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Ensemble climate-impact modelling: extreme impacts from moderate meteorological conditions

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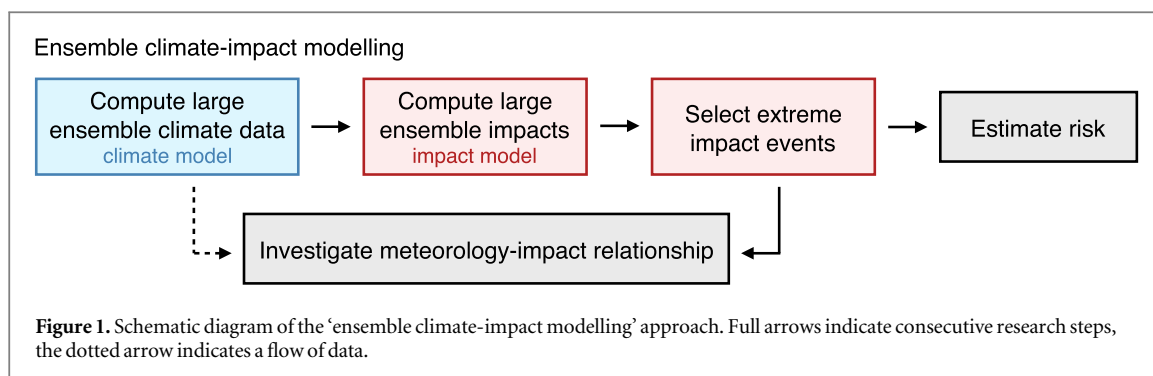
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Abstract

The investigation of risk due to weather and climate events is an example of policy relevant science. Risk is the result of complex interactions between the physical environment (geophysical events or conditions, including but not limited to weather and climate events) and societal factors (vulnerability and exposure). The societal impact of two similar meteorological events at different times or different locations may therefore vary widely. Despite the complex relation between meteorological conditions and impacts, most meteorological research is focused on the occurrence or severity of extreme meteorological events, and climate impact research often undersamples climatological natural variability. Here we argue that an approach of ensemble climate-impact modelling is required to adequately investigate the relationship between meteorology and extreme impact events. We demonstrate that extreme weather conditions do not always lead to extreme impacts; in contrast, extreme impacts may result from (coinciding) moderate weather conditions. Explicit modelling of climate impacts, using the complete distribution of weather realisations, is thus necessary to ensure that the most extreme impact events are identified. The approach allows for the investigation of high-impact meteorological conditions and provides higher accuracy for consequent estimates of risk.

1. Introduction

Human and natural systems around the world experience daily weather and ongoing climate change, and are therefore susceptible to the impacts of adverse meteorological conditions. Whether a meteorological event leads to an extreme impact depends on many factors, including exposure (people, assets or ecosystems in places that could be affected) and vulnerability (inability to cope with external pressure, Agard *et al* 2014). For example, damage due to tropical cyclones depends on both the storm characteristics and on the local situation at landfall (Pielke *et al* 2008); the danger of extreme heat is related to local demographics and social context (Reid *et al* 2009, Mora *et al* 2017). For these reasons, to support science-informed policy, it is obvious that meteorological and climate change research needs to explicitly include the associated societal or natural impacts (e.g. Smith 2011, Baklanov *et al* 2018).

However, a large proportion of meteorological research is focused on the occurrence and/or severity of extreme meteorological events. Examples include studies of heavy rain events, meteorological droughts, heatwaves and tropical cyclones, based on variables readily available from climate models (e.g. Stott *et al* 2004, Van Oldenborgh *et al* 2017, Herring *et al* 2019). Though such research advances our understanding of the physical climate system and changes therein, it does not provide information on the impact of specific weather events (e.g. flooding, wildfires, coral bleaching, biodiversity loss, crop losses, property damage, health impacts, financial losses, loss of life). Its direct use for policy makers is therefore fairly limited. Here we will show that investigating meteorology and extremes therein, and evaluating impacts based on these extreme events can lead to a significant underestimation of risk.

Climate impact research is concerned with assessing the impacts of weather and climate change on

