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REVIEW ARTICLE

Quantifying crop vulnerability to weather-related extreme events and climate change through vulnerability curves

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Abstract

Weather extremes have been responsible for widespread economic damage at global scale in the last decades. Agriculture alone absorbed 26% of the overall impact caused by natural hazards in low- and middle-income countries and even in high-income countries yield losses due to extreme weather are relevant. Vulnerability curves are traditionally used to quickly estimate the damage due to extreme events. This study maps the articles published from January 2000 to May 2022 implementing crop vulnerability curves to weather-related extreme events and climate change. Fifty-two articles have been identified through the use of Scopus, Web of Science, Google Scholar and the references of the selected papers. The selected papers have been analysed to determine for which extreme events vulnerability curves have been proposed, which crops have been studied, which explanatory variables have been used to create the curves, which functions are used to develop vulnerability curves and the number of parameters on which the proposed functions rely. Comparisons among the vulnerability curves for the various extremes are proposed, as well as indications of the main drawback of the developed vulnerability curves. Finally, areas where further research is needed are proposed together with recommendations on which elements should be included in vulnerability curve development.

Keywords Vulnerability curves · Weather-related extreme events · Crops · Climate change

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1 Introduction

In the last decades, extreme weather has been responsible for widespread economic and social damages at global scale. Between 1980 and 2019, extreme weather caused the death of 1.15 million people, with droughts being the event causing the highest number of deaths (around 50% of fatalities due to climate extremes), followed by storms and floods (Cesarini et al. 2021). Weather and climate have always been strictly linked with agricultural productivity. Climate variability accounts for roughly a third of yield variability globally, while in the substantial areas of the global breadbaskets more than 60% of yield variability can be explained by climate variability (Ray et al. 2015).

Agriculture is particularly vulnerable to natural hazards too. Over the 2000–2018 period in low- and middle-income countries, agriculture alone absorbed the 26% of the overall impact caused by medium- to large-scale natural disasters. Losses in agriculture relative to the combined industry, commerce and tourism sectors in the same period accounted for 63% of the whole losses from natural disasters (FAO 2021). Even in high-income countries such as the European ones, agricultural losses due to extreme events are relevant. As an example, historical drought and heat waves in Europe reduced cereal yields on average by 9% and 7.3%, respectively, while non-cereal yields declined by 3.8–3.1% during the same set of events (Brás et al. 2021).

The increase in both number and frequency of extreme events observed over the past years poses a significant challenge to agriculture, compromising global food security (Chavez et al. 2015). Climate change is expected to increase frequency and severity of weather-related extreme events such as floods, droughts and storms (IPCC 2022), and therefore, the losses that the agricultural sector is going to experience in the next years are expected to increase (Cammalleri et al. 2020).

The quantification of the hazard severity alone is not sufficient to develop methodologies to manage the risk (Bachmair et al. 2017). Vulnerability is a key component of the risk chain (Wu et al. 2021); therefore, understanding crops vulnerability to both extreme weather events and climate change is essential to develop appropriate adaptation strategies to effectively reduce yield losses. A traditional approach to assess the negative effects of extreme events is the use of vulnerability curves, also called vulnerability functions, stage damage functions or damage curves (Dutta et al. 2003; Michel-Kerjan et al. 2013; Tarboton et al. 2015).

It is worth defining properly the concept of vulnerability, to understand vulnerability (or damage) functions (or curves). According to (Adger 2006), "vulnerability" is defined as "the degree to which the system is susceptible to and is unable to cope with adverse effects of change". The United Nation International Strategy for Disaster Risk Reduction (UNISDR 2009) provided a more comprehensive definition of vulnerability as "the characteristics and circumstances of a community, system or asset that make it susceptible to the damaging effects of a hazard". This definition encompasses many aspects of vulnerability, arising from various physical, social, economic and environmental factors (e.g., poor design and construction of buildings, inadequate protection of assets, lack of public information and awareness, among others). Following this definition, vulnerability is a characteristic of the element at risk which is independent of its exposure to any hazard. However, the term vulnerability is often used more broadly to include the element's exposure in the quantitative assessment of the risk associated with a specific hazard.

Vulnerability curves express physical vulnerability as a function of the intensity of the hazard and the degree of loss (Papathoma-Köhle 2016). They have been widely applied to assess buildings' response to hazards such as earthquakes and floods (Englhardt et al. 2019; Polese et al. 2013).

In the agricultural sector, the exposure to a hazard is represented by the crop yield, while the vulnerability is described as the degree of yield loss with respect to the expected crop yield, thus reflecting the damage of the asset (e.g., cropland) affected by a hazard. It is expressed on a scale from 0 (no loss) to 1 (total loss) (UNDRO22, 76, 1984). In this context, vulnerability functions estimate the damage ratio and consequent loss, respectively, generated by a hazard, according to a specified exposure. In particular, such curves relate an explanatory variable expressing the hazard intensity, such as water depth in case of floods, wind speed for storms and a drought index for droughts, to the negative effects of the hazard on crops, expressed in terms of percentage of crop yield loss (Fig. 1).

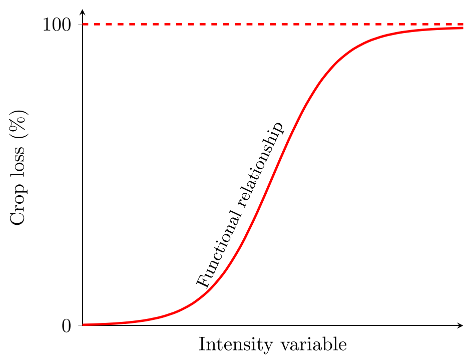
Over the past years, the interest in event-specific crop vulnerability functions has increased all over the world since such functions are extremely useful in drawing risk management plans, establishing the most appropriate risk reduction strategies or designing parametric insurance contracts (Ming et al. 2015).

In addition, the integration of vulnerability curves in early warning systems is helpful in providing information on the possible impacts of future weather conditions on crop yield and thus can support farmers in their choices of cultivars, sowing date and crop management (Guo et al. 2021).

The existing literature reviews on the topic of crop vulnerability to natural hazards have principally focused on the assessment of the economic flood damages to agriculture. For example, Merz et al. (2010) reviewed the approaches to estimate flood damage to agriculture in economic terms, finding that simplified approaches for damage estimation are frequently applied. The study also highlighted that a great attention is traditionally paid to hazard modelling, while the economic damage estimation is treated with less attention. Moreover, the developed models are rarely validated. Brémond and Grelot (2013) proposed another relevant literature review on this topic; the paper focused its attention on the evaluation of economic damages due to flood in the European agricultural sector. In this review, focus has been given on existing papers which developed or used vulnerability or damage functions for crops and various agricultural assets such as buildings, machineries and livestock. Both studies deal with damage due to floods only.

The present work instead aims at reviewing the studies proposing crop vulnerability curves not only for floods but also for the other weather-related extreme events. Crop vulnerability to nine weather-related extreme events has been explored. In addition, climate change has been included in the review as well, since the projected temperature increase

Fig. 1 Schematic representation of a hypothetical vulnerability curve



will play a key role in reducing crop yields (Webber et al. 2018). In particular, this study addresses the following topics:

1. Type of extreme events for which crop vulnerability curves have been developed;
2. Crops for which vulnerability curves are available;
3. Methodologies and research techniques applied to develop the curves;
4. Variables that have been used to construct the vulnerability curves;
5. Types of functions considered in curve developing and number of function's parameters;
6. Main gaps and shortcomings in the developed vulnerability functions.

This work focuses exclusively on studies published between January 2000 and May 2022 that propose crop vulnerability curves to different extreme events. The outcomes are of fundamental importance to explore how the topic of crop vulnerability to extreme events has been investigated over the past years and to understand where improvements are needed to better characterize crop losses due to weather extremes and climate change.

In particular, focus will be given to a pragmatic classification of the available literature, following different criteria, i.e.,

- Evidencing different kind of hazards each reviewed paper focuses on
- Distribution of reviewed papers' case studies among the globe
- Distinction of analysed crop types
- Distinction of the different methodological approaches for curve development applied in each paper
- Distinction of the different curve shapes and type of functions developed in each paper
- Investigate on the main co-occurrence of keywords
- Investigate on the main co-author networking on the topic

2 Journal articles selection criteria

The first step of this study involves the identification of the relevant scientific literature published between January 2000 and May 2022 on the topic of crop vulnerability curves to different natural hazards. Therefore, a bibliometric review has been performed through the use of the online collection of three research tools: Scopus (https://www.scopus.com/), Web of Science, WoS (https://www.webofscience.com/) and Google Scholar (https://scholar.google.com/). The three tools are the main online databases available for scientific research and are widely recognised among the scientific community for their reliability and multidisciplinary. The primary criterion for the inclusion of a scientific study was its publication as article or review in a peer-reviewed journal. In addition, only studies published in English have been considered since they are comprehended by the majority of scientists and stakeholders (Droulia and Charalampopoulos 2021). Multiple search queries have been performed in the three online databases by applying different combinations of the keywords shown in Fig. 2. Only weather-related extreme events have been considered in this review since are the ones impacting on agricultural production (FAO 2015). The considered extreme events, shown in Fig 2, were selected based on the classification proposed by the Centre for Research on the Epidemiology of Disasters, (CRED), which groups the weather-related extreme events in meteorological (extreme temperature, fog, storms),

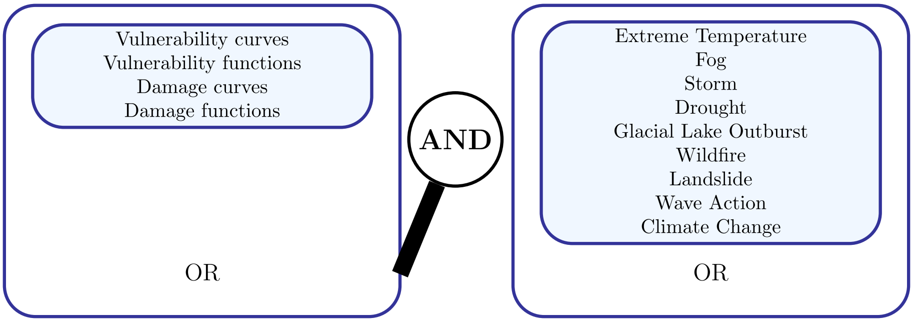


Fig. 2 Search strategy: keywords used to define the functions and the extreme events

hydrological (flood, landslide, wave action) and climatological (drought, glacial lake outburst, wildfire) (CRED 2021). In addition, climate change has been added to the list of extreme events since the increase in temperature will influence crop growth (Malhi et al. 2021; Moriondo et al. 2010).

After that, the studies were further screened based on their relevance to the subject, given by the actual implementation of a vulnerability function in the form of curve or surface relating the hazard intensity to crop losses. A systematic assessment of the references in the key identified publications was then performed to search for additional studies. Finally, the articles were alphabetically sorted by author and accompanied by information on the event type, the location of the case study area and the crop type. In addition, details on the variables used to build the vulnerability curve have been collected to understand which indicators are traditionally used to express the hazard intensity, together with the type of functions used to fit the collected data and the number of parameters on which the curve function depends (Fig. 3).

Following the above-mentioned criteria, fifty-two studies have been selected and are listed in Table 1 (studies investigating the effects of climate change on crops), Table 2 (studies on crops response to extreme temperatures), Table 3 (studies evaluating the effects of storms on crops), Table 4 (papers assessing the response of crops to floods) and Table 5 (papers evaluating the response of crops to drought), together with information on the extreme event considered in the article, the crop, the case study location, the implementation of curves for different crop growth stages, the indicators used to build the curves (or the surfaces), the type of functions applied and the number of parameters of the curve's function. Among the research journals, "The International Journal of Disaster Risk Reduction" and "Natural Hazards" are the ones that published the highest number of papers on the topic of crop vulnerability curves to weather-related extreme events, both with seven published papers. "Environmental Research Letters" published four papers, "Agricultural Water Management" three, while two papers are published in "Natural Hazards and Earth System Science," "Journal of Hydrology" and "Agricultural Systems." The topic is mainly investigated in journals dealing with environmental sciences and earth and planetary sciences. The interest in crop vulnerability curves to weather-related extreme events has increased over the years, as demonstrated by the increase in the number of studies on the topic that have been published in the last 5 years.

