

Impacts of climate change, land-use change and phosphorus reduction on phytoplankton in the River Thames (UK)

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Abstract

Potential increases of phytoplankton concentrations in river systems due to global warming and changing climate could pose a serious threat to the anthropogenic use of surface waters. Nevertheless, the extent of the effect of climatic alterations on phytoplankton concentrations in river systems has not yet been analysed in detail. In this study, we assess the impact of a change in precipitation and temperature on river phytoplankton concentration by means of a physically-based model. A scenario-neutral methodology has been employed to evaluate the effects of climate alterations on flow, phosphorus concentration and phytoplankton concentration of the River Thames (southern England). In particular, five groups of phytoplankton are considered, representing a range of size classes and pigment phenotypes, under three different land-use/land-management scenarios to assess their impact on phytoplankton population levels. The model results are evaluated within the framework of future climate projections, using the UK Climate Projections 09 (UKCP09) for the 2030s. The results of the model demonstrate that an increase in average phytoplankton concentration due to climate change is highly likely to occur, with the magnitude varying depending on the location along the River Thames. Cyanobacteria show significant increases under future climate change and land use change. An expansion of intensive agriculture accentuates the growth in phytoplankton, especially in the upper reaches of the River Thames. However, an optimal phosphorus removal mitigation strategy, which combines reduction of fertiliser application and phosphorus removal from wastewater, can help to reduce this increase in phytoplankton concentration, and in some cases, compensate for the effect of rising temperature.

Keywords: phytoplankton modelling; climate change; land use change; river water quality; River Thames; scenario-neutral approach

1 Introduction

Phytoplankton blooms are a potential threat to the use of water, especially for drinking and irrigation water supply, fisheries and recreational purposes (Paerl and Huisman, 2009). For example, cyanobacteria can produce harmful toxins (Carmichael, 1992). Furthermore, increasing nutrient loading, warming climate and growing CO₂ emissions are likely to favour cyanobacterial expansion in a broad range of aquatic ecosystems (Paerl and Huisman, 2009). However, the effect of environmental change on phytoplankton blooms and its consequences on water quality has only been addressed recently for lakes (Elliott, 2012; Thackeray et al., 2008), and not yet tackled for river systems, except through some qualitative description of potential impacts by Arnell et al. (2015), Johnson et al. (2009) and Whitehead et al. (2009). These studies agree that phytoplankton are likely to increase their concentration above current levels in the future (Johnson et al., 2009), due to lower flows, reduced velocities and higher water residence (Whitehead et al., 2009), also reducing oxygen levels in rivers (Whitehead et al., 2009). An important step forward would be to develop a quantitative approach to assess the effects of environmental change on phytoplankton populations in river systems. This could include the impact of both climatic and human stressors, such as variations in precipitation and temperature, but also the combined effect of land use/land management and climate change. For example, the expansion of intensively-cultivated agricultural land cover is likely to increase in phosphorus concentrations (Crossman et al., 2013) and thus improve conditions for phytoplankton growth.

Phytoplankton populations can be influenced by climate, including precipitation, temperature and solar radiation. Precipitation and temperature firstly act on water discharge, which is widely acknowledged to be a dominant factor influencing phytoplankton in river systems (Lack, 1971; Malone, 1991). The largest phytoplankton blooms always occur during periods of low flows and reduced velocity, when the residence times are longer (Bowes et al., 2012). Furthermore, seasonal rises in water discharge are often coincident with a decline in phytoplankton abundance (Lack, 1971). Air temperature also strongly influences water temperature (warmer air means warmer water). Solar radiation is also a key factor for phytoplankton development (Whitehead and Hornberger, 1984) which is likely to vary in the future due to climate change and anthropogenic factors (Stanhill and Cohen, 2001).

The purpose of this study is to evaluate the combined impact of environmental stressors on phytoplankton populations in a river system, through the use of a phytoplankton model previously implemented (Whitehead et al., 2015a), whose calibration was based on a detailed flow cytometry dataset (Read et al., 2014). Specifically, the effect of climate change, land-use change and phosphorus reduction measures on the Thames's phytoplankton populations are quantified and discussed. The River Thames (UK) case study was chosen because of its high relevance for water supply to fourteen million people (Whitehead et al., 2013) and as a wastewater recipient from almost four million inhabitants (Kinniburgh and Barnett, 2009). In this study, we adapted the "bottom-up"-type scenario-neutral approach (Prudhomme et al., 2010) to assess the impact of climate change, land-use change and phosphorus reduction strategies on phytoplankton biomass and community composition. This approach consists in an analysis of the model sensitivity to climatic stressors, such as precipitation and temperature. Climatic alterations were applied on time series of observed precipitation and temperature. In particular, uniform changes in precipitation and temperature were found to exert stronger control on phytoplankton than other climatic alterations (Lack, 1971; Malone, 1991; Bowes et al., 2012), such as changes in solar radiation. For this reason, manually-altered time series of precipitation and temperature were considered in this study and were used to drive a hydrological and water quality model (the INCA hydrological and water quality model; Whitehead et al., 1998) under different scenarios of land-use (Castellazzi et al., 2010) and mitigation strategies (Crossman et al., 2013). Then, the results of the hydrological and water quality model (water flow and phosphorus concentration) were used to drive a phytoplankton model (Whitehead et al., 2015a), and climate-altered phytoplankton abundance series were obtained for each of the considered land-use and mitigation scenarios. This results were put into context of future climatic scenarios for the 2030s (Murphy et al., 2009) and discussed.

2 Methods

2.1 Study area

The River Thames is located in the south of England (Figure 1). The non-tidal Thames catchment (9,948 km²) includes a part of the UK's capital, London, as well as other major urban areas such as Swindon, Oxford, Slough, Maidenhead and Reading (Figure 1). The Thames provides drinking water to around 14 million people (Whitehead et al., 2013). The climate is temperate with oceanic influence. Low flows take place in summer and floods usually during autumn to spring. Mean annual precipitation varies in space from 715 to 745 mm (Bowes et al., 2012), mean daily air temperature is 11 °C (Crossman et al., 2013), mean summer temperature is 16.4°C and mean winter temperature is 4.6°C.

The lower Thames is highly urbanised, while the uplands are characterised by predominant arable land and pasture land use (Bowes et al., 2014). The River Thames is strongly impacted by human population, with 36 major sewage treatment works (population equivalent of 2,705,600, Kinniburgh and Barnett, 2009) discharging into the river system. Furthermore, up to 36 locks are located along its course. This increases the residence time, allowing the phytoplankton population to reach potentially very high concentrations (Lázár et al., 2012). Some of the tributaries are also connected to extensive canal systems, which have slower flows and higher residence time (i.e. more favourable conditions for phytoplankton growth), resulting in maximum chlorophyll-a concentrations that are six times higher than rivers not connected to canals (Bowes et al., 2012). The River Thames is considered particularly vulnerable to phytoplankton blooms, with its gentle slopes and relatively slow flow (also slowed by the presence of several weirs and locks), although there is still considerable uncertainty over the magnitude of future phytoplankton concentrations and their sensitivity to climate change (Johnson et al., 2009).

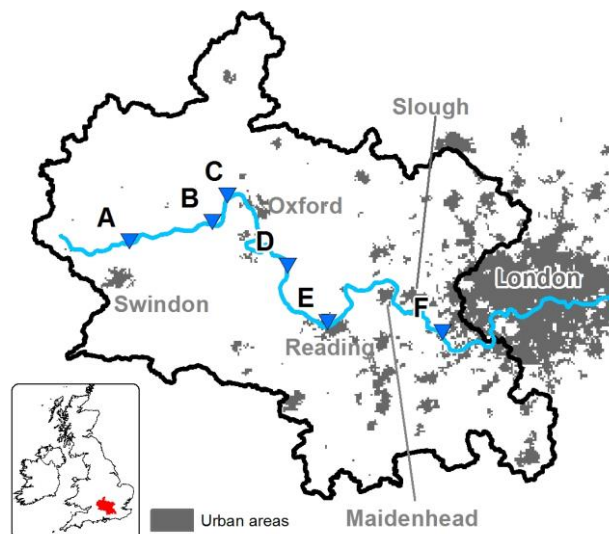


Figure 1 – Location of the study catchment. Reach sections are indicated with triangles (A: Hannington, B: Newbridge, C: Swinford, D: Wallingford, E: Sonning, F: Runnymede).

