Dynamic response of land use and river nutrient concentration to long-term climatic changes

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Abstract

The combined indirect and direct impacts of land use change and climate change on river water quality were assessed. A land use allocation model was used to evaluate the response of the catchment land use to long-term changes in precipitation and temperature. Its results were used to drive a water quality model and assess the impact of the same climatic alterations on freshwater nitrate and phosphorus concentration. A scenario-neutral framework was used to evaluate the system response to changes in annual precipitation and annual temperature, and probabilistic climatic projections were employed to estimate the likelihood of such response. The River Thames catchment (UK) was used as a case-study, given the widespread presence of agriculture and its importance for freshwater supply. If land use is considered as static parameter, according to the model results, climate change alone should reduce the average nitrate concentration, although just by a small amount,by the 2050s in the Lower Thames, due to reduced runoff (and lower export of nitrate from agricultural soils) and increased instream denitrification, and should increase the average phosphorus concentration by 12% by the 2050s in the Lower Thames, due to a reduction of the effluent dilution capacity of the river flow. However, the results of this study also show that these long-term climatic alterations are likely to lead to a reduction in the arable land in the Thames, replaced by improved grassland. This change is mainly driven by a decrease in agriculture profitability in the UK in comparison to other areas of Europe. Taking into account the dynamic co-evolution of land use with climate, the average nitrate concentration is expected to be decreased by around 6% by the 2050s in both the upper and the lower Thames, following the model results, and the average phosphorus concentration incerased by 13% in the upper Thames and 5% in the lower Thames. This study shows the importance of incorporating the indirect impacts of climate change, through considering the response of the whole catchment, into assessments of future water quality.

Keywords: water quality, land use change, scenario-neutral, INCA model, River Thames.

1 Introduction

Human action has considerably modified the Earth's environments and landscape, and continues to do so. Between one-third and one-half of the Earth's land has been transformed by human interventions (Vitousek et al., 1997). Human-induced land use/land cover changes alter processes such as runoff generation, nutrient cycles and soil erosion to a similar or greater extent than other major drivers, such as climate change (Sterling et al., 2013). In recent centuries, land use change has had much greater effects on ecological processes than climate change (Dale, 1997).

Although land use is widely acknowledged as a key driver of change in catchment processes and properties, it is challenging to predict how it will change in the future subject to stressors such as climate change, technology change and human population increases. Its future evolution is uncertain (Mehdi et al., 2015), as land use and land management are changed to adjust to changes in climate, policy, food demand etc. Natural vegetation also responds dynamically to climatic variations (Ruiz-Pérez et al., 2016). These adaptations can have hydrological and ecological effects (Dale, 1997).

One example of widespread human-induced land use change is agriculture. Modern agriculture is recognised as one of the most significant non-point sources of water pollution (Johnes, 1996), especially for nutrients like nitrogen and phosphorus (Tong and Chen, 2002). At the global scale, agriculture is the economic sector that is likely to suffer the greatest financial impact as a result of climate change (Lobell et al., 2011). Farmers are expected to adapt to climate change by switching activities to those that are most profitable, given the new conditions they will face (Fezzi et al., 2015). This adaptation is likely to have a strong effect on river water quality (Fezzi et al., 2015), for example by increasing/decreasing nitrogen leaching to the aquifer, or by altering the nutrient export from agricultural soils.

Scenarios are commonly used as tools to examine plausible developments of change (Mehdi et al., 2015). Nevertheless, scenarios are usually characterised by a high degree of subjectivity and do not describe the response of the land use to climatic changes. An alternative to understand the response of land use to drivers such as climate variability is through the use of spatially-explicit land use allocation models. These models estimate the future evolution of land use/land cover through land use conversion, based on climate, population and peoples' responses to economic opportunities, as mediated by institutional factors (Lambin, 1997; Lambin et al., 2001).

Despite the importance of climatic and socio-economic changes on water resources and water quality management, there is still a strong need for quantitative approaches that can evaluate the impact of these drivers of change and assist catchment and river management, compensating for the lack of objectivity that socioeconomic and emission scenarios holds. Moreover, only a few studies so far have presented integrated assessments of the joint impact of climate and land use change on water quality. Other studies evaluated the impacts of climate change and/or land use change in the Thames catchment or in other catchments in the UK, although none assessed the impact of the dynamic co-evolution of land use with long-term climatic changes, to the authors' knowledge. The findings of this study in terms of phosphorus substantially agree with the ones of Crossman et al. (2013) concentration, who used the same model (INCA – INtegrated CAtchment model) but a different methodology, with a set of static land use scenarios. Bussi et al. (2016b) also provided estimates of the impacts of climate and land use change on total phosphorus concentration using the INCA model and a scenario-neutral methodology (i.e. a methodology that does not use emission scenarios or socio-economic scenarios to drive a hydrological model, but rather makes a sensitivity analysis on the model input), but employing a set of static land use change scenarios that were not linked to agricultural supply and demand.

The objectives of this study are:

- To develop a methodology for the combined evaluation of direct and indirect impacts of climate change on river water quality, taking into account the response of land use and agriculture to changes in climate.
- To understand the relative importance of the direct and indirect impacts of climate change on nitrate and phosphorus concentration in the River Thames

A land use allocation model, embedded within an integrated modelling platform, is coupled to a hydrological and water quality model to assess the impact of a changing climate on water quality taking into account the land use/land cover response to changing crop suitability and profitability under the same climatic variations. This is done by means of a scenario-neutral methodology (Bussi et al., 2016a, 2016b; Prudhomme et al., 2010), which allows the system response to changes in climate to be assessed without having to rely on specific climate and/or land use scenarios. The water quality model used is the INCA model for nitrogen and phosphorus (Wade et al., 2002a, 2002b, Whitehead et al., 1998a, 1998b). This model is applied to the River Thames catchment (UK).

2 Study area

This paper focuses on River Thames catchment upstream of London (Figure 1, 9,927 km^2), located in southern England and draining toward the city of London. This river provides freshwater supply to fourteen million people (Whitehead et al., 2013), most of whom live downstream within London, and receives treated wastewater from approximately three million people (Kinniburgh and Barnett, 2009). The climate is temperate with Atlantic and continental influences. The average annual precipitation is 730 mm (1960-2014, with a minimum of 538 mm in 1973 and a maximum of 974 mm in 2000) and the annual average temperature is 10.7°C (1960-2014, minimum: 8.6°C in 1963, maximum 12.1°C in 2014), with a difference of around 1.5-2°C between the interfluve and the valleys. The average summer temperature is 16.5 °C and the average winter temperature is 4.7°C. The average daily flow is 67 m^3 s^{-1} at the catchment outlet in London, with a daily Q5 (discharge exceeded only 5% of the time) of 206 m^3 s^{-1}. High flows usually occur in winter to early spring and low flows in summer to late autumn (Bussi et al., 2016a).

The catchment geology is dominated by chalk, with limestone in the headwaters, and clay/mudstone and sandstone also present both upstream and downstream of the chalk area (Bloomfield et al., 2011). The catchment is dominated by arable land alternated with grassland in its upper part (around 80% of the catchment draining to reach 4 in Figure 1 is dedicated to arable agriculture or improved grassland), with little urban land in the headwaters. The urban land portion increases in the Western part of the catchment (up to 30% of the lowermost sub-catchments in Figure 1). Around 13% of the catchment is covered by woodland.

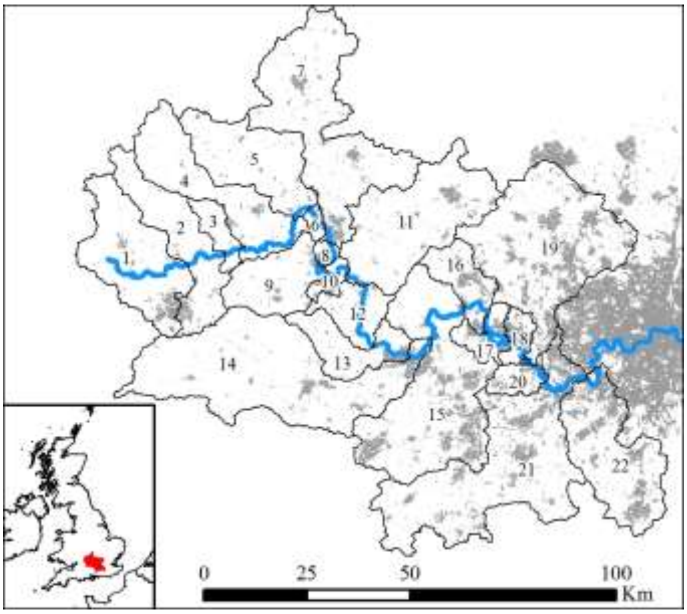

Figure 1 – Location of the River Thames catchment (UK). The INCA model sub-catchments are also shown. The grey areas show the location of the urban areas.

