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Estimating impact likelihoods from probabilistic projections of climate and socio-economic change using impact response surfaces

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ABSTRACT

Estimates of future climate change impacts using numerical impact models are commonly based on a limited selection of projections of climate and other key drivers. However, the availability of large ensembles of such projections offers an opportunity to estimate impact responses probabilistically. This study demonstrates an approach that combines model-based impact response surfaces (IRSs) with probabilistic projections of climate change and population to estimate the likelihood of exceeding pre-specified thresholds of impact.

The changing likelihood of exceeding impact thresholds during the 21st century was estimated for selected indicators in three European case study regions (Iberian Peninsula, Scotland and Hungary), comparing simulations that incorporate adaptation to those without adaptation. The results showed high likelihoods of increases in heat-related human mortality and of yield decreases for some crops, whereas a decrease of NPP was estimated to be exceptionally unlikely. For a water reservoir in a Portuguese catchment, increased likelihoods of severe water scarce conditions were estimated for the current rice cultivation. Switching from rice to other crops with lower irrigation demand changes production risks, allowing for expansion of the irrigated areas but introducing a stronger sensitivity to changes in rainfall.

The IRS-based risk assessment shown in this paper is of relevance for policy making by addressing the relative sensitivity of impacts to key climate and socio-economic drivers, and the urgency for action expressed as a time series of the likelihood of crossing critical impact thresholds. It also examines options to respond by incorporating alternative adaptation actions in the analysis framework, which may be useful for exploring the types, choice and timing of adaptation responses.

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1. Introduction

Estimates of future climate change impacts using numerical impact models are commonly based on a limited selection of projections of climate and other key drivers, to simulate the effects of these projected conditions on the system being modelled (e.g. Hoegh-Guldberg et al., 2018). Since each impact estimate is tied closely to the scenario¹ being used, a large number of scenarios are needed to explore a plausible range of alternative future conditions. This top-down scenario approach (downscaling global projections of key drivers via impact models to estimate regional impacts) has been used for several decades in impact studies (e.g. Parry and Carter, 1998; Wilby and Dessai, 2010).

There have been various attempts to represent uncertainties in future projections of climate variables as probability density functions (PDFs), often based on statistical analysis of multi-model and perturbed-parameter ensembles of climate model simulations and involving elements of expert judgement (e.g. Räisänen and Palmer, 2001; Murphy et al., 2004). Probabilistic projections of regional climate that have been reported, intended primarily for use in impact assessment, are usually conditional on the scenario of radiative forcing assumed (e.g., Räisänen and Ruokolainen, 2006; Harris et al., 2013; Lowe et al., 2018).

Probabilities have also been assigned to some socio-economic variables. Lutz and Scherbov (2007) have estimated PDFs for future regional population based on an expert elicitation to estimate the input parameters of their population model. A data-driven approach in a Bayesian framework was used for official country-level population projections of the United Nations (Gerland et al., 2014; United Nations, 2017). Neither type of population projection is conditional on a single scenario of birth, death and migration rates; rather, they represent the uncertainty of an average case or the uncertainty over a range of scenarios.

As mentioned earlier, the primary motivation for developing PDFs of climate or socio-economic variables has been to quantify the uncertainty of the projections. For climate, there are prominent examples in reports by the Intergovernmental Panel on Climate Change (IPCC) that show percentile ranges of global and regional projections based on ensemble simulations (Collins et al., 2013; Hewitson et al., 2014; Gutiérrez et al., 2021). However, the currently available multi-model ensembles that are used to construct probabilistic climate projections are still ‘ensembles of opportunity’ (Stainforth et al., 2007), and hence have been criticized as providing a potentially false impression of accuracy while falling short of providing the true range of uncertainty (Dessai and Hulme, 2004; Nissan et al., 2019). Therefore, it is important to be open about the assumptions and limitations behind probabilistic projections.

For climate change impact, adaptation and vulnerability assessments, probabilistic projections of climate or socio-economic variables offer an opportunity to quantify impact risks by tracing probabilities of the drivers through to occurrence probabilities of given levels of impact (Jones, 2001). Few impact studies to date have attempted this, with examples in water resource planning (New et al., 2007; Borgomeo et al., 2014) and the thermal performance of buildings (Tian and de Wilde, 2011). In these studies, a large number of climate projections, interpreted as representing the distribution of future outcomes based on ensemble climate model-based projections that can themselves be depicted as PDFs, were used as input to impact models. However, this direct method of applying ensemble climate model projections, often involving thousands of separate scenarios, can offer computational challenges for impact modelling.

The direct use of PDFs of the drivers is also possible, as an alternative impact modelling approach to the top-down use of scenarios, where the order of analysis is reversed through the use of impact response surfaces (IRSs – Fronzek et al., 2010; Jones, 2000). First, impact model simulations are used to construct IRSs, which show responses systematically across a range of conditions (Van Minnen et al., 2000). Second, any scenario (or scenario PDF) of those changed conditions can then be defined and located in the appropriate region of the IRS to determine the estimated response (Jones, 2000). This ‘scenario-neutral’ approach (Prudhomme et al., 2010) has some advantages over the conventional scenario-based approach: 1) it allows more rigorous testing of impact models (across many possible future conditions); 2) arising from 1), it can improve understanding of the basic model behaviour; 3) it allows the identification of critical impact thresholds which might be missed if only a few climate scenarios are tested; 4) it facilitates systematic evaluation of simulated adaptation options; and 5) if drivers can be quantified probabilistically, the impact analysis can produce estimates of risk. The use of IRSs has gained popularity in recent years, and several of these studies have used IRSs in combination with probabilistic projections of climate, for example for water resources (Wetterhall et al., 2011; Weiß, 2011; Holmberg et al., 2014; Kay et al., 2014; Prudhomme et al., 2015), permafrost habitats (Fronzek et al., 2010; Fronzek et al., 2011), forest fires (Mäkelä et al., 2014) and agriculture (Børgesen and Olesen, 2011; Pirttioja et al., 2019). A probabilistic IRS approach has also been applied to evaluate adaptation options (Pirttioja et al., 2019).

In a previous study, covering multiple sectors and comparing regions in Europe, the IRS approach was used for the first time with socio-economic drivers in addition to climate variables, but these were not combined with probabilistic projections of the drivers (Fronzek et al., 2019). The current paper extends our previous work by combining IRSs for indicators relevant for agriculture and heat-related human mortality with probabilistic projections of climate and population, using a suite of impact models that have also been employed in a stakeholder-supported multi-sector analysis (Harrison et al., 2019). The analysis focuses on three regions in different parts of Europe that span a wide climatic gradient.

The specific objectives of this study are:

1. to demonstrate the use of the IRS approach with probabilistic climate and population projections for quantifying uncertainties in driving variables that are commonly treated using scenarios and rarely considered in combination;

¹ Here a scenario is to be understood as a plausible characterisation of the future, which may comprise one or more quantitative projections of that future along with other assumptions (for example, concerning adaptation).

2. to estimate likelihoods of crossing thresholds of a set of representative impact indicators; and
3. to apply the approach to simulate the effectiveness of adaptation measures in reducing risks or exploiting potential benefits.

