Scenarios and implications of land use and climate change on water quality in mesoscale agricultural watersheds

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"Essentially, all models are wrong, but some are useful."

George E.P. Box, 1987

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ABSTRACT

A comparative study in two mesoscale, agricultural watersheds located in mid-latitude, developed regions (Altmühl River, Germany; and in Pike River, Canada) investigated potential future land use change and climate change impacts on surface water quality. The two watersheds provided a unique opportunity to compare potential impacts of change in similar physical and climatological regions, yet under different political settings related to agricultural policies as well as water quality management and protection. The objectives of the research were to develop agricultural land use scenarios to apply to a hydrological model simultaneously with climate change simulations. This modelling framework allowed quantifying these combined impacts on streamflow, sediment loads, nitrate-nitrogen loads and concentrations, as well as total phosphorus loads and concentrations to the 2050 time horizon. The impacts of climate change were evaluated alone and then with land use change.

Overall, the quality of surface water simulated in both watersheds will be deteriorated according to environmental standards set by the ministries by 2050 due to higher mean annual nutrient loads transported into the rivers. Climate change impacts were greater than land use change impacts; however land use change can have an important influence on water quality, depending on the magnitude of crop changes taking place.

Field-level adaptation strategies in the Pike River were simulated to determine the extent of reducing the combined impacts of land use and climate change. The strategies were able to mitigate the combined impacts, and also to improve the quality of surface water compared to the in-stream nutrient concentrations in the reference simulation.

In both watersheds, it was determined that the combined interaction between climate change and land use change in the hydrological model are non-linear. Examining the combined impacts are necessary to determine potential alterations in water quality in a basin since the direction and the magnitude are not predictable from the individual changes alone.

RESUMÉ

Une étude comparative de deux basins versants de mésoéchelle situés dans les latitudes moyennes, dans des régions développées (la rivière Altmühl en Allemagne, et le Rivière-aux-Brochets (Pike River) au Canada) a examiné les impacts des changements d'utilisation des terres future ainsi que les changements climatiques futurs sur la qualité des eaux de surface. Les deux bassins ont fourni une occasion unique de comparer les impacts potentiels des changements dans les régions physiquement et climatologiquement similaires, mais dans différents contextes politiques liés à l'agriculture et à la gestion et à la protection de la qualité de l'eau. Les objectifs de la recherche étaient de développer des scénarios d'utilisation des terres agricoles pour appliquer à un modèle hydrologique, simultanément avec des simulations climatiques futures. Ce cadre de modélisation a permis de quantifier à l'horizon 2050 les effets combinés sur : le débit, les charges de sédiments, les charges et les concentrations d'azote-nitrate, ainsi que les charges et les concentrations de phosphore total. Les impacts du changement climatique ont été évalués seuls, et ensuite avec les scenarios d'utilisation des terres agricoles.

Dans l'ensemble, la qualité de l'eau de surface simulée dans les deux bassins versants se détériorera en 2050 en raison de charges moyennes annuelles élevés d'éléments nutritifs transportées vers la rivière. Les impacts du changement climatique étaient plus grands que les effets de l'utilisation des terres; cependant l'utilisation des terres agricoles peut avoir une influence importante sur la qualité de l'eau, en fonction de l'ampleur des changements des cultures.

Des stratégies d'adaptation au niveau des champs ont été simulées pour bassin versant de la Rivière-aux-Brochets afin de déterminer l'ampleur de la réduction des effets combinés de l'utilisation des terres agricoles et des changements climatiques. Les stratégies d'adaptation ont été en mesure d'atténuer les effets combinés, et aussi d'améliorer la qualité des eaux de surface par rapport aux concentrations de nutriments dans la rivière dans la simulation de référence. Dans les deux bassins versants, l'interaction des simulations du changement climatique combinée avec des scénarios de changement d'utilisation des terres agricoles dans le modèle hydrologique était unique et non-linéaire. Donc, examiner les effets combinés est primordial pour déterminer les modifications éventuelles à la qualité de l'eau dans un bassin puisque la direction et l'ampleur du changement ne sont pas prévisibles à partir des changements individuels.

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I have also benefitted from the valuable aid and friendship of a research assistant, Colline Gombault, who updated an existing set-up of the SWAT model for the Pike River with up-to-date data, and also calibrated this set-up. Colline helped me with other tasks as well, including climate data preparation, land use data cleaning, coding R statistical package to generate Figure 6.5, and engaging in some very stimulating research discussions. I owe you my sanity. As well, thank you to Frank Ferber who gave me an initial training crash-course on SWAT, and provided me with the necessary climate data formatted for the Altmühl watershed. Also, to Jochen Scholtes, a research assistant who helped me during one summer to compile historic land use data for the Pike River; thank you and best of luck in your continued endeavours with "SWIVA".

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PREFACE & CONTRIBUTIONS OF AUTHORS

Chapters 3 to 7 inclusive are written as manuscripts in a format that is suitable for publication in peer-reviewed scientific journals, with the exception that all of the references are listed at the end of this thesis. Chapter 3 has been published while Chapters 4 to 7 will be submitted to peer-reviewed journals. For each of these five chapters, I am the primary first author on the manuscripts. The research idea and scientific questions, the research plan and execution, the objectives, the required model framework as well as the analysis and interpretation of the results and the write-up were my contributions, carried out under the guidance and direction of my supervisor, Bernhard Lehner. Hence, all of these chapters are co-authored with Bernhard Lehner, who specifically has offered overall intellectual guidance, aided in the research planning, provided advice and discussion on the analysis of the results, provided editorial feedback and contributed financially to the completion of the research.

As in most large environmental sciences research projects, I benefitted from the collaboration of other scientists beyond my primary supervisor. The additional assistance received is acknowledged through co-authorship on the manuscripts. The specific contribution of the co-authors is as follows:

Chapters 3 to 6 pertain to research in the Altmühl watershed and therefore were co-authored with my co-supervisor, Ralf Ludwig, who assisted with the research logistics and planning in Germany, providing the initial contact to the stakeholders, and providing intellectual input on the analysis of the results and discussion, as well as providing repeated financial support for travel.

Chapter 5. "Evaluating the impacts of parameter non-uniqueness on future surface water quality in an agricultural watershed" by Mehdi, B., Ludwig, R, Schulz, K., Ferber, F., Lehner, B.: Karsten Schulz provided intellectual input, discussions and helpful suggestions throughout the manuscript. Frank Ferber formatted the historic and the future climate data to the subwatershed level necessary for SWAT input. He also undertook the necessary monthly conversion calculations of the raw phosphorus and nitrogen data for the Altmühl basin that was obtained from the water management authorities.

Chapter 7. “Implications of agricultural best management practices on surface water quality to mitigate future climate change and land use change impacts” by Mehdi, B., Lehner, B. Gombault, C., Michaud, A., Beaudin, I., Sottile, M-F., Blondlot, A. This chapter is the result of a research project funded by the Ouranos Consortium, Montréal, Québec, which was a collaboration between several Québec researchers, led by Bernhard Lehner (principal investigator) and myself. Colline Gombault, under my guidance, set-up the SWAT model for the Pike River watershed and calibrated/validated the model, as well as input the field management practices, and processed the model outputs into a format that could be analysed. Co-authors Aubert Michaud and Isabelle Beaudin provided the initial SWAT model set-up that was modified for Québec which included a sub-surface drainage routine. They also provided the DEM for the Pike River, the initial land use data, the soils data and the water quality data, as well as valuable guidance and expertise with the SWAT model. Marie-France Sottile provided the future, bias corrected climate simulation data stemming from the Canadian Regional Climate Model. Anne Blondlot assisted with project coordination as well as with the editing of the final project report.

1. INTRODUCTION

The Intergovernmental Panel on Climate Change (IPCC) Working Group II stated in their 2007 report on Impacts, Adaptation and Vulnerability: the magnitude of the impacts of future changes to agricultural land on the quality of water is largely unknown (Kundzewicz et al., 2007). This spurred the original idea for undertaking my doctoral research. The topic of climate change has become a major topic for scientific research in the past 30 years (Nabout et al., 2012), with impact studies focusing on a suite of sectors including hydrology (Jackson et al., 2001). Yet, as highlighted by the IPCC, few hydrological studies have examined the impacts of climate change on water quality aspects.

In addition to climate change, land use will continue to evolve in a watershed, and may affect water quality. Agriculture is an important economic sector and is arguably the largest contributor to non-point source pollution (Bouwer, 2000). If the growing season is extended due to a warming climate, opportunities may arise for farmers in temperate climates to adjust their farming practices to the longer season. A significant transformation in agricultural activity in a watershed will likely affect the quality of the contiguous surface water to some degree. Historical agricultural land use change has been found to increase nitrate concentrations in surface water (Green et al., 2014), and the nitrate, phosphorus and sediment loads (Schilling et al., 2008) but research pertaining to combined future climate and agricultural land use change is very limited. A study by Abler et al. (2002) investigated maize farmers and showed how their decisions impact nitrogen loadings in watersheds. Wu et al. (2012a) found land use changes (urban, cropland, grassland, forest) had insignificant impacts on water quality compared to climate change, but did not focus specifically on alterations in crop types.

Best farming practices implemented as adaptation strategies to improve water quality can help to alleviate the negative impacts on water quality (Michaud et al., 2008; Rousseau et al., 2013) and transport mechanisms from within the whole watershed need to be addressed for managing nutrient export (Rousseau et al., 2002; Nielsen et al., 2012), but such practices need to be investigated to determine whether they will withstand potentially important impacts of climate and land use conversions (CCA, 2013). Furthermore, in order to adapt to the future impacts, decision-makers are in need of information regarding the uncertainty of modelled predictions.

The main objective of my doctoral research is to determine the impact of possible future climates and of agricultural crop land use changes on surface water quality – individually and in combination - to a 2050 time horizon. This aim is achieved by using a modelling approach with multiple scenarios applied to two geographic regions. Primarily, physically based mathematical models were used to simulate changes that may occur in the mid-term future of 2050. Specifically, for each watershed, climate simulations from regional climate models were chosen to obtain a suite of future climates spanning the time period 2040-2070. Also, land use scenarios were developed using storylines of the future that examine a range of possible agricultural crop changes. For one of these land use scenarios, a farmer survey was undertaken in both regions to help develop a descriptive land use storyline. All the land use storylines were applied to a dynamic land use model that was able to spatially distribute the land use changes in both respective watersheds for the next 30 years; these were referred to as land use scenarios. Finally, the climate simulations were applied alone and in combination with the land use change scenarios in a hydrological model to determine their unique and synergetic impacts on surface water quality. In one of the regions, field-level management strategies were investigated regarding their effectiveness to counteract the negative impacts on water quality to 2050.

Two mesoscale watersheds located in developed countries are the focus of this research; the first one is the Altmühl River located in Bavaria (Germany) and the second one is the Pike River situated in Québec (Canada). They are both found in mid-latitude regions with humid climatic conditions and four distinct seasons. The basins also have similar biophysical traits, and the main agricultural activities in the watersheds are comparable and are undertaken with high intensity. As a result, both areas experience challenges (i.e. eutrophication) pertaining to non-point source pollution stemming from agricultural activities.

Bavaria and Québec have recently implemented water policies (in 2002 and 2000, respectively) based on the principle of integrated water resources management where the watershed is the unit of focus. In Bavaria, the Water Framework Directive (WFD) and in Québec, the National Water Policy (NWP) aims to protect and/or ameliorate water quality now and into the future. The water policy of Québec has several similarities with Europe's directive, but it also very different in how it is applied to protect water resources. The European WFD introduces an approach to water management based on an integrated river basin approach, and linking physical water resources management with water plans (Kaika, 2003) to achieve "good ecological status" and "good chemical status" for water. The main focus of Québec's NWP is also on integrated water resources management to improve water quality to meet specific water quality guidelines set by the Ministry, and like the WFD, describes water as being a cultural right and heritage. Both policies call for water management plans to be in place for enhancing (and protecting, in the case of the WFD) water quality. However, in Québec there is a more pro-active approach on the part of the government for setting up the watershed organizations and involving local actors as key players. Europe's WFD adopts a loose approach for each Member State to determine the extent they wish to include stakeholders and organizations in the management plans, and the WFD stops short of specifying the organizational structures for river basin management (Moss, 2004). These characteristics made the basins ideal for comparing land use and climate change impacts to water quality under somewhat different political settings.

To understand how water quality will be impacted at the meso- (watershed) scale by agricultural change in a future climate, the local (farm) scale was studied in detail. The local scale enables a closer examination of the processes of agricultural change and their impacts on nutrient transport. The local scale is represented by the farmer who makes decisions pertaining to field management every year. Also, farmers in developed regions such as Bavaria and Québec are strongly reliant on government support in the form of farm income stabilization programs. Therefore, agricultural policies also influence how farmers make decisions. In addition, global scale changes, such as to the precipitation and temperature plays a key role as they affect crop suitability in a region, and also nutrient transportation processes from farmland. This research examines detailed changes at the local scale (decisions pertaining to agricultural land use) and at the regional scale (policy drivers of agricultural land use) to develop land use change scenarios, coupled to changes to global scale process (climate). How these combined effects may impact water quality at the mesoscale basin level is of principal interest. The hydrological parameters examined were: streamflow, sediment loads, nitrate nitrogen (NO_3^--N) loads and concentrations, as well as total phosphorus (TP) loads and concentrations.

The implications of this research are not only for the scientific community, but also for stakeholders and decision-makers. Several important policies are currently in place to safeguard future water quality, yet it is unknown if these policies will hold under future conditions.

The **specific objectives** and key findings of my research (and the chapters in which they are addressed) include:

1) **Description of the methodological approach to develop land use scenarios (Chapter 3).** The importance of developing land use scenarios that can be applied to the modelling framework for subsequent hydrological research is presented for the Altmühl watershed. The general lack of land use change information at the farm level required a questionnaire-based approach to be undertaken to build storylines for future land use scenario development. This chapter lays the foundation for how the future land use scenarios were developed in the following chapters.

2) **Determination of the predominant drivers of land use change at the farm level (Chapter 4)**. Four independent groups of farmers were questioned (two in each watershed) to determine their driving factors of crop change. With this information, scenarios of future land use change, driven by farmer decisions, in the respective watersheds were developed. A second land use scenario based on the agricultural policies in each region was also developed to compare a more top-down approach of land use change to the farmer-driven scenario. A key finding from the farmer-driven scenario was that explicit financial factors did not stand out as being the predominant driver of land use change for farmers. The categorization and the quantification of the driving factors important to farmers helped integrate drivers of land use change into a storyline that was associated with quantities of land use change. A dynamic land use model was then used to distribute the land use types in the watersheds.

3) **Quantifying the range of uncertainty in the calibrated hydrological model (Chapter 5).** During the calibration of the hydrological model for the Altmühl watershed, non-unique parameters were identified that satisfied the objective criteria. These were applied to the hydrological model to provide a range of uncertainty for all simulated variables, and thus a wider range of uncertainty was reported. A key finding was that integrating both the non-unique parameters for determining uncertainty bounds and an ensemble of climate change simulations led to a different range of potential outcomes than using the best parameter set.

4) **Applying future land use and climate change scenarios to a hydrological model to quantify sediment, N, and P loads (Chapter 6)**. In the Altmühl watershed, a hydrological modeling framework was employed with climate simulations alone, and then combining each climate simulation in turn with one of three agricultural land use change scenarios. The simulated outputs of NO_3^--N and TP loads and concentrations were compared. The key finding was that by 2050 the nutrient loads increased significantly more when land use change scenarios were combined with climate change simulations, so that in-stream TP and NO_3^--N concentrations also increased during each month. Another important finding was that the impact on water quality variables of the combination of climate simulations with land use change scenarios was non-linear. Thus, considering the climate change and the land use change individually in a hydrological model will not provide sufficient information on the direction or the magnitude of impacts simulated, compared to when both changes are considered together.

5) **Determining the effectiveness of field level adaptations to mitigate the combined impacts of land use and climate change (Chapter 7)**. Climate change simulations were applied alone in the hydrological model, then the land use change scenarios were applied alone in the hydrological model, and then both were applied in combination in the hydrological model to examine the impacts on surface water quality for 2050 in the Pike River. Three adaptation scenarios were developed together with stakeholders to determine the effectiveness of field level adaptations on one combined land use and climate scenario. The key findings were that TP loads were impacted by climate simulations and by land use changes alike, but the climate simulations increased NO_3^--N loads up to 10 times more than land use changes. The interactions of coupled climate and land use changes were confirmed again to be non-linear. All three adaptation strategies improved water quality in the most severe combination of climate and land use change scenario, and one adaptation strategy improved nutrient concentrations to levels below those in the reference scenario. The TP loads were greatly reduced in winter, whereas NO_3^--N loads were reduced in winter, spring and fall. Despite these reductions, the “good” water quality criteria for TP set by the government (0.02 mg/L) was still exceeded in every month.

Part of the research was carried out in the Altmühl watershed in southern Germany. The Altmühl's source is near the village of Erlach and from there it flows into the canal connecting the Main River to the Danube River. The upper portion of the Altmühl watershed was examined; from its source, to the gauge in Treuchtlingen (48^o 57'11.31"N, 10^o 54'48.91"E) encompassing a total area of 980 km^2.

The land use in the watershed is primarily agricultural and forest. After discussions with local government stakeholders in the watershed, I was informed that in recent years, there has been a shift from pasture to maize in the watershed. The rapid land use change is driven by biogas plants that are being built which require silage corn as a feedstock. Hence, farmers are growing more maize at the expense of pasture land. The quality of the Altmühl River and the Altmühl Lake (into which the river flows) is considered to be critically contaminated. The quality of water in the Altmühl Lake has also been plagued in recent years with algal blooms.

A second part of the research was carried out in the Pike River watershed, comprising an area of 629 km^2 and straddling Québec and Vermont; 99 km^2 of its territory is in the state of Vermont. The Pike River source is near Lake Carmy (Vermont), from there the river flows into the Missisquoi Bay (45° 4'11.77"N, 73° 5'51.69"W), which is the northern part of Lake Champlain. The watershed is also mainly agricultural and forest. The Missisquoi Bay has been afflicted with elevated phosphorus levels for decades that have caused regular outbreaks of cyanobacterial blooms.

Previous research has been undertaken in the Pike River with a hydrological model (SWAT) to examine the impacts of climate simulations (2041-2070) on sediment, P and N loads transported in the watershed (Gombault, 2012). Part of the research in this thesis builds on pre-existing work and examines further changes that may occur in the Pike River basin and how these will impact the surface water quality.

Figure 1.1. Altmühl River near the gauge in Treuchtlingen.

Figure 1.2. Impressions of the agricultural landscape in the watershed near the Altmühl Lake showing a mixture of pasture and row crops, at Nesselbach, and near the outlet at Treuchtlingen.

Figure 1.3. Typical agricultural landscape of maize fields in spring in the Pike River watershed, taken near Bedford.

Figure 1.4. The Pike River on the left and its tributary (Walbridge) on the right. Buffer strips were planted around most of the tributaries in 2007 to reduce direct runoff into the stream.

2. LITERATURE REVIEW

This literature review presents a synopsis of the state of knowledge pertaining to climate change impacts on agricultural land use; how these changes can affect non-point source pollution, particularly how sediments and key crop nutrients (i.e. nitrogen and phosphorus) are transported. The focus of the overview is on the two regions encompassing the research sites located in mid-latitudes (Québec, Canada; and Bavaria, Germany). The review also provides the state of knowledge of how crop land use changes in the future may affect non-point source pollution. Finally, the effectiveness of current best management practices implemented at the field scale to reduce non-point source pollution is also presented.

2.1. Climate models

Climate models are based on fundamental physical laws, so that the standard Atmosphere-Ocean General Circulation Model (AOGCM or GCM) is a mathematical model that represents the physical processes in the atmosphere, ocean, cryosphere and land surface in a three-dimensional space (surface of the globe divided into grids, plus the atmosphere and ocean layers) and is used to assess the dynamics of the physical components of the climate system (Randall et al., 2007). Regional climate models (RCMs) represent the same physical processes but they cover a limited-area of the globe and use the boundary conditions provided by a separate GCM simulation to dynamically downscale the simulation for a particular geographic region so that finer spatial fields can be examined (Plummer et al., 2006), and typically they do not have the interactive ocean and sea ice components (Flato et al., 2013). The most useful outputs of climate models for most impacts and adaptation research purposes are simulations of temperature and precipitation at time-steps that vary from a few minutes to several hours. However, climate models are able to simulate climatological phenomena and thus any climate-related variable, such as evapotranspiration, solar radiation, wind, cloud cover and even river discharge can be derived from climate model simulations because the complete hydrological cycle is simulated.

Earth System Models (ESMs) are now the current state-of the art models as they include representations of several biogeochemical cycles (i.e. carbon or sulphur cycles) and also increasingly detailed management of crops and their interactions with the landscape that the

AOGCMs did not include, and therefore ESMs provide the most comprehensive tools for simulating the climate system to external forcings (Flato et al., 2013).

Substances (such as GHGs (e.g. CO_2, CH_4, N_2O) and aerosols) and processes (such as volcanic eruptions) that alter the earth's energy budget are the drivers of climate change. The consequent change in energy fluxes can be quantified by the radiative forcing. The increase in atmospheric CO_2 concentration since 1970 has been the largest contribution to radiative forcing (IPCC, 2013). To simulate a future climate, climate models are driven by GHG and aerosol forcings. The atmospheric GHG (mostly CO_2) concentrations in the climate model are made to vary depending on the future socio-economic development scenario chosen to be represented (Nakicenovic et al., 2000; Moss et al., 2010); these range from energy intensive futures, to futures that try to mitigate GHGs and limit mean global surface temperature increase to stabilize around 2^oC.

There are a myriad of GCMs and RCMs available and all are based on physical processes. Yet, disparities between the models remain which are mainly related to the differences in model parameterizations. Many important processes that determine how a model responds to changes in radiative forcing need to be resolved at the sub-grid level, and this requires parameterization of parameter values to solve the processes such as cloud formation (Randall et al., 2007). Thus, each climate model provides a slightly different set of climate variables, depending on the physical process description parameter values and on the radiative forcings. Therefore, using a suite of multi-climate model ensembles allows for a range of the uncertainty in future climate predictions to be covered and provides more robust information than any single climate model.

Describing climate models is a complex task which is beyond the scope of this thesis. The purpose of my research was not to evaluate the impacts of various climate change models available, but rather to apply a suite of climate change simulations to determine the potential impacts (and adaptation possibilities). Through my collaboration with a research group at the Ludwig Maximilian University of Munich, a suite of regional climate models was pre-chosen in an existing QBIC[3] project (Ludwig et al., 2012). For the Québec research, I collaborated with the Ouranos Consortium who provided access to regional model simulations and assisted with selecting the appropriate climate models (see Chapter 7).

2.2. Impacts of a future climate on agriculture

2.2.1. Changes to surface air temperatures

Canada is getting less cold (Bonsal et al., 2001). From 1900-1998, annual mean temperatures in southern Canada have increased on average by 0.9^{o}C (Zhang et al., 2000). During this period, the growing degree days (GDD; base 5.5^{o}C) have increased significantly in Canada mainly due to increases in minimum daily temperatures. The length of the frost free interval has also increased significantly, principally due to warmer temperatures in spring (Bonsal et al., 2001). Similar trends have been found for southern Québec (Yagouti et al., 2008) over the same time period.

In central and western Europe, the warm and cold extreme temperatures have also been shifting to the warmer range over the entire 20th century (Moberg and Jones, 2005). From 1958-2001, the western side of the Rhine basin (Germany) showed an average increase in the 90th percentile daily maximum temperature in winter of 2.7^{o}C, and in the summer 90th percentile daily maximum of 1.4^{o}C. Similarly, the 10th percentile daily minimum temperature increased in winter by 2.1^{o}C; and in summer by 1.1^{o}C (Hundecha and Bardossy, 2005). The growing season in Europe from 1989-1998 started earlier by 8 days compared to 1969-1988 (Chmielewski and Rötzer, 2002). In Germany, during 1959-2009, mean monthly temperatures during the oat growing season (March-August) increased by approximately 0.3^{o}C per decade (Siebert and Ewert, 2012).

Plants rely on nature's cues to develop; in particular temperature shifts evoke plants to undergo physiological transformations, for example warmer surface air temperatures lead to accelerated crop development. Several observed advances in spring phenological developments of plants (shifts in leaf unfolding and blooming dates) in North America and in Europe have been attributed to anthropogenic climate change (Rosenzweig, 2008). In the U.S. Great Plains, the heading and flowering dates of the Kharkof cultivar of winter wheat occurred 6-10 days earlier during recent years (5 out of 6 sites showing significant trends) in a time series analyzed from 1948 to 2004 (Hu et al., 2005), similar results were obtained for winter wheat in central Europe (Trnka et al., 2012). In Germany, Siebert and Ewert (2012) found significantly earlier phenological development in oats (heading, yellow ripeness, and harvest) in recent years when analyzing data from 1959 to 2009.

Using climate simulations, the flowering and maturity of cereals in Europe by 2040 are projected to advance by 1-3 weeks (greatest changes were found for grain corn and smallest changes for winter wheat) compared to 1985-2009 (Olesen et al., 2012). Modeled results for maize to 2055 in the U.S. Great Lakes region also show increased air temperatures to result in an earlier flowering period (Southworth et al., 2000). Earlier flowering on-set of crops, such as wheat, can lead to lower yields per unit area by reducing assimilates for example during the grain-fill stage (Butterfield and Morison, 1992; Ewert, 2012). Lower yields under warmer temperatures were found for small grain crops in Ontario, Québec and in central Europe (Bootsma et al., 2004; Brassard and Singh, 2008; Trnka et al., 2012). But, where the grain-fill period is extended due to the warmer temperatures (i.e. in northern latitudes), yields can increase, such as for maize in northern U.S. Great Lakes area (Southworth et al., 2000).

Crops that necessitate cooler temperatures to develop (measured by the minimum temperature at which growth can occur, i.e. base $0^{o}C$ for winter wheat or spring barley), are very sensitive to seasonal mean maximum and seasonal mean temperature changes; even to a mean change of $+1^{o}C$ (Trnka et al., 2012). Plants with base $5^{o}C$ or $10^{o}C$ (rapeseed or soybean, respectively), are more tolerant to higher mean temperatures.

C_4 crops, such as maize are better able to withstand higher air temperatures and drought conditions due to their efficient use of water. Yet, every crop has a maximum temperature tolerance limit, after which yields start to decline; i.e. July and August daily maximum temperatures $>33.3^{o}C$ are negatively correlated to maize yields (Rosenzweig, 1993) and daytime temperatures $>31^{o}C$ around the first week of July are associated with yield reductions in canola (Kutcher et al., 2010). High temperatures during key stages of crop development may also negatively affect yields, e.g. during silking or tassling for maize (Southworth et al., 2000). Thus, for long-season crops, such as maize, a longer season dominated by a middle period of high maximum daily temperatures can be critical for unfavorable crop development (Southworth et al., 2000).

Studies examining the changes in maize, wheat and rice yields in a future climate show that temperate regions may benefit under low to moderate warming, especially in the first half of the century (Challinor et al., 2014). Cropping conditions may especially improve for maize and wheat in northern European regions due to a warming climate (Elsgaard et al., 2012), yet the probability of adverse events occurring during the wheat growing season will increase in Europe (Trnka et al., 2014).

Generally, a temperature increase is beneficial only if it brings the crop closer to its optimum temperature for growth and development, without exceeding its biological optimum temperature range. For example, Québec June-July-August temperatures in the range of 18-26^{o}C are expected to be beneficial for soybeans and maize, but not for wheat or potatoes (Brassard and Singh, 2008). Adequate moisture, nutrients and soil conditions are essential for ensuring optimum yields. Boostma et al. 2001 (in Bootsma et al., 2004) calculated the increased yield potential of grain corn and soybeans, given adequate moisture supply, could be 0.6 Mg ha^{-1} and 0.15 Mg ha^{-1}, respectively for each increase in 100 corn heat units (CHU), up to the seasonal average of 3500 CHU (afterwards, yields decline due to limited soil moisture and limiting soil conditions).

Warmer surface air temperatures will lead to a longer growing season in mid-latitudes compared to the reference period 1979-2008. The Agroclimate Atlas of Québec (Agrométéo Québec, 2012), used a multi-regional climate model approach to predict an earlier start of the growing season in 2041-2070, by 15-17 days. In southern regions of Québec and Ontario a future longer growing season was calculated from global climate models of 30-43 days for maize, by 2070-2099 due to planting dates advancing to mid-April and killing frost dates being delayed to late October/early November (Bootsma et al., 2004).

In Europe, the start of the growing season for tree species had been calculated to have advanced by 8 days between 1989-1998 (Chmielewski and Rötzer, 2002). By 2050, in Saxony, Germany, the growing season for trees was determined (from global climate models) to be extended because of a 3-27 day earlier start in spring, depending on the tree species (Chmielewski et al., 2005).

Adaptation strategies (e.g. new varieties, irrigation, residue management, adjusting planting dates) can increase crop yields under a warmer climate (Challinor et al., 2014). In areas where the grain-fill period is reduced due to earlier on-set of flowering, the planting dates can be adjusted by famers, thereby maintaining or even increasing yields. For example, delaying future planting dates of short-season crops or hybrids can prevent them to flower too early and diminish yield losses (Butterfield and Morison, 1992; Southworth et al., 2002a; Southworth et al., 2002b). Also, planting earlier-ripening wheat cultivars in southern regions in Europe may be beneficial in the future (Trnka et al., 2014). In Germany, there is some indication that farmers have started to adopt faster maturing varieties of oats to compensate for the longer growing season (Siebert and Ewert, 2012). Using a global crop model, adjusting the planting and harvesting dates of maize, soybeans and spring wheat to climatic conditions in temperate regions were simulated to prevent up to 70% of the crop losses due to climate change (Deryng et al., 2011).

Surface temperature is only one climate factor which affects crop yields; there are several others and the interactions between climate factors on crop development are often complex and poorly understood. For example, by examining 30 years of past maize and climate data in southwestern Québec, Almaraz et al. (2008) found the variables of "July temperatures" and "May precipitation amounts" together account for 62% of the maize yield variability due to climate. Precipitation is also a key factor because the quantity received in spring is a key determinant for producers being able to seed their crops; it can determine how quickly excess water will drain from the soil so it is sufficiently dry to handle tractor traffic, and therefore how early the seeds can be planted. In the U.S. Corn Belt, Kucharik (2008) examined data from 1979-2005 and noted for every 10 mm of precipitation received in April, the planting was delayed by one day.

2.2.2. Changes in precipitation

From 1900-1998, the annual precipitation has increased by 12% in southern Canada; amounts have increased from 5% to 30%, depending on the region (everywhere, except southern Alberta and Saskatchewan experienced increases) (Zhang et al., 2000). From 1900-2003, the number of days with precipitation and the number of days with rain increased at all recording stations in southern Canada. On average, compared to 1900, in 2003 there were 43 more days of precipitation (> trace), of which 29 are with rain (Vincent and Mekis, 2006).

In a modeling exercise, Sushama et al. (2010) examined the occurrence of mean dry days from April-September for the 2050 and 2080 horizons, and found the dry days (threshold of 0.5, 1, 2 and 3 mm of rain) to remain unchanged or to increase very slightly (by 5-10 days) compared to 1971-2000 for southern Québec. Multiple regional climate model precipitation projections show a precipitation increase of 5% to 10% in JJA (June, July and August) for almost all regions in Canada by 2041-2060 (Plummer et al., 2006), indicating that not only for Canada, but also Québec also has simulated increases in future precipitation.

Precipitation in Europe has increased and become more extreme during 1950-2008 (Zolina et al., 2010); heavy precipitation events associated with longer wet periods have intensified by 12-18%. For central and western Europe, an increasing precipitation trend during the 20th century for the winter season of 5-10% per decade was found by Moberg and Jones (2005), but no significant trends were found during summer. In western Germany, since 1950, heavy and extreme precipitation events (95th and 99th percentiles, respectively) indicated positive changes of 5-13% per decade in winter, spring and autumn and decreasing tendencies of 3-9% per decade during summer (Zolina et al., 2008). Local studies found similar results where precipitation increased more in winter, and decreased in summer. In Saxony, Germany, an analysis of precipitation records by Franke et al. (2004), from 1951 to 2000, showed that in autumn and winter precipitation significantly increased by 20%. A decrease of 30% in summer precipitation also occurred during this period, with the persistence and frequency of droughts from April-June increasing. And, in summer, strong precipitation events (>20 mm d^{-1}) increased fivefold from 1971-2000, compared to 1961-1990.

For the Rhine basin, daily extreme heavy precipitation (90th percentile rain-day) showed increasing trends in magnitude and in the frequency of occurrence for all seasons, except in summer (from 1958-2001); the average percentage change of the daily extreme precipitation increase was most significant in winter (up to 20%) in summer it decreased by 6% (Hundecha and Bardossy, 2005). In southern Bavaria, from 1950-2008, a strong increase in the 95th percentile of the duration of wet spells was found from October to March of more than 10% per decade (i.e. 7 days over 60 years), and a shortening of the wet period from April-September of 2-5% per decade (Zolina, 2014).

Extreme precipitation events can be expected to gain importance, particularly towards the beginning of 2100. It should be noted that in Canada, extreme precipitation events (>90th percentile) were not found to increase significantly in the 20th century, neither in frequency nor intensity (Zhang et al., 2001). Yet, several model predictions expect extreme precipitation events in Canada, and globally, to increase in the future, in part because the atmospheric water vapour content will increase due to warmer air temperatures, and provide for a greater thermodynamic instability of the atmosphere (Kunkel, 2003). Model simulation results from the global coupled model of the Canadian Centre for Climate Modelling and Analysis show increases in extreme precipitation for almost everywhere on the globe by the end of 21st century (Kharin and Zwiers, 2000). On average, the return periods for extreme events will be halved by the end of this century, compared with 1975-1995 (Kharin and Zwiers, 2005). This corroborates with findings for southern Québec by Mailhot et al. (2007), who analyzed Canadian Regional Climate Model (CRCM) outcomes and found return periods will be approximately halved in a future climate (2041-2070), compared to the 1961-1990 climate.

Heavy precipitation trends in the future are expected to continue over Germany, however there is much uncertainty surrounding these predictions (Tomassini and Jacob, 2009). Winter is projected to have a greater increase in extreme precipitation than summer (Radermacher and Tomassini, 2012).

The impact of increased rainfall on crop yields is difficult to predict since a lot of variability and conflicting results have been found for most crop types studied (Changnon and Hollinger, 2003, Kutcher et al., 2010). Increasing rainfall intensity impacts on crop yields has hardly been researched to date. Rosenzweig et al. (2002) simulated the effect of excess soil moisture on maize yields in the U.S. Midwest due to intense rainfall events and found the probability of damage could be 90% greater in 2030 and 150% greater in 2090 than under current conditions, which may add significant pressure on crop yields.

2.3. Impacts of a future climate on surface water quality

2.3.1. Sediments

From 1972-2002, in the U.S., the lowest 30-min precipitation intensity, storm kinetic energy and storm erosivity index tended to occur in winter, and the highest occurred in summer. During this period, in the primary agricultural areas (central U.S.), significant increases in fall and winter mean erosivity indices were found when the vegetation cover was low (Angel et al., 2005). Although there is much spatial variation across the globe in terms of the amount of soil loss, there appears to be a general consensus that the soil loss is enhanced through higher precipitation amounts and greater intensities (SWCS, 2003; Hancock, 2012). Modelling experiments, such as the Water Erosion Prediction Project (WEPP) model (Nearing et al., 1989) used future climate data to simulate soil loss from three locations in the U.S., on three different soil types, from four crop types and three slope steepness. They found when daily precipitation was increased with a corresponding expected increase in intensity, on average, a 1% increase in total precipitation caused a 2.4% increase in soil loss. Soil loss is more sensitive to changes in the amount and intensity of rainfall in a day, rather than the number of wet days (Pruski and Nearing, 2002).

A study by O'Neal et al. (2005) simulated soil erosion losses to the year 2050 using WEPP-CO_2 (Favis-Mortlock and Savabi, 1996) from 11 regions of the Midwest USA for maize, soybean and wheat (all chisel ploughed). Although there was quite a bit of variation, the study found soil loss to increase (+10 to +274%) through almost all of the eastern U.S. Corn Belt relative to 1990-1999, mainly due to higher precipitation (10% to 20% increase) associated with changes in runoff (approximately 300%), and less interception from crops (due to later planting dates, lower maize yields which led to lower interception, and wider row spacing because wheat was replaced by soybean).

As well, in Saxony, Germany, downscaled global climate model (GCM) outputs were applied to a soil erosion model (EROSION 2D/3D) which resulted in increases in rainfall intensities (>0.1 mm/min) of up to 23% for the 2031-2050 time period (Michael et al., 2005). Their soil erosion model results showed these increased intensities translated into increased soil erosion losses of 22% and 66% on two test slopes of clay silt and sandy-loamy silt, respectively.

However, it should be kept in mind that soil erosion predictions will vary with the climate model and the erosion model as well as on the type of input data available. For example, the average soil erosion losses as related to expected changes in rainfall erosivity for the future was found to have large ranges (magnitude change of 16-58% for the continental USA), depending on the GCM and on the equation used to calculate the prediction (Nearing, 2001).

Nevertheless, soil erosion is related to the amount of rainfall and the rainfall intensity as well as to land cover (Nearing et al., 2005). As well, in Québec, the snowmelt period in spring is particularly prone to soil erosion and a consequent transport of nutrients (Beaudet et al., 2008). Liu et al. (2014) found rainfall intensity to be indicative of surface runoff, and also the vegetation fraction to be an important factor in curbing runoff as well as N and P losses. Therefore, adequate soil and residue management practices that increase rainfall interception, such as no-till, cover crops or perennial crops, may curb soil erosion rates during intense precipitation events or during snowmelt by providing a physical barrier and reducing the rainfall erosivity.

2.3.2. Nutrients

Nitrogen (N) exists in many valance states, from highly oxidized to highly reduced, thus it can readily transform into several states. The mineral forms of N most available to plants are nitrate (NO_3^-) and ammonium (NH_4^+) (Batlle-Aguilar et al., 2011). Ammonium is readily adsorbed on clay minerals or assimilated by microorganism and plants, or it is transformed into ammonia gas (NH_3) when soil temperatures are >5^{o}C, therefore ammonium is not prone to movement. Nitrate on the other hand is highly soluble and easily transported by hydrological flow pathways such as leaching, throughflow or deep percolation (Lapp et al., 1998).

In the soil, phosphorus (P) combines with other ions to form insoluble compounds that can precipitate out of solution. This characteristic allows for P to be available for transport, primarily by surface runoff. There are soluble forms of P that are plant available; these are the inorganic forms known as orthophosphates ($H_2PO_4^-$ or HPO_4^{-2}). These forms are mobile, and can be transported by diffusion or by surface water flow into field drains, but they are easily adsorbed to clay particles or immobilized by organic matter and therefore are limited to the upper soil layers (Hillel, 1982). Nutrient transportation from land surfaces will be affected by changes occurring to the magnitude and the frequency of precipitation. Through field experiments, losses of N and P were determined to be positively correlated with rainfall intensity and the antecedent soil moisture content (Liu et al., 2014).

In simulation studies from snowfall regions that examined the impacts of climate change on nutrient transport, warmer air temperatures caused the spring peak flow to advance by a few weeks, entailing higher flows and sediment transport earlier during the year (Marshall and Randhir, 2008) and earlier P transport (Chang et al., 2001).

Sediments and nutrients transported from the land are also known as “loads” and are measured in mass weight. Increase in precipitation typically increases loads, and reduces in-stream nutrient concentrations due to increased river flows while a decrease in precipitation has the opposite effect. For example, in a mesoscale watershed in northern Germany, Hesse et al. (2008) found streamflow increases tended to be related to increased N and P loads, while the reverse was also true; lower streamflow was equated with less nutrient loss from fields. Furthermore, seasonal differences in nutrient transport are evident in several studies, whereby the summer tends to have less nutrient loss than the winter season. In the Chesapeake Bay, using the Generalized

Watershed Loading Function (GWLF) model (Haith et al., 1992), streamflow decreased in a few months during the growing season which entailed lower N and P loadings, but N loads increased in winter (Chang et al., 2001). In northern UK, Bouraoui et al. (2002) applied the Soil and Water Assessment Tool (SWAT) and found increased crop growth and nutrient uptake during spring and summer and therefore no total N loss during this time, but an increase in N loss in winter. In central Greece, a warmer drier climate in the future climate simulations applied led to simulated reduced surface and lateral flows in SWAT which in turn resulted in less nitrate loss from crop fields (Varanou et al., 2002). This was especially true during the growing season; however, some climate simulations showed increases in nitrate during the winter and spring.

Due to the future warmer air temperatures, water temperatures will also be raised which induces changes in biological processes (e.g. nitrification, denitrification, plant uptake). There is indication for the Danube River that larger amounts of nitrate will be transported downstream in winter, whereby loads in summer will decrease (Zweimüller et al., 2008). All of the above studies assumed the land use configuration did not change and that the crops were fertilized the same as in the current climate.

2.4. Hydrological water quality modelling

A water quality model requires two overarching components, namely; runoff and runoff-quality routing. Precipitation-runoff relations are a critical component for water quality modelling because agricultural non point source pollution has a strong relation to precipitation events (Viessman et al., 1989) and watershed hydrology (Novotny, 2003).

To model the generation and transportation of diffuse pollution it is essential to consider the processes causing and contributing to water quality degradation, starting with the nutrient inputs into the system, their transportation mechanisms and travel paths, and their deposition and accumulation mechanisms into receiving water bodies. Thus, land use information is crucial for dictating the nature of inputs, the timing of their introduction into the system and their amounts. Three hydrological models GWLF, HSPF and SWAT were developed for agricultural purposes, and contain the critical model components of hydrology, chemical, sediment suitable for modeling water quality.

The Generalized Watershed Loading Function (GWLF) model (Haith et al., 1992) is an empirical, continuous, combined distributed/lumped model. The objective of the model is to simulate nutrient and sediment loads from point and nonpoint sources from complex watersheds. The GWLF land use includes forest, urban and agricultural; however no farm management component (e.g. specifying tillage practices) is present (Chang et al., 2001).

The Hydrological Simulation Program-Fortran (HSPF) model (Bicknell et al., 2001) is a lumped, empirical, continuous model developed to determine agricultural management practices on water quality and allows farm management practices to be altered (Saleh and Du, 2004). It considers most of the processes involved in moving sediments and nutrients through a watershed (Merritt et al., 2003) and is able to accommodate flexibility in water quantity/quality modeling. HSPF has three operating modules representing river reaches, impermeable land, and permeable land. Each module contains several utilities (akin to components). The user can choose the overall model structure by selecting the relevant modules along with only the required utilities of interest. The degree of model complexity will vary accordingly.

The Soil and Water Assessment Tool (SWAT) model (Arnold et al., 1998) is a semi-distributed, physically based, continuous model. SWAT was developed specifically for the purpose of determining agricultural management effects on water quality by allowing considerable spatial detail in a watershed and simulating farm management scenarios. The concept of the model is to link an agricultural management model with routing components to capture land management effects on river basins (Arnold et al., 1998; Arnold and Fohrer, 2005).

The effects of agricultural land should be assessed in models through parameters relevant to crop type, such as root depth (infiltration) or leaves (interception). The more sophisticated models have a separate crop component, a tillage component, and a management component which allows a high selection of land use and management parameters. Both the HSPF and SWAT have separate routines for taking into consideration land use and management practices. SWAT has the widest array of agricultural management practice options (tillage, irrigation, fertilization, pesticide and grazing), whereas HSPF is limited to nutrient and pesticide management (Borah and Bera 2003). The GWLF model simply requires a land use/land cover map to differentiate land use types.

2.5. Land use change and the underlying drivers

Land use has been defined as “the purposes for which humans exploit the land cover” (Lambin and Geist, 2006). Changes in agricultural land involve altering the location, the nature, or the quantity of units per area of agricultural crop or livestock production (Smit and Skinner, 2002). To assist in determining future changes, land use models can be useful tools to build plausible scenarios which can assist to visualize the spatial representation of future land patterns to consequently determine their impacts on the environment. Developing scenarios is a means of characterizing the future and its uncertainties through structured and coherent assumptions of key driving forces and relationships. Storylines are the descriptive components of a scenario that depict the future (Rounsevell et al., 2010).

Land use scenarios are based on a range of possible driving factors that lead to alterations in the landscape. Drivers of land use change can be distinguished into two broad categories; direct and underlying drivers (Lambin and Geist, 2006). Direct drivers are immediate actions or activities which cause a change in land cover. These causes are usually - but not always - local in scale (i.e. producer or household level) and involve a physical action limited to a specific set of activities, such as farming. Underlying drivers are more diffuse in nature and usually operate at a larger scale, i.e. regional or national level. They influence the direct drivers through incentives or other guiding principles, for example economic, technological, or demographic (Lambin and Geist, 2006). Both direct and underlying factors interact and have feedbacks to which each is sensitive.

The drivers are fed into land use models that can be applied to different geographic scales. The types of land use models include: economic; behavioral; and spatially explicit (Veldkamp and Lambin, 2001; Agarwal, 2002). The scales used for studying land use change include: global (world); continental (continents); national (country level, defined by national boundaries); regional (major watershed, or defined region, e.g. province or state); local (sub-watershed or municipality); or farm (individual level).

At the global level, the main drivers of cropland change since 1960 have been linked to population growth, crop yield increases, per-capita caloric consumption and processing losses (Huber et al., 2014). At the other extreme of the geographic scale, the farm level, the drivers of agricultural land use change tend to be much more specific as they operate at a local level. For example: the farm characteristics (intensity of farming, and farm size) (Reidsma et al., 2009); the type of producer (based on age, education, innovation and farm characteristics) (Bakker and van Doorn, 2009); the economic return available for the land (Dockerty et al., 2006); social characteristics (Veldkamp and Lambin, 2001); geophysical features, accessibility to markets, demand for food, available technology, and government subsidies (Bürgi et al., 2004; Schröter et al., 2005; Busch, 2006); were all found to influence agricultural land use. Yu et al. (2013) found external factors (market, policy, cropping systems, agricultural disasters) to be specifically relevant for farmers crop choices in northeastern China. Although climate *per se* was not found to be a direct driver of land use change at the global scale (Schröter et al., 2005) nor at the local scale (Reidsma et al., 2009), at the farm scale it remains yet to be examined.

Driving factors are usually determined specifically for their geographic area of application. As such, it is unclear how valid and transposable these drivers are to other regions of the world. A thorough determination of land use driving factors requires that any preconceived notions of drivers be carefully verified and examined in each individual study area of interest.

In land use change studies, the farm is often not the spatial scale of choice (Overmars and Verburg, 2005; Houet et al., 2010), perhaps due to the required integration of social and physical sciences (Verburg et al., 2004) which is not undemanding; or because it is difficult to predict the evolution of crop land use at a watershed scale due to the complex relationships between producers and their management of land resources (Lambin et al., 2000); or because the spatial-temporal evolution of land use is highly site-specific. In any case, it is difficult to draw out generalizations that can be plugged into a larger scale land use model. As well, to ascertain drivers of change at the farm level, due to their interaction several levels need to be considered; national, regional and local (Bürgi et al., 2004).

Examining the farm scale sheds light on the human decision-making processes, but this calls for detailed studies of the individual farm or watershed; often due to resource constraints this is not undertaken. As a result, the information necessary at the farm level for input into land use models has tended to be assumed based on knowledge of the area, rather than collected (Verburg et al., 2002), and usually the assumptions are based on economic incentives for the producer (O'Neal et al., 2005). Yet, proper parameterization and validity of a land use model depends on producer decision-making, rather than on mere observations (Verburg et al., 2004). Studies that have collected data at the farm level (Overmars and Verburg, 2005; Overmars et al., 2007) found that the data helped explain current land uses and also improved deductive analyses when projecting land use changes into the future.

2.5.1. Land use change driven by climate change

Exploring how producers will adapt their activities to a future climate (particularly through their crop choices and practices) is in its infancy. Abler et al. (2002) used an economic model to gauge farmer choices regarding maize in the future. They found that the climate impacted farmers' economic choices of management regimes on maize which consequently resulted in either more or less N in the Chesapeake Bay, depending on their management. There remain many unknowns**,** regarding producers' future cropping practices (including uncertainties in future producer responses, development of new cultivars, and climate models). It is also unknown how renewable energy incentives or climate change will increase maize acreage for biofuel production (Schilling et al., 2008). The prediction of future crop management is a key uncertainty that could benefit from more research (O'Neal et al., 2005).