The results of this study are shown at two reaches: reach 4, representative of the upper Thames, and reach 19, representative of the lower Thames. Reach 4 drains sub-catchments 1 to 4, which have an extension of 1610 km^2. The land use is predominantly agricultural, with 50% of arable land and 28% of improved grassland. Forest land is 6% of the total area. Only 5% of the catchment is occupied by urban land, with less than 300,000 population equivalent discharging effluents into the river. Reach 19 drains sub-catchments 1 to 19. The part of the Thames catchment drained by reach 5 to 19 has an extension of 6540 km^2. The land use is also dominated by agriculture, with a portion of arable land of 42% and 28% of improved grassland. Forest land is 11% and urban land is also 11%. The population equivalent of this portion of catchment is slightly less than 3,000,000.

Meteorological inputs for the INCA model, namely daily precipitation and temperature time series, were obtained from the UK Met Office (Met Office, 2012). More details can be found in Bussi et al. (2016a). Records of continuous daily water discharge at the several sections of the river were obtained from the National River Flow Archive (NRFA, ceh.ac.uk/data/nrfa/). Weekly nutrient data, in particular nitrate concentration and total phosphorus concentration, were obtained from the Thames Initiative (TI) research platform dataset (Bowes et al., 2012). Intermittent nutrient data, collected with a frequency of around four weeks, were also obtained from the Environment Agency of England and Wales.

3 Methodology

3.1 Land use allocation model

Land use allocation was simulated using the IMPRESSIONS Integrated Assessment Platform (IAP), which is an update of the CLIMSAVE IAP (Harrison et al., 2016, 2015, 2014; Holman et al., 2016). The platform integrates a suite of models to assess the impacts of, and adaptation to, climate and socio-economic change across a range of sectors including urban development, coastal and fluvial flooding, agriculture, forests, water resources and biodiversity (see Figure 2). The computationally efficient models within the IAP (details of which can be found in Holman and Harrison (2011) have been validated and subject to extensive sensitivity (Kebede et al., 2015) and uncertainty (Brown et al., 2014; Dunford et al., 2014) analyses. The platform is run across the European Union countries plus Norway and Switzerland on a 10’x10’ grid (approximately 16km x 16km) of over 23,000 gridcells (with each grid cell containing multiple soil types), and over 4 time slices (baseline, 2011-2040, 2041-2070 and 2071-2100).

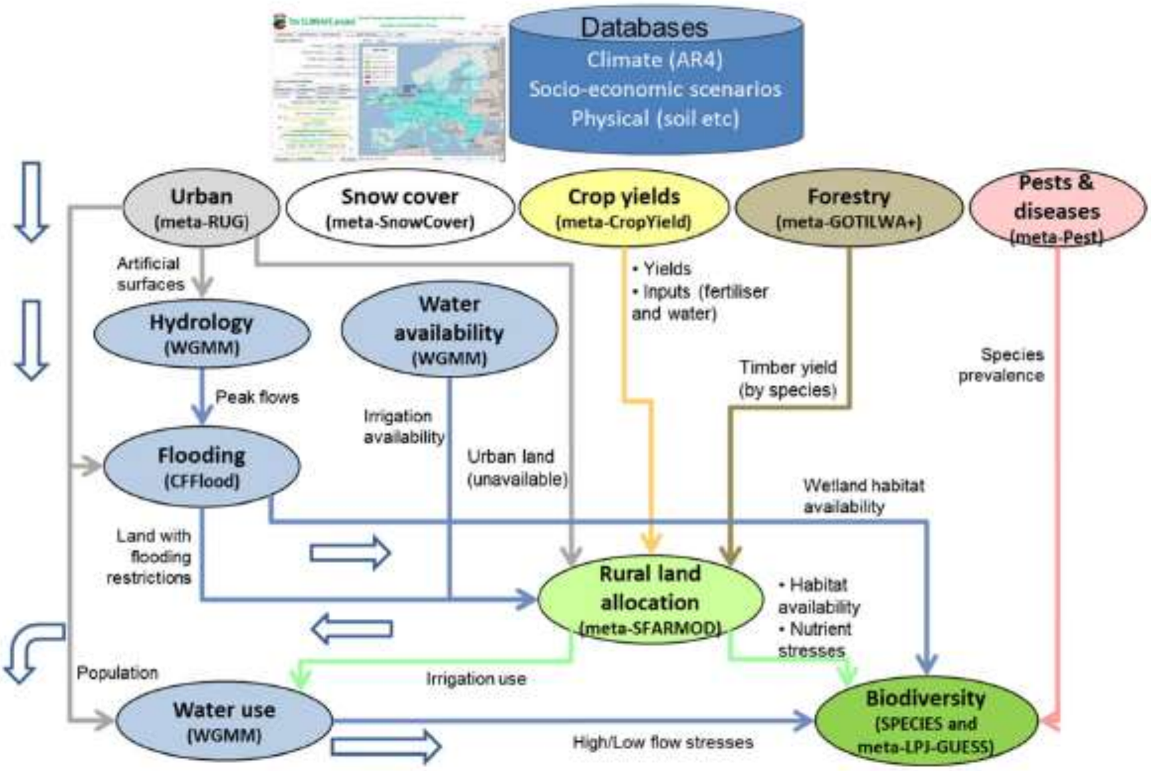

Figure 2 –Schematic showing the structure of the linked models within the IMPRESSIONS IAP2.

The rural land use allocation metamodel in the IAP (Audsley et al., 2014) is based on the Silsoe Whole Farm Model (SFARMOD-LP - Annetts and Audsley, 2002) a constrained optimising linear programming model of long-term land use. The model spatially allocates land uses (intensive arable, intensive grassland, extensive grassland, managed forest, unmanaged forest and unmanaged land), and associated rainfed and irrigated crops and tree species, based on relative economic profitability and subject to a range of constraints. These include areas subject to urban development, flood risk, environmentally protected areas (such as Natura 2000 sites) and water resource availability. The model works iteratively to find a spatial land use allocation solution that meets demand for the commodities of timber, meat, milk, fibre, protein, roots, oils and cereals across Europe, in response to spatial simulated changes in profitability driven by changing crop yields, fodder production (influencing milk and meat production) and timber yield. Price factors are used to stimulate or reduce production of a given commodity across Europe to meet demand (by making its production more/less economically advantageous). In the context of the current study, land use in the Thames catchment can change as a result of intra- and inter-catchment changes in crop and timber yields and profitability, reflecting the large-scale markets of such commodities where prices and supply are driven by national and international demand. For this study, the baseline socio-economic conditions within the IAP were maintained, so that European food demand (driven by population, GDP and dietary preferences and net imports) and agricultural technology (crop breeding, mechanisation, etc.) remained constant. The simulated baseline land use for the River Thames catchment (i.e., the current land use) is shown in Figure 3.

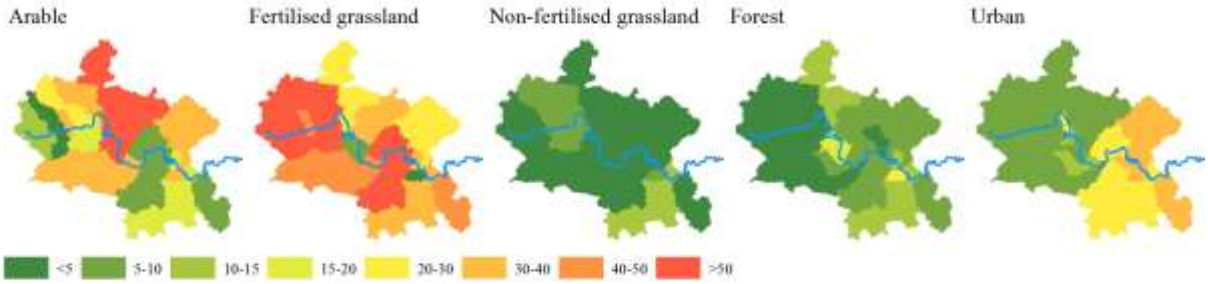

Figure 3 – Simulated percentage land use of the River Thames catchment per sub-catchment under current climate (i.e., no alterations of precipitation and temperature).