Figure 1. Schematic diagram of the 'ensemble climate-impact modelling' approach. Full arrows indicate consecutive research steps, the dotted arrow indicates a flow of data.
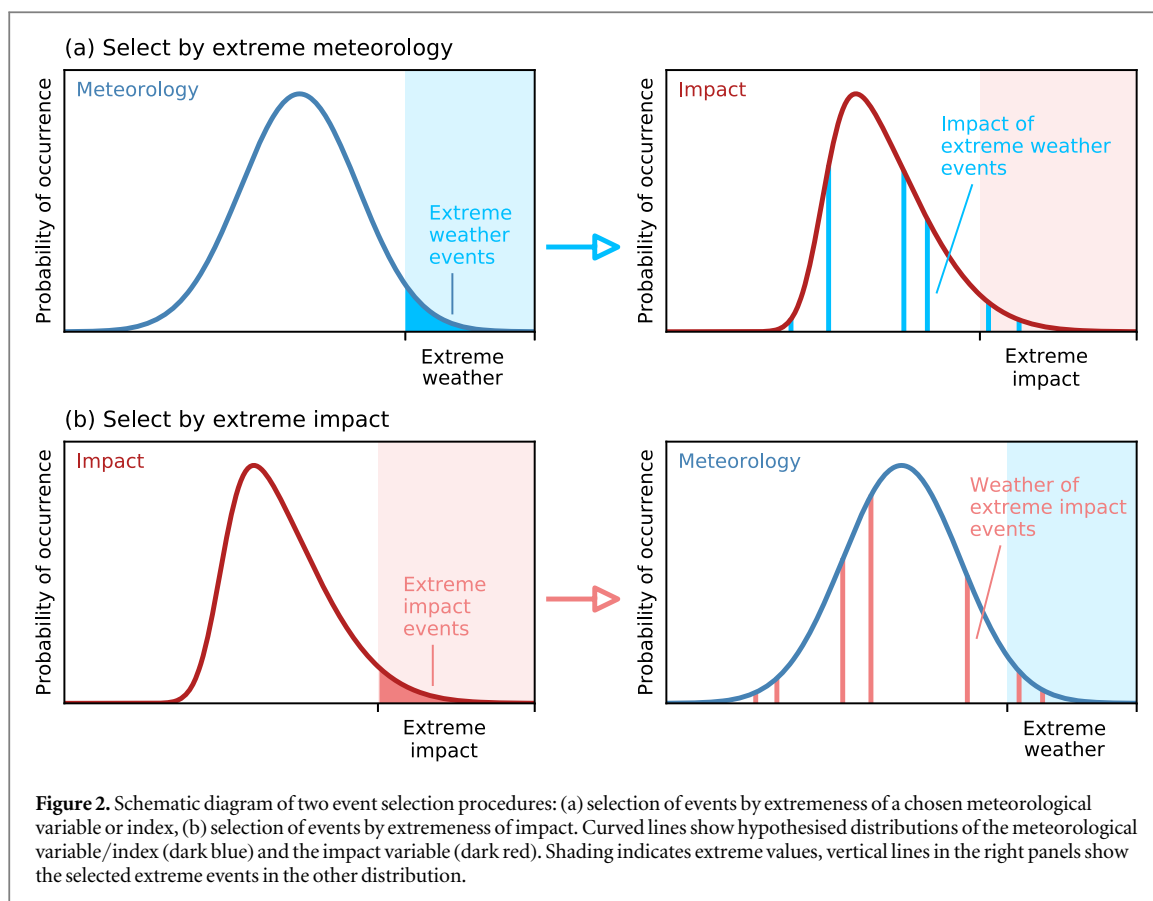
human and natural systems, addresses some of these issues. However, often uncertainties in impact mechanisms and feedbacks take a more prominent role than uncertainty due to meteorological variability (e.g. Davie *et al* 2013, Yang *et al* 2017, McSweeney and Jones 2016). This limits the understanding of the variety of meteorological conditions that may lead to a common impact, and the possible neglect of so called 'Black Swan' events (Nassim 2007).

The aim of this essay is two-fold: first, to highlight the nontrivial meteorology-impact relation and the significance of considering actual impacts when investigating the effects of severe weather and climate change on communities and ecosystems, and second, to promote an integrated climate and impact modelling approach that addresses this complicated relationship. We argue that the ensemble modelling practice common in physical climate science (Deser *et al* 2020) should be extended with an ensemble impact modelling approach to investigate extreme impact events (figure 1). We think that such impact-driven science, which must be built on collaboration between a wide range of academic specialisations as well as stakeholders (Vera 2018), will help gain new insights since societal or ecological vulnerabilities can be more accurately linked to (changing) meteorological conditions. By means of an illustrative case study we show that ensemble climate-impact modelling (i) allows the investigation of events of highest impact, (ii) advances our understanding of the meteorological drivers of extreme impacts and (iii) helps to more accurately estimate (changes in) societal risk from meteorological conditions. The advocated method provides a framework for the analysis of compound events (combinations of events that amplify each other's impact, or moderate events that lead to an extreme impact when combined; Seneviratne *et al* 2012, Zscheischler *et al* 2018), by reducing these multi-variate events to an univariate impact variable. With climate changing and meteorological extremes becoming more common, obtaining accurate estimates of impacts and improved insights into the interactions between physical drivers and societal impacts is vital.

2. Methods: event selection based on extreme impact

Much meteorological research starts from the meteorological extreme and considers the societal impacts afterwards. From large ensembles of climate data, the hottest, wettest, driest or windiest events are selected ('*extreme weather events*'), after which the societal impact of such events is evaluated and often stressed as motivation for further study into the changing nature or predictability of these extreme weather events. However, not all extreme weather events result in extreme impacts (schematically outlined in figure 2(a)), and trends in extreme weather events may be different from trends in extreme impact events. For example, climate change made the rainfall of Hurricane Harvey 15% more intense (Van Oldenborgh *et al* 2017), but land use changes magnified the effects of climate change during the consequent flooding disaster, resulting in an 84% higher peak of discharge (Sebastian *et al* 2019). Besides meteorological drivers, other physical factors (e.g. pre-existing land state, coincident weather events) or societal factors (e.g. vulnerability, exposure, resilience, preparedness) play a large role in determining which weather events lead to extreme impact and which do not.

To aid future studies on the specific weather events that result in the most extreme impacts, we advocate an interdisciplinary approach for the selection of such events: 'ensemble climate-impact modelling'. We suggest that the large ensembles of climate data commonly used in meteorological research (Deser *et al* 2020) are used in their entirety as input for impact models, resulting in large ensembles of impact data. From this dataset of societal/natural impacts the most extreme events ('*extreme impact events*') can be selected (figure 1). These events can guide further research into the physical origin of the extreme impact, into the links between impact and meteorology (figure 2(b)), and can be used for estimates of risk. Impacts that may be investigated in this way include, for example, human well-being using thermal comfort models, agricultural production using crop growth models, river flooding using hydrological models, and energy security using renewable energy models.