It remains that producer choices of future crops and management practices will determine, in large part, the potential for nutrient transport (Abler et al., 2002) and soil erosion to occur. Field crops with wide row spacing (i.e. maize and soybean) and with no residue cover on the soil, present the largest potential for erosion to occur (SWCS, 2003). If these types of crops make up the primary crops in a watershed, coupled with a shift in planting and harvesting dates, the amount of soil erosion may increase due to the greater exposure of the soil to climate elements. As well, increased amounts of fertilizer may be required to grow the crops in a future climate (Brassard and Singh, 2008) which may amplify the runoff or leaching of nutrients from agricultural fields, especially given the risk of more intense precipitation events.

2.6. Modelling land use change

Within the suite of land use and land cover models, there are several which are able to model historical and future land use. Some of these models focus on the quantities (rates of) changes, whereas others model the spatial distribution of land. Land use models can be classified into two types of broad model categories; processed based and statistical. The former category is considered to be dynamic because these models are temporally distinct, with a predefined time step and run length. They are also able to account for feedbacks and competition between land uses. Therefore, they can project trends of land use into the future. Within the latter category, the models are considered as static because they reveal the relationships that exist regarding land use processes by means of regression equations for a set point in time in the future. While they are able to predict land use change, they lack the dynamic feedbacks and path dependencies. They tend to be particularly useful for examining the underlying drivers of land use change.

For this research, a process based, dynamic land use model was required that could provide spatial distribution of agricultural land uses at a yearly time step for both study watersheds. Furthermore, because the farm level was the unit of interest, decision-making processes other than economics needed to be included in the modeling process. As such, a limited number of land use models were available.

Chomitz and Grey (1996) developed an econometric land use model able to predict natural vegetation, semi-subsistence agriculture and commercial agriculture. However, human decision-making is limited to the variables that impact land rental, distance to market and soil quality, which have strong underpinnings in Von Thünen principals (Von Thünen, 1942). The ProLand model (Möller et al., 1999) simulates land use driven by legal and economic boundary conditions and environmental factors are also considered. However, the main assumption is that land rental prices dictate the spatial distribution of agricultural and forest production systems. LUCAS (Berry et al., 1996) is able to model land use changes but is restricted in terms of the agricultural category, as it was developed for land cover changes to assess the impact on species habitat.

The CLUE model (Veldkamp and Fresco, 1996) is able to predict land use and land cover in the future based on a wide range of biophysical and human drivers at different temporal and spatial scales. The model does not have one theoretical framework because of the various dominant processes related to land use change depending on the study region chosen. Thus, the user can choose the most relevant drivers for a given region.

2.7. Impacts of climate change and agricultural land use on water quality

In watersheds where agricultural activities dominate, it is not uncommon for the quality of water to be compromised (Zebarth et al., 1998; van Bochove et al., 2007; Patoine et al., 2012; Green et al., 2014). Nielsen et al. (2012) found a high correlation between the amount of agricultural land and total nitrogen and total phosphorus concentrations in lakes. The area of maize cropland has been shown to be especially strongly correlated to N and P amounts in water bodies (Donner, 2003). The main culprits of agricultural non-point source water pollution are sediments, nutrients from fertilizers and pesticides (FAO, 1996a; Scanlon et al., 2007).

Changes in precipitation amounts, such as increases that are predicted for Québec and Bavaria (see section 2.1.2.), can affect soil water conditions. If the soil becomes wetter and remains saturated for a longer period of time, the soil denitrification rate will increase causing greater N_2O emissions to be produced (Elmi et al., 2009). The movement of water through the soil and below ground is an important pathway for nutrient movement, especially of NO_3^--N via leaching processes (Mehdi and Madramootoo, 1999), these may be enhanced during more frequent precipitation events. Also, during more (and heavier) precipitation events, surface runoff can increase, thereby enabling surface erosion and higher P transport (Eastman et al., 2010).

A knowledge gap is to what extent water quality in a region will be compromised when a combination of impacts such as climate change and land use concurrently occur. To determine the impacts of future climate combined with land use change, hydrological simulation models are required to explore possible future scenarios and their corresponding influences on surface water quality.

When this research commenced, there were very few studies examining the impacts of climate change together with land use change on hydrology, and those that did, tended to focus on water quantity (streamflow, water yield, runoff). These studies found that changes in land use can significantly affect the hydrology of meso- and macro-scale basins whereby the response to changes in land use depends on the fractional area of the alteration and on the natural conditions being maintained (Klöcking et al., 2003). If vegetation cover is strongly altered (especially to urban areas), significant impacts to important hydrological processes such as surface runoff, infiltration or evaporation may occur that can be exacerbated by future climate simulations (Chang, 2003; Pfister et al., 2004; Wang et al., 2008; Park et al., 2011).

Land use changes can subsequently cause alterations to the evaporative properties of a basin, thereby affecting the hydrology and the groundwater recharge for example, when converting grassland to forest (Van Roosmalen et al., 2009), or when partially or completely deforesting the land (Mango et al., 2011). Yet, in these studies climate change affected the hydrological components significantly greater than land use changes. Other studies also pointed to the likelihood that the impacts of land use change on monthly average streamflow will not be as high as those simulated by changes in climate (Qi et al., 2009; Wang et al., 2013).

Since climate change will affect water balance components, the literature shows that climate change will also lead to shifts in timing and magnitude of N and P loads thereby affecting in-stream nutrient concentrations and that this effect is land use dependent. For example, Chang (2004) employed GWLF and found climate change to increase the N and P loads due to increasing precipitation. The P loads were more sensitive to changes in climate than N loads were. Agricultural land use expansion brought about less increase in N and P loads than urban expansion did; and increasing the forested areas decreased the N loads. The climate change impact was stronger than changes to land use in 3 out of 5 sub basins where row crops areas were significantly reduced and urban expansion took over.

Another study using the GWLF model (Tu, 2009) found that simulated streamflow was more sensitive to climate change than to extrapolated trends of historic land use change (mainly converting forest to urban land). Mean monthly N loads were sensitive to both climate change as well as to land use change; the increases were higher when both changes were considered. However, sometimes the signal of land use change alone was opposing the results of climate change alone; in such cases the combination led to mixed results, with increases and decreases in mean monthly N loads simulated.

Two studies focused on climate change impacts and intensive agricultural watersheds. One study (Tong et al., 2012) applied the HSPF model to a watershed in the U.S. with climate change simulations and extrapolated historic land use change scenarios (agricultural land increased 24% from 1980-2001); they found that the wettest climate scenario coupled with the land use scenarios increased mean daily nutrient concentrations more than the dry climate scenario (TP concentrations increased >20% and concentrations exceeded 0.4 mg/L, while land use change alone increased TP by 4%; and mean daily N concentrations increased >11%, while land use change alone was 3%). The second study (Wu et al., 2012a) applied the SLURP model to a watershed in China and determined that the impacts of climate change increased simulated total N and total P loads more than changes in livestock density or agricultural population.

It should be noted that this research does not consider the direct implications of higher CO_2 levels on crop production, although increasing levels of atmospheric CO_2 concentrations are predicted to occur in the future. Higher atmospheric CO_2 concentrations will have significant effects on crop growth, development and biomass (e.g. Brassard and Singh, 2008) especially for

C_3 type plants (Long et al., 2006) which may cause higher crop water demands, and consequently, the evapotranspiration (ET) may be altered, as well as other crop development needs such as nutrient uptake. Others found simulating elevated CO_2 concentrations in a hydrological model was a key driver in changes to streamflow, in part because vegetation had reduced ET, thus increasing surface runoff and groundwater flow (Jha et al., 2006; Ficklin et al., 2009; Wu et al., 2012b).

In this research, the concentrations of atmospheric CO_2 are an input for the crop growth sub model that is embedded in the hydrological model. However, the ambient CO_2 concentration in the hydrological model remains constant at 330 ppmv, with only temperature and precipitation varying.

2.8. Farm best management practices

Macro nutrients such as N and P are applied to crops mainly in the forms of inorganic fertilizers or manure. In Canada, the production of inorganic N fertilizer since record keeping (1950) has increased 75-fold (Schindler et al., 2006). The abundant use of fertilizer amendments in developed countries has led to the contamination of surface and ground water in watersheds where cropping activities are of significant economic importance (e.g. USA: Kraft and Stites, 2003; Canada: Tran and Giroux, 1998; Germany: Meissner et al., 1998; Spain: Cavero et al., 2003: Australia: Heathwaite, 2003).

Agricultural best management practices (BMPs) are practices employed at the field level that improve soil conservation and/or minimize nutrient movement offsite. They include practices related to landscape management (e.g. buffer strips, agroforestry, terraces), soil tillage (e.g. no-till, minimum tillage, or conservation tillage), residue cover management, fertilizer management, crop rotations and on-farm water management. BMPs can help to improve the environment and even to mitigate the impacts of climate change (Delgado et al., 2011). Despite efforts in recent decades to improve the quality of water with BMPs, there remain a number of water bodies in which the concentrations of nutrients still exceed water quality guidelines (e.g. Adhikari et al., 2007). A recent study examining water quality (NO_3^- and NO_2^-) changes in Iowa from 1970-2012 suggests there is a long-term sensitivity to maize fertilizer inputs in watersheds (Green et al., 2014), hinting that cleanup efforts may only bear fruit in decades to come.

Modeling simulations investigating the effectiveness of BMPs in Québec (Canada) showed that no-till farming in maize fields was one of the most efficient BMPs to implement for substantial reductions in sediment, N and P exports (Michaud et al., 2008). Often, to achieve the greatest reduction in nutrient transport in a basin, the most vulnerable land (in terms of the most nutrient export) must be targeted with BMPs. For example, planting cover crops on 10% of the land that transported the most TP would result in approximately a 20% drop in TP loads at the watershed outlet (Michaud et al., 2007).

Under climate change simulations in southern USA, contour farming and terracing practices were most effective at reducing non-point source pollution at the field and at the watershed scale (Woznicki et al., 2011), and interestingly several other BMPs were effective at performing at the field scale, but did not affect pollution reduction at the watershed outlet.

A main unknown to manage river systems sustainably in the future is whether present management strategies and policies are sufficiently robust to cope with the impacts of climate change on several sectors, including agriculture (Scanlon et al., 2007; IPCC, 2008). The development of adaptation strategies at the field level requires more thorough investigation in light of the changes expected in a watershed.

2.9. Summary

The literature review has outlined that climate change impacts on agriculture will be varied in mid-latitudes, but for the most part increases in crop yields can be expected due to warmer surface temperatures and a longer growing season, however extreme temperatures may affect the development of certain crops. Adjusting planting and harvesting dates can be helpful to adapt to changes in the planting season. Annual precipitation amounts and extreme precipitation events are simulated to increase, for the most part, which may lead to greater transportation of sediments and nutrients from fields. Studies have shown precipitation increases may compromise the quality of surface water in the future. Furthermore, agricultural areas (especially maize areas) in a basin have been shown to be correlated to poor surface water quality.

Hydrological models are necessary to investigate the impacts of potential changes in a watershed on water quality. Few studies have examined both climate and land use changes concurrently on the impacts to water quality. The identification of best management practices that diminish the combined impacts of both climate and land use changes is also lacking.

CONTEXT OF CHAPTER 3 WITHIN THESIS

The following study provides a methodological outline of the land use research component in the Altmühl watershed applied to the modelling framework in my subsequent research. To develop scenarios of land use change, farmers in the watershed were questioned on their past, current and possible future choices of crops which allowed me to identify the drivers of crop land use change. The drivers were used to develop future scenario storylines of land use in the basin. These scenarios were consequently applied to the hydrological model that was used to simulate nitrogen and phosphorus outputs in both study areas. This chapter sets the stage for the social part of my research by providing an overview of the tools used to determine land use change drivers. This chapter was written as a contribution to a workshop on watershed modelling (*Workshop zur Großskaligen Hydrologischen Modellierung* in Tutzing (Germany) from November 3-5, 2010) therefore it highlights critical issues when researching land use change for hydrological applications, and lays the foundation for further steps in my research.

This article was published in *Advances in Geosciences 31: 9–14, 2012*. Minor modifications have been made for this thesis.

3. DETERMINING AGRICULTURAL LAND USE SCENARIOS IN A MESOSCALE BAVARIAN WATERSHED FOR MODELLING FUTURE WATER QUALITY

3.1. Abstract

Land use scenarios are of primordial importance when implementing a hydrological model for the purpose of determining the future quality of water in a watershed. This paper provides the background for researching potential agricultural land use changes that may take place in a mesoscale watershed, for water quality research, and describes why studying the farm scale is important. An on-going study in Bavaria examining the local drivers of change in land use is described.

3.2. Introduction

Hydrological models necessitate a number of input parameters to perform adequate simulations. Usually, one important layer of input information required for hydrological modeling is knowledge of the land cover or land use for the watershed under investigation. The land cover or land use description is specifically essential for determining the partitioning of water relevant to fluxes between the soil-vegetation-atmosphere; such as interception, evapotranspiration, infiltration, or runoff.

For example, the amount and type of vegetation in the watershed (model) will dictate how much precipitation reaches the soil surface and how much is evaporated. As well, the vegetation type partly governs the three dimensional spatial distribution of water in the soil (Shuttleworth et al., 2005). The influence of land cover on hydrological processes is taken into consideration through parameters which affect these hydrological processes, i.e. through the parameters of rooting depth, canopy albedo or leaf area index (Alcamo et al., 2003).

Land use information is particularly critical for modelling the quality of water (Stonestrom et al., 2009), as such, land use considerations are prominent in water quality models. For example, the hydrological model SWAT (Arnold et al., 1998) contains numerous parameters that define the agricultural management components: information is required for tillage, irrigation, fertilization, grazing, and conservation management practices. Additionally, the model has separate sub-models related to pesticides (GLEAMS; Leonard et al., 1990) and crop growth (EPIC; Williams et al., 1984).

When applying water quality models to primarily rural watersheds, agricultural land use should be represented in sufficient detail because this governs processes (i.e. surface runoff) which significantly influence sediment and nutrient transport. For example, arable land is more prone to generate surface runoff than pasture or forest areas (Eckhardt et al., 2003), and certain land uses (i.e. the area of maize cropland) have been found to be particularly strongly correlated to inorganic pollutant amounts in water bodies (Donner, 2003). Therefore, accounting for agricultural land use is critical when assessing the quality of water in rural areas.

Several watershed studies, in various parts of the world, have examined the impacts of future changes on water quality (e.g. Wilby et al., 2006; van Vliet and Zwolsman, 2008; Ficklin et al., 2009). However, the magnitude of the impacts of future changes on agricultural landscapes, and the consequent impacts of climate change on the quality of water are largely unknown (Kundzewicz et al., 2007). Most studies examining the impacts of climate change on water quality have assumed a static landscape. Our study undertakes an examination of the surface water quality in a future temporal frame while considering the possibility of an evolving landscape in the watershed, so that the relevant land cover and land use parameters can be adequately represented in the hydrological model. To do this, future land use scenarios must be determined.

This paper will describe the concepts of agricultural land use modelling, with a particular focus on the farm level scale of modelling, and the drivers of cropping system change. It will also describe an on-going study in Bavaria examining the drivers of land use change at the farm level.

3.3. Concepts for modelling agricultural land use change

Land use has been loosely defined by Lambin and Geist (2006) as “the purposes for which humans exploit the land cover”. A term frequently used to denote agricultural land use systems is “cropping systems”. In agricultural sciences, a cropping system is defined by FAO (1996b) as: “A system (or land use unit), comprising soil, crop, weeds, pathogen and insect sub-systems, that transforms solar energy, water, nutrients, labour and other inputs into food, feed, fuel or fibre”.

From an agricultural view point, land use is perhaps of greater interest than land cover, because land use includes a breakdown of the crops in the landscape, and sometimes also provides the different tillage and residue management practices, which land cover data cannot capture. For example, the CORINE land cover database (EEA, 2010) has four categories related to agricultural land cover (non-irrigated arable land; pastures; complex cultivation patterns; land principally occupied by agriculture, with significant areas of natural vegetation). A land use based classification, however, subdivides agricultural areas into specific types of cropland (e.g. GLOWA-Danube Project (Mauser et al., 2004)), specifying the dominant crop or vegetation type in each pixel.

To determine future agricultural land uses or cropping systems in a region, land use models can be interesting tools to apply since they can provide a range of potential future scenarios. Land use models which represent the spatial distribution of land type (e.g. CLUE, Veldkamp and Fresco, 1996; Land Use Scanner, Kuhlman et al., 2005; ProLand, Möller et al., 1999) are particularly useful for applying to water quality modeling research because they provide the spatial proximity of crops to surface water bodies.

Land use models specifically developed to model agricultural land use changes, for example the CLUE model (Veldkamp and Fresco, 1996), require in depth knowledge as well as data of the agricultural sector in the study area, and tend to be applied to the regional, or finer spatial scales. To determine future agricultural land use changes that may take place, land use models build scenarios based on a range of plausible vectors of change, known as driving factors.

In the following sections, two main concepts will be elaborated on: the scales of land use modelling, particularly the scale relevant for agricultural land use modelling; and the drivers of change relevant to agricultural land use.

3.3.1. Scale of land use modelling

Some of the spatial scales used for studying land use change include: global (world); continental (continents); national (country level, defined by national boundaries); regional (major watershed, or defined region, e.g. province or state); local (sub-watershed or municipality); or farm (individual field level).

The spatial scale used by the researcher for land use scenario modeling will vary depending on the level of detail necessary in the study. Usually coarse spatial scales (greater than 1 km by 1 km) are useful to reveal the general trends and relations between land use and its determining factors. Factors that influence land cover over a considerable distance also use the coarse scale. The finer scale is used for understanding processes pertaining to a specific region, or understanding a certain type of behaviour, such as decision-making or planning. For regional studies, the scale of 1 km by 1 km or less can be used, whereas the household or farm system scale uses resolutions of less than 250m by 250m (FAO, 1996b; Verburg et al., 2008).

A change in agricultural land use involves altering the location, nature, or quantity of agricultural crop or livestock production units per area (Smit and Skinner, 2002). To ascertain drivers of change at the farm level, several levels need to be considered (Bürgi et al., 2004). Larger scale drivers (e.g. markets or policies) tend to influence decisions made at the farm level. Often there is an iterative interaction between these two scales, as is evident from one of the more influential agricultural policies implemented in Europe, the Common Agricultural Policy (Lobley and Butler, 2010).

A farm system is defined as (Fresco, 1990): "A decision making unit, comprising the farm household, cropping and livestock systems that produces crop and animal products for consumption and/or sale". Most land use models do not tend to examine the farm level (Overmars and Verburg, 2005; Houet et al., 2010), perhaps due to the required integration of social and physical sciences (Verburg et al., 2004) which is not undemanding, or because it is difficult to predict the evolution of crop land use at a watershed scale due to the complex relationships between producers and their management of land resources (Lambin et al., 2000), or because the spatial-temporal evolution of land-use is highly site-specific and thus difficult to draw out generalizations that can be plugged into a larger scale model.

Examining the farm scale calls for detailed studies of the individual watershed, and often due to resource constraints this is not undertaken. As a result, the information necessary at the farm level for input into non-economic type land use models has tended to be assumed based on knowledge of the area, rather than collected from farmers, and usually the assumptions for land use change are based on economic incentives for the producer (O'Neal et al., 2005). There is a general lack of research undertaken in developed countries that examine land use drivers at the farm scale. Yet, such studies are important, to reveal if drivers other than financial drivers are responsible for land use decisions in the watershed; such as tradition, local culture, family know-how and technology. And to what extent these are important drivers of future land use change.

3.3.2. Driving factors of land use change

Drivers of land use change can be distinguished into two broad categories; direct and underlying drivers (Lambin and Geist, 2006). Direct drivers are immediate actions or activities which cause a change. These causes are usually – but not always – local in scale (i.e. producer or household level) and involve a physical action limited to specific agricultural activities. Underlying drivers are more diffuse in nature and usually operate at a larger scale, such as the regional or national level. They influence the direct drivers through incentives, such as economic, technological, or demographic (Lambin and Geist, 2006). Both direct and underlying factors interact with one another and have feedbacks with each other.

The literature contains few direct or indirect driving factors influential at shaping land use in developed regions at the local (farm) scale. By examining the literature relevant for Europe, the following drivers influencing agricultural land use were found: the type of producer (based on age, education, innovation and farm characteristics) (Bakker and van Doorn, 2009); the economic return available for the land (Dockerty et al., 2006); social characteristics of the farmers (Veldkamp and Lambin, 2001); geophysical features, accessibility to markets, demand for food, available technology, and government subsidies (Bürgi et al., 2004; Schröter et al., 2005; Busch, 2006).

The challenge of applying drivers of land use change is that they are site-specific, and scale-dependent. Therefore, they are not necessarily transposable to watersheds other than those for which they were determined (Bürgi et al., 2004), nor at a different scale (Overmars and Verburg, 2006), unless very similar conditions prevail in the watersheds, and the same spatial resolution is examined. As such, it may be necessary to carry out independent studies determining the drivers of land use change for each watershed studied. This can be an onerous and resource intensive undertaking, as much quantitative and qualitative data is required (Overmars and Verburg, 2005; Verburg, 2002).

3.4. Determining land use change at the local scale

In an on-going study in southern Bavaria, future land use scenarios for the upper Altmühl watershed, to the gauge at Treuchtlingen, (980 km2), are being developed to the year 2040 (Figure 3.1). A spatial resolution (pixel) of 50m by 50m is used. This unit coincides with the unit of decision-making (the farm), since the average farm size in the watershed is 10 to 20 ha (BLSD, 2010). Three spatial levels are being studied; the farm level (individual and local), the regional level (rural district and state) and the national level (country or continental). A particular emphasis is placed on the farm (local) level which is relevant to decision-making for land use change in the mesoscale watershed. Land use change studies have scale extents and resolution. Figure 3.2 depicts the various spatial, temporal and actor scales used for determining future land use scenarios in the study.

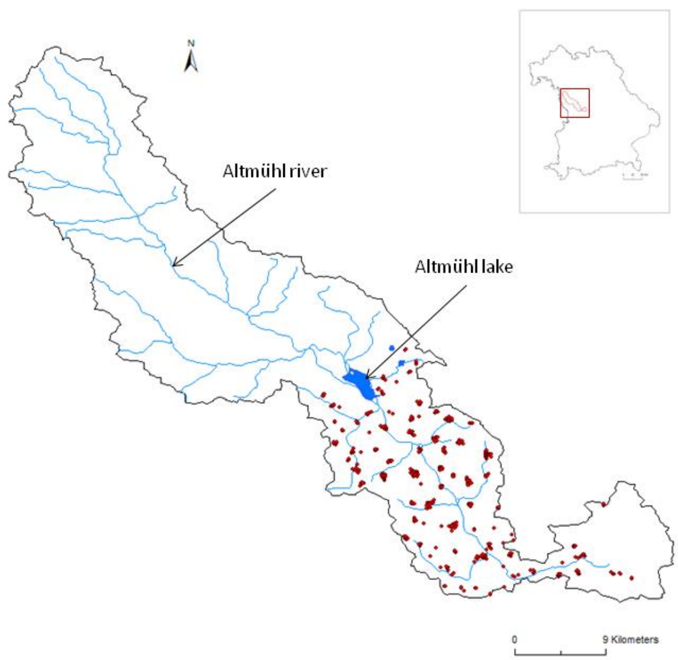


Figure 3.1. Location of farms in the study area (upper Altmühl watershed) where a questionnaire was sent (each dot represents a farm address). Inset shows location of the watershed in the State of Bavaria, Germany. Map source information: Bayerisches Vermessungsverwaltung, 2010.

In order to describe land use change at the farm scale, current driving factors of change were determined based on local factors influencing the decisions made by producers in the watershed. First, a detailed, in depth study of the environmental, socio-economical, political, and cultural aspects was conducted in the watershed. This involved several site visits, attending local conferences on water quality, and reading relevant literature. The information gathered was helpful for identifying casual relationships of land use, which are essential to land use modelling (Bürgi et al., 2004). Furthermore, a number of additional, detailed, steps were undertaken, which included liaising with a local university; meetings and discussions with relevant agricultural and water management stakeholders (ministries and local authorities); querying farmers; and collecting or requesting the relevant digital data pertaining to the watershed (e.g. DEM, soil, topography, precipitation, historic land use/land cover) from government sources mostly.

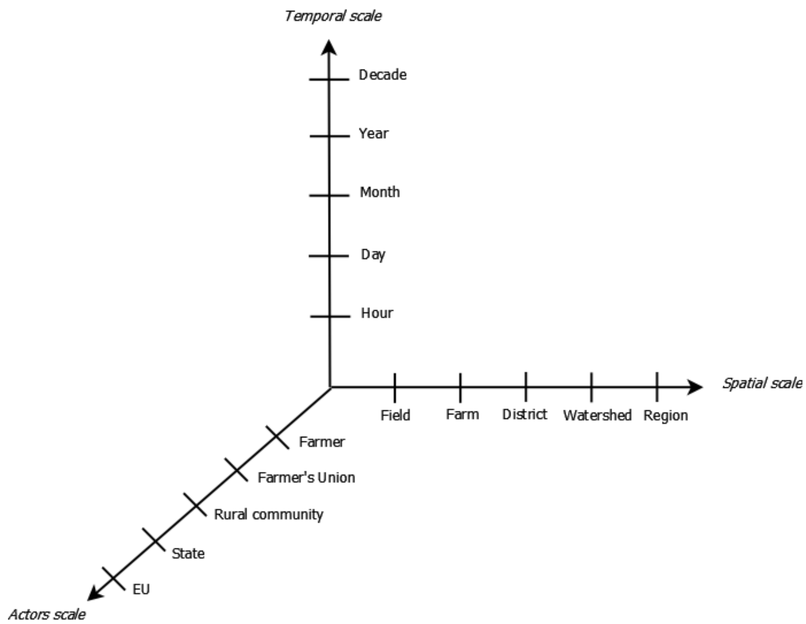


Figure 3.2. Temporal, spatial and actor scales, showing both the extent and resolution studied for determining future scenarios of land use change (adapted from Bürgi et al., 2004).

For the purpose of investigating potential future direct drivers of land use change at the farm level, the administration of a postal questionnaire in a subset of the watershed was undertaken. The questionnaire was compiled with input from partner universities, the regional administrative office for Food, Agriculture and Forests, as well as the Farmers' Union. The questionnaire consisted of 23 questions (time to complete was less than 30 min) and was sent to all producers located below the Altmühl Lake; a total of 666 farms (Fig. 1). The questionnaire was voluntary, and could be filled out anonymously. The responses (received responses from 8% of the farmers questioned) were used to ascertain decision-making factors that govern current crop land use on the farm, as well as to determine drivers which apply to changes in growing crops in the future. To determine larger scale drivers, regional and national drivers of land use change were established through the literature and through consultation with experts (Ministries and agricultural stakeholder groups). The information from these drivers will be incorporated into a land use model.

The CLUE-S model (Conversion of Land Use and its Effects-Small scale; Verburg et al., 2002) is an example of a model that is able to dynamically forecast agricultural land use change at the local level, and integrate the various spatial levels and their driving factors related to land use change. Based on empirically quantifiable relationships between land use and driving factors, CLUE-S is applied to the watershed to simulate several scenarios of the spatial distribution of land use to 2040 in the Altmühl watershed. The information gleaned from the questionnaire responses will be used to determine drivers and to guide the development of future storylines regarding changes that may occur.

3.5. Description of CLUE-S land use model

The CLUE-S model simulates the spatial distribution of land use patterns in the near future based on present and historical land use, and on competition between land use in space and time. The model is based on an analysis of the spatial structure of the land rather than on the economy, or on the individual behaviour (Verburg et al., 2004). The model uses logistical regression equations based on historic land use changes to determine the location suitability of a crop. The driving factors that determine land uses locations historically in the Altmühl watershed are provided in Table 3.1; they differ according to the crop type. Table 3.1 provides an impression of the breadth of diverse (qualitative and quantitative) factors found to be statistically significant from an even larger suite of possible factors, at the regional scale.

As there is no prior knowledge of why certain land uses occur in the study watershed, a stepwise logistic regression analysis was used to explore a suite of biophysical variables determining current land use. A stepwise forward binary logistical regression was implemented for each land type of interest, using a significant entry value of 0.01, and a significant removal value of 0.02. The relative operating characteristic (ROC; Pontius and Schneider, 2001) is a measure of the land use suitability allocated by CLUE-S compared with the probability of land use change for each pixel. The sample size is the percentage of land use pixels used to determine the ROC.

Table 3.1. Significant local biophysical factors for determining the location of crop types in the upper Altmühl watershed (based on data from 2008-2010).

Land use	**Location factor 1**	**Location factor 2**	**Location factor 3**	**Location factor 4**	**Location factor 5**	**Location factor 6**	**Location factor 7**	**Location factor 8**	**Location factor 9**	**ROC**[1]	Sample size[2]
Cereal	Density of pigs	Density of cows	Density of chicken	Density of cattle	Loam	Loamy sand	Heavy loam	Distance to river	Slope	0.68	30%
Maize	Density of cattle	Density of pigs	Density of cows	Loam	Loamy sand	Heavy loam	Strong loamy sand	Slope		0.70	30%
Oilseeds	Loam	Heavy loam	Loamy sand	Distance to urban	Slope					0.65	100%
Legumes	Density of cows	Density of pigs	Loam	Heavy loam	Heavy loamy sand	Slope				0.65	100%
Tubers	Distance to urban area	Slope	Loam	Loamy sand	Distance to roads					0.79	100%
Pasture	Distance to rivers	Clay soil	Loam	Loamy sand	Density of sheep	Density of horses	Distance to road			0.86	30%
Set aside land and KULAP areas	Erosion prone areas	Distance to forest	Density of horses	Loam	Loamy sand	Clay				0.65	100%
Natural grasslands, transitional woodland-shrub	Clay	Distance to forest	Slope	Distance to urban areas						0.80	100%
Vegetables	Population density	Distance to river								0.78	100%
Perennial crops (orchards, berries, nuts, trees)	Distance to urban area	Heavy loamy sand								0.65	100%
Forest	Distance to urban areas	Slope	Loam	Loamy sand	Clay	Distance to road				0.80	30%
Urban areas	Population density	Distance to roads	Distance to forest	Slope						0.86	50%
Other (turf, miscanthus)	Loam	Slope	Distance to urban							0.74	100%

[1]ROC= relative operating characteristic (Pontius and Schneider, 2001); [2] Sample size based on the total area of crop type in watershed

The CLUE-S model allows the user to specify demands for each crop type for every simulation year. Through this demand table, the model accounts for changing conditions of land use requirements as well as shifting demands for agricultural products. The competition between crop land uses can be defined, and the overall flexibility of a land use to transform can be defined. The model is particularly interesting for examining agricultural scenarios at the farm scale because it is able to integrate drivers of land use change at different spatial levels (e.g. the farm level, the regional level, and the national level) through the logistical regression equations (for detailed information see Verburg et al., 2004).

Factors related to individual behaviour are taken into consideration when the aggregate amount of land area for each crop type is determined each simulation year, which is how the information from the questionnaires is taking into consideration.

The outputs of the CLUE model are ASCII files that can be imported into a Geographic Information Systems (GIS) to view maps of spatially allotted land use types. These correspond to the land use quantities (demand table) defined by the user each year, and depicts their spatially allocation according to the location suitability, the competition between crops, the flexibility of each land use to change, and other defining factors, such as neighbourhood functions, etc..

The future land use scenarios will be inserted into a hydrological model to determine the impacts on surface water quality. Of particular interest is the expansion of crop acreage related to biofuels, such as maize, as these may lead to water quality challenges, since they require higher nutrient inputs. The yearly land use scenarios will provide information on the quantities of different crops in the watershed, as well as their spatial distribution. From this, we can infer the quantities of fertilizer applied, as well as farm management practices. Finally, relevant crop parameters such as rooting depth, transpiration and water uptake will also be able to be deduced. All of this information is important for modelling hydrological surface water quality for the future.

3.6. Summary

Land cover and land use are important because they provide parameters relevant to water quality modelling. Future land use scenarios can be developed through the application of land use models, which necessitate determining the driving factors of land use change. The determining factors for land use should be determined at several spatial levels.

Agricultural land use change is highly site specific and therefore the local scale of study can be very helpful to link specific land uses to impacts on water quality. The general lack of land use change information at the farm level in the literature requires a large number of assumptions for modelling purposes, and contributes to uncertainties in the scenario development exercise. By applying the CLUE-S model in combination with a household questionnaire we hope to provide insight into drivers of land use change at the farm level.

CONTEXT OF CHAPTER 4 WITHIN THESIS

This study continues to focus on the land use modelling component of the research and carries out the methodology described in Chapter 3, in both study regions, by assessing the decision-making processes of farmers. By questioning the farmers in the respective watersheds, first-hand information was collected on the driving factors that govern farmer's crop choices. A ranking of farmer influencing factors for crop changes in developed regions, has not, to my knowledge been carried out previously. The information on the drivers of land use change was incorporated into the land use scenario storyline exercise. In total, a suite of three future scenario storylines were developed with stakeholder input (farmers as well as watershed organizations, and local government authorities in the basin). The storyline outputs from this study fed directly into a land use model which spatially distributed the future crop changes each year. This study also links into Chapters 6 and 7 by providing the required future land use change information for the hydrological model.

This chapter will be submitted to the journal *Land Use Policy*.

4. DRIVERS OF AGRICULTURAL LAND USE CHANGE IN DEVELOPED REGIONS FOR FUTURE SCENARIO DEVELOPMENT

4.1. Abstract

Four independent groups of farmers in two agricultural areas located in mid-latitude, developed regions (Altmühl River, Bavaria (Germany) and the Pike River, Québec (Canada)) were asked to rank decision-making factors being considered for planting crops, or for changing the types of crops grown on their farm. Responses showed that the drivers of land use (as well as land use change) were composed of a suite of factors, of which the directly-related financial factors made up approximately half of the factors. For some questions, the indirectly-related financial factors (i.e. access to farm equipment, the farm experience, and climate) ranked higher, or just as high, as the explicit financial factors. The ranked drivers as well as the categorization of drivers were helpful for the development of a farmer driven scenario storyline to 2040 in both regions. A second scenario storyline for each region was derived based on agricultural subsidies, income support, crop insurance, and policies. The scenarios depicted divergent land uses in 2040. In the farmer driven scenario, the area under maize increased the most, whereas in the policy driven scenario, more crop diversification took place and cash crops occupied less importance in the basin. Questioning farmers on their driving factors can lead to changes that may otherwise not be captured by models, specifically related to planting new crops. The quantification of the driving factors aided to build scenario storylines for application to other simulation models (e.g. hydrological models).

4.2. Introduction

Due to the growing awareness of land use change impacts on ecosystems (e.g. Sala et al., 2000; Fish et al., 2014), there is an increasing need to develop future land use scenarios. Knowing how landscapes may evolve can guide policies and management strategies. As well, future land use scenarios are required for applying to other simulation models, for example to wildlife models (Malawska et al., 2014) or to hydrological models (Mehdi et al., 2013) in order to better manage natural systems in light of potential impacts that may take place.

In mid-latitudes, agricultural activities have forced forests, woodland, grasslands and steppes to yield way to crops and pasture (Ramankutty and Foley, 1999). In 2000, 35% of all agricultural land was located in North America and Europe; and yielded 40% of the global agricultural production (Monfreda et al., 2008). At the same time, these continents dominated the amount of non-point source pollution stemming from agriculture (i.e. from inorganic nitrogen inputs) (Galloway and Cowling, 2002). Understanding decision-making processes that drive local, regional and global changes in the land system require empirical land change research; particularly information about land managers values or preferences (Rounsevell et al., 2012a).

The farmer remains the chief executor of decisions pertaining to farm management, and ultimately is responsible for the existing pattern and quantity of crops and livestock in a given region. In this context, the farmer (driven by a suite of factors) is an important decision-maker, also because agricultural/environmental/regulatory policies are targeted to affect the farmer and their decision-making at the farm scale.

Farmers' decisions are complex as they are comprised of internal drivers (inherent to the farmer) and external drivers (relating to the biophysical and socio-economic context of the farm) (Irwin and Geoghegan, 2001; Polhill et al., 2010; Karali et al., 2011; Schaller et al., 2012). Incorporating farm-level decisions in land use models requires detailed studies of the farm as well as of the specific local conditions. Such studies are resource intensive and often not undertaken. Therefore, while the land use/land cover community recognizes that a myriad of factors are responsible for land use change (Geist and Lambin, 2001; Lambin et al., 2001; An, 2012), land use models are inherently limited by the paucity of data available, and the complex information necessary at the regional level for model-input often relies on poor data, instead of understanding the underlying driving factors (Verburg et al., 2002). Agent-based modelling efforts have made advances in collecting information from social surveys that are used to identify goals, motivations and behaviours that are translated into computer representations of agents in social simulations models (Rounsevell et al., 2012b).

Despite the development of several land use models which are able to incorporate degrees of complexity regarding human decision-making (Agarwal, 2002), and whilst agent-based models have focused the most attention on decision-making processes of farmers, overall, farmer decisions are not well represented in the current generation of land use models (Lambin et al., 2000; Verburg et al., 2004; Edwards-Jones, 2006; An, 2012; Rounsevell et al., 2012; Malawska et al., 2014).

In this paper, we identify drivers of agricultural land use change for a specific type of farmer; one located in developed, mid-latitude regions, where farming is undertaken as an economically important activity with modern technology and good access to local, regional and global markets. We performed a questionnaire-based exploration of agricultural land use change in Altmühl, Bavaria (Germany) and in the Pike River, Québec (Canada) to determine drivers pertaining to crop choices at the farm level in these two regions. Our ultimate purpose was to develop future land use change scenarios for these regions that could be applied to a simulation framework with a hydrological model and climate change simulations.

Studies that have collected primary data from farmers in developed countries on decision-making influences, e.g. related to choices of livestock (Murray-Prior, 1998; McGregor et al., 2001) or crops (Aubry et al., 1998; Willock et al., 1999; Polhill et al., 2010; Karali et al., 2011), have provided thematic analysis, farmer objectives and their implementation, as well as descriptives of change; all of which are useful to gain a better understanding of how farmers make decisions. Here, we present a first attempt to itemize as well as quantify the driving factors considered for crop land use change with the purpose of developing future land use scenarios. Two categories of drivers were focused on: directly-related and indirectly-related financial factors.

Using the respective driving factors of importance to farmers in the Altmühl River and in the Pike River watersheds, a future farmer-driven land use change scenario storyline was developed for each region. To compare this approach to a more traditional method, a second land use change scenario storyline was developed based on agricultural policies. These depict two different land use scenario development approaches.

4.3. Materials and methods

The research undertook a comparative analysis between two watersheds; one located in Bavaria (Germany) and one in Québec (Canada). They were chosen because they are not overly limited by climate constraints for undertaking agricultural activities, they both have strong viable agricultural sectors, offering many divers possibilities of production and access to markets, as well as the possibility to expand production if desired. Additionally, ample government support is accessible to farmers. Both regions also offer financial incentives for farmers to adhere to agricultural best management practices. Both Bavaria and Québec have undertaken intensive farming activities during the past 100 years.

An in-depth study of the environmental, socio-economical, political, and cultural aspects of both watersheds was undertaken. Over the course of four years, detailed information on the agricultural activities in both areas was gathered by liaising with local researchers; querying farmers, keeping abreast of issues relevant to farmers, holding meetings with targeted agricultural and water management stakeholders (ministries and local authorities) to discuss current agricultural challenges in the watershed. Additionally, attending local conferences and combing through the regional literature (e.g. newspapers, farming magazines) in both watersheds was helpful for identifying and understanding farmer relationships to land management.

4.3.1. The Altmühl watershed

The first watershed is located in the state of Bavaria, Germany, where the Altmühl River is located which ultimately flows into the Main-Danube canal. The part of the Altmühl basin included in this study comprises an area from its source (in Erlach village) to the gauge in Treuchtlingen (48 ^{o}57’11.31”N, 10^{o}54’48.91”E); encompassing a total area of 980 km^2. In 2008, forested area made up 39% of the watershed, and urban area 3%. The agricultural area comprised 56% (54 880 ha) of the basin; mostly cereals and permanent grassland. The farmers in one of the rural districts (Weissenburg-Gunzenhausen) were 55% producers of livestock (mostly cattle and swine; 129 and 164 animals/100 ha of agricultural land, respectively), 28% crop farmers (mostly cereals and maize; 26% and 19% of agricultural area, respectively), and 16% were mixed farmers (BLfSD unpublished data available from www.statistik.bayern.de; and AELF unpublished data available from www.aelf-wb.bayern.de/daten_fakten/18591/index.php).

4.3.2. The Pike River watershed

The second study watershed is located mainly in the province of Québec, Canada. The Pike River watershed area is 629 km^2 and straddles Québec and Vermont; a fifth of its territory is in the state of Vermont. The river source is near Lake Carmy, in Vermont, approximately 8 km south of the Québec-Vermont border. From there the river flows into the Missisquoi Bay (45^{o}04’16.69”N, 73 ^{o}05’47.89”W), located at the northern most tip of Lake Champlain. In 2011, the land use was 40% forest, 1% urban and the total agricultural land occupied 54% (34 013 ha) that was mostly hay (22%) and annual row crops (especially maize occupying 20% of the area) (FADQ, 2011). Livestock occupy an important sector in the basin; the mean animal density in the watershed in 2006 was 130 animals/100 ha of cropland). Of the livestock, 49% were swine, 35% were cattle, 7% were poultry, and 5% were other (Statistics Canada, 2006).

4.3.3. Driving factors of land use change

To assess the current and future driving factors of crop land use changes based on local factors influencing the decisions made by producers in the watershed, a questionnaire was administered to active farmers living in the two study areas as well as to students enrolled in a farming program in professional agricultural colleges located in both regions. All of the students were living and/or working on farms and were therefore considered to be active farmers.

In total, the questionnaire was administered to four independent groups of farmers (Table 4.1), in two regions. The purpose of questioning 4 groups was to represent farmers from distinct regions, generations, and farm types in order to gauge differences with respect to current choices and their outlooks regarding the future of their farms, so that, for example, a slightly older generation was compared with a somewhat younger one in the regions.

- Group 1 consisted of farmers living downstream from the Altmühl Lake in Bavaria. This area encompassed 376 km^2 and corresponded to 38% of the total watershed area. Farm addresses were obtained from the Bavarian Ministry of Agriculture. A total of 666 questionnaires were sent to farms.
- Group 2 consisted of young farmers studying advanced farm management at the University of Applied Sciences in Triesdorf, located in the Altmühl watershed. The questionnaire was distributed to 24 students in one of the classes. The questionnaire was answered in class.
- Group 3 consisted of farmers in the Pike River watershed in Québec. The questionnaires were sent directly to farms in the watershed by the local office of the MAPAQ-Bedford. In total, 210 questionnaires were sent to full-time farmers.
- Group 4 consisted of young farmers enrolled in their last year of the Farm Management Technology Program at Macdonald College, in Ste-Anne-de-Bellevue, Québec. The questionnaire was distributed to 23 students in one of their classes. The questionnaire was answered in class.

The core research questions pertained to the nature and causes of land use change and the drivers of these (see Supplemental Material at the end of this chapter). The questionnaire consisted of 23 questions (designed for an average total completion time of less than 30 minutes) and focused on why certain crop changes had taken place historically on the farm, and what factors would bring about a future possible change of crops on the farm. The questionnaire was voluntary, and could be filled out anonymously.

The questionnaire was compiled by the authors, together with local stakeholders. In the Altmühl watershed it was developed together with the local administrative office of Agriculture in Ansbach (Amt für Ernährung Landwirtschaft und Forsten; AELF -Ansbach), and the local branch of the Farmer's Union (Bauernverband Weissenburg-Gunzenhausen). In the Pike River watershed the questionnaire was developed together with stakeholders from the local administrative office of Agriculture (Ministère de l'Agriculture des Pêcheries et de l'Alimentation; MAPAQ- Bedford), the local water authorities (Ministère du Développement durable, de l'Environnement et des Parcs- MDDEP l'Estrie et de la Montérégie), the Québec Farmer's Union (Union des Producteurs du Québec; UPA) as well as researchers at the Ouranos Consortium, and the Institut de recherche et de développement en agroenvironnement (IRDA). Once the farmer responses were obtained and compiled, these were presented during meetings to the respective stakeholders in each watershed to obtain their reactions and feedback to the responses.

Table 4.1. Characteristics of the four farmer groups questioned

Group	Number of respondents / population size	Region where farmers were questioned	Mode age of group (yrs)	Average farming experience (yrs)	Average farm size (ha)	Two main crops grown
1	52 / 666	Altmühl watershed, Bavaria, Germany	40-60	34	31	Sm.grains, maize
2	24 / 24	Triesdorf University, Bavaria, Germany	20-40	8	125	Maize, sm. grains
3	51 / 210	Pike River watershed, Québec, Canada	40-60	33	93	Maize, soybean
4	23 / 23	Macdonald College, Québec, Canada	20-40	11	168	Maize, soybean

4.3.4. Influencing Factor (IF) Weights

From the questionnaire, responses to three particular questions pertaining to crop choices are presented in detail (Supplemental Material, Questions 10, 11 and 13; in this paper they are referred to as Question A; Question B and Question C, respectively). For each of these three questions, farmers could rank suggested driving factors from 1 to 3; with 1 being the most important and 3 the least important. They also had the choice not to rank a factor if it was not considered by them (in this case the rank was set to 0). They could also add and rank (from 1-3) other driving factors that were not listed. To evaluate the importance of each driving factor, we calculated a farmer "influencing factor" (IF) for every driver in the three questions. The IF represents the weighted importance that was attributed to each driving factor and was composed of the rankings indicated by the farmers within each of the four groups.

To calculate the IF for each question, and for each of the four groups, a weight for each rank was assigned that was multiplied by the number of times a factor was chosen. These were summed for each driving factor. A weight of 3 was assigned to the rank 1; 2 to rank 2; 1 to rank 3; and 0 if a factor was not ranked so that it was not considered. (We also tested different weight assignments for ranks 1, 2 and 3, such as 10, 8, 3, respectively; 100, 60, 20, respectively; and 1, 0, 0, respectively to check if this changed the final ranking of the factors for each question. Although the absolute values changed, the ranking order did not change).

$$S_j = \sum_i h_{ij} \, . \, w_i \qquad \text{[Equation 4.1]}$$

where S_j is the total weighted representation of each driving factor, h_{ij} is the number of votes for driving factor (j) and ranking (i), and w_i is the weight assigned to the ranking (i) (i.e. w_1=3, w_2=2, and w_3=1).

To establish the relative importance of each driving factor, a farmer "influencing factor" (IF) was calculated for each question, in each group, for every decision factor (similar to Sattler and Nagel, 2010), where IFj is the influence weight that each driving factor carries:

$$\mathrm{IF}_j = \mathrm{S}_j \, / \sum_j S_j \qquad \text{[Equation 4.2]}$$

IF$_j$ ranges from 0 to 1, with a value of 1 meaning that all participants only chose that particular factor (j) as being the most important, and considered none of the other factors as having any influence (i.e. other factors were not ranked and hence assigned values of 0).

4.3.5. *Future land use scenarios*

The land use change scenarios we wanted to develop were for the purpose of modelling with climate change simulations, both applied to a hydrological model. For this, spatially distributed land use scenarios were required with quantitative changes of each land use type for the future. By using the responses from the questionnaire where qualitative information could be quantified was one step towards resolving the challenge of modelling farmer choices. The predicament of translating qualitative data into quantitative data is often encountered in land use change science, especially where surveys have been carried out, and has been coined "pixelizing the social" (Geoghegan et al., 2001). One method to overcome this complex problem is by using narratives of scenarios or storylines (e.g. Westhoek et al., 2006).

Thus, land use scenarios to 2040 were developed for both watersheds by using exploratory scenario storylines (Rounsevell and Metzger, 2010). The storylines were based on the casual relationships of change determined from knowledge gained of the respective study sites.

For each watershed, a farmer driven scenario was developed based on questionnaire responses obtained. To compare our approach to a more traditional scenario development method, a policy driven scenario was outlined for each watershed based on agricultural policies. These two future land use scenarios depict two different modelling approaches. On the one hand, future agricultural land use from a farmer perspective is presented, and on the other hand from a desirable governmental perspective. These scenarios represent certain views on modelling, where the first takes a bottom-up approach from the farm level, and the second has a top-down regional approach.

Farmer driven scenario

The results from the questionnaires in each watershed were used to develop justifiable storylines from the farmers' perspective, by providing the causes for changes based on the questionnaire responses as well as input from the respective local stakeholders involved in the project.

