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An enhanced version of the D-Risk decision support webtool for multi-scale management of water abstraction and drought risks in irrigated agriculture

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ABSTRACT

Due to it having the lowest priority for water allocation during drought events and the consequent agronomic and economic impacts of abstraction restrictions, UK irrigated agriculture has been identified as a key business sector 'at risk'. An enhanced version of the D-Risk webtool has been developed to help agricultural stakeholders and catchment water managers to evaluate the joint multi-scale risks of abstraction restrictions (voluntary and mandatory) and having insufficient irrigation volumes during drought events. The webtool uses annual maximum potential soil moisture deficit as the agroclimate index to calculate monthly and annual volumetric irrigation demand for the selected crop mix, soil available water capacity and location. Simulated river flows are used to identify days not under abstraction restrictions. Annual probability distributions of irrigation deficit and licence utilisation (headroom) are derived from a monthly time-step water balance model that calculates whether the farm irrigation demand in each month can be met, taking account of river flow-based abstraction restrictions, daily and annual volumetric licensed abstraction limits, the licenced abstraction period(s) and any on-farm reservoir storage. The enhanced D-Risk tool provides a more holistic understanding of drought risk on irrigated agriculture from individual farm to catchment scales and supports improved collaborative decision-making regarding future water sharing, water trading and on-farm reservoir investment to reduce business vulnerability to drought and regulatory change.

1. Introduction

Irrigated farming faces severe threats from water scarcity and drought driven by competition from other water users (Garrick et al., 2019), over-abstraction, new water regulation and increasing climate variability and climate change (Iglesias & Garrote, 2015). These threats are not only confined to arid and semi-arid regions (Azadi et al., 2018; Kuwayama et al., 2019), but are also important in humid countries such as UK (Rey et al., 2017; Parsons et al., 2019). The UK is often perceived to be a 'wet' country, but has experienced multiple droughts (Rey et al., 2017) in recent decades, of which the 1975–1976 drought is regarded as the most severe. Climate projections for the UK show a trend towards warmer temperatures, with summers likely to get hotter and drier in the future (Lowe et al., 2018), which may cause more extensive financial impacts and farming losses.

In the UK, irrigation is usually supplemental to buffer the effects of seasonal rainfall variability (Met Office, 2020) and supports the production of high quality horticultural and fruit crops, which generate substantial financial benefits (Rey et al., 2016). In common with many countries (e.g. Santato et al., 2016), abstractions for irrigation in the UK requires a licence or permit which stipulates the water source, location and fixed annual and daily volumetric limits (Henriques et al., 2008). In dry years, these licence conditions often limit the ability of farmers to apply sufficient irrigation to meet crop water demands, with consequences for both yield and crop quality. In addition, abstractions for agricultural irrigation have the lowest priority for water allocation during drought years to protect drinking water supplies and environmental flows, so that voluntary and mandatory abstraction restrictions further exacerbate the drought impacts. Farmers thus need to improve their drought risk management strategies (Knox, et al., 2020a; 2020b) by balancing the probability of being unable to fully meet the irrigation needs of their cropped area within their licence constraints in drought

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years against the opportunity costs of having a smaller irrigated area in the greater number of non-drought years.

Drought management in the farming sector is usually undertaken at the farm–level. There are few tools available to support individual farming enterprises either to understand drought resilience (e.g. Drought Resilience Self-Assessment Tool (DR.SAT) – DAFF, 2022), to make decisions on infrastructure investments (WaterWorks- Khan et al., 2010) or to manage their farm-level agricultural drought risks (e.g. D-Risk -Haro-Monteagudo et al., 2019). However, multi-scale drought management frameworks across different spatial scales (farm to catchment) can enable long-term adaptation strategies to increase agricultural resilience to future droughts (Holman et al., 2021). There are no known operational tools that integrate the hydrological and farming systems to provide a holistic understanding of agricultural and hydrological drought risk to support agricultural drought responses at individual farm to catchment scales.

This paper describes how the original individual farm scale D-Risk webtool (Haro-Monteagudo et al., 2019) has been further developed for application at farm and catchment scales by integrating flow-based abstraction restrictions, water resource reliability and climate change impacts into its decision support functionality. This provides greater support for water regulatory and environmental protection agencies and to agricultural stakeholders representing farming interests. With increasing global interest in collaboration and partnership (Margerum & Robinson, 2015) and the Catchment Based Approach (CaBA: Collins et al., 2020) in the UK, the enhanced D-Risk webtool supports more collaborative catchment-based abstraction and water management approaches to reconcile drought risks with water availability whilst enabling more efficient use of licensed water during periods of water scarcity. To demonstrate this potential, a case study example of assessing the drought risk reduction benefits from water sharing (Rey et al., 2021) has also been included in this paper.

2. D-Risk webtool enhancements

The D-Risk webtool was originally developed to help individual farmers understand and respond to their drought risk, expressed through probability distribution functions of annual irrigation deficit and license headroom. Irrigation deficit is defined as the total volumetric irrigation demand that cannot be supplied in a given year. License headroom is the percentage of the fixed annual volumetric abstraction licence allocation that is not used in a given year e.g. a headroom of 0 % means that the business has reached its licensed volumetric abstraction limit and cannot abstract any further water for irrigation or for refilling reservoirs. However, the original tool assumed that the availability of the licensed volume each year was unaffected by seasonal local river flow conditions and associated abstraction constraints (Haro-Monteagudo et al., 2019), thereby significantly under-estimating actual drought risk.

