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Key Points:

- Simulated water availability from a national water resource system model are integrated with a macroeconomic model to assess drought risk
- The use of a large ensemble of synthetic drought simulations supports the risk-based analysis of direct and indirect economic losses
- The method supports national economic assessment of the implications of climate change and different water management strategies

Supporting Information:

Supporting Information may be found in the online version of this article.

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An Integrated Framework for Risk-Based Analysis of Economic Impacts of Drought and Water Scarcity in England and Wales

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Abstract Drought and water scarcity pose a risk to the economy, particularly sectors where water is a crucial input to the production process. This paper describes integrated simulations of water shortages from a dynamic national water resource systems model with a static economic input-output (I-O) model to assess total drought risk to the economy. To quantify the economic risks of drought and water scarcity, the analysis: (a) integrates a large ensemble of simulated meteorological droughts, propagated through a national hydrological model and water resource systems model to simulate water availability from reservoirs and groundwater; (b) assesses implications of restrictions on water availability for multiple water user categories, representing natural and human contributions to water scarcity; (c) investigates how water shortages propagate into economy-wide direct and indirect impacts. The study focuses on England and Wales where the water supply system is considered under strain, with growing recognition of the economic risk of prolonged and widespread shortages. The direct Expected Annual Loss (EAL) to water users, averaged over an ensemble equivalent to 2800 years of synthetic daily weather, is estimated to be £11.7 million in the 2011 base-year. Accounting for indirect economic losses results in a total EAL of £30.2 million in 2011. The most severe event simulated results in a total loss of £1.4 billion in 2011, equivalent to 0.11% of GVA. The analysis provides a framework to assess what the economically efficient level of system reliability should be, and for deciding upon appropriate water management regulations and strategic investments.

1. Introduction

Droughts are slow onset, spatially extensive events that can affect regions for weeks, months, or years. Droughts can cause severe impacts to the environment, society and the economy. The widespread European drought and heatwave of 2003 is estimated to have cost almost €15 billion, the second most costly climate event felt by EU member states to date (European Environment Agency, 2019). Yet, the unique characteristics of droughts are considered harder to identify and more complex to analyze and plan for than other natural hazards such as floods or storms (Logar & van den Bergh, 2013; Wilhite et al., 2007). The lack of observable physical damage to assets and capital can also hinder assessments of economic losses (Below et al., 2007). Economic impacts are sector specific, with changes to productive output, value added or employment focused on activities that use water as a critical or important part of their production process, such as public water supply, agriculture, or electricity supply (Freire-González et al., 2017a).

Droughts also can cause large indirect economic losses (Wilhite et al., 2007). Direct impacts to business of a reduction in water supply and quality can affect productivity and the flow of goods and services through sectoral interlinkages and supply chains. Severe droughts will impact household demand for goods and services and may impact the workforce. As such, droughts can affect economic sectors where water is not a critical or important part of their production process. Impacts can continue to be felt after a drought has ended and there is the potential for these impacts to affect regions beyond the original event (Jenkins, 2013).

The characteristics of a drought and its subsequent economic impacts are also profoundly influenced by water management and policy decisions, made over the short and long-term, to pre-empt or respond to water scarcity concerns (Freire-González et al., 2017a). Van Loon et al. (2016) highlight the importance

of acknowledging the human role in both mitigating and enhancing drought impacts, and the need to integrate both physical and social influences on drought within a single integrated framework for effective management.

Whilst the UK is not conventionally regarded as a water-scarce country, a combination of socio-economic and hydrological conditions mean that drought and related water scarcity pose a substantial threat to the environment, economy and society, with the water supply system already considered to be under strain. Water scarcity can directly impact on agricultural production; reduce river flows for water-cooled thermoelectric power generation (Byers et al., 2014, 2016, 2020); and reduce water availability at abstraction points used by industry, affecting industrial production (AECOM, 2016). Over the last 40 years several droughts have brought water use restrictions for households and businesses (Water UK, 2016). This pressure on water users will be exacerbated in the future due to climate change (Defra, 2018), increasing population (especially in the drier South and East of England) and stricter licensing requirements on water withdrawals from surface and groundwater bodies, to protect the aquatic environment (NIC, 2018). The risk of shortages in water supply have been highlighted by the UK's Committee on Climate Change as a priority climate risk where more action is needed by the government to manage the risk (Committee on Climate Change, 2017; Humphrey & Murphy, 2016). To inform such action one challenge is to provide a robust, risk-based approach to assess the economic costs of drought and related water scarcity events, including under different scenarios of climate change, and the role of different water management strategies. Assessments of drought impacts have tended to focus on specific historical drought events, rather than providing a comprehensive analysis of risks, integrated across the possible range of drought severity, extent and duration. Moreover, proper accounting for economic impacts requires a large-scale perspective, ideally national scale and beyond, which incorporates the large-scale spatial structure of hydrological droughts and the propagation of the economic impacts of water scarcity geographically and across sectors.

The following section provides background to the England and Wales case study. Section 3 provides an overview of the economic I-O modeling of drought impacts. Section 4 describes the methodology including data inputs and a description of the hydro-economic I-O model. Section 5 presents results, with the discussion and conclusions presented in Sections 6 and 7.

2. The Risks of Droughts and Water Scarcity in England and Wales

2.1. Approach to Management of Drought Risk

There has been growing concern about drought risk to water supplies in England and Wales, in particular following a period of unprecedented low flows in some parts of the country in early 2012, which threatened restrictions to water supply during the London Olympic Games. The 2014 Water Act introduced a duty upon the Secretary of State and Ofwat (the economic regulator) to further the resilience of the water industry in England and Wales. Water companies are already required to plan to ensure the resilience of their operations to drought. Under the Water Industry Act 1991, each water company must produce a Water Resource Management Plan (WRMP), updated every 5 years, to ensure sufficient supply of water to meet anticipated demands of customers over a 25-year planning period (including under water stress). As well as investment planning, water companies produce operational drought plans, which set out how they would manage water supplies in the event of impending or actual drought events (Water UK, 2016).

Table 1 outlines water restrictions that can be implemented to manage water demand during varying levels of drought severity, such as restrictions on non-essential uses of water, including Temporary Use Bans (TUBs). For private water abstractors Hands off Flow (HoF) limits can be applied to abstraction licenses, where allowable withdrawals are limited if the river flow falls below a specified threshold. Under Section 57 of the Water Resources Act 1991, the Environment Agency (EA) or Natural Resources Wales (NRW), who regulate abstractions in England and Wales respectively, can restrict or stop the abstraction of water for spray irrigation. In more severe droughts (Level 3) the water company can seek an Ordinary Drought Order, extending restrictions to the non-domestic sector. At Level 4, Emergency Drought Orders can be granted to increase supply, for example, increased abstractions for Public Water Supply (PWS) outside that permitted by an abstraction license. Restrictions can be placed on household water use, for example, by shutting off

Table 1
Water Restrictions

Severity	Household	Non-household		
	Public water supply (PWS)	Public water supply (PWS)	Private abstraction	Spray irrigation
Level 1	Media campaigns and communications			
Level 2	Temporary Use Bans (TUBs)	TUBs	Hands off Flow (HoF) limits apply	Partial restriction (Section 57)
Level 3	TUBs	Ordinary Drought Order	Ordinary Drought Order	Full restriction (Section 57)
Level 4	Emergency Drought Order	Emergency Drought Order	Ordinary Drought Order	Full restriction (Section 57)

Note. Adapted from Water UK Summary Report (2016).

water supplies to neighborhoods based on a daily rota or distributing water only from standpipe taps in streets or from trucks.

2.2. Previous Estimates of Drought Risk Impacts in England and Wales

It is estimated that large parts of England are exposed to the risk of such emergency restrictions at a likelihood in the order of 1% every year (Environment Agency, 2015). Yet, one concern is that some recent droughts have been more severe than the historical droughts widely used as benchmarks for planning by the water industry (Water UK, 2016). The National Infrastructure Commission (NIC) (2018) estimated that a drought that has a 1 in 4 chance of occurring (1% annual probability) between now and 2050 (used as a proxy for the worst drought recorded in recent history) would result in water deficits to six water companies, serving almost 40% of households in England. For a more severe drought that has a 1 in 7 chance of occurring by 2050 (0.5% annual probability) this increases to 10 companies, serving almost 60% of households.

