4.~~2~~3 Application of the vulnerability curves

By analysing the distribution of characteristic parameters ~~distribution~~, it is found that the winter wheat vulnerability in Europe is lower to the south, particularly in the surrounding areas of the Mediterranean, which is consistent with Mäkinen's findings based on experimental data on wheat varieties (Mäkinen et al., 2018).

In addition to reflecting the spatial differences in vulnerability, the characteristic information can accurately express the response feature to drought in various regions and more effectively guide drought risk management. In southern Europe (mainly the L-L-L and L-L-M loss-type vulnerability curves), there is a strong tolerance to mild drought with a Di_1 greater than 0.4, and we should pay more attention to moderate and severe drought reduction. In most of the central region (mainly M-M-M and H-H-H loss-type vulnerability curves), there is a low tolerance to varying degrees ~~to~~ of drought, and we should pay attention to the construction of fortification capacity. In the north-eastern region (the L-M-H vulnerability curve), there is susceptibility to droughts with ~~a~~ Di values ranging from 0.3 to 0.6, which is a critical stage for drought mitigation. In addition, in regions with H-H-H and L-M-H loss-type vulnerability curves, the Lr relatively slowly increases when the Di is greater than 0.6. At this time, the cost of engineering mitigation means is high, and non-engineering means can be considered.

The ~~extent to which~~ impact of climate change ~~affects~~ on crop yield depends not only on the temporal and spatial patterns of climate change but also on species characteristics (Trnka et al., 2014;Semenov et al., 2014). The vulnerability curve based on the crop growth process simulation helps to understand the risk from a vulnerability perspective. From the perspective of climate change, precipitation will decrease and evaporation will increase in southern Europe in the future, and drought risk is more likely to increase compared to that of other regions of Europe (IPCC, 2012;Olesen et al., 2011). However, it was found that under the RCP4.5 scenario and using the HadGEM2-ES and MPI-ESM-MR model data for simulation, the increase in drought effects ~~increase~~ in the southern region will be less than or near those of the central and north-eastern regions (Webber et al., 2018), which may be related to a lower vulnerability.

5 Conclusion

Quantitative crop-drought vulnerability assessment and analysis are an important basis for drought risk assessment and drought risk management. Taking European winter wheat as an example, we generate series data of ~~water stress~~ WS and scenario yield based on EPIC model simulation and then construct S-type drought vulnerability curves. Through characteristic parameters analysis and clustering analysis of vulnerability curves, the loss extent and loss ~~variation~~ change characteristics are mapped to identify the regional vulnerability pattern and drought response characteristics. The results provide quantitative ideas for the study of the impact of the environment on vulnerability and provide scientific guidance for regional drought- mitigation resource allocation and strategy development.

The winter wheat drought vulnerability in Europe is higher in the south and lower in the north with a latitudinal zonality, which may be related to environmental variables such as elevation, slope, average temperature during growth period and soil sand content. In the southern region, the Di values of the key points~~' drought index~~ are high, and the ~~cumulative loss rate is~~ Clr values are low, indicating a low vulnerability, while the northern region shows the opposite trend.

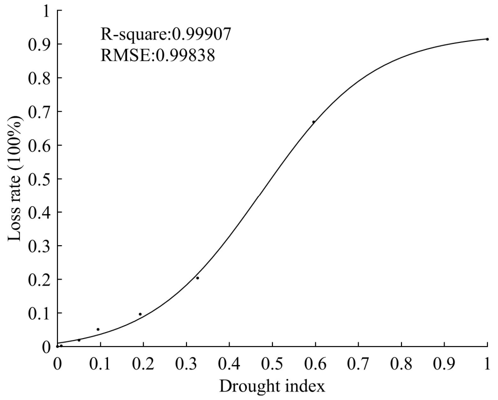
The vulnerability curves can be divided into five loss types: ~~Low-Low-Low (~~L-L-L~~)~~, ~~Low-Low-Medium (~~L-L-M~~)~~, ~~Medium-Medium-Medium (~~M-M-M~~)~~, ~~High-High-High (~~H-H-H~~)~~ and ~~Low-Medium-High (~~L-M-H~~)~~. It is recommended to improve the ability to address drought with a greater than 0.4 intensity in the L-L-L or L-L-M loss-type areas and a drought range from 0.3-0.6 intensity in the L-M-H loss-type areas, as well as improve ~~the ability fo~~r drought prevention and mitigation in the M-M-M or H-H-H loss-type areas.

