Earth's Future

RESEARCH ARTICLE
10.1029/2018EF001092

Key Points:
- A novel probabilistic approach of the risk of economic losses in irrigated agriculture due to climate change and drought management is shown
- Future water restrictions on irrigation in England and Wales are projected to increase in duration, severity, and frequency
- Hydroclimatic variability, drought management, and the distribution and sensitivity of crops to water stress shape the economic impacts

Supporting Information:
- Supporting Information S1

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Citation:
Salmoral, G., Rey, D., Rudd, A., de Margon, P., & Holman, I. (2019). A probabilistic risk assessment of the national economic impacts of regulatory drought management on irrigated agriculture. *Earth's Future*, *7*, 178–196. https://doi.org/10.1029/2018EF001092

Received 8 NOV 2018
Accepted 30 JAN 2019
Accepted article online 3 FEB 2019
Published online 27 FEB 2019

A Probabilistic Risk Assessment of the National Economic Impacts of Regulatory Drought Management on Irrigated Agriculture

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Abstract Drought frequency and intensity is expected to increase in many regions worldwide, and water shortages could become more extreme, even in humid temperate climates. To protect the environment and secure water supplies, water abstractions for irrigation can be mandatorily reduced by environmental regulators. Such abstraction restrictions can result in economic impacts on irrigated agriculture. This study provides a novel approach for the probabilistic risk assessment of potential future economic losses in irrigated agriculture arising from the interaction of climate change and regulatory drought management, with an application to England and Wales. Hydrometeorological variability is considered within a synthetic data set of daily rainfall and river flows for a baseline period (1977–2004) and for projections for near future (2022–2049) and far future (2072–2099). The probability, magnitude, and timing of abstraction restrictions are derived by applying rainfall and river flow triggers in 129 catchments. The risk of economic losses at the catchment level is then obtained from the occurrences of abstraction restrictions combined with spatially distributed crop-specific economic losses. Results show that restrictions will become more severe, more frequent, and longer in the future. The highest economic risks are projected where drought-sensitive crops with a high financial value are concentrated in catchments with increasingly uncertain water supply. This research highlights the significant economic losses associated with mandatory drought restrictions experienced by the agricultural sector and supports the need for environmental regulators and irrigators to collaboratively manage scarce water resources to balance environmental and economic considerations.

Plain Language Summary Droughts are expected to become more common in many regions worldwide due to climate change. During droughts events, environmental regulators can impose water abstraction restrictions for irrigation to protect drinking water supplies and meet the minimum water requirements for the natural environment. This study provides a novel approach to evaluate the risk of economic losses in irrigated agriculture due to water abstraction restrictions implemented during current and future drought conditions under climate change, using England and Wales as a case study. A data set of modeled daily rainfall and river flow for a baseline period (1977–2004) and for near future (2022–2049) and far future (2072–2099) is used. Decisions regarding when to implement restrictions in 129 catchments are made considering a set of rainfall and river flow thresholds, with the associated economic losses calculated by crop type. Results show that in the future water abstraction restrictions for irrigation will become more severe, more frequent, and longer. The highest economic losses will affect the most drought-sensitive crops, which are located in water stressed catchments and have a high financial value in the food market. This research highlights the importance of a collaborative work between environmental regulators and irrigators to manage scarce water resources and balance environmental and economic considerations under drought.

1. Introduction

Global aridity and drought-affected regions have increased substantially since the middle of the twentieth century (Dai, 2011; Dai & Zhao, 2017), with climate projections suggesting future increases in drought frequency and severity in Europe (Lehner et al., 2017; Spinoni et al., 2017). Wanders et al. (2015) showed the proportion of Europe with higher future drought frequency and greater drought severity to be 55–85% and 30–35%, respectively, by the end of the 21st century. Such increases in drought frequency and severity are likely to cause significant impacts and associated economic damages to many sectors of the economy, with agriculture expected to be one of the most adversely affected due to its drought sensitivity (Thi Tran et al., 2016).

Many previous studies have evaluated the impacts of drought on crop yields for rainfed (e.g., Popova et al., 2014; Potopová et al., 2016) and irrigated (e.g., Daryanto et al., 2016, 2017; Sweet et al., 2017; Trnka et al., 2016) systems. This has also extended into the economic impacts of drought using market prices and production functions at the basin scale (e.g., Kirby et al., 2014), input-output analysis (e.g., Pérez y Pérez & Barreiro-Hurle, 2009), Ricardian cross-sectional analysis of net revenues, and computable general equilibrium models to capture economy-wide and global-scale changes of climate change (Mendelsohn & Dinar, 2009). Econometric studies (Gil et al., 2011, 2013) and optimization models (Ward, 2014) have been used to estimate the economic value of irrigated production and farmers' income, with integrated biophysical-agroeconomic models used to simulate crop physiology under drought (Holden & Shiferaw, 2004; Logar & van den Bergh, 2013). Coupled hydroeconomic modeling has also been applied to optimize farm profit (Maneta et al., 2009) and as decision support systems in water resources planning to evaluate the economic impacts of water supply failures (e.g., Martínez-Paz et al., 2016; Ward & Pulido-Velazquez, 2012). Logar and van den Bergh (2013) reviewed available methods for assessing both drought damage costs and costs arising from adopting policy measures. However, studies that consider uncertainties due to natural hydrometeorological conditions in the evaluation of the economic impacts on agriculture are still needed.

A range of approaches using stochastic programming have been employed to allow for hydrometeorological variability within the assessment of the economic impacts of drought on irrigated agriculture. These have been limited to using probabilistic distributions of historical conditions to generate a series of weather and water supply (e.g., Torres et al., 2016), randomly generated synthetic data series of future weather (e.g., Rowan et al., 2011), and autoregressive time series of historical conditions to forecast water inflows (e.g., Lopez-Nicolas et al., 2017), with a focus on single farms (e.g., Rowan et al., 2011) and single river basins (e.g., Lopez-Nicolas et al., 2017; Rowan et al., 2011; Torres et al., 2016). There remains a gap for using national-scale dynamically downscaled climate scenarios to capture the spatiotemporal distributed hydroclimate variability and the related economic losses in irrigated agriculture following a probabilistic risk-based approach.

Furthermore, all of the aforementioned studies have only addressed the impacts of drought on crop yield and have ignored the important economic impacts arising from reduced crop quality. In contrast to arid and semiarid regions, where crop production is dependent on irrigation, supplemental irrigation in humid temperate climates is used to optimize production (Kresović et al., 2016) and increase quality for high-value crops, including horticulture and soft fruit (Knox et al., 2000; Morris et al., 2014). As a result, having access to insufficient irrigation water in a drought can have significant economic impacts in humid temperate countries. In England and Wales, the resultant on-farm financial losses for a design dry year during the irrigation period from April to September were estimated at £660 million (Rey et al., 2016), with the related economic losses due to crop yield and quality varying by crop drought sensitivity and by crop growth stages (Daryanto et al., 2017; Morris et al., 1997).

The economic impacts of drought on irrigated agriculture ultimately arise from the timing and severity of the lack of rainfall and irrigation water. While annual and interannual water availability is constrained by the weather, regulatory drought management to restrict irrigation abstraction, in order to protect public water supply and the aquatic environment, can play a key role in determining the economic impacts on the agricultural sector. During drought events, restrictions may be put in place to reduce water use and abstractions, as occurred in 2014 in California (Legislative Analyst's Office, 2016) and in Cape Town in 2017 (Luker & Rodina, 2017). In the United Kingdom, Section 57 of the Water Resources Act (Parliament of the United Kingdom, 1991) allows the Environment Agency to impose emergency restrictions on surface water abstractions for irrigation during droughts. Those restrictions can partially limit surface water abstractions or, in case of severe drought, totally ban them (Environment Agency, 2015). Consequently, the timing, duration, and severity of water abstraction restrictions need to be considered in combination with crop sensitivity to drought when evaluating the actual economic impacts on irrigated agriculture.

This paper therefore aims to provide an approach for the probabilistic risk assessment of the current and future economic impacts from catchment to national scale of water abstraction restrictions on irrigated agriculture due to regulatory drought management and considering current and future hydrometeorological variability, with England and Wales used as a case study for the first national-scale assessment. The probability and economic impacts of mandatory abstraction restrictions under uncertain climatic conditions are evaluated using a baseline scenario (1977–2004) and two climate change scenarios: near future (2022–2049) and far future (2072–2099). Two methodological innovations for a probabilistic risk-based economic assessment in irrigated agriculture are presented. First, it applies current environmental regulatory triggers to daily catchment-scale rainfall from dynamically downscaled and bias-corrected climate projections (Guillod et al., 2017; Guillod et al., 2018) and simulated river flow from a national-scale hydrological model (Bell et al., 2009), to obtain the current and future timing, frequency, severity, and duration of abstraction restrictions. Second, a probabilistic risk-based analysis of economic losses in irrigated agriculture from catchment to national scale is performed through applying crop-specific loss functions to a national spatial data set of irrigated cropping (Rey et al., 2016) according to the timing, duration, and severity of the restrictions. The study develops and demonstrates an approach to evaluate the economic implications of water restrictions during drought conditions, which can be applied elsewhere to support environmental regulators and farmers toward making informed decisions based on the economic risks associated with water abstraction restrictions.

