Hydrological modelling and artificial influences: performance assessment & future scenarios

CS-NOW-D2 – Future water availability for water intensive energy infrastructure

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CS-NOW

Climate services for a net zero resilient world

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About CS N0W

Commissioned by the UK Department for Energy Security and Net Zero (DESNZ), Climate Services for a Net Zero Resilient World (CS-N0W) is a 4-year, £5.5 million research programme, that will use the latest scientific knowledge to inform UK climate policy and help us meet our global decarbonisation ambitions.

CS-N0W aims to enhance the scientific understanding of climate impacts, decarbonisation and climate action, and improve accessibility to the UK's climate data. It will contribute to evidence-based climate policy in the UK and internationally, and strengthen the climate resilience of UK infrastructure, housing and communities.

The programme is delivered by a consortium of world leading research institutions from across the UK, on behalf of DESNZ. The CS-N0W consortium is led by Ricardo and includes research **partners Tyndall Centre for Climate Change Research**, including the Universities of East Anglia (UEA), Manchester (UoM) and Newcastle (NU); institutes supported by the **Natural Environment Research Council (NERC)**, including the British Antarctic Survey (BAS), British Geological Survey (BGS), National Centre for Atmospheric Science (NCAS), National Centre for Earth Observation (NCEO), National Oceanography Centre (NOC), Plymouth Marine Laboratory (PML) and UK Centre for Ecology & Hydrology (UKCEH); and **University College London (UCL)**.

Contents

Glossary

Abstraction demand	Measurements or scenarios of abstraction demand (m^3) from surface water and groundwater
Artificial Influences (AI)	Abstractions and Discharges
Business as usual (BAU)	Future AI scenario
CS-NOW	The Climate services for a Net Zero resilient world project
Discharge	Measurements or scenarios of effluents from sewage treatment works and other large direct discharges to the river system
eFLAG	Enhanced Future Flows and Groundwater projections
Economic Growth (EG)	Future AI scenario
G2G abstracted water simulations	Abstraction demand (m^3) that <u>could</u> be met in G2G
G2G un-abstracted water	Abstraction demand (m^3) that <u>couldn't</u> be met in G2G simulations
Grid-to-Grid (G2G)	A grid-based hydrological model
Hands-Off-Flow (HoF)	Flow condition (m^3/s) to protect surface water and groundwater resources
MaRIUS	The Managing the risks, impacts and uncertainties of droughts and water scarcity project
MeanAI	Temporal mean of Observed Artificial Influences
NALD	National Abstraction Licensing Database
NATURAL	Refers to river flows in catchments with no artificial influences
NRFA	National River Flow Archive
ObsAI	Observed Artificial Influences
Potential Evaporation (PE)	also known as Potential Evapotranspiration (PET)
Q70/Q90/Q95	Flow (m^3/s) which was equalled or exceeded for 70%, 90%, or 95% of the specified time period (i.e. low flow parameters)
RCM	Regional Climate Model
RCP	Representative Concentration Pathway, a greenhouse gas concentration trajectory adopted by the IPCC
simobs	Observation-driven hydrological simulations
simrcm	RCM-driven hydrological simulations
Sustainability (SUS)	Future AI scenario
UKCP18	UK Climate Projections 2018
WRGIS	Water Resources Geographical Information System
WRZ	Water Resource Zone

1. Executive summary

There have been numerous assessments of potential impacts of climate change on river flows and groundwater for the UK. One of the most recent, the eFLaG (enhanced Future Flows and Groundwater) project, provides national and spatially consistent hydrological projections based on UKCP18 regional projections up to 2080. Although eFLaG and many other projects provide scenarios of flow projections, they do not explicitly estimate artificially influenced (AI) river flow after the net impact of abstractions and discharges has been accounted for'. For example, eFLaG provides either natural flows or flows calibrated to current conditions, including AIs. In both cases, it makes no assessment of possible future changes in abstractions/discharges, as well as the need for 'environmental flows' (flows that leave adequate supply for the environment) which will constrain future water availability.

This project, CS-N0W (WPD2), aims to provide future projections of AI-impacted flows across England up to 2080, by accounting for possible future changes in abstractions/discharges. This report presents the modelling approach and datasets used to derive the future flow projections, together with an assessment of how the AI-impacted hydrological model (Grid-to-Grid or "G2G") performs for historical periods. A comparison of simulated and observed river flows for 626 catchments across England between 1999 and 2014 indicates that model simulation of river flows is generally improved at gauged locations. The main improvement is in the simulation of low flows, for which the median performance is improved by 12.5%, while the improvement in the simulation of high flows is a more modest 1.5%.

A companion report, Tanguy et al. (2023), presents an analysis of these scenarios and provides key indicators and statistics of water availability for historical, current and future timescales to 2080.

2. Introduction

This report presents the method used to derive England-wide scenarios of Artificial Influence (AI)-impacted river flows from 1980 to 2080 to support a national-scale assessment of future flow regimes and water availability scenarios.

The approach uses future scenarios of surface and groundwater abstractions and discharges which were recently developed by Baron et al. (2023) to capture the range of impacts that artificial influences may have on future flows and groundwater. Three scenarios were provided, ranging from '*Sustainability*' to '*Economic Growth*' demand projections together with a '*Business as Usual*' scenario. These AI scenarios are used as input to a hydrological model (Grid-to-Grid, (Bell et al., 2009)) that was recently enhanced to take account of recorded discharges and monthly abstractions (Rameshwaran et al., 2022).

This report summarises the future AI scenarios and how they are used in the Grid-to-Grid (or "G2G") hydrological model. The G2G simulations of AI-impacted river flows are assessed with respect to observed river flows for 626 English catchments during a historical period for which AI data are available. Following the performance assessment, the AI-impacted G2G was run for longer historical (1st December 1980 to 31st December 2020) and projected future (1st January 2020 to 30th November 2080) periods. The G2G-simulated AI-impacted flows are used to support a separate analysis of projected-future flow regimes (Tanguy et al., 2023). In particular they support derivation of historical and projected-future Q95, Q90, Q70, mean annual and monthly flows, along with drought metrics such as duration, intensity, and severity.

The CS-N0W G2G hydrological projections developed here are comparable with the eFLaG UKCP18-driven climate and hydrological projections (Hannaford et al., 2023), since the same G2G model implementation is driven by the same climate data (eFLAG bias-corrected UKCP18 regional projections), and results are provided for the eFLAG catchments that lie in England (plus other MaRIUS catchments). The difference between CS-NOW and eFLAG G2G projections is the use of abstractions and discharges in the CS-NOW G2G simulations. Note that this analysis focuses primarily on AI-impacted flows, as the eFLaG project already conducted an analysis of natural flows as simulated by G2G (Parry et al., 2023).

In this report, we aim to demonstrate the benefits of using high-quality spatio-temporal abstraction and discharge data in distributed hydrological (and potentially land-surface) models. By including AI data, we can enhance our understanding of anthropogenic influences on hydrological regimes at a national scale and inform decision-making processes at regional and national levels.

3. Data used in the modelling analysis.

This section outlines the climate and artificial influence (AI) data used in the hydrological modelling (section 4). The climate data used to drive climate projections consist of the eFLaG bias-corrected 12-member UKCP18 regional climate projections which are available at 1 km resolution (section 3.6).

3.1 Study area

While in practice hydrological modelling has been undertaken for mainland Britain, model outputs are only applicable for English catchments, albeit with a modest overlap of the Welsh border. This is because, to-date, only English AI data have been obtained and processed for model use (section 3.2), and suitable AI data have not been available for areas outside England. We requested these data from other UK regions but were not able to access them. Thus, gridded G2G hydrological model outputs (e.g. river flows, G2G estimates of monthly water volumes abstracted from rivers) are provided on a 1km × 1km grid across England and include 5 catchments that cross the border into Wales (specifically UK National River Flow Archive (NRFA) catchments 54001, 54032, 54057, 54029 and 54008). Note that abstractions and discharges for these 5 border-crossing catchments are likely to be underestimated as we do not have AI data for Wales. The CS-N0W region for which G2G model outputs are provided is shown in Figure 1(a). Modelled flows are also provided for individual gauging-station locations downstream of 626 catchments across England (Figure 1(b)). These catchments comprise all 605 MaRIUS project catchments (Rameshwaran et al., 2022), together with an additional 21 eFLaG catchments (Hannaford et al., 2022, Hannaford et al., 2023), that were not used in MaRIUS. In the eFLaG catchment selection strategy, both research and industry needs were considered whereas in MaRIUS only catchments with areas above 50 km^2 are considered. The complete list of all 626 catchments, a significant proportion (>60%) of the NRFA gauging station network for England, is presented in Appendix A, Table 4.

3.2 Artificial Influence (AI) data

The AI data (licence/consents/returns) used here have been sourced from the UK Environment Agency (EA) under licence. Specifically, monthly surface- and groundwater abstraction data were obtained from the EA's **NALD** database for 1999 to 2014, and annual discharges (2017) and Hands-off-Flow (HoF) conditions were obtained from the EA's Water Resources GIS (**WRGIS**) database. The impacts of other AIs such as reservoir impoundments and releases are not considered here, and the G2G does not take account of abstractions from lakes or reservoirs.

Although abstraction and discharge data are available from the EA's WRGIS database, these data were not used in CS-NOW as they provide only recent actual *annual* point-purpose abstractions, which are also an average over the last 6 years. Instead, NALD *monthly* actual abstraction values at specific geographical locations were considered more suitable for distributed hydrological modelling.at a 1km × 1km spatial resolution.

The benefit of using spatially-distributed NALD abstraction data from 1999 to 2014 was that the true monthly distribution and the inter-annual variability of abstractions (shown in Figure 3, Rameshwaran et al. (2022)) could be accounted for in our modelling. However, the disadvantage of using NALD abstraction data was that the discharge and HoF data could only be obtained from WRGIS and were associated with a different period (2017). Use of WRGIS abstraction and discharge data for the same historical period will be preferred for many applications, but for high-resolution hydrological modelling, the monthly data only available from NALD were more suitable.

Rameshwaran et al. (2022) outlined the methodology used for the conversion of these point abstraction and discharge data into monthly 1 km × 1 km grids across England for each of the 57 primary uses (Appendix A, Table 5). Various pragmatic assumptions were made to resolve apparent inconsistencies in licence returns or to overcome uncertainties associated with missing information. One important factor to consider was that the derived monthly grids represent total water abstracted but do not take account of water immediately returned to river by the licence holder (e.g. from vegetable washing).

(a)

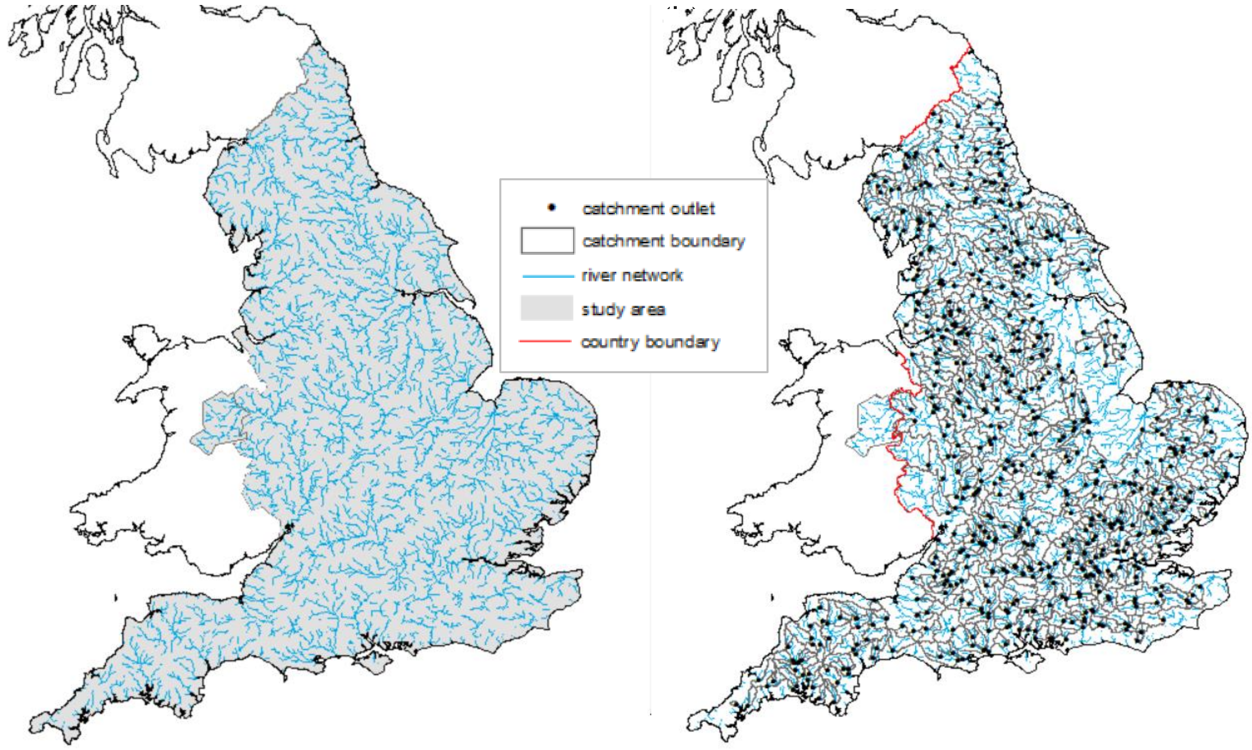

Figure 1 Maps showing the CS-N0W study region: (a) the region for which spatially distributed 1kmx1km G2G outputs are available (grey shading), and (b) gauging stations (black dots) and catchment boundaries (grey lines) for which daily flow time-series are provided. Regional boundaries with Scotland and Wales are shown in red.

Although, in reality, abstractions and discharges datasets are related, it was not possible to link individual abstraction licences and discharge permits. To minimise the uncertainty in net abstraction associated with these immediate water returns, use was made of the loss factor term associated with surface water abstractions (Appendix A, Table 5). The four loss factor categories (EA, 2020a) are High (100%), Medium (60%), Low (3%) and Very Low (0.3%). For three of these categories (high, medium and low abstraction losses), an assumption is made here that any water returned to the river is accounted for in the discharge dataset. However, for the abstractions associated with ‘Very Low’ losses (termed ‘Through Flows’, e.g. Fish Pass/Canoe Pass, River

Recirculation, Hydroelectric Power Generation) the returns are so high and localised that an assumption that returns are included in discharges cannot be made. For these 'Very Low' loss abstractions we have assumed that only 0.3% of the water volume is removed mainly due to conveyance losses. The basis of this assumption is described in Rameshwaran et al. (2022).

