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**Climate change is expected to impact agricultural land use. Steadily accumulating changes in temperature and water availability can alter the relative profitability of different farming activities and promote land use changes. There is also potential for high-impact 'climate tipping points' where abrupt, non-linear change in climate occurs - such as the potential collapse of the Atlantic Meridional Overturning Circulation (AMOC). Here, using data from Great Britain, we develop a methodology to analyse the impacts of a climate tipping point on land use and economic outcomes for agriculture. We show that economic/land use impacts of such a tipping point are likely to include widespread cessation of arable farming with losses of agricultural output, an order of magnitude larger than the impacts of climate change without an AMOC collapse. The agricultural effects of AMOC collapse could be ameliorated by technological adaptations such as widespread irrigation, but the amount of water required and the costs appear prohibitive in this instance.**

Tipping points can occur in elements of the climate system[1], in ecosystems[2], and in coupled social-ecological systems[3] where, often because of prior cumulative effects, a small change in drivers generates an abrupt response in a system - qualitatively changing its future state. The potential difficulties of reversing changes caused by tipping points[4] means there is a pressing need to understand their potential impacts and the extent to which such impacts can be ameliorated. However, economic assessments of the impacts of large-scale climate tipping points are rare[4-6], typically of low resolution[7], and often contested[8,9].

To address these issues, we consider a well-studied tipping point; collapse of the Atlantic Meridional Overturning Circulation (AMOC)[10,11]. The AMOC includes surface ocean currents that transport heat from the tropics to the northeast Atlantic region benefiting Western Europe, including the agricultural system of Great Britain (GB). We contrast the impacts of conventional (hereafter ‘smooth’) climate change with that of a climate tipping point involving AMOC collapse on agricultural land use and its economic value in GB, with or without a technological response. Our climate projections span 2020 to 2080 and use a mid-range climate change scenario as a baseline (Figure 1a-f; see Methods, subsequent discussion of uncertainties such as weather variability, and sensitivity analysis in Extended Data; results reported in the main paper are mean effects). We take an existing simulation of the effects of AMOC collapse[12,13] and treat it as a set of anomalies that can be linearly combined with the baseline (smooth) climate change scenario. We nominally assume AMOC collapse occurs over the time period 2030 to 2050 (Figure 1g-l; see Methods). This is a low probability fast and early collapse of the AMOC compared to current expectations[14], emphasising the idealised nature of our study and our focus on assessing impacts. That said, the AMOC has recently weakened by ~15%[15] and models may be biased to favour a stable AMOC relative to observations[16].

We predict the production decisions of individual farms at 2 km x 2 km grid resolution building upon an econometric land-use model[17] and the detailed dataset[18] employed by the Natural Environment Valuation (NEV) model, which underpinned the UK National Ecosystem Assessment[19]. Smooth changes in climate (Figure 1a-f) alter the relative profitability of agricultural products generating changes in land-use. For example, arable production is generally more profitable than grassland meat production in GB (see Extended Data Figure 1) but is limited by physical restrictions, such as topography or low temperatures. Climate change can raise temperatures, extending the area where cropping is economically viable provided that rainfall is sufficient[18]. Relative to ‘smooth’ climate change, a climate tipping point is likely to induce more abrupt land-use changes. For example, an AMOC collapse (Figure 1g-l) is expected to induce significant reductions in rainfall[20], which could rapidly shift land out of arable production[21]. A technological response to rainfall reductions in the agriculturally productive lowlands of the south and east might be to irrigate them. These climate and technological responses lead to four scenario combinations of land-use change under climate change; with or without AMOC collapse and with or without a technological (irrigation) response[22].

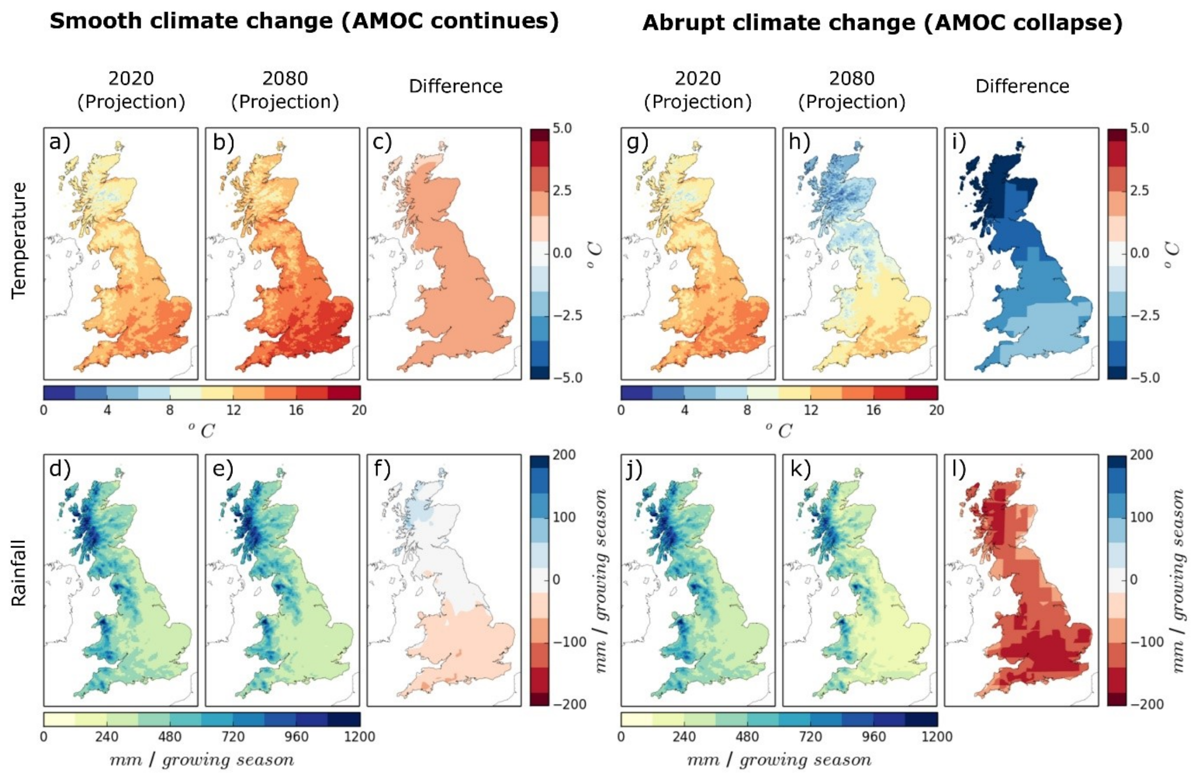


**Figure 1. Temperature and rainfall for the growing season (April to September) in 2020 and 2080.** *a) - c) Temperature in $^{o}$C under smooth climate change. g) - i) Temperature in $^{o}$C under abrupt climate change. d) - f) Rainfall in mm/growing season under smooth climate change. j) - l) Rainfall in mm/growing season under abrupt climate change. a), d), g), j) Climate data for 2020. b), e), h), k) Climate data for 2080. c), f), i), l) Difference between 2020 and 2080 climate variables; a positive (negative) value represents an increase (decrease) in 2080 compared to 2020.*

**Land use change under smooth climate change**

Figure 2a maps land-use in 2020 as predicted by the agricultural model based on a spatially explicit analysis of physical environment, climate, economic, and policy data from the 1960s to the present day, allowing for climate trends over that period. Here physical constraints and cool temperatures are expected to constrain high value arable production mainly to the lowlands of south and east GB.

Our smooth climate change scenario results in a substantial 1.9ºC mean warming in the growing season in 2080 relative to 2020 (from an average of 12.6ºC, Figure 1a, c, see Methods) together with a modest 20 mm mean decline in growing season rainfall (from an average of 445 mm, Figure 1d,f). Assuming that the AMOC is maintained then climate change is likely to induce a significant and profitable increase in the intensity of arable production across most lowland areas (Figure 2b, c, contrast with Figure 2a). These results indicate a modest increase in overall arable area, but in parts of eastern England, high temperatures and declining rainfall result in a reduction in arable production (Figure 2b). Taking these differing effects into account, overall, GB arable area rises from 32% to 36% of total agricultural area (see Extended Data Figure 2, Extended Data Figure 3), increasing agricultural output value by approximately £40million per annum by 2080 (assuming 2017/18 agricultural prices). This value may increase further if, as best estimates suggest[22,23], real (inflation adjusted) agricultural prices increase somewhat over the period as a result of climate change[23-26] and other factors[27,28].