2. Material and methods

2.1. Study regions

The analysis was conducted for three regions in different parts of Europe spanning a wide climatic gradient (Fig. 1) – Hungary, the Iberian Peninsula and Scotland – using indicators with climatic drivers alone or, in the case of Scotland, with both climatic and population drivers. An additional local case study was carried out within the Iberian Peninsula for the Vale do Gaio reservoir in southern Portugal, with more detailed analysis of its runoff and irrigation demand.

2.2. Impact models

Four contrasting climate change impact models were employed that simulate aspects of terrestrial ecosystems, agriculture, hydrology and human health (Table 1). Three of the models were also used in a previous IRS study and are described in more detail there (Fronzek et al., 2019).

Net primary production (NPP). The ecosystem model Vegetation Integrative Simulator for Trace gases (VISIT) was used to simulate terrestrial NPP (Ito and Inatomi, 2012). VISIT simulates the carbon cycle and NPP of terrestrial ecosystems using soils data and information on climate variables (temperature, precipitation, humidity and radiation) at a monthly time-step on a $0.5^\circ \times 0.5^\circ$ global latitude-longitude grid. Ecophysiological responses of photosynthesis and stomatal conductance to ambient CO_2 concentration ($[\text{CO}_2]$) were included. Biome-specific parameters were used to describe eco-physiological characteristics of 16 different biome types. Results were aggregated to the three case study regions as grid cell averages. Simulations were carried out using the same setup as in Fronzek et al. (2019), except that now increases in $[\text{CO}_2]$ and seasonal differences in climate perturbations (see section 2.4) were also accounted for. Adaptation was not simulated.

Crop yield. The process-based crop model M-GAEZ simulates yields of major crops on a $1^\circ \times 1^\circ$ global latitude-longitude grid using monthly temperature, precipitation, wind speed and solar radiation, $[\text{CO}_2]$, soils and land-use information (Masutomi et al., 2009; Hasegawa et al., 2015). Yields were calculated for all the varieties incorporated in the M-GAEZ model for each crop (8 for rice, 16 for wheat, 19 for maize, 4 for potato) and all planting dates under current or future climate conditions. One set of simulations was carried out for the optimal crop variety and planting date selected for the baseline period. Adaptation was simulated by selecting the optimal (yield maximising) variety and planting date for each simulation with perturbed climate and increased $[\text{CO}_2]$. Simulations assumed present-day proportion of irrigated to non-irrigated area per grid cell that represents the conditions around the year 2000 (Portmann et al., 2010). Results were averaged to the three case study regions – maize and rice simulations for Scotland were excluded as their



Fig. 1. Case study regions.

Table 1

Study details: impact indicators, impact models, their spatial resolution (latitude/longitude) and domain, drivers perturbed in the sensitivity analysis, types of adaptation simulated, critical impacts and study region. Acronyms: T - temperature; P - precipitation; Pop - population; [CO₂] - atmospheric carbon dioxide concentration; WEI – water exploitation index; Hun - Hungary; IP - Iberian Peninsula; IP (G) - Vale de Gaio, Portugal; Sco - Scotland; UK - United Kingdom.

Sector	Model	Resolution /domain	Indicator (unit)	Drivers	Adaptation	Critical impact relative to reference	Study regions
Ecosystems	VISIT ^a	0.5°/global	Net primary production (kg m ⁻² yr ⁻¹)	T, P, [CO ₂]	None	Decline	IP, Hun, Sco
Agriculture	M-GAEZ ^b	1°/global	Crop yield (kg ha ⁻¹)	T, P, [CO ₂]	Optimal sowing date; cultivar change	20% yield reduction	IP, Hun, Sco
Water resources	SWAT & irrigation model ^c	-/reservoir	Inflow (mill m ³ yr ⁻¹)	T, P	Cultivation changes	Decreased inflow	IP(G)
Human health	TRM-Tsukuba ^d	0.5°/global	WEI (proportion) Irrigation area for WEI ≤ 0.5 (ha) Heat-related mortality (per 100000)	T, Pop	Shift threshold temperature by 0.2 °C/decade	WEI > 0.5 (stress) Decreased area Increase to more than double	IP, Hun, UK

^a Ito and Inatomi 2012;

^b Hasegawa et al., 2015;

^c Nunes et al., 2017,

^d Honda et al., 2014.

simulated baseline yields were 0 kg ha^{-1} .

Water resources. The Soil & Water Assessment Tool (SWAT), a process-based catchment-scale ecohydrological model, was used to simulate the river flow into the Vale do Gaio reservoir in southern Portugal (Nunes et al., 2017). The reservoir has a useable volume of 63 hm^3 and is located at the lower end of the Xarrama watershed with an area coverage of 528 km^2 in the dry region of southern Portugal. SWAT is driven by climate variables (in this work, daily minimum and maximum temperature, and total precipitation), land management and external in- and outflows. Irrigation demand for different crops was estimated using FAO methods (Allen et al., 1998). This takes into account potential evapotranspiration (PET; calculated from temperature using the Hargreaves method), time-varying crop water demands adjusted for each month and crop (calculated from PET using the crop coefficient approach), and time-varying crop water deficits calculated from crop water demand, rainfall, and soil water balance (Thorntwaite-Mather method - Stigter et al., 2014). Simulations of irrigation demand were carried out for rice cultivation, which is the current main cultivation in c. 1942 ha of the irrigated area linked to the reservoir; and adaptations to the rice cultivation by switching to four other crops with a smaller water demand (winter wheat, olive trees, sunflower, corn) using crop coefficients calculated following Allen et al. (1998) or taken from Stigter et al. (2014). Following the simulation setup of the earlier work, effects of changes in temperature on the cropping calendar were not accounted for by keeping planting and harvesting dates at present-day values. The performance of SWAT to simulate inflow to the reservoir and the irrigation water use was validated as “good” or “very good” by Nunes et al. (2017), depending on performance metric. Simulations results were averaged for 30-year periods for inflow, irrigation demand and the Water Exploitation Index (WEI) defined as the ratio between irrigation demand and runoff.

Heat-related human mortality. The global-scale epidemiological Temperature-Related Mortality (TRM)-Tsukuba model was used to estimate the excess number of people dying because of heat-stress (Honda et al., 2014). The model contains statistical relationships between mortality statistics and daily temperature and extrapolates these spatially with daily temperature and population density data on a $0.5^\circ \times 0.5^\circ$ global grid. The temperature-mortality relationships are location-specific and assume that population are acclimatized to their local climate conditions (Honda et al., 2014). Simulations for perturbations in temperature and population were carried out by retaining the statistical relationships. As an adaptation to climate change, the temperature-mortality relationship was shifted towards higher temperatures by $0.2 \text{ }^\circ\text{C/decade}$, which is motivated by epidemiological evidence of observed acclimatization to warming (Gasparrini et al., 2015; Gosling et al., 2017). Gridded simulation results were summed up for the three study areas.

Three of the models, VISIT, M-GAEZ and TRM-Tsukuba, are typically applied in global studies and for computational efficiency have been developed with relatively coarse spatial resolutions over latitude-longitude grids of $0.5^\circ \times 0.5^\circ$ or $1^\circ \times 1^\circ$ (Takakura et al., 2019). This was regarded as a sufficient resolution for the country-scale analysis used in this study, as results were shown as averages over the case study regions.