Figure 2. Schematic diagram of two event selection procedures: (a) selection of events by extremeness of a chosen meteorological variable or index, (b) selection of events by extremeness of impact. Curved lines show hypothesised distributions of the meteorological variable/index (dark blue) and the impact variable (dark red). Shading indicates extreme values, vertical lines in the right panels show the selected extreme events in the other distribution.
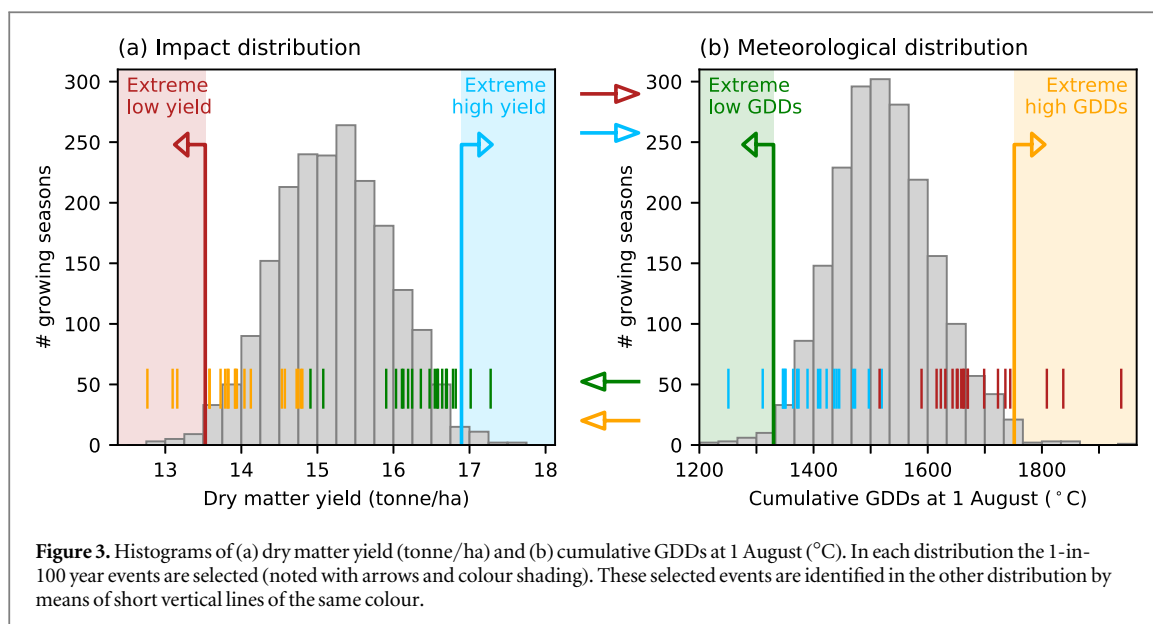
The ensemble climate-impact modelling approach has a number of advantages over a purely meteorological approach. First and foremost, events of highest societal interest due to large impact are selected. Extreme impact events may of course result from severe weather conditions (e.g. De Bono *et al* 2004, Van der Wiel *et al* 2017, Van Oldenborgh *et al* 2017), but also from rare coincidences of different meteorological variables of moderate strength. Such compound events would be very difficult, if not impossible, to identify from meteorological data alone. Impact modelling is a way to translate multivariate drivers into a univariate impact, which therefore simplifies event selection. Secondly, this approach may lead to the discovery of unexpected (combinations of) weather events that result in extreme impacts (Smith 2011). Nonlinear meteorology-impact relationships generally hide such 'Black Swan' events (Nassim 2007, Ben-Ari *et al* 2018). Finally, estimates of risk or changes therein can be computed directly from the full distribution of impact data. If certain extreme impact events are systematically missed because of their compound nature or unknown drivers, resulting estimates of risk may significantly underestimate the true risk. Improved risk estimates are useful to inform society, to plan adaptation strategies and are valuable for the insurance industry.

Some historic examples of large impact from moderate meteorology include the 2014 Jakarta floods, which were caused by a 1-in-4 year rainfall event (Siswanto *et al* 2015), emergency evacuation in the Netherlands because of compounding surge and rainfall events in 2012 (Van den Hurk *et al* 2015), the 2013/14 winter in North America in which near-normal cold air outbreaks caused extensive problems (Van Oldenborgh *et al* 2015), and a sequence of cloudy days leading to much lower crop yields in South America in 2016 (Vera 2018). Previous studies following a similar ensemble impact approach have, for example, led to insights in the meteorological drivers leading to extreme carbon fluxes from forests (Zscheischler *et al* 2014), trends in economic damage from tropical cyclones (Gettelman *et al* 2018), probabilistic estimates of changes in extreme discharge in the river Thames (New *et al* 2007) and the weather causing high risk for European energy security (Van der Wiel *et al* 2019a).

Crucially, the quality of event selection and consequent analysis depends on two factors: the quality of the climate simulations, including effects of bias correction and/or downscaling when applied, and the quality of the impact model, i.e. its sensitivity to relevant changes in the physical environment and societal factors. A perfect selection, i.e. selected events could also have happened in the real world, is only possible if all processes that influence the impact variable are modelled in a realistic way. Depending on the impact variable, drivers may be purely physical or a combination of physical and societal effects. For example, in 2010 a severe heatwave, drought and wildfires resulted in grain crop losses in Russia (physical processes,

Figure 3. Histograms of (a) dry matter yield (tonne/ha) and (b) cumulative GDDs at 1 August (°C). In each distribution the 1-in-100 year events are selected (noted with arrows and colour shading). These selected events are identified in the other distribution by means of short vertical lines of the same colour.

