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What controls current and future background vulnerability of rivers to eutrophication and pathogens?

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ABSTRACT

To have confidence managing rivers under changing environmental pressures we must demonstrate thorough understanding of their response. Models express our understanding quantitatively. For 30 rivers in England, catchment attributes were combined with hydro-climatic time-series in hourly-resolution water quality model applications over a 15-year period. Retaining high-resolution input observations within simplified catchment representations makes geographically widespread application of process-based models achievable, whilst still representing diurnal cycles and quantifying ecosystem functioning. Background vulnerability assessments revealed eutrophic conditions (>30 μg chlorophyll-a L^{-1} as diatoms), oxygen stress (<5 mg DO L^{-1}), and violation of safe pathogen levels (>9 CFU mL^{-1} of the faecal indicator organism, *Escherichia coli*) in 10, three, and 11 rivers respectively. Pathogen risk only considered treated effluent sources, not covering intermittent discharges or livestock contributions. By 2050, under a backdrop of uncertain change in climate, river quality is expected to worsen by 4.7 % for 10th percentile DO and 27.5 % for 90th percentile *E. coli*, with urban influence strongly determining sensitivity to change. Whilst deoxygenation vulnerability appears not widespread, faster future deteriorations are projected than elsewhere, such as in the USA. Eutrophication shows much spatio-temporal variability in change (with an average 5.1 % decrease in 90th percentile chlorophyll-a), seemingly controlled by local hydraulic factors and top-down biotic interactions. Across all indicators, riparian condition and channel hydrodynamics appear more important in controlling variability than regional differences in hydro-climatology. Assessment of comprehensive government-mandated interventions suggests partial offsetting of worsening DO, and further eutrophication decrease. *E. coli* deteriorations are effectively offset, although land management actions alone lead to further worsening.

1. Introduction

Continuing to adequately protect river environments under increasing pressure from climate and urbanisation drivers is challenging. Threats posed to river ecology, for example through habitat degradation and toxic pollution (Lemm et al., 2021), and to human health, such as through impairment of potable water supply and recreational hazards (e.g. pathogen exposure (Oliver et al., 2016; Kay et al., 2008)) require our urgent and ongoing attention, but are hard to resolve as they encompass complex and multi-faceted environmental pathways (Birk et al., 2020; Grizzetti et al., 2017). To support this endeavour, process-based water quality models are powerful as they represent a simplified understanding of cause and effect. However, they typically suffer from onerous resource outlay and constraints to knowledge transfer beyond site-specific findings. Researchers have sought to overcome this shortcoming by adopting data-driven approaches to simulation, employing statistics, and more recently, artificial intelligence (Cojbasic et al., 2023; Zanoni et al., 2022). Large datasets, often much more spatially extensive than those covered by process-based models, can be interrogated using these empirical methods. They are undeniably powerful in identifying key driving variables, but problematically, themselves are also deficient, as unless coupled with

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deterministic approaches their empirical basis can hinder confident identification of effective mitigation options (Noori et al, 2020).

In river environments, many fundamental bio-physical phenomena have long been well understood, for example channel hydrodynamic controls on travel time and bed sediment interactions (of nutrients, organic carbon and dissolved oxygen), kinetics of factors limiting biogeochemical reactions, and temperature controls on microbially-mediated processes (Chapra, 2008). Statistical approaches cannot retain the dynamics of these insightful relationships. It is important to retain such knowledge when supporting river basin management decision-making. Also, process-based modelling enables rates of processes as well as states (concentrations) to be simulated. Knowing how rapidly purification or degradation processes occur and how these respond to environmental factors is paramount for understanding the resilience of aquatic ecological systems to change (von Schiller et al., 2017). River channel processes are important. At a European scale, the riverine nitrate sink is broadly equivalent to the entire emission flux from wastewater (Grizzetti et al., 2008).

With these considerations in mind, it is imperative that we retain in-channel process-representation whilst still enabling rapid assessments of responses to change. Hutchins et al. (2024) presented an example for urban river environments, QUESTOR-YS, a simplification of the extensively tested QUESTOR model (Pathak et al., 2022). In QUESTOR-YS, representation of complex urban hydrology was simplified yet still retained predictive capability for specific purposes, in this case the simulation of river eutrophication response to changing riparian tree canopy coverage. In the present paper, we further explore this approach in two respects. Firstly, we consider a nationwide set of 30 representative river basins in England across varying size and land cover attributes. Secondly, we consider a wider set of river quality state variables including indicators of pathogens as well as eutrophication, alongside a set of fluxes representing components of net ecosystem metabolism (an integrated measure of ecosystem health) and gas exchange.

To carry out the necessary model applications, we exploit a multi-domain dataset of river physical, hydrological, chemical, and biological attributes; this covers 1,519 English sites across 44 years, and was assembled for the purpose of assessing how multiple stressors affect wildlife in rivers (ChemPop: Bachiller-Jareno et al., 2024). We couple the simplified model (QUESTOR-YS) with this resource, and combine it with additional physical attributes and hydro-climatic timeseries data from readily-available online sources. We use model applications to pose four questions: (Q1) Based on tractable geographic inputs and driven by hydro-climatic time-series data, how well does the model describe spatio-temporal vulnerability in river water quality? (Q2) How important are local-scale spatio-temporal variations in biotic factors? (Q3) How important are urban pressures, for example treated effluent, in determining vulnerability? (Q4) To which descriptors of geo-climatic variability is water quality most sensitive? In addressing these questions, we focus attention on achieving realistic simulations during summer low flows when water temperature is highest, and therefore when water quality is especially vulnerable to extended spells of deterioration. This coincides also with periods of enhanced recreational water use. To support policy interventions for safeguarding future water resources, the approach potentially enables rapid model applications to determine how geographically-driven variability influences river water quality response at a national scale. Future scenario analysis is presented, and we outline the suitability of the model for supporting national-scale river ecological assessments, a hitherto elusive role for process-based simulation.

2. Methodology

2.1. Rationale

For 30 individual river basins, a process-based model was set up, supported by data held by regulators and other organisations. Although it was developed for England, it can be reasonably assumed that necessary data are readily-available in highly developed countries, which gives the approach scope for wider international application. The model is driven by a small set of nationally-extensive information on abiotic attributes together with input time-series data of hydroclimatic variables. Use of comprehensive hydroclimatic driving data enable what is a simplified model to still retain sensitivity to diurnal cycles. In using a single set of model parameters across rivers nationwide and in multiple years of simulation, biotic properties are assumed uniform and their dynamics solely controlled by abiotic factors. Inter-relations and feedback between biotic communities are not represented. We retain representation of fundamental river channel biophysical processes but simplify the spatial depiction of river networks by summarising morphometric knowledge, thereby working within the inevitable uncertainties posed by complex catchment systems. Whilst extensive applications of water quality models are undoubtedly achievable and of undeniable value (e.g. Abbaspour et al., 2015), these are uncommon, as the necessary geographically-specific influences and river basin properties require arduous pre-processing and are often lacking or inaccessible at a sufficiently detailed resolution. To bridge this gap therefore, the primary focus of the present study is to use a simplified process-based model for extensive characterisation of background vulnerability across multiple rivers, rather than to accurately simulate finer details of time series response at individual sites. Characterising background vulnerability pinpoints typical conditions and aligns less with representing acute events which can be elusive to capture due to localised and stochastic characteristics. We focus efforts on accurate simulation of those water quality indicators approaching levels of concern in summer, namely phytoplankton biomass (chlorophyll-a), dissolved oxygen, and *E. coli*, rather than attendant determinants such as nutrient species. The simplified approach makes geographically extensive application of process-based river models achievable.