For each watershed, after the questionnaire was filled out and the responses were endorsed by local stakeholders, the information was used to guide a scenario driven by farmer choices. The semi-qualitative information pertaining to the driving factors (semi because it was ranked) from the three questions from each farmer group were used to calculate the IFs. These influences were considered and were developed into storylines to reflect the farmer actions as much as possible. The proportion of directly- and indirectly- related financial factors deemed important to the farmers was considered as well. Responses from other questions in the questionnaire were integrated as well to expand the scenario. For example, from one question, we could gauge if the farmer was satisfied with the types of crops currently being grown. From other questions we could determine the types of crops grown historically and now. Further questions guided the planting of future crops, e.g. if the growing season was longer. With all the valuable information collected, a scenario storyline of land use change was developed to 2040 that was coherent with the quantitative data gathered.

Thus, for each watershed, the scenario storyline allowed us to quantify the changes for each crop type where the farmer decisions were used as driving factors. The storyline and well as the final spatially distributed scenario of land use change was brought to the stakeholders where land use locations were discussed and validated or refined with their expertise.

Policy driven scenario

In order to evaluate the land use changes in a regional context, a second land use change scenario was developed for each basin whereby the driving factors were based on government-driven influences from policies that are either in place or yet to come. In particular, information from programs providing income stabilization to farmers, or available crop insurance, or environmental programs were used.

These drivers included financial as well as non-financial drivers. This scenario storyline developed from the literature and policies was also brought to the stakeholders, where it was further refined with their expertise, and the land use locations were also discussed.

4.3.6. Spatial distribution of land use scenarios in the basin

Once the stakeholders approved the land use storylines, a land use model was applied to spatially distribute the quantities of land use types for each of the storylines in each watershed, and in each year from 2011- 2040. To allocate the quantities of land use types, the CLUE-S model (Conversion of Land Use and its Effects-Small scale; Verburg et al., 2002) was set-up on a 50 m raster of the Altmühl watershed, and on a 30 m raster of the Pike River basin. CLUE-S is a dynamic model that spatially allocates land uses in a basin by drawing on empirically quantified relationships (logistic regressions) between the historic driving forces of changing land use patterns (e.g. soil type, distance to market, demographics, etc.) and iterations of land use competition based on user-defined ease of land use change.

The logistic regression equations were only based on relevant biophysical data pertaining to the watershed (e.g. DEM, soil, topography, precipitation, land use/land cover), which was collected from government sources. Once the spatial scenarios were simulated, the Relative Operating Characteristic (ROC; Pontius Jr. and Schneider, 2001) was applied to test for the goodness-of-fit. The ROC statistical test depicts how well the modelled scenario confers with the map of land use suitability (a probability map) for each category. Any ROC value >0.5 is better than randomly assigned land uses in the watershed. For the Altmühl River land use types, the ROCs varied between 0.63 and 0.83, and for the Pike River, they ranged from 0.59 to 0.98.

Validation of CLUE-S was a difficult task due to lack of fine resolution historical land use data. Verburg et al. (1999) recognized that if historic land use data is not available, reliance on expert knowledge can be used to validate the CLUE-S model. Therefore, stakeholder consultation was carried out to validate the plausibility of the spatially simulated land use change scenarios. Workshops were held in both watersheds with the regional government authorities, farmer union representatives, watershed organizations and researchers (listed in section 2.3) where the scenarios were presented, discussed and refined. Stakeholders provided feedback on the quantity and on the spatial distribution of the crops in the watershed, as well as on the hot-spots of change. Since the stakeholders were involved in all stages of the scenario development (including validating the farmer responses to the questionnaires and developing the storylines), the adjustments after the workshop remained only minor.

4.4. Results

In total, the questionnaire was distributed to 923 farmers; responses from 150 farmers were received and analyzed. The majority (77%) of the farmers who responded to the questionnaire undertook agricultural activities as an economically viable pursuit as their main employment (i.e. were not “hobby farmers”), the production type for each group is depicted in Figure 4.1. Several sources of government support were available to all farmers questioned in the form of direct payments, subsidies or income support.

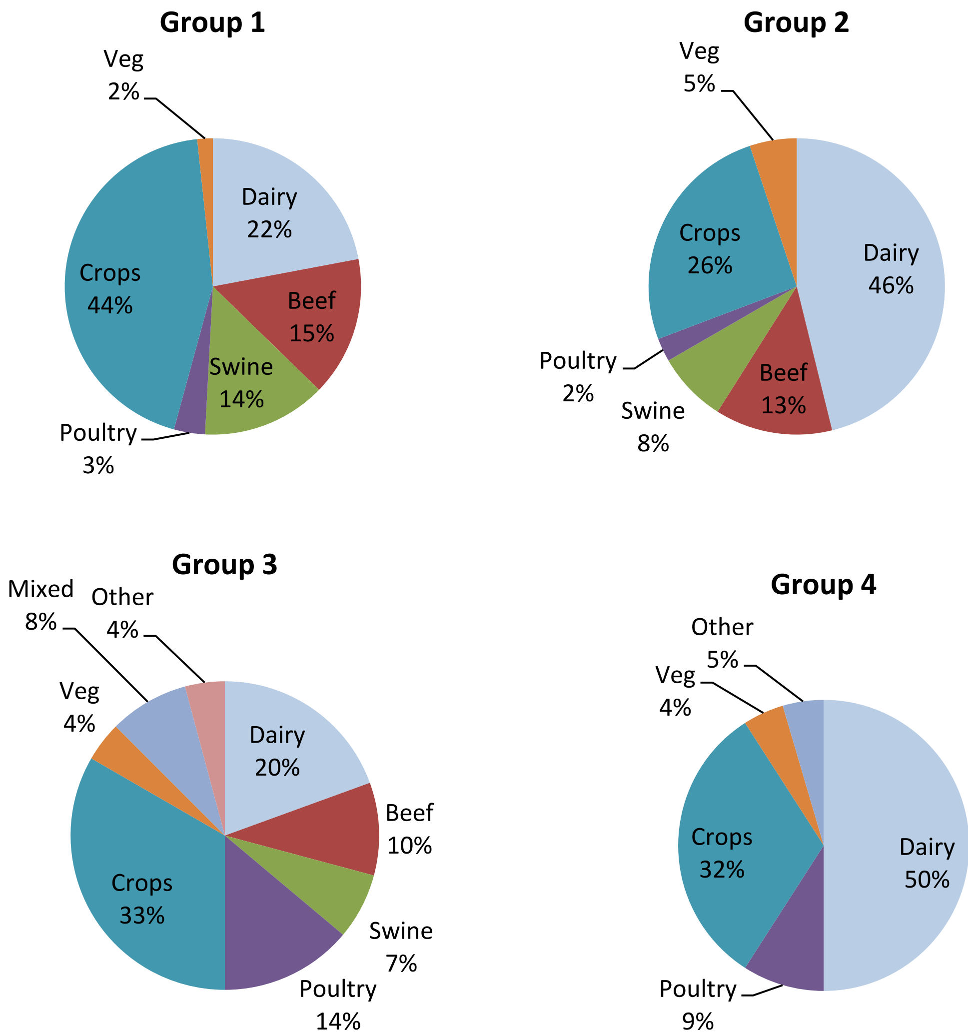


Figure 4.1. Farm classification belonging to the farmers in each group.

In the Altmühl watershed, 8% of farmers in Group 1 responded to the questionnaire. Comparative statistics confirmed that this sample was representative of the general population in the corresponding rural district (data not shown). The respondents represented 1469 ha of agricultural land (or 6.5% of the agricultural land in the area questioned) and all of the farmers who responded obtained government subsidies for their production. In Group 2, all 24 students responded to the questionnaire (5 out of 24 students lived in the watershed proper), and all except 1 obtained government subsidies.

Using a nonparametric statistical test (Mann-Whitney), Group 1 and 2 were found to be statistically different ($p>0.05$) in terms of their farm size (31 ha and 125 ha, respectively); the number of people living on the farm (2 and 3, respectively); and the number of years of farm working experience (34 and 8 years, respectively). In Group 1, 50% of farmers were considering abandoning their farm for unspecified reasons (additionally, 4 of the questionnaires were returned stating they had already abandoned their farm), and 11% wanted to expand their farming activities; in Group 2, none would abandon the farm and 72% wanted to expand. Both groups noticed climate change impacts to similar extents; 64% and 72%, respectively. However, a statistically significantly larger proportion of farmers in Group 2 would switch crops if the growing season increased (examples of crops cited were soybean, sorghum, miscanthus, lupin and sudangrass). Otherwise, there were no significant differences between Group 1 and 2, and the decision-making factor rankings to grow crops on their farms were very similar.

For the Pike River watershed, the response rate was higher in Group 3 as 24% of the farmers responded to the questionnaire, and of these, 58% obtained government subsidies for their production. In Group 4, all 23 students responded (1 student lived in the watershed proper) and 44% benefitted from government subsidies for production. Group 3 and Group 4 differed statistically in terms of their average experience in farming (33 versus 10 years, respectively) and in the size of the farms they worked on (93 versus 168 ha, respectively). The major crops grown in 2011 for Group 3 were: maize 51%, soybean 22% and hay 12%. The remaining land use areas were divided between forest, cereals, and pasture. Group 4 presented a greater variation in crops. The main crop grown was maize, but at a smaller proportion (33%), then hay (26%) and soybean (18%). Group 4 also had more area devoted to vegetables, pasture, cereals and alfalfa, and that the younger group tended to produce a wider range of crops. Otherwise, there were no significant differences between Group 3 and 4, and the decision-making factor rankings to grow crops on their farms were very similar.

4.4.1. Ranking of decision-making factors for crop choices

The four farmer group responses were combined and compiled for the three questions pertaining to ranking the driving factors (Figure 4.2) and the results are also presented as IFs for each group (Table 4.2). For Question A: “In your opinion, how much influence do the following factors have on the choice of which types of crops to grow on your farm?” the most important influencing factor stated was the “economic return of the crop”. This was followed by the “time expenditure to cultivate the crop” and by “access to markets for the crop”, “access to farm equipment, machinery and technology” and “the farm experience that you (or your family) has”. The lowest ranked factor of “other” was mostly related to growing fodder for own livestock.

The results to Question A were confirmed by the factors that farmers chose as having influenced their past actions in Question B: “What has prompted you, in the past 10 years, to grow crops that you previously had not grown on the farm before?”. Only farmers who had made changes in the past 10 years responded to this question (n = 71). Responses showed the monetary factors of “market factors (e.g. sale difficulties, changing demands)” and “financial factors or incentives (including government subsidies)” to have the most influence, followed closely by the influences “minimize the risk from crop failure” and “pest, weeds and diseases”. The next factors “climatic factors”, “speaking with farmers/neighbours/friends”, “access to new information (e.g. production guides, internet)” were not directly related to finances.

To assess how farmers may be prompted to change their current land use in the future, Question C asked: “What would influence your decision to cultivate other or additional types of crops from the ones you have grown?”. The market factor was the foremost driver, ahead of the climate factor. Interestingly, the climatic factor ranks in second place as a possible future driver, compared to its fifth place as a reason for changing land use in the past (Question B), possibly due to an increasing awareness of climate change, or because sometimes farmers’ stated preferences are not necessarily what they actually do (Mandryk et al., 2014). Another direct financial factor “government subsidies” was in third rank. The “others” category was associated with planting crops for demand reasons and/or for biofuels.

The decision-making factors identified in these questions can be categorized into directly-related (explicit) financially factors, indirectly-related financial factors, and those that are overlapping. A colour coding was applied to the driving factors to distinguish these categories from each other (see captions in Figure 4.2 and Table 4.2).

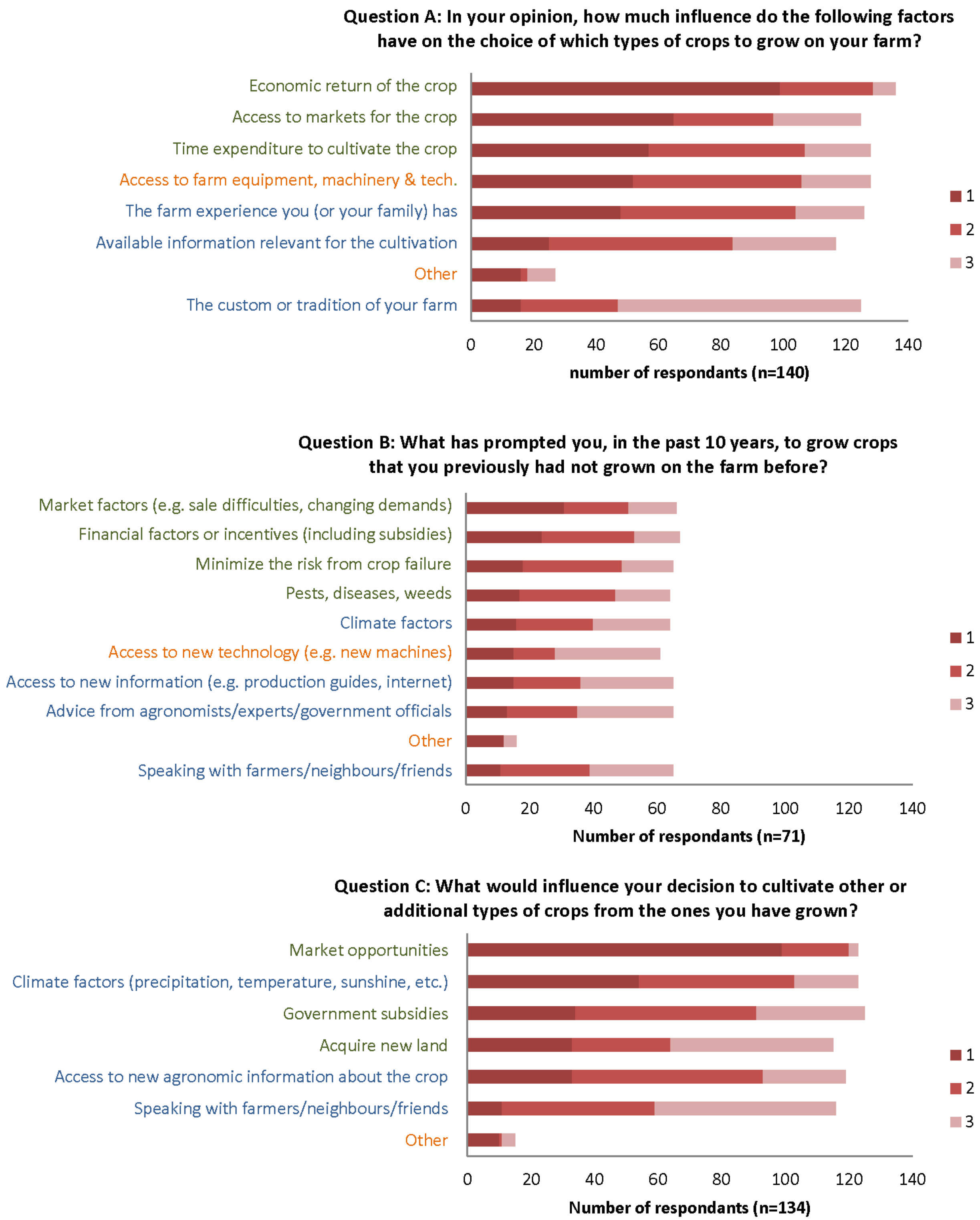


Figure 4.2. Combined ranking of driving factors from the four farmer groups. The factors are ordered by their first ranking. Colour coding: green = directly-related financial factors; blue = indirectly-related financial factors; orange = factors that may be financially related or not.

Table 4.2. Influencing Factor (IF) weights range from 0 to 1, with 0 being not influential and 1 being solely influential. Colour coding: green = directly-related financial factors; blue = indirectly-related financial factors; orange = factors that may be financially related or not. In each question, the factors are ordered by the weighted average IF.

Factors	Group			
	1	2	3	4
Question A: In your opinion, how much influence do the following factors have on the choice of which types of crops to grow on your farm?				
	(n=42)	(n=24)	(n=48)	(n=15)
Economic return of the crop	0.19	0.17	0.20	0.16
Time expenditure to cultivate the crop	0.15	0.16	0.14	0.16
The farm experience that you (or your family) has	0.15	0.15	0.13	0.14
Access to markets for the crop	0.14	0.15	0.15	0.13
Access to farm equipment, machinery and technology	0.15	0.14	0.14	0.15
Available information relevant for the cultivation of crop	0.11	0.12	0.11	0.12
The custom or tradition of your farm	0.10	0.08	0.10	0.10
Other	0.02	0.04	0.03	0.04
Question B: What has prompted you, in the past 10 years, to grow crops that you previously had not grown on the farm before?				
	(n=20)	(n=10)	(n=26)	(n=15)
Market factors (e.g. sale difficulties, changing demands)	0.17	0.13	0.11	0.11
Financial factors or incentives (including subsidies)	0.15	0.13	0.11	0.11
Minimize the risk from crop failure	0.11	0.11	0.12	0.12
Pests, diseases, weeds	0.12	0.13	0.09	0.12
Climate factors	0.09	0.11	0.11	0.11
Speaking with farmers/neighbours/friends	0.09	0.11	0.10	0.09
Access to new information (e.g. production guide, internet)	0.08	0.10	0.12	0.09
Advice from agronomists/experts/government officials	0.06	0.09	0.11	0.12
Access to new technology (e.g. new machines)	0.07	0.08	0.09	0.11
Other	0.07	0.02	0.02	0.03
Question C: What would influence your decision to cultivate other or additional types of crops from the ones you have grown?				
	(n=42)	(n=24)	(n=44)	(n=23)
Market opportunities	0.23	0.23	0.23	0.18
Climate factors (precipitation, temperature, sunshine, etc.)	0.19	0.17	0.18	0.18
Government subsidies	0.18	0.16	0.15	0.16
Access to new agronomic information about the crop	0.17	0.13	0.16	0.16
Acquire new land	0.11	0.17	0.12	0.18
Speaking with farmers/neighbours/friends	0.11	0.13	0.12	0.13
Other	0.02	0.01	0.04	0.02

Directly-related financial factors are those from which a farmer will gain immediate income, such as the market price of a crop. Indirectly-related factors include: the climate, which may be a trigger to plant higher value crops that will ultimately render more profit to the farmer; or, the experience a farmer has, which is beneficial in terms of saving time in farm operation and management tasks. Factors that are overlapping include, for example, access to information as this can be directly related to finances (e.g. information on best time to sell the crop) or indirectly-related factor (e.g. informing on how to increase crop yields).

Figure 4.3 depicts the extent to which directly-related and indirectly-related financial factors were answered for two questions, for each of the four farmer groups. The length of the radius for each circle is proportional to the number of factors in the circle. From the relative circle sizes, it is evident that the explicit financial factors occupy a slightly greater – or similar - weight to the indirectly-related financial factors for all groups. In a meta-analysis investigating the drivers of tropical deforestation, Geist and Lambin (2001) also found several synergetic drivers, of which the economic factors were found to be within the most frequently cited groups of influential drivers.

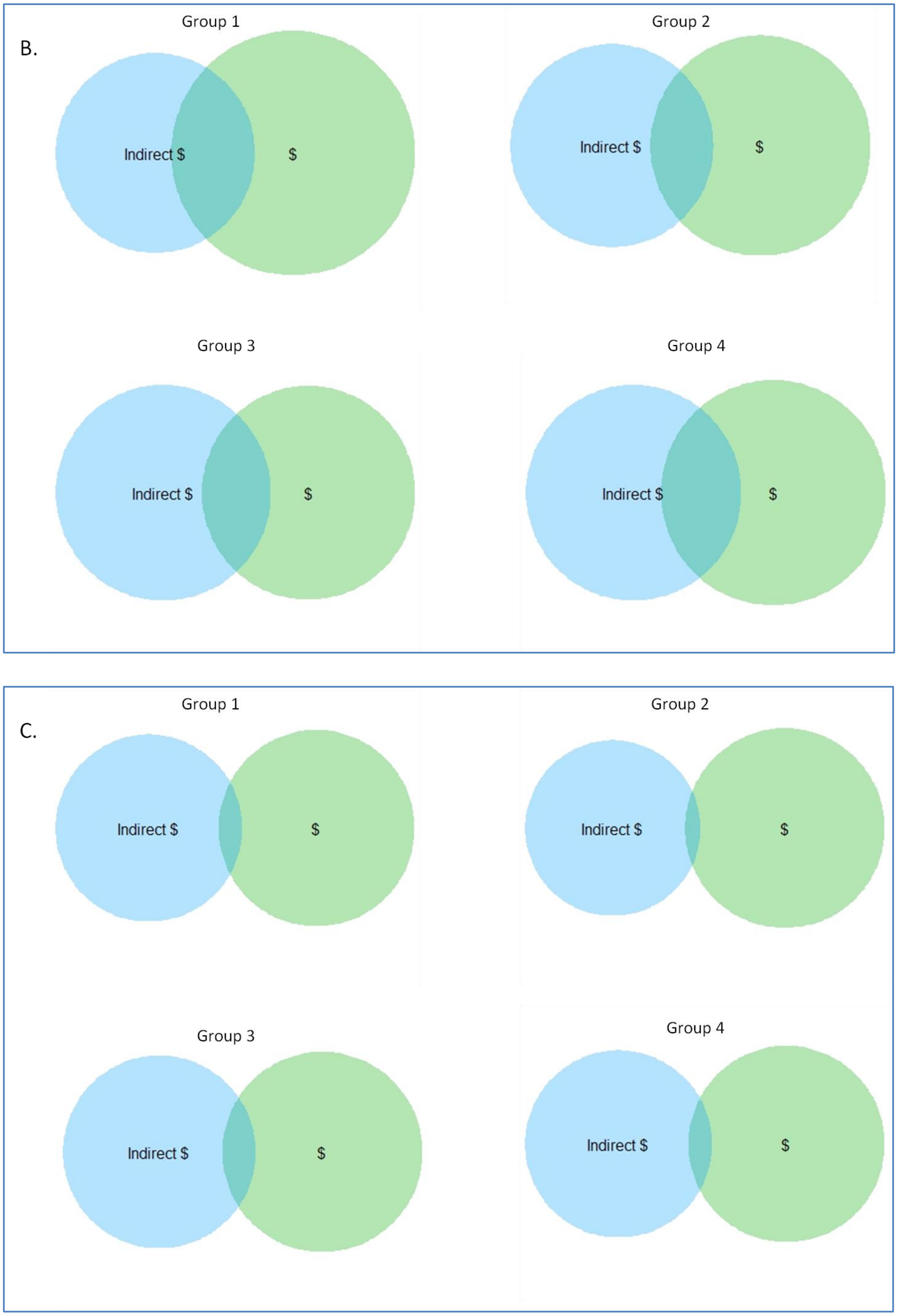


Figure 4.3. Circle sizes proportionally depict the importance of indirectly-related financial factors (Indirect $) and directly-related financial factors ($) or both (overlapping area) as determined from the four farmer groups, for Question B (upper) and Question C (lower panel).

4.4.2. The Altmühl River land use change

Farmer driven scenario

In this scenario, the total area of agricultural land decreased by 4% (compared to -5% historically) due to the increasing pressure for more cropland. Almost half of the farmers in Group 1 stated they would be abandoning their farm, while nearly two-thirds of farmers in Group 2 wanted to expand their farm, but constraints to expand agricultural areas are the high prices of land rental (up to € 800 ha^{-1}) and the shortage of crop land.

The main crops grown by the farmers were cereals and maize. Forages (clover), vegetables, oilseeds (rape seed), potatoes and sugar beets were grown to lesser extents. Over 85% of farmers in Group 1 and 75% in Group 2 indicated they would continue to grow the same main crops in the future. Approximately 15% in Group 1 and 40% in Group 2 indicated they would plant crops they had not planted before, such as biofuel crops or soybean, because of an opportune marketing potential, the climate or new knowledge gained. As well, almost half of the farmers in both groups 1 and 2 indicated they would possibly alter some of their crops or management practices in the future if the growing period was extended by 4 weeks, mostly by changing the crop type and the crop rotation.

Farmers are interested in switching mostly to maize, because of the myriad of family run biofuel plants that offer an available and accessible market and create a driving force to plant more silage corn (58% of the feedstock for biogas plants stems from silage corn; Röhling and Wild, 2008), so the area under maize increases by 8.3% of the total agricultural land[1].

The other important row crop being considered is soybean, the area under legumes (soybean and peas) will increase since soybean will be more productive in a warmer climate and are considered to be a good fodder crop as well as rotation crop for maize (legumes increase by 6.8%).

The wheat areas decrease because farmers indicated it was not profitable to grow and that they were willing to replace it with maize. Areas under cereals (especially wheat) and tubers (especially potatoes) decrease in this scenario by 6.4% and 0.6%, respectively because they are

[1] All of the percentages of crop changes provided are in relation to the total amount of agricultural land in the watershed.

generally less profitable. Pasture areas decline by 9.6% because one additional cut of hay is possible in the future and land for new cropping options were important to farmers. Perennials (switchgrass and miscanthus) increase by 0.9% because they are potential biofuel crops. In both scenarios, urban land use increases at the same rate as historically.

Overall, the changes in the watershed are not drastic (Table 4.3) since inertia to change is inherent due to the farmers' experience, family traditions or available machinery and markets. Figure 4.4b depicts these land use changes and their spatial distribution in 2040 as modelled by CLUE-S.

Policy driven scenario

In Bavaria, most farmers rely on government support to assist their farming practices. The Common Agricultural Policy (CAP) of the European Commission (CEC, 2008) and the regional environmental program KULAP (*Kulturlandschaftsprogramm*; StMELF, 2011) are two such programs. The CAP program period 2007-2013 has two pillars; the first pillar is based on direct payments to farmers, also known as single farm payments which are contingent with "cross-compliance" conditions pertaining to agricultural and environmental standards of production. The second pillar of the CAP is related to rural development: it involves improving competitiveness of the agricultural sector and aims to improve the environment of the countryside. In this study, the recent CAP 2013 reforms were not included.

The KULAP encourages a variety of farm best management practices such as ecological agricultural practices; maintaining good practices on pasture management; undertaking less intensive agriculture; implementing cover crops or green manures; and improving farm crop diversification.

Europe's biomass policy is another driving force for change; it stipulates that by the year 2020, 10% of each member state's energy for transport should stem from biofuels (CEC, 2008). The biofuel policy will help to create an alternative outlet for farm produce and help to develop rural areas (Wiesenthal et al., 2009).

In the "policy driven scenario", based on the above programs, income stabilization from single farm payments helps to keep farmers in the business. The total agricultural land decreases by

3%, which is less than historically and less than in the farmer driven scenario. Forested areas increase by 2% of the watershed area.

The programs also allow farmers to maintain good practices (by decoupling production from payments). The rangeland (composed of set aside land and natural grasslands) increases by 0.7% because of several factors: the cancellation of the obligatory set-aside quota decreases the rangeland slightly and land abandonment is slowed, but the least productive land is still taken out of production which causes rangeland to increase. The preservation of permanent grassland is continued.

Overall, crop production is less intensive as the production of food has become secondary to the protection of rural natural resources and cultural landscapes. Due to slower demographic and economic growth as well as less meat consumption, livestock production is consequently also lower. Fodder crops such as legumes (especially alfalfa and fodder crops) decrease by 1.1% and pasture areas decrease by 0.5%. Crop diversification augments because of the instruments in place that encourage farmers to follow market signals. The cash crops such as maize and cereal areas increase more slowly than historically, by 1.3% and 2.2%, respectively, or decrease altogether, as in the case of oilseeds (-2.2%). Figure 4.4c depicts these land use changes and their spatial distribution in 2040 as modelled by CLUE-S.

Table 4.3. Land use areas in the Altmühl watershed with percentage crop change for each scenario

	2008	**Farmer scenario 2040**		**Policy scenario 2040**	
	ha	ha	*%*	ha	*%*
Cereals	22331	17932	*-19.7*	22777	*+2.0*
Forest	38322	39831	*+3.9*	39089	*+2.0*
Legumes (soybean, peas)	1269	4840	*+281.4*	634	*-50.0*
Maize (silage or grain corn)	8236	12301	*+49.4*	8648	*+5.0*
Oilseeds (rapeseed, sunflower)	2788	3079	*+10.4*	1514	*-45.7*
Other (orchard, nuts, berries)	199	266	*+33.7*	199	*0*
Pasture (including hay)	20900	14855	*-28.9*	20482	*-2.0*
Perennials (switchgrass, miscanthus)	38	500	*+1216*	38	*0*
Rangeland	1517	1236	*-18.5*	1865	*+22.9*
Urban	2893	4008	*+38.5*	3603	*+24.5*
Tubers & vegetables	371	14	*-96.2*	14	*-96.2*

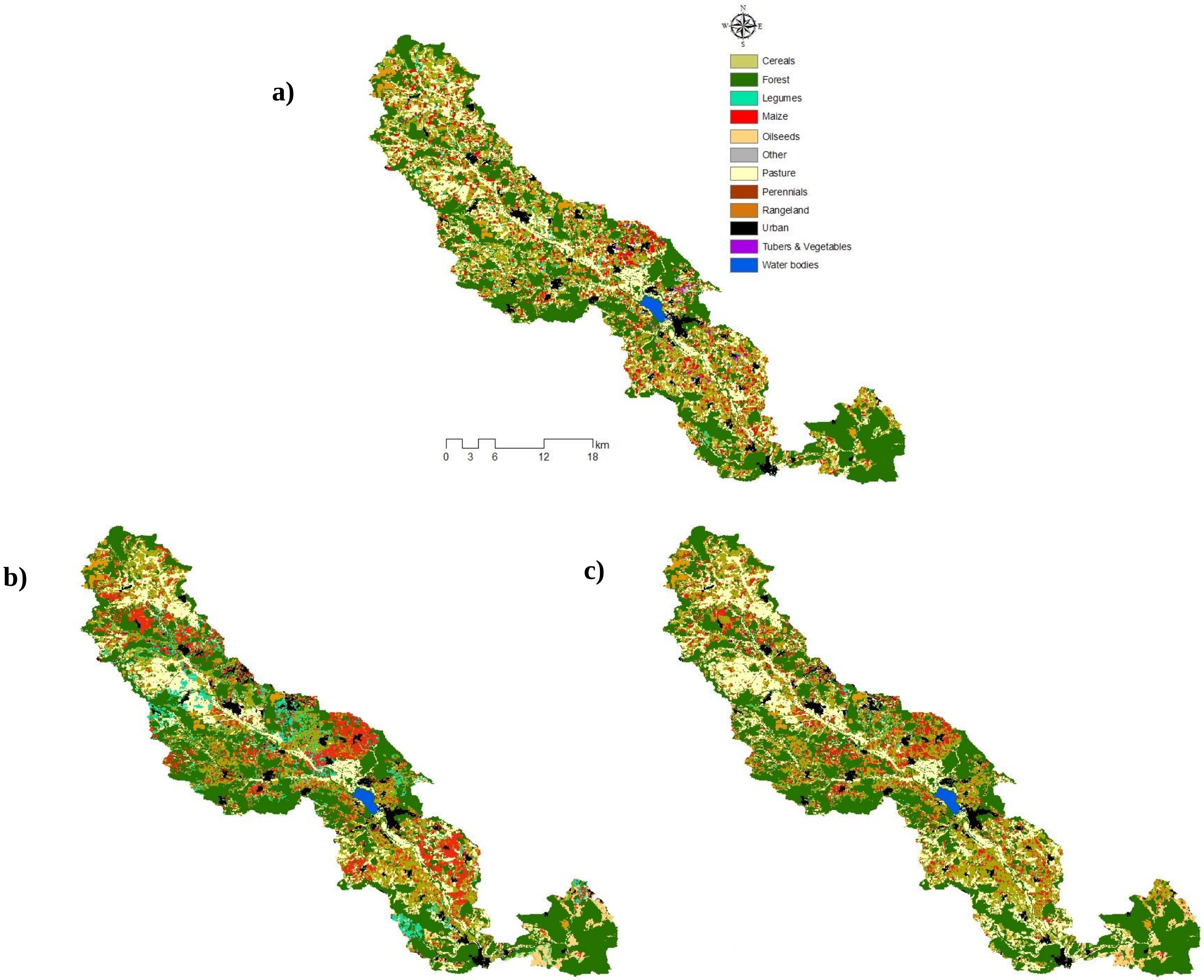


Figure 4.4. Altmühl watershed land use configuration a) from 2008; b) farmer driven scenario in 2040; and c) policy driven scenario in 2040.

4.4.3. Pike River land use change

Farmer driven scenario

Despite the pressure to augment agricultural activities (only very few farmers indicated wanting to abandon their farm and 80% of Group 4 farmers wanted to grow or expand their farm), the amount of available agricultural land is limited, so the total agricultural land does not increase but remains constant throughout the simulation period (occupying 54% of the basin) also because the forested area is protected by a law introduced in 2004 preventing deforestation (*Loi sur l'aménagment et l'urbanisme*).

The two main crops grown by the famers were maize and soybean. Hay, cereals, apples, vegetables and berries were also grown to a smaller extent. Over 90% in Group 3 and 80% in Group 4 stated they were planning on continuing to grow their same main crops in the future. Yet, almost 30% of the farmers (mostly wheat and hay growers) indicated they were planning on growing new crops in the future that they had not grown on their farm until now, and mentioned potential ones being vegetables, wheat, maize, soybean, hops, or orchards. Also, 56% of Group 3 and 78% of Group 4 indicated that they would adapt their practices to a longer growing season, foremost by changing crop varieties. As a second measure, Group 3 would implement more crop rotations, while Group 4 indicated that they would implement more cuts of hay.

In the "farmer driven scenario" there is a pronounced increase in maize production (7.0%) because of its suitability to a warmer climate and farmers being content with the profitability of this crop as it is part of the income stabilization program and was also heavily subsidized in the past, therefore maize areas have expanded over the past decades as grain for livestock feed increased (it is the most widely grown crop in Québec) and farmers are familiar with this crop and they have the necessary machinery and silos required.

The soybean area increases by 0.5%, as there are well-established markets and export opportunities (i.e. to Japan) are increasing. The increased maize and soybean areas occur at a detriment to hay production (-1.6%) in part because farmers will be able to harvest 4 cuts and therefore require less land to produce for the same amount of hay.

Cereal areas (wheat, barley, oats) increase (0.2%) as indicated by the farmers' willingness to plant more. Niche crops, such as vegetables (e.g. sweet corn, squash) occupy a slightly greater area. Other changes in crop areas include cherry trees replacing the apple trees as these can be grown for the nearby urban areas in Montréal. The amount of forested area decreases at the same rate as that of urban expansion. Figure 4.5b depicts these land use changes and their distribution by the year 2040 as modelled by CLUE-S.

Policy driven scenario

In Québec, farmers obtain some compensation from the income stabilization program (ASRA) of Québec's Agricultural Financial Ministry (La Financière Agricole du Québec; FADQ) which is based on commodity market prices (FADQ, 2014) and compensates farmers when the market price is lower than the cost of production. The ASRA is a voluntary program to adhere to, yet approximately 90% of crops in the watershed are part of this program each year. According to recent years of historic ASRA compensation data, maize and beef were most profitable to produce, soybean were next most well compensated, and cereals were compensated at a lower rate (half of soybean). The value of cash receipts since 2010 for maize increased by 41%, potatoes by 24%, and oats by 36%.

Additionally, farmers can also obtain different levels of crop insurance from the FADQ that reimburses farmers for the loss of their crops in the event of a disaster. The stakeholders emphasized that the ASRA is perceived amoung farmers to be a source of revenue, whereas crop insurance is considered to be a risk management tool. Historically, the ASRA has been important in shaping farmers' crop choices (e.g. shift from dairy farming to swine production in the 1990s).

The following government documents were also consulted to determine future policy directions for Québec's agricultural sector *Donner le goût du Québec : Livre vert pour une politique bioalimentaire* (MAPAQ, 2011), *Rapport sur Agriculture et agroalimentaire: assurer et bâtir l'avenir* (CAAAQ, 2008), and *Activité bioalimentaire au Québec en 2011: Bilan et perspectives* (MAPAQ, 2012). Overall, the Québec government aims to promote Québec products internationally and remain competitive in global markets. Most of Québec's produce currently goes to USA, but emerging markets are China and India. The government also has the mission to continue to contribute to sustaining the Québec population. The government strongly emphasizes crop diversity and health.

In the “policy driven scenario” (Table 4.4), the amount of total agricultural land increases by 2.4%, mainly by expanding into the rangeland (-2.0%). Maize areas increase albeit at a slow rate (4.3%), therefore the main rotation crop, soybean, experiences a decrease (by 2%). Cereal areas decrease (by 2.1%) since they are not as well compensated by ASRA.

The diversity of crops in the watershed increases as niche markets evolve for exportation. The MAPAQ (2011) predict that the new crops in the area may include grapes, blueberries, squash, linseed and cherries. Thus, the area of agricultural land will increase for vegetables (0.6%), berries (0.3%) and orchards (0.1%) as will vineyard areas (1.0%; in “other ag land”). Figure 4.5c depicts these land use changes and their spatial distribution in 2040 as modelled by CLUE-S

Table 4.4. Land use areas in the Pike River watershed with the percentage land use change for each scenario

	2011	**Farmer scenario 2040**		**Policy scenario 2040**	
	ha	ha	*%*	ha	*%*
Cereals	677	742	*+9.6*	50	*-92.6*
Forest	24253	24139	*-0.5*	23213	*-4.3*
Maize	10552	12984	*+23.0*	12199	*+15.6*
Hay (pasture, grass, alfalfa)	8087	7650	*-5.4*	7300	*-9.7*
Orchard	1031	1020	*-1.1*	847	*-17.8*
Other ag land	8824	6882	*-22.0*	11537	*+30.7*
Rangeland	1252	1247	*-0.4*	0	*-100.0*
Soybean	3250	3462	*+6.5*	2844	*-12.5*
Switchgrass	102	51	*-50.0*	0	*-100.0*
Urban	1508	1630	*+8.1*	1630	*+8.1*
Vegetables	237	356	*+50.2*	443	*+89.9*

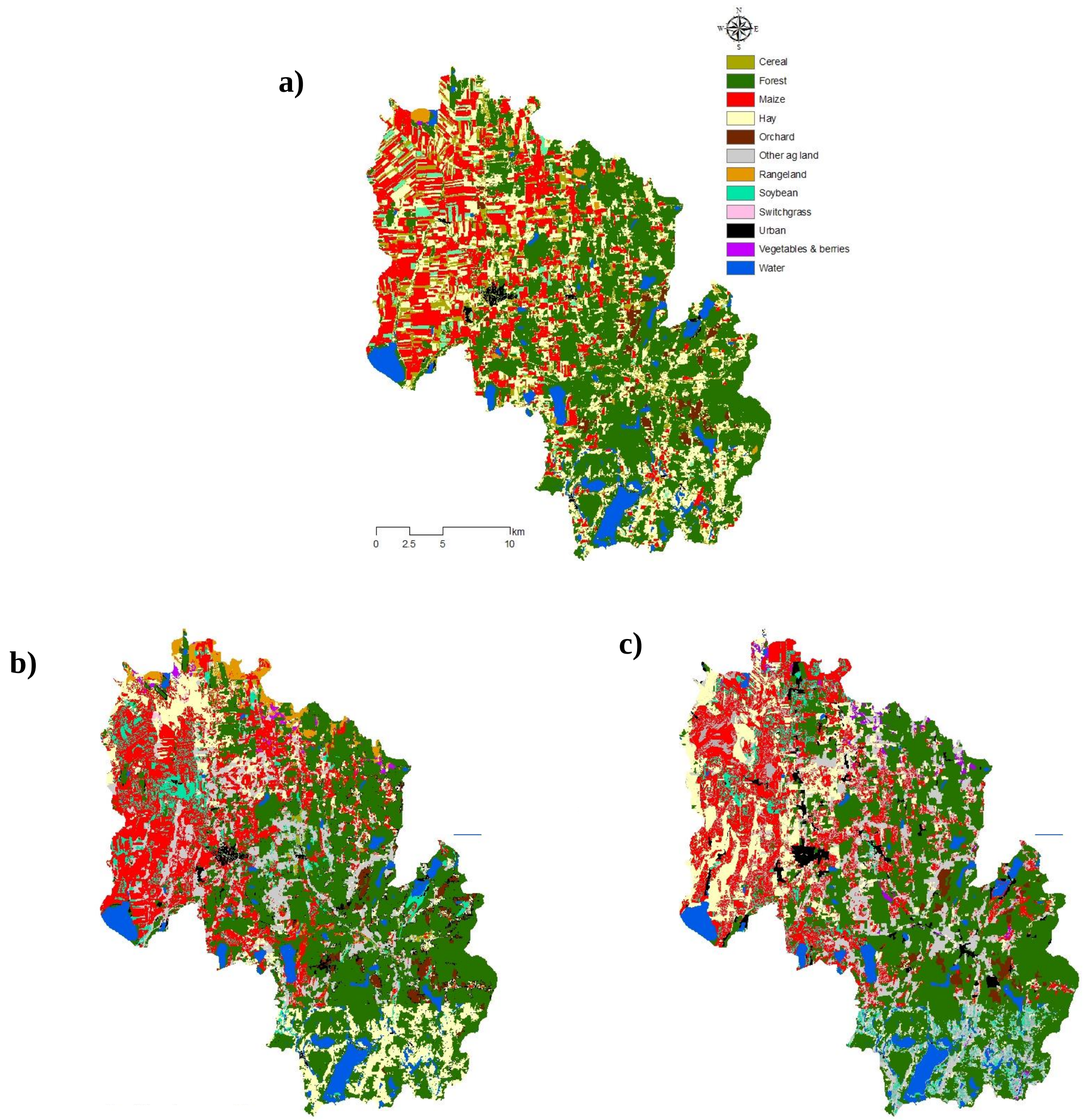


Figure 4.5. Pike River watershed land use configuration a) from 1999; b) for the farmer driven scenario in 2040; and c) for the policy driven scenario in 2040.

4.5. Discussion

Despite the differences in the farmer characteristics between the two groups in each region (i.e. age, geographic location, farming experience), farmers in all groups ranked the driving factors very similar. Especially the indirectly-related financial factors had almost identical rankings, indicating regional and generational consistencies amongst the farmers surveyed. Also inter-regional group responses were very similarly ranked.

The replies indicate that while the explicit financial income for the farmer plays an important role, it does not clearly stand out as being the only driver for land use; there appear to be multi-factorial drivers of comparable influence involved in choosing which crops to plant. Although directly-related financial factors (e.g. revenue, markets, subsidies, etc.), are important drivers for farmers, farmers also consider indirectly-related financial factors such as climate, available technology, information, their experience, and their farming tradition.

In developed regions, where farming is highly intensive, competitive and in some cases rather lucrative, one could imagine land use drivers to be especially related to the explicit financial factors. However, responses showed that proportionally similar directly-related financial and indirectly-related financial factors were considered by farmers to change their crop land use.

Research on landscape managers and changes to land show there is intricacy in decision-making regarding land cover changes, conservation practices, and on-farm water utilization. A study by White and Selfa (2013) also found farmers (in Kansas) to make complex decisions when deciding whether to plan biofuels; they categorized the influences on farmer decisions broadly into four classes: new practices; the natural environment; the farmer; the decision setting. The directly-related financial factors in their cataloguing fall under “new practices”; one of the four categories. Studies that questioned farmers in Germany on their reasons for setting aside land (Siebert et al., 2010) and for implementing conservation practices (Sattler and Nagel, 2010) also found that economic factors were not the most important driver. Instead, reasons like the associated risks and the time or effort required were in most cases more important to farmers. We classified such reasons as indirectly-related financial factors.

The quantities of land type change were dictated through the storylines developed based on the farmer influences, and the spatial distribution of these changes was dynamically modeled by CLUE-S, which is based on historical locations of change and competition for land types.

The “farmer driven scenario” storylines assisted to capture the influencing factors of the farmer, who is not explicitly represented in CLUE-S. An agent-based model would have also been appropriate to represent such processes of land use change. However, agent-based models have their own drawbacks (e.g. they poorly link the behaviour of the agents to their land use units). Ultimately, there is no perfect model to describe all processes at the desired spatial and temporal scales. We chose CLUE-S because it is able to integrate information from several spatial scales, and furthermore, the spatially distributed raster layers can be applied to other simulation models, such as to a hydrological model.

The “farmer driven scenario” highlighted that in both regions farmers were mostly willing to switch to maize, but for different reasons. In the Pike River, the ASRA program and existing technology and infrastructure were important reasons. In the Altmühl River, biofuel incentives was the main driver, which corroborates with estimates that by 2020, 15% of Europe’s arable land will be used for biofuel production (EC, 2007). The spatial distribution of increasing maize areas in both basins highlighted particularly important hot spots of future change. The stakeholders in the Altmühl basin confirmed the area of intensive maize area transformation depicted by CLUE-S, to the north of the Altmühl Lake, which corresponded to the historic area of change.

The “farmer driven scenario” also reflected that farmers are almost equally as sensitive to indirectly-related financial factors as they are to explicit financial factors, and that the former play an important role in their decision to change crop land use. For example, the results portrayed the ability, willingness and knowledge on the part of producers to adapt their management practices if the growing season proves to be longer. Specifically, more soybeans would be planted in the Altmühl basin in the future. In the Pike River, soybeans are already widely grown and farmers would potentially switch to better suited crop varieties or add more rotations in a warmer climate. In both regions farmers would also seed less hay since more cuts of hay can be obtained in the future on the same land. Some of the farmer indicated changes may not come to be realized, for example in the Pike River farmers stated growing wheat as a new crop, however this may not be entirely realistic since under a warmer climate wheat yields are predicted to decrease, unless a switch to short season maturing varieties is undertaken to maintain yields (see Trnka et al., 2014).

The farmer driving factors provided insights into their preferences which were not captured by the “policy driven scenario”. In the Altmühl River, almost 100% of the farmers received government support, so that government programs were strong determinants of land use change. The CAP is a demand driven policy, it allows farmers to produce food in response to market signals (due to the single farm payment), while at the same time allowing farmers to benefit from direct income payments. Cash crops (cereals, maize, and pasture for livestock) are prominent, but there is more crop diversity and less intensive agriculture. Therefore, pasture areas increase more than in the farmer scenario because overall, land use policies that encourage protection of biodiversity and extensification of farm land are in place. Forested areas also increase. This scenario is a more environmentally friendly scenario.

A study in the Upper Danube (Henseler et al., 2008), which focuses on reforming the CAP of 2003 shows in one of their scenarios (“Modulation Scenario”) a strong shift away from payments of the first pillar to payments of the second pillar. Their scenario assumes that by 2020 the area of cereals increases by 6%, set-aside land decreases by 5% and fodder crops decrease by 2%. Grasslands shift from intensive to extensive production. This is comparable to the “policy driven scenario” in the Altmühl basin.

In the Pike River, just over half of the farmers receive government support for production, and they represent almost 90% of the crops in the watershed. Based mainly on the income stabilization program, the area under maize expands to a similar extent as in the “farmer driven scenario” and the area in cereal decreases. The stakeholders emphasized that the ASRA plays an important part in shaping the land use because it masks market price signals. For example, during 1986 and 2006, the prince of grain corn declined by 9% in Ontario, but under the same conditions, it increased by 86% in Québec. Thus, the policies are often a reflection of a societal pressure (CAAAQ, 2008).

From these scenarios it appears the farmers are driven by factors that are of immediate importance and relevance (e.g. biofuel plants) to them, they focus on the recent past to make decisions, whereas policies tend to have a longer-term planning horizon since they specifically aim to shape the future of farm landscapes. Several of the government documents consulted were planning for the next 10-20 years ahead. We recognize the “policy driven scenario” as being simplistic; a more integrated approach of farmers’ land use decisions coupled to government agents to reward or penalize the decisions (as e.g. Polhill et al., 2010) would have been more rigorous. Yet, the two approaches in this study capture the drivers as we described them in the storylines, and the scenarios were deemed plausible by the stakeholders. The “policy driven scenario” demonstrates how a different modelling philosophy driven by a different (arguably more frequently applied) set of drivers can shape future land use, compared to how the farmer perceives change.

The questionnaire purposefully proposed broad drivers of change to the farmers, as the specific reason for switching crops was not relevant here. Farmers do not make decisions in a void, and the reason for a farmer to change crops will depend on the purpose (i.e. for soil conservation, to protect biodiversity, or for income), which is related to farmer behaviour, experience and attitude (Just et al., 1990; Willock, 1999; Edward-Jones, 2006; Briassoulis, 2008; Karali et al., 2011). We wanted to gauge drivers of any crop change, regardless of the willingness or the ability of the farmer. Our lack of providing a reason for change may explain why the IFs amoung the groups were so consistent, because the farmers’ attitudes and characteristic specific traits (i.e. being risk adverse) were not relevant here. A detailed farmer typology within the groups was not carried out but may provide more insights into specific drivers related to farmer characteristics.

4.6. Conclusion

We identify direct and indirectly-related financial factors that influence crop land use change in developed regions, and provided a ranking of their importance as perceived by the farmers questioned. Our results contribute to supporting the message that a complex interaction of drivers needs to be considered for agricultural land use modelling, because farmers’ decisions to plant certain crops each year are not predominantly determined by explicit financial factors alone (neither now nor in the future).