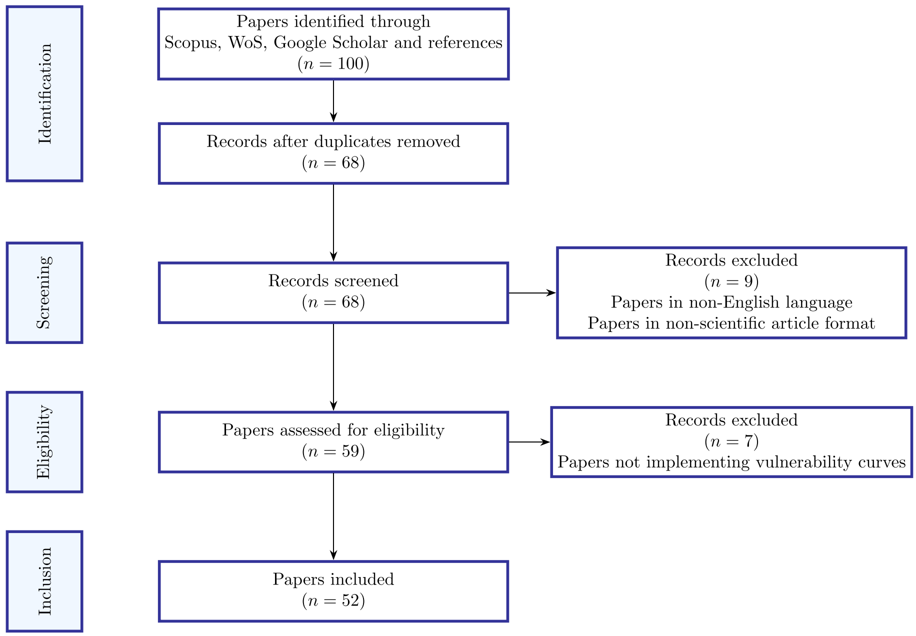


Fig. 3 Process and criteria applied to search and select the articles to include in the review. Number of records identified in each step is also reported

2.1 Article classification based on the type of hazard

A major part of the considered studies (27) proposed crop vulnerability curves for drought (see Table 5 for the complete list of papers). Flood is the second most represented event (reported in 18 papers, Table 4). Four papers implemented crop vulnerability curves to climate change (Table 1), while only two papers designed vulnerability curves for storms (Table 3) and one for extreme temperatures (Table 2), considering the effect of extreme cold on crops (Fig. 4a). Most of the considered articles proposes case study areas locate in China (16). Six studies implemented vulnerability curves in Italy, while three proposed global analysis (Fig. 4b). Thirteen of the 16 papers having Chinese areas as case study evaluate the effect of droughts on crops, while two the effects of floods. For what concerns Italy, three papers investigate the impact of climate change on crops, two the impacts of floods and two the effects of droughts. Articles proposing crop vulnerability curves for storms selected Japan and the Philippines as case study, while the paper showing functions for extreme temperature considers a case study in China.

2.2 Article classification based on crop type and growth stage

In the 52 selected papers, the crops for which vulnerability curves have been developed are mainly cereals, in particular maize, rice and wheat. Maize is the most represented crop, studied in sixteen papers, followed by rice, reported in twelve papers. Fifteen papers present results for more than one crop. Wheat is considered in four studies, while sorghum,

Table 1 List of the selected studies proposing vulnerability curves for climate change and information on the crop, the case study location and the explanatory variables used to build the curves. ET: Evapotranspiration

Reference	Crop	Case study location	Axis x	Axis y	Axis z	Methodology	Equation
Alfieri et al. (2019)	Olive	Italy	Relative soil water deficit (RSWD)	Relative yield (Yr)		Experimental	$\mathrm{Yr} = \begin{cases} 1 & \text{if } \mathrm{RSWD}_{\mathrm{obs}} \leq \mathrm{RSWD}_{\mathrm{threshold}} \\ a\mathrm{RSWD}_{\mathrm{obs}} + b & \text{if } \mathrm{RSWD}_{\mathrm{obs}} > \mathrm{RSWD}_{\mathrm{threshold}} \end{cases}$
Bennett and Harms (2011)	Multiple	Canada	ET	Yield		Empirical	$Yr = aET - b$
Bonfante and Bouma (2015)	Maize	Italy	Relative ET Deficit	Yield reduction		Experimental	Ramp—not reported
Monaco et al. (2014)	Multiple	Italy	Relative ET Deficit	Relative yield		Experimental	Ramp—not reported

Table 2 List of the selected studies proposing vulnerability curves for extreme temperatures and information on the crop, the case study location and the explanatory variables used to build the curves

Reference	Crop	Case study location	Axis x	Axis y	Axis z	Methodology	Equation
Li et al. (2021)	Maize	China	Chilling Index	Yield loss		Modelling	Quadratic regression—not reported

Table 3 List of the selected studies proposing vulnerability curves for storms and information on the crop, the case study location and the explanatory variables used to build the curves

Reference	Crop	Case study location	Axis x	Axis y	Axis z	Methodology	Equation
Blanc and Strobl (2016)	Rice	Philippines	Typhoon return period	Yield loss		Statistical modelling	Logarithmic—not reported
Masutomi et al. (2012)	Rice	Japan	Typhoon intensity	Damage Area ratio		Empirical	Weibull—not reported

Table 4 List of the selected studies proposing vulnerability curves for floods and information on the crop, the case study location and the explanatory variables used to build the curves

Reference	Crop	Case study location	Axis x	Axis y	Axis z	Methodology	Equation
Bhuiyan and Al Baky (2014)	Multiple	Bangladesh	Water depth	Vulnerability		Expert knowledge	Point interpolation—not reported
Dutta et al. (2003)	Multiple	Japan	Flood duration	Crop damage	Water depth	Empirical	Polynomial—not reported
Ganji et al. (2012)	Rice	Iran	Water depth, water velocity, shear stress, Reynolds number (Re)	Loss rate (L)		Experimental	$L = aln(Re) + b$
Hendrawan and Komori (2021)	Rice	Indonesia	Water depth, water velocity, flood duration (x)	Yield change (Y)		Modelling	$Y = a + bln(x)$
Kwak et al. (2015)	Rice	Cambodia	Water depth	Relative damage		Empirical	Ramp—not reported
Li et al. (2012)	Multiple	China	Rainfall (x)	Affected area of crops (y)		Empirical	$y = ae^{bx}$
Ming et al. (2015)	Multiple	China	Rainfall (x)	Loss ratio (L)	Wind speed (y)	Empirical	$y = a + bx + cy + dx^2 + exy + fy^2$
Molinari et al. (2019)	Multiple	Italy	Water depth, water velocity, flood duration	Water depth, water velocity, flood duration	Yield reduction	Expert knowledge	Ramp—not reported
Nguyen et al. (2017)	Rice	Vietnam	Water depth (x)	Damage ratio (y)		Empirical	$y = ax^2 + (1 - a)x$ $y = \frac{1}{a-1}(a^x - 1)$ $y = \frac{1}{a-1}(a^x - 1)$
Nguyen et al. (2021)	Rice	Vietnam	Flood duration	Damage ratio (y)	Water depth (x)	Empirical	$y = ax^2 + (1 - a)x$ $y = \frac{1}{a-1}(a^x - 1)$ $y = \frac{x^b}{a+x^b}$

Table 4 (continued)

Reference	Crop	Case study location	Axis x	Axis y	Axis z	Methodology	Equation
Scorzini et al. (2021)	Multiple	Italy	Water depth, water velocity, flood duration	Yield reduction		Expert knowledge	Ramp—not reported
Shrestha et al. (2016)	Rice	Philippines	Water depth	Yield loss		Expert knowledge	Ramp—not reported
Shrestha et al. (2016b)	Rice	Philippines	Water depth (Wd)	Yield loss (Yl)		Expert knowledge	$\mathrm{Yl} = \begin{cases} 0 & \text{if } Wd \leq Wd_{\min} \\ aWd + b & \text{if } Wd_{\min} < Wd < Wd_{\max} \\ n & \text{if } Wd > Wd_{\max} \end{cases}$
Shrestha et al. (2019)	Rice	South East Asia	Water depth	Yield loss		Expert knowledge	Ramp—not reported
Shrestha and Kawasaki (2020)	Multiple	Myanmar	Probability of damage	Economic damage		Statistical modelling	Polynomial—not reported
Shrestha et al. (2021)	Rice	Myanmar	Water depth (Wd)	Yield loss (Yl)		Expert knowledge	$\mathrm{Yl} = \begin{cases} 0 & \text{if } Wd \leq Wd_{\min} \\ aWd + b & \text{if } Wd_{\min} < Wd < Wd_{\max} \\ n & \text{if } Wd > Wd_{\max} \end{cases}$
Sianturi et al. (2018)	Rice	Java	Reynolds number	Relative damage		Experimental	Curves used in Ganji et al. (2012)
Vega-Serratos et al. (2018)	Multiple	Mexico	Flood exceedance probability	Economic damage		Statistical modelling	Polynomial—not reported

Table 5 List of the selected studies proposing vulnerability curves for drought and information on the crop, the case study location and the explanatory variables used to build the curves

Reference	Crop	Case study location	Axis x	Axis y	Axis z	Methodology	Equation
Explanatory variable: water stress							
Cui et al. (2018)	Soybean	China	Accumulated crop water deficit (ACWD)	Loss rate (LR)		Experimental	$\mathrm{LR} = \mathrm{LR}_{\max}/(1 + ae^{-b\mathrm{ACWD}})$
Guo et al. (2016)	Maize	World	Water stress derived by the EPIC model	Loss rate	Environmental indicators	Modelling	Surface—not reported
Guo et al. (2021)	Rice	Global	Normalized values of accumulated Water stress derived by EPIC	Loss rate		Modelling	Logistic—not reported
Jia et al. (2012)	Maize	China	Water stress derived by the EPIC model (Hs)	Yield loss (Ls) rate		Modelling	$\mathrm{Ls} = 1/(1 + ae^{-bHs}) + c$
Li et al. (2022)	Maize	China	Water stress derived by AquaCrop (DHI)	Biomass Loss Rate (Ls)		Modelling	$\mathrm{Ls} = a/(1 + be^{-c\mathrm{DHI}})$
Monteleone et al. (2022)	Maize	Italy	Water stress derived by APSIM (Ws)	Yield loss (Yl)		Modelling	$\mathrm{Yl} = aWs/(b + Ws)$ $\mathrm{Yl} = c + (d - c)(1 - e^{-e^{b(Ws-a)}})$
Wang et al. (2013)	Wheat	China	Water stress derived by the EPIC model (Hs)	Yield loss ratio (Ls)		Modelling	$\mathrm{Ls} = a/(1 + be^{-cHs}) + d$
Wei et al. (2019)	Maize	China	Soil Water Deficit computed through CERES (DHI)	Grain loss yield (Lr)		Modelling	$\mathrm{Lr} = \mathrm{Lr}_{\max}/(1 + ae^{-b\mathrm{DHI}})$
Wu et al. (2021)	Wheat	Europe	Water stress derived by the EPIC model (DI)	Loss rate (Lr)		Modelling	$\mathrm{Lr} = a/(1 + be^{-c\mathrm{DI}}) + d$
Yin et al. (2014)	Maize	Global	Water stress derived by the EPIC model	Loss rate		Modelling	Logistic—not reported
Yue et al. (2015)	Wheat	China	Water stress derived by the EPIC model	Yield loss ratio		Modelling	Logistic—not reported
Zhu et al. (2021)	Maize	China	Water stress derived by AquaCrop (DHI)	Yield loss rate (Lr)		Modelling	$\mathrm{Lr} = a/(1 + be^{c\mathrm{DHI}}) + d$

Table 5 (continued)

Reference	Crop	Case study location	Axis x	Axis y	Axis z	Methodology	Equation
Explanatory variable: drought indices							
Chen et al. (2019)	Maize	China	SPI values on maize grow period (Hs)	Loss rate (Ls)		ANN	$\mathrm{Ls} = a/(1 + be^{-cHs})$
Fu et al. (2019)	Multiple	China	SPEI	Climatic yield (Yc)		Empirical	$\mathrm{Yc} = a + b\mathrm{SPEI}$
Jayanthi et al. (2013)	Maize	Malawi	SPI	Yield reduction (Yr)		Empirical	$\mathrm{Yr} = a + b\mathrm{SPI}$
Jayanthi et al. (2014)	Maize	South Africa	End Of Season Water Requirement Satisfaction Index (x)	Relative yield deficit (y)		Empirical	$y = a + bx$
Jiang et al. (2018)	Multiple	China	Drought Stregth measured through SPI	Lost harvest rate		Empirical	Point interpolation—not reported
Kamali et al. (2018)	Maize	Sub-Saharan Africa	Drought Exposure index related to SPI and SPEI (DEI)	Crop sensitivity index (CSI)		Modelling	$\mathrm{CSI} = \mathrm{DEI}^b$
Li et al. (2021b)	Wheat	China	SPI, Relative LAI, SSMI	Yield Impact Rate		Modelling	Spline—not reported
Naumann et al. (2015)	Multiple	Europe	Sum of the absolute values below zero of the drought indicator during drought events (SPI, SPEI, RDI) (S)	Cereal production (C)		Empirical	$C = aS^b$
Skakun et al. (2016)	Multiple	Ukraine	VHI	Damage (D)		Empirical	$\mathrm{D}=\begin{cases} 0 & \text{if VHI} > 40 \\ 1 - \mathrm{VHI}/40 & \text{if VHI} \leq 40 \end{cases}$
Todisco et al. (2013)	Sunflower	Italy	Relative severity drought index (RSI)	Yield (Y)		Modelling	$Y = a/(b + ce^{d\mathrm{RSI}})$
Wang et al. (2019)	Maize	China	Meteorological Drought Degree	Relative meteorological yield		Empirical	Polynomial—not reported