The five reaches of the River Thames considered in this study (Table 1, Figure 1(Whitehead et al., 2015a) are spread along 158 km of the River Thames. All associated sections were monitored since 2011 as part of the Centre for Ecology and Hydrology's Thames Initiative Research Platform (Bowes et al., 2012) with a weekly frequency. Samples were analysed for water temperature, suspended sediment, several phosphorus and nitrogen species (total phosphorus, soluble reactive phosphorus, nitrate, nitrite and ammonium among others) and dissolved silicon concentration, as well as five phytoplankton groupings (diatoms, chlorophytes, picoalgae, cyanobacteria and *Microcystis*-like cyanobacteria) using flow cytometry. The groupings were identified based on fluorescence (chlorophyll, phycocyanin and phycoerythrin) and size characteristics (Read et al., 2014). The flow cytometry data

of these five groups were used to calibrate and validate the phytoplankton model developed in a previous study (Whitehead et al., 2015a).

Table 1 – Description of the model reaches (from Whitehead et al., 2015).

Reach	Upstream section	Downstream section	Length (m)	Reach drainage area at downstream section (km ²)
1	Hannington	Newbridge	28,000	1558
2	Newbridge	Swinford	10,800	1625
3	Swinford	Wallingford	39,300	4178
4	Wallingford	Sonning	25,300	4600
5	Sonning	Runnymede	55,000	8156

2.2 Models

2.2.1 PERSiST

PERSiST (Futter et al., 2014) is a catchment-scale rainfall-runoff model which is specifically designed to provide input series for the INCA family of models. It is a semi-distributed model, i.e. the different meteorological variables and model parameters can be defined separately for each sub-catchment or each river reach (as opposed to a lumped model, where all the variables are lumped over the whole catchment). It is based on a tank structure, where a user-specified number of inter-connected tanks can be used to represent different hydrological processes, such as snow melting, direct runoff generation, soil storage, aquifer storage and stream network movement. The highly-flexible structure of this model allows the user choosing the number of tanks, which define the hydrological response. Tanks can store water, return it to the atmosphere through evapotranspiration, transfer it to other buckets or to surface waters. Tanks can be conceptualized as dual-porosity reservoirs in which water is divided into stagnant and freely draining fractions. In this study, three tanks were used, conceptualising the direct runoff, sub-superficial flow and base flow responses respectively.

The model inputs are daily precipitation and air temperature series averaged over the catchment. For this study, this was obtained as spatial average of all the UK Met Office daily precipitation and temperature stations within the River Thames catchment. Some of the outputs are water discharge at the catchment outlet, evapotranspiration, flow components (direct runoff, sub-superficial flow and base flow), SMD (the difference between the current depth of water and the water holding capacity) and HER (the fraction of precipitation which contributes to runoff). PERSiST model calibration was achieved by comparing modelled water discharge with observed flow data. In this study, the calibrated PERSiST model of the River Thames catchment was used to produce altered series of SMDs and HERs using altered time series of precipitation and temperature as input. More information about the PERSiST model application to the River Thames catchment can be found in Futter et al. (2014).

2.2.2 INCA

The INCA model (Whitehead et al., 1998b) is a process based dynamic hydrological and water quality model developed to reproduce land and in-stream biogeochemical processes. In particular, in this study, the INCA-P model was used (Wade et al., 2002). This model is especially designed to reproduce the hillslope and river channel phosphorus dynamics. The model simulates the spatial variations in phosphorus export from different land uses using a semi-distributed representation, thus accounting for the impacts of different management practices, such as fertiliser application and wastewater discharge. The model equations are divided into land phase and in-stream. The land phase sub-model includes a simplified representation of direct runoff, soil water and groundwater flows and the soil processes that involve phosphorus. These processes include mineralisation, microbial decomposition, immobilisation, plant uptake and conversion of readily available phosphorus to firmly bound (and vice versa). The in-stream sub-model is a multi-reach component that routes water and phosphorus downstream. Phosphorus uptake by macrophytes and epiphytes is taken into account, as well as sorption/desorption

and interactions with bed sediment. INCA-P simulates organic and inorganic phosphorus concentrations in soils, and total phosphorus (dissolved plus particulate phosphorus) concentration in the river channel flow. Stream water temperature is modelled as a linear function of the air temperature.

The required inputs (daily time series) are precipitation, temperature, SMD and HER, the latter produced by the PERSiST model. The model also requires phosphorus inputs (atmospheric deposition, fertiliser and manure application and wastewater discharge) and spatial data describing the major land uses. For the Thames, proportions of urban, intensive agriculture (arable and horticulture), non-intensive agriculture (grassland), wetlands (heath, bog and water bodies) and forest (both conifer and deciduous) were identified from the UK 2007 Land Cover Map (Smith et al., 2007). For each land use, a phosphorus daily application rate was defined, based on fertiliser usage and number of grazing animals, using statistics from the Department for Food and Rural Affairs (DEFRA) and literature values (Johnes and Butterfield, 2003). A detailed description of the INCA-P parameterisation and model application to the River Thames catchment is provided in Crossman et al. (2013) and Whitehead et al. (2013). The model outputs include several hydrological and water quality variables. In this study, we used the model developed and calibrated by in Crossman et al. (2013) and Whitehead et al. (2013). The model parameters were slightly adjusted in order to reproduce accurately more recent total phosphorus concentration values measured as part of the Centre for Ecology and Hydrology's Thames Initiative Research Platform (Bowes et al., 2012). The model calibration/validation was satisfactory, in line with the results provided by Crossman et al. (2013). In this study, water discharge, water temperature and phosphorus concentration were used to drive the phytoplankton model.

2.2.3 Phytoplankton model

The phytoplankton model used in this study is a mass-balance model applied on a single river reach (Whitehead and Hornberger, 1984; Whitehead et al., 2015a). This model takes into account phytoplankton growth and death and the following controlling processes: water temperature, phosphorus concentration in water, solar radiation, or self-shading and silicon concentration (only for the diatom group).

The phytoplankton concentration in each reach is described by Eq. 1:

$$\frac{dx}{dt} = \frac{x_{IN}-x}{T_c} - k_{death}x + k_{growth}x \cdot CF_T \cdot CF_P \cdot CF_{RAD} \cdot CF_{SS} \cdot CF_{Si} \quad \text{Equation 1}$$

where x_t is the live phytoplankton concentration for a specific phytoplankton group (cells ml⁻¹) at the time-step t , x_{IN} is the upstream phytoplankton concentration flowing into the reach (cells ml⁻¹), T_c is the residence time (s) (Whitehead et al., 1998a, 1986), k_{death} is the maximum death rate at 20°C, (day⁻¹), k_{growth} is the maximum growth rate at 20C (day⁻¹). CF_T is a water temperature control factor, CF_P is a phosphorus concentration control factor, CF_{RAD} is a solar radiation control factor, CF_{SS} is a self-shading control factor and CF_{Si} is a silicon concentration control factor (for more details about the formulation of these factors see Whitehead et al., 2015). The model inputs are water temperature, solar radiation and, from the upstream section of the reach, water discharge, incoming phytoplankton concentration, phosphorus and silicon concentrations. The model was implemented at the daily time step.

The phytoplankton model was implemented and tested previously (Whitehead et al., 2015a), using a Multi-Objective General Sensitivity Analysis (Bastidas et al., 1999). This technique allowed quantifying the sensitivity of a model to its parameters within a Monte Carlo framework. Several model simulations were carried out using a large number of randomly-generated parameter sets, which were divided into behavioural and non-behavioural depending on the corresponding model results (i.e. if the model results were above a threshold of two given metrics, the parameter set was defined as behavioural). The difference in the distribution functions of the behavioural and non-behavioural values of a parameter defined the sensitivity of the model to this parameter. In Whitehead et al. (2015), the model was calibrated and validated with a daily time-step, and the model parameters were adjusted for each reach to reproduce the observed phytoplankton population series of the associated five phytoplankton groups

considered (Table 3). Table 2 shows the calibrated values of the model parameters, from Whitehead et al. (2015). The model results were satisfactory, with Nash-Sutcliffe validation efficiencies greater than 0.5 for 12 cases out of 25. The most relevant errors were due to failure in reproducing very high and sudden algal blooms or, in some cases, to external natural or anthropogenic disturbances (see Whitehead et al. (2015) for further information about the model performance). Table 3 shows the phytoplankton model results reach by reach and for each phytoplankton groups in terms of coefficient of determination (R^2) between the model results and the measured values of phytoplankton concentration, aggregated to the monthly scale.