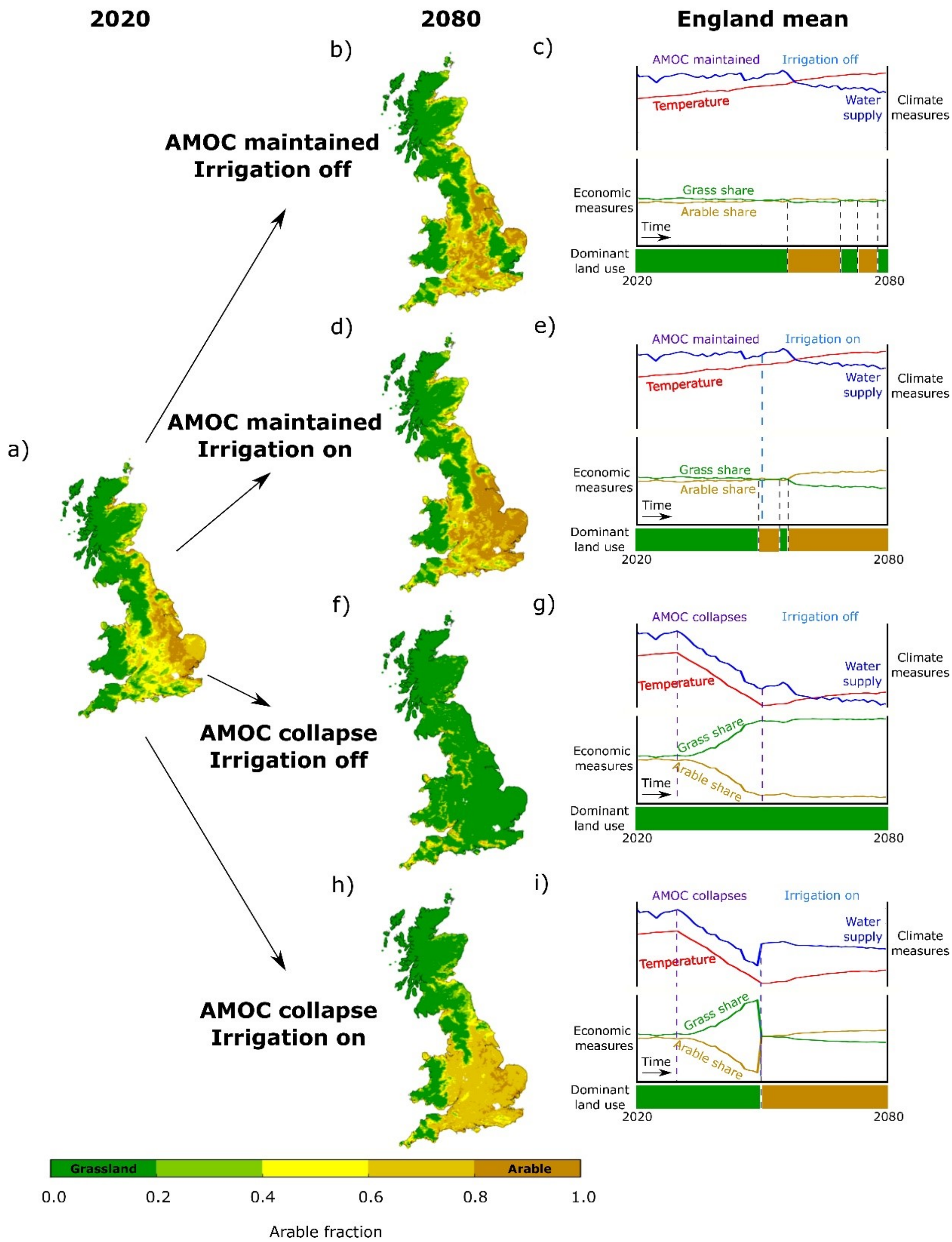


**Figure 2. Impact of smooth and abrupt climate and economic change on the share of arable farmland in 2020 and 2080.** *a) Arable farmland for 2020. b), d), f), h), arable farmland for 2080 under the four scenarios considered. c), e), g), i) Time series (England only) for mean climate and economic measures from 2020 to 2080 under the four scenarios considered. Water supply refers to the combination of rainfall and irrigation (if applicable).*

Under smooth climate change, approximately 14% of GB is likely to be rainfall-limited by 2080 (Figure 4). If this proportion was irrigated from 2050, this would lead to an even greater rise in arable area—up from 32% to 42% of total agricultural land (Figure 2d, e, Extended Data Figure 3). This generates an increase in agricultural production value of £125million per annum by 2080. The overall water requirements for such an intervention are relatively modest, with average demand across irrigated areas equivalent to approximately 18 mm of extra rainfall during the growing season. Nevertheless, recent estimates of the costs of

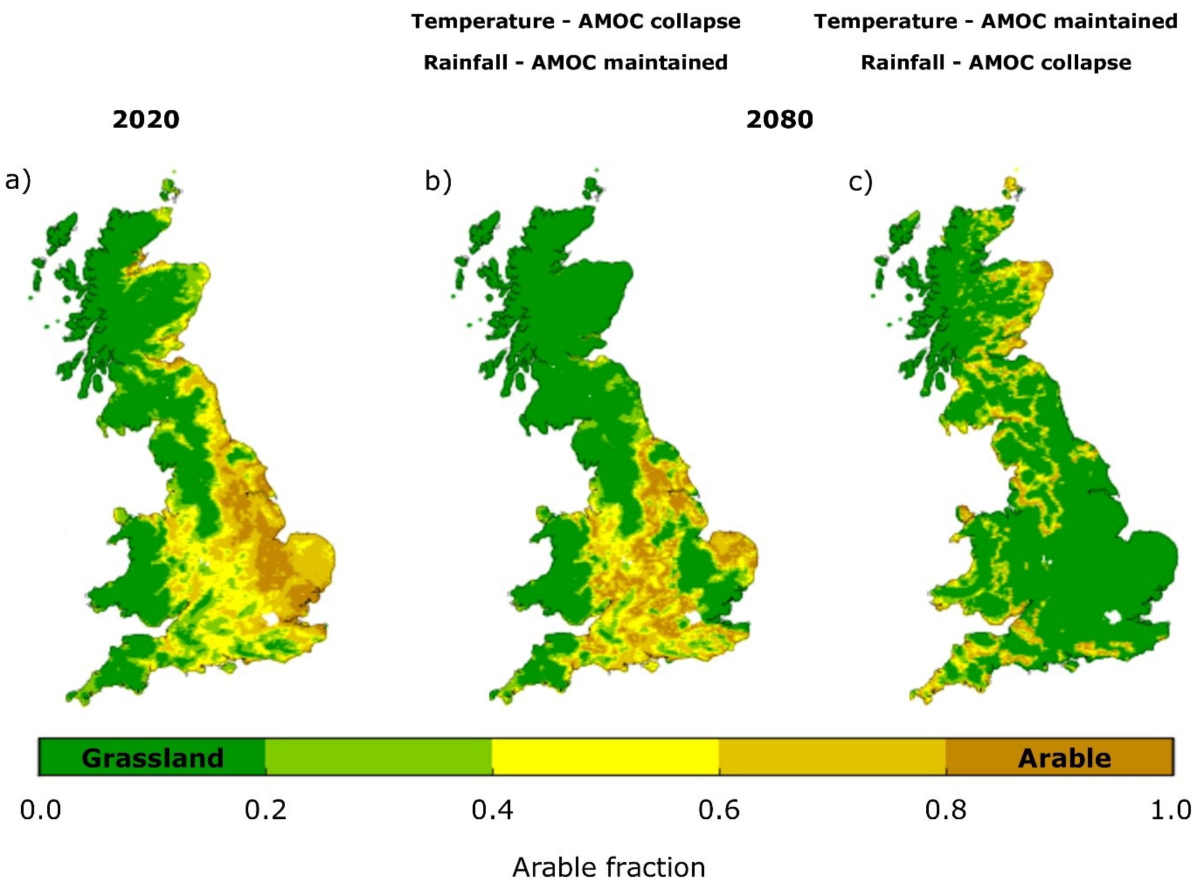


**Figure 3. Limiting factors from an AMOC collapse on the share of arable land.** *a) Arable farmland for 2020. b) Arable farmland for 2080 with temperature based on an AMOC collapse and rainfall under smooth climate change (no AMOC collapse). c) Arable farmland for 2080 with rainfall based on an AMOC collapse and temperature under smooth climate change (no AMOC collapse).*

irrigating GB wheat production[29] show that these costs exceed the value of additional production; in short, from an economic perspective, unless future arable crop prices rose sufficiently, such investment may not be worthwhile.

**Land use change under a climate tipping point**

Our remaining scenarios impose a collapse of the AMOC over the period 2030-2050 overlaid on the smooth climate change trend. A previous study that combined a rapid AMOC collapse with future climate projections demonstrated that temperatures will continue to rise globally, but with a delay of 15 years, while GB temperatures will be dependent upon the AMOC[12,30-32]. In the present study, the AMOC collapse reverses the warming seen in the smooth climate change scenarios, generating an average fall in temperature of 3.4°C by 2080 accompanied by a substantial reduction in rainfall, falling by 123 mm during the growing season (Extended Data Figure 2 and Extended Data Figure 4).

Holding real prices constant, then in the absence of a technological response (i.e. irrigation), rainfall (and to a lesser extent temperature) limitation due to AMOC collapse is predicted to affect arable farming in many areas (Figure 2f, g). The expected overall area of arable production is predicted to fall dramatically from 32% to 7% of land area (Extended Data Figure 2, Extended Data Figure 3). This in turn generates a major reduction in the value of agricultural output, falling by £346million per annum (Table 1), representing a ~10% reduction in total income from GB farming[33]. The key driver of the arable loss seen across GB is climate drying due to AMOC collapse, rather than cooling (Figure 3b, c). This adds considerably to the part of Eastern England that is already vulnerable to arable loss due to drying under baseline climate change (green band in Figures 2b, 3b). Part of eastern Scotland has a potential gain in arable production suppressed by the cooling effects of an AMOC collapse (contrast Figures 2f and 3c), but the loss of potential arable production due to cooling is small compared to the impacts of drying. However, the assumption of constant real prices is less plausible under the major global food system dislocation caused by a collapse of the AMOC. While firm estimates are not available, substantial food price increases are thought likely[22,34]. With the physical limits imposed by AMOC collapse constraining farm production, such price increases mean that wellbeing losses may be significantly higher than those calculated here, implying that our results should be viewed as lower bound, conservative estimates of the impacts of such a scenario.

| | **Smooth climate change, no technological change** | **Smooth climate change, with technological change** | **Abrupt climate change, no technological change** | **Abrupt climate change, with technological change** |
|---|---|---|---|---|
| AMOC | Maintained | Maintained | Collapse | Collapse |
| Irrigation | No | Yes | No | Yes |
| Agricultural change value (£M p.a.) | 40 | 125 | -346 | 79 |
| Irrigation cost (£M p.a.) | 0 | -284 | 0 | -807 |
| Net value change (£M p.a.) | 40 | -159 | -346 | -728 |

**Table 1. Net impact on GB agriculture of smooth versus tipping point (AMOC collapse) climate change, with and without ameliorative measures (technological response).**

With a change in technology to implement sufficient irrigation from 2050, the drying effects of the AMOC collapse on arable production could be substantially offset (Figure 2h, i). In this scenario, land area under arable production still rises from 32% to 38% by 2080 with an accompanying increase in output value of £79million per annum (Table 1, Extended Data Figure 3). Nevertheless, this increase in extent and value are lower than under the second scenario where the AMOC is maintained, due to lower temperatures (contrast Figure 2h with 2b). Furthermore, the more extreme reduction in rainfall caused by the AMOC collapse means that water required for adequate irrigation is much greater than under the scenario where the AMOC is maintained. Under the AMOC collapse scenario, 54% of GB grid cells now require irrigation, with demand exceeding 150 mm in the growing season for some areas in the south and east of England (and an average demand across irrigated areas of 70 mm of extra rainfall) (Figure 4). This would require water storage (across seasons) or spatial redistribution across the country from areas of higher rainfall in the north and western uplands of GB. Irrigation costs incurred in this scenario are estimated at over £800million per year, more than 10 times the value of the arable production it would support (see Methods). So, again, irrigation costs outweigh amelioration benefits under climate change; a difference which is massively inflated by the climate tipping point of AMOC collapse. Our analysis also indicates the level of food cost increase (nearly three-quarters of a billion pounds) necessary to justify such irrigation expenditure costs.