The enhanced D-Risk webtool now provides drought risk profiles for annual irrigation deficit and headroom for individual farms or groups of farms that (1) take account of volumetric licence limits and storage volumes and (2) also consider abstraction constraints imposed by local river flow conditions, thereby allowing the relative importance of each to overall drought risk to be evaluated. In addition, to baseline period (1974–2004), the enhanced tool also offers scenario evaluation for future climate (2020–2049) conditions to support longer-term decision-making (such as on-farm reservoir construction). Expected future climate conditions beyond 2050 were not incorporated as that is beyond the decision-making horizon of farming enterprises. A schematic of the enhanced D-Risk multi-scale approach is shown in Fig. 1 and a detailed flowchart with data, inputs and methods is provided in Figure S1 of supplementary material.

3. User interface and application features

The enhanced D-Risk webtool guides the user through a simple two-step data entry module: farm location and data (Figure.S2). The location input module allows the user to specify the catchment (gauging station)

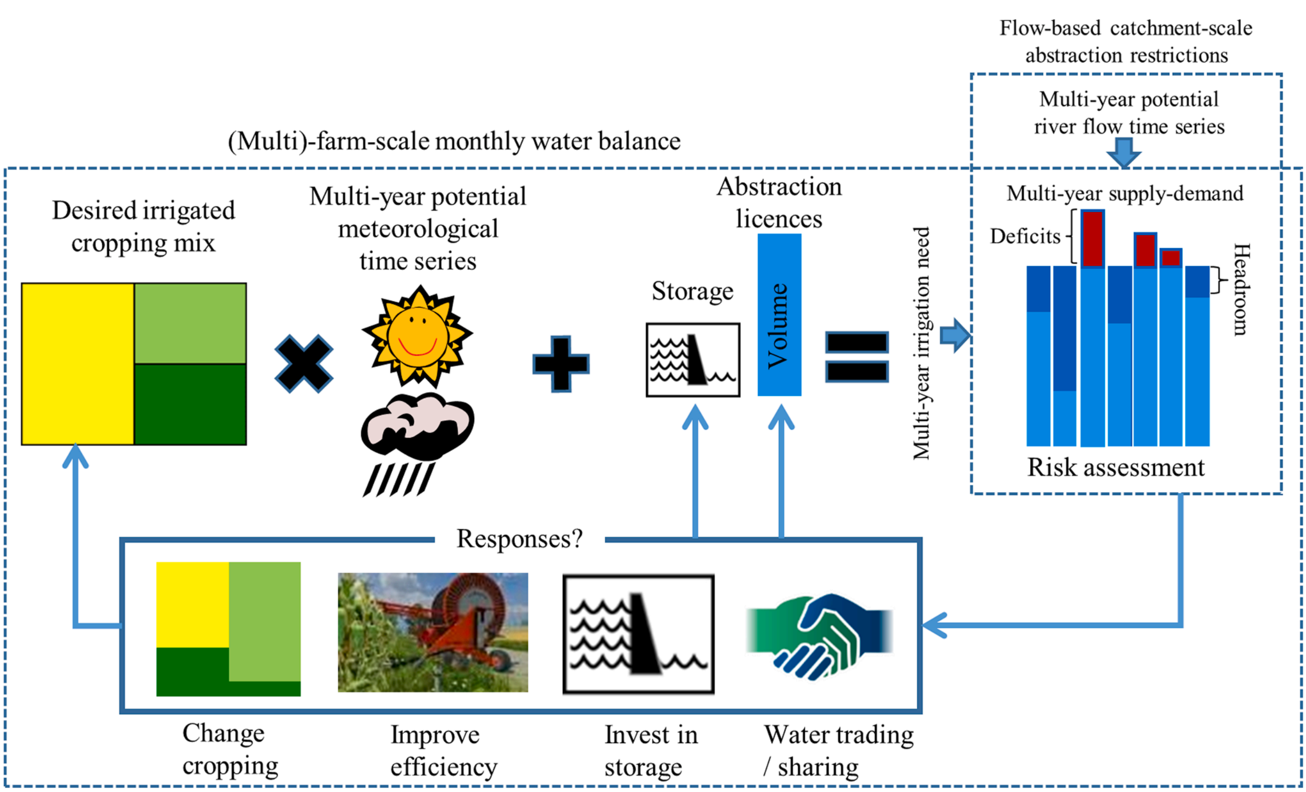

Fig. 1. Schematic of the enhanced D-Risk multi-scale approach.

and farm location (postcode) and period of analysis (baseline/near future), which are then used to retrieve simulated gridded weather and hydrological data for the selected location. The available gauging stations within the UK are structured in a drop-down list by country and county, with an external link provided to the National River Flow Archive (https://www.nrfa.ceh.ac.uk) interactive gauging station map to facilitate identification. The selected gauging station is later used to calculate abstraction constraints on a given abstraction licence imposed by the simulated river flow conditions. The farm data input module allows entry of information on the irrigated crop types (from an expanded list of 19 options), soil types (based on available water capacity classes), crop planting month, irrigated area, abstraction licence details and total 'live' on-farm reservoir storage (if applicable). The updated abstraction licence data input section considers, for each licence, the water source (surface or groundwater), purpose (direct abstraction or storage), maximum abstraction limits (annual, daily, absolute), allowable months for abstraction and any flow-based abstraction restrictions (if applicable).