Table 5 (continued)

Reference	Crop	Case study location	Axis x	Axis y	Axis z	Methodology	Equation
Zhang et al. (2019)	Maize	China	Combination of remote sensing index and classical ones (DI)	Loss rate of LAI, grain number, grain weight (Ls)		Modelling	$\mathrm{Ls} = ae^{b\mathrm{DI}}$
Explanatory variable: drought indicators							
Eggen et al. (2019)	Sorghum	Ethiopia	Rainfall	Yield		Modelling	Lowess fit—not reported
Mehdikhani et al. (2017)	Multiple	Iran	Return period (R)	Crop damage (D)		Statistical modelling	$D = aR^b$
Su et al. (2021)	Maize	USA	Precipitation fluctuation (FLU)	Coefficient of variation of yield (CV)	Elevation	Modelling	$\mathrm{CV} = a\mathrm{FLU} + b$ $\mathrm{CV} = ae^{\mathrm{bFLU}}$ $\mathrm{CV} = a\ln(\mathrm{FLU}) + b$ $\mathrm{CV} = a\mathrm{FLU}^b$

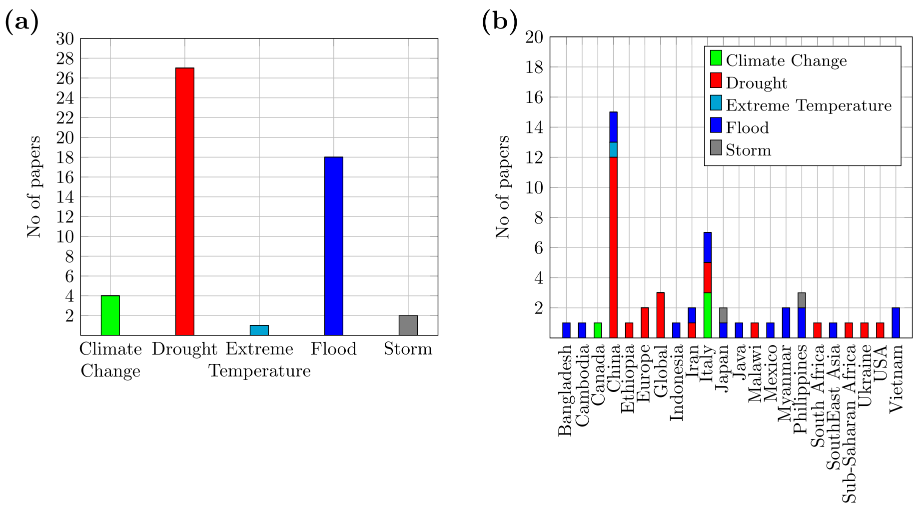


Fig. 4 **a** Number of papers proposing crop vulnerability curves grouped based on the considered extreme event; **b** number of papers proposing crop vulnerability curves per event and country

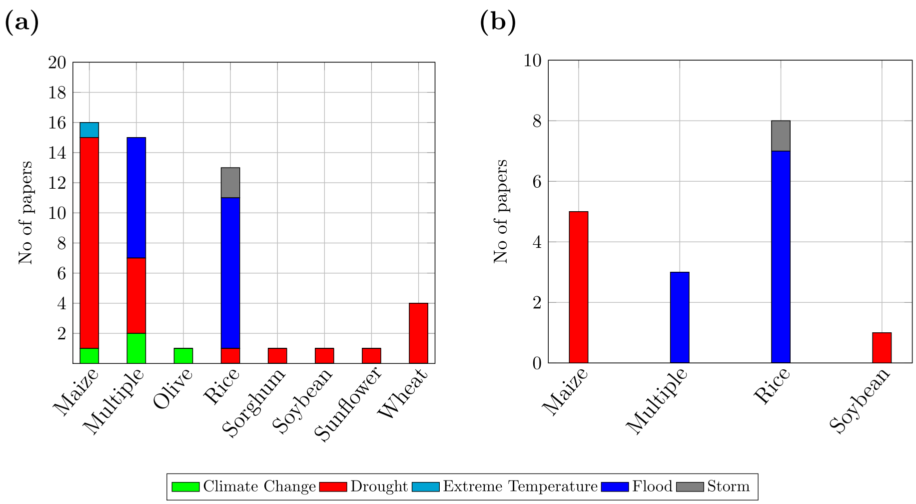


Fig. 5 **a** Number of papers dealing with each crop for the considered extreme events; **b** number of papers analysing the effect of crop growth stages on final yield losses per crop type and event

soybean, sunflower and olive are analysed each in one paper (Fig. 5a). Maize vulnerability is evaluated for drought, climate change and extreme temperature, rice vulnerability is estimated for floods, storms and drought, while the vulnerability of wheat, sorghum, soybean and sunflower is estimated only for drought. Olive vulnerability is studied for climate change only. Seventeen papers analyse the effect of the selected extreme event on the different crop growth stages (Fig. 5b). The crop response to a weather-related stress varies according to the growth stage since the effect the extreme event produce on the final crop yield strongly depends on the sensitivity of the growth stage (Steduto et al. 2012). Thus, the development of stage-specific vulnerability functions could help in providing more detailed information on the crop damages due to an extreme. Five papers investigated the effects of drought on maize growth stages (Li et al. 2022; Monteleone et al. 2022; Wang et al. 2019; Zhang et al. 2019; Zhu et al. 2021), while one explored the sensitivity of the different soybean growth stages to drought (Cui et al. 2018). Ten papers evaluated the sensitivity of various crop growth stages to floods: seven works focused their attention on rice (Ganji et al. 2012; Nguyen et al. 2021; Shrestha and Kawasaki 2020; Shrestha et al. 2016, 2016b, 2019; Sianturi et al. 2018) and three on multiple crops (Molinari et al. 2019; Scorzini et al. 2021; Vega-Serratos et al. 2018). Masutomi et al. (2012) instead assessed the impact of tropical storms on various rice growth stages. A major part of studies investigating the response of maize to extreme events are tailored to the Chinese context (8 out of 16, see Fig. 6), two studies have been conducted on Italian case studies, while two propose curves which are applicable at global level. The studies proposing vulnerability curves for multiple crops are again mainly tailored to China and Italy, while the studies assessing the response of rice to extreme events present case studies from Asian countries such as the Philippines, Vietnam, Indonesia and Cambodia.

2.3 Methodologies for vulnerability curve development

The methodological approaches applied to derive vulnerability curves in the 52 selected papers include:

1. empirical methods, in which the values of the explanatory variable accounting for the hazard magnitude are plotted versus observed crop damages (De Groot 1969);
2. experimental methods, in which field trials or laboratory experiments are executed to derive the relationship between the hazard and the damage (Flowerdew 2009);
3. expert knowledge, in which information from farmers or local experts are used to relate hazard and damage;

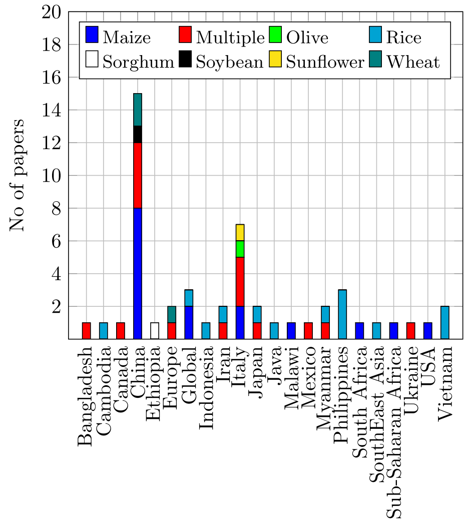


Fig. 6 Number of papers per case study location per crop

4. statistical modelling, in which hazard and/or damage are derived from statistical interpolation (Fisher 1992);
5. modelling, in which the hazard and/or the damage are derived from the application of models such as for example crop models;
6. machine learning, in which methods such as artificial neural networks or random forests are used to derive the hazard and the damage (Mitchell 1997).

Nineteen out of 52 considered papers derived vulnerability curves through the application of processed-based simulation models, mainly crop models (Fig. 7). Crop models are used in eighteen works; the most widespread are the Environmental Policy Integrated Climate (EPIC) Model (Williams et al., 1989), which is applied in nine studies among which Guo et al. (2021); Jia et al. (2012) and Kamali et al. (2018); AquaCrop (Steduto et al. 2009), preferred in three cases (Li et al. 2022; Todisco et al. 2013; Zhu et al. 2021) and CERES (Basso et al. 2016), again used in three studies (Li et al. 2021b; Wei et al. 2019; Zhang et al. 2019). Other crop models used to derive drought vulnerability curves are APSIM (Monteleone et al. 2022), MCWLA-Wheat (Li et al. 2021b) and DSSAT (Eggen et al. 2019). The CERES crop model is also applied to develop crop vulnerability curves to extreme cold temperatures in Li et al. (2021). Hendrawan and Komori (2021) instead developed a model to predict the effect of floods on rice yield in Indonesia starting from satellite measures of Normalized Difference Vegetation Index and Enhanced Vegetation Index, which are used as yield predictors, and the application of the rainfall–runoff inundation model to simulate the flood water depth. Vulnerability functions are derived through empirical methods in seventeen studies. Seven of them developed functions showing the response of crop to droughts (Fu et al. 2019; Jayanthi et al. 2013, 2014; Jiang et al. 2018; Naumann et al. 2015; Skakun et al. 2016; Wang et al. 2019), six investigate the effect of floods on crops (Dutta et al. 2003; Kwak et al. 2015; Li et al. 2012; Ming et al. 2015; Nguyen et al. 2017, 2021), and the remaining two papers evaluated the crops response to storms (Masutomi et al. 2012) and climate change (Bennett and Harms 2011). Curves derived from expert knowledge, i.e., interview with local farmers or agronomists, are proposed in

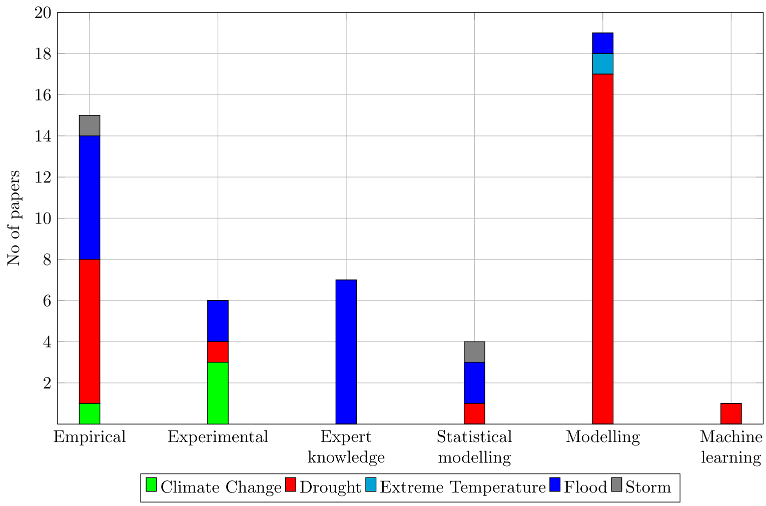


Fig. 7 Number of papers developing vulnerability curves through the use of different research techniques

seven papers, all of them exploring the effects of floods on crops (Bhuiyan and Al Baky 2014; Molinari et al. 2019; Scorzini et al. 2021; Shrestha et al. 2016, 2016b, 2019, 2021). Experimental yield response curves are developed in six studies. Three of them focus their attention on climate change (Alfieri et al. 2019; Bonfante and Bouma 2015; Monaco et al. 2014), one on drought (Cui et al. 2018) and two on floods (Ganji et al. 2012; Sianturi et al. 2018). The studies developing vulnerability curves for climate change and drought applied field tests and measurements to get the necessary variables. Ganji et al. (2012) explored the effects of floods on crops performing laboratory experiments to evaluate the sensitivity of rice to both water depth and velocity. Sianturi et al. (2018) applied the functions developed by Ganji et al. (2012) to a specific case study. Statistical modelling is adopted in four studies: Mehdikhani et al. (2017) showed the relationship between drought return period and crop damage, Blanc and Strobl (2016) assessed the effect of storms on rice, Shrestha et al. (2021) established a relationship between flood probability and economic losses and Vega-Serratos et al. (2018) related the flood exceedance probability to the economic losses. Finally, one study (Chen et al. 2019) applied machine learning techniques, specifically artificial neural network, to relate drought intensity to maize loss rate.