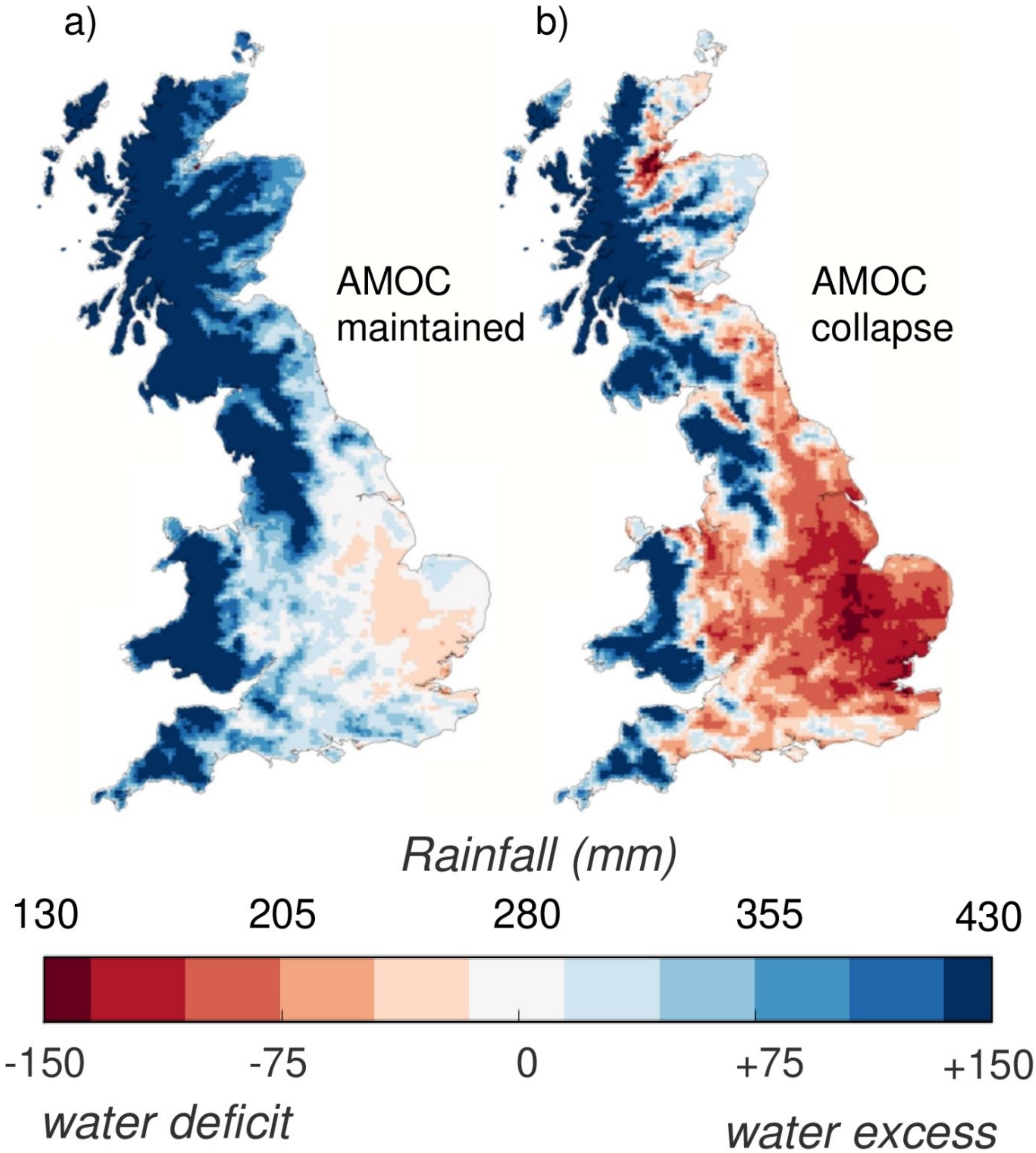


**Figure 4. GB water balance in 2080 during the growing season with irrigation available under the climate scenarios of the AMOC either maintained or collapsed.** *Water deficits (< 280 mm) during the growing season (April-September) where irrigation occurs (red) and areas with excess water (> 280 mm) (blue) during the growing season when a) AMOC is maintained or b) AMOC collapsed.*

## Future agriculture in Great Britain

Table 1 summarises results from our analysis of the impacts of both smooth and abrupt climate change upon agriculture in GB. In the absence of a climate tipping point, smooth climate change results in an elevation of temperature with modest falls in water availability. Given the cool, moist present-day conditions of GB this results in a relatively small increase in agricultural net profits (smooth climate change, no technological change). A few areas, notably in Eastern England, experience rainfall limitations but the costs of irrigation outweigh the benefits of addressing these constraints (smooth climate change, with technological change). However, the introduction of a climate tipping point in the form of an AMOC collapse removes the possibility of any positive outcome for GB agriculture. Reductions in temperature, and especially rainfall, result in major losses in the value of agricultural production (abrupt climate change, no technological change). While technological change in terms of widespread irrigation can ameliorate reductions in arable output (abrupt climate change, with technological change), in the absence of major price increases (which are plausible but uncertain) the costs of such investments dwarf the benefits they would provide.

Alongside economic uncertainties, agricultural land use, production and its value will also respond to a number of other variables including changes in farming systems[41], technology[35,36], national and international policy[37,38]. Even holding all of these factors constant, climate futures may themselves bring increased variability including more frequent weather extremes which may not be well reflected in mean temperature and rainfall trends[26,39]. A sensitivity analysis is therefore discussed in Methods with findings presented in Extended Data. This reveals substantial variability in results, however the key findings and relative comparison across our four scenarios remain. There are a number of reasons for expecting such relativities to be robust. First, while there is uncertainty between models regarding the net effect of global warming and AMOC collapse on GB temperatures, this is not the major control on arable fraction. Instead, predicted drying due to AMOC collapse is the key control and this is robust across climate models (see Extended Data Figure 5). The climate model we use is conservative in its predicted drying, but nevertheless arable production is still largely eliminated under AMOC collapse. Hence using another climate model with greater predicted drying has relatively little scope to alter this key result. The major source of uncertainty in the economic analysis concerns future prices. Under smooth climate change real prices are generally expected to increase although only modestly. For example, IPCC[23] estimate a median increase of 7.6% (range of 1 to 23%) in cereal prices by mid-century under smooth climate change. Previous analyses using the same agricultural land use model show that such price increases, if sustained, could yield similar scale effects to those induced by smooth climate change[40]. Given that potentially transformational improvements in food production technology[28] and diets could dampen these effects, overall this suggests that the estimates reported in the present paper, which assume constant real prices, should be seen as lower bound but of appropriate magnitude. There are several other expected impacts of AMOC collapse on GB that are not considered. These include harsher winters, with greater storminess, and shortening of the growing season[20,41]. These would further tend to suppress arable production and challenge farming more generally. Weather variability is expected to increase under AMOC collapse and could lead to farmers diversifying their activity. Thus, whilst we already predict a nearly complete cessation of arable farming, the overall impact of AMOC collapse on farming activity and associated income could be considerably greater than we predict.

## Conclusion

We have presented the first detailed case study of the national impacts of a climate tipping point on land-use, agricultural production and its economic value, together with an assessment of the potential for technological change to ameliorate impacts. While smooth climate change can result in major changes in land-use and accompanying economic values, we show that passing a climate tipping point has the potential to generate order-of-magnitude greater economic impacts and that even these may be lower bound estimates. Our case study concerns just one sector in one country, within which we only examine one impact of the substantial land-use changes predicted. While agricultural production is obviously important, changes in land-use generate multiple impacts; the need to understand these changes, and their impacts on further sectors and countries, underlines the importance of many more such analyses.

## Methods

### *Climate data*

Observational temperature and rainfall data from 1981-2010[42] were used to estimate the land-use model on agricultural census data (June Agricultural Census panel from EDINA). Specifically, the surface observations, provided at 5 km x 5 km resolution, are averaged over the growing seasons (April to September) and bilinearly interpolated (ignoring topography) onto the 2 km x 2 km grid cell resolution used in the agricultural census.

The projected future climate data used in the agricultural model is supplied by the Met Office Hadley Centre Regional Model Perturbed Physics Ensemble simulations for the 21st Century for the UK domain (HadRM3-PPE-UK)[43]. The runs consist of daily data that spans 1950-2100 at 25 km x 25 km resolution over the UK and forms part of the UK Climate Projections, UKCP09[44]. The ensemble is designed to simulate the regional climate over the UK for the historical and medium emissions scenario SRES-A1B[45]. In this paper, we chose the standard run, where parameters are kept at their unperturbed values, corresponding to a 3.5K global climate sensitivity and again we bilinearly interpolate the data onto the 2 km grid used for the agricultural model. The climate projections used in the agricultural model for any given year consist of the mean temperature and rainfall for the growing seasons (April to September) of the preceding 30 years. To correct for any systematic bias in the modelled climate projections the climate projections are bias corrected. The bias correction was performed by shifting the future projections by the mean bias between the modelled and observed data for 1960-1989 (the mean temperature and rainfall for 1960-1989 during the growing season is shown in Extended Data Figure 6).

For simulation of an AMOC collapse, we use data from an experiment that used the HadGEM3 model with the global configuration 2 (GC2), N216 atmospheric (~60 km) and ORCA025 ocean (~25 km)[46]. The coupled climate model simulations are a present-day control simulation and a simulation where the AMOC is collapsed using freshwater hosing after which the model is allowed to run freely[13,20]. Both runs contain seasonal mean averages for a 30-year period (again consistent with the time span used for estimation of the agricultural model) for temperature and rainfall once the model has reached steady state. Specifically, the data period 50 to 80 years after freshwater perturbations had ended were used for temperature and rainfall seasonal averages. Note the results of Mecking, et al.[13] suggest that the reduction of rainfall over the North Atlantic following the collapse reduces with time, however, this effect is believed to be negligible at GB latitudes. Extended Data Figure 4 shows the temperature and rainfall for the spring and summer (effectively exchanging September for March in the growing season) for the AMOC maintained and AMOC collapse scenarios.

Combining the difference between the HadGEM3 runs and the difference between the transient runs with the observation data we were able to simulate an idealised AMOC collapse. This is consistent with findings from Drijfhout[12], where a freshwater hosing run and a control run showed that the difference in surface air temperature after an AMOC collapse between the two runs remains approximately constant. A progressive (not instantaneous) collapse of the AMOC was simulated by applying a linear weighting function to the AMOC difference data during the prescribed years the AMOC is weakening, namely 2030-2050. It should be noted that the speed of collapse is relatively fast and the linearity assumption idealised compared to what is predicted in some models.

