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Decreases in global beer supply due to extreme drought and heat

Wei Xie[1*], Wei Xiong[2,3,4], Jie Pan[2], Tariq Ali[1], Qi Cui[5], Dabo Guan[6,7*], Jing Meng[8], Nathaniel D. Mueller[9], Erda Lin[2*] and Steven J. Davis[9,10]

Beer is the most popular alcoholic beverage in the world by volume consumed, and yields of its main ingredient, barley, decline sharply in periods of extreme drought and heat. Although the frequency and severity of drought and heat extremes increase substantially in range of future climate scenarios by five Earth System Models, the vulnerability of beer supply to such extremes has never been assessed. We couple a process-based crop model (decision support system for agrotechnology transfer) and a global economic model (Global Trade Analysis Project model) to evaluate the effects of concurrent drought and heat extremes projected under a range of future climate scenarios. We find that these extreme events may cause substantial decreases in barley yields worldwide. Average yield losses range from 3% to 17% depending on the severity of the conditions. Decreases in the global supply of barley lead to proportionally larger decreases in barley used to make beer and ultimately result in dramatic regional decreases in beer consumption (for example, −32% in Argentina) and increases in beer prices (for example, +193% in Ireland). Although not the most concerning impact of future climate change, climate-related weather extremes may threaten the availability and economic accessibility of beer.

Rising incomes are strongly correlated with increases in consumption of resource-intensive animal products (meat and dairy)[1,2], processed foods[3] and alcoholic beverages[4] (Supplementary Figs. 1 and 2). Despite concerns that such trends are not healthy or environmentally sustainable[2,5,6], global demand for these foods and beverages will continue to grow as economic development proceeds[7].

At the same time that demand for such products is increasing, climate change threatens to disrupt the supply of agricultural products[8–12]. A substantial and increasingly sophisticated body of research has begun to project the impacts of climate change on world food production, focusing on staple crops of wheat[13,14], maize[15,16], soybean[17,18] and rice[19,20]. However, if adaptation efforts prioritize necessities, climate change may undermine the availability, stability and access to 'luxury' goods to a greater extent than staple foods. Although some attention has been paid to the potential impacts of climate change on luxury goods such as wine and coffee[21–23], the impacts of climate change on the most popular alcoholic beverage in the world, beer, have not been carefully evaluated.

Here, we assess the vulnerability of the global beer supply to disruptions by extreme drought and heat events that may occur during the twenty-first century as the climate changes—these are the main mechanisms by which climate damages crop production[24,25]. Details of our analytical approach are in the Methods and Supplementary Information Section 2. In summary, we develop an extreme events severity index for barley based on extremes in historical data (1981–2010) and use it to characterize the frequency and severity of concurrent drought and heatwaves (that is, extreme events severity) under climate change, as projected by five different Earth System Models (ESMs) during the period 2010–2099. Extreme events years are classified as those with concurrent drought and heat (1) during the barley-growing season, (2) in areas where barley is now grown and (3) more severe than 100-year events in the historical record (as a weighted average of the barley-growing grid cells). Among the 450 modelled years (90 years × five ESMs) of each Representative Concentration Pathway (RCP), we identify 17, 77, 80 and 139 such extreme events years under RCP2.6, RCP4.5, RCP6.0 and RCP8.5, respectively. We then model the impacts of these extreme events on barley yields (the primary agricultural input to most beer[26]) in 34 world regions (most of which are individual countries with significant barley or beer production, consumption, and/or trade, both in total and per capita terms) using a process-based crop model (Decision Support System for Agrotechnology Transfer, DSSAT). Next, we examine the effects of the resulting barley supply shocks on the supply and price of beer in each region using a global economic general equilibrium model (Global Trade Analysis Project model, GTAP). Finally, we compare the impacts of extreme events with the impacts of changes in mean climate and test the sensitivity of our results to key sources of uncertainty, including extreme events of different severities, technology and parameter settings in the economic model[27,28]. Thus, we assess future sudden changes in barley production and subsequent changes in beer consumption across the world in years when extreme drought and heat occur. We do not consider how demand for beer may change in the future because such extreme events could occur in any future year and it is not possible to anticipate how agricultural and socio-economic systems will evolve. We therefore analyse impacts based on the recent geographical distribution of barley production, recent levels of

[1]China Center for Agricultural Policy, School of Advanced Agricultural Sciences, Peking University, Beijing, China. [2]Institute of Environment and Sustainable Development in Agriculture, Chinese Academy of Agricultural Sciences, Beijing, China. [3]International Maize and Wheat Improvement Center, Texcoco, Mexico. [4]College of Agronomy, Henan Agricultural University, Zhengzhou, Henan, China. [5]School of Economics and Resource Management, Beijing Normal University, Beijing, China. [6]Department of Earth System Science, Tsinghua University, Beijing, China. [7]School of International Development, University of East Anglia, Norwich, UK. [8]Department of Politics and International Studies, University of Cambridge, Cambridge, UK. [9]Department of Earth System Science, University of California, Irvine, CA, USA. [10]Department of Civil and Environmental Engineering, University of California, Irvine, CA, USA. *e-mail: xiewei.ccap@pku.edu.cn; dabo.guan@uea.ac.uk; linerda@caas.cn

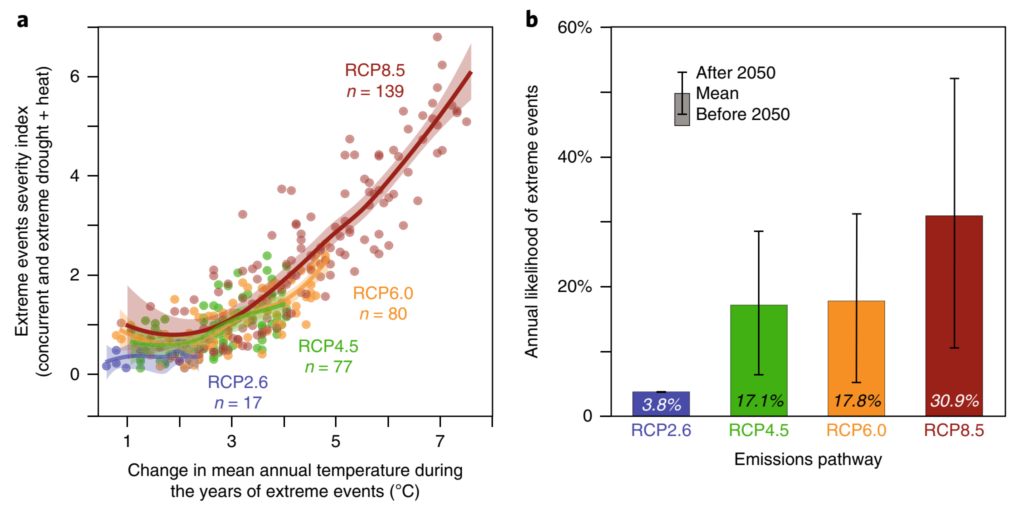

Fig. 1 | Extreme events severity and frequency in barley-growing regions and during the barley-growing season under future climate change. a, The relationship between change in global mean (land) surface temperature in extreme events years (relative to the 1981–2010 observational mean) and the severity of concurrent drought and heat in barley-growing regions and during the barley-growing season, where the solid curve represents polynomial regression and the shaded envelopes the 95% confidence interval ($n=17$, 77, 80 and 139 extreme events under RCP2.6, RCP4.5, RCP6.0 and RCP8.5, respectively). **b**, Annual likelihood of concurrent extreme events under each of the RCPs as projected by five ESMs ($n=450$ independent experiments for each RCP). Top and bottom whiskers indicate the annual likelihood of extreme events after 2050 and before 2050, respectively.

economic development and structure, recent population, and recent demands for barley and beer (as of 2011, which is the latest available year for data for our economic model).