2.4 Explanatory variables used for vulnerability curve development

The variables used to develop crop vulnerability curves strongly depend on the considered extreme event. Thus, the following section is divided into three subsections, one for each of the considered hazard: drought, flood and other extremes.

2.4.1 Drought

The papers dealing with drought present crop vulnerability curves generally proposing a measure of the severity of the drought on the *x*-axis and the crop yield (in kg/m^2 or equivalent units) or a yield loss rate (expressed in percentage or with values going from 0 to 1) on the *y*-axis. The proposed drought hazard indices are various and can be divided in three groups. The first group includes the traditional drought indices such as the Standardized Precipitation Index (SPI), the Standardized Precipitation Evapotranspiration Index (SPEI), the Standardized Soil Moisture Index (SSMI), the Reconnaissance Drought Index (RDI). In the second group there are the remote sensing drought indices as the Vegetation Health Index (VHI), the Vegetation Condition Index (VCI) or the Leaf Area Index (LAI). The third group includes indices that are computed according to different methodologies. The studies simulating the yield through the use of calibrated and validated crop models as EPIC (the Environmental Policy Integrated Climate model (Williams et al. 1989)), AquaCrop (Steduto et al. 2009), APSIM, the Agricultural Production System sIMulator (Keating et al. 2003) and CERES, derives the drought index from the daily water stress retrieved from the model simulation. EPIC and its derivative GEPIC (the georeferenced version of EPIC) is the most widespread crop model, utilized in nine studies (Guo et al. 2016, 2021; Jia et al. 2012; Kamali et al. 2018; Su et al. 2021; Wang et al. 2013; Wu et al. 2021; Yin et al. 2014; Yue et al. 2015), AquaCrop is applied in three studies (Li et al. 2022; Todisco et al. 2013; Zhu et al. 2021); CERES in two (Wei et al. 2019; Zhang et al. 2019), while APSIM was applied in one stydy (Monteleone et al. 2022). The studies deriving the drought severity from observations choose the sum of the SPI over the crop growth period (Chen et al. 2019; Jiang et al. 2018) or the sum of the absolute values below zero of the selected drought indicator during a given drought event, where the indices are again the SPI, the SPEI or the RDI (Naumann et al. 2015). Other indicators are also used to derive the drought vulnerability curves. As an example, Kamali et al. (2018) uses a Drought Exposure Index, which is again related to the SPI and the SPEI over the crop growth season.

The work by Guo et al. (2016) should be mentioned because it shows multiple crop drought vulnerability surfaces, with the water stress derived from EPIC on the *x*-axis, the loss rate on the *y*-axis and an environmental indicator (selected between elevation, slope and seven soil properties such as the bulk density) on the *z*-axis. The innovative approach is highly interesting due to the inclusion in the analysis of environmental indicators, such as soil type, that provide additional information on crop's exposure.

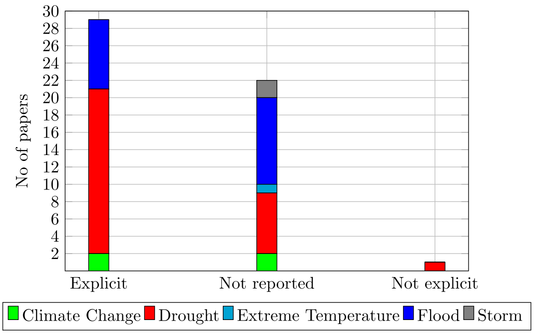
2.4.2 Flood

The papers dealing with flood do not simulate yield through crop models but generally rely on observations of yield losses due to reported events. The methodological choice is attributable to the renowned poor performance of the major part of existing crop models in simulating the effect of water excess on crops (Liu et al. 2020). Among the 17 papers reporting crop vulnerability curves to flood, ten use the water depth as *x*-axis indicator (Bhuiyan and Al Baky 2014; Ganji et al. 2012; Hendrawan and Komori 2021; Kwak et al. 2015; Molinari et al. 2019; Nguyen et al. 2017; Scorzini et al. 2021; Shrestha et al. 2016b, 2019, 2021) while the remaining seven utilize other indicators such as the flood duration (Nguyen et al. 2021), the Reynolds number (Sianturi et al. 2018), the flood exceedance probability (Shrestha and Kawasaki 2020; Vega-Serratos et al. 2018) or rainfall (Li et al. 2012; Ming et al. 2015). Some papers present vulnerability surfaces or assess the crop damage based on more than one indicator. As an example, Dutta et al. (2003) propose vulnerability curves based on the flood duration for different water depths. The same approach is followed in Molinari et al. (2019); Scorzini et al. (2021). Vulnerability surfaces are defined in Ming et al. (2015). The authors show how crop damage is related to rainfall and wind speed.

2.4.3 Other extremes

Four papers implement vulnerability curves to climate change. In three of the studies, vulnerability curves are based on evapotranspiration or the relative crop evapotranspiration deficit (Bennett and Harms 2011; Bonfante and Bouma 2015; Monaco et al. 2014), while in Alfieri et al. (2019) the relative soil water deficit is preferred. Crop evapotranspiration is strongly linked with crop productivity, as already underlined by Steduto et al. (2012). In addition, the temperature increase foreseen in a climate change context will alter the crop evaporative demand. Only two papers design crop vulnerability curves to storms, even if storms caused relevant yield losses. Blanc and Strobl (2016) relate the typhoon return period to crop yield losses, while Masutomi et al. (2012) link the ratio of damaged area with the typhoon intensity. Finally, one paper deals with crop vulnerability curves to extreme temperature, in this case extreme cold (Li et al. 2021). The paper applied the CERES crop model to relate a Chilling Index to yield losses. The Chilling Index is based on various indicators such as the deviation of the Growing Degree Days from normal and the Leaf Area Index (LAI), retrieved from satellite records.

Fig. 8 Number of papers proposing explicit and non-explicit vulnerability curves and papers not reporting the function's equation



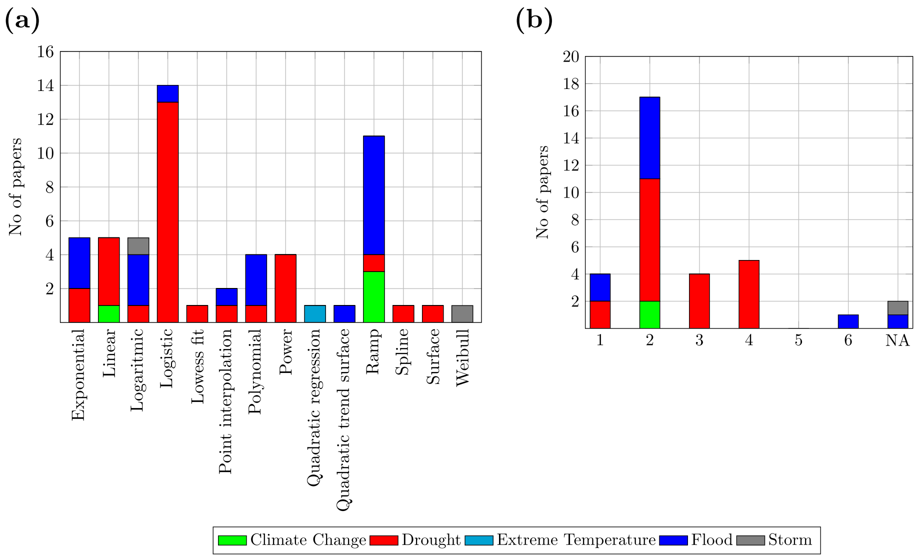


Fig. 9 **a** Types of functions applied to derive crop vulnerability curves in the considered papers; **b** number of parameters used to parametrize the curves

2.5 Types of vulnerability functions

Among the 52 considered papers, 29 applied explicit functions and reported both the equation and the parameters of the equation used, one proposed a non-explicit function (Jiang et al. 2018) while 22 did not report the function's equation (Fig. 8).

Some studies applied more than one function to develop vulnerability curves: 1) to assess which one best represents the observations, 2) to investigate the response of different crop growth stages to the extreme event (thus, the function type could change according to the growth stage) or 3) to evaluate the response of different crops to the extreme event.

The preferred function is the logistic (or S-shaped curve), applied in 14 cases (Fig. 9a). The logistic seems to be particularly appropriate to simulate the crops response to drought, in fact 13 out of the 14 studies selecting this function for drought vulnerability curves. The second preferred function is the ramp function, applied in 11 studies. The ramp function is applied in seven studies dealing with floods, three with climate change and one with drought. Linear, logarithmic and exponential functions are applied each one in five studies; the linear functions are applied to develop vulnerability curves for climate change (Bennett and Harms 2011) and drought (Fu et al. 2019; Jayanthi et al. 2013, 2014; Su et al. 2021), while logarithmic functions are preferred for floods (Ganji et al. 2012; Hendrawan and Komori 2021; Sianturi et al. 2018) and are used also for storms (Blanc and Strobl 2016) and drought (Su et al. 2021). Exponentials again are used for floods (Li et al. 2012; Nguyen et al. 2017, 2021) and droughts (Su et al. 2021; Zhang et al. 2019). Other applied functions are polynomials and power, employed in four studies. Polynomials are used in Dutta et al. (2003); Shrestha and Kawasaki (2020); Vega-Serratos et al. (2018) to evaluate crops response to floods and in Wang et al. (2019) to assess maize response to drought. Power functions are used only to evaluate crops response to drought (Kamali et al. 2018; Mehdikhani et al. 2017; Naumann et al. 2015; Su et al. 2021).

Other types of functions used in fewer studies are the Lowess fit (Eggen et al. 2019), the quadratic regression (Li et al. 2021), the spline (Li et al. 2021b) and the Weibull (Masutomi et al. 2012). Two studies proposed vulnerability surfaces (Guo et al. 2016; Ming et al. 2015) and two studies simply show the results of an interpolation of points (Bhuiyan and Al Baky 2014; Jiang et al. 2018).

The major part of the selected functions (17) depends on two parameters (Fig. 9b). The curves parametrized through the use of two parameters are the linear functions, the logarithmic, the power, the exponential and one type of logistic. Six functions used to develop drought vulnerability curves depend on four parameters. (In all cases, the functions are logistics.) Four curves (two for drought and two for floods) depend on one parameter, and four curves depend on three parameters (all for drought). Ming et al. (2015) developed a quadratic trend surface that depend on six parameters. Finally, two studies define the type of function applied to derive the curve but do not report the functions equations; thus, the determination of the number of parameters has not been done.

3 Discussion

The section proposes some qualitative investigations on the network of authors developing vulnerability functions and the main keywords of the studies. In addition, the section compares the analysed vulnerability functions, individuating the main issues and shortcomings of the functions and proposing future developments of the research. For simplicity, the section is divided in five subsections proposing qualitative investigations on the selected studies, remarks on vulnerability functions for drought, floods and other extremes and some general considerations.

