Decreases in global beer supply due to extreme drought and heat

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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, despite projected increases in the frequency and severity of such extremes under future climate change, the vulnerability of beer to future climate-related disasters has never been assessed. Here, we couple five Global Climate Models (GCMs), a process-based crop model (DSSAT) and a global economic model (GTAP) to evaluate the effects of disasters (defined as concurrent drought and heat extremes) projected under a range of future climate scenarios. We find that such disasters would cause substantial decreases in barley yields worldwide, with average losses ranging from 3% to 19% depending on the severity of the conditions. In turn, these biophysical stresses would lead to similarly large decreases in global supply of barley, even larger proportional decreases in barley used to make beer, and ultimately some dramatic regional decreases in beer consumption (e.g., -37%) and increases in beer prices (e.g., +300%). Although certainly not the most concerning impact of future climate change, our findings that climate-related weather extremes may threaten the availability and economic accessibility of beer nevertheless adds insult to injury.

[200 words]

With few exceptions around the world, 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](the trend can be seen in Fig. SI-1 and Fig. SI-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 in future[7].

At the same time as 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 before such important food crops. Although some attention has been paid to the potential impacts of climate change on luxury crops 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 21st-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 Methods and in Section 2 of SI. In summary, we develop a disaster 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 (i.e. disaster severity) under climate change as projected by five different global (CMIP5) climate models. “Disaster year” is a year with concurrent extreme drought and heat (more severe than 100-year events in the historical record) during barley growing season in areas where barley is now grown that are. Among the 450 modeled years of each Representative Concentration Pathway (RCP; 2010-2099 projections in each of the five models), we identify 48, 69, 68, and 98 such disaster years in RCP2.6, RCP4.5, RCP6.0, and RCP8.5. We then model the impacts of these disasters on barley yields (the primary agricultural input to most beer[26]) in 34 world regions (most of which are individual countries) using a process-based crop model (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 model (GTAP, a computable general equilibrium model). Finally, we test the sensitivity of our results to disasters of different severities and by varying parameter settings in the economic model[27,28]. Thus, we are not assessing future changes in barley production due to changes in incremental changes in precipitation and temperatures, but rather the sudden changes in production, economic accessibility, and consumption in different countries in a year when extreme drought and heat cause crop failures. Results for the different RCPs thus do not reflect the effect of climatological changes but are rather a proxy for more widespread and severe drought-heatwave disasters. Furthermore, because such extreme disasters could occur in any future year and it is not possible to anticipate how socio-economic and agricultural systems will evolve, we analyze impacts based on the recent geographical distribution of barley crops, recent levels of economic development and structure, recent population, and recent demands for barley and beer (i.e. as of 2011, which is the latest available year of our economic model) .

Fig. 1a shows the relationship between future increases in global mean (land) surface temperatures and the index of disaster severity (i.e. the prevalence and magnitude of concurrent extreme drought and heat during barley growing season and over barley-growing regions) for each “disaster year” we identify (Fig. SI-10 shows historical trend). The positive trend is approximately linear as global mean (land) surface temperatures increase up to ~3°C, above which there is a rapid increase in disaster severity up to ~6°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 disasters projected by the climate models over the 21st century is ~11% in RCP2.6 (i.e. an emissions pathway likely to avoid 2°C of mean temperature increase during this century), increasing to ~15% in RCP4.5 and RCP6.0 (temperature increases of 3-4°C), and up to ~22% in RCP8.5 (temperature increases >4°C). Importantly, the likelihoods of disasters in the second half of the century (top of error bars in Fig. 1b) are considerably greater, with disasters occurring roughly 1 in every 5 years in RCP6.0 (top whisker of orange bar in Fig. 1b) and roughly 1 in every 3 years in RCP8.5 (top whisker of red bar in Fig. 1b) (Fig. SI-11 and Fig. SI -12 show spatial pattern).

In turn, crop modeling of each disaster year projects the average barley yield losses shown in Fig. 2 (see Fig. SI-18 for uncertainty of yield losses). The greatest losses occur in tropical and semi-tropical areas such as South Asia, central and South America and central

Africa (Fig. 2). In the same years, yields in temperate barley-growing areas such as the Europe and southeastern Australia decrease rather moderately (orange and dark yellow in Fig. 2) or even increase somewhat (light yellow and green in Fig. 2), including northern parts of the U.S. and northwest Asia.

The box-and-whisker plots at the right in Fig. 2 show the global distribution of barley yield changes. Global mean barley yields decrease during disaster years, with more severe disasters and yield losses associated with higher emission pathways; average yield reductions during these years are -3%, -7%, -8%, and -19% in RCP2.6, RCP4.5, RCP6.0, and RCP8.5, respectively. Yield impacts are thus well-matched with increases in disaster severity (See correlation of yield loss and severity index in Fig. SI-17).