Table 2 – Calibrated parameter sets (from Whitehead et al., 2015).

Parameter name	Chlorophytes	Cyanobacterias	Diatoms and large chlorophytes	<i>Microcystis</i> -like	Picoalgae
Death rate (d^{-1})	0.15	0.20	0.05	0.15	0.10
Growth rate (d^{-1})	0.40	1.00	0.20	0.20	1.00
P half-saturation ($mg\ l^{-1}$)	0.04	0.03	0.00	0.00	0.05
Self-shading ($cell\ ml^{-1}$)	30,000	1,000,000	30,000	1,000,000	30,000
Si half-saturation ($mg\ l^{-1}$)	-	-	2.5	-	-

Table 3 – Phytoplankton model results (monthly R^2 , from Whitehead et al., 2015).

Phytoplankton group	Reach 1	Reach 2	Reach 3	Reach 4	Reach 5
Chlorophytes	0.78	0.93	0.43	0.86	0.94
Cyanobacteria	0.28	0.97	0.80	0.97	0.97
Diatoms and large chlorophytes	0.33	0.54	0.33	0.90	0.96
<i>Microcystis</i> -like cyanobacteria	0.38	0.78	0.61	0.80	0.79
Picoalgae	0.78	0.97	0.87	0.89	0.93

2.3 Stressors

2.3.1 Climate scenarios

Among the climatic stressors that can influence phytoplankton concentrations and composition, precipitation and temperature are likely to be the most significant ones, as they drive water discharge (Lack, 1971; Malone, 1991; Bowes et al., 2012). Air temperature also affects water temperature, which is a highly relevant factor for phytoplankton growth. However, phytoplankton concentrations in rivers are not only affected by hydro-climatic stressors but also by nutrient supply, such as phosphorus (Bowes et al., 2012). It has been shown that an expansion of agricultural land can increase the phosphorus concentrations, and that combined mitigation strategies of fertiliser reduction and phosphorus removal from wastewater can lead to significant decreases in phosphorus concentration (Crossman et al., 2013; Whitehead et al., 2013).

With the aim of reproducing variable hydrological conditions (water flow and water temperature), changes in precipitation and air temperature were considered in this study. Fifteen uniform changes (i.e. using a delta change method, see for example Hay et al., 2000) were applied to the current precipitation series (2011-2014), from -30% to +40% with a 10% step, providing fifteen altered precipitation series. Similarly, fifteen uniform changes were applied to the current air temperature series (2011-2014), from -1°C to +6°C with a 0.5°C step, obtaining fifteen altered air temperature series. These uniform shifts largely include the outcomes of available climate scenarios, including the UK Climate Projections 09 – UKCP09 (Murphy et al., 2009). These altered precipitation and temperature series were combined to obtain 225 climate-altered scenarios, which were used to drive the PERSiST model and, in turn, the INCA model and obtain series of water discharge, water temperature, phosphorus and suspended sediment concentration.

These variables were obtained for each reach of the River Thames (described in the study area section) and used to drive the phytoplankton model (Whitehead et al., 2015a). As stated above, the phytoplankton model also needs a phytoplankton series coming from the upstream section. In this model application, the observed (2011-2014) phytoplankton concentration was used as phytoplankton reach input from upstream, rather than the phytoplankton concentration provided by the model for the upstream reach. This means that each river reach is modelled independently (i.e. the reaches were not modelled as a “cascade”). This was done for two reasons: *i*) the aim of this work was to estimate variations in phytoplankton growth attributable to each of the River Thames reaches following different climate and land management scenarios, and to understand how the geo-physical characteristics of each reach modulate the climatic and nutrient controls on phytoplankton concentrations and composition in each reach, rather than computing the actual phytoplankton concentration flowing towards downstream, and *ii*) to avoid the propagation of modelling errors and associated uncertainty downstream. Obviously, modelling river reaches as a cascade (i.e., the upstream reach phytoplankton concentration used to drive the downstream reach model) will lead to an accumulation of the effects. The result was 225 series of phytoplankton populations for each of the five phytoplankton groups and each of the five reaches. These series were subsequently combined to response surfaces (Prudhomme et al., 2010) showing the variation in mean phytoplankton concentration due to climatic alterations. This allows quantifying how the phytoplankton concentration could be affected by changing climate and understanding how the dynamics of the different phytoplankton groups might evolve with climate.

2.3.2 Land use/land management scenarios

In order to take into account land use and land management effects on phytoplankton concentration and composition, three scenarios were considered: *i*) current land use; *ii*) future land use, i.e. expansion of agricultural land due to increased food demand and *iii*) future land use with enhanced phosphorus mitigation strategies. The future land use scenario (*ii*) describes an increase in agricultural land area and was quantified using the land cover model LandSFACTS (Castellazzi et al., 2010) which focuses on crop arrangement scenarios, considering food security as a dominant driving force for land use change. For the River Thames, this land-use scenario projects a shift from an almost equal proportion of arable land and grassland to a clear prevalence of arable land. Specifically, the arable land is projected to double under this scenario, at the expenses of forest land and grassland. The future land use scenario and mitigations strategy (*iii*) describes a situation where the agricultural land expands but optimal phosphorus removal mitigation strategies have also taken place, based on a combined reduction of fertiliser and phosphorus removal from wastewater. This strategy was found to be the most effective for phosphorus control by Crossman et al. (2013) and Whitehead et al. (2013). These scenarios were taken into account by modifying the INCA model parameters. The increase in agricultural land was modelled by increasing the fraction dedicated to this land use in the INCA model parameterisation (and reducing accordingly grassland and forest land fractions). The phosphorus mitigation strategy was parameterised by reducing by 20% the fertiliser application rates and applying and limit of 0.3 mg L⁻¹ of total phosphorus in wastewater discharge from sewage treatment works. More details about the model parameterisation for land use and management impact analysis in the River Thames can be found in Crossman et al. (2013).

2.4 Modelling approach

Traditionally, two complementary approaches have been taken to analyse climate change impact on water resources and water quality (Singh et al., 2014): the “traditional forward propagation” approach and the “bottom-up analysis” approach. The first category includes a ‘cascading’ methodology in which emissions scenarios are used to drive climatic models and climatic model outputs are used to drive a variety of environmental models and provide possible scenarios of a variable of interest. In the second category, an environmental model is used to analyse the sensitivity of the variable of interest to this changing climatic conditions. An advantage is that it can be implemented independently from climate scenarios projections (which are only used to determine the projected changes) and it allows exploring climatic alterations which may not be reproduced by the range of available climate models. This means

that its results can be compared with updated scenarios without repeating the study, and hence providing a practical and usable tool for practitioners, agencies and governing body. Some examples are Bastola et al. (2011), Fronzek et al. (2011), Wetterhall et al. (2011), Brown et al. (2012) and Poff et al. (2015).

In this study, a “bottom-up”, or “scenario-neutral” approach to climate change impact assessment (Prudhomme et al., 2010) was employed to evaluate the effect of climate change on phytoplankton concentrations and composition. It consists in (i) identifying sources of climatic alteration that are likely to affect the variable object of the study, (ii) applying these possible alterations to the observed climate to produce altered climatic series (usually precipitation and/or temperature), (iii) driving a mathematical model (hydrological, water quality, water systems, eco-hydrological, phytoplankton, etc.) with the altered climatic series and (iv) comparing the sensitivity framework with any available climatic scenario to determine the likelihood of changes.

