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Groundwater Representation in Water Resource Planning: The Spatial and Temporal Sensitivity of Groundwater Supplies in England

Rachel Pugh[1] | Anna Murgatroyd[2] | Richard Rowan-Robinson[3] | Jim Hall[1]

[1]Environmental Change Institute, School of Geography and the Environment, University of Oxford, Oxford, UK | [2]School of Engineering, Newcastle University, Newcastle upon Tyne, UK | [3]Environment Agency, Horizon House, Bristol, UK

Correspondence: Rachel Pugh (rachel.pugh@ouce.ox.ac.uk)

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ABSTRACT

Groundwater makes an important contribution to public water supplies, yet the dynamics of groundwater availability are often simplified in large-scale water resource assessments. This study addresses that challenge on a national scale in England by integrating an empirically based groundwater supply model with a national-scale water resource system simulation model. Through comparison of dynamic and steady groundwater representation and the use of a large-ensemble climate dataset, we illustrate the contribution of groundwater to system supply and performance at a national scale and highlight regional differences in response. The south-east showed particular sensitivity to groundwater flow: In the far-future scenario, the median number of days with restrictions increased by 40% following the introduction of our dynamic groundwater model, compared to simulations based on licensed groundwater yields. Our results emphasise the importance of dynamic representation of groundwater supplies in large-scale water resource assessments.

1 | Introduction

As a key component of the hydrological cycle, groundwater is an important natural resource. Globally, groundwater accounts for approximately 25% of all water abstractions (Margat and Gun 2013), so it is a critical contributor to water, food, energy, ecological and economic security (Famiglietti 2014; Gleeson et al. 2020). Its use in irrigation is notably prevalent, providing a flexible and accessible source of water even in arid and semi-arid settings (Siebert et al. 2010). Groundwater is also used extensively by public water utilities, for example accounting for 100%, 90% and 80% of supply in Denmark, Indonesia and Costa Rica, respectively, providing supplies that may be more reliable than surface water sources, as well as often having water quality benefits (Foster et al. 2022).

In the United Kingdom, groundwater resources provide a valuable source of potable water for domestic supply, whereas <2% of licensed abstractions are used for agricultural irrigation in England and Wales (Hess et al. 2010). Groundwater supplies around one-third of all public water in England (BGS 2023), and accounts for approximately 15000 and 30000 private water supplies in Wales (Farr et al. 2022) and Scotland (SEPA 2009), respectively. England's public water supply system is highly complex (Murgatroyd et al. 2022) and interconnected (Dobson et al. 2020), spanning multiple groundwater dominant regions (Allen et al. 1997). As groundwater is an important contributor to the system supply at a national scale, it is imperative to represent well the spatial and temporal sensitivity of groundwater supplies in water resource planning.

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Summary

- The representation of groundwater in large-scale water resource assessments is explored through the use of an empirical groundwater model and a simulation model of England's water supply system.
- The importance of the dynamic representation of groundwater is demonstrated, as the system is shown to be sensitive to variable groundwater flows, particularly under extreme future climate scenarios.
- Future improvements to groundwater representation within water system models can only strengthen water resource management decisions in uncertain futures.

Water managers in England must contend with an array of challenges to secure water supply into the future. Systems are increasingly constrained by predicted increases in demand associated with demographic and economic growth (Water UK 2016) and unreliable supply driven by climate change, including from an anticipated increase in drought events and reduction in summer river flows (Arnell et al. 2019; Kay 2021; Prudhomme et al. 2014) and the degradation of water supply quality (Ward and Wentworth 2021). The adoption of environmental targets aiming to address unsustainable abstractions and ensure environmental resilience (Environment Agency 2020) impacts the availability of water for supply and changes in regulatory governance (Defra 2026) can create uncertainty for future planning. Consequently, there has been a growing emphasis on improving the resilience and preparedness of ageing water systems through the implementation of solutions including demand management, leakage reduction and infrastructure development (NIC 2018), in addition to increased focus on supply sustainability.

Effective management and planning of groundwater resources is therefore essential to ensure water practitioners are prepared for future social, environmental and economic challenges to water systems. A number of tools exist to help practitioners manage resources effectively. Water resource system simulation models allow water practitioners to explore system behaviour and test resilience to climate extremes (Borgomeo 2022; Hall et al. 2020). Numerical groundwater models are regularly used at a local scale in England by regulators and water resource managers to predict groundwater behaviour (Whiteman et al. 2012), including solutions such as MODFLOW (McDonald and Harbaugh 1988), FEFLOW (Koskinen et al. 1996) and ZOOM3QD (Jackson and Spink 2004). But the development of the British Groundwater Model (Bianchi et al. 2024) may provide the opportunity for national-scale assessments in the future. Coupled models, integrating groundwater and water system behaviour, have been developed across a variety of international settings (e.g., Abbas et al. 2022; Hoff et al. 2011; Osorio Olivos et al. 2024). However, intensive computer processing requirements (Ascott et al. 2021) limits integration, particularly under large climate ensembles. Water resource managers therefore commonly rely on borehole-specific data to estimate yield or output predictions (Beeson 2000; Misstear and Beeson 2000). Yet, such approaches typically have high localised data requirements and may fail to represent the operational and physical interdependencies between sources at large-scales, thus restricting dynamic integration of groundwater into system models. Groundwater behaviour within water system models may therefore often be simplified (Ascott et al. 2021; Murgatroyd 2020), for example, by representing groundwater as a constant supply (e.g., Majid et al. 2021; Murgatroyd and Hall 2021), without reference to climatic or operational constraints.

There is a growing body of literature exploring the response of groundwater to a changing climate in the United Kingdom, including to groundwater recharge (Hughes et al. 2021), groundwater levels (Jackson et al. 2015), borehole yields (Ascott et al. 2019) and groundwater droughts (Bloomfield et al. 2019; Parry et al. 2024; Tanguy et al. 2023), in addition to studies assessing the impact of water management practices on groundwater droughts and groundwater–surface water interactions (Bloomfield et al. 2021; Wendt et al. 2020, 2021), and work that more generally emphasises the importance of groundwater representation within hydrological models (Condon et al. 2021; Gleeson et al. 2021). Yet, there is limited literature directly linking such impacts to groundwater with the performance of public water systems and reliability of supply, particularly at large scales.

Without adequate representation of groundwater supply performance, the capability of system simulation models to effectively explore whole-system behaviour under climate extremes is limited. Notwithstanding that groundwater contributes extensively to overall supply availability in England, surface and groundwater resources can respond differently to meteorological drought. Due to aquifers' high storage capacity, groundwater may show a lagged and attenuated response to low rainfall (Brauns et al. 2020; Van Loon 2015), offering the potential to act as a buffer to surface water deficits (Wendt et al. 2021). Where groundwater response is simplified in water planning tools, there is limited opportunity to model the cumulative impacts to overall water supply from drought events, as the sensitivity of system performance to groundwater supply is overlooked. Consistent representation of surface and groundwater supplies is therefore important, particularly where spatial variations in supply dominance exist, to inform improved management and decision making at a holistic system scale.

This study analyses the resilience of England's public water supply to future climatic events, focusing on the contribution of and sensitivity to groundwater supply. To overcome the methodological issues discussed above, an empirical groundwater supply model, driven by both climate and operational data, is developed to dynamically represent groundwater system performance. The empirical model offers a data- and time-efficient method to represent groundwater supply variability in a national-scale water resource system model, and simulate system behaviour under a large ensemble of climate scenarios. This study provides novel insights into the performance of a complex, interconnected and large-scale water system and quantifies the importance of sensitive groundwater sources to the wider public water supply network in England.

2 | Methodological Framework

Figure 1 presents the methodological framework used in this study. The approach taken consists of three phases: (A) selection of climatological scenarios, (B) hydrological modelling of surface and groundwater supply and (C) water resource system simulation modelling.

In order to evaluate the role of groundwater within system performance and justify the benefits of an integrated approach to groundwater resource representation, the sensitivity to groundwater behaviour must be explored. To achieve this, water resource model simulations with the dynamic empirical groundwater supply model are compared with system behaviour assuming steady groundwater supplies.