The subsequent cooling and drying observed following an AMOC collapse is consistent amongst models (see Extended Data Figure 5). Furthermore, the spatial pattern of greatest cooling in north west GB and least cooling in south east GB is prominent in an ensemble of freshwater hosing experiments in different climate models[48].

***Agricultural model***

The agricultural land-use model builds on the data and the econometric methodology developed by Fezzi and Bateman[17], subsequently forming an essential component of the UK National Ecosystem Assessment (e.g., Bateman, et al.[47], NEA[19]). This approach is also recently used by Fezzi and Bateman[18] to appraise the environmental impact of climate change adaptation on land-use and water quality. We use a simpler version of the model that focuses on understanding the determinants of agricultural land-use allocation between arable and grassland. While agricultural revenues change greatly with output prices, arable land is typically the highest-value agricultural activity in GB (exceptions are some very intensive dairy farms located in the South West of the country), and therefore provides a proxy for understanding the effects of climate change on the 72% of UK land area under agricultural production[33].

The land-use data are derived from the June Agricultural Census (JAC) panel from EDINA (www.edina.ac.uk), which are collected on a 2 km x 2 km grid (400 Ha) basis covering the entirety of GB for eleven unevenly spaced years from 1972 to 2010. This generates around 55,000 grid-square records per year.

The model integrates germane environmental determinants of land-use among which are climate, soil characteristics and land gradient. Crop yield is not fixed but rather is allowed to depend on climate, soils, input levels, etc. and can therefore change across space and time. So crop productivity is allowed to alter as climate changes and farmers are allowed to adapt by changing crop varieties, fertilization methods etc. What we are not changing is the bundle of crop possibilities available to farmers. So, for example, no new genetically modified crops are brought into the analysis. The approach taken, not modelling yield directly but focusing on land use via a discrete choice model, is the most established statistical land use model approach, with contributions going back to Wu and Segerson[48] and more recently Lubowski, Plantinga and Stavins[49] as well as our own exposition of the approach given in Fezzi and Bateman[5]. Recent research[50] also shows that such an approach implies underlying and theoretically consistent profit and yield functions.

To account for non-linear effects, rainfall and temperature in the growing season (April to September) are modelled using piecewise linear functions. This approach allows us to capture changes in the proportion of land allocated to arable cropping resulting from different growth factors over a range of values (cf.[18,51]). An interaction term is also included to allow the effect of rainfall to depend on the effect of temperature and vice versa[18,52]. Soil characteristics include shares of peat, (s_peat), gravel (s_gravel), stones (s_stoney), or fragipan soil (s_fragipan) and three dummy variables representing soil texture, namely share of fine, medium and coarse soils (s_fine, s_medium, s_coarse). We used data from the Harmonised World Soil Database (HWSD): a 30 arc-second (approximately 1 km resolution) raster (regular gridded) database with over 16,000 different soil mapping units[53]. Finally, we include mean altitude (elev) and slope represented as mean slope (slope), both derived from the 50 m resolution Integrated Hydrological Digital Terrain Model (IHDTM) licensed from the Centre for Ecology and Hydrology[54].

In order to address potential spatial autocorrelation, the approach in Fezzi and Bateman[5] is followed and a cell every four along both the horizontal and vertical axis is sampled. We define grassland as the sum of rough grazing, permanent grassland and temporary grassland, and arable land as the sum of cereals, oilseed rape, root crops, and all other agricultural lands. The only significant agricultural land-use category excluded from the agricultural model is rural woodland, whose expansion and contractions are mainly driven by governmental subsidies which we assume remain constant across our climate change scenarios. As described on the source data website (www.edina.ac.uk), grid square land-use estimates can sometimes overestimate or underestimate the amount of agricultural land within an area, since their collection is based on the location of the main farm house. This feature is corrected by rescaling the sum of the different agricultural land-use areas assigned to each grid square to match with the total agricultural land derived using satellite land cover data and ancillary spatial data[55] (Meridian Developed Land Use Areas, OS roads, OS railways; the National Inventory for Woodland and Trees) to locate areas that are used for agricultural production, urban activities, etc.

For policy determinants of land-use decisions the share of each grid square designated as National Park (*npark*), Environmentally Sensitive Area (*esa*) and Greenbelts (*greenbelt*) are included. Environmentally Sensitive Areas, introduced in 1987 and extended in subsequent years, were launched to conserve and enhance areas of particular landscape and wildlife significance. Digital boundary data were downloaded from Natural England[56] and the Scottish Government[57]. Spatial data for English greenbelts were licensed by Defra from the Ordinance Survey[55]. Presently, there is no national digital spatial boundary dataset for Scottish greenbelts. Each council provided information and PDF maps or ESRI shapefiles. For Wales, there is currently only one area of greenbelt (Newport and Cardiff), and its boundaries were derived from local development plans.

The dependent variable of the model is the share of agricultural land devoted to arable. We model this variable as a function of all the determinants of land-use in a reduced-form specification. After applying a logit transformation, this model can be estimated via quasi-maximum likelihood (QML)[58,59]. The estimation results are reported in Extended Data Figure 7. It can be observed that favourable environmental and topographical features (e.g. soil quality and less elevated areas), significantly increase the share of arable. It is also apparent that policy factors are in line with expectations, in this case reducing the share of arable as these reflect a greater amount of protected areas: such as for national parks. Almost all of the parameter estimates of the rainfall and temperature effects are also highly statistically significant. These non-linear impacts can also be observed in Extended Data Figure 8.

Similarly, it emerges from Extended Data Figure 8 that warmer temperatures are beneficial for arable as this promotes plant growth with the trend increasing quite rapidly at first, and then more gradually. In the full sample, higher temperature extremes can have adverse impacts, but this is based on a small number of observations with average growing season temperatures above 14ºC. For this reason, a subsample is taken as the non-linear climate effects are sensitive to the inclusion of these few observations. The estimates of all other variables are very similar regardless of basing the estimations on the full or subsample. A simple quadratic specification shows increases in predicted arable share with increasing temperature; this provides further evidence of the robustness of the study's results to the model specification.

It is also evident that higher accumulated rainfall over the growing season negatively affects arable share (e.g. from flooding or waterlogging) (Extended Data Figure 8). When all observations are used, the estimates also corroborate a downward trend of arable with respect to average rainfall of less than 300 mm but few observations exist below 290 mm. The few observations with lower rainfall levels are also those with observed higher average temperatures. However, under the smooth and abrupt (AMOC collapse) climate change scenarios we consider in this study there is a growing shift towards less rainfall in the summer and therefore the functional form requires extending below 290 mm. We apply a conservative approach by applying a linear extrapolation to the downward trend (Extended Data Figure 8). Using land cover data from the European Space Agency Climate Change Initiative[60] and average growing season rainfall values from 1988-2017 (CRU TS4.02[61]), we have provided arable share for rainfall values that go outside the range of GB data. We used the CCI-Land Cover Tools (v. 3.14) to regrid the land cover data from the original 300 m spatial resolution to the half-degree resolution of the CRU data. Two regions were selected based on comparable agricultural extent and climate with GB: US Great Plains (87W to 113W; 35N to 49N) and an area covering northern Eurasia (10W to 50E; 43N to 60N). We also include data from over the UK, which shows a similar increasing trend in arable share with lower rainfall values (above 300 mm). We define arable as rain-fed crops, including land with herbaceous, tree or shrub cover, and pasture is defined as mosaic herbaceous and grassland. The turning point estimated for GB is similar to that observed for the US Great Plains and a little lower for EurAsia (the latter might reflect differences in crop types used). In both cases the fall in arable share for rainfall below the turning point is sharper than our estimation, suggesting that we apply a conservative approach. In addition to complex rainfall patterns being more difficult to predict, there is also the issue of predicting how evenly distributed the rainfall is over the growing season. This would be interesting to explore in another study, as well as crop variations.

Our agricultural model does not explicitly account for the introduction of technological advances in the form of new crops, etc., which could also help to attenuate the negative impacts of the AMOC collapse. Effects other than temperature and rainfall, in particular $CO_2$ fertilization are not accounted for, and $CO_2$ fertilization has the potential to increase the water-use efficiency of C3 crop plants and thus reduce the corresponding irrigation demand[62]. Any agricultural model should be sensitive to prices and subsidies, and ours is no exception. Arable farm profit margins are typically higher than for beef and sheep livestocking. While dairy farms currently enjoy high per hectare margins (see the statistics in Fezzi, et al.[63]), the capital costs of moving into such production are prohibitive for most livestock farms and many small dairy farms are uneconomic[64].

***Economic analysis***

Estimates of changes in farm profitability for the four scenarios are calculated using country estimates of arable and grassland profitability. Profitability figures are taken from the Farm Business Survey (FBS)[65] for England and Wales and the Farm Business Income (FBI) survey for Scotland[57]. Arable profitability is calculated as the average profitability per hectare from cereal and general-cropping farming for a medium sized farm. Grassland profitability is dependent on whether the land is classified as being in Less Favoured Areas (LFAs). LFAs were introduced by the European Union to support farming where production conditions are difficult and are defined according to the different physical and socio-economic characteristics across the regions. LFAs are available for England in https://magic.defra.gov.uk/Dataset_Download_Summary.htm, Scotland in https://data.gov.uk/dataset/a1ba43dd-569c-47e9-9623-21664aaf49ff/less-favoured-areas. For Wales we estimate LFAs by taking the lowland areas classified in LandMap (http://lle.gov.wales/catalogue/item/LandmapVisualSensory/?lang=en). Extended Data Figure 1 shows the changes in farm profitability for farms in England, Scotland and Wales under the four scenarios. Agricultural prices and irrigation costs are fixed throughout the economic analyses assuming 2017/18 prices.

In principle, the irrigation water demands considered in our analyses could be met from either storage of water during the wetter, non-growing season, or spatial redistribution from those areas of GB with surplus rainfall. Irrigation costs are estimated using values from a recent study on the costs of irrigating wheat production in the East of England[35] which estimates total system costs for irrigation at £163.60 per hectare. Under the scenario with smooth climate and technological change, areas in GB with insufficient rainfall for arable production (14% of GB grid cells) require, on average, an additional 18 mm of rainfall in the growing season. Under a scenario with abrupt climate and technological change, areas in GB that require irrigation (54% of grid cells), require an additional 70 mm in the growing season. To meet this latter shortfall, water could be redistributed across the country from areas that do not require irrigation—there is an average excess (after use) of 167 mm of rainfall in the growing season in these areas. This equates to a positive difference of 39 mm across GB: in other words, there is sufficient rainfall within GB to meet all irrigation needs. However, as discussed in the main text, the costs of these technological interventions dwarf the benefits they would provide (Table 1).