2.2. Underpinning QUESTOR model

2.2.1. Water temperature, eutrophication and ecosystem metabolism

QUESTOR is a process-based 1-D model of flow, water temperature, nutrient dynamics, eutrophication and ecosystem metabolism in river networks. A network comprises a set of reaches bounded by influences such as headwater tributaries and treated effluents (WRCs). Flow routing in reaches of constant-width and variable-depth is informed by riverbed condition and gradient, and defined using non-linear equations to relate travel-time, water depth and discharge. By linking flow routing to biogeochemical processes (nutrient transformations, water column and riverbed heterotrophic respiration, reaeration, phytoplankton metabolism, particulate settling), the reach structure represents advection and dispersion. Applications to new rivers involve estimating biogeochemical process rates either by calibration using water quality observations or by translation from other applications. Magnitudes of biogeochemical fluxes primarily depend on river flow velocity and meteorological drivers, including solar radiation. A more extensive summary is given in Appendix A and full details provided elsewhere, most recently by Pathak et al. (2022).

For simulation of water temperature (WT), chlorophyll-a (Chl-a, as represented by a centric diatom assemblage (with silica cell wall and of a symmetrically radial rather than elongated form)) and dissolved oxygen (DO), good performance has been achieved in various rivers in the UK including the middle River Thames between the towns of Reading and Egham (e.g. Pathak et al., 2021; 2022) and the River Deben in Suffolk (e.g. Hutchins et al., 2021). A 14-year application in the lower Thames downstream of Egham (Appendix A) showed good fits at Teddington, with Kling Gupta Efficiency values of 0.95, 0.72, and 0.48 achieved for WT, Chl-a, and DO respectively. Close-fitting percentage biases of −1.5, 9.1, and −4.3 were achieved for mean values of WT, Chl-a, and DO respectively.

2.2.2. Pathogen sub-model

A new sub-model was established to represent key processes determining pathogen concentration profiles in a river network, namely bacterial growth, mortality, light inactivation and particulate settling. This represents a more sophisticated representation of in-channel processes than widely-used existing approaches (e.g. Arnold et al., 2012; Whitehead et al., 2016) which typically derive a single total degradation flux; it allows the influence of individual factors to be identified. Numeric representations of component fluxes have been proposed for aquatic environments (Weiskerger and Phanikumar, 2020), but not yet been implemented in river simulations. The QUESTOR pathogen model was calibrated using laboratory-controlled experimental *E. coli* observations using river water from the Thames, successfully identifying component flux pathways. Under normal and low flow conditions, the model simulated a good fit to *E. coli* observations at two locations along the main River Thames during the 2022 and 2023 summer seasons (May-September) of heightened contact recreational use (when UK rivers can be officially designated as “bathing waters”, a terminology used hereafter). This was achieved despite the lack of quantitative information on the incidence of untreated inputs from wastewater or livestock, for example during storm events, and only indirect knowledge of *E. coli* observations in specific upstream treated effluents. Description of the model development, and assessment of its performance in the River Thames is provided in Appendix B.

2.3. QUESTOR-YS model structure and input data

The QUESTOR-YS model is a simplified version of QUESTOR. The equations are identical. A conceptual summary of the simplification and its application for scenario analysis is illustrated (Fig. 1). To represent sub-national geographic variation, QUESTOR-YS applications were categorised at English regional level (North-east (NE), Midlands (MI), Anglian (AN), Thames (TH), Southern (SO), South-west (SW) and North-west (NW)). Rather than preserving representation of the finer details of river network branches and precise locations of influences, each river application used a uniform catchment structure. Sets of catchment-specific attributes were identified (Table 1) and together with hydro-climatic time series data this set of information satisfied model input data requirements.

Table 1
Catchment attributes, mean and range for the 30 selected catchments, and source dataset. Where for ChemPop, original source is (1) EA Freshwater River Macroinvertebrate Survey (FRMS) dataset (2) EA water quality data archive (WIMS) (3) LF2000-WQX model.

Attribute	Mean	Range	Source
Distance to source (km)	67.4	8.9–211.0	ChemPop[1]
Width (m)	19.4	4.3–40.0	ChemPop[1]
Catchment area (km^2)	893.8	50–4325	NRFA
Altitude at catchment outlet (m)	26.4	4.5–84.2	NRFA
Median catchment altitude (m)	132.4	46.3–264.4	NRFA
Tree occupancy within 20 m riparian buffer (%)	20.6	4.9–46.5	LCM
Mean nitrate-N concentration (mg L^{-1})	6.14	0.63–17.74	ChemPop[2]
Mean ammonium-N concentration (mg L^{-1})	0.14	0.02–1.20	ChemPop[2]
Mean soluble reactive phosphorus (SRP) concentration (mg L^{-1})	0.282	0.011–1.629	ChemPop[2]
Mean suspended solids concentration (mg L^{-1})	14.1	6.1–25.2	ChemPop[2]
River discharge at 5th percentile level (Q95) (m^3 s^{-1})	2.47	0.034–10.9	NRFA
Wastewater dilution factor (fraction of river at Q95 from effluent)	25.7	1.0–73.2	ChemPop[3]

2.3.1. Time-series data

For each river application, daily river discharge data collected by Environment Agency were obtained (NRFA, 2025). A single air temperature dataset of daily maximum and minimum values for each region (UK MetOffice, 2024) was used to estimate upstream daily mean water temperature (Mohseni et al., 1998). Thenceforth an upstream daily mean dissolved oxygen time series was derived. A level of 90 % saturation was assumed, guided by values spanning 1942–2011 from a study of global extent (Piatka et al., 2021) coupled with evidence of long-term trends in river deoxygenation (Zhi et al., 2023). Hourly solar radiation (Copernicus Atmosphere Monitoring Service, 2020) was also obtained at a regional resolution (a single time series extracted for each regional centroid) and applied accordingly to catchments within respective regions.