Responding to a severe drought like this would likely cost tens of billions of pounds. Water UK (2016) estimated that for England and Wales as a whole there could be up to a 37% loss in Gross Value Added (GVA) if Level 4 restrictions were applied to all business and non-household public sector water users, equivalent to £1.4 billion per day. The economic losses were estimated by applying pre-defined percentage reductions in GVA for 41 economic sectors, to the sectoral GVA levels of 40 regions. The GVA percentage reductions were primarily taken from NERA (2006), which assigned values to sectors using assumptions about how businesses would be affected per day of Level 3 and 4 water use restrictions, based on a review of literature documenting two past drought events. NERA (2006) used these GVA percentage reductions to estimate the economic cost of a drought in London of similar magnitude to the 1975/76 drought event, with a focus on Level 3 and 4 restrictions. The study estimated a GVA loss of £4.9 billion to industry if no further action was taken. The above studies provide high-level estimates assuming all regions and sectors are affected uniformly. In reality, the losses would need to be scaled to match the sectoral GVA of the affected region(s) during a specific drought period.

In contrast, AECOM (2016) estimated the cost to GVA in England of a severe drought lasting one year as £260 million, rising to £477 million under an extreme drought where more stringent demand restrictions are imposed. Losses increase to £880m for a 3-years severe or extreme event but are still considered modest compared to previous estimates. In this study, reductions in water for consumption by sectors were defined using a set of water use restriction values for PWS and non-PWS. The GVA loss proportion was assumed to be the same as the volume-reduction proportion, sector by sector.

The large differences in the estimated economic impacts illustrate the need for more in-depth analysis of the processes by which droughts impact the economy and the dynamics of how those impacts materialize in space and time. Nonetheless, these previous analyses illustrate the potential threat droughts pose to the economy in England and Wales and emphasize that future planning needs to strike a balance between the costs of water restrictions and the costs of avoiding such restrictions by investing in additional supply or demand measures. This is paramount given the challenges the water industry is likely to face in the future. Yet these studies are limited by their focus on a small sub-set of hypothetical drought events; speculative assumptions on the relative use of water by different sectors; focus on direct losses only; and the lack of

evidence upon which the sectoral GVA loss factors are based. As such, providing a more sophisticated approach to quantify the magnitude and distribution of economic losses from drought and water scarcity in England and Wales, whilst considering the complex interaction between natural and human processes, is critically important to help decision makers, water suppliers and private actors understand the potential scale of economic risks that may be faced, to understand the trade-offs which may be required between uses of water, and ultimately inform the need for investment and regulatory action.

3. Economic I-O Modeling of Drought Impacts

For macroeconomic impacts both input-output (I-O) and computable general equilibrium (CGE) models have become prominent approaches in disaster impact analysis (Koks et al., 2016), including application to drought and water scarcity (see Text S1 for further comparison of these methods). I-O analysis provides an analytical framework to examine the interdependencies of industries within an economy (Miller & Blair, 2009), based on the premise that each industry produces goods and/or services, consuming goods from other industries to produce such goods, ultimately to satisfy final household demand or exports. In its traditional form an I-O model represents a demand-driven, static, linear, approach with the economy defined through interrelationships between sectors and other consumers. Beginning in the 1960s traditional I-O models were theoretically extended to capture economic and environmental interactions, by incorporating physical information within the I-O framework in Environmentally Extended I-O (EEIO) tables (Duarte & Yang, 2011). For example, Daly (1968) proposed incorporating “ecological commodities,” complementary to the flow of “economic commodities” within the framework, whilst, amongst others, Leontief (1970) illustrated the potential application to pollution. Whilst water initially received less attention within EEIO analysis (Duarte & Yang, 2011) early examples include Lofting and McGauhey (1968), who incorporated water requirements as an input in a traditional I-O model of the Californian economy via a physical production factor (Velázquez, 2006). The 21st century has seen wide growth in the application of I-O models to water, with many studies focused on virtual water flows and water footprints (Duarte & Yang, 2011). These account for water consumption within sectoral production, including in Multi-Regional I-O models (MRIO), to see how embedded resources are traded (e.g., Lenzen, 2009; White et al., 2015). Although some links to water scarcity have been made, the general focus of such studies is calculating indirect impacts related to consumption activities or the amount of embedded environmental goods traded (Kitzes, 2013).

In other applications, I-O studies have assessed the indirect costs from historic drought, often focused on agriculture and energy production, at a regional and national level (e.g., Diersen & Taylor, 2003; Perez y Perez & Barreiro-Hurle, 2009; Wheaton et al., 2008) as well as for hypothetical and simulated events, including under projections of climate change (Eamen et al., 2020; Freire-González et al., 2017b; Jenkins, 2013). However, these studies tend to use exogenous estimates of direct drought costs and embed these in the models to calculate indirect losses. Freire-González et al. (2017b) estimate direct costs of drought by converting exogenous data on water shortfalls to a reduction in sectoral production via GVA-water elasticities. In Eamen et al. (2020), water intake data is converted to monetary units so a given change in the value of raw water intake can be equated to a direct change in sectoral gross output. Both studies also consider implications of climate change and water management scenarios on water supply. However, these scenarios are based on *hypothetical* assumptions rather than integrating data from climate, hydrological or water resource model simulations. Also of relevance in these studies is the use of the Ghosh (1958) or supply side I-O model. Counter to the traditional approach, shocks are applied to the supply side which can be particularly useful when estimating the impacts of supply constrained economies, including for water scarcity analysis (e.g., Bogra et al., 2016; Davis & Salkin, 1984; Eamen et al., 2020; Freire-González, 2011; Freire-González et al., 2017b; Perez y Perez & Barreiro-Hurle, 2009).

Yet, there are challenges in using water accounting methods in I-O (and CGE, see Text S1) models given differences in the spatial and temporal dynamics of hydrologic data versus modeled economic systems (Bekchanov et al., 2017). First, time scales in hydrological models often refer to days, months or seasons, while in many economic models time scales are longer, typically years (Brouwer & Hofkes, 2008). Although, it is possible in some cases to disaggregate underlying I-O data tables in time to provide a more dynamic view of trends and seasonal effects (Galbusera & Giannopoulos, 2018), this raises its own challenges. Second, I-O models are often applied in a comparative static analysis, whereby a shock is applied to the

model and the consequential new equilibrium is quantified. This does not capture the dynamic process by which water supplied can become progressively constrained during a drought and reallocated by regulatory drought management actions. Dynamic I-O models, which are solved sequentially make contributions here (Galbusera & Giannopoulos, 2018; Wittwer, 2012). Third, hydrologic data pertaining to water bodies, watersheds and basins are usually represented in geographical units, whilst economic models traditionally use coarser national or administrative boundaries (Brouwer & Hofkes, 2008; Hertel & Liu, 2016). This gives rise to a need to “scale” the hydrologic and economic data to an equivalent level. More recent applications aim to address this spatial component through integrated hydro-economic modeling, taking either a hybrid or modular approach to combine models (Bekchanov et al., 2017). The objective is to use the strengths of both the economic and water models without having to over simplify either (Hertel & Liu, 2016). Integrated hydro-economic models can represent regional scale hydrologic, engineering, environmental and economic aspects of water resource systems within a coherent framework, to support decision making (Booker et al., 2005; Harou et al., 2009, 2010). However, when focused on water quantity changes, integrated hydro-economic models have mainly focused on identifying optimal water management practices, often related to one sector such as agriculture, or reflecting one region or sub-basin (Eamen et al., 2020). Of the economy-wide I-O studies, the methods mainly link hydrologic data via water accounts, water balance or water quality models (e.g., Eamen et al., 2020; Guan & Hubacek, 2008; Jiang et al., 2014).

In this study, a supply side I-O approach is adopted (following Eamen et al., 2020; Freire-González, 2011; Freire-González et al., 2017b), to assess direct and indirect economic costs of drought and water scarcity on commercial water consumers and major abstractors in England and Wales, and the economy-wide sectoral impacts. The I-O model follows the conceptual framework of Freire-González et al. (2017b) but has been significantly extended to be applied over a large, heterogeneous spatial domain for a large ensemble of synthetic droughts. Methodological advances described in this paper include: (a) spatial and temporal characteristics of meteorological and hydrological droughts based on a synthetic drought event set (Coxon et al., 2019; Guillod et al., 2018); (b) the temporal and spatial distribution of shortfalls from the Water Resource Model for England and Wales (WREW) (Dobson et al., 2020); (c) heterogeneities in water scarcity events in terms of the magnitude and spatial pattern of shortfalls for different abstractor groups; (d) the relative importance of water to sectoral production; and (e) how shortfalls of different durations and spatial extent will impact different economic sectors, benefiting from the use of highly sectorally disaggregated I-O tables and water accounts.

As such, the I-O model integrates novel, highly disaggregated data on shortfalls in available water at the catchment and abstractor group level from WREW. WREW captures complex spatial patterns of water scarcity, including interconnections across 80 catchments in England and Wales, underpinned by detailed information on operator preferences and complex regulation of water withdrawals, based on data from the Environment Agency’s National Abstraction License Database (Environment Agency, 2013). The I-O model translates these catchment and abstractor specific shortfalls into restrictions on productive capacity of directly affected sectors, and the indirect consequences of this on the wider economy.