3.3 Application of Hands-off-Flow conditions

Surface water abstraction is constrained by a HoF flow value (m^3 day^{-1}), requiring abstraction to cease (or reduce) if the river flow falls below this threshold. This requirement is designed to prevent detrimental impact of excessive abstraction on the environment and protect river ecosystems during periods of low flows particularly during drier years. This means that during drought periods when the river flow is below the local HoF threshold, the licence holder will be temporarily unable to abstract their full licensed amount. Here, HoF conditions for surface water abstractions were obtained from the EA Water Resources Geographic Information System (WRGIS; provided under licence in 2017).

For this CS-N0W study, the way in which the HoF condition is included in the hydrological modelling has been improved. Previously, when the HoF condition was implemented in the G2G, river flows at the abstraction site were compared with the HoF condition (Rameshwaran et al., 2022). In reality, the HoF condition is often applied with reference to river flows at a different location, the "HoF impact location". HoF impact locations are referenced in the EA's WRGIS system and consist of (sometimes non-local) sub-catchments or waterbodies, rather than point locations. To make use of this information in the G2G hydrological model, the most downstream 1km grid-cell of each HoF impact waterbody was used as the "HoF impact grid-cell", at which G2G-simulated flows are compared with the HoF condition to establish whether an abstraction can take place.

3.4 Future scenarios of AI data

Estimates of abstraction and discharges for projected future period (2020 to 2080) were based on three future AI scenarios introduced by Baron et al. (2023). The derived scenarios were constructed from various published scenario reports and datasets (e.g. Water Resources National Framework (EA, 2020b) and Water Resource Management Plans (WRMP19: Anglian_Water (2019)). These underlying reports and datasets were developed at different times for different purposes and were not expected to be used in combination with each other, with the result that there are some inconsistencies when they are used together. The result of these inconsistencies is that no AI scenario is always higher or lower than another, so it is not possible to identify a high, medium or low AI scenario. These scenarios are described in detail in Table 2 of Baron et al. (2023) and summarised below:

- ***'Sustainability (SUS)' AI scenario***: sustainability is prioritised, high levels of water efficiency are achieved, low population growth, innovation and societal change to achieve Net Zero energy production ahead of schedule, reduction in meat consumption and food waste, additional environmental constraints. Typically this scenario results in lower surface-water and groundwater abstraction volumes than for the two other scenarios, but the overall change relative to the present day depends on individual catchments and the future time period.
- ***'Business as Usual (BAU)'* AI scenario**: current ambitions for water efficiency are achieved with no further efficiencies implemented, best-estimate population growth, a move to green energy production consistent with current projections, and environmental considerations kept at current levels. BAU is typically (but not always) a “central” AI scenario, with abstractions higher than for the SUS scenario, but the overall change relative to the present day depends on individual catchments and the future time period.
- ***'Economic Growth (EG)'* AI scenario**: economic growth is prioritised over sustainability, no water efficiencies, high population growth, continued use of fossil fuels and water-intensive agriculture (e.g. high meat consumption and increase of irrigated area), and some relaxation of environmental considerations. Typically (but not always) this scenario results in higher surface-water and groundwater abstraction volumes than for the SUS and BAU, but the

overall change relative to the present day depends on individual catchments and the future time period. Note that the assumption that EG is high-abstraction scenario does not always hold, and for some catchments (e.g. 39001) BAU abstractions are higher than for EG for some future time-periods.

For each of the three AI scenarios (above), corresponding **future scenarios of discharge** have been constructed by scaling present day discharges with the same factors used to scale abstractions (Baron et al., 2023). For example, discharges related to Public Water Supply (PWS), were scaled similarly to PWS abstractions but with adjustments to remove the effects of leakage change.

3.5 Present day (observed) climate data

The G2G hydrological model performance assessment was undertaken on a 60-year historical period (January 1961 – December 2020: Section 4) for which daily observations of rainfall, air temperature and monthly potential evaporation (PE) were available. The driving datasets were chosen to be exactly the same as those used in the eFLaG project (Hannaford et al. 2023), with the addition of a further two years of more-recent data (2019 and 2020):

- Precipitation and temperature: daily HadUK-Grid 1km x 1km dataset (Hollis et al., 2019), the national standard gridded meteorological dataset and observational product associated with UKCP18.
- Potential Evaporation (PE). monthly MORECS data (Hough and Jones, 1997), an established, national gridded PE product on a 40km grid. Other PE datasets such as CHESS (Robinson et al., 2020) and more recently Hydro-PE (Robinson et al., 2022) are available, but the decision to use MORECS here was based on the requirement for consistency with the eFLAG hydrological projections (Hannaford et al., 2022).

3.6 Future scenarios of climate data

Like the previous eFLaG project (Hannaford et al., 2023), CS-N0W modelling of future conditions is driven by the UKCP18 dataset, specifically the ‘Regional’ 12km projections.

These were created using perturbed-parameter runs of the Hadley Centre Global Climate Model (GCM, HadGEM3-GC3.05) and Regional Climate Model (RCM, HadREM3-GA705) (Murphy et al., 2017). These provide a set of 12 high resolution (12km) spatially consistent climate projections over the UK, covering the period Dec 1980-Nov 2080. The 12-member RCM Perturbed Parameter Ensemble (PPE) is valuable to represent climate model parameter uncertainty. RCM ensemble members are numbered 01–15, corresponding to GCM PPE members, but exclude 02, 03 and 14 as there are no RCM equivalents for these (see Murphy et al. (2018) and Section 4.3); 01 is the standard parameterisation. However, it is important to note that, as all ensemble members are based on the same high emissions scenario (RCP8.5) and underlying climate model structure, they do not represent the full climate uncertainty. The CS-N0W climate change simulations used the UKCP18 RCM output as previously processed by the eFLAG project (Hannaford et al., 2023) to provide the variables needed for hydrological modelling – namely, bias-corrected 1km gridded daily time-series of available precipitation (i.e. after the application of a snow module) and Potential Evapotranspiration (PET).

Note that the Hadley Centre climate model uses a simplified 360-day year, consisting of twelve 30-day months. The RCM precipitation and temperature time-series similarly are only available for a 360-day calendar, and thus the climate-data-driven hydrological model outputs are also provided for this 360-day year.

3.7 Observed river flow data

Across the UK, flow records for river flow gauging stations are readily available on the UK National River Flow Archive (NRFA, https://nrfa.ceh.ac.uk/ and Dixon et al. (2013)). For CS-N0W, the NRFA was the source of the validated river flow data used to assess the performance of the G2G at 626 gauging stations.

4. The Hydrological Modelling setup

The previous eFLaG project used two lumped catchment models, PDM (Moore, 2007) and the GR suite (Perrin et al., 2003), and one distributed grid-based hydrological model, Grid-to-Grid (G2G; Bell et al. (2009)) to make projections of river flows from present day (1980) to 2080. The use of different model structures and spatial representations in eFLaG provided an opportunity to explore how sensitive future river flow projections are to hydrological model choice. However, the requirement to use future projections of AIs in CS-N0W reduced opportunities to explore model structural uncertainty, as lumped catchment models such as PDM and GR are calibrated to observed river flows including artificial influences and thus cannot easily incorporate scenarios of AIs. Thus, only the one eFLaG model, G2G, has been taken forward in CS-N0W.

4.1 The Grid-to-Grid hydrological model

G2G is a national-scale hydrological model that provides estimates of river flows, runoff and soil moisture on a 1 km × 1 km grid across Great Britain (Bell et al., 2009, Moore et al., 2006). The G2G model formulation represents the processes of runoff-production and flow routing over a wide area and, across Great Britain, is typically run with a time-step of 15 minutes. G2G has been widely tested and is used operationally for countrywide forecasting over England and Wales by the Flood Forecasting Centre (Price et al., 2012) and, over Scotland, by the Scottish Flood Forecasting Service (Maxey et al., 2012, Cranston et al., 2012). G2G has also been used to assess the potential impact of climate change on floods (Bell et al., 2012, Bell et al., 2016), low flow frequency (Kay et al., 2018) and droughts (Rudd et al., 2017, Rudd et al., 2019). G2G output consists of a value of river flow for every 1 km × 1 km grid-cell across Great Britain, including ungauged sites. A particular advantage of G2G is that it has one spatially consistent configuration for the whole model domain and is able to represent a wide range of hydrological regimes due to use of spatial datasets of terrain, soil/geology and land-cover.

The G2G model has recently been enhanced to account for gridded monthly values of AI, specifically surface- and ground-water abstraction and discharge volumes (Rameshwaran et al. 2022). To enable AI data to be included in the G2G, thousands of point source abstraction and discharge measurements across England were transformed into 1 × 1 km resolution gridded data. These newly-gridded AI data were used as input to an enhanced formulation of the Grid-to-Grid (G2G) hydrological model in which the impact of abstractions and discharges on river flows were mathematically represented. A comparison of G2G simulated and observed (gauged) river flows catchments across England indicated that model simulations were generally improved at gauged locations downstream of abstraction/discharge sites, particularly for low flows, for which the median performance across >600 catchments was improved by 10.7%, however, the impact on simulation of high river flows is more modest (1.5% improvement). Further details are provided by Rameshwaran et al. 2022.

The overall modelling setup is summarised in Figure 2, which highlights how point abstraction and discharge data are converted to 1km grids before being used as monthly AI input to the G2G hydrological model.

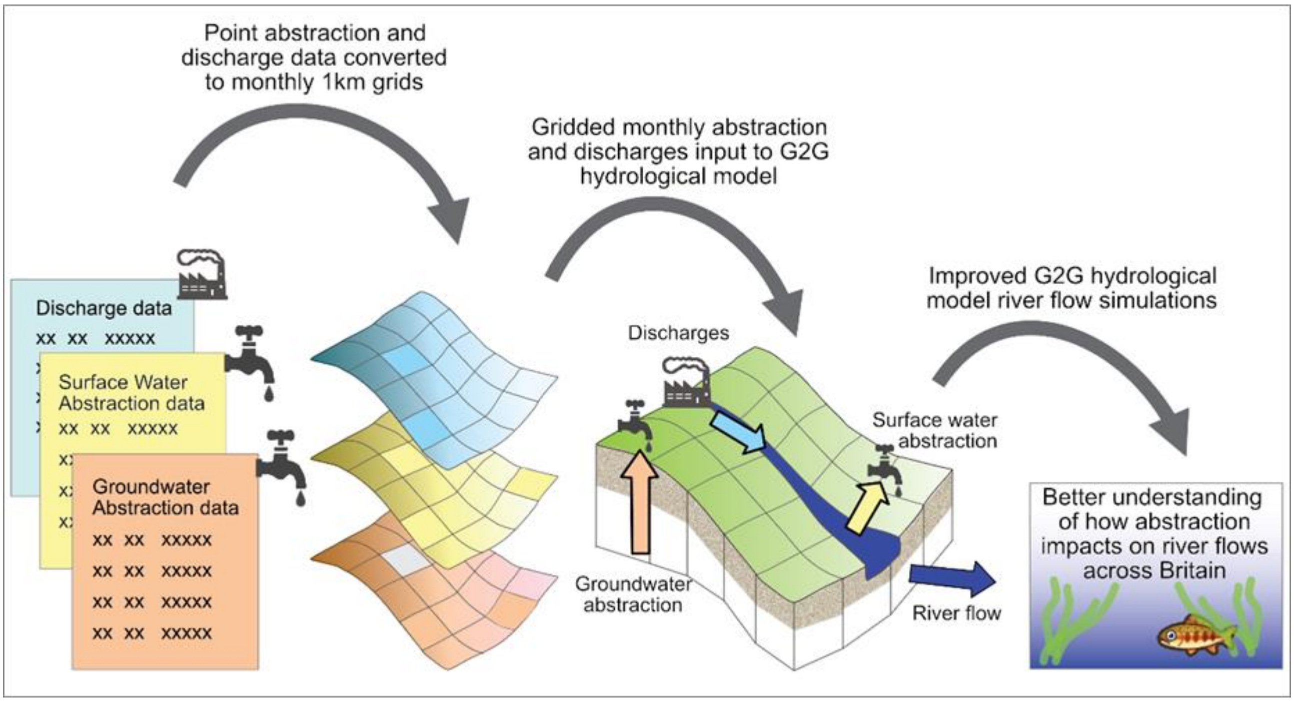

Figure 2 Schematic of the modelling chain used in CS-N0W (Rameshwaran et al., 2022)

4.2 Model setup for CS-N0W

The model setup and evaluation of G2G in CS-N0W aims to emulate the approach used in eFLaG as far as possible to enable both sets of future projections to be compared. By its nature, G2G requires no specific calibration; so, none was undertaken in either project. However, the period over which flow projections from G2G-with-AI were evaluated in CS-N0W is different to eFLaG because observed monthly AI data were only available for the period 1999-2014.

There are two overall sets of model output in CS-N0W, described below. To identify types of model run, eFLaG-based terminology (Hannaford et al., 2023) is adopted throughout (in eFLAG, simobs = observations-driven simulations, simrcm = RCM-driven simulations).

- **simobs**: observation-driven simulations (i.e. simulations for the observed period, driven by observational climate and AI datasets). Here, the simobs period covers the period January 1961 – December 2020 (two years longer than for eFLAG), but model runs using limited observed AI data are for a shorter period (1999-2014).
- **simrcm**: UKCP18 RCM-driven simulation (12 ensemble members) and future AI scenarios (i.e. the 3 future AI ensemble members, SUS, BAU and EG, as described in Section 3.4). There are 36 climate-driven realisations, consisting of 12 RCMs each with 3 AI scenarios, all available from 1980 to 2080. The simrcm runs from the observed period (1980 -2020) can be compared *statistically* with the simobs data, and the impact of future scenarios of AI and climate change can be evaluated by comparing baseline (1980-2020) and future (2020-2080) simrcm runs.

In all cases, climate forcing data was the same as that used in eFLAG (Sections 3.5 and 3.6).