2.3. Impact thresholds

Thresholds were defined for each impact indicator for which risks (or opportunities) were quantified as likelihoods of falling short of or exceeding the threshold (cf. section 2.5). Watkiss and Betts (2021) identify four types of thresholds of climate change impacts: biophysical (e.g. defining the suitability for crops), engineering (e.g. associated with design standards), performance (beyond which an action is no longer suitable) and policy thresholds (politically determined levels of acceptable risk). They also note that while biophysical thresholds can be natural or intrinsic, the other types often reflect policy or practical choices (cf. Arnell et al., 2021).

Thresholds selected for the impact indicators in this study fall in the categories of performance or policy thresholds. For NPP, the critical impact selected was whether or not there is a decline in productivity relative to the baseline (Table 1). For the four simulated crop species, the critical threshold was a 20% reduction in yields. Three thresholds were defined for the water resources example in the southern Portuguese catchment: a decrease in inflow compared to the baseline, WEI above 0.5 and an increase in the area that can be irrigated with $\text{WEI} = 0.5$ compared to the baseline situation for rice cultivation (Table 1). A WEI of 0.5 or higher is regarded as representing conditions of severe water stress (Nunes et al., 2017). For heat-related mortality, the selected threshold was a doubling of mortality cases compared to the baseline.

2.4. Probabilistic projections of climate change and population

Joint probabilistic projections of temperature and precipitation changes were derived from climate model output by applying the resampling ensemble technique of Räisänen and Ruokolainen (2006). In this approach, the sample size of an ensemble of climate model projections of future change relative to the baseline is significantly increased. This is achieved by identifying other time periods in the model simulations with the same ensemble global mean temperature change as for the pair of baseline and future periods for which the probabilistic projection is to be determined and using these additional pairs for an improved estimate of regional climate change. The method takes advantage of the quasi-linear relationship between simulated regional changes with the change in global mean temperature (Tebaldi and Arblaster, 2014). We used 20th and 21st century simulations of an ensemble of 42 Global Climate Model (GCM) simulations from the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012) for the intermediate (RCP4.5) and high (RCP8.5) representative concentration pathways (RCP, describing the radiative forcing of the climate; van Vuuren et al., 2011). We calculated the simulated changes in annual and seasonal temperature and precipitation relative to the 1981–2010 baseline period for seven overlapping 30-year periods in the 21st century (2011–2040, 2021–2050, ..., 2071–2099) and applied the resampling ensemble technique to increase the sample from 42 to between 126 and 714, depending on the period and RCP (Pirttioja et al., 2019). Area averages were then calculated for the study regions (Fig. 2).

Country-level probabilistic population projections for the 21st century were obtained from the University of Washington's

BayesPop research group (Raftery et al., 2012; United Nations, 2017)². These were constructed using a Bayesian approach that quantifies PDFs for fertility and mortality rates constrained by historical data. The third component used in population modelling, migration, was simulated with a deterministic approach (i.e. using a single parameter value instead of a PDF). The same approach has also been used in official United Nations' projections (United Nations, 2017). It is worth noting that an additional study in which migration was also quantified probabilistically resulted in considerably wider uncertainty ranges (Azose et al., 2016), however, this was not used here because of the exploratory nature of the population projection. For comparison, population projections for Shared Socioeconomic Pathways (SSPs) were used, which are more widely applied in climate change research. Deterministic country-level population projections for five SSPs and covering the 21st century were obtained for the countries of the study regions (KC and Lutz, 2017). These projections are based on scenario assumptions for fertility, mortality and migration rates for different groups of countries based on judgement from a large number of demographic experts. Hence, while the probabilistic projections from Raftery et al. (2012) are data-driven, the SSP projections are based on expert opinion regarding future demographic trends under a wider range of scenario assumptions (Rozell, 2017). To allow the deterministic SSP projections to be used for risk assessment, simplified PDFs were constructed as an assumed uniform distribution between the SSP3 and SSP5 projections, which span the full SSP range for all countries in the study regions (cf. Fig. S1, Supplementary Material).

Joint distributions of two variables were constructed for temperature change (for a 30-year period) and population (using the end year of the same period). The sample size of temperature change was artificially increased to 1000 (the same size as the population projection) by randomly sampling while allowing the same ensemble member to be drawn several times. The larger sample therefore retained the distribution of the original sample. Pairs of temperature and population changes were then randomly selected to construct a joint distribution such that the 30-year period mean for temperature change was joined with the population change for the end of the period. The random resampling and pairing of values were repeated 30 times to check that the resulting joint distributions were stable (cf. Fig. S2). A basic assumption for this pairing is that temperature and population change are independent of each other.

2.5. Modelling protocol and impact response surface analysis

The impact models above were applied following a common modelling protocol that defined a set of simulations for a baseline and a sensitivity analysis by perturbing two driver variables simultaneously. Baseline simulations were carried out using climate data for the period 1981–2010 and population data for the year 2010. Variables were selected to represent key climate and socio-economic sensitivities. These were mean temperature and precipitation perturbations (applied to daily data throughout the year) for the crop yield, NPP and water resources models and population (change in totals) and temperature perturbations (applied to monthly data) for the heat-related mortality model (Table 1).

The ranges of perturbations in the three driver variables were selected to span a wide range of projections for the 21st century for each of the study regions and divided into 8 to 11 intervals (Table 2). For temperature and precipitation changes, the ranges were defined to contain the 1st to 99th percentiles of probabilistic projections calculated for each RCP forcing and time period. This was done to exclude extreme outliers based on models for which there is documented low confidence in projections over Europe (e.g. Luomaranta et al., 2014). For population, the full range of projections was included in the perturbations.

When using temperature and precipitation as the driving variables, rather than apply a constant change throughout the year the annual change was, instead, scaled with seasonal weighting factors calculated from the ensemble medians of RCP8.5 probabilistic projections for the end of the 21st century (see Section 2 of Appendix A). This approach has been adopted in previous IRS studies to represent the pattern of seasonal variation in projected regional climate change commonly found across model simulations, though with some uncertainty in its timing and intensity (Fronzek et al., 2010; Pirttioja et al., 2019). For the crop yield and NPP models, simulations were carried out for levels of [CO₂] according to 21st century projections for RCP4.5 and RCP8.5 (Table S1). Other input variables were kept at their baseline values.

Simulation results were analysed according to the following steps (Fig. 3): results of the impact model simulations (step 1a) were plotted as 2-dimensional IRSs (1b) that show the interpolated model response to each paired perturbation of the driver variables from the baseline (Fronzek et al., 2010); probabilistic projections of the drivers were constructed as joint PDFs of two variables (2a + b); these were superimposed on the IRS (3a) and the IRS was evaluated at the locations defined by the driver variables to estimate a PDF of the impact variable (3b); by defining a critical impact threshold (3c), the likelihood of exceeding this threshold was then calculated from the impact PDF (3d).

3. Results

3.1. Impact model sensitivity

The temperature optimum for NPP was simulated at higher temperatures than the baseline for the Iberian Peninsula and Hungary and with higher values for increased precipitation (Fig. 4) and reached higher values for elevated [CO₂] (Fig. S3). In Scotland, NPP was insensitive to change in precipitation and the maximum value for NPP was simulated for the warmest perturbation.