Extreme events limit beer supply

Figure 1a shows the relationship between future increases in global mean (land) surface temperatures and the index of extreme events severity (that is, the prevalence and magnitude of concurrent extreme drought and heat during barley-growing seasons and in barley-growing regions) for each 'extreme events year' identified (Supplementary Fig. 13 shows the historical trend). The trend is relatively flat as global mean (land) surface temperatures increase up to ~3 °C, above which there is a rapid increase in extreme events severity up to ~8 °C of warming (RCP8.5, Fig. 1a). The corresponding annual likelihoods of concurrent drought and heatwave in the pathways and models are summarized by the bars in Fig. 1b. On average, the annual likelihood of such extreme events projected by climate models over the twenty-first century is ~4% under RCP2.6 (that is, an emissions pathway likely to avoid 3 °C of mean temperature increase during this century), increasing to ~17–18% under RCP4.5 and RCP6.0 (temperature increases of 4–5 °C) and up to ~31% under RCP8.5 (temperature increases >5 °C). The likelihoods of extreme events in the second half of the century (top of error bars in Fig. 1b) are considerably greater, with extreme events occurring roughly one in every three years under RCP6.0 (top whisker of orange bar in Fig. 1b) and roughly one in every two years under RCP8.5 (top whisker of red bar in Fig. 1b) (Supplementary Figs. 14 and 15 show corresponding spatial patterns).

Crop modelling using the weather conditions from each extreme events year projects the average barley yield losses, as shown in Fig. 2 (see Supplementary Fig. 21 for the uncertainty of yield losses). The greatest losses occur in tropical areas such as Central and South America and Central Africa (Fig. 2). In the same years, yields in temperate barley-growing areas such as Europe decrease moderately (yellow in Fig. 2) or even increase (blue and dark blue in Fig. 2), including in northern parts of the United States and Northwest Asia.

The box-and-whisker plots on the right in Fig. 2 show the global barley yield changes. Global mean barley yields decrease during extreme events years, with more severe extreme events and yield losses associated with higher emission pathways; average yield reductions during these years are −3%, −9%, −10% and −17% under RCP2.6, RCP4.5, RCP6.0 and RCP8.5, respectively. Yield impacts are thus well-matched with increases in extreme events severity (see the correlation of yield changes and severity index in Supplementary Fig. 20).

Although we assume that the current geographical distribution and area of barley cultivation is maintained, final barley production may not decrease to the same degree estimated by the weather-driven crop model if agronomic inputs, such as labour, machinery, fertilizer and irrigation, are diverted to barley production during extreme events (for example, as in Nelson et al.[28] and Iglesias et al.[29]). The contribution of these inputs is modelled in the GTAP model as the nonlinear reduction of labour and other inputs. For example, under RCP8.5, increases in labour and capital factors of production mean that a 17% mean decrease of DSSAT-modelled barley yields worldwide (Fig. 2a) corresponds to only a 15% reduction in the global barley production (see the global panel in Fig. 3; also see Supplementary Figs. 21 and 22 for national/regional barley yield/production changes).

Our economic modelling shows that global- and country-level barley supply declines progressively in more severe extreme events years (that is, under higher emissions pathways; solid bars in Fig. 3), with the largest mean supply decrease of 27–38% under RCP8.5 projected for some European countries (Belgium, the Czech Republic and Germany). Barley supply changes are not only affected by shifts in barley production, but also by international trade among countries. For example, in some net-importing countries whose domestic production decreases (for example, Brazil; see the hatched areas), trade between countries mediates the effects of changes in local production on country-specific barley supply, with an increasing share of imported barley consumed. On the other hand, depending on the magnitude of production losses, barley-exporting countries may conserve their domestic production via reduced net exports (for example, Australia; decreasing length of red hatched areas in Fig. 3) or increase their exports to meet demand in other countries (for example, the United States); however, the larger decreases in barley supply occur in countries that rely heavily on barley imports (for example, China, Japan and Belgium) because demand for such imports exceeds any increases in exports.

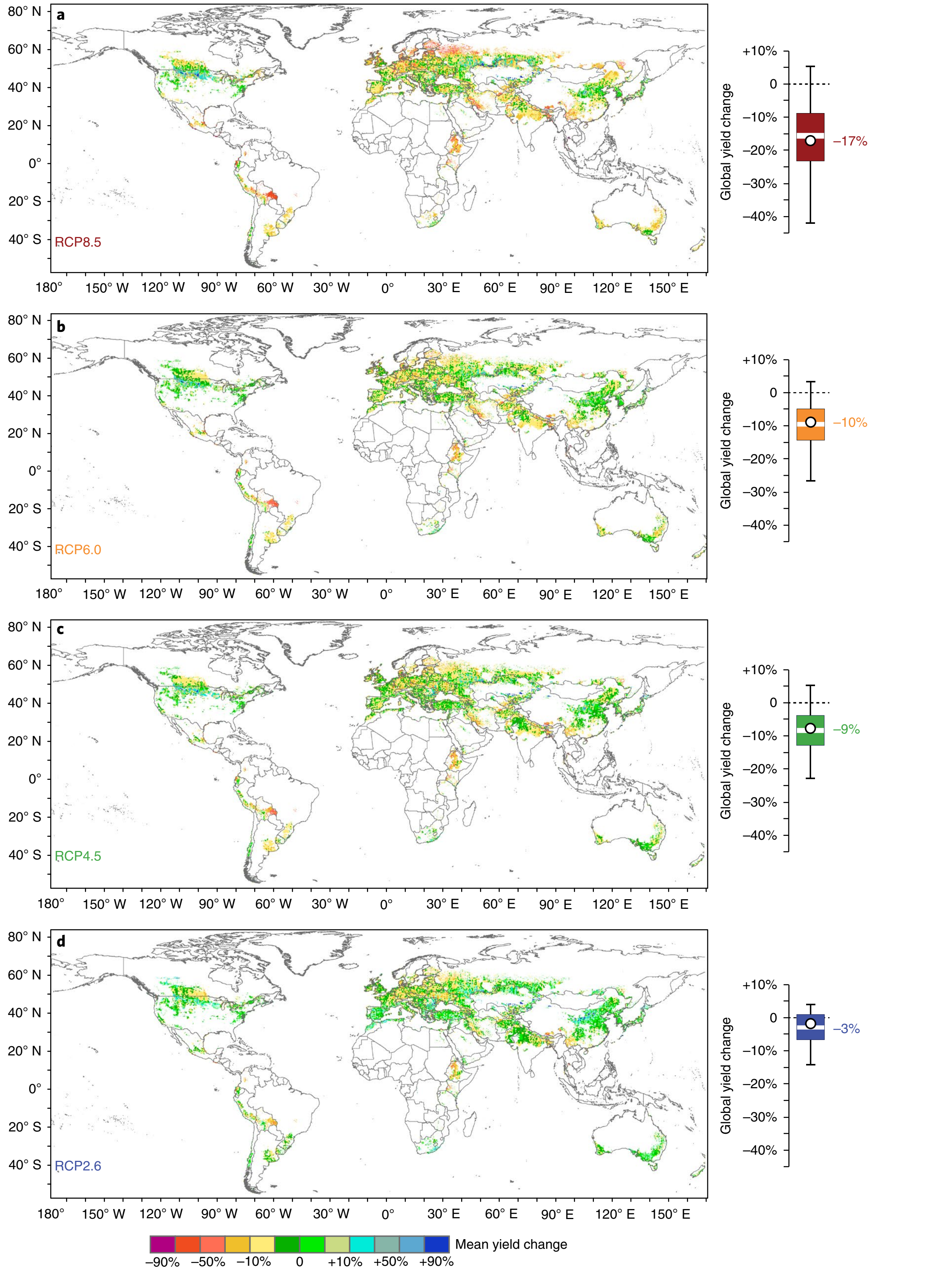

Fig. 2 | Average barley yield shocks during extreme events years. a–d, Gridded average yield change with 0.5° × 0.5° resolution across all predictions of extreme events years (left) and global aggregated change in barley yield (right) under RCP8.5 (**a**), RCP6.0 (**b**), RCP4.5 (**c**) and RCP2.6 (**d**) compared to the average yield from 1981–2010. Box-and-whisker plots to the right show the range of global changes, with white points indicating the mean; white lines the median; top and bottom of the box the 25th and 75th percentiles; and whiskers the minimum and maximum of all data ($n = 17$, 77, 80 and 139 extreme events under RCP2.6, RCP4.5, RCP6.0 and RCP8.5, respectively); dashed lines indicate no yield change. We map all grid cells where the barley harvested area exceeded 1% of the grid cell area. The grid cell barley areas are from the gridded global dataset in 2000 and combined two data products from ref. [51] and Spatial Production Allocation Model (SPAM)[52].