4.3 G2G simulations using observed AI data

Here, natural and AI-impacted simulated daily river flow time series are compared against gauged flows for 626 catchments, including English eFLaG catchments, to demonstrate that flows are realistically simulated. These simobs simulations are all driven by observed climate data (Section 3.5)

Three model simulations were undertaken for the historical period 1st January 1999 to 31st December 2014 for which observed AI data are available, to evaluate the impact of including abstractions and discharges in G2G model simulations of river flows:

- Simobs_NATURAL: standard G2G simulated flows with no abstractions or discharges (comparable to eFLAG simobs from G2G).
- Simobs_ObsAI: G2G simulated flows with time series of observed AI
- Simobs_MeanAI: G2G simulated flows with time series of mean monthly observed AI

The Simobs_MeanAI simulated flows evaluate the sensitivity of the G2G to using mean AI (mean monthly abstractions for the period 2010 to 2014) instead of observed AIs. Future AI scenarios are based on this 5-year mean of observed monthly AI. The purpose of the Simobs_MeanAI evaluation run was to quantify whether the use of mean monthly AI adversely affects the performance of the model in simulating observed flows. Table 1 in Section 4.4 summarises the naming convention used for different model runs.

4.4 G2G simulations for historical and projected future periods

This next step perturbs the current water availability assessment into the future, to account for future climate change *and* potential changes in water abstractions/consumptions and returns. Future gridded ‘natural’ water availability is already available within eFLaG, as a 12-member ensemble of daily estimates from 1981 to 2080, on the UKCP RCM projections. The future AI scenarios (see (Baron et al., 2023) and Section 3.4 of this report) perturb the current AI ‘net impacts’ layer, according to 3 possible scenarios of future water consumption, which are themselves based on predictions in the National Framework for Water Resources (EA, 2020b) and water company and regional WRMPs, as well as assessments of future environmental flow requirements. All 3 scenarios are derived from the 1 km gridded baseline mean monthly artificial influenced (MeanAI) data. Broadly, the abstraction data are split into sectors (PWS, industry, energy, agriculture) and scaling factors (additive or multiplicative) are applied at the finest resolution available. For example, if a sector has a national scaling factor then this will be applied to all the grid, if the scaling factor varies by WRZ then the specific scaling factor will be applied only to the grid cells covered by that WRZ. Temporally, annual scaling factors are applied to the monthly baseline data, with interpolation between specified time slices where necessary. More details are provided by (Baron et al., 2023). The resulting 3 scenarios of future demand (SUS, BAU and EG, Section 3.4) have been applied to the present-day AI dataset (the 5-year MeanAI data, Section 4.3) to produce 3 continuous and transient datasets of projected future monthly abstractions and yearly discharges.

For the UKCP18-driven climate simulations, G2G model runs were undertaken for the period 1st December 1980 to 30th November 2080 as follows:

- Simrcm_NATURAL: driven by the UKCP18 projected climate (no abstractions or discharges, comparable with eFLAG, see Parry et al. (2023)).
- Simrcm_MeanAI: driven by the UKCP18 projected climate and using *observed mean AI (2000 and 2014) and observed discharges* instead of future AI scenarios
- SimrcmAI_SUS: uses the sustainability (SUS) AI scenario. From 1980 to 2020 the AI_SUS data for 2020 is used, and from 2020 to 2080 the transient AI_SUS scenario is used.
- SimrcmAI_BAU: uses the Business as usual (BAU) AI scenario. From 1980 to 2020 the AI_BAU data for 2020 is used, and from 2020 to 2080 the transient AI_BAU scenario is used.
- SimrcmAI_EG: uses the Economic growth (EG) AI scenario. From 1980 to 2020 the AI_EG data for 2020 is used, and from 2020 to 2080 the transient AI_EG scenario is used.

In each case, the AI_XXX 2020 scenario is used for the baseline RCM period (1980 to 2020), and for the future RCM period (2020 to 2080) the transient AI_XXX scenario is used. For example, for the SUS AI scenario model runs, AI_SUS abstraction and discharge data for 2020 are used for the baseline period from 1980 to 2020, then the transient AI_SUS scenario data are used from 2020 to 2080 (Figure 3).

Figure 3 Schematic showing how future AI scenarios are used in the simrcm G2G model runs from 1980 to 2080.

Table 1 summarises the naming convention used for different model runs. Note that the CS-NOW naming convention is based on that used by the previous eFLAG project, but with an additional identifier for the type of AI data used (if any).

Table 1 naming convention used for different model runs/outputs

Model run	*Climate data*	*Artificial influences (AI)*	*Period*
	eFLAG		
simobs	Observed	none	1961-2018
simrcm	RCM	none	1980-2080
	CS-NOW		
simobs_NATURAL (= simobs)	Observed	none	1961-2020
simobs_ObsAI	Observed	Observed monthly AI	1999-2014
simobs_MeanAI	Observed	Mean monthly observed AI*	1961-2020
simrcm_NATURAL (= simrcm)	RCM	none	1980-2080
simrcm_MeanAI	RCM	Mean monthly observed AI*	1980-2080
simrcm_SUSAI	RCM	Sustainability (SUS)	1980-2080
simrcm_BAUAI	RCM	Business As Usual (BAU)	1980-2080
simrcm_EGAI	RCM	Economic Growth (EG)	1980-2080

*Mean AI = mean monthly abstractions for the period 2010 to 2014

4.5 Performance assessment criteria

Four performance scores were used to quantify different aspects of the agreement between modelled and gauged flows: two based on the daily time series, one based on the magnitude of flow errors, and one based on the flow duration curve (FDC) low flow percentiles. The same performance scores were used within eFLaG (Hannaford et al. (2023) Table 2). They are considered to capture different aspects of the flow regime, from high- to low-flows.

The two time series performance scores are based on the model efficiency criterion of Nash and Sutcliffe (1970), defined as:

$$NS = 1 - \frac{\sum_{i=1}^{n}\left(Q_{o,i} - Q_{m,i}\right)^2}{\sum_{i=1}^{n}\left(Q_{o,i} - \overline{Q_o}\right)^2} \qquad (1)$$

where $Q_{o,i}$ is the gauged flow for time step i, $Q_{m,i}$ is the modelled flow for time step i, $\overline{Q_o}$ is the mean of observed data and *n* is the number of time steps. The NS can range between -□ and 1 where NS = 1 means a perfect match between modelled and observed data, NS = 0 indicates that the modelled data are as accurate as the mean of the observed data and NS < 0 indicates that the mean of the observed data is a better predictor of the flow than the model. The original formulation of NS is more suitable for assessing model performance at high flows, so, for assessing low flows, it is adapted by taking the natural logarithm of the flow data, to increase sensitivity to low and mid-range flows;

$$NS_{log} = 1 - \frac{\sum_{i=1}^{n}\left(\ln\left(Q_{o,i}+\varepsilon\right) - \ln\left(Q_{m,i}+\varepsilon\right)\right)^2}{\sum_{i=1}^{n}\left(\ln\left(Q_{o,i}+\varepsilon\right) - \ln\left(\overline{Q_o+\epsilon}\right)\right)^2} \qquad (2)$$

where ε is a small number usually defined as $\varepsilon = \overline{Q_o}/100$. The NS_{log} can range between -□ and 1, which is interpreted the same as for NS.

The $BIAS$ indicates the magnitude of errors in modelled daily flows relative to gauged daily flows:

$$BIAS = 100 \times \frac{\sum_{i=1}^{n}\left(Q_{m,i} - Q_{o,i}\right)}{\sum_{i=1}^{n} Q_{o,i}}. \qquad (3)$$

The *BIAS* can range from -∞ to +∞. A value > 0 indicates model overestimation, while a value < 0 indicates model underestimation.

The FDC performance score, the percentage bias in low flow volume lfv, compares the statistical characteristics of the flows rather than the time-step equivalence. It is calculated from the low flow end of the FDC, which is obtained by ranking the flows from a (daily) time series and selecting the flow corresponding to the percentile point *p* (between 1 and 100); $Q_{m,p}$ and $Q_{o,p}$ are thus the flow equalled or exceeded *p%* of the time. Following Kay et al. (2015):

$$lfv = 100 \times \frac{\sum_{p=70}^{95}\left(f(Q_{m,p}) - f(Q_{o,p})\right)}{\sum_{p=70}^{95} f(Q_{o,p})} \qquad (4)$$

where the function f is taken as the square root. lfv only compares up to the 95th percentile flow (from the 70th) so as not to include extreme low flow values, which can be more severely affected by errors in flow measurements due to instrument inaccuracies in shallow flows or low velocities, changes in channel shape and/or weed growth and sedimentation (Petersen-Øverleir et al., 2009, Coxon et al., 2015). For a perfect model simulation the *lfv* value would be zero. A positive lfv value indicates that the modelled flow is generally higher than gauged flow, with typical values of *lfv* for individual catchments varying from -20 to 20%, indicating that the error in low flow volume is typically up to 20% of the flow observation.

The performance of the G2G simulations of daily mean river flow are assessed by comparing with gauged daily river flow data for 626 catchments (Figure 1b). Flow data for as many catchments as possible were used in the performance assessment. Catchments in England were only excluded from the analysis if no observations were available for the assessment period (1999 to 2014), and only 20 catchments out of 626 had <50% observations over the assessment period. The large number of catchments provides good spatial coverage across England but, as many smaller catchments are nested within larger catchments, there is some overlap.

5. Results

This section summarises the analysis of the CS-N0W model predictions, beginning with the G2G performance assessment (1999 to 2014) and then summarising the scenario runs (1980 to 2080).

5.1 Abstraction and Discharge Impact on River Flows

As expected, model simulations show that significant abstractions in a catchment reduce river flows while discharges increase flows. The net effect varies, depending on whether catchment AIs are dominated by abstractions or discharges. The maps in Figure 4 show the locations of the 626 catchment outlets, and whether the observed AIs for those catchments are dominated by abstraction (259 catchments: red shading) or river discharges (359 catchments: blue shading). For 8 catchments there were no abstractions or discharges and they are shown with yellow shading. Gradations of colour in Figure 4 a&b denote overlapping sub-catchments.

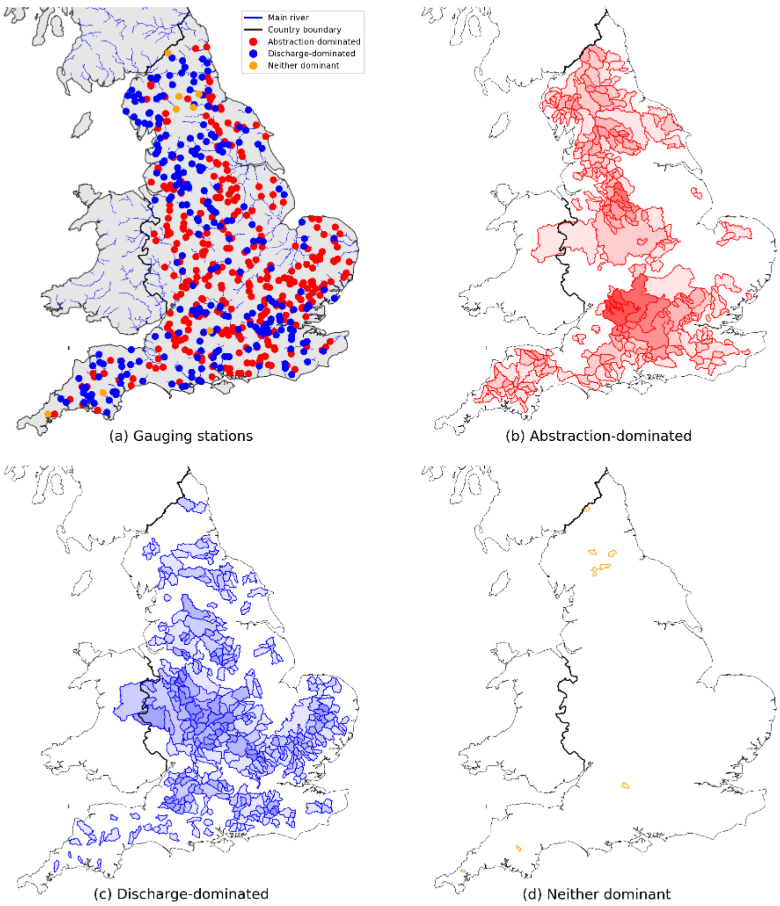

Figure 4. Maps showing a) gauging station locations within England (Abstraction-dominated in red, discharge-dominated in blue and neither dominated in yellow) and the main river network, catchment boundaries for b) the 259 abstraction-dominated catchments, c) the 359 discharge-dominated catchments and d) the 8 catchments with no AI, used in the model performance analysis.

For example, the Thames at Kingston (catchment area 9,948 km^2) is abstraction-dominated, but subject to both abstractions and discharges. The May to June 2012 hydrographs in Figure 5 demonstrate the influence of individual anthropogenic interventions in turn: ObsAI flows with abstraction (A) only are much lower than G2G-estimated natural flows. When discharges (D) are added ObsAI (A&D) river flows are much higher, but still less than G2G natural flows. In the Thames to Kingston, there is very little difference between using observed AI and a 5-year mean AI, but use of 5-year MeanAI with A&D leads to slightly lower flows in 2012. Many SW abstractions in the Thames Basin are subject to HoF conditions which will limit SW abstraction during periods of low flows with the aim of maintaining sufficient river flow to support a healthy freshwater environment. Across England, the net influence of abstractions, HoF conditions and discharges varies between catchments, and because *monthly* abstraction data are used, the net AI influence can also vary through the year.