Simulated potato yields in Scotland were insensitive to changes in precipitation but showed a strong sensitivity to temperature

² Data were downloaded from <https://bayespop.ccss.washington.edu/download/#probtrajs>, assessed 14 January 2019.

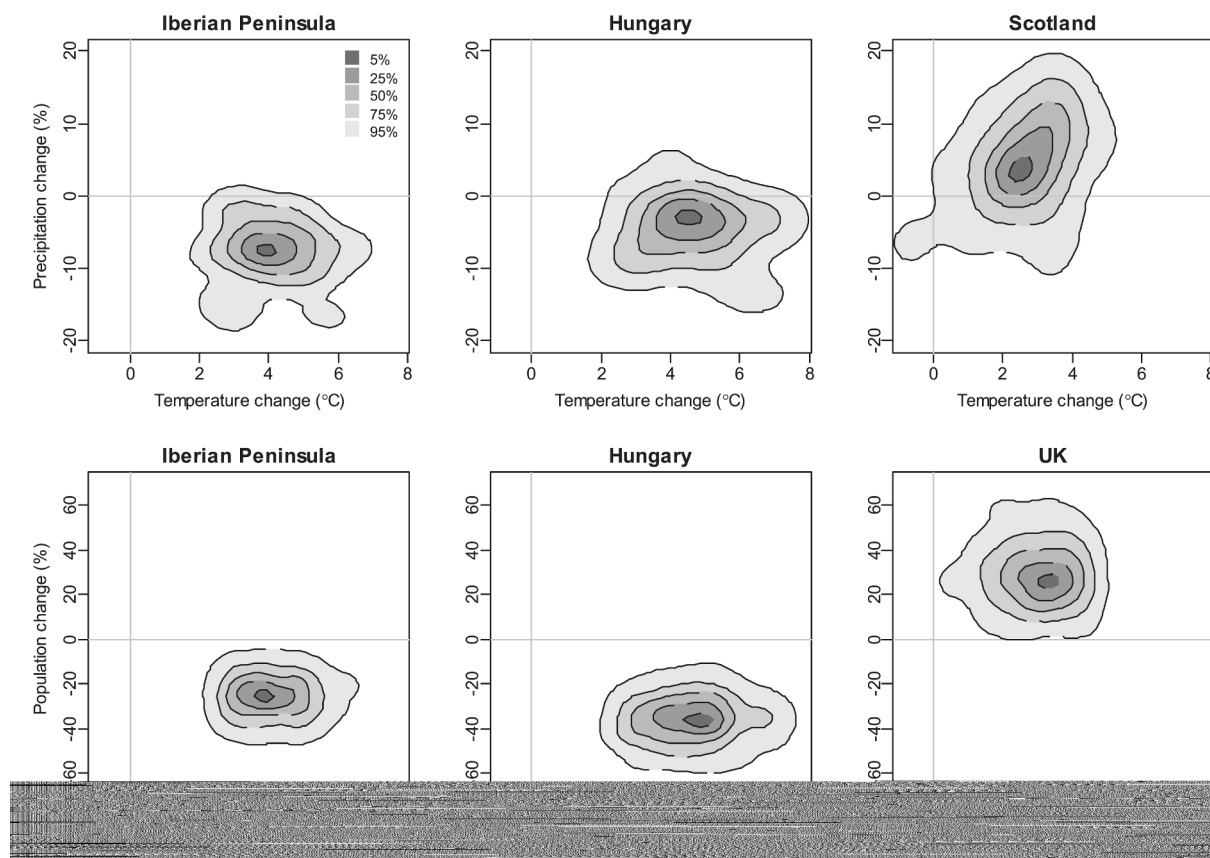


Fig. 2. Probabilistic projections of joint temperature and precipitation changes (top row) and temperature and population changes (bottom row) under RCP8.5 climate forcing (2071–2100 relative to 1981–2010) and the UN2017 population projection (for the year 2100 relative to 2010) for case study regions, Iberian Peninsula, Hungary, Scotland and the UK. Probabilities are depicted as the percentage of projections enclosed within grey-shaded zones.

Table 2

Minimum and maximum 21st century changes for driving variables, intervals and their number used in the sensitivity analysis. For temperature (in °C) and precipitation changes (in %), the range is calculated as the 1st and 99th percentiles of projections from resampled CMIP5 simulations across four RCPs and seven time periods relative to 1981–2010 (see text for details). For population changes (in %), the range is across five SSPs and seven time periods relative to 2010 (see text for details). Intervals are defined in equal steps, except one additional interval for temperature change at +0.5 °C for addressing 1.5 °C global warming since pre-industrial times.

Region	Minimum	Maximum	Intervals used in sensitivity analysis	Number of intervals
<i>Annual temperature change (°C)</i>				
Scotland	-2.9	4.5	-3, -2, -1, 0, 0.5, 1, 2, 3, 4, 5	10
Iberian P.	-0.3	6.3	-1, 0, 0.5, 1, 2, 3, 4, 5, 6, 7	10
Hungary	-0.7	7.0	-1, 0, 0.5, 1, 2, 3, 4, 5, 6, 7, 8	11
<i>Annual precipitation change (%)</i>				
Scotland	-8.6	16.4	-9, -6, -3, 0, 3, 6, 9, 12, 15, 18	10
Iberian P.	-38.1	15.7	-42, -36, -30, -24, -18, -12, -6, 0, 6, 12, 18	11
Hungary	-28.1	9.8	-30, -25, -20, -15, -10, -5, 0, 5, 10	9
<i>Population change (%)</i>				
UK	-20.6	106.9	-30, -15, 0, 15, 30, 45, 60, 75, 90, 105, 120	11
Iberia	-40.0	51.6	-60, -45, -30, -15, 0, 15, 30, 45, 60	9
Hungary	-59.9	6.7	-70, -60, -50, -40, -30, -20, -10, 0, 10, 20	10

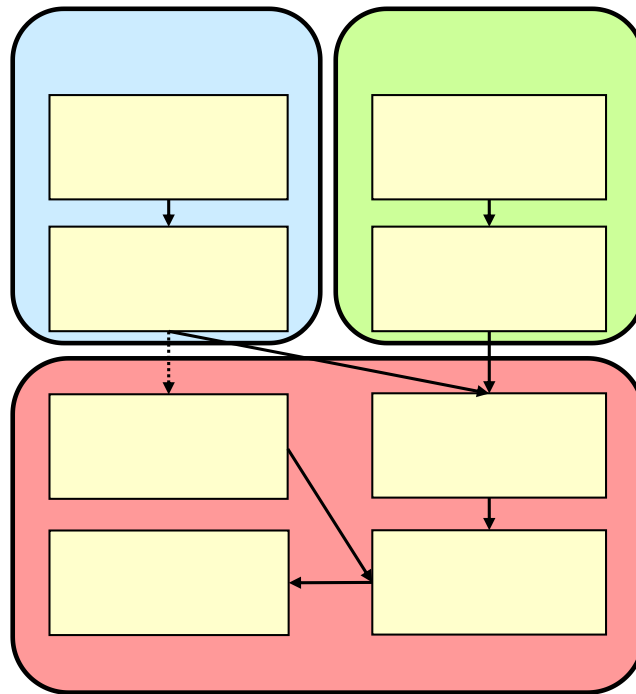


Fig. 3. Analysis steps of the study combining impact model simulations with probabilistic projections of drivers to an impact risk analysis. PDF: probability density function.

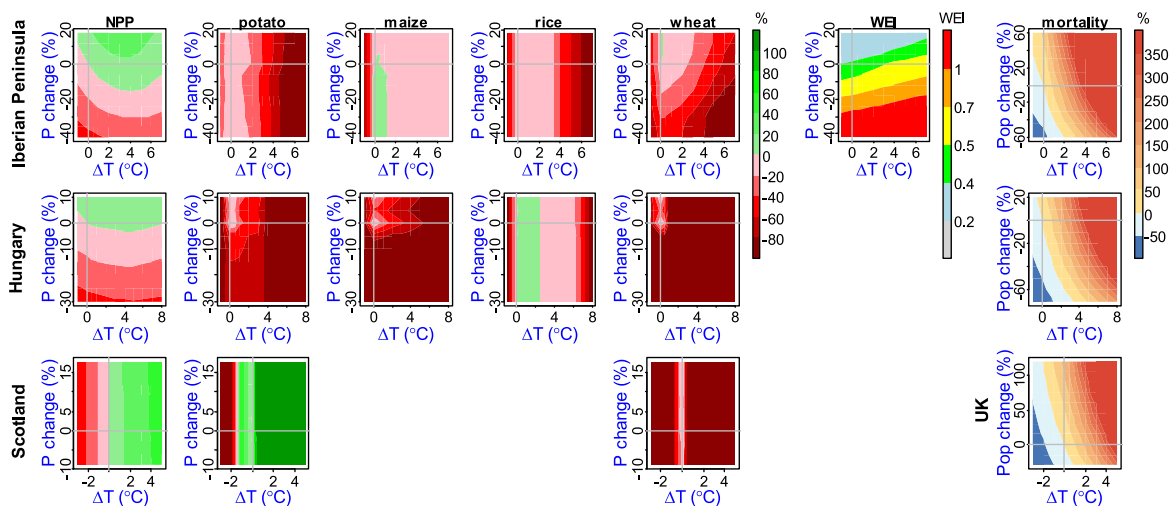


Fig. 4. Impact response surfaces of impact indicators for the Iberian Peninsula, Hungary and Scotland/UK under perturbations of temperature (ΔT), precipitation (P change) or population (Pop change). Impact indicators are shown as changes relative to the baseline simulation without adaptation except for the Water Exploitation Index (WEI), which is shown as the absolute WEI; a larger value of WEI indicates increased risk of water shortage. NPP and crop yield change are shown without the CO_2 effect. Crops for which the baseline simulation was 0 kg ha^{-1} (maize and rice in Scotland) are not shown. WEI was calculated for a reservoir in Portugal.

changes under baseline $[\text{CO}_2]$ (Fig. 4). Similarly, potato yields also show a relatively low sensitivity to changes in precipitation in Hungary and the Iberian Peninsula, but with yield decreases both for warming and cooling, indicating that the yield optimum is found under current climate conditions. Adaptation improves the potato yield, although in Hungary this is not enough to compensate the negative effect of drier conditions (Fig. S4). Modelled maize yields decreased in response both to cooling and to warming above 1.5°C under baseline $[\text{CO}_2]$ in the Iberian Peninsula (Fig. 4) and showed small increases for higher $[\text{CO}_2]$ (Fig. S3) and in the adaptation simulation (Fig. S4). Large decreases in maize yields are simulated in Hungary for climate conditions other than the baseline under

both current and increased $[\text{CO}_2]$ as well as with adaptation. Yields from (irrigated) rice cultivation showed relatively small decreases up to a warming of 3°C in the Iberian Peninsula, with steep declines under additional warming, and small increases in Hungary for a warming of less than 2°C , with steep declines above 6°C (Fig. 4), with yield improvements under increased $[\text{CO}_2]$ (Fig. S3). The severe temperature-related decline disappeared for the adaptation simulation for both regions (Fig. S4). Wheat yields in the Iberian Peninsula had their temperature optimum at the baseline temperature with decreases to the cooler and warmer side and these were stronger for drier conditions (Fig. 4). In the adaptation simulations, the temperature optimum was shifted to much warmer conditions (Fig. S4). The wheat yield IRSSs for Hungary and Scotland showed a narrow range around the baseline temperature with high yields, but yield values close to 0 kg ha^{-1} (indicating conditions of crop failure) under both cooler and warmer temperature around this range (Fig. 4 and S3). The adaptation simulations for wheat yields in Scotland expanded this range considerably, with yield increases between 0°C and 3°C warming (Fig. S4).

The inflow to the Vale do Gaio reservoir increased with higher precipitation and had a relatively low sensitivity to temperature with small decreases under warming (Fig. S5). The irrigation demand for rice had a stronger sensitivity to changes in temperature than precipitation (Fig. S5). The WEI under rice cultivation, calculated from these two IRSSs for the current rice cultivation area, showed that severe water stress ($\text{WEI} > 0.5$) would be encountered under warming of 3°C or more for no change in precipitation or for declines in precipitation exceeding 15% for no change in temperature (Fig. 4). Water stress also increased with warming. Other crops that could be cultivated as an adaptation had smaller irrigation demands per unit area with differences at baseline climate between -84% for winter wheat and -41% for corn (cf. Fig. S5). The sensitivity of irrigation demand to temperature was relatively more important for olive and winter wheat than for sunflower, corn and (the least) rice, as can be seen by the gradient of the equal-increment contour lines (Fig. S5). The area that can be irrigated without exceeding a WEI of 0.5 was largest for winter wheat and smallest for rice (reverse order of the irrigation demand), with the shape of the contour lines being similar for all crops despite their differences in irrigation demand.

Simulated heat-related mortality increased with temperature and population up to more than tenfold for the tested range of perturbations, with a stronger effect of warming in the Iberian Peninsula; e.g. the increase for a warming of 2°C at baseline population was 153% in the Iberian Peninsula compared to 115% in Hungary and 116% in the UK (Fig. 4). The increase in mortality was considerably reduced in the adaptation simulations by up to 45% relative to the simulation without adaptation (Fig. S6).

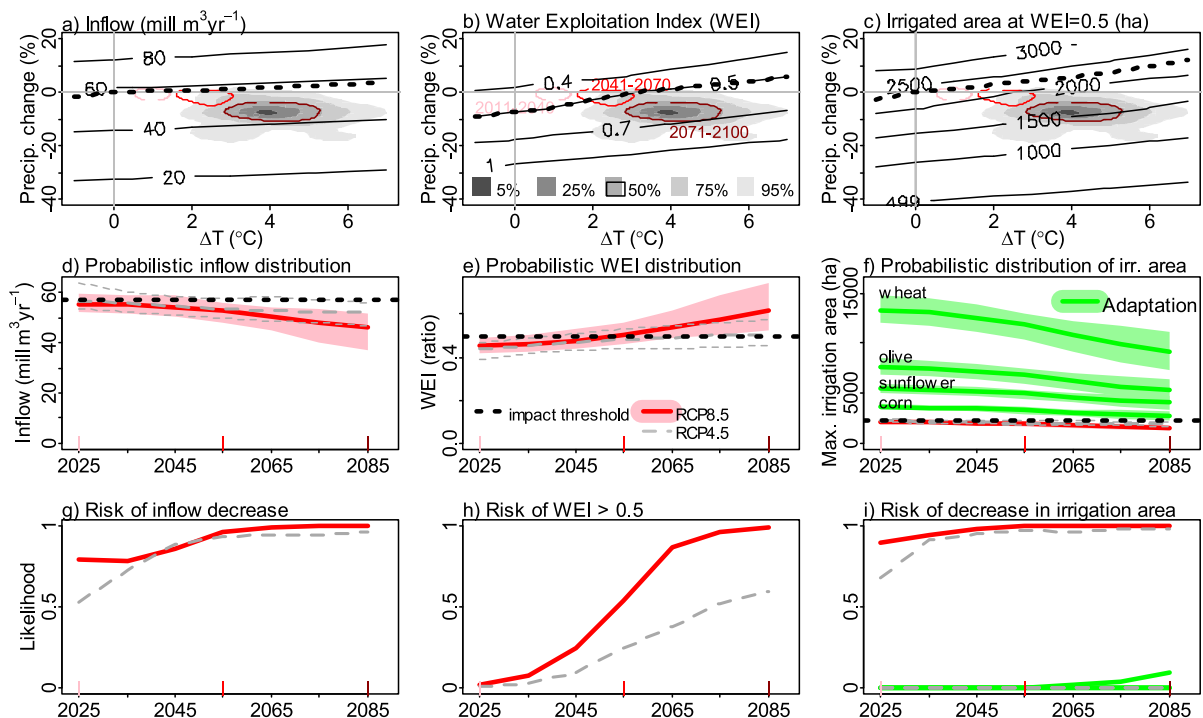


Fig. 5. Derivation of impact likelihoods for three indicators at the Vale do Gaio reservoir (Portugal): inflow to reservoir (left column); water exploitation index (WEI) for current rice cultivation (middle column); maximum irrigated area of rice (red) and alternative crops (green) for $\text{WEI} = 0.5$ (right column). Top row (a-c): impact response surfaces with superimposed joint probabilistic projection of temperature and precipitation change over the Iberian Peninsula by 2071–2100 wrt. 1981–2010 for RCP8.5 (grey shading; 50 percentile highlighted in dark red) and impact thresholds (black dashed lines); 50 percentiles are also shown of climate change projections for 2011–2040 (orange line) and 2041–2070 (red line). Middle row (d-f): median (solid lines) and 5–95 % range (shading) of the indicator values as a function of time for RCP8.5; median for RCP4.5 (dashed grey line) is also shown; these can be compared to the impact threshold (black dashed line). Lower row (g-i): estimated likelihood of values exceeding the impact thresholds for RCP8.5 (red line for rice; green lines for other crops) and RCP4.5 (dashed grey line). The x-axis in panels d-i shows central years of 30-year time periods between 2011 and 2040 and 2071–2100.

3.2. Probabilistic impact assessment

When overlaying the IRS with joint probabilistic projections of the drivers, their uncertainty can be translated into probabilistic distributions of impact indicators and by applying a relevant impact threshold, the likelihood of crossing the threshold can be quantified. An example is shown for the water resource indicators (Fig. 5). Overlaying the IRSs with probabilistic climate change projections shows that the area of the IRS space occupied by the RCP8.5 climate change projection for 2071–2100 lies almost entirely above the critical threshold for WEI (Fig. 5b) and below thresholds for inflow (Fig. 5a) and the irrigation area at WEI = 0.5 (Fig. 5c). For earlier time periods indicated in Fig. 5a–c, the impact thresholds intersect the probabilistic projection. The median estimate of the inflow to the reservoir decreased throughout the 21st century both for RCP8.5 and RCP4.5 with increasing climate change-related uncertainty around this estimate over time (Fig. 5d). The likelihood of a decrease in inflow relative to the baseline reached estimates between 0.8 (0.5) and 1.0 (0.95) for RCP8.5 (RCP4.5) throughout the 21st century (Fig. 5g). The WEI increases under both RCPs from a baseline value of 0.43 to median estimates above 0.5 for both RCPs and 5th–95th percentile ranges of 0.53–0.75 (RCP8.5) and 0.46–0.58 (RCP4.5) by 2071–2100 (Fig. 5e). Exceeding a threshold of 0.5 which indicates water scarce conditions increases from <5% likelihood in the period 2011–2040 to >99% likelihood for RCP8.5 by 2071–2100 and about as likely as not (33–66% likelihood for RCP4.5 (Fig. 5h). The area that can be irrigated without exceeding a WEI of 0.5 also decreases throughout the 21st century. However, considerably larger areas could be put under irrigation if rice was replaced by crops with a smaller water demand: the potential irrigation area for winter wheat would be 6 times larger and for corn 2 times larger than that for rice (Fig. 5f). A decrease in irrigation area without exceeding a WEI of 0.5 is extremely likely (>99% likelihood) for rice from the period 2041–2070 onwards for RCP8.5, whereas it was estimated with a low likelihood for corn and as extremely unlikely (<1% likelihood) for winter wheat, olive and sunflower (Fig. 5i).

The likelihoods of exceeding impact thresholds for all sectors and regions are shown in Fig. 6. Generally, for most impact indicators and regions, the likelihoods were increasing over time, with the exception of indicator thresholds that had zero likelihoods in all time periods (which was the case for the decrease in NPP in all regions and the reduction in potato yield of 20% in Scotland). The likelihoods of yield reductions of at least 20% were largest in Hungary for maize, potato and wheat, while a doubling of heat-related mortality was slightly less likely in Hungary compared to the other two regions due to the projected decrease in Hungarian population. Adaptation reduced the likelihood of exceeding critical thresholds already from near future periods onwards (Fig. 6), whereas the effect of mitigation (as shown by comparing results for RCP4.5 to RCP8.5) was more prominent towards the end of the 21st century (cf. Fig. S8). Simulated adaptation options also reduced likelihoods more effectively than mitigating from RCP8.5 to RCP4.5 (cf. Fig. S8). More detail of these risk estimates is shown in time series figures of probabilistic projections of impacts and the likelihood of exceeding impact thresholds in the [supplementary material](#) (Figs. S7 and S8).

4. Discussion

4.1. Realism of modelled patterns of response

Simulated changes relative to the baseline shown in IRSs for NPP and crop yield have slightly smaller values than in the comparable IRSs reported by Fronzek et al. (2019). This is an effect of including seasonal scaling factors that increased warming and drying in the summer in all regions (cf. Figs. S9 and S10). Accounting for seasonal differences in climate changes have previously been shown to

Fig. 6. Likelihood of exceeding impact thresholds estimated for Hungary, Iberian Peninsula and Scotland or UK during three time periods in the 21st century for the RCP8.5 climate. Simulations are without adaptation (first column) and with adaptation (second column, italics). For mortality, probabilistic projections are for temperature and UN2017 population (cf. Fig. S1). Likelihoods are shown for impact thresholds defined as: a decline in NPP relative to the baseline, a 20% reduction in crop yields for maize, potato, rice and wheat, and a doubling of heat-related mortality. Crops for which the baseline simulation was 0 kg ha⁻¹ (maize and rice in Scotland) are not shown. NPP and crop yield simulations used future atmospheric CO₂ concentrations.

increase the credibility of IRSs when combining these with probabilistic projections for climate change (Fronzek et al., 2010; Pirttioja et al., 2019).

NPP and potato yields in Scotland were insensitive to changes in precipitation for the range of changes tested; however, a U-shape of the IRS is also to be expected for Scotland for precipitation decreases greater than the maximum (-10%) that was tested here, as was the case for the British Isles where NPP decreases were simulated for a decrease in precipitation of 30% (Fronzek et al., 2019). The crop yield simulations for the baseline had yield levels that were often lower than official yield statistics, which might have been caused, in part, by the averaging step over large regions that included grid cells with sub-optimal climate at the edge of the cultivation zone. One way to reduce this problem is to look at relative changes in yield relative to the baseline, as we did in plotting the IRSs and in defining critical thresholds of change, which can be regarded as more robust results than absolute yield changes (Challinor et al., 2014; Pirttioja et al., 2015). The crop yield simulations assume present-day irrigation areas, without knowledge of how these might credibly be changed in the future, which in any case may not be plausible under drier conditions in drought risk areas. Rather, the area that can be irrigated might be smaller, as has been shown by our results for the Portuguese reservoir. The proportion of irrigated crop land is relatively high in the Iberian Peninsula, where the difference between rain-fed and irrigated simulations is also largest, but there is little irrigation in Hungary and Scotland (Webber et al., 2018). Adaptation was simulated by selecting varieties and sowing that maximize yield under a given climate, but without including an increase in irrigation area as a possible adaptation option, for which there would only be little possibility as water resources in large parts of the Iberian Peninsula are already nowadays exploited to a large extent (EEA 2019). This resulted in large yield increases, for which a possible explanation might be that grid cells previously at the edge of the current cultivation zones might become more suitable in the adaptation simulation. Switching to better suited cultivars and adjusting sowing dates can be regarded as autonomous adaptation, as farmers are used to adjusting their activities to weather conditions. Hence, the simulation without adaptation may be regarded as a less plausible “dumb farmer” approach (Easterling et al., 1992).

The inflow to the dry Portuguese reservoir simulated with the SWAT model has a very similar pattern, but larger changes and hence a larger sensitivity to precipitation than IRSs based on simulations with the global hydrological model WaterGap for other similar catchments in the Iberian Peninsula (Weiß and Alcamo, 2011; Fronzek et al., 2019). This could be because the catchment of the reservoir is relatively small, or because of model differences, although a comparison of SWAT and WaterGAP for Central Europe concluded that these were very consistent for mean annual water flows (Piniewski et al., 2013). The IRSs of irrigation demand were estimated with a simplified approach for crop growth, which could underestimate the crop water demand (Nunes and Seixas, 2011 p. 374). Nevertheless, it clearly showed differences between crops in their water demand, but also in their sensitivity to precipitation changes (as can be seen by the orientation of the contour lines in Fig. S5). The latter depends on whether a crop grows in the wet season (winter to spring), which would be expected to result in a stronger sensitivity to precipitation, whereas summer crops (like rice) have a higher degree of irrigation and hence are less sensitive to precipitation. The area that can be irrigated is determined by the crop-specific irrigation demand, i.e. crops with smaller water demands can be irrigated over a larger region, but the relative sensitivity to temperature and precipitation does not differ much between the crops. The reservoir is used to smooth out the interannual variability by storing water in wetter years for use in drier years. The Vale do Gaio reservoir is capable of storing 1.6 years of water demand (Nunes et al., 2017). It would be interesting to expand the analysis in future research to explore an increase of the available water resources (e.g. through the reuse of waste water, interlinking reservoirs and extracting groundwater) or an improved water use efficiency (e.g. through an uptake of drip irrigation technologies, modernization of irrigation networks, and the adoption of nature-based solutions such as mulching) as other adaptation options (Dias et al., 2020). Another possible extension would be to combine the analysis with land-use scenarios that define the area under cultivation for different crops (Nunes et al., 2017), with a subsequent economic evaluation of the profitability of the alternative crops, as there are large differences between crops in the productivity per area and in the economic value per unit weight of produce.

4.2. Evaluation of impact risk estimates

The probabilistic projections of temperature and precipitation changes have been estimated with a relatively simple resampling method and rely on the CMIP5 ensemble of climate model simulations. The resulting distribution is wider than that of the original multi-model ensemble of projections (Räisänen and Ruokolainen, 2006) and similar to probabilistic projections that have been developed using more sophisticated approaches that combine perturbed physics experiments with multi-model ensembles (Harris et al., 2013). In the dataset that we used, equal weight was given to all members of the multi-model CMIP5 ensemble, whereas attempts have been made to weight models according to performance metrics with resulting shifts of the distribution (Knutti et al., 2017; Kaspar-Ott et al., 2019). Such approaches could also be combined with the resampling methods used here; however, defining weights depends on an ultimately subjective choice of criteria.

The UN projections used here as the main source for probabilistic population projections represent the uncertainty for a medium case. Due to differences in model assumptions and approaches, UN and SSP differ substantially in their projections especially for African and global population (Rozell, 2017). In fact, some SSPs are outside the 95% range of the UN probabilistic projections and while its median estimates are close to the (intermediate) SSP2 projection for Hungary and the UK, this is not the case for the Iberian Peninsula (cf. Fig. S1). The UN also publishes high and low variants spanning a much wider range than the probabilistic projection, but without a quantification of their uncertainties. The uniform distribution spanning the SSP range can be regarded as a somewhat arbitrary and therefore exploratory approach, but it helps to put the probabilistic UN medium case into a perspective of the wider SSP projections. There has also been an attempt to fit PDFs for population projections for each SSP separately (Engström et al., 2016), with these showing narrower uncertainty ranges than those of the UN probabilistic dataset.

The assumption when combining projections of temperature change and population into joint distributions is that these two variables are independent of each other. In reality, this probably is not quite true as population growth affects emissions and climate change has been recognized as affecting migration, though the latter may be regarded as having only minor effects compared to total population numbers (Lutz, 2017) and is not explicitly accounted for in the UN projection (United Nations, 2017). Climate projections based on radiative forcing levels can be treated separately from socio-economic assumptions and then combined using a scenarios matrix (van Vuuren et al., 2014). However, some combinations are regarded implausible: the high forcing level of RCP8.5 can only be reached in an SSP5 world, whereas the low forcing RCP2.6 is incompatible with SSP3 (Riahi et al., 2017; Tebaldi et al., 2021).

The estimated probabilistic projections of impact indicators and risk can be compared with scenario projections available in the literature. Our results for the crop yield simulation without adaptation are broadly consistent with studies presenting simulation results on a European grid for irrigated crops for wheat and maize (Ciscar et al., 2018; Webber et al., 2018), but differ from simulations without irrigation for maize, wheat and potato in the Iberian Peninsula (Supit et al., 2012). The estimates of water inflow to the Portuguese reservoir are also in good agreement with other studies. A similar decline in the mean inflow was estimated for the same reservoir in climate-only scenarios by Nunes et al. (2017) and it is also consistent with projections of a decline in water availability for selected catchments in the Iberian Peninsula (Weiß and Alcamo, 2011). Increases in irrigation demand for rice were slightly larger in our results than those estimated by Nunes et al. (2017). Projected increases in heat-related mortality are consistent with other studies in Europe (Baccini et al., 2011; Ostro et al., 2012; Martinez et al., 2016), even though exact numbers are sometimes difficult to compare as methods differ for defining baseline mortality, choosing scenarios and estimating relative risks. Our results indicate the importance of considering future changes in population, which is the case in only few scenario-based mortality studies (e.g. Sanderson et al., 2017). The effect of adaptation on reducing heat-related mortality is also comparable to results of Gosling et al. (2017), even though they found a wide range of outcomes when comparing the approach applied here with other adaptation modelling methods.

Our estimates of impact risks reflect the uncertainty in climate and population projections alone, but neglect sources of impact model uncertainty. These in principle could be incorporated in an IRS approach as has been demonstrated for the parameter uncertainty of a simple permafrost model (Fronzek et al., 2011). Structural impact model uncertainty was also studied with IRSs using crop model ensembles, but these have not been combined with probabilistic projections of their drivers (Pirttioja et al., 2015; Fronzek et al., 2018; Ruiz-Ramos et al., 2018). Another limitation is that the climate perturbations in the impact model sensitivity analysis did not account for changes in variability of the climate drivers except applying ensemble average seasonal weights. This is a common feature of impact modelling studies that use simple change factors to construct scenarios (Fronzek and Carter, 2007). Changes in temperature and precipitation extremes do not necessarily scale with mean changes, which has been found in CMIP5 projections, for example for the Mediterranean region with an intensification of heat and water stress (Sillmann et al., 2013). One way to incorporate variability changes in the sensitivity analysis is the use of weather generators to systematically perturb parameters affecting the variability, such as the number of wet days, in addition to the total precipitation (Rötter et al., 2011; Culley et al., 2019).

Transferring climate change PDFs to impact PDFs could also be achieved by directly using large climate ensembles as input to the impact model. In practice this can be a computationally more demanding task both to conduct impact model simulations and for preparing climate projections. While the number of impact model simulations required to construct an IRS can also be quite large (e.g. in this study we used 80–110 perturbations), climate ensembles that can be interpreted as PDFs are usually larger. The construction of probabilistic projections of climate might also require a further step of analysis to downscale GCM projections to a region of interest, such as by using dynamical or statistical downscaling approaches (e.g. Jacob et al., 2020), which may also involve use of a weather generator (e.g. Borgomeo et al., 2014) – a step with its own sources of uncertainty.

The estimates of impact likelihoods presented here are, of course, wholly dependent on the impact thresholds selected. Our choice of thresholds was primarily for illustrative purposes, to permit a likelihood comparison between scenarios, regions and adaptation options. Most thresholds selected were largely arbitrary, including that for NPP (a decline), crop yields (-20%) and heat-related mortality (a doubling), all relative to baseline levels. However, the water resource threshold of WEI = 0.5 was based on criteria describing severe water stress reported in the literature. In reality, aside from biophysical, engineering or performance thresholds (defined in section 2.3, above), most potential thresholds are associated with subjective choices concerning levels of acceptable risk. This implies that in order to identify thresholds that are salient in assessing the urgency for adaptation responses, there is a need for active engagement of relevant experts and other stakeholders (Carter and Fronzek, 2022).

4.3. Towards an analytical risk framework for impacts and adaptation

So how can IRS-based estimates of impact likelihoods add to our preparedness for climate risks and opportunities? The IRS approach presented in this paper has three aspects that are of potential relevance for policy making (Carter and Fronzek, 2022):

1. *sensitivity* of an impact to key climate and socio-economic drivers is directly quantified in an IRS;
2. *urgency* of action is achieved through the identification of impact thresholds that can be regarded as critical and then assigning probabilities evolving over time of crossing these thresholds; and
3. *response* through mitigation by analysing alternative scenarios and through adaptation by simulating adaptation options.

Arguably, IRSs can help to better understand system behaviour by directly relating model response to drivers and hence can improve the interpretation of probabilistic impact estimates. A probabilistic approach adds transparency to the depiction of uncertainties and can therefore provide a more sound basis for decision making. Indeed, there are already examples of IRS application in a decision-making context for planning adaptation. Brown et al. (2012) proposed IRSs as a stress-test for system resilience that supports

robust adaptation decision-making under a wide range of plausible climate conditions. Modelling adaptation responses is often limited to selected adaptation options that can easily be incorporated into existing modelling frameworks, and hence these tend to be fragmented, simplistic and fail to recognize adaptation as a complex human process (Holman et al., 2019). This is also true for the adaptation options explored in this paper. For example, a decision to switch from rice cultivation in the Portuguese watershed to crops with a smaller water demand will require a farm-level assessment of the costs and benefits, which have not been analysed here, and a consideration of alternative adaptation options (such as water-saving soil improvements or enlarging the water reservoir).

The probabilistic IRS analysis would therefore ideally be part of a wider stakeholder-driven process that includes the assessment of alternative adaptations, also those that cannot be modelled, and considers their systemic context beyond the drivers that are incorporated in the model sensitivity analysis. The “Climate risk informed decision analysis” (CRIDA) methodology developed by UNESCO is providing such a framework, in which an IRS analysis is one of several steps in the adaptation decision-making process (Mendoza et al., 2018), with an example of its practical implementation in guidelines for the hydropower sector (International Hydropower Association, 2019). Better understanding impact risks helps to identify the urgency for adaptation and to prioritise adaptation measures in a given region and context. These could also be introduced in stages to develop robust adaptation pathways (Haasnoot et al., 2013).

5. Conclusions

In light of the discussion above we can draw the following conclusions from our results:

- We demonstrated an approach using IRSs in combination with probabilistic projections of climate change and, for the first time, also of population. IRSs are scenario-neutral, such that the impact model analysis is done first, but results can then be used to translate any probabilistic projections of the drivers to probabilistic distributions of the impacts (i.e. using any new scenarios, as they become available). The approach involved the development of new methods to estimate joint probabilistic distributions of temperature and population changes.
- Impact likelihoods were estimated for selected indicators in three European case study regions (Iberian Peninsula, Scotland and Hungary). These showed high likelihoods of increases in heat-related mortality and of yield decreases for some crops, whereas a decrease of NPP was estimated as extremely unlikely (<1% likelihood). For a water reservoir in a Mediterranean catchment, increased likelihoods of severe water scarce conditions were estimated for continued current rice cultivation, which implies insufficient water resources for irrigation under average conditions. Switching from rice to other cultivations with lower per-hectare irrigation demand changes production risks, enables expansion of irrigated areas but introduces a stronger sensitivity to changes in rainfall. We also demonstrated that both mitigation and adaptation reduce impact risks.
- The IRS-based risk assessment shown in this paper is of relevance for policy making by addressing the sensitivity of impacts to key climate and socio-economic drivers, the urgency for action expressed as a time series of the likelihood of crossing critical impact thresholds, and the response, by incorporating alternative adaptation actions in the analysis framework, which may be useful for exploring the types, choice and timing of adaptation responses.

Declaration of Competing 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.

Data and code availability

Data will be made available on request. Code availability: Software implementing the IRS methods presented in this paper is available as an R package available from the GitHub repository (<https://github.com/fronzek/IRSanalysis>). Release version 1.0.0 of the package was used for analysis presented in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.crm.2022.100466>.

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