Lau and Kim 2012), subsequently this resulted in domestic food price spikes (due to crop losses, but amplified by political decisions and hoarding by the population, Kramer 2010, Wegren 2011). Another example concerns wildfires, which may occur due to natural causes, but human behaviour can both lead to locally increased or decreased fire risk (Bowman *et al* 2011). It is therefore important to consider model limitations and the assumptions under which the event selection and analysis are made, both must take a prominent role in any analysis. In section 4 we discuss these in more detail.
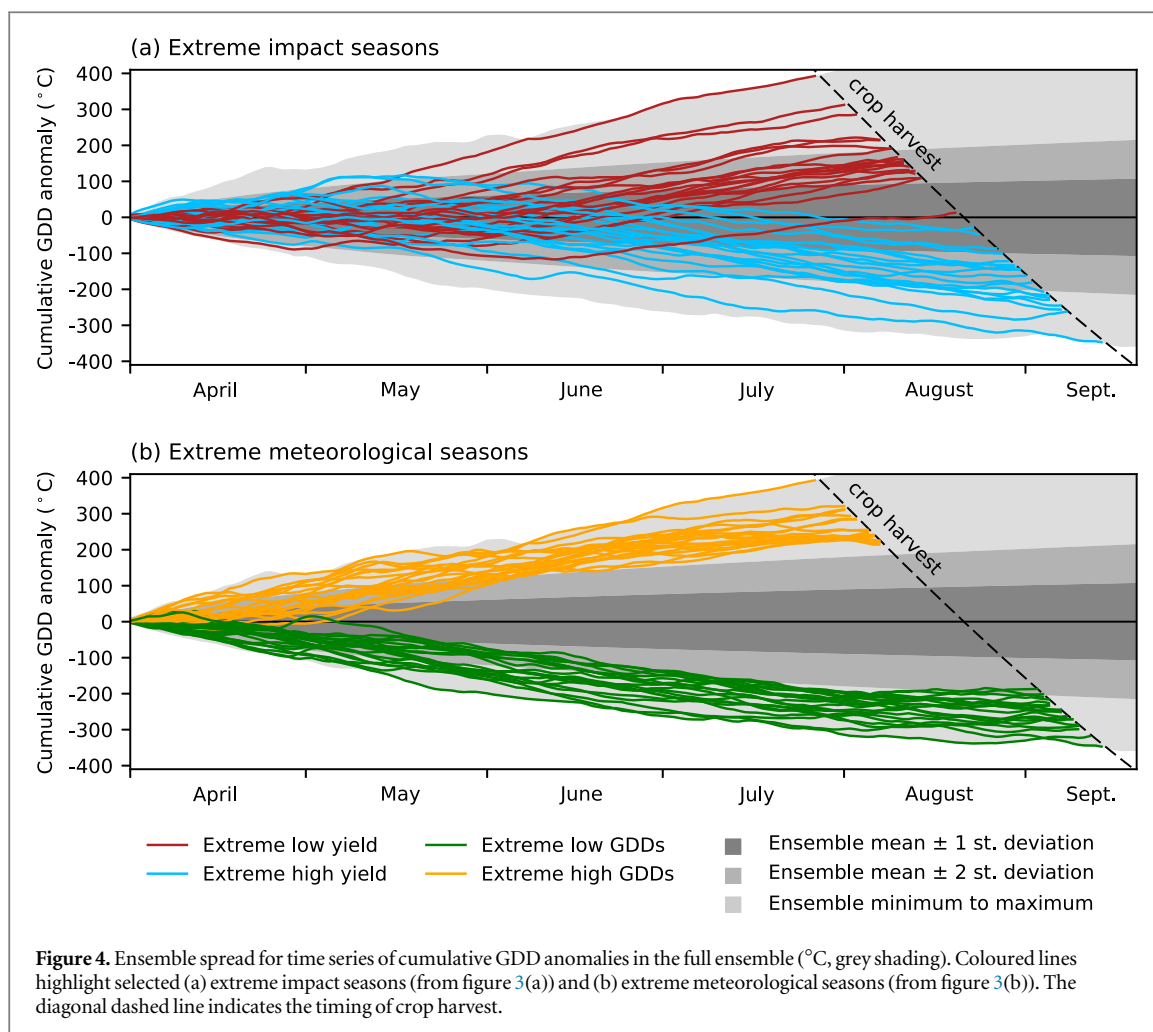
3. Illustrative example of nonlinear meteorology-impact relationship

To illustrate the ensemble climate-impact modelling approach outlined above, we present a case study regarding the meteorological impacts on potato farming in the Netherlands. Many factors determine the success of a farmer: the quality and quantity of yield (determined by temperature, precipitation, irrigation, diseases, condition of the land at time of harvest, etc, Langeveld *et al* 2003) but also the price at which the yield can be sold (determined by demand, financial contracts, success/failure of similar crops in remote regions, etc, Pavlista and Feuz 2005). We limit the impact modelling to the physical side, i.e. the hazard, and do not fully consider the vulnerability and exposure of the farmer's success to external or societal factors.

We simulate a large ensemble of crop yields based on a large ensemble of climate model data. The climate data were simulated using the EC-Earth global coupled climate model (Hazeleger *et al* 2012), for which two ensembles of 2000 years are available ('present-day' and '2 °C-warming', Van der Wiel *et al* 2019b). Annual potato yields were modelled using

AquaCrop-OS v5.0a (Foster *et al* 2017), an open-source crop growth model based on the United Nations (UN) Food and Agriculture Organization (FAO) crop model (Vanuytrecht *et al* 2014, Raes *et al* 2017). In our illustrative example we assume perfect water availability, therefore plant growth depends solely on daily minimum and maximum temperatures through the accumulation of growing degree days (GDDs). Even in this simple experimental setup the nontrivial relationship between meteorology (daily temperatures) and impact extremes (low/high yield) can be demonstrated, including the consequences for scientific analyses. If we can show the relevance of ensemble climate-impact modelling in this relatively simple context, it must certainly be relevant in a more complex case. Note that it is not our intention to make a qualitative assessment of yields in the Netherlands, we have purposely simplified the weather-crop relationship to better illustrate the advantages of climate-impact modelling. More details on the climate model ensembles and the crop growth model are provided in the supporting information available online at stacks. iop.org/ERL/15/034050/mmedia.