2. Materials and Methods

The approach has two main components to evaluate the implications of regulatory drought management on water abstraction restrictions in a context of hydrometeorological variability and the resultant direct economic impacts on irrigated agriculture. First, an evaluation of the frequency, duration, timing, and severity of abstraction restrictions implemented by environmental regulators during drought is performed through application of rainfall and river flow triggers to large data sets of potential current and future hydrometeorological variability for three periods: baseline (1977–2004) and two future periods (near future, 2022–2049, and far future, 2072–2099; Figure 1). Second, loss functions describing crop-specific sensitivity to abstraction restrictions (i.e., impact on crop yield and crop quality) and data on the distribution of irrigated crops and surface water irrigation are used to perform a probabilistic risk analysis of the economic losses due to the implemented water abstraction restrictions.

2.1. Synthetic Hydrometeorological Ensemble Members

Current and future potential daily rainfall and river flows are required to determine when restrictions on irrigation abstraction might be implemented. The hydrometeorological data set used in this study was produced within the MaRIUS project (http://www.mariusdroughtproject.org/; Managing the Risks, Impacts and Uncertainties of droughts and water Scarcity), using the weather@home2 modeling framework (Guillod et al., 2017; Massey et al., 2015), in which the HadAM3P atmosphere-global climate model is dynamically downscaled by the HadRM3P regional climate model. Accounting for uncertainty through application of small perturbations to the temperature field in the initial conditions (Massey et al., 2015) and sampling from the CMIP5 uncertainty range in sea surface temperature and sea ice extent allowed a large number (100) of spatial-temporally consistent ensemble members to be generated for the recent past and for the future (Guillod et al., 2018). The data set by Guillod et al. (2018) provides synthetic daily weather time series for the United Kingdom at a 25-km × 25-km resolution. The baseline (1977–2004) data set provides 100 simulated climate ensemble members that could have occurred in the past, while the near future (2022–2049) and far future (2072–2099) represent climate time series that might occur in the future under the Representative Concentration Pathway 8.5 (RCP8.5) emissions scenario. This weather@home2 data set has been previously successfully applied for risk analysis in water resources planning in the Thames basin (Borgomeo et al., 2018).

The weather@home2 climate ensemble (Guillod et al., 2018) has been used to drive the national Grid-to-Grid (G2G) hydrological model (Bell et al., 2009) to provide simulated daily river flows for the baseline, near future, and far future periods (Bell, Kay, et al., 2018; Bell, Rudd, et al., 2018). For each period, 100 simulations of daily mean river flow for each of 129 catchments across England and Wales have been used in this study. The G2G is a national-scale gridded (1 km × 1 km) hydrological model which uses spatial data sets (e.g., soil type and land cover) in preference to parameter identification via calibration. Where model parameters are required, such as the kinematic wave speeds used in lateral routing,

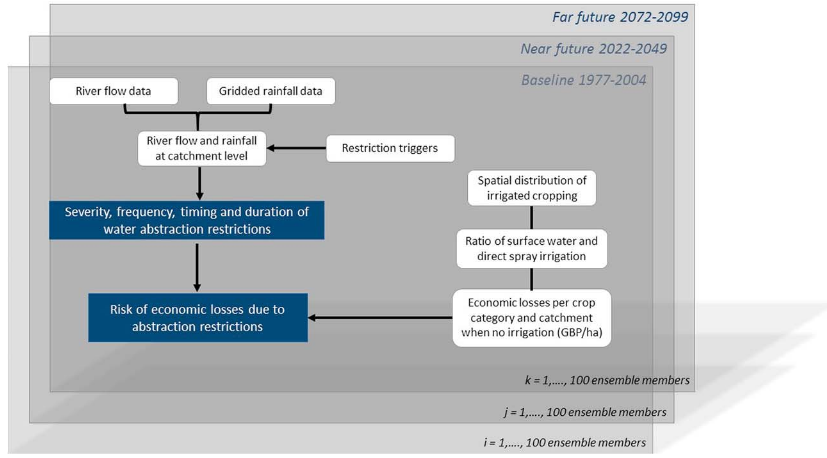

Figure 1. Schematic of the developed approach.

nationally applicable values are used, thus, calibration has not been used to identify separate model parameters for individual catchments. The model does not currently include the effect of artificial influences such as abstractions and discharges; it therefore estimates daily mean natural flows. G2G requires as input the time series of precipitation and potential evaporation. For this study, bias-corrected precipitation is used and for the future periods the potential evaporation is adjusted to allow for closure of stomata under increased carbon dioxide concentrations. The optional snow module (Bell et al., 2016) is not used here; thus, precipitation input to G2G is assumed to be rain. Although this needs to be borne in mind, its effect on drought is likely to be limited. G2G has been shown to perform well for a wide variety of catchments across Britain (Bell et al., 2009) and has recently been shown to perform well specifically for low flows and for historical drought identification (Rudd et al., 2017). The weather@home2 hydrological data set has been used to analyze potential future changes in low flows and drought characteristics (Kay et al., 2018).

2.2. Frequency, Duration, Timing, and Severity of Irrigation Abstraction Restrictions

Due to their focus on protecting river ecology during drought, only abstractions for direct spray irrigation from surface water are susceptible to be restricted by the Environment Agency because (1) groundwater and tidal sources are not restricted unless there is evidence that abstraction is negatively affecting river flows and (2) abstraction for reservoir-filling and antifrost irrigation take place during winter months when restrictions are very rarely imposed and thus not considered in our analysis. A threshold level method based on river flow and rainfall conditions is used by the Environment Agency to trigger the decision to impose abstraction restrictions on surface water. However, similar to drought identification (Rudd et al., 2017; Tijdeman et al., 2018), there is no standard national way of defining these thresholds. We have therefore reviewed the regional drought management plans (Environment Agency, 2012a, 2012b, 2012c, 2012d, 2012e, 2012f, 2015) and derived a representative set of rules to impose, change the severity (i.e., level), and remove surface water abstraction restrictions during the irrigation season between April and September, inclusive. The method captures the consequence of multiyear droughts on the continuous river flow simulations and therefore the imposition of restrictions. The triggers used include (1) the proportion of long-term average (LTA) catchment rainfall over a rolling previous 90 days, (2) the daily river flow for each month within the baseline period with a probability of exceedance of 95%, 98% and 99% (i.e., $Q95$, $Q98$, and $Q99$, respectively), and (3) the undefined "little or no rainfall forecast" ($\text{rain}_{\text{forecast}}$; Rio et al., 2018). Following a sensitivity analysis of different accumulated rainfall depths (supporting information Table S1 and Figures S2 and S3) and individual discussions with water resources planners from the Environment Agency, $\text{rain}_{\text{forecast}}$ is defined as a fixed value of 15 mm of accumulated rainfall in the following 5 days.

The specific set of rules using the triggers of LTA, monthly $Q95$, $Q98$, and $Q99$ and $\text{rain}_{\text{forecast}}$ are applied on a daily basis to the daily rainfall (from the synthetic data set) and simulated river flow (Q_{day}; from the G2G model) to identify potential drought conditions and implement surface water restrictions under drought. The specific set of rules is explained in detail in the supporting information (section 1 and Figure S1) and is summarized below:

- A catchment is identified as being in a potential drought when the daily cumulated rainfall over a rolling previous 90 days is <65% of the LTA catchment rainfall across all ensemble members. If there is a potential drought by the end of June, the potential drought condition is assigned for the remaining months in the summer, because the rainfall from winter to spring is used to define the potential drought state in summer;
- If $Q_{day} < Q95$ for the given month and there is no significant $rain_{forecast}$, a catchment is then identified as being under drought conditions and irrigators are requested to apply voluntary restrictions for a maximum of 2 weeks to help reduce the likelihood of subsequent mandatory restrictions. Given that these restrictions are not mandatory and depend on irrigators' decisions, any resultant reduction in surface water abstraction volumes and the related economic losses are not assessed in this study;
- If after the 2-week period of voluntary restrictions $Q98 < Q_{day} < Q95$, level 1 formal restrictions (i.e., 50% reduction) are implemented in surface water abstraction volumes for that month. Level 1 restrictions are removed when $Q_{day} \geq Q95$.
- If for two consecutive days $Q99 < Q_{day} < Q98$, level 2 formal restrictions (70% mandatory reduction) are implemented. When Q_{day} recovers, level 2 restrictions can be lowered to level 1 ($Q98 < Q_{day} < Q95$) or be removed ($Q_{day} \geq Q95$).
- If for two consecutive days $Q_{day} < Q99$, level 3 formal restrictions (100% mandatory reduction) are implemented in surface water abstraction volumes. When Q_{day} recovers, level 3 restrictions can be lowered to level 2 ($Q99 < Q_{day} < Q98$) or level 1 ($Q98 < Q_{day} < Q95$) or be removed ($Q_{day} \geq Q95$).