3.2 Water quality model

The INCA hydrological and water quality model was employed to reproduce the water quality dynamics of the River Thames (UK). This model was chosen because it combines the simplicity required to reproduce water quality processes at the catchment scale with the accuracy that is necessary to produce estimates of flow and nutrient concentration. Furthermore, it is a very well-known water quality model, used in several catchments in the UK and in the rest of the world since the late 90s, with an extensive body of publications to support it (some of which are detailed below). The INCA model is particularly suitable for the scale of this study, as it was developed as a catchment-scale model, with the possibility of disaggregating the catchment in several sub-catchments. Furthermore it offers the possibility of analysing the effect of land use change on water quality, given that different land use units with different characteristics and parameters can be defined within each sub-catchment.

The INCA model was initially developed as a nitrogen (Whitehead et al., 1998a) and phosphorus (Wade et al., 2002b) model, although several other sub-models were added later, such as a soil erosion and sediment transport sub-model (Lázár et al., 2010), a faecal indicator model (Whitehead et al., 2016) and an organic contaminant model (Lu et al., 2016). The hydrological and water quality sub-models of INCA have been applied to several basins across the UK and Europe, and, in particular, to the River Thames catchment (Bussi et al., 2016b; Crossman et al., 2013b; Jin et al., 2012; Lu et al., 2016; Whitehead et al., 2016, 2013). INCA is a semi-distributed process-based model which simulates the transformation of rainfall into runoff and the propagation of water through a river network (Wade et al., 2002a). Its inputs are daily time series of precipitation, temperature, hydrologically effective rainfall, and soil moisture deficit. The latter two are estimated using another semi-distributed hydrological model, called Precipitation, Evapotranspiration and Runoff Simulator for Solute Transport model - PERSiST (Futter et al., 2014), which is specifically designed to provide input series for the INCA family of models. It is based on a user-specified number of linear reservoirs which can be used to represent different hydrological processes, such as snow melt, direct runoff generation, soil storage, aquifer storage and stream network movement. The description of its application to the river Thames can be found in Futter et al. (2014).

The nitrogen sub-model of INCA (Wade et al., 2002a; Whitehead et al., 1998a, 1998b) reproduces the cycle of nitrogen from its main sources (atmospheric deposition, fertilisers, wastewater, etc.) to the river. The most important soil processes are included, such as denitrification, nitrification, immobilisation, mineralisation and leaching towards the aquifer. Nitrification and denitrification processes in the streams are also taken into account. The phosphorus sub-model of INCA (Wade et al., 2002b) incorporates the main sources of phosphorus, both diffuse (fertilisers) and point (wastewater), as well as the main processes involving phosphorus, such as sorption/desorption. The phosphorus sub-model of the INCA model also includes a sediment sub-model, which computes the detachment of soil particles from the hillslopes and their transport towards the catchment outlet. The INCA model has already been applied to the River Thames catchment (Crossman et al., 2013b; Jin et al., 2012; Lu et al., 2016; Whitehead et al., 2016, 2013). In this study, the same model structure is used, where the catchment is divided into 22 sub-catchments and the river into 22 corresponding reaches (Figure 1). The land uses of the Thames catchment were categorised as follows: forest (including both managed and unmanaged forest), unfertilised grassland (i.e., extensive grassland), fertilised grassland (i.e., intensive grassland), arable (i.e., intensively farmed land) and urban. The land use configuration used for model calibration was obtained from the IAP model rather than from land use maps to ensure consistency between the baseline and the scenario results.

Based on a prior general sensitivity analysis of the INCA model of the River Thames (Spear and Hornberger, 1980; Whitehead et al., 2015) and the modeller's knowledge, the following 22 parameters were identified as the most influential:

- Hydrology (Bussi et al., 2016a; Jackson-Blake and Starrfelt, 2015): rainfall excess proportion (the proportion of excess rain that is converted into direct runoff), soil water and ground water residence times (i.e., flow velocity for sub-superficial flow and base flow), maximum infiltration rate, flow-velocity coefficient (the coefficient of a power law used to calculate channel flow velocity from discharge), flow threshold for saturation excess direct runoff. (,
- Nitrogen (Jin et al., 2012; Wade et al., 2002a): soil denitrification coefficient, nitrification, mineralisation and immobilisation rates in the soil, nitrogen uptake rate by crops, groundwater nitrate concentration, instream nitrification rate and instream denitrification rate,
- Sediment,(Bussi et al., 2016a; Lázár et al., 2010):,splash and flow erosion parameters (defining the erodibility fo soils), flow erosion direct runoff threshold (defining the threshold above which flow erosion occurs), transport capacity scaling factor (which adjusts the transport capacity on the hillslopes), transport capacity non-linear coefficient (which adjusts the transport capacity on the hillslopes), instream sediment transport parameters (which adjust the transport capacity in the channel)
- Phosphorus (Bussi et al., 2016a; Jackson-Blake and Starrfelt, 2015): soil matrix sorption coefficient (which adjusts the sorption capacity of the soils),water column sorption coefficient (which adjusts the sorption capacity of the water column), stream bed sorption coefficient (which adjusts the sorption capacity of the be sediment).

More information on INCA model sensitivity analysis and Monte Carlo calibration can be found in Jackson-Blake and Starrfelt (2015) and Bussi et al. (2016a).

The feasible ranges of variation of these influential model parameters, informed by previous studies, were sampled randomly, and 10,000 different parameter sets were generated. Subsequently, the INCA model was run with each of these parameter sets, and its performance was assessed based on observed values of flow and water quality at two stations (reach 4 and reach 19), using data from 2010 to 2014. The metric used for model assessment was the Nash and Sutcliffe Efficiency (NSE - Nash and Sutcliffe, 1970) for the flow and the percent bias (PBIAS - Bennett et al., 2013) for nitrate and sediment on the daily results. The best model was selected and used in the rest of the study. The results are shown in Figure 4, where the grey-shaded area represents the calibration period (2010-2014), which was chosen to ensure that the model reflects current, rather than historical, catchment conditions, in particular, wastewater treatment standards, fertiliser and manure use and stocking densities. The performance indices for calibration and validation are shown in Table 1.