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 as biophysical barley yields if agronomic inputs are diverted to barley production during disaster—labor, machinery, fertilizer, irrigation, etc. (same as Nelson 2014[27]; Iglesias 2012[29]). The contribution of these inputs is modeled in the GTAP model as the nonlinear reduction of land and other inputs. For example, under RCP8.5, increases in labor and capital factors of production mean that an 19% mean decrease of barley yields worldwide (Fig. 2a) corresponds to only a 17% reduction in the global barley production (Fig. 3, “global” panel).

However, our economic modeling shows that global- and country-level barley supply declines progressively in more severe disaster years (i.e., under higher emissions pathways; solid bars in Fig. 3), with mean consumption decreasing by 25-43% under RCP8.5 in some European countries (Belgium, Germany, Czech and U.K.). Trade between countries mediates the effects of changes in local production on country-specific barley supply, with an increasing share of imported barley being consumed in some countries whose domestic production decreases (e.g., Brazil, relative area of black hatching). On the other hand, depending on the magnitude of production losses, barley-exporting countries may conserve their domestic production via reduced net export (e.g., Australia; decreasing length of red hatches in Fig. 3), or increase their exports to meet demand in other countries (e.g., the U.S.). The domestic supply of barley in countries like the U.S. and Russia (the leading barley producers) does not change substantially, even in the most severe disaster years. The largest decreases in barley consumption occur in countries which rely heavily on barley imports (e.g., China, Japan, and Belgium), as demand for such imports exceeds any increases in exports.

Changes in barley supply due to disasters will affect the barley available for making beer somewhat differently in each region as 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 recent years, the beer sector consumes around 17% of global barley production, but as seen in Fig. 3, this share varies drastically across major beer-producing countries, for example from 83% in Brazil to 9% in Australia. Further analyzing the relative changes in shares of barley use, we find that in most cases barley-to-beer shares shrink more than do barley-to-livestock shares, lending support to our assertion that food commodities (in this case, animals fed on barley) will be prioritized over luxuries such as beer during disaster years. At the global level, the most severe disasters (i.e. RCP8.5) cause the barley supply to decrease by 17% (ranging from 9-26% in our uncertainty analysis over 25-75 percentiles), but the share of barley-to-beer decreases by 23% (from the initial 17% of all barley down to 13%). Among countries, we see that the reduction in barley consumption in RCP8.5 is greatest in Belgium (43% with uncertainty range of 25-64%), where the barley to beer share decreases by 53% (from initial 28% to final 13%). Therefore, future drought-heat disasters 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 (also see Fig. SI-21 for changes in relative percentage shares).

Ultimately, our modeling suggests that increasingly widespread and severe droughts and heat under climate change will cause considerable disruption in global beer consumption and increase beer prices. During the most severe disasters (e.g., RCP8.5), our results indicate that global beer consumption would decline by 18% (9-28%) (roughly equal to the U.S.'s total annual beer consumption in recent years), and that beer prices would on average double (140-300% of recent prices). Even in less severe disasters (e.g., those occurring in the first half of the century in RCP2.6 simulations), global beer consumption drops by 4% (1-6%) and prices jump by 16%(2-20%).

Fig. 4 shows, for each RCP, ten key countries according to changes in total beer consumption by volume (left column; Figs. 4a-4d), changes in the price of beer (middle column; Figs. 4e-4h), and changes in the per capita consumption of beer (right column; Figs. 4i-4l). For comparison, consumption data from ten key countries in recent years is shown in Fig. 5(see Fig. SI-3 to 5 for additional details). The total beer consumption decreases most under climate change in the countries that consume the most beer by volume in recent years (Fig. 4a). For example, the volume of beer consumed in China—today the largest consuming country by volume (Fig. 5a)—decreases by more than any other country as the severity of disasters increases (Figs. 4b-d). Meanwhile, some countries with smaller total beer consumption face prodigious reductions in their beer consumption: the volume of beer consumed in Argentina, Japan, and Canada decreases by 18 % (6-29%), 8 % (1-11%), and 10 % (1-15%) even in the least severe disasters (i.e. in RCP2.6; Fig. 4b), respectively, and consumption falls by 37% (32-47%) in Argentina during more severe disasters (i.e. RCP8.5; Fig. 4d).

Countries where beer is currently most expensive (e.g., Australia and Japan) are not necessarily where future price shocks will be the greatest (Figs. 4e-4h). Changes in the price of beer in a country relates to consumers' ability and willingness to pay more for beer rather than consume less, such that the largest price increases are concentrated in relatively affluent and historically beer-loving countries. For reference, the $5.95 ($1.52-9.84) increase in the price of a five-hundred-mL bottle projected for Ireland under RCP8.5 is equivalent to a price hike of $25.30 ($6.47-41.91) per 6-pack of 12-ounce beers.

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 years (Figs. 4i-4l). For example, the highest levels of annual per capita consumption, in the Czech Republic and Ireland, are today 274 and 276 five-hundred-mL bottles, respectively (equivalent to ~5 bottles per week or a bit more than a 6-pack per week). The projected impacts of climate change would cause a decrease in these countries of 25-90 bottles per year (Figs. 4i-4l). Proportional but somewhat smaller absolute decreases occur in other countries, including Germany, Austria, and Belgium.