***Sensitivity analysis***

We performed a sensitivity analysis to assess the impact the climate variables (temperature and rainfall) have on arable share. Extended Data Figure 2 provides the lower and upper quartiles of the temperature and rainfall for selected years, over the previous 30 years (as used in the agricultural model). Using the different combinations of the lower and upper quartiles of the temperature and rainfall, together with the means used in the original analysis, we generate eight additional arable fraction values. The ranges of these outputs are displayed in Extended Data Figure 2 and Extended Data Figure 9 for the different scenarios.

The ranges of arable fractions suggest that the ranking of the scenarios is consistent when compared to the ranking obtained using the means. The worst scenario for the arable fraction remains the abrupt climate with no technological change which drops from a range of 19% - 34% in 2020 to 3% - 16% by 2080. The best scenario remains the smooth climate with technological change which increases from 19% - 34% in 2020 to 28% - 52% by 2080. The results show that climate projection variance is important in determining land use outputs. The arable fraction ranges presented in Extended Data Figure 2 are wide, reflecting the uncertainty in the climate projections. This uncertainty also translates into uncertainty in the economic analysis, the economic value ranges from the sensitivity analysis are displayed in Extended Data Figure 10 for the different scenarios. Despite the wide ranges around the economic values, the patterns are still consistent with those reported in the main text, abrupt climate change generates a major reduction in the value of agricultural output, falling by £218 to £393million per annum, representing a substantial reduction in total income from GB farming. The ranges on the costs of irrigation become very wide as the upper quartile for rainfall results in lower demand for irrigation while the lower quartile results in higher demand leading to wider uncertainty about the costs of scenarios 2 and 4.

**Data Availability**

The modelled output data that support the findings of this study are openly available from Smith and Ritchie[66].

**References**


1 Lenton, T. M. *et al.* Tipping elements in the Earth's climate system. *Proceedings of the national Academy of Sciences* **105**, 1786-1793 (2008).

2 Scheffer, M., Carpenter, S., Foley, J. A., Folke, C. & Walker, B. Catastrophic shifts in ecosystems. *Nature* **413**, 591 (2001).

3 Milkoreit, M. *et al.* Defining tipping points for social-ecological systems scholarship—an interdisciplinary literature review. *Environmental Research Letters* **13**, 033005 (2018).

4 Lenton, T. M. & Ciscar, J.-C. Integrating tipping points into climate impact assessments. *Climatic Change* **117**, 585-597 (2013).

5 Kopp, R. E., Shwom, R. L., Wagner, G. & Yuan, J. Tipping elements and climate–economic shocks: Pathways toward integrated assessment. *Earth's Future* **4**, 346-372 (2016).

6 Vaughan, D. G. & Spouge, J. R. Risk estimation of collapse of the West Antarctic Ice Sheet. *Climatic Change* **52**, 65-91 (2002).

7 Boulton, C. A., Allison, L. C. & Lenton, T. M. Early warning signals of Atlantic Meridional Overturning Circulation collapse in a fully coupled climate model. *Nature communications* **5**, 5752 (2014).

8 Link, P. M. & Tol, R. S. Estimation of the economic impact of temperature changes induced by a shutdown of the thermohaline circulation: an application of FUND. *Climatic Change* **104**, 287-304 (2011).

9 Tol, R. S. The economic effects of climate change. *Journal of economic perspectives* **23**, 29-51 (2009).

10 Hofmann, M. & Rahmstorf, S. On the stability of the Atlantic meridional overturning circulation. *Proceedings of the National Academy of Sciences* **106**, 20584-20589 (2009).

11 Rahmstorf, S. *et al.* Exceptional twentieth-century slowdown in Atlantic Ocean overturning circulation. *Nat Clim Change* **5**, 475 (2015).

12 Drijfhout, S. Competition between global warming and an abrupt collapse of the AMOC in Earth's energy imbalance. *Sci Reports* **5**, 14877 (2015).

13 Mecking, J., Drijfhout, S., Jackson, L. & Graham, T. Stable AMOC off state in an eddy-permitting coupled climate model. *Climate dynamics* **47**, 2455-2470 (2016).

14 Stocker, T. F. *et al.* (Cambridge University Press, 2013).

15 Caesar, L., Rahmstorf, S., Robinson, A., Feulner, G. & Saba, V. Observed fingerprint of a weakening Atlantic Ocean overturning circulation. *Nature* **556**, 191-196, doi:10.1038/s41586-018-0006-5 (2018).

16 Liu, W., Xie, S.-P., Liu, Z. & Zhu, J. Overlooked possibility of a collapsed Atlantic Meridional Overturning Circulation in warming climate. *Science Advances* **3**, e1601666, doi:10.1126/sciadv.1601666 (2017).

17 Fezzi, C. & Bateman, I. J. Structural agricultural land use modeling for spatial agro-environmental policy analysis. *American Journal of Agricultural Economics* **93**, 1168-1188 (2011).

18 Fezzi, C. & Bateman, I. The impact of climate change on agriculture: Nonlinear effects and aggregation bias in Ricardian models of farmland values. *Journal of the Association of Environmental and Resource Economists* **2**, 57-92 (2015).

19 NEA. UK National Ecosystem Assessment: Technical Report [United Nations Environmental Programme–World Conservation Monitoring Centre (UNEP-WCMC). (Cambridge, 2011).

20 Jackson, L. *et al.* Global and European climate impacts of a slowdown of the AMOC in a high resolution GCM. *Climate dynamics* **45**, 3299-3316 (2015).

21 Cook, B. I., Ault, T. R. & Smerdon, J. E. Unprecedented 21st century drought risk in the American Southwest and Central Plains. *Science Advances* **1**, e1400082 (2015).

22 Benton, T. *et al.* Environmental tipping points and food system dynamics: Main Report. (The Global Food Security Programme, UK, 2017).

23 IPCC. Climate Change and Land. (Intergovernmental Panel on Climate Change, Geneva, Switzerland, 2019).

24 Porter, J. R. *et al.* in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (eds C.B. Field *et al.*) 485-533 (Cambridge University Press, 2014).

25 Mbow, C. *et al.* Food Security in Climate Change and Land, Intergovernmental Panel on Climate Change. (Geneva, Switzerland, 2019).

26 (GFS), G. F. S. Extreme weather and resilience of the global food system. (The Global Food Security Programme, UK, 2015).

27 (WEF), W. E. F. Shaping the Future of Global Food Systems: A Scenarios Analysis. (World Economic Forum, Geneva, Switzerland, 2017).

28 Defence, M. o. Global Strategic Trends: The future starts today (sixth edition). (Development, Concepts and Doctrine Centre, Shrivenham, 2018).

29 El Chami, D., Knox, J., Daccache, A. & Weatherhead, E. The economics of irrigating wheat in a humid climate–A study in the East of England. *Agricultural Systems* **133**, 97-108 (2015).

30 Swingedouw, D. *et al.* Impact of Freshwater Release in the North Atlantic under Different Climate Conditions in an OAGCM. *Journal of Climate* **22**, 6377-6403, doi:10.1175/2009jcli3028.1 (2009).

31 Vellinga, M. & Wood, R. A. Global Climatic Impacts of a Collapse of the Atlantic Thermohaline Circulation. *Climatic Change* **54**, 251-267, doi:10.1023/a:1016168827653 (2002).

32 Jacob, D. *et al.* Slowdown of the thermohaline circulation causes enhanced maritime climate influence and snow cover over Europe. *Geophysical Research Letters* **32**, doi:10.1029/2005gl023286 (2005).

33 National Statistics. Agriculture in the United Kingdom 2017. (The Department for Environment, Food and Rural Affairs; Department of Agriculture, Environment and Rural Affairs (Northern Ireland); Welsh Assembly Government, The Department for Rural Affairs and Heritage; The Scottish Government, Rural and Environment Science and Analytical Services, 2018).

34 Nordhaus, W. & Boyer, J. (Cambridge, MA: MIT Press, 2000).

35 Dinesh, D., Campbell, B., Bonilla-Findji, O. & Richards, M. Vol. CCAFS Working Paper No. 215 (CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), Wageningen, The Netherlands, 2017).

36 Madramootoo, C. *Emerging Technologies for Promoting Food Security: Overcoming the World Food Crisis*. (Woodhead Publishing, 2015).

37 Benton, T. G., Froggatt, A., Wright, G., Thompson, C. E. & King, R. *Food Politics and Policies in Post-Brexit Britain* (Chatham House, London, 2019).

38 Challinor, A. J. *et al.* Transmission of climate risks across sectors and borders. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* **376**, 20170301, doi:doi:10.1098/rsta.2017.0301 (2018).

39 Benton, T. G., Gallani, B., Jones, C., Lewis, K. & Tiffin, R. Severe weather and UK food chain resilience. (Government Office for Science (GO-Science), London, UK, 2012).

40 Fezzi, C. *et al.* Valuing provisioning ecosystem services in agriculture: the impact of climate change on food production in the United Kingdom. *Environmental and Resource Economics* **57**, 197-214 (2014).

41 Brayshaw, D. J., Woollings, T. & Vellinga, M. Tropical and Extratropical Responses of the North Atlantic Atmospheric Circulation to a Sustained Weakening of the MOC. *Journal of Climate* **22**, 3146-3155, doi:10.1175/2008jcli2594.1 (2009).

42 Met Office. UKCP09: Met Office gridded land surface climate observations - long term averages at 5km resolution. (Centre for Environmental Data Analysis, date of citation., 2017).

43 Hadley Centre for Climate Prediction and Research. UKCP09: Met Office HadRM3-PPE UK model runs. (NCAS British Atmospheric Data Centre, date of citation., 2014).