Additionally, whilst previous hydro-economic model studies have tended to quantify a small number of scenarios, the framework presented here is underpinned by a large ensemble of synthetic droughts, which statistically could have happened given the climatology of the 20th century (Guillod et al., 2018), to facilitate quantification of drought risk to the economy, which accounts for hydrological variability. The coupling with the WREW model and use of the large ensemble of synthetic droughts contributes to the limited modeling studies applied to England and Wales (Section 2) as well as contributing to the global literature on drought risk analysis.

4. Methodology

A whole-systems approach to quantifying drought impacts needs to account for the impacts of reduced precipitation directly on agricultural land, and increased evapotranspiration, as well as the impacts of water availability in surface and groundwater sources. This is particularly important in England and Wales where the majority of agriculture is rain-fed and a relatively small proportion of freshwater withdrawals are for irrigation. We therefore carefully distinguish between (a) direct precipitation that infiltrates into the root

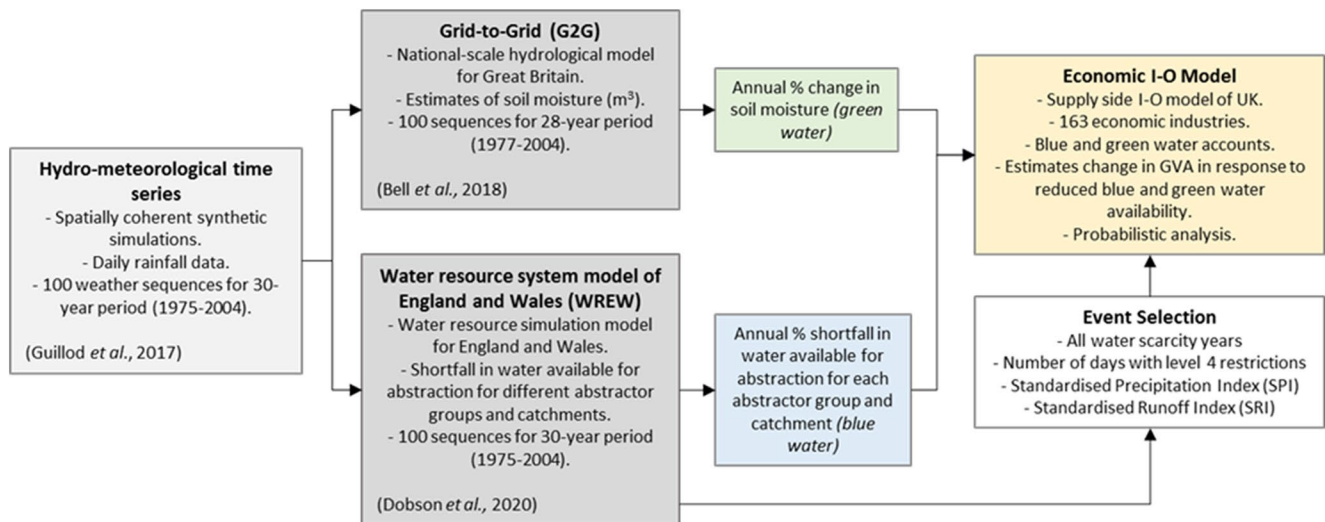


Figure 1. Integrated system of models and data.

zone of plants and is used for biomass production, particularly important for agricultural water management and (b) water that can be withdrawn from water bodies, such as lakes, reservoirs, rivers, or subsurface storage such as aquifers, that is, managed water. Direct precipitation onto land is hereafter referred to as “green water”, whilst water that can be withdrawn from water bodies, that is, managed water, is referred to as “blue water” (Sood et al., 2014). Whilst terminology such as “direct precipitation” or “managed water” could be used, the use of blue and green water color terminology is used here, as in other papers such as Freire-González et al., 2017b and Stadler et al. (2018), as a concise way of communicating the link between impacts with the degree of control that policymakers or water managers have over different water sources (i.e., the scope for action in relation to blue water impacts is greater than for green water).

Figure 1 outlines the various models used in this study to consider the complex interactions between natural and human processes in determining water scarcity, and the associated economic impacts. The following sections first summarize existing model inputs. The economic I-O model is then described in Section 4.4.

4.1. Hydro-Meteorological Simulations

Droughts arise from the spatial and temporal dynamics of meteorology and their interaction with Earth surface processes. Though statistical methods have been widely used to analyze drought frequency and severity (Serinaldi et al., 2009), process-based methods that use climate model simulations can represent meteorological forcing on the hydrological system and soil moisture feedbacks for a range of spatial and temporal scales (Guillod et al., 2018). We use the weather@home2 climate modeling system which encompasses a global climate model (GCM) with prescribed sea surface temperatures (SSTs) and sea ice, and a nested regional climate model (RCM) over the region of interest. It leverages the computing power of volunteers around the world to generate large ensembles of GCM–RCM simulations particularly useful for the investigation of extreme weather (Guillod et al., 2017). Based on this system Guillod et al. (2018) created a new set of bias-corrected, spatially and temporally consistent, continuous hydro-meteorological time series for the UK. The created time series represent mean climate and extreme hydro-meteorological events relatively well (see Guillod et al. [2018] for details).

The data set includes sets of 100×30 -year time series simulations generated for a baseline time-period, 1975–2004, providing 3,000 years of daily data. This is beneficial in this case study where the few observed droughts in England and Wales do not allow for robust risk-based analysis of drought management practices. Given the long duration, spatial variability and multivariate nature of droughts, large sets of potential drought events are required for this. The simulated hydro-meteorological time series applied here reflect drought events which statistically could have happened given the climatology of the 20th century, but did not, and allows the examination of the impacts of very rare and extreme events (Guillod et al., 2018).

4.2. Estimating Restrictions on Green Water

The industries that depend on green water are agriculture, including the cultivation of crops, livestock pastures and forestry, logging and related service activities. To understand how any reductions in rainfall may affect these industries, soil moisture estimates from the Grid-to-Grid (G2G) national scale hydrological model for Great Britain are used (Bell et al., 2018a). G2G has been widely used for a variety of hydrological studies and the model has been found to perform well for a wide range of catchments across Britain and for drought identification (Rudd et al., 2017). As an input, G2G requires time series of precipitation and potential evaporation (PE), driven by the above-mentioned hydro-meteorological time series data. As an output G2G provides monthly averages of daily mean soil moisture (m^3) for the 1975–2004 baseline time-period, and for each of the 100 simulations (Bell et al., 2018a, 2018b). In the first two years of the baseline data simulation G2G was being “spun up” (Bell et al., 2018a) so soil moisture estimates for the first two years are ignored and all results presented here reflect the simulated baseline period 1977–2004.

Monthly data is advantageous here, given that the consequences of drought on rain-fed crops depend on seasonal timing as well as total precipitation (Water UK, 2016). Effects of droughts vary seasonally with crop type with April to August (*Ibid.*) considered the most critical season for the UK. As such, data on soil moisture is used for April to August only. The long-term average soil moisture is calculated across these months. Seasonal deviations in soil moisture from this long-term average are calculated for each year. Any negative deviations are assumed to reflect a shortfall in available green water and provide input to the economic I-O model. In the future, better mechanisms for accounting for impacts of soil moisture on cultivation of crops could include focusing on optimal soil conditions, for given regions and crop types. However, in this first integration the use of the long-term average soil moisture provides a proxy for establishing potential shortfalls in green water.

4.3. Estimating Restrictions on Blue Water Use

The Water Resource England and Wales (WREW) framework (Dobson et al., 2020) is used to estimate water in surface water and groundwater available for use by various sectors of the economy. WREW uses the WATHNET water resource simulation software (Kuczera, 1992). Graphical representation of the system is based on a spatial network of nodes and arcs. Nodes represent source, demand or transfer points on the water network, most commonly reservoirs, junctions and demand centers. The arcs represent the flow paths, typically rivers or pipes. A benefit of this software is that it allows simulation of systems changing over time, for example, the implication of droughts of differing severity and magnitude. Testing how the system responds to dynamically evolving drought conditions can thus provide crucial information to support risk-based water resource planning (Borgomeo et al., 2018; Hall et al., 2019). A second advantage is that the explicit representation of observable quantities, such as reservoir levels, enables custom scripts to include region-specific operational preferences, and conditions which would trigger Level 3 or level 4 restrictions and their subsequent consequences.

The WATHNET software has been used in many water resource planning applications (Mortazavi-Naeini et al., 2014, 2015), including the Thames Basin (Borgomeo et al., 2018; Hall et al., 2019). The WREW model extends these studies and includes all major water supply infrastructure connected into England and Wales's wider water network via rivers or transfers; abstraction license conditions based on the Environment Agency's National Abstraction License Database, NALD (Environment Agency, 2013); operational rules; and asset locations. It incorporates 80 catchments to cover more than 90% of England and Wales's population and water demand (Dobson et al., 2020).