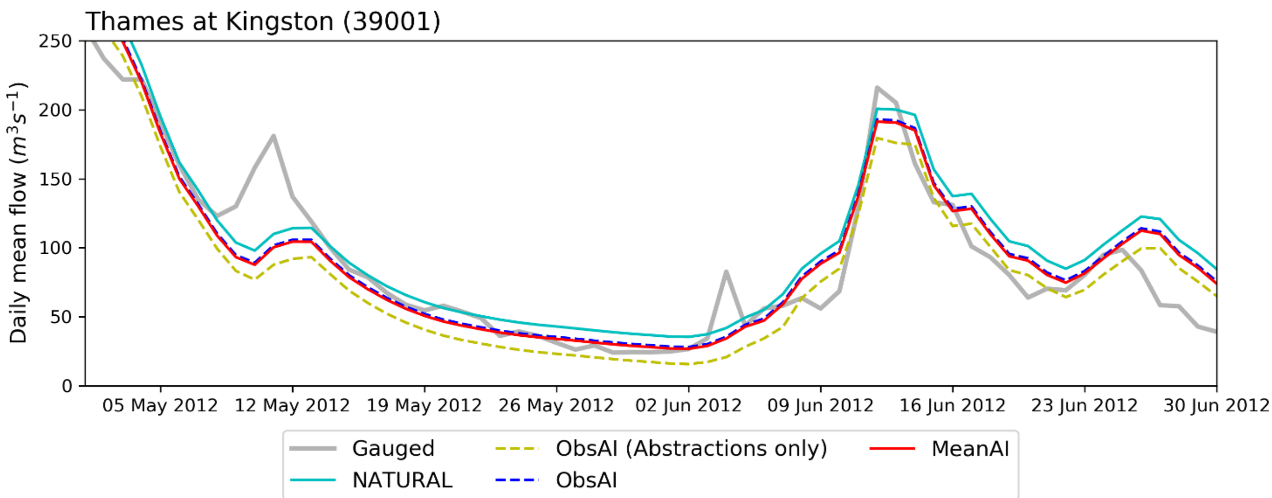

Figure 5 Example flow hydrographs for the Thames to Kingston (39001) for the period 1 May to 30 June 2012 showing observed flows and G2G model simulations using different combinations of abstractions and discharges

Figure 6 compares gauged and G2G-simulated daily river flows for three catchments from 1st May 2012 to 31st August 2012. For the heavily abstracted Thames at Kingston catchment, the G2G flow simulations with AI are lower than the “Natural” model simulation as expected, but in the discharge-dominated Trent at Drakelow Park, where there are no “Very Low” loss abstractions, the influence of discharge dominates. In this catchment, the G2G-simulated “Natural” flows are low in May and August but when AI are included, G2G-simulated flows are higher and much closer to observed (gauged) flows.

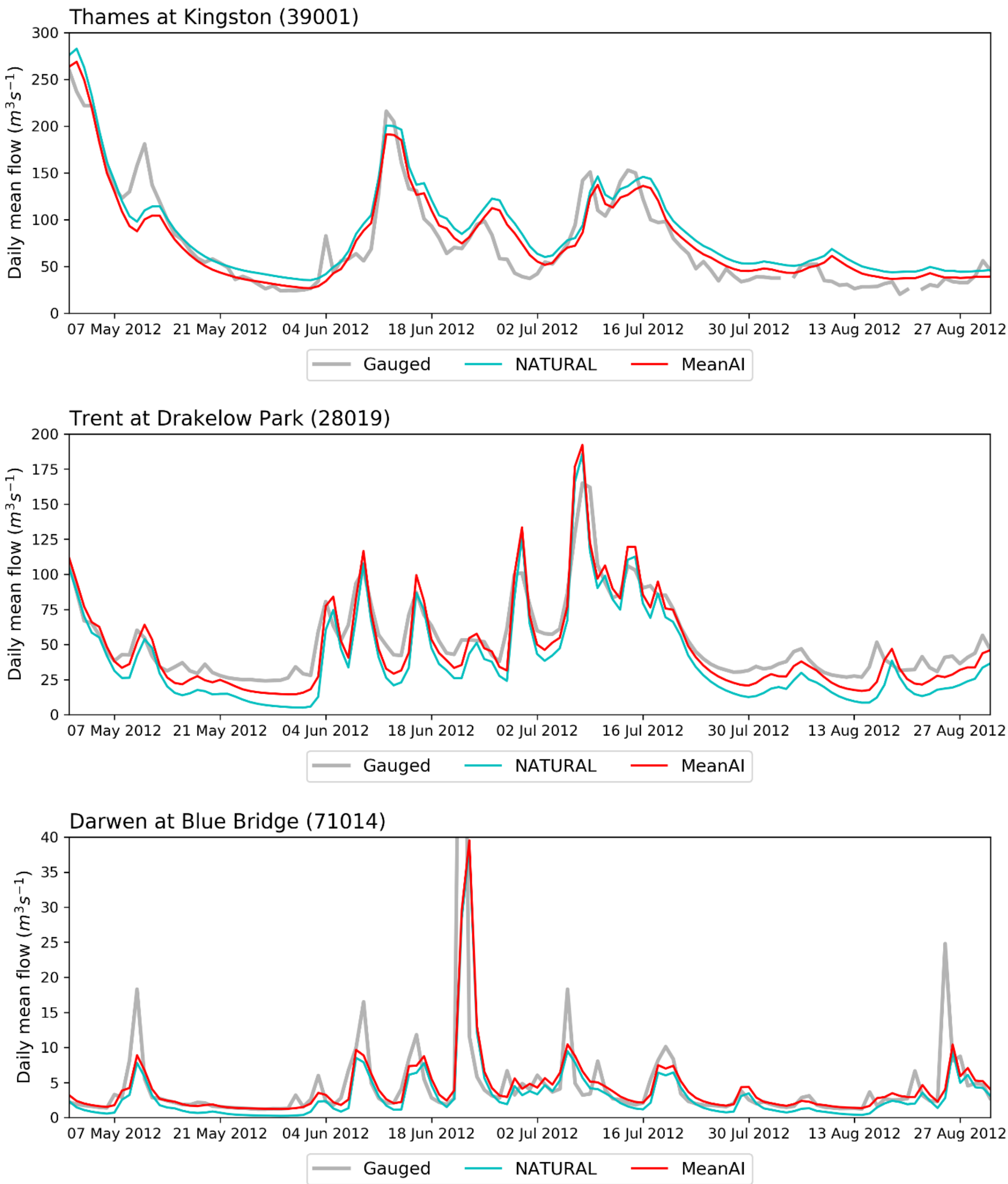

Figure 6 Example flow hydrographs for 3 catchments (Thames at Kingston (39001), Trent at Drakelow Park (28019) and Darwen at Blue Bridge (71014)) for the period 1 May to 30 June 2012 showing observed flows and the G2G simulation using MeanAI.

5.2 Model Performance Assessment

G2G model simulated flows (Simobs) are compared to gauged daily flows across all the CS-N0W catchments as boxplots of performance skill scores in Figure 7. Results are presented for three sets of catchments: all 626 catchments, 259 abstraction-dominated, and 359 discharge-dominated. The boxplots compare the skill scores (NS, NS_{log}, $BIAS$, and lfv) from standard G2G model for “Natural” flows, G2G with “Observed AI” and G2G with “Observed Mean AI”.

Generally, use of AI data in the G2G hydrological model improves model performance during low flow periods, but has less of an impact when flows are higher. As shown in Table 2, the median value of NS_{log} (a measure of model performance at low flows) increases from 0.56 for the “Natural” G2G simulation to 0.63 for the ObsAI and MeanAI (12.5% improvement). The spatial maps of the G2G model skill scores (NS and NSlog) shown in Figure 8 highlight the spatial performance of G2G when driven by ObsAI.

Across all the catchments, the median model *BIAS* is better (1.9%) for the Natural simulation than for the ObsAI and MeanAI simulations (3.9%) indicating the G2G slightly overestimates flow. However, median *lfv* is improved when AI are used (*lfv* is −5.61% for the Natural run, rising to −0.94% and −1.20% for the ObsAI and MeanAI runs respectively). Overall, the median performance across all 626 study catchments is improved through the use of AI data in the G2G hydrological model; such improvements are most apparent in discharge dominated catchments for low flows. In abstraction-dominated catchments, the improvements in model performance through the use of AI data are more modest.

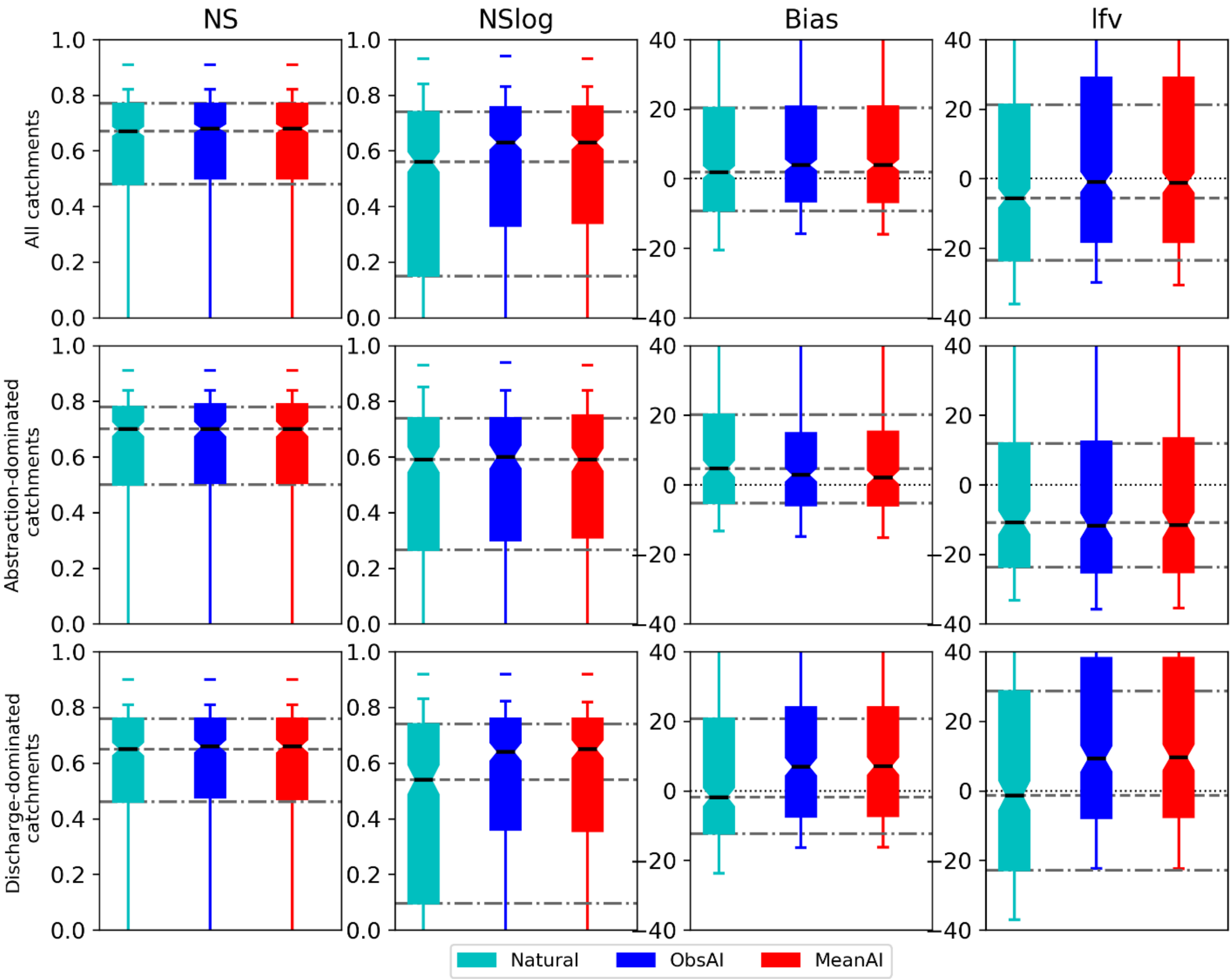

Figure 7 Boxplots of flow-simulation performance scores (*NS*, NS_{log}, *BIAS*, and *lfv*) for SW-abstraction-dominated and discharge-dominated catchments with three different G2G model simulations: 'Natural', 'ObsAI' and 'MeanAI'.

Table 2 Median model performance scores (*NS*, NS_{log}, *BIAS*, and *lfv*)

AI used in the model run	*NS*	NS_{log}	*BIAS (%)*	*lfv (%)*
All catchments (626)				
NATURAL	0.67	0.56	1.9	-5.61
ObsAI	0.68	0.63	3.9	-0.94
MeanAI	0.68	0.63	3.9	-1.20
Abstraction-dominated catchments (259)				
NATURAL	0.70	0.59	4.6	-10.92
ObsAI	0.70	0.60	2.8	-11.81
MeanAI	0.70	0.59	2.1	-11.60
Discharge-dominated catchments (359)				
NATURAL	0.65	0.54	-1.8	-1.33
ObsAI	0.66	0.64	6.9	9.21
MeanAI	0.66	0.65	7.1	9.62

(a) NS

(b) NSlog

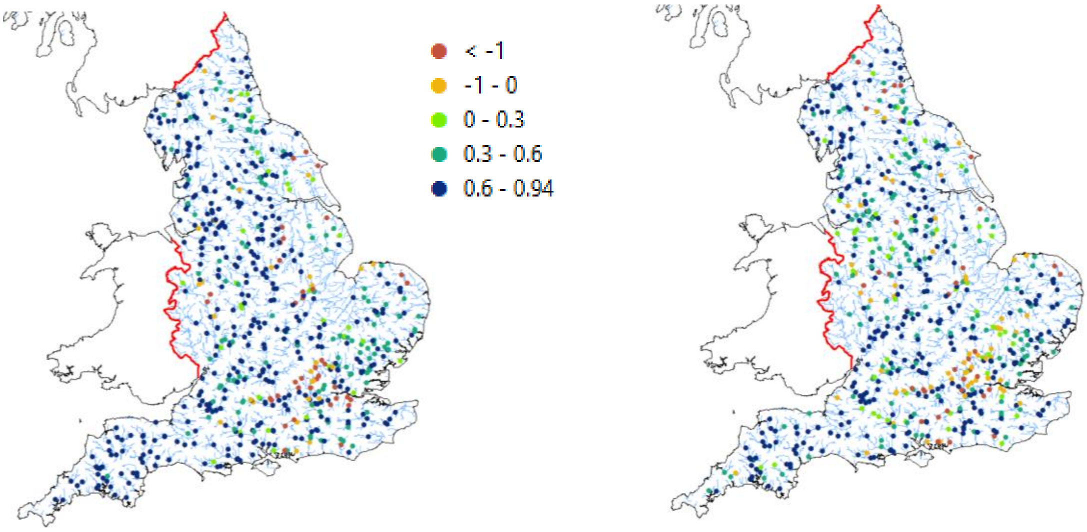

Figure 8 Maps of the G2G model performance skill scores *NS* and NS_{log} (ObsAI), when comparing simulated and observed river flows.

5.3 Temporal and Mean Variation in Abstraction Data Use

The work presented here shows how records of "monthly" and "mean monthly" (2000 to 2014) abstraction and discharge data can be incorporated in process-based hydrological models, leading to improvements in model performance in anthropogenically influenced catchments. The G2G model performance statistics in Table 2 are provided for model runs using monthly (ObsAI) and mean-monthly (MeanAI), and they suggest that accuracy of <u>high flow</u> simulations is identical in both cases (*NS* criteria identical to 2 decimal places), but there is a small difference in the accuracy of <u>low flow</u> simulations (a difference in NS_{log} of 1%), and a 4% difference in lfv. Intriguingly, in abstraction-dominated catchments the use of MeanAI leads to *improvements* in some skill scores: ~25% improvement in *%BIAS* and 1% improvement in *lfv* (which would generally be expected to occur during summer periods).