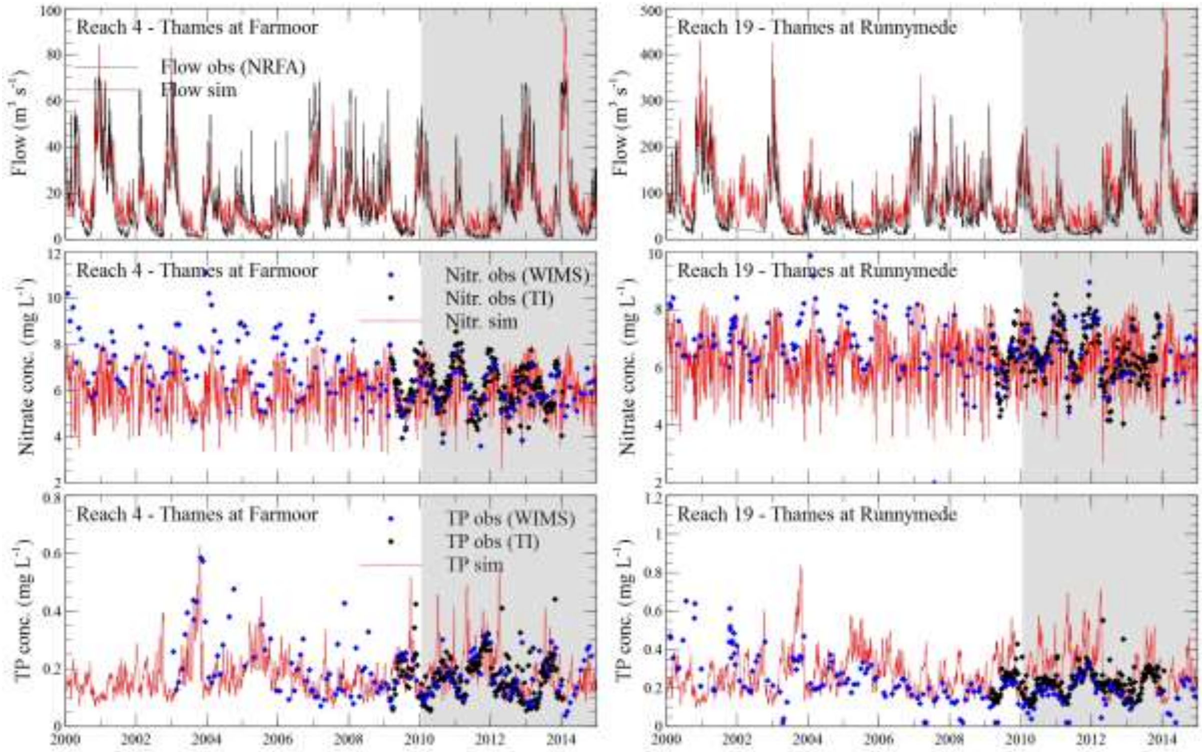

Figure 4 – INCA model calibration and validation results at two locations on the River Thames. Observed data: NRFA (National River Flow Archive, daily flow, 2000-2015), TI (Thames Initiative dataset, weekly nitrate and total phosphorus, 2009-2014) and WIMS (Water Information Management System database, monthly nitrate and total phosphorus, 2000-2015). The grey-shaded area represents the calibration time period.

	Reach	Flow NSE	Flow PBIAS	Nitrate R2	Nitrate PBIAS	Phosphorus R2	Phosphorus PBIAS
Calibration 2010-2014	**Reach 4**	0.81	3	0.49	-1	0.30	12
	Reach 19	0.85	7	0.49	0	0.18	31
Validation 2000-2010	**Reach 4**	0.73	1	0.56	-4	0.28	22
	Reach 19	0.79	11	0.56	2	0.42	53

Table 1 – Performance indices of the INCA model (calibration and validation). NSE: Nash and Sutcliffe Index, R2: correlation coefficient, PBIAS: percent bias.

As Figure 4, the model results can be considered generally satisfactory in terms of reproduction of the system response to climatic variations, given the uncertainty that characterises both model results and measured data values. It is important to note that this model is not used to provide daily forecasts of nitrate and phosphorus concentrations in the River Thames, but rather to disentangle the average catchment response to long-term changes in the climatic conditions and its consequent modifications of the land use.

Concerning the phosphorus simulation reach 19, the PBIAS is slightly unsatisfactory, especially for validation, although the R2 shows acceptable values (0.42 for validation). The interpretation of this is likely to be the impact of phosphorus effluent concentrations on the river concentration. At this location in the river, a large amount of wastewater effluent is discharged into the river and impacts greatly the phosphorus concentration. In this study, we used a constant phosphorus concentration for the effluent as input to the water quality model, due to the lack of better data. However, this concentration is likely to vary in time, and it was probably higher in the early years of the 2000s and lower in the present, due to the improvements in phosphorus stripping techniques (as the decreasing trend in the observed concentration seems to show). Using an average concentration as model input can therefore introduce an important bias. Although this is likely to affect the results of this study, the phosphorus model results for reach 19 are shown anyway, since the methodology employed in this paper is still valid.

3.3 Scenario-neutral methodology for climate variability impact assessment

A scenario-neutral approach was used to assess the impact of long-term climate change and climate variability on land use and water quality. As opposed to top-down approaches, which use climate model outputs to drive hydrological and environmental models, the scenario-neutral methodology is based on a bottom-up approach. Environmental vulnerability indicators (in this case, river water quality) are used as end-variable, and a response surface of these indicators to changes in some climatic features is built using environmental models (Singh et al., 2014). The likelihood of these climatic changes is then assessed by integrating information about future climate (often from climate models) into the results of this methodology (Prudhomme et al., 2010). The main advantages of this methodology is that it does not need to choose a specific emission scenario or a specific climate model from the available tools (which is often a difficult and slightly arbitrary task) and it does not need a bias-correction procedure (which can also be complex to perform in certain cases).

In this study, the following methodology was set up. First, the climatic stressors most likely to impact water quality were identified. Alterations in these climatic stressors were then applied to the current climatic observed series of daily precipitation and temperature from 1960 to 2015. This allowed the creation of a number of combinations of perturbed input time series (precipitation and temperature) which were used to drive both the land use model and the water quality model (Figure 5). The final result was a set of nitrate and phosphorus concentration time series resulting from all the combinations of the altered climatic time series. The advantages of using this methodology are that no climate model output is required to drive the land use and water quality models, and therefore no assumptions have to be made on future greenhouse gas emission/concentration scenarios, and no bias correction of a climate model output is required (Prudhomme et al., 2010). Furthermore, in this particular case, this methodology seems even more appropriate because this study focuses on long term changes, without necessarily having to relate the resulting changes in land use and water quality with a future time horizon or a prescribed time by which the scenario is thought to occur.

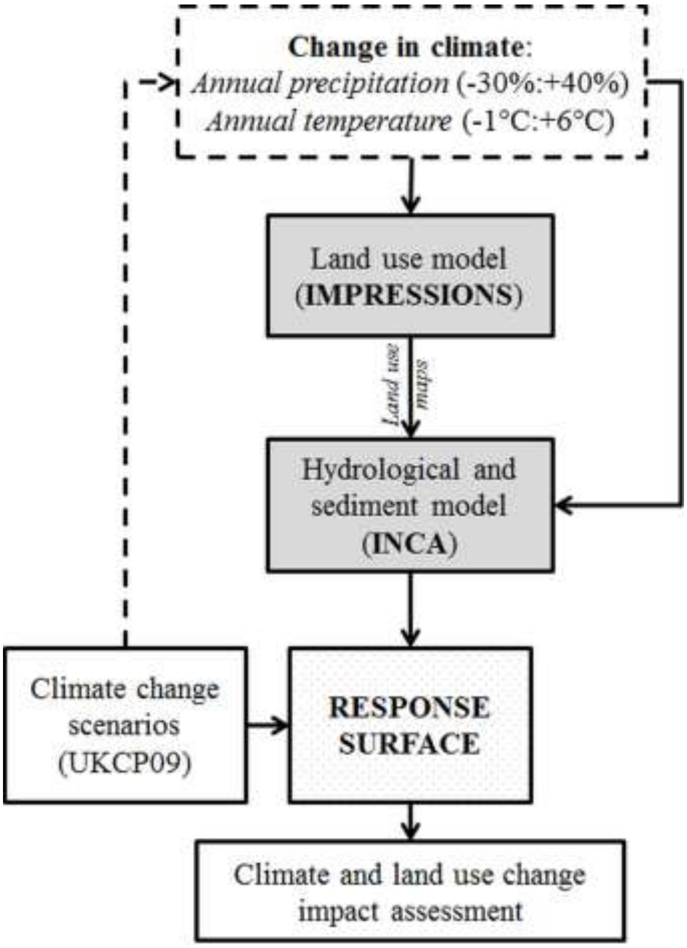

Figure 5 – Scheme of the methodology used in this study.

Alterations to average precipitation and average temperature were introduced by means of a uniform "delta change" transformation (Hay et al., 2000) applied to observed daily precipitation and temperature values. The alterations were chosen to cover the projected changes in annual precipitation and temperature by climate models, but also to stress the system further, with the aim of assessing not only future plausible changes but also the response of the system under very extreme conditions. Following Christensen et al. (2007), for Northern Europe the annual temperature is expected to increase up to 5.3°C by 2080-2099, while annual precipitation is expected to vary between 0 and +16% (although a decrease in summer precipitation is also forecasted, up to 21%). Therefore, seven alterations were applied to the temperature (from +0°C to +6°C with a 1°C step) and eight alterations to the precipitation time series (from -30% to +40% with a 10% step), creating in total 56 combinations of manually-altered climate. For each time series, the IAP was first run to compute the corresponding land use for the Thames catchment given the long-term climatic changes dictated by the scenario-neutral climatic alterations. Then, the water quality model was run, driven by the altered precipitation and temperature time series and using the land use map obtained at the previous step. An additional model run was also carried out for each of the 56 climate alteration combinations, using altered climate but unaltered land use (i.e., the current land use), in order to isolate the effect of considering land use as a dynamic variable. The results of the water quality model were analysed in terms of average nitrate concentration and average total phosphorus concentration (the averages were computed over all the time period considered, i.e. 1960-2015), at two locations on the River Thames (reach 4: Thames at Farmoor – i.e., upper Thames, and reach 19: Thames at Runnymede – i.e., lower Thames).