For several reasons, the simulated disruptions in beer consumption and related price shocks during future climate disasters are likely conservative. First, we report changes in consumption and price by averaging across all years in which concurrent extreme drought and heat occur, whether such disasters are geographically narrow, occur early in the century, or whether they span multiple continents later in the century. This method averages out some of the most extreme disruptions, for example beer consumption in one RCP8.5 disaster year fell by 43% and global prices increased by a factor of 7 (see Fig. SI-23 and Fig. SI-24). Second, the crop model we use (DSSAT) is known to underestimate yield damage caused by spikelet sterility and leaf senescence under drought and heatwave[30,31], and neglects the possibility that pest and disease attacks could also happen concurrently[32]. Third, we use the future extreme weather events to predict sudden changes in beer supply and prices under current economic conditions. Shocks from these sudden disasters may be exacerbated by the impacts of changing alcohol consumption pattern in the future[33].

We assess disruptions to beer consumption assuming no socio-economic changes, and static demand for beer. Several studies have also followed the similar idea[34,35], which has the advantage of minimizing the assumptions on future economic evolution, and particularly the details of economic structure, trade, and the evolution of beer consumption due to income, demographic, and lifestyle changes in each region. Yet the Shared Socio-economic Pathways (SSPs)[36,37] project continued population and economic growth: in SSP2, global population increases by 35% in 2050 relative to 2010 and global 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 whose per capita beer consumption is highest in recent years, such as Ireland, Belgium and Czech, 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.

In conclusion, concurrent extremes of drought and heat can be anticipated to cause both substantial decreases in beer consumption and increases in beer price, and the frequency and severity of these disasters is correlated with future increases in mean surface temperature increases under climate change. Although the effects on beer may seem modest 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[38,39], and still today for many people, beer has been an important component of social gatherings and human celebration. Thus, although it may be argued that consuming less beer isn't itself disastrous—and may even have health benefits, there is nevertheless little doubt that for millions of people around the world, the climate impacts on beer consumption will add insult to injury.

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Methods

Framework of integrated model. Our integrated model (frameworks are in Fig. SI-Fig.6 and SI-Fig.7) links global climate models (GCMs, including GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, NorESM1-M) with a crop model (DSSAT) and a global economic model (GTAP). The GCMs estimate the severity and frequency of disaster years under four scenarios (RCP2. 6, RCP4.5, RCP6.0, and RCP8.5). DSSAT simulates global changes in barley yield during disaster years. GTAP, which contains a detailed classification of the agricultural and food sectors, simulates the changes in global beer consumption and prices based on barley production shocks.

Source of historical and future weather data. For historical data (1981-2010), daily weather data come from the AgMERRA dataset. The AgMERRA is a post-processing of the NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA) suitable for agricultural modeling, featuring considerable bias adjustment and integration of additional observational datasets from situ observation network and satellites[40]. The data of growth duration and planting region of barley come from FAOSTAT. For future data (2011-2099), the climate scenario data was extracted from output archives of five GCMs under four Representative Concentration Pathways (RCP2.6, RCP4.5, RCP6.0, RCP8.5) retrieved from CMIP website (http://cmip-pcmdi.llnl.gov/cmip5). The data was interpolated into 0.5°x0.5°horizontal resolution and bias-corrected with respect to historical observation by[41] to remove systematic errors.

Disaster years selected using global climate model (GCM).

First, precipitation anomalies (*ΔP*) and growing degree days 30℃+ (GDD) are calculated for each grid (‘g’) and each year (‘y’) in global barley planting region during growth period of barley (spring and winter barley) using the historical data from 1981-2010.

Second, drought is classified into four levels according to the ΔP value during growing season in each grid and each year:

light drought: $-50 < \Delta P \leq -25$;
moderate drought: $-70 < \Delta P \leq -50$;
heavy drought: $-80 < \Delta P \leq -70$;
excessive drought: $\Delta P \leq -80$.

The annual global barley drought index is calculated using the following equation:

$$\mathrm{DI_y} = \sum_{i=1}^{4} \mathrm{A_{i,y}} \times \mathrm{B_i} \tag{1}$$

where y is year; i is drought level (i=1,2,3,4 is light, moderate, heavy and excessive drought, respectively); $\mathrm{A_{i,y}}$ is the scaling factor equal to the ratio of grid amount for level i and year y in total grid amount in global barley planting region; $\mathrm{B_i}$ is the drought weight coefficient for level i (the weight coefficient equals to 1,2,3,4 when i=1,2,3,4, respectively) and $\mathrm{DI_y}$ is global barley drought index for year y.

For extreme heat, the annual global barley heat index (HI_y) is calculated using the similar method with drought index, in which heat weight coefficients are growing degree days.

Third, we fit the annual global barley drought and heat indices with Pearson-III distributions, and use the fitted curves to derive the global barley drought index DI_{100} and heat index HI_{100}corresponding to 1 in 100 year probability. Here, we get the global barley drought and heat disaster threshold values.

Next, using the same method in step 1 and 2 to calculate the global barley drought index (DI_y) and heat index (HI_y) for 4 RCPs and 5 GCMs in the future (2011-2099).