For scenarios with steady groundwater supply, flows are generated under the assumption of constant groundwater yields equal to the maximum annual abstraction volume as licensed by the regulator (excluding any licence to licence aggregation conditions). This simplistic approach presents a best-case scenario of groundwater supply into the future. For scenarios with dynamic groundwater supply, groundwater flows are simulated by the empirical groundwater model, consisting of three stages that are discussed in detail in the hydrological modelling section. The groundwater model defines the proportion of flows that are considered sensitive and calculates the available water for each time step given antecedent precipitation and antecedent operational abstractions. This approach aims to present a more realistic, dynamic representation of groundwater flows.

2.1 | Climate Scenarios

The selection of an appropriate climate scenario, with which to drive groundwater and surface water models, is an important decision for hydrological modellers. Datasets derived from downscaled global climate models (GCM) are often used for national- and regional-scale assessments.

However, climate projections contain inherent uncertainty (Lemos and Rood 2010), so the use of large-ensemble climate datasets, which also offer spatially coherent projections, provides the opportunity to assess climate-sensitive systems under uncertainty, aiding the exploration of spatial system robustness through meteorological stress testing. To explore the performance of our system under climate extremes, a large-ensemble climate dataset, which can be consistently implemented across the surface water, groundwater and system simulation models, has therefore been selected. The weather@home (w@h) is a climate modelling framework (Guillod et al. 2018; Guillod, Jones, Bowery, et al. 2017; Massey et al. 2015) comprised of a coupled global (HadAM3P) and regional (HadRM3P) climate model. The GCM is downscaled via one-way coupling to the regional climate model (RCM), which has a native resolution of 0.22°. Bias correction is applied to precipitation via a linear correction and grid cell smoothing. Thus providing a downscaled, bias-corrected and validated dataset (Guillod, Jones, Kay, et al. 2017) for the United Kingdom at a 25 km resolution.

Precipitation from w@h ensembles for three time-periods is used here, each with 100 realisations: baseline (1975–2004), near future (2020–2049) and far future (2070–2099). The latter two periods are derived under the RCP 8.5 greenhouse gas emissions pathway (Meinshausen et al. 2011) and therefore contain examples of extreme weather events, which extend beyond those seen in the historical record. This, in combination with the large number of replicates, allows for a full exploration of system performance under uncertain and extreme future climates.

The use of historic and/or observational climate data is also important, as to allow calibration of system performance and generate baseline scenarios for comparison. For this study, the CEH-GEAR dataset (Tanguy et al. 2021) is used as a reference historic climate scenario. CEH-GEAR provides gridded estimates of precipitation for the United Kingdom based on historic observational data. A subset of the CEH-GEAR dataset has been selected to represent historic conditions (1965–2015).

2.2 | Hydrological Modelling

2.2.1 | Empirical Groundwater Model

Groundwater models fundamentally aim to simulate the behaviour and/or availability of groundwater with time, so they can guide estimations of groundwater resource yield. Physically based distributed (e.g., MODFLOW, McDonald

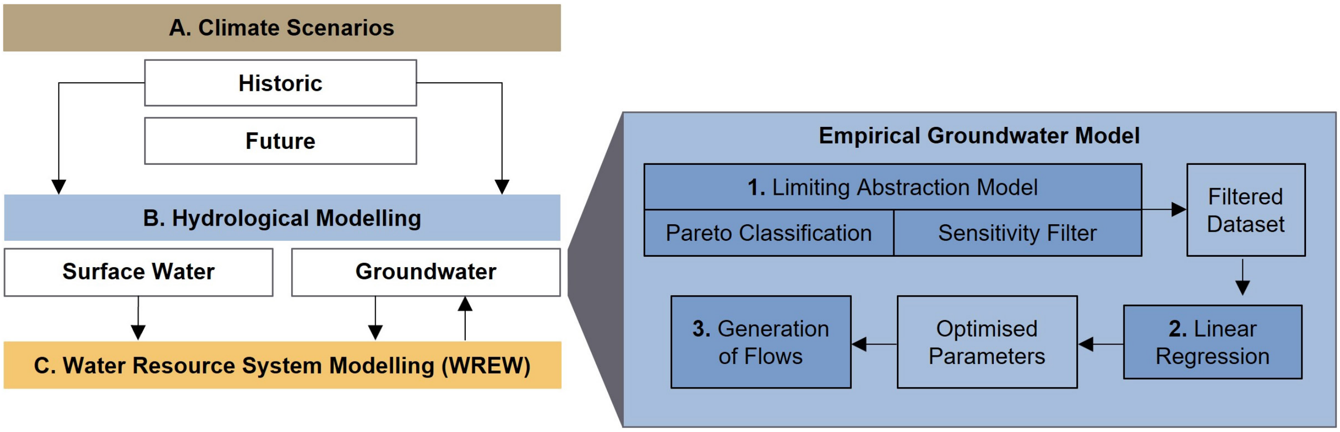


FIGURE 1 | An overview of the three phase methodological framework used within this study.

and Harbaugh 1988) and localised (e.g., AquiMod, Mackay et al. 2014) groundwater models are frequently used to simulate groundwater variables. However, uncertainty in hydrogeological parameterisation may constrain the ability of such models to be used predictively in groundwater resource management (Fletcher et al. 2019). Furthermore, although a national-scale distributed groundwater model for Great Britain has recently been developed (Bianchi et al. 2024), the spatial scales of many physical models can be limited.

Alternatively, data-driven models can also efficiently represent groundwater variables, particularly at high spatial and temporal resolutions, aiding decision making under uncertainty (Miro et al. 2021). An empirical groundwater model, which builds upon the groundwater abstraction model by Dobson et al. (2020), was therefore developed. The use of an empirical model within this study (i) facilitates the dynamic integration of groundwater into a complex and large-scale water resources systems simulation model without the requirement to develop a large number of localised, physically based groundwater models and (ii) offers the flexibility to efficiently perturb groundwater resources and ensure continuity with surface water representation under multiple future climate scenarios.

Water system analysis needs to capture the variability of source performance, which, while constrained by the physical characteristics and status of the groundwater body, will also be dependent upon local conditions and operation (Ascott et al. 2019). Common industry practice in the United Kingdom is to relate groundwater level to the yield of groundwater sources, while also considering operational limitations such as regulator limits or infrastructure constraints (Beeson 2000). Correspondingly, our empirical model identifies those groundwater sources that may be sensitive to groundwater levels and assumes that antecedent conditions will limit their yield. Precipitation has previously been used as an indicator for groundwater recharge (Bloomfield et al. 2003), whereas abstraction is known to alter the dynamics of groundwater systems (Konikow and Leake 2014). The magnitude of antecedent precipitation and magnitude of antecedent operational abstractions are therefore selected as constraining antecedent conditions.

The model operates in three stages, as detailed in Figure 2. Initially, a limiting abstraction model (Stage 1) predicts which sources may be considered sensitive, that is, constrained by antecedent precipitation and abstraction conditions. This is achieved by the identification of a Pareto front of extreme historic events for each source, which is compared to a defined sensitivity threshold (β). A multivariate linear regression (1) model (Stage 2) is then solved for each of four hydrogeological productivity classifications (BGS 2020), such that

$$A_t = A_{\min} + \left(A_{\max} - A_{\min}\right)\left(\theta_1 + \theta_2 \sum_{t-X}^{t} P + \theta_3 \sum_{t-Y}^{t-1} A' + \theta_4 A'_\mu\right) \tag{1}$$

where A_t is the water available for abstraction, A_{max} is the maximum historic abstraction, A_{min} is the minimum historic abstraction and A'_μ is the normalised mean historic abstraction for the source; P is the cumulative precipitation; A' is the cumulative normalised abstraction; and θ_1, θ_2, θ_3 and θ_4 are the model coefficients; and X and Y are the lag period for the antecedent precipitation and abstraction. If A_{max} for the source is greater than the licensed abstraction limit, A_{max} is set as equal to the maximum licensed abstraction limit.

Stages 1 and 2 of the model are run iteratively within a user-defined parameter space (Table 1), which defines the performance and coarseness of the Pareto filter, length of antecedent lag periods and sensitivity thresholds. In order to reflect the potential for fast and slow system response, lag periods for antecedent precipitation and abstraction were ranged between 6 and 36 months. Sensitivity thresholds (β) were also varied over a wide parameter range. A minimum number of Pareto points was set equal to 5, and the model was run with a k-fold cross validation of 5. Historical climate (CEH-GEAR; Tanguy et al. 2021) and abstraction (Environment Agency 2023) datasets were used to train and test the regression model. To avoid model bias in selecting a solution that classified a small number of sources as sensitive, solutions that fell below a variance threshold or those that were considered unphysical were excluded (e.g., negative θ_2 or positive θ_3 coefficients). The optimal solution was identified as one which minimised the mean absolute error (MAE) between the actual historic abstractions and the model calculated A_t values.