44 Jenkins, G. UK climate projections: briefing report. (Met Office Hadley Centre, 2009).

45 Nakicenovic, N. *et al. Special report on emissions scenarios (SRES), a special report of Working Group III of the intergovernmental panel on climate change*. (Cambridge University Press, 2000).
46 Safta, C. *et al.* Global sensitivity analysis, probabilistic calibration, and predictive assessment for the data assimilation linked ecosystem carbon model. *Geoscientific Model Development (Online)*, Medium: ED; Size: p. 1899-1918 (2015).
47 Bateman, I. J. *et al.* Bringing Ecosystem Services into Economic Decision-Making: Land Use in the United Kingdom. *Science* **341**, 45-50, doi:10.1126/science.1234379 (2013).
48 Wu, J. & Segerson, K. The impact of policies and land characteristics on potential groundwater pollution in Wisconsin. *American Journal of Agricultural Economics* **77**, 1033-1047 (1995).
49 Lubowski, R. N., Plantinga, A. J. & Stavins, R. N. Land-use change and carbon sinks: econometric estimation of the carbon sequestration supply function. *Journal of Environmental Economics and Management* **51**, 135-152 (2006).
50 Carpentier, A. & Letort, E. Multicrop production models with Multinomial Logit acreage shares. *Environmental and Resource Economics* **59**, 537-559 (2014).
51 Schlenker, W. & Roberts, M. J. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences* **106**, 15594-15598 (2009).
52 Morison, J. & Morecroft, M. (Blackwell Publishing, Oxford, 2006).
53 Van Liedekerke, M., Jones, A. & Panagos, P. ESDBv2 Raster Library—A Set of Rasters Derived from the European Soil Database Distribution v2. 0. *European Commission and the European Soil Bureau Network, CDROM, EUR* **19945** (2006).
54 IHDTM. Integrated Hydrological Digital Terrain Model. (Centre for Ecology and Hydrology, 2002).
55 Ordinance Survey. Meridian 2 Developed Land Use Area. (Ordinance Survey, 2013).
56 Natural England. Digital map boundaries download. (2012).
57 Scottish Government. Scottish Government Spatial Data File Download. (2012).
58 Papke, L. E. & Wooldridge, J. M. Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of applied econometrics* **11**, 619-632 (1996).
59 Papke, L. E. & Wooldridge, J. M. Panel data methods for fractional response variables with an application to test pass rates. *Journal of Econometrics* **145**, 121-133 (2008).
60 ESA. Vol. Version 2.0 (2017).
61 Harris, I., Jones, P. D., Osborn, T. J. & Lister, D. H. Updated high-resolution grids of monthly climatic observations – the CRU TS3.10 Dataset. *International Journal of Climatology* **34**, 623-642, doi:10.1002/joc.3711 (2014).
62 Long, S. P., Ainsworth, E. A., Leakey, A. D. B., Nösberger, J. & Ort, D. R. Food for Thought: Lower-Than-Expected Crop Yield Stimulation with Rising CO<sub>2</sub> Concentrations. *Science* **312**, 1918-1921, doi:10.1126/science.1114722 (2006).
63 Fezzi, C., Rigby, D., Bateman, I. J., Hadley, D. & Posen, P. Estimating the range of economic impacts on farms of nutrient leaching reduction policies. *Agricultural Economics* **39**, 197-205, doi:10.1111/j.1574-0862.2008.00323.x (2008).
64 MacDonald, J. M. *et al.* Profits, costs, and the changing structure of dairy farming. *USDA-ERS Economic Research Report* (2007).
65 DEFRA. Farm Business Survey. (Department for Environment, Food & Rural Affairs, UK, 2018).

66 Smith, G. S. & Ritchie, P. D. L. (NERC Environmental Information Data Centre: doi.org/10.5285/e1c1dbcf-2f37-429b-af19-a730f98600f6, 2019).

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**Author contribution statement**

I.J.B. and T.M.L. designed and directed the research and P.D.L.R. and G.S.S. helped shape the research. P.D.L.R., G.S.S., K.J.D., I.J.B. and T.M.L. wrote the manuscript with C.F., C.A.B., A.B.H., A.V.G.S., J.V.M., S.H.V. and S.A.S. providing support and revisions. P.D.L.R., G.S.S. and K.J.D. planned and conducted simulations for all analyses. C.F. designed and ran the original agriculture land use model with A.R.B., B.H.D. and I.J.B. providing support. C.F. and S.H.V. further developed the agricultural land use model from a global analysis of agricultural land use by A.B.H. and A.V.G.S. The climate data was sourced and corrected for modelled bias by P.D.L.R., and J.V.M. designed and ran the AMOC climate simulations.

**Competing interest**

The authors declare no competing interests.

## Extended Data Figures

| Panel a: Changes in farm profitability for England, Scotland and Wales | | |
|---|---|---|
| **England** | **Change in Agricultural profit 2020 to 2060 (£ Million)** | **Change in Agricultural profit 2020 to 2080 (£ Million)** |
| Smooth climate, no technological change | +47 | +29 |
| Smooth climate with technological change | +82 | +114 |
| Abrupt climate, no technological change | -313 | -315 |
| Abrupt climate, with technological change | +61 | +90 |
| **Scotland** | | |
| Smooth climate, no technological change | -10 | +3 |
| Smooth climate with technological change | -10 | +3 |
| Abrupt climate, no technological change | -40 | -35 |
| Abrupt climate, with technological change | -35 | -26 |
| **Wales** | | |
| Smooth climate, no technological change | +6 | +8 |
| Smooth climate with technological change | +6 | +8 |
| Abrupt climate, no technological change | -1 | +4 |
| Abrupt climate, with technological change | +9 | +15 |
| **Total** | | |
| Smooth climate, no technological change | +43 | +40 |
| Smooth climate with technological change | +78 | +125 |
| Abrupt climate, no technological change | -354 | -346 |
| Abrupt climate, with technological change | +35 | +79 |

| Panel b: Estimates of average Farm Profitability for England, Scotland and Wales | | | |
|---|---|---|---|
| | **Arable (£ per Ha)** | ***Lowland grassland (Lowland Grazing Livestock) (£ per Ha)*** | **Upland grassland (Less Favoured Areas Grazing Livestock) (£ per Ha)** |
| **England[a]** | 351.30 | 262.30 | 222.50 |
| **Scotland[b]** | 195.00 | 141.50 | 82.60 |
| **Wales[a]** | 351.30[c] | 306.50 | 225.50 |

**Notes: [a] England and Wales farm profitability is reported as the net profits from the Farm Business Survey (FBS) 2017/2018[65]. [b] Scottish farm profitability is calculated from the Scottish farm business income (FBI): annual estimates 2016-2017[57]. [c] Farm Business Survey values are not available for arable profit in Wales, for which values from England are used. Note that this comparison excludes dairy production as this tends to be limited by the availability of high levels of capital input which in turn is heavily influenced by historic access to milk quota subsidies that have now been abandoned.**

**Extended Data Figure 1. Changes in farm profitability between 2020 and 2060 and between 2020 and 2080.**

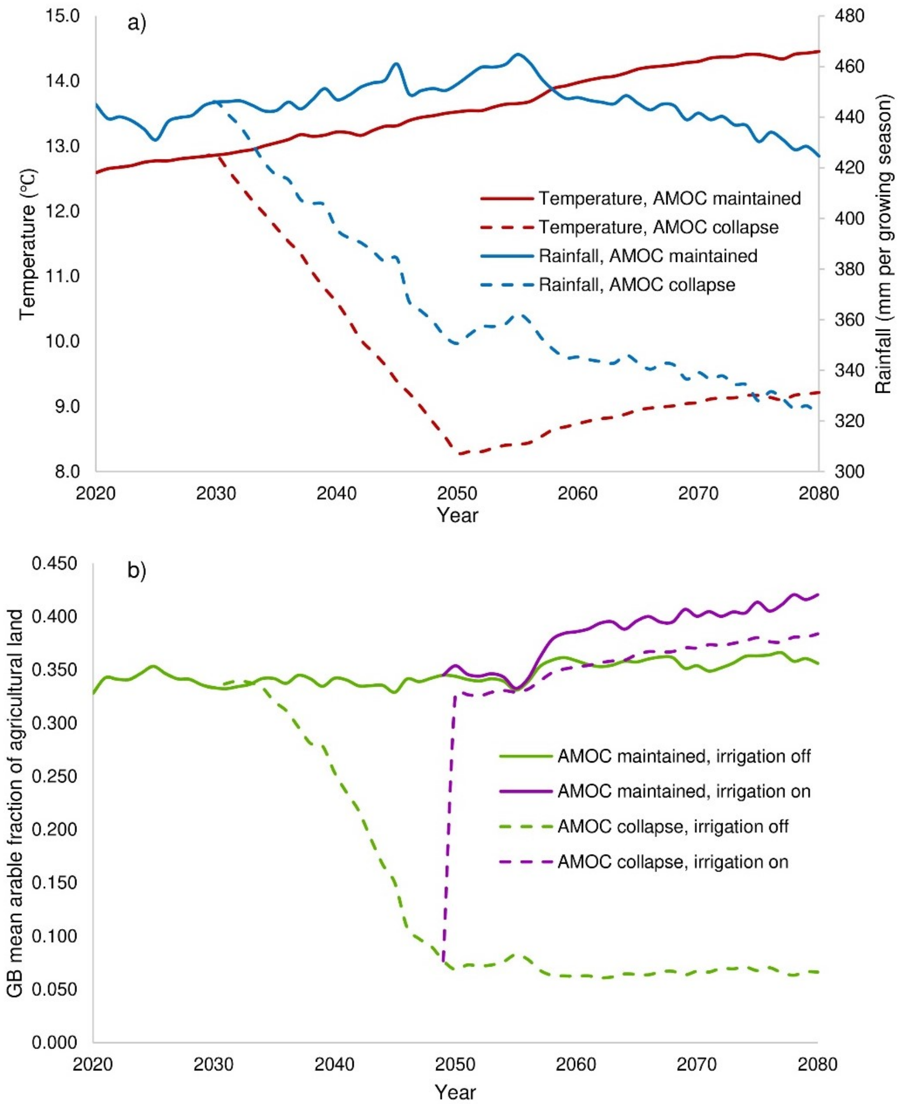
**Panel a: Mean temperature and rainfall for previous 30-year growing seasons (April-September) when the Atlantic meridional overturning circulation (AMOC) is maintained or collapses.**

| | AMOC maintained | | | | AMOC collapse | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Mean arable area (percent) | | | | Mean arable area (percent) | |
| Year | Temp ($^oC$) | Rain ($mm$) | Smooth climate, no technological change | Smooth climate, technological change | Temp ($^oC$) | Rain($mm$) | Abrupt climate, no technological change | Abrupt climate, technological change |
| 2020 | 12.6 | 445 | 32% | 32% | 12.6 | 445 | 32% | 32% |
| 2030 | 12.9 | 446 | 33% | 33% | 12.9 | 446 | 33% | 33% |
| 2040 | 13.2 | 447 | 34% | 34% | 10.6 | 396 | 25% | 25% |
| 2050 | 13.5 | 453 | 34% | 35% | 8.3 | 351 | 7% | 33% |
| 2060 | 14.0 | 448 | 36% | 39% | 8.7 | 345 | 6% | 35% |
| 2070 | 14.3 | 442 | 35% | 40% | 9.1 | 339 | 7% | 37% |
| 2080 | 14.5 | 425 | 36% | 42% | 9.2 | 322 | 7% | 38% |