3.1 Qualitative investigations

Based on the selected papers (presented in Tables 1, 2, 3, 4 and 5), some qualitative investigations are made using Mendeley reference manager and VOSviewer software. In Fig. 10, network of authors and main cooperation on the topic of crop vulnerability curves to weather extremes are shown. Each link represents the co-authorship of at least one paper, each colour represents the main time period in which paper has been published and the name's size represents the numerosity of contribution in terms of number of papers in the selected database. Six clusters can be identified. BB. Shrestha is the author who published the highest number of papers (five), developing flood vulnerability curves. The

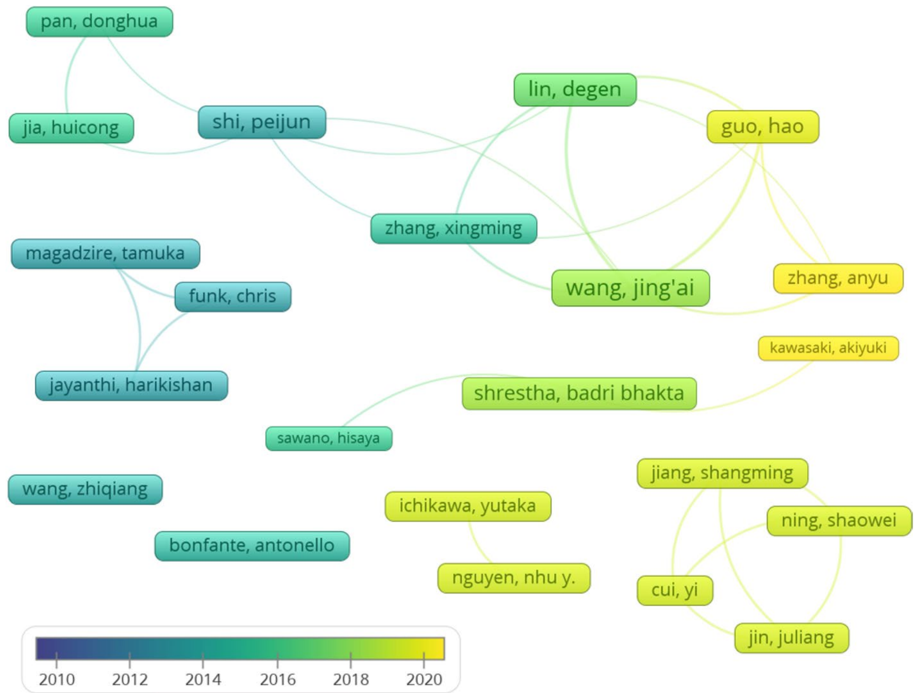


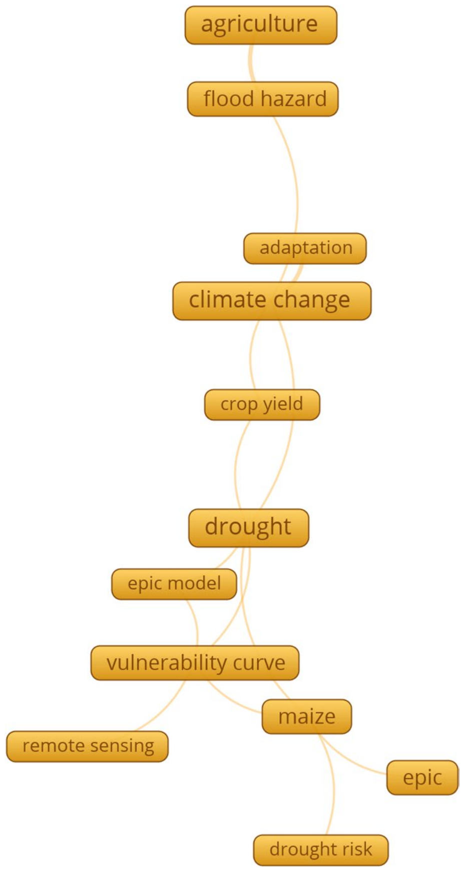
Fig. 10 Authors' network in reviewed papers. The boxes colours represent the year of the collaborations, while the boxes sizes and the font sizes indicate the number of collaborations

group including Guo, Wang and Shi proposed drought vulnerability curves, the research team of Jayanthi published two papers on drought vulnerability curves. Nguyen wrote two papers on flood vulnerability curves, and Cui worked on drought vulnerability curves as well as Wang. A similar analysis is made for the co-occurrence of keywords in the papers' titles (Fig. 11). The font size of the various words gives the number of occurrences in the dataset of titles, while links between words show the co-occurrence between them in the same paper. Relevant recurrence is for the words "climate change," which is connected to both "drought" and "flood hazard," then "drought" which is the main issue evidenced in this review and of course "vulnerability curves." Relevant is also the presence of "maize" as keyword, as it is one of the most investigated cereals, and "EPIC" or "EPIC model" keywords, as it represents a commonly used crop model for vulnerability analysis. "Adaptation" concept is also of interest, strictly connected with the climate change issue. The network summarizes the results of the analysis done in this review, by evidencing that drought is the extreme event for which the highest number of vulnerability curves has been developed and that maize is the crop analysed by the major part of studies. In addition, it clearly emerges that EPIC is the most commonly applied crop model.

3.2 Remarks on crop vulnerability functions for drought hazard

Drought is the extreme event for which the highest number of vulnerability functions has been proposed; in fact, 27 papers out of the 52 included in this review implemented drought

Fig. 11 Co-occurrence of keywords in selected papers. The boxes and the font size indicate the number of times a keyword is present



vulnerability curves. As a matter of fact, drought is the extreme event that causes most of the crop yield losses. It is indeed the first economic sector that suffers because of drought (Monteleone et al. 2020); insufficient soil moisture triggered by low precipitation produced devastating effects on crop yield. In addition, drought is a long-lasting extreme event (Wilhelmi and Wilhite 2002); its duration goes from weeks to months or even years, unlike in the case of the other meteorological extreme events. Thus, it is not surprising that a lot of attention has been dedicated to investigate the effects of drought on crops. As evidenced by the analysis of the 27 studies showing drought vulnerability functions, there is a significant inhomogeneity in the variables used to relate the effect of drought on crop losses. The high number of indicators used to measure the drought intensity/severity is clearly due to the large number of drought indices available in the scientific literature (World Meteorological Organization (WMO) and Global Water Partnership (GWP) 2016; Zargar et al. 2011) and to the difficulties in finding a universal drought definition (Lloyd-Hughes 2014). The variables used can be grouped into traditional drought indices based on ground observation, remote sensing drought indices and variables expressing the crop water deficit (mainly derived from crop models). The selection of a specific explanatory variable strongly depends on the available data. The studies selecting traditional drought indices and indicators (as the SPI; the SPEI, rainfall, etc.) as explanatory variables generally derive

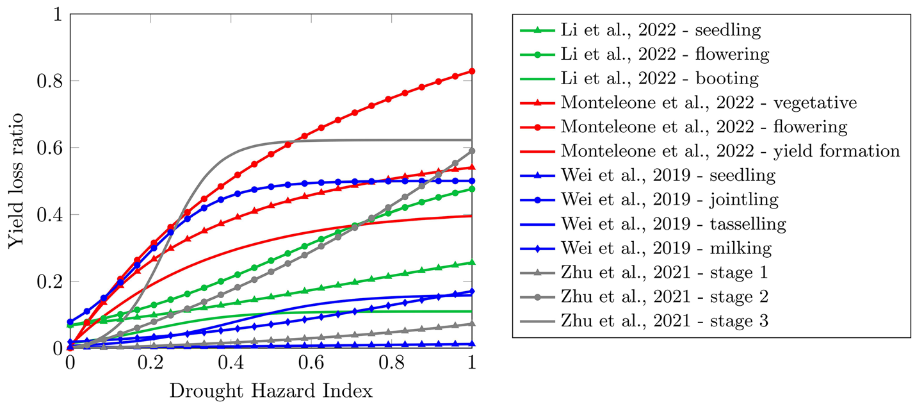


Fig. 12 Comparison among stage-specific drought vulnerability curves for maize. The values reported in Zhu et al. (2021) have been scaled to the 0–1 range to enable a comparison with the functions reported in the other three studies

them from station measurements of simple weather parameters as rainfall and temperature or from Global Climate Models (GCMs). In addition, those studies relate the explanatory variables to yield losses derived from the analysis of national or regional databases, as the FAOSTAT or the China Economic and Social Development Statistical Database. The studies preferring remote sensing indices as the LAI (derived from MODIS) or the VHI simulate the yield through the use of crop models, calibrated by weather data obtained from automatic weather stations or satellite images. Thus, a huge amount of data is necessary to develop such curves. Finally, the studies applying crop models to derive both the explanatory variable and the crop damage require as input a consistent amount of data on weather (rainfall, temperature, wind speed, solar radiation, etc.) and soil, plus information on crop management practices as fertilization or sowing date. Moreover, a careful calibration of the crop model is necessary to ensure the reliability of the obtained results. Crop models calibration often relies on the assumption that the period over which it is performed is representative of the situation in terms of both weather, soil and crop productivity as well as management practices.

The comparison of drought vulnerability curves is challenging, given the diversity of the explanatory variables. However, considering the papers which report the vulnerability curves equations and use comparable explanatory variables, an illustrative comparison among stage-specific drought vulnerability curves for maize is proposed in Fig. 12. The curves are reported in four studies (Li et al. 2022; Monteleone et al. 2022; Wei et al. 2019; Zhu et al. 2021) that apply different crop models (AquaCrop in Li et al. (2022); Zhu et al. (2021), CERES in Wei et al. (2019) and APSIM in Monteleone et al. (2022)) to derive both the Drought Hazard Index, which is the water deficit experienced by maize, and the yield loss ratio. The results obtained in the studies are quite different. Li et al. (2022) consider the Shijin Irrigation District in the Hebei province as case study area and applies the AquaCrop model; the study concludes that the booting stage is the most sensitive to water stress. The Aquacrop model is applied also in Zhu et al. (2021), which consider 241 prefecture-level administrative regions in the five main maize-growing regions of China as case study. In this paper the tasseling–milking stage was found to be the most sensitive to water stress. Wei et al. (2019); Zhang et al. (2019) apply the CERES model in the Huaibei plain and in the Jilin Province, respectively. The first study concludes that the jointing stage in the most sensitive to water stress, while in the second study the most drought sensitive stage is the jointing–heading. Monteleone et al. (2022) applied APSIM in the Po River Basin and found that the flowering stage is the most sensitive to drought.

Even if the four studies classifies maize growth stages in slightly different ways, all of them agree on the fact that the flowering stage is the most sensitive stage to water deficit, but the yield losses of the flowering stage varies from 16% in Wei et al. (2019) to 82% in Monteleone et al. (2022). The comparison in any case is only indicative since the case study locations are different, and thus, the model calibration plays a crucial importance in influencing the results. The fact that flowering is the most drought sensitive stage holds for other crops too. Cui et al. (2018) explored the sensitivity of soybean to drought based on observations and field experiments in China and found that the drought stress during the flowering–podding and the seed filling stages on yield formation were greater than those during the branching and seedling stages.

The preferred type of function used to represent the effects of drought on crops is the logistic, which is applied in 13 studies on drought, among which there are all the four studies proposing the stage-specific vulnerability curves for maize reported in Fig. 12. Logistic functions are found to be appropriate for other crops beyond maize; in fact, they are applied for rice, wheat, sunflower and soybean too. Together with the logistic, linear and power functions are used to represent the effects of drought on maize and cereals in general. However, the comparison among these functions is not possible, given the different variables used to relate the drought effect to the crop damage.

An evaluation of how well the selected functions fit to the data points in the case of drought is generally performed through the R^2 metric (used in 15 studies). Generally, the logistic functions are the ones showing the best performances, with R^2 ranging from 0.68 to 0.98. Linear functions show lower R^2 values, ranging from 0.14 to 0.79 (Fu et al. 2019; Jayanthi et al. 2013, 2014), while the exponential functions proposed in Su et al. (2021) and Zhang et al. (2019) fit well to the data, with R^2 going from 0.6 to 0.88. However, linear and exponential functions are simpler than the logistics and depend on a lower number of parameters (two instead of the three or four parameters generally present in the logistics). The use of simpler functions relying on few parameters makes their practical application more appealing with respect to the logistics. The use of exponential and power functions could be a good compromise to avoid having a huge number of parameters.

The main issues found in drought vulnerability curves are related to the complexity of the explanatory variables used to define the drought severity and intensity. In fact, the major part of the explanatory variables considered in the reviewed studies are computed through the elaboration of weather variables traditionally measured from automatic weather stations (drought indices) or through an interpolation of the results obtained from remote sensing images or should be inserted in a crop model that needs to be specifically calibrated for the selected location. Thus, a practical use of the drought vulnerability functions is challenging. The development of curves using a directly measurable variable as explanatory variable could be precious to exploit the curves in risk prevention programmes or insurance policy. In addition, the development of experimental drought vulnerability curves is recommended since only one study (Cui et al. 2018) performed field experiments to evaluate crop sensitivity to drought.

3.3 Remarks on crop vulnerability functions for flood hazard

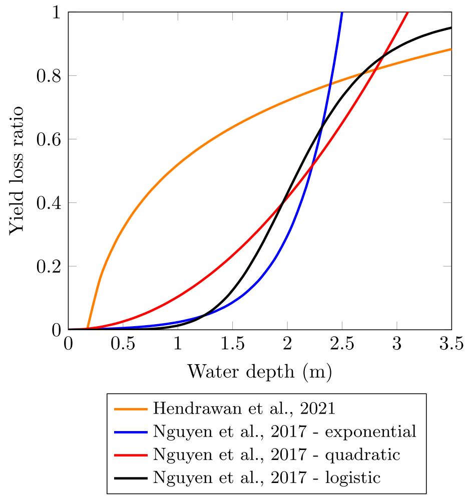
Eighteen of the 52 articles investigated the effects of floods on crops, mainly rice and multiple crops. Usually, agricultural areas are located near rivers or lakes or water bodies because the easy access to water is fundamental for irrigation. However, those areas are also the more flood prone ones. There is more homogeneity in the variable used to measure flood intensity with respect to the case of drought. Water depth is considered in twelve cases, flood duration in five studies, rainfall and the Reynolds number in two studies and the flood exceedance probability in one study. Some studies reported vulnerability curves relating crop damages to both water depth and flood duration, while others propose vulnerability functions for more than one variable. (For example, Ganji et al. (2012) propose a function with water depth as explanatory variable, another with shear stress and another with the Reynolds number.)

