Response to Anonymous Referee #2

Dear Anonymous Referee:

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

Point 1: *Other than an English proofing that prevented me from understanding some sentences properly, ...*

Response 1: Thank you so much for your comment. 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. The editing certificate can be found in supplementary document.

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

Response 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 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 2-2 and 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 2-3).

Revision 2-1: Supplementary validation time series in the section of data and method

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

…

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

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

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

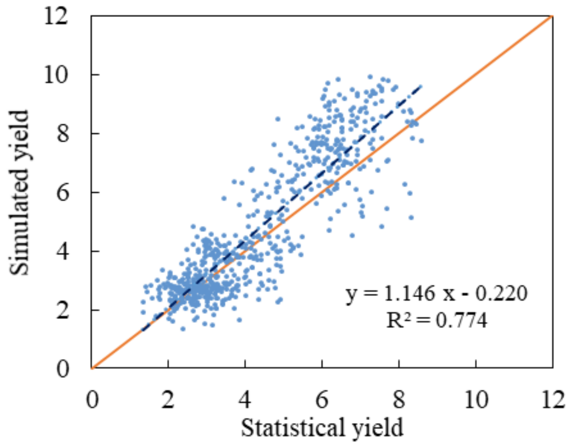

Figure 1: Comparison of national winter wheat yield reported by FAO and simulated by calibrated EPIC during the period from 1974-2004 (excluding calibration year of 2000).

Revision 2-3: Supplement as the first section of the discussion

4.1 Uncertainty analysis

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

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

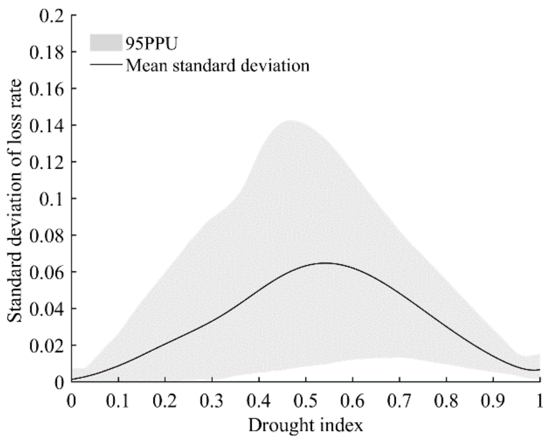

Figure 7: Distribution of standard deviation of loss rate under different drought index. The mean standard deviation and 95 % prediction uncertainty band (95PPU) are calculated by the standard deviations of sample grids, which are randomly selected from the five vulnerability curves at a proportion of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

Point 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 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 3).

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

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

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.

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

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

Yours sincerely,

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References

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