Even though there is an increasing realization to adopt a pluralist approach to model farmer decisions and to look further than the financial factors that prompt farmers to react, the challenge of integrating the quantitative and qualitative drivers into land use models remains high. Our approach was to quantify the driving factors of change that are important to farmers by calculating influencing weights and integrating these into scenario storylines. The quantification helped to develop storylines of future land use change and was also useful to present the information to stakeholders.

The two land use scenarios developed in each region to 2040 portray two modelled outcomes based on scenario storylines arguably perceived from different viewpoints (one purely based on the local actor's feedback and one based on the government programs to steer the farmers). They provide indications of changes that may be modelled depending on the types of drivers of land use change that are emphasized in the scenario building phase. The quantitative information from the farmers led to changes that the scenario driven by policy was not able to capture because the motivations were different.

Capturing the farmers' intentions as driving factors can help to supplement the human decision-making component for land use models, and provide explanations for current agricultural land use patterns not explained by financial factors. Since it is challenging to quantify the non-economical drivers in, for example, cellular automata or agent-based models, they often implement the farm sector with quantitative functions, such as income maximization. We hope to add to the discourse on quantifying the qualitative by providing a quantification of non-economical drivers, which may be incorporated in conjoint analyses or used as a basis for participatory model development in the future. Agricultural land use depends on a multitude of drivers, which are often very site-specific therefore the extent to which farmers in other regions of the world will base their decisions on these drivers remains to be determined.

McGill

4.S. Supplemental Material <u>QUESTIONNAIRE FOR PRODUCERS</u>

This questionnaire is intended for the person managing the farm on a daily basis. <u>This questionnaire is anonymous and all answers shall remain strictly confidential</u>. It is composed of 23 questions regarding crop choices and farm land use. It should take less than 30 minutes to fill out the questionnaire. If you do not have all of the information requested, you may answer to the best of your knowledge.

<u>The farm business</u>

1. What kind of farm would describe yours as (*please check the relevant boxes*)?

   Dairy □/ Swine- or hog finishing □ / Poultry □/ Cash crops □ / Vegetable□ / Fruit and vegetable processing □ / Mixed □ (*which?*) ____
   / Other (*please describe*) ____

2. How many people assist with making decisions regarding this farms' operations, in the following age categories (including yourself):

   __ Younger than 20 yrs old

   __ 20-40 years old

   __ 40-60 years old

   __ Older than 60 years

3. How long have you been farming?_____________ years

   a. How long have you been on this particular piece of land? ___________ years

4. Have you sold □ / acquired or rented more land since you started farming? (*please circle the answer*) **yes** **no**

   a. If so, what is the total percentage of crop land that you own today compared with when you started? ________________ % more , or ___________________ % less

<u>Information on field crops</u>

5. What % of your agricultural crop land does not provide your farm with any direct income (e.g. brush, forested land, abandoned land)? ________________ %

   a. How much percent land do you currently have in pasture or hay?______________%

   b. Did the amount of pasture/hay land on your farm change over the past 10 years? (*please circle your answer*) **yes** **no**

   If yes, by approximately how much more___________ *% more, or* ________**%** less?

6. In a typical year, normally what crops do you grow?________________________________
____
____
    a. Which would you say are your two main crops?
    ____
    b. Do you plan on continuing to grow these same crops as your main crops in the future? (*please circle your answer*) **yes** **no** **unsure**
        i. If not, or if unsure, why?
        ____
        ____

7. List all the additional crops that you have grown on this particular farm since you started farming the land (*as far as you can remember*)?
____
____
____

8. If relevant, can you name some of the deciding factors why you <u>do not</u> choose to plant certain crops on your farm anymore? For example (*please check the appropriate boxes*)

- ☐ Monetary reasons (including subsidies)
- ☐ Demand for product
- ☐ Pests, diseases
- ☐ Replacement of crops by biofuel crops
- ☐ Climate factors
- ☐ Rotation
- ☐ Other (*please specify*)____

9. Which crops are you growing this year? *(for each crop type, please indicate the % of area of each*)

Crop	% surface cultivated	Crop	% surface cultivated
____________	____________%	____________	____________%
____________	____________%	____________	____________%
____________	____________%	____________	____________%
____________	____________%	____________	____________%
____________	____________%	____________	____________%

10. In your opinion, how much influence do the following factors have on the choice of which types of crops to grow on your farm? (*Please rank: 1= large influence, 2= medium, 3=little influence*)

Economic return of the crop	1	2	3
The custom or tradition of your farm	1	2	3
The farm experience that you (or your family) have	1	2	3
The time expenditure required to cultivate the crop	1	2	3
Access to farm equipment, machinery and technology	1	2	3
Access to markets for the crop	1	2	3
Available information relevant for the cultivation of the crop	1	2	3
Other (*please explain*)____	1	2	3

Changes in cultivation

11. What has prompted you, in the past 10 years, to grow crops that you previously had not grown on the farm before? *(please circle all relevant factors by ranking the following where 1=very important, 2 = medium, and 3=low. If nothing has changed in the past 10 years, tick this box:* ☐

Speaking with farmers/neighbors/friends	1	2	3
Advice from agronomists/experts/government officials	1	2	3
Minimize the risk from crop failure	1	2	3
Financial factors or incentives (including government subsidies)	1	2	3
Market factors (e.g. sale difficulties, changing demands)	1	2	3
Pests, diseases, weeds	1	2	3
Climate factors	1	2	3
Access to new information (e.g. production guides, internet)	1	2	3
Access to new technology (e.g. new machines)	1	2	3
Other (*please explain*)____	1	2	3

12. Are you planning on growing any new crops in the future that were not grown on your farm until now? (*please circle your answer*) **yes** **no**
    a. If yes, which ones? ____

b. If they require irrigation, will you install an irrigation system? (*please circle your answer*)
   yes **no**
   i. If so, for what area? ____ha

13. What would influence your decision to cultivate other or additional types of crops from the ones you have grown? (*please determine the importance of all relevant factors by ranking the following where 1=very important, 2 = medium, and 3=low*).

Market opportunities	1	2	3
Government subsidies	1	2	3
Acquired new land	1	2	3
Climate factors (precipitation, temperature, sunshine, etc.)	1	2	3
Speaking with farmers/neighbors/friends	1	2	3
Access to new agronomic information about the crop	1	2	3

<u>Other agricultural changes</u>

14. If you plan to expand or intensify your current production, will you (*please check all relevant boxes*):

☐ Purchase new farm land?

☐ Lease more land?

☐ Intensify your existing operations (i.e. intercropping)

☐ Other (*please specify)*____?

15. Are you concerned with any potential negative future impacts that might occur on your farm? (any developments at the local, regional or national levels?) (*please circle your answer*) **yes** **no**
    a. If so, which ones?

    ____

    ____

    b. When the impacts occur, are you planning on taking protective measures? (*please circle your answer*) **yes** **no**

    (or are you already taking any protective measures? (*please circle your answer*) **yes** **no**)

    i. If so, which ones?

    ____

16. If the growing season length would increase by four weeks due to changes in the future climate, do you think this would this affect your crop choice decisions, or change your agricultural practices? (*please circle your answer*) **yes** **no**
    a. If yes, in which ways?

    ____

    ____

17. In the past thirty years, have you noticed a change in the climate? (*please circle your answer*) **yes** **no**

If yes,

a. What has changed?

____
____

b. Have the changes affected your farm production? (*please circle your answer*) **yes** **no**

i. If yes, how so? -
____
____

18. Which erosion protection measures are you implementing on your agricultural land?

____

a. Have you noticed a decrease or even a prevention of soil erosion through the implementation of these measures? (*please circle your answer*) **yes** **no**

General questions

19. What are your plans for the farm over the next 30 years? (*please check the appropriate boxes*)

☐ Family member (or other) will take over and continue farming

☐ Abandoning the farm is likely

☐ Growing and expanding the farm

☐ The land will be developed on from urban areas

☐ Other (*please specify*)
____

20. How would you estimate the overall quality of the topsoil on your agricultural land?

☐ good ☐ average ☐ rather poor

21. In which township or village are the majority of your agricultural fields located?

____

22. Is your farm currently benefitting from any government subsidies that are available for your production? (*please circle your answer*) **yes** **no**

    or from environmental protection measures (measures against soil erosion for example available in the Prime-Vert)? (*please circle your answer*) **yes** **no**

23. Where do you obtain advice and recommendations for your agricultural business with regards to the optimizing your farm productivity?

    ☐ Agronomists

    ☐ Government sources

    ☐ Agricultural magazines

    ☐ Internet

    ☐ Other (*please specify*)____

Thank you for your participation!

This questionnaire is anonymous and your answers will remain strictly confidential and serve only to improve my scientific research. If you have questions or comments, you are welcome to contact me:

Bano Mehdi Geography Department McGill University 805 Sherbrooke Street Montreal, Quebec, H3A 2K6	E-mail: bano.mehdi@mail.mcgill.ca Website: http://www.geog.mcgill.ca/grad/mehdi/mehdi.html

Other comments:

____
____
____
____
____
____

CONTEXT OF CHAPTER 5 WITHIN THESIS

This chapter shifts the focus onto the hydrological modelling component of my research. The hydrological model SWAT was set up and calibrated to be applied to the Altmühl watershed. During the calibration process, a suite of parameters were identified as satisfying the objective criterion. The aim of this study was to assess how much uncertainty was added to the nutrient outputs simulated by the hydrological model if these non-unique parameters are considered along with the suite of climate simulations. Uncertainties are a key information needed by stakeholders, therefore I report several types of uncertainties for the modelling simulations; i.e. uncertainties resulting from the output simulations pertaining to nutrients, including those from using a suite of climate models, and uncertainties from the calibration parameters in the hydrological model. The parameter non-uniqueness has not, to my knowledge, been investigated for multiple water quality variables to assess the uncertainty under climate change conditions.

This chapter is intended for submission to the *Journal of Hydrology: Regional Studies*.

5. EVALUATING THE IMPACTS OF PARAMETER NON-UNIQUENESS ON FUTURE SURFACE WATER QUALITY IN AN AGRICULTURAL WATERSHED

5.1. Abstract

When examining the impacts of a future climate, the uncertainties associated with the scenarios are routinely considered (mostly by using a suite of climate simulations). However, uncertainties pertaining to subsequent hydrological simulations are rarely reported, and are particularly lacking for water quality predictions. In this study, the Altmühl watershed (in Bavaria, Germany), was examined for changes in future surface water quality (streamflow, nitrate nitrogen (NO_3^--N) and total phosphorus (TP)). The semi-automated procedure Sequential Uncertainty Fitting Algorithm (SUFI-2) was used for calibrating and for determining uncertainty bounds of the hydrological model Soil and Water Assessment Tool (SWAT). After calibration, the best parameter set was implemented in SWAT using reference and future climate data. A suite of seven bias corrected climate change simulations provided reference (1975-2000) and future (2046-2070) climate data. To determine the hydrological modelling uncertainty, once the model was calibrated, the hydrological parameter non-uniqueness uncertainty was considered for the reference period (with the observed climate data) by taking into account near-optimal parameter sets that met a multi-variable objective criteria using SUFI-2. The behavioural simulation parameter ranges provided the parameter uncertainty for a reference period. The resulting prediction uncertainty of the output variables indicated the overall SWAT model uncertainty for predicting streamflow, NO_3^--N and TP loads. Thereafter, flow and nutrient loads in a future climate were simulated by using the same range of behavioural parameters that met the objective function under reference conditions and propagating these through SWAT with each future climate simulation, thereby providing an additional layer of uncertainty. Integrating both the non-unique parameters for determining uncertainty bounds and an ensemble of climate change simulations led to a different range of potential outcomes than just using the best parameter set. This was mainly due to the stricter objective criteria used when determining the non-unique parameters. Integrating both uncertainties provides a more accurate global indication of the uncertainty on account of the hydrological model and the climate simulations. The

research quantifies the confidence in the modelling prediction approach, and assists stakeholders to make informed decisions based on available knowledge, with its limitations, of the future simulations. We outline a simple approach that can easily be replicated for similar hydrological studies.

5.2. Introduction

To make informed decisions about climate change adaptation, water resource managers, policymakers and decision makers require knowledge on how much (un)certainty can be attributed to a hydrological prediction (Kundzewicz, 2007).

When improving, or safeguarding, the quality of surface water, non structural modifications are often considered as adaptation strategies to climate change (Wilby and Wood, 2012), which may include planting buffer strips along riverbanks, or setting aside farm land. Although such alterations may not have as large financial investments as do structural adaptations, they often have considerable policy investments. For example, the European Water Framework Directive (2000/60/EC) (EC, 2000) is a comprehensive, legally binding document whose purpose is to improve water quality in Europe's aquatic environments by 2027 to achieve "good" ecological status through the implementation of river basin management plans. Since almost 50% of the EU territory is farmland, the Framework strongly emphasizes sustainable agricultural practices.

Studies that determine which agricultural management practices improve water quality under future climate conditions are therefore valuable (i.e. Woznicki et al., 2011), yet the uncertainty pertaining to modelled water quality variables when considering climate change is not well known (Beven, 2011). The routine implementation of incorporating uncertainty bounds when reporting future changes to hydrology quantity and quality simulations is not wide-spread, especially not amongst the latter. Sohrabi et al. (2003) and Shirmohammadi et al. (2006) advocated for uncertainty quantification when reporting hydrological water quality simulations; however, due to the often complex and nontrivial nature of determining uncertainties and the computing time required to run thousands of simulations, this task remains challenging.

Reporting the uncertainty of modelled outputs is essential for proper decision-making. In studies that examine the impacts of a future climate, the uncertainties are being taken into account and routinely reported in the form of using an ensemble of future simulations, or several greenhouse gas emissions scenarios, and/or downscaling techniques. In contrast, the uncertainties related to the hydrological models and their parameters that are employed in such climate change impacts studies are typically less rigorously investigated. This study focuses on reporting the uncertainty with a hydrological model considering parameter non-uniqueness for simulating future streamflow, nitrate nitrogen (NO_3^--N) and total phosphorus (TP) variables and also incorporating climate change ensembles.

5.2.1. Uncertainties related to climate change simulations and hydrological modelling

The uncertainties associated with future climate change impact simulations can be grouped into the following five types based on i) natural climate variability; ii) greenhouse gas emission scenario; iii) general circulation model (GCM) structure; iv) downscaling technique; and v) impact (hydrological) model utilized (Wilby, 2005; Poulin et al., 2011). In addition, the application of bias-correcting techniques adds to the uncertainty of the climate change signal (Muerth et al., 2013).

When examining hydrological changes due to a future climate, some of the above (ideally all) uncertainties ought to be considered. One possibility of taking into account the uncertainty of future climate predictions is by using an ensemble of climate models (Harvey, 1997; Meehl, 2007) which cover one (or several) of the above uncertainty classes to force one (or several) hydrological models in order to determine a range of possible outcomes. For example, Ludwig et al. (2009) and Velazquez et al. (2013) applied climate models with different complexities, resolutions and perturbed initial conditions (Collins et al., 2006) to force a suite of hydrological models of different complexities, to provide several hydrological scenarios of the future.

A more limited approach is to only use one or several regional climate models forced by one global climate model (e.g. Radermacher and Tomassini, 2012). Several GCMs can also be run with different greenhouse gas concentrations (Nakicenovic et al., 2000; Moss et al., 2010) to increase the range of future projections.

In short, applying an ensemble of climate model simulations to an impact model will allow for a greater variety of equally plausible future outcomes to be obtained. This way, a given possible range of likely outcomes can be examined. A decision-maker may then consider several means from which, for example, a probability distribution function can be obtained to better estimate the likelihood of occurrence of a future event.

In this study, an ensemble of future climate simulations developed from several GCMs downscaled by RCMs to the region of interest is used to drive one hydrological model. Such an ensemble represents a range of future climate uncertainty which can then be compared to the hydrological modelling uncertainty.

5.2.2. Uncertainties of hydrological modelling

A given hydrological model has three sources of uncertainty: 1) input data (sampling and measurement); 2) conceptual (structural) uncertainty in the model where processes may not replicate the reality, or processes may be omitted; and 3) parameter uncertainty reflecting scale and/or inexact hydrological knowledge and understanding (Abbaspour et al., 2007; Renard et al., 2010).

During the hydrological modelling process, expert knowledge is required to determine realistic parameter range limits. Normally, more attention is paid to parameters that control processes which are considered to be sensitive, or to be hydrologically important in the watershed. Even with expert input, the model will not simulate flawlessly, so determining the uncertainties related to the choice of input parameters and their ranges is critical to proper model performance and reporting.

A well-established body of methods has been developed to determine the output consequences of parameter choices in any hydrological model. For example, first order error analysis (Carrera and Neuman, 1986), Markov chain Monte Carlo methods (MCMC; Kuczera and Parent, 1998), Generalized Likelihood Uncertainty Estimation (GLUE; Beven and Binley, 1992), Sequential Uncertainty Fitting algorithm (SUFI; Abbaspour et al., 2004), Parameter Solution (ParaSol; van Griensven and Meixner, 2007), and several other Bayesian statistical methods exist. Each of these methods is able to examine different input parameter values (for example those that are most uncertain, or those that are most sensitive) and their impact on the model output. One, or many, objective function(s) can also be specified when calibrating to ensure a certain model performance. The parameters able to provide a time series of simulated variables that meet the objective criteria are referred to as behavioural parameters and can be considered for further use. Often, several parameter sets will give equally suitable outcomes. In this study, we consider these sets determined for a reference period, after the model is calibrated, to provide uncertainty bounds for the future. This method is based on the calibration of different periods (Gharari et al.,

2013) to determine parameter values that perform well for several sub-periods. Model transposability is especially relevant for climate change studies, where the model is applied to non-stationary conditions, and its parameters and process descriptions should be transferable (Hartmann and Bárdossy, 2005).

5.2.3. Combined uncertainties of climate change impacts on hydrology

Few statistical frameworks have been implemented to construct uncertainty bounds for hydrological simulation estimates under climate change. Steinschneider et al. (2012) characterize the hydrological flow prediction with a likelihood function combined with prior distributions of parameters using Bayes Theorem, and then use MCMC sampling to evaluate the posterior distributions of hydrological and error model parameters. The uncertainties in the hydrological model response are integrated into a range of climate change projections.

In another study, Khan and Coulibaly (2010) used a Bayesian Neural Network approach to estimate the uncertainty (the mean ensemble flow and its 95% confidence intervals) of the hydrological prediction, and then generated the uncertainty of future streamflow and reservoir inflow from the mean of an ensemble of climate members.

In this study, we use an approach that implements one of the semi-automated calibration and uncertainty analysis tools available in SWAT CUP (Soil and Water Assessment Tool Calibration and Uncertainty Program; a freely available program that contains a suite of robust uncertainty analysis techniques: MCMC, ParaSol, GLUE, SUFI-2). The SUFI-2 method (Abbaspour et al., 2004) can be used to calibrate SWAT, and can be applied to the calibrated model to determine optimum sets of parameter values that minimize the difference between observed and simulated output variables. To capture all the possible best parameter fits, SUFI-2 provides a range of solutions that fall within the 95% prediction uncertainty (95PPU) for the variable(s) in the objective function; this can be interpreted as providing uncertainty bounds. Here, to ascertain the uncertainty bounds for NO_3^--N and TP, the range of parameter sets which met a given objective function for the period of interest were subsequently implemented in the hydrological model.

Few studies have used confidence intervals or 95PPU to account for the uncertainties in hydrological flow simulations under climate change (e.g. Abbaspour et al., 2009; Faramarzi et al., 2009), and even fewer studies have reported the uncertainty of modeled agricultural non-point source pollution in a future climate. To the authors' knowledge only Ficklin et al. (2013) have examined potential future temperature and precipitation ranges (+0 to 6.4^{o}C, and -20% to +20%, respectively) to evaluate the sensitivity of these on outputs of sediment and NO_3^--N. They then determined the 95% uncertainty bounds under a range of temperature and precipitation conditions. However, they assumed the relationship between temperature and precipitation was independent.

The specific objective of this paper is to quantify the contribution of parameter non-uniqueness in a hydrological model to determine a fuller range of uncertainty when assessing climate change impacts on future surface water quality for NO_3^--N and TP. This overall uncertainty encompasses: the input data uncertainty, the parameter uncertainty, the measured variable uncertainty on calibration, the climate model uncertainty, the greenhouse gas scenario uncertainty, and the natural climate variability.

5.3. Materials and Methods

5.3.1. Description of the study watershed

The upper part of the Altmühl watershed (located northwest of Munich in Bavaria, Germany) was studied, which includes 130 km of river length from the source of the Altmühl, to the outlet gauge in Treuchtlingen (10^{o}54'48.91"E, 48 ^{o}57'11.31"N) encompassing a total basin area of 980 km^2 (Figure 5.1). The elevation ranges from 406 m at the gauge, to 660 m. The soils in the upper part of the basin are mainly loamy clay and loamy gravelly sand, with pockets of gravelly sand. Located along the floodplain, below the Altmühl Lake are mainly clayey silt soils. Near the outlet, clay loam soils are predominant, with a few areas of Karst in the most southwestern tip of the basin. The land use in the watershed is primarily agricultural and forested area. In 2008, agricultural activities (consisting mainly of cereals and permanent grassland) covered 56% of the total area, forest made up 39% of the basin, and urban areas covered 3% of the watershed.

Annually, the Altmühl watershed receives approximately 700 mm of precipitation. Evapotranspiration comprises 475 mm and runoff in the basin is 175 mm (StLfW, 1996), the remaining 50 mm is lost to deep aquifer recharge.

Although water quality in the basin has improved since the 1950s, in part due to regulated increases in minimum flows as well as new water treatment plants and storm water treatment facilities, water quality problems in the Altmühl River and in the Altmühl Lake remain elevated (Schrenk-Bergt et al., 2004). The Altmühl River is considered to be “critically contaminated” (class II) in the upper reaches before, and just after, the Altmühl Lake. The main challenges are related to non-point source pollution, possibly stemming from agricultural activities, producing elevated nitrate and phosphorus levels, of which the latter is more of a problem (StMLU, 2002).

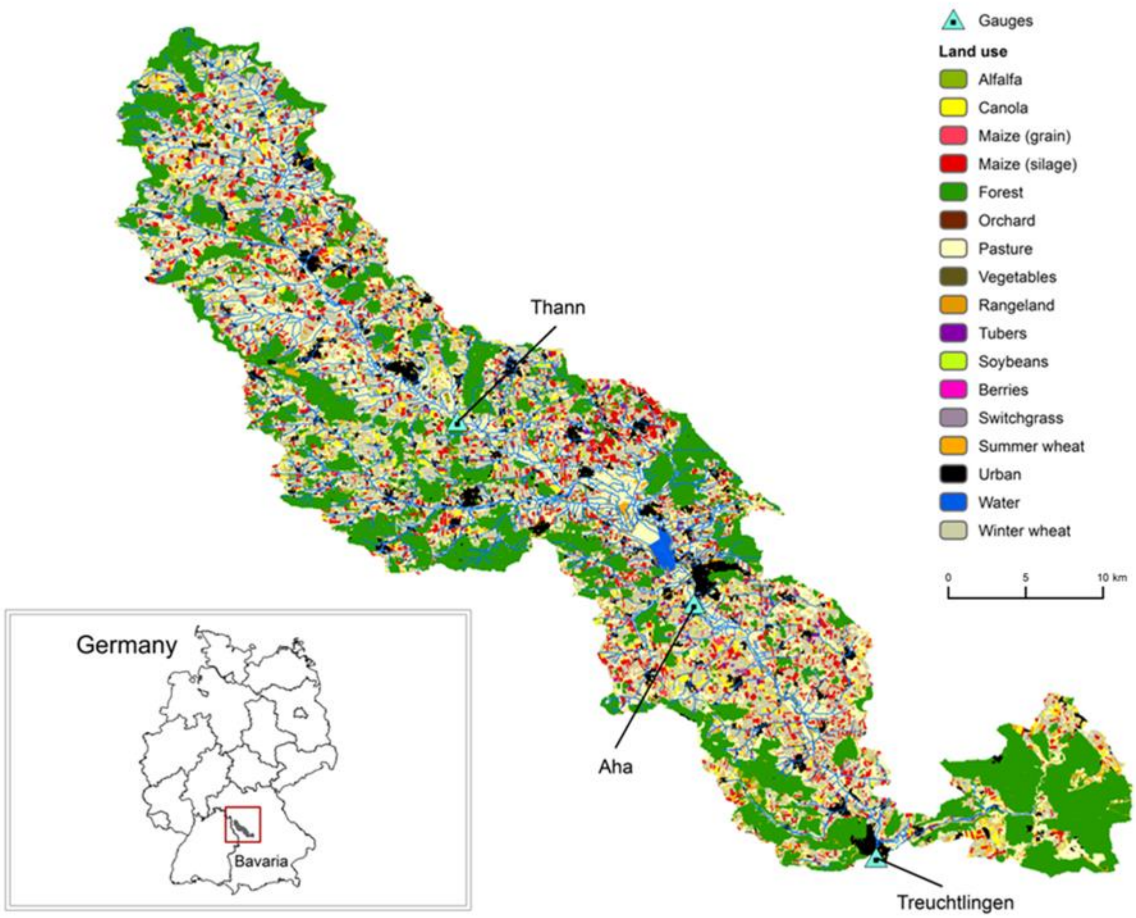


Figure 5.1. The location of the upper Altmühl watershed, depicting 2008 land use. Data sources: Agricultural land use from the Bavarian State Office for Agriculture; Forested areas: Bavarian State Office for Forest, and CORINE Land Cover 2006 (50 m), European Environmental Agency; River network: Bavarian State Office for the Environment; Urban areas: VEKTOR 500, Bavarian Surveying Administration.

5.3.2. The hydrological model SWAT

The hydrological model Soil and Water Assessment Tool (SWAT; Arnold et al., 1998) was developed by the United States Department of Agriculture principally to reflect the impacts of changes in land use and agricultural management practices on streamflow, agricultural chemical yield and sediment yield in large ungauged basins. SWAT is a semi-distributed, process based hydrological model that can be run on a daily time step (Gassman et al., 2007; Arnold et al., 2012). Here, we apply the model to examine streamflow, as well as NO_3^--N and TP loads for both a historic and a future period. Available climate data for these periods existed from 1970-2000 ("reference period"), and 2041-2070 ("2050 time horizon"), respectively. However, a 5-year warm up period was used with SWAT simulations; therefore outputs were examined and presented from 1975-2000, and 2046-2070, respectively.

ArcSWAT version 510 was run on an ArcGIS 9.3.1 (ESRI 2009, California, USA) platform. The setup for our watershed was based on a 50 m Digital Elevation Model (Table S5.1) that mapped the Altmühl watershed onto an area of 993.4 km^2 divided into 17 subbasins (based on an upstream drainage area >200 ha). The watershed is divided into subbasins and then further into hydrological response units (HRUs) which act as heterogeneous cells (grouping similar soil textures, land uses and slopes in each subbasin). A threshold (percentage) can be specified whereby soil types, land uses and/or slopes are not considered in the subbasins if their areas are below the threshold, and the minority classes are reappointed so that 100% of the area is modeled. Here, thresholds of 0%, 10% and 0% were applied to land use, soil type and slope, respectively, this gave a total of 2038 HRUs.

In SWAT, all calculations are conducted at the HRU level. The water balance is the driver behind all hydrological processes and is represented in each HRU by five storage volumes: canopy interception, snow pack, soil profile (0-2 m), shallow aquifer (2-20 m) and deep aquifer (>20 m). Simulated processes include infiltration, surface runoff, evaporation, plant water uptake, lateral flow and percolation to shallow and deep aquifers. Flow, sediment and nutrients are summed across the HRUs in a subbasin, and the flows and pollutant loads are then routed through channels, ponds, and reservoirs to the watershed outlet. The volume of surface runoff is estimated using the modified SCS curve number (CN) method (USDA, 1972), which takes into account precipitation, abstractions and soil storage; the lower the CN, the more permeable the surface. The CN is adjusted at each time step, depending on how much soil moisture is available. In this study, potential evapotranspiration was estimated using the Penman-Monteith method.

Crop growth was modeled with the EPIC sub-model (Williams et al., 1984) that bases the phenological development of the plant on accumulated plant heat units (PHU; Boswell, 1926) which are a function of the minimum and maximum air temperatures. The PHUs were adjusted for the specific crops in the watershed. SWAT is able to modify the crop radiation-use and water-use efficiency if elevated CO_2 concentrations are input. In this study, the increased atmospheric CO_2 was only indirectly accounted for through the changes given by the temperature in the future climate simulations.

The SWAT model has three major forms of nitrogen that it models in mineral soils: 1) organic N associated with humus; 2) mineral forms of N held by soil colloids; and 3) mineral forms of N in solution (Neitsch et al., 2011).

Nitrogen is a highly reactive element; therefore it has an ability to exist in a number of valences. In SWAT, there are five main pools that are associated with the nitrogen forms: two inorganic pools (NH_4^+ and NO_3^-) and three organic pools (fresh plant residue, stable humic substances and active humic substances). For details of the transformation processes see Neitsch et al. (2011).

The phosphorus (P) cycle contains three major sources of P in mineral soils: the organic pool associated with humus, a plant-available pool in the soil solution, and an insoluble inorganic component.

SWAT models six different pools of P in the soil; three pools are associated with the inorganic forms of P (solution, active and stable) and the other three with the organic P forms (fresh, stable and active). The fresh organic pool is associated with the crop residues and microbial biomass. The active and stable organic P pools are both associated with the soil humus, which is partitioned into these two pools to allow for the P to transform from humic substances to mineralized substances. The P mineralization algorithms are net mineralization algorithms which take into account immobilization.

The inorganic P in solution is the available form of P that plants can take up. This pool is in rapid equilibrium with the active pool. The primary movement of soluble P in the soil is by diffusion due to a concentration gradient in the soil. Organic and inorganic P may be transported through attachment to soil particles. A more detailed description of the processes is provided in Neitsch et al. (2011).

Data Sources

The SWAT model requires several types of data input relevant to climate, hydrological processes and plant growth (Table S5.1). The observed climate data stemmed from measured sub-daily temperature, precipitation, relative humidity, cloud cover, and hours of sunshine for the period 1961-2005, provided by the German Meteorological Service (Deutscher Wetterdienst, 2011). These were aggregated to a daily scale and interpolated to a 1 km grid using an elevation dependent inverse distance method (Mauser and Bach, 2009).

Observed daily flows at the Thann (1981-2010), Aha (1975-2010) and Treuchtlingen (1948-2006) gauges were made available through the Water Management Authority in Ansbach. Measured monthly in-stream NO_3^--N and TP concentrations (mg/L) were available at the Thann gauge (1982-2011) from the Bavarian State Office for the Environment (no sediment data was available). The baseflow filter program (Arnold and Allen, 1999) was applied to streamflow records from three gauges in the watershed to determine the groundwater recharge and establish the baseflow recession constants for SWAT.

Soil parameters stemmed mainly from the GLOWA-Danube project (Muerth, 2008). Some of the soil organic carbon values were considered to be too high for soils in this particular watershed (>10%) and were adjusted according to the guidelines from the Bavarian State Office for Agriculture (Wendland, 2011). Agricultural crop management data such as crop seeding, tillage, and fertilization application dates and amounts, as well as crop harvesting dates were mostly obtained from the Bavarian State Office for Agriculture annual crop reports, and any missing information was looked up from the Association for Technology and Structures in Agriculture (KTBL, 1995; 2009).

Field management practices are imperative to implement in SWAT for proper nutrient simulation. Specific soil conservation statistics relevant to the watershed were more difficult to obtain from official sources. The number of farmers implementing conservation practices was therefore guided by responses received from a research questionnaire distributed in the Altmühl watershed (Mehdi et al., 2012), in which 30% of farmers indicated they implement soil conservation practices. Estimates from Pöhler (2006) were in concordance; between 30-40% of farmers practiced conservation tillage in the nearby state of Saxony.

5.3.3. Climate simulation ensembles

Through the research project QBIC[3] (Ludwig et al., 2012), an ensemble of RCM data generated and supplied by the Ouranos Consortium on Regional Climatology and Adaptation to Climate Change was available for this research. Each simulation from the RCMs was driven by a coupled GCM for the time periods 1970-2000 and 2041-2070, with one of two SRES scenarios (Table 5.1). In total, seven coherent sets of climate variables of temperature, precipitation, relative humidity, solar radiation and wind speed were available to drive the SWAT hydrological model. This ensemble of climate models was chosen to represent a broad spectrum of future predictions of climate, as suggested by Harvey (1997).

Table 5.1. Climate model simulations considered in this study. All simulations are bias corrected. Regional climate models: Rossby Centre Regional Atmospheric Climate Model (RCA), Regional Atmospheric Climate Model (RACMO), Canadian Regional Climate Model (CRCM). Driving Global climate models: Bergen Climate Model (BCM), ECHAM version 5 (members 1, 2 and 3), and Hadley Centre Coupled Model (HadCM3), Canadian General Circulation Model (CGCM).

RCM	Driving GCM	SRES	Grid size (km)	Name of simulation
RCA	BCM	A1B	50	RCA-BCM-50K
RCA	ECHAM5-r3	A1B	50	RCA-ECM-50K
RCA	HadCM3Q3	A1B	50	RCA-HCM-50K
RACMO2	ECHAM5-r1	A1B	50	RAC-ECM-MB1-50K
RACMO2	ECHAM5-r2	A1B	50	RAC-ECM-MB2-50K
RACMO2	ECHAM5-r3	A1B	50	RAC-ECM-MB3-50K
CRCM 4.2.3	CGCM3	A2	45	CRC-CGC-45K

The global climate models were based on projections using A2 or A1B SRES greenhouse gas scenarios (Nakicenovic et al., 2000). In the A2 scenario, global CO_2 emissions reach 29 GtC by 2100; this is an increase of more than four times the 1990 levels (6 GtC). The A1B scenario has

CO_2 emissions peaking around 2050, at 16 GtC; a level 2.7 times that of 1990, and fall to around 13 GtC by 2100. Both of these SRES represent the higher greenhouse gas contribution scenarios.

Outputs from RCMs tend to exhibit a bias, especially for precipitation (Teutschbein and Seibert, 2012). Temperature for each climate simulation member of the RCM ensembles was bias-corrected using a monthly correction factor based on the difference between the ensemble-mean of the 30-year mean monthly minimum and maximum air temperature and the 30-year monthly means of the daily-observed minimum and maximum air temperature. As well, a bias-correction method for precipitation using the Local Intensity Scaling (Schmidli et al., 2006) at a sub-daily time step was applied to all climate simulations. Finally, the RCM outputs were scaled to a finer resolution of a 1 km grid with the scaling tool SCALMET (Marke, 2008) which preserves energy and mass at the scale of the RCM grid. For more detailed explanations of the climate simulations post-processing see Muerth et al. (2013).

5.3.4. SWAT calibration and quantification of modelling uncertainty

The Sequential Uncertainty Fitting algorithm (SUFI; Abbaspour et al., 2004) in SWAT-CUP version 4.3.2 (Abbaspour, 2011) is a semi-automated inverse modelling procedure that was used for calibrating the SWAT simulated outputs to the available time series data of streamflow, NO_3^--N and TP loads. It was also used for finding the non-unique parameter sets. SUFI-2 is a stochastic procedure drawing independent parameter sets using Latin Hypercube sampling (LHS). Briefly, the parameter sensitivities are analyzed by a global search algorithm that examines the behaviour of the given objective function by analyzing an output Jacobian matrix for parameter sensitivity. The lower bound of the parameter covariance that is derived from the Hessian matrix is then calculated by following the Gauss-Newton method. Based on the Cramer-Rao theorem, an estimate of the lower bound of the parameter covariance matrix is calculated. The estimated standard deviation and 95% confidence interval of a parameter are calculated from the diagonal elements of the matrix. Parameter sensitivities are calculated with multiple regressions using the LHS parameters generated with the objective function. New parameter ranges are determined centered on the best simulation. For a detailed description of the SUFI-2 procedures see Abbaspour et al. (2004).

The SUFI-2 method was chosen because it is applied to parameter sets, as opposed to one-at-a-time parameter analysis. Thus, a certain amount of interaction between parameters in the model during each sampling LHS round is preserved. Furthermore, the SUFI-2 method expresses several sources of uncertainty, such as those of driving variables (i.e. precipitation), those of the conceptual model, those of parameters as well as those of the measured data. Importantly in our case, compared to other methods of uncertainty analysis, SUFI-2 requires the least amount of runs to obtain satisfactory results (Yang et al., 2008). Lastly, which may be of importance to stakeholders, SUFI-2 is highly accessible for SWAT users, through SWAT CUP (Abbaspour et al., 2007; Arnold et al., 2012).

The parameters used to calibrate SWAT were chosen based on a literature review (Shen et al., 2008; Ullrich and Volk, 2009; Sexton et al., 2011), combined with a sensitivity analysis carried out for parameters relevant for the streamflow, NO_3^--N and TP variables. Also, if a parameter was not sensitive, but its values were unknown, or less certain, it was included in the calibration. Table 5.2 lists all parameters included in the calibration process, as well as their final ranges.

The SWAT model was calibrated sequentially for streamflow, NO_3^--N, and TP as per Arnold et al. (2012). SWAT was first calibrated (1964-1974) at the outlet gauge (Treuchtlingen) for surface flow at a daily time step (validated from 1975-1984). Because of data limitations, NO_3^--N and TP were calibrated (1982-1983) at the monthly time step at the Thann gauge (and validated in 1984). These simulations had a 3-year warm up period to initialize soil processes. Results were evaluated at all of the watershed gauges.

The water balance was verified after each calibration, and the SWAT simulated plant yields were checked against available data for the region (Table S5.1). To avoid over-parameterising the model (overfitting the noise), after the streamflow was calibrated, the final calibration parameter ranges for streamflow were applied during the calibration of NO_3^--N, during which only parameters specific for nitrogen were selected to be calibrated. The final ranges for streamflow as well as for NO_3^--N were then used during the calibration of TP, in which phosphorus specific parameters were only allowed to vary during the calibration (see Table 5.2).

Table 5.2. SWAT final calibrated parameter ranges used for determining non-unique parameter sets

Parameter[a]	Description	Min	Max	Units
r_CN2	SCS Curve Number for soil moisture II	-12.8%	+6.3%	-
v_GWQMN	Threshold depth of water in the shallow aquifer	1.195	2.593	mm
v_ESCO	Soil evaporation compensation factor	0.809	0.923	-
v_CH_N2	Manning's "n" value for the main channel	0.072	0.216	-
v_CH_K2	Effective hydraulic conductivity in main channel alluvium	86.07	143.4	mm/hr
v_ALPHA_BNK	Baseflow alpha factor for bank storage	0.284	0.852	days
r_SOL_AWC	Available water capacity of the soil layer	-4.9%	+26%	mm/mm
v_SURLAG	Surface runoff lag coefficient	7.952	13.69	
v_CH_K1	Effective hydraulic conductivity in tributary channel alluvium	2.57	5.12	mm/hr
v_GW_REVAP	Coefficient for groundwater transfer from the shallow aquifer to the root zone	0.151	0.200	-
v_CANMX	Maximum canopy storage	0	33.33	mm
v_TIMP	Snow pack temperature lag factor	0.632	0.877	-
v_SNOCOVMX	Minimum snow water content corresponding to 100% snow cover	0	319.8	mm
v_SNO50COV	Fraction of snow volume represented by SNOCOVMX that corresponds to 50% snow cover	0	0.590	
v_SFTMP	Snowfall temperature	-1.686	4.946	^{o}C
v_SMTMP	Snow melt base temperature	-5.336	1.556	^{o}C
v_SMFMX	Melt factor for snow on June 21	3.344	10.04	mm/^{o}C
v_SMFMN	Melt factor for snow on December 21	2.574	7.726	mm/^{o}C
v_CH_N1	Manning's "n" value for the tributary channel	0.106	0.297	-
v_*RCN*	*Concentration of N in rainfall*	*0.759*	*3.586*	*mg N/L*
v_*CMN*	*Rate factor for humus mineralization of active organic N, P*	*0.0001*	*0.0004*	-
v_*SDNCO*	*Denitrification threshold water content*	*0.547*	*1.641*	-
v_*SOL_NO3*	*Initial* NO_3^- *concentration in the soil layer*	*36.02*	*108.1*	*ppm*
v_**SOL_ORGP**	**Initial organic P concentration in the soil layer**	**66.09**	**288.7**	**ppm**
v_**SOL_SOLP**	**Initial soluble P concentration in the soil layer**	**36.57**	**109.7**	**ppm**
v_**ERORGP**	**P enrichment ratio for loading with sediment**	**0**	**2.724**	**-**
v_**PHOSKD**	**P soil partitioning coefficient**	**137.4**	**212.1**	**m^3/Mg**
v_**K_P**	**Michaelis-Menton half-saturation constant for P**	**0.010**	**0.037**	**mg P/L**
v_**RS5**	**Organic P settling rate in the reach at 20^{o}C**	**0.008**	**0.069**	**day^{-1}**
v_**BC4**	**Rate constant for mineralization of organic P to dissolved P in the reach at 20^{o}C**	**0.282**	**0.825**	**day^{-1}**
v_**RSDIN**	**Initial residue cover**	**0**	**5268**	**kg/ha**

[a]Parameters in normal font were used to calibrate the flow, parameters in *italics* were used to calibrate nitrate nitrogen, parameters in **bold** were used to calibrate for total phosphorus.

In SUFI-2, the user may specify the percentage error in the measured data, which is an independent error as it is a standard deviation added to the measured data. Here, we provided a

10% error for flow measured data and a 20% error for nitrogen and phosphorus related measurements, as per Harmel et al. (2006).

The SWAT model contains over 100 parameters that can potentially be calibrated. The choice of number of simulations (*n*) to run in SUFI-2 is determined mainly by the number of input parameters (*k*) to calibrate, and by the time it takes for a computer run. The SWAT model can be thought of as having *k* input parameters, (X_1, X_2, X_3, ..., X_k) from which an output *Y* is simulated. The model function is denoted as *f*, so that the relationship between *Y* and X_1, X_2, X_3, ..., X_k becomes

$$Y = f\,(X_1, X_2, X_3, \ldots, X_k) \qquad \text{[Equation 5.1]}$$

Since *Y* is a function of the random variables X_1, X_2, X_3, ... , X_k, *Y* is also a random variable. Summary statistics, such as the mean and variance, and the lower and upper quartiles for *Y*, can be used to measure the uncertainty of the model simulation.

SUFI-2 was run until satisfactory results were achieved. For calibrating streamflow, SUFI-2 was run with 500 simulations; for the consequent water quality parameters it was run for 1500 simulations each for NO_3^--N, and TP.

In SUFI-2, the degree to which the calibrated model accounts for the uncertainties is defined by two measures. The first is the p-factor and involves measuring the percentage of observed data that falls within the 95PPU of the simulated outputs. The second criterion is the r-factor which is a measure of the average distance between the 2.5th percentile and the 97.5th percentile that should be smaller than the standard deviation of the measured data. Ideally, the p-factor should be close to 100, and the r-factor should be less than 1 (Abbaspour et al., 2004). Depending on which objective function is chosen, these factors will vary. The Nash-Sutcliffe Efficiency (NSE; Nash and Sutcliffe, 1970) was chosen as the primary objective function for calibration. The NSE is a statistical criterion that determines the relative magnitude of the variance of the residuals compared to the variance of the observed data. It is very commonly used in hydrological studies to evaluate model performance. Using a single goodness-of-fit measure is inappropriate to evaluate model performance alone, due to the restrictions any single measure carries with it. Thus, several other objective functions were performed post-validation (PBIAS, R^2, bR^2, SSQR) so that a variety of best-fit criteria were used to show the quality of model performance. Values of the calibrated SWAT model are provided in Table 5.3a-c.

Table 5.3a. SWAT calibration/validation results for streamflow (m^3/s) at Treuchtlingen.

	Calibration 1964-1974			**Validation 1975-1984**		
	Yearly	Monthly	Daily	Yearly	Monthly	Daily
Best run						
NSE	0.96	0.77	0.57	0.81	0.75	0.68
PBIAS	1.4	13.5	13.8	0.67	13.3	3.34
R^2	0.96	0.79	0.59	0.83	0.78	0.69
bR^2	0.96	0.68	0.39	0.84	0.73	0.53
SSQR	0.12	1.35	3.31	0.09	0.72	1.32

Table 5.3b. SWAT sequential calibration and validation (monthly time step) at Thann. NO_3^--N and then TP were calibrated using final daily calibrated flow parameter ranges.

	Calibration 1982-1983		**Validation 1984**	
	NO_3^--N + flow	TP + flow (stable NO_3^--N parameters)	NO_3^--N + flow	TP + flow (stable NO_3^--N parameters)
Best run				
NSE	0.77	0.47	0.72	0.52
PBIAS	-11.8	33.5	16.6	27.7
R^2	0.77	0.71	0.71	0.70
bR^2	0.59	0.77	0.75	0.67
SSQR	280564000	3485482	100659032	1029454
NSE for flow	0.83	0.80	0.87	0.59

Table 5.3c. Best solution for non-unique parameters at Treuchtlingen (monthly time step) from 1975-2000 using SUFI-2, for an NSE≥0.3 for all variables simultaneously (equally weighted).

Evaluation	**1975-2000** (Treuchtlingen)	**1982-2000** (Thann)	**1982-2000** (Thann)
	Streamflow	NO_3^--N	TP
Best run			
NSE	0.66	0.39	0.28
PBIAS	-0.53	42.7	49.7
R^2	0.69	0.54	0.56
bR^2	0.56	0.24	0.39
SSQR	1.89	384376704	2196273
p-factor	*26*	*25*	*18*
r-factor	*0.18*	*0.20*	*0.18*

The PBIAS measures the model bias in percent, of the average tendency of the simulated data to be larger or smaller than the observed data. A value of 0 represents a bias-free simulation. Low negative values indicate the simulation greatly overestimates the observed values, and high positive values indicate a large underestimation of the model to observed values (Gupta et al., 1999).

The coefficient of determination (R^2) describes the proportion of the observed variance that can be captured by the simulations as per Legates and McCabe Jr., (1999). Whereas the bR^2 multiplies the R^2 by the coefficient of the regression line to account for both the magnitude of the signal and their dynamics (Abbaspour, 2011).

The SSQR fits the frequency distributions of the observed data series to the simulated data. After independently ranking the measured and the simulated data, the new pairs are considered. The simulated value is subtracted from the measured value, the result is squared, and values are summed (Abbaspour, 2011). SSQR values are a function of the measured units of the variable; relatively larger values indicate higher deviations.

Once the model was deemed to perform satisfactory, SUFI-2 was used to find the non-unique parameter sets using multi-variables for a reference period (1975-2000) to determine the uncertainty for this period. This uncertainty was subsequently transposed to a future period (2046-2070) by applying the same non-unique parameter sets to the future climate simulations.

SUFI-2 implements a stochastic process, therefore no one best calibration solution (*Y*) exists; in fact, there are a number of parameter-set solutions which produce a satisfactory output *Y*. In inverse modelling (making inferences about the physical system from a set of modelled output variables), it is inherent that there exists a non-uniqueness of parameter sets that will fit *Y*; a term Beven (1996) coined “equifinality”. The calibrated solution therefore, is the final parameter ranges. Any prediction with the calibrated model should be based on these ranges. To indicate the prediction uncertainties of the hydrological simulation, the calibrated parameter solution ranges can be implemented in SWAT to report their uncertainty (Abbaspour et al., 2004).

In consequence, the key output of SUFI-2 is a “best range” for each calibrated parameter (Abbaspour et al., 1997), which corresponds to the best estimated parameter set with the ranges for each of the tested parameters that have met the objective function.

SUFI-2 also provides a “best estimate”; this is a parameter set (one value for each parameter) found during calibration that most accurately fits the defined objective function. Most hydrological studies use this one parameter set to validate and evaluate the model, and apply it to all subsequent model operations. The ranges of other possible parameter solutions are rarely considered to determine model output variables, even though they are just as valid. In this study, the typical "best estimate" method is examined along with the "best range" of parameter sets that met a multi-variable objective criterion for a reference period of interest.

Once the SWAT model was satisfactorily calibrated and validated, it was run with i) the calibrated best parameter set, and ii) the final calibrated parameter ranges applied to the reference period to find behavioral parameter sets, and these were subsequently applied to the future climate simulation data.

5.3.5. Quantifying the uncertainties related to climate change simulations

Climate uncertainties were captured by using a suite of climate models. The natural climate variability was estimated by applying the reference climate simulations through SWAT. The natural variability is irreducible even if perfect models were available. Each reference climate simulation is used to compare the future climate simulation to.