2.3.2. Attribute data

The river environment was represented using a single main stem

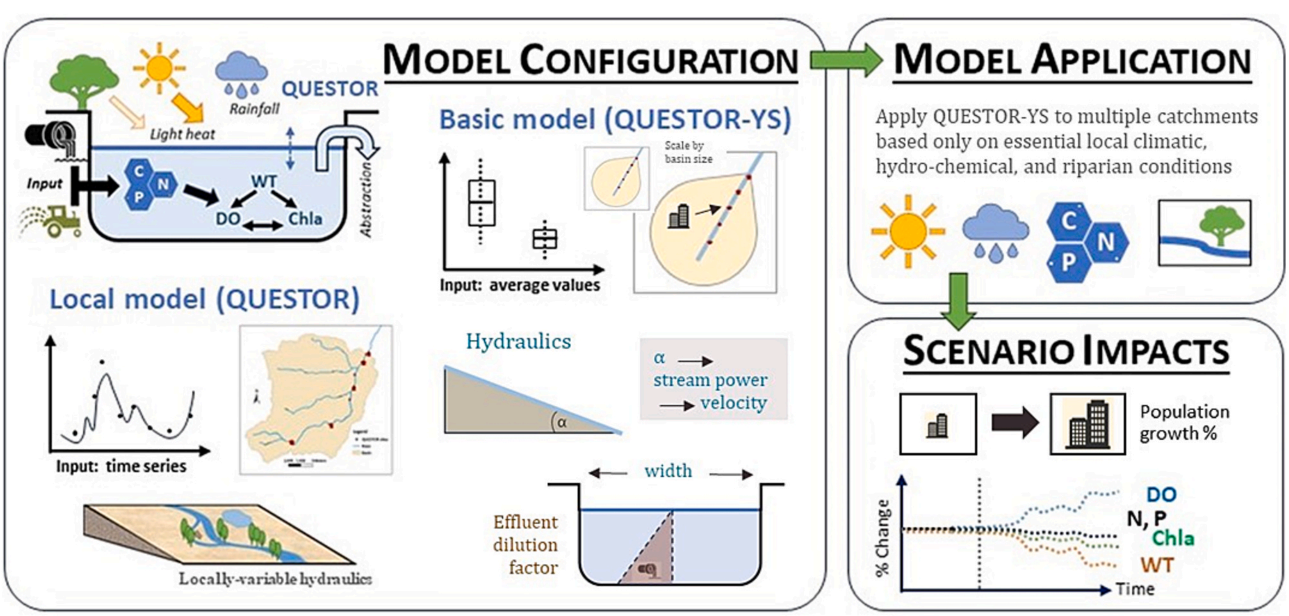

Fig. 1. Process for simplifying and applying QUESTOR-YS, illustrating how spatial detail is homogenised within a basin area. Increase in population is shown as an example scenario. Equations are identical in QUESTOR and QUESTOR-YS.

river channel divided into 10 equal reaches. The length of the river channel was assumed to be two-thirds of "distance to source" rather than equivalent to it, as the distance is determined by a digital terrain model rather than by measuring to the most upstream location of a permanent watercourse. Width of each segment was related to "width" data with value at the 10th reach (catchment outlet, i.e. the location of a flow gauging station) equal to "width" with a linear scaling down upstream to 70 % of this value in the 1st reach. Urban areas were assumed to lie centrally within the catchment and were represented by a single pair of effluent and abstraction influences in the 5th reach. Effluent discharge was estimated from wastewater dilution statistics at low flows (the long-term 30-year Q95 statistic from NRFA data) using values from the LF2000-WQX model (Williams et al., 2009). Abstraction, as taken for purposes of treatment and anthropogenic consumption, was assumed to be equal to the effluent volume. Water transfers between basins were not considered.

Rural land uses were assumed homogenous throughout in terms of runoff and water quality fluxes per unit area. Catchment-wide land use shares were obtained from UKCEH Land Cover Map (LCM) 2019 statistics (https://www.ceh.ac.uk/data/ukceh-land-cover-maps). Riparian tree shade was calculated by estimating bankside (20 m width) occupancy by trees (using UKCEH LCM 2019).

To represent hydraulic channel conveyance, discharge (Q) was related to velocity (V) using a non-linear relationship (Eq. (1)), where b = 0.5) (Leopold and Maddock, 1953). The scalar parameter (a) was defined (Eq. (2)) as a function of stream power, as widely adopted for sediment movement in river channels and hillslopes (Shih & Yang, 2009). It represents the lower catchment slope, where the trigonometric "tan (α)" is approximated as the ratio of difference in altitude between median (h_{med}) and minimum (h_{min}) (from digital terrain mapping) to the square root of the "catchment area" (A). The value of a scalar multiplier (a_s) was fixed at 35, being constrained based on values used in a previous optimised application in the Thames basin (Hutchins, 2024) which included three tributaries (River Windrush, River Cherwell and River Thame: Sites 1, 2 and 3 in Fig. 2) common to the new QUESTOR-YS application.

$$V = aQ^b \tag{1}$$

$$a = a_s.[h_{med} - h_{min}]/\sqrt{(A)} \tag{2}$$

Seasonal mean site values of nutrient and suspended solids concentrations, held in the ChemPop dataset, defined upstream diffuse inputs to the river channel. These values were scaled to account for biogeochemical channel sources and sinks. For each determinant, this was achieved by running the model for all 30 catchments and calculating the mean percentage bias between simulated mean concentrations and the observed concentrations from ChemPop at the catchment outlets. The scalar factors were then iteratively adjusted to minimise the magnitudes of the mean percentage biases. Calibrated scalar values were 1.15 (nitrate and ammonium), 1.5 (SRP and particulate phosphorus), and 1.0 (suspended solids). These values reflect aggregated river channel transformation fluxes. Nitrogen sinks dominate over sources, and conversely, phosphorus sources dominate over sinks. High loads of nutrients may occur in storm runoff (Wang et al., 2023), but these are hard to represent at larger scale, as they reflect the often-intractable figments of local agricultural practice. Although simple and not capturing these transient storm dynamics, the adopted representation in QUESTOR-YS is appropriate because model applications are focused on eutrophication impacts in highly populated English river systems where nutrients are not substantially limiting phytoplankton growth, which, though appreciable, is only seen in drier conditions.

Nutrients, suspended solids, and other water quality variables defining point source inputs were taken from default values used in previous applications (Hutchins et al., 2021). Similarly, default values for upstream diffuse Biochemical Oxygen Demand and Chl-a inputs were adopted, based on values from small English rivers held in the Environment Agency (EA) WIMS database.

2.4. QUESTOR-YS applications

QUESTOR-YS was applied for the period 01/02/2004 to 31/12/2018 in 30 catchments across England (Fig. 2 and Table C1.1) where BIOSYS macroinvertebrate data are held (Bachiller-Jareno et al., 2024), alongside nearby water quality and river flow observations. In addition, sites were chosen where estimates of wastewater dilution, as derived for 2008 effluent volumes, were available (Williams et al., 2009). Values for the prerequisite model parameters (Tables A1.1 and B1.1) were applied to all catchments.

2.5. Scenario analysis

Projection of future scenarios was undertaken with the primary objective of quantifying benefits of policy measures. Four scenarios of background vulnerability represent: present day (A), 2050 projection without any mitigation actions (B), 2050 with landuse mitigation

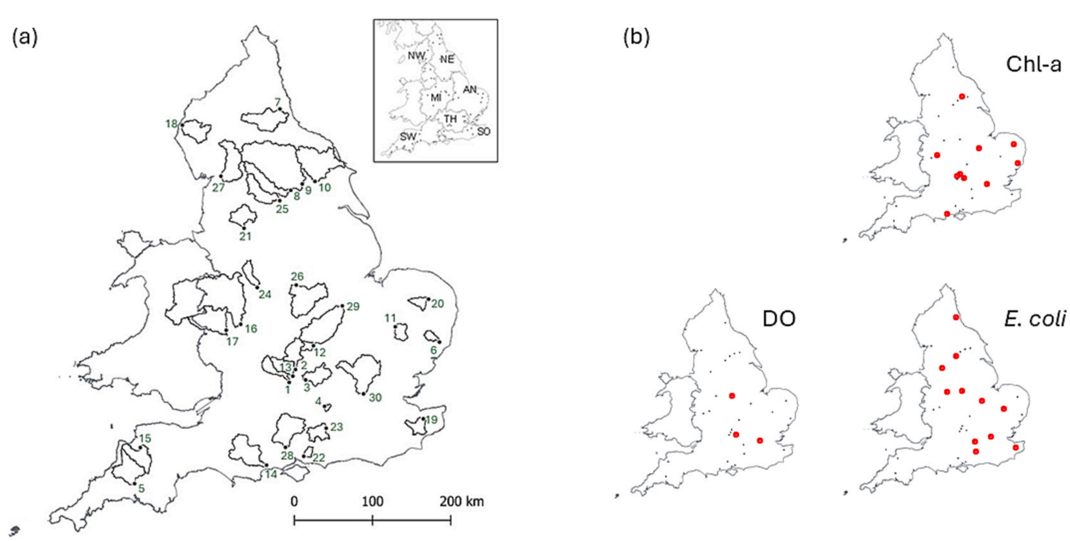

Fig. 2. (a) location map of 30 river sites for model application and their contributing catchment areas (see Table C1.1 for further details) (and inset regional map) (b) maps highlighting those sites currently violating water quality criteria when simulated by QUESTOR-YS.

measures (C), 2050 with landuse and water use mitigation measures (D). Details of the 2050 future scenarios are described below.