Voluntary and level 1 restrictions are not a prerequisite for level 2 and level 3 because formal restrictions can be enforced due to the existing low flow conditions. Level 3 restrictions can also be enforced without level 1 and 2 restrictions having been in place. By applying the restriction triggers to the daily rainfall and river flow data sets per catchment, the days under restriction are identified by timing (i.e., month and year), duration, and level of restriction in each standalone ensemble member and period.

2.3. Assessment of the Economic Losses in Irrigated Agriculture

The direct economic impacts of the restrictions on irrigated agriculture will differ depending on the crop type (i.e., drought sensitivity and crop economic value), the proportion of irrigation abstraction from surface water, and the timing of surface water abstraction restrictions and their severity.

First, the spatial distribution of irrigated crops at a 2-km × 2-km grid resolution from Rey et al. (2016) was used, for eight representative irrigated crop categories: early potatoes, maincrop potatoes, cereals, sugar beet, vegetables, soft fruit, orchard fruit, and grass. This is currently the only available data set on the spatial distribution of irrigated crops in England and Wales. Second, the proportion of the total licensed volume for all irrigation purposes (direct, storage, and antifrost) that is licensed for direct (spring-autumn) abstraction from surface water was calculated for each catchment (Figure S4 in the supporting information) using the most recent available abstraction license data (2014 in England and 2016 in Wales). This catchment-specific surface water ratio is applied to the spatial distribution of irrigated crops to identify those irrigated areas susceptible to economic losses caused by surface water restrictions. Third, the on-farm economic losses due to irrigation restrictions, based on losses of yield and quality assurance benefits, are estimated for each crop category (pounds per hectare, using national average prices for each crop over the past three drought episodes in the United Kingdom; 2003, 2004–2006, and 2010–2012) building on the methodology developed by Morris et al. (1997) and updated by Rey et al. (2016). It is assumed that there is a linear and positive relationship between the level of restriction in a given month (and, by inference, reduction in irrigation application) and monthly economic damages, up to a maximum value represented by the total cessation damages from Morris et al. (1997; updated in Rey et al., 2016) representing level 3 restrictions. As the monthly damages in Morris et al. (1997) are associated with restrictions being imposed for the whole of each month, we assumed that economic losses in a given month are proportional to the number of days under restriction in the month. Finally, the total monthly and annual economic losses due to all levels of mandatory surface water abstraction restrictions under drought management are calculated, by catchment and crop for each of

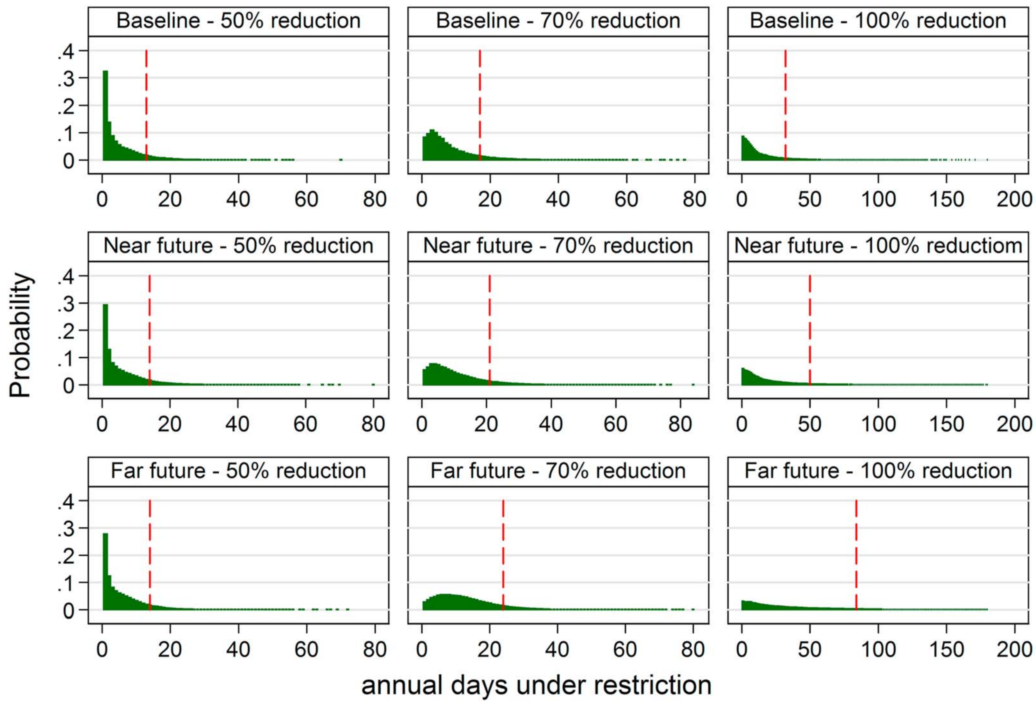

Figure 2. Probability density function of the annual days under restriction for all catchments under study by severity level and period. Only events that incur restriction are considered (i.e., when a restriction does not occur, it is not considered in the probability). The dashed red line indicates the number of days under restriction with a 0.1 probability of exceedance.

the 100 ensemble members and for each period, to derive the changing probabilistic risk of damages in space and time.

3. Results

3.1. Probability of Surface Water Abstraction Restrictions

Figure 2 shows the national annual probability density function of restriction length and severity for the three time periods. Looking only at restrictions with high values of exceedance probability, the annual length of restrictions increases from level 1 (i.e., 50% reduction in abstraction) to level 3 (100% reduction). For example, for a 0.1 exceedance probability of a single catchment anywhere in the country being under restriction in the baseline, the duration increases from 13 days to 17 to 31 days under levels 1, 2, and 3, respectively (Figure 2). In the future, there are generally a greater number of days under restriction. The largest changes are projected to occur in the far future when the 0.1 annual exceedance probability of level 3 restrictions is projected to be 84 days (Figure 2).

However, the probability of restrictions being imposed is not spatially uniform across England and Wales. At the catchment level and for the baseline, the annual probability of a mandatory restriction (i.e., any severity level of more than 1-day) being implemented is everywhere less than 0.3, with most catchments in the south and east of England having an annual probability of less the 0.2 (or 1 in 5 years). The slightly higher probabilities in the north and west reflect the generally lower buffering of river flows by groundwater. The future annual probability of restrictions increases over time across England and Wales, mostly in the central and southern catchments, with annual probabilities in the far future between 0.6 and 0.78 for all catchments (Figure 3).

The probability of restrictions also differs in the timing of implementation, which influences their agricultural impacts. Focusing on longer restrictions (rather than restrictions of any duration as in Figure 3), Figure 4 shows how the differences in probability for month-long (30-day) restrictions vary across months, catchments, and time periods. In the baseline, monthly probabilities of such long restrictions generally

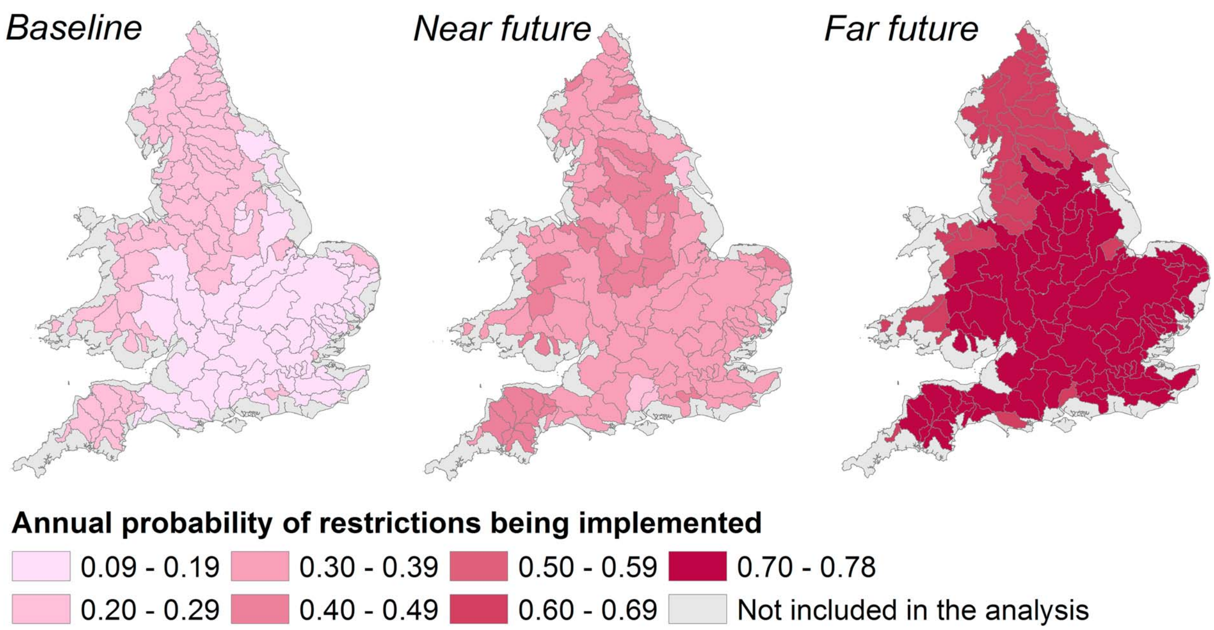

Figure 3. Annual probability of a mandatory restriction (without distinction of the severity) of any length being implemented by catchment and time period.

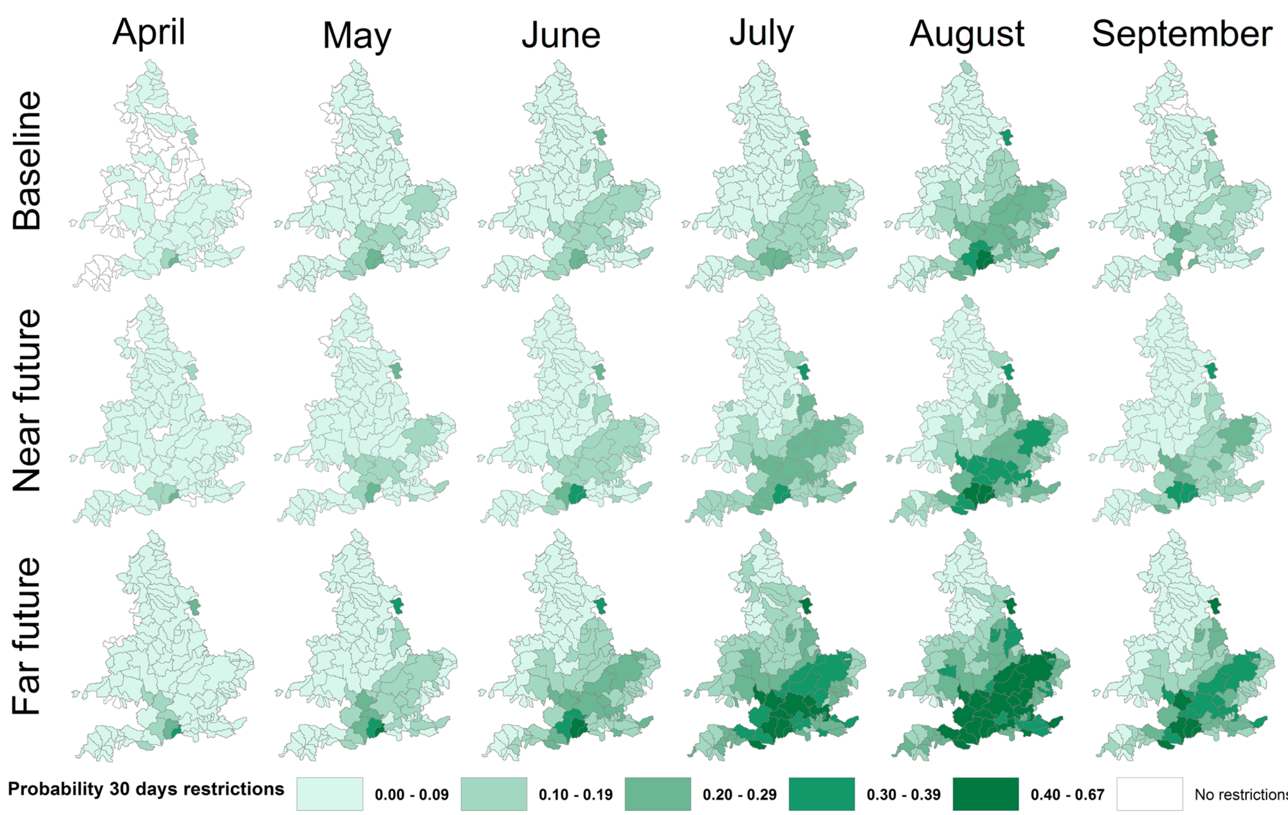

Figure 4. Probability of implementing month-long (30-day) restrictions for each period, without differentiating the severity of the restrictions.

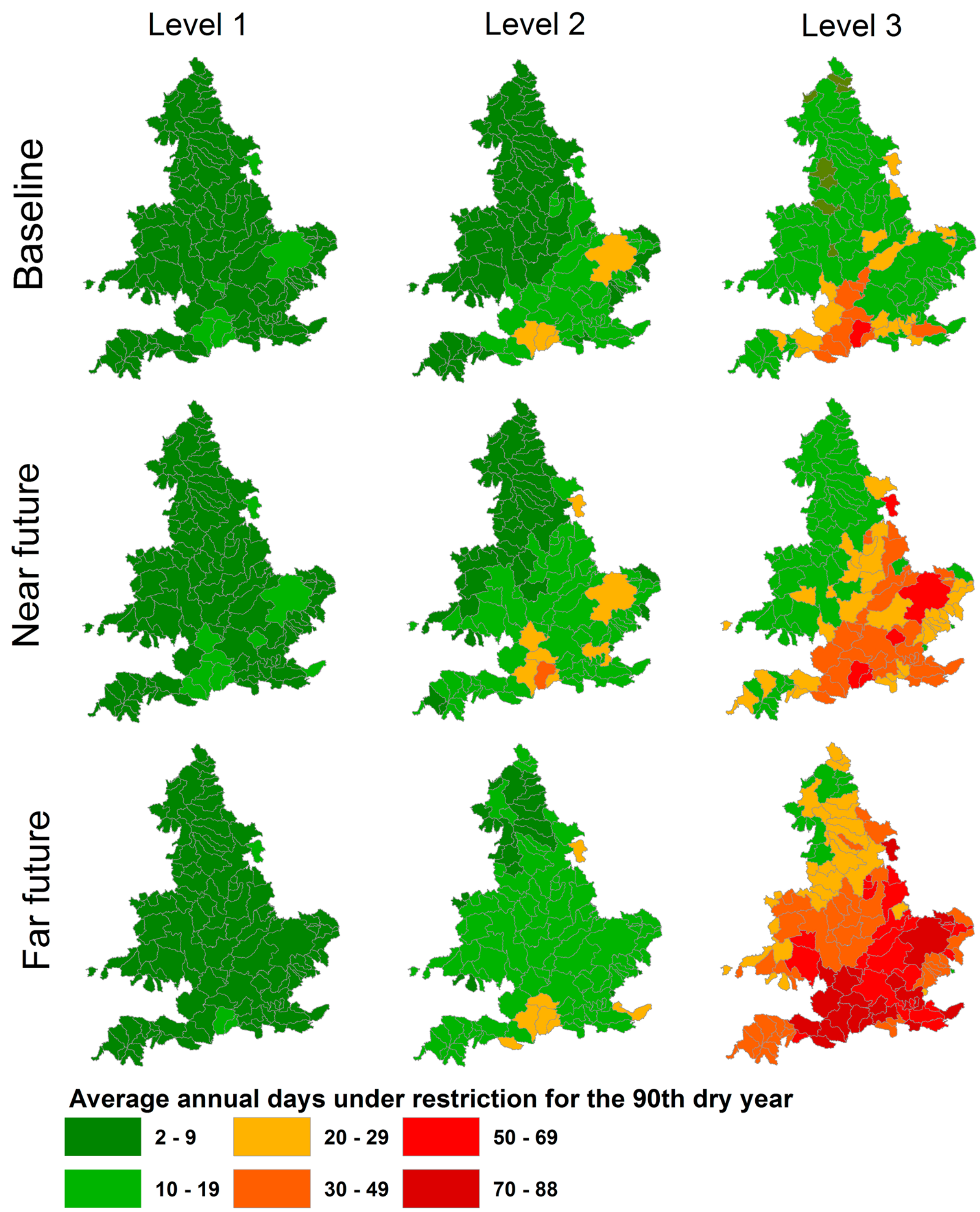

Figure 5. Severity of the average annual days under restriction for the 90th dry year of each ensemble member by period and catchment. Only events that incur restrictions are considered.

increase through the spring and summer in the south and east, peaking in August and rapidly reducing in September, with five catchments having a probability of greater than 0.3 during August. In the near future, there are small increases in probability but little change in the spatial extent of catchments with a probability greater than 0.1. In contrast, the probability of month-long restrictions increases significantly and in spatial extent in all months in the far future (especially from May to September).

3.2. Severity and Total Duration of Restrictions Under Current and Future Climate Variability

The previous section has highlighted the uneven probabilities of implementing abstraction restrictions across England and Wales due to hydrometeorological variability. In this section, we use the 90th percentile dry year, defined as the year with a 10% probability of nonexceedance of annual rainfall, for each

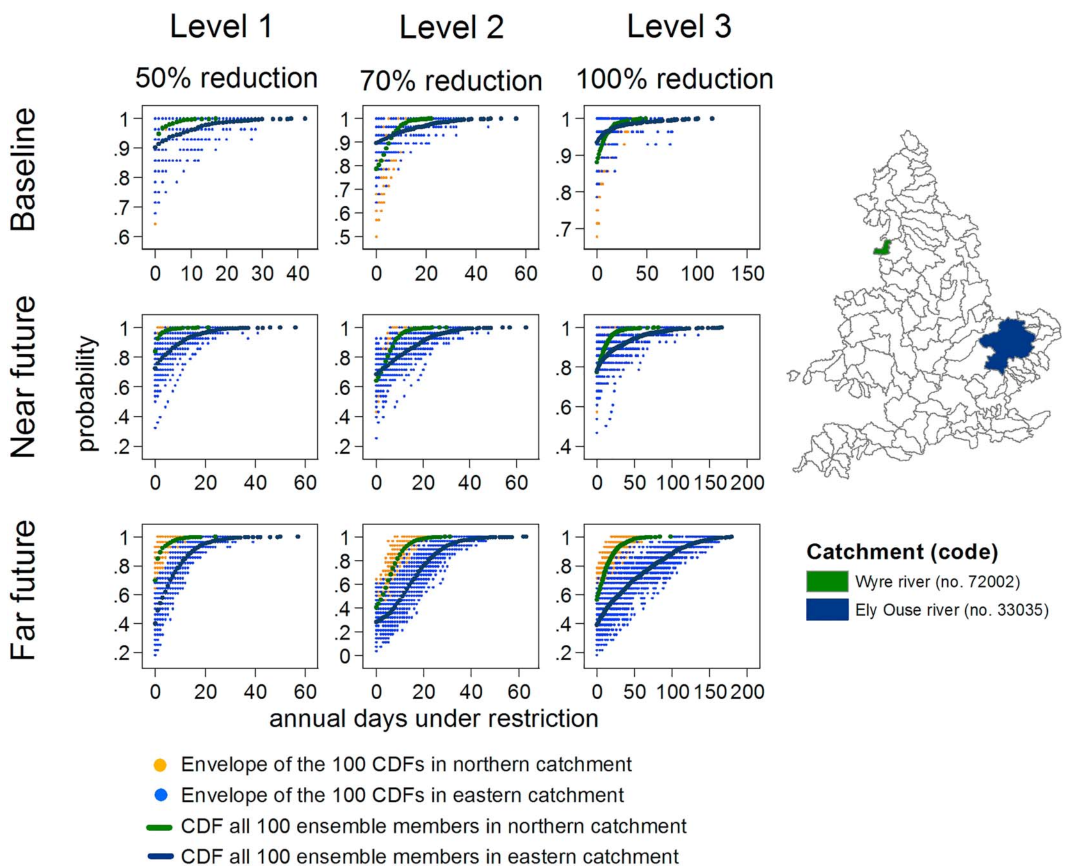

Figure 6. Cumulative distribution function (CDF) of annual days under restriction for two selected catchments (Wyre and Ely Ouse Rivers). Uncertainty of the standalone 100 ensemble member is shown with the small dots (envelope) in the graphs, while the line refers to the CDF of all 100 ensemble members. The graphs include all years under study, even those when restrictions have not been implemented.

catchment and ensemble member to evaluate the severity and total duration of restrictions in all catchments (Figure 5). In the baseline, average annual durations are typically less than 30 days (with the exception of 10 catchments (out of 129) under level 3 restrictions) and there is no clear pattern. In the future projections, more severe and longer periods under restriction are expected for the 90th percentile dry year in each catchment. The far (near) future reaches a total of 86 (34) catchments with level 3 restrictions longer than one month. Catchments with seasonal total restrictions of more than 30 days become widespread throughout much of England and Wales in the far future, indicating that future dry years will be associated with far more extensive and severe restrictions.

Two contrasting catchments are selected to show how the cumulative distribution function (CDF) of annual days under the different restriction levels differ between a runoff-dominated catchment (72002, Wyre at St Michaels) in the wetter northwest of England and a groundwater dominated catchment (33035, Ely Ouse at Denver Complex) in the drier east of England (Figure 6). The mean annual rainfall in the northern catchment for the 90th percentile dry year of each ensemble member is 1,206, 1,195, and 1,172 mm in the baseline, near future, and far future, respectively. For the eastern catchment, the equivalent totals are 451 mm (baseline), 438 mm (near future), and 419 mm (far future). Looking at all time periods and restriction severity levels, the catchment located in the east tends to have a lower non-exceedance probability for a given total days under restriction, with this catchment being more likely to be under restriction and for longer periods. However, the northern runoff-dominated catchment in the wetter area is more likely to be under short-duration level 2 and 3 restrictions due to the lack of groundwater buffering (Figure S4). The future climate projections under the same regulatory drought management rules will generally lead to longer periods of more severe water abstraction restrictions but with wider ranges of annual days under restriction due to the considerable natural climate uncertainty within the synthetic 100 ensemble members.

3.3. Economic Losses Linked to Water Abstraction Restrictions

The economic impacts from the catchment-specific abstraction restrictions on irrigated agriculture depend on the irrigated areas, crop sensitivity to drought, and the proportion of the area supplied by direct surface water abstraction. The catchments under study have an estimated total irrigated area of 68,150 ha, of which 30,920 ha are considered to be susceptible to surface water abstraction restrictions after applying the surface water ratio (section 2.3). Most of the irrigated areas are in the east of England (the Anglian and Humber River Basin Districts [RBD] identified for the Water Framework Directive contain 55% and 19% of the total irrigated area, respectively) with smaller areas in eastern Wales and central and southern England (Figures S5 and S6).

Figure 7 shows the CDF of national annual on-farm economic losses due to all surface water restrictions by time period. For the baseline, there is a 0.4 probability across the country of there being no aggregate economic losses due to the drought management restrictions, while the 90th percentile probability of nonexceedance of total annual economic losses is £29M, although this ranges from £4 to £155M across the 100 ensemble members. These relatively low damages result from the limited (subnational) spatial extent of most droughts, the resilience of surface water flows within the main irrigated areas in eastern England due to high groundwater contributions to river flow, and the systemic resilience represented by rules that aim to avoid mandatory abstraction restrictions in all but extreme low flow conditions during drought. However, in more extreme droughts, annual economic losses can exceed £250M.

Under the climate change projections, the nonexceedance probability of no damages reduces from 40% to 19% and 4% in the near future and far future, respectively, indicating that some degree of economic losses will become the norm in most years (Figure 7). The 90th percentile of the CDF for total annual economic losses will increase from £29M to £111M (£22 to 227M uncertainty envelope) in the near future and £226M (£124 to 258M uncertainty envelope) in the far future. The similar maximum annual economic loss between all time periods ~£260M) arises as the single most severe drought year in the 2,800 baseline years, is similar to that under climate change (albeit that such events with very low rainfall and river flow values will have a higher frequency in the future), demonstrating the significance of natural climate variability in determining damages.

The spatial distribution of the projected 90th percentile annual economic losses is shown in Figure 8. Four catchments within the Severn, Thames, and Humber RBDs have estimated on-farm losses of greater than £1M, which are characterized by relatively large areas under irrigation (i.e., more than 470 ha per catchment) and a large proportion of high-value crops such as soft fruit, maincrop potatoes and/or vegetables (Table S2 and Figure S5). In the near future and far future, damages in these catchments increase to > £4M. However, the catchment with the largest losses in the near future (£28.6M) and far future (£39.4M) is located within the Anglian RBD, where restrictions increase significantly in duration and severity (Figures 4 and 5). This catchment has the largest irrigated area (11,460 ha), consisting of 36% maincrop potatoes, 26% cereals, and 22% vegetables.

The range of economic losses is influenced by the sensitivity of crops to water scarce conditions in terms of the proportional yield and quality premium losses, their price in the market, and the existing climatic conditions where crops are distributed, which influences the shape of the CDF by crop and time period (Figure S7). The magnitude of economic losses is largest for soft fruit, followed by orchard fruit, maincrop potatoes, and vegetables. In the baseline, for a 90th percentile nonexceedance probability, the largest average economic losses across the catchments are for soft fruit (£32,935/ha), followed by orchard fruit (£3,820/ha), maincrop potatoes (£2,835/ha), and vegetables (£2,290/ha). Average losses for sugar beet, early potatoes, cereals, and grass are generally low. However, there is significant variability within the 100 individual ensemble member with the 90th percentile economic losses reaching values of £54,225/ha in soft fruit, £4,515/ha in orchard fruit, £4,235/ha in maincrop potatoes, and £3,735/ha in vegetables (Figure S7). Between time periods, there is also a significant increase in economic losses by crop. In the far (near) future the 90th percentile economic losses average £52,320/ha (£44,940/ha) for soft fruit, £4,500/ha (£4,295/ha) for orchard fruit, £4,070/ha (£3,730ha) for maincrop potatoes, and £3,620/ha (£3,070/ha) for

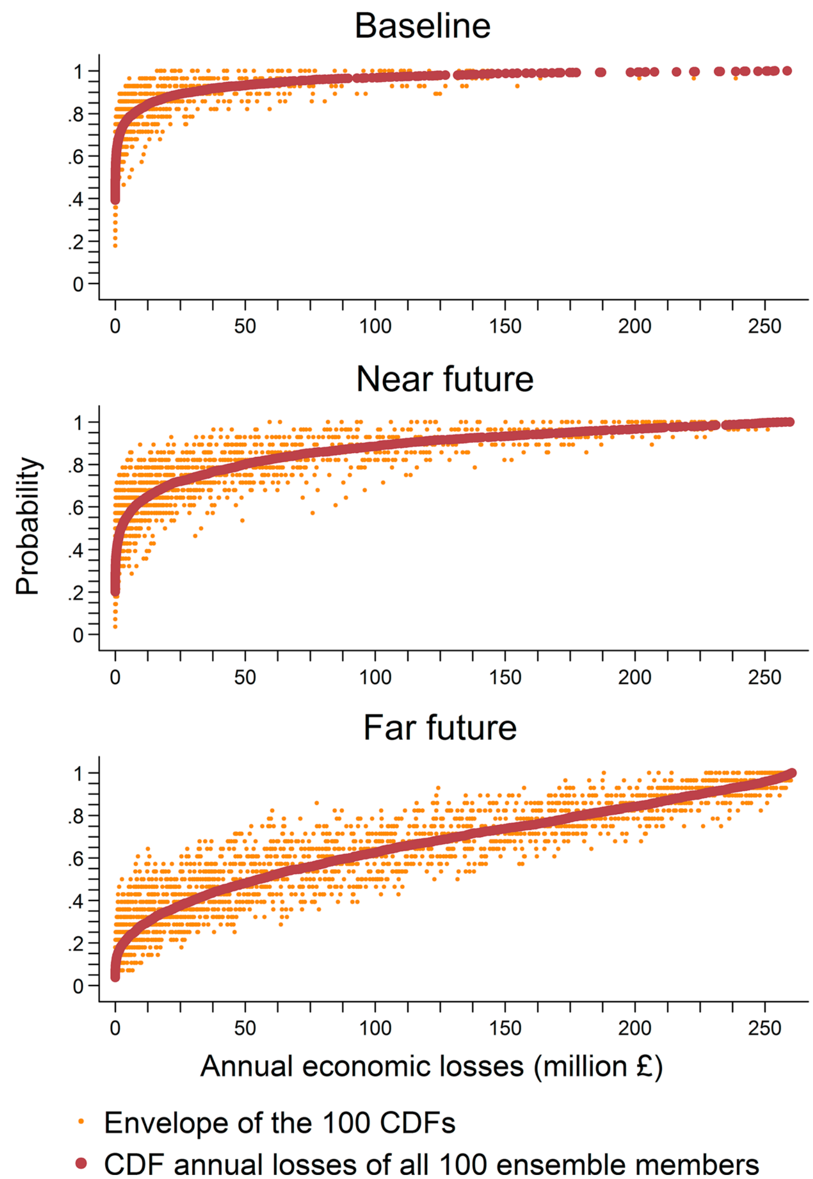

Figure 7. Cumulative distribution function (CDF) of annual economic losses (£) by time period under study. Uncertainty of the standalone 100 ensemble member is shown with the small dots (envelope) in the graphs, while the larger dots (line) refer to the CDF of all 100 ensemble members. The graphs include all years under study, even those when any restriction has not been imposed.

vegetables (Figure S7). In the future the slope of the CDFs becomes less pronounced due to the more severe and longer restrictions. Ultimately these losses arise from both crop yield and crop quality losses (Figures S8 and S9), but the losses due to crop quality are dominant in soft fruit (Figure 9).

4. Discussion

4.1. A Probabilistic Risk-Based Approach to Evaluate Economic Losses in Irrigated Agriculture

The Climate Change Act requires the U.K. Government to compile its assessment of the risks and opportunities arising for the United Kingdom from climate change every 5 years. While the most recent U.K. Climate Change Risk Assessment recognizes the “Risks of shortages in the public water supply, and for agriculture, energy generation and industry” and “Risks to domestic and international food production and trade” as two

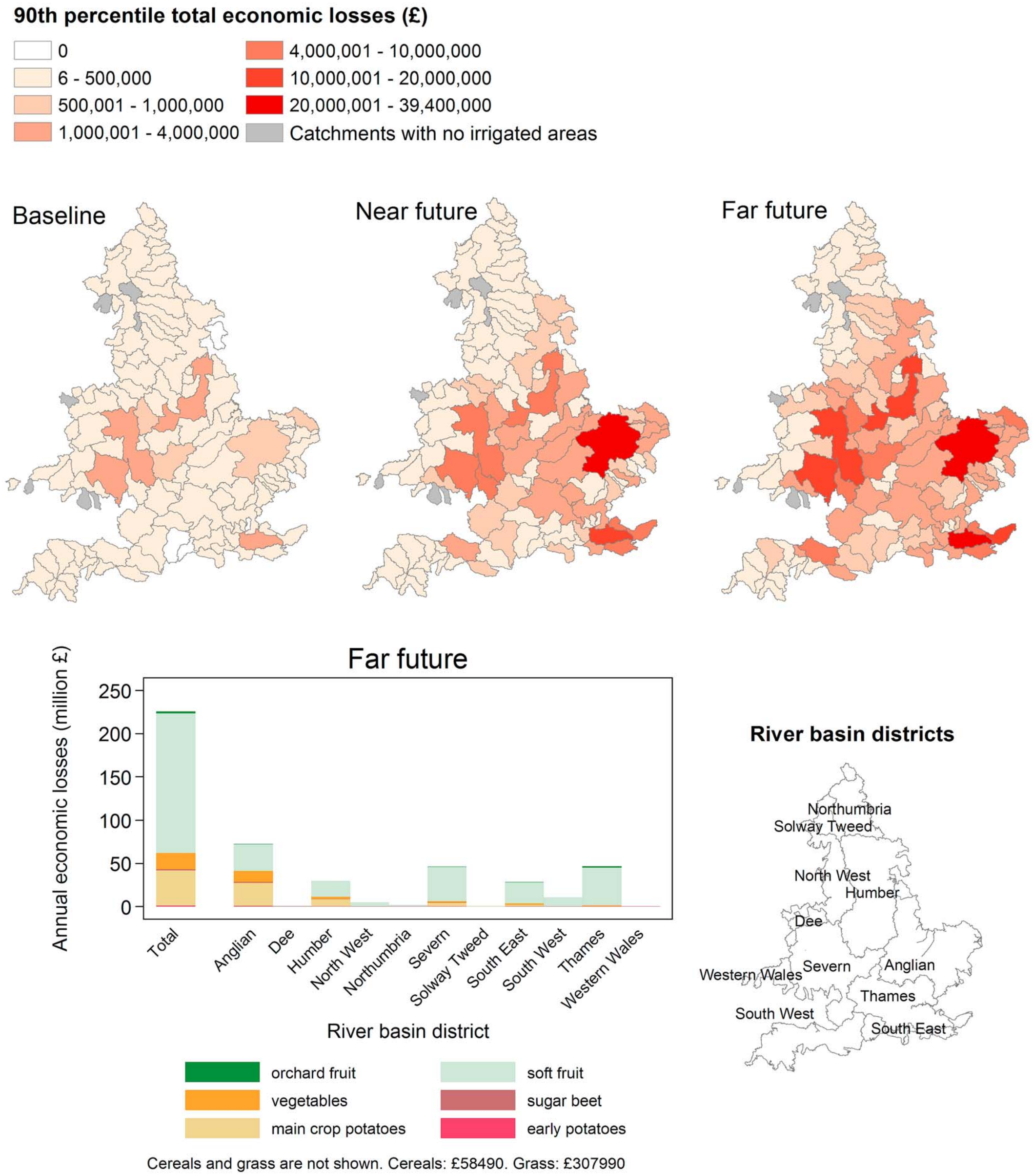

Figure 8. (top) The 90th percentile of the annual economic losses (£) by period and catchment for all 100 ensemble members. (bottom) The 90th percentile of annual economic losses (million pounds) by river basin district and crop classification in the far future.

of the six top areas of interrelated climate change risks for the United Kingdom, the associated probabilities to those risks are not included (Committee on Climate Change, 2016). In general, existing national climate risk assessments that consider drought-relevant risk metrics only explore a small number of future emission scenarios, such changes in soil moisture (United States; Wehner et al., 2017), water resource availability (United Kingdom; HR Wallingford, 2015), or agricultural land suitability (United Kingdom; ECI et al., 2013; Keay et al., 2013), but lack a description of the full range of probabilities and the related economic impacts. Dealing with low-probability and high-consequence outcomes (i.e., the tails of probability distributions) has also been identified as a challenge for climate risk quantification (Weaver et al., 2017). With probabilistic models, a large number of synthetic events can be reproduced providing a more complete picture of the full spectrum of future risks than with historical data (United Nations Office for Disaster Risk Reduction, 2015). Our approach goes beyond the state of the art by capturing spatially at a national scale the

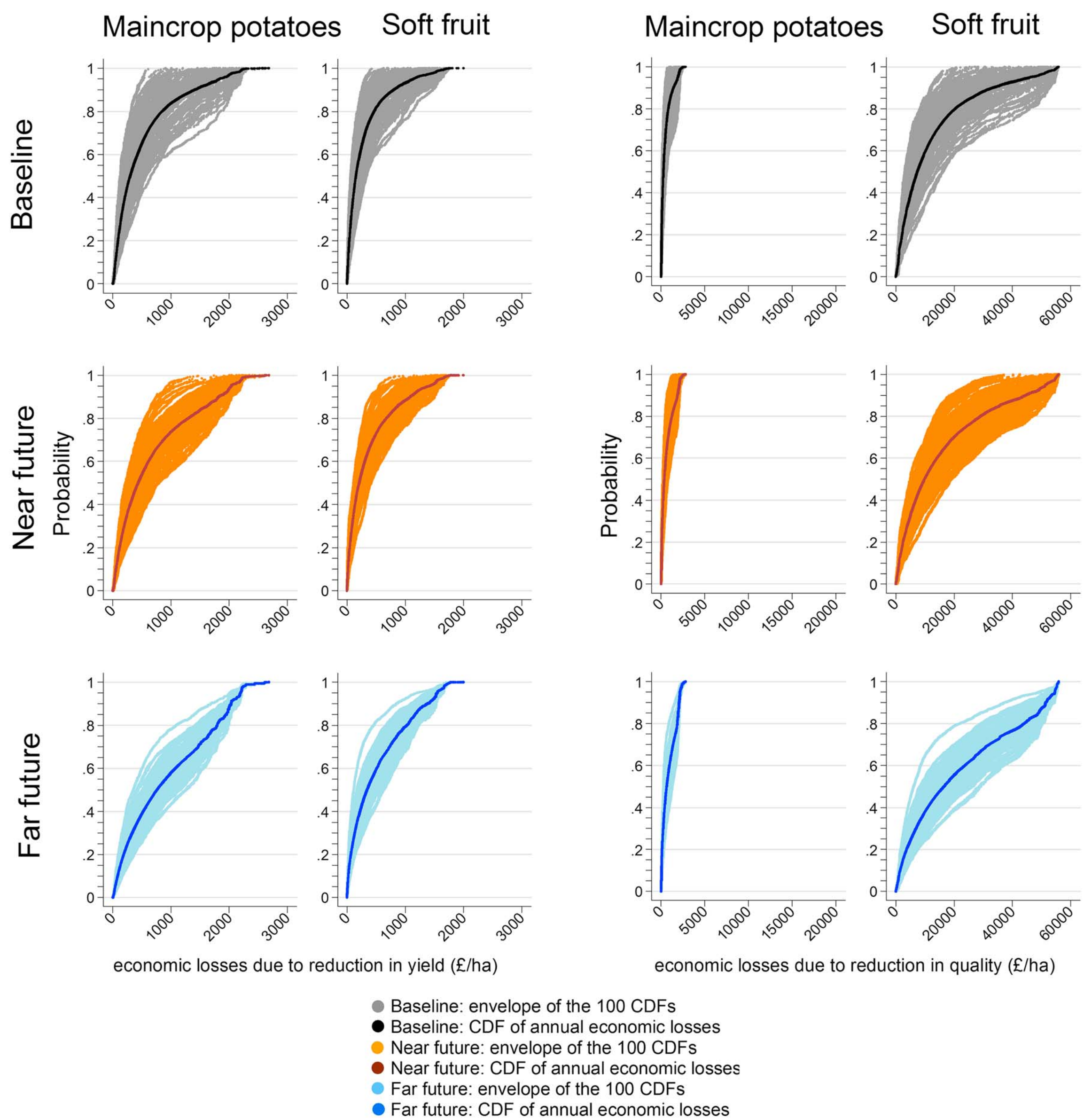

Figure 9. Cumulative distribution function (CDF) of the average economic losses per catchment in pounds per hectare related to crop yield (left) and crop quality (right) reductions for two selected crops (maincrop potatoes and soft fruit) and by period. The graphs only include years when any restriction has been imposed.

probabilistic risk-based economic losses in irrigated agriculture due to water abstraction restrictions under drought conditions, using dynamically downscaled climate scenarios to derive river flow conditions. Our approach overcomes the limitations of previous studies by using probability envelopes, which embrace extremes events and includes a fuller range of climate variability, as previously suggested from a disaster risk management perspective (De Perez et al., 2014). Furthermore, the probabilistic risk-based assessment of economic losses in irrigated agriculture can complement the current U.K. national assessment of climate risks (Dawson et al., 2018), where irrigation is not currently considered as an infrastructure asset under risk.

4.2. Economic Impacts on Irrigated Agriculture Under Drought

By applying current river flow thresholds available from drought management plans, this study has identified the location and evaluated the expected economic losses due to restrictions on direct surface water abstraction for irrigation, under current and future climatic variability. The current estimated annual on-farm economic damages in England and Wales are significant under extreme drought conditions (reaching £260M) and unevenly distributed in space and by crop type (Figures 9 and S7). These damages in the irrigated subsector in England and Wales are comparable with those from other drier countries with significant agricultural production; for example with the €710M losses in the arable sector in Spain during the extreme 2003 drought and heatwave (COPA-COGECA, 2003) or the $810M crop revenue losses in the 2014 California drought (Howitt et al., 2014).

The significance of the economic damages from surface water abstraction restrictions in irrigated agriculture can be put into a wider economic context by comparing with estimates of damages resulting from restrictions in public water supply and from flooding. For example, Thames Water Utilities Limited, who supply a population of nine million inhabitants across London and the Thames Valley, estimates that a Temporary Use Ban (commonly known as a “hosepipe ban”) that takes place 1 year in 20 on average causes daily economic losses of £6.8M (Thames Water, 2015). The losses associated with such a 1-month Temporary Use Ban (~£204M with a 5% probability of exceedance) are equivalent to our total economic damages in irrigated agriculture for England and Wales with a 0.5% (0–4% uncertainty envelope) probability exceedance in the baseline (Figure 7). The economic losses can also be compared with the damages caused by the most frequent extreme climatic event in England, flooding. During the 2013–2014 winter, the United Kingdom experienced widespread flooding from an extreme storm surge, a series of intense storms, and the cumulative effects of heavy and persistent rainfall (Huntingford et al., 2014; Thorne, 2014). However, while the floods affected around 45,000 ha of agricultural land, the economic damages to the agricultural sector were about £19M (Chatterton et al., 2016). These are equivalent to the losses due to drought management in irrigated agriculture for England and Wales with a 13% (0–25% uncertainty envelope) exceedance probability for the baseline (Figure 7).

We recognize that our estimates of restriction probabilities and economic losses due to regulatory drought management are affected by two confounding assumptions. First, the G2G river flow simulations are for natural river flow conditions. This does not allow identification of already stressed catchments due to human water abstractions, which could potentially underestimate the economic losses on irrigated agriculture due to lower magnitudes of drought intensity and frequency (Wada et al., 2013). However, the distribution of catchments with baseline probabilities of 30-day-long restrictions of >10% within Figure 4 matches almost exactly the distribution of areas of “serious” water stress within Environment Agency (2007). Second, while we have consistently applied current river flow thresholds available from drought management plans and a realistic interpretation of “little or no rainfall forecast,” in reality the environmental regulator's staff will follow a less rigid multivariate decision making process, using local environmental indicators such as water quality (Mosley, 2015) and ecology, when deciding to implement water abstraction restrictions. Given the recognition of severity for the consequences of restrictions, the environmental regulator has significantly changed its relationship with the agricultural community with a stronger proactive intent to avoid mandatory abstraction restrictions (Rey et al., 2017).

The sensitivity of different crops to drought and the timing and severity of restrictions with respect to the crop growth cycle determines the yield and quality reductions caused by a lack of water. Consequently, the probability of economic damages are projected to increase in the future with climate change, due to warmer, drier summers and an increased probability of extreme events. Uncertainty in projections of future climate change arises from multiple sources—in particular, internal climate variability, climate model uncertainty, and emissions uncertainty. Our study has used the future meteorological data of Guillod et al. (2018) who used a single global climate model-regional climate model (with sampling from the CMIP5 uncertainty range in sea surface temperature and sea ice extent) and “worst-case” RCP (RCP8.5). However, Kirtman et al. (2013) demonstrate that the uncertainty due to emissions for the near future is minimal, given the limited divergence in global greenhouse gas emissions associated with each RCP and ocean-atmosphere system lags. Emissions uncertainty continues to explains less than 10% of the total variance in summer (June, July, and August) precipitation in the far future period in the British Isles (Hawkins & Sutton, 2011) and less than 50% of the total variance in mean surface air temperature (Hawkins & Sutton, 2009). However, climate model uncertainty tend to become the dominant cause of variance in climate projections for the British Isles toward the far future (Hawkins & Sutton, 2009, 2011).

In England and Wales the future highest risks of total economic losses are projected to be in highly irrigated catchments with high-value crops, mostly located in the drier south and east of England within the Anglian, Severn, Thames, and Humber RBDs, which will also be increasingly exposed to more frequent, longer duration, and more severe restrictions. This importance of geographical differentiation in water availability and/or cropping in influencing the economic impacts of droughts has been found elsewhere, such as in Mediterranean river basins (Musolino et al., 2017). We have assumed that there is no feedback between reduced yields and increased prices due to the common usage of fixed-price forward contracts and the diverse supply chains of food retailers in the United Kingdom, but such price feedbacks during drought can lead to reductions in economic losses or even winning situations in other regions, such as in Southern Europe (Musolino et al., 2018).

We acknowledge that our estimation of the economic losses associated with future water abstraction restrictions is sensitive to the future spatial extent and spatial distribution of each of the irrigated crop types, especially of soft fruit due to its high economic value, which we assume to be constant. The future spatial distribution of agricultural land use and crop selection is uncertain due to the sensitivity of agricultural decision making to future uncertain socioeconomic conditions, including costs, prices, subsidies, imports, and regulation (Holman et al., 2017). In addition, it has been found that soil suitability restrictions and water resource availability for new abstraction licenses under climate change can constrain future opportunities for expansion and/or migration of irrigated cropping (Daccache et al., 2012). While future autonomous adaptation by farmers is inevitable, modeling tools do not currently enable confident projections of spatial change for specific high-value (and sometime niche) crops (Holman et al., 2018).

4.3. Implications for Future Drought Management

Under current climate variability, the risk of economic damages in irrigated agriculture from regulatory drought management restrictions is relatively small in comparison to those arising from public water supply restrictions, although larger than flood damages to agriculture. Nevertheless, agricultural economic losses are locally and regionally important, will magnify through the supply chain (Rey et al., 2017; Street et al., 2016), and will increase in probability in the future. These characteristics highlight the importance of considering agriculture as a spatially heterogeneous industry with highly variable spatiotemporal sensitivity to drought and the need for improved hydrometeorological and crop-based risk assessments to guide environmental regulators' decisions when implementing water abstraction restrictions under drought. According to our results, water restrictions are projected to be more frequent, longer, and more severe in the future and become more widespread across England and Wales. This is consistent with previous studies assessing climate change impacts on water availability for irrigation in England, looking at both license use and abstraction restrictions (Rio et al., 2018). Adaptive responses in drought management to reduce the impacts will require the integration of changes to top-down regulatory approaches with bottom-up farmer and agricultural sector decisions (Girard et al., 2015; Holman & Trawick, 2011).

Decision makers need to understand how climate change may interfere with their plans and compromise their objectives, so they can adapt existing policies and develop new strategies (Weaver et al., 2017). From the regulatory side, changes in water abstraction management as an adaptation measure to climate change are being implemented in many areas around the world, such as in the U.S. Fourth National Climate Assessment (Wuebbles et al., 2017), the Climate Change Research Plan for California (CalEPA, 2015), and National Adaptation Plans by developing countries such as Brazil (Ministry of Environment, 2016). In the United Kingdom, the government is designing a new water abstraction licensing system (Department for Environment, Food and Rural Affairs, 2016) to improve environmental protection and increase water access. Irrigators may benefit from increased resilience to water shortages due to the planned introduction of more flexible water trading (Rey et al., 2018), consent to abstract surface water at any time of the year during high flows to fill up on-farm reservoirs (Department for Environment, Food and Rural Affairs, 2016), and the possible reallocation of unused licensed water.

However, this reform might also enforce more restrictive low flow conditions during drought than those presented here, in which river flow triggers are based on a historical monthly varying threshold of the low river flow conditions from a baseline period. As highlighted in previous studies (Kay et al., 2018), reductions in river flows are expected in the future. In contrast to this conventional variable threshold approach in which the thresholds do not adjust to the hydrological consequences of a changing climate, Wanders et al. (2015)

applied a nonstationary transient variable threshold in which the threshold is based on the river flow of the previous 30 years. As the transient threshold adjusts to the changes in hydrological regime over time, Wanders et al. (2015) found that both drought duration and water deficit volume increased over the 21st century in only 27% of the global area, compared to 62% when using the conventional variable. While the use of such a transient approach in drought management will benefit water users such as agriculture, by reducing the likelihood of abstraction restrictions, it is uncertain whether ecosystems will be able to adapt to the new river flow regimes (van Tiel et al., 2018).

Given the projected increasing risk of economic losses due to surface water abstraction restrictions, farm-level behavioral, infrastructural, and technological changes are likely to continue to occur within the sector (Freire-González et al., 2017). These will include investments to secure water supply (e.g., on-farm reservoir construction, multiple abstraction sources, rainwater harvesting), changes to more drought-tolerant or less water-intensive crop varieties; soil management practices to increase water retention (Rey et al., 2017), water recycling, and the use of soil moisture monitoring and decision support tools for improved irrigation scheduling (Gadanakis et al., 2015). Yet, while the relatively low marginal cost of water in irrigation techniques, such as precision irrigation, does not currently encourage farmers to apply them in humid climate regions, benefits such as reduced variability in crop quality and reduced environmental impact may increasingly convince growers of the associated benefits (Daccache et al., 2015). Although drought impacts are generally seen to be negative, farmers who are well adapted and proactive in drought risk management can gain considerable economic benefits from such events (Musolino et al., 2018).

In the future, environmental regulators, the agricultural sector and other water users will need to work together to reduce or mitigate the increased risk of economic losses due to drought (or low flow) conditions that may threaten the viability of irrigated agricultural businesses. Governmental actors will need to effectively communicate with water users in order to enhance coordination and drought response (Urquijo & De Stefano, 2016). The challenge of balancing the multiple competing demands for water (including the environment) within a changing climate, while supporting food security and rural livelihoods, will require a multiscale adaptive drought management framework (Holman & Trawick, 2011) that brings together regulators, collective action, and farmers' response (Rey et al., 2017), reconciles their competing demands (Knox et al., 2018), and learns from international drought management experiences (e.g., Iglesias et al., 2018).

5. Conclusions

This study applies a novel transferable probabilistic risk-based approach to assess the economic losses in irrigated agriculture from drought at catchment to national scale, implementing surface water abstraction restrictions and using dynamically downscaled climate ensembles to derive river flow conditions. The regulatory drought management is set up with the use of rainfall and river flow triggers to decide when restrictions are imposed, changed, or removed at the catchment level for current and future climate scenarios. Assuming a series of stationary drought management rules, the study shows for England and Wales that water abstraction restrictions are projected to last longer, become more severe, and more frequent in the future and emphasizes the role of regulatory drought management on determining the economic impacts on the irrigated agriculture sector. As well as hydroclimatic variability and drought management, the distribution of crops and their sensitivity to water scarce conditions shape the economic impacts on irrigated agriculture. The highest economic risks occur for the most drought-sensitive crops, which have a high financial value and are concentrated in catchments with increasingly uncertain water availability. This situation highlights the need for hydrometeorological and spatially explicit crop-based risk assessments to guide environmental regulators' decisions to implement water abstraction restrictions across contrasting catchments. Our novel risk-based approach for estimating the current and future economic losses due to regulatory drought management of surface water can contribute to more informed decisions to collaboratively manage scarce water resources and balance environmental and economic considerations.

Acknowledgments
This research forms part of the Natural Environment Research Council (NERC) program on Droughts and Water Scarcity, funded through the Historic Droughts (NE/L010070/1) and MaRIUS (NE/L010186/1 and NE/L010208/1) research projects. The authors acknowledge access to the MaRIUS weather@home2 event sets (NE/L010364/1, NE/L010208/1, NE/L010399/1, and NE/L010186/1), which are available on the Centre for Environmental Data Analysis (CEDA) platform (see https://doi.org/10.5285/0cea8d7aca57427fae92241348ae9b03). The Grid-to-Grid model estimates of daily mean river flow for gauged catchments in Great Britain driven by the weather@home2 (climate model) driving data (MaRIUS-G2G-WAH2-daily) are available at the CEH website (https://doi.org/10.5285/f6cac471-7d92-4e6d-be8a-9f7887143058). All additional data supporting this study are openly available at the website (https://doi.org/10.17862/cranfield.rd.7613192). We would like to thank the editor and two anonymous reviewers for the comments they provided to improve the quality of this paper.

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