The first part of the methodology consisted of running the SWAT model with the best calibrated parameter set, and forcing it with each of the reference and the future climate simulations. From here on, this approach will be referred to as the "*best run*" approach, where one parameter set is run through SWAT to produce one time series output. A minimum objective function representing a satisfactory performance of NSE >0.5 was used for streamflow and for nutrients. This type of method is used in the overwhelming majority of climate change research.

The second approach set out to determine the ranges of potential streamflow, NO_3^--N and TP loads that met an objective function. In this case, the final calibrated parameter ranges for each of the three variables (streamflow, NO_3^--N and TP; listed in Table 5.2) were run simultaneously in SUFI-2 to find sets of behavioural parameters that met a common objective function for the reference period of interest (1975-2000). Since multiple variables are used where an individual NSE criterion is applied for each variable, the common objective function can be expressed as

$$g = \sum w_i NSE_i \quad \text{[Equation 5.2]}$$

where *g* is the objective function, *w* is the weight of the parameter and *i* is the variable.

Equal weights were used in this study for the variables; however decision makers can change the weights depending on their priorities. The objective criterion used was NSE ≥0.3 for each variable to accommodate the challenge of simultaneous calibration with nutrient variables. When SUFI-2 was run with all three variables simultaneously (streamflow, NO_3^--N and TP) 1000 simulations were performed. The resulting behavioral SWAT model parameter ranges were then implemented in SWAT with each of the seven climate simulations, respectively. This produced 28 simulations of streamflow, NO_3^--N and TP (7 climate simulations x 4 sets of non-unique parameters; Table S5.2). Their performance was measured by the p-factor and the r-factor. This approach will henceforth be referred to as the "*parameter non-uniqueness"* approach, where a range of non-unique parameters providing satisfactory model results for the reference period are implemented in SWAT for a future time period.

5.4. Results and discussion

5.4.1. Future climate and expected changes to temperature and precipitation

The future climate (2041-2070) shows that compared to the respective reference climate (1970-2000), mean monthly precipitation changes in the range of -20% to +74%, and increases in mean monthly temperatures of 0.75°C to 4.0°C are possible.

All climate simulations were bias-corrected. Since this correction intends to maintain the natural variability, and not force the model to match the observations, some differences may still occur (Figures 5.2a and b), especially with precipitation (Teutschbein and Seibert, 2012). Due to the bias-correction applied, a direct comparison could be made between the SWAT simulations using observed climate and those using future climate simulations. However, in order to remove the errors brought about by the SWAT model, as well as by the climate models, comparisons were mostly made from SWAT outcomes using climate simulations from the reference period and SWAT outcomes using the climate simulations for the future period.

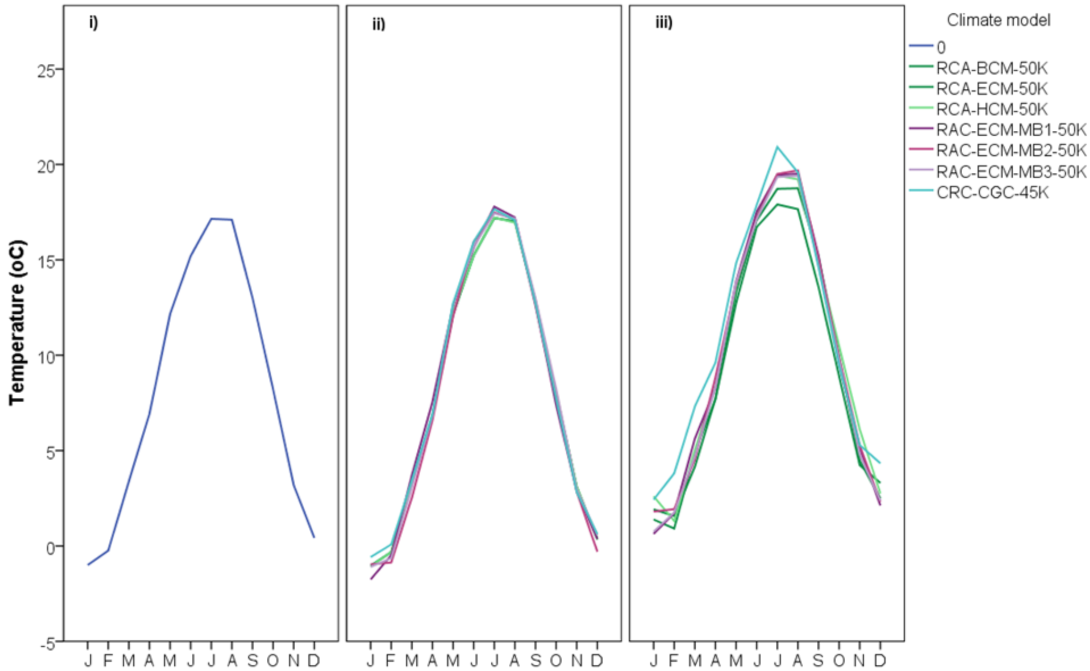


Figure 5.2a. i) Observed mean monthly temperature (1970-2000) compared to the **ii)** climate simulated reference temperature data (1970-2000) and **iii)** future temperature data (2041-2070).

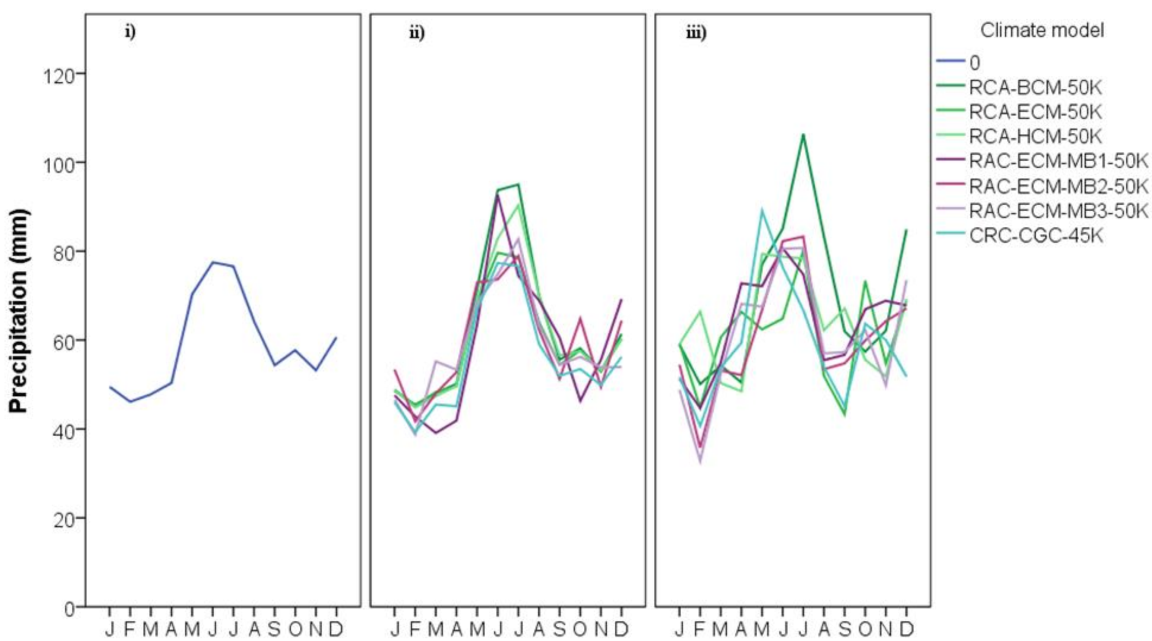
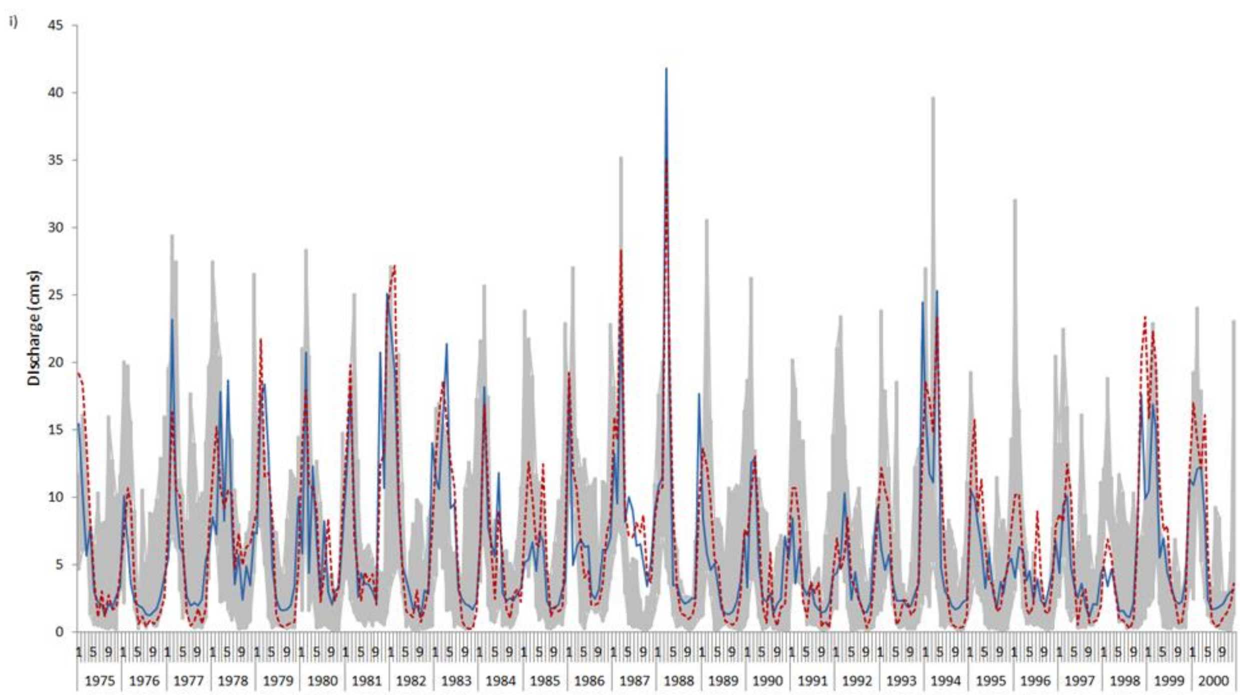


Figure 5.2b. i) Observed mean monthly precipitation (1970-2000) compared to **ii)** climate simulated reference precipitation data (1970-2000) and **iii)** future precipitation data (2041-2070).

5.4.2. *Evaluating SWAT performance*

The simulated outputs, resulting from the best set of calibrated parameters, demonstrate that SWAT is able to reproduce the timing of daily dry spells and peak flows well (Figures 5.3i and 5.1S). The magnitude of flows was also modelled satisfactory, although SWAT tended to underestimate the flow (PBIAS= 13.8%; Table 5.3a), in particular those of the low flow events. This may be in part due using the NSE as an objective function in the calibration process, since it is sensitive to high values due to the squared differences (Moriasi et al., 2007). Figures 5.4, 5.5 and Table 5.3b show that NO_3^--N and TP simulations well represent the timing of the events, although modelled TP also had overall lower values (PBIAS 33.5%), whereas NO_3^--N was overestimated by SWAT (PBIAS -11.8%). For a SWAT performance to be judged as satisfactory, the NSE values should exceed 0.5 for streamflow and nutrients at the monthly time-step (Moriasi et al., 2007). Based on this and the other performance criteria (Table 5.3a-b), the sequential calibration of the three variables in SWAT (i.e. incorporating the best parameter set into the next calibration) led to a satisfactory performing model.



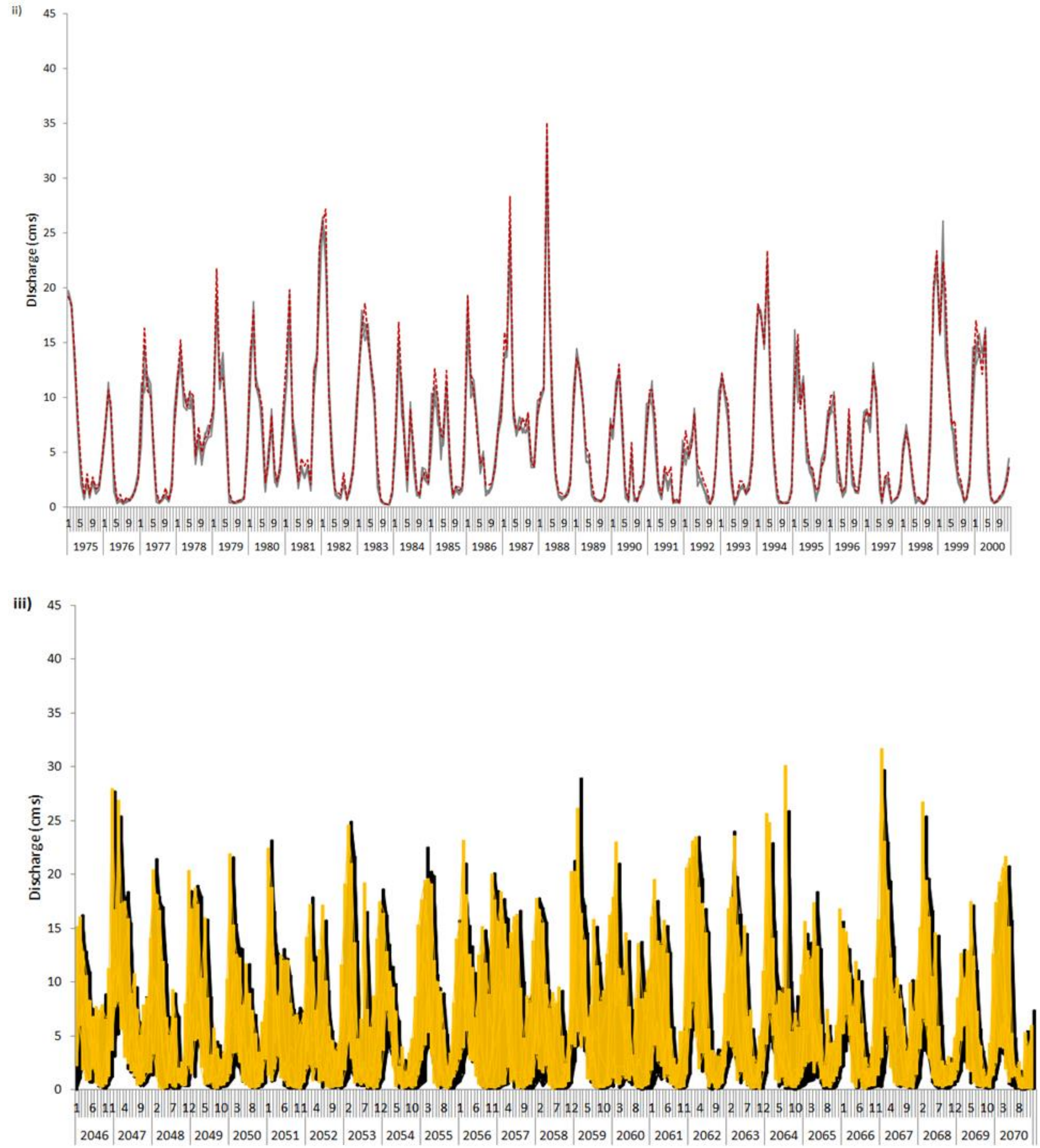


Figure 5.3 i) to iii). Streamflow at Treuchtlingen for i) the reference period with observed data (blue line) and the SWAT simulated with observed climate and the best parameter set (red line) and with the suite of climate simulations and the best parameter sets (grey lines); ii) the reference period using SWAT simulated with observed climate and the best parameter set simulated (red line), and using observed climate and the non-unique behavioural parameter sets (grey lines; p-factor 26%, r-factor 0.18); iii) the future period with SWAT simulated using the suite of climate simulations and the best parameter sets (black lines) and using the non-unique parameters sets (orange lines).

5.4.3. Historic and future streamflow, NO_3^--N and TP using the "best run" approach

The streamflow, NO_3^--N and TP loads simulated with the best parameter set in SWAT using the observed climate data 1975-2000 are depicted in Figures 5.3i), 5.4 and 5.5, respectively. The simulations were compared with observed data to provide statistics of best fit. The simulations based on the best run provide no information about their degree of certainty since they only involve a comparison between two signals (one modeled signal with one observed data set). Thus, the only source of uncertainty can be gleaned from the model error between observed and simulated data (Table 5.3a).

The best parameter set (best run) was also run with each of the seven reference climate simulations in SWAT. The grey shaded area in Figure 5.3i) depicts the irreducible climate variability of modelled streamflow. Discrepancies in the simulated results are due to climate model disparities caused by the differences in the physical processes represented in the models, and/or in the different initial conditions with different members from the same model. These discrepancies represent the natural climate variability (Braun et al., 2012).

The best parameter set in SWAT was finally run with each of the seven future climate simulations. Figure 5.3iii) depicts the future scenarios of streamflow output, with the black area showing the irreducible climate uncertainty in addition to any climate change signal.

Examining the data by month (Figures 5.6, 5.7, 5.8 and 5.2S), most of the future streamflow decreases took place from August to February. When the suite of mean future monthly streamflows was compared statistically (independent t-tests, $p<0.05$) to SWAT outputs using reference climate simulations (Table S5.3), the mean streamflow in September was significantly lower in the future, whereas in spring (April, May and June) the mean streamflow was simulated to be significantly higher than the historic values, due to the greater amounts of precipitation simulated. A comparison between the extreme flows (10^{th} and the 90^{th} percentiles) of the reference and future simulations for each season (DJF, MAM, JJA, SON) provided an indication of climate change. The 10^{th} and 90^{th} percentiles of the future streamflow (Table S5.4 and Figure S5.3), were lower than the reference simulations, indicating a shift in the hydrograph towards a longer low flow period, and attenuated spring melt and earlier summer dry spells. The best run approach simulated significantly higher future 90^{th} percentiles in March to May and June to August, indicating a tendency towards more heavy rainfall events in spring through summer.

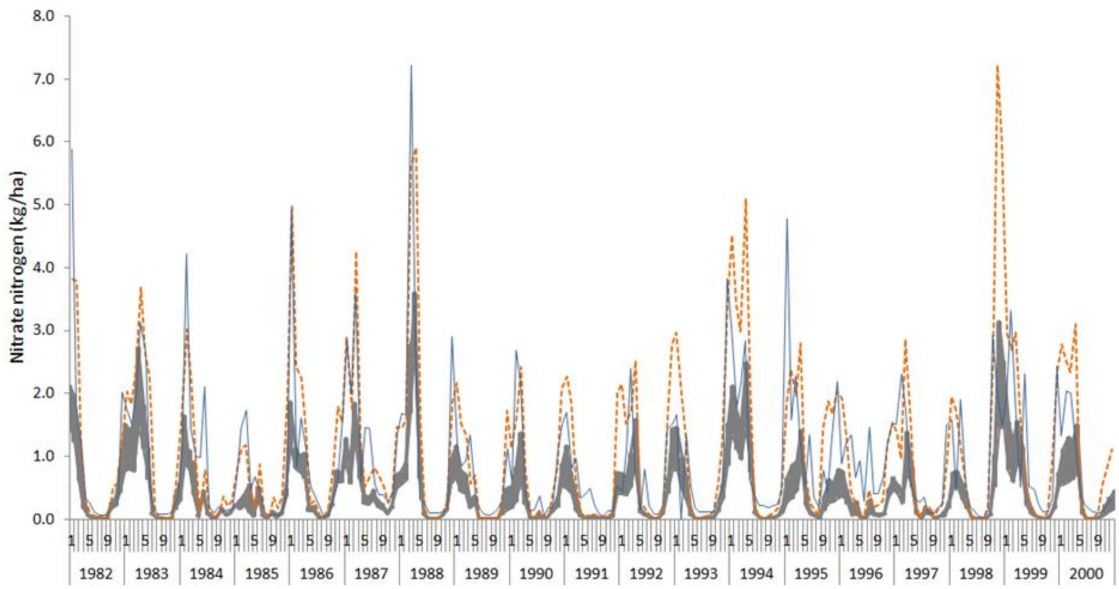


Figure 5.4. Nitrate nitrogen at Thann for the period of observed data (blue line) and from SWAT simulated with the observed climate and the best parameter set simulated (orange line) and with the non-unique behavioural parameters found (from 1975-2000 multi-variable NSE≥0.3) p-factor 25%, r-factor 0.20 (grey lines).

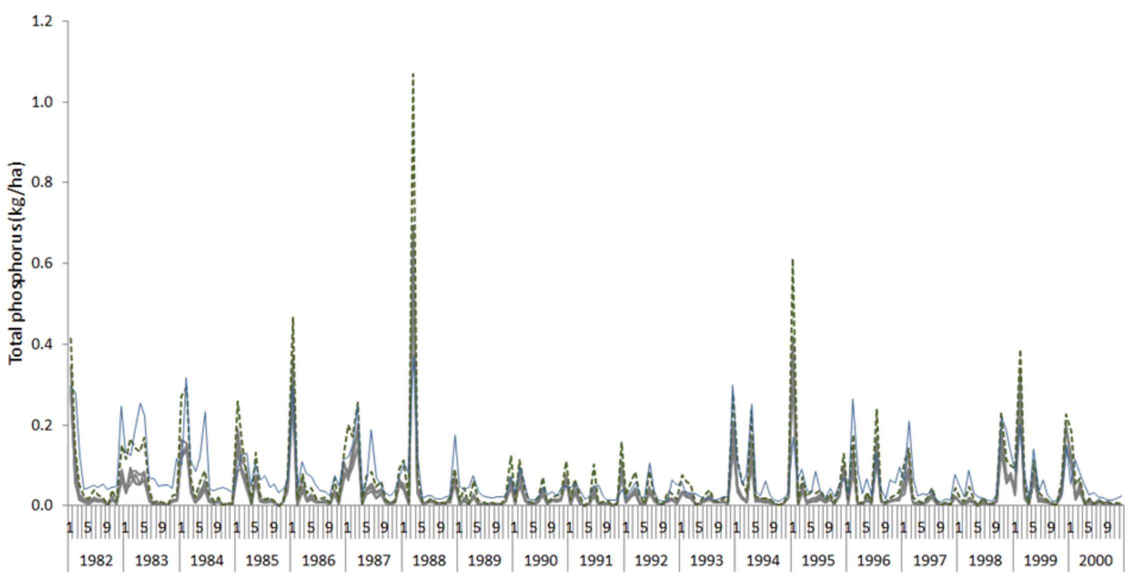


Figure 5.5. Total phosphorus at Thann for the period of observed data (blue line) and from SWAT simulated with the observed climate and the best parameter set (green line) and with the non-unique behavioural parameters found (from 1975-2000 multi-variable NSE≥0.3) p-factor 18%, r-factor 0.18 (grey lines).

The mean monthly future NO_3^--N values increased significantly in January, May to July and October to November (Table S5.5). The NO_3^- molecule is highly soluble in water, whereas mineral phosphorus binds to soil particles. Thus, NO_3^--N loads are not only driven by surface flow, but also by infiltration and throughflow. The NO_3^--N loads are more sensitive to precipitation and infiltration changes, as can be seen by the higher variability, and they do not follow the same general pattern as the changes in sediment or TP loads which tend to increase the most with greater streamflow. The NO_3^--N loads 90th percentiles were simulated to increase significantly in all seasons, while the 10th percentiles were no different than for the reference climate simulations (Table S5.6 and Figure S5.4); indicating higher NO_3^--N loadings that occur more often.

The mean TP loads in winter months (December to March) were simulated to be significantly lower, as well as in August and September. However, in April and May they were higher (Table S5.7). TP in the reach is driven by flow, and therefore the changes with seasonality followed the streamflow pattern more closely than NO_3^--N. The 10th and 90th percentiles were simulated to be significantly lower in December to February (Table S5.8 and Figure S5.5).

Using the best run approach, the differences between the median of the future simulations and the median of the reference simulation indicate changes ranging from -0.5 to 0.9 m^3/s for streamflow; changes of 0.01 to 0.27 kg/ha in median NO_3^--N loads; and changes of -0.031 to 0 kg/ha in median TP loads. Considering the basin size of 99335 ha, the mean median NO_3^--N loads increased by 1.0 to 26.8 Mg; and mean median TP loads decreased by 3.1 to 0 Mg, depending on the season, at the outlet of the basin.

5.4.4. Future streamflow, nitrate nitrogen and total phosphorus with "parameter non-uniqueness"

In this approach, the final calibrated parameter ranges corresponding to all variables were first implemented in SWAT for the period of interest (1975-2000) to find behavioural parameter sets that simultaneously met the common objective function (NSE $\geq$0.3 for streamflow, NO_3^--N and TP) based on measured data. SUFI-2 was used for this task (i.e. similar to performing a calibration using multi-variables). Then, the parameter sets which simulated variables that satisfied the objective criteria were implemented in SWAT using the future climate data. The complete range of behavioural parameter sets was used to capture the future uncertainty.

Using the parameter non-uniqueness approach, all the uncertainties (input, parameter and model) were combined and attributed to the parameter ranges and ultimately depicted by the uncertainty bounds. Consequently, a range of future streamflow, as well as NO_3^--N and TP loads was examined using dissimilar parameter sets which produce similarly acceptable outcomes. In this case, 0.4% of the runs met the objective function (Table S5.2).

The NSE in this approach was purposefully lower than that used for the sequential calibration so that the objective criterion could be met. A stricter common objective criterion (higher NSE) reduced the uncertainty width; however no behavioural parameter sets were found when the NSE was increased to ≥0.4 because TP was the limiting variable.

Also, we tried giving more weight to flow (NSE≥0.6), while keeping nutrients at NSE≥0.3, this allowed 9 times more behavioural parameters to be found, but the final ranges were twice as wide (r-factors of 0.48-0.52) than when keeping equal weights for the objective function (results not shown).

For the reference period, the simulation runs using the parameter non-uniqueness approach yielded uncertainty of the simulated variables for streamflow (Figure 5.3ii) where the SUFI-2 p-factor indicated that 26% of the simulations bracketed the measured flow data. For NO_3^--N, 18% of the simulated outputs bracketed the observed data (Figure 5.4), and 25% of the TP simulations bracketed their observed values (Figure 5.5). The more measured data is captured, the better the simulation. All of the r-factors lay between 0.18 and 0.20, which indicates a low deviation from the measured data.

Using parameter non-uniqueness, the streamflow simulations for the period 2046-2070 were comparable to the best run approach, except for the significantly lower 10th and 90th percentiles from June to August (Table S5.4). However, the changes in nutrients were significantly different than for the best run approach (Tables S5.6 and S5.8). The 10th and 90th percentiles for NO_3^--N were significantly lower in all of the seasons, compared with the best run approach. The simulations for TP were also significantly lower in almost all seasons. This finding suggests that for this study, the variability in the parameter non-uniqueness approach is smaller than for the best run approach.

For parameter non-uniqueness, seasonal changes in the median streamflow provided lower values than the best run, with simulated changes of -0.8 to 0.2 m^3/s. The simulated nutrients showed greater changes of -1.19 to -0.08 kg/ha in median NO_3^--N loads; and of -0.057 to -0.003 kg/ha in median TP loads. Depending on the season, this amounts to a reduction of 118.2 to 8.0 Mg in the mean median NO_3^--N loads and a reduction of 5.7 to 0.3 Mg in the mean median TP loads, at the basin outlet.

The reason for the discrepancies between the two approaches is mainly attributed to the time period used to find the non-unique parameters, the sequential calibration and the type of objective function. The parameter non-uniqueness approach using the multi-variable calibration (NSE $\geq$0.3) from 1975-2000 found behavioural parameter solution sets which better matched the TP peaks, but this entailed lowering the overall TP predictions, and thereby also greatly affecting NO_3^--N simulations. By comparison, if the parameter ranges from the sequential calibration of the three variables from 1982-1983 (one at a time calibration with each NSE $\geq$0.5 at Thann) are used to find non-unique parameters, and these are then run through SWAT from 1982-2000, a PBIAS of 64.4 for NO_3^--N, and -0.7 for TP is obtained; with a corresponding NSE of 0.62 and -0.13, respectively (results not shown), indicating that TP is being better modelled. Calibrating for individual periods and using a stricter objective criterion for the reference period may come at a cost of potentially reducing performance, but the model performs more reliably in the evaluation period.

Both the parameter non-uniqueness approach and the best run approach simulated significant changes to occur in a future climate, however these changes vary from each other because the best parameter set in the best run approach is not encompassed in the parameter non-uniqueness sets. Yet, the future simulated flows vary relatively little between both approaches. The changes in the median values for TP of the best run approach are also comparable to the non-unique approach, despite the larger range of changes simulated (Figure 5.7). However, for NO_3^--N the expected changes using the best parameter approach are almost three times larger in magnitude and have the reverse signal of change (Figure 5.8).

Using non-unique parameters rather than a fixed best parameter set provides improved information in terms of the uncertainty bounds and the p- and r-factors. The parameter non-uniqueness approach delivers prediction uncertainty bounds for each variable.

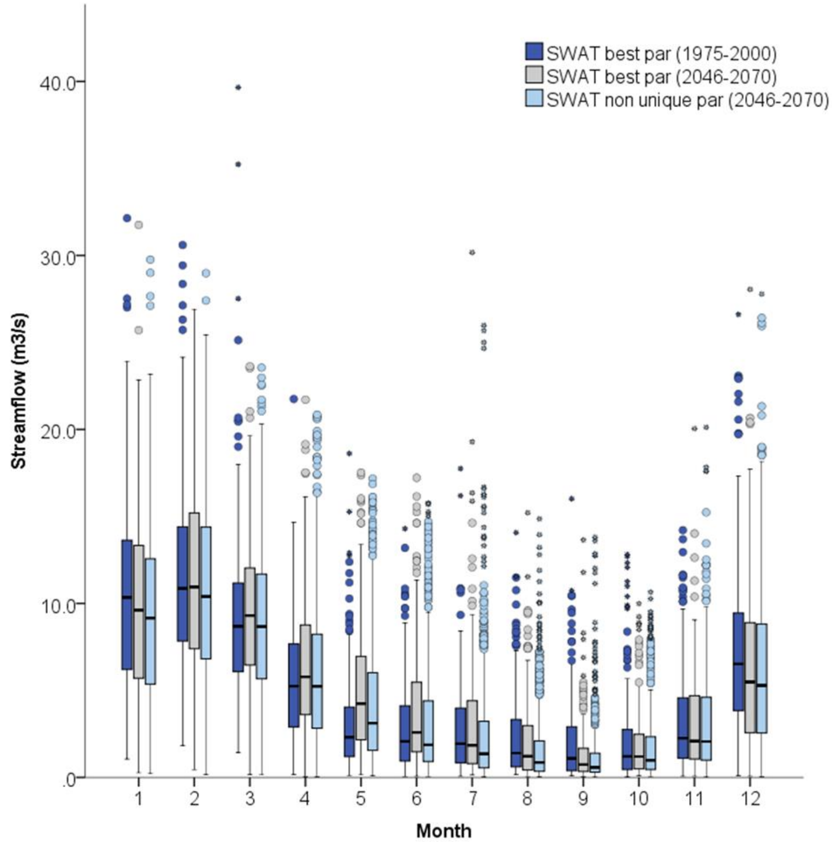


Figure 5.6. SWAT simulated monthly flow at Treuchtlingen, using the best run approach with reference climate simulations (1975-2000) and future climate simulations (2046-2070), and the non-unique approach with future climate simulations (2046-2070).

Boxplots show the central mark as being the median, the upper and lower edges of the box are the 75th and 25th percentile, respectively, and the whiskers extend to the values that lie inside one and half box lengths from the quartiles. The circles represent values which lie one and a half box lengths away from the quartile (considered outliers), and the asterisks are values that lie more than three box lengths away from the quartile (considered extremes).

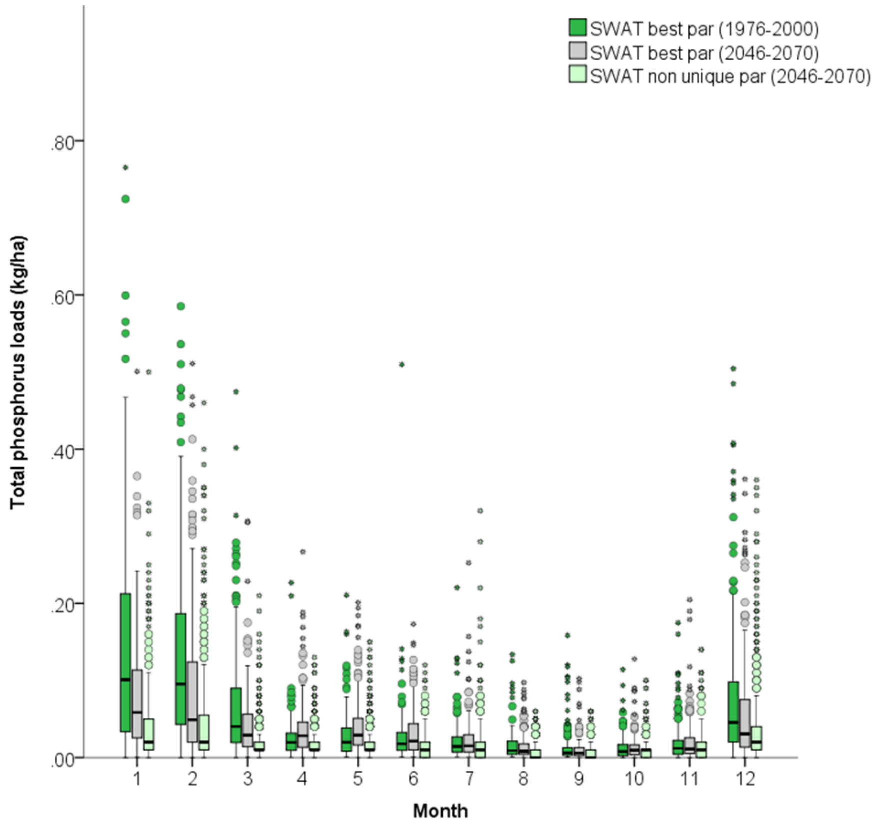


Figure 5.7. SWAT simulated monthly total phosphorus loads (kg/ha) at Treuchtlingen, using the best run approach with reference climate simulations (1975-2000) and future climate simulations (2046-2070), and the non-unique approach with future climate simulations (2046-2070).

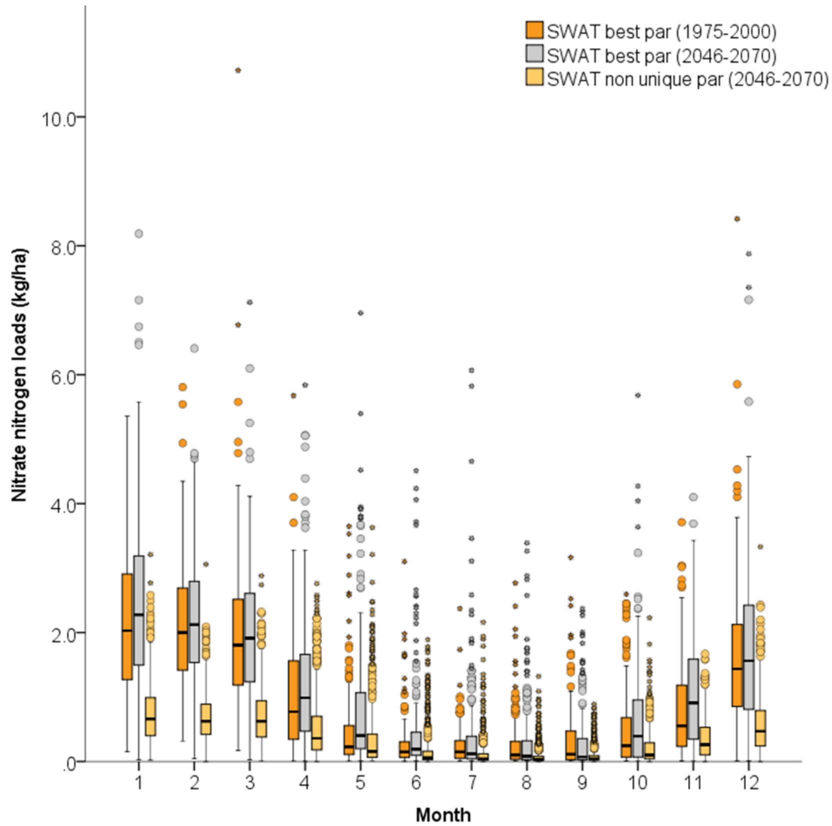


Figure 5.8. SWAT simulated monthly nitrate-nitrogen loads (kg/ha) at Treuchtlingen, using the best run approach with reference climate simulations (1975-2000) and future climate simulations (2046-2070), and the non-unique approach with future climate simulations (2046-2070).

5.4.5. Multi-variable calibration

A discussion on the calibration methodology of SWAT is warranted, as different approaches to calibration produce different results. Several different procedures were tried for calibration.

i. The variables can be calibrated sequentially, i.e. first streamflow, then NO_3^--N then TP; always using the best parameters from the proceeding variable to find the best fit of the new variable.
ii. After the flow is calibrated, the best flow ranges can be included with the NO_3^--N parameter ranges, to calibrate for NO_3^--N; and then, the same best flow ranges can be included with the TP parameters when calibrating for TP.
iii. All three variable ranges can be calibrated together.

Calibrating on any one variable alone will yield a higher NSE. In our sequential calibration, we obtained an NSE of 0.47 and 0.52 for TP during the calibration and validation, respectively (Table 5.3b), yet the highest NSE achieved for TP during the multiple variable simulation was 0.28 (Table 5.3c). When NO_3^--N loads were calibrated with flow alone, an NSE of 0.78 was achieved, but this dropped to 0.39 when TP parameters were added. Multi-variable objectives affected the solution by creating more limitations and constraints to be met. Ficklin et al. (2013) simultaneously calibrated SWAT using streamflow, sediment, nitrate and chlorpyrifos (pesticide) variables at multiple gauging stations. The NSE's obtained during their multi-variable calibration varied from 0.11 (sediments) to 0.94 (streamflow). Abbaspour et al. (2007) also calibrated SWAT simultaneously for discharge, sediments, nitrate and total phosphorus at the watershed outlet, using an objective function that maximized the NSE for each variable. During calibration, their p-factor and d-factor (which is the r-factor multiplied by the standard deviation of the variable) were highest for discharge (91% and 1.0, respectively); for sediment they were 80% and 1.5, respectively; TP was 78% and 1.35, respectively; and nitrate 82% and 1.0, respectively.

This phenomenon is most likely due to a combination of factors, such as the correlation between streamflow and individual nutrients, such as TP, and the lack of correlation between the nutrients themselves. For example, the CN directly influences runoff and therefore all other aspects of the water balance. Soil erosion is greatly affected by the CN which directly impacts the amount of TP transported, but not so much NO_3^--N transportation. For all of the parameter sets in the non-unique approach, the CN values decreased anywhere from 6 to 11%. In the best run approach, the CN was increased by 5%. Calibrating for multi-variables leads to a tug-of-war between variables vying for their "preferred" streamflow parameters. The variation of any nutrient load is affected by the uncertainty of the parameters associated with the streamflow process (Shen et al., 2008).

Also, the number of runs conducted in SUFI-2 will influence the number of behavioural parameters obtained with either the parameter non-uniqueness method, or the best run approach. In this study, we ran simulations 500, 1000 or 1500 times, depending on the outcomes obtained and how satisfied we were with the results. The number of runs to undertake depends on several factors, but in our case was dominated by the time required to run an iteration, which was mainly a function of the number of input variables. Sohrabi et al. (2003) found that the choice of sample size (n) using the LHS technique gave good results when $n > (4/3)k$, where k is the number of input variables.

Finally, the choice of objective function is critical. For example, objective functions based on the NSE favour good agreements with peak flows and peak nutrient loads (Moriasi et al., 2007). Applying multi-objective functions may provide solutions which attenuate the partiality of any particular objective function statistic. The greater the number of multi-variables, multi-objectives and multi-gauges the more constraints are placed on the number of solutions that can be found using the parameter non-uniqueness method.

No uniform coherent guidelines exist for calibrating hydrological water quality models (Moriasi et al., 2012). A recent paper by Arnold et al. (2012) provides a solid overview of best practices for model calibration and validation, but does not address multi-variable calibration techniques.

5.5. Conclusion

In conclusion, a readily available uncertainty tool with a simple to implement methodology was outlined that provided the overall uncertainty of hydrological model state variables integrated with future climate scenarios. For any given hydrological model, many satisfactory solutions can exist within a realistic parameter sampling space, so that several parameter sets may be associated with a given objective function threshold. The contribution of this parameter non-uniqueness to the uncertainty of modelled outputs under future climate conditions has rarely been examined.

Applying the parameter non-unique approach provides a scope of the integrated uncertainty when using the SWAT model for predicting future water quality. Here, using seven climate simulations, the future variability using the parameter non-uniqueness approach was smaller than that provided by the best parameter approach.

However, parameter non-uniqueness uncertainty as determined by SUFI-2 depends on several factors, such as the objective criteria threshold chosen; the number of objective criteria; the number of variables being calibrated for at any one time; and the number of gauges used during the calibration process.

Although not studied in this paper, areas of further research on how uncertainty bounds are affected include analyses testing the choice of the calibration method (i.e. SUFI-2, GLUE, Parasol, etc.); the calibration time period chosen; the data available for calibration (sampling frequency and truthfulness); the number of simulation runs; the number of parameters; and the range of parameters used in the calibration.

Beyond the calibration process itself, predicting uncertainty bounds of water quality variables also depends on the hydrological model conceptual structure; the hydrological model input data uncertainties; and the period of simulation.

As well, when looking at future scenarios, other changes occurring in the watershed, such as land use change, may also add to the uncertainty of the modelled outcome.

Changes to any one of the factors listed above will provide a different outcome in the uncertainty. As there are a number of subjective judgements that must be taken, these should be clearly stated in research projects and communicated in ensuing publications so that results can be replicated; the findings can be better interpreted; and researchers or decision-makers can alter any of the judgements in order to study and compare the ensuing changes in uncertainty ranges.

The parameter non-uniqueness approach as introduced in this study allows a probability to be associated with the modelled outcome (e.g. though a cumulative frequency graph). This method can be applied to a wide range of adaptation studies using SWAT, or other hydrological models. Reporting the range of uncertainties associated with future streamflow and water quality outcomes portrays the true ambiguities of the scientific tools available, and also provides added knowledge as compared to providing only the mean values. Box plots, cumulative frequency distributions and probability distributions of possible simulated outcomes give a sense of the potential ranges of outcomes. Dealing with the uncertainty in decision-making is another topic requiring further research.

5.S. Supplemental Material

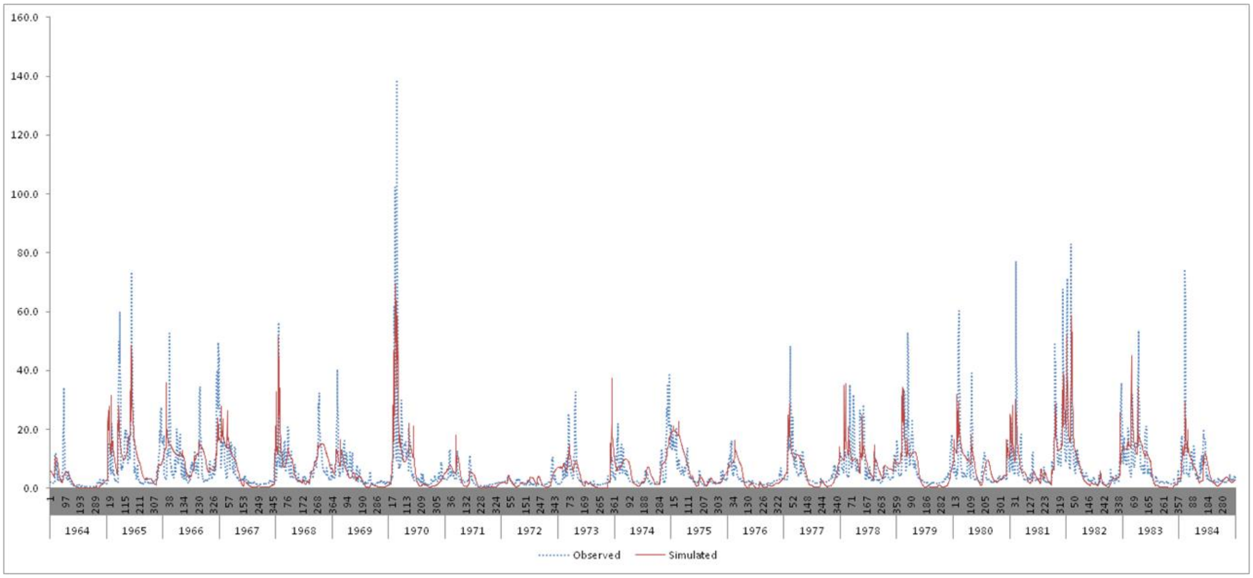


Figure S5.1. Observed and simulated daily streamflow, at Treutchlingen, for the calibration and validation periods.