The optimal parameters for each hydrogeological group are listed in Table 1. The optimal abstraction lag period was highly variable, ranging from 6 to 30 months. The optimal precipitation lag period was 18 months for unproductive strata ('rocks with essentially no groundwater') and 6 months for low, moderately and highly productive aquifers. For the resulting model coefficients (θ_{1-4}), unproductive strata had the smallest precipitation (θ_2) and abstraction (θ_3) coefficients, suggesting these controls are less important relative to the more productive strata.

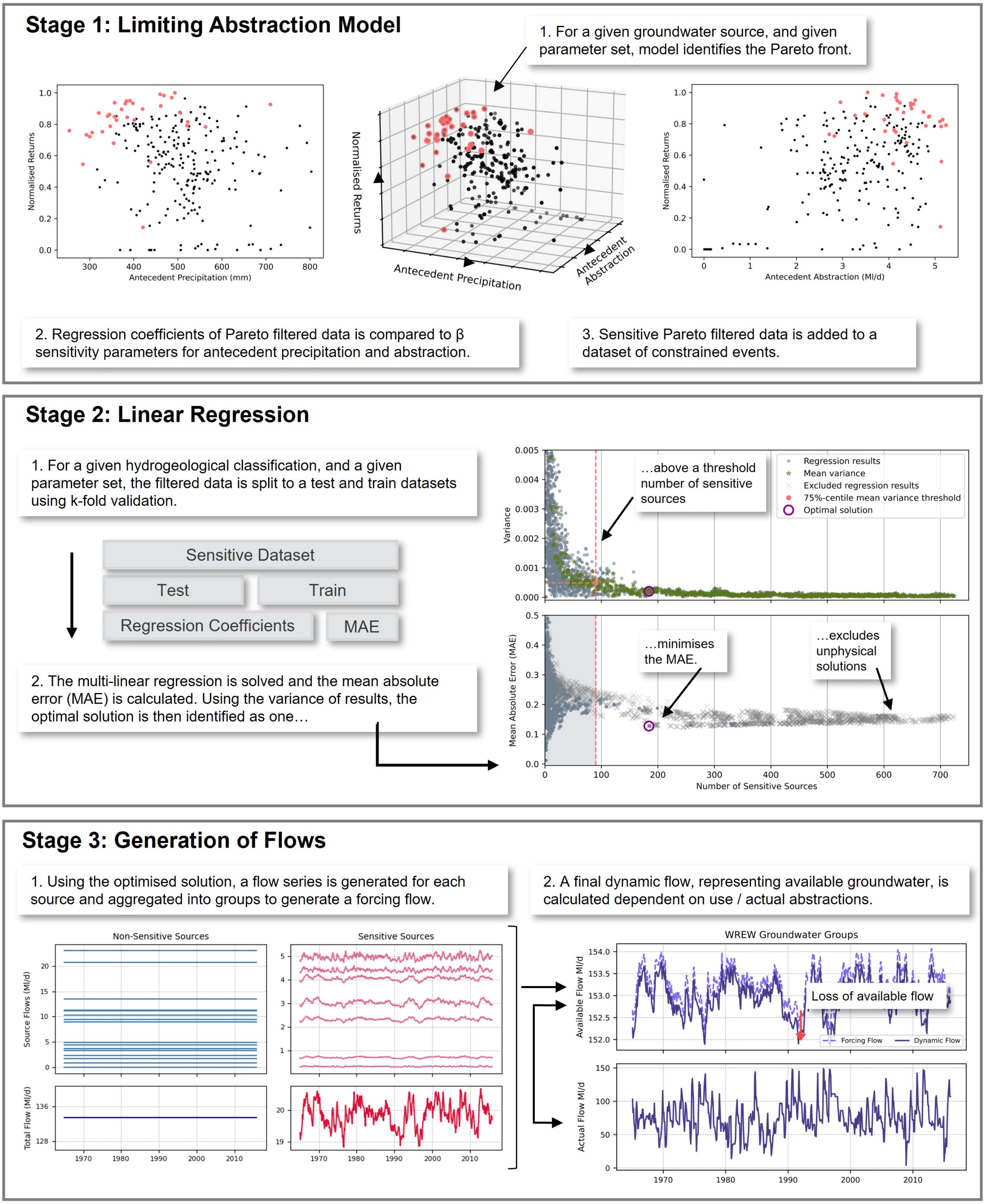
Following optimisation of the empirical model parameters and regression coefficients, Stage 3 of the model generates aggregated groundwater flows for given groups of groundwater sources. Where sources are considered non-sensitive, flows are set equal to A_{max} or the maximum licensed abstraction limit, whichever is smaller. For sensitive sources, flows are generated using the optimised model for a given climate scenario. This produces an aggregated forcing flow A_f (2) for each of the groundwater groups, such that

$$A_f = A_{\min} + \left(A_{\max} - A_{\min}\right)\left(\theta_1 + \theta_2 \sum_{t-X}^{t} P + \theta_4 A'_\mu\right) - A_{\min}\,\theta_3 Y \tag{2}$$

Finally, the forcing flow is used within the water system simulation model to interactively derive a final 'dynamic flow' at each time step, driven by the simulated actual antecedent abstractions.

2.2.2 | DECIPHeR

DECIPHeR is a lumped conceptual hydrological model (Coxon et al. 2019) that is used to generate surface water flows across



Stage 1: Limiting Abstraction Model

1. For a given groundwater source, and given parameter set, model identifies the Pareto front.

2. Regression coefficients of Pareto filtered data is compared to β sensitivity parameters for antecedent precipitation and abstraction.

3. Sensitive Pareto filtered data is added to a dataset of constrained events.

Stage 2: Linear Regression

1. For a given hydrogeological classification, and a given parameter set, the filtered data is split to a test and train datasets using k-fold validation.

2. The multi-linear regression is solved and the mean absolute error (MAE) is calculated. Using the variance of results, the optimal solution is then identified as one…

…above a threshold number of sensitive sources

…minimises the MAE.

…excludes unphysical solutions

Stage 3: Generation of Flows

1. Using the optimised solution, a flow series is generated for each source and aggregated into groups to generate a forcing flow.

2. A final dynamic flow, representing available groundwater, is calculated dependent on use / actual abstractions.

Loss of available flow

FIGURE 2 | Outline of the three-stage empirical groundwater model.

multiple catchments and hydrological settings. The model is designed to simulate the flux of water within and between connected hydrological response units (HRU), each HRU representing sub-surface processes through lumped stores such as the root, unsaturated and saturated zone. DECIPHeR has been shown to perform well against multiple metrics, including its representation of low flow volumes (Coxon et al. 2019). It further benefits from modest processing requirements, enabling it

TABLE 1 | Optimal parameters and model coefficients for different hydrogeological groups.

		Hydrogeological productivity classification			
	Parameter range	Rocks with essentially no groundwater	Low productivity aquifer	Moderately productive aquifer	Highly productive aquifer
Number of Pareto cycles	1–5	5	5	5	5
Precipitation lag X (months)	6–36	18	6	6	6
Precipitation sensitivity β_1	0–0.008	0.004	0.002	0.002	0.008
Abstraction lag Y (months)	6–36	18	18	30	6
Abstraction sensitivity β_2	0–0.08	0.00	0.00	0.00	0.00
Model coefficient θ_1		-6.06×10^{-2}	-1.89×10^{-2}	-3.09×10^{-3}	-4.14×10^{-3}
Model coefficient θ_2		1.29×10^{-4}	1.88×10^{-4}	1.67×10^{-4}	2.20×10^{-4}
Model coefficient θ_3		-4.95×10^{-5}	-4.90×10^{-3}	-6.06×10^{-4}	-3.01×10^{-3}
Model coefficient θ_4		1.02	1.14	1.08	1.06

to run efficiently with large-ensemble climate data. DECIPHeR has therefore been used widely in studies exploring climate change impacts (Byers et al. 2020; Chengot et al. 2023; Lane et al. 2022). For their analysis of drought and spatial water scarcity in England and Wales, Dobson et al. (2020) used the DECIPHeR framework to produce calibrated model parameters for 338 catchments. Parameter selection was optimised through use of a Monte Carlo simulation to capture parametric uncertainty, and evaluation of modelled flows used flow gauge data from the Environment Agency. The optimal parameter set was selected as that which minimised both the Nash–Sutcliffe efficiency (high flows) and log Nash–Sutcliffe efficiency (low flows). Daily, naturalised flows generated from these parameter sets have been simulated for the historic and w@h climate scenarios. The w@h climate data were further downscaled to a 5-km grid for this application using methods similar to those presented by Guillod et al. (2018).