Data availability

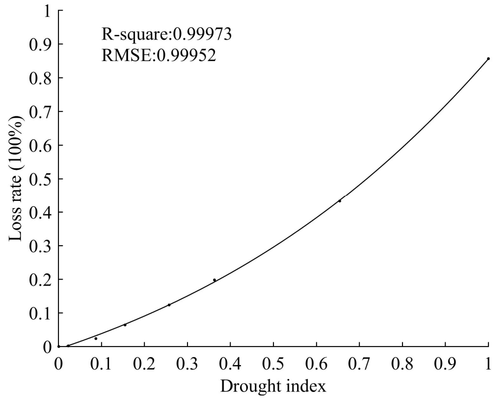
The sources of raw data can be found in section 2.2. The code is written for MATLAB, which is available upon request by contacting Yanshen Wu (wuyanshen1012@mail.bnu.edu.cn).

Appendices

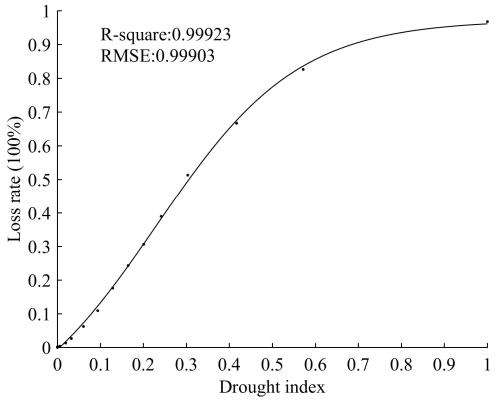
Appendix A: Examples of European winter wheat grid vulnerability curves to drought



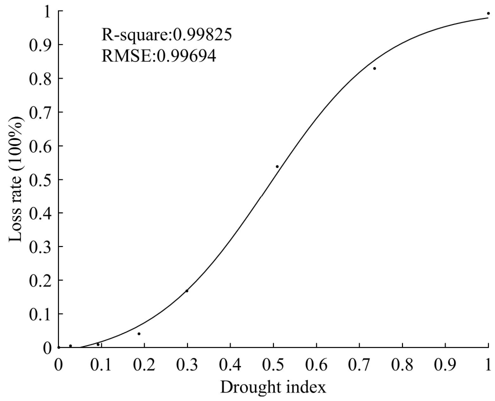
France (grid centre: 1.75° E, 49.25° N)



United Kingdom (grid centre: 2.25° W, 53.75° N)



Germany (grid centre: 9.75° E, 54.25° N)



Ukraine (grid centre: 33.25°E, 47.75°N)

Appendix B: Clustering effect of different cluster quantities

Quantity of cluster	Quantity of vulnerability curves in each cluster							Within-cluster sum of squared errors (SSE)
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	
3	235	1082	707	-	-	-	-	3711.9
4	257	641	891	235	-	-	-	3340.2
5	475	409	692	245	203	-	-	2794.3
6	3	474	688	410	245	204	-	2538.0
7	3	156	711	157	195	256	546	2519.9

Appendix C: Classificatory key points and cumulative loss rates calculated by category vulnerability curves

Category vulnerability curve	Di_1	Lr_1	Di_2	Lr_2	Di_3	Lr_3	CLr
L-L-L	0.44	0.19	0.67	0.48	0.90	0.76	0.33
L-L-M	0.40	0.19	0.55	0.46	0.69	0.73	0.42
M-M-M	0.28	0.18	0.47	0.47	0.65	0.75	0.50
H-H-H	0.19	0.15	0.38	0.45	0.57	0.76	0.57
L-M-H	0.33	0.19	0.44	0.47	0.56	0.75	0.53
Europe	0.27	0.17	0.47	0.46	0.68	0.75	0.48

Appendix D: Descriptive statistics of environmental variables in various loss-type regions

		L-L-L	L-L-M	M-M-M	H-H-H	L-M-H	Regional
Elevation (m)	Median	677	315	165	140	160	181
	Interquartile Range	636	468	154	125	103	241
Slope (°)	Median	23	12	6	3	3	6
	Interquartile Range	25	17	9	3	3	9
Soil sand content (%)	Median	43	43	43	52	52	43
	Interquartile Range	4	10	22	9	0	12
Precipitation during growth period (mm)	Median	960	646	599	599	638	629
	Interquartile Range	306	198	128	131	53	158
Average temperature during growth period (℃)	Median	7.1	7.8	7.5	6.9	3.9	7.1
	Interquartile Range	3.5	3.6	2.1	1.9	1.1	2.9
Relative humidity during growth period (%)	Median	79.9	80.6	77.5	77.1	80.2	78.8
	Interquartile Range	2.7	3	3.9	3.1	2.1	3.9

Author contribution

Jing'ai Wang proposed overarching idea and formulated overarching research goals and aims. Hao Guo implemented EPIC model calibration, simulation and vulnerability curves construction. Yanshen Wu and Anyu Zhang developed the vulnerability curves characteristics analysis methods and carried them out. Yanshen Wu drafted and revised manuscript with contributions from all co-authors.

Competing interests

The authors declare that they have no conflict of interest.

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