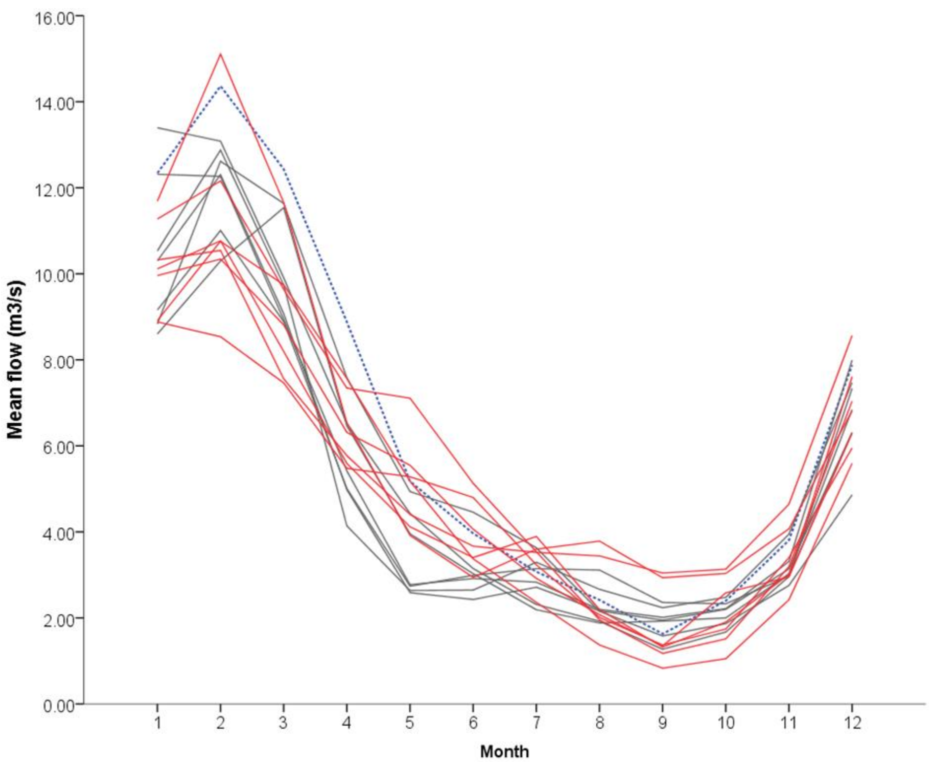
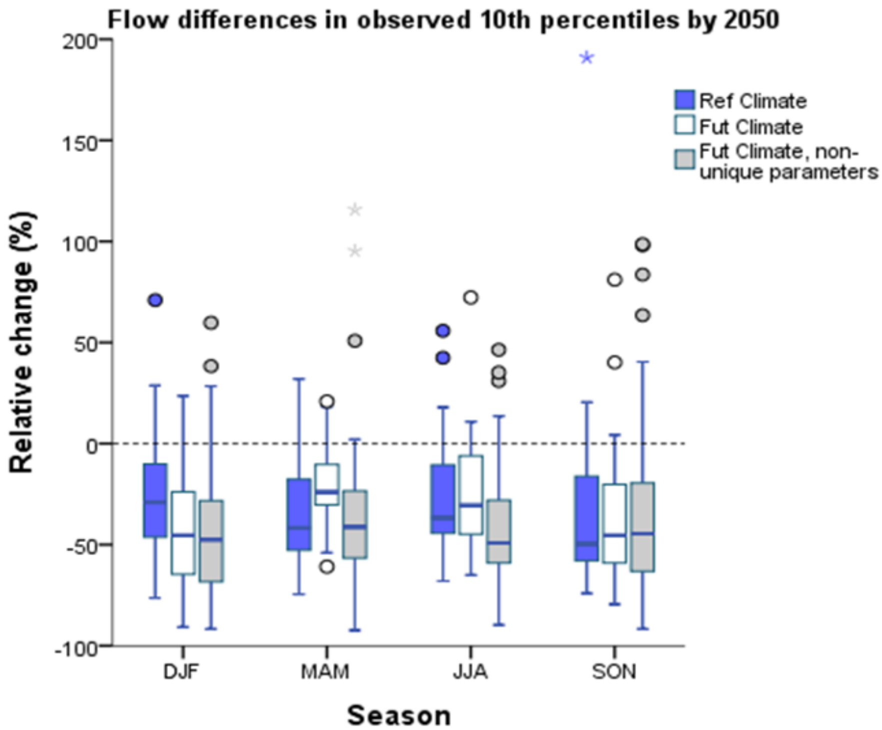


Figure S5.2. Simulated mean monthly streamflow at Treuchtlingen. Blue dotted line is simulated with observed data (1975-2000); grey lines are the simulated with climate model reference data (1975-2000); red lines are the simulated with climate model future data (2046-2070).

a)



b)

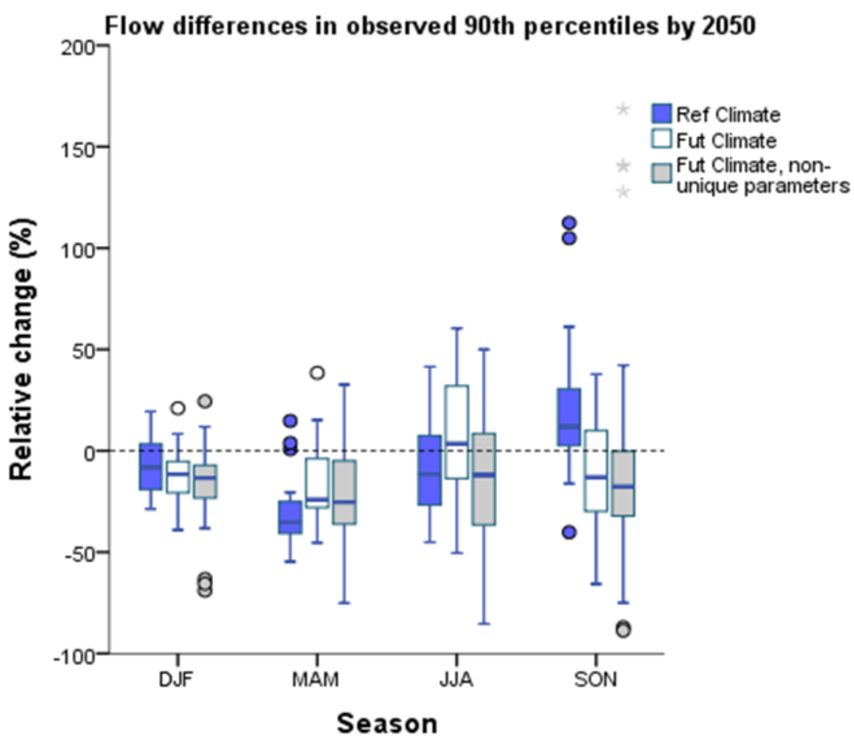
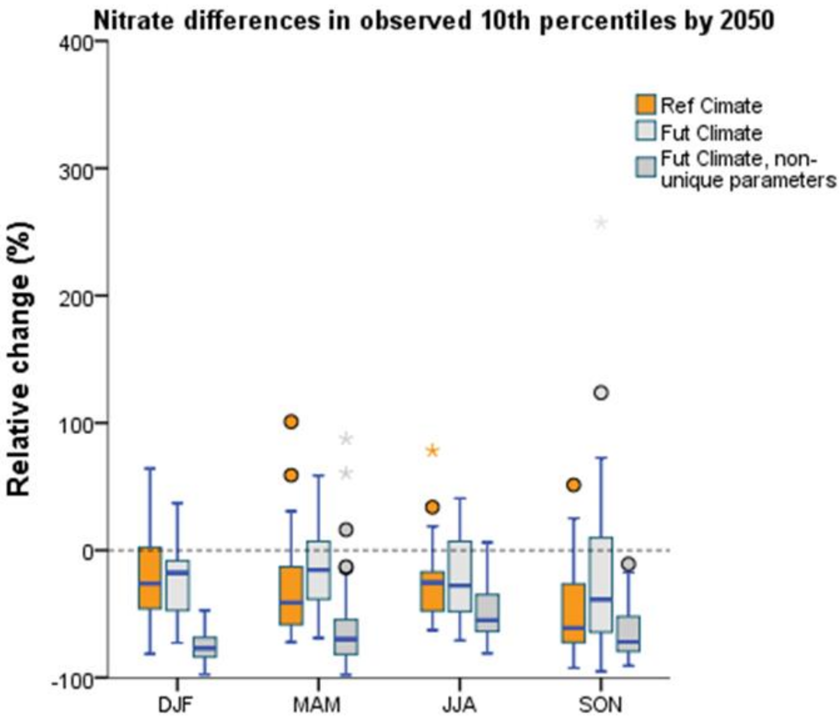


Figure S5.3a-b. Relative change in a) 10th and b) 90th percentiles for streamflow, comparing SWAT simulated with observed data (zero line) and SWAT simulated with climate model reference and future data, using the best run approach and the non-unique parameter approach.

a)



b)

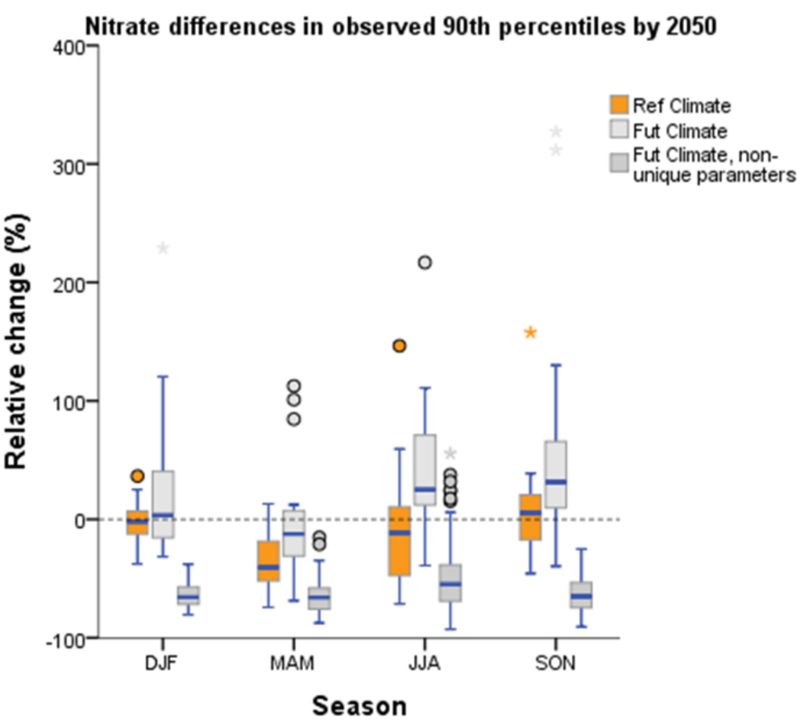
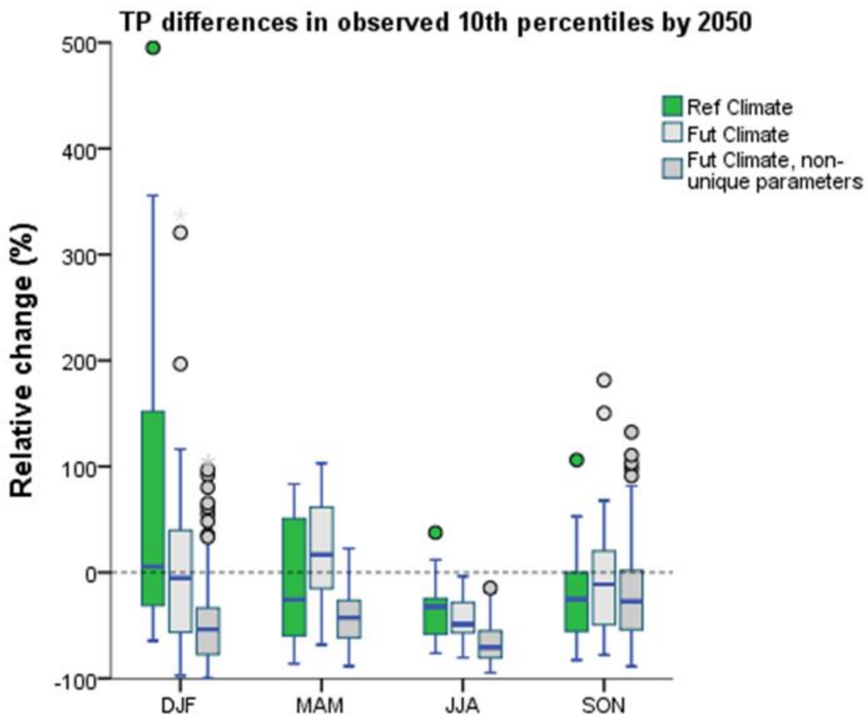


Figure S5.4a-b. Relative change in a) 10th and b) 90th percentiles for nitrate nitrogen, comparing SWAT simulated with observed data (zero line) and SWAT simulated with climate model reference and future data, using the best run approach and the non-unique parameter approach.

a)



b)

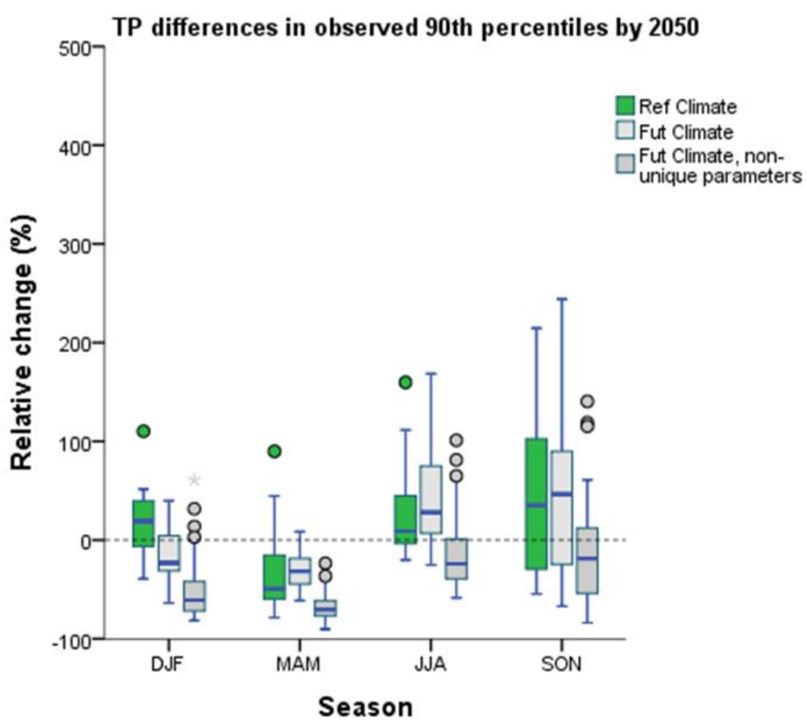


Figure S5.5. Relative change in 10th and 90th percentiles for total phosphorus, comparing SWAT simulated with observed data (zero line) and SWAT simulated with climate model reference and future data, using the best run approach and the non-unique parameter approach.

Table S5.1. Sources of data used for setting up the Altmühl watershed in ArcSWAT.

Data	Source	Database / type of data	Time period	Scale / resolution	Reference
Digital Elevation Model	Bavarian Geodetic Survey	Raster		50 m raster from 1:25000	DGM25, Bayerische Vermessungsverwaltung
Land cover for Europe	European Environmental Agency	Raster	2006	50 m	European Environmental Agency CORINE land cover v.15, www.eea.europa.eu
Protected areas	European Environmental Agency	Shape file	2000	Shape file	NATURA 2000, European Environmental Agency www.eea.europa.eu
General land use	Bavarian State Office for the Environment	Shape file	2010	Shape file	VEKTOR 500, Bayerische Vermessungsverwaltung
Forest cover	Bayerische Landesanstalt für Land und Forstwirtschaft	Shape file	2009	Shape file	FFH Lebensraumtypenkarte, Bayerische Forstverwaltung
Agricultural land use	Bayerische Landesanstalt für Landwirtschaft	Shape file	2008	Field level	FNN Feldstückgeometrien
Soil data	Bavarian Geodetic Survey; and GLOWA-Danube	Shape file; Raster		Shape file; 1:1000000	Bodenschätzung Bayern v1.4, Bayerische Vermessungsverwaltung; www.glowa-danube.de
River network	Bavarian State Office for the Environment	Shape file	2005	1:25000	WGN25, Digitales Gewässerverzeichnis, www.lfu.bayern.de/wasser/gewaesserverzeichnisse/digitales_gewaesserverzeichnis/index.htm
Hydrological and water quality data	Bavarian State Office for the Environment	Excel	1948-2011	Gauges Thann, Treuchtlingen	Wasserwirtschaftsamt Ansbach; Referat 85, Bayerisches Landesamt für Umwelt
Farm type and size	Bavarian State Office for Statistics and Dataprocessing	Excel		Farm level	Landesamt für Statistik und Datenverarbeitung www.statistik.bayern.de
Crop management	Bavarian State Office for Agriculture	Report	2008	Crop level	Bayerische Landesanstalt für Landwirtscahft www.lfl.bayern.de/ipz/getreide
Fruit management	Bavarian State Office for Viticulture and Horticulture	Report	2007-2011	Crop level	Bayerische Landesanstalt für Weinbau und Gartenbau www.lwg.bayern.de/gartenbau/gemuesebau

Table S5.2. Parameter set solutions that best meet the objective criterion using the best run approach, and the parameter non-unique approach.

Parameter	Best run	Non-unique parameter sets			
r__CN2.mgt	0.050115	-0.0755	-0.08809	-0.06158	-0.11403
v__GWQMN.gw	2.286751	1.398697	1.711717	1.592937	1.854253
v__ESCO.hru	0.911377	0.868442	0.890843	0.836312	0.92252
v__CH_N2.rte	0.163875	0.077171	0.122214	0.199349	0.166681
v__CH_K2.rte	112.3787	141.3552	102.6625	104.8981	122.2095
v__ALPHA_BNK.rte	0.363951	0.454543	0.787942	0.46931	0.460222
r__SOL_AWC(1).sol	0.244948	0.092969	-0.01322	0.157238	0.049191
v__SURLAG.bsn	13.4075	13.244	13.18089	11.71226	10.63373
v__CH_K1.sub	3.827467	5.056229	2.583361	2.795614	3.005309
v__GW_REVAP.gw	0.157412	0.160169	0.160608	0.182853	0.158412
v__CANMX.hru	0.766589	0.849914	0.383295	0.149985	0.216645
v__TIMP.bsn	0.753781	0.787054	0.74089	0.720999	0.697671
v__SNOCOVMX.bsn	211.3879	3.357902	66.03873	281.2643	0.4797
v__SNO50COV.bsn	0.051314	0.044531	0.082869	0.122387	0.391934
v__SFTMP.bsn	3.546645	1.832276	4.259583	-0.2767	-0.61493
v__SMTMP.bsn	0.983965	1.332011	-2.00372	1.104575	-3.08576
v__SMFMX.bsn	6.362092	8.312808	9.263071	5.589167	6.151294
v__SMFMN.bsn	6.865611	6.744539	6.296317	4.173699	4.843457
v__CH_N1.sub	0.20933	0.21344	0.289525	0.174251	0.238483
v__SOL_ORGP(1).chm	267.1191	2.10645	2.31345	2.70675	2.65385
v__SOL_SOLP(1).chm	86.09882	0.000415	0.001737	0.000777	0.001644
v__ERORGP.hru	1.805973	1.0315	1.0255	1.3645	1.1035
v__PHOSKD.bsn	167.3491	80.5167	85.92098	64.66416	65.0965
v__K_P.wwq	0.01778	283.2597	126.7521	139.2193	195.5442
v__RS5.swq	0.051121	64.99297	59.43303	64.84666	81.23387
v__BC4.swq	0.386544	0.856679	0.401781	0.426297	0.587009
v__RSDIN.hru	4409.191	201.6999	152.2108	166.8631	150.7904
v__RCN.bsn	2.130082	0.012079	0.020503	0.033731	0.02984
v__CMN.bsn	0.000553	0.02901	0.039069	0.016804	0.040357
v__SDNCO.bsn	1.421064	0.433007	0.748736	0.346059	0.7145
v__SOL_NO3(1).chm	68.51921	2157.185	3921.915	3842.897	4954.414

Table S5.3. Simulated streamflow (m^3/s) at Treuchtlingen for 2046-2070 using the best parameter approach. Independent t-tests compare the mean of the future climate simulations to the mean of the reference climate simulations (1975-2000). An asterisk indicates a rejection of the test, the value after the asterisk indicates the difference.

Month	Mean	Standard Deviation	10^{th} Quartile	Median	90^{th} Quartile	t-test $\mu_o=\mu_1$ ($p>0.05$)
J	9.95	5.51	2.92	9.62	16.82	
F	11.47	5.74	4.48	10.95	19.09	
M	9.59	4.47	4.04	9.3	15.49	
A	6.63	4.12	2.10	5.78	12.54	*1.16
M	5.16	4.04	0.80	4.24	11.21	*1.8
J	4.02	3.71	0.74	2.59	9.47	*1.04
J	3.31	3.96	0.36	1.85	8.10	
A	2.22	2.51	0.24	1.22	5.81	
S	1.51	2.0	0.17	0.74	4.06	*-0.96
O	1.96	2.17	0.29	1.20	4.76	
N	3.12	2.93	0.38	2.09	6.54	
D	6.31	4.81	1.23	5.49	12.53	

Table S5.4. Percentiles for simulated streamflow (m^3/s) at Treuchtlingen. Independent t-tests ($p<0.05$) carried out on the 10th and 90th percentiles (within rows different letters denote significant difference), comparing the best run approach for the reference climate simulations, the best run approach for future climate simulation, and the non-unique approach for the future climate simulations.

Season	**Percentile**	**Best run approach**		**Non-unique**
		Reference climate simulations (1975-2000)	Future climate simulations (2046-2070)	Future climate simulations (2046-2070)
DJF	10	3.1 a	2.2	2.0 b
	Median	9.1	8.6	8.3
	90	18.4 a	17.4	16.6 b
MAM	10	1.2	1.7	1.2
	Median	5.4	6.3	5.6
	90	11.5 b	13.4 a	13.0 a
JJA	10	0.4 a	0.4 a	0.3 b
	Median	1.8	1.9	1.4
	90	6.5	7.6 a	6.4 b
SON	10	0.2	0.3	0.2
	Median	1.5	1.3	1.1
	90	7.0 a	5.4 b	5.5 b

Table S5.5. Simulated nitrate nitrogen (kg/ha) for 2046-2070 using the best parameter approach. Independent t-test compare the mean of the future climate simulations to the mean of the reference climate simulations (1975-2000). An asterisk indicates a rejection of the test, the value after the asterisk indicates the difference.

Month	Mean	Standard Deviation	10^{th} Quartile	Median	90^{th} Quartile	t-test $\mu_o=\mu_1$ ($p>0.05$)
J	2.47	1.40	0.96	2.28	4.28	*0.3
F	2.23	1.02	1.00	2.12	3.48	
M	2.02	1.09	0.83	1.91	3.17	
A	1.26	1.10	0.25	0.99	2.70	
M	0.87	1.14	0.07	0.40	2.46	*0.41
J	0.51	0.83	0.05	0.19	1.48	*0.23
J	0.45	0.89	0.02	0.12	1.28	*0.2
A	0.36	0.63	0.01	0.08	1.12	
S	0.34	0.54	0.01	0.07	1.29	
O	0.70	0.88	0.03	0.39	1.78	*0.21
N	1.09	0.90	0.08	0.91	2.48	*0.3
D	1.82	1.23	0.49	1.56	3.33	

Table S5.6. Percentiles for simulated nitrate nitrogen (kg/ha) at Treuchtlingen. Independent t-tests ($p<0.05$) carried out on the 10th and 90th percentiles (within rows different letters denote significant difference), comparing the best run approach for the reference climate simulations, the best run approach for future climate simulations, and the non-unique approach for the future climate simulations.

Season	**Percentile**	**Best run approach**		**Non-unique**
		Reference climate simulations (1975-2000)	Future climate simulations (2046-2070)	Future climate simulations (2046-2070)
DJF	10	0.65 a	0.74 a	0.19 b
	Median	1.78	2.05	0.59
	90	3.45 b	3.75 a	1.25 c
MAM	10	0.11 a	0.16 a	0.06 b
	Median	0.85	1.09	0.38
	90	2.61 b	3.06 a	1.18 c
JJA	10	0.02 a	0.02 a	0.01 b
	Median	0.13	0.14	0.05
	90	0.64 b	1.27 a	0.35 c
SON	10	0.02 a	0.02 a	0.01 b
	Median	0.29	0.38	0.10
	90	1.52 b	1.91 a	0.60 c

Table S5.7. Simulated total phosphorus (kg/ha) for 2046-2070 using the best parameter approach. Independent t-test compare the mean of the future climate simulations to the mean of the reference climate simulations (1975-2000). An asterisk indicates a rejection of the test, the value after the asterisk indicates the difference.

Month	Mean	Standard Deviation	10^{th} Quartile	Median	90^{th} Quartile	t-test $\mu_o=\mu_1$ ($p>0.05$)
J	0.084	0.080	0.011	0.059	0.191	*-0.06
F	0.089	0.103	0.004	0.049	0.241	*-0.04
M	0.044	0.047	0.007	0.029	0.096	*-0.03
A	0.038	0.039	0.007	0.029	0.082	*0.015
M	0.042	0.040	0.009	0.029	0.101	*0.014
J	0.033	0.033	0.005	0.021	0.086	
J	0.024	0.031	0.004	0.015	0.050	
A	0.015	0.018	0.002	0.008	0.038	
S	0.011	0.016	0.001	0.006	0.021	
O	0.015	0.018	0.001	0.010	0.031	
N	0.021	0.030	0.002	0.011	0.049	
D	0.060	0.073	0.005	0.031	0.163	*-0.02

Table S5.8. Percentiles for simulated total phosphorus (kg/ha) at Treuchtlingen. Independent t-tests ($p<0.05$) carried out on the 10th and 90th percentiles (within rows different letters denote significant difference), comparing the best run approach for the reference climate simulations, the best run approach for future climate simulations, and the non-unique approach for the future climate simulations.

Season	**Percentile**	**Best run approach**		**Non-unique**
		Reference climate simulations (1975-2000)	Future climate simulations (2046-2070)	Future climate simulations (2046-2070)
DJF	10	0.012 a	0.007 b	0.003 c
	Median	0.077	0.046	0.020
	90	0.291 a	0.197 b	0.095 c
MAM	10	0.005 b	0.008 a	0.003 c
	Median	0.026	0.029	0.013
	90	0.090 a	0.090 a	0.041 b
JJA	10	0.003 a	0.003 a	0.002 b
	Median	0.014	0.014	0.007
	90	0.043 a	0.059 a	0.032 b
SON	10	0.001	0.002	0.001
	Median	0.009	0.009	0.006
	90	0.037 a	0.035 a	0.022 b

CONTEXT OF CHAPTER 6 WITHIN THESIS

The following study takes place in the Altmühl River watershed and integrates the climate change simulations with the land use change scenarios in the hydrological model. The aim of this study was to assess the magnitude of the suite of climate change effects, as simulated by a suite of climate model runs, on nutrient loads and concentrations when applied individually or combined with the land use change scenarios. This study builds on the land use change scenarios developed in Chapter 4 for the Altmühl River and links with the hydrological model calibration assessed in Chapter 5. By simulating the combined impacts of climate change and land use change I can determine a wider scale of potential impacts that may take place in the basin, and determine whether agricultural land use change is a significant factor leading to water quality degradation *vis à vis* climate change. The combination of climate with and without land use change on several water quality variables has not been previously published, to my knowledge.

This chapter will be submitted to *Water Resources Research*.

6. IMPACTS OF CLIMATE CHANGE AND AGRICULTURAL LAND USE CHANGE ON SURFACE WATER QUALITY IN A MESOSCALE WATERSHED

6.1. Abstract

The objective of this research was to quantify the impacts of potential future environmental changes in an agricultural-intensive watershed, on the surface water quality to 2050. The Altmühl watershed (980 km^2) in Bavaria, Germany, was selected for this study. A hydrological modeling framework was used with climate simulations alone, and then combining each, in turn, with an agricultural land use change scenario. A suite of seven combinations of regional climate models (RCMs) for the time horizon 2041-2070 under two SRES scenarios (A1B and A2) were applied to the hydrological model Soil and Water Assessment Tool (SWAT) to determine their impacts on total phosphorus (TP) and on nitrate nitrogen (NO_3^--N). Compared with the reference simulation from 1971-2000, the impacts of climate change adversely affected surface water quality in the watershed; mean annual changes at the outlet in the range of -183 to +222 Mg/yr were simulated for NO_3^--N loads; and the TP loads ranged from -9 to +2 Mg/yr. The mean monthly NO_3^--N loads increased significantly from July to September to yield up to 0.21 ±0.07 kg/ha more NO_3^--N per month than in the reference simulation. The mean TP load was significantly higher (0.08 ±0.04 kg/ha) only during November.

Furthermore, three agricultural land use change scenarios for 30 years into the future were developed with local stakeholders. The land use types in each scenario were spatially distributed in the watershed using the Conversion of Land Use and its Effects (CLUE-S) model. For each land use scenario, the corresponding raster layers where applied in SWAT, with each RCM simulation respectively, to examine the compounded effects of potential changes that may occur. The combined climate and land use change impacts showed a further deterioration of the water quality, whereby the mean annual NO_3^--N loads increased 3 fold, and TP loads 8 fold: the range of simulated annual changes in NO_3^--N loads of +62 to +672 Mg/yr; and TP loads of -1 to +17 Mg/yr at the outlet. The months from May-November had significantly higher simulated NO_3^--N loads compared with the reference simulation. As well, nutrient loads were transported into the streams for a longer period during the year. The water quality criterion of 50 mg/L for nitrate (11 mg NO_3^--N/L) was surpassed every month, with the greatest exceedances occurring from

October to December. TP loads were significantly higher from May-September and in November. Mean TP concentrations were significantly higher in June-August and in November. For every month the TP concentrations were higher than the 0.05 mg/L water quality criterion. Surface water quality was degraded by the impacts of climate change alone, and to an even greater extent through the combined impacts of climate with agricultural land use changes. In the basin, silage corn was responsible for the greatest TP loss, while winter wheat was the main crop contributing to NO_3^--N loads. Hotspots of future land use change were identified that may be targeted to reduce nutrient loads.

6.2. Introduction

Protecting and safeguarding water quality is a priority in the EU. This is formalized by the European Water Framework Directive (2000/60/EC) (EC, 2000) which aims to improve water quality in Europe’s aquatic environments to achieve “good” ecological status through the implementation of river basin management plans.

It is particularly relevant to examine future crop changes that may occur within agricultural basins. In watersheds where agricultural activities dominate, it is not uncommon for the quality of water to be compromised (Zebarth et al., 1998; Tong and Liu, 2006; van Bochove et al., 2007; Volk et al., 2009; Patoine et al., 2012). For example, non-point source pollution stems from the transport of applied fertilizers to water bodies (Scanlon et al., 2007), also row crops with wide-row spacing and no residue cover on the soil present the largest potential for erosion to occur (SWCS, 2003), and maize areas have been significantly correlated to a degradation in water quality (Schilling et al., 2008).

While there remains uncertainty in the rate and magnitude of climate change, higher average seasonal temperatures and higher growing degree days for mid- and high latitude regions are expected to occur (IPCC, 2013). Agricultural producers may adjust to these shifts and advantageous temperatures by diversifying their crops, planting new hybrids or varieties, applying new management strategies, or expanding or intensifying their farming activities. As well, increased amounts of fertilizer may be required to grow the crops for a longer time (Brassard and Singh, 2008), which may amplify the runoff or leaching of nutrients from agricultural fields, especially given the risk of more intense precipitation events (Tomassini and Jacob, 2009).

An integrative approach is necessary to examine the combination of multiple stressors that may influence the outcomes of restoring water quality in a watershed. For example, climate change impacts on the quality of lakes and rivers in the future should be considered. As well, agricultural land use in Europe has changed considerably in the past decades (Rabbinge and Van Diepen, 2000), so it is unreasonable to assume the future agricultural landscape will remain status quo.

Land use scenarios developed with stakeholders can be helpful to examine potential changes in crop types and their spatial distribution due to different drivers (Rounsevell and Metzger, 2010). The scenarios can be examined simultaneously with climate change simulations, using a hydrological model, to determine the combined impacts on water quality.

The Altmühl River in Bavaria, Germany, was chosen for this study because it is considered to be of "critically contaminated" quality (class II) in the reaches before and just after the Altmühl Lake, located in the centre of the basin. The main water quality challenges are related to non-point source pollution causing elevated nitrate and phosphorus levels, of which the latter are considered to be more problematic (BMLU, 2002) as these are linked to cyanobacteria outbreaks in the lake (Schrenk-Bergt et al., 2004). Since 1982, water quality improvements in the Altmühl River and lake have been observed due to upgrades on water treatment plants and storm water treatment facilities as well as environmental regulations introduced (i.e. limiting phosphates contained in detergents). Also, from 1990-1996, measures were undertaken to reduce surface runoff on more than 450 ha, which included the creation of hedges, field buffer strips, and stream bank re-vegetation along 200 km (BMLU, 2002). Nevertheless, water quality problems in the Altmühl River and Lake remain elevated (Schrenk-Bergt et al., 2004) with phosphorus concentrations of 0.3 and 0.2 mg/L, respectively.

The objective of this research was to quantify the impacts of climate change impacts alone, and then combined with land use change scenarios, on the surface water quality (total phosphorus and nitrate) in the Altmühl watershed. A hydrological modeling framework was used, first with a suite of climate simulations alone and then combined with agricultural land use change scenarios.

6.3. Methods

6.3.1. Site description

The Altmühl watershed is located in Bavaria, Germany. The upper part of the Altmühl watershed was examined, which comprises 130 km of river, from its source to the outlet gauge in Treuchtlingen (10°54’48.91”E, 48 °57’11.31”N); this encompasses a total basin area of 980 km^2 (Figure 6.1). The chief rural districts in the watershed are Weissenburg-Gunzenhausen and Ansbach, including Ansbach city. The elevation ranges from 406 m at the gauge, to 660 m in the north. The soils in the upper part of the basin are mainly loamy clay and loamy gravelly sand, with pockets of gravelly sand. Located along the floodplain, below the Altmühl Lake are mainly clayey silt soils. Near the outlet, clay loam soils are predominant, with a few areas of Karst in the most southwestern tip of the basin. The land use in the watershed is primarily agricultural (56%) and forest (39%). The 2008 land use map provided by the Bavarian State Office for Agriculture shows the land use to be 23% (22 331 ha) cereals (mainly winter- and summer- wheat), 20% (20 900 ha) pasture, 8% (8236 ha) maize, 3% (2788 ha) oilseeds (mainly rapeseed), 3% (2847 ha) urban, 1.4% (1136 ha) natural grassland, 1.2% (1269 ha) legumes, and 0.6% (342 ha) tuber crops (mostly potatoes).

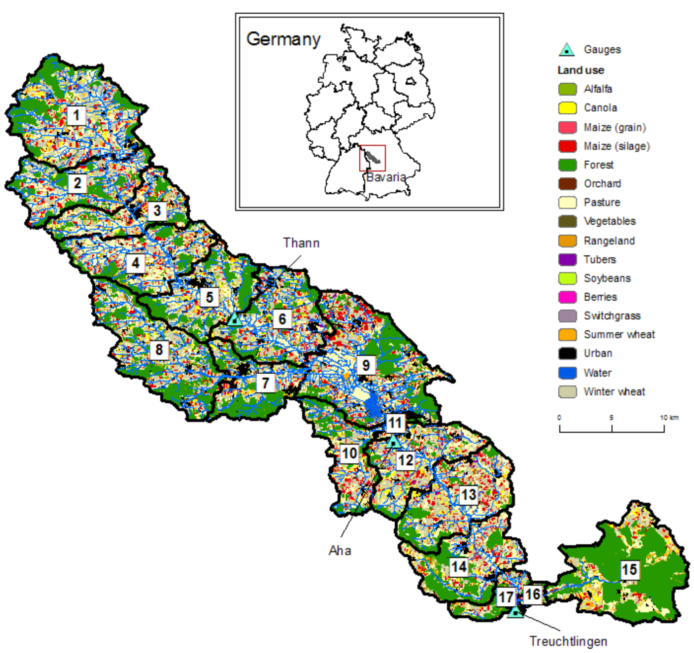


Figure 6.1. Altmühl watershed with 17 subbasins and the 2008 land use (reference simulation set-up).

Average long-term precipitation and temperature measurements for the watershed reveal the watershed to receive approximately 700 mm of precipitation annually; actual evaporation comprises 475 mm, and runoff is 175 mm (BLfW, 1996), the remaining 50 mm is presumabaly longer term subsurface water storage. The flow regime of the Altmühl River is perennial, with peak flows occurring in spring (February-March) caused by snowmelt and saturated soil conditions. Low flows occur in summer (August-October) due to vigorous plant growth, high evapotranspiration and lower soil moisture contents. The average annual flow (1941-2008) at the Treuchtlingen gauge is 5.73 m^3s^{-1}, with a flow range of 0.28 m^3s^{-1} to 183 m^3s^{-1} (BLfU, 2012).

The Altmühl Lake (4.5 km^2), located nearly 20 km NW of Treuchtlingen, is an artificial reservoir (building period from 1976-1984; in operation since 1985), built on flat ground with a ring dam surrounding it. Hence, the lake is shallow and never more than 4 m deep (average 2.5 m). It is a multi-purpose lake, functioning principally as a reservoir to divert water into the neighbouring Brombach Lake and watershed to supply water to northern Bavaria, but also to serve as an important floodwater control structure whereby the water retention is increased and peak flow is delayed, thus mitigating downstream flooding of agricultural land (approximately 10% of the floodwater is stored (BMLU, 2002)). The lake has helped to improve water quality downstream by keeping the minimum flows higher (25 m^3/s in summer for the Regnitz River) than the previous minimum flow levels. Larger floods occur once every 8-10 years, and these cannot be mitigated. Finally, the lake is used for recreational purposes, bringing in about €150 million in annual tourist revenues.

6.3.2. Future climate change simulations

An ensemble of regional climate model (RCM) data from the QBIC3 project was available for this research (Ludwig et al., 2012). Each RCM simulation was driven by a coupled general circulation model (GCM) for the time period 2041-2070, with one of two SRES scenarios (Table 6.1). In total, seven coherent sets of climate variables of temperature, precipitation, relative humidity, solar radiation and wind speed were available to drive the hydrological model. This ensemble of climate models was chosen to represent a broad spectrum of future predictions of climate (Harvey, 1997).

Table 6.1. Climate model simulations considered in this study. All simulations are bias corrected. Regional climate models: Rossby Centre Regional Atmospheric Climate Model (RCA), Regional Atmospheric Climate Model (RACMO), Canadian Regional Climate Model (CRCM). Driving Global climate models: Bergen Climate Model (BCM), ECHAM version 5 (members 1, 2 and 3), and Hadley Centre Coupled Model (HadCM3), Canadian General Circulation Model (CGCM).

RCM	Driving GCM	SRES	Grid size (km)	Name of simulation
RCA	BCM	A1B	50	RCA-BCM-50K
RCA	ECHAM5-r3	A1B	50	RCA-ECM-50K
RCA	HadCM3Q3	A1B	50	RCA-HCM-50K
RACMO2	ECHAM5-r1	A1B	50	RAC-ECM-MB1-50K
RACMO2	ECHAM5-r2	A1B	50	RAC-ECM-MB2-50K
RACMO2	ECHAM5-r3	A1B	50	RAC-ECM-MB3-50K
CRCM 4.2.3	CGCM3	A2	45	CRC-CGC-45K

The global climate models were based on projections using A2 or A1B SRES greenhouse gas scenarios (Nakicenovic et al., 2000). In the A2 scenario, global CO_2 emissions reach 29 GtC by 2100; an increase of more than four times the 1990 levels. The A1B scenario has CO_2 emissions peaking around 2050, at 16 GtC; a level 2.7 times that of 1990, and fall to around 13 GtC by 2100. Both SRES scenarios represent the higher greenhouse gas contributions and have been chosen since current CO_2 levels have already surpassed 400 ppm (Monastersky, 2013).

The temperature for each member of the ensemble was bias-corrected using a monthly correction factor based on the difference between the ensemble-mean of the 30-year mean monthly minimum and maximum air temperature and the 30-year monthly means of the daily-observed minimum and maximum air temperature. As well, a bias-correction method for precipitation using the Local Intensity Scaling (Schmidli et al., 2006) at a sub-daily time step was applied to all climate simulations. Finally, the RCM outputs were scaled to the hydrological model resolution of a 1 km grid with the scaling tool SCALMET (Marke, 2008) that preserves energy and mass at the scale of the RCM grid. More detailed explanations of the climate change (CC) simulations and their post-processing is provided in Muerth et al. (2013).

The observed climate data stemmed from measured daily temperature, precipitation, relative humidity, cloud cover, and hours of sunshine for the period 1970-2000, provided by the German Meteorological Service (Deutscher Wetterdienst). These were interpolated to a 1 km grid using an elevation dependent inverse distance method (Mauser and Bach, 2009).

6.3.3. Future land use change scenarios

Three potential trajectories of agricultural change for the next 30 years in the watershed were developed with stakeholder input (Bavarian State Office for Agriculture (BLfL); Bavarian State Office for the Environment (BLfU); Administrative Office for Food, Agriculture and Forest (AELF) in Ansbach; Water Management Authority (WWA) in Ansbach; and the Farmer's Union (BV) in Weissenburg-Gunzenhausen), and after consultation and consent through the presentation of the final land use scenarios. The scenarios were constructed using drivers of change derived from expert consultation and relevant policies. Drivers of land use change are distinctive influences affecting either a change in the spatial distribution of the crop, or a significant change in the total area allocated to a specific crop. The three land use change (LUC) scenarios were as follows:

<u>Business as usual (BAU)</u>

This scenario assumes that the current land use trends continue. Regional district statistics for the watershed area were compiled from the Bavarian State Office for Statistics (BLSD) from 1980-2010. During this time, the population increased by 12%, but since 2005 has started to decline by 2%. The total agricultural area in the rural districts of Ansbach and Weissenburg-Gunzenhausen decreased by 8%, while forest and urban areas increased by 0.4% and 3%, respectively. From 1995-2007, maize increased by 4695 ha (1.5%), pasture decreased by approximately 3000 ha (1%) and tubers by 1300 ha (0.4%). The area of cereals initially increased until 2003 (by 16 370 ha), but then decreased somewhat by 2160 ha. Oilseeds increased by 750 ha (0.2%). These general trends were extrapolated to 2011-2040 by means of a linear regression carried out on each historic land use area change. For crops with large increases or decreases (cereals, maize and pasture), the land use change increments each year were adjusted using exponential growth or decay curves and small manual corrections were performed to fit all the crop areas in the watershed.

Farmer decisions prevail (FARM)

This scenario is based on input from stakeholders active in the watershed as well as by means of a questionnaire sent to farmers. The questionnaire was developed with the AELF-Ansbach and the BV Weissenburg-Gunzenhausen and comprised 23 questions that were set out to determine decision-making factors related to past, current and potential future crop choices. It was sent to two independent groups of farmers. The first group (n=666), lived downstream of the Altmühl Lake where they operated farms (this geographic subbasin area was selected to allow farmers to provide unbias responses and not have the responses influenced by current government recommendations for safeguarding the lake's water quality). The second group (n=24) were agricultural students studying at the Agricultural College in Triesdorf, located in the watershed. This group was chosen to obtain responses from a younger (future) generation of farmers.

Agricultural policies dominate (CAP)

This scenario was developed assuming market forces, subsidies and monetary stimuli in general are primary drivers of land use change. As such, it focuses on the available markets, the agricultural subsidies and income stabilization available to farmers in the region, principally guided by the Common Agricultural Policy (CAP) and the Cultural Landscape Program (KULAP). Direct payments to farmers from these programs allow them to be stewards of their land. The dissociation of payments to farmers from their production amounts (i.e. decoupling production from payments) helps to keep farmers in the business whilst allowing them to maintain good practices. In the CAP, land use policies encourage protection of biodiversity. The preservation of permanent grassland, natural grassland, and set-aside land practices are encouraged through payments and there is less land abandonment. The extensification of farm land is also encouraged through both programs.

6.3.4. Spatially distributing the land use areas in each scenario

In order to simulate each land use change scenario in SWAT, the quantities of land use types each year had to be spatially distributed in the watershed. Therefore, the areas related to the land use types for each year were distributed in the watershed using CLUE-S (version Dyna-CLUE: Conversion of Land Use and its Effects at a Small regional extent (Verburg et al., 2002)). The CLUE-S model has two distinct modules. The first is a land use demand module, where the area covered by different land use types is specified per year. These land use quantities are a direct input for the second module. The second module is a dynamic spatial allocation procedure which uses a combination of empirical analysis, spatial analysis and dynamic modelling. To begin with, empirically derived relations (logistic regression equations) of location factors and land use describe the relationship between the current spatial distribution of land and the dominant driving factors (i.e. location preferences or suitability) as well as constraints associated with these (Verburg et al., 2004). Based upon the regression results, a probability map is calculated for each land use type, per year. For grid cells that are allowed to change, using the probability maps, the decision rules in combination with the actual land use map, and the demand for different land use types, the most suitable location is chosen for each land use. This is an iterative process and when allocation equals demand, the final map is saved and the calculations continue for the next time step (Verburg et al., 2002).

6.3.5. The hydrological model

The Soil and Water Assessment Tool (SWAT (Arnold et al., 1998)) model was used to determine impacts of changes on the surface water quality. SWAT is a semi-distributed, process based hydrological model run at a daily time step. By design, SWAT is well-suited to reflect the impacts of changes in land use and agricultural management practices on streamflow, agricultural nutrient transport and sediment yield (Gassman et al., 2007; Arnold et al., 2012). The model was applied to examine streamflow, nitrate-nitrogen (NO_3^--N) and total phosphorus (TP) loads.

ArcSWAT version 510 was run on an ArcGIS 9.3.1 (ESRI 2009) platform. The set-up for the watershed was based on a 50 m Digital Elevation Model that mapped the Altmühl study area onto a 993.4 km^2 watershed (Figure 6.1). The watershed was divided into 17 subbasins and then further into HRUs which act as heterogeneous cells (grouping similar soil textures, land uses and slopes). All model calculations are conducted at the HRU level. A threshold (percentage) can be specified whereby soil types, land uses and/or slopes are not considered in the subbasins if their areas are below the threshold, and the minority classes are reappointed so that 100% of the area is modeled. In this project, thresholds of 0%, 10% and 0% were applied to land use, soil type and slope, respectively, to yield a total of 2038 hydrological response units (HRUs).

In SWAT, the water balance is the driver behind all hydrological processes and is represented in each HRU by five storage volumes: canopy interception, snow pack, soil profile (0-2 m), shallow aquifer (2-20 m) and deep aquifer (>20 m). Simulated processes include infiltration, surface runoff, evapotranspiration, plant water uptake, lateral flow and percolation to shallow and deep aquifers. Flow, sediment and nutrients are summed across the HRUs in a subbasin, and the flows and pollutant loads are then routed through channels, ponds, and reservoirs to the watershed outlet. The volume of surface runoff is estimated using the modified Soil Conservation Society curve number (CN) method (USDA, 1972). The CN is adjusted at each time step, depending on how much soil moisture is available. In this study, potential evapotranspiration was estimated using the Penman-Monteith method. The plant heat units were adjusted for the specific crops and regional climate.

Crop growth is modeled with the EPIC sub-model (Williams et al., 1984) that bases the phenological development of the plant on accumulated heat units which are a function of the minimum and maximum air temperatures. SWAT is able to modify the crop radiation-use and water-use efficiency if elevated CO_2 concentrations are input. In this study, the increased atmospheric CO_2 was only indirectly accounted for through the changes in temperature in the future climate simulations.

The SWAT model has three major forms of nitrogen that it models in mineral soils: 1) organic N associated with humus; 2) mineral forms of N held by soil colloids; and 3) mineral forms of N in solution (Neitsch et al., 2011). SWAT models six different pools of P in the soil; three pools are associated with the inorganic forms of P (solution, active and stable) and the other three with the organic P forms (fresh, stable and active) (Neitsch et al., 2011).

The SWAT model requires several types of input data relevant to climate, hydrological processes and plant growth. The observed climate data stemmed from measured sub-daily temperature, precipitation, relative humidity, cloud cover, and hours of sunshine for the period 1961-2005, provided by the German Meteorological Service (Deutscher Wetterdienst, 2011). These were aggregated to a daily scale and interpolated to a 1 km grid using an elevation dependent inverse distance method (Mauser and Bach, 2009).

Observed daily flow at the Thann (1981-2010), Aha (1975-2010) and Treuchtlingen (1948-2006) gauges were made available by WWA-Ansbach. Measured monthly in-stream nutrient concentrations (1982-2011) at the Thann gauge were obtained from the BLfU. Data on point-source contributions of nutrients were not available.

Soil parameters stemmed from Muerth (2008) and Wendland (2011). Agricultural crop management data (i.e., crop seeding, tillage, and fertilization application dates and amounts; and crop harvesting dates) were obtained from the BLfL annual crop reports (available from www.lfl.bayern.de/ipz/index.php), and additional necessary information was consulted from the Association for Technology and Structures in Agriculture (KTBL, 1995; 2009).

The number of farmers implementing conservation practices in the region was guided by Pöhler (2006) as well as by the responses received from a research questionnaire sent to farmers in parts of the Altmühl watershed (Mehdi et al., 2012), which indicate that 30% of farmers implement soil conservation practices.

The Sequential Uncertainty Fitting algorithm (SUFI (Abbaspour et al., 2004)) is a semi-automated inverse modelling tool that was used for calibrating the SWAT simulated outputs to the available time series data of streamflow, NO_3^--N and TP loads. SUFI-2 is a stochastic procedure drawing independent parameter sets using Latin Hypercube sampling.

SWAT was calibrated sequentially for streamflow, NO_3^--N, and TP as per Arnold et al. (2012). SWAT was first calibrated (1964-1974) at the outlet gauge (Treuchtlingen) for surface flow using a daily time step (validated from 1975-1984). Because of observed water quality data, NO_3^--N and TP were calibrated (1982-1983) at the monthly time step at the Thann gauge (validated in 1984). The simulations had a 3-year warm up period to initialize the soil processes.

<u>Inserting land use scenarios into SWAT</u>

To examine the variability of land use change for a future period, a trajectory of land use change is applied in SWAT, where an evolving land use configuration of 30 years is considered; one layer of land use is applied to one year of climate for the duration of the simulation period (sensu Quilbé et al., 2008; Jha et al., 2010; Park et al., 2011).

The coupling of the land use layers from CLUE-S into SWAT was carried out using the beta version of SWAT2009_LUC (Pai and Saraswat, 2011). This tool is able to accept CLUE-S raster layers as input and spatially allocate new land use configurations to existing HRUs in the SWAT model thereby maintaining the physical autocorrelation of soil and slope whenever possible in each subbasin. For each of the three LUC scenarios, a raster layer is produced corresponding to one map of land use for each year of simulation. These 30 maps (one map per year) are read by the SWAT2009_LUC coupling tool which calculates the changed area fraction of each HRU for every layer within the 30-year period and transmits this information to SWAT. SWAT then simulates land use change by increasing or diminishing the area of the initial HRUs as stipulated in each of the future land use layers.

According to Pai and Saraswat (2011), a certain amount of deviation in the area of land use transformed in each subbasin may occur when HRU thresholds are provided in the model set-up. For this reason, once the LUC scenarios were simulated in SWAT, a verification of the total amount of land use change (land use type in each subbasin) which actually occurred was undertaken.

6.4. Results

6.4.1. Future temperature and precipitation changes

The suite of future CC simulations (2041-2070; Figure 6.2a-b) showed mean monthly precipitation changes in the range of -27% to +56%, and increases in mean monthly temperatures of 0.5^{o}C to 4.0^{o}C compared with the observed station data. A precipitation increase in March was consistent in all simulations. The months of April, October and November also showed mainly increases in precipitation, while a decrease in precipitation was more prominent during August and September. The increase in mean surface air temperature showed much variability between the simulations. The largest and most consistent increases took place in winter; from December to February.