This modeling represents feedbacks between human and environmental systems through its ability to map climate-induced droughts, through hydrological processes, to risk at the reservoir scale and disruptions of this to water users (*ibid.*). The WREW model outputs that are used as inputs to the I-O model include catchment-specific data on the daily shortfall in abstracted blue water for different abstractor categories, calculated as (supplied water)/(requested water) and the number of days affected by shortfalls per year. PWS is treated slightly differently as demand management restrictions are imposed in the model when shortfalls would occur, and which result in reduced demands based on Level 3 or 4 restrictions. The daily percentage shortfall for PWS reflects the (reduced demand)/(unrestricted demand). Outputs represent the standard

Table 2
Categories of Water Users Included in the Model, Based on Environment Agency (EA) Abstractor Categories

	EA code	EA secondary category name
1	AGR	Agriculture
2	AQF	Aquaculture fish
3	CHE	Chemicals
4	ELC	Electricity
5	IND	Industrial/commercial/energy/public services
6	MEC	Mechanical non-electrical
7	MTL	Metal
8	OTE	Other environmental improvement
9	OTI	Other industrial/commercial/public services
10	PAP	Paper & printing
11	PET	Petrochemicals
12	PWS	Public water supply
13	WAT	Water supply related

model set up which prioritizes PWS over non-PWS during drought. If shortfalls remain then Level 1–4 water restrictions are applied to PWS within the model.

Currently nodes are included in the WREW model for a sub-set of the 62 EA abstractor categories. The categories accounting for the greatest share of abstractions (93% of total maximum annual license quantity) were selected (Table 2). Water withdrawals reflect the level of the licensed abstractions based on data from the EA NALD. This assumption will result in larger deficits being seen more frequently when modeled by WREW as actual abstractions may be less than maximum licensed amounts. However, reliable data on long-term actual water use is not readily available, so using licensed abstraction limits provides an approximation to the impact of droughts relative the amount of water that is legally available for withdrawal.

100 × 30-years model simulations are run using the baseline climate data and hydrological flow modeling which underpins WREW (Coxon et al., 2019). Outputs capture the dynamic process by which water supplied can become progressively constrained during a drought and reallocated by regulatory drought management actions. For each of the 13 abstractor categories and catchments WREW provides 3,000 years of data on the average daily shortfall in blue water available for abstraction and the number of days affected by shortfalls per year. As for green water,

data from 1977 to 2004 are used below and shortfalls in water available for agricultural abstractors are based on average daily shortfalls during April to August only.

4.4. Economic I-O Model

The I-O model is developed using the most recent data for 2011 from the EXIOBASE data set (Stadler et al., 2018). This is one of the most extensive global detailed multi-regional environmentally extended I-O databases available. The I-O tables for the UK include 163 industrial sectors, and include water accounts that differentiate between green and blue water consumption, reflecting water embedded in production processes, for each sector. These tables form the basis of the hydro-economic supply side I-O model. In the model total production of an individual sector j can be disaggregated as the sum of the productive inputs used in its production x_{ij} , plus its added value g (Equation 1):

$$x_j = x_{1j} + x_{2j} \dots x_{nj} + g_j \quad (1)$$

or, in vector notation:

$$x' = \mathbf{i}'X + g' \quad (2)$$

where, X is the total output of an economic sector, \mathbf{i} is the unit vector of dimension; x' is the sectoral output; and g' represents the sectoral GVA. In contrast to the demand-side model coefficients are horizontally determined, and called allocation coefficients instead of technical coefficients (i.e., the input from sector i required by sector j for each unit of output). The allocation coefficients matrix is defined as the amount of distributed production over total production. Individually, they can be obtained using Equation 3, where d_{ij} is the allocation coefficient of sector i in relation to sector j ; x_{ij} is the production of sector i distributed to sector j ; and x_i is the total production of sector i .

$$d_{ij} = \frac{x_{ij}}{x_i} \quad (3)$$

Equation 3 can be substituted into Equation 2, and in matrix terms expressed as:

$$x' = x'D + g' \quad (4)$$

Simplifying, Equation 4 can be written as:

Table 3
Estimated GVA-Water Elasticities Used in the Model

Aggregated economic sector	Estimated elasticity
Agriculture, forestry, fishing	0.12
Mining, quarrying	0.18
Manufacturing	0.19
Electricity production	1.00
Electricity transmission/trade and gas, steam, supply	0.44
Water supply, sewage, waste	0.24
Other services	0.37

$$x = g'(I - D)^{-1} \quad (5)$$

This can also be expressed as:

$$\Delta x = \Delta g'(I - D)^{-1} \quad (6)$$

Equation 6 allows estimation of total economic system output given variations in the individual value added of different economic sectors, in this case direct impacts on productivity due to water scarcity. In practical terms, this means making assumptions as to how a given percentage change in available water will equate to a reduction in sectoral value added. Whilst some anecdotal evidence exists, for example, a constant relationship between water and production is reported for the power generation sector (AECOM, 2016, Annex C), more specific data on water elasticities were not available for England and Wales. As such, output

elasticities of water were estimated for six aggregate economic sectors by this study, following the approach of Freire-González (2011) (see Text S2 for the estimation method and sensitivity analysis). The GVA-water elasticities, summarized in Table 3, are used to transform variations of water supply into changes in direct GVA.

Returning to Equation 6 GVA (g') is the exogenous variable in the model. The elements of the inverse matrix transform the estimated variations in GVA during water scarcity events into production variations. The sum of the row elements constitutes the supply multiplier, measuring the indirect impacts on other economic sectors.

The total output in the EXIOBASE I-O tables is equal to intermediate consumption plus final demand, as such exogenous variables such as value added of each sector (g), net taxes (t) on products and imports (i) are included in the model:

$$\begin{aligned} x_1 &= d_{11}x_1 + d_{21}x_2 \dots d_{n1}x_n + g_1 + t_1 + i_1 \\ x_2 &= d_{12}x_1 + d_{22}x_2 \dots d_{n2}x_n + g_2 + t_2 + i_2 \\ &\dots \\ x_n &= d_{1n}x_1 + d_{2n}x_2 \dots d_{nn}x_n + g_n + t_n + i_n \end{aligned} \quad (7)$$

Rearranging, this becomes:

$$\Delta x = \Delta[g' + t' + i'](I - D)^{-1} \quad (8)$$

The I-O model is a static model applied in a comparative static analysis. The results can be interpreted as the variance between different possible states of the economy in terms of the 2011 base-year versus any given water scarcity year. These water scarcity years reflect potential conditions that could occur during the 20th century.

4.5. Integrating Data

Given the spatial (UK) and temporal (annual) scale of the I-O model a series of additional processing steps are applied to weight the catchment (c) and EA abstractor category (e) data. First, to reflect the temporal aspect data from WREW on the average daily shortfall for a given year (Sav) is first weighted based on the number of days affected per year (n):

$$Sann_{c,e} = Sav_{c,e} \frac{n_{c,e}}{365} \quad (9)$$

Second, to reflect the spatial scale of shortfalls at the catchment level, each catchment is assigned to the NUTS1 region it falls within (Eurostat, 2018). Where NUTS1 regional boundaries are crossed the catchment is assigned to the region where its largest area is located (see Text S3 for further details). Although NUTS1 regions are spatially large, this reduces the likelihood of catchment boundaries being intersected by one or more economic regions, allowing a clearer link to be made to the economic structure of the region the

catchments lie within. As NUTS1 regions may rely on more than one catchment for water, the annualized blue water shortfalls (*Sann*) are further weighted proportional to the share of total abstractions made by all catchments within a NUTS1 region. This allows the impacts of shortfalls within a single catchment to be estimated and then aggregated up to the regional level. The weighting applied reflects the absolute licensed abstractions allowable (*A*), for each catchment (*c*) and EA abstractor category (*e*) from the EA NALD. For each catchment in a given NUTS1 region, where, *m* is the number of catchments in each NUTS1 region, the weighted shortfall (*S*) is:

$$S_{c,e} = Sann_{c,e} \left(A_{c,e} / \sum_{c=1}^m A_{c,e} \right) \quad (10)$$

Third, as the data from WREW is provided for 13 EA abstractor categories a link is established to the 163 economic industries in the I-O model. This is based on the EA abstractor secondary heading name and the EXIOBASE sector name, to proportion the weighted shortfalls in blue water to one or more of the 163 sectors. For example, agriculture (AGR) is linked to 17 disaggregated agricultural sectors. This link also reflects that many industries also use PWS in their operations. In 2011 non-domestic sectors in the UK accounted for 33.9% of all PWS use (ONS, 2014), including the manufacturing sector which used 4.3%. As such the EA category PWS is linked to relevant economic industries based on the ONS (2014) report and data from Water UK (Water UK, 2016, Annex A Table 0.12) and AECOM (2016, Annex C Table 2–1) on the split in PWS and non-PWS usage by sector.