The simulation performance results in Table 2 and Figure 7 show the median and range in the ObsAI and MeanAI impacts on G2G performance, but don't indicate how many catchments are particularly affected by this choice of AI data. To understand this, Figure 9 presents scatterplots of G2G simulation performance for all 626 catchments using MeanAI (from 2010 to 2014) and ObsAI. In general, model performance across the

15-year assessment period is very similar and there are ~7 catchments where the *NS*, NS_{log}, *BIAS*, and *lfv* values are substantially different between the ObsAI and MeanAI runs (Colne at Colne Bridge (27031), Roch at Rochdale (69803), Don at Sheffield Hadfields (27006), Exe at Pixton (45009), Lark at Temple (33014), Ouse at Gold Bridge(41005), and Eye Brook at Eye Brook Reservoir (31001)). Further investigation indicates that for these catchments, abstractions during the 5-year period over which MeanAI abstractions were calculated differ substantially from recorded abstractions over the 16-year assessment period, often because of changes in abstraction licences. For most other catchments, abstraction changes over this period were more modest, which was why observations of abstractions could be replaced by a monthly mean with greater success.

Overall, these analyses suggest that use of mean-monthly abstraction totals for a relatively recent period (2000 to 2014) provides a reasonable baseline for developing future AI scenarios, though investigation into the use of derived relationships between observed AI and monthly rainfall might be beneficial in the derivation of future scenarios of monthly abstractions.

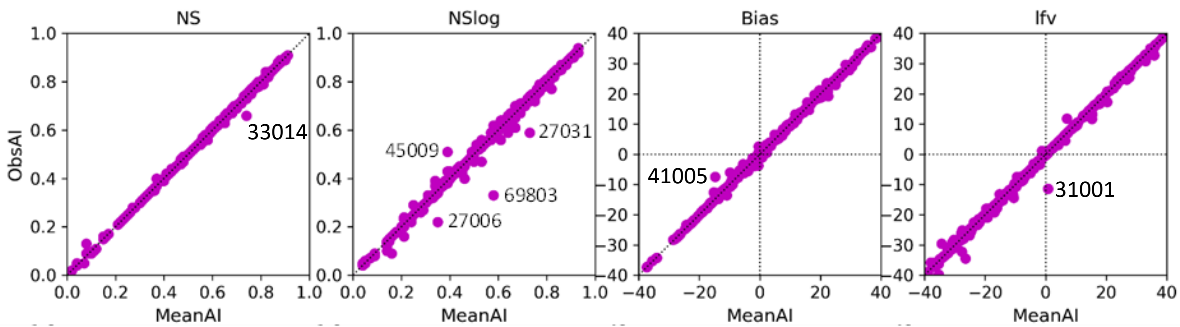

Figure 9. Scatter plots of the *NS*, NS_{log}, *BIAS*, and *lfv* for the actual (ObsAI) and mean abstraction (MeanAI) runs. Outlier catchments are labelled using their catchment ID.

5.4 G2G-simulated future scenarios of AI-impacted river flows

For the 12-member ensemble of UKCP18-driven climate simulations (Section 3.6), G2G model runs were undertaken for the period 1st December 1980 to 30th November 2080 for the 3 future AI scenarios (Section 3.4). The output consists of 36 UKCP18-driven climate-simulations in total, which are analysed in a separate report (Tanguy et al., 2023).

By way of example, Figure 10 presents a 12-member ensemble of daily mean river flows (m^3s^{-1}) for the Thames at Kingston (39001) corresponding to 12 UKCP18 RCMs (the BAU demand scenario) for a 1-year period from 1st January to 30th December 2050. Monthly hydrographs for all 12 RCM members are plotted together to highlight the variability in projected future flows.

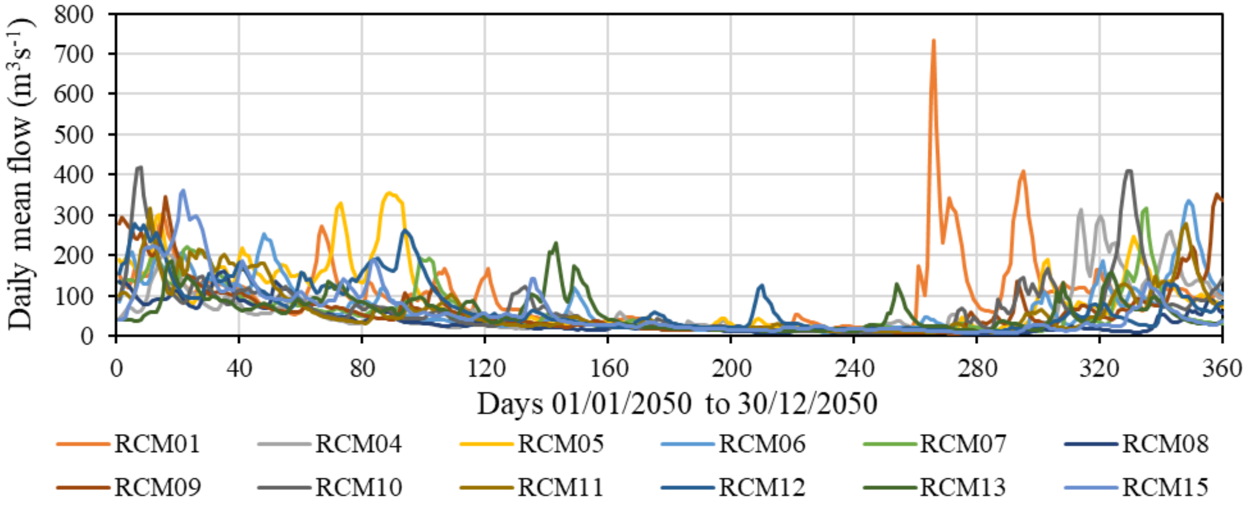

Figure 10. Example plots of daily mean river flows for the Thames at Kingston (Station No. 39001) from 12 RCM ensemble members according to the BAU AI scenario (BAUAI)

For the 3 AI scenarios (Baron et al., 2023), which are summarised in Section 3.4, it has not been possible to identify a consistently low, central or high AI scenario, and for some catchments the scenarios even cross. For example, in the Thames to Kingston, the surface water abstraction scenarios for BAU and EG intersect around 2040, as shown in Figure 11. Thus from 2040 onwards the BAU SW abstraction scenario results in higher SW abstraction demand than for EG. The scenario graphs also highlight that, at the starting point of the scenarios (2020), there are small differences between the 3 scenarios, because the underlying reports on which they are based initialise their “future” scenarios at different times leading to different demand projections for the year 2020.

In a follow-on report (Tanguy et al., 2023), the future AI-impacted flows are analysed for water resource applications and drought analyses at different climate warming thresholds. The scenarios can also be explored to understand the impact of projected climate and AI scenarios on low flows and environmental flows.

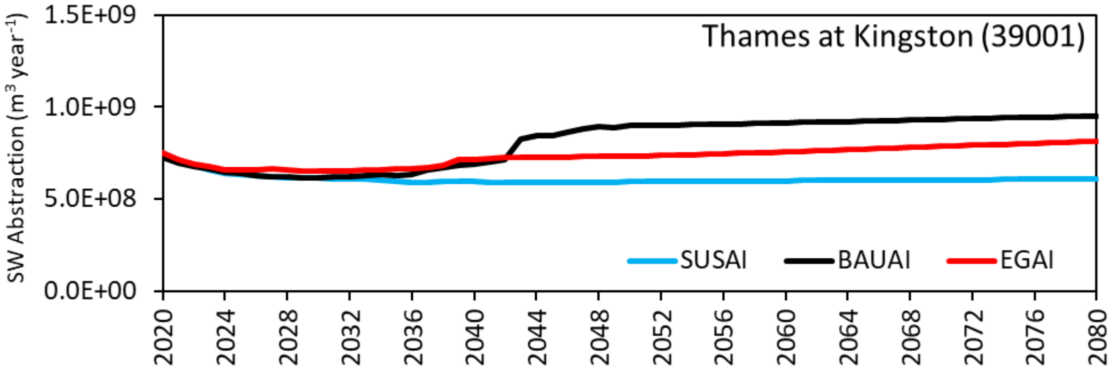

Figure 11. Graphs of the three future SW abstraction scenarios (m^3/month) for the Thames to Kingston (39001) for the period 2020 to 2080:

For example, Figure 12 presents transient moving windows from 1980 to 2080 of Q95 (the flow exceeded 95% of the time) for three catchments 39001, 28019, 71014, assuming the BAU AI scenario. For catchment 39001, an abstraction-dominated catchment, median Q95 decreases by 23.6% until the 2020-centred time period, then decreases further by 48.5% to the final 2065-centred moving window; similarly, for catchment 71014 median Q95 decreases are 3.8% and 17.6% over the same periods. By comparison, for the example discharge-dominated catchment 28019, median Q95 decreases by just 5.3% and 2.5% over the same periods. Analyses such as these could be used to support investigations into the use of flow exceedance thresholds as a suitable means of determining minimum environmental flow requirements which are defined by flow exceedance thresholds such as Q70 and Q95 (Environment Agency (2020), Appendix 4).

It has not been possible to present results for all catchments, scenario and time periods in report form, but these information are being made available in a CS-NOW project web-tool, which will allow the user to explore future simulations for individual catchments and English regions. Parallel work is exploring options for open publication of CS-NOW datasets and model simulations on the EIDC or CEDA data centres, following the approach of Hannaford et al., 2022 who published the eFLAG future flow and groundwater simulations.

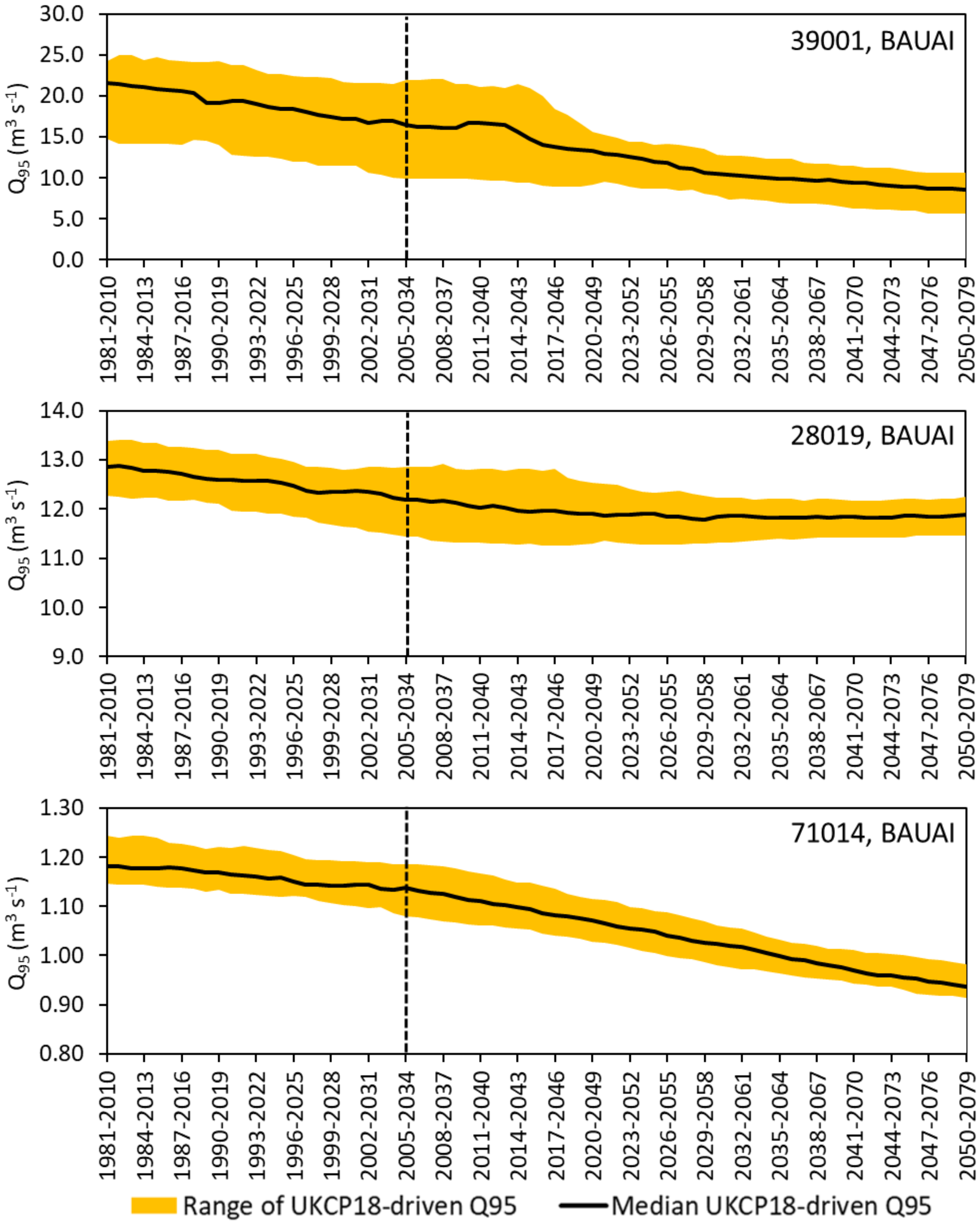

Figure 12. 30-year transient moving windows from 1980 to 2080 of Q95 (the flow exceeded 95% of the time) for three catchments 39001, 28019, 71014, for the BAU AI scenario and UKCP18 regional climate projections. Orange shading shows the spread of the 12 UKCP18-driven derived Q95 values, the black line shows the median, and the dashed vertical line indicates the start of the 30-year period after which future AIs are included.

5.5 Summary of G2G model output

The output from both the observation-driven and UKCP18-driven G2G simulations consists of .csv files of daily flows at 626 English gauging stations, 1km resolution grids of AI-impacted river flows, and 1km grids of total monthly abstracted water, total monthly un-abstracted water (water that could not be abstracted from surface or groundwater), and number of days per month abstraction demand could not be met. The outputs are summarised in Table 3, and a full list is provided in Appendix A, Table 6. The project team are exploring options for open publication of CS-NOW datasets and model following the approach of Hannaford et al., 2022 who published the eFLAG simulations on the EIDC.