The distribution of simulated yields is shown in figure 3(a). The median simulated dry matter yield is 15.2 tonne/ha; within the ensemble, yields vary from 12.8 tonne/ha to 17.6 tonne/ha. We select extreme impact events with a 1-in-100 year return period from each tail in the distribution (i.e. 20 events from 2000 years of data). Based on the simulations, the 1-in-100 year low yield is 13.5 tonne/ha, while the high yield threshold lies at 16.9 tonne/ha. These extreme impact events are then identified in a distribution of cumulative GDDs near the end of the growing season (figure 3(b)). Seasonal cumulative GDDs were chosen as the most relevant meteorological variable because, given our assumptions, plant growth solely depends on GDDs. The choice of meteorological

Figure 4. Ensemble spread for time series of cumulative GDD anomalies in the full ensemble (°C, grey shading). Coloured lines highlight selected (a) extreme impact seasons (from figure 3(a)) and (b) extreme meteorological seasons (from figure 3(b)). The diagonal dashed line indicates the timing of crop harvest.
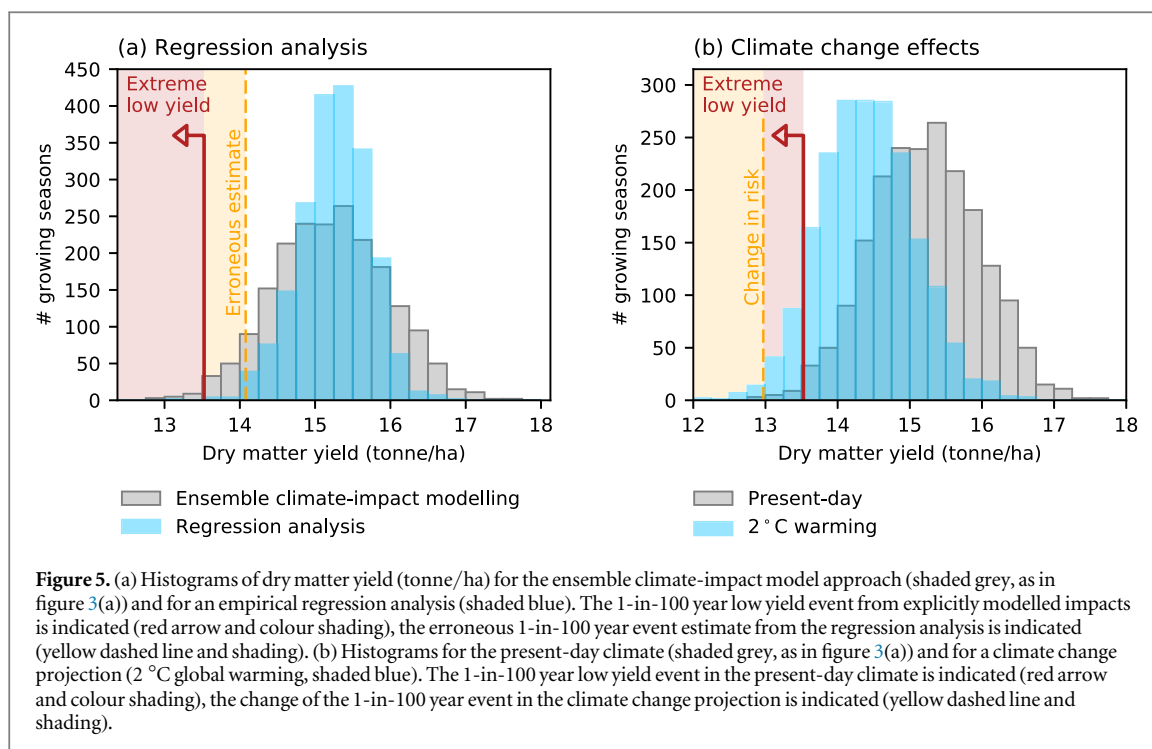
variable will influence this analysis. Note that if event selection is done by impact, it is no longer necessary to make assumptions regarding the most relevant meteorological variable(s).

Just three of the selected 20 extreme low yield events are extreme in meteorological terms (cumulative GDDs exceeding 1752 °C, figure 3(b)). Hence, the vast majority (85%) of extreme impact events result from non-extreme meteorological conditions; these impact events would have been missed if the event selection had been based on extremeness of the meteorological variable. Despite the fact that yield and GDDs are significantly correlated ($r = -0.61$), this analysis confirms that meteorological extremes have only limited bearing on extreme impacts. Other meteorological variables were tested, the results were comparable and this conclusion holds.

The selected extreme impact events can now be investigated in terms of their meteorology: what conditions lead to high impact? In the first month and a half of the growing season there is no systematic difference between the seasons of extreme low and extreme high yield (figure 4(a)). Such differences start to develop in the second half of May: extreme low yields seasons experience long relatively warm periods (fast accumulation of GDDs, positive slope of the time

series in figure 4(a)), the opposite is true for seasons of extreme high yield. At the harvest date all selected low yield seasons have a positive cumulative GDD anomaly, indicating the growing season was warmer than normal. Despite this similarity, there is large variety in the temporal development of GDD accumulation (i.e. variety in meteorological conditions) that lead to extreme yields. The temporal evolution of extreme meteorological seasons (figure 4(b)) is qualitatively different and more homogeneous: throughout the growing season all events converge towards the tails of the distribution. The physical relations in the impact model of choice can provide insights into the impact sensitivities. Here, the timing of warm and cool periods and the amount of canopy cover during such a period determines biomass growth and end-of-season yield; the effect of a heatwave late in the growing season is much bigger than a heatwave early in the growing season. Such nonlinear effects remain elusive when impact mechanisms are not explicitly considered.