Most of the studies on flood vulnerability curves derives the explanatory variable of from direct observations or from station measurements (prevalently streamflow and rainfall). Ganji et al. (2012) instead performed a laboratory experiment and thus had the complete control of all the explanatory variables, while Hendrawan and Komori (2021) applied the rainfall–runoff inundation model to simulate the flood extent and water depth. For what concerns yield data, again the highest number of studies derives them from national or regional loss database. Hendrawan and Komori (2021) and Kwak et al. (2015) derived yield from MODIS satellite images. Generally, the variables used to develop flood vulnerability functions are easier to measure with respect to the ones used for crop vulnerability curves related to drought hazard. In fact, water depth and flood duration are easy to measure and to understand. The Reynolds number instead requires the availability of four parameters (the liquid density, the flow velocity, the linear dimension and the fluid viscosity) and thus is used only in laboratory experiments, even if Ganji et al. (2012) underlines that it reproduces crop damages better than the other explanatory variables (water depth, flood duration, etc.)

Since rice is the crop on which the major part of studies is focused, a comparison among the flood vulnerability functions developed in the works relating flood water depth to yield losses is proposed. Two studies developing flood vulnerability functions for rice are compared, namely the one by Hendrawan and Komori (2021) and the one by Nguyen et al. (2017). Both studies relate water depth to rice yield losses, expressed as loss ratio ranging from 0 to 1 and do not consider the effect of floods on the different growing stages. Hendrawan and Komori (2021) propose a logarithmic function, while Nguyen et al. (2017) test an exponential, a quadratic and a logistic function and estimates that the logistic is the best choice to reproduce the observed losses Fig. 13.

The stage-specific functions proposed by Shrestha et al. (2016, 2016b, 2021), presented in Fig. 14 for a flood duration of four days, are ramp functions specifically derived for Southeast Asian countries. The ripening stage is considered only in Shrestha et al. (2016) and is the most tolerant to prolonged submergence, and the reproductive stage is instead the most sensitive to the excess of water. Overall, rice seems to be more sensitive to floods in Myanmar than in the Philippines. The functions are derived from expert knowledge and interviews with local farmers, so it is plausible that the observed response to floods is different in the two contexts. The six papers assessing flood effects on rice growth stages based their conclusions on field experiments or observations and all the works consider Asian countries as case study areas. Ganji et al. (2012) show that for rice, yield loss increases in the following order: after transplanting, shooting, harvesting and clustering

Fig. 13 Comparison among flood vulnerability functions for rice developed in Hendrawan and Komori (2021) and Nguyen et al. (2017)



stages. The Reynolds number is the parameter selected to represent the flood characteristics. Nguyen et al. (2021) evidence that at the ripening stage, the rice yield loss caused by complete submergence is the most critical with a reduction in yield up to 30–50% when complete submergence is imposed for only 2–4 days. In the case of 5–8 days of submergence, the yield loss was equally detrimental to the vegetative stage (approximately 50–90%). The submergence at the ripening and vegetation stages for 4–5 days was equally harmful as that of 7 days at the reproductive stage. Shrestha et al. (2016) evidenced that damage occurs if the flood depth reaches 0.2 m in the newly planted and vegetative stages, while in the reproductive, maturity and ripening stages damage occurs if the water depth is greater than 0.5 m. The same functions are considered in Shrestha et al. (2021). Finally, Sianturi et al. (2018) affirm that crop damage is low in clustering, moderate at harvesting, high at shooting and very high at transplanting.

The preferred type of functions to assess rice vulnerability to floods are the ramp functions, applied in five studies, followed by the logarithmic, applied in three papers. The response of rice to floods exhibits huge variations among the various studies and is strictly related to the flood duration, as shown in Shrestha et al. (2021). The three studies taking into account multiple crops are quite different among them. Vega-Serratos et al. (2018) use Mexican data on floods and crop harvested areas to produce damage functions for maize, soybean, groundnut, rice, tomato, sorghum, watermelon, bean and pepper. However, the paper shows the results obtained for corn only. A table with the economic damage associated with different flood duration in each month of the year is proposed, and the different sensitivity of the crop growth stages to the flood is reflected in the different damage associated with each month of the year. Molinari et al. (2019) consider four crops: maize, wheat, rice and alfalfa. The vulnerability curves for the different crops at the various growth stages are obtained from a French study (Agenais et al. 2013) for maize, wheat and alfalfa, and from Shrestha et al. (2016) for rice. Besides maize, Scorzini et al. (2021) include wheat and grassland, vegetables (cabbage, spinach, lettuce and bean) and grapevine in the analysis. The framework applied is the same proposed in Molinari et al. (2019). The yield reduction due to flood varies greatly according to the crop type and the growth stage. The studies considering the effects of floods on multiple crops apply mainly polynomial functions to relate the water depth to the yield losses (Dutta et al. 2003; Shrestha and Kawasaki 2020;

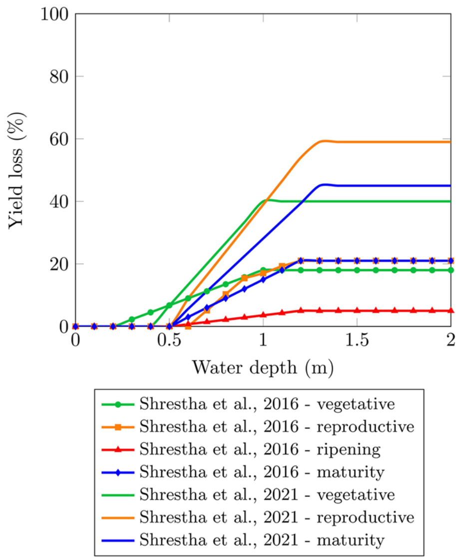


Fig. 14 Comparison among stage-specific rice vulnerability functions developed in Shrestha et al. (2016, 2016b) and Shrestha et al. (2021) for a flood duration of 3–4 days. The functions developed in Shrestha et al. (2016, 2016b) are tailored to the Philippines, while the ones proposed in Shrestha et al. (2021) are tailored to Myanmar

Vega-Serratos et al. 2018). However, none of them reports the function's equation; therefore, the analysis on the number of parameters of the polynomial is not possible. The R^2 of the functions with respect to the data points is reported only in four studies (Hendrawan and Komori 2021; Li et al. 2012; Ming et al. 2015; Shrestha and Kawasaki 2020). All of them use different functions and different explanatory variables; however, the performance of the selected functions is high since the R^2 values range from 0.71 to 0.98.

With respect to drought vulnerability curves, the application of the flood ones in practical contexts is easier, given the lower number of input data used to derive the functions and the fact that the proposed functions are mathematically simpler, relying on a lower number of parameters. However, flood vulnerability functions are often very specific for the considered case study location and the difference among the locations is huge, as underlined in Fig. 14. Most of the reviewed functions are developed using national loss databases or expert knowledge; thus, their transferability to other context with respect to the one for which they are developed should be carefully evaluated.

3.4 Remarks on crop vulnerability functions for other extreme events

Four papers discuss the effects of climate change on crops. Alfieri et al. (2019) assess the response of olive to the relative soil water deficit, Bonfante and Bouma (2015) again use the soil water deficit as an indicator of maize response to climate change, Monaco et al. (2014) relate the evapotranspiration to maize losses due to climate change, and Bennett and Harms (2011) assess the response of multiple crops to evapotranspiration. The first three studies propose ramp functions derived from field experiments, while Bennett and Harms (2011) select linear functions based on the methodology shown in Steduto et al. (2012) and applying crop parameters specifically derived for the Canadian case study. The comparison among the developed functions is difficult since the crops and the case study locations considered are different. While three studies (Alfieri et al. 2019; Bonfante and Bouma 2015; Monaco et al. 2014) show the results of field trials and thus had the opportunity to directly measure both the explanatory and the damage variables, the fourth one (Bennett and Harms 2011) uses weather station data combined with the information retrieved from losses dataset at national level. The major drawback of such functions is their scalability; in fact the transferability of the functions based on field trials should be proved, while the curved developed in Bennett and Harms (2011) are specifically tailored to Canada. None of the studies evaluated the R^2 of the developed functions. One paper shows the relation between damage area ratios and typhoon intensity for different growth stages of rice in Japan (Masutomi et al. 2012). It concludes that the heading stage of paddy rice is the stage with the highest vulnerability to typhoons in Japan; Weibull functions are applied to relate the damage area ratio to the storm intensity. The impact of storms on rice is investigated in Blanc and Strobl (2016) too that propose a logarithmic function to relate yield losses to storm return period. Again, in this case the function equations are not reported; a comparison of the obtained results would have been challenging in any way given the differences in both the explanatory variable and the loss indicator adopted in the two studies. Both the papers selected as case study Asian countries (Japan and the Philippines), underlined the importance rice has in Southeast Asia. Finally, Li et al. (2021) apply a quadratic regression to investigate the effects of extreme cold on maize in China. The paper based its results on the application of the CERES crop model given the lack of direct observations of crop losses due to extreme cold. Although the computation of the Chilling Index is not straightforward, the index is promising to assess the effect of extreme cold on crops and its application in insurance programmes could be evaluated.

3.5 General considerations

While the impacts of droughts and floods are extensively studied, as witnessed by the fact that 45 of the 52 reviewed studies dealt with these two extreme events, the effect of other extremes on crops should be analysed. The impact of storms deserves further analysis since it has been investigated in two articles only. All the two articles proposed case studies located in Asia. An analysis on the effect of storms in other areas, such as North and Central America, could be interesting since the area is exposed to devastating hurricanes with impacts on crop production. The effect of extreme temperature on crops should be deepened too. Among the 52 studies here considered, only one evaluated the crop sensitivity to extreme cold. Since it is well known that extreme cold in critical crop growth stages can produce devastating effects on final crop yield, studies investigating the relationship between anomalous cold waves and final crop yield will provide an interesting advance to the state of the art. The effect of hot waves on crop is partially included in the articles evaluating crops response to drought, but the proposed articles mainly focus their attention on water stress (which includes a temperature component) without explicitly mentioning high temperatures. The studies dealing with climate change mainly use evapotranspiration as an indicator of crop vulnerability and therefore take into consideration the temperature effect on crop. However, the effect of extreme temperature and hot waves should be better investigated to produce temperature vulnerability curves for crops.

The effect on crops of the other meteorological extreme events listed in Fig. 2 is never considered. Wildfires, due their high destructive power, simply cancel all the crops grown in an area, as well as landslides. Glacial lake outbursts and fog are not known to affect crops, while wave action is not significant since only a few fields are located in the proximity of the sea and in that case the major issue for crops is the saline intrusion, which alters the soil PH and affects crop growth.

For what concern crop types, the major part of articles deals with cereals (maize, rice, wheat and sorghum). The choice of annual crops can be explained by the fact that damages on annual crops are easier to evaluate with respect to that on perennial crops, where inter-annual variability of the factors influencing crop growth can be difficult to evaluate. However, the effect of extreme events on vegetables and perennial crops such as grapevine and orchards deserves further attention. In this review, only Alfieri et al. (2019) investigated the sensitivity of olive to climate change, while Scorzini et al. (2021) proposed flood vulnerability curves for vegetables and grapevine. Further attention on the topic is needed since perennial crops and vegetables are important productions from the economic point of view. The effects of flood on crops other than rice should be explored, including the flood impact on growth stages in the analysis. Effects of climate change on crop vulnerability are also investigated. In three of the papers implementing vulnerability curves to climate change, the indicators used to build the curves are evapotranspiration or relative crop evapotranspiration deficit (Bennett and Harms 2011; Bonfante and Bouma 2015; Monaco et al. 2014). It is well known that evapotranspiration is a key component in the water balance evaluation in hydrology and water resources management (Borzì and Bonaccorso 2021; Borzì et al. 2020; Zhao et al. 2013), and from this review, it emerges that it has relevant effects also in crop vulnerability analysis. In the fourth paper which implement vulnerability curves to climate change, the indicator used on the *x*-axis of the curve is the soil water deficit (Alfieri et al. 2019). The issue of soil water content in hydrology has been widely explored by explicit representation of soil in hydrological modelling (Borzì et al. 2019; Jakeman and Hornberger 1993) and crop modelling (APSIM, EPIC, Aquacrop, etc.). Furthermore, soil water content influence on crop vulnerability evaluation has been evidenced even in recent studies.