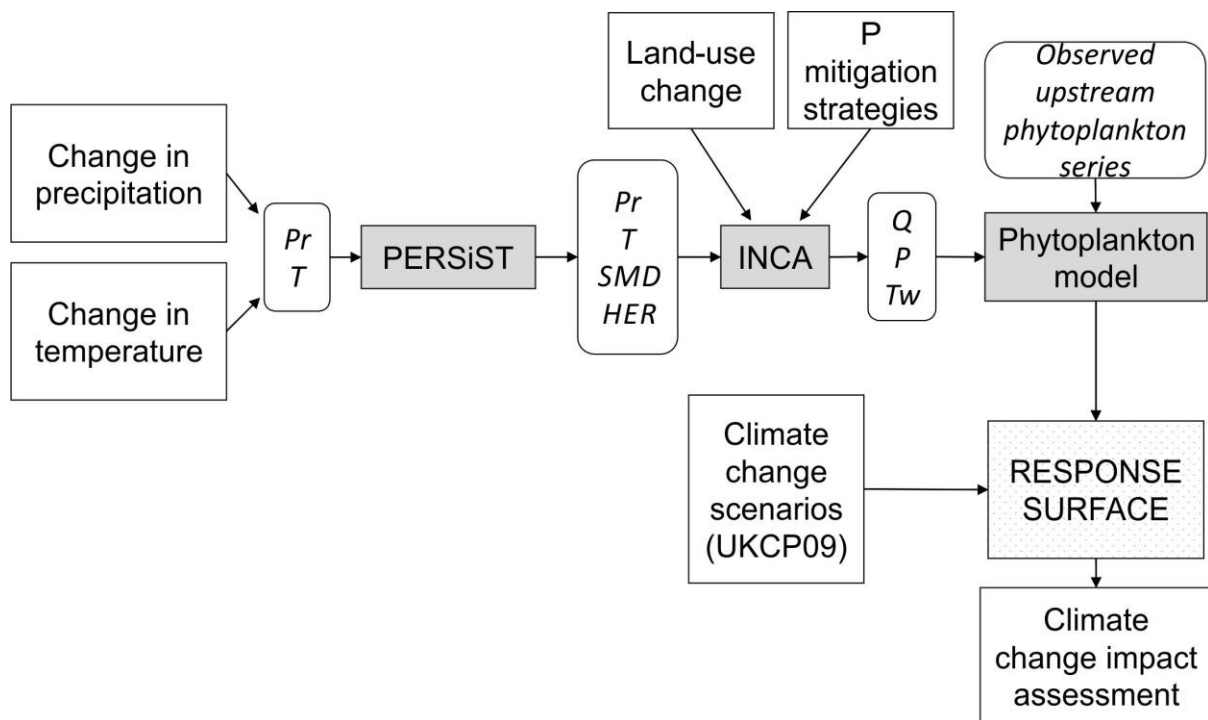


Figure 2 – Scenario-neutral methodology scheme followed in this study. Pr: precipitation, T: air temperature, SMD: Soil Moisture Deficit, HER: Hydrological Effective Rainfall, Q: water discharge, P: phosphorus concentration, Tw: water temperature.

The scheme of this methodology is depicted in Figure 2. Precipitation and temperature series are used to drive the PERSiST hydrological model, which produces series of soil moisture deficit (SMD) and hydrological effective rainfall (HER). These, along with precipitation and temperature, are used to drive the INCA water quality model, which produces water discharge, phosphorus and water temperature series for each river reach (water temperature is also computed by the INCA model, linear function of the air temperature, the water temperature at the previous time-step and a lag factor). These series are then input into the phytoplankton model, along with observed upstream phytoplankton series. The phytoplankton model returns series of concentration of five phytoplankton groups in water, which is the ultimate output of the modelling chain. The hydrological PERSiST model was run with climate-altered inputs of precipitation and air temperature, and its outputs used to run the INCA model. This enabled the generation of the series of climate-altered water discharge, phosphorus concentration and water temperature series used to drive the phytoplankton model, along with the incoming observed (from 2011 to 2014) phytoplankton concentration at the upstream section as model input. This procedure was repeated for all the five phytoplankton groups and all the five reaches, obtaining climate-altered series of phytoplankton populations.

2.5 Risk of change in phytoplankton concentration

Finally, the response surfaces were compared to the UKCP09 projections for the 2030s to assess the risk of change in phytoplankton concentration. UKCP09 are probabilistic projections developed by the UK Met Office to provide climate change projections of climate change over the UK with greater spatial and temporal detail than previous climate scenarios. They are based on the results of the HadCM3 coupled ocean-atmosphere Global Circulation Model (Gordon et al., 2000), run as a perturbed physics ensemble to sample model and parameter uncertainties (Murphy et al., 2007). HadCM3 projections were then downscaled on a 25 km grid over seven overlapping 30-yr time periods based on an ensemble of 11 variants of the regional climate model HadRM3, and a statistical procedure was applied to build local-scale distributions of changes for various climate variables. UKCP09 gives projections for three scenarios of the Special Report on Emissions Scenarios (Nakicenovic and Swart, 2000). These scenarios are A1FI - called High in UKCP09, A1B - Medium and B1 - Low. Among the available outputs, expected changes in average precipitation and temperature following the different emission scenarios can be obtained. In this study, the projections for the 2030s corresponding to the A1FI scenario were employed. We assessed the effect of changes precipitation and temperature forecasted by a set of 10,000 precipitation and temperature change factors. The UKCP09 change factors are a subset of the variations in precipitation and temperature considered in this study, which consequently defines a sub-region of the system response defined previously. This region of system response was used to assess the risk of changes in phytoplankton variation for the 2030s.

3 Results

3.1 Impacts on phosphorus concentration

The effect of climate change and land-use change on phosphorus loads in rivers has already been analysed in literature (Withers and Jarvie, 2008). Specifically, for the River Thames it was found that an increase in the agricultural fraction of the catchment and runoff is likely to trigger an increase in phosphorus due to diffuse sources (Crossman et al., 2013; Whitehead et al., 2013). On the other hand, decreasing runoff and increased abstractions will reduce river flows and reduce dilution of effluents from the point sources such as sewage treatment works (Bowes et al., 2008).

Figure 3 shows the combined effects of climatic alterations (uniform changes in precipitation and temperature) and land use and phosphorus removal strategies on the average phosphorus concentrations of the River Thames at Runnymede, approximately 12 km upstream of the tidal limit. Under current land-use and phosphorus removal mitigation strategies, average phosphorus concentrations range from 0.11 to 0.16 mg L⁻¹, being inversely proportional to precipitation due to the dominance of sewage effluent inputs at this site (Bowes et al., 2015). When an increase in agricultural land use is applied, the average phosphorus concentration increases up to between 0.15 and 0.18 mg L⁻¹. In this case, phosphorus concentration is still inversely proportional to rainfall, although for increases in precipitation greater than 20% this trend inverts and precipitation is directly proportional to phosphorus concentration. This suggests a shift from a point source-dominated to a diffuse source-dominated regime, due to the joint effect of increased rainfall and expansion of agricultural land. The average phosphorus concentration drops to 0.07-0.09 mg L⁻¹ if a combined phosphorus removal strategy is implemented. For changes in precipitation between -30% and +20% the phosphorus concentration is directly proportional to the precipitation (phosphorus supply mainly from diffuse sources) while for high increases in precipitation and low temperatures the relationship is inverse.

Following the mean increases in precipitation and temperature projected by UKCP09 (Murphy et al., 2009), the average phosphorus concentration range is 0.110-0.152 mg L⁻¹ ($p=0.95$) under current conditions of land-use and current phosphorus removal mitigation strategies, 0.157-0.186 mg L⁻¹ under future land-use – expansion of agricultural land – but no implementation of further phosphorus mitigation strategies, and 0.072-0.088 mg L⁻¹ under future land-use and implementation of a combined strategy

of phosphorus removal. The reference value (baseline) resulting from a model run with no climatic alterations is 0.118 mg L⁻¹.

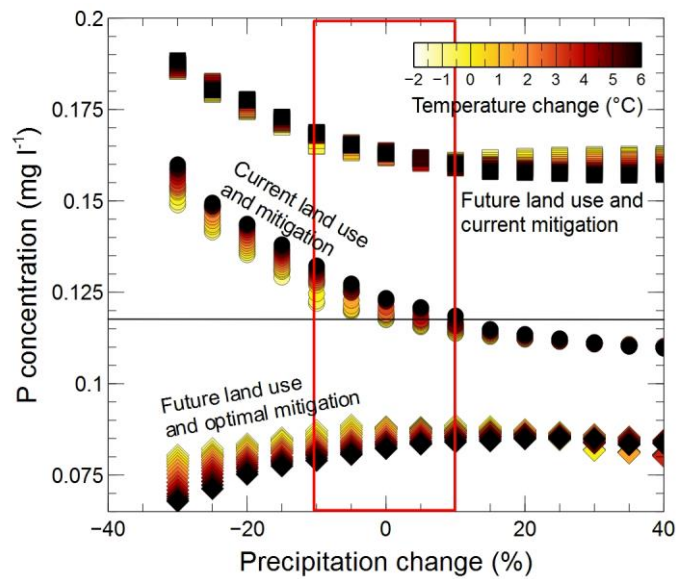


Figure 3 – Effect of combined climate alteration (precipitation and temperature), land-use change and phosphorus removal mitigation strategies on the average phosphorus content of the River Thames (UK) at Runnymede. Circles: current conditions of land-use and current phosphorus removal mitigation strategies; squares: expansion of agricultural land and current phosphorus removal mitigation strategies; diamonds: expansion of agricultural land and optimal phosphorus removal mitigation strategies (combined reduction of fertiliser and phosphorus removal from wastewater). The horizontal solid line represents the current average phosphorus concentration. The red rectangle defines the space of precipitation changes forecasted by the UKCP09.