2.5.1. Changes by 2050 reflecting future climate projection and population growth

Future climate projections entail a likely shift in river flow, air temperature and solar radiation levels which are represented directly in QUESTOR-YS hourly time-series inputs. Given the emphasis on assessing policy impacts, a preliminary single analysis undertaken here includes a simple 1.5 °C increase in air temperature (all year) and 15 % reduction in flow (April-October). Whilst the simplification makes for highly uncertain projections, these change factors informed by UKCP18 summaries at national level (UK MetOffice, 2022) are assumed to best represent likely change by 2050 in summer conditions when water quality is vulnerable. The simplicity of the approach also enables the sensitivity of summer river water quality to increases in temperature and decreases in flow to be demonstrated clearly. In practice, the approach involved transplanting the observed 2004–18 patterns perturbed by the simple change factors. Any possible shift towards greater variance in climate drivers was not represented, and therefore 2050 scenarios may under-represent future stress to river quality. No significant future change in nutrient concentrations from diffuse sources was assumed, based on evidence from process-based modelling studies of the River Thames (Bussi et al., 2017). A 20 % increase in abstraction and effluent flow volumes was included to reflect a 20 % increase in population above 2008 levels (ONS, 2022) representing future stresses on water infrastructure in 2050. More detailed future projections should follow; the potential of specific approaches is discussed (Section 4.4), but is out of scope of the present study.

2.5.2. Mitigative actions

Two actions for adapting to adverse climate and population growth effects were explored: (a) current UK environmental policy stipulations (Defra, 2023) covering (i) reductions in nutrient pollution to represent environmentally-sensitive agricultural practice, namely a 40 % reduction of total P, total N, and suspended solids from agricultural sources, (ii) an 80 % reduction in total P from wastewater, and (iii) a 20 % improvement in water use efficiency, (b) establishment of additional riparian tree shade (25 % of the bankside area alongside all rivers to undergo additional tree planting), as guided by a UK government target for 16.5 % tree cover across England by 2050 (Defra, 2022). The effects of the actions were explored first in Scenario C by addressing those affecting landuse (planting trees and reducing agricultural pollution) and then in Scenario D adding those related to water resource management (reducing demand and improving wastewater P removal).

3. Results

3.1. Validation

For a subset of seven of the 30 catchments, weekly data from the UKCEH Thames Initiative (Evenlode, Windrush, Cherwell, Thame and Cut: Bowes et al., 2018) and monthly data from EA WIMS (Deben and Tamar) had previously been used for calibration of river-specific models. In the present study, no further calibration was undertaken, the intention being to support extensive national applications using a default set of rate constants defining the key biogeochemical processes (Tables A1.1 and B1.1).

Calculated as summaries of hourly data across the entire simulation period, comparison of 90th percentile Chl-a simulation with observations shows a model capable of successfully discriminating between productive and non-productive sites (Fig. 3: best fit line: y = 0.879x, r^2 = 0.65). Of the 30 sites modelled, 25 have sufficient observations at or near the gauging station. Most sites have over 100 observations within the 2004–18 period. Six of the unproductive sites have between 30–100 observations, two of which (Sites 7 and 12) only have data post 2018.

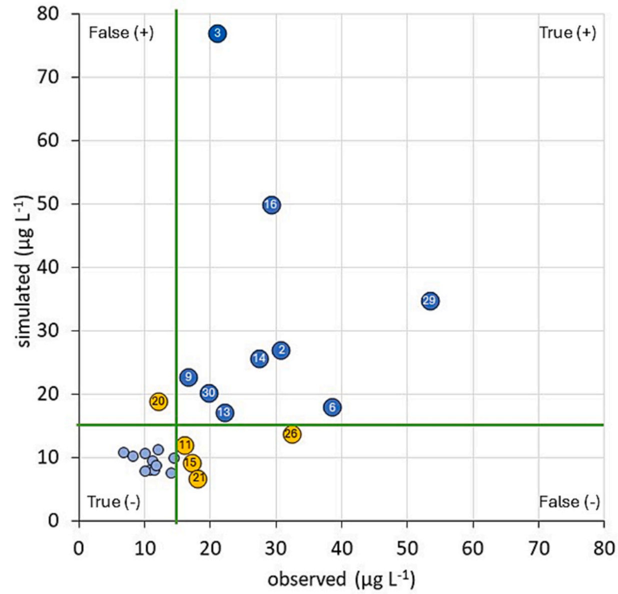

Fig. 3. Performance scatter plot of 90th percentile Chl-a concentrations; a 15 μg L^{-1} threshold determines bounds for a confusion matrix which estimates a predictive capability at 80 % (site numbers included for productive sites, false negative and false positive sites highlighted in orange). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Using a Chl-a threshold of 15 μg L^{-1} for primary productivity for water column diatoms (above which the model simulates instantaneous occurrences above 30 μg L^{-1} at frequency of more than one day per year), a confusion matrix approach shows 80 % of the 25 sites are predicted correctly. These comprise nine productive (true positive) and 11 non-productive (true negative) sites. Incorrect predictions are predominantly where the model fails to simulate a productive site (false negative: four sites) rather than vice-versa (false positive: one site).

An example time series plot of model performance against 10 years of weekly data at Site 2 (Fig. C1.1) demonstrates skill when simulating nutrient and temperature dynamics as well as the overall magnitude of diatom biomass in summer (90th percentile Chl-a). This is despite not explicitly attempting to capture acute pulses of nutrients in runoff during storms. Seasonal and interannual variability are largely captured for nutrients and water temperature, although underestimation of nitrate becomes more apparent in later years. Interannual variability in Chl-a is more challenging to capture. Whilst discrimination between productive and less productive years is mostly successful, the largest peak values are often underestimated. Wider implications of the performance are discussed later (Section 4.1).

3.2. Nationwide background vulnerability

Key indicators of dissolved oxygen, Chl-a and *E. coli* for all 30 sites are grouped by region (Fig. C2.1a-c). This highlights absence of clear regional differences.