The use of an impact model in which the mechanisms leading to impact (here growth of canopy and biomass) are considered, enables investigation of potential nonlinear, complex relationships. Without explicit modelling, one inevitably must make assumptions regarding these relationships or rely on statistical

Figure 5. (a) Histograms of dry matter yield (tonne/ha) for the ensemble climate-impact model approach (shaded grey, as in figure 3(a)) and for an empirical regression analysis (shaded blue). The 1-in-100 year low yield event from explicitly modelled impacts is indicated (red arrow and colour shading), the erroneous 1-in-100 year event estimate from the regression analysis is indicated (yellow dashed line and shading). (b) Histograms for the present-day climate (shaded grey, as in figure 3(a)) and for a climate change projection (2 °C global warming, shaded blue). The 1-in-100 year low yield event in the present-day climate is indicated (red arrow and colour shading), the change of the 1-in-100 year event in the climate change projection is indicated (yellow dashed line and shading).

relationships. To show the limits of such a statistical analysis, we compare our ensemble climate-impact modelling approach to a regression model. The regression model is based on the statistically significant relationship between cumulative GDDs and yield ($r = -0.61$), and it is trained on 100 randomly selected years from the full ensemble and then applied to the full ensemble of weather conditions. Though the median yield is captured in the regression model, the range of yields is much smaller in this regression-based ensemble (figure 5(a)). Since nonlinear effects (the sensitivity to the timing of warm and cool periods) are not considered, the extremeness of possible impacts is underestimated. For example, the 1-in-100 year low yield event is estimated to be 14.1 tonne/ha, instead of 13.5 tonne/ha when impacts are calculated explicitly. This error leads to an erroneous estimate of risk; from the explicitly calculated impacts we can determine that the regression-based estimate of the 1-in-100 years low yield event is in fact a 1-in-16.4 years event. Note that in this regression model extreme weather events lead to extreme impact by design. The the ensemble climate-impact modelling method gives more accurate estimates of impacts and risks as compared to purely statistical analyses.

Finally, we illustrate the use of the ensemble climate-impact modelling approach for questions regarding changes in extreme impacts due to climate change. Climate change leads to faster accumulation of GDDs throughout a growing season, which, without adaptation, leads to a decrease of crop yields (figure 5(b), future median 14.0 tonne/ha). The lowest yield in the 2 °C-warming ensemble is 11.9 tonne/ha, which is outside the range of the present-day ensemble. The change in return times of extreme events can

be computed directly from the ensemble of data. From a meteorological perspective, the 1-in-100 year high GDD event is 12.7 times more likely in the 2 °C-warming ensemble (future: 1-in-7.9 years); explicit impact modelling reveals that extreme low yield events are 22 times more likely due to global warming (future: 1-in-4.6 years). In this case, the effect of climate change on changes in the probability of occurrence of the meteorological extreme events is almost double as large as the effect of climate change on changes in probability for extreme impact events. Accurate assessment of changes in risk for policy making should be based on explicit impact calculations rather than be inferred from changes in meteorological extremes.

As with any analysis, conclusions from an ensemble climate-impact modelling study are valid given the assumptions made, and with consideration of the limitations and uncertainties of the climate data and impact model. Here the strict assumptions were designed to provide a relatively simple link between meteorology and extreme impacts. Different assumptions or choices for another case study, e.g. rain-fed potato crops which respond to wet and dry periods (Langeveld *et al* 2003) or farmer earnings rather than yield as impact variable (Pavlista and Feuz 2005), would add further nonlinear mechanisms increasing the importance of explicit impact modelling.

4. Discussion

When doing an analysis following the ensemble climate-impact modelling approach, careful consideration must be given to the choices and assumptions involved. First of all, we note the importance of

choosing a relevant impact variable. This variable should be as close as possible to the societal or natural problem of interest. The choice of variable may be limited by what can be modelled given the availability and quality of climate and impact models.

Coarse climate model resolution, errors in physical parameterisations and missing processes result in biases in simulated meteorological variables. Because most societal or ecological impacts are in some form dependent on the exceedance of threshold levels (e.g. strong human heat stress occurs when thermal indices exceed 32 °C, and many biological processes change at particular temperature or precipitation values, Easterling *et al* 2000, Bröde *et al* 2012), these biases need to be corrected before such simulated data can be used as a forcing in an impact model. For compound events multi-variate bias adjustment techniques are preferred to conserve dependencies between different variables (Ehret *et al* 2012, Vrac and Friederichs 2015, Cannon 2016, Zscheischler *et al* 2019). When downscaling techniques are used to increase spatial or temporal resolution, the physical consistency of boundary conditions and downscaled output need to be considered (Ehret *et al* 2012, Maraun 2013, Milly and Dunne 2017).

Imperfect parameterisations and missing processes in impact models may lead to incorrect sensitivities of simulated impacts to climate or environmental variables. A comparison against observed data and observed climate-impact relationships is necessary to evaluate the modelling chain. Note however that it is unlikely that these relationships can be constrained much for extreme events, given the often limited lengths of observational time series. A multi-model approach can help determine whether results are robust across models and generally helps to reduce model biases (Tebaldi and Knutti 2007). Ideally, both the climate modelling and impact modelling (figure 1) are done with a range of independent models. The ISI-MIP and AGMIP (Rosenzweig *et al* 2014, Schellnhuber *et al* 2014) projects are examples of such multi-model climate-impact ensembles.