4 Conclusions

This work presented a review of the articles published between January 2000 and May 2022 on the topic of crop vulnerability curves to weather-related extreme events and climate change. The articles have been retrieved from Scopus, Web of Science and Google Scholar, and additional studies mentioned in the reference section of the collected papers have been examined. In the end, 52 articles implementing crop vulnerability curves to weather-related extreme events and climate change have been considered. Fifty-two percent of the considered studies (27 out of 52) implemented drought vulnerability curves, 35% developed flood vulnerability curves, and 8% showed vulnerability curves to climate change, 4% to storms and 2% to extreme temperature (cold). In the case of drought vulnerability curves, there is a clear inhomogeneity in the explanatory variables proposed. Flood vulnerability curves base the evaluation of the flood intensity on water depth, flood duration or the Reynolds number. Climate change vulnerability functions determine the magnitude of the phenomenon using evapotranspiration or indicators derived from the evapotranspiration. Storm damage functions used the typhoon return period or the crop damaged area to define the hazard intensity, while a Chilling Index, determined from indicators such as the deviation of the current year Growing Degree Days (GDD) from normal and the Leaf Area Index (LAI), is applied to express the magnitude of extreme temperatures. Vulnerability curves have been implemented prevalently for cereals, with 16 articles developing functions for maize, 13 for rice, three for wheat and one for sorghum. The damage due to extreme events on annual crop is easier to determine than the damage on perennial crops, such as orchards or grapevine. Only two studies provided vulnerability curves for perennial crops (olive and grapevine). Fifteen papers showed vulnerability curves for more than one crop. In this case, cereals were always present, while other crops such as forage and vegetables were considered. Maize vulnerability is evaluated for drought, climate change and extreme temperature, rice vulnerability is estimated for floods, storms and droughts, while the vulnerability of wheat, sorghum, soybean and sunflower is estimated only for drought. Olive vulnerability is studied for climate change only. Seventeen papers analysed the effect of extreme events on the different crop growth stages. The yield losses caused by droughts happening at different growth stages are investigated for maize (five papers), wheat and soybean (one paper each). The response to the different crop growth stages to floods is instead evaluated in ten papers; seven of them deals with rice while three consider multiple crops. One paper investigated the response of the different rice growth stages to storms. The analysis considered also the functions used to develop the vulnerability curves and the number of the corresponding parameters on which the function depends. The preferred function is the logistic, mainly applied in the drought vulnerability curves, while ramp and logarithmic functions are applied in the case of floods.

Based on the analysis, some key points for future work have been identified:

1. The investigation of crop vulnerability to other extremes than floods and droughts should be deepened. In fact, the effect of extreme cold happening at specific growth stages could be highly dangerous for the final crop yield and cause high crop losses as well as hot waves and extreme hot temperatures. Storms too could have a devastating impact on crop production in hurricane prone areas.
2. Vulnerability curves for crops other than cereals should be implemented, given the importance that perennial crops and vegetables have in terms of economic value. Functions for forage crops (alfalfa, pastures or similar) could be useful to evaluate the impacts of extreme events on livestock and have not been considered in none of the reviewed studies.
3. The inclusion of field experiments to assess the effect of extremes on the different crop growth stage should be better studied by including field observations in the analysis, rather than using crop models results.

In addition, some recommendations to develop vulnerability functions are proposed:

1. A compromise between the vulnerability function's complexity and its reliability should be searched. In fact, very complex functions, relying on many parameters, are of difficult practical use.
2. The equation of the developed function and its parameters should be reported in the study. In addition, an evaluation of how well the developed vulnerability curve fits to the data points should be performed to assess the reliability of the proposed curve.
3. Explanatory variables should be easily measurable (such as water depth or rainfall) or directly linked with measured variables. In fact, the application of functions considering explanatory variables derived from models is complex since models often require a huge amount of location-specific data to be initialized and a careful calibration.
4. A validation of the developed vulnerability functions is recommended, although it is difficult due to the scarcity of measured loss data.

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Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Adger WN (2006) Vulnerability. Glob Environ Change 16(3):268–281. https://doi.org/10.1016/j.gloenvcha.2006.02.006 (https://linkinghub.elsevier.com/retrieve/pii/S0959378006000422)

Agenais A, Grelot F, Bremond P, et al (2013) Dommages des inondations au secteur agricole, Guide méthodologique et fonctions nationales. Tech. rep., IRSTEA, UMR G-EAU ŠGestion de l'Eau, Acteurs et Usages, Montpellier

Alfieri SM, Riccardi M, Menenti M et al (2019) Adaptability of global olive cultivars to water availability under future Mediterranean climate. Mitig Adapt Strategies Glob Change 24(3):435–466. https://doi.org/10.1007/s11027-018-9820-1

Bachmair S, Svensson C, Prosdocimi I et al (2017) Developing drought impact functions for drought risk management. Nat Hazards Earth Syst Sci 17(11):1947–1960. https://doi.org/10.5194/nhess-17-1947-2017 (https://nhess.copernicus.org/articles/17/1947/2017/)

Basso B, Liu L, Ritchie JT (2016) A comprehensive review of the CERES-wheat, -maize and -rice models' performances. Adv Agron 136:27–132. https://doi.org/10.1016/bs.agron.2015.11.004

Bennett DR, Harms TE (2011) Crop yield and water requirement relationships for major irrigated crops in Southern Alberta. Can Water Resour J 36(2):159–170. https://doi.org/10.4296/cwrj3602853

Bhuiyan SR, Al Baky A (2014) Digital elevation based flood hazard and vulnerability study at various return periods in Sirajganj Sadar Upazila, Bangladesh. Int J Disaster Risk Reduct 10:48–58. https://doi.org/10.1016/j.ijdrr.2014.06.001

Blanc E, Strobl E (2016) Assessing the impact of typhoons on rice production in the Philippines. J Appl Meteorol Climatol 55(4):993–1007. https://doi.org/10.1175/jamc-d-15-0214.1

Bonfante A, Bouma J (2015) The role of soil series in quantitative land evaluation when expressing effects of climate change and crop breeding on future land use. Geoderma 259–260:187–195. https://doi.org/10.1016/j.geoderma.2015.06.010

Borzì I, Bonaccorso B (2021) Quantifying groundwater resources for municipal water use in a data-scarce region. Hydrology 8(4):184. https://doi.org/10.3390/hydrology8040184 (https://www.mdpi.com/2306-5338/8/4/184)

Borzì I, Bonaccorso B, Fiori A (2019) A modified IHACRES rainfall-runoff model for predicting the hydrologic response of a river basin connected with a deep groundwater aquifer. Water 11(10):2031. https://doi.org/10.3390/w11102031 (https://www.mdpi.com/2073-4441/11/10/2031)

Borzì I, Bonaccorso B, Aronica GT (2020) The role of DEM resolution and evapotranspiration assessment in modeling groundwater resources estimation: a case study in Sicily. Water 12(11):2980. https://doi.org/10.3390/w12112980 (https://www.mdpi.com/2073-4441/12/11/2980)
Brás TA, Seixas J, Carvalhais N et al (2021) Severity of drought and heatwave crop losses tripled over the last 5 decades in Europe. Environ Res Lett. https://doi.org/10.1088/1748-9326/abf004
Brémond P, Grelot F (2013) Review article: economic evaluation of flood damage to agriculture : review and analysis of existing methods. Nat Hazards Earth Syst Sci 13(10):2493–2512. https://doi.org/10.5194/nhess-13-2493-2013
Cammalleri C, Naumann G, Mentaschi L et al (2020) Global warming and drought impacts in the EU. Publications Office of the European Union, Luxembourg. https://doi.org/10.2760/597045
Cesarini L, Figueiredo R, Monteleone B et al (2021) The potential of big data and machine learning for weather index insurance. Nat Hazards Earth Syst Sci 21:1–52. https://doi.org/10.5194/nhess-21-2379-2021220
Chavez E, Conway G, Ghil M et al (2015) An end-to-end assessment of extreme weather impacts on food security. Nat Clim Change 5(11):997–1001. https://doi.org/10.1038/nclimate2747 (https://www.nature.com/articles/nclimate2747)
Chen F, Jia H, Pan D (2019) Risk assessment of maize drought in China based on physical vulnerability. J Food Qual. https://doi.org/10.1155/2019/9392769
CRED (2021) EM-DAT The international disaster database. http://emdat.be/emdatdb/
Cui Y, Jiang S, Jin J et al (2019) Quantitative assessment of soybean drought loss sensitivity at different growth stages based on S-shaped damage curve. Agric Water Manage 213:821–832. https://doi.org/10.1016/j.agwat.2018.11.020
De Groot A (1969) Methodologies. Mouton, Hague
Droulia F, Charalampopoulos I (2021) Future climate change impacts on European viticulture: a review on recent scientific advances. Atmosphere 12(4):495. https://doi.org/10.3390/atmos12040495 (https://www.mdpi.com/2073-4433/12/4/495)
Dutta D, Herath S, Musiake K (2003) A mathematical model for flood loss estimation. J Hydrol 277(1–2):24–49. https://doi.org/10.1016/S0022-1694(03)00084-2
Eggen M, Ozdogan M, Zaitchik B et al (2019) Vulnerability of sorghum production to extreme, sub-seasonal weather under climate change. Environ Res Lett. https://doi.org/10.1088/1748-9326/aafe19
Englhardt J, de Moel H, Huyck CK et al (2019) Enhancement of large-scale flood risk assessments using building-material-based vulnerability curves for an object-based approach in urban and rural areas. Nat Hazards Earth Syst Sci 19(8):1703–1722. https://doi.org/10.5194/nhess-19-1703-2019 (https://nhess.copernicus.org/articles/19/1703/2019/)
FAO (2015) Impact of natural hazards and disasters on agriculture and food security and nutrition. Tech Rep May, http://www.fao.org/3/a-i4434e.pdf
FAO (2021) The impact of disasters and crises on agriculture and food security: 2021. Tech Rep FAO Rome. https://doi.org/10.4060/cb3673en
Fisher RA (1992). Stat Methods Res Work. https://doi.org/10.1007/978-1-4612-4380-9_6
Flowerdew R (2009) Scientific method. In: international encyclopedia of human geography. Elsevier, DOI: https://doi.org/10.1016/B978-008044910-4.00511-3
Fu J, Niu J, Kang S et al (2019) Crop production in the Hexi Corridor challenged by future climate change. J Hydrol. https://doi.org/10.1016/j.jhydrol.2019.124197
Ganji Z, Shokoohi A, Samani JMV (2012) Developing an agricultural flood loss estimation function (case study: rice). Nat Hazards 64(1):405–419. https://doi.org/10.1007/s11069-012-0250-1
Guo H, Zhang X, Lian F et al (2016) Drought risk assessment based on vulnerability surfaces: a case study of maize. Sustainability (Switzerland). https://doi.org/10.3390/su8080813
Guo H, Wang R, Garfin GM et al (2021) Rice drought risk assessment under climate change: based on physical vulnerability a quantitative assessment method. Sci Total Environ. https://doi.org/10.1016/j.scitotenv.2020.141481
Hendrawan VSA, Komori D (2021) Developing flood vulnerability curve for rice crop using remote sensing and hydrodynamic modeling. Int J Disaster Risk Reduct 54:102058. https://doi.org/10.1016/j.ijdrr.2021.102058
IPCC (2022) Climate change 2022: impacts, adaptation, and vulnerability. ontribution of working group II to the sixth assessment report of the intergovernmental panel on climate change. Tech rep, IPCC, https://www.ipcc.ch/report/ar6/wg2/
Jakeman AJ, Hornberger GM (1993) How much complexity is warranted in a rainfall-runoff model? Water Resour Res 29(8):2637–2649. https://doi.org/10.1029/93WR00877

Jayanthi H, Husak GJ, Funk C et al (2013) Modeling rain-fed maize vulnerability to droughts using the standardized precipitation index from satellite estimated rainfall-Southern Malawi case study. Int J Disaster Risk Reduct 4:71–81. https://doi.org/10.1016/j.ijdrr.2013.02.001

Jayanthi H, Husak GJ, Funk C et al (2014) A probabilistic approach to assess agricultural drought risk to maize in Southern Africa and millet in Western Sahel using satellite estimated rainfall. Int J Disaster Risk Reduct 10(B):490–502. https://doi.org/10.1016/j.ijdrr.2014.04.002 (https://linkinghub.elsevier.com/retrieve/pii/S2212420914000314)

Jia H, Wang J, Cao C et al (2012) Maize drought disaster risk assessment of China based on EPIC model. Int J Digit Earth 5(6):488–515. https://doi.org/10.1080/17538947.2011.590535

Jiang S, Yang R, Cui N et al (2018) Analysis of drought vulnerability characteristics and risk assessment based on information distribution and diffusion in Southwest China. Atmosphere. https://doi.org/10.3390/atmos9070239

Kamali B, Abbaspour KC, Lehmann A et al (2018) Spatial assessment of maize physical drought vulnerability in sub-Saharan Africa: linking drought exposure with crop failure. Environ Res Lett 13(7):074010. https://doi.org/10.1088/1748-9326/aacb37