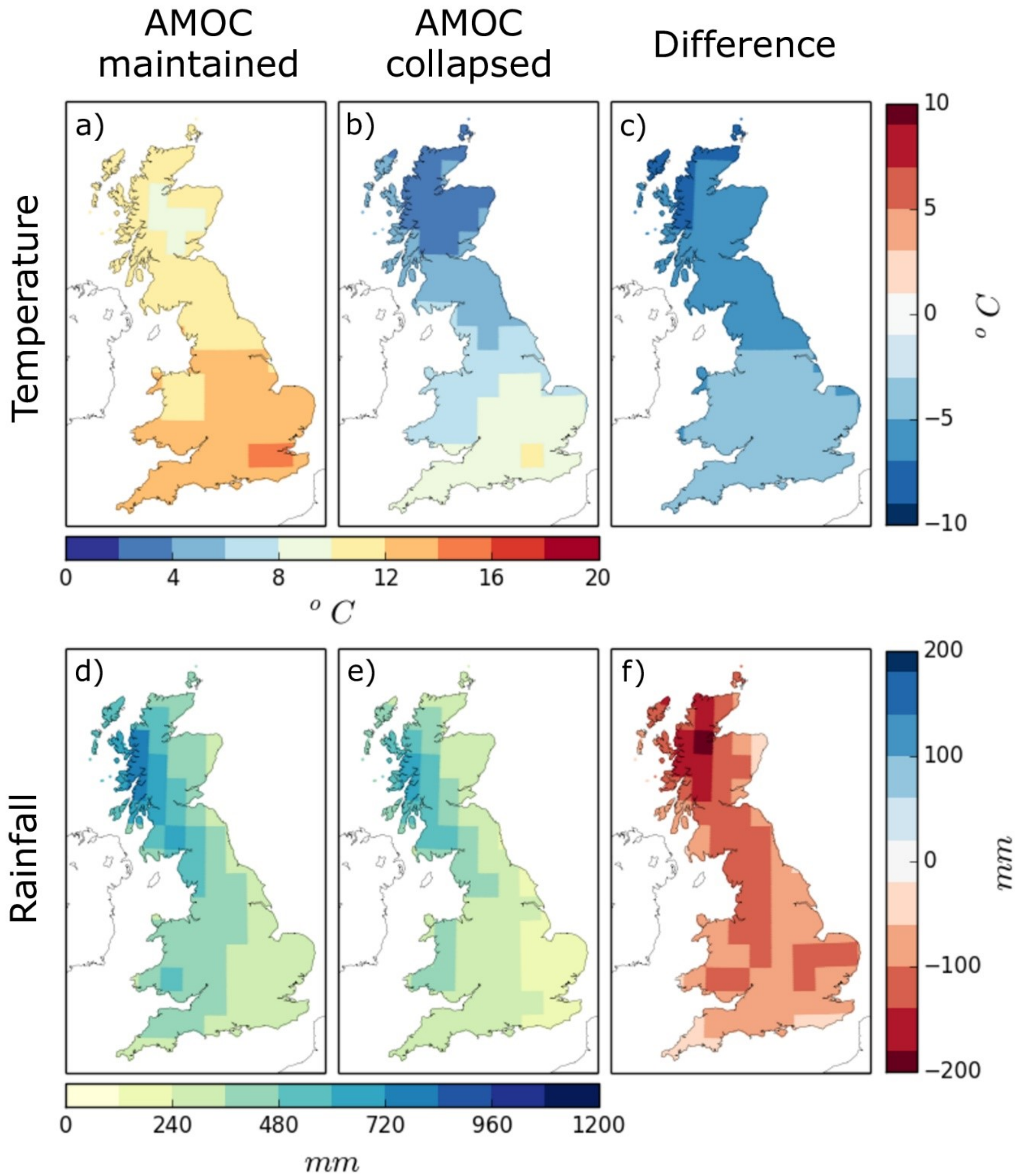
**Panel b: Combinations of lower and upper quartiles of temperature and rainfall for previous 30-year growing seasons (April-September) when the Atlantic meridional overturning circulation (AMOC) is maintained or collapses.**

| | AMOC maintained | | | | AMOC collapse | | | |
|---|---|---|---|---|---|---|---|---|
| | | | Mean arable area ranges (percent) | | | | Mean arable area ranges (percent) | |
| Year | Temp ($^oC$) | Rain ($mm$) | Smooth climate, no technological change | Smooth climate, technological change | Temp ($^oC$) | Rain($mm$) | Abrupt climate, no technological change | Abrupt climate, technological change |
| 2020 | 11.9 - 13.1 | 369 - 517 | 19% - 34% | 19% - 34% | 11.9 - 13.1 | 369 - 517 | 19% - 34% | 19% - 34% |
| 2030 | 12.2 - 13.3 | 367 - 526 | 18% - 34% | 18% - 34% | 12.2 - 13.3 | 367 - 526 | 18% - 34% | 18% - 34% |
| 2040 | 12.7 - 13.7 | 372 - 522 | 19% - 35% | 19% - 35% | 10.1 - 11.1 | 320 - 471 | 9% - 26% | 9% - 26% |
| 2050 | 13.1 - 14.0 | 377 - 531 | 19% - 35% | 19% - 47% | 7.8 - 8.8 | 275 - 428 | 3% - 23% | 24% - 37% |
| 2060 | 13.4 - 14.5 | 372 - 526 | 18% - 37% | 21% - 49% | 8.2 - 9.2 | 270 - 423 | 3% - 23% | 27% - 40% |
| 2070 | 13.7 - 14.7 | 361 - 523 | 17% - 36% | 23% - 50% | 8.5 - 9.5 | 258 - 421 | 3% - 23% | 30% - 41% |
| 2080 | 13.9 - 14.8 | 355 - 494 | 19% - 36% | 28% - 52% | 8.6 - 9.6 | 252 - 391 | 3% - 16% | 32% - 42% |

**Extended Data Figure 2. Predicted farm allocation to arable land for individual years between 2020 and 2080 per 2 km grid cell.**




**Extended Data Figure 3. Time series of mean temperature, total rainfall for the growing season and arable share for the four scenarios considered.** *a) Temperature and rainfall in Great Britain with AMOC maintained and collapsed over 2020 to 2080. b) Mean arable fraction of agricultural land in Great Britain with AMOC maintained or collapsed and irrigation on or off, over the period 2020 to 2080.*

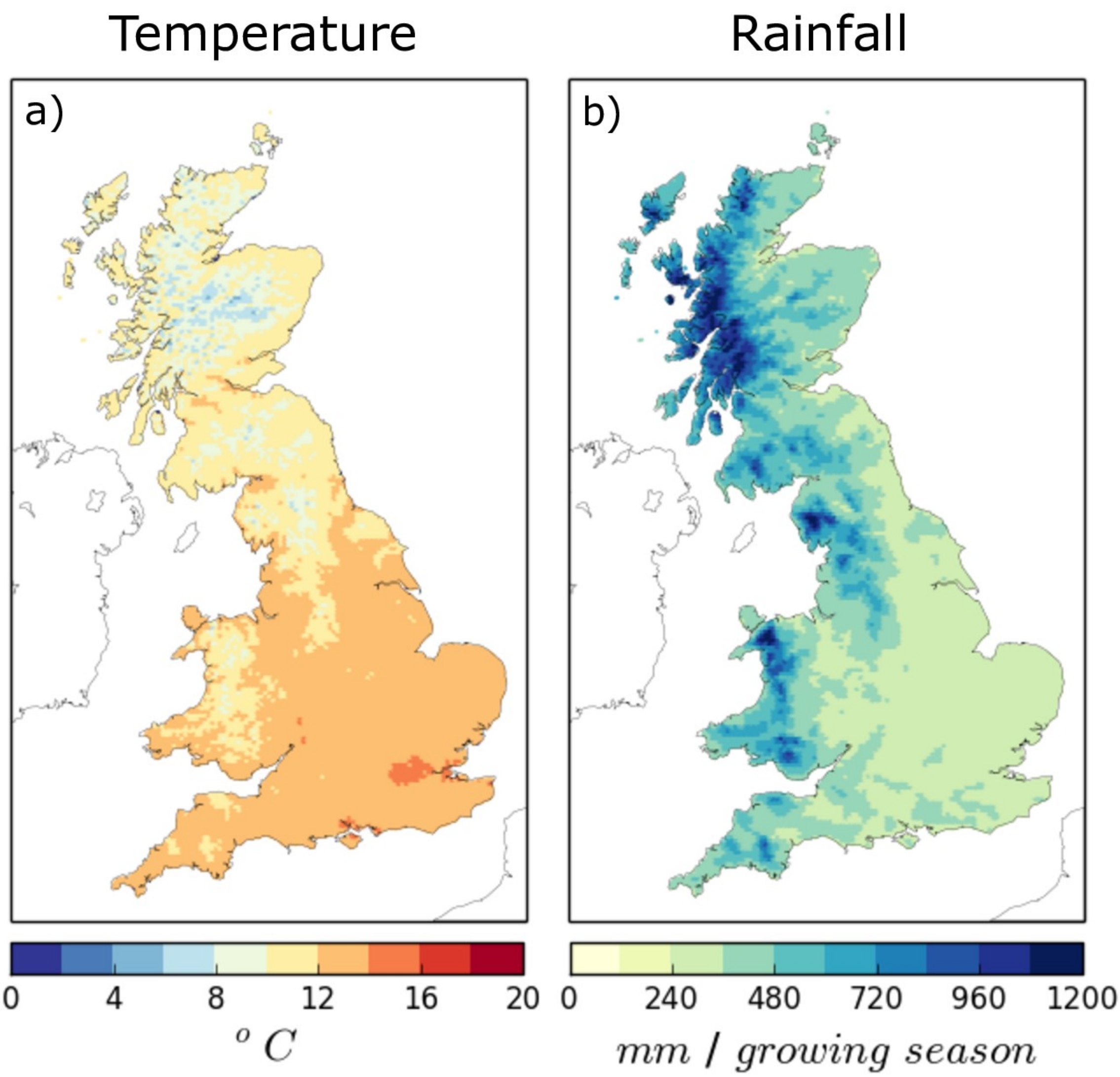



**Extended Data Figure 4. Mean temperature and total rainfall for spring and summer (March-August) in steady state runs of the AMOC maintained and collapsed.** *a) - c) Mean temperature and d) – f) mean total rainfall for a), d) a maintained AMOC and b), e) collapsed AMOC*[13,20]*. c), f) Plots the difference between the means of the AMOC maintained and collapsed; a positive (negative) value represents an increase (decrease) for an AMOC collapse compared to the AMOC maintained.*

| Reference | Model | Temperature (Cooling) | Rainfall (Drying) | Notes |
|---|---|---|---|---|
| Jackson et al., 2015 | HadGEM3 GC2 | 5.0°C growing season | 85 mm/growing season (21%) | Model used in this study, 1980's $CO_2$ levels (difference between AMOC maintained and collapsed in 2080, see Extended Data Table 1) |
| Drijfhout, 2015 | ECHAM5/MPI-OM | 2-4°C | Not provided | Global atmosphere-ocean general circulation model, 5member ensemble, SRES-A1B, 15 years after onset |
| Jacob et al., 2005 | ECHAM5/MPI-OM & REMO | 2-3°C | ~20% | REMO is a regional atmospheric model, summer values |
| Vellinga & Wood, 2002 | HadCM3 | 2-3°C | 100-150 mm/growing season | Pre-industrial GHG emissions, 20-30 years after collapse |
| Vellinga & Wood, 2008 | HadCM3 | 2-5°C | 90 mm/growing season | IS92a emissions scenario |
| Swingedouw et al., 2009 | IPSL CM4 | ~2°C | 90 mm/growing season | Ocean-atmosphere-sea ice-land coupled GCM, 5 sets of experiments over different epochs, largest weakening – Last Glacial Maximum (LGM) – 12Sv circulation decline |