The case study in section 3 provided an example of a physical impact, a hazard. To consider all aspects of societal risk also exposure and vulnerability (E&V) should be assessed, since not all hazards lead to impacts: if food can be imported, low yields may not cause societal problems, and the risk of human heat stress is much lower if air conditioning is available. There are a number of ways to include E&V in the ensemble climate-impact modelling framework. If possible, it can be added in the impact modelling step (figure 1), e.g. by adding a financial module (e.g. Hsiang *et al* 2017) or by using agent-based models. Alternatively one can rely on storylines and work out the impacts of certain hazards given specific E&V conditions (Hazeleger *et al* 2015).

5. Closing remarks

In this essay we argue that meteorological research should more frequently be extended with an ensemble climate-impact modelling approach to assess extreme climate-induced societal impacts (figure 1). Ensemble climate-impact modelling provides the tools to explore scientific questions (which mechanisms drive impacts?) as well as societal questions (what are society's risks?). Without explicit modelling of impacts, nonlinear interactions between drivers and impacts are ignored, potentially leading to significant errors in the estimation of risks. Large ensembles are required to adequately sample internal variability in the physical climate system. We have found that such research is best done in collaboration between physical climate scientists and climate impact scientists, and that both disciplines can benefit from such interdisciplinary work. Improved understanding of impacts and risks facilitates potential adaptation of societies to reduce vulnerability and provides improved information to determine the cost of insurance. Given climate change (IPCC 2013) and increasing human populations in exposed regions (Vörösmarty *et al* 2000, Das Gupta 2014) accurate understanding of impacts and risks are crucial.

Data availability

The data that support the case study are openly available online.

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References

Agard J *et al* 2014 IPCC 2014 Annex II: Glossary *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* pp 1757–76

Baklanov A *et al* 2018 From urban meteorology, climate and environment research to integrated city services *Urban Clim.* **23** 330–41

Ben-Ari T, Boé J, Ciais P, Lecerf R, Van der Velde M and Makowski D 2018 Causes and implications of the unforeseen

2016 extreme yield loss in the breadbasket of france *Nat. Commun.* **9** 1627

Bowman D M *et al* 2011 The human dimension of fire regimes on Earth *J. Biogeogr.* **38** 2223–36

Bröde P, Fiala D, Błażejczyk K, Holmér I, Jendritzky G, Kampmann B, Tinz B and Havenith G 2012 Deriving the operational procedure for the universal thermal climate index (utci) *Int. J. Biometeorol.* **56** 481–94

Cannon A J 2016 Multivariate bias correction of climate model output: matching marginal distributions and intervariable dependence structure *J. Clim.* **29** 7045–64

Das Gupta M 2014 Population, poverty, and climate change *World Bank Res. Obs.* **29** 83–108

Davie J C *et al* 2013 Comparing projections of future changes in runoff from hydrological and biome models in ISI-MIP *Earth Syst. Dyn.* **4** 359–74

De Bono A, Peduzzi P, Kluser S and Giuliani G 2004 Impacts of summer 2003 heat wave in EuropeUnited Nations Environment Programme vol 2 pp 21–4 (https://unisdr.org/files/1145_ewheatwave.en.pdf)

Deser C *et al* 2020 Insights from Earth system model initial-condition large ensembles and future prospects *Nat. Clim. Change* at press (https://doi.org/10.1038/s41558-020-0731-2)

Easterling D R, Meehl G A, Parmesan C, Changnon S A, Karl T R and Mearns L O 2000 Climate extremes: observations, modeling, and impacts *Science* **289** 2068–74

Ehret U, Zehe E, Wulfmeyer V, Warrach-Sagi K and Liebert J 2012 Hess opinions should we apply bias correction to global and regional climate model data? *Hydrol. Earth Syst. Sci.* **16** 3391–404

Foster T, Brozović N, Butler A, Neale C, Raes D, Steduto P, Fereres E and Hsiao T 2017 AquaCrop-OS: an open source version of FAO's crop water productivity model *Agric. Water Manage.* **181** 18–22

Gettelman A, Bresch D N, Chen C C, Truesdale J E and Bacmeister J T 2018 Projections of future tropical cyclone damage with a high-resolution global climate model *Clim. Change* **146** 575–85

Hazeleger W, Van den Hurk B, Min E, Van Oldenborgh G, Petersen A, Stainforth D, Vasileiadou E and Smith L 2015 Tales of future weather *Nat. Clim. Change* **5** 107–13

Hazeleger W *et al* 2012 EC-Earth V2.2: description and validation of a new seamless earth system prediction model *Clim. Dyn.* **39** 2611–29

Herring S C, Christidis N, Hoell A, Hoerling M and Stott P 2019 Explaining extreme events of 2017 from a climate perspective *Bull. Am. Meteorol. Soc.* **100** S1–117

Hsiang S *et al* 2017 Estimating economic damage from climate change in the united states *Science* **356** 1362–9

IPCC 2013 *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* ed T F Stocker *et al* (Cambridge and New York: Cambridge University Press) p 1535

Kramer A E 2010 Russia, crippled by drought, bans grain exports *The New York Times* (http://nytimes.com/2010/08/06/world/europe/06russia.html) (accessed: 24 July 2017)

Langeveld J, Verhagen A, Van Asseldonk M and Metselaar K 2003 Coping with increasing extremes in agriculture: an exploration for the Netherlands *World Resour. Rev.* **15** 446–61

Lau W K and Kim K-M 2012 The 2010 Pakistan flood and Russian heat wave: teleconnection of hydrometeorological extremes *J. Hydrometeorol.* **13** 392–403

Maraun D 2013 Bias correction, quantile mapping, and downscaling: revisiting the inflation issue *J. Clim.* **26** 2137–43

McSweeney C F and Jones R G 2016 How representative is the spread of climate projections from the 5 CMIP5 GCMs used in ISI-MIP? *Clim. Serv.* **1** 24–9