Finally, We select disaster years when both extreme drought ($DI_y \geq DI_{100}$) and extreme heat ($HI_y \geq HI_{100}$) concurrently strike in the same year. Then we calculate an integrated disaster severity index (D_y) for the selected years based on the following equation:

$$\mathrm{D_y} = \frac{\mathrm{DI_y} - \mathrm{DI_{100}}}{\mathrm{DI_{100}}} + \frac{\mathrm{HI_y} - \mathrm{HI_{100}}}{\mathrm{HI_{100}}} \tag{2}$$

All modeled disaster years where $DI_y \geq DI_{100}$ and $HI_y \geq HI_{100}$ are selected to simulate global barley yield using the crop model and subsequently beer supply and price using the economic model (details in SI section 2.2).

Simulation of barley yield change using crop model (DSSAT).

According to the disaster years selected above, we simulate global barley yield change due to disasters on gridded level by the CSM-CERES-Barley, which is part of the Decision Support System for Agrotechnology Transfer (DSSAT) version 4.6[42]. DSSAT is a process-oriented crop growth model that has been widely used over the global in evaluating interactions between environment, management, crop genotype, and crop growth.

Before feeding into the input database, we adapted the source code of DSSAT for parallel computations at a 0.5°x0.5° grid resolution on High Performance Computers (HPC), and then gridded formatted inputs used to drive the model include 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 Data set (WISE)[43]. 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 (DSMW) (FAO, 1990). Soil retention and hydraulic parameters were calculated using pedotransfer functions[44]. Soil parameters for organic soils missing in WISE data set were adopted from Boogaart et al (1998)[45].
- Crop calendar data set was obtained from the Center for Sustainability and Global Environment (SAGE). This data set is the result of digitizing and georeferencing existing

observations of crop planting and harvesting dates, at a resolution of 5' [46]. The data set 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 data set (by 5') of nitrogen, phosphorus, and potash fertilizer application for the world (around the years of 1999 or 2000) was used in our simulation to setup current fertilizer application rate for barley in each grid cell. This dataset was developed by integrating national and subnational fertilizer application data from a variety of sources[5,47,48].

Then we first model barley yields across the world during the historical period (1981-2010). Barley yield was simulated as 0.5°x0.5° grid scale, with two main production systems (spring barley and winter barley) and two water management scenarios (fully irrigated and rainfed). Historical national barley production is aggregated from simulated gridded yield, and weighted by grid cell barley areas around 2000 from the gridded global dataset by combining two data products of Monfreda et al (2008)[49] and Spatial Production Allocation Model[50]. Second, 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 (Fig. SI-13 to SI-16). Third, barley yields across the world are simulated during disaster years. Fourth, global and national yields were aggregated from gridded values. Finally, national/regional and global yield change is calculated, which is the deviation from the national/regional or global yield average of 1981-2010(details in SI section 2.3).

Simulation of beer consumption and price change using global economic model (GTAP).

The barley yield changes from the crop model are used to carry out simulations using GTAP for changes in barley production and the impact on beer production and price. GTAP is a well-know and widely used global general equilibrium economic model developed by the Department of Agricultural Economics at Purdue University[51,52]. 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 areas like climate change, food security policy, energy, poverty and migration, etc.

Our simulations use a comparative static analysis approach to simulate the impact of climate changes on beer supply and prices under current economic conditions (e.g. as in Ciscar et al., 2011[34]; Hsiang et al., 2017[35]). Utilizing current economic conditions has the advantage of minimizing assumptions and model uncertainties related to future economic conditions. For using GTAP model to realize the purpose of the study:

First, we improved the database by splitting barley and beer from existing sectors in the model.

Barley was split out from “other grains” sector and beer from “beverage and tobacco” sector using the routines from Splitcom method[53]. In this procedure, the old flows of data both at national and trade level are allocated between the new flows using weights. The national weights include 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; the splitting of new industry's use of each new commodity. Barley use is mainly shared between feed, food, processing and others (seed, waste, etc.). In our process, we assume that processing is mainly covered by beer production, so we allocate all the "processing" share of barley as input to beer sector. The newly created beer sector is allocated to wholesalers/retailors, restaurants/bars and private household consumption(we got the beer consumed by "food" and other sectors from FAO. Then the proportion of beer used by "food" sector was allocated to three sectors i.e. "wholesalers/retailors, 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, e.g., seed used to sow "barley" or electricity used by the "electricity" sector) of barely was taken from the "seed"; for beer the own use was kept to zero as beer doesn't have self-use. Moreover, we have covered only barley-based beer in our "beer" sector, while the beer produced from other feedstocks (wheat, corn etc) are placed under "otherbt" sector. Trade shares allocate 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 FAO (SI-Table 1). The trade shares matrix was calculated based on the data from UN Comtrade Database[54].