**Note: The last three entries of the change in rainfall (drying) have been converted (assuming rainfall is evenly distributed throughout the year) to mm/growing season for consistency.**

**Extended Data Figure 5. Impact of an AMOC collapse on temperature and rainfall across various climate model freshwater hosing experiments. First row, model used in this study.**

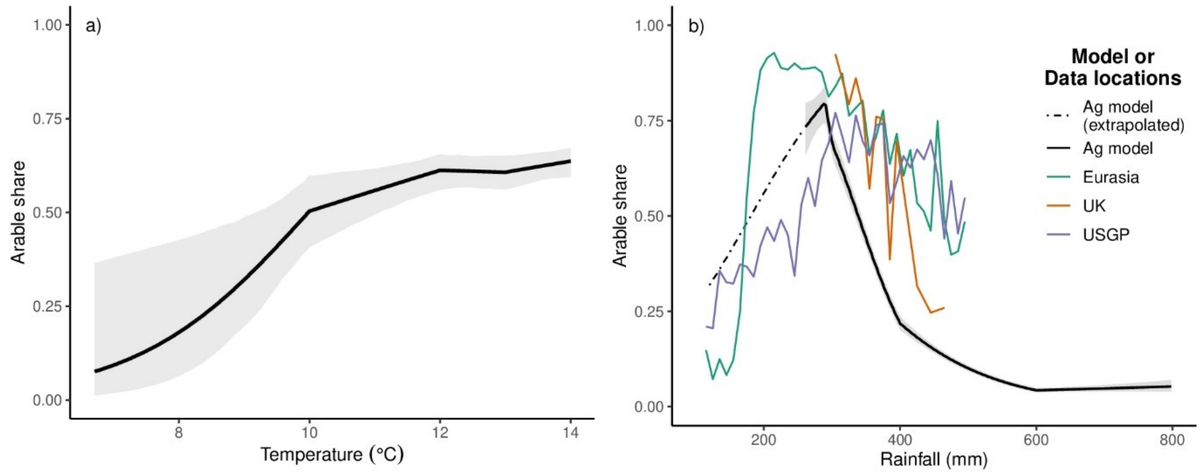



**Extended Data Figure 6. Surface observations of the mean temperature and total rainfall for the growing season for 1960-1989.** *a) Mean temperature and b) mean total rainfall for the growing season (April-September) from surface observations for the period 1960-1989.*

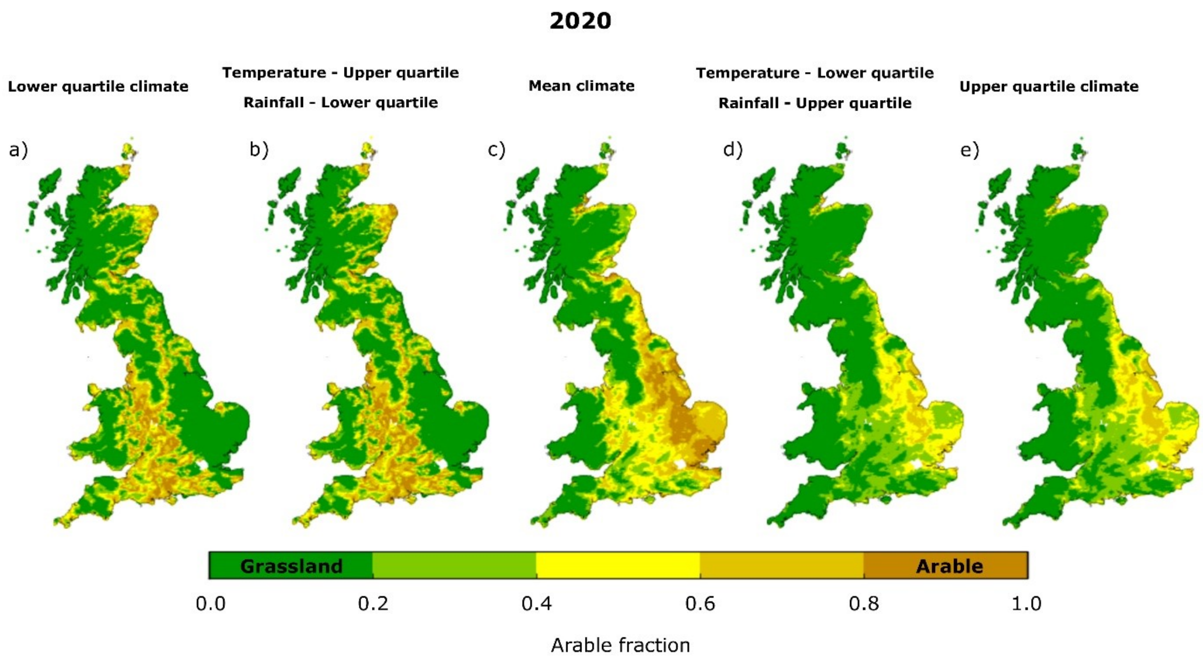
| | Estimate | Std. Error | Z-test | P-value | |
|---|---|---|---|---|---|
| rain | 0.146 | 0.087 | 1.672 | 0.094 | . |
| rain >= 290 | -0.313 | 0.128 | -2.442 | 0.015 | * |
| rain >= 300 | 0.147 | 0.041 | 3.559 | <2e-16 | *** |
| rain >= 400 | 0.009 | 0.001 | 6.754 | <2e-16 | *** |
| rain >= 600 | 0.010 | 0.001 | 9.970 | <2e-16 | *** |
| temp | 0.738 | 0.332 | 2.224 | 0.026 | * |
| temp >= 10 | -0.542 | 0.312 | -1.740 | 0.082 | . |
| temp >= 12 | -0.243 | 0.128 | -1.898 | 0.058 | . |
| temp >= 13 | 0.147 | 0.140 | 1.048 | 0.295 | |
| rain*temp | 0.000 | 0.000 | 0.301 | 0.764 | |
| elev | -0.003 | 0.000 | -7.710 | <2e-16 | *** |
| slope | -0.060 | 0.011 | -5.546 | <2e-16 | *** |
| npark | -0.004 | 0.001 | -2.881 | 0.004 | ** |
| esa | -0.002 | 0.001 | -2.750 | 0.006 | ** |
| greenbelt | -0.002 | 0.001 | -2.947 | 0.003 | ** |
| dist300 | -0.001 | 0.000 | -3.455 | 0.001 | *** |
| s_peat | -0.587 | 0.157 | -3.738 | <2e-16 | *** |
| s_gravel | -0.613 | 0.125 | -4.883 | <2e-16 | *** |
| s_stoney | -0.077 | 0.076 | -1.012 | 0.312 | |
| s_fragipan | -1.278 | 0.173 | -7.376 | <2e-16 | *** |
| s_coarse | 0.238 | 0.069 | 3.463 | 0.001 | *** |
| s_fine | -0.345 | 0.063 | -5.487 | <2e-16 | *** |
| constant | -47.352 | 25.079 | -1.888 | 0.059 | . |
| pseudo-$R^2$ | 0.76 | | | | |

**Notes: . *, ** and *** indicate 10% 5% 1% and 0.1% significance levels respectively. Model estimated via QML. N = 22,220. The dependent variable is arable land share. The high pseudo-$R^2$ provides an indication of good model fit. Details of variable definitions are presented in the methods section. The model includes a time fixed effect to account for potential time-varying unobserved determinants such as commodity prices. As these are not relevant to the focus of this study, they are omitted from the table but are available from the authors.**

**Extended Data Figure 7. Model estimates of land-use (arable land share).**




**Extended Data Figure 8. Estimated impact of temperature and rainfall on arable land share in Great Britain from the agricultural model.** *Estimated fraction of arable share in Great Britain based on a) temperature and b) rainfall. For b) only: arable shares based on land cover data from Northern Eurasia (Eurasia), United Kingdom (UK), and the US Great Plains (USGP).*




**Extended Data Figure 9. Impact sensitivity analysis of climate variables has on arable land share for 2020.** *a) GB map of arable farmland for using the lower quartile temperature and rainfall. b) GB map of arable farmland for using the upper quartile temperature and lower quartile rainfall. c) GB map of arable farmland for using the mean temperature and rainfall. d) GB map of arable farmland for using the lower quartile temperature and upper* *quartile rainfall. e) GB map of arable farmland for using the upper quartile temperature and rainfall.*

| | Smooth climate change, no technological change | Smooth climate change, with technological change | Abrupt climate change, no technological change | Abrupt climate change, with technological change |
|---|---|---|---|---|
| AMOC | Maintained | Maintained | Collapse | Collapse |
| Irrigation | No | Yes | No | Yes |
| Agricultural change value (£M p.a.) | -169 to +48 | -63 to +271 | -393 to -218 | -7 to +139 |
| Irrigation cost (£M p.a.) | 0 | -1 to -882 | 0 | -527 to -952 |
| Net value change (£M p.a.) | -169 to +48 | -945 to +270 | -393 to -218 | -959 to -388 |

**Extended Data Figure 10. Net impact range on GB agriculture of smooth versus tipping point (AMOC collapse) climate change, with and without ameliorative measures (technological response) using lower and upper quartile of temperature and rainfall for previous 30-year growing seasons (April-September).**