Keating B, Carberry P, Hammer G et al (2003) An overview of APSIM, a model designed for farming systems simulation. Eur J Agron 18(3–4):267–288. https://doi.org/10.1016/S1161-0301(02)00108-9 (https://linkinghub.elsevier.com/retrieve/pii/S1161030102001089)

Kwak Y, Shrestha BB, Yorozuya A et al (2015) Rapid damage assessment of rice crop after large-scale flood in the cambodian floodplain using temporal spatial data. IEEE J Sel Top Appl Earth Obs Remote Sens 8(7):3700–3709

Li F, Manjing Z, Yaoze L (2022) Quantitative research on drought loss sensitivity of summer maize based on AquaCrop model. Nat Hazards. https://doi.org/10.1007/s11069-022-05218-w

Li K, Wu S, Dai E et al (2012) Flood loss analysis and quantitative risk assessment in China. Nat Hazards 63(2):737–760. https://doi.org/10.1007/s11069-012-0180-y

Li Z, Zhang Z, Zhang J et al (2021) A new framework to quantify maize production risk from chilling injury in Northeast China. Clim Risk Manage. https://doi.org/10.1016/j.crm.2021.100299

Li Z, Zhang Z, Zhang L (2021) Improving regional wheat drought risk assessment for insurance application by integrating scenario-driven crop model, machine learning, and satellite data. Agric Syst 191:103141. https://doi.org/10.1016/j.agsy.2021.103141

Liu K, Harrison MT, Shabala S et al (2020) The state of the art in modeling waterlogging impacts on plants: what do we know and what do we need to know. Earth's Future. https://doi.org/10.1029/2020EF001801

Lloyd-Hughes B (2014) The impracticality of a universal drought definition. Theo Appl Climatol 117(3):607–611. https://doi.org/10.1007/s00704-013-1025-7

Malhi GS, Kaur M, Kaushik P (2021) Impact of climate change on agriculture and its mitigation strategies: a review. Sustainability 13(3):1318. https://doi.org/10.3390/su13031318 (https://www.mdpi.com/2071-1050/13/3/1318)

Masutomi Y, Iizumi T, Takahashi K et al (2012) Estimation of the damage area due to tropical cyclones using fragility curves for paddy rice in Japan. Environ Res Lett. https://doi.org/10.1088/1748-9326/7/1/014020

Mehdikhani H, Saghafian B, Arasteh PD (2017) A new damage-probability approach for risk analysis of rain-fed agricultural systems under meteorological drought. KSCE J Civ Eng 21(4):1453–1461. https://doi.org/10.1007/s12205-016-0510-y

Merz B, Kreibich H, Schwarze R et al (2010) Review article "assessment of economic flood damage''. Nat Hazards Earth Syst Sci 10(8):1697–1724. https://doi.org/10.5194/nhess-10-1697-2010 (https://nhess.copernicus.org/articles/10/1697/2010/)

Michel-Kerjan E, Hochrainer-Stigler S, Kunreuther H et al (2013) Catastrophe risk models for evaluating disaster risk reduction investments in developing Countries. Risk Anal 33(6):984–999. https://doi.org/10.1111/j.1539-6924.2012.01928.x

Ming X, Xu W, Li Y et al (2015) Quantitative multi-hazard risk assessment with vulnerability surface and hazard joint return period. Stoch Environ Res Risk Assess 29(1):35–44. https://doi.org/10.1007/s00477-014-0935-y

Mitchell T (1997) Machine learning. McGrow Hill, New York

Molinari D, Rita Scorzini A, Gallazzi A et al (2019) AGRIDE-c, a conceptual model for the estimation of flood damage to crops: development and implementation. Nat Hazards Earth Syst Sci 19(11):2565–2582. https://doi.org/10.5194/nhess-19-2565-2019

Monaco E, Bonfante A, Alfieri SM et al (2014) Climate change, effective water use for irrigation and adaptability of maize: a case study in southern Italy. Biosyst Eng 128:82–99. https://doi.org/10.1016/j.biosystemseng.2014.09.001

Monteleone B, Bonaccorso B, Martina M (2020) A joint probabilistic index for objective drought identification : the case study of Haiti. Nat Hazards Earth Syst Sci 20:471–487. https://doi.org/10.5194/nhess-20-471-2020
Monteleone B, Borzí I, Bonaccorso B et al (2022) Developing stage-specific drought vulnerability curves for maize : the case study of the Po River basin. Agric Water Manage 269(107):713. https://doi.org/10.1016/j.agwat.2022.107713
Moriondo M, Bindi M, Kundzewicz ZW et al (2010) Impact and adaptation opportunities for European agriculture in response to climatic change and variability. Mitig Adapt Strategies Glob Change 15(7):657–679. https://doi.org/10.1007/s11027-010-9219-0
Naumann G, Spinoni J, Vogt JV et al (2015) Assessment of drought damages and their uncertainties in Europe. Environ Res Lett 10(12):124013
Nguyen NY, Ichikawa Y, Ishidaira H (2017) Establishing flood damage functions for agricultural crops using estimated inundation depth and flood disaster statistics in data-scarce regions. Hydrol Res Lett 11(1):12–18. https://doi.org/10.3178/hrl.11.12
Nguyen NY, Kha DD, Ichikawa Y (2021) Developing a multivariable lookup table function for estimating flood damages of rice crop in Vietnam using a secondary research approach. Int J Disaster Risk Reduct 58(102):208. https://doi.org/10.1016/j.ijdrr.2021.102208
Papathoma-Köhle M (2016) Vulnerability curves versus. Vulnerability indicators: application of an indicator-based methodology for debris-flow hazards. Nat Hazards Earth Syst Sci 16(8):1771–1790. https://doi.org/10.5194/nhess-16-1771-2016
Polese M, Di Ludovico M, Prota A et al (2013) Damage-dependent vulnerability curves for existing buildings. Earthq Eng Struct Dyn 42(6):853–870. https://doi.org/10.1002/eqe.2249
Ray DK, Gerber JS, Macdonald GK et al (2015) Climate variation explains a third of global crop yield variability. Nat Commun 6:1–9. https://doi.org/10.1038/ncomms6989
Scorzini AR, Di Bacco M, Manella G (2021) Regional flood risk analysis for agricultural crops: insights from the implementation of AGRIDE-c in central Italy. I J Disaster Risk Reduct 53:101999. https://doi.org/10.1016/j.ijdrr.2020.101999
Shrestha B, Okazumi T, Miyamoto M et al (2016) Flood damage assessment in the Pampanga river basin of the Philippines. J Flood Risk Manage 9(4):355–369. https://doi.org/10.1111/jfr3.12174
Shrestha BB, Kawasaki A (2020) Quantitative assessment of flood risk with evaluation of the effectiveness of dam operation for flood control: a case of the Bago River Basin of Myanmar. Int J Disaster Risk Reduct. https://doi.org/10.1016/j.ijdrr.2020.101707
Shrestha BB, Sawano H, Ohara M et al (2016b) Improvement in flood disaster damage assessment using highly accurate IfSAR DEM. J Disaster Res 11(6):1137–1149. https://doi.org/10.20965/jdr.2016.p1137
Shrestha BB, Perera EDP, Kudo S et al (2019) Assessing flood disaster impacts in agriculture under climate change in the river basins of Southeast Asia. Nat Hazards 97(1):157–192. https://doi.org/10.1007/s11069-019-03632-1
Shrestha BB, Kawasaki A, Zin WW (2021) Development of flood damage functions for agricultural crops and their applicability in regions of Asia. J Hydrol: Reg Stud. https://doi.org/10.1016/j.ejrh.2021.100872
Sianturi R, Jetten VG, Sartohadi J (2018) Mapping cropping patterns in irrigated rice fields in West Java: towards mapping vulnerability to flooding using time-series MODIS imageries. Int J Appl Earth Obs Geoinf 66:1–13. https://doi.org/10.1016/j.jag.2017.10.013
Skakun S, Kussul N, Shelestov A et al (2016) The use of satellite data for agriculture drought risk quantification in Ukraine. Geomat, Nat Hazards and Risk 7(3):901–917. https://doi.org/10.1080/19475705.2015.1016555
Steduto P, Raes D, Hsiao TC, et al (2009) Concepts and applications of aquaCrop: the FAO crop water productivity model. In: crop modeling and decision support. Springer Berlin, (p 175–191)
Steduto P, Hsia TC, Fereres E, Raes D (2012) FAO irrigation and drainage paper 66, Crop yield response to water. Rome, ISBN 978-92-5-107274-5
Su P, Li S, Wang J et al (2021) Vulnerability assessment of maize yield affected by precipitation fluctuations: a northeastern united states case study. Land. https://doi.org/10.3390/land10111190
Tarbotton C, Dall'Osso F, Dominey-Howes D et al (2015) The use of empirical vulnerability functions to assess the response of buildings to tsunami impact: comparative review and summary of best practice. Earth-Sci Rev 142:120–134. https://doi.org/10.1016/j.earscirev.2015.01.002
Todisco F, Mannocchi F, Vergni L (2013) Severity duration frequency curves in the mitigation of drought impact an agricultural case study. Nat Hazards 65(3):1863–1881. https://doi.org/10.1007/s11069-012-0446-4

UNDRO22, 76, (1984) Disaster prevention and mitigation: a compendium of current knowledge, vol 11. Preparedness aspects, New York
UNISDR (2009) UNISDR terminology on disaster risk reduction. https://www.undrr.org/publication/2009-unisdr-terminology-disaster-risk-reduction
Vega-Serratos BE, Domínguez-Mora R, Posada-Vanegas G (2018) Seasonal flood risk assessment in agricultural areas. Tecnol y Cienc del Agua 9(3):92–127. https://doi.org/10.24850/j-tyca-2018-03-04
Wang Y, Zhao W, Zhang Q et al (2019) Characteristics of drought vulnerability for maize in the eastern part of Northwest China. Sci Rep 9(1):1–9. https://doi.org/10.1038/s41598-018-37362-4
Wang Z, He F, Fang W et al (2013) Assessment of physical vulnerability to agricultural drought in China. Nat Hazards 67(2):645–657. https://doi.org/10.1007/s11069-013-0594-1
Webber H, Ewert F, Olesen JE et al (2018) Diverging importance of drought stress for maize and winter wheat in Europe. Nat Commun 9(1):1–10. https://doi.org/10.1038/s41467-018-06525-2
Wei Y, Jin J, Jiang S et al (2019) Simulated assessment of summer maize drought loss sensitivity in Huaibei plain, China. Agronomy. https://doi.org/10.3390/agronomy9020078
Wilhelmi OV, Wilhite DA (2002) Assessing vulnerability to agricultural drought: a Nebraska case study. Nat Hazards 25(1):37–58. https://doi.org/10.1023/A:1013388814894
Williams JR, Jones CA, Kiniry JR et al (1989) The EPIC crop growth model. Trans Am Soc Agric Eng 32(2):497–511. https://doi.org/10.13031/2013.31032
World Meteorological Organization (WMO) and Global Water Partnership (GWP) (2016) Handbook of drought indicators and indices. In: Svoboda M, Fuchs BA (eds) Integrated drought management programme (IDMP), Integrated drought management tools and guidelines series 2. Geneva. https://doi.org/10.1007/s00704-016-1984-6
Wu Y, Guo H, Zhang A et al (2021) Establishment and characteristics analysis of a crop-drought vulnerability curve: a case study of European winter wheat. Nat Hazards Earth Syst Sci 21(4):1209–1228. https://doi.org/10.5194/nhess-21-1209-2021
Yin Y, Zhang X, Lin D et al (2014) GEPIC-V-R model: a GIS-based tool for regional crop drought risk assessment. Agric Water Manage 144:107–119. https://doi.org/10.1016/j.agwat.2014.05.017
Yue Y, Li J, Ye X et al (2015) An EPIC model-based vulnerability assessment of wheat subject to drought. Nat Hazards 78(3):1629–1652. https://doi.org/10.1007/s11069-015-1793-8
Zargar A, Sadiq R, Naser B et al (2011) A review of drought indices. Environ Rev 19(NA):333–349. https://doi.org/10.1139/a11-013
Zhang F, Chen Y, Zhang J et al (2019) Dynamic drought risk assessment for maize based on crop simulation model and multi-source drought indices. J Clean Prod 233:100–114. https://doi.org/10.1016/j.jclepro.2019.06.051
Zhao L, Xia J, Cy Xu et al (2013) Evapotranspiration estimation methods in hydrological models. Journal of Geographical Sciences 23(2):359–369. https://doi.org/10.1007/s11442-013-1015-9
Zhu X, Xu K, Liu Y et al (2021) Assessing the vulnerability and risk of maize to drought in China based on the AquaCrop model. Agric Syst. https://doi.org/10.1016/j.agsy.2020.103040