3.2 Impacts on phytoplankton concentration

Changes in average phytoplankton concentration, calculated over the whole 2011-2014 modelling period, for each grouping associated with the 225 climate alteration scenarios under current land use and current phosphorus mitigation strategy were assessed using the reach model and shown in Figure 4, with colours corresponding to changes in average phytoplankton (white: decrease, green: small variation, light blue: medium increase, blue: strong increase, black: very strong increase) and axes mean annual changes in precipitation (x-axis) and temperature (y-axis). Figure 4 refers to changes in phytoplankton for reach 1. A vertical line indicates no change in current precipitation and a horizontal line indicates no change in current air temperature. They show the different dynamics of different phytoplankton groupings linked with a change of climatic patterns.

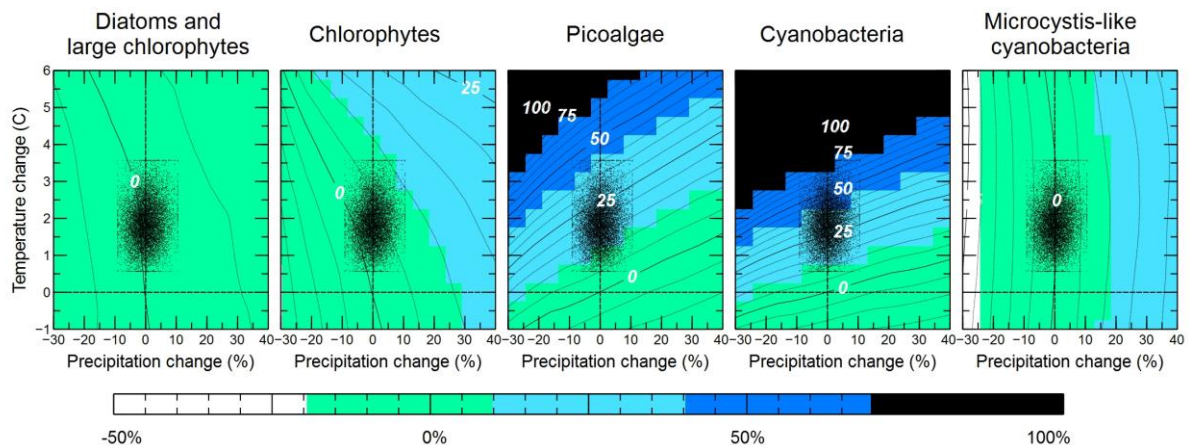


Figure 4 – Change in the 2011-2014 average phytoplankton abundance in the River Thames (UK) in reach 1 due to climate alteration (precipitation and temperature), under current conditions of land-use and current phosphorus removal mitigation strategies. In each plot, the x-axis represents the alteration in temperature (°C), the y-axis the alteration in precipitation (%), while the resulting change in average phytoplankton cell abundance is represented with colours. Each plot is associated with a different phytoplankton group (diatoms, chlorophytes, picoalgae, cyanobacteria and *Microcystis*-like cyanobacteria). The black dots represent the changes in precipitation and temperature of 10,000 UKCP09 change factors.

It can be seen that precipitation, and hence flow, is the key control for *Microcystis*-like cyanobacteria and diatoms and large chlorophytes: i.e. phytoplankton concentration for these groups is much more sensitive to changes in precipitation than to changes in temperature, within the range of changes considered in this study. On the other hand, temperature is the main control for cyanobacteria – although cyanobacteria are also sensitive, to a lesser extent, to changes in precipitation. Picoalgae appear to be driven in a similar way by both precipitation and temperature. Similarly, Chlorophytes are driven by both climatic stressors, although for low values of temperature change, precipitation seems to prevail as the key control. It can also be seen that the magnitude of phytoplankton concentration changes in response to precipitation and temperature changes (i.e. the sensitivity of phytoplankton to climate change) is smaller for diatoms, chlorophytes and *Microcystis*-like cyanobacteria and higher for picoalgae and cyanobacteria. This means that variations in precipitation and temperature affect different phytoplankton groups in different ways and to different extents. For example, while cyanobacteria can double their average concentration in reach 1 for an increase in temperature of +3°C (and no change in precipitation), chlorophytes only show variations an increase between 5 and 10% under the same climate alterations. Similarly, for an increase in precipitation of 20% (and no change in temperature), *Microcystis*-like cyanobacteria concentration in reach 1 increases by almost 15%, while diatoms and large chlorophytes concentrations increases by only less than 5%. All groups show the same sensitivity to temperature (increasing temperature means increasing phytoplankton concentration, although with different proportionality) but the response to changes in precipitation varies. Chlorophytes, diatoms and *Microcystis*-like cyanobacteria decrease their concentration along with precipitation, while cyanobacteria and picoalgae increase their concentration responding to increasing precipitation.

Figure 5 shows the response of phytoplankton concentrations to climatic changes under all the considered land use/land management configurations (scenarios *i*, *ii* and *iii*). The boxplots indicate the range of variations of the response surfaces, i.e. the change in average phytoplankton concentration due to the climatic variability considered in this study. These plots, representing the range of possible responses to climate variability and land use/land management changes, indicate whether the two future scenarios considered in this study make some difference in terms of phytoplankton concentration compared to the current land-use scenario. Scenario *ii* (expansion of agricultural land and current phosphorus mitigation strategy), depicted in yellow in Figure 5, causes a general increase in phytoplankton concentration. Nevertheless, this increase appears to be larger in the upland reaches (especially reach 1 and 2) than in the lowland reaches. For example, scenario *ii* is responsible for an average increase of 54% in cyanobacteria concentration in reach 1 but only for an average increase of 9% in reach 5. Diatoms, large chlorophytes and *Microcystis*-like cyanobacteria do not appear to be very sensitive to an increase in agricultural land. Conversely, the scenario *iii* (expansion of agricultural land and combined phosphorus reduction strategy) appears to be effective in reducing phytoplankton concentration in all reaches, and the magnitude of the reduction seems to be similar from upstream to downstream. For example, the average reduction of chlorophyte concentrations due to the combined phosphorus removal strategy proposed in scenario *iii* (computed as the reduction in phytoplankton concentration from scenario *ii* to scenario *iii*) is 15%, 5%, 8%, 10% and 19% for reach 1, 2, 3, 4 and 5 respectively. On the other hand, the land use and phosphorus removal scenarios considered in this study show different effects depending on the phytoplankton group. Scenario *ii* has a larger effect on cyanobacteria and picoalgae than on chlorophytes, diatoms and *Microcystis*-like cyanobacteria. Analogously, scenario *iii* appears to be more effective in reducing the concentration of cyanobacteria and picoalgae than chlorophytes, diatoms and *Microcystis*-like cyanobacteria. For example, the combined phosphorus removal strategy causes an average reduction in cyanobacteria concentration of 43% but only an average reduction of diatom concentration of 6%. While the combined phosphorus

removal strategy considered in this study appears to be effective under all the climatic alterations considered, its effectiveness can vary depending on the climate scenario. The effectiveness (i.e. the net reduction in phytoplankton concentration from scenario *ii* to scenario *iii*) is larger under higher temperature and under lower precipitation, for all the phytoplankton groups (and especially for cyanobacteria and picoalgae).