3.2.1. Overall national situation

Across all 30 sites under present day conditions, the mean concentration values for 90th percentile Chl-a, 10th percentile DO and 90th percentile *E. coli* are 16.58 μg L^{-1}, 8.35 mg L^{-1} and 11.78 CFU mL^{-1} respectively. Total incidences (days per year) summed across all 30 sites of undesirable conditions for Chl-a, DO and *E. coli* are 333.4, 97.4 and 2711.8 respectively. For *E. coli*, we calculated an indicator of persistence, the percentage of the load emitted from the treated effluent remaining in the river downstream at the catchment outlet. The mean persistence across all sites at the catchment outlet is 43.7 %. The *E. coli* removal rate per kilometre of river is 3.32 %. This value of removal per unit river length indicates the ecosystem functioning provided by river channels across England.

3.2.2. Sites violating threshold levels

Dissolved oxygen below 6 mg L^{-1} at the 10th percentile level is simulated at two sites (Sites 26 and 30). Both these sites and Site 3 exhibit levels dropping below the level of aquatic biotic stress (5 mg L^{-1}). Three of the 30 sites are classified as eutrophic, with 90th percentile values exceeding 30 μg L^{-1} Chl-a. At 19 of the 30 sites, phytoplankton biomass never exceeds the 30 μg L^{-1} Chl-a threshold. Eleven of the 30 sites violate the 90th percentile level for *E. coli* (9 CFU mL^{-1}); occurrence is widespread except in the southwest region.

3.3. Impact of scenarios

The distribution of background vulnerability across the 30 sites, along with its potential changes under future conditions, is illustrated for indicators of phytoplankton biomass, dissolved oxygen and pathogens (Fig. 4).

3.3.1. 2050 Projection without ameliorative actions (Scenario B)

A deterioration in DO levels is projected. An additional river (Site 3) is expected to dip below 6 mg L^{-1} at 10th percentile level. Nevertheless, no further sites are projected to exhibit aquatic biota stress. Across the 30 river sites, the 10th percentile level is projected to deteriorate by 0.39 ± 0.13 mg DO L^{-1} by 2050. This approximates to a decrease of 4.7 %. The decrease is most severe in sites currently showing the lowest levels (e.g. 0.84 mg DO L^{-1} at Site 26 and 0.64 mg DO L^{-1} at Site 3). Most sites show very similar deteriorations of between 0.3 and 0.45 mg DO L^{-1}). Sites which are currently at risk of eutrophication (i.e. showing Chl-a above 30 μg L^{-1}) are expected to see a more rapid than average future decrease in 10th percentile DO (0.47 ± 0.16 mg L^{-1}). Many of these sites have large effluent components. Sites with high effluent dilution (less than 4 % effluent at Q95 flow) appear more resistant to future deoxygenation stress (0.31 ± 0.01 mg L^{-1}).

The total incidence of biotic oxygen stress conditions across all 30 sites is projected to increase from 97.4 to 181.9 days per year, an increase of 86.9 % (Fig. 5). Overall, conditions at sites already at appreciable risk of deoxygenation are projected to deteriorate considerably faster than those at other sites currently facing less stress.

In contrast to DO, Chl-a concentrations are projected to improve (decrease) slightly by 2050. Total eutrophic days across all sites will decrease from 333.4 to 286.6 per year (Fig. 5), a decrease of 14.0 %. Across the 30 river sites, the 90th percentile level is projected to decrease by 0.84 ± 2.06 μg Chl-a L^{-1} by 2050. The greatest improvements are in sites with currently high phytoplankton biomass. Any increases are very small (less than 0.3 μg L^{-1}), but these are at sites which are more vulnerable to future oxygen depletion.

Especially substantial increase in pathogen vulnerability is expected. This comprises a 27.5 % increase in the 90th percentile *E. coli* concentration, with attendant increases in persistence downstream of effluent sources. Frequency of conditions violating safe thresholds is much greater than that of DO and Chl-a (Fig. 5).

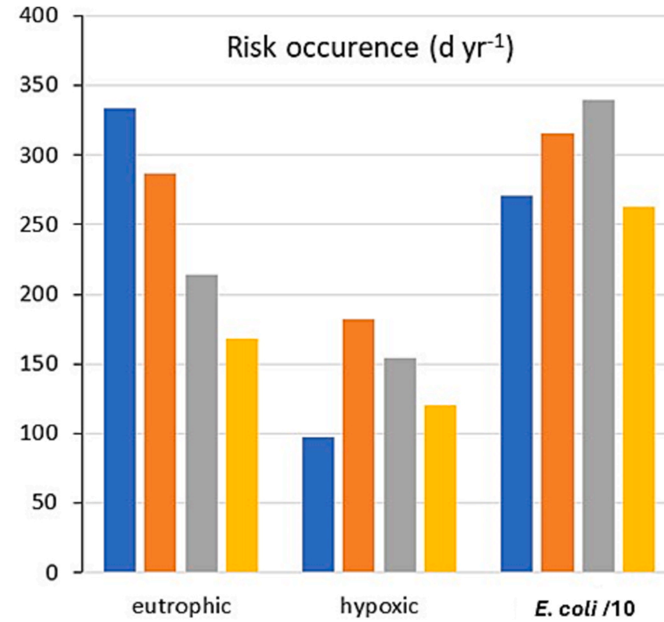

Fig. 5. Bar charts of risk occurrence summed across all 30 sites representing incidence above 30 μg L^{-1}, below 5 mg L^{-1}, and above 9 CFU mL^{-1} (note *E. coli* scale) respectively for eutrophic, oxygen stress and *E. coli* health risk.

3.3.2. 2050 Projection with ameliorative actions (Scenarios C and D)

The introduction of extra tree shading and large cut in nutrient inputs (Scenario C) reduces the prevalence of blooms and incidence of low oxygen. For phytoplankton growth, nutrient concentrations at most sites are in excess of levels likely to limit growth (Chapra, 2008), even under

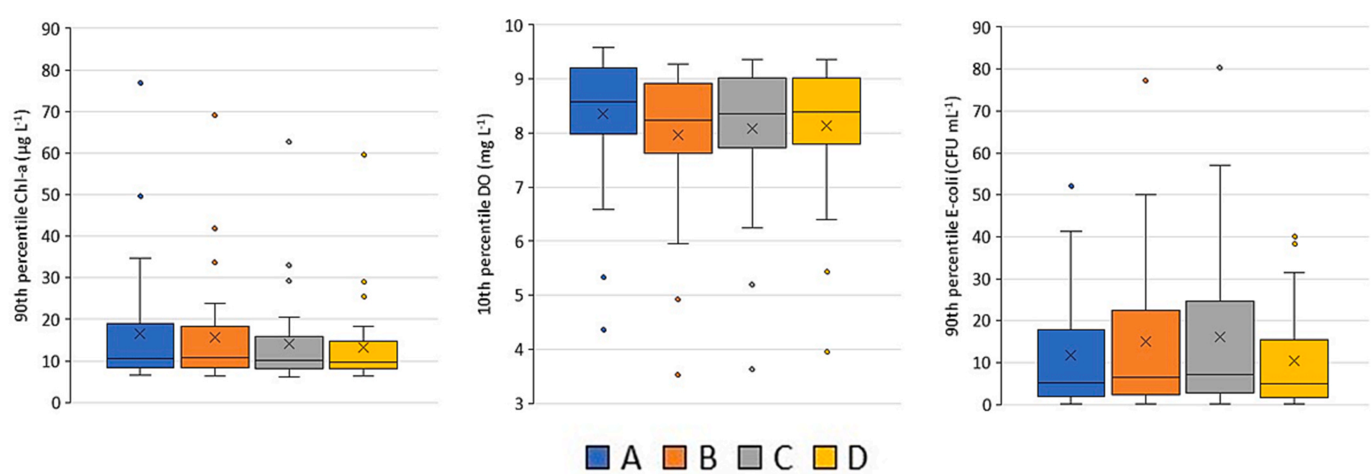

Fig. 4. Box-whisker plots for 30 river sites showing change in distribution of background risk summary statistics between present day (A), future conditions under population growth and climate change (B), future with landuse mitigation measures (C), and future with all mitigation measures (D) for Chl-a, dissolved oxygen, and *E. coli*.

future reductions, whereas shading lowers water temperature and reduces incident light, effectively suppressing phytoplankton and preventing oxygen levels from falling to stressed levels for biota (Hutchins et al., 2010; Hutchins et al., 2018). In contrast, elevated future *E. coli* concentrations are projected to increase further under mitigation. This is because an increase in tree shade reduces light penetration and lessens the suppressive effect of light inhibition on pathogen abundance.