3.1. Maximum potential soil moisture deficit (PSMDmax) database

The webtool uses an agroclimate index called annual maximum potential soil moisture deficit (PSMDmax) to calculate monthly and annual volumetric irrigation demand for the selected crop mix, soil available water capacity (AWC) and location (Knox et al., 1997). The PSMDmax has been widely used to quantify irrigation needs at different spatial scales and to assess climate change impacts on water demand (Knox et al., 1997, 2010; De Silva et al., 2007; Rodríguez Díaz et al., 2007). This index is also used by the regulatory authority in England and Wales in determining irrigation need as part of the assessment process for awarding licences for irrigation abstraction (Rees et al., 2003). A key advantage of PSMDmax over other commonly used agroclimatic indicators such as Standardised Precipitation Index is that it takes into account of the absolute distribution of rainfall and ET throughout the year, and thus identifies the absolute dryness or wetness of a specific location for a given year (Rey et al., 2016; Parsons et al., 2019) that influences irrigation need. The annual PSMDmax is calculated from a gridded daily weather dataset composed of 100 ensemble members of 31 years of equally probable precipitation and potential evapotranspiration time series termed the "MaRIUS event set" (Guillod et al., 2017, 2018). The ensemble is derived from the Weather@home2 climate modelling framework which consists of a global and regional climate model with prescribed sea surface temperatures (SST) and sea ice that has been used to simulate climate conditions over Europe (Guillod et al., 2017). The MaRIUS event set provides a large number of spatio-temporally consistent and long-time series for the UK, enabling drought risk to be comprehensively assessed. Daily precipitation and potential evapotranspiration (derived via Penman-Monteith with the stomatal resistance adjusted for future time slices) from two scenarios were used:

- 100 × 31-year (1974–2004) baseline ensemble (that uses historic SST and sea ice from HadISST (Rayner et al., 2003; Titchner & Rayner, 2014),
- 100 × 31-year (2020–2049) near future ensemble (that uses the 50th percentile sea surface temperature [SST] and sea ice from CMIP5 (Taylor, Stouffer & Meehl, 2012), assuming the high greenhouse gas emission scenario RCP8.5 (Representative Concentration Pathway 8.5; Meinshausen et al., 2011). Although other near future climate series for RCP8.5 were developed by Guillod et al. (2017) based on sampling across the uncertainty range in simulated future SST and sea ice (see their Table 2), this ensemble was selected as being representative / central for the 'worst case' emissions scenario and is also the most complete ensemble available. Other RCPs were not simulated by Guillod et al. (2018).

The precipitation is bias corrected using the linear bias correction method as presented in Guillod et al. (2018). The potential evapotranspiration data was not bias corrected as the biases were relatively small (Guillod et al., 2018). Detailed description of Weather@home2 climate modelling framework and the derivation of the MaRIUS event set are given in Guillod et al., 2017 and 2018 respectively. An explanation of the derivation of annual PSMDmax for each ensemble member is given in Haro-Monteagudo et al., 2019. Application of D-Risk at the individual farm scale uses the annual PSMDmax series for the grid that contains the postcode centroid whereas catchment-scale analyses use the maximum PSMDmax grid pixel value within the catchment.

3.2. Derivation of hydrological datasets

To simulate daily river flows at each gauging station, the DECIPHeR (Dynamic fluxEs and ConnectIvity for Predictions of HydRology) hydrological modelling framework (Coxon et al., 2019) was used. DECIPHeR is a flexible hydrological modelling framework that can simulate flows across multiple catchments with different hydrological characteristics, and which has been previously shown to perform well for four different evaluation metrics across a wide range of catchments (Coxon et al, 2019). DECIPHeR groups together similar parts of the landscape into spatially connected hydrological response units (or HRUs) to minimise model run time and enable it to run large ensembles of climate simulations and provide probabilistic flow simulations essential for risk analysis. Detailed information on the DECIPHeR model and the model code are given in Coxon et al., 2018.

To calibrate the model, daily data of precipitation, potential evapotranspiration and discharge for a 55-year period from 1 January 1961 to 31 December 2015 were used to run and assess the model. Daily 1 km^2 gridded rainfall estimates from 1961 − 2015 for Great Britain (GB) were obtained from the CEH Gridded Estimates of Areal Rainfall (CEH-GEAR) dataset (Keller et al., 2015;Tanguy et al., 2016). Daily 1 km^2 gridded estimates of potential evapotranspiration from 1961 − 2015 estimated using the Penman-Monteith equation were obtained from the CEH Climate hydrology and ecology research support system potential evapotranspiration dataset for Great Britain (CHESS-PE) (Robinson et al., 2016). The model was evaluated against observed daily streamflow data for 1,366 gauges obtained from the National River Flow Archive.

DECIPHeR was then run within a Monte-Carlo simulation framework whereby 10,000 parameter sets were randomly sampled from a uniform prior distribution. These parameters were applied uniformly across each catchment and used within a single model structure. Given the wide range of hydro-climatic conditions across GB, sampling of the feasible parameter space was ensured by using wide sampling ranges based on previous studies that used the Dynamic TOPMODEL (Beven & Freer, 2001; Freer et al., 2004; Page et al., 2007). The behavioural ensemble of parameter sets provided in this dataset was quantified by evaluating model performance using four evaluation metrics: (i) NSE (Nash & Sutcliffe, 1970), (ii) logNSE, (iii) Bias in Runoff Ratio (Yilmaz et al., 2008) and (iv) Low Flow Volume (Yilmaz et al., 2008) (Table 1). These

Table 1
Model performance metrics.

Evaluation metric	Equation	Focus
Nash Sutcliffe Efficiency	$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{obs} - Q_{sim})^2}{\sum_{i=1}^{n}(Q_{obs} - \overline{Q_{obs}})^2}$	High Flows
Nash Sutcliffe Efficiency log flows	$NSE_{log} = 1 - \frac{\sum_{i=1}^{n}(\log(Q_{obs}) - \log(Q_{sim}))^2}{\sum_{i=1}^{n}(\log(Q_{obs}) - \log(\overline{Q_{obs}}))^2}$	Low Flows
Bias in Runoff Ratio	$absPBIAS = \left\lvert\frac{\sum(Q_{sim} - Q_{obs})}{\sum Q_{obs}}\right\rvert * 100$	Water Balance
Low Flow Volume	$LFV = 100\frac{\sum_{p=50}^{100}(\sqrt{QP_{sim}} - \sqrt{QP_{obs}})}{\sum_{p=50}^{100}(\sqrt{QP_{obs}})}$	Low Flows

metrics were chosen to reflect simulations that captured high flows, low flows and the water balance of each catchment. To calculate a combined multi-objective score, each metric was ranked in turn and ordered by the sum of the ranks with an equal weighting for each metric. The top ranked simulation was then used as the parameter set for the future simulations with good model performance found for a range of catchment characteristics (Coxon et al, 2019).

The ensemble of past and near future precipitation and potential evapotranspiration from Guillod et al. (2018) were downscaled to a 5 km grid and then used as input values to DECIPHeR using the top-ranked parameter set for each catchment so that 100 31-year daily flow simulations for 1,366 catchments for two time slices were derived.

3.3. Abstraction restrictions

In the UK, an abstraction licence is required from the Environment Agency (EA) to abstract more than 20 m^3/day from surface or groundwater (Environment Agency, 2008). However, having an irrigation abstraction licence does not entitle the licence holder to always abstract, as the EA can impose partial restrictions or total bans on abstraction from water sources during droughts to protect public water supplies and the aquatic environment (Environment Agency, 2017). Two types of abstraction restrictions have been incorporated into the enhanced D-Risk webtool: (i) Hands-off Flow (HoF) restrictions [applied to surface water licences] and (ii) emergency drought (ED) restrictions [generally applied to surface water abstractions]. HoFs are specified on some individual surface water licences and impose constraints on abstraction based on local river flows. ED restrictions impose abstraction constraints to protect drinking water supplies and river ecology during extreme low flows and are usually applied to all surface water irrigation abstractions within a catchment. There are no fixed approaches to imposing ED across the UK, and hence we considered different defined levels of ED restrictions (i.e. Level 1 = 50 % reduction; Level 2 = 75 % reduction; Level 3 = 100 % reduction) within increasingly extreme low flows according to Salmoral et al. (2019). We also allow the user to specify whether groundwater licences may be subject to Level 3 ED restrictions.

Irrigation abstraction from a given surface water licence is only possible on days during the licence period which are not restricted by a HoF and/or ED. The days not under abstraction restriction (DNUAR) by HoF for a given licence are calculated for the specified licence-specific flow percentile using the DECIPHeR simulated river flows. To do this, an absolute discharge value for the flow percentile is derived across all of the 100 ensemble members of 31-years simulated baseline river flows. This absolute threshold value is then applied to each individual member to estimate DNUAR for both the baseline and near future. Similarly, if ED are enabled, days in each month that are not affected or partially affected under different levels of restrictions (Level 1, Level 2 and Level 3 ED restrictions for surface water licences; and Level 3 restrictions for groundwater licences) are identified e.g. 1 day under Level 1 (50 % reduction) restriction is treated as 0.5 day of abstraction restriction. Finally, as HoFs and EDs can occur on the same day, the overall DNUAR are calculated for each month in each ensemble member.

3.4. Modelling irrigation demand and risk profiles

The calculation of volumetric irrigation demand for the selected crop types and soil types uses the relationships between theoretical irrigation need and PSMDmax based on Knox et al. (1997). Although this provides a unique relationship to estimate theoretical irrigation need for each crop type-soil type combinations throughout the UK, the estimated theoretical irrigation need of a given crop type-soil type combinations can be modified to reflect actual practice using the 'Irrigation correction factor'. A monthly time-step water balance model was then used to calculate whether the total irrigation demand can be met, considering the daily and annual licensed abstraction limits, the specified start and end months of each licence and any on-farm storage. It assumes that licenses dependent on surface water are given priority by farmers and used before licensed groundwater sources due to their greater vulnerability to abstraction restrictions and that direct abstraction is preferred before reservoir storage. Abstraction is possible only on the DNUAR based on the abstraction restrictions that are in action at the selected location on specified licences.

Using a water balance model, the 100 sets of 31-year time series of the annual irrigation deficit (representing the volumetric proportion of the annual irrigation demand that is not met) and the licensed abstraction 'headroom' (defined as the proportion of the total licensed volume that is not abstracted) are calculated. The enhanced D-Risk provides two sets of results (with and without abstraction constraints) from the series of annual irrigation deficits and headroom expressed as cumulative distribution functions (cdf) in both graphical (Fig. 2) and tabular form. It presents the 'median' cdf of irrigation deficit or headroom by assuming that the future probability is equally based on all of 100 sets of 31-year time series. It also derives the cumulative distribution functions of irrigation deficit or headroom separately for the 100 sets of 31-year time series, given that each event set is equally probable given natural climate variability. From these cdfs, it presents the best and worst cases to provide an uncertainty boundary (envelope) around the 'median'. The code used to develop the enhanced D-Risk webtool is provided in the Supplementary Material.

4. Application of the enhanced D-Risk webtool

The enhanced D-Risk webtool enables individuals or groups of farming enterprises to better evaluate their drought risk profiles considering potential abstraction restrictions. In doing so, D-Risk inevitably makes a number of simplifications and assumptions, such as using pre-existing crop-soil specific relationships between PSMDmax and irrigation need. However, it provides the functionality to calibrate irrigation need to reflect farm practice and explicitly depicts the uncertainty in the consequence of future climate variability. Consequently, the use of D-Risk should lead to improved business planning and infrastructural investments in water storge and irrigation equipment. At the individual business scale, it can help farmers to (i) support their business case for maintaining their existing licensed allocation during the abstraction licence renewal process (usually conducted on a 6 year rolling cycle) through improved characterisation of the effects of natural climate variability on their irrigation demands and abstraction profiles; (ii) to understand how modifying their planting programmes and crop mix could mitigate risks to their business associated with the possible future licensed reductions and/or more severe Hands-off Flow (HoF) conditions and (iii) to assess how irrigated crop expansion to fully utilise their licensed volume allocation might increase their drought risk due to reduced licensed headroom in drought years.

However, there is also increasing interest in supporting more collaborative approaches to abstraction management between agricultural water users, such as water abstractor groups (Weatherhead et al., 2014) and supporting multi-sector collaboration (Knox et al., 2018). This enhanced D-Risk tool can help stakeholders to better understand drought risks and water availability at catchment scales to explore the potential benefits of collective action on the use and allocation of water resources particularly in water-stressed catchments where irrigation demand is concentrated. The comparison of risk profiles between individual farms and aggregated farms at different spatial scales can help in evaluating the potential benefits of water sharing (e.g. Chengot et al., 2021), and shared water storage. The enhanced D-Risk webtool enables agricultural abstractor groups to identify opportunities to increase high-value food production and maximise the economic benefits of irrigation through water sharing within their existing licensed allocations and flow-based abstraction constraints, thereby supporting regional economic growth and improved food security within existing environmental constraints.

Although D-Risk has been specifically developed for UK use, the

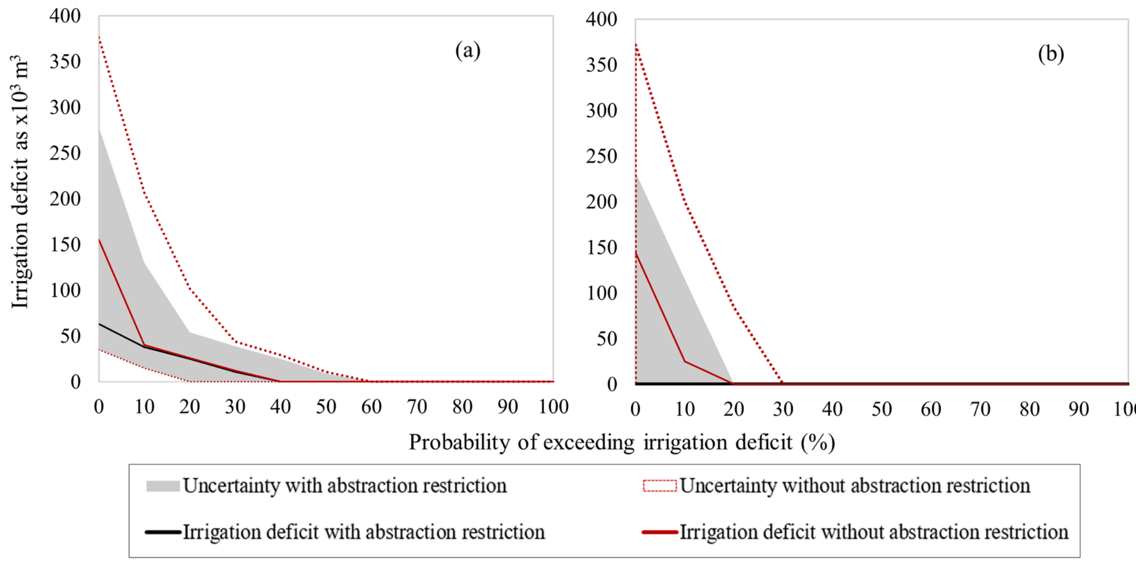

Fig. 2. Annual probability distribution of irrigation deficits 'with' and 'without' simulated river-flow based abstraction restrictions when (a) the two individual businesses operate independently; and (b) when the two businesses collaborate to make best use of their combined licenced.

methodological framework of integrating hydrological flows, abstraction licence / permit conditions (flow-based thresholds and/or volumetric limits) and reservoir storage within a farm-scale irrigation water balance could be applied in other countries.

4.1. Example application

A theoretical case study example is provided to demonstrate the applicability of D-Risk, in this particular case to assess the potential benefits of collaborative water sharing between nearby irrigated farm businesses to reduce water resources risks in agriculture during severe drought years. Two hypothetical irrigated farms (Business 1 and Business 2) located in the "Flit at Shefford (33028)" catchment in Bedfordshire, with direct surface water, direct groundwater and surface water storage abstraction licences were considered. The input data used to run D-Risk are given in Table 2. To reflect local practice, the actual design dry year irrigation need of maincrop potatoes, onions and parsnips were adjusted to 300 mm, 200 mm and 200 mm respectively.

With no water sharing, the two businesses have a combined annual irrigation deficit of around 26,000 m^3 at a 20 % annual probability, although this ranges between 0 and 102,000 m^3 across individual climate ensemble members (shaded uncertainty zone) (Fig. 2). Water sharing between Business 1 (which has no irrigation deficit during a design-dry year and significant headroom (Figure S3)) and Business 2 (which has a significant design-dry year irrigation deficit (Figure S4)) shows that the design dry year irrigation deficit can be completely removed (zero deficit with a 20 % annual probability) (Fig. 2).

More example case study applications are provided on the D-Risk website at https://www.d-risk.eu/index.php?params=casestudies.

5. Conclusions

The D-Risk webtool was designed to support national drought risk management within UK irrigated agriculture; the enhanced version of the tool provides much greater functionality to inform drought risk assessment for both individual and multiple farms and for catchment scale analyses. The tool enables the end user to better plan for expected increasing water scarcity associated with future climate change and supports improved collaborative decision-making for realising the benefits of water sharing. Although D-Risk webtool was specifically developed for the UK irrigated farming context, it could be readily transposed for application in other countries facing pressures on agricultural water allocation, drought risks and water scarcity.

CRediT authorship contribution statement

Rishma Chengot: Methodology, Investigation, Validation, Writing – original draft, Data curation. **Jerry W. Knox:** Conceptualization, Writing – original draft, Funding acquisition. **Gemma Coxon:** Investigation, Writing – original draft. **George Cojocaru:** Software, Visualization. **Ian P. Holman:** Conceptualization, Funding acquisition, Project administration, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table 2
Input data used to run D-Risk example application.

	Irrigated cropping details				Abstraction licence n details					Storages
Farm.	Irrigated crop type	Soil AWC*	Planting month	Irrigated area (ha)	Water source /Purpose	Annual licensed volume (m^3)	Daily licenced limit (m^3)	Abstraction period	HoF (m^3/*sec*)	Reservoir storage (m^3)
1	Maincrop potato	Medium	March	70	SW-S	190,000	1818	1/11–31/3	0.860	180,000
	Onion	Low	March	65	GW-D	210,000	5400	1/3–31/10	N/A	
2	Maincrop potato	Medium	March	30	SW-D	90,922	1100	1/4–31/10	None-	N/A
	Parsnips	Medium	April	10						

[*] Available Water Capacity; [**]SW-D: Surface water (direct), SW-S: Surface water (storage), GW-D: Groundwater (direct), GW-S: Groundwater (storage).

Data availability

No data was used for the research described in the article.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2022.107516.

References

Azadi, H., Keramati, P., Taheri, F., Rafiaani, P., Teklemariam, D., Gebrehiwot, K., Hosseininia, G., Van Passel, S., Lebailly, P., Witlox, F., 2018. Agricultural land conversion: Reviewing drought impacts and coping strategies. Int. J. Disaster Risk Reduct. 31, 184–195. https://doi.org/10.1016/J.IJDRR.2018.05.003.

Beven, K., Freer, J., 2001. A dynamic TOPMODEL. Hydrol. Process. 15 (10), 1993–2011. https://doi.org/10.1002/HYP.252.

Chengot, R., Knox, J.W., Holman, I.P., 2021. Evaluating the Feasibility of Water Sharing as a Drought Risk Management Tool for Irrigated Agriculture. Sustain. 13 (3), 1456. https://doi.org/10.3390/SU13031456.

Collins, R., Johnson, D., Crilly, D., Rickard, A., Neal, L., Morse, A., Walker, M., Lear, R., Deasy, C., Paling, N., Anderton, S., Ryder, C., Bide, P., Holt, A., 2020. Collaborative water management across England – An overview of the Catchment Based Approach. Environ. Sci. Policy 112, 117–125. https://doi.org/10.1016/J.ENVSCI.2020.06.001.

Coxon G., Freer J., Lane R., Dunne T., 2018. DECIPHER User Manual. Available at https://doi.org/10.5281/zenodo.2604120.

Coxon, G., Freer, J., Lane, R., Dunne, T., Knoben, W.J.M., Howden, N.J.K., Quinn, N., Wagener, T., Woods, R., 2019. DECIPHeR v1: Dynamic fluxEs and ConnectIvity for Predictions of HydRology. Geosci. Model Dev. 12 (6), 2285–2306. https://doi.org/10.5194/gmd-12-2285-2019.

Department of Agriculture, Fisheries and Forestry (DAFF), 2022. Drought Resilience Self-Assessment Tool (DR.SAT). https://www.agriculture.gov.au/agriculture-land/farm-food-drought/drought/future-drought-fund/drought-resilience-self-assessment-tool.

De Silva, C., Weatherhead, K., Knox, J., Rodriguez-Diaz, J., 2007. Predicting the impacts of climate change—a case study of paddy irrigation water requirements in Sri Lanka. Agric. Water Manage. 93, 19–29.

Environment Agency, 2008. *Abstracting water - A guide to getting your licence*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/716363/abstracting-water-guide-to-getting-licence.pdf. (accessed on 25 June 2021).

Environment Agency, 2017. *Drought response: our framework for England.* https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/625006/LIT_10104.pdf. (accessed on 25 June 2021).

Freer, J.E., McMillan, H., McDonnell, J.J., Beven, K.J., 2004. Constraining dynamic TOPMODEL responses for imprecise water table information using fuzzy rule based performance measures. J. Hydrol. 291 (3–4), 254–277. https://doi.org/10.1016/J.JHYDROL.2003.12.037.

Garrick, D., De Stefano, L., Yu, W., Jorgensen, I., O'Donnell, E., Turley, L., Aguilar-Barajas, I., Dai, X., De Souza Leão, R., Punjabi, B., Schreiner, B., Svensson, J., Wight, C., 2019. Rural water for thirsty cities: a systematic review of water reallocation from rural to urban regions. Environ. Res. Lett. 14 (4), 043003 https://doi.org/10.1088/1748-9326/AB0DB7.

Guillod, B.P., Jones, R.G., Bowery, A., Haustein, K., Massey, N.R., Mitchell, D.M., Otto, F.E.L., Sparrow, S.N., Uhe, P., Wallom, D.C.H., Wilson, S., Allen, M.R., 2017. Weather@home 2: Validation of an improved global-regional climate modelling system. Geosci. Model Dev. 10 (5), 1849–1872. https://doi.org/10.5194/GMD-10-1849-2017.

Guillod, B.P., Jones, R.G., Dadson, S.J., Coxon, G., Bussi, G., Freer, J., Kay, A.L., Massey, N.R., Sparrow, S.N., Wallom, D.C.H., Allen, M.R., Hall, J.W., 2018. A large set of potential past, present and future hydro-meteorological time series for the UK. Hydrol. Earth Syst. Sci. 22 (1), 611–634. https://doi.org/10.5194/hess-22-611-2018.

Haro-Monteagudo, D., Knox, J.W., Holman, I.P., 2019. D-Risk: A decision-support webtool for improving drought risk management in irrigated agriculture. Comput. Electron. Agric. 162855–858 https://doi.org/10.1016/J.COMPAG.2019.05.029.

Henriques, C., Holman, I.P., Audsley, E., Pearn, K., 2008. An interactive multi-scale integrated assessment of future regional water availability for agricultural irrigation in East Anglia and North West England. Clim. Change 90 (1–2), 89–111. https://doi.org/10.1007/S10584-008-9459-0.

Holman, I.P., Hess, T.M., Rey, D., Knox, J.W., 2021. A multi-level framework for adaptation to drought within temperate agriculture. Front. Environ. Sci. 8, 589871 https://doi.org/10.3389/fenvs.2020.589871.

Iglesias, A., Garrote, L., 2015. Adaptation strategies for agricultural water management under climate change in Europe. Agric. Water Manag. 155, 113–124. https://doi.org/10.1016/J.AGWAT.2015.03.014.

Keller, V.D.J., Tanguy, M., Prosdocimi, I., Terry, J.A., Hitt, O., Cole, S.J., Fry, M., Morris, D.G., Dixon, H., 2015. CEH-GEAR: 1 Km resolution daily and monthly areal rainfall estimates for the UK for hydrological and other applications. Earth Syst. Sci. Data 7 (1), 143–155. https://doi.org/10.5194/ESSD-7-143-2015.

Knox J.W., Kay M.G., Holman I.P., Hess T., 2020a. *Irrigation water strategy for UK agriculture and horticulture.* https://www.nfuonline.com/nfu-online/science-and-environment/irrigation-and-abstraction/irrigation-water-strategy-for-uk-agriculture-and-horticulture/. (accessed on 25 June 2021).

Knox J.W., Kay M.G., Hess T.M., Holman I.P., 2020b. The challenges of developing an irrigation strategy for UK agriculture and horticulture in 2020: industry and research priorities. *CAB Rev.: Perspect. Agric. Vet. Sci. Nutr. Nat. Resour.*15(050).DOI: 10.1079/PAVSNNR202015050.

Khan, S., Mushtaq, S., Chen, C., 2010. A decision support tool for irrigation infrastructure investments. Irrig. Drain. 59, 404–418. https://doi.org/10.1002/ird.501.

Knox, J.W., Haro-Monteagudo, D., Hess, T.M., Morris, J., 2018. Identifying trade-offs and reconciling competing demands for water: Integrating agriculture into a robust decision-making framework. Earth's Future 6 (10), 1457–1470.

Knox, J., Morris, J., Hess, T., 2010. Identifying future risks to UK agricultural production: putting climate change in context. Outlook Agric. 39 (4), 249–256.

Knox, J.W., Weatherhead, E.K., Bradley, R.I., 1997. Mapping the total volumetric irrigation water requirements in England and Wales. Agric. Water Manag. 33 (1), 1–18. https://doi.org/10.1016/S0378-3774(96)01285-1.

Kuwayama, Y., Thompson, A., Bernknopf, R., Zaitchik, B., Vail, P., 2019. Estimating the Impact of Drought on Agriculture Using the U.S. Drought Monitor. Am. J. Agric. Econ. 101 (1), 193–210. https://doi.org/10.1093/AJAE/AAY037.

Lowe J.A., Bernie D., Bett P., Bricheno L., Brown S., Calvert D., Clark R., Eagle K., Edwards T., Fosser G., 2018. *UKCP18 ScienceOverview Report* (Exeter: Met Office Hadley Centre). https://www.metoffice.gov.uk/pub/data/weather/uk/ukcp18/science-reports/UKCP18-Overview-report.pdf. (accessed on 11 July 2022).

Margerum, R.D., Robinson, C.J., 2015. Collaborative partnerships and the challenges for sustainable water management. Curr. Opin. Environ. Sustain. 12, 53–58. https://doi.org/10.1016/J.COSUST.2014.09.003.

Meinshausen, M., Smith, S.J., Calvin, K., Daniel, J.S., Kainuma, M.L.T., Lamarque, J.-F., Matsumoto, K., Montzka, S.A., Raper, S.C.B., Riahi, K., et al., 2011. The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. Clim. Change 109 (1–2), 213.

Met Office, 2020. UK regional climates https://www.metoffice.gov.uk/research/climate/maps-and-data/regional-climates/index. (accessed on 26 April 2021).

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I — A discussion of principles. J. Hydrol. 10 (3), 282–290. https://doi.org/10.1016/0022-1694(70)90255-6.

Page, T., Beven, K.J., Freer, J., Neal, C., 2007. Modelling the chloride signal at Plynlimon, Wales, using a modified dynamic TOPMODEL incorporating conservative chemical mixing (with uncertainty). Hydrol. Process. 21 (3), 292–307. https://doi.org/10.1002/HYP.6186.

Parsons, D.J., Rey, D., Tanguy, M., Holman, I.P., 2019. Regional variations in the link between drought indices and reported agricultural impacts of drought. Agric. Syst. 173, 119–129. https://doi.org/10.1016/J.AGSY.2019.02.015.

Rayner N.A.A., Parker D.E., Horton E.B., Folland C.K., Alexander L. V, Rowell D.P., Kent E.C., Kaplan A., 2003. Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. *J. Geophys. Res. Atmos.*, 108 (D14).

Rees B., Cessford F., Connelly R., Cowan J., Bowell R., Weatherhead E.K., Knox J.W., Twite C.L., Morris J., 2003. Optimum Use of Water for Industry and Agriculture. Phase III. R&D Technical Report W6-056/TR1. Environment Agency, Bristol.

Rey D, Holman I, Knox J. (2021) Towards the operationalization of water sharing for irrigation in England, Project Report, July 2021, Cranfield University. Available at http://dspace.lib.cranfield.ac.uk/handle/1826/17290.

Rey, D., Holman, I.P., Daccache, A., Morris, J., Weatherhead, E.K., Knox, J.W., 2016. Modelling and mapping the economic value of supplemental irrigation in a humid climate. Agric. Water Manag. 173, 13–22. https://doi.org/10.1016/J.AGWAT.2016.04.017.

Rey, D., Holman, I.P., Knox, J.W., 2017. Developing drought resilience in irrigated agriculture in the face of increasing water scarcity. Reg. Environ. Chang. 17 (5), 1527–1540. https://doi.org/10.1007/S10113-017-1116-6/FIGURES/4.

Robinson, E.L.; Blyth, E.; Clark, D.B.; Comyn-Platt, E.; Finch, J.; Rudd A.C., 2016. Climate hydrology and ecology research support system potential evapotranspiration dataset for Great Britain (1961-2015) [CHESS-PE] - EIDC. *NERC Environ. Inf. Data Centre. (Dataset).*.

Rodríguez Díaz, J.A., Weatherhead, E.K., Knox, J.W., Camacho, E., 2007. Climate change impacts on irrigation water requirements in the Guadalquivir River Basin in Spain. Reg. Environ. Change. 7, 149–159.

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 Futur. 7 (2), 178–196. https://doi.org/10.1029/2018EF001092.

Santato, S., Mysiak, J., Pérez-Blanco, C.D., 2016. The Water Abstraction License Regime in Italy: A Case for Reform? Water 103 8 (3), 103. https://doi.org/10.3390/W8030103.

Tanguy, M.; Dixon, H.; Prosdocimi, I.; Morris, D. G.; Keller V.D.J., 2016. Gridded estimates of daily and monthly areal rainfall for the United Kingdom (1890-2015) [CEH-GEAR]. *NERC Environ. Inf. Data Centre.* https://doi.org/10.5285/ee9ab43d-a4fe-4e73-afd5-cd4fc4c82556.

Taylor, K.E., Stouffer, R.J., Meehl, G.A., 2012. An overview of CMIP5 and the experiment design. Bull. Am. Meteorol. Soc. 93 (4), 485–498.

Titchner, H.A., Rayner, N.A., 2014. The Met Office Hadley Centre sea ice and sea surface temperature data set, version 2: 1. Sea ice concentrations. J. Geophys. Res. Atmos. 119 (6), 2864–2889.

Weatherhead K., Knox J., Daccache A., Morris J., Groves S., Hulin A., Kay M., 2014. Water for agriculture: collaborative approaches and on-farm storage FFG1112 Final Report. https://www.fensforthefuture.org.uk/admin/resources/water-for-agriculture-final-report-march-2014.pdf. (accessed on 15 March 2022).

Yilmaz K.K., Gupta H. V., Wagener T., 2008. A process-based diagnostic approach to model evaluation: Application to the NWS distributed hydrologic model. *Water Resour. Res.* https://doi.org/10.1029/2007WR006716.