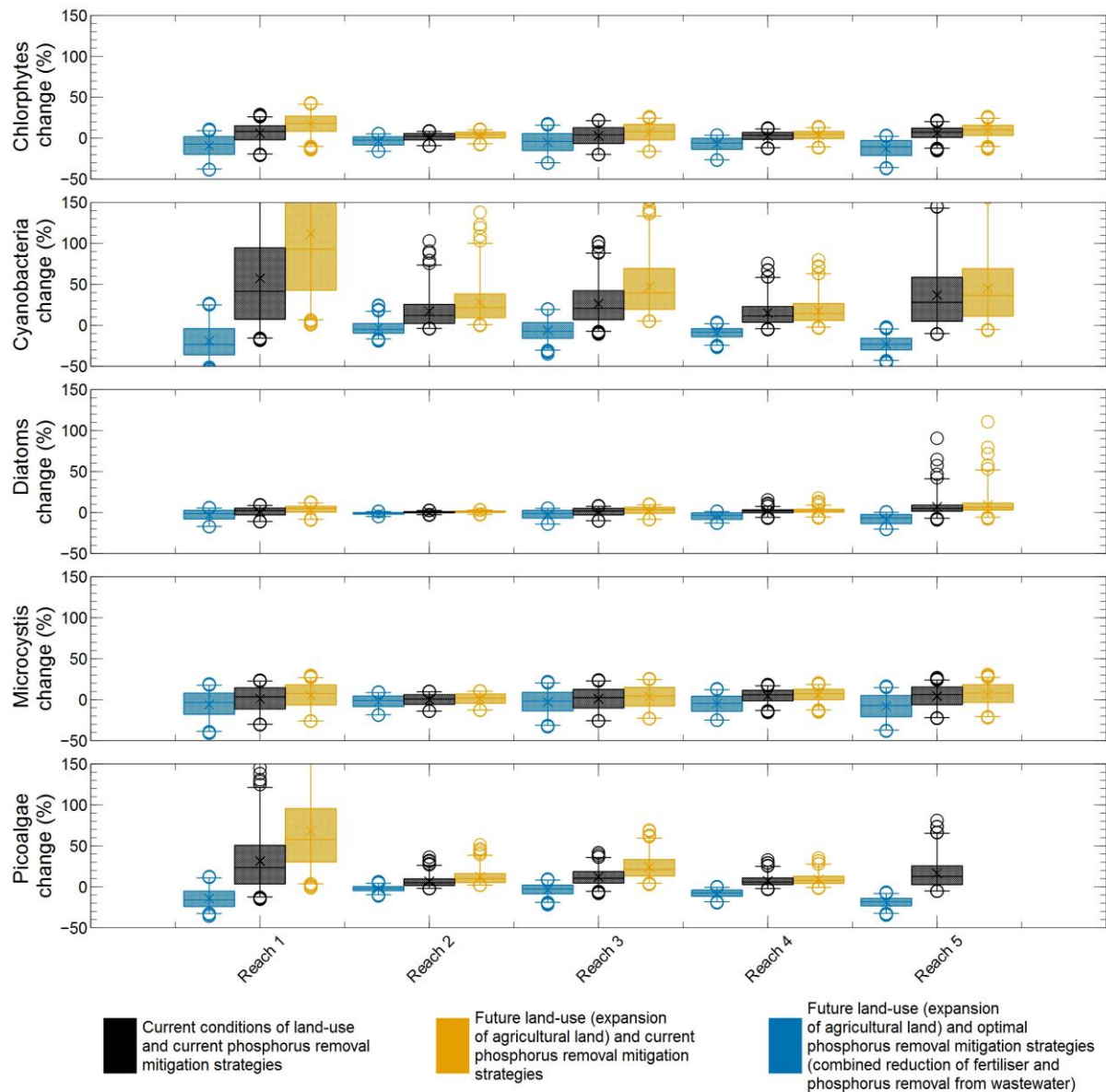


Figure 5 – Effect of climate alteration (precipitation and temperature) on the average phytoplankton content of the River Thames (UK), under different conditions of land-use and different phosphorus removal mitigation strategies.

In Figure 6, the results of the sensitivity framework showed above are contextualised within the climatic changes projected by the UKCP09. The grey areas represent the interquartile range of changes in phytoplankton concentration in response to the space of changes in precipitation and temperature projected by the UKCP09 for the 2030s. The lines represent the median phytoplankton concentration change. The difference between Figure 5 and Figure 6 is that Figure 6 represents the response of the system to a smaller range of climatic variations than the ones considered in this study. For this reason, the changes in phytoplankton concentration depicted in Figure 6 are in general smaller than the ones reported in Figure 5. From Figure 6, it can be noticed that diatoms, large chlorophytes and *Microcystis*-

like cyanobacteria are not very sensitive to the projected climate changes, and their concentration is likely to increase very little in the future in response to both changes in climate and in land use/land management. On the other hand, chlorophytes, picoalgae and especially cyanobacteria show much larger sensitivities to climate change and are likely to increase their concentration significantly. In the same way, these groups are also more sensitive to changes in land use and phosphorus mitigation strategies.

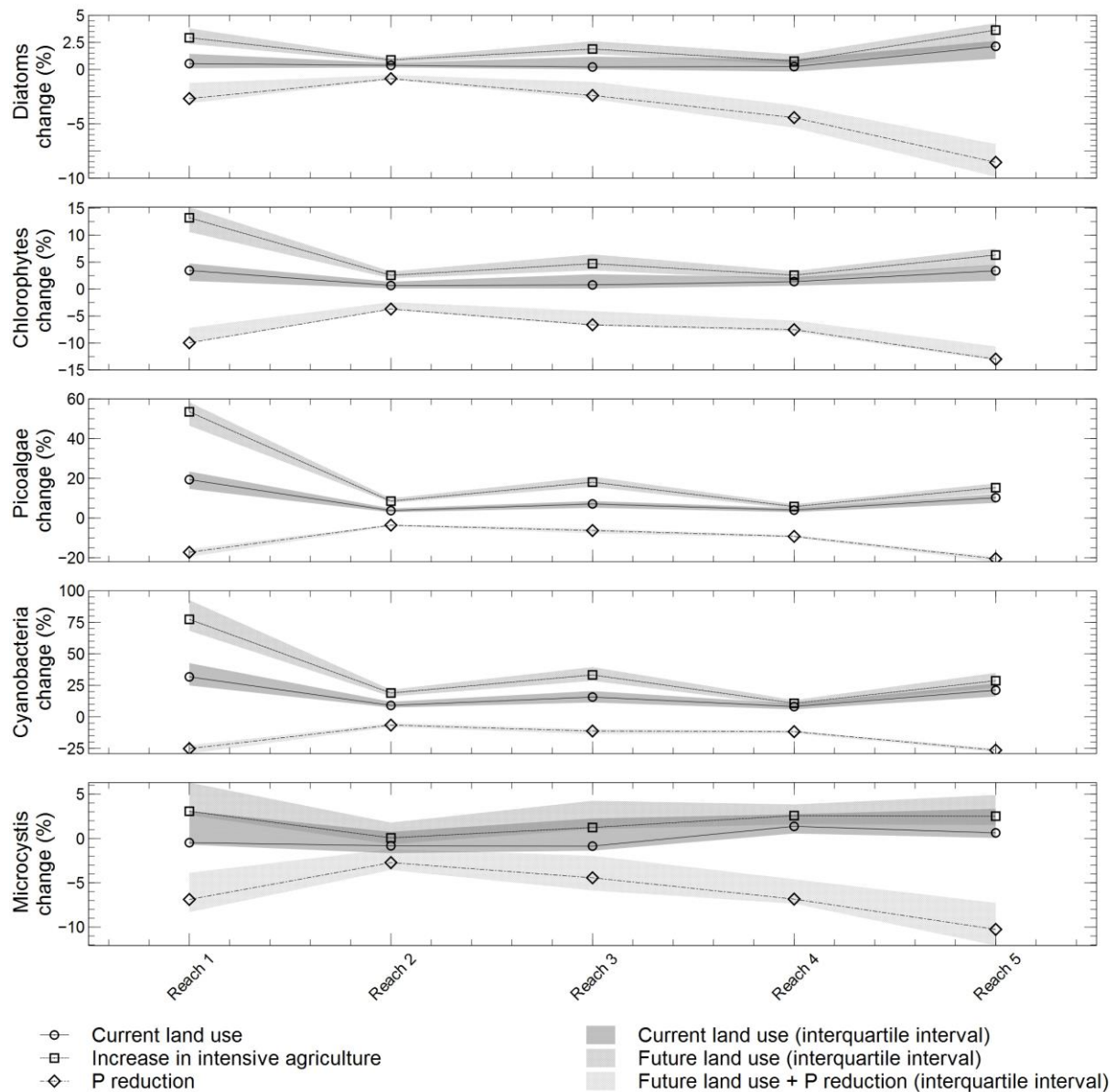


Figure 6 – Median effect of climate alteration (precipitation and temperature) on the average phytoplankton content of the River Thames (UK) and interquartile range, based on the UKCP09 climate projections, under different conditions of land-use and different phosphorus removal mitigation strategies. Note the different scales.

4 Discussion

Both precipitation and temperature seem to control phytoplankton growth in the River Thames, with no clear predominance of one over the other. Both precipitation and temperature act on river flow: increasing precipitation causes increasing river flow, while increasing temperature increases evapotranspiration and thus decreases river flow. River discharge is inversely proportional to residence time, which is a key factor in phytoplankton development, and thus to phytoplankton concentration. Air

temperature variations also have a directly proportional effect on water temperature (and increasing water temperature increases phytoplankton concentration), which sum to the aforementioned increase of evaporation and reduction of flow effect. Water temperature was computed as a linear function of air temperature, and therefore no dependency of water temperature on river flow was considered.

In general, the model results suggest that temperature is always directly proportional to phytoplankton concentration (higher air temperature means larger phytoplankton concentrations, both because of lower flow and higher water temperature). However, different patterns of phytoplankton response to precipitation were found. Some phytoplankton groups seem to be much more sensitive to precipitation than temperature (diatoms, chlorophytes and *Microcystis*-like cyanobacteria), and the magnitude of the response may also vary depending on the phytoplankton group. Precipitation-sensitive groups also increase their concentration when water discharge increases (synergistic response) while temperature-sensitive groups decrease their concentration when water discharge increase (antagonistic response). Figure 7 shows an attempt to explain this dual behaviour. It shows the modelled response of chlorophytes (b) and cyanobacteria (c) to two precipitation and associated river discharge scenarios (a), given the same temperature scenario. Synergistic response can be observed for chlorophytes (increases of concentration with larger discharge) but antagonistic response can be seen for cyanobacteria (decrease of phytoplankton concentration with larger discharge), especially during phytoplankton blooms.

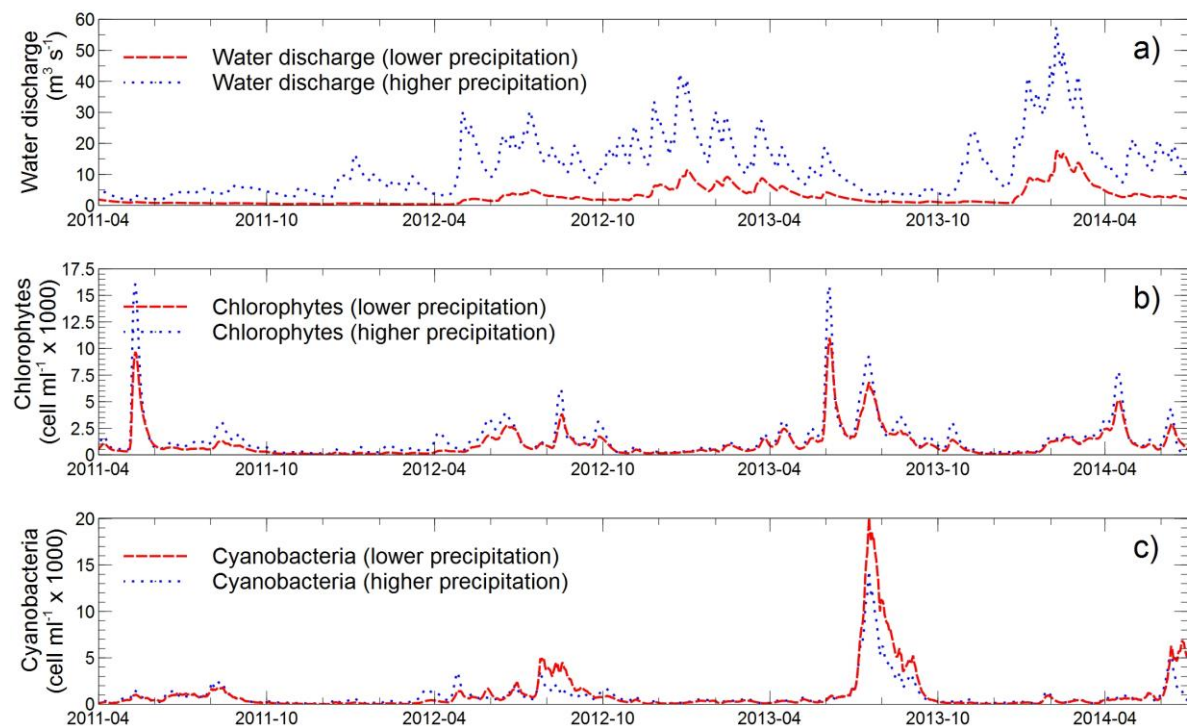


Figure 7 – Example of model results obtained with two different precipitation series (higher precipitation, +40% compared to the current climate, and lower precipitation, -30% compared to the current climate) and the same temperature series, for reach 1. a) water discharge; b) chlorophyte concentration; c) cyanobacteria concentration.

From a modelling perspective, the different behaviours are due to different combinations of k_{growth} and k_{death} parameter values (growth rates and death rates respectively) from Eq. 1 associated with each phytoplankton group. The ratio between these two parameters controls the occurrence and magnitude of phytoplankton blooms, subject to the value of the other state variables (water discharge, water temperature, phosphorus concentration, solar radiation, etc.). Two categories emerge from the calibrated parameters: the ratio between growth rate and death rate is greater than 3 for picoalgae, cyanobacteria and diatoms and large chlorophytes (10, 5 and 4 respectively), and lower than 3 for chlorophytes and *Microcystis*-like cyanobacteria (2.7 and 1.3 respectively). For the first category,

average phytoplankton concentration is inversely proportional to total precipitation, while, for the second category, average phytoplankton concentration is directly proportional to total precipitation.

In terms of magnitude of the impact of climatic variations on phytoplankton groups, cyanobacteria and picoalgae were found to have the largest sensitivity. In terms of spatial variations of phytoplankton response, it was found that reaches 1 and 5 appear to be more sensitive to climatic variations than reaches 2, 3 and 4. Regarding reach 1, this is the reach showing the smallest phytoplankton concentration. This may be the cause of its larger sensitivity to environmental changes. On the other hand, an increase in the absolute concentration of phytoplankton would imply a less serious problem than in other reaches. Regarding reach 5, this reach is characterised by small slopes and slow flow. The larger sensitivity showed by this reach may be due to better conditions for phytoplankton growth given by increasing temperature, which in turn increases residence times, especially in slow-flow river reaches. In fact, in slow moving and deep rivers like the Thames in its downstream reaches, phytoplankton dynamics might start to behave like in lakes, where larger growth rates and larger blooms take place (Walks, 2007). In such reaches, even small flow variations can cause large changes in phytoplankton concentration.

The impact of an agricultural land expansion on phytoplankton was also found to impact differently on upstream and downstream reaches. In particular, upper reaches are showing more sensitivity to an increase in agricultural land. This is because baseline phosphorus concentration is larger in the lower reaches than in the upper ones, due to a larger number of wastewater discharges in the lowlands. The phosphorus concentration in the lowlands has already been showed not to be limiting phytoplankton concentration in the Thames (Bowes et al., 2014; Whitehead et al., 2015a), and thus an increase in phosphorus concentration due to expansion of agricultural land does not have a great effect on phytoplankton growth.

The response surfaces allow understanding and quantifying the dynamic of phytoplankton responses to climate and land use/land management. Therefore it allows evaluating the effectiveness of phosphorus removal strategies under a broad range of climatic variations, from upstream to downstream, where effectiveness is the net effect of the phosphorus removal measures (in this case, the difference between the variation in phytoplankton concentration under the agriculture expansion scenario and the variation in phytoplankton concentration under the phosphorus removal scenario). Following the model results, the combined phosphorus removal strategy proposed in Crossman et al. (2013) and considered in this study appears to be consistently reducing phytoplankton under all the climatic combinations analysed, thus proving to be a robust mitigation strategy. This is because this strategy tackles both point- and diffuse-source phosphorus inputs, thus effectively reducing phosphorus concentration both in the upper and lower reaches (see Figure 3) and limiting phytoplankton growth. As shown previously by Crossman et al. (2013), a phosphorus removal strategy focused only on reduction of phosphorus in waste water, or only on reduction of fertiliser usage would not be as effective in decreasing consistently phosphorus concentration under a range of different flow conditions. Its effectiveness was found to be increasing from upstream to downstream. This is because the combined phosphorus removal strategy is especially effective in reducing phosphorus pollution from wastewater, which is responsible for the high baseline phosphorus concentration found in the lowermost reaches (where the majority of sewage treatment works and other human-related sources of pollution are located). Furthermore, the mitigation strategy was also found to be more effective under growing temperature and low precipitation (i.e. under lower flows). This is because, under the mitigation strategy, the River Thames was shown to shift from a point-sources-dominated river to a diffuse-sources-dominated river (see Figure 3). Therefore, under low flows the concentration of phosphorus would decrease proportionally, increasing the effectiveness of the mitigation measures on reducing phytoplankton concentration. This is especially interesting if framed within the climate projections of UKCP09, which forecast a rise in temperature between +0.5°C and +3.5°C.