Although, as said above, this methodology does not require the use of climate model results as inputs to the modelling, these are used to compute the likelihood of the catchment response to climatic alterations by assigning a probability of occurrence to the combinations of climate alterations considered in this study. The probabilistic change factors from the UK climate projections 09 (UKCP09, Murphy et al., 2009) were used to determine the likelihood of the precipitation and temperature changes used to drive the land use and water quality models. The UKCP09 scenarios were developed by the UK Met Office to provide climate change projections over the UK accounting for uncertainties in global climate models. These projections are based on the results of the HadCM3 coupled ocean-atmosphere Global Circulation model (Gordon et al., 2000), which was run as a perturbed physics ensemble to sample model and parameter uncertainties (Murphy et al., 2007). HadCM3 projections were 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 each of three of the IPCC's Special Report on Emissions Scenarios (SRES) scenarios (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 are given (change factors). The change factors were used to assess the likelihood of the water quality alterations that follows the climatic alterations detailed above. No daily or monthly time series were employed, and no downscaling/bias correction is required within the framework of a scenario-neutral methodology. The likelihood of changes in water quality was computed by comparison with climatic properties taken from a set of 10,000 change factors for the River Thames catchment under the A1FI emission scenario (the most severe scenario) for several future time slices (from the 2020s to the 2080s). These change factors were downloaded from the UK climate projections website of the Met Office.

4 Results

4.1 Impacts of climate variability on land use

As the IAP model simulates a decrease in arable area across the Thames catchment and the UK with increasing temperature (Figure 6), it simulates a corresponding significant increase in arable area in parts of Central and Eastern Europe. Higher crop yields due to increased temperatures result in greater relative profitability of arable land in these regions. Therefore growing arable crops within the UK no longer maximises profit so that such land is converted to fertilised (intensive) grassland. However, the model indicates that a large increase in temperature of +6°C would cause a return of arable agriculture in the Thames catchment (although not at the current level). **Error! Reference source not found.**C illustrates an expansion of the arable area under such conditions in Europe as increased drought and heat stresses reduce crop yields and productivity across much of Europe. As a result, demand for arable commodities is not met and increased profitability of arable land within the UK prompts conversion of grassland to arable land.

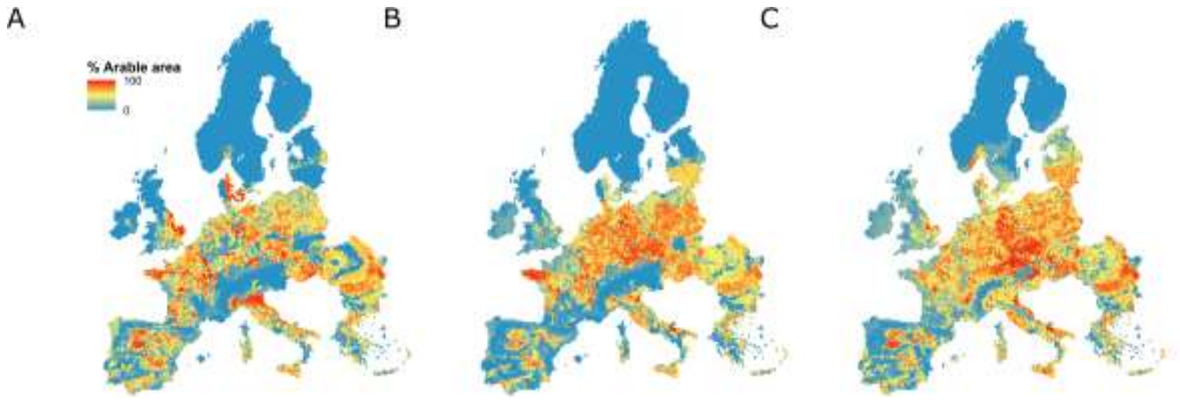

Figure 6 –Percentage arable area per grid cell simulated by the IAP2 model for A: Baseline (current) climate, B: +3°C, and C: +6°C and -30% precipitation.

Figure 7 and Figure 8 show the simulated arable, fertilised grassland, non-fertilised grassland and forest areas of the River Thames catchment across the range of precipitation and temperature changes, expressed as a percentage of the undeveloped catchment area. Figure 7 shows the response of the land use to change in climate for the upper Thames, i.e., the sub-catchment drained by reach 4 (Thames at Farmoor). Figure 8 shows the response of the lower Thames catchment (i.e., the part of the Thames catchment drained by the River Thames between reach 4 and reach 19 – Thames at Runnymede). The baseline land use fractions are shown in Figure 3. The results show that the simulated agricultural land use in the Thames catchment is highly sensitive to small changes in climate in Europe. In particular, both the arable land and the fertilised grassland fractions of the Thames catchment appear to be especially sensitive to increases in temperature and to increases in precipitation under conditions of low temperature increases.

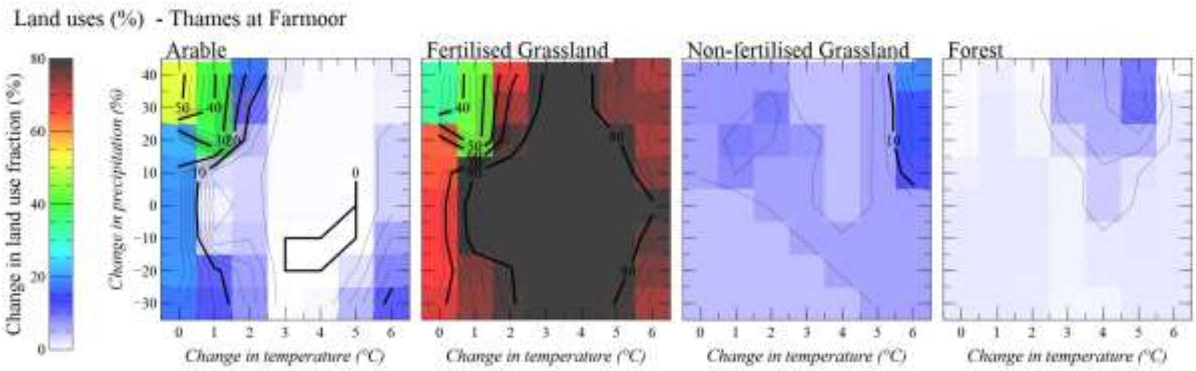

Figure 7 – Response of the land use in the upper Thames catchment to long-term changes in the climate (sub-catchment drained by reach 4 – Thames at Farmoor), in terms of land use fraction of the catchment. Black lines are surface contour lines (bold lines every 10% land use fraction, thin lines every 2.5%).

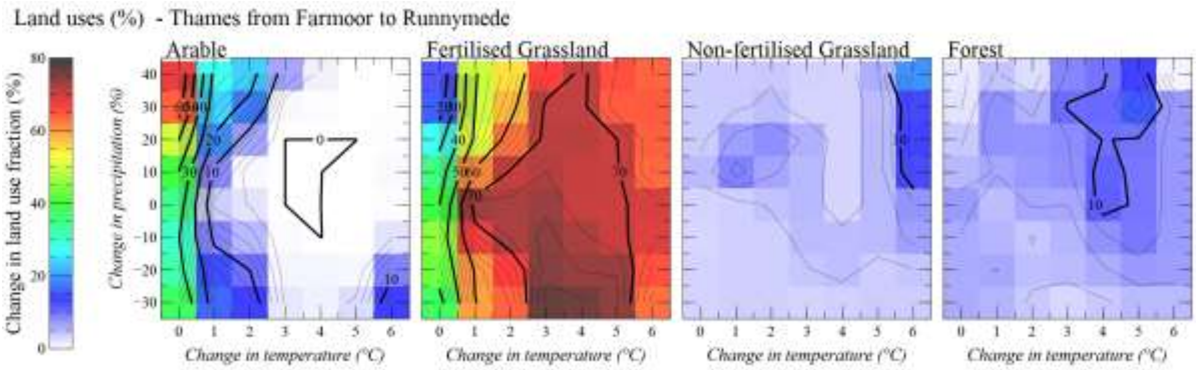

Figure 8 – Response of the land use in the lower Thames catchment to long-term changes in the climate (sub-catchments drained by the River Thames from reach 4 to reach 19 – Thames at Runnymead), in terms of land use fraction of the catchment. Black lines are surface contour lines (bold lines every 10% land use fraction, thin lines every 2.5%).