Individual sites show a range of responses to future stressors and to mitigative actions. Expected percentage change from present day (Scenario A) to future without mitigation (Scenario B) and with mitigation (Scenario D) is compared (Fig. 6). Across almost all sites for all three indicators, mitigation is successful in reducing harmful impacts of future change. Compared to change in DO and *E. coli*, change in phytoplankton biomass in future appears more scattered and variable from site to site. Most sites with low urban influence show increased biomass under future conditions. For DO, deterioration is widespread and not greatly offset by mitigation. Those sites already suffering from low DO are most sensitive to future changes. Sites with higher amounts of effluent as a volumetric proportion of river flow appear more sensitive to change. Under future climate and population growth, large increases in *E. coli* are expected at all sites, especially at Site 26 (by almost 50 %). However, mitigation is likely successful in reducing *E. coli* levels well below present day levels. No regional variation in response of the three indicators is evident.

4. Discussion

The QUESTOR-YS model captures wastewater-emitted pathogen vulnerability under low flow conditions, and identifies transient periods (events) when thresholds triggering eutrophic or hypoxic conditions are crossed. By simulating river channel transformation processes it can quantify important fluxes such as river ecosystem respiration and pathogen degradation that control water quality status. Simplifications adopted in QUESTOR-YS mean it cannot be expected to simulate hourly dynamics for multiple parameters as accurately as a detailed model application. However, as underpinned by a tested approach in English rivers, we argue that the model reliably quantifies the physico-chemical controls on background river quality vulnerability. Because it is applied at 30 sites with accompanying long-term records of macroinvertebrates (ChemPop), the approach can potentially disentangle the relative importance of top-down biotic factors alongside physico-chemical factors. In the following sections, we highlight various key aspects related to phytoplankton biomass and eutrophication (Section 4.1), and water purification fluxes (pathogen removal and oxygen supply) in river channels (Section 4.2). Findings are illustrated with more detailed assessments at three sites within the Thames region (Windrush (1) Cherwell (2) and Thame (3)). In Section 4.3 we put the results in context of other studies and discuss implications for decision-making. Finally, future recommendations are made (Section 4.4).

4.1. Model performance: Phytoplankton biomass and higher trophic levels

Due to the preponderance of intensive agricultural land use and high levels of urbanisation, phytoplankton growth in English rivers is rarely limited by nutrients, but is instead controlled by physical factors such as light availability and water temperature (Bowes et al., 2024). Whilst QUESTOR-YS simulations reflect this situation and can successfully discriminate between eutrophic and oligo-/*meso*-trophic rivers (Fig. 3), capability to simulate magnitude of specific phytoplankton blooms is more limited (e.g. Fig. C1.1). Choice of parameter values was mostly guided by previous detailed studies in the Thames. The approach relies on these being sufficiently representative elsewhere. The limitation in capability is unsurprising, and would be even if local calibration were to be undertaken (Waylett et al., 2013). Local calibration would be unlikely to make an appreciable difference because temperature-controlled rates of reaction should be broadly similar in any river. Across the 15-year period, biomass is overestimated in some cases (e.g. Site 3) and underestimated in others (e.g. Site 6).

Hydrological simplifications in QUESTOR-YS can introduce biased estimates. For example, although local standing waters were not considered in model setup, they can provide inocula (Krajenbrink et al., 2019). The influence of standing waters such as canals plausibly explains variations in bloom magnitude across Thames tributaries (Bowes et al., 2012). Further afield, at Site 29 for example, such influences may account for QUESTOR-YS underestimation of eutrophication vulnerability (Fig. 3).

The model successfully discriminates between the Windrush where blooms are scarce and nearby sites where large blooms can occur (Cherwell and Thame). Of these three sites, macroinvertebrate community abundance and complexity is much the highest in the Windrush in all years (Fig. C2.2). This is indicative of a healthy and resilient biotic structure in the Windrush, functioning effectively across trophic levels and supported by macrophytes and phytobenthos. The interannual macroinvertebrate profiles highlight where local knowledge is lacking. In the Cherwell and Thame, it is unclear how phytoplankton and macroinvertebrate abundance co-influence each other. In the Thame, phytoplankton biomass is overestimated in most years, yet when the model performed best in a year with high Chl-a observations (2009),

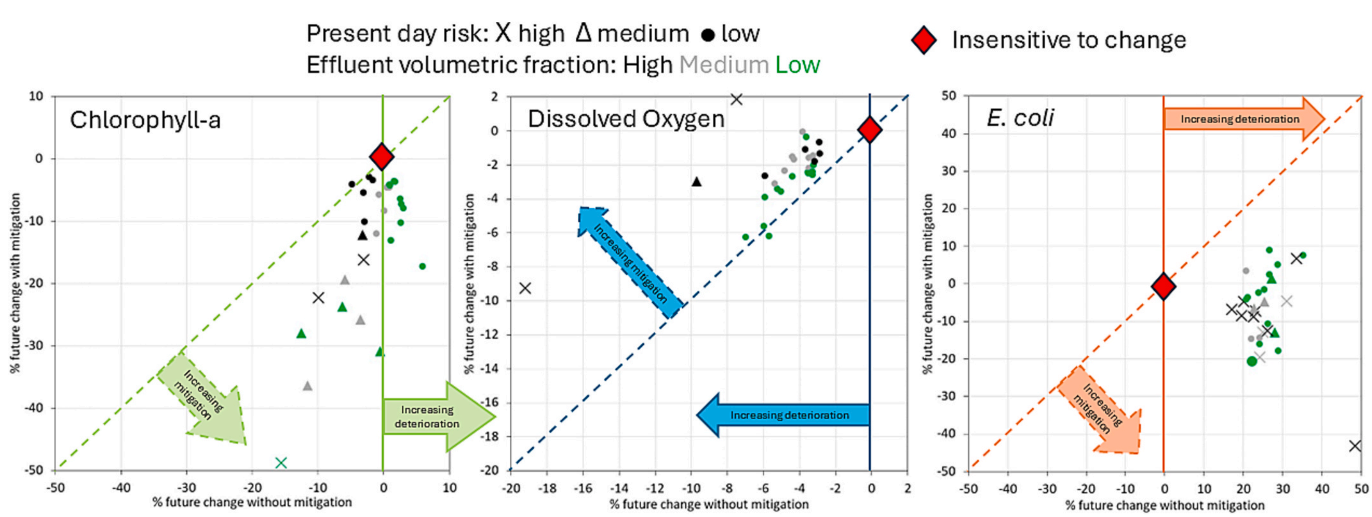

Fig. 6. Scatter plots of future change in background risk at all 30 sites for 90th percentile Chl-a, 10th percentile DO and 90th percentile *E. coli* (identified by present day risk level and by effluent volumetric contribution), showing directions of increasing magnitudes of future deterioration and related net mitigation.

gastropod populations (known grazers of phytoplankton (Lv et al., 2022)) were also at their most abundant. Overestimation could also be caused by other factors, such as enhanced fungal and bacterial parasitic stress. More generally at national scale, interpretation is hampered by the restricted availability of long-term observations of those grazers which directly constrain phytoplankton biomass, such as bivalve filter feeders and zooplankton.