Table 3 Summary of AI-impacted G2G model output for present-day and UKCP18 scenarios

Frequency	G2G output	unit	File format
Daily	Time-series of G2G flows at 626 gauged locations	m^3/s	csv
Daily	Gridded G2G flows on a 1km across England	m^3/s	netcdf
Monthly	Gridded volume of surface water abstracted by G2G	m^3	netcdf
Monthly	Gridded volume of groundwater abstracted by G2G	m^3	netcdf
Monthly	Gridded volume of surface water NOT abstracted by G2G	m^3	netcdf
Monthly	Gridded volume of groundwater NOT abstracted by G2G	m^3	netcdf
Monthly	Gridded number of days/month not all surface water can be abstracted by G2G	days	netcdf
Monthly	Gridded number of days/month not all groundwater can be abstracted by G2G	days	netcdf

Together, the monthly datasets of G2G-simulated abstracted water, water demand that couldn't be met in the G2G ("unabstracted water"), and number of days per month when abstraction demand cannot be met, can be used to provide an estimate of when and where future demand exceeds water availability, and how it changes over time. Figure 13 presents an example map of G2G-simulated abstracted surface water for August 2014, highlighting the spatial variation in the volume of water (m^3) that could be abstracted during the model run. The water volume that is available for abstraction will always be less than or equal to the abstraction demand. Maps similar to Figure 13 can be produced for future periods showing where surface water and groundwater abstraction demand can/cannot be met, and for different AI scenarios.

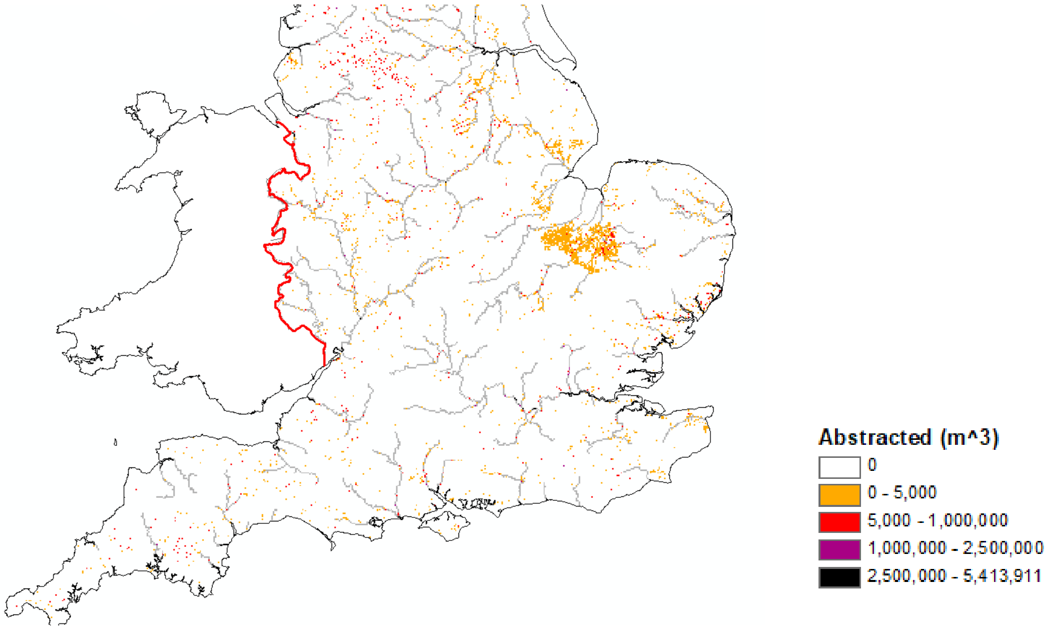

Figure 13. Map of G2G-estimated abstracted surface water (m^3) for August 2014

A comparison of (observed) SW abstraction demand (yellow line) and G2G-simulated abstracted surface water (green line) is presented in Figure 14 for two years, 2011 and 2012. The difference in the two graphs illustrates the difference between recorded abstraction demand (m^3), and the volume of water (m^3) the G2G model was able to abstract from this catchment (39001, the Thames to Kingston). The difference in the two time-series highlights that the volume of river water available for abstraction (green line) may not always be enough to satisfy the local abstraction demand (yellow line).

Further work will be needed to understand why this is the case, but reasons might include abstraction limited locally by a HoF condition, an abstraction demand that cannot be fulfilled by the current G2G model configuration, such as reservoir abstraction, estuary/tidal abstraction, groundwater abstraction from an aquifer not simulated by the G2G, or even just a large abstraction incorrectly attributed to a minor river channel during discretisation to a 1km grid. Figure 14 also illustrates the monthly and interannual variability in observed SW abstraction, highlighting the importance of using actual monthly abstraction data where possible rather than an annual mean.

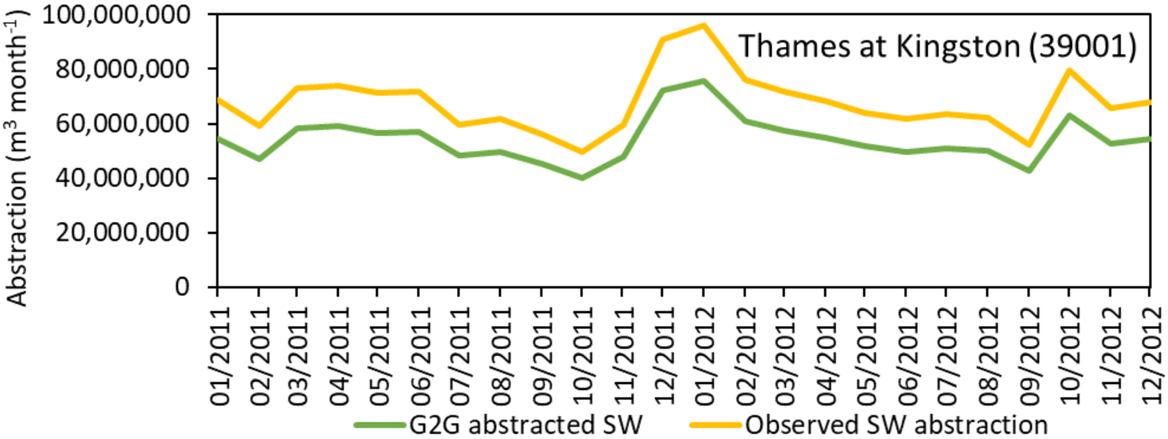

Figure 14. Observed SW abstraction and G2G-simulated abstracted surface water (January 2011 to December 2012) for the Thames to Kingston

6. Discussion

A grid-based hydrological model (G2G) has been modified to account for artificial influences (AIs: abstractions and discharges) and used to simulate historical and projected future river flows and water demand comparable with the recently-published eFLaG dataset (Hannaford et al., 2023). The relative success with which actual abstraction values for most catchments can be replaced by 5-year mean values (section 5.3) supports the use of mean monthly abstraction values as a basis for the 3 future scenarios of water demand developed by Baron et al. (2023) and used here for the future AI scenarios.

However, it is important to acknowledge the wider uncertainties in the model simulations developed here. These uncertainties, which include the observed AI data (specifically the use of NALD rather than WRGIS data), how the AI data are discretised to a 1km grid in the G2G, how AI data are incorporated in the G2G national-scale model are discussed in detail in (Rameshwaran et al., 2022). Use of future scenarios, for both AIs and UKCP18-projected climate, adds another level of uncertainty. In many ways, uncertainty is explored through the use of *ensembles* of AI and UKCP18 RCM scenarios, although it's important to note that the UKCP18 RCM data used here are for RCP8.5, a high emissions scenario representing a rather pessimistic view of the UK's climate future. The median projected impact of this (UKCP18 RCM/RCP8.5) scenario on mean river flows across Britain is ~9% higher flows in winter and 45% lower flows in summer (Kay, 2021), with similar projected impacts on extreme flows (Lane and Kay, 2021) found >10% increase in 10 year return period high flows and -90 to -27% decrease in 10 year return period low flows). (Hannaford et al., 2023) discuss other uncertainties associated with eFLaG (around observational data and bias correction choices, e.g. choice of observational PE, choice of bias correction). It must also be considered that only one hydrological model is used in CS-N0W, thus AI-impacted model structural uncertainty cannot be quantified here.

It is also worth noting that with the current G2G formulation, the true abstraction demand may not always be met as G2G does not include all freshwater anthropogenic influences, such as impounding reservoirs and releases, canals and lakes. For example, in dry summer months, simulated river flows falling below the HoF condition will prevent the surface water abstraction from taking place. There is currently no functionality in the G2G model to enable an unmet abstraction demand to be satisfied by compensation flows from reservoirs, which happen in reality. Similarly, some groundwater abstraction demands will not be met because of the simple approach to groundwater and the way in which groundwater abstraction is implemented in the G2G (no account has been taken of the groundwater abstraction impact zone which can extend some distance from the actual abstraction location). . In such situations the G2G model typically will *underestimate* the true water consumption leading to downstream river flows being slightly higher than they would be.

7. Summary

This report was produced for the CS-N0W project (WPD2) which aims to provide future projections of AI-impacted flows across England up to 2080, taking account of possible future changes in abstractions/discharges. The report summarises the modelling approach and datasets used to derive the future flow projections, together with an assessment of how the AI-impacted hydrological model (Grid-to-Grid or "G2G") performs for historical periods. A second report, Tanguy et al. (2023), presents an analysis of these scenarios and provides key indicators and statistics of water availability for historical, current and future timescales to 2080.

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Appendix A

Table 4 Gauging stations for which daily flows are estimated by the G2G Model

Site	Gauging station	Catchment area (km^2)
22001	Coquet at Morwick	570
22006	Blyth at Hartford Bridge	269
22007	Wansbeck at Mitford	287
22009	Coquet at Rothbury	346
23001	Tyne at Bywell	2176
23002	Derwent at Eddys Bridge	118
23003	North Tyne at Reaverhill	1008
23004	South Tyne at Haydon Bridge	751
23006	South Tyne at Featherstone	322
23007	Derwent at Rowlands Gill	242
23008	Rede at Rede Bridge	344
23009	South Tyne at Alston	119
23011	Kielder Burn at Kielder	59
23016	Ouse Burn at Crag Hall	55
23017	Team at Team Valley	62
23022	North Tyne at Uglydub	242
24001	Wear at Sunderland Bridge	658
24002	Gaunless at Bishop Auckland	93
24003	Wear at Stanhope	172
24004	Bedburn Beck at Bedburn	75
24005	Browney at Burnhall	179
24008	Wear at Witton Park	455
24009	Wear at Chester le Street	1008
25001	Tees at Darlington Broken Scar	818
25004	Skerne at Darlington South Park	250
25005	Leven at Leven Bridge	196
25006	Greta at Rutherford Bridge	86
25008	Tees at Barnard Castle	509
25009	Tees at Low Moor	1264
25018	Tees at Middleton in Teesdale	242
25020	Skerne at Preston le Skerne	147
25021	Skerne at Bradbury	70
25023	Tees at Cow Green Reservoir	58
25029	Leven at Foxton Bridge	184
26002	Hull at Hempholme Lock	378
26005	Gypsey Race at Boynton	240
26012	Foulness at Holme House Farm	70
26013	Driffield Trout Stream at Driffield	53
27001	Nidd at Hunsingore Weir	484
27002	Wharfe at Wetherby Flint Mill	759
27003	Aire at Beal	1932
27005	Nidd at Gouthwaite Reservoir	114
27006	Don at Sheffield Hadfields	373
27007	Ure at Westwick	915
27009	Ouse at Skelton	3315
27021	Don at Doncaster	1256
27022	Don at Rotherham Weir	826
27023	Dearne at Barnsley Weir	119
27025	Rother at Woodhouse Mill	352
27026	Rother at Whittington	165
27028	Aire at Armley	692
27029	Calder at Elland	342
27030	Dearne at Adwick	311
27031	Colne at Colne Bridge	245
27034	Ure at Kilgram Bridge	510
27035	Aire at Kildwick Bridge	282
27040	Doe Lea at Staveley	68
27041	Derwent at Buttercrambe	1586
27042	Dove at Kirkby Mills	59
27043	Wharfe at Addingham	427
27048	Derwent at West Ayton	127
27049	Rye at Ness	239
27052	Whitting at Sheepbridge	50
27053	Nidd at Birstwith	218
27055	Rye at Broadway Foot	132
27056	Pickering Beck at Ings Bridge	69
27057	Seven at Normanby	122
27059	Laver at Ripon Laver Weir	88
27060	Kyle at Newton On Ouse	168
27061	Colne at Longroyd Bridge	72
27062	Nidd at Skip Bridge	516
27064	Went at Walden Stubbs	84
27065	Holme at Huddersfield Queens Mill	97
27069	Wiske at Kirby Wiske	216
27071	Swale at Crakehill	1363
27072	Worth at Keighley	72
27075	Bedale Beck at Leeming	160
27076	Bielby Beck at Thornton Lock	103
27077	Bradford Beck at Shipley	58
27079	Calder at Methley	930
27080	Aire at Oulton Lemonroyd	865
27083	Foss at Huntington	118
27085	Cod Beck at Dalton Bridge	209
27086	Skell at Ripon Alma Weir	120
27087	Derwent at Low Marishes	458
27088	Calder at Mytholmroyd	142
27089	Wharfe at Tadcaster	818
27090	Swale at Catterick Bridge	499
27091	Crimple at Blackstones	77
27092	Esk at Briggswath	325
27096	Wharfe at Netherside Hall	215
28001	Derwent at Yorkshire Bridge	126
28002	Blithe at Hamstall Ridware	163
28003	Tame at Water Orton	408
28007	Trent at Shardlow	4400
28008	Dove at Rocester Weir	399
28009	Trent at Colwick	7486
28011	Derwent at Matlock Bath	690
28012	Trent at Yoxall	1229
28014	Sow at Milford	591
28015	Idle at Mattersey	529
28018	Dove at Marston on Dove	883
28019	Trent at Drakelow Park	3072
28022	Trent at North Muskham	8231
28023	Wye at Ashford	154
28024	Wreake at Syston Mill	414
28026	Anker at Polesworth	368
28027	Erewash at Sandiacre	182
28031	Manifold at Ilam	149
28032	Meden at Church Warsop	63
28035	Leen at Triumph Road Nottingham	111
28036	Poulter at Twyford Bridge	128
28039	Rea at Calthorpe Park	74
28040	Trent at Stoke-On-Trent	53
28043	Derwent at Chatsworth	335
28046	Dove at Izaak Walton	83
28047	Oldcotes Dyke at Blyth	85
28048	Amber at Wingfield Park	139
28049	Ryton at Worksop	77
28050	Torne at Auckley	136
28052	Sow at Great Bridgeford	163
28053	Penk at Penkridge	272
28055	Ecclesbourne at Duffield	50
28056	Rothley Brook at Rothley	94
28060	Dover Beck at Lowdham	69
28061	Churnet at Basford Bridge	139
28066	Cole at Coleshill	130
28067	Derwent at Church Wilne	1178
28068	Lathkill at Pickering Wood	90