Fourth, when calculating the direct change in sectoral GVA (Δg) a weighting is applied assuming that any disruption will be greatest in NUTS1 regions where that type of abstractive industry is more important economically. For example, if large shortfalls affect agricultural abstractors in the East of England, where agriculture contributes ~19% of GVA, then these economic impacts will be weighted more significantly within the national I-O model, than a similar shortfall in for example, London, where agriculture only comprises ~0.3% of GVA (ONS, 2018). Data on regional GVA in 2011 for each NUTS1 region are provided by the ONS (2018). This data includes a breakdown by industry (based on UK SIC 2007; ONS, 2009), allowing a weighting to be assigned to each EA abstractor category and catchment.

In summary, the above weightings adjust the regional and temporal scale of water shortfall data from WREW when applied to the annual, national I-O model. The I-O model is run for each catchment in turn, with results aggregated, per year and run, to provide a regional (NUTS1) and national scale picture of annual drought and water scarcity losses. The analysis integrates a hydrological baseline (1975–2004), which represents late 20th century climatology, with the latest available EXIOBASE I-O tables for 2011. We are therefore predicting the economic impacts of drought and water scarcity given the economic status and structure estimated for 2011.

The annual outputs are first run through the I-O model with total output losses estimated for any year with a given shortfall in water. These events are also filtered to assess the worst events based on (a) the loss to direct GVA (%) from the 2011 baseline; (b) the largest shortfalls in blue water, across all abstractor categories; (c) the lowest SPI-12 index; (d) the lowest SRI-12 index; and (e) the most days with level 4 water restrictions.

5. Results

5.1. Translation of Water Scarcity Metrics Into Direct Economic Impacts

Figure 2 shows the distribution of losses based on the five selection criteria outlined above. To illustrate how suitable different metrics may be in identifying the most severe events in terms of direct economic losses, results are displayed and compared for the worst 10th percentile of events for each of the selection criteria. The first box plot represents the costliest events in terms of direct losses to GVA (million £) from the 2011 baseline, as a benchmark for comparing the other selection criteria. The second box reflects the distribution of direct losses to GVA for the 10th percentile of events, filtered based on the most severe shortfalls in water. Whilst the median is comparable the dispersion of results is much narrower, although this metric generally identifies the outlier events with the highest economic losses. These differences reflect that the modeled economic implications of events will depend not only on the shortfall reported by each of the EA abstractor groups in a given catchment, but also the number and regional importance of economic sectors these

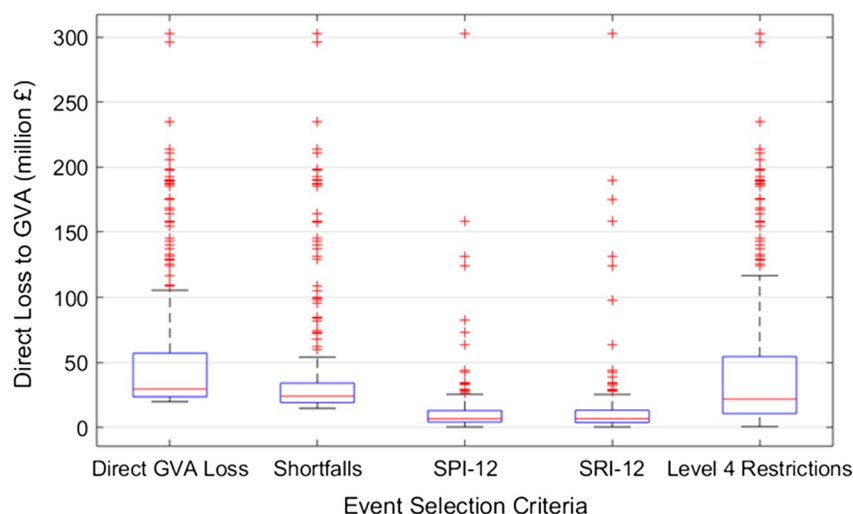


Figure 2. The distribution of direct losses to GVA (million £) from 2011 baseline, for different event selection criteria.

abstractor groups are linked to and the corresponding importance of water to production for these sectors. For example, events where PWS is largely affected, even if other abstractor groups are not, results in less severe total shortfalls in water. Yet, as PWS is of high importance and linked to many economic sectors the direct losses can still be significant.

Filtering events based on the highest incidence of Level 4 water restrictions identified the events with the highest economic losses, including outliers. However, a slightly broader distribution is seen. When Level 4 restrictions are in place, the water consumed is reduced (Table 1). As such, if Level 4 restrictions occur then reduced demand can in turn lead to reduced shortfalls over the year. In some situations, these interventions may be successful, and the system quickly recovers, hence the relations to less costly events. Alternatively, if the drought continues and shortfalls remain or worsen over the year then economic losses become much higher. These dynamics increase the variability in losses during Level 4 restrictions seen in Figure 2.

We also show events filtered based on the most severe 12-months Standardized Precipitation Index (SPI-12) (McKee et al., 1993) and Standardized Runoff Index (SRI-12) (Shukla & Wood, 2008). These indices are less likely to identify events with the highest economic losses. Consequently, the type of metric used when assessing the severity of a water shortage event and its subsequent loss will be important. If the focus is solely on the costliest events, such events may not necessarily be identified as the most severe in terms of other drought related metrics such as the SPI or SRI.

5.2. Water Scarcity Costs in England and Wales

Figure 3 shows the distribution of indirect, direct and total annual economic losses aggregated for England and Wales. As expected, the distributions show many small drought events, with a long thin right-hand tail representing extreme events with the greatest impact. An advantage of the large ensemble of synthetic drought simulations, fed through the WREW model and into this analysis, is that it captures costs of rare but potentially extreme events, which cannot be modeled using only observed data, and can be used to stress-test for the current system. Indirect economic impacts of these most extreme events can greatly exceed direct impacts. The Expected Annual Loss (EAL) is calculated based on the sum of annual losses estimated from the ensemble of 2800 years of synthetic daily weather divided by the number of years reporting a loss. At the national scale the direct EAL from water scarcity is estimated to be £11.7 million. The most extreme event modeled, in terms of direct loss, equates to £303 million, equivalent to 0.02% of GVA. However, if indirect losses are factored in, then the total EAL is £30.2 million. The most expensive event results in a total loss of £1.4 billion, equivalent to 0.11% of GVA. Averaging across the ensemble of events, the ratio of direct to indirect losses is 0.59, highlighting that, on average, direct losses outweigh the indirect losses. However, as highlighted in Figure 3, there is a large range in the scale of indirect losses. The ratio varies

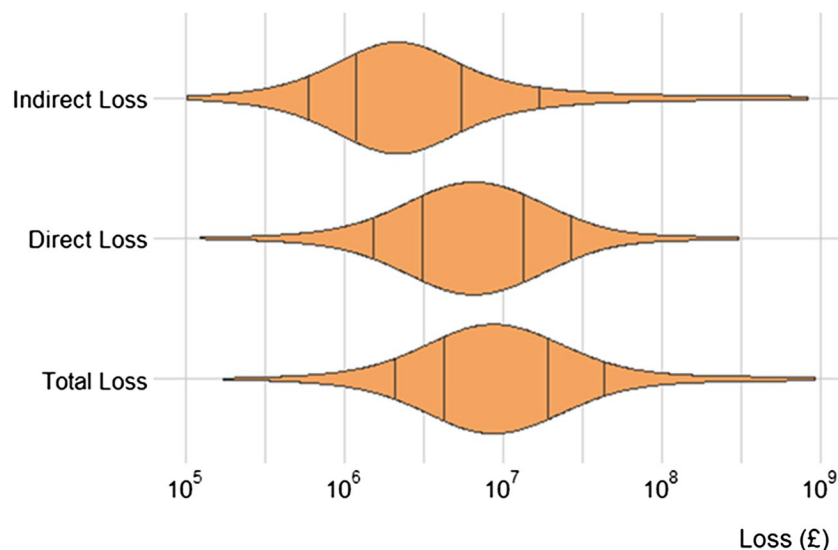


Figure 3. Distribution of indirect, direct and total losses to GVA (£, 2011). The black lines represent the 50% and 90% intervals.

across events from 0.3 to 4.1, highlighting that for some events indirect losses can surpass direct losses. The relationship between direct and indirect costs reflects differences in the underlying make-up of the economic sectors affected by any given drought event and the significance of inter-sectoral relationships related to these sectors. For each event the number and type of sectors affected can vary greatly given the spatial pattern of drought risk and underlying EA abstractor groups affected by shortfalls. For example, indirect losses can exceed direct losses for sectors included under the “electricity, gas, steam and air conditioning supply” category. This reflects the significant inter-sectoral relationships between sectors in this category as well as any indirect impacts that may occur due to inter-sectoral linkages with sectors outside this category that may occur in parallel. Hence, the different combination of sectors affected under each drought, and the inter-sectoral relationships linked to affected sectors will vary given the large ensemble of spatial droughts that underpin the analysis.