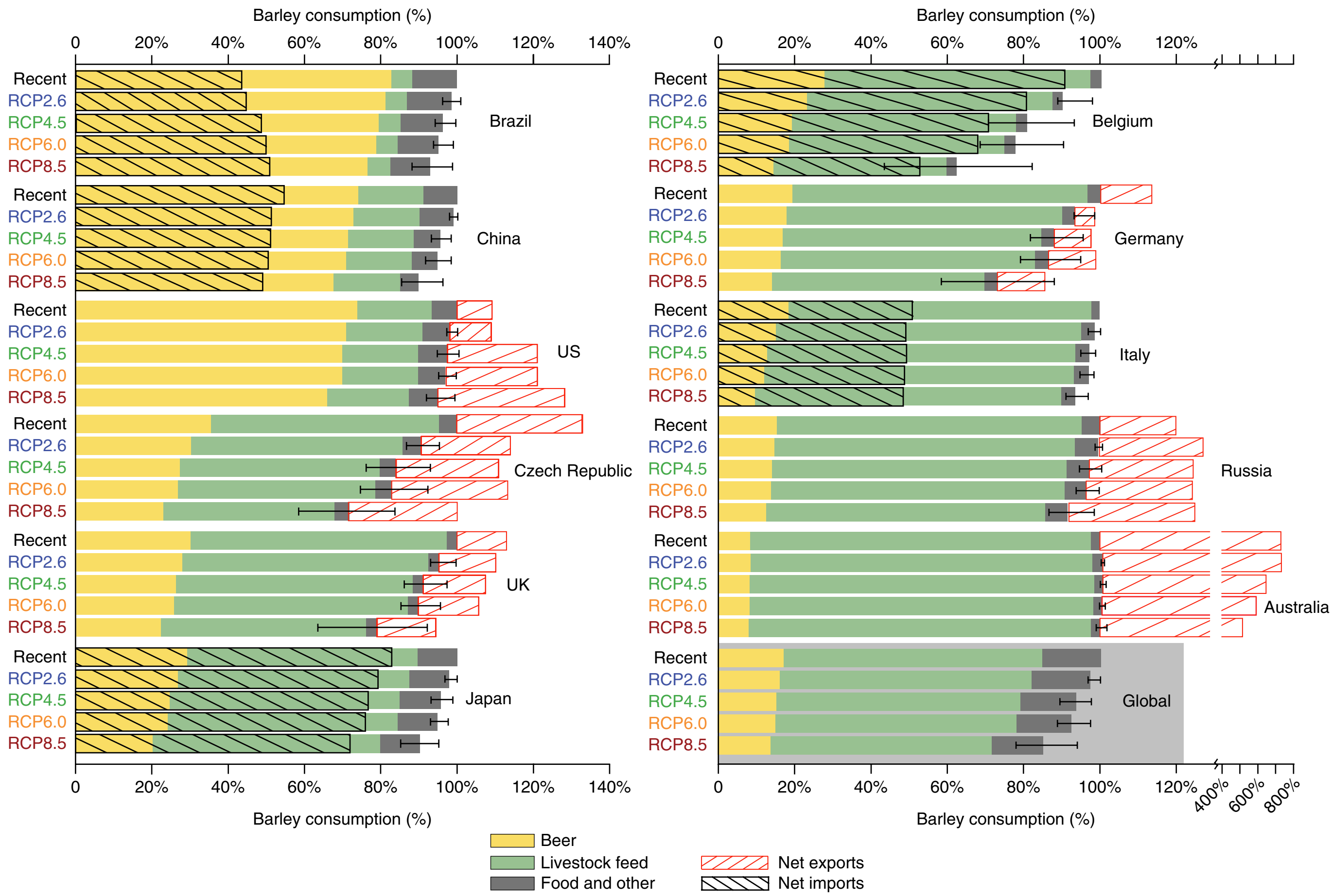

Fig. 3 | Barley consumption by country and globally under future climate change. For each country and the global aggregate, the bars show the total consumption of barley averaged over all extreme events years during 2010–2099 and the share for different barley uses. Whiskers indicate the 25th and 75th percentiles of all total consumption changes ($n=17$, 77, 80 and 139 extreme events under RCP2.6, RCP4.5, RCP6.0 and RCP8.5, respectively). The source of the shares in recent years (2011) is the improved GTAP database. The selected countries are a mix of countries that have one or more of significant barley production, consumption, export and/or import. Supplementary Figs. 24 and 25 show the absolute and relative shares for all the countries.

Changes in barley supply due to extreme events will affect the barley available for making beer differently in each region because the allocation of barley among livestock feed, beer brewing and other uses will depend on region-specific prices and demand elasticities as different industries seek to maximize profits (Fig. 3, yellow bars indicate barley allocated to the beer sector). In 2011, the beer sector consumed around 17% of global barley production but, as seen in Fig. 3, this share varied drastically across major beer-producing countries, from 83% in Brazil to 9% in Australia. Further analysing the relative changes in shares of barley use, we find that in most cases barley-to-beer shares shrink more than barley-to-livestock shares, showing that food commodities (in this case, animals fed on barley) will be prioritized over luxuries such as beer during extreme events years. At the global level, the most severe climate events (that is, RCP8.5) cause the barley supply to decrease by 15% (ranging from 6% to 22% in our uncertainty analysis over 25th–75th percentiles), but the share of barley-to-beer decreases by 20% (from the initial 17% of all barley to 14%). Among countries, we see that the reduction in barley consumption under RCP8.5 is greatest in Belgium (38% with uncertainty range of 18–57%), where the barley-to beer share decreases by 50% (from the initial 28% of all barley to14%). Therefore, future drought and heat events will not only lower the total availability of barley for most key countries, but will also reduce the share of barley used for beer production (see Supplementary Figs. 24 and 25 for the changes in absolute and relative shares in all countries/regions).

Global reductions in beer consumption

Ultimately, our modelling suggests that increasingly widespread and severe droughts and heat under climate change will cause considerable disruption to global beer consumption and increase beer prices (Supplementary Figs. 26 and 27). During the most severe climate events (for example, under RCP8.5), our results indicate that global beer consumption would decline by 16% (0–41%) (roughly equal to the total annual beer consumption of the United States in 2011), and that beer prices would, on average, double (100–656% of recent prices). Even in less severe extreme events (for example, those occurring under RCP2.6 simulations), global beer consumption drops by 4% (0–15%) and prices jump by 15% (0–52%).