Second, our sectoral aggregation scheme for GTAP ensures that all the competing and complimenting sectors for both barley and beer are present in the most disaggregated form. For example, for barley, other crops compete for inputs of production and both livestock and households (in addition to beer production) are major users of barley (see SI Appendix Table A1). Beer is consumed locally by wholesalers/retailors (covered in "Trade" sector), restaurants/bars (covered in "Recreational services" sector), and bought by private consumers (represented by the default "Private Households"). For regional aggregation, we kept the details for all the main beer producing, consuming, and trading regions, both in volumetric and per capita terms (see SI Appendix Table A2).

Third, the yield shocks for barley were incorporated into GTAP model via changes in land use efficiency for the land used by barley production in each region (parameter "afe" in Eq. 3). Land use efficiency affects both price and demand for land in the following two equations.

Equation of Price of primary factor composite in each sector/region(The following equations are in percentage form, same here after):

$$pva(j,r) = sum(k,SVA(k,j,r) * [pfe(k,j,r) - afe(k,j,r)]) \qquad \textbf{(3)}$$

where

j = production commodity (industry) ; r = region; k = endowment commodity

pva = firms' price of value added in industry j of region r

pfe = firms' price for endowment commodity k in ind. j, region r

SVA = share of k in total value added in j in r

afe = sector/region specific average rate of primary factor k augmenting technology change

In the improved model, to reflect the difficulty of substitution between land and other key agronomic inputs like labor and capital, we surveyed the existing literate in this area. The literature shows that in case of disasters, it is hard for farmers to substitute land with other key inputs for crop production and is reflected by the lower value of the elasticity of substitution between land and the other inputs. Therefore, for barely production in the disaster years, we choose a fraction of the original value. Specifically, we changed the elasticity of substitution between endowments (ESUBVA, Eq. 4, and SI Fig. 8) for barely to a low level of original value according to previous vast literature (for details see SI section 2.4). Considering the uncertainty of the key parameter, we have further analyzed the sensitivity analysis for the key parameter (SI section 2.5 and 3.5)

Endowment commodities' input to each regions/industries:

qfe(k,j,r) = - afe(k,j,r) + qva(j,r) - ESUBVA(j) * **[**pfe(k,j,r) - afe(k,j,r) - pva(j,r)**]** **(4)**

where

qfe = demand for endowment k for use in industry j in region r

qva = value added in industry j of region r

ESUBVA = elasticity of substitution between capital/labor/land, in production of value added in j

In the original GTAP model, capital and labor can freely move between production activities, while for land and natural resources such movement is largely restricted (Eq. 5, 6; SI 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 first want to ensure their food security by expanding the area for staple food crops (like wheat) rather than that of barley, resulting in 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 can hardly expand in short time. While we assume that labor, machinery and other inputs to barley (e.g., fertilizers, irrigation, etc.) can be augmented by increasing the working hours or additional investment. So, 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) in during disaster (ETRAE = 0).

Allocation of the sluggish endowments across sectors:

qoes(k,j,r) = qo(k,r) + ETRAE(k) * [pm(k,r) - pmes(k,j,r)] **(5)**

where

qoes = supply of sluggish endowment k used by j in r

qo = industry output of commodity k in region r

ETRAE = Elasticity of transformation for sluggish primary factor endowments (non-positive, by definition)

pm = market price of commodity k in region r

pmes = market price of sluggish endowment k used by j in r

Composite price for sluggish endowments:

pm(k,r) = sum(j,PROD_COMM, REVSHR(k,j,r) * pmes(k,j,r)) **(6)**

where

REVSHR = share of endowment use by different industries

Mobile endowments (capital and labor) were allowed to behave normally as they can be provided via higher investment under the extreme event (Eq. 7, 8).

Allocation of the mobile endowments across sectors:

qo(k,r) = sum(j,PROD_COMM, SHREM(k,j,r) * qfe(k,j,r)) **(7)**

where

SHREM = share of mobile endowment k used by sector j at market prices

Composite price for mobile endowments:

$$pm(k,r) = VFM(k,j,r)/qfe(k,j,r) \quad \textbf{(8)}$$

where

VFM = Producer expenditure on endowment k by industry j in r valued at market prices

We also add 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 after experiencing the barley production change, we consider regional differences in allocation of barley to all users (beer, feed, food and others). In the normal year, barley shares to different uses come from FAO (see SI Table 1). In the disaster year, barley is distributed to different users according to the profit maximization principle. Final beer consumption for each country also contains net beer import.

Uncertainty

This study uses 5 GCMs and 4 RCPs to develop the drought and heat disasters indices and their evolution over time. There are certain limitations to each climate model, and we only assess a subset of all available models (for details see SI section 2.5 and 3.5).

Our shocks to the economic model (GTAP) were implemented by changing the land use efficiency for the land used by bartley production in each region. According to the study by Nelson et al. (2014)[27], ease of land use conversion and the substitution of land and other inputs are key differences between economic models used to assess climate change effects on agriculture. Since we held cropland area constant to baseline conditions, the other key parameter which affects barley output is the elasticity of substitution between endowments. Although many CGE models all have their roots in the Global Trade Analysis Project database and the CGE optimizing approach[50], parameterization choices can result in very different outcomes. Therefore, we also tested our results against different values (±50%) of ESUBVA parameter adopted for the analysis. The corresponding results are discussed in Supplementary Section 3.4.