By 2041-2070, a longer growing season was calculated for each CC simulation using the method by Chmielewski and Köhn (1999). According to the simulations, on average, the growing season will start at the end of February instead of at the end of March (i.e., earlier by 4 weeks). As well, a warmer growing period was calculated (as per Gordon and Bootsma (1993)), with an additional 318-496 growing degree days (GDD) from April 1–October 31 for base 0^{o}C; 303-469 GDD for base 5^{o}C; and 250-397 GDD for base 10^{o}C. To account for these alterations in the season, adjustments were made to the farm management files in SWAT when simulating the LUC scenarios with the CC simulations (Table 6.2). Specifically, planting dates were shifted (guided by Deryng et al. (2011)), harvesting dates for maize and soybean took place later due to the assumption that late-maturing cultivars will be planted (Southworth et al., 2002b), as well, to allow crops to dry in the field longer, the switchgrass and summer wheat were harvested 2 weeks later, also strawberries were harvested for 2 weeks longer. Pasture land was harvested four (instead of three) times a year with an additional fertilizer application of manure (40 kg/ha N and11 kg/ha P), and maize fertilizer was augmented to meet the increase in biomass. The fertilizer by-laws and regulations were also respected in the future scenarios.

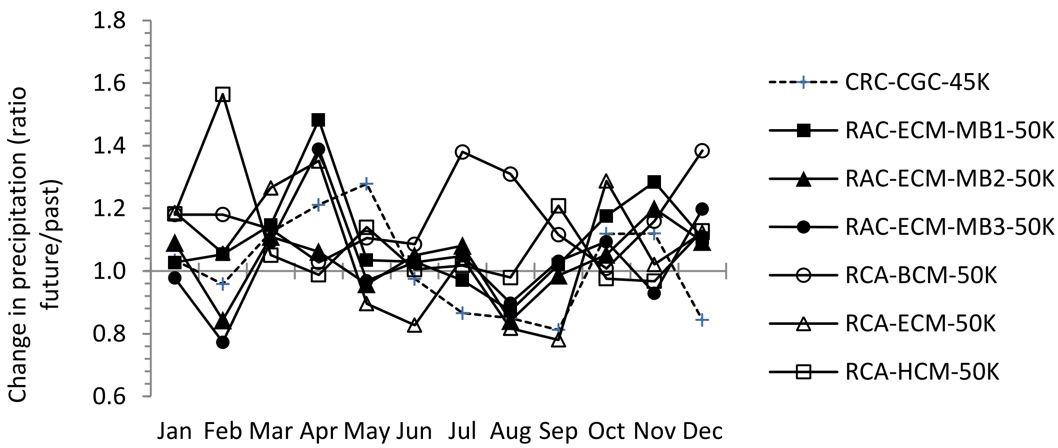


Figure 6.2a. Future change in precipitation: bias corrected model simulations (2041-2070), compared with observed interpolated station data (1971-2000).

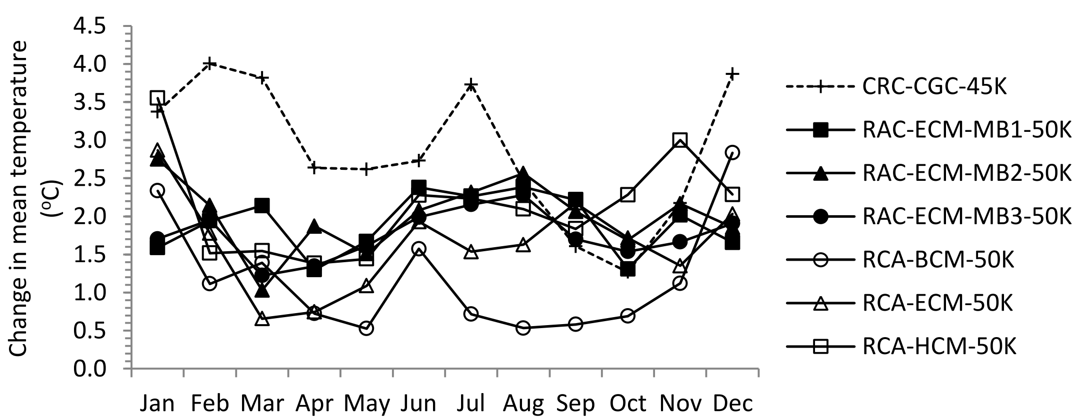


Figure 6.2b. Future change in mean temperature: bias corrected model simulations (2041-2070) compared with observed interpolated station data (1971-2000).

Table 6.2. Crop management (seeding / harvesting dates, fertilizer application) for 2041-2070

Crop	Seeding date / harvest date	N kg/ha (type)*	P kg/ha (type)*	Summary of field management changes for 2041-2070, compared to 1971-2000
Corn (silage)	April 21 / October 10	30 (2) 20 (1) 115 (3)	34 (2) 25 (3)	Seed 10 days earlier; fertilize with additional 20 kg N/ha (3 weeks after seeding); fertilize with 45 kg N/ha, 25 kg P/ha additional during season; harvest 2 weeks later; fall tillage 4 weeks later
Corn (grain)	April 21 / November 7	35 (2) 30 (1) 130 (3)	39 (2) 28 (3)	Seed 10 days earlier; fertilize with additional 30 kg N/ha (3 weeks after seeding); fertilize with additional 45 kg N/ha, 28 kgP/ha during season; harvest 2 weeks later; fall tillage 10 days later
Winter wheat	September 20 / July 7	45 (3) 125 (1)	10 (3) 70 (6)	Fertilize in spring 3 weeks earlier; harvest 2 weeks earlier; fertilize in fall 4 weeks earlier; tillage 3 weeks earlier in fall; seed 2.5 weeks earlier
Summer wheat	March 21 / August 15	50 (3) 40 (1) 30 (4)	11 (3) 13 (4)	Fertilize 4 weeks earlier in spring; harvest 2 weeks later; tillage 2.5 weeks later in fall
Pasture	Cut on: May 30 / July 20 / August 29 / October 5	200 (5)	55 (5)	Additional 4th cut in fall followed by fertilizer application
Rapeseed	September 3 / July 23	150 (1)	60 (6)	Fertilize 10 days earlier in spring
Potato	April 12 / September 29	100 (1)	120 (6)	Seed 10 days earlier
Soybean	April 1 / September 7	-	45 (6)	Seed 1 week earlier; harvest 1 week later; fall fertilize and till 10 days later
Strawberry	Harvest: July 15	70 (3) 75 (1)	15 (3)	Harvest 2 weeks later; fall fertilize 2 weeks later
Switchgrass	Cut: October 15	100 (1)	0	Harvest 2 weeks later
Sugarbeet	March 12 / October 1	110 (2)	24 (2) 70 (6)	N/A
Alfalfa	Cut on: May 19 / June 24 / July 26 / September 8	-	200 (6)	N/A
Orchard	-	45 (1)	-	N/A

*Fertilizer type: (1) elemental N; (2) diammonium phosphate; (3) calcium ammonium nitrate; (4) ammonium phosphate; (5) beef manure; (6) elemental P.

6.4.2. Land use scenarios

In each of the three scenarios, the errors that occurred after coupling the CLUE-S layers to SWAT (with the SWAT2009_LUC tool) remained within the acceptable range of 5-10% per land use per subbasin (Pai and Saraswat, 2011). Figure 6.3 depicts the final land use changes that took place in each scenario. Descriptions of the major changes in the LUC scenarios are as follows:

<u>BAU</u>

Given the historic trends continue in this scenario, the recent population decline continues, and the amount of agricultural land decreases for the next 30 years by a total of 15%. The greatest change to cropland is a continued increase in maize area (3.4%). The rural district of Ansbach (upper half of the watershed) has the largest concentration of biogas plants in Bavaria (BLfL, 2007) with the feedstock for these being primarily silage corn. Currently, 10% of all agricultural land in Ansbach is being used to produce feedstock for the biogas plants. Thus, the trend of maize areas replacing pasture lands continues. Hence, the pasture areas decrease by 2.8%. The recent downward trend of cereals (mainly wheat) and legumes (soybean) also continues (4.4% and 0.9%, respectively). Rangeland (set-aside and natural grasslands) increases (3.8%) to replace the abandoned farmland.

<u>FARM</u>

In June 2010, the questionnaires were sent to 666 farmers in Group 1, encompassing an area of 306.2 km^2 (30.8% of the watershed). The response rate was 8% (n=52). It should be noted however, that in 2010, 69% of farmers in the rural district Weissenburg-Gunzenhausen (lower half of the watershed) were categorized as “hobby” farmers; their principal income did not stem from farming (AELF, 2010). Therefore, it is likely that the actual number of full-time farmers possessing cropland in the questioned area was closer to 250. Using comparative statistics, it was determined that the farmers who responded to the questionnaire were representative of the general population in the corresponding rural district. The respondents represented 1469 ha of agricultural land (or 27% of the agricultural land in the downstream area questioned). In Group 2, all 24 students responded to the questionnaire (5 out of 24 students lived in the watershed proper).

Using the nonparametric statistical test (Mann-Whitney), Group 1 and 2 were found to be statistically different ($p>0.05$) in terms of their farm size (31 ha and 125 ha, respectively); the number of people living on the farm (2 and 3, respectively); and the number of years of farm working experience (34 and 8 years, respectively). Both groups noticed climate change impacts to the same extent. However, a significantly larger proportion of farmers in Group 2 would switch crops if the growing season increased; examples cited were soybean, sorghum, miscanthus, lupin and sudangrass. In Group 1, 50% were considering abandoning their farm, and 11% wanted their farm to enlarge; in Group 2, none would abandon the farm and 72% wanted to expand. Otherwise, in Group 1 and 2 there were no significant differences, and the reasons for choosing crops to grow on their farms were driven by very similar factors.

In both groups, current crop choices were closely associated to economic incentives. However, farmers also consider several other important drivers, such as time investment; access to markets; machinery and technology; and experience. Drivers for changing crops on their farms included marketing potential; climate factors; new information; new land acquisition; and government subsidies (for full results see Chapter 4).

In this scenario, due to the planting of new crops and the increasing pressure for more cropland the total area of agricultural land remains relatively constant and decreases only slightly by 2.4%. More silage corn is grown for biofuels (the area under maize increases by 3.6%) and legume crops, such as soybean, also increase (1.8%) since they are more productive in a warmer climate. Oilseeds continue to increase by 0.4%. Areas under cereals and tubers decrease by 3.4% and 0.1%, respectively, because they are no longer profitable. Pasture areas decline by 2.5% as one additional cut of hay is possible to meet demands.

CAP

In this scenario, the population generally declines as seen in recent trends (by 2%), and the gradually aging population is more conscious of a healthy lifestyle. The present widely grown crops remain important in this scenario: cereals, silage maize, tubers and oilseeds to meet local markets and also for export. Technological advances increase crop productivity, which leads to less cropland required for production. There is relatively slower economic and demographic growth and also less meat consumption. Livestock production is therefore reduced and there is less demand for fodder crops. For these reasons, crop production is somewhat lower. The least productive land is taken out of production.

Overall, although there is less demand for agricultural production, the total agricultural land area only decreases by 3.3%. This is less than in the BAU scenario due to extensification. The rangeland increases by 0.2%. The areas of cereals (0.6%) and maize (0.5%) increase slightly since markets for these will remain relatively important (also for export). Decreases in oilseed (1%), legume (0.4%) and pasture (2%) areas occur because of less demand for crops for human consumption while fodder crops will not be as needed due to the decrease in livestock numbers.

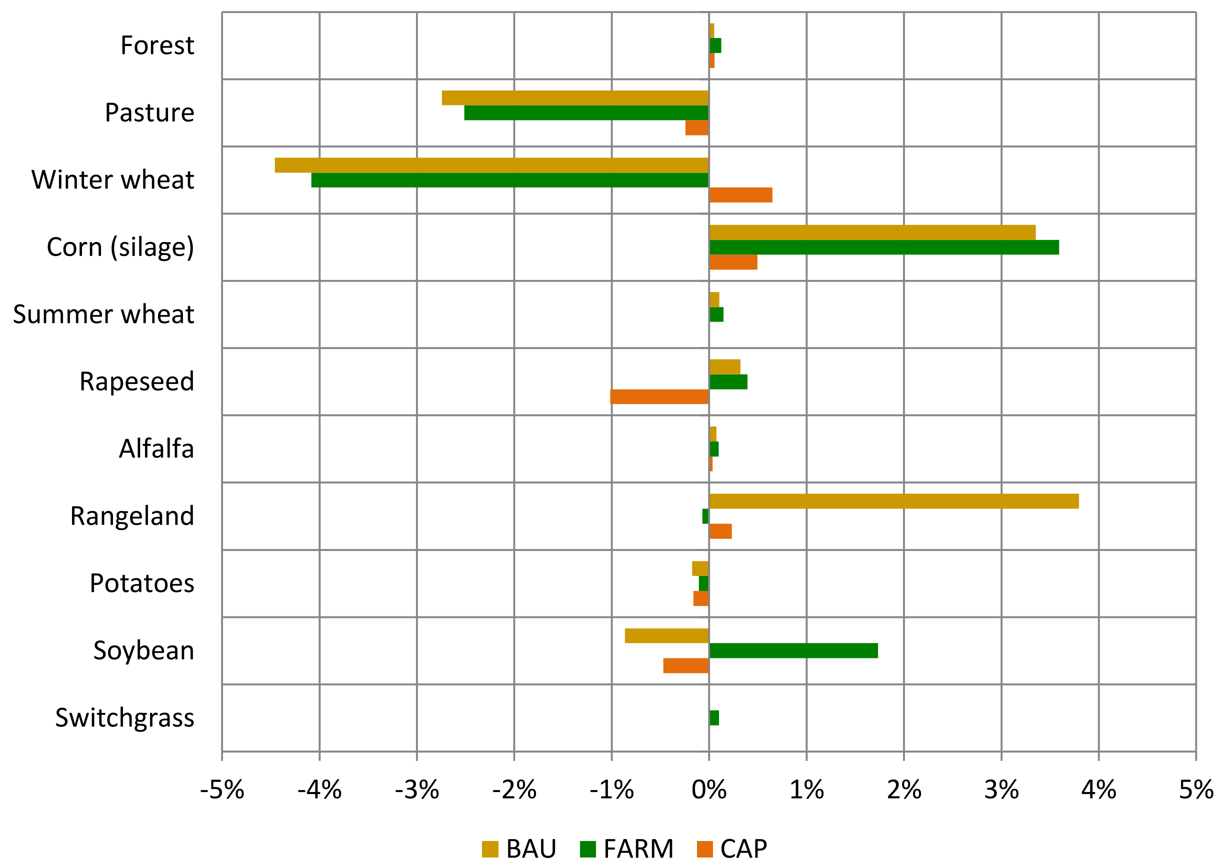


Figure 6.3. Land use changes for the Altmühl as applied in SWAT for each of the land use scenarios by the end of 30 years of simulation.

6.4.3. SWAT performance

The SWAT simulated outputs, resulting from the best set of calibrated parameters, demonstrate that the model is able to reproduce the timing of daily dry spells and peak flows (Figure 6.4a). The magnitude of flows was also modelled within reasonable boundaries, although the PBIAS statistics indicate that SWAT tended to underestimate the monthly flow (by 13%; Table 6.3a), in particular those of the low flow events. Figures 6.4b-c and Table 6.3b show that NO_3^--N and TP simulations represent the timing of the events well, although the simulated TP was overall lower and NO_3^--N was overestimated. Based on Moriasi et al. (2007) and on the performance criteria in Tables 6.4a-b, the sequential calibration of the three variables in SWAT resulted in a satisfactory model performance.

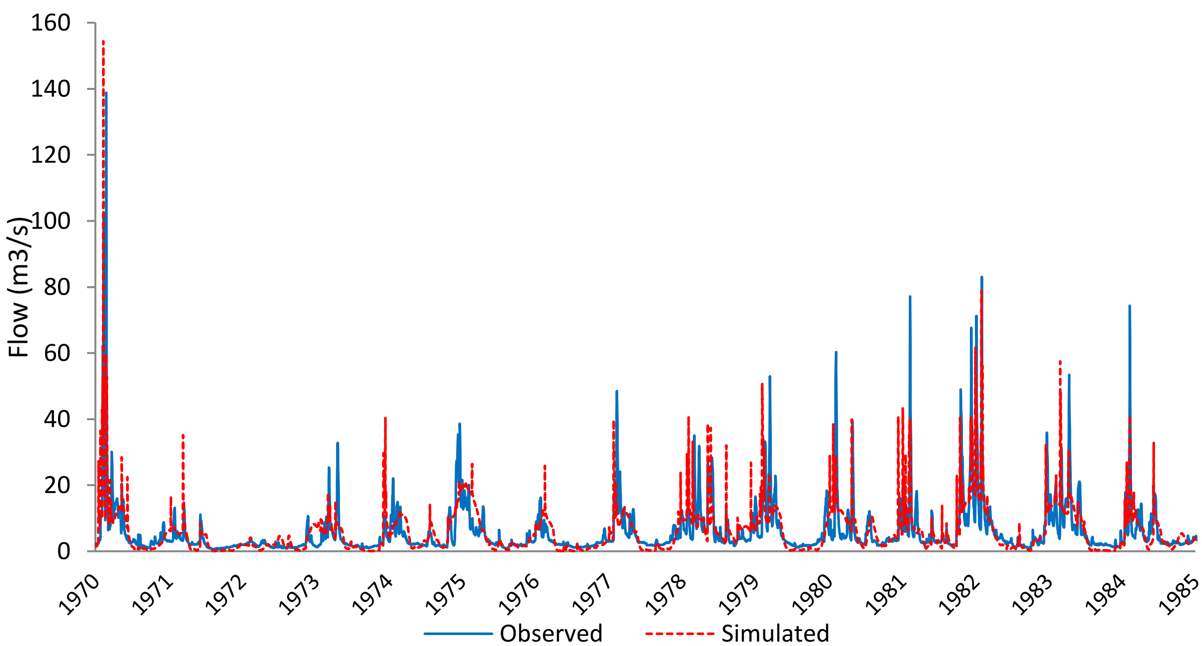


Figure 6.4a. Daily observed streamflow data (blue solid line) at Treuchtlingen and the SWAT simulated streamflow using observed climate and the 2008 land use layer (red dotted line).

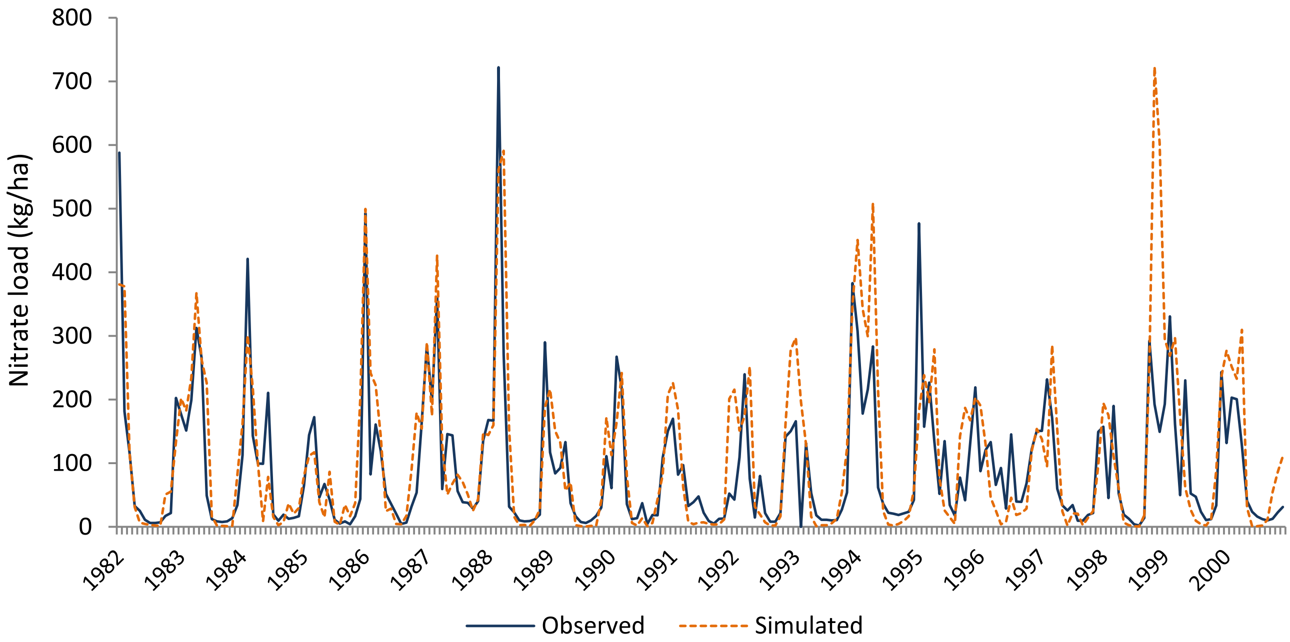


Figure 6.4b. Monthly measured nitrate nitrogen loads (blue solid line) at Thann and the SWAT simulated loads using the observed climate and the 2008 land use layer (orange dotted line).

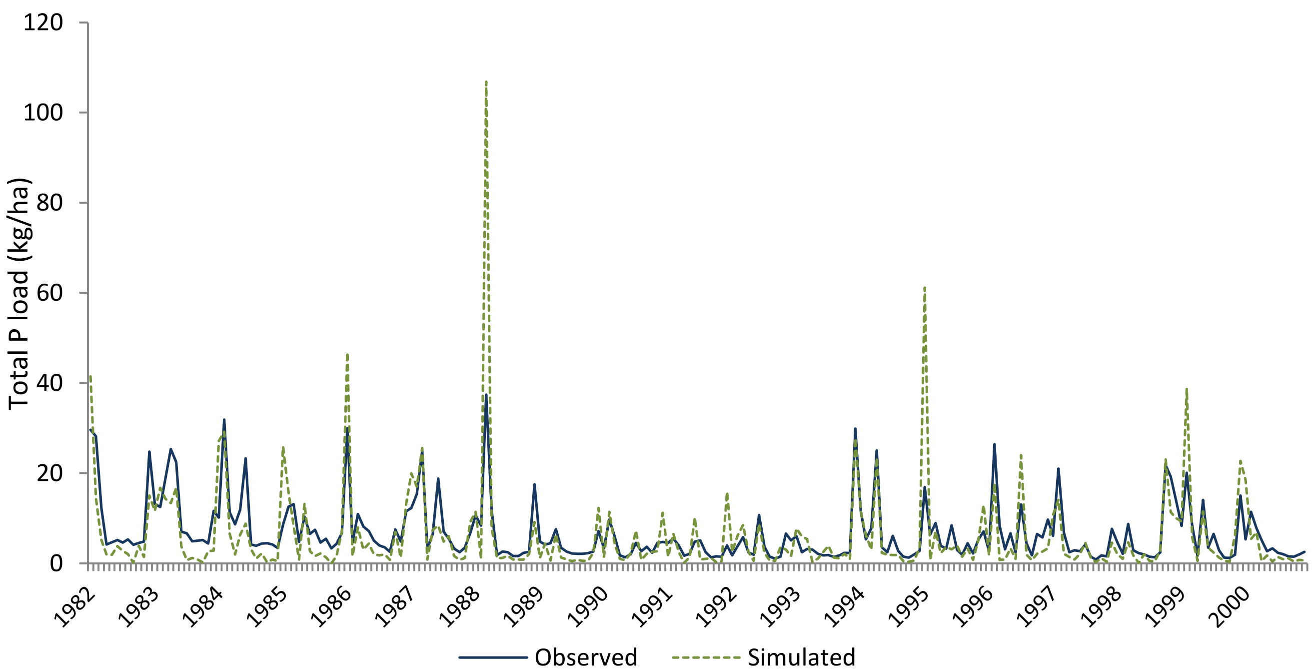


Figure 6.4c. Monthly measured total phosphorus loads (blue solid line) at Thann and the SWAT simulated loads using the observed climate and the 2008 land use layer (green dotted line).

Table 6.3a. SWAT calibration and validation statistics* for streamflow (m^3/s) at Treuchtlingen.

	Calibration 1964-1974			**Validation 1975-1984**		
	Yearly	Monthly	Daily	Yearly	Monthly	Daily
NSE	0.96	0.77	0.57	0.81	0.75	0.68
PBIAS	1.4	13.5	13.8	0.67	13.3	3.34
R^2	0.96	0.79	0.59	0.83	0.78	0.69
bR^2	0.96	0.68	0.39	0.84	0.73	0.53
SSQR	0.12	1.35	3.31	0.09	0.72	1.32

Table 6.3b. SWAT sequential calibration and validation (monthly time step) statistics at Thann. First NO_3^--N and then TP was calibrated using the daily calibrated flow parameter ranges.

	Calibration 1982-1983		**Validation 1984**	
	NO_3^--N + flow	TP + flow (stable NO_3^--N parameters)	NO_3^--N + flow	TP + flow (stable NO_3^--N parameters)
NSE	0.77	0.47	0.72	0.52
PBIAS	-11.8	33.5	16.6	27.7
R^2	0.77	0.71	0.71	0.70
bR^2	0.59	0.77	0.75	0.67
SSQR	280564000	3485482	100659032	1029454
NSE for flow	0.83	0.80	0.87	0.59

*NSE= Nash-Sutcliffe Efficiency; PBIAS = percentage bias; R^2 = coefficient of determination; bR^2 = coefficient of determination multiplied by the coefficient of the regression line; SSQR aims at fitting the frequency distributions of the observed and the simulated series.

The SWAT simulation using the observed climate (1971-2000) and the 2008 land use layer (kept static for the simulation period) is the initial set-up and henceforth referred to as the "reference simulation" (REF). Since a bias-correction was applied to the CC simulations, a direct comparison was made between the SWAT outputs stemming from the future CC simulations (2041-2070) and the REF. Independent t-tests, with a significance level of $p<0.05$, were carried out to determine significant differences between the REF and the future simulations.

Figure 6.5 depicts the SWAT outputs for four of the main agricultural land uses (pasture, winter wheat, silage corn and summer wheat) in the watershed and how these contribute to nutrient loads.

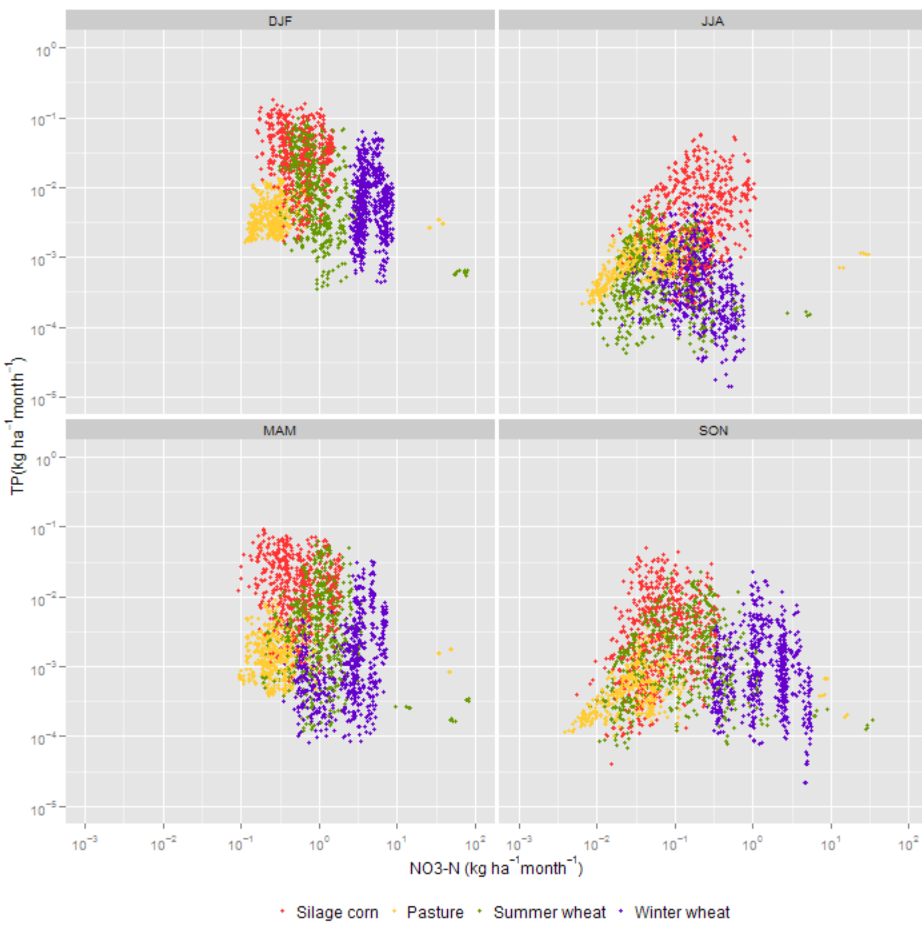


Figure 6.5. Simulated contributions to TP *versus* NO_3^--N loads (kg/ha) for four different crops at the basin outlet, during all seasons in the reference simulation (1971-2000). Each dot represents one month. (DJF=December, January, February; MAM= March, April, May; JJA=June, July, August; SON=September, October, November).

6.4.4. Climate change impacts on streamflow and nutrient loads

Mean annual impacts

Overall, the mean annual streamflow decreased by all but one of the simulations (+3% to -16%) due to the impacts of climate change. By the 2050 horizon, mean annual flows were simulated to range from 5.2 to 6.4 $m^{3/}s$ (instead of the current 6.2 $m^{3/}s$; Table 6.4).

At the annual step, five of the CC simulations increased mean NO_3^--N loads (2% to 16%) while two simulations showed lower loads (-10% and -14%). The mean annual change in NO_3^--N loads at the outlet was simulated to be in the range of -183 to +222 Mg/yr.

Annually, mean TP loads were mostly decreased (-8% to -17%) by CC simulations, except in one simulation where TP loads increased by 4%. Overall, mean annual TP load changes were simulated to vary between -9 and +2 Mg/yr.

Table 6.4. Absolute mean monthly values (with standard deviations) for the reference simulation (1971-2000).

Month	**Flow (m^3/s)**	**NO_3^--N (kg/ha)**	**TP (kg/ha)**
1	11.4 ±5.2	2.3 ±1.1	0.11 ±0.10
2	13.3 ±5.6	2.3 ±0.9	0.10 ±0.09
3	11.8 ±6.6	2.3 ±1.2	0.07 ±0.12
4	8.3 ±5.3	1.7 ±1.4	0.04 ±0.04
5	4.8 ±3.6	0.8 ±0.8	0.04 ±0.04
6	3.8 ±3.4	0.4 ±0.5	0.03 ±0.02
7	3.1 ±2.2	0.2 ±0.2	0.02 ±0.01
8	2.4 ±2.2	0.2 ±0.3	0.01 ±0.01
9	1.6 ±1.7	0.2 ±0.3	0.01 ±0.01
10	2.2 ±2.6	0.5 ±0.6	0.02 ±0.04
11	3.7 ±4.2	0.9 ±1.1	0.01 ±0.02
12	8.0 ±5.6	1.8 ±1.2	0.08 ±0.08
Annual	6.2 ±5.8	13.6 ±4.4	0.54 ±0.2

Mean monthly impacts

Under climate change, the mean monthly streamflow was simulated to decrease from December to April in at least 6 of the 7 simulations (Figure 6.6). However, statistically, only the mean streamflow from the suite of simulations in March was significantly lower (-2.0 ±0.9 m^3/s) than the REF, this was caused by the snowmelt period being shifted to one month earlier (mostly February), thus the snowmelt contribution to the flow in March was reduced despite the general increase in future precipitation during March.

The mean monthly NO_3^--N loads from the suite of simulations, increased significantly during the growing season (July to September) to yield up to 0.21 ±0.07 kg/ha more NO_3^--N per month than in the REF (Figure 6.7, grey boxes). This period also corresponds to when future precipitation changes were highly variable in the simulations (June-September), yet a strong signal of increasing NO_3^--N was detected. The summer and fall months are currently a critical period of NO_3^--N loss from major crops (i.e., winter wheat) grown in the watershed (see Figure 6.5) therefore nitrate movement towards streams should be minimized during this time and even more so under climate change conditions.

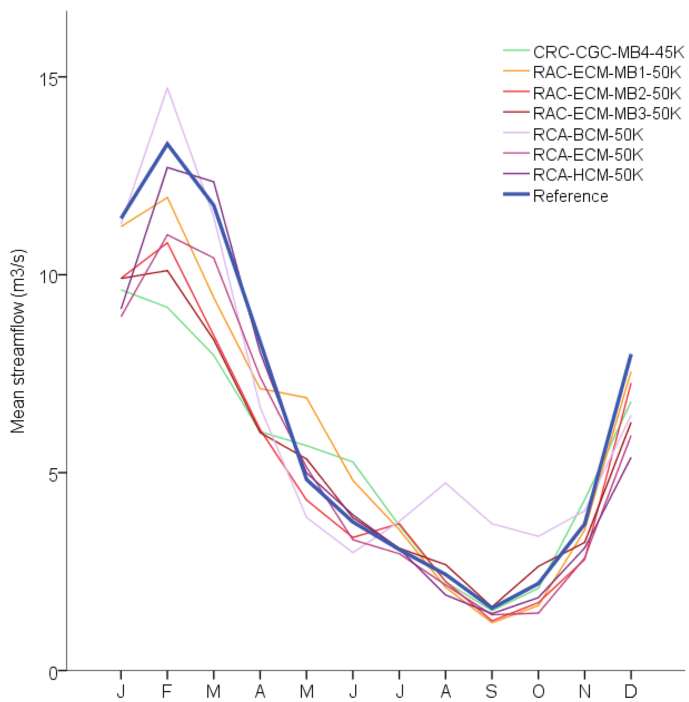


Figure 6.6. SWAT simulated streamflow at the Treuchtlingen gauge for the reference simulation (1971-2000) and with the climate simulations (2041-2070).

In November, the mean TP load from the suite of simulations was significantly higher (0.08 ±0.04 kg/ha) than in the REF (Figure 6.8, grey boxes), partly because most phosphorus (in the form of particulate phosphate) is transported by sorption to sediments (Michaud and Laverdière, 2004) and can make up over 75% of the simulated TP originating from fields. When precipitation is predicted to generally increase (i.e. during November) and when the soil is devoid of crops to intercept the rainfall, sediment particles (laden with P) are more easily transported by surface runoff. A positive correlation between mean monthly streamflow and mean monthly TP loads was found (R^2=0.74), which also explains the decrease in simulated annual streamflow and simulated annual TP loads.

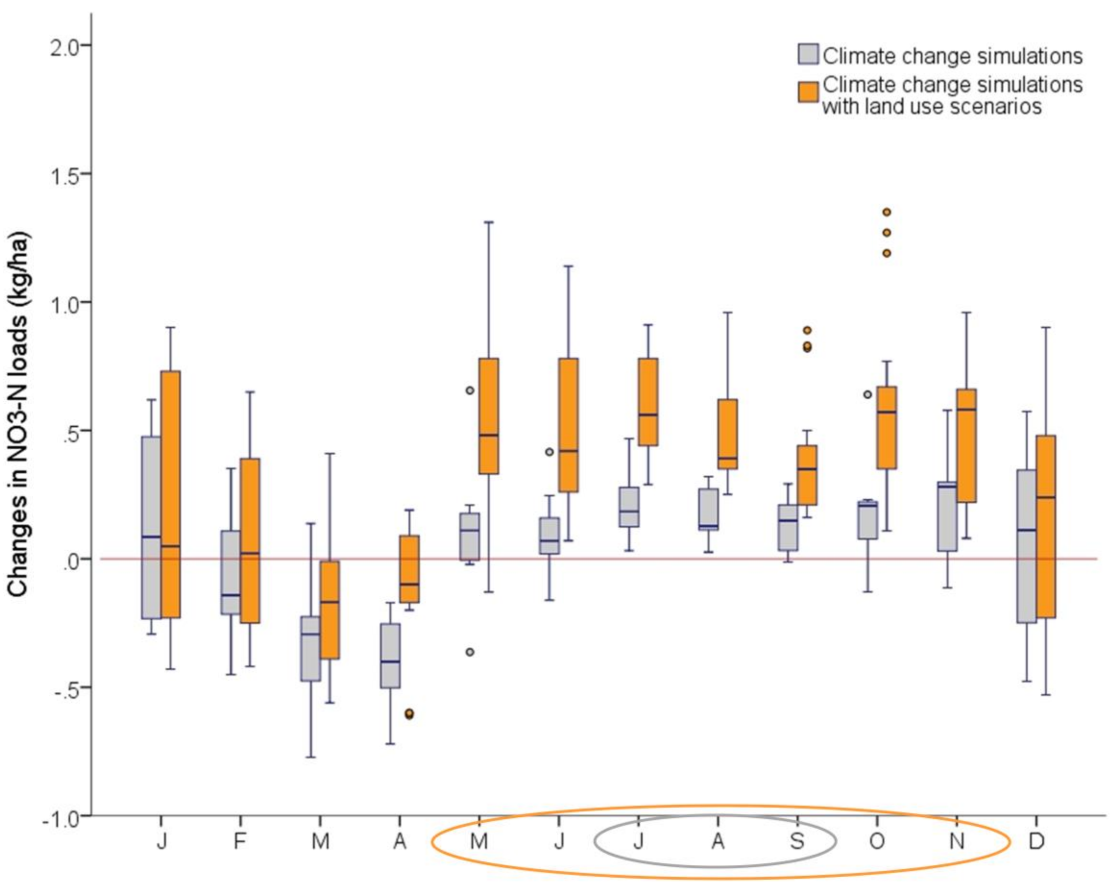


Figure 6.7. Changes in SWAT simulated mean monthly NO_3^--N loads for climate change simulations (grey boxes) and for climate change simulations with land use change scenarios (orange boxes), compared with the reference simulation (red zero line), at the basin outlet. The months in which the mean climate change simulations were significantly (p <0.05) different from the reference simulation are circled in grey; the months in which the mean combined climate and land use change simulations were significantly different are circled in orange.

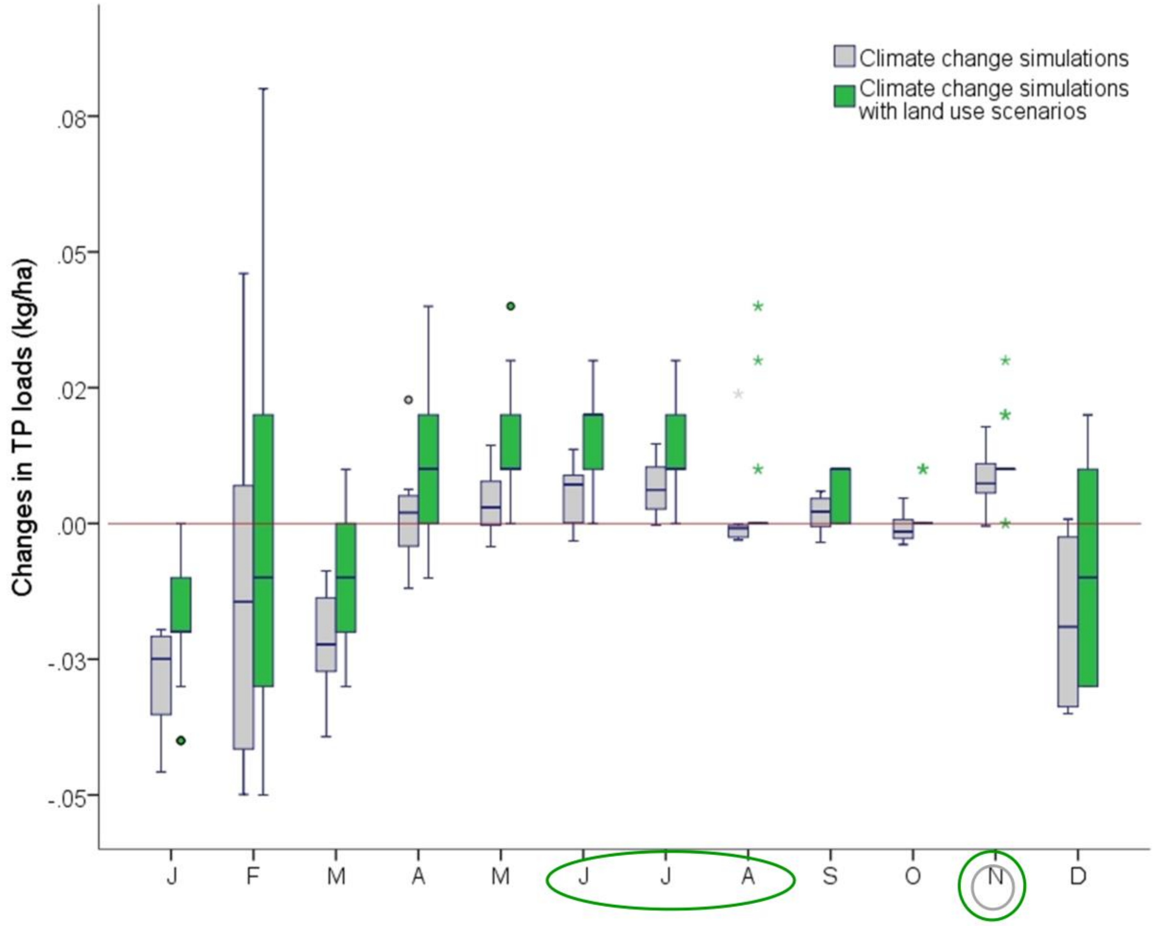


Figure 6.8. Changes in SWAT simulated mean monthly TP loads for climate change simulations (grey boxes) and for climate change simulations with land use change scenarios (green boxes), compared with the reference simulation (red zero line), at the basin outlet. The months in which the mean climate change simulations were significantly ($p < 0.05$) different from the reference simulation are circled in grey; the months in which the mean combined climate and land use change simulations were significantly different are circled in green.

Boxplots show the central mark as being the median, the upper and lower edges of the box are the 75th and 25th percentile, respectively, and the whiskers extend to the values that lie inside one and half box lengths from the quartiles. The circles represent values which lie one and a half box lengths away from the quartile (considered outliers), and the asterisks are values that lie more than three box lengths away from the quartile (considered extremes).

6.4.5. Combined impacts of climate change and land use change on water quality

Nutrient loads

Each of the three LUC scenarios was run with every CC simulation, in turn, to yield 21 simulations of impacts that may occur to the surface water quality in the future. Figures 6.9 and 6.10 graphically show the NO_3^--N and TP loads, respectively in these combinations. For the statistical analysis, boxplots were used to depict the spread of all of the combined scenario changes (Figures 6.6 and 6.7).

When a LUC scenario is combined with a future CC, an important shift towards higher NO_3^--N loads is apparent. All simulations predicted annual additional loads, with a range of 5% to 50% (62 to 672 Mg/yr) at the outlet. This is significantly higher than currently observed.

Mean monthly NO_3^--N loads were significantly higher from May to November (up to 0.6 ±0.07 kg/ha in July). Specifically, the FARM and CAP scenarios coupled with the CC simulations showed significantly higher NO_3^--N loads from May to November. The BAU scenario coupled with the CC simulations demonstrated significantly higher NO_3^--N loads for a somewhat shorter period; from May to October. The BAU scenario had the greatest decrease in winter wheat areas, which is a large contributor to NO_3^--N loads in the fall (Figure 6.5). As well, the BAU scenario had the greatest decline of total agricultural land and the largest increase in rangeland, and both factors reduced the overall fertilizer amounts in the BAU scenario.

The BAU, CAP and FARM scenarios have average N fertilizer applications on cropland of 107 kg/ha, 112 kg/ha and 108 kg/ha, respectively; the REF had 67 kg/ha. As a result of more fertilizer inputs into the future farming system (i.e., on maize and pasture areas; see Table 6.2), the period during the year when NO_3^--N loads were significantly higher was extended compared with the CC simulations alone; adding the LUC scenarios supplied significant additional NO_3^--N loads to the waterways in May, June, October and November (Figure 6.7). Also, in the LUC scenarios, more N fertilizer is applied earlier in the season, and a delayed harvest of certain crops due to longer maturing varieties and drying being able to take place in the field, consequently translates into fall post-fertilizer applications being deferred to later in the year (Table 6.2). Thus, when the LUC scenarios were combined with the CC simulations, NO_3^--N loads were additionally elevated at the beginning and at the end of the growing season.

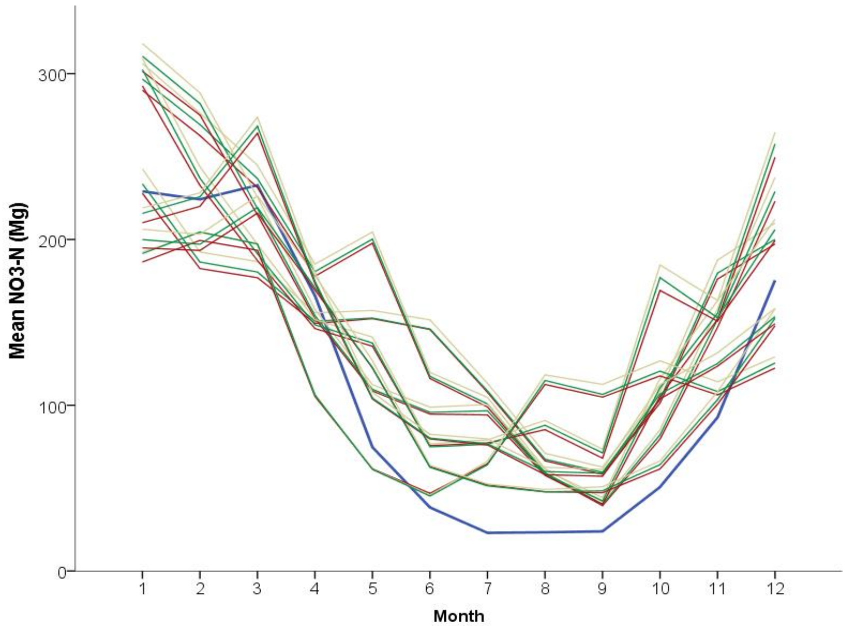


Figure 6.9. SWAT simulated NO_3^--N loads at Treuchtlingen for the combined CC and LUC simulations (2041-2070). The dark blue line is the reference (1971-2000); red lines represent the BAU scenario with each of the climate simulations; green lines represent the FARM scenario with each of the climate simulations; light brown lines represent the CAP scenario with each of the climate simulations.

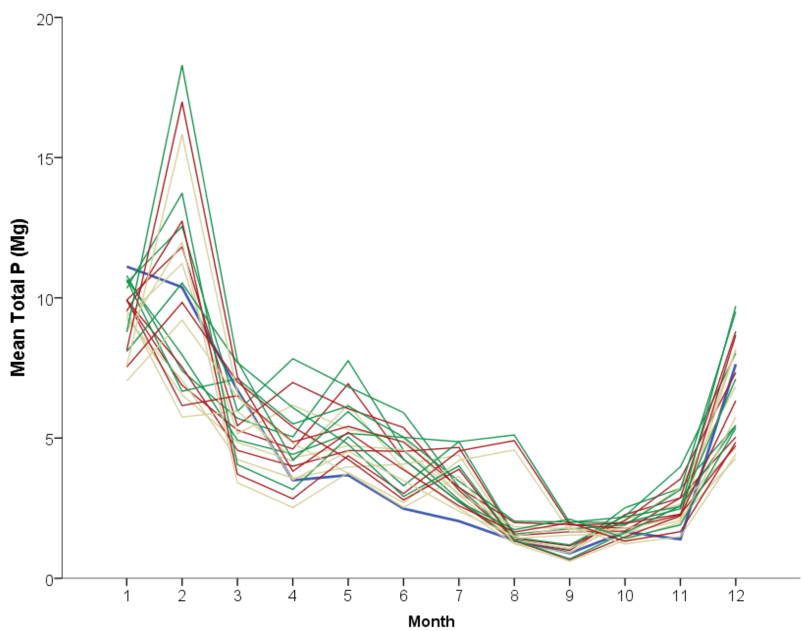


Figure 6.10. SWAT simulated TP loads at Treuchtlingen for the combined CC and LUC simulations (2041-2070). The dark blue line is the reference (1971-2000); red lines represent the BAU scenario with each of the climate simulations, the green lines represent the FARM scenario with each of the climate simulations; light brown lines represent the CAP scenario with each of the climate simulations.

For the TP loads, mean annual changes at the outlet were simulated to range from -2% to +34% (-1 to +17 Mg/yr); 16 simulations (out of 21) predicted increases. This is a stark contrast to the CC simulations alone, where almost all simulations predicted a decrease in TP loads.

Mean monthly TP loads are significantly higher in numerous months of the year, compared with the REF (Figure 6.8); namely from June to August and also in November (up to 0.02 ±0.004 kg/ha in July). The BAU and CAP scenarios, in combination with the CC simulations, had significantly higher TP loads from June to September and in November. The FARM scenario, coupled with the CC simulations, had higher loads also during these months, as well as in the month of May, possibly because soybean areas increase in FARM and require P inputs after seeding in April (in the other 2 scenarios the soybean areas decrease). The BAU, CAP and FARM scenarios had average P inputs on the cropland of 35 kg/ha, 36 kg/ha and 35 kg/ha, respectively (the REF had 26 kg/ha).