Even a small increase in temperature causes a sharp decrease in arable land, and corresponding increase of fertilised grassland. As temperature increases above ~2°C, the arable area decreases to ~0% in most of the catchments under all precipitation scenarios. This does not reflect the inability of such arable crops to grow under these conditions, but rather that it is more profitable to meet demand in other parts of Europe.

4.2 Impacts of climate variability on water quality

The INCA model results provided an assessment of the response of the River Thames water quality to changes in annual precipitation and temperature. In Figure 9 and Figure 10 the response surfaces are shown for the two different river reaches (Figure 9: reach 4 – Thames at Farmoor, Figure 10: reach 19 – Thames at Runnymede), and for the two water quality variables analysed in this paper (nitrate concentration: left part of the plots, total phosphorus concentration: right part of the plots). Two water quality response surfaces are shown for each variable: the response under fixed (baseline) land use representing the direct impact of climate change on hydrological functioning, nutrient transport and in-river processes; and the response under variable land use that also includes the indirect changes associated with long-term autonomous land use change and associated changed agricultural nutrient inputs.

Nitrate in the Thames catchment is mainly due to diffuse sources (fertilisers used in agriculture, Jin et al., 2012), hence its concentration in the river is proportional to runoff. An increase in temperature increases evapotranspiration and, as a consequence, causes a decrease in runoff (Figure 9 and Figure 10). In the same way, a decrease in precipitation entails a decrease in runoff and thus a decrease in nitrate concentration. Furthermore, a decrease stream flow means reduced velocity, increased residence times and hence enhance the denitrification processes, reducing nitrate concentration (Jin et al., 2012). On the contrary, the main sources of phosphorus in the Thames are household effluents discharged by sewage treatment plants (Crossman et al., 2013b; Whitehead et al., 2013), and therefore phosphorus concentration is inversely proportional to flow (i.e., less flow means less dilution capacity and higher phosphorus concentration). This means that an increase in temperature causes an increase in phosphorus concentration, while an increase in precipitation causes a decrease in phosphorus concentration (Figure 9 and Figure 10).

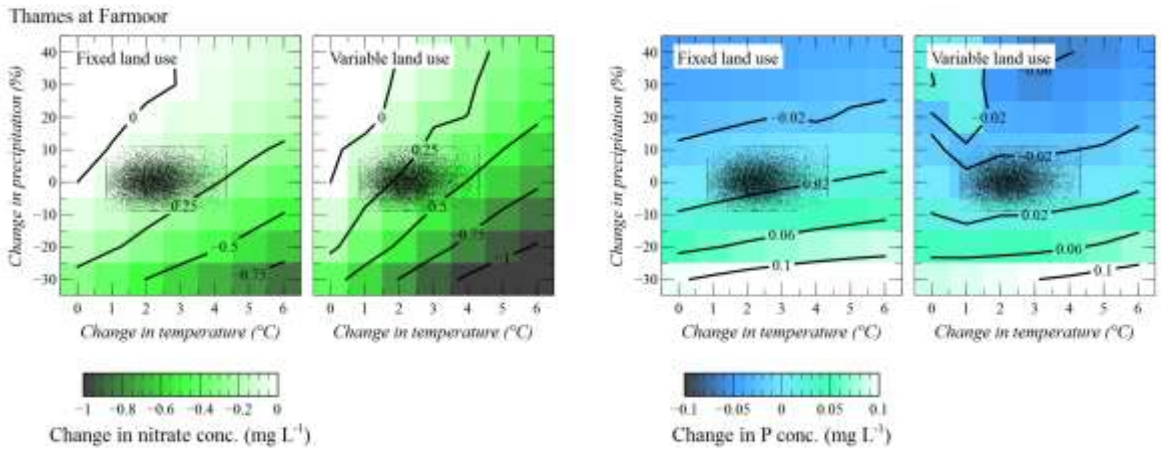

Figure 9 – Response to climate variability on the water quality of the River Thames at Farmoor – reach 4. The black dots represent the space defined by the UKCP09 change factors for the 2040s. The black lines are surface contour lines (every 0.5 mg l^{-1} for nitrate, every 0.04 mg l^{-1} for phosphorus).

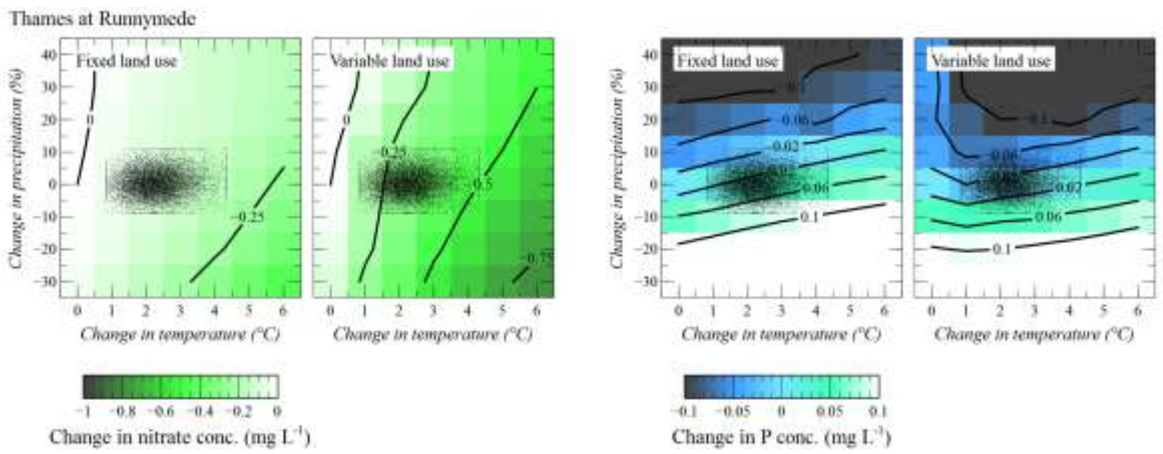

Figure 10 – Response to climate variability on the water quality of the River Thames at Runnymede – reach 19. The black dots represent the space defined by the UKCP09 change factors for the 2040s. The black lines are surface contour lines (every 0.5 mg l^{-1} for nitrate, every 0.04 mg l^{-1} for phosphorus).

The change in nitrate concentration is inversely proportional to temperature and directly proportional to precipitation, with a similar pattern of control exerted by both drivers of change (changes in precipitation and temperature), at least within the range of variations considered in this study. On the other hand, phosphorus has a different behaviour, with marked increases due to a decrease in precipitation, and also a direct proportionality with temperature, although weaker than with precipitation. This is more evident at reach 19 (lower Thames), while for reach 4 (upper Thames) the pattern is not as clear, and the response surface gradient is not homogeneous.

From Figure 9 and Figure 10 it can also be observed that some important differences in water quality behaviour arise by allowing the land use to autonomously adjust to the climate rather than remaining static. The variable land use appears to enhance the proportionality between increase in temperature and decrease in nitrogen concentration. In terms of phosphorus concentration, considering variable land use introduces a very significant change in the catchment response, where it appears to offset the effect of decreasing precipitation in increasing phosphorus concentration. This effect appears more evident in the rural reach 4, where the relative contribution of diffuse sources of phosphorus is higher than at reach 19, and thus the catchment is more sensitive to changes in land use.

Figure 9 and Figure 10 also allow analysing the spatial patterns of the catchment response. In terms of nitrate concentration, the model results suggest that the upper Thames is more sensitive to changes in climate than the lower Thames, while for phosphorus concentration the opposite effect is observed. Additionally, the sensitivity of the response to the drivers of change considered in this study is different depending on the sub-catchment. For example, in the lower Thames nitrate concentration seems to be less sensitive to changes in precipitation than in the upper Thames, as the gradient of the response surfaces shows.

4.3 Likelihood of water quality changes

The response surfaces shown in Figure 9 and Figure 10 provide an assessment of the system sensitivity to some drivers of change, but do not offer any information on the likelihood of the simulated changes in water quality happening in the future. Nevertheless, climatic model outputs can provide a value of likelihood of the drivers of change considered. In Figure 9 and Figure 10, a white-shaded area is shown on each of the response surfaces, indicating the area defined by 10,000 combinations of UKCP09 precipitation and temperature change factors for the 2040s, under the A1FI emission scenario. Computing the catchment response in terms of water quality corresponding to each of these 10,000 pairs of annual precipitation/temperature changes allows a probability function of the expected changes in the river water quality to be derived.