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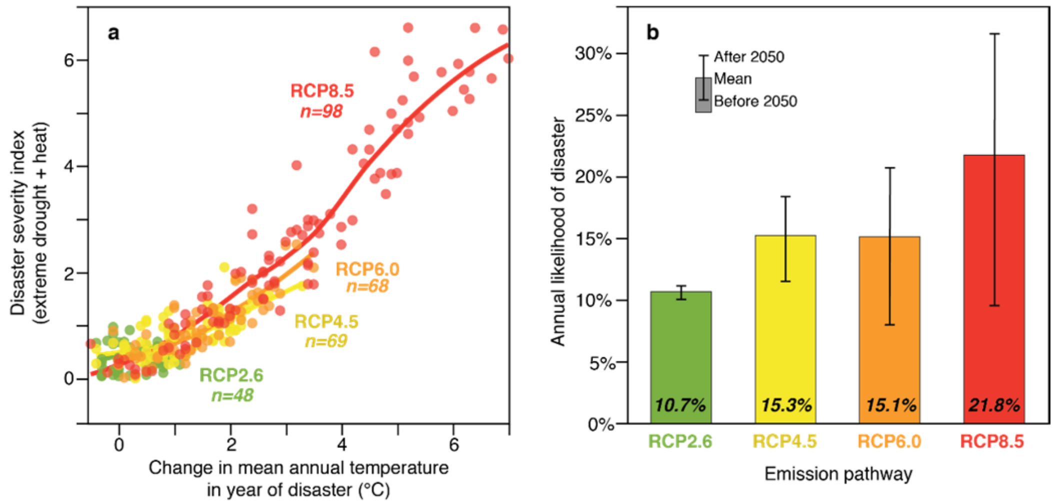

Figure 1 | Disaster severity and frequency under future climate change. a, The relationship between change in global mean (land) surface temperature in year of disaster (relative to the mean of observation from 1981-2010) and the severity of concurrent drought and heat, where the curve is binomial regression curve. **b,** Annual likelihood of a concurrent disaster under each of the Representative Concentration Pathways as projected by five CMIP5 models.