28072	Greet at Southwell	46
28074	Soar at Kegworth	1292
28079	Meece Brook at Shallowford	86
28080	Tame at Lea Marston Lakes	799
28082	Soar at Littlethorpe	184
28083	Trent at Darlaston	195
28085	Derwent at St Mary's Bridge	1054
28086	Sence at South Wigston	113
28091	Ryton at Blyth	231
28093	Soar at Pillings Lock	1108
28095	Tame at Hopwas Bridge	1422
28112	Churnet at Quixhill	213
28116	Maun at Whitewater Bridge	157
28117	Derwent at Whatstandwell	755
28118	Meden at Perlethorpe	97
29001	Waithe Beck at Brigsley	108
29002	Great Eau at Claythorpe Mill	77
29003	Lud at Louth	55
29005	Rase at Bishopbridge	67
30001	Witham at Claypole Mill	298
30002	Barlings Eau at Langworth Bridge	210
30003	Bain at Fulsby Lock	197
30004	Lymn at Partney Mill	62
30005	Witham at Saltersford Total	126
30011	Bain at Goulceby Bridge	63
30033	Brant at Brant Broughton	66
31001	Eye Brook at Eye Brook Reservoir	60
31004	Welland at Tallington Total	717
31006	Gwash at Belmesthorpe	150
31007	Welland at Barrowden	412
31008	East Glen at Manthorpe	136
31009	West Glen at Shillingthorpe	173
31010	Chater at Fosters Bridge	69
31013	East Glen at Irnham	72
31021	Welland at Ashley	251
31028	Gwash at Church Bridge	77
32003	Harpers Brook at Old Mill Bridge	74
32004	Ise Brook at Harrowden	194
32006	Nene/Kislingbury at Upton Total	223
32007	Nene/Brampton at St Andrews Total	233
32008	Nene/Kislingbury at Dodford	107
32010	Nene at Wansford	1530
32012	Wootton Brook at Lady Bridge	53
32019	Slade Brook at Kettering	58
32031	Wootton Brook at Wootton Park	74
33002	Bedford Ouse at Bedford	1460
33006	Wissey at Northwold Total	275
33007	Nar at Marham	153
33011	Little Ouse at County Bridge Euston	129
33012	Kym at Meagre Farm	138
33013	Sapiston at Rectory Bridge	206
33014	Lark at Temple	272
33015	Ouzel at Willen	277
33018	Tove at Cappenham Bridge	138
33019	Thet at Melford Bridge	316
33020	Alconbury Brook at Brampton	202
33021	Rhee at Burnt Mill	303
33022	Ivel at Blunham	541
33024	Cam at Dernford	198
33026	Bedford Ouse at Offord	2570
33027	Rhee at Wimpole	119
33028	Flit at Shefford	120
33029	Stringside at Whitebridge	99
33031	Broughton Brook at Broughton	67
33032	Heacham at Heacham	59
33033	Hiz at Arlesey	108
33034	Little Ouse at Abbey Heath	689
33035	Ely Ouse at Denver Complex	3430
33037	Bedford Ouse at Newport Pagnell Total	800
33039	Bedford Ouse at Roxton	1660
33044	Thet at Bridgham	278

33046	Thet at Redbridge	145
33050	Snail at Fordham	61
33051	Cam at Chesterford	141
33053	Granta at Stapleford	114
33055	Granta at Babraham	99
33056	Quy Water at Lode	76
33057	Ouzel at Leighton Buzzard	119
33058	Ouzel at Bletchley	215
33063	Little Ouse at Knettishall	101
33066	Granta at Linton	60
33070	Lark at Fornham St Martin	110
34001	Yare at Colney	232
34002	Tas at Shotesham	147
34003	Bure at Ingworth	165
34004	Wensum at Costessey Mill	571
34005	Tud at Costessey Park	73
34006	Waveney at Needham Mill	370
34007	Dove at Oakley Park	134
34010	Waveney at Billingford Bridge	149
34011	Wensum at Fakenham	162
34012	Burn at Burnham Overy	80
34014	Wensum at Swanton Morley Total	398
34018	Stiffkey at Warham	88
34019	Bure at Horstead Mill	313
35002	Deben at Naunton Hall	163
35003	Alde at Farnham	64
35004	Ore at Beversham	55
35010	Gipping at Bramford	298
35013	Blyth at Holton	93
36002	Glem at Glemsford	87
36003	Box at Polstead	54
36005	Brett at Hadleigh	156
36006	Stour at Langham	578
36007	Belchamp Brook at Bardfield Bridge	59
36008	Stour at Westmill	225
36010	Bumpstead Brook at Broad Green	28
36012	Stour at Kedington	76
36013	Brett at Higham	195
36015	Stour at Lamarsh	481
37001	Roding at Redbridge	303
37002	Chelmer at Rushes Lock	534
37003	Ter at Crabbs Bridge	78
37005	Colne at Lexden	238
37006	Can at Beach's Mill	228
37007	Wid at Writtle	136
37008	Chelmer at Springfield	190
37009	Brain at Guithavon Valley	61
37010	Blackwater at Appleford Bridge	247
37011	Chelmer at Churchend	73
37012	Colne at Poolstreet	65
37013	Sandon Brook at Sandon Bridge	75
37014	Roding at High Ongar	95
37015	Cripsey Brook at Chipping Ongar	62
37016	Pant at Copford Hall	63
37017	Blackwater at Stisted	139
37019	Beam at Bretons Farm	50
37020	Chelmer at Felsted	132
37022	Holland Brook at Thorpe le Soken	55
37023	Roding at Loughton	269
37024	Colne at Earls Colne	154
37031	Crouch at Wickford	72
37034	Mar Dyke at Stifford	91
38001	Lee at Feildes Weir	1036
38002	Ash at Mardock	79
38003	Mimram at Panshanger Park	134
38004	Rib at Wadesmill	137
38011	Mimram at Fulling Mill	99
38013	Upper Lee at Luton Hoo	71
38014	Salmon Brook at Edmonton	21
38017	Mimram at Whitwell	39
38018	Upper Lee at Water Hall	150

38023	Lee flood relief at Low Hall	1243
38026	Pincey Brook at Sheering Hall	55
38029	Quin at Griggs Bridge	50
38030	Beane at Hartham	175
38031	Lee at Rye Bridge	758
38032	Lee at Lea Bridge	1364
38033	Upper Lee at Luton East Hyde	71
39001	Thames at Kingston	9948
39002	Thames at Days Weir	3445
39003	Wandle at South Wimbledon	176
39004	Wandle at Beddington Park	122
39006	Windrush at Newbridge	363
39007	Blackwater at Swallowfield	355
39008	Thames at Eynsham	1616
39010	Colne at Denham	743
39011	Wey at Tilford	396
39012	Hogsmill at Kingston upon Thames	69
39013	Colne at Berrygrove	352
39014	Ver at Hansteads	132
39016	Kennet at Theale	1033
39019	Lambourn at Shaw	234
39020	Coln at Bibury	107
39021	Cherwell at Enslow Mill	552
39022	Loddon at Sheepbridge	165
39023	Wye at Bourne End Hedsor	137
39025	Enborne at Brimpton	148
39026	Cherwell at Banbury	199
39027	Pang at Pangbourne	171
39028	Dun at Hungerford	101
39029	Tilling Bourne at Shalford	59
39030	Gade at Croxley Green	184
39031	Lambourn at Welford	176
39032	Lambourn at East Shefford	154
39034	Evenlode at Cassington Mill	430
39035	Churn at Cerney Wick	124
39037	Kennet at Marlborough	142
39039	Wye at High Wycombe	68
39040	Thames at West Mill Cricklade	185
39042	Leach at Priory Mill Lechlade	77
39043	Kennet at Knighton	295
39044	Hart at Bramshill House	84
39046	Thames at Sutton Courtenay	3414
39049	Silk Stream at Colindeep Lane	29
39053	Mole at Horley	90
39056	Ravensbourne at Catford Hill	120
39057	Crane at Cranford Park	62
39068	Mole at Castle Mill	316
39069	Mole at Kinnersley Manor	142
39071	Thames at Ewen	64
39072	Thames at Royal Windsor Park	7046
39073	Churn at Cirencester	84
39074	Ampney Brook at Sheepen Bridge	74
39076	Windrush at Worsham	296
39077	Og at Marlborough Poulton Fm	59
39078	Wey (North) at Farnham	191
39079	Wey at Weybridge	1008
39081	Ock at Abingdon	234
39087	Ray at Water Eaton	84
39088	Chess at Rickmansworth	105
39089	Gade at Bury Mill	48
39090	Cole at Inglesham	140
39093	Brent at Monks Park	118
39094	Crane at Marsh Farm	81
39101	Aldbourne at Ramsbury	53
39102	Misbourne at Denham Lodge	95
39103	Kennet at Newbury	548
39104	Mole at Esher	470
39105	Thame at Wheatley	534
39106	Mole at Leatherhead	371
39109	Coln at Fossebridge	82
39110	Coln at Fairford	130

39111	Thames at Staines	8120
39114	Pang at Frilsham	90
39115	Pang at Bucklebury	109
39117	Colne Brook at Hythe End	930
39120	Caker Stream at Alton	88
39121	Thames at Walton	9292
39122	Cranleigh Waters at Bramley	110
39125	Ver at Redbourn	63
39127	Misbourne at Little Missenden	47
39128	Bourne (South) at Addlestone	90
39129	Thames at Farmoor	1609
39130	Thames at Reading	4634
39131	Brent at Costons Lane Greenford	146
39138	Loddon at Twyford	690
39140	Ray at Islip	290
39141	Wey at Guildford	690
39142	Windrush at Bourton on the Water	66
39143	Dikler at Bourton on the Water	91
39144	Sor at Bodicote	88
39148	Thames at Maidenhead	6910
40003	Medway at Teston / East Farleigh	1256
40004	Rother at Udiam	206
40005	Beult at Stilebridge	277
40007	Medway at Chafford / Colliers Land Bridge	255
40008	Great Stour at Wye	230
40009	Teise at Stonebridge	136
40010	Eden at Penshurst / Vexour Bridge	224
40011	Great Stour at Horton	345
40012	Darent at Hawley	191
40013	Darent at Otford	101
40016	Cray at Crayford	120
40018	Darent at Lullingstone	118
40020	Eridge Stream at Hendal Bridge	54
40022	Great Stour at Chart Leacon	73
40023	East Stour at South Willesborough	59
40029	Len at Lenside	70
41003	Cuckmere at Sherman Bridge	135
41004	Ouse at Barcombe Mills	396
41005	Ouse at Gold Bridge	181
41006	Uck at Isfield	88
41009	Rother at Hardham	346
41010	Adur W Branch at Hatterell Bridge	109
41011	Rother at Iping Mill	154
41012	Adur E Branch at Sakeham	93
41014	Arun at Pallingham	379
41015	Ems at Westbourne	58
41018	Kird at Tanyards	67
41019	Arun at Alfoldean	139
41022	Lod at Halfway Bridge	52
41023	Lavant at Graylingwell	87
41025	Loxwood Stream at Drungewick	92
41029	Bull at Lealands	41
41035	North at Brookhurst	54
42001	Wallington at North Fareham	111
42003	Lymington at Brockenhurst	99
42004	Test at Broadlands	1040
42005	Wallop Brook at Broughton	54
42006	Meon at Mislingford	73
42007	Alre at Drove Lane Alresford	57
42008	Cheriton Stream at Sewards Bridge	75
42009	Candover Stream at Borough Bridge	71
42011	Hamble at Frogmill	57
42012	Anton at Fullerton	185
42014	Blackwater at Ower	105
42016	Itchen at Easton	237
42023	Itchen at Riverside Park	415
42024	Test at Chilbolton Total	453
42025	Lavant Stream at Leigh Park	55
42026	Wallop Brook at Bossington	61
42027	Dever at Bransbury	122

43003	Avon at East Mills Total	1478
43004	Bourne at Laverstock	164
43005	Avon at Amesbury	324
43006	Nadder at Wilton	221
43007	Stour at Throop	1073
43008	Wylye at South Newton	445
43009	Stour at Hammoon	523
43010	Allen at Loverley Farm	94
43012	Wylye at Norton Bavant	112
43014	East Avon at Upavon East	86
43018	Allen at Walford Mill	177
43021	Avon at Knapp Mill	1706
43022	Moors River at Hurn Court	143
43023	Ebble at Nunton Bridge	107
43024	Wylye at Stockton Park	255
44001	Frome at East Stoke Total	414
44002	Piddle at Baggs Mill	183
44004	Frome at Dorchester Total	206
44014	Piddle at Briantspuddle	112
45001	Exe at Thorverton	601
45002	Exe at Stoodleigh	422
45003	Culm at Woodmill	226
45004	Axe at Whitford	289
45005	Otter at Dotton	203
45007	Exe at Trews Weir	1191
45008	Otter at Fenny Bridges	104
45009	Exe at Pixton	160
45011	Barle at Brushford	128
45012	Creedy at Cowley	262
46002	Teign at Preston	381
46003	Dart at Austins Bridge	248
46005	East Dart at Bellever	22
46008	Avon at Loddiswell	102
46013	Bovey at Bovey Parke	87
46014	Teign at Chudleigh	232
47001	Tamar at Gunnislake	917
47004	Lynher at Pillaton Mill	136
47005	Ottery at Werrington Park	121
47006	Lyd at Lifton Park	223
47007	Yealm at Puslinch	55
47008	Thrushel at Tinhay	113
47009	Tiddy at Tideford	37
47010	Tamar at Crowford Bridge	77
47011	Plym at Carn Wood	79
47015	Tavy at Ludbrook	197
47018	Thrushel at Hayne Bridge	58
47019	Tamar at Polson Bridge	470
47020	Inny at Bealsmill	105
47024	Tavy at Tavistock Abbey Bridge	96
48003	Fal at Tregony	87
48004	Warleggan at Trengoffe	25
48005	Kenwyn at Truro	19
48011	Fowey at Restormel	169
49001	Camel at Denby	209
50001	Taw at Umberleigh	826
50002	Torridge at Torrington	663
50006	Mole at Woodleigh	328
50007	Taw at Taw Bridge	71
50008	Lew at Gribbleford Bridge	71
50010	Torridge at Rockhay Bridge	258
50011	Okement at Jacobstowe	82
50012	Yeo at Veraby	54
50014	Yeo at Collard Bridge	80
51001	Doniford Stream at Swill Bridge	76
52003	Halsewater at Halsewater	88
52004	Isle at Ashford Mill	90
52005	Tone at Bishops Hull	202
52006	Yeo at Pen Mill	213
52007	Parrett at Chiselborough	75
52009	Sheppey at Fenny Castle	60
52010	Brue at Lovington	135