In Figure 11, the empirical probability distribution functions of expected average nitrate concentration change and expected average total phosphorus concentration changes, corresponding to the 10,000 UKCP09 precipitation and temperature change factors, for both fixed and variable land use are given. In all cases considering variable land use introduces considerable changes in the final outcome. For reach 4, the median expected change in the total phosphorus concentration even shifts from positive to negative, thus highlighting the effect of land use in mitigating climate change. This is reflected also in Table 2, where the median expected changes and their standard deviations are shown, based on the results depicted in Figure 11.

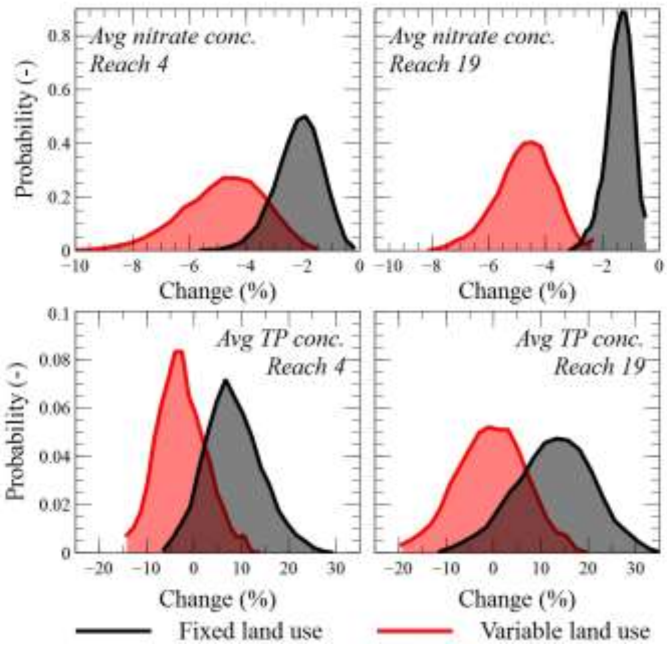

Figure 11 – Probability distribution function of expected changes in water quality (average concentration of nitrate and total phosphorus), according to the UKCP09 change factors for the 2040s, for two reaches of the River Thames (reach 4 – Thames at Farmoor and by reach 19 – Thames at Runnymead).

Table 2 also shows the model results for 2060s and 2080s. The change of the system response according to the UKCP09 for different time slices is also represented in Figure 12, for reach 19, and considering variable land use. The decrease in nitrate concentration and increase in phosphorus concentration increase in time, due to a stronger signal of warming, which reduces runoff and stream flow.

			Reach 4		**Reach 19**	
Water quality variable	**Time slice**	**Land use**	**Median change**	***Standard deviation***	**Median change**	***Standard deviation***
Average nitrate concentration	2040s	Fixed land use	-2.2	*0.8*	-1.4	*0.5*
	2040s	Variable land use	-4.9	*1.4*	-4.8	*1.0*
	2060s	Fixed land use	-3.3	*1.2*	-2.1	*0.7*
	2060s	Variable land use	-7.0	*2.1*	-6.3	*1.4*
	2080s	Fixed land use	-4.2	*1.5*	-2.8	*0.9*
	2080s	Variable land use	-8.7	*2.3*	-7.6	*1.5*
Average total phosphorus concentration	2040s	Fixed land use	6.9	*5.9*	11.8	*8.2*
	2040s	Variable land use	-3.7	*5.0*	-1.4	*7.3*
	2060s	Fixed land use	10.4	*7.6*	16.7	*9.5*
	2060s	Variable land use	-1.8	*6.4*	2.6	*8.5*
	2080s	Fixed land use	12.4	*9.5*	19.1	*11.3*
	2080s	Variable land use	0.0	*8.4*	4.7	*10.2*

Table 2 – Median values and standard deviations of the expected changes (%) in water quality according to the UKCP09 projections for the 2040s, 2060s and 2080s.

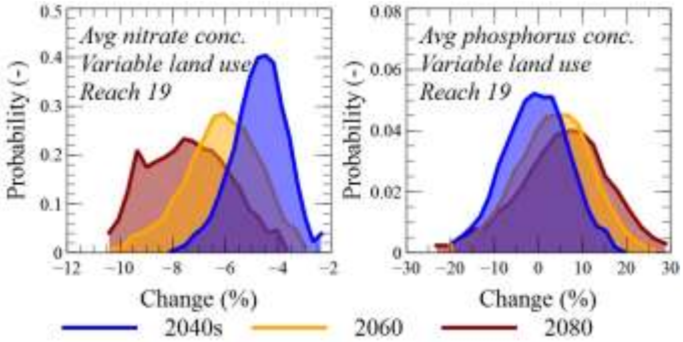

Figure 12 – Probability distribution function of expected changes in water quality (% change in average concentration of nitrate and total phosphorus), according to the UKCP09 change factors for the 2040s, 2060s and 2080s for reach 19 (Thames at Runnymead), with variable land use.

5 Discussion

The results of this study show that market-driven adaptation of land use to climate change and long-term climate variability can lead to significant changes. An increase in precipitation across Europe appears to lead to a large expansion of the total agriculture land represented by arable and fertilised grassland within the Thames catchment, while a decrease in precipitation would not bring very significant changes to the agricultural fraction of the Thames catchment. In contrast, the non-fertilised grassland and forest fractions of the catchment are not subject to significant changes, unless both precipitation and temperature increase sharply.

In the Thames catchment, this translates into an expansion of fertilised grassland at the expense of arable land. This is in apparent contradictions with the findings of Olesen and Bindi (2002), who stated that global warming is expected to lead to the expansion of suitable cropping areas in the North of Europe, although the Thames catchment is situated in the warmest and driest area of the UK, with Figure 3 showing expansion of arable areas in the Baltic states, Republic of Ireland, Scotland and southern Scandinavia. However, the IMPRESSIONS IAP used in this study simulates land use based on a range of trade-offs between multiple sectors and considers production and demand across Europe as a whole, assigning land use based on resulting profitability. The model results do not indicate that the Thames catchment (or the UK) becomes unsuitable for crops under warming scenarios, but that they become less profitable compared to their cultivation in other areas in Europe or compared to other land use types in the catchment. In the Thames catchment the increase in arable land in other areas of Europe in response to climate change alone appears to be the main driver of land use change, leading to a reduction in the profitability of agricultural land within the catchment. However, studies investigating the combined impacts of climate and socio-economic change (such as population, dietary preferences, GDP, and the level of food imports) on European landuse allocation have shown major divergence in land use allocation between socio-economic scenarios (Harrison et al., 2014) and a significant decrease in certainty of land use change (Holman et al., In Press). A broader range of land use change outcomes in the Thames catchment would therefore be likely under future socio-economic scenarios associated with changed European agricultural productivity, food demand and trade relationships.

Olesen and Bindi (2002) report potential implication of nutrient leaching due to the impact of global warming on agriculture. Nutrient pollution is the result of the combination of diffuse and point sources from a variety of land uses and interactions. For example, in the upper Thames fertilised grassland is the main land use, while intensively cultivated land is secondary; in the lower Thames agriculture is predominant, but with important proportions of forest land. The co-evolution of this mosaic of land uses and their implications on water quality could not be evaluated without using mathematical models (Tong and Chen, 2002). This study shows a methodology that couples a land use model with a water quality model to assess dynamically the impact of climate change on the nutrient concentration of the River Thames. It is clear from Figure 9 and Figure 10 that the co-evolution and adaptation of land use to changes in climate is a key factor in nutrient export towards the river system, and must be taken into account. Furthermore, the results of the present study suggest that the impact of climate change alone will be to enhance phosphorus concentration during low flows, similarly to what was found by both Crossman et al. (2013) and Bussi et al. (2016b).

In terms of nitrate concentration, Jin et al. (2012) also provided climate change impact estimates in the River Thames catchment, using the INCA model in a top-down frame (i.e., coupling the water quality model with climate model projections), reporting increased river nitrate concentration in winter and decreases in summer, following wetter winters and drier summers. These findings also agree with the results of the present study, which pointed to a similar response of the Thames catchment to increases and decreases in precipitation. In another study, Ferrier et al. (1995) found that Climate change will alter flow regimes, temperature and nitrogen mineralization patterns in the River Don (Scotland). They found that increased mineralization of nitrogen in the soil will be triggered by climate change, but also that nitrate concentrations will be reduced slightly by the increased temperatures and decreased summer flows, both of which enhance denitrification processes.