4.2. Ecosystem functions: role of river channels in water purification

The contribution of river systems to delivery of ecosystem services is increasingly recognised and valued (Petsch et al., 2023). The QUESTOR-YS model quantifies river ecosystem functioning and identifies differing capabilities of channel environments to deliver water purification and response to future change. For example, on average across all rivers, pathogen removal per unit channel length is projected to decrease from 3.32 % km^{-1} (Scenario A) to 2.70 % km^{-1} (Scenario B), yet this can be offset by mitigation (3.53 % km^{-1} under Scenario D). Regionally, removal appears more efficient in south-eastern areas (Fig. C2.1d, especially at Sites 4 and 22, and generally high in Anglian region). This does not appear consequent of between-region variations in climatic factors, but rather of topographic factors. Most *E. coli* is removed near the source, especially in slower flowing rivers, hence sites with highest removal rates (>5% km^{-1}) occur in small catchments with low river gradients.

Net ecosystem metabolism (NEM) and the overall net DO supply is lower (0.76 mg m^{-2} hr^{-1}) in a vulnerable river (Thame: Site 3) than in nearby apparently unimpacted rivers (4.65 mg m^{-2} hr^{-1} at Site 1 and 1.76 mg m^{-2} hr^{-1} at Site 2). This is largely attributable to a smaller supply from aeration (controlled by river flow and channel gradient) rather than a greater NEM flux (−0.50 mg m^{-2} hr^{-1} at Site 3 compared to −7.53 mg m^{-2} hr^{-1} at Site 1 and −1.71 mg m^{-2} hr^{-1} at Site 2). If deoxygenation vulnerability is considered in isolation, this suggests that managing river hydrodynamics, for example via artificial reaeration at dams, is more effective than limiting supply of degradable organic matter. In practical context, management considerations will cover multiple net zero issues, notably suppression of greenhouse gas emissions and energy use.

4.3. Response to future change

4.3.1. Comparison with other studies

Our analysis provided snapshot estimates of present day and future water quality. Assuming progressive linear trends in stressors and responses, the future deterioration of mean DO concentrations across the 30 sites is expected to be 0.098 ± 0.025 mg L^{-1} per decade. This exceeds values for USA and Central Europe of 0.068 ± 0.028 and 0.051 ± 0.038 mg L^{-1} per decade respectively (Zhi et al., 2023). We found three of 30 rivers to be at risk of falling below levels of biotic stress (< 5 mg DO L^{-1}). Zhi et al (2023) found smaller proportions; 35 of 580 rivers in the USA and 0 of 216 rivers in Central Europe (Austria/Germany) failed to meet this criterion. In the present study, the river most depleted in DO (Site 26) is projected to experience 14.8 more days of biotic oxygen stress per decade in the future. In contrast, Zhi et al. (2023) did not find any USA rivers with future deterioration accelerating at a rate of more than nine days per decade.

Future population growth pressures, included in the present study, might drive higher rates of future deoxygenation than those in other studies solely considering climate influences. Nevertheless, five of our rivers (Sites 5, 17, 18, 22, and 27) have a very low effluent dilution factor at Q95 (of less than 4 %). These have minimal population growth pressures; any change is predominantly attributable to climate factors. Here, deterioration is very similar between sites (0.075–0.080 mg DO L^{-1} per decade). These declines are still more severe than those reported for USA or Central Europe (Zhi et al., 2023).

Bussi et al. (2016) forecast little change in mean diatom biomass in the Thames across a 25 year forward projection of climate drivers. Our present study found similarly small changes in tributaries of the Thames (Sites 1, 2, 3, 4, 13, and 23).

In Sweden, river pathogen modelling across terrestrial and aquatic domains suggests *E. coli* concentrations will increase under climate change at the 95th percentile level (by over 50 %) but not at the 50th percentile level (Bergion et al., 2025). This represents a larger deterioration than our projections, which indicated a 29.2 % mean deterioration in the 95th percentile. Bergion et al. (2025) identified scope for offsetting these changes through technological advances in water treatment and land use change. Similarly, our study suggests future regulatory measures, if fully implemented, would be successful in suppressing future increases in risk.

4.3.2. Implications for decision-making

The model predicts substantial future DO declines in English rivers, even with mitigation considered. This negative prognosis is tempered by current levels being for the most part sufficient for biota and the likelihood that no additional sites will become at risk of oxygen stress. However, the selected sample of rivers masks the full picture, as none of the 27 rivers currently complying for DO have concentrations sufficiently close to vulnerable levels. We conclude that other English rivers currently showing 10th percentile DO of 7.0 ± 0.25 mg L^{-1} will likely be at risk of future stress. It is recommended that interventions, such as riparian tree planting, be prioritised on these potentially vulnerable rivers, especially those which experience diatom blooms. Sites exhibiting Chl-a above 30 μg L^{-1} have higher projected future DO declines (0.12 ± 0.04 mg L^{-1} per decade) than the overall average.

Characterising sites with a single percentile level indicator over multiple years inevitably masks details. Precautionary management should focus on protection under the most vulnerable conditions. Between sites, there is considerable uniformity in year-to-year variations in background vulnerability, which is determined by inter-annual hydro-climatic differences. Lowest DO was simulated in 2018 at 26 of the 30 sites (Fig. C1.3) when a warm and dry summer was noteworthy. Similarly, all productive sites (with 90th percentile Chl-a above 15 μg L^{-1}) were simulated to have largest phytoplankton blooms in 2011. Inter-annual variability of 10th percentile DO is ± 0.3–0.5 mg L^{-1} at most sites. Site 29, currently not at risk, may experience oxygen stress in future in approximately one in every four years. Currently, Site 3 shows DO fluctuations greater than typically expected (±0.8 mg L^{-1}) and appears vulnerable to adverse consequences of future changes in roughly three of every four years. More generally, the need for hourly-resolution simulation to diagnose extreme hypoxic events (DO < 2.0 mg L^{-1}) is underlined, as these are especially acute, typically complete in a few hours and very rarely last more than a week (Blaszczak et al., 2023).

For pathogens, enhanced threats posed by future changes and benefits achieved by measures to offset those threats are clear and consistent across all sites. The overriding factor controlling future river *E. coli* concentrations is change in wastewater effluent load. Aside from the model only considering *E. coli* sources from treated effluent, there is much uncertainty in the levels of removal of *E. coli* in individual wastewater treatment plants and the resultant effluent concentrations. This uncertainty extends to whether these concentrations would substantially change under improved water use efficiency; the assumption made in the model applications was of no significant change.