52011	Cary at Somerton	82
52014	Tone at Greenham	57
52017	Congresbury Yeo at Iwood	67
53002	Semington Brook at Semington	158
53004	Chew at Compton Dando	130
53005	Midford Brook at Midford	147
53006	Frome (Bristol) at Frenchay	149
53007	Frome (Somerset) at Tellisford	262
53008	Avon at Great Somerford	303
53009	Wellow Brook at Wellow	73
53013	Marden at Stanley	99
53017	Boyd at Bitton	48
53018	Avon at Bathford	1552
53022	Avon at Bath ultrasonic	1605
53023	Sherston Avon at Fosseway	90
53024	Tetbury Avon at Brokenborough	74
53025	Mells at Vallis	119
53026	Frome (Bristol) at Frampton Cotterell	79
53028	By Brook at Middlehill	102
53029	Biss at Trowbridge	78
54001	Severn at Bewdley	4325
54002	Avon at Evesham	2210
54004	Sowe at Stoneleigh	262
54006	Stour (Worcs) at Kidderminster Callows Lane	324
54007	Arrow at Broom	319
54008	Teme at Tenbury	1134
54010	Stour (Warks) at Alscot Park	319
54011	Salwarpe at Harford Hill	184
54015	Bow Brook at Besford Bridge	156
54017	Leadon at Wedderburn Bridge	293
54018	Rea Brook at Hookagate	178
54019	Avon at Stareton	347
54020	Perry at Yeaton	181
54023	Badsey Brook at Offenham	96
54024	Worfe at Burcote	258
54027	Frome at Ebley Mill	198
54029	Teme at Knightsford Bridge	1480
54032	Severn at Saxons Lode	6850
54036	Isbourne at Hinton on the Green	91
54040	Meese at Tibberton	168
54041	Tern at Eaton upon Tern	192
54044	Tern at Ternhill	93
54046	Worfe at Cosford	55
54048	Dene at Wellesbourne	102
54049	Leam at Princes Drive Weir	362
54050	Leam at Eathorpe	300
54057	Severn at Haw Bridge	9895
54063	Stour (Worcs) at Prestwood Hospital	90
54088	Little Avon at Berkeley Kennels	134
54089	Avon at Bredon	2674
54094	Strine at Crudgington	96
54096	Hadley Brook at Wards Bridge	53
54102	Avon at Lilbourne	109
54106	Stour (Warks) at Shipston	185
54107	Arrow at Studley	93
54112	Leam at Kites Hardwick	100
54113	Itchen at Southam	106
54114	Avon at Warwick	1012
54115	Piddle Brook at Wyre Piddle	105
68001	Weaver at Ashbrook	622
68003	Dane at Rudheath	407
68004	Wistaston Brook at Marshfield Bridge	93
68005	Weaver at Audlem	207
68007	Wincham Brook at Lostock Gralam	148
68018	Dane at Congleton Park	145
68020	Gowy at Bridge Trafford	156
68044	Dane at Hug Bridge	73
69002	Irwell at Adelphi Weir	559
69003	Irk at Scotland Weir	73
69005	Glaze Brook at Little Woolden Hall	152

69006	Bollin at Dunham Massey	258
69007	Mersey at Ashton Weir	660
69008	Dean at Stanneylands	59
69012	Bollin at Wilmslow	73
69015	Etherow at Compstall	156
69017	Goyt at Marple Bridge	183
69020	Medlock at London Road	58
69022	Irwell at Irwell Vale	101
69023	Roch at Blackford Bridge	186
69024	Croal at Farnworth Weir	145
69027	Tame at Portwood	150
69028	Mersey at Brinksway	517
69030	Sankey Brook at Causey Bridges	154
69032	Alt at Kirkby	90
69037	Mersey at Westy	2030
69041	Tame at Broomstairs	113
69043	Irk at Collyhurst Weir	72
69044	Irwell at Bury Ground	140
69045	Bollin at Bollington Mill Total	257
69803	Roch at Rochdale	111
70002	Douglas at Wanes Blades Bridge	198
70003	Douglas at Wigan	55
70004	Yarrow at Croston Mill	74
70005	Lostock at Littlewood Bridge	56
71001	Ribble at Samlesbury	1145
71004	Calder at Whalley Weir	316
71006	Ribble at Henthorn	456
71008	Hodder at Hodder Place	261
71009	Ribble at New Jumbles Rock	1053
71010	Pendle Water at Barden Lane	108
71011	Ribble at Arnford	204
71014	Darwen at Blue Bridge	128
72002	Wyre at St Michaels	275
72003	Hindburn at Wray	84
72004	Lune at Caton	983
72005	Lune at Killington	219
72008	Wyre at Garstang	114

72009	Wenning at Wennington	142
72011	Rawthey at Brigflatts	200
72014	Conder at Galgate	29
72015	Lune at Lunes Bridge	142
72016	Wyre at Scorton Weir	89
73002	Crake at Low Nibthwaite	73
73003	Kent at Burneside	74
73005	Kent at Sedgwick	209
73008	Bela at Beetham	131
73010	Leven at Newby Bridge	247
73011	Mint at Mint Bridge	66
73012	Kent at Victoria Bridge	183
73013	Rothay at Miller Bridge House	64
73014	Brathay at Jeffy Knotts	57
73017	Kent at Bowston	71
74001	Duddon at Duddon Hall	86
74005	Ehen at Braystones	126
74007	Esk at Cropple How	70
75002	Derwent at Camerton	663
75003	Derwent at Ouse Bridge	363
75004	Cocker at Southwaite Bridge	117
75005	Derwent at Portinscale	235
75007	Glenderamackin at Threlkeld	65
75016	Cocker at Scalehill	64
75017	Ellen at Bullgill	96
76003	Eamont at Udford	396
76004	Lowther at Eamont Bridge	159
76005	Eden at Temple Sowerby	616
76007	Eden at Sheepmount	2287
76008	Irthing at Greenholme	335
76009	Caldew at Holm Hill	147
76010	Petteril at Harraby Green	160
76014	Eden at Kirkby Stephen	69
76015	Eamont at Pooley Bridge	145
76017	Eden at Great Corby	1373
76019	Roe Beck at Stockdalewath	63

Table 5 EA abstraction uses and associated loss factors

Use Description	Code	Loss Fact
Animal Watering & General Use in Non Farming Situations	10	Medium
Boiler Feed	20	Medium
Conveying Materials	30	Medium
Drinking, Cooking, Sanitary, Washing, (Small Garden) - Commercial/Industrial/Public Services	40	Medium
Drinking, Cooking, Sanitary, Washing, (Small Garden) - Household	50	Medium
Dust Suppression	60	High
Effluent/Slurry Dilution	70	Very Low
Evaporative Cooling	80	High
Fish Farm/Cress Pond Through flow	90	Very Low
Fish Pass/Canoe Pass	100	Very Low
Gas Suppression/Scrubbing	110	Medium
General Cooling (Existing Licences Only) (High Loss)	120	High
General Cooling (Existing Licences Only) (Low Loss)	130	Low
General Farming & Domestic	140	Medium
General Use Relating to Secondary Category (High Loss)	150	High
General Use Relating to Secondary Category (Medium Loss)	160	Medium
General Use Relating to Secondary Category (Low Loss)	170	Low
General Washing/Process Washing	190	Medium
Heat Pump	200	Very Low
Horticultural Watering	210	Medium
Hydraulic Rams	220	Very Low
Hydraulic Testing	230	Very Low
Hydroelectric Power Generation	240	Very Low
Lake & Pond Through flow	250	Very Low
Large Garden Watering	260	Medium
Laundry Use	270	Medium
Make-Up or Top Up Water	280	High
Milling & Water Power other than Electricity Generation	290	Very Low
Mineral Washing	300	Low
Non-Evaporative Cooling	310	Low
Pollution Remediation	320	Very Low
Potable Water Supply - Direct	330	Medium
Potable Water Supply - Storage	340	Medium
Process Water	350	Medium
Raw Water Supply	360	Medium
River Recirculation	370	Very Low
Spray Irrigation - Anti Frost	380	Medium
Spray Irrigation - Anti Frost Storage	390	Medium
Spray Irrigation - Direct	400	High
Spray Irrigation - Spray Irrigation Definition Order	410	High
Spray Irrigation - Storage	420	High
Supply to a Canal for Through flow	430	Very Low

Supply to a Leat for Through flow	440	Very Low
Transfer Between Sources (Pre Water Act 2003)	450	Very Low
Vegetable Washing	460	Low
Water Bottling	470	Medium
Water Wheels not used for Power	480	Very Low
Impounding (for any purpose excluding impounding for HEP)	490	Non-Chargeab
Trickle Irrigation - Direct	600	High
Trickle Irrigation - Under Cover/Containers	610	High
Trickle Irrigation - Storage	620	High
Flood Irrigation, Including Water Meadows, Warping and Pest Control	630	Very Low
Wet Fencing and Nature Conservation	640	Very Low
Transfer Between Sources (Post Water Act 2003)	650	Very Low
Dewatering	660	Very Low
Hydraulic Fracturing	670	High

Table 6 Full list and naming convention for observed- and UKCP18-driven G2G model simulations

Data	Driving Climate Data	Name of Ascii or NetCDF file
Daily River Flows for Gauging Stations	Observed (OBS)	G2G_DailyRiverFlow_NATURAL_OBS_19610101_20201231.dat G2G_DailyRiverFlow_MeanAI_OBS_19610101_20201231.dat G2G_DailyRiverFlow_ObsAI_OBS_19990101_20141231.dat
Daily River Flows - Gridded	Observed (OBS)	G2G_DailyRiverFlow_NATURAL_OBS_19610101_20201231.nc G2G_DailyRiverFlow_MeanAI_OBS_19610101_20201231.nc G2G_DailyRiverFlow_ObsAI_OBS_19990101_20141231.nc
Daily River Flows for Gauging Stations	UKCP18 RCMs	G2G_DailyRiverFlow_NATURAL_RCMXX_19801201_20801130.dat G2G_DailyRiverFlow_MeanAI_RCMXX_19801201_20801130.dat G2G_DailyRiverFlow_FutureSUSAI_RCMXX_19801201_20801130.dat G2G_DailyRiverFlow_FutureBAUAI_RCMXX_19801201_20801130.dat G2G_DailyRiverFlow_FutureEGAI_RCMXX_19801201_20801130.dat
Daily River Flows - Gridded	UKCP18 RCMs	G2G_DailyRiverFlow_NATURAL_RCMXX_19801201_20801130.nc G2G_DailyRiverFlow_MeanAI_RCMXX_19801201_20801130.nc G2G_DailyRiverFlow_FutureSUSAI_RCMXX_19801201_20801130.nc G2G_DailyRiverFlow_FutureBAUAI_RCMXX_19801201_20801130.nc G2G_DailyRiverFlow_FutureEGAI_RCMXX_19801201_20801130.nc
Monthly Abstracted Surface Water (SW) - Gridded	UKCP18 RCMs	G2G_MonthlyAbstractedSW_MeanAI_RCMXX_198012_208011.nc G2G_MonthlyAbstractedSW_FutureSUSAI_RCMXX_198012_208011.nc G2G_MonthlyAbstractedSW_FutureBAUAI_RCMXX_198012_208011.nc G2G_MonthlyAbstractedSW_FutureEGAI_RCMXX_198012_208011.nc
Monthly Abstracted Ground Water (GW) - Gridded	UKCP18 RCMs	G2G_MonthlyAbstractedGW_MeanAI_RCMXX_198012_208011.nc G2G_MonthlyAbstractedGW_FutureSUSAI_RCMXX_198012_208011.nc G2G_MonthlyAbstractedGW_FutureBAUAI_RCMXX_198012_208011.nc G2G_MonthlyAbstractedGW_FutureEGAI_RCMXX_198012_208011.nc
Monthly Non-Abstracted Surface Water (SW) - Gridded	UKCP18 RCMs	G2G_MonthlyNonAbstractedSW_MeanAI_RCMXX_198012_208011.nc G2G_MonthlyNonAbstractedSW_FutureSUSAI_RCMXX_198012_208011.nc G2G_MonthlyNonAbstractedSW_FutureBAUAI_RCMXX_198012_208011.nc G2G_MonthlyNonAbstractedSW_FutureEGAI_RCMXX_198012_208011.nc
Monthly Non-Abstracted Ground Water (GW) - Gridded	UKCP18 RCMs	G2G_MonthlyNonAbstractedGW_MeanAI_RCMXX_198012_208011.nc G2G_MonthlyNonAbstractedGW_FutureSUSAI_RCMXX_198012_208011.nc G2G_MonthlyNonAbstractedGW_FutureBAUAI_RCMXX_198012_208011.nc G2G_MonthlyNonAbstractedGW_FutureEGAI_RCMXX_198012_208011.nc
Number of Days Not Abstracted Surface Water (SW) - Gridded	UKCP18 RCMs	G2G_NdaysNotAbstractedSW_MeanAI_RCMXX_198012_208011.nc G2G_NdaysNotAbstractedSW_FutureSUSAI_RCMXX_198012_208011.nc G2G_NdaysNotAbstractedSW_FutureBAUAI_RCMXX_198012_208011.nc G2G_NdaysNotAbstractedSW_FutureEGAI_RCMXX_198012_208011.nc
Number of Days Not Abstracted Ground Water (GW) - Gridded	UKCP18 RCMs	G2G_NdaysNotAbstractedGW_MeanAI_RCMXX_198012_208011.nc G2G_NdaysNotAbstractedGW_FutureSUSAI_RCMXX_198012_208011.nc G2G_NdaysNotAbstractedGW_FutureBAUAI_RCMXX_198012_208011.nc G2G_NdaysNotAbstractedGW_FutureEGAI_RCMXX_198012_208011.nc

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