Milly P and Dunne K A 2017 A hydrologic drying bias in water-resource impact analyses of anthropogenic climate change *J. Am. Water Resour. Assoc.* **53** 822–38

Mora C, Counsell C W, Bielecki C R and Louis L V 2017 Twenty-seven ways a heat wave can kill you: deadly heat in the era of

climate change *Circ.: Cardiovascular Qual. Outcomes* **10** e004233

Nassim N T 2007 *The Black Swan: The Impact of the Highly Improbable* (New York: Random House)

New M, Lopez A, Dessai S and Wilby R 2007 Challenges in using probabilistic climate change information for impact assessments: an example from the water sector *Phil. Trans. R. Soc.* A **365** 2117–31

Pavlista A D and Feuz D M 2005 Potato prices as affected by demand and yearly production *Am. J. Potato Res.* **82** 339–43

Pielke R A Jr, Gratz J, Landsea C W, Collins D, Saunders M A and Musulin R 2008 Normalized hurricane damage in the United States: 1900–2005 *Nat. Hazard. Rev.* **9** 29–42

Raes D, Steduto P, Hsiao T C and Fereres E 2017 *AquaCrop, Version 6.0 Reference Manual* (Rome, Italy: Food and Agriculture Organization of the United Nations) (http://fao.org/aquacrop/resources/referencemanuals/en/)

Reid C E, Oneill M S, Gronlund C J, Brines S J, Brown D G, Diez-Roux A V and Schwartz J 2009 Mapping community determinants of heat vulnerability *Environ. Health Perspect.* **117** 1730

Rosenzweig C *et al* 2014 Assessing agricultural risks of climate change in the XXI century in a global gridded crop model intercomparison *Proc. Natl Acad. Sci.* **111** 3268–73

Schellnhuber H J, Frieler K and Kabat P 2014 The elephant, the blind, and the intersectoral intercomparison of climate impacts *Proc. Natl Acad. Sci.* **111** 3225–7

Sebastian A, Gori A, Blessing R B, Van der Wiel K and Bass B 2019 Disentangling the impacts of human and environmental change on catchment response during Hurricane Harvey *Environ. Res. Lett.* **14** 124023

Seneviratne S I *et al* 2012 Changes in climate extremes and their impacts on the natural physical environment *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC)* ed C B Field *et al* (Cambridge and New York) pp 190–230

Siswanto, Van Oldenborgh G J, Van der Schrier G, Lenderink G and Van den Hurk B 2015 Trends in high-daily precipitation events in Jakarta and the flooding of January 2014 *Bull. Am. Meteorol. Soc.* **96** S131–5

Smith M D 2011 An ecological perspective on extreme climatic events: a synthetic definition and framework to guide future research *J. Ecol.* **99** 656–63

Stott P A, Stone D A and Allen M R 2004 Human contribution to the European heatwave of 2003 *Nature* **432** 610–4

Tebaldi C and Knutti R 2007 The use of the multi-model ensemble in probabilistic climate projections *Phil. Trans. R. Soc.* A **365** 2053–75

Van den Hurk B, Van Meijgaard E, de Valk P, Van Heeringen K-J and Gooijer J 2015 Analysis of a compounding surge and precipitation event in the Netherlands *Environ. Res. Lett.* **10** 035001

Van der Wiel K, Stoop L P, Van Zuijlen B, Blackport R, Van den Broek M and Selten F 2019a Meteorological conditions leading to extreme low variable renewable energy production and extreme high energy shortfall *Renew. Sustain. Energy Rev.* **111** 261–75

Van der Wiel K, Wanders N, Selten F and Bierkens M 2019b Added value of large ensemble simulations for assessing extreme river discharge in a 2 °C warmer world *Geophys. Res. Lett.* **46** 2093–102

Van der Wiel K *et al* 2017 Rapid attribution of the August 2016 flood-inducing extreme precipitation in south Louisiana to climate change *Hydrol. Earth Syst. Sci.* **21** 897

Van Oldenborgh G J, Haarsma R, De Vries H and Allen M R 2015 Cold extremes in North America versus mild weather in Europe: the winter of 2013–14 in the context of a warming world *Bull. Am. Meteorol. Soc.* **96** 707–14

Van Oldenborgh G J *et al* 2017 Attribution of extreme rainfall from Hurricane Harvey, August 2017 *Environ. Res. Lett.* **12** 124009

Vanuytrecht E, Raes D, Steduto P, Hsiao T C, Fereres E, Heng L K, Vila M G and Moreno P M 2014 Aquacrop: FAO's crop water

productivity and yield response model *Environ. Modelling Softw.* **62** 351–60

Vera C 2018 Farmers transformed how we investigate climate *Nature* **562** 9

Vörösmarty C J, Green P, Salisbury J and Lammers R B 2000 Global water resources: vulnerability from climate change and population growth *Science* **289** 284–8

Vrac M and Friederichs P 2015 Multivariate-intervariable, spatial, and temporalbias correction *J. Clim.* **28** 218–37

Wegren S K 2011 Food security and Russia's 2010 drought *Eurasian Geogr. Econ.* **52** 140–56

Yang X, Tian Z, Sun L, Chen B, Tubiello F N and Xu Y 2017 The impacts of increased heat stress events on wheat yield under climate change in China *Clim. Change* **140** 605–20

Zscheischler J, Fischer E M and Lange S 2019 The effect of univariate bias adjustment on multivariate hazard estimates *Earth Syst. Dyn.* **10** 31–43

Zscheischler J *et al* 2014 Impact of large-scale climate extremes on biospheric carbon fluxes: an intercomparison based on mstmip data *Glob. Biogeochem. Cycles* **28** 585–600

Zscheischler J *et al* 2018 Future climate risk from compound events *Nat. Clim. Change* **8** 469–77