The situation with phytoplankton is more complex. At eutrophic sites, occurrence of blooms (>30 μg L^{-1}) is simulated in most years. At most sites, bloom incidence is predicted to decrease in future (Scenario B). This is most likely because optimal water temperature conditions will be reached earlier in the year when river flows are still high. Drier conditions in summer when longer channel residence times give greatest potential for bloom development will increasingly coincide with when rivers are too warm for diatoms. Concerns persist regarding whether diatoms will be succeeded by harmful cyanobacteria under such conditions. Between-site variation in response to future changes is larger for

Chl-a than for DO and *E. coli* indicators (Fig. 6). This highlights the importance of setting local intervention strategies, especially in sites with lower effluent contributions where blooms are likely to increase in future.

4.4. Recommendations

4.4.1. Refinements to model structure and scenario specification

Model applications should be extended to additional sites to increase confidence in the selection of rivers being representative and provide robust summaries at the regional level. Caution is needed when using the overall background vulnerability of phytoplankton blooms, low oxygen and pathogen persistence as proxies for observations. We should not lose sight of opportunities to improve model structure, and detailed model applications will often be more appropriate. Low DO and deoxygenation risk are strongly governed by local factors. These, such as local river hydrodynamics, riparian conditions and channel control structures should be included in applications focused on local river basin management objectives (Hutchins et al., 2021). Further refinements can also be informed by large-scale analyses, for example those that identify spatial variability in decomposition of cellulose organic matter (Tiegs et al., 2024). These can help constrain uncertainty in heterotrophic respiration rate, which is likely spatially variable and determined by riverbed sediment properties (Hutchins et al., 2020). Similarly, detailed analysis can identify site-specific vulnerability or resilience to phytoplankton bloom development (Bowes et al., 2024).

Compared to Chl-a and DO, river observations of *E. coli* are scarce. Therefore, uncertainties in model process representation are much greater. Outside of hosts, there is evidence for survival and growth of *E. coli* in riverbed sediment (Droppo et al., 2009). However, identifying how re-suspension processes might be best parameterised is unclear and requires additional primary research. The pathogen sub-model in QUESTOR-YS depends on reliable simulations of water temperature, suspended solids concentration and phytoplankton biomass. Although this introduces additional uncertainty, it facilitates scenario analysis which would otherwise be unattainable.

In parallel with model structural improvements, more sophisticated scenario analyses should be undertaken. The summary results for future change (Fig. 6) are best viewed as preliminary exercises to give broad indications of site sensitivity. Currently, scope for improvement appears to lie in four areas: (1) representing targeted land use interventions in tandem with more detailed representations of diffuse pollution (e.g. InVEST: Redhead et al., 2018) (2) including new digital datasets of individual trees (Forest Research, 2025) to guard against possible underestimation of light attenuation by riparian trees which currently solely considers larger woodland patches and linear features, (3) incorporation of regional-specific projections of population change (Rees et al., 2012), (4) using ensembles of future hydro-climatic projections to account for uncertainty, local variation, and change in weather patterns (e.g. eFlag: Hannaford et al., 2023). Representation of future impact of larger storm events on water quality should also be investigated, such as increased organic matter loadings to rivers and alteration of nutrient dynamics.

4.4.2. Arising opportunities

Four examples are highlighted for future applications of the QUESTOR-YS approach.

Hourly simulations of pathogen vulnerability can be incorporated into near-real-time forecasting systems to better inform the public of recreational risks at popular inland river bathing waters. They can also be used to identify the viability of additional proposed sites. As we pinpoint many non-compliant sites, even without considering intermittent untreated effluent discharges, our results show that identifying new inland bathing water sites to satisfy UK government aspirations will be challenging.

Quantification of river greenhouse gas emissions under national-scale IPCC reporting requirements can be supported. Riverine N_2O emissions through microbial denitrification are of increasing concern (Beaulieu et al., 2011). QUESTOR-YS can support investigations by quantifying denitrification fluxes and identifying periods of low oxygen concentrations, during which the proportion of gaseous N emissions as N_2O is likely greater than in normal conditions.

As it can quantify a range of water purification ecosystem functions, QUESTOR-YS provides key information to facilitate valuation studies by environmental economists (e.g. via public willingness-to-pay surveys). Combining these techniques can improve societal awareness of conditions and processes in aquatic systems that are currently overlooked, particularly those related to river biodiversity.

Of greatest potential are foundations provided for more comprehensive assessments of freshwater macroinvertebrate data. Errors in simulating phytoplankton biomass may be diagnostic of fluctuating and uncertain levels of grazer activity, in turn likely related to macroinvertebrate populations (Section 4.1). Extending and deepening our analysis to couple QUESTOR-YS simulation with macroinvertebrate abundance data across all 30 sites could uniquely disentangle highly complex effects across trophic levels. Output from QUESTOR-YS can support macroinvertebrate modelling by characterising inter-annual and short-term variability in key attributes (e.g. primary productivity, oxygen condition, water temperature, light penetration, river velocity and water level). Summaries of hourly resolution simulations and estimates of extreme values not captured in routine surveys can potentially inform and refine existing statistical approaches for modelling macroinvertebrate diversity and abundance (Qu et al., 2023; Johnson et al., 2025; Sadykova et al., 2025, submitted). To underpin investigation of wider biotic responses to key future stressors, additional biotic processes such as Lotka-Volterra predator–prey relationships (Chapra, 2008) can be incorporated into process-based models, either within QUESTOR-YS itself or in bespoke models of macroinvertebrate abundance.

5. Conclusion

Results provide a broad overview of background vulnerability in English rivers. Of 30 rivers tested, modelling reveals 11 are experiencing pathogen risk, 10 are at risk of eutrophication, and three at risk of oxygen stress. We reflect on the questions posed at the end of Section 1. QUESTOR-YS simulations capture spatio-temporal variability in water quality with sufficient skill to be of value to decision-making processes (Q1). This is despite our findings highlighting the complex nature of biotic interactions and local sources of phytoplankton (Q2). Urban extent was found to be a key control for both background vulnerability and sensitivity to change (Q3). Regional variations in water quality appear largely driven by topographic and geographic attributes rather than factors directly related to climate drivers (Q4). In contrast, year-on-year variation, reflective of meteorological influence, is consistent across sites. Sites in urbanising basins in drier regions with slow flowing rivers and long channel residence times are the most sensitive to changes in stressors. The more sensitive sites also appear to have greater capacity to recover faster than others in response to mitigative actions. Land management actions alone will provide little benefit; for pathogens the situation will worsen. A full set of proposed interventions should effectively protect rivers from increases in phytoplankton blooms and pathogen outbreaks, but may be less effective at reversing declines in DO.

CRediT authorship contribution statement

Michael Hutchins: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Emma Gardner:** Writing – review & editing, Funding acquisition. **Lisa Gechelle:** Writing – review & editing, Visualization, Methodology. **Andrew Johnson:** Writing – review & editing, Resources. **Yueming Qu:** Writing – review & editing, Visualization, Validation, Methodology, Formal analysis. **Dinara Sadykova:**

Writing – review & editing. **Michael Bowes:** Writing – review & editing, Resources. **Daniel Read:** Writing – review & editing, Funding acquisition. **Claire Robertson:** Writing – review & editing, Resources.

Declaration of competing interest

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

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2025.134713.

Data availability

Data will be made available on request.

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