In Figure 3 the largest events tend to reflect those which also have large PWS losses that affect numerous sectors who may rely on PWS either partially or fully. This includes many service sectors, with indirect losses being propagated through extensive inter-sectoral linkages between such sectors and reflecting the contribution of services to national GVA.

Following the approach of Sieg et al. (2019), Figure 4 presents sectoral results aggregated from the 163 economic sectors of EXIOBASE to broader sectoral groups based on UK SIC 2007. The magnitude of direct losses can vary significantly within a sector, and between sectors. Variation in the distributions reflects the regional location and scale of shortfalls in available water, the number and importance of economic industries affected and aggregated within sector groups, and the corresponding importance of water to production for these sectors. Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning; and water supply, sewerage, waste management and remediation activities are particularly vulnerable. Manufacturing faces some of the largest direct losses, with a direct EAL of £5 million, and a total EAL of £13 million, reflecting the large number of industries within this category, the value of the manufacturing sector, and the relative importance of blue water for production. The above sectors are also very likely to be affected by water shortfalls to EA abstractor groups in one or more catchments in any given year.

In contrast, for public and private service-orientated sectors, such as financial and insurance activities there are fewer years with water shortages, reflecting that losses to these sectors are primarily from shortages to PWS, which is prioritized over other abstractor categories in the WREW model. There is a large range in the magnitude of direct losses. For example, the direct EAL to the financial and insurance activities sector is estimated to be £0.76 million, but with a maximum potential loss of £50.6 million. Losses are particularly high

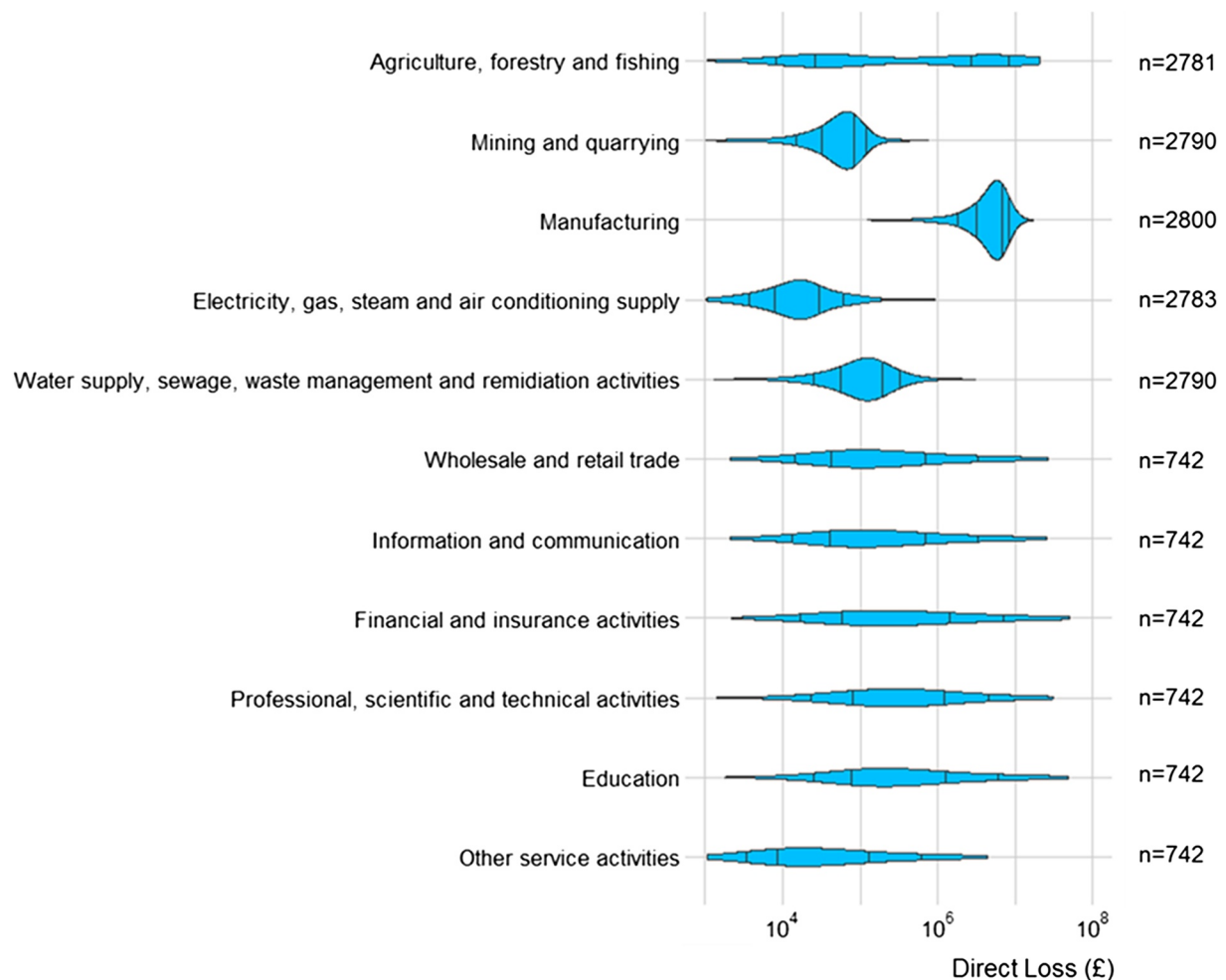


Figure 4. Distribution of estimated direct losses to GVA (£, 2011) per sector. The black lines represent the 50% and 90% intervals, n represents the number of years affected.

when PWS shortfalls are large and events are situated in the South East and London, given the economic structure of these regions and the contribution of services to regional and national GVA.

The distribution for the agriculture, forestry and fishing sector is broad and bimodal, reflecting that this sector can be affected by shortfalls in both blue and green water, which can happen in different years and in combination. After manufacturing, this sector has the largest direct EAL of £2.7, and maximum direct loss of £20.9 million (for a full summary of sectoral results see Table S4).

Indirect economic losses are shown in Figure 5, also highlighting a large variation in the magnitude of losses across different sectors. The indirect losses reflect the propagation of the initial direct economic shock through the wider economy, hence the inclusion of additional sectors not directly impacted. Losses are reported every year for the below sectors ($n = 2,800$). Manufacturing suffers the highest indirect EAL of £7.9 million, with a maximum estimated loss of £438 million. Other sectors with large indirect losses include water supply, sewerage, waste management and remediation activities, with an indirect EAL of £2.7 million and maximum loss of £183 million. The indirect EAL for agriculture, forestry and fishing; and electricity, gas, steam and air conditioning supply are both estimated to be £1.3 million.

At the sectoral level, whilst there is variance between events, the ratio between the direct and indirect EAL for manufacturing (1.36); electricity, gas, steam and air conditioning supply (12.0); water supply, sewerage, waste management and remediation activities (17.4); mining and quarrying (11.8); other services (4.8); and professional, scientific and technical activities (1.7) highlight that, when considered on average, indirect