Figure 4 shows, for each RCP, ten key countries according to changes in total beer consumption by volume (Fig. 4a–d), changes in the price of beer (Fig. 4e–h) and changes in the per-capita consumption of beer (Fig. 4i–l) (see percentage changes for all main beer-consuming countries in Supplementary Figs. 26–28 and absolute changes in Supplementary Figs. 30–32). For comparison, consumption data from ten key countries in recent year (2011) are shown in Fig. 5 (see Supplementary Figs. 3–5 for additional details). Total beer consumption decreases most under climate change in the countries that consume the most beer by volume in recent year (2011) (Fig. 4a). For example, the volume of beer consumed in China—the largest consuming country by volume (Fig. 5a)—decreases by more than any other country as the severity of extreme events increases (we model a decrease in consumption in China

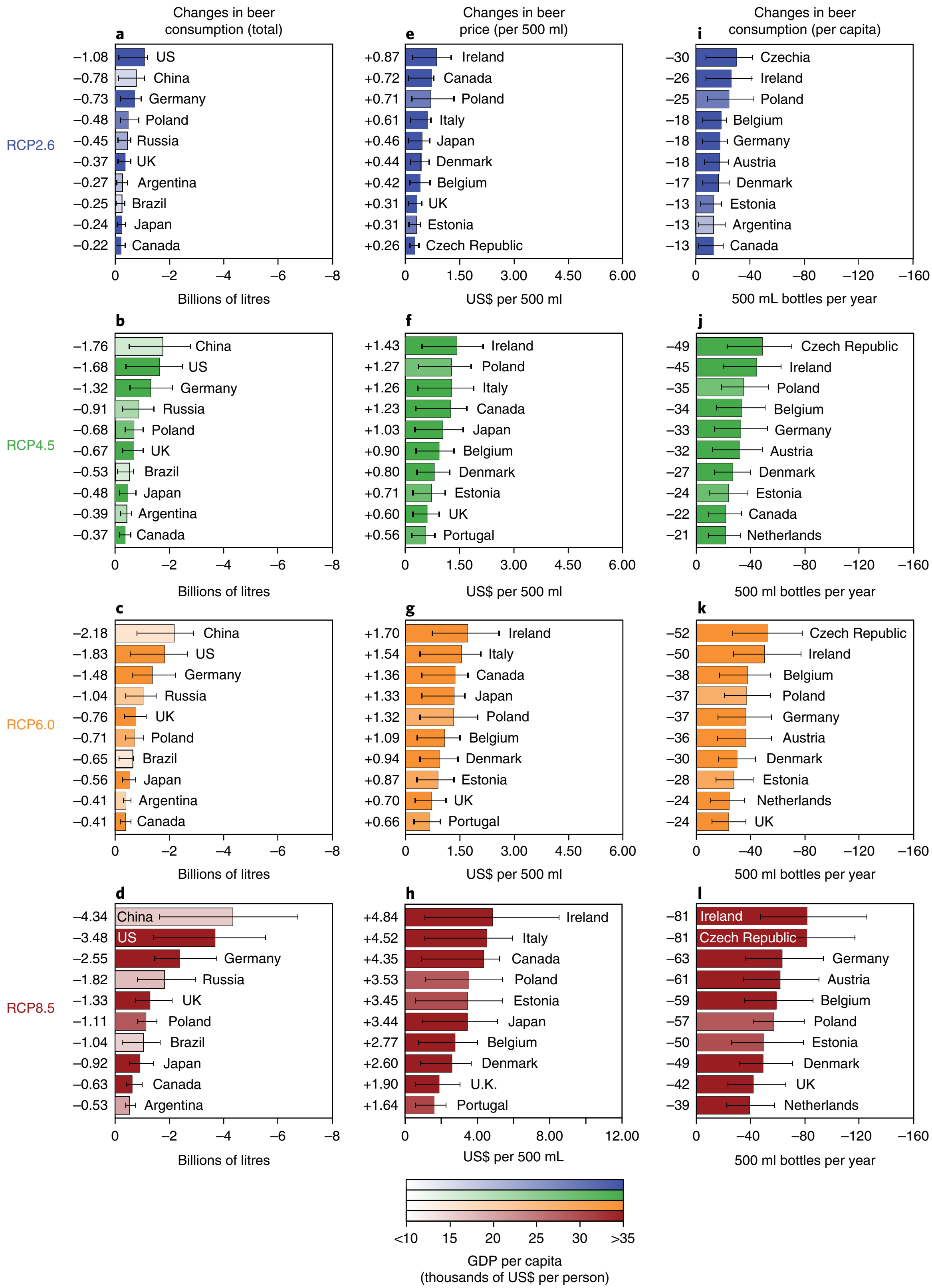

Fig. 4 | Changes in beer consumption and price under increasingly severe drought-heat events. Each column presents the results for the ten most affected countries in the regional aggregation of this study. **a–d**, Absolute change in the total volume of beer consumed. **e–h**, Change in beer price per 500 ml. **i–l**, Change in annual beer consumption per capita. The severity of extreme events increases from top to bottom. The length of the bars for each RCP shows average changes of all modelled extreme events years from 2010 to 2099, which are shown to the left of each bar, and the colours of the bars represent per-capita gross domestic product (see colour scale). Whiskers indicate the 25th and 75th percentiles of all changes (n = 17, 77, 80 and 139 extreme events under RCP2.6, RCP4.5, RCP6.0 and RCP8.5, respectively; see percentage changes with full range for all main beer-consuming countries in Supplementary Figs. 26–28; absolute changes in Supplementary Figs. 30–32).

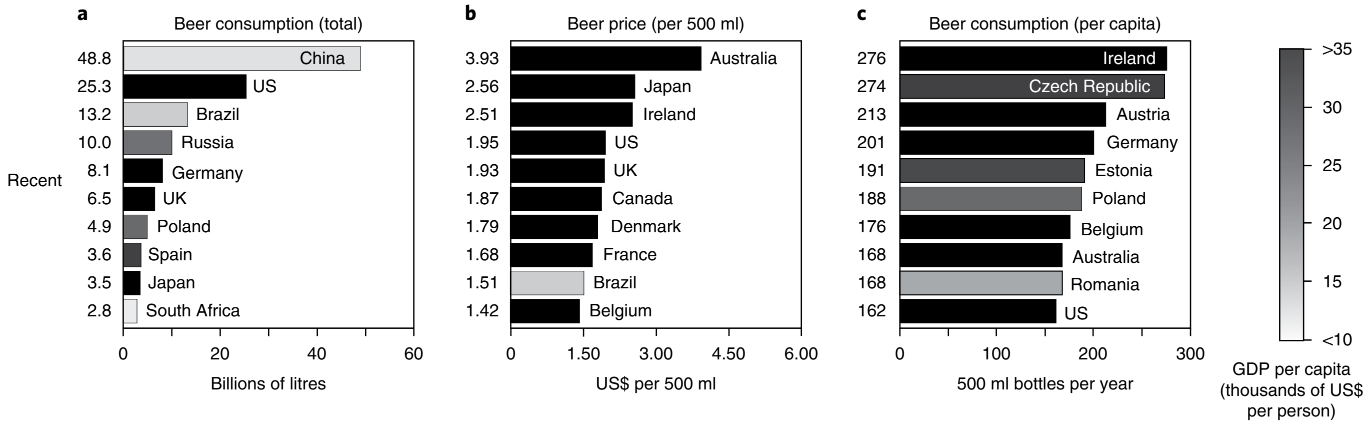

Fig. 5 | Beer consumption and price in recent years. a–c, Each column presents the recent levels for the top ten countries in the regional aggregation of this study by total volume of beer consumed in 2011 (**a**), beer price per 500 ml in 2016 (**b**) and annual per capita beer consumption in 2011 (**c**). The corresponding values are presented to the left of each bar and the colours of the bars represent per capita gross domestic product (see colour scale). Total beer consumption and population data are from FAOSTAT (ref. [69]). The beer price was taken on 6 April 2017 from the cost of living in Numbeo's survey (www.numbeo.com).

of 8.9% under RCP8.5, equivalent to 4.34 billion litres, Fig. 4d). Meanwhile, some countries with smaller total beer consumption face prodigious reductions in their beer consumption—the volume of beer consumed in Argentina during more severe climate events (that is, RCP8.5; Fig. 4d) falls by 0.53 billion litres (0.38–0.74 billion litres), equivalent to a 32% (23–45%) reduction. Even for the least severe climate events (that is, under RCP2.6; Fig. 4a), total beer consumption in Argentina and Canada decreases by 0.27 billion litres (0.03–44 billion litres), equivalent to 16% (2–27%) and 0.22 billion litres (0.03–34 billion litres), equivalent to 11% (2–17%), respectively.

Countries where beer is currently most expensive (for example, Australia and Japan) are not necessarily where future price shocks will be the greatest (Fig. 4e–h and Fig. 5b). Changes in the price of beer in a country relate to consumers' ability and willingness to pay more for beer, rather than only produce less, such that the largest price increases are concentrated in relatively affluent and historically beer-loving countries. For reference, the US$4.84 (US$1.07–8.49) increase in the price of a 500-ml bottle projected for Ireland under RCP8.5 is equivalent to a price hike of US$20.61 (US$4.55–36.15) per six-pack of 355 ml beer, that is, an increase of about 193% (43–338%) from the average pre-event price (Fig. 4h).

At the level of individuals in each country, the greatest reductions tend to better align with those countries that consume the most beer per capita in recent year (2011) (Fig. 4i–l). For example, the highest levels of annual per-capita consumption in Ireland and the Czech Republic are 276 and 274 500-ml bottles, respectively (equivalent to about five bottles per week or a bit more than a six-pack per week). The projected impacts of climate change would cause a decrease in Ireland and Czech Republic of 81 (47–125) and 81 (55–117) 500 ml bottles per year under RCP8.5, respectively (Fig. 4l). Proportional but somewhat smaller absolute decreases occur in other countries, including Germany, Austria and Belgium.

Impacts of changes in mean climate

We assessed the impacts of changes in mean climate on barley yield and beer supply globally and also at specific-country levels (Supplementary Figs. 33–37). Under RCP2.6, gradual changes in temperature and precipitation slightly reduce global barley yields (Supplementary Fig. 34). Under higher warming pathways, changes in mean temperatures and precipitation substantially decrease barley yields, although not as much as during years with extreme drought and heat (Supplementary Fig. 33). In the long term, adaptation efforts might offset mean damages to barley production from climate change through changes in agronomic practices, cultivars or barley-growing areas; however, extreme events are difficult to manage under any climate regime. Although the magnitude of potential climate adaptations in the agricultural sector remains a topic of much debate[30], it is clear that extreme climatic events will pose serious supply disruptions. For example, assuming that adaptation efforts are successful in preventing yield decreases due to changes in mean climate, extreme events will still result in increasingly large production losses, and the frequency and severity of these events increase with temperature increases (Fig. 1 and Supplementary Fig. 33). Our focus is therefore on the impact of extreme events that could occur in any year.

Uncertainties and limitations

We perform a sensitivity analysis to test the relative importance of different input parameters (Supplemenary Information Section 3.6). We vary each input by ±10% in turn, observing the effect on global beer consumption. The results are shown in Supplementary Figs. 38 and 39. The efficiency with which barley is converted to beer (the 'technology' bar) has the largest effect across all emissions pathways, followed by physical shocks of, for example, drought/heat severity and stockpiling, with elasticities and other economic parameters.

Our methodological approach in this study also has some important limitations, including our use of a single crop model to estimate barley yields, and the fact that our estimates of impact are based on the current agricultural practices, global economy, population and prevailing dietary/beverage preferences.

A single crop model (DSSAT) is used to evaluate the effects of drought and heat on barley yields. The DSSAT model is known to underestimate yield damage caused by spikelet sterility and leaf senescence in droughts and heatwaves[31,32], and it neglects the possibility that pest and disease attacks could also happen concurrently[33]. However, numerous studies demonstrate model skill in reproducing historical barley yields[34–38], and an intercomparison European-focused model shows that yields projected by the DSSAT model are near the mean of nine crop models[39].

Our results reflect impacts of extreme events as though they happened in the present day. We do not assess the effect of future changes in barley agriculture, such as increases in farm productivity due to new technology; the use of different, more drought- or heat-tolerant barley cultivars; or increases in barley stockpiling (we review challenges of stockpiling barley for beer in Supplemetary Information Section 2.4). Global population and socio-economic conditions are also held constant. Further studies may incorporate these factors for a more complete picture of beer supply in the future; as a first step, we seek to isolate the effects of extreme climatic events holding all other conditions constant.

Limiting assumptions about socio-economic change is also a common approach to isolating the influence of climate change[40,41], although changes to actual future beer consumption will also be influenced by changes in economic structure, trade, income, demographic and lifestyle changes[42] in each region. Shared Socioeconomic Pathways (SSP)[43,44] project continued population and economic growth, for example in the 'middle-of-the-road' SSP2, global population increases by 35% in 2050 relative to 2010 and global gross domestic product (GDP) triples over the same period. In the countries with the greatest total beer consumption in recent years, such as China, Brazil and Russia, SSP2 projects GDP to increase by a factor of 3–6. Under such growth, per-capita beer demand is also likely to increase. Similarly, population in the countries where per-capita beer consumption is highest in recent years, such as Ireland, Belgium and Czech Republic, increases by 10–40% in SSP2, which will probably also lead to an increase in the total beer demand. Although we do not explicitly model these trends, they are likely to exacerbate the beer shortages and related price increases that we model during barley crop failures.

Conclusions

In conclusion, concurrent extremes of drought and heat can be anticipated to cause both substantial decreases in beer consumption and increases in beer price. The frequency and severity of these extreme events, which are correlated with future increases in mean surface temperature, increase under climate change. Although the effects on beer may seem inconsequential in comparison to many of the other—some life-threatening—impacts of climate change, there is nonetheless something fundamental in the cross-cultural appreciation of beer. For perhaps many millennia[45,46], and still at present for many people, beer has been an important component of social gatherings and human celebration. Although it may be argued that consuming less beer is not disastrous—and may even have health benefits—there is little doubt that for millions of people around the world, the climate impacts on beer consumption will add insult to injury.

Methods

Framework of integrated model. Our integrated model (frameworks are in Supplementary Figs. 6 and 7) links ESMs, including GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM and NorESM1-M, with a crop model (DSSAT) and a global economic model (GTAP), similar to the framework in an integrated assessment model (such as C^{3}IAM)[47]. The ESMs estimate the severity and frequency of extreme events under four scenarios (RCP2.6, RCP4.5, RCP6.0 and RCP8.5). DSSAT simulates global changes in barley yield. GTAP, which contains a detailed classification of the agricultural and food sectors, simulates the changes in global beer consumption and prices based on barley yield shocks.

Source of historical and future weather data. Historical daily weather data (1981–2010) are from the AgMERRA dataset. AgMERRA is a post-processing of the NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA) data suitable for agricultural modelling and features consistent, daily time-series data. The dataset substantially improves the representation of daily precipitation distributions of extreme events[48].

For future years (2010–2099), the original climate scenario data were extracted from output archives of five ESMs under four RCPs retrieved from the CMIP website and were interpolated into 0.5°×0.5° horizontal resolution and bias-corrected with respect to historical observations by Hempel et al.[49] to remove systematic errors. The barley growth durations data come from Sacks et al.[50]. The data of barley-planting regions are from the gridded global dataset in 2000 by combining two data products of Monfreda et al.[51] and SPAM[52].

Extreme years selected using ESMs. First, standard precipitation index (SPI)[53] and extreme degree days 30 °C+(EDD) were calculated for each grid cell (g) and each year (y) in global barley-planting regions during the growth period of barley using historical data from 1981 to 2010.

Second, the annual global barley drought index (DI) was calculated using the following equation based on the SPI:

$$\mathrm{DI}_y = \sum_{g=1}^{n} A_g \times \mathrm{SPI}_{g,y} \quad \text{when } \mathrm{SPI}_{g,y} \leq -1.0 \tag{1}$$

where A_g is the scaling factor equal to the ratio of the area for g to total area in global barley-growing regions, $\mathrm{SPI}_{g,y}$ is the standardized precipitation index for g and y, and n is the total number of grid cells containing barley.

For extreme heat, the annual global barley heat index (HI) was calculated similarly using EDD. The threshold (30 °C) is consistent with the existing literature, which shows that exposure to temperatures in excess of 30 °C is harmful to barley growth[54–56].

Third, we fitted the annual global barley drought and heat indices to Pearson-III distributions (the best universal model for describing probability distribution of extreme events[57]; see the Kolmogorov–Smirnov test in Supplementary Information Section 2.2) and used the fitted curves to derive the global barley drought index DI^{100} and heat index HI^{100} corresponding to a 1-in-100-year probability.

Next, we used the same method to calculate DI_y and HI_y for four RCPs and five ESMs for 2010–2099.

Finally, we selected extreme events years when both extreme drought ($\mathrm{DI}_y \geq \mathrm{DI}^{100}$) and extreme heat ($\mathrm{HI}_y \geq \mathrm{HI}^{100}$) occurred concurrently. Then, we calculated an integrated extreme events index (EEI_y) for the selected years based on the following equation:

$$\mathrm{EEI}_y = \begin{cases} \dfrac{\mathrm{DI}_y - \mathrm{DI}^{100}}{\mathrm{DI}^{100}} + \dfrac{\mathrm{HI}_y - \mathrm{HI}^{100}}{\mathrm{HI}^{100}} & \text{when } \mathrm{DI}_y \geq \mathrm{DI}^{100} \text{ and } \mathrm{HI}_y \geq \mathrm{HI}^{100} \\ -1 & \text{when } \mathrm{DI}_y < \mathrm{DI}^{100} \text{ or } \mathrm{HI}_y < \mathrm{HI}^{100} \end{cases} \tag{2}$$

We selected all modelled extreme events years where $\mathrm{EEI}_y \geq 0$ to simulate global barley yield using the crop model, and subsequently the beer supply and price using the economic model (details in Supplementary Information Section 2.2).

Simulation of barley yield change using DSSAT. According to the extreme events years selected, we simulated global barley yield changes due to extreme events compared with the average yield during 1981–2010 on grid level using CSM-CERES-Barley, which is part of DSSAT version 4.6[58]. DSSAT-Barley has been tested in various environments worldwide. For example, barley-specific analyses using DSSAT for the Czech Republic show that the coefficient of determination between simulated and experimental yields is 0.88[34]. Other applications in Argentina, Central Europe, Ireland and West Asia all demonstrate the reliability of CERES-Barley in different environments, with root mean squared error for yield of less than 15%[35–38]. An intercomparison European-focused model also shows that yields projected by the DSSAT model are near the mean of nine crop models[39].

We adapted the source code of DSSAT for parallel computations at a 0.5°x0.5° grid resolution on high performance computers, and then gridded formatted inputs used to drive the model, which included daily weather data, soil parameters, crop calendar data and management information. Weather data inputs for DSSAT include maximum and minimum temperatures, precipitation, total radiation and humidity, derived from the sources described above. Soil parameters (soil texture, bulk density, pH, organic carbon content and fraction of calcium carbonate for each of five 20 cm thick soil layers) were obtained from International Soil Profile Dataset (WISE)[59]; Soil parameters were allocated to each simulation grid cell based on the spatially dominant soil type taken from the Digital Soil Map of the World[60]. Soil retention and hydraulic parameters were calculated using pedotransfer functions[61]. Soil parameters for organic soils missing in the WISE dataset were adopted from ref. [62]; Crop calendar data were obtained from the Center for Sustainability and Global Environment (SAGE), which digitizes and georeferences existing observations of crop planting and harvesting dates at a resolution of 5 min[50]. This dataset provides ranges of crop planting and harvesting dates for different crops in each grid; Management information requires fertilizer applications, irrigation and other management practices. A crop-specific gridded dataset (by 5 min) of nitrogen fertilizer application for the world was used in our simulation to set up current fertilizer application rates for barley in each grid cell, with the assumption of unlimited availability of phosphorous and potash. This dataset was developed by integrating national and subnational fertilizer application data from a variety of sources[5,63,64].

First we modelled barley yields across the world during the historical period 1981–2010. Barley yield was simulated at the 0.5° × 0.5° grid scale, with two main production systems (spring barley and winter barley; see Supplementary Information Section 2.3 for details on the selection of spring and winter barley in each grid) and two water management scenarios (fully irrigated and rain-fed). Historical national barley production is aggregated from simulated gridded yield and weighted by grid cell barley areas in 2000 from the gridded global dataset by combining two data products from ref. [51] and SPAM[52]. Second, we adopted genetic parameters of specific cultivars of barley from previous works, including previous works (such as Trnka et al.[34]) for the initial parameters. However, applying parameters of a few specific cultivars on a global scale is complicated, for example cultivars from Europe may not able to germinate in tropical and semi-tropical conditions and vice versa. Given the lack of observations on the geographic distribution of cultivar traits, we tuned and calibrated model parameters related to crop genotype characteristics so that the simulated yields from 1981–2010 were comparable to the statistical data (Supplementary Figs. 17–19) following the method in Xiong et al.[65] (see details in Supplementary Information Section 2.3). Third, barley yields across the world were simulated. Fourth, global and national yields were aggregated from gridded values. Finally, changes in national/regional and global yields were calculated, as the deviation from the national/regional or global yield average for 1981–2010 (details in Supplementary Information Section 2.3).

Simulation of beer consumption and price change using GTAP. The barley yield changes from the crop model are used to carry out simulations using GTAP to investigate changes in barley production and the impact on beer production and price. GTAP is a well-known and widely used global general equilibrium economic model developed by the Department of Agricultural Economics at Purdue University[66,67]. The model assumes cost minimization by producers and utility maximization by consumers. In a competitive market setup, prices adjust until supplies and demands of all commodities equalize. The model and database have been extensively used in research areas such as climate change, food security policy, energy, poverty and migration, and so on.

Our simulations use a comparative static analysis approach to simulate the impact of climate changes on beer supply and prices under current economic conditions (for example, as in refs [40,41]). Utilizing current economic conditions has the advantage of minimizing assumptions and model uncertainties related to future economic conditions.

First, to use the GTAP model for our study, we improved the GTAP database by splitting barley and beer from existing sectors in the model. Barley was split from the 'other grains' sector and beer from the 'beverage and tobacco' sector using the routines from Splitcom[68]. In this procedure, the old flows of data at national and trade levels were allocated to the new flows using weights. The national weights included the division of each unsplit user's use of the original split commodity among the new commodities, the division of unsplit inputs to the original industry between the new industries, and the splitting of the new industry's use of each new commodity. Barley use is mainly shared between feed, food, processing and others (seed, waste, and so on)[69]. In our process, we assumed that processing was mainly covered by beer production, and so we allocated all of the 'processing' share of barley as input to the beer sector. However, we performed a sensitivity analysis for these shares to reflect the technology change (the possibility of producing more or less beer using the same quantity of barley input) in the future (Supplementary Information Section 3.6). The newly created beer sector was allocated to wholesalers/retailers, restaurants/bars and private household consumption (beer consumed as 'food' and other sectors was from FAOSTAT[69]). The proportion of beer used by the 'food' sector was allocated to three sectors—'wholesalers/retailers', 'restaurants/bars' and 'private household consumption'—based on the respective share of the original 'b_t' sector by these three sectors. The 'own use' (defined as self-use of a sector of its own output, for example seed used to sow 'barley' or electricity used by the 'electricity' sector) of barley was taken from the 'seed'; the 'own use' of beer was kept to zero because beer does not have self-use. We covered only barley-based beer in our 'beer' sector, and the beer produced from other feedstocks (wheat, corn, and so on) was placed under the 'other b_t' sector. Trade shares allocated the original slice of the split commodity into the new commodity for all elements of basic price value, tax and margin. Finally, we used the RAS method for balancing the newly created database. The values for the national shares matrix were obtained from FAOSTAT[69] (Supplementary Table 1). The trade shares matrix was calculated from the data from the UN Comtrade Database[70]. Regarding the choice of correct parameter values during the split process, we paid extra attention to the consumers' preferences (income elasticity) and consumers' response to price changes (price elasticity), as they are the main factors affecting beer demand. The values for the relevant parameters related to income elasticity and price elasticity for beer in our analysis were carefully selected based on the literature[71]. Due to their critical role in beer consumption, we also tested the sensitivity of our results to the choice of the parameter values (see Supplementary Information, section 3.6 for details).

Second, our sectoral aggregation scheme for GTAP ensured that all competing and complementing sectors for both barley and beer were present in a disaggregated form. For example, for barley, other crops compete for inputs of production, and both livestock and households on the demand side are kept (see Supplementary Information Table A1). Beer is bought locally by wholesalers/retailers (covered in the 'trade' sector), restaurants/bars (covered in 'recreational services' sector) and consumed by private consumers (represented by the default 'private households'). For regional aggregation, we kept the details for all the countries with significant barley/beer production, consumption and/or trade, both in total and per capita terms; for other counties, we aggregated as the rest of the corresponding continents (see Supplementary Information Table A2).

Third, the yield shocks for barley were incorporated into the GTAP model via changes in land-use efficiency for the land used by barley production in each region (parameter 'afe' in equation (3), the conventional method for translating yield perturbations into economic models[28,29,72]. Land-use efficiency affects both price and demand for land, as shown in equations (3) and (4).

The price of primary factor composite in each sector/region is calculated by (the following equations are in terms of percentage):

$$\mathrm{pva}_{j,r} = \sum\nolimits_{k=1}^{n} (\mathrm{SVA}_{k,j,r} \times (\mathrm{pfe}_{k,j,r} - \mathrm{afe}_{k,j,r})) \tag{3}$$

where j is the production commodity (industry), r is the region, k is the endowment commodity, pva is the firms' price of value added, pfe is the firms' price for endowment commodity k, SVA is the share of endowment commodity k in total value added and afe is primary factor augmenting technology change, specific to each sector of each region.

In the improved model, to reflect the difficulty of substitution between land and other key inputs such as labour and capital, we surveyed the existing literature in this area. The literature shows that during sudden events it is hard for industrial sectors to substitute land with other key inputs, which is reflected by the lower value of the elasticity of substitution between land and other inputs[73,74]. For barley production in the extreme events years, we therefore chose a fraction of the original value. Specifically, we changed the elasticity of substitution between endowments (ESUBVA, equation (4) and Supplementary Fig. 8) for barley to 10% of original value as suggested in previous vast literature[73,74]. Considering the uncertainty of the key parameter, we further analysed the sensitivity of the key parameters (Supplementary Information Sections 2.5 and 3.6).

The input of the endowment commodities to each region/industry is calculated by:

$$\mathrm{qfe}_{k,j,r} = -\mathrm{afe}_{k,j,r} + \mathrm{qva}_{j,r} - \mathrm{ESUBVA}_{j} \times (\mathrm{pfe}_{k,j,r} - \mathrm{afe}_{k,j,r} - \mathrm{pva}_{j,r}) \tag{4}$$

where qfe is the demand, qva is the value added and ESUBVA is the elasticity of substitution between capital/labour/land in certain industry j.

In the original GTAP model, capital and labour can move freely between production activities, while for land and natural resources such movement is largely restricted (equations (5) and (6); Supplementary Fig. 9). By default, different crops can adjust their demand for land within some margin (with transformation elasticity ETRAE = −1). However, under the drought and extreme heat conditions of the real world, people may want to ensure their food security by expanding the area for staple food crops (such as wheat) rather than for barley, resulting in a reduced barley-planted area. In this study, we made a less severe assumption that land shares will stay unchanged for barley and other competing crops, considering the total supply of land cannot expand in a short period. We assume that labour, machinery and other inputs to barley (for example, fertilizers, irrigation, and so on) can be augmented by increasing the working hours or additional investment. In our improved model, the acreage of land used for barley (or any other crops) in the normal year is still used for barley (or any other crops) during the extreme events year (ETRAE = 0).

The allocation of the sluggish endowments across sectors is

$$\mathrm{qoes}_{k,j,r} = \mathrm{qo}_{k,r} + \mathrm{ETRAE}_{k} \times (\mathrm{pm}_{k,r} - \mathrm{pmes}_{k,j,r}) \tag{5}$$

where qoes is the supply of sluggish endowment, qo is the industry output of endowment, ETRAE is the elasticity of transformation for sluggish primary factor endowments (non-positive, by definition), pm is the market price of endowment and pmes is the market price of sluggish endowment.

The composite price for sluggish endowments is

$$\mathrm{pm}_{k,r} = \sum\nolimits_{j=1}^{n} (\mathrm{REVSHR}_{k,j,r} \times \mathrm{pmes}_{k,j,r}) \tag{6}$$

where REVSHR is the share of endowment use by different industries.

Mobile endowments (capital and labour) were allowed to behave normally because they can be provided by higher investment under the extreme events (equations (7) and (8).

Allocation of mobile endowments across sectors is

$$\mathrm{qo}_{k,r} = \sum\nolimits_{j=1}^{n} (\mathrm{SHREM}_{k,j,r} \times \mathrm{qfe}_{k,j,r}) \tag{7}$$

where SHREM is the share of mobile endowment at market prices.

The composite price for mobile endowments is

$$\mathrm{pm}_{k,r} = \mathrm{VFM}_{k,j,r} / \mathrm{qfe}_{k,j,r} \tag{8}$$

where VFM is the producer expenditure on endowment valued at market prices.

We also added the changes in barley foreign trade to production for each country, thereby simulating the changes in barley supply.

Finally, for simulating the changes in beer consumption and price following changes in barley production, we considered regional differences in allocation of barley to all users (beer, feed, food and others). In a normal year, the barley shares for different uses come from FAOSTAT[69] (see Supplementary Table 1). In extreme events years and mean climate change years, barley is distributed for different uses according to the profit maximization principle. Final beer consumption for each country also contains net beer import.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The historical weather data (1981–2010) that support the analysis with ESMs in this study are publicly available online at https://data.giss.nasa.gov/impacts/agmipcf/; the future climate scenario data (2010–2099) that support the analysis with ESMs in this study are publicly available online at https://pcmdi.llnl.gov/?cmip5 and https://esgf-node.llnl.gov/projects/esgf-llnl/. The spatial data of harvest area, yield, crop calendar, irrigation portion and chemical N input for barley that support the simulation with crop model (DSSAT) in this study are publicly available at http://mapspam.info/ (SPAM) and http://www.sage.wisc.edu (SAGE); the soil data that support the simulation with crop model (DSSAT) in this study are publicly available from the WISE database (https://www.isric.online/index.php/) and the Digital Soil Map of the World (DSMW) (http://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1026564/). The data and parameters that support the economic model in this study are available from the GTAP 9 database (https://www.gtap.agecon.purdue.edu/databases/v9/default.asp), which was used under license for the current study. Data are available with permission from the GTAP Center. The other data that support splitting barley and beer from the original database GTAP 9 are publicly available at FAOSTAT (http://www.fao.org/faostat/en/#data) and from the UN Comtrade Database (https://comtrade.un.org/data). All other relevant data are available from the corresponding authors.

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Author contributions

W.Xie coordinated the study. W.Xie, D.G. and E.L. conceived the study. J.P. and E.L. conducted the ESMs analysis. W.Xiong and E.L. conducted the crop model simulations. W.Xie, T.A. and Q.C. conducted the economic analysis. W.Xie, D.G., S.J.D. and N.D.M. interpreted the final results. W.Xie, S.J.D., W.Xiong, J.P. and D.G. wrote the paper. N.D.M., T.A., Q.C., J.M. and E.L. contributed to revising the paper.

Competing interests

The authors declare no competing interests.

Additional information

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Correspondence and requests for materials should be addressed to W.Xie. or D.G. or E.L.

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Corresponding author(s): Wei Xie, Dabo Guan, Erda Lin

Reporting Summary

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Statistical parameters

When statistical analyses are reported, confirm that the following items are present in the relevant location (e.g. figure legend, table legend, main text, or Methods section).

n/a	Confirmed	
☐	☒	The exact sample size (n) for each experimental group/condition, given as a discrete number and unit of measurement
☒	☐	An indication of whether measurements were taken from distinct samples or whether the same sample was measured repeatedly
☐	☒	The statistical test(s) used AND whether they are one- or two-sided *Only common tests should be described solely by name; describe more complex techniques in the Methods section.*
☒	☐	A description of all covariates tested
☒	☐	A description of any assumptions or corrections, such as tests of normality and adjustment for multiple comparisons
☐	☒	A full description of the statistics including central tendency (e.g. means) or other basic estimates (e.g. regression coefficient) AND variation (e.g. standard deviation) or associated estimates of uncertainty (e.g. confidence intervals)
☐	☒	For null hypothesis testing, the test statistic (e.g. F, t, r) with confidence intervals, effect sizes, degrees of freedom and P value noted *Give P values as exact values whenever suitable.*
☒	☐	For Bayesian analysis, information on the choice of priors and Markov chain Monte Carlo settings
☒	☐	For hierarchical and complex designs, identification of the appropriate level for tests and full reporting of outcomes
☐	☒	Estimates of effect sizes (e.g. Cohen's d, Pearson's r), indicating how they were calculated
☐	☒	Clearly defined error bars *State explicitly what error bars represent (e.g. SD, SE, CI)*

Our web collection on statistics for biologists may be useful.

Software and code

Policy information about availability of computer code

Data collection	No software were used to collect data in this study.
Data analysis	DSSAT version 4.6; Standard GTAP Model, Version 7

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors/reviewers upon request. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Research guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:
- Accession codes, unique identifiers, or web links for publicly available datasets
- A list of figures that have associated raw data
- A description of any restrictions on data availability

The historical weather data (1981-2010) that support the simulations with Earth System Models (ESMs) in this study are publicly available online at https://data.giss.nasa.gov/impacts/agmipcf/; the future climate scenario data (2010-2099) that support the simulations with ESMs in this study are publicly available online at https://pcmdi.llnl.gov/?cmip5 and https://esgf-node.llnl.gov/projects/esgf-llnl/.

The spatial data of harvest area, yield, crop calendar, irrigation portion and chemical N input for barley that support the simulation with crop model (DSSAT) in this study are publicly available at (SPAM) http://mapspam.info/ and (SAGE) HYPERLINK "http://www.sage.wisc.edu/" http://www.sage.wisc.edu; the soil data that support the simulation with crop model (DSSAT) in this study are publicly available at WISE database (https://www.isric.online/index.php/), digital Soil Map of the World (DSMW) (http://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1026564/).
The data and parameters that support the economic model in this study are available from GTAP 9 database (https://www.gtap.agecon.purdue.edu/databases/v9/default.asp), which were used under license for the current study. Data are however available with permission of GTAP center. The other data that support splitting barley and beer from the original database GTAP 9 are publicly available at FAOSTAT (http://www.fao.org/faostat/en/#data) and UN Comtrade Database (https://comtrade.un.org/data). All other relevant data are available from the corresponding authors.

Field-specific reporting

Please select the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

☐ Life sciences ☐ Behavioural & social sciences ☒ Ecological, evolutionary & environmental sciences

For a reference copy of the document with all sections, see nature.com/authors/policies/ReportingSummary-flat.pdf

Ecological, evolutionary & environmental sciences study design

All studies must disclose on these points even when the disclosure is negative.

Study description

Beer is the most popular alcoholic beverage in the world by volume consumed, and yields of its main ingredient, barley, decline sharply in periods of extreme drought and heat. Yet, although the frequency and severity of drought and heat extremes increase substantially in range of future climate scenarios by 5 Earth System models, the vulnerability of beer supply to such extremes has never been assessed. Here, we couple a process-based crop model (DSSAT) and a global economic model (GTAP) to evaluate the effects of concurrent drought and heat extremes projected under a range of future climate scenarios.

Research sample

The historical (1981-2010) daily weather data was selected due to its suitability for agricultural modeling, featuring consistent, daily time series data. The dataset also substantially improves the representation of daily precipitation distributions of extreme events.
The climate scenario data for the future years (2010-2099) was used based on the standard practice in the field of climate change studies such as IPCC.
The economic data from GTAP was selected as this is the most commonly used and widely recognized global database for CGE simulation.

Sampling strategy

We do not use any sampling procedure to conduct our study.

Data collection

W. Xiong and J.P. extracted the following data from respective sources: AgMERRA dataset and the future climate scenario data (2010-2099) that support the simulations with ESMsw were extracted https://data.giss.nasa.gov/impacts/agmipcf/; https://pcmdi.llnl.gov/?cmip5 and https://esgf-node.llnl.gov/projects/esgf-llnl/.
The spatial data of harvest area, yield, crop calendar, irrigation portion and chemical N input for barley that support the simulation with crop model (DSSAT) were extracted from http://mapspam.info/ and (SAGE) HYPERLINK "http://www.sage.wisc.edu/" http://www.sage.wisc.edu; the soil data that support the simulation with crop model (DSSAT) in this study were collected from WISE database (https://www.isric.online/index.php/); digital Soil Map of the World (DSMW) was collected from (http://www.fao.org/land-water/land/land-governance/land-resources-planning-toolbox/category/details/en/c/1026564/).
W. Xie and T.A. downloaded the data and parameters for economic model from (https://www.gtap.agecon.purdue.edu/databases/v9/default.asp); they also extracted other data that support splitting of barley and beer from the original database GTAP 9 from FAOSTAT (http://www.fao.org/faostat/en/#data) and UN Comtrade Database (https://comtrade.un.org/data).

Timing and spatial scale

The timing of the historical analysis sample and the future projection sample ranges over 1981-2010 and 2010-2099, respectively. The spatial scale of future (2010-2099) climate scenario data, selection of extreme years and changes in barley yield change was 0.5° x0.5°horizontal resolution. The timing of the economic data was 2011 and the corresponding spatial scale was country/region at global level.

Data exclusions

No data were excluded from the analyses.

Reproducibility

Our study did not involve comparisons of treatment groups or populations so we did not employ traditional experimental design and ANOVA techniques. Therefore, replication of experimental units is not applicable to our study design. The reliability of our results was evaluated based on reported uncertainty analyses.

Randomization

We use crop model and economic supply-demand model, so randomization is not relevant.

Blinding

Ours is an integrated method including crop model and economic model, so no relationship with blinding.

Did the study involve field work? ☐ Yes ☒ No

Reporting for specific materials, systems and methods

Materials & experimental systems

n/a	Involved in the study
☒	☐ Unique biological materials
☒	☐ Antibodies
☒	☐ Eukaryotic cell lines
☒	☐ Palaeontology
☒	☐ Animals and other organisms
☒	☐ Human research participants

Methods

n/a	Involved in the study
☒	☐ ChIP-seq
☒	☐ Flow cytometry
☒	☐ MRI-based neuroimaging