Concerning land use impacts on nitrate concentration in the Thames, Howden et al. (2010) reported that the main driver of historical observed change is land use, and that long-term changes in agricultural land use are more important that recent changes in farming practice. They found that once a step-change in land use intensification (principally a shift from low intensity grassland to highly intensive arable agriculture) has occurred, nitrate concentrations remain intractably high despite large-scale and sustained management intervention. These changes are irreversible unless a significant area of arable land is converted to low intensity grassland or forest (Howden et al., 2010). In their paper, Howden et al. (2010) also urged caution before implementing policies (usually market-driven) that encourage massive land conversions as their impact on fresh and marine waters could persist for many decades. Similarly, Whitehead et al. (2002), after reconstructing the past land use changes in the River Kennet catchment (a tributary of the Thames), found that a sharp increase in agricultural land since the 1930s caused a major shift in the short term dynamics of nitrate in the river with increased river and groundwater concentrations caused by non-point source pollution from agriculture. In light of these statements, the methodology described in the present study offers a robust tool to analyse the long-term impact of large changes in arable land extension due to variations in crop productivity and demand, rather than to short term changes in farming practices.

One of the main contributions of this study is the assessment of the co-evolution of the land use with changes in climate. Figure 9 and Figure 10 show the differences in the response if the variation of land use with climate is taken into account or not. In general, there is an inverse relationship between temperature and nitrate concentration, because an increase in temperature causes increased evapotranspiration and reduced runoff from agricultural soils, as well as increased instream denitrification due to lower flows. If variable land use is introduced, this relationship is enhanced, because with an increase in temperature the total arable area is reduced (Figure 9 and Figure 10), and thus the sources of nitrate are further reduced. This is a synergistic impact of land use and warming on nitrate concentration in rivers.

In terms of phosphorus, temperature has the opposite effects, i.e. it increases the phosphorus concentration in the river, because it reduces the river flow which is used to dilute the effluent coming from sewage treatment plants. If variable land use is introduced, the reduction of arable agriculture caused by increased temperature causes a decrease of phosphorus inputs from agriculture (principally due to erosion and sediment transport from seasonal bare soil surfaces), and partially compensates for the increase in phosphorus due to lower flows. In this case, the land use adaptation to climate is mitigating the negative effects of climate change on phosphorus concentration. This is especially evident for reach 4 under the UKCP09 climate projections (Figure 11, bottom-left plot). In this sub-catchment, the model results show that land use can reverse the impact of climate change.

Figure 6 shows that the results of this methodology strongly depend on the location. Different catchments experience very different alterations in their land use under the same combinations of precipitation and temperature change. Therefore, the results of this study cannot be extrapolated to other catchments. Nevertheless, they can be informative of the interplays that can occur between land use and climate and their effects on agriculture and water quality, such as for example the expansion or reduction of arable land due to changes in climate in different regions of the world. Additionally, this paper shows that for catchment like the Thames, where the human-affected land is predominant, socio-economic drivers of change must be considered, and they need to be taken into account at a very large (continental or world) scale.

A key limitation of this study is that it did not take into account policy responses to changes in nutrient concentration, such as for example the implementation of buffer strips to retain the excess of nutrients moving towards the river network. Buffer strips are taken into account in the INCA parameterisation, through the in-channel module of the INCA model versions. Some example of its applications are Crossman et al. (2013), Flynn et al. (2002) and Whitehead et al. (2010). However, the coarse resolution of the land use model did not allow accounting for variations in the buffer strips to respond to changes in the river nutrient concentrations. This is surely a very important point that must be addressed in future investigations.

Although a comprehensive analysis of the model uncertainty was not among the aims of this paper, it is important to analyse the sources of uncertainty that affects the results of this study. In particular, the modelling chain employed in this study (a “cascade” of two models: IMPRESSIONS and INCA) propagates errors from the inputs down to the outputs. The uncertainty of the INCA model was assessed separately in different studies. For example, 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. Bussi et al. (2016) also showed a sensitivity analysis of the sediment version of INCA (included in INCA-P), providing an estimation of the parametric uncertainty of the model results. The parametric uncertainty of the whole combination of these two models was not quantified in this study, although it can be assessed qualitatively. This modelling combination involves around 25-30 influential parameters, based on previous uncertainty assessments (Bussi et al., 2016; Dean et al., 2009; Futter et al., 2014; Jackson-Blake and Starrfelt, 2015; Raat et al., 2004; Rankinen et al., 2006; Whitehead et al., 2015). As stated for example by Skeffington et al. (2007), in a modelling chain the output uncertainty is typically less than the summed uncertainty in the input parameters. 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 in the literature, in particular when reproducing highly uncertain processes. It is also worth pointing out that uncertain models can still provide extremely useful information for planners and managers, especially for scenario analysis where the factors of change in the variable of interest are used rather than the absolute values of those variables (Cosby et al., 1986). 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 a very relevant source of uncertainty in climate change impact assessment studies (Kay et al., 2009; Prudhomme and Davies, 2009a, 2009b; Wilby and Harris, 2006). Here, climate models were not used in the modelling cascade, but they were still employed to define the “probable” area of the response surfaces. UKCP09 projections were 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 water quality variations due to changes in average precipitation and temperature 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.

Lastly, the methodology used in this study has certain limitations that must be accounted for and stressed. The scenario neutral methodology, as stated in other studies (Bussi et al., 2016b; Prudhomme et al., 2010) is based on selecting the main drivers of change given a selected variable. In this case, the variable is water quality and the drivers of change are changes in annual precipitation and changes in annual temperature. Other drivers of changes could be considered. For example, Prudhomme et al. (2010) considered alterations in the seasonality of precipitation, and Bussi et al. (2016a) took into account changes in extreme precipitation. In this paper we did not address the changes in nutrients caused by climatic changes other than variations in the average precipitation and temperature. Clearly, this is a very important limitation, given that changes in extreme events and seasonality can also cause alterations in the water quality, independently from the variations in the mean. However, in this paper we only analysed changes in the long-term mean of nutrient concentration, and thus it seems reasonable to consider only alterations in the average climate. This limitation should also be assessed in future developments of this study.

6 Conclusions

An assessment of the impact of long-term climatic changes on land use and water quality was carried out, using the INCA water quality model within a scenario-neutral framework, for the River Thames catchment (UK). Contrary to most of the previous studies in the field of climate and land use/land cover changes impact assessment, in the present study the land use was not treated as a static parameter of the catchment, but rather as a dynamic variable, which varies depending on the long term response of European agriculture and forestry to climate change (especially precipitation and temperature).

Using a land use allocation model coupled with a water quality model, this study demonstrated a methodological approach to evaluate the joint impact of climate and land use changes on water quality, taking into account the autonomous adaptation of land use and agriculture to a changing climate. The European scale of application of the land use allocation reflects an appropriate scale for the representation of food and timber production systems and markets. This study also proved the importance of such a dynamical approach in reproducing land use response to climate, showing that considering this factor can, in some circumstances, lead to results that are completely different than if the land use adaptation is not considered.

This study showed how temperature warming is expected to cause a shift from arable land to fertilised grassland in the River Thames catchment, although this pattern could be slightly altered depending on the long-term variations of the annual precipitation. Climate change is expected to decrease the average concentration of nitrate in the River Thames, due to increased evapotranspiration and reduced runoff from agricultural soils, as well as increased denitrification in the streams caused by lower flows, while it is expected to increase the average phosphorus concentration, due to a reduction of the river flow that is necessary to dilute effluents from sewage treatment works. Land use change is likely to enhance the reduction in nitrate concentration, due to a reduction of the fertilised agriculture area, and it is likely to mitigate the phosphorus concentration increase, especially in the upper Thames, although less so in the lower Thames, where the contribution from diffuse sources of phosphorus (e.g., agriculture) are relatively small compared with the contribution from point sources (effluents). This study demonstrated the importance of representing catchment land use change as a dynamic variable responding to climate change in future water quality assessments, considering land use allocation in a way that reflects large-scale market supply and demand.

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