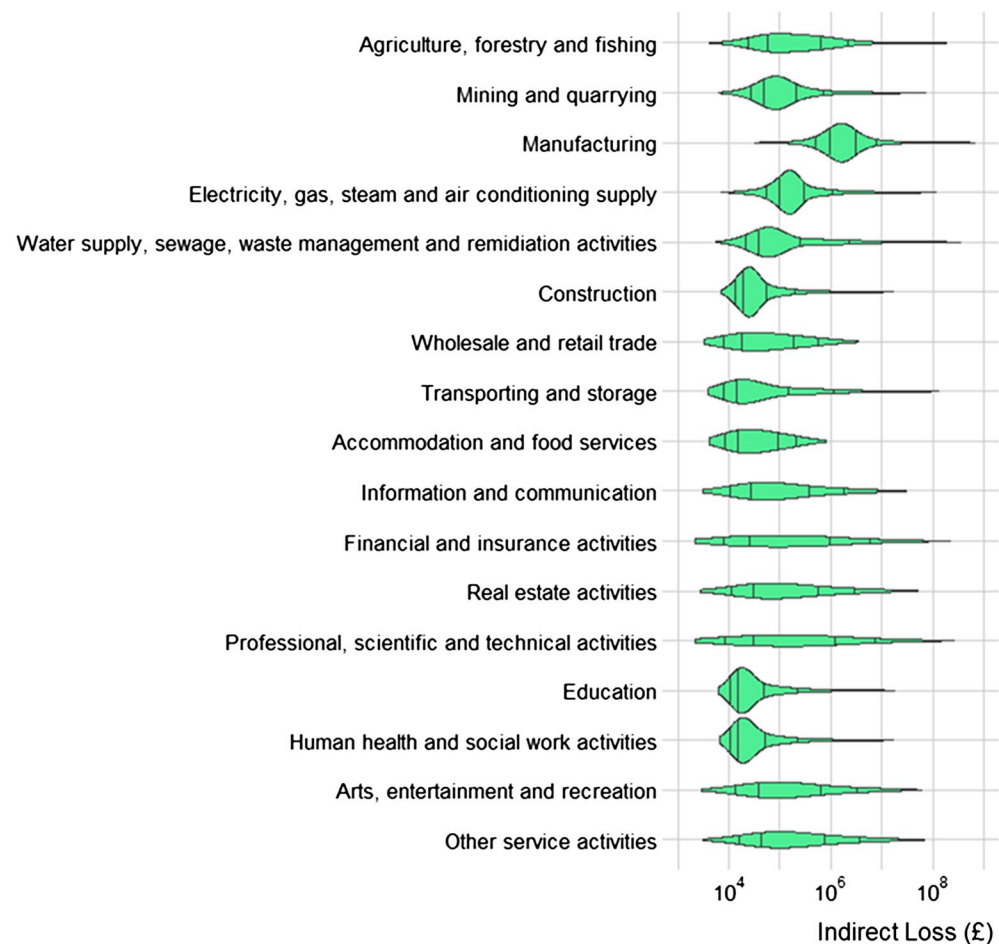


Figure 5. Distribution of estimated indirect losses to GVA (£, 2011) per sector. The black lines represent the 50% and 90% intervals.

impacts exceed direct impacts and can dominate total losses for these sectors. Whilst direct losses to electricity, gas, steam and air conditioning supply are modest when compared to for example, manufacturing, the indirect losses are much higher resulting in the large ratio seen. This reflects the large dependence of other sectors on electricity, which determines the scale of indirect losses. A similar picture is seen for water supply, sewerage, waste management and remediation activities, which faces relatively moderate direct impacts (noting that data from EXIOBASE on blue water consumption reflects water used in the production process, rather than the body of water itself that is supplied), but much higher indirect losses. This highlights the importance of the inclusion of indirect losses within drought loss estimates.

Lastly, Figure 6 summarizes the regional pattern of direct, indirect, and total EAL at the NUTS1 level (see Table S5 for a full summary of results). Direct losses are predicted to be highest in the East Midlands, reflecting the interplay between the spatial pattern of droughts and the importance of the manufacturing industry in this region, with a direct EAL of £3.3 million. London, the West Midlands, and South East face the next largest losses of £2.7 million, £1.9 million and £1.5 million respectively, also reflecting the spatial pattern of drought risk and vulnerability of sectors in these regions, manufacturing in the West Midlands and service sectors, which are particularly impacted by shortages to PWS and contribute largely to GVA, in London and the South East. This is also reflected in the scale of indirect losses, where key sectoral linkages result in an indirect EAL in London of £11.6 million, and in the South East of £3.8 million, exceeding the direct EAL estimates. For all other regions the ratio of indirect to direct losses are lower than one, with direct costs larger than indirect costs. London, the South East and East Midlands face the largest total EAL, estimated at £14.3 million, £5.3 million and £4.7 million respectively.

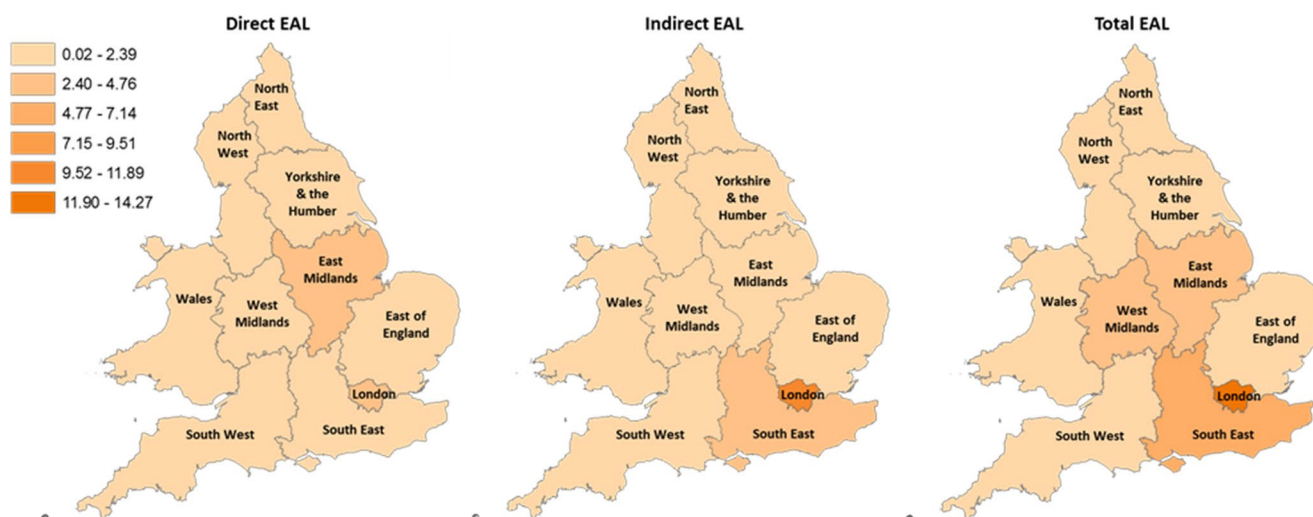


Figure 6. The direct, indirect and total Expected Annual Loss (EAL) to GVA (million £, 2011) defined by NUTS1 region.

6. Discussion

Our analysis shows that in aggregate, the costliest events may not necessarily be the most severe in terms of hydrologic metrics such as the SPI or SRI. Whilst drought indices provide some indication of the relative severity of droughts, they are all, arguably, somewhat arbitrary (Hall & Leng, 2019), and few indices have been tested against impact data (Blauhut et al., 2015). What should be of interest to decision makers is the economic effects of drought and water scarcity, as calculated in this paper, alongside other observable outcomes for society and the environment.

The method presented transforms catchment-specific blue water shortfalls, from the large-scale water resources simulation model WREW, into sectorally detailed direct and indirect economic losses. Unlike many previous I-O studies where limitations exist due to the scalability of the integrated data (Bekchanov et al., 2017), the disconnect in temporal and spatial scales of water resource systems and the I-O model have been accounted for. The most up-to-date and detailed data have been utilized and scaled accordingly. Advantages from linking WREW with the I-O model are first, that WREW is underpinned by detailed data on abstraction license conditions from the EA's NALD, which are explicitly linked to the highly detailed sectors in the I-O model. Second, the ability to focus on a wide range of droughts, including potential extreme events that surpass historical experience, as the integrated analysis is underpinned by the large ensemble of synthetic drought simulations. The method presented here to deal with the long time series of spatial events economically, to generate genuine drought risk estimates, is novel.

Floods cause more frequent and severe economic losses in England than droughts, so it is possible to generate empirical estimates of economic losses from flooding based on insurance data, from which direct EAL is estimated to be approximately £100 million (Penning-Rowsell, 2020). This first probabilistic estimate of economic losses from droughts has yielded an EAL of £11.7 million, which, as we would expect, is significantly less than the expected loss from flooding, but still significant. A known source of sensitivity is the estimated elasticity of water use to GVA applied within the model, which is hard to validate. The estimates used here present a first reasonable establishment of such numbers, that can be readily updated in the future, and address the criticism that I-O models applied to water scarcity normally consider economic output to be a linear function of water consumption (Bekchanov et al., 2017). The sensitivity analysis in Text S2 highlights that losses would be much larger, although still plausible, if a proportional reduction in GVA to water shortfalls was used, with a direct EAL of £49.8 million.

The sensitivity to water-GVA elasticity was highlighted in the earlier studies of economic impacts of droughts in England and Wales which assumed losses to GVA ranging from 25%-75% (Water UK, 2016) dependent on the sector and drought severity. The evidence upon which these loss factors were based was very limited, with the reports noting that economic estimates should be treated with caution for this very

reason. In comparison, the values in this study are lower, in the range of 12%–44%, except for power generation where, based on reported evidence, a linear relationship is assumed. More detailed analysis of the impacts of droughts on electricity markets in Britain is provided by Byers et al. (2020), though that analysis does not express the losses in terms of GVA.