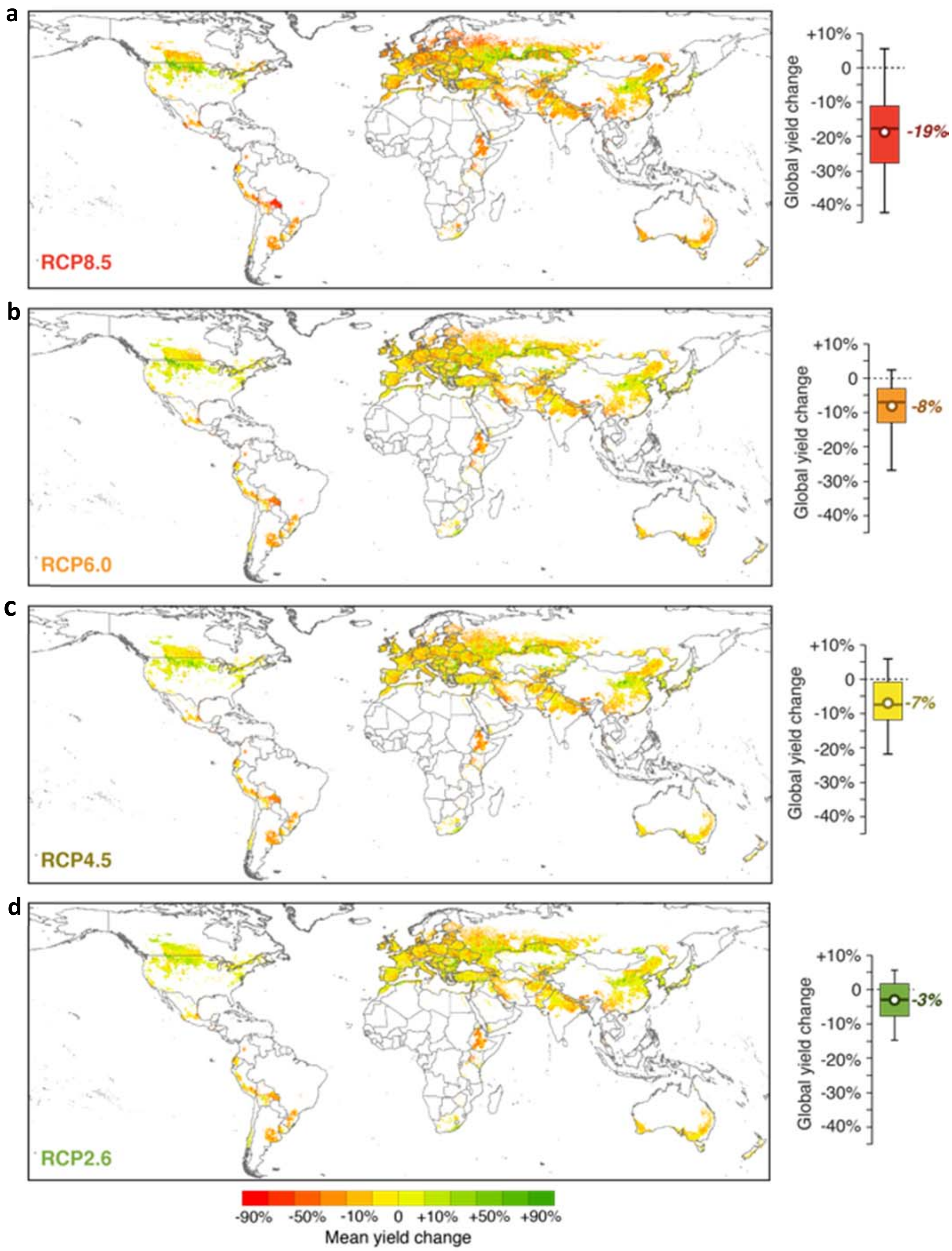

Figure 2 | Average barley yield shocks during disaster years. Gridded average yield change with 0.5°x0.5° resolution across all predictions of the disaster years (left) and global aggregated change in barley yield (right) under RCP8.5 **(a)**, RCP6.0 **(b)**, RCP4.5 **(c)** and RCP2.6 **(d)**. Box-and-whisker plots to the right show the range of global changes, with white points indicated the mean, dark lines indicating the median, top and bottoms of the box at the 25th and 75th percentiles, and whiskers indicating the minimum and maximum of all data. We map all grid cells where barley harvested area exceeds 1% of grid cell area.

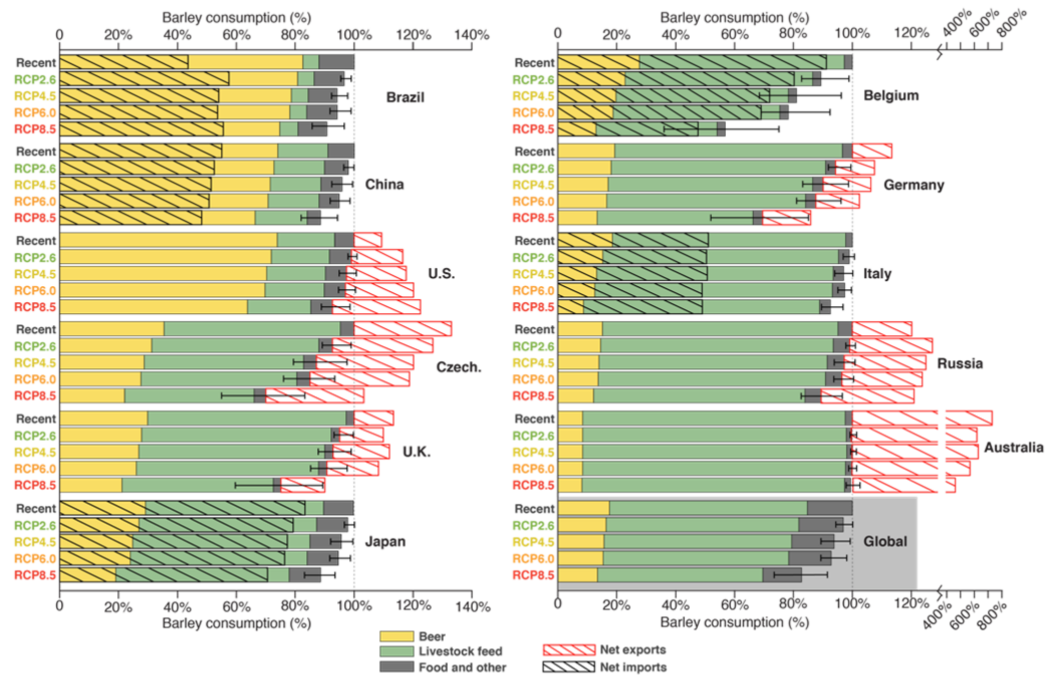

Figure 3 | Barley consumption by country and globally under future climate change. For each country and the global aggregate, the bars show the total consumption of barley averaged over all disaster years 2010-2099, and the share for different barley uses (also see Fig. SI-21 for changes in relative percentage shares). Whiskers indicate the 25th and 75th percentiles of all total consumption changes (See SI figure 20 for full range). Hatching indicates the fraction of consumption imported on net (black) and production exported on net (red), if any.