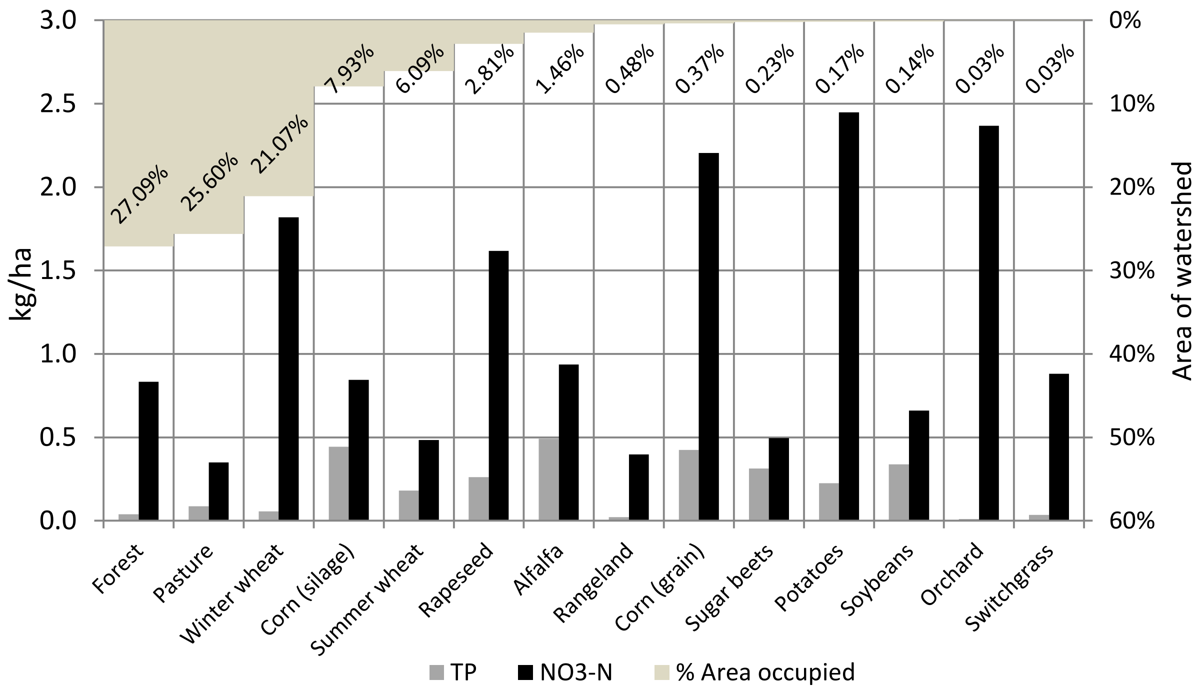


Figure 6.11. Contributions of crops to mean monthly TP and NO_3^--N loads (kg/ha) into the reach, as simulated by SWAT using the land use from 2008 and the climate from 1975-1980, but applying future seeding, fertilizer and tillage management practices. The TP loads comprise the organic P transported with sediments into the reach, the mineral P sorbed to sediments, and the soluble P in the surface runoff to the reach. The NO_3^--N loads stem from the surface runoff, the lateral flow to the reach, plus the groundwater flow contribution to the reach. The percent area occupied by each land use is shown on the top horizontal axis.

Overall, LUC scenarios combined with CC simulations cause additional significant increases in TP loads during the growing season. Under future field management regimes, the cropland from which the most mean monthly TP is lost (>0.1 kg/ha), in ranked order, is: alfalfa, maize, soybean, sugar beets, rapeseed, potatoes and summer wheat (Figure 6.11). For alfalfa fields, the P loads simulated are essentially soluble P (68%) due to the exclusive application of manure; for the other crops, the soluble P makes up less than 4% of the loads (data not shown). However, in 2008, the alfalfa area occupied 1.5%. Sediment-P is more critical as it made up 68-70% of the TP loads stemming from soybean, rapeseed, and maize areas, and it is prone to be transported by surface runoff during rainfall, which will increase.

Concentrations of nutrients

The water quality criteria as set by the regulation on the protection of surface waters by the German Federal Ministry of Justice (*Verordnung zum Schutz der Oberflächengewässer*) are 50 mg/L for nitrate (11 mg NO_3^--N/L), and 0.05 mg/L for TP. Determining the in-stream concentrations of nutrients involved using simulated monthly nutrient loads transported from fields in conjunction with the simulated streamflow volumes to calculate concentrations in mg/L.

Generally, the flow was decreased from December-April (in at least 18 out of the 21 simulations). The mean monthly streamflow for the simulations during March was significantly lower by -2.1 ±0.9 m^3/s (this outcome is similar to the CC simulations alone, and therefore mainly explained by the lack of snowmelt rather than increased evapotranspiration from the land use changes), July had significantly higher flows (+1.2 ±0.4 m^3/s).

The simulated NO_3^--N concentrations at the basin outlet, for every month of the year, had significantly higher mean concentrations compared with the REF (Figure 6.12). This was not the case with the CC simulations alone (when only January, Febrary, July, August, and October to December showed mean higher values than the REF).

The combined simulated impacts cause reason for concern since the NO_3^--N concentration limit of 11 mg/L was frequently surpassed at the Thann, Aha and Treuchtlingen gauges, especially during the fall and winter months (October to January) which also coincide with a decrease in future streamflow. The extreme values (shown by the outliers in Figure 6.7) caused by the high variability in NO_3^--N concentrations always surpassed the water quality criterion every month, which was previously not observed from 1971-2000.

Simulated TP concentrations at the basin outlet were significantly higher in April, and from September to November (with CC simulations alone, only the months of April and October were significanlty higher). TP concentrations remained well above the 0.05 mg/L threshold at the Thann, Aha and Treuchtlingen gauges. The critical conditions for high TP concentrations to occur is during low or no canopy (i.e. before crops are established and after harvest) intersecting with the period when fertilizer is applied (i.e. early spring and late fall). The high variability in TP simulated also led to concentrations exceeding 1.0 mg/L at the basin outlet every month, which was a rare occurrence in the REF (Figure 6.13).

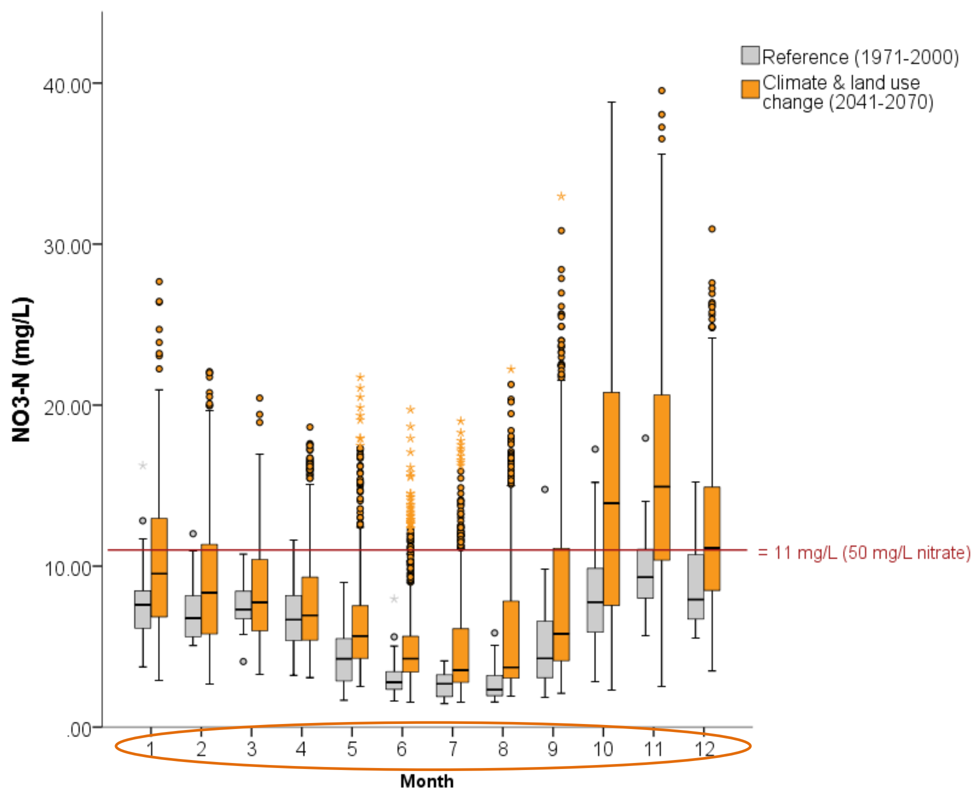


Figure 6.12. Concentration of SWAT simulated NO_3^--N (mg/L) at the basin outlet for the climate simulations with land use change scenarios (2041-2070; orange boxes), compared with the reference simulation (grey boxes). The red line is the water criterion of 11 mg NO_3^--N/L. The months in which the mean combined climate and land use change simulations were significantly different from the reference simulation are circled in orange.

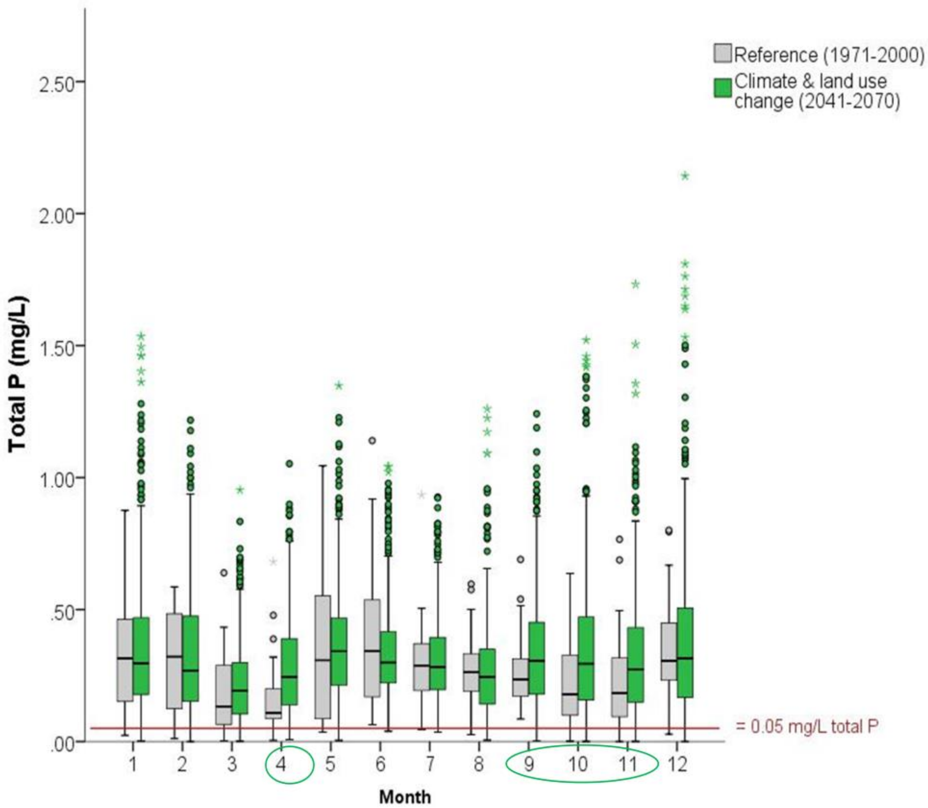


Figure 6.13. Concentration of SWAT simulated TP (mg/L) at the basin outlet for the climate simulations with land use change scenarios (2041-2070; green boxes), compared with the reference simulation (grey boxes). The dotted line is the water criterion of 0.05 mg TP/L. The months in which the mean combined climate and land use change simulations were significantly different than the reference simulation are circled in green.

6.5. Discussion

In Bavaria, in the 1970s and 80s, farm sizes of 10-20 ha dominated the landscape. In the 90s, a gradual transition to most of the farmland being owned by the 30-40 ha size farms occurred, and in the early 2000's, a leap to larger scale farming was brought on. Most of the farmland today belongs to farms whose average size is 50-75 ha; the crops grown consist mainly of maize and cereals. In the past, a variety of crops were seeded, including potatoes, beets, clover, beans and peas. During discussions with local government stakeholders in the watershed, it was brought to light that in recent years, there had been a noticeable shift from pasture to maize crops in the watershed, as maize is used as feedstock for the many biofuel plants in the region.

Agricultural systems are constantly evolving due to the interactions between farmers and the influences from exogenous natural and socio-economic factors. Therefore, farmers make decisions that are not independent of their surroundings (Polsky and Easterling III, 2001). In an attempt to capture these drivers, the LUC scenarios were developed based on distinctly separate driving forces and consequently are divergent in their crop changes.

As dissimilar as the three LUC scenarios were (the BAU depicted a more maize-intensive scenario, the FARM an intermediate path of change, and the CAP tended towards conservative changes with elements of a natural landscape), they all demonstrated similar impacts on in-stream water quality. When coupled with CC simulations, the land use scenarios had overall increased NO_3^--N and TP loads and concentrations at the basin outlet.

The water quality degradation can be traced back to the fertilizer inputs which were not as high in the REF or in the CC simulations. The economically important crops which, in the past, have contributed the most to NO_3^--N and TP loads were identified in SWAT (Figure 6.5).

Historically, high mean monthly NO_3^--N loads (>1 kg/ha) were lost during fall, winter and spring (September-May), the chief loads stemmed principally and regularly from winter wheat fields (three applications of N fertilizer took place from February-April). During the growing season (JJA) NO_3^--N loads were overall lower with contributions in the 0.1-1 kg/ha range that were spread equally between maize and winter wheat. Loads <0.1 kg/ha were simulated for summer wheat and pasture.

Historically, the critical period for TP transport from the main crops (i.e., when mean monthly loads are consistently high between 0.001 and 0.1 kg/ha) is in winter (DJF), during these months, mean TP loads between 0.1 to 0.01 kg/ha were transported from maize, summer- and winter wheat. TP is easily transported when fields are bare of crops. TP losses also extend into the spring period (MAM) when crops start to emerge. The highest TP loads stemmed from maize (in all seasons). In spring (MAM), the maize, summer- and winter wheat TP loads remained elevated, yet decreases in loads <0.001 kg/ha were simulated often. During the growing season (JJA), when crop uptake of nutrients is elevated, TP losses were lower overall, however mean monthly losses >0.01 kg/ha occurred frequently for maize. In fall (SON), TP loses were mostly <0.02 kg/ha, yet higher loads tended to occur mostly for maize plots. The pasture, made up of perennials, had less TP losses than the row crops (range of 0.01–0.001 kg/ha).

From a water quality point of view, TP is more problematic in the Altmühl basin than NO_3^--N, as the TP water quality limits are currently surpassed in every month, and this was simulated to continue and to be exacerbated in the future with climate and land use change. With crops managed under the given future management regimes (altered seeding dates, fertilizer amounts and timings, and harvesting dates), the SWAT results showed alfalfa, maize (silage corn, grain corn), and soybean to contribute to the highest TP loads (Figure 6.11). The wide-row annual crops contribute proportionally more sedimentary P, while perennials contribute P in the soluble form.

As well, in the future LUC scenarios, more N fertilizer was mainly applied to the increasing maize areas in all of the LUC scenarios (after 30 years, the area of maize expanded to 11 701 ha, 12 301 ha and 8649 ha in the BAU, FARM and CAP scenarios, respectively). The area of maize in a watershed has been correlated with P and N amounts in water bodies (Donner, 2003). The subbasins which showed future increases in maize of >200 ha per subbasin, were, in order of importance: 9, 6, 13, 2 and 1 in the BAU scenario; subbains 9, 13, 6, 2, 1 in the FARM scenario; and subbasin 6 in the CAP scenario (see Supplementary Material). The hotspot of maize change in all of the LUC scenarios is subbasin 6, located just above the Altmühl Lake, in the eastern part of the watershed, this is also a region of the watershed which contains the highest density of biofuel plants.

The future combined simulations demonstrated that although N is not of great concern now, the NO_3^--N loads may regularly (monthly) exceed water quality guidelines and become a real problem to cope with in the future (e.g. possibly causing eutrophication). Given more fertilizer inputs on cropland, a longer growing season, and higher annual precipitation, NO_3^--N has a greater potential to be transported to streams (by several pathways, i.e. leaching, lateral flow, surface runoff, and throughflow (given a lag time of 36 to 48 hours, depending on the HRU) and to increase the concentrations throughout the year. These results corroborate with Booty et al. (2005) who found TP and NO_3^--N loads to increase most under future wetter climates compared with future dry climates, and Tong et al. (2012) found similar results regarding TP and NO_3^--N concentrations.

The predicted precipitation under climate change is generally higher than the historic mean from October to May in most of the RCM projections, yet the streamflow is simulated to be lower for the most part during this period, compared with the REF. The land use scenarios combined with the climate simulations do not alter streamflow to any significant effect (see Supplementary Material). This result suggests that the warmer temperatures have a strong influence on streamflow, mostly because actual evapotranspiration is simulated to be higher during these months. Wang et al. (2008) also found similar results when SWAT was applied to a basin in northwest China. Generally, the months in which mean future streamflow is lower than the REF are the ones that are at risk of having augmented nutrient concentrations.

During the lower streamflow months in the future, especially for the months of October-February, the 75th percentile of NO_3^--N exceeded 11 mg/L. The SWAT simulations showed the NO_3^--N in surface water, lateral flow and groundwater were higher in the combined simulations, compared to the CC simulations alone. Groundwater was found to contribute at least 65% of the mean monthly NO_3^--N per crop type (average groundwater NO_3^--N contribution across crops is 90%). The lateral flow contributes <6% in each crop and the remainder NO_3^--N stems from surface runoff. Increases in future precipitation intensity may also contribute to more nutrients being transported by water; however, storm intensity was not captured in this study since no sub-daily precipitation data was used.

The nutrient loads and concentrations are impacted by CC, but particularly by the combination of CC and LUC. Our results show that the critical period during which streamflow is affected by higher nutrient concentrations will be longer in the future. The NO_3^--N concentrations will be significantly increased throughout the year, whereas the TP concentrations increase mostly in the fall. The timing of TP loads is critical as any increases during the season could affect eutrophication (Nicholls, 1995). To prevent negative environmental impacts, nutrient loads should be reduced from subbains in which certain crops are dominant that are prone to high TP and NO_3^--N loads, such as maize and winter wheat. Options would include controlling TP loadings through reduced fertilizer inputs, for example by using slow release fertilizers such as manures (Crossman et al., 2013), or by implementing a combination of buffer strips, bank erosion control and agroforestry on steep slopes (Mehdi et al., 2013).

6.5.1. Uncertainties in the results

As in all modelling exercises, it should be cautioned that these results contain a number of inherent uncertainties. For example, the modelling uncertainties due to applying climate simulations in a hydrological model are related to the natural climate variability; greenhouse gas emission scenario; GCM structure; downscaling technique (from GCM to RCM); the choice of the hydrological model, the data input, as well as the calibration process (Wilby, 2005; Poulin et al., 2011). Also, there are a number of hypotheses in the development of the land use scenarios. However, the purpose was not to explicitly predict the future land use but rather explore possible agricultural transitions. Another set of LUC scenarios and crop management practices may provide results with different magnitudes of change. Therefore, these results should be interpreted with caution and ought to provide an indication of what changes may occur given these scenarios, and modelling tools.

6.6. Conclusion

Climate change simulations alone as well as climate change combined with land use change scenarios contributed to a deterioration of the future surface water quality in the Altmühl River. We found that CC simulations alone had a considerable impact on surface water quality, however when considering a wider scope of impacts on hydrology in a region, both climate change and land use change exerted a significantly amplified, negative, influence on TP and NO_3^--N distribution and transport than the climate change alone and therefore must be considered since the combined impacts may lead to additional significant increases in nutrient losses. In our study, mean annual NO_3^--N loads increased 3 fold, and TP loads 8 fold when LUC was combined with CC, compared to CC simulations alone. As well, nutrient loads were transported into the streams for a longer period during the year.

In turn, the increased loads affected concentrations of TP and NO_3^--N in streams. The months with lower than historic flows were especially critical for nutrient concentrations to be exceeded. Historically, maize contributes the most to TP loads during winter, and winter wheat contributes greatly to NO_3^--N loads from fall to spring. In the future, certain crops will have earlier seeding dates, higher fertilization rates and later harvesting dates, so that the period when TP loads are transported remain important in DJF with increased variability, and the period JJA becomes critical. NO_3^--N loads have more variability each month and increased loads were simulated to take place each month. Also, in all months the water quality criteria for TP and NO_3^--N were critically exceeded. Although TP concentrations are currently of greater concern in the Altmühl

Lake and River, rising NO_3^--N concentrations may become a real threat to water quality by the 2050 horizon.

The main causes for the deteriorated water quality (manifested by higher in-stream NO_3^--N and TP concentrations throughout the year), are due to a combination of the increased annual precipitation in future climate simulations and the additional fertilizer input into the system. In all LUC scenarios, fertilizer amounts were higher than in the REF to meet the needs of the increased biomass in the future growing season simulated in this region. It is unsure if other regions in Germany will be presented with similar crop management conditions in the future to the same extent.

In this study, the three land use change scenarios, although divergent in their agricultural changes, did not have distinctly diverse impacts on surface water quality when combined with the climate change simulations. The subbasin located upstream of the Altmühl Lake was pinpointed as a hotspot area for increasing maize. Therefore, targeting the implementation of beneficial practices in this particular subbasin may be paramount to achieving positive repercussions for improved water quality in the river and in the lake in the future.

6.S. Supplemental Material

Figures S6.1 depict the quantities of each crop located in every sub-basins in the Altmühl watershed for the three separate future land use scenarios. In each land use scenario, a comparison is made between the initial land use in 2008 and the final changes after 30 years.

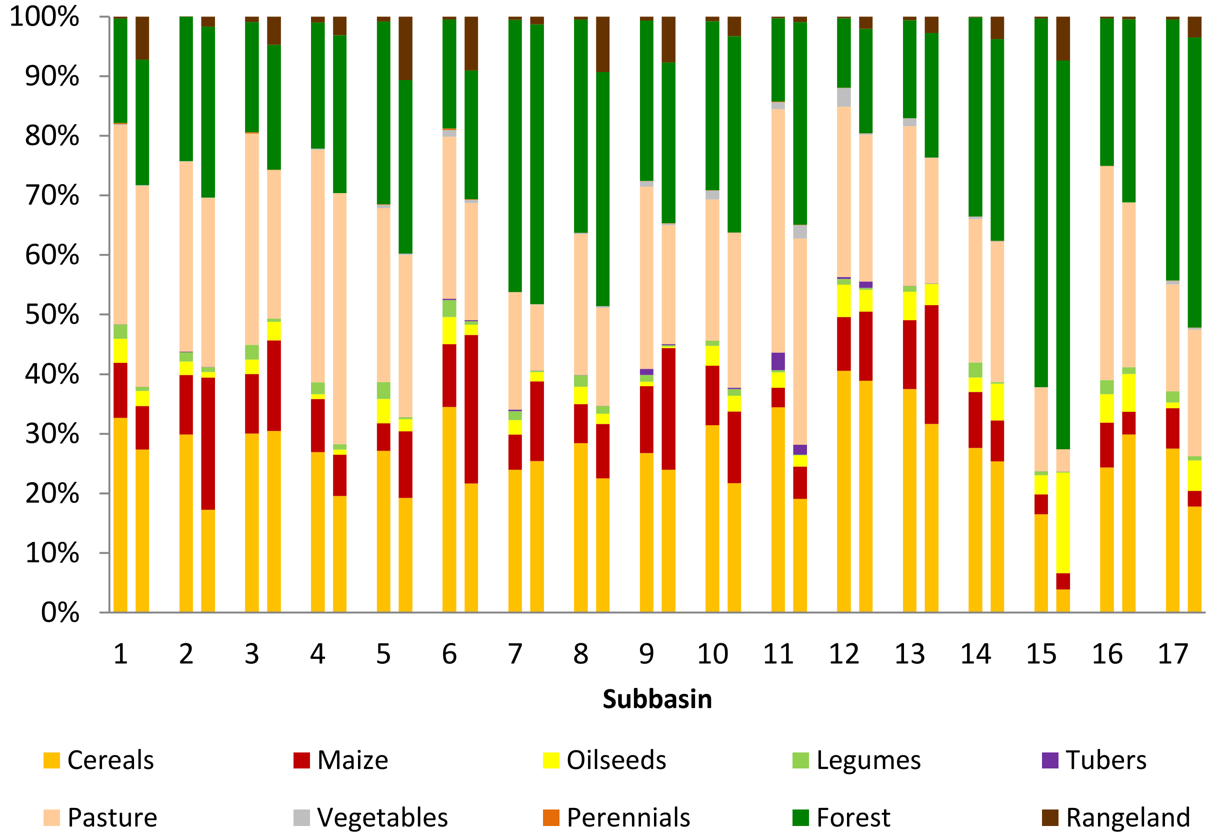


Figure S6.1a. BAU land use distribution per sub-basin. For each sub-basin, the initial land use of 2008 is represented by the left bar, and the final land use after 30 years of simulation is represented by the right bar.

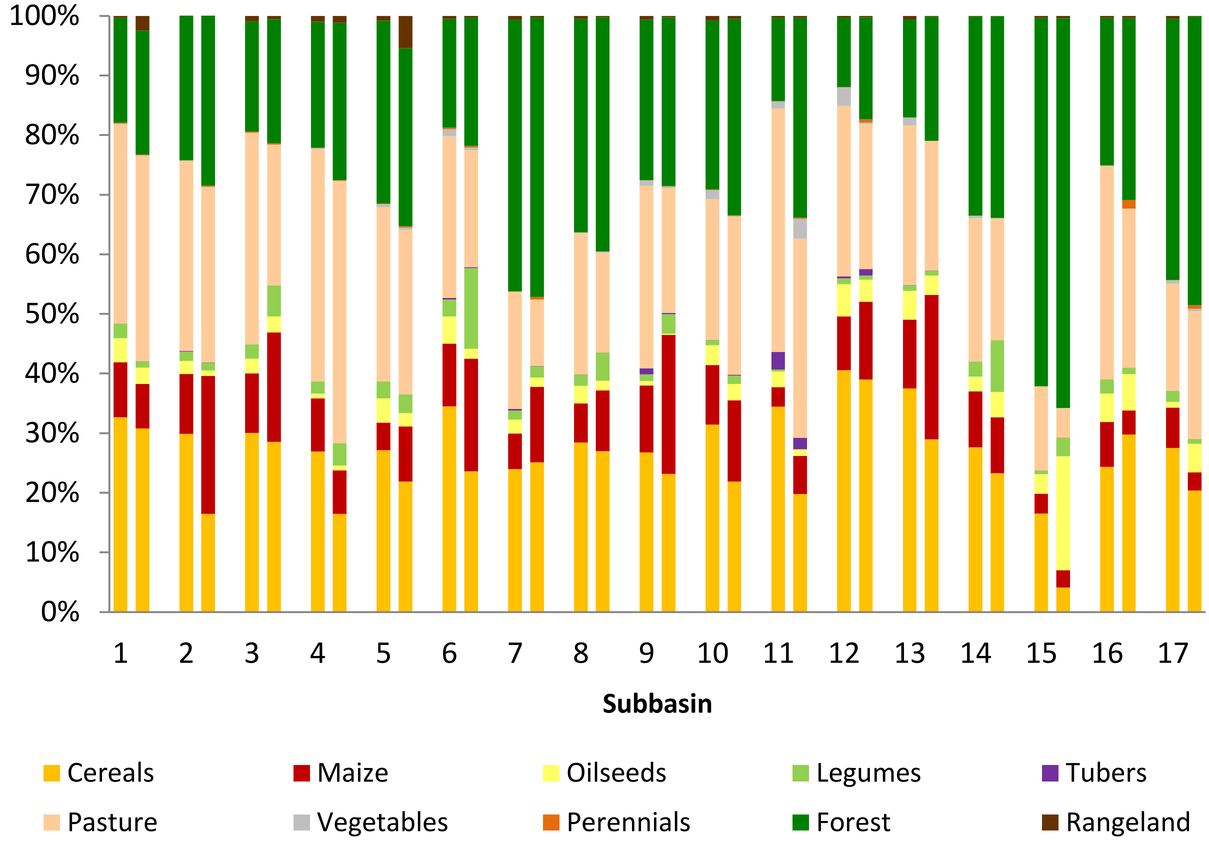


Figure S6.1b. FARM land use distribution per sub basin. For each sub-basin, the initial land use of 2008 is represented by the left bar, and the final land use after 30 years of simulation is represented by the right bar.

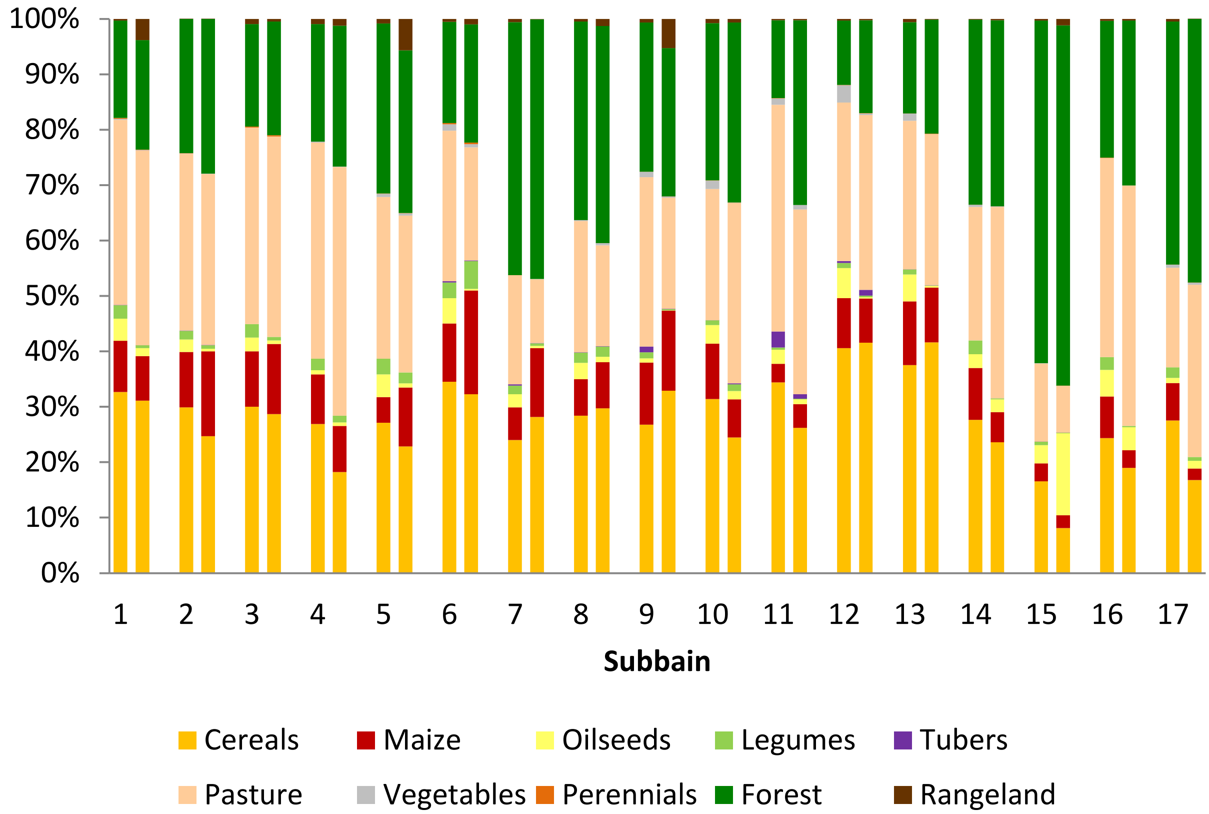


Figure S6.1c. CAP land use distribution per sub-basin. For each sub-basin, the initial land use of 2008 is represented by the left bar, and the final land use after 30 years of simulation is represented by the right bar.

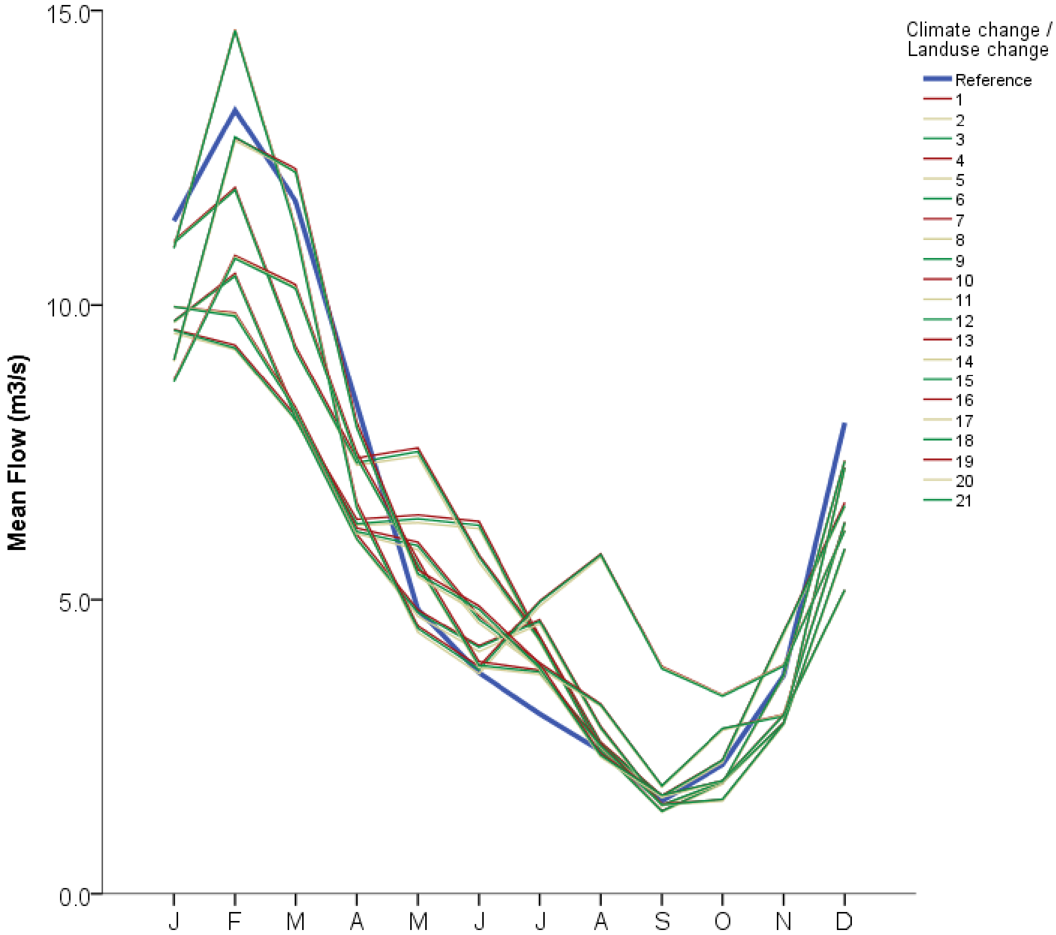


Figure S6.2. SWAT simulated stremflow at Treuchtlingen for the combined CC and LUC simulations (2041-2070). The dark blue line is the reference (1971-2000); red lines represent the BASE scenario with each of the climate simulations; green lines represent the FARM scenario with each of the climate simulations; light brown lines represent the CAP scenario with each of the climate simulations.

CONTEXT OF CHAPTER 7 WITHIN THESIS

The last study focuses on the Pike River watershed and builds on Chapter 6 by carrying out a similar but more elaborate version of the previous study. Here, all of the previous elements are tied together. I apply the suite of future climate simulations to the hydrological model individually, then I apply two future land use change scenarios to the hydrological model individually, and finally I combine two selected climate simulations with two land use scenarios to run each of these four combined scenarios in the hydrological model. By evaluating the magnitude of the climate change simulations and the land use scenarios separately in the hydrological model, I can determine if nutrient loads are impacted independently of climate change. This study also integrates the land use scenarios from Chapter 4.

As well, field-level adaptation strategies are examined. The importance of adaptation measures that can be applied today to reduce nutrient loads in the watershed are assessed by choosing one combined climate and land use change simulation and carrying out 3 scenarios of field level management changes that were guided by stakeholders. Determining the effectiveness of modelled field management adaptation practices to counter the combined impacts of climate change and agricultural land use change has not, to my knowledge, been carried out previously.

This chapter will be submitted to *Agriculture, Ecosystems & Environment*.

7. IMPLICATIONS OF AGRICULTURAL BEST MANAGEMENT PRACTICES ON SURFACE WATER QUALITY TO MITIGATE FUTURE CLIMATE CHANGE AND LAND USE CHANGE IMPACTS

7.1. Abstract

Scenarios of climate change and land use change were applied alone, and in combination, to the hydrological model SWAT to examine the impacts of potential changes on surface water quality for a 2050 time horizon in the Pike River (located in southern Québec/northern Vermont). From the simulations, one combined land use and climate scenario was chosen. Three adaptation scenarios (based on agricultural land management practices) were then developed together with stakeholders to determine the effectiveness of these adaptations to safeguard or improve surface water quality under future conditions. Results from the climate change simulations alone increased mean streamflow the most in February by up to 111%, and decreased it in April the most by up to 54% compared to the reference simulation (1971-2000). The median TP concentrations were higher during the winter months and lower in March. For the rest of the year they remain relatively unchanged. Decreases were modelled for NO_3^--N concentrations during the winter, but in April, they were higher than the reference simulation. Results from the land use scenarios alone in SWAT showed little impact on TP or NO_3^--N concentrations, likely due to the high inter-annual variability and to the conservative changes in the agricultural crop areas. When combining a climate change simulation with a land use change scenario in the SWAT model, the impacts to water quality were mostly driven by the climate change. The combined impacts of climate and land use change however, demonstrated a non-linear behavior. Thus, both changes must be considered for vulnerability, impact and adaptation studies to obtain the full scope of synergistic outcomes. The mean annual reference loads for sediments were 3740.8 ±885.3 Mg, for TP they were 35.5 ±13.2 Mg, and for NO_3^--N they were 1530.4 ±289.5 Mg. According to the scenarios of combined climate and land use change, the simulated impacts on surface water quality by 2041-2070 led to a deterioration of water quality. Additional mean annual sediment loads at the outlet increased by 301 ±201 Mg; additional mean TP loads by 9 ±4 Mg; and additional mean NO_3^--N loads by 151 ±74 Mg. If adaptation strategies are implemented to reduce the impacts caused by the most severe combination of climate and land use change

scenario, the transport of mean annual sediments can be statistically significantly reduced in SWAT by up to 2422 ±217 Mg; and the mean TP loads by up to 20 ±4 Mg. At the monthly time step, mean TP load reductions in winter, and mean NO_3^--N load reductions in winter, spring and fall were achieved that were below levels found in the reference simulation. Despite the reductions obtained by the adaptation scenarios, the water quality criterion of 0.02 mg/L for TP was not consistently attained for each month. Although there is substantial uncertainty in the rate and magnitude of the expected changes, this study presents a first model demonstration of how planned adaptation strategies can safeguard water quality from future changes that may occur in the basin.

7.2. Introduction

Although there is a wide range in the outcomes of climate change simulation, the future climate in Québec is expected to experience an increase in mean air temperatures and a greater amount of precipitation (Plummer et al., 2006; Vincent and Mekis, 2006; Yagouti et al., 2008). Beyond the negative impacts of a warming climate (e.g. increased temperature variability, higher precipitation intensities, flooding), crop production in Québec will be presented with several opportunities in the future, such as the possibility of earlier planting dates; multi harvests per year; planting higher value crops; and cultivating new areas of land (Ramankutty et al., 2002; Bootsma et al., 2004; Deryng et al., 2011).

Agricultural land use is determined by farmer decisions which are based on climate conditions, bio-geographic as well as socio-economic factors. Accordingly, agricultural land use is expected to evolve over time in response to various drivers (climate, market prices, regulations, etc.) and has the potential to negatively affect the quality of streams, rivers and lakes. For example expanding the area of particularly nutrient intensive crops in a watershed, such as maize, has an increasingly negative impact on the surface water quality (Schilling et al., 2008). The magnitude of such changes in a basin remains largely unknown.

Although very rarely applied, studies in temperate, humid regions examining the impacts of agricultural land area change in combination with climate change simulations on surface water quality show a tendency towards increased surface runoff and worsening water quality in spite of different land use changes and climate simulations applied; however detailed crop changes were not examined. These studies found the combined scenarios to increase runoff as well as the N and P loads (Park et al., 2011; Wu et al., 2012a). Research on the ability of adaptation scenarios to alleviate such impacts is not available.

Once the impacts of the climate change scenarios and of future land use on the surface water quality are determined, adequate adaptation strategies can be developed to mitigate some of the potential changes. Several researchers (e.g. Schröter et al., 2005; Scanlon et al., 2007) have stressed the need to conduct studies on the adequacy of existing water policies under the influence of anticipated future changes.

The Pike River is a sub-basin of the Missisquoi Bay, which was identified in 2002 by the Québec government as a priority watershed in need of integrated water resources management. The river is plagued with annual amounts of excessive nutrients, in particular total phosphorus (TP), which exceeds the Québec guidelines on surface water quality, as well as the TP limit set for the Missisquoi Bay (LCBP, 2013). The excess nutrients are an important factor contributing to the regular cyanobacteria algae blooms (Blais, 2002; Simoneau, 2007) that appear almost every year in the bay since 2000. The water management plan (*Plan Directeur de l'Eau*; PDE) for the Missisquoi Bay (OBVBM, 2011) outlines strategies to enhance water quality. Together with stakeholders from the Organisme de Bassin Versant de la Baie Missisquoi (OBVBM); Ministère de l'Agriculture, Pêcheries et Alimentation (MAPAQ); Ministère du Développement durable, Environnement, Faune et Parcs (MDDEFP); and the Centre d'expertise hydrique du Québec (CEHQ) we determined if adaptation strategies similar to those in the PDE are effective at improving water quality in the Pike River watershed under potential changes that may occur in the future.

The surface water quality in the Pike River was examined by simulating a variety of changes in a hydrological model: first, by applying future climate simulations only; then by applying alterations to the agricultural land use only; next, by applying a combination of climate change and land use change scenarios; and finally by simulating modifications to field management practices (adaptation strategies) suggested by stakeholders to improve the quality of the water. This approach allowed for the application of complex modelling tools to examine incremental impacts to the quality of surface water brought on by climate change and land use change scenarios. A main goal of the research is to identify the relative importance of the different changes (i.e. climate *versus* land use change) so that improved adaptation strategies can consequently be developed.

7.3. Methodology

7.3.1. Study area

The Pike River watershed covers an area of 629 km^2 and straddles the Province of Québec (530 km^2) and the State of Vermont (99 km^2), and is located at the northern tip of Lake Champlain (Figure 7.1). The elevation in the watershed ranges from 710 m to 50 m AMSL. The soils are predominantly clays (gleysolic) of marine and lacustrine origin situated in the low-lying areas. Calcareous tills and shale tills (brunisolic and podzolic) are found in the higher elevations (Deslandes et al., 2007).

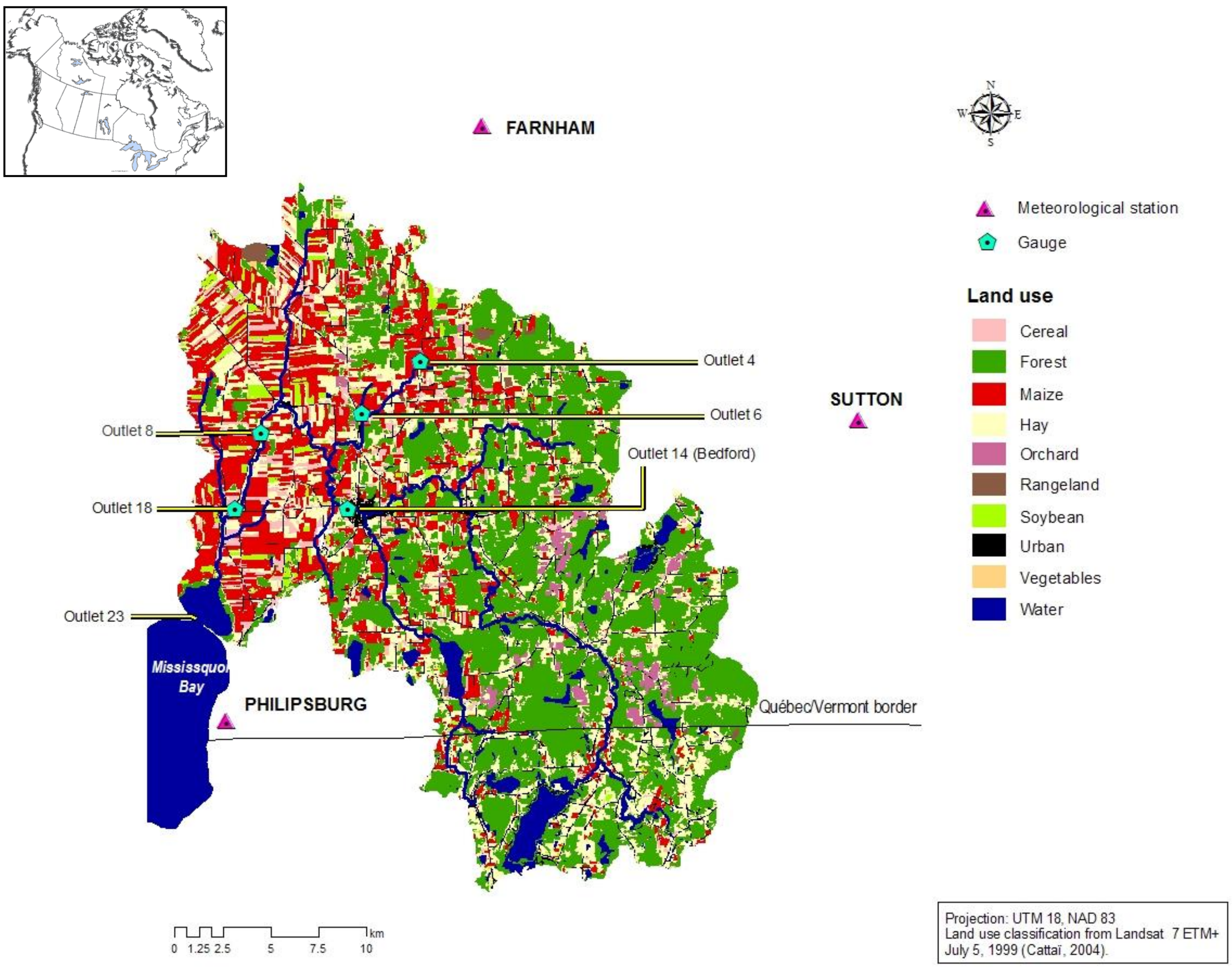


Figure 7.1. The Pike River watershed showing a land use configuration from 1999.

The basin receives approximately 1270 mm of annual precipitation of which approximately 235 mm is snow water equivalent (SWE). Snow falls mainly from November to April (Environment Canada, 2013). The mean annual measured discharge at the river outlet is 8.9 m^3/s (OBVBM, 2011). The hydrological regime of the basin is driven principally by snowmelt from March to April, with annual peak flows occurring in April and gradually decreasing to summer (June, July, August). The lowest flows occur during the growing season, in July. A normal growing season starts at the beginning of April and ends at the end of October. During this period, the average monthly surface air temperature is 14^{o}C and average monthly precipitation equals 105 mm. The temperature in mid-November drops to below freezing and remains so until March.

In 1999, almost 54% (339.7 km^2) of the watershed was under agricultural land use. A land use map from Landsat ETM+ imagery (Cattaï, 2004) shows the watershed composition to be: 22% hay, 20% maize, 8% cereal, 2% soybean, 2% orchard, 40% forest, 5% water and 1% urban. Approximately 75% of the area located west of the town of Bedford is cultivated land.

7.3.2. Hydrological model

The hydrological water quality model SWAT (Soil and Water Assessment Tool; Arnold et al., 1998) was used to evaluate the quality of surface water. SWAT is a comprehensive physically based, semi-distributed, continuous model operating at the daily time step, designed to simulate water quality of intensive agricultural watersheds, and developed specifically for the purpose of being able to allow for considerable spatial detail (Arnold et al., 1998). In this study, ArcSWAT2009 version 458, modified to incorporate tile drainage for Québec conditions (Michaud et al., 2008) was run on an ArcGIS 9.3.1 (ESRI 2009) platform. The SWAT model was based on a 30 m resolution digital elevation map (Deslandes et al., 2002). A Landsat 7 ETM+ image showing land use from July 5, 1999 (Cattaï, 2004) was used as the crop layer input. Crop sowing dates, fertilizer application and tillage operations were carried out as per Gombault (2012), with updated information from the *Financière Agricole du Québec* (unpublished data *État des cultures* available from www.fadq.qc.ca) and the *Guide de reference en fertilization*" (CRAAