Quantifying risks avoided by limiting global warming to 1.5 or 2 °C above pre-industrial levels

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Abstract

The Paris Agreement aims to constrain global warming to 'well below 2 °C' and to 'pursue efforts' to limit it to 1.5 °C above pre-industrial levels. We quantify global and regional risk-related metrics associated with these levels of warming that capture climate change–related changes in exposure to water scarcity and heat stress, vector-borne disease, coastal and fluvial flooding and projected impacts on agriculture and the economy, allowing for uncertainties in regional climate projection. Risk-related metrics associated with 2 °C warming, depending on sector, are reduced by 10–44% globally if warming is further reduced to 1.5 °C. Comparing with a baseline in which warming of 3.66 °C occurs by 2100, constraining warming to 1.5 °C reduces these risk indicators globally by 32–85%, and constraining warming to 2 °C reduces them by 26–74%. In percentage terms, avoided risk is highest for fluvial flooding, drought, and heat stress, but in absolute terms risk reduction is greatest for drought. Although water stress decreases in some regions, it is often accompanied by additional exposure to flooding. The magnitude of the percentage of damage avoided is similar to that calculated for avoided global economic risk associated with these same climate change scenarios. We also identify West Africa, India and North America as hotspots of climate change risk in the future.

Keywords Climate change · Mitigation · Paris Agreement · Avoided impacts · Economic damages · Fluvial flooding · Hotspots

1 Introduction

The United Nations Framework Convention on Climate Change Paris Agreement (UNF-CCC 2016) aims to constrain global warming to 'well below 2 **°C**' and to 'pursue efforts' to limit it to 1.5 °C above pre-industrial levels. However, assessments of the risks associated with warming (IPCC 2014; Melillo 2014; Committee on Climate Change 2017) have

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tended to focus on outcomes associated with warming of 2 °C and above. Those that do explore the risks associated with 1.5 °C warming have hitherto tended to focus on single sectors. Here, we use a set of climate change impacts models, driven by a common set of climate change projections, to explore risks avoided in emission scenarios which limit warming in 2100 to 1.5 °C as compared with 2 °C with 66% probability. We also compare the risks with those of a baseline scenario in which warming of 3.66 °C occurs by the end of the century. Our risk-related metrics are the changes in human exposure to heat and water stress, vector-borne disease, coastal and fluvial flooding and changes in agricultural yields. Our analysis utilises the IMAGE implementation of the 'middle-of-the-road' development in terms of mitigation and adaptation space known as the Shared Socioeconomic Pathway-2 (SSP2; Riahi et al. 2017; van Vuuren et al. 2017) and a set of mitigation scenarios based on the Paris Climate Agreement targets. All metrics and risk indicators are projected spatially explicitly but without adaptation, except for the case of coastal flooding where a sensitivity study including adaptation is provided (Supplementary Methods). Finally, we identify spatially the regions where the increases in our risk metrics (relative to the 1961–1990 baseline) lie in the top quintile; weighting them equally we identify multisectoral hotspots of climate change risk.

In their seminal paper, Schleussner et al. (2016) provide a comparison of projected climate change risk at warming levels of 2 °C and 1.5 °C above pre-industrial levels, using five Global Circulation Models (GCMs) to capture regional uncertainty in climate projection. The present study complements this and the more recent Byers et al. (2018) study well by covering coastal flooding and disease risk, and by applying a different modelling approach to simulate agricultural impacts, water stress and flooding (Supplementary Methods) as well as providing an independent analysis of hotspots. Arnell et al. (2016) use an approach based on damage functions and projections from 25 GCMs to explore heat extremes, water resources, fluvial and coastal flooding, agriculture and energy use rather than detailed model simulations as in this study, while the damage functions applied themselves emerge from different underlying impact models. Byers et al. (2018) provide a risk assessment and hotspot analysis for a similar range of sectors and metrics across a consistent set of climate change scenarios from 5 GCMs, exploring a wider range of future socioeconomic scenarios than was possible in this study but is based on the analysis of existing databases of projected risk metrics such as ISIMIP-Fast Track (Warszawski et al. 2014), whereas in this study, we explicitly create our own risk simulations using sophisticated modelling approaches. Piontek et al. (2014) previously explored hotspots, but unlike Byers et al. (2018) and our study, based the analysis on a comparison of regional changes in hazards emerging from the projections of three GCMs only, without considering population exposure.

2 Methodology

2.1 Scenarios

We quantify risk-related metrics related to the water, agriculture and human health sectors for three climate change scenarios, and compare these with our published corresponding projections of aggregate global economic damages (Warren et al, 2021). All three scenarios were first developed using the IMAGE model.

1   SSP2 baseline scenario in which no climate policies are implemented additional to the Cancun pledges. In this scenario, global mean temperature increases to 3.66 °C above

pre-industrial levels by 2100 (red line in Figure S1a). By 2100 in SSP2, population reaches 9 billion. In our 30-year time slice centred on 2100, population is assumed to remain constant between 2100 and 2115. Global-scale socioeconomic data (population and GDP) quantitatively and qualitatively consistent with SSP2 were taken from IIASA (Riahi et al. 2017) and Jones and O'Neill (2016) with the 2010 value from this data set used to represent population under the observed baseline climate of 1961–1990.

2   A scenario in which stringent climate change mitigation is employed from 2020 onwards through carbon taxes, constraining warming in 2100 to below 2 °C with a probability of 66% (van Vuuren et al. 2017). This means that median estimate of global mean temperature is at 1.72 °C above pre-industrial in 2100 (green line in Figure S1a). A corresponding scenario constraining warming to below 1.5 °C with 66% probability, reaching 1.37 °C above pre-industrial in 2100 (van Vuuren et al. 2017, blue line in Figure S1a).

The IMAGE model combines a detailed representation of the energy and land-use system with representations of land cover and climatic change. The system also covers key environmental feedbacks of climate change (Stehfest et al. 2014; see also SM).

The UNEP emission gap analysis (UNEP 2020) estimated that the Nationally Determined Contributions (NDCs) to year 2030 emission reductions in the Paris Agreement imply a warming of 3.0–3.5 °C above pre-industrial levels by 2100 and are insufficient to meet the long-term temperature goal of 'pursuing efforts' to limit global warming to 1.5 °C, even if incremental improvements are made to the 2030 targets (Geiges et al. 2020). The SSP2 baseline scenario (1) thus is representative of the current policy range.

The IMAGE climate change mitigation scenarios (2) and (3) are designed to likely meet the Paris goals. They are derived from the SSP2 scenario, assuming a global climate policy approach to reduce emissions. The climate policy is implemented using the corresponding 'shared policy assumptions' (SPA2) (Kriegler et al. 2014) in which there are delays to mitigation in the short-term due to fragmentation (lack of co-operation between countries) and there is then a linear transition to a globally uniform carbon price by 2040 in all countries.

Land-use trends, in the baseline (1), show a slow-down of deforestation and even, at a global scale, some net afforestation in the second half of the century. This is a result of reforestation in high-income regions and further deforestation in several low-income regions (van Vuuren et al. 2017). In the mitigation scenarios (2) and (3), three types of land-based climate mitigation are implemented: bio-energy, REDD (avoided deforestation) and reforestation. The demand for bioenergy in climate change mitigation scenarios is a result of the energy system dynamics in response to the carbon price (changes in energy efficiency, the competitiveness of fossil fuels and other renewables). The levels of REDD and reforestation are calibrated to abatement curves on avoided deforestation (Kindermann et al. 2008) as described in Van Vuuren et al. (2017) (resulting a rapid decline in deforestation rates and increased afforestation). Given the stringent 2 °C and 1.5 °C targets, these levels are fully implemented. Further information please see Warren et al. 2021.

The global, annual mean temperature time series (Figure S1a) are shown relative to pre-industrial levels as simulated by IMAGE (using MAGICC version 6.3.07). Note that the simulated global warming from pre-industrial to the 1986–2005 mean (0.62 °C) is almost identical to the 0.61 °C used in the 2013 IPCC assessment (Kirtman et al. 2013), based on the observed warming between 1850–1900 and 1986–2005.

Since the mean temperatures in 2100 of these scenarios are below 2 °C and 1.5 °C, respectively, a sensitivity study was also carried out for a limited set of risk indicators driven by a 30-year climate time slice created to be consistent with the IMAGE

scenarios but with average global temperatures prescribed to be exactly 2 °C and 1.5 °C above pre-industrial levels respectively. For our treatment of sea level rise, see SM.

2.2 Creation of climate data sets to drive sectoral models

For all sectors apart from coastal flooding due to sea level rise, the climate inputs required for the impact models were generated by the pattern-scaling technique, using ClimGen (Osborn et al. 2016). Pattern-scaling assumes that there is a linear relationship (possibly after a transformation for precipitation) between the change in a climate variable in a grid cell and the change in global-mean surface temperature and that this relationship is invariant under the range of climate changes being considered here. The linear scaling factors are diagnosed from GCM simulations. This is a commonly used method; see Tebaldi and Arblaster (2014) for a discussion of its strengths and limitations and James et al. (2017) for a review of its specific application to global warming targets in comparison with other methods. A notable modification to this standard approach is that in ClimGen, the monthly precipitation variability is also perturbed according to the changes in precipitation variability simulated by the GCM, thus representing increases or decreases in future precipitation variance and distribution skewness (Osborn et al. 2016). For further details, see SM.

2.3 Quantification of risk-related metrics

We quantify the risk-related metrics associated with these three different scenarios in 30-year time slices centred on 2100 (and in some cases also 2050), using an established set of climate change impacts models (Supplementary Methods), focusing on implications for agriculture, water resources, extreme weather events and the prevalence of disease.

We quantify globally human population exposure in 2050 and 2100 to (i) moderate to extreme heat stress (defined as simplified wet bulb globe temperature (sWBGT) above 32 [e.g. Zhao et al. (2015); see Supplementary Methods]), (ii) extreme 12-month drought (Standardised Precipitation-Evapotranspiration Index, SPEI_12 < -1.5, see Supplementary Methods), (iii) water scarcity (runoff < 1000m^3 capita^{-1} year^{-1}) and (iv) fluvial flooding (magnitudes that exceed floods which are currently experienced only once in 100 years; Q100). We also calculate (v) changes in runoff; (vi) % changes in crop yields, aggregated across the major crops wheat, rice, maize and soybean; (vii) human population exposure to malaria infection; (viii) cumulative land lost to submergence (km^2); and (ix) number of people at risk from coastal flooding (people/year) associated with sea level rise (Figure S1b). We also quantify exposure to dengue fever infection in S America only (Colon-Gonzalez et al. 2018).

All metrics are quantified as changes relative to an observed baseline climate of 1961–1990 on a 0.5° × 0.5° grid (Supplementary Methods, Figures S2, S3a). The sum of these changes in risk-related metrics, aggregated across the globe for each metric individually, is calculated for each warming level in 2100 and is used to estimate the % risks avoided in 2100 that result in each sector from constraining warming to the lower level compared to the higher level.

2.4 Climate-related risk

Climate-related risk is the product of exposure of vulnerable systems to climate-related hazard. Since the time-evolving socioeconomic scenario used (SSP2) is the same for warming scenarios explored, vulnerability, although not quantified, remains constant across the scenarios. Quantifying spatial vulnerability to each climate related hazard is beyond the scope of this work. However, an important way in which vulnerability manifests is the ability or not to adapt: however adaptation is excluded by design in this work (except for coastal flooding, as previously mentioned). Therefore, in this study, our quantified % reductions in exposure of people or land to climate-related hazards (i)–(ix) can be considered a strong indicator of corresponding reductions in risk.

2.5 Hotspot analysis

To identify those regions where climate change risk is projected to increase the most with 1.5 °C or 2 °C of average global warming by 2100 (associated therefore with much larger regional levels of warming in most land areas) under socioeconomic scenario SSP2, we selected for each of the nine metrics assessed globally, the regions where the increases in risk indicators relative to the baseline were at or above the 80th percentile level. Weighting each metric equally, we then summed them and produced a multi-sectoral risk hotspot map where the intensity of the colour indicates the number of metrics for which the risk increase relative to the observed baseline period is above the 80th percentile level.

3 Results and discussion

3.1 General overview

Figure 1a indicates large aggregate global benefits from constraining warming by 2100 (with 66% probability) to 1.5 °C rather than 2 °C in terms of reduced exposure to drought and fluvial flooding, heat stress, disease and for crop yields. Error bars and ranges indicate the implications of using alternative global circulation model (GCM) patterns in downscaling. Avoided risks range in percentage terms from 10 to 44%, with largest benefits in percentage terms accruing for reduced exposure to fluvial flooding (44% reduction) and reduced exposure to drought and crop yields (~27% reduction). Benefits accruing in terms of cumulative land lost due to submergence and people at risk from coastal flooding tend to be smaller in percentage terms than other benefits owing to the time lag associated with the response of sea level rise to reductions in greenhouse gas emissions (known as the commitment to sea-level rise). Our projections of absolute additional levels of risk indicators globally at 1.5 °C and 2 °C warming relative to the observed baseline are given in Table S1.

Globally, water scarcity decreases slightly with increased climate change; however, this should not be interpreted as a benefit, since there are regional increases and decreases, and where there is reduced water scarcity, there is often an associated increase in runoff and consequently flood risk. One risk metric relating to the prevalence of malaria indicates a benefit from climate change in parts of Africa and South
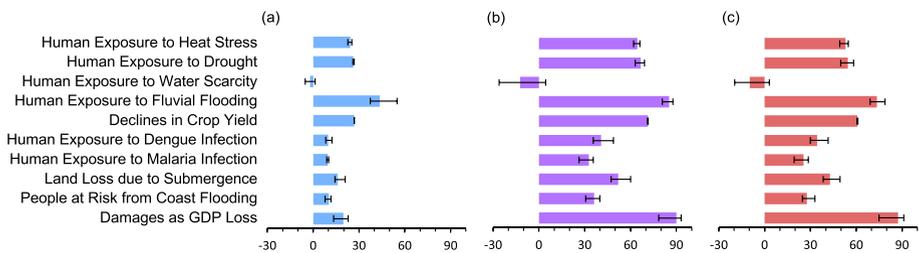
Figure 1 Avoided increases in risk indicators associated with different levels of warming in 2100 under socioeconomic pathway SSP2 expressed as percentage changes projected to result from limiting warming to a lower level rather than a higher one as follows: **a** 1.5 °C relative to 2 °C, **b** 1.5 °C relative to 3.66 °C and **c** 2 °C relative to 3.66 °C. Bars indicate the avoided % change in (i) population (thousands) exposure to moderate to extreme heat stress, defined as sWBGT above 32; (ii) population (thousands) exposed per month to severe drought [with magnitude SPEI12 < -1.5]; (iii) population exposure to water scarcity, defined as < 1000 m^3/capita/year; (iv) population (thousands) living in the modelled inundation areas in which the discharge exceeds the 100-year flood in 1961–1990; (v) crop yield loss; (vi) population exposure (thousands) to dengue infection in South America only; (vii) population (thousands) exposed to malaria infection; (viii) cumulative land lost due to submergence (thousands km^2); and (ix) population exposure (millions) per year to coastal flooding due to sea level rise. All indicators are global totals except for crop yield changes which are crop-area weighted means. For comparison purposes, values of global aggregate economic damages (GDP loss) are taken from Warren et al. (2021) for the same climate change scenarios and SSP2 and are shown on the same chart. Error bars indicate the range of uncertainty associated with the use of alternative regional climate change patterns associated with the CMIP5 ensemble of global circulation models. All indicators are global totals except for crop yield changes which are crop-area weighted means

America: Here, a drying climate reduces the risk of infection in many areas, and limiting global warming may prevent this net benefit being realised; however, overall globally, population exposure to malaria and dengue is 10% lower if warming is constrained to 1.5 °C rather than 2 °C.

Benefits within sectors accruing from constraining warming to 1.5 °C rather than 3.66 °C are projected to be notably larger (32 to +85%) than those accruing from constraining warming to 2 °C rather than 3.66 °C (26 to +74%) (Figure 1b,c). Benefits of limiting warming to 1.5 **°C** rather than 3.66 **°C** reach 87% for population exposure to fluvial flooding and over 70% for population exposure to drought and reductions in crop yields. These numbers are similar to the estimates emerging from our parallel study (Warren et al. 2021) which also uses the same climate change scenarios and finds that economic damages at 1.5 °C warming are 92% lower than mean losses of 3.67% of GDP (range 0.64–10.77%) associated with global warming of 3.66 °C.

The fact that our pathways to 1.5/2 °C warming achieve this with a probability of 66% rather than 50% is an advantage, since it provides greater confidence that limits might be attained. Avoided risks due to following pathways that constrain warming to 1.5 °C rather than 2 °C by 2100, with 66% probability, are also projected to accrue already in the 2050s (Table S3) for aggregate economic damages, exposure to dengue infection and crop yields. Crop specific projections for crop yields are given in Table S4.

Figure 2 maps the differences between indicators of risk in 2100 for the pathway constraining warming to 1.5 °C rather than 2 °C, each with 66% probability, for each risk indicator examined. When aggregated regionally, benefits, expressed as avoided increases in risk indicators, or as avoided percentage changes in risk indicators, vary significantly (Figure S5a, b, Table S2). Figure S4b and c map the regional increases in risk indicators resulting from the combination of socioeconomic changes and climate changes by the year 2100,

(a) Human Exposure to Heat Stress (thous.)

(b) Human Exposure to Drought (thous.)

(c) Human Exposure to Water Scarcity (thous.)

(d) Total Run off (mm/yr)

(e) Human Exposure to Fluvial Flooding (thous.)

(f) Human Exposure to Malaria Infection (thous.)

(g) Land Loss due to Submergence (thous. km²)

(h) People at Risk from Coastal Flooding (million/yr)

(i) Decline in Crop Yield (percent)
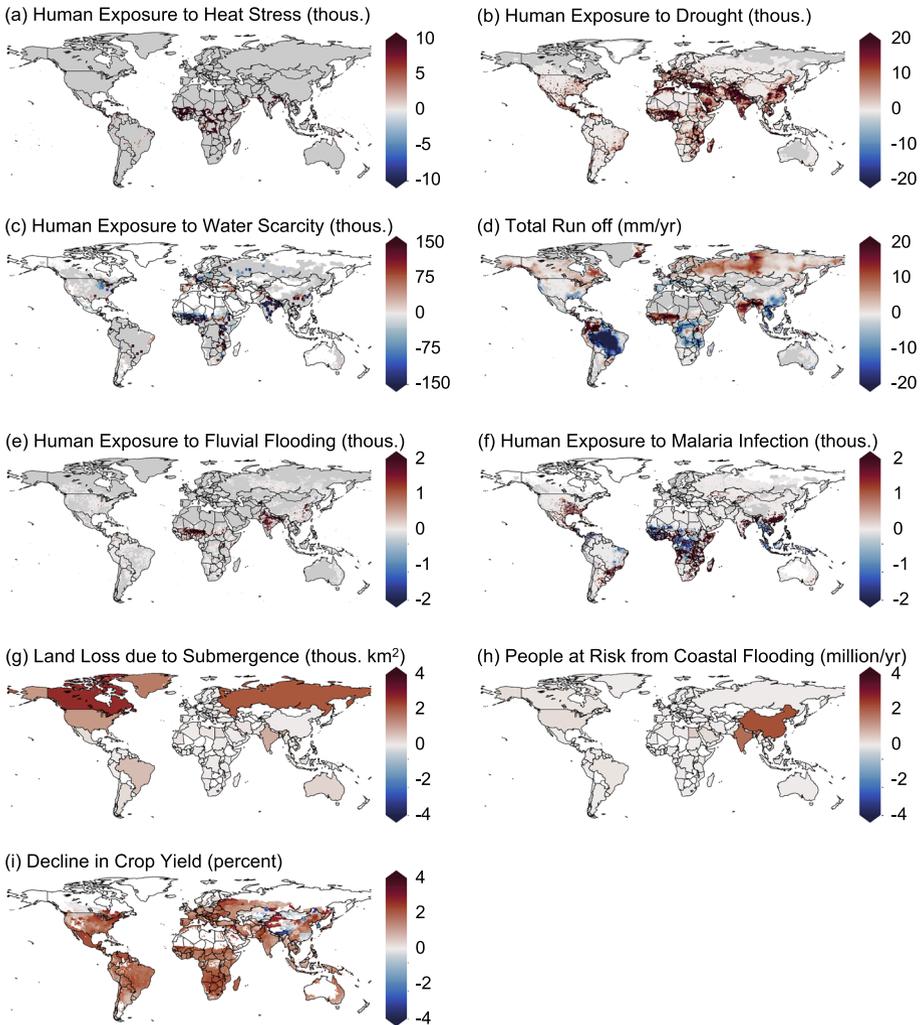
Figure 2 Showing the differences between indicators of risk quantified at 1.5 °C and 2.0 °C global warming at a spatial resolution of 0.5°×0.5°. Panels indicate changes in **a** population (thousands) exposure to moderate to extreme heat stress, defined as sWBGT above 32; **b** population (thousands) exposed per month to severe drought [with magnitude SPEI12 < -1.5]; **c** population exposure to water stress, defined as < 1000 m³/capita/year; **d** total water runoff in mm per year; **e** population (thousands) living in the modelled inundation areas in which the discharge exceeds the 100-year flood in 1961–1990; **f** %crop yield loss; **g** population (thousands) exposed to malaria infection; **h** cumulative land lost due to submergence (thousands km²); **i** population exposure (millions) per year to coastal flooding due to sea level rise. Metrics **g** and **h** represent totals per country

at 1.5 °C or 2 °C warming respectively for a subset of risk indicators, excluding those for which indicators are by definition close to zero in the baseline.

Figure S4a provides absolute total global projected risk indicators at each warming level in 2100, showing that the largest absolute benefits globally in terms of quantified reduction of risk indicators arising from constraining warming by 2100 (with 66% probability) to 1.5 °C rather than 2 °C are in the avoidance of population exposure to drought.

Figure S4d and e map regionally the percentage and absolute levels of risk indicators at 1.5 °C and 2 °C warming. While considerable spatial variation is apparent, there remains a predominant trend that risks tend to increase with warming.

Figure S5, S6 and S7 detail and compare regionally percentage and absolute differences between levels of risk indicators at 1.5 °C vs. 3.66 °C warming and also between 2 °C vs. 3.66 °C.

Risk analysis carried out in this study using sWBGT finds hundreds of millions of people to be additionally affected by heat stress at each (successively higher) warming level. This result is consistent in magnitude with other recent studies, such as Matthews et al. (2017) who project 350 million more megacity region inhabitants to be exposed to deadly heat by 2050 for an end of century warming level of 1.5 °C. Andrews et al. (2018) also project hundreds of millions of people to be exposed to extreme heat for warming levels of 1.5 °C and above. As has been shown in other multi-sectoral impacts, studies which include humid heat metrics (e.g. Byers et al. 2018) projected heat exposure is most pronounced in the tropics, and as such, we identify benefits of reduced exposure associated with limiting warming in low-latitude regions. Our study focuses on applying targeted climate scenario data to calculate global (combined urban and rural) population heat stress using the sWBGT metric. While sWBGT can produce an overestimate of heat exposure risk during cloudy or windy conditions and vice versa, Willett and Sherwood (2012) argue that changes in solar radiation and wind speed are unlikely to impact significantly on global patterns. Population impacts of exposure to heat stress will depend on the activity of the person concerned and the choices that they make.

We estimate a continuous increase in global drought risk and find hundreds of millions of people to be additionally affected by drought at each (successively higher) warming level, which is well aligned with previous research (Prudhomme et al. 2014; Smirnov et al. 2016; Lehner et al. 2017; Arnell et al. 2018; Naumann et al. 2018; Liu et al. 2018). A direct comparison in terms of affected people and impact avoided with any of these studies, however, is complicated due to the use of different drought indices, metrics and population data. For example, Naumann et al. (2018) also use the SPEI-12, but they use event length and magnitude as a measure of impact, while Smironv et al. (2016) use the SPEI-24 but calculate the number of people affected. This shows that more studies are needed that use sets of indices, metrics and data that intersect with already existing ones to enable a better comparison. Other studies are based on SPI which is easier to calculate, but by definition excludes evapotranspiration meaning that the drought estimation is conservative as it fails to allow for the important role of temperature rise in contributing to potential evapotranspiration.

Here, we focus on a comparison with Arnell et al. (2018) because they use the same approach to calculate the number of people affected from drought frequency and the same socioeconomic scenario (SSP2). Their analysis is, however, based on the standardised runoff index (SRI). Arnell et al. (2018) report a median 39% (36–51% for the 10–90% range) impact avoided between 1.5 and 2.0 °C, with 630–1300 million people exposed to drought at 1.5 °C and 710–1600 million people exposed at 2.0 °C (Figure 1). Our mean values of 1406 million and 1752 million, respectively, are slightly above the upper end of their ranges, while our mean value of 26% impact avoided is below theirs. This might be due to the choice of SPEI compared to SRI. The SPEI might capture anomalies in which the projected proportional increase in precipitation is smaller than the proportional increase in PET. Such conditions are linked to increasing drought conditions (Naumann et al. 2018), and capturing those additionally could explain the higher numbers of people affected and the smaller proportion of avoided impacts. In a comparison of different drought metrics (including SRI and SPEI) in a single basin, SPEI-12 indicated a more severe drought than

SRI-12 for more of the years 1970–2017 than the reverse (Dikici 2020). SRI is usually used as a measure of hydrological drought, while SPEI (and others) are used for agricultural, meteorological and hydrological drought. Thus, SPEI captures the water that may be captured in ways other than run-off and in food stocks. Differences between values of these projected metrics would therefore be expected.

Our regional projections indicate a mixed picture, similar to the results obtained by Arnell et al. (2018). Overall, we identify Africa, India and the Middle East as hotspots for increased exposure to drought. While the number of people exposed to drought conditions is expected to increase in most of Southern America, Europe and East Asia, we also find that there are regions which could see lower numbers of people affected in the future, particularly in Russia, China, Indonesia and parts of South America (Figure 3). When limiting global warming to 1.5 °C rather than 2.0 °C, most inhabited areas in the world would benefit, apart from a few isolated patches in Russia, Indonesia and South America (Figure 2), which is well in line with the analysis of Arnell et al. (2018).

Annual runoff increases considerably with global warming in large parts of Russia, Canada, India, north-east China, northern and central Europe, West Africa and some small parts in central and eastern Africa. Runoff drops as the warming increases from 1.5 to 2.0 °C in the southern USA, central region of South America, large parts of central Africa, south-east China and the Mediterranean. We focus on a comparison with Hirabayashi et al. (2013) which utilises the same CaMa-Model and finds that on average, the global flood exposure to (present-day) Q100 floods in the RCP8.5 scenario for 2071-2100 is projected to lie between 37 and 163 million. Similarly, we projected global flood exposure to Q100 floods in 2086–2115 with 3.66 °C warming obtaining a range of 81 to 195 million people. The findings are of the same order of magnitude and overlap in range, but are not identical as is to be expected given differences in the selection of the time period, population data sets and regional climate change projections used.

Population exposure to water scarcity is most evident in western India and northern region of West Africa. It is worth noting that the population in the northern region of West Africa is project to experience both fluvial flooding and water scarcity, less so at 2 °C than at 1.5 °C global warming. However, like Gosling and Arnell (2016), we also found relatively small differences in water scarcity between the 1.5 and 2 °C warming scenarios when compared with differences arising from uncertainties in regional climate change projection.
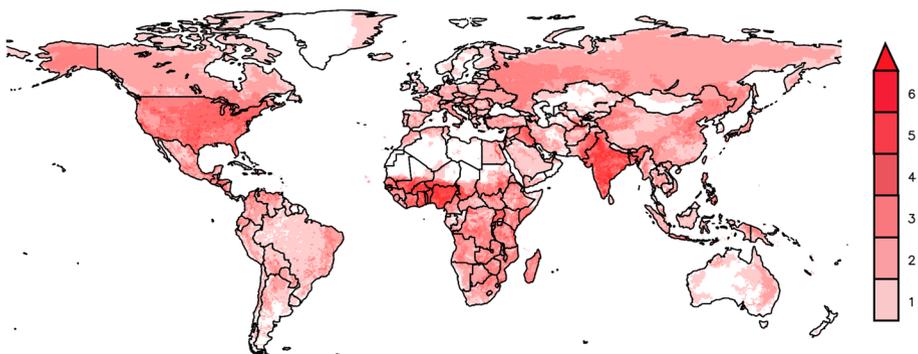
Figure 3 Hotspots of multi-sectoral additional climate change risk at 1.5 °C global warming, given SSP2 socioeconomic projections, indicating spatial location of the top quintiles of the nine changes in risk shown in Figure 2 and Figure S4b. Each location variously lies in the top quintile for between 0 and 9 of the risk metrics. Equal weighting is given to each of the nine

The additional exposure to fluvial flooding risk (Figure 2) is mostly evident in West Africa, India and parts of central East Africa, aligning with the identification of hotspots with multi-sector risk in West Africa and South Asia. Our study also shows that large areas of inhabitants in sub-Saharan Africa and southern Asia would be exposed to Q100 floods at the higher degree warming. Thus, our findings agree mostly with previous studies such as Piontek et al. (2014), Gosling and Arnell (2016) and Byers et al. (2018) who projected that the poor and vulnerable populations in Africa and southern Asia would be disproportionately impacted by multi-sectors impacts.

The constantly reducing crop yields we obtain under increasing global temperature align well with results in the existing literature using both process-based models and statistical models (see SM), although compared to these studies, our results appear to be conservative. Projections for regional changes in crop yields are consistent with a previous study (Schleussner et al. 2016) identifying Africa, SE Asia, and C&S America as hotspots for projected declines in yield and indeed for projected avoided risks if warming is limited to 1.5 °C rather than 2 °C (Figure 2). Equally, they are well aligned with the hotspots identified by Byers et al. (2018) and Piontek et al. (2014). Similar to Arnell et al. (2016), our results indicate that reductions of maize yield in all regions and soybean yields are projected to potentially increase in Europe, North America and Australasia but to decline in other regions. In case of wheat, we project declines in all regions, while Arnell et al. (2016) obtained mixed results. We suspect that this is due to the different types of wheat that were analysed. For rice, our projections indicate strong losses in Africa and South-East Asia but increasing yields in Europe and Australasia. Limiting global warming to 1.5 °C rather than 2 °C would provide benefits for most regions across the globe, particularly in the Americas, Europe and Africa (Figure 2), which is also in line with the findings of Arnell et al. (2016). Overall, our results suggest an inequality in risk of crop yield loss between the Northern and Southern hemispheres and especially tropical and non-tropical regions. The main limitation of the models used here is that they are based on unevenly spaced national data and that the area harvested was assumed to remain constant so that potential future land use change is not accounted for.

Our estimates of future climate-driven malaria risk are in line with previous research indicating that such risk is confined to specific regions (Piontek et al. 2014; Caminade et al. 2014; Ryan et al. 2020). Our results suggest that climate change is likely to increase the risk of dengue transmission across vast areas in Latin America in agreement with previous studies (Colón-González et al. 2018; Messina et al. 2019; Watts et al. 2019).

A limited number of studies have analysed the impacts or costs of sea-level rise specifically at 1.5 °C and 2.0 °C at a global scale, including Schleussner et al. (2016), Brown et al. (2018), Nicholls et al. (2018), Rasmussen et al. (2018) and Jevrejeva et al. (2018), whilst others, such as Hinkel et al. (2014), Vousdoukas et al. (2018) and Yokoki et al. (2018), have analysed impacts following the Representative Concentration Pathway scenarios. Whilst each study has produced different sea-level rise scenarios, the exposure and impact metrics produced are of a similar order of magnitude, taking account differences such as adaptation. For example, Nicholls et al. (2018) projected 33–117 million people/year at risk from flooding globally for the 1.5 °C scenario (0.24–0.54 m of sea-level rise) and 42–132 million people/year at risk from flooding globally for the 2.0 °C scenario (0.31–0.65 m of sea-level rise) in 2100, assuming no additional adaptation from the baseline (1995). In comparison, our results, indicate 41–88 million people/year at risk from flooding globally for the 1.5 °C scenario (0.24–0.56 m of sea-level rise) and 45–95 million people/year at risk from flooding globally for the 2.0 °C scenario (0.27–0.64 m of sea-level rise) in 2100, assuming no additional adaptation from

the baseline (1995). Our projections of human exposure coastal flood risk are similar in magnitude to earlier studies including Nicholls et al. (2018), with differences emerging from the use of a mean across Shared Socioeconomic Pathways (SSP) 1–5, in that study as compared with SSP2 here. No comparable results are available for land loss due to submergence. Regionally, the greatest number of people at risk from coastal flooding, who stand to benefit the most from limiting warming to 1.5 °C rather than 2 °C, are in east and south Asia, especially China and India (Figure 2, SM4b,c). Additionally, land potential subject to submergence is projected in lower lying northern latitudes including North America and many of the world's delta regions.

Our projected SLR is higher than some other projections (e.g. Goodwin et al. 2018; Geiges et al. 2020), but still within a plausible range. The difference here between the < 1.5 °C and < 2.0 °C scenarios is 0.06 m in 2100. This is less than the best estimate that Hoegh-Guldberg et al. (2018) conclude from a range of studies, of approximately 0.1 m difference in sea-level rise between the 1.5 and 2.0 °C scenarios, but within their uncertainty range. The sea-level rise projections here do not include the non-linear Antarctic ice sheet dynamics effects on sea-level rise proposed by DeConto and Pollard (DeConto and Pollard 2016; Edwards et al. 2019) that are projected to accelerate ice melt and sea-level rise in the latter half of the twenty-first century for high-warming scenarios (Hope 2013). Our projected estimates of avoided sea-level rise are thus lower than in Schleussner et al. (2016) due to a linear treatment of ice-sheet dynamics in our study, and also the effect of a small mid-century overshooting of 1.5 °C by of 0.1 °C mid-century in our mitigation scenario which is not present in Schleussner et al. (2016) (other models used in this study do not reflect the dynamics of temperature change during the twenty-first century, and hence the implications of this small overshoot do not affect our other estimates of risk). There is evidence that this non-linear ice sheet dynamics effect is not required to reproduce past sea level observations and reconstructions (Edwards et al. 2019), and if it does occur, it is not thought to significantly affect sea-level rise for warming pathways around 1.5 °C (Hope 2013). However, potential non-linear ice sheet dynamics effects imply that our projections of sea-level rise for higher warming scenarios (above 1.5 °C) may be conservative. The simulations presented here assume that defences have not been upgraded as sea-levels rise. In reality, defence standards are likely to increase following common practice. The results for land loss due to submergence and the number of people flooded assuming upgrades with adaptation are shown in the Supplementary Results (Tables S5, S6, S7, Figures S8, S9).

For further discussion of sector specific projections and further comparison with other literature, see SM.

In summary, using mean estimates taking into account a range of alternative regional climate projections, our process-based models estimate that constraining warming to 1.5 °C rather than 2 °C would variously avoid 10–44% of the increases in indicators of climate change risk that would otherwise accrue in various disparate categories by 2100. A parallel analysis of global aggregate economic damages arising from these same climate change scenarios with PAGE09 (Warren et. al. 2021) indicates avoided economic impacts of 20% in the global aggregate from constraining warming to 1.5 °C rather than 2 °C, corresponding to a net present value of damages of 39 (range 13–108) US $trillion rather than 61 (range 15–140) US $trillion. Avoided damages (Warren et al. 2021) reach 87% (74–91%) from constraining to 2 °C rather than 3.66 °C, when damages reach 484 (60–1590) US $trillion, and 90% (77–93%) when warming is constrained to 1.5 °C rather than 3.66 °C. This implicitly assumes that the results from the scenarios are perfectly correlated, which is a reasonable assumption as high values for the transient climate response (TCR) and impact function parameters will give high global risks in all scenarios, and vice

versa. Thus, estimates of the percentage of risks avoided by limiting global warming to lower, rather than higher, levels are comparable if an independent economic model is used to simulate aggregate climate change damages, with the mean estimate across assessed risk indicators of 20% risks avoided falling in the range projected from the physically based models.

Benefits vary across regions and between sectors, being greatest for fluvial flooding, with 38–55% risks avoided depending on regional climate projections used. However, some regions are exposed to a range of risks simultaneously and may become 'hotspots' of climate change risk.

3.2 Hotspot analysis (Figure 3)

Early studies explored annual mean (Giorgi 2006) climate change hotspots, but focused entirely on the hazard component of risks related to projected annual average changes in precipitation and temperature, and identified the Mediterranean, the northern hemisphere high-latitude regions and Central America as the most prominent hotspots. Giorgi et al. (2006) went on to include socioeconomic factors, and also sea-level rise, but did not include projected increases in population: This approach highlighted China and Bangladesh as the most threatened nations on a gross population basis, followed by India, Russia, Brazil, and the USA. Later, Diffenbaugh and Giorgi (2012) conducted a statistical analysis in multi-dimensional climate space, including changes in seasonality but excluding sea-level rise or socioeconomic factors, but based on new CMIP5 projections, this identified the Amazon, the Sahel and tropical West Africa, Indonesia and the Tibetan Plateau as persistent regional climate change hotspots throughout the twenty-first century in a range of forcing pathways. In addition, areas of southern Africa, the Mediterranean, the Arctic, and Central America/western North America at higher levels of forcing.

Our regional analysis of the regional distribution of additional risks arising from the combination of climate change and socioeconomic change by 2100 (Figure S4b,c) and the associated hotspots map highlights India, West Africa and North America as regions at particular risk, at both 1.5 °C (Figure 3) and 2 °C (not shown, but almost identical): The overall distribution of risk is very similar at both warming levels, but as previously mentioned, there is a large percentage reduction in risks levels at 1.5 °C compared with 2 °C. This is broadly consistent with earlier work on hotspots that included aspects of exposure and vulnerability, most notably the distribution of human populations, in that it generally indicates that South Asia and Africa become hotspots of climate change risk, especially for water related indicators (Arnell et al. 2018; Byers et al. 2018). This is despite the fact that Byers et al. (2018) use different sets of climate change risk indicators (including the use of different thresholds in cases where indicators are threshold-based); cover different sectors (our study includes coastal flooding and excludes nitrate leaching); aggregate the indicators using an expert scoring procedure as compared with uniform weighting in our study; and are based on the outputs of different risk projection models/data sets and the use of different socioeconomic scenarios.

There are some notable differences however between the various studies. Byers et al. (2018) project larger risks in China than in our own study, probably because of the inclusion of a greater number of land-based climate change risks than in our own study. Similarly, Arnell et al. (2016) estimate heat events and hydrological drought irrespective of human exposure, identifying Australasia as an area at particular risk, which does not emerge from our study. This is because our study focused heavily on population exposure

to hazards, and hence areas experiencing large increases in drought or water scarcity but with low human population do not emerge strongly in our analysis.

Changes in risk associated with different levels of warming will also depend strongly on the socioeconomic pathway (Arnell et al. 2018; Byers et al. 2018), which in this study was set to a 'middle of the road' scenario in which population rises to 9.4 billion in 2070 and declines thereafter. For example, for larger (smaller) increases in population, the absolute levels of populations exposed to the various risks included in this study would be expected to be larger (smaller), and the benefits associated with limiting warming correspondingly larger (smaller) in absolute terms, although not necessarily in percentage terms (e.g. Supplementary Material of Arnell et al. 2018). For risk-related metrics which are associated with a threshold (such as the heat stress, water stress and flooding metrics explored here), levels of avoided exposure will depend on the threshold selected. Another important factor is the uncertainty between exposure/impact models. Such uncertainties can be large, as currently being explored by the ISIMIP model comparison exercise (Warszawski et al. 2014). Sensitivity studies exploring these issues would be of interest, but were beyond the scope of this study.

In general, there is good agreement with other studies, although our projections of climate change impacts on crop yields and exposure to heat stress may be relatively conservative. Projected risks to biodiversity which were beyond the scope of this study will also be important and will interact, via loss of ecosystem services, with the projected risks to human systems estimated here (Fischlin et al. 2007; Warren et al. 2013, 2018).

Declarations

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