Given this is the first study to integrate climate, hydrological and water resource system simulations with an I-O model to estimate costs of water scarcity for England and Wales, it is hard to directly compare results with previous studies focused on a few severe droughts, particularly given their wide-ranging estimates (from £260 million per year to £1.4 billion per day, as discussed in Section 2). The differences in estimates undoubtedly reflect differences in assumptions and modeling approaches, as alluded to above. For example, the direct economic losses reported here are much lower than the recent estimate of Water UK (2016), of a loss of 37% of GVA to England and Wales (Water UK, 2016). However, this high-level estimate assumes Level 4 restrictions are applied to all regions and sectors uniformly as well as more speculative assumptions on the relative use of water by different sectors. In contrast, this study is based on modeled water scarcity at a catchment and abstractor level, based on outputs from a detailed and highly disaggregated national water resource simulation model, underpinned by a large ensemble of synthetic drought events that are representative of 20th century climate. The direct reduction in GVA in this study is estimated via the I-O model and accounts for the heterogeneities in water scarcity events in terms of the magnitude and spatial pattern of shortfalls for different abstractors; duration of daily shortfalls; the importance of blue water to productive output of 163 economic sectors based on the detailed EXIOBASE water accounts and sector specific GVA-water elasticities; and the regional importance of water shortfalls in terms of related economic activity.

Whilst previous studies have not provided an estimate of the EAL, a comparison can be made to loss estimates at the far end of the distribution, that reflect the most severe and wide-ranging events. The most expensive event was estimated to cause a direct loss of £303 million (0.02% of GVA). This is not dissimilar to the report by AECOM (2016), which estimated the current cost to GVA in England of a severe drought lasting one year as £260 million, rising to £477 million under an extreme drought where more stringent demand restrictions are imposed. The method employed by AECOM (2016) differs to the higher end estimates made by for example, Water UK (2016), in that reductions in water for consumption by sectors are defined using a set of water use restriction values for PWS and non-PWS. Considering indirect losses results in a maximum total loss of £1.4 billion (0.11% of GVA). These findings are also aligned with some studies of past droughts in other countries, where the average impact of a drought event in a developed industrial economy is often less than 1% of GDP. For example, the extreme 2012–2016 drought in California is estimated to have caused total losses equivalent to 0.09% of the state's economy (Lund et al., 2018).

Yet, as with any modeling exercise there are underlying uncertainties that arise both within and across the integrated components. The approach to link models aims to overcome the disconnect between WREW and the I-O model in terms scaling temporal and spatial data. However, for some sectors, for example, agriculture, drought can be highly seasonal. The approach used to annualize daily blue water shortfalls may therefore underestimate losses for certain sectors. Likewise, when estimating the direct change in sectoral GVA a weighting is applied based on the economic size and structure of the NUTS1 region a catchment falls within. As the distribution of economic activity within NUTS1 regions will be spatially uneven, losses could potentially be under or overestimated depending on the specific location of the catchment. Furthermore, while WREW captures the dynamic process by which water supplied can become progressively constrained during a drought and reallocated by regulatory drought management actions, the I-O model is (comparative) static which means that losses do not consider the dynamic adjustments in the economy. Our approach to modeling longer-term droughts involves linear combinations of these effects, though in practice the effects may be non-linear, thus exceeding the estimates presented here.

Use of I-O methods for analysis of drought events that are far from the historic record suffers from the inevitable limitations of any model that extrapolates from the limited range of observations that were used to parameterize the model. The fact that I-O analysis is fundamentally linear does help to guarantee the stability of the approach in extrapolation. Whilst we might expect the response to be non-linear, to some extent, we do not have the empirical evidence with which to parameterize a non-linear relationship. The other model components deal very carefully with non-linearity of hydrological drought response and abstraction

regulations (which are fundamentally non-linear) whilst using I-O for the economic impacts. This is a pragmatic solution to a difficult problem.

Other limitations include the data from EXIOBASE on water consumption, which still has potential for improvement (Stadler et al., 2018). There is also a mismatch in timescales between the hydrological baseline (1975–2004) and static economic baseline of 2011. We do not consider this mismatch to be significant at the national level as the impacts of hydrological non-stationarity between the late 20th Century and 2011 are expected to be negligible. Parts of central, eastern and southern England and Wales experienced a prolonged period of below average rainfall from 2010 to early 2012 (Kendon et al., 2013), meaning that the baseline contains the effects on economic structure of these dry conditions. Given that our method then super-imposes drought effects relative to this baseline, any influence of distortions in the baseline will be small compared to the calculation of drought impact.

The estimated economic losses would also be higher if all EA abstractor categories were considered, although the 13 categories that are included represent 93% of the total maximum annual license quantity estimated from the EA NALD. As noted above, it is also assumed that water withdrawals are made at the licensed amounts which will likely overestimate actual abstractions. Making data on actual water withdrawals available, if necessary in a suitable anonymized form, is a priority if we are to better understand the potential impacts of droughts in England and Wales.

Furthermore, the current model configuration does not account for the potential for some industries to be adaptive during times of drought and/or on longer timescales, for example, through water saving policies, or for technological innovation, all of which could prevent reductions in output and lower loss estimates presented here. Evidence from industry suggests that many industry abstractors would switch to PWS, despite higher costs, to avoid interrupting production (AECOM, 2016). Such scenarios could be tested in the future through the inclusion of adaptive actions within the specification of different abstractor categories within WREW. There is also potential for adaptive behavior to be incorporated at the industry level within the I-O model. For example, the resilience of the power and electricity generation sector given flexibility of alternative supplies and the national electricity grid (Environment Agency, 2017); or changes in organization such as seen in irrigated farming in the UK, whereby some farmers have formed water abstractor groups to collectively share their risks (Rey et al., 2016).

Moving forward the framework is flexible in its potential to expand on and build in more data as it becomes available. Major advances will include updating the economic model to use regional I-O data for England and Wales so outputs can be tailored to specific water providers; disaggregating I-O data to a monthly time-step to better capture the temporal dimensions of the WREW model; and potential to include more EA abstractor categories. The integrated framework can already help address the implications of climate scenarios on water scarcity and economic impacts via the W@H2 data set which includes data for 2020–2049 (near-future scenario) and 2070–2099 (far-future scenario). In estimating costs for future time-periods additional assumptions will need to be made about the changing structure and importance of different economic sectors, the potential for changes in underlying water infrastructure, and the potential for investment and adaptation at the industry level.

Lastly, a key benefit of this specific model integration is the ability to test alternative arrangements for water allocation. This could include prioritization of different abstractor categories to minimize economic impacts. Currently, during periods of water shortage, domestic use, industry, and the environment generally take precedence, whilst the EA can partially or fully restrict water withdrawals for spray irrigation (Table 1). This has occurred during recent droughts (Rey et al., 2016), leading to calls to also prioritize water for irrigation (Knox et al., 2020). The effects of such policy on direct and indirect losses felt by agriculture could be explored, as well as the implications of this for other economic sectors who in turn may face further restrictions. Likewise, analysis could focus on different investment decisions, such as an increase in reservoirs or water transfers which will affect the scale and magnitude of water scarcity events and subsequent economic costs. In this manner, the integrated suite of models could provide information on how changing policy and regulations will help alleviate or contribute to future drought and water scarcity, and the economic benefits and implications of such decisions for England and Wales.

7. Conclusions

We present and demonstrate a framework that integrates outputs from regional climate simulations with national hydrological and water resource simulation models, which map climate-induced droughts through hydrologic processes to shortfalls in reservoirs and restrictions on water use, and then transform these water shortages into direct and indirect economic losses. Integrating data from the WREW model addresses calls to consider the role of both natural and human processes in drought and water scarcity formation, including representing downstream implications of any restrictions or water management policies to provide a national picture of the cascade of effects. The use of a large ensemble of synthetic drought simulations supports calls for a risk-based analysis. The integration of these models provides an important first step to extend outputs from the WREW model to capture economic implications; adds to present studies on drought risk in the study area, addressing many of their shortfalls; illustrates the potential scale of economic risks that may be faced; and paves the way for future risk-based analysis, considering the implications of both climate change and different water management strategies. Such outputs will be crucial to understand the trade-offs which may be required between users of water and ultimately inform the need for investment and regulatory action.

Data Availability Statement

The data and models used are outlined in the text and listed in the references. These include the weather@home2 sequences (Guilod et al., 2018), which can be downloaded from the Centre for Environmental Data Analysis (CEDA) repository at <http://catalogue.ceda.ac.uk/uuid/0cea8d7aca57427fae92241348ae9b03>. The Grid-to-Grid model estimates of monthly mean flow and soil moisture for Great Britain (Bell et al., 2018b), which can be downloaded from the NERC Environmental Information Data Centre repository at <https://doi.org/10.5285/3b90962e-6fc8-4251-853e-b9683e37f790>. The Water Resource England and Wales (WREW) model cannot be shared due to security reasons. The EXIOBASE Environmentally Extended Input-Output Tables are available to download from <https://www.exiobase.eu/>.

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