2.3 | Water Resource System Simulation Modelling

2.3.1 | WREW

To represent England's supply network, a modified version of the Water Resources of England and Wales (WREW) system simulation model has been utilised. WREW is built using the WATHNET-5 modelling software (Kuczera 1992). The software models water supply networks as a series of nodes and arcs and provides the opportunity for efficient, multi-objective optimisation and user customisation of operational rules and constraints. As such, WATHNET-5 has been widely used to explore water resource availability under future climates.

As a national-scale model, WREW represents the water system at a lower resolution than that which would typically be achieved at an individual water company or regional level. However, an acceptable level of model validation has been obtained using simulated reservoir storage levels provided by water companies (Ofwat 2022). As such, WREW has been used by both regulators and within academia (Dobson et al. 2020; Murgatroyd et al. 2022) to investigate large-scale system resilience to climate change, regulatory reform and infrastructure development. Further model validation is provided in the Supporting Information.

Surface water and groundwater supply are spatially represented in WREW as a series of distributed inflow nodes. Each groundwater node represents an aggregate of multiple groundwater (borehole) sources that are typically grouped by water resource zones (a geographical area defined for the management of water resources in England and Wales). The representation of groundwater in WREW (Figure 3) has been updated where possible to reflect current groundwater use (as specified by provisional 2024 water resource management plans [WRMP24]) and as to enable use of the empirical groundwater model. In total 69 groundwater groups (nodes) are characterised in this way. A proportion of groundwater sources managed by Affinity Water and Portsmouth Water are not currently represented by the empirical model. Instead, groundwater is modelled in WREW using water company specific data as to guide system performance in these areas. Therefore, the performance of the water supply systems for Affinity and Portsmouth Water is excluded from the results presented in this study. Nodal abstractions are calculated by WREW for each time-step to meet the requested demand, subject to operational rules and restrictions built into the model.

Present-day (2025) and future (2050) demand scenarios for public water are based on estimates reported in draft WRMP24 data tables, covering the 25-year water resources planning horizon. Demand estimates for 2050 assume industry targets for per capita consumption (PCC), leakage and population change are achieved. In addition to public water requirements, WREW also simulates non-public water and agricultural water use. Non-public water use, which accounts for approximately 25% of abstracted water (Dobson et al. 2020), is estimated

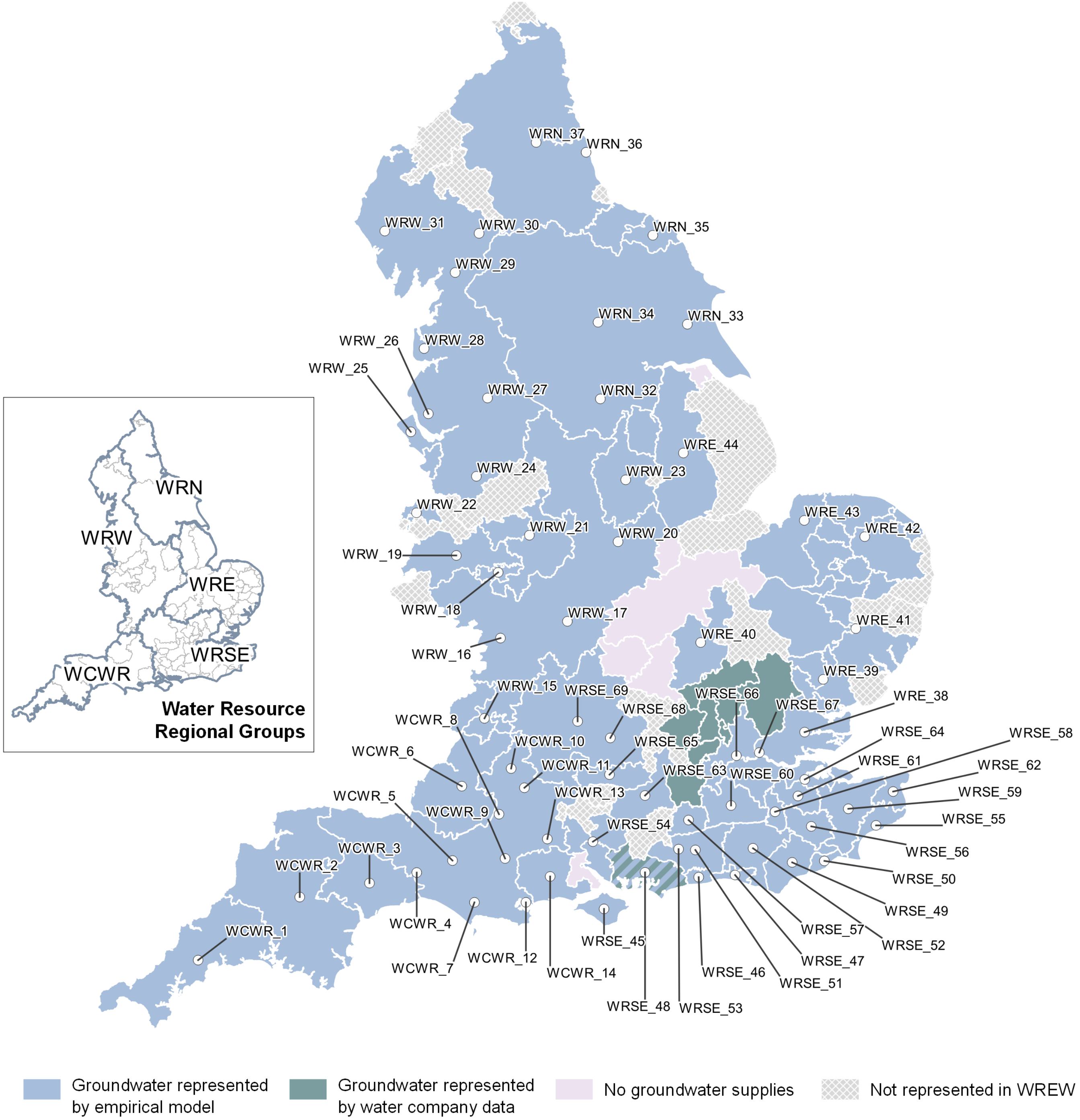


FIGURE 3 | The spatial representation of groundwater in WREW via 69 aggregated groundwater groups (inflow nodes) distributed across England's five water resource regions; 1–14: West Country Water Resources (WCWR); 15–31: Water Resources West (WRW); 32–37: Water Resources North (WRN); 38–44: Water Resources East (WRE); and 45–69: Water Resources South East (WRSE). *NB:* As the database used to drive the groundwater model represents groundwater licences within England only, the groundwater model is not currently applied to Wales.

on a catchment level using historic average abstractions (Environment Agency 2023). Agricultural and irrigated water is modelled using WaSIM software (Hess 1996).

2.3.2 | Water System Performance Metrics

The severity, frequency and duration of water-use restrictions has been proposed as a metric for system performance and resilience (Borgomeo et al. 2014; Hall et al. 2020). Restrictions are implemented by water companies to protect the level of service (LoS) provided to customers during drought events. The level of restrictions is set independently but typically progresses from media campaigns and/or hosepipe bans (Level 1/2) to more severe measures such as drought orders, rota cuts and standpipe use (Level 3/4). Level 4 restrictions are extreme measures and are considered equivalent to system failure. Triggers of such restrictions are most commonly linked to reservoir storage.

3 | Results

3.1 | Groundwater Availability

In order to demonstrate the contribution of groundwater to England's water supply system, the behaviour of the simulated groundwater flows generated for this study was explored. It should be noted that the analysis excludes the contributions of groundwater from the small number of water resource zones not represented in WREW and water resource zones where groundwater is represented by water company data.

The steady groundwater supply scenario presents flows generated under the assumption of constant groundwater yields, equal to the current regulator abstraction limits, presenting a best-case scenario of maximum groundwater availability. To highlight the spatial variability of groundwater across England, the distribution of groundwater flows under the steady scenario is presented in Table 2. Results are presented per water resource region, representing the south-east (WRSE), east (WRE), north (WRN), west (WRW) and south-west (WRWC) of England, respectively (as illustrated in Figure 3). The table illustrates, in part, the spatial distribution of productive groundwater bodies (Allen et al. 1997), with total groundwater flow in the south-east shown to be more than five times greater than the north of England.

Table 2 further presents the proportional distribution of groundwater in the context of public water demand under 2025 and 2050 scenarios during a historic (1965–2015) climate simulation. The steady groundwater scenario is able to meet the majority of the demand in the south-west (52.4%–61.1%), south-east (55.8%–59.7%) and east (55.0%–55.8%) of England and a notable proportion in the west (35.1%–41.4%) and north (24.3%–28.0%) regions, highlighting the importance of groundwater as a public water resource nationally. Furthermore, the magnitude of groundwater use during the simulations, representing water taken by the model to satisfy demand requirements, is lower than the total available in all regions for both demand scenarios. This indicates that groundwater does not typically limit the ability of the system to meet public water demand under historic conditions. The results suggest that either a surplus of total supply exists under the scenarios explored, that transfer infrastructure is limiting the distribution of supply or that water from surface water abstractions and/or reservoir storage is taken in preference to groundwater supply. The proportion of buffer capacity (the difference between used and available groundwater) differs between regions and the demand scenarios. Groundwater appears notably underutilised by the model in the west and east, suggesting that surface water supply and/or storage in these regions are able to better meet demand with supplementary supply from groundwater. In contrast, the south-west appears to show a greater reliance on groundwater, with a residual capacity equal to between 1.6% and 9.8% of total demand.

Whereas the steady groundwater supply scenario is based on regulator licensed limits, the assumption of constant groundwater yields is unrepresentative of the potential operational and hydrogeological constraints to groundwater supply. In contrast, dynamic flows generated using the empirical groundwater model reflect elements of source sensitivity to antecedent conditions and are constrained by historic operational use. A comparison of the steady and dynamic groundwater flow simulations for each groundwater group is presented in Figure 4. The variation observed between the steady and dynamic simulations represents the magnitude by which groundwater flow is reduced when dynamically represented. In general, all regions show a notable decline in groundwater flow when dynamically represented. Proportional reduction, using the mean historic dynamic flow, is greatest in the west (28.2%) and south-east (24.3%) regions of England and smallest in the south-west (20.5%). As the dynamic groundwater flows are regulated in part by historic abstraction records, these results suggest that groundwater use

TABLE 2 | The regional distribution of total groundwater flows in WREW under the steady groundwater scenario, as derived from the reported maximum annual licence data (Environment Agency 2023), and the percentage of available groundwater and mean groundwater use relative to requested demand simulated under the historic climate (1965–2015) scenario, presented in the context of the mean requested demand for 2025 and 2050. Groundwater buffer represents the residual groundwater, the difference between used and available groundwater flows, that is not used during the simulations. Total licensed groundwater and derived flows presented are indicative and should be viewed in the context of this study only. Total volume of licensed groundwater is fixed for both 2025 and 2050 scenarios.

		WCWR	WRW	WRN	WRE	WRSE	England
	Total Licensed groundwater (Ml/d)	660	1350	467	807	2539	5823
	Regional distribution	11.3%	23.2%	8.0%	13.9%	43.6%	
2025	Requested demand (Ml/d)	1261	3847	1918	1468	4552	13 046
	Groundwater available	52.4%	35.1%	24.3%	55.0%	55.8%	44.6%
	Groundwater use	50.8%	15.4%	11.3%	26.3%	42.1%	28.8%
	Groundwater buffer	1.6%	19.7%	13.0%	28.7%	13.7%	15.8%
2050	Requested demand (Ml/d)	1082	3262	1668	1447	4251	11 710
	Groundwater available	61.1%	41.4%	28.0%	55.8%	59.7%	49.7%
	Groundwater use	51.3%	10.3%	9.4%	26.9%	41.7%	27.4%
	Groundwater buffer	9.8%	31.1%	18.6%	28.9%	18.0%	22.3%

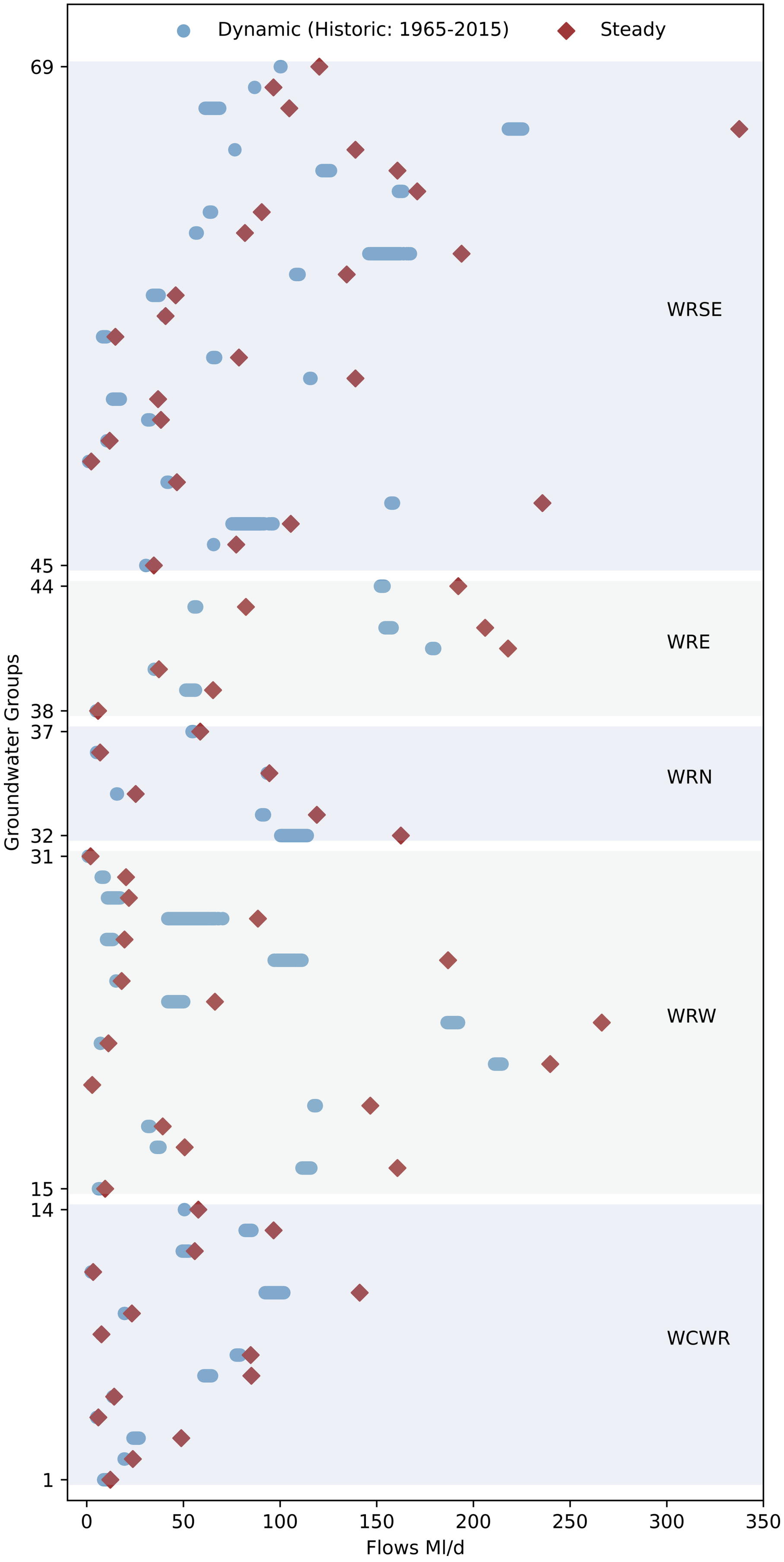


FIGURE 4 | Legend on next page.

FIGURE 4 | Comparison between flows under the historic (1965–2015) dynamic groundwater scenario and steady groundwater scenario where flows are derived from the reported maximum annual licence limit. Flows are shown for 69 groundwater groups represented in WREW and are presented by water resource region. All flows presented are indicative and should be viewed in the context of this study only.

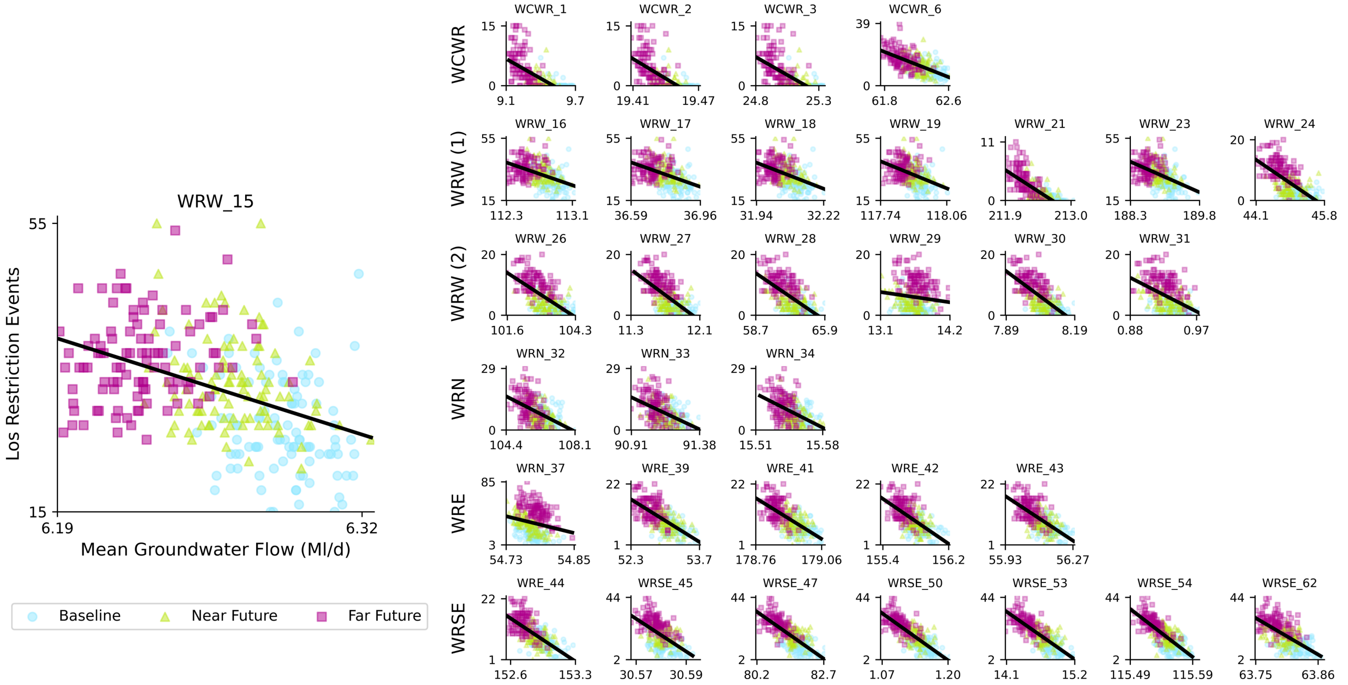


FIGURE 5 | Relative comparison between the mean dynamic groundwater flow per simulation and the number of LoS restriction events. Each LoS event is defined at a water company level as a period of consecutive days in which the restriction level is greater than zero within the WREW model simulation. Figure shows all sensitive groundwater groups where there is at least one LoS restriction event across all w@h climate scenario replicates.

in the south-west may have been historically closest to current regulator limits, relative to other regions. Reaffirming our previous analysis that identifies the south-west as showing the greatest reliance on groundwater to satisfy public water demands.

The variation of the dynamic flows between groundwater groups reflects the sensitivity of the modelled groundwater supply to antecedent conditions, with 55 of the 69 groundwater groups demonstrating sensitive flows. The allocation of individual groundwater sources to each group is typically by water resource zone. Consequently, direct comparison of the simulated flows between groundwater groups is inappropriate. However, there is notable diversity in the magnitude and variability of flows between water resource regions. Spatially this is greatest in the south-east and west of England, where the total variation in dynamic flows is 84 and 83 Ml/d, equivalent to 1.8% and 2.2% of 2025 public water demand, respectively. However, for many groundwater groups, the magnitude of variation is small. Flows in the east and north vary by just 13 and 16 Ml/d, equivalent to 0.9% and 0.8% of 2025 public water demand, respectively. The characterisation of supply sources by the empirical groundwater model signifies their potential vulnerability to future extreme climates. Regions where groundwater supply is less variable show less sensitivity and therefore offer the greatest robustness under uncertain futures, where robustness represents the ability of the system to perform under varying scenarios.

3.2 | Water Supply System Sensitivity to Groundwater

To evaluate the sensitivity of the water supply system to groundwater, LoS water-use restrictions within the model are used as a metric for system performance and resilience. The analysis of performance excludes those water companies where groundwater is (partially) represented by water company data. Simulations comparing the availability of groundwater and the occurrence of restrictions are computed for each of the three large-ensemble w@h climate scenarios (baseline: 1975–2004; near future: 2020–2049; and far future: 2070–2099). The 300 × 30-year simulations are run with dynamic groundwater behaviour to produce a portfolio of varying groundwater flows, as sensitive groundwater groups respond to antecedent climate conditions and operational abstractions. Figure 5 presents the relationship between the number of LoS restriction events and mean groundwater flow under each climate scenario replicate for the sensitive groundwater groups. Restriction events, derived per water company, are considered as a period of consecutive days of any restriction level (1–4) within the WREW model. The steepness of the negative relationship between the magnitude of mean groundwater flow and the number of restriction events reflects the groundwater sensitivity of public water supplies in the groundwater group.

Understanding the response of water systems to groundwater droughts is an important step towards better managing future supply risk. To explicitly examine the sensitivity of England's system to climate-driven groundwater supply, the forcing flows A_f (2) for each of the groundwater groups are analysed. For sensitive groups, these flows represent available groundwater as determined by the antecedent precipitation and historic abstraction records, prior to reduction driven by dynamic operational use.

Each w@h climate scenario is composed of 100 equiprobable replicates of climate conditions. The replicates with the 10% highest and 10% lowest total forcing flows have been identified for each groundwater group. This classification isolates the extreme ‘wet’ and ‘dry’ groundwater scenarios, under which the system's performance can be evaluated. Selection of replicates is unique to each groundwater group, due to variations in the optimal lag period, in addition to spatial variation in the simulated rainfall.

Figure 6 presents the distribution of system performance outcomes under high and low forcing flows. Results from the complete dataset of 100 replicates for each ensemble (all) are also included for comparison. Here, system performance is assessed using the annual mean number of days with any level (1–4) of

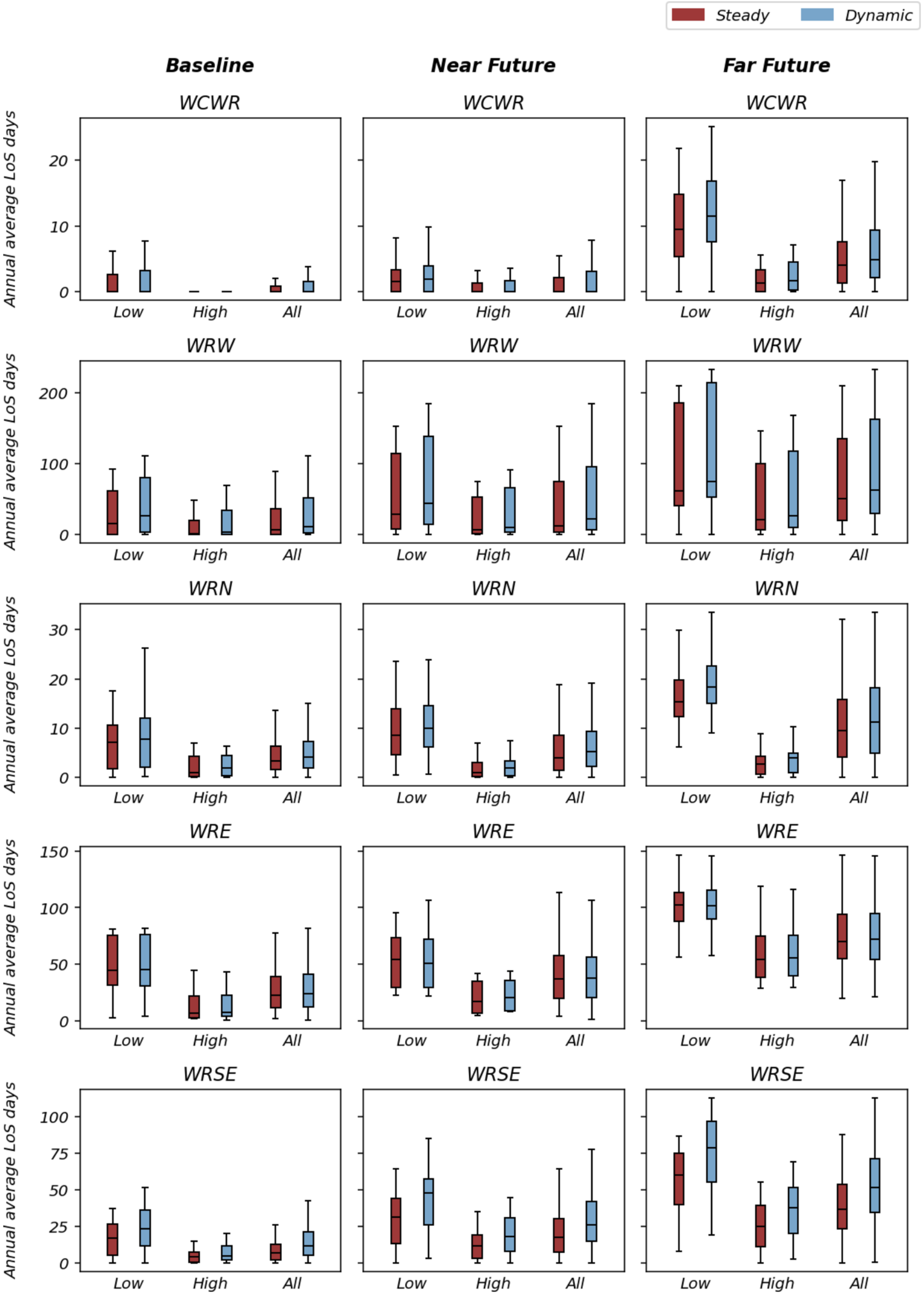


FIGURE 6 | The distribution of the annual mean days of a LoS restriction > 0 under dynamic and steady groundwater flow simulations for each w@h climate scenario, grouped by region. Low and high represent the 10% of replicates in each 100-replicate ensemble with the lowest and highest total forcing (climate-driven) groundwater flow for each groundwater group, respectively. ‘All’ represents the results when all replicates are simulated. No outliers are shown. Groundwater groups that are not sensitive and/or have no associated LoS restrictions are excluded from the figure.

LoS restriction. Simulations under dry replicates with the lowest forcing flows show a higher median (50th percentile) level of restrictions when compared to the wetter replicates with the highest flows. This is true for all regions and all w@h climate scenarios presented, except for the south-west under the baseline scenario where the median restriction metric is zero across high, low and all flow replicates. Results from far-future (2070–2099) simulations present the most extreme variation between high and low flows. For example, the change in median days of restriction between high and low flows was on average 32.1 days for dynamic simulations in the far future, compared to 20.8 days and 17.0 days in the near-future and baseline simulations respectively. The results clearly illustrate the dynamic, but geographically variable, influence of groundwater flows under extreme conditions on supply system performance.

To exclude the possibility that system performance under replicates with high or low flows may be driven by the overall climate sensitivity of the model, repeat simulations with steady groundwater flows were computed. Thus, isolating the contribution of groundwater to the system's water balance from surface water variability. Results from these simulations are presented in Figure 6. These indicate that in general, performance of the system worsens using dynamic flows (where groundwater availability is reduced) relative to steady simulations under the same climate conditions. The contrast is notable in the south-east of England: For far-future simulations, the median restrictions increase by 18.3 (~30%), 12.3 (~50%) and 14.6 (~40%) days per year for low, high and all replicates, respectively, when comparing the steady to the dynamic groundwater scenario. Variation in the north, south-west and east of England is less significant (with a median difference of < 3 days). Under low flows, dynamic simulations in the east demonstrate a slightly improved performance relative to the steady scenarios, suggesting low groundwater sensitivity. However, in general, these results indicate that at a national scale, the water supply system is responsive to climate-driven groundwater availability while acknowledging there is regional variation in this sensitivity.

3.3 | Dynamic Representation of Groundwater Supply

An additional comparison between steady and dynamic simulations is presented in Figure 7. These results detail the change in probability of an extreme LoS restriction event between simulations run with dynamic and steady groundwater scenarios. Here, extreme LoS restriction events are classified as those of either a Level 3 or 4 magnitude, the latter of which are associated with severe restriction measures such as the use of standpipes or implementation of rota cuts and as such may be viewed as a proxy for supply failure. Results are presented by water resource regions, where the maximum simulated level of restriction within each region is selected to represent regional performance at each time-step. The results indicate either a negligible change (−0.01–0.01) or decreasing probability between dynamic and steady simulations under all simulated scenarios. This further demonstrates the sensitivity of the whole system to groundwater, with regional differences in magnitude of response; the east and south-west of England appear insensitive to changes in groundwater representation, other than under a far-future climate, whereas the west and south-east regions show a greater sensitivity. Simulations under the lowest regional forcing flows, and those under the far-future climate scenario, typically show the greatest change in probability between dynamic and steady groundwater scenarios, aligning with the previous analysis (Figure 6).

4 | Discussion

Comparisons of simulations run with dynamic and steady groundwater flow scenarios, and simulations run with varying climate conditions, have demonstrated the system's sensitivity to variable groundwater flows, especially during drought conditions. Tangible impacts to system performance, as assessed through the probability of LoS restrictions, have been shown to correspond with the magnitude of groundwater flow. In general, the performance of the system worsens under constrained, dynamic flows relative to an assumption of steady regulator licensed abstraction limits. However, it is notable that flows generated under the dynamic groundwater scenario have a lower mean value compared to the corresponding steady state simulations, limiting the overall supply of water within the system. Dynamic simulations run under a far-future climate scenario, inclusive of more extreme weather events, also result in a greater impact to system performance compared to baseline conditions. Through comparison of model performance under extreme high and low dynamic groundwater flow scenarios, isolating groundwater from whole-system climate sensitivity, our analysis has further illustrated system responsiveness to groundwater alone. Such results indicate that England's water supply system can be considered sensitive to groundwater and demonstrate the value of a dynamic and more sophisticated representation of groundwater to facilitate the improved understanding of water system behaviour.

There are spatial variations in response, which align with regional differences in the variability of the simulated groundwater flows. The south-east and west of England have the greatest licensed groundwater abstractions, and they also show the greatest variation in flows under a historic climate, indicating increased sensitivity to antecedent conditions. Our results from these regions correspondingly show the greatest change in system performance between steady and dynamic simulations, illustrating the importance of groundwater supply to meet public water demands in these areas. Simulated variations in flow are smaller for the east and north of England. The east of England shows limited sensitivity to the most severe restriction events (LoS 3 or 4), despite the presence of highly productive aquifers in this region (Allen et al. 1997), though this may reflect the simplified representation of water resource zones, including aggregation, within the simulation model.

Our study has examined the role of groundwater at a national scale. Such an approach is facilitated by the availability of historic abstraction and licensing records in England. However, the resolution of these data and scale of assessment means the results presented are not intended to be comparable to the levels of assessment achieved with localised data and expert knowledge. Although the WREW used in this study is the best existing representation of national supply, the scale

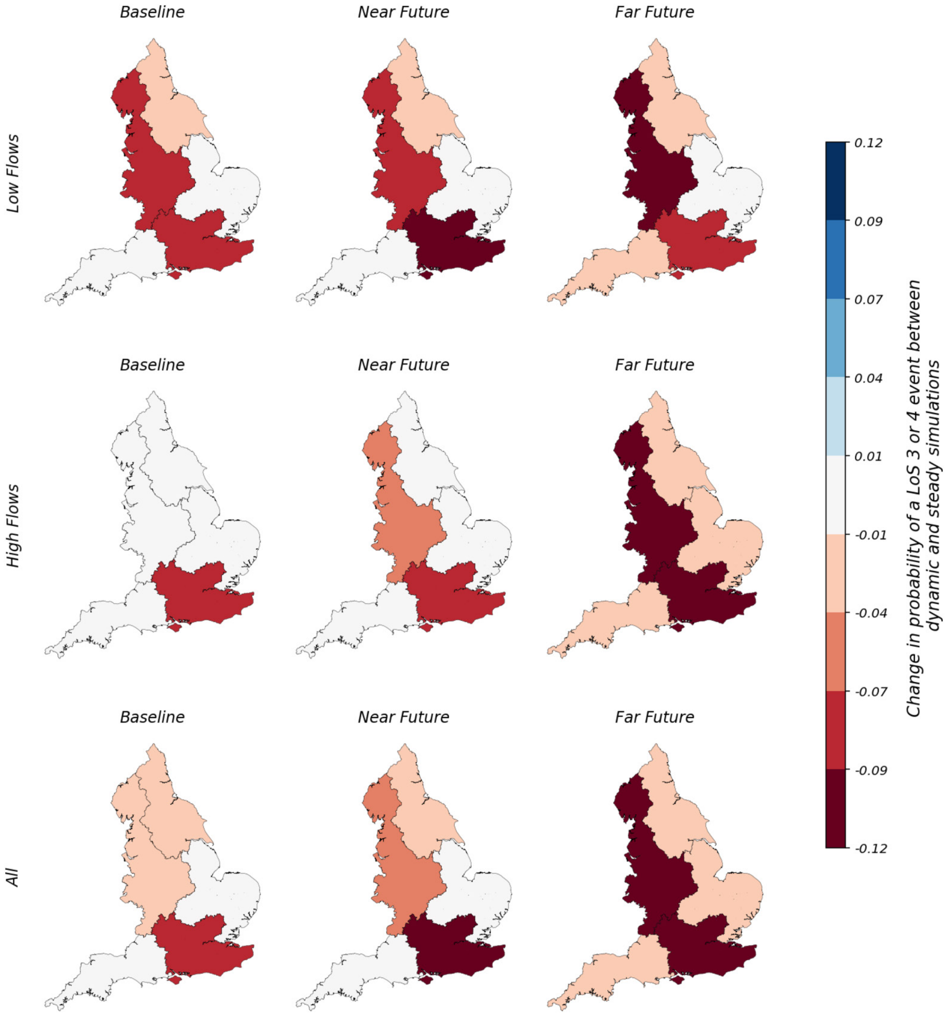


FIGURE 7 | The change in probability of a LoS 3 or LoS 4 restriction event between dynamic and steady groundwater simulations (calculated as steady – dynamic), for each w@h climate scenario. Results are presented at a regional level, representing the maximum LoS restriction within the region. Low and high represent the 10% of replicates in each 100-replicate ensemble with the lowest and highest total regional groundwater forcing (climate-driven) flow, respectively. 'All' represents the results when all replicates are simulated. Groundwater groups that are not sensitive are excluded from the analysis.

of the system represented means that generalisations and simplifications of network dynamics are unavoidable (further detailed by Dobson et al. 2020). The assessment also excludes groundwater from those water resource zones that are currently not modelled in WREW or where groundwater supply is represented with water company data (highlighted in Figure 3). As such, our study provides insight into the generalised behaviour of a large-scale, complex and interconnected water supply system and should not be used to infer localised performance. Further work to improve the calibration of the system model and improve modelled groundwater representation of 'excluded' areas would only strengthen the validity of future research.

An important benefit to our use of an empirical groundwater model is the opportunity to represent groundwater supply dynamically by reflecting the evolving state of groundwater resources in response to groundwater abstractions and climate conditions. In general, dynamic groundwater flows generated using the empirical model reduce the magnitude of flow available when compared to regulator abstraction limits and incorporate supply variability. However, the behaviour of the variability observed could be improved with further model development. Typically, the optimisation of the multivariate regression results in our model constraining supply by small, regular reductions in flow. In reality, it is expected that groundwater sources are more likely to experience extreme, but infrequent reductions in performance, due to delayed but prolonged periods of groundwater drought (Van Loon 2015) and threshold constraints associated with asset infrastructure (e.g., pump cut-out level) (Misstear and Beeson 2000). Future work should therefore focus on improving the responsiveness of groundwater supply to antecedent conditions and better represent resource behaviour under drought. The sensitivity of the groundwater model to alternative hydrogeological classifications (e.g., no classifications or subdividing hydrogeological units further, e.g., by flow mechanism) could also provide an interesting avenue for future exploration.

It is also acknowledged that the use of our empirical model is limited by an assumption of stationarity, as the derived relationship between groundwater source performance, abstractions and climate may not be representative into the future. Although non-stationarity has not been tested for, it is plausible to consider that source sensitivity to extreme rainfall may diverge from historic norms. Equally, changes to abstraction licensing and/or operational use may result in a similar deviation. Adjustments to the model to better reflect non-stationarity should therefore be considered in future work while balancing increased model complexity against the desire for an efficient, dynamic representation of groundwater.

5 | Conclusion

Water resource simulation models allow exploration of system performance under a range of input conditions and are an important tool with which to 'stress-test' system behaviour (Hall et al. 2019). Yet, comprehensive representation of groundwater within simulation models is infrequently achieved, despite groundwater's widespread use in public water supply. As such, the contribution of groundwater to water supply systems, particularly under future climate extremes, is underexplored. This study addresses this by presenting a methodological approach that integrates a water resource system model with an empirical groundwater model. This has been applied in the context of England's water supply system, to offer novel insights into groundwater's behaviour and contribution at a national system scale.

The work presented here emphasises the importance of dynamic representation of groundwater supply within water resource systems models by demonstrating the sensitivity of system performance to groundwater availability, with a notable increase in restrictions shown under dynamic representation and/or future extreme climates for the most sensitive regions. The use of an empirical groundwater model offers an efficient and flexible way to represent groundwater dynamically, reflecting drivers of resource availability, including antecedent climate conditions and operational abstractions, thus simulating, in part, the complex behaviour of groundwater supply resources. Future improvements to groundwater representation within water system models can only strengthen understanding of system behaviour and aid management decisions in uncertain futures.

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Conflicts of Interest

Rachel Pugh is partially funded by Thames Water for her DPhil, and declares that her spouse is an employee of Severn Trent Water and owns shares as part of their employee share scheme. The remaining authors have no conflicts of interest to declare.

Data Availability Statement

The weather@home climate sequences can be downloaded from the Centre of Environmental Data Analysis (https://doi.org/10.5285/0cea8d7aca57427fae92241348ae9b03). CEH-GEAR climate data can be downloaded from the UK CEH Environmental Information Data Centre (10.5285/dbf13dd5-90cd-457a-a986-f2f9dd97e93c). The DECIPHeR flow series is available at 10.5523/bris.2pkv9oxgfzvts235zrui7xz00g. Hydrogeological data for the United Kingdom can be downloaded from the British Geological Survey (https://www.bgs.ac.uk/datasets/hydrogeology-625k). Historic abstraction and licensing data was provided under licence from the Environment Agency. The WREW model and associated data cannot be made available because of commercial limitations by English water companies.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Figure S1:** Error (relative RMSE) between 24 reservoir levels modelled in WREW under dynamic and steady groundwater representation and water company simulated reservoir levels during four key periods of historic drought and for the whole historic (1965–2015) simulation. The relative error is calculated as the total RMSE divided by the summed mean simulated level (~1260000 Ml) for all reservoirs. Differences between the demand scenarios within WREW and water company simulations may contribute towards a discrepancy between simulated levels. Additionally, as a national-scale systems model, WREW is unable to represent processes at a complexity likely included within water company simulations. **Figure S2:** Comparison of modelled level of service (LoS) for each water resource region for the historic (1965–2015) dynamic and steady simulations and years where drought orders were issued as recorded in the historic droughts inventory (Durant and Counsell 2020).