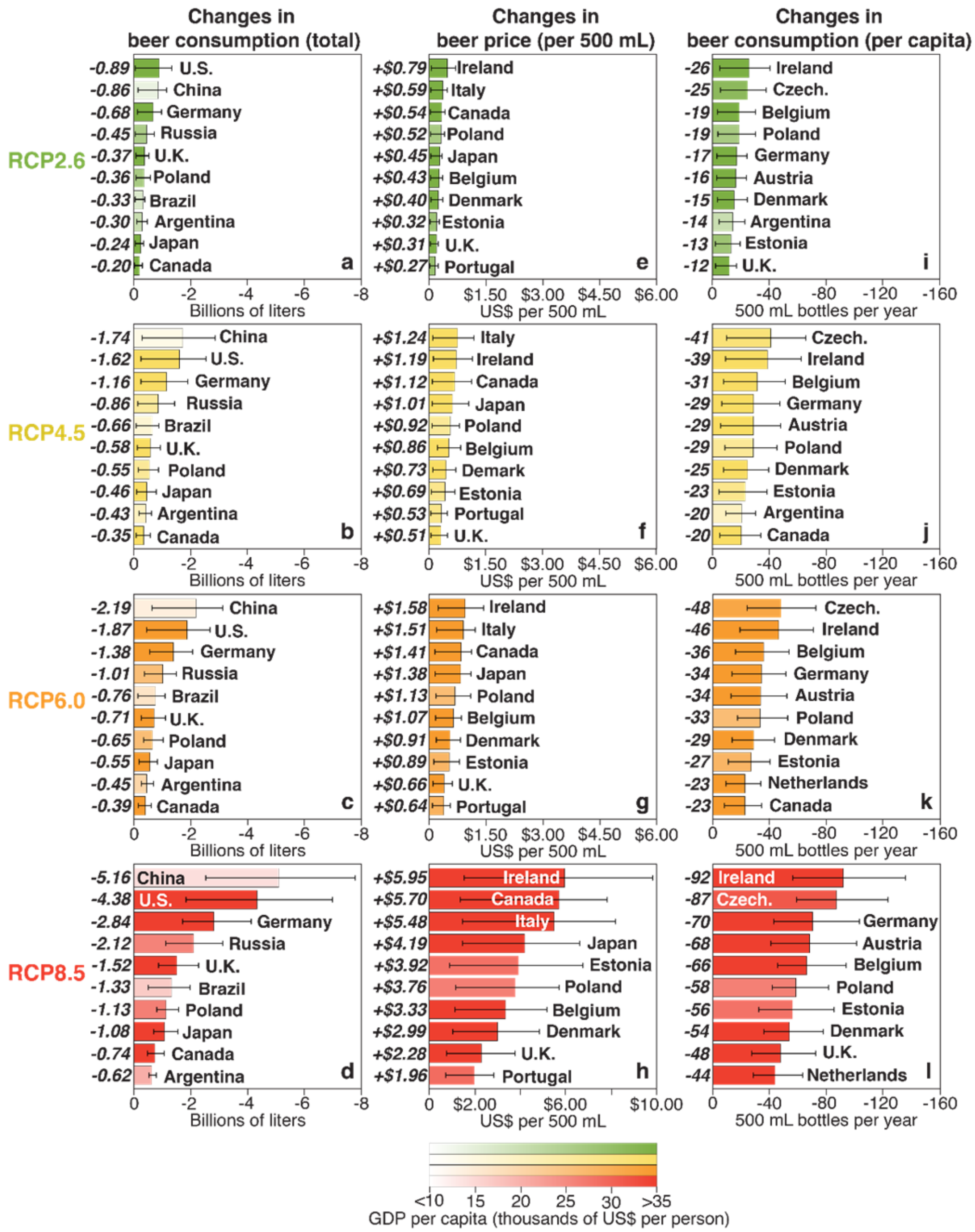

Figure 4 | Changes in beer consumption and price under increasingly severe drought-heat disasters. Key countries by absolute change in the volume of beer consumed (**a-d**), beer price (**e-h**), and beer consumption per capita (**i-l**). The severity of disasters increases from top to bottom. The length of the bars for each RCP show average changes of all modeled disaster years 2010-2099. Whiskers indicate the 25th and 75th percentiles of all changes (See SI Figure 23 and 24 for full range).

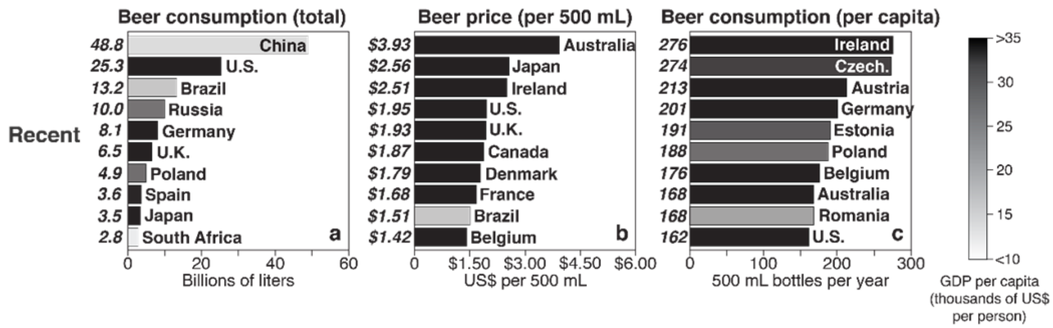

Figure 5 | Beer consumption and price in recent years. The data source of total beer consumption and population is FAOSTAT. The beer price is collected from Numbeo's survey of cost of living (www.numbeo.com).