The UKCP09 allows associating a probability of change over a certain time horizon (the 2030s, in this study). By looking at where these changes are within the system response surface allows inferring what variation will be more likely to impact on phytoplankton concentration, and consequently what action might be required to mitigate its effects. Again, for the case study of the River Thames, no climatic driver appears to be dominant over the other, within the range of the climatic variations forecasted by the UKCP09, as can be seen in Figure 4 (in particular, within the region defined by the cloud of black dots). However, from Figure 6 some considerations can be drawn on the possible range of variation of future phytoplankton concentration forecasted for the 2030s. Cyanobacteria appear to show the largest variations (between +8% and +93%, interquartile range), while diatoms and large chlorophytes were found to be the most stable group, with an expected change in average concentration between 0% and +3% (interquartile range) under current land use and current phosphorus mitigation strategy. This finding substantially agrees with other studies carried out in lakes, such as Arheimer et al. (2005), who found a strong increase of cyanobacteria, up to 80%, for a lake in southern Sweden, and Markensten et al. (2010), who stated that increasing warming conditions could lead to a shift in phytoplankton groups to favour nitrogen-fixing cyanobacteria at the expense of diatoms for a shallow lake in central Sweden. It is interesting to note that almost no reduction in average phytoplankton concentration is forecasted for the 2030s within the interquartile range for all the considered phytoplankton groups, under current land use and current phosphorus mitigation strategy. This is clearly indicating that, following the UKCP09 projections, a uniform alteration in total precipitation and average air temperature is highly likely to cause an increase in phytoplankton concentration in the River Thames system, although the magnitude of this increment is more uncertain and may vary depending on the extent and magnitude of climate change. Conversely, no increase in average phytoplankton concentration is forecasted for the 2030s within the interquartile range following the application of the combined phosphorus mitigation strategy, showing once again that this is a robust and effective strategy for phytoplankton control in the River Thames.

Although a comprehensive analysis of the model uncertainty was not among the scopes of this paper, it is relevant to mention the possible sources of uncertainty that affects the results of this study. In particular, the model structure used in this study (a “cascade” of three models: PERSiST, INCA and a phytoplankton mode) can lead to the propagation of the model errors down the modelling chain. The uncertainty of the models employed in this study has been assessed separately in different studies. For example, Futter et al. (2014) implemented a Monte Carlo-based approach for sensitivity and parameter uncertainty analysis of the PERSiST model for River Thames, finding that the model results were especially sensitive to evapotranspiration parameters and residence times. The uncertainty of the INCA model has been assessed in several papers, such as for example Raat et al. (2004), who pointed out the problem of equifinality and suggested a multi-objective calibration approach, as well as the use of frequent measurements (fortnightly frequency) as reference values for calibration. Dean et al. (2009) applied a generalised likelihood uncertainty estimation (GLUE) framework to the INCA-P model, and concluded that the uncertainty due to the model structure and parameterisation was similar to the uncertainty of the measured values of total phosphorus in the river. Rankinen et al. (2006) also applied a GLUE approach to evaluate the uncertainty of the INCA-N model results, integrating “soft data”, or experimental knowledge of the processes, into the calibration procedure. Concerning the phytoplankton model, a paper by Whitehead et al. (2015) analysed the sensitivity of the model to its parameters, and, although the model uncertainty was not explicitly assessed, the results showed great sensitivity of the model to the phytoplankton death and growth rates. The parametric uncertainty of the whole combination of these three models was not quantified in this study. However, it can be assessed qualitatively. This modelling combination involves around 20-25 influential parameters, based on previous uncertainty assessments on the models used in this study (Dean et al., 2009; Futter et al., 2014; Raat et al., 2004; Rankinen et al., 2006; Whitehead et al., 2015b). However, as stated for example by Skeffington et al. (2007), translating input uncertainties into uncertainty in the outputs is typically less than the summed uncertainty in the input parameters. Whitehead et al. (2009) suggests that complex behaviour patterns can surprisingly reduce variability in model outputs. Therefore, it can be reasonably stated that the final uncertainty of the modelling chain is of the same order of magnitude than the

uncertainty of the single models. This level of uncertainty is normally considered acceptable for climate change and land-use change analysis within the hydrological and water quality modelling community, especially in highly uncertain processes like the ones reproduced in this study. It is also worth mentioning that, as pointed out by Cosby et al. (1986), uncertain models can still provide extremely useful information for planners and managers, especially for scenario analysis (climate change and land-use change) where the factors of change in the variable of interest are used rather than the absolute values of those variables. Furthermore, the model parametric uncertainty must be considered along with other sources of uncertainty, among which the most important is probably the climate scenarios uncertainty. This is acknowledged to be the most important source of uncertainty in climate change impact assessment studies by several authors (Kay et al., 2009; Prudhomme and Davies, 2009a, 2009b; Wilby and Harris, 2006). In the present study, climate model outputs were not used as model input (and one of the reasons is because of the large uncertainty they propagate through the modelling chain), but they were used to define likely ranges of variations in the phytoplankton concentration. The UKCP09 projections were especially developed to include a very broad range of possible future climate outcomes, given the large uncertainty affecting climate model results. Therefore, it is reasonable to think that the ranges of phytoplankton variations due to the stressors considered in this study include both the uncertainty regarding future climate and the modelling chain parametric uncertainty (the latter probably being much lower than the former). Nevertheless, as stated before, a much more comprehensive study is needed to quantify with more accuracy the uncertainty of the modelling chain results.

Finally, some of the limitations of the present study should be highlighted. Only two sources of climatic disturbance, or climatic stressors, were employed in this study, both uniform through the year: change in precipitation and in air temperature. This strategy was adopted because it was recognised that temperature and residence time (strictly dependent on water discharge, and thus on precipitation) are the likely to be the most significant factors affecting phytoplankton concentrations and composition, as widely recognised in literature (Garnier et al., 1995; Reynolds, 2000; Desortová and Punčochář, 2011; Bowes et al., 2012). Nevertheless, other sources of climatic alteration may be relevant for the purpose of this study. For example, a change in precipitation seasonality, or intra-annual climate change could also be considered (Prudhomme et al., 2010) to evaluate the variations in peak discharge of two catchments in the UK, as a shift in raining season could affect soil moisture and therefore the hydrological cycle. Although seasonality of precipitation is less relevant than other factors such as a shift in average temperature or total precipitation, it can be an important factor affecting phytoplankton growth and phenology too, adding a third dimension to the response surfaces. Drier summers are likely to enhance the effect of decreasing precipitation, i.e. they should decrease slightly chlorophytes and *Microcystis*-like cyanobacteria concentration and increase picoalgae, cyanobacteria and diatom concentration. Solar radiation was not considered either as a variable climatic stressor in this study. Solar radiation is a key factor for phytoplankton development (Whitehead and Hornberger, 1984; Hardenbicker et al., 2014), and it is likely to vary due to climate change and anthropogenic factors. In fact, an increase in aerosols and other air pollutants during the past 50 years may have triggered a significant reduction in solar radiation reaching the Earth's surface (the so-called "solar dimming", Stanhill and Cohen, 2001). A reduction in solar radiation is likely to lead to a decrease in average phytoplankton concentration. Nevertheless, the range of forecasted solar radiation variations (around -10% for the UK in the next 30 years, Stanhill and Cohen, 2001) is smaller than the range of forecasted water discharge variations (from -12% to +18% change in water yield for the River Thames at London for the 2030s, following the Future Flow Projections, Prudhomme et al., 2013) and hence it is not clear yet if this would have a marked effect. Radiation can also be modified by tree shading. Nevertheless, this is not expected to impact greatly on the River Thames, which in its lowermost reaches has a width of more than 50 m (and thus tree shading only affects a small riparian area). This study also did not consider the role of grazers in phytoplankton control and limitation. In the River Thames, surveys suggest that zooplankton are in higher abundance than in other similar lowland rivers (Kaur, 2012). The effect of climate change on the relationship between phytoplankton and zooplankton has not been documented in literature yet, but some authors (Waylett et al., 2013) pointed out the importance of

phytoplankton predation by grazers in the River Thames. This effect could be taken into account in a more detailed modelling process, although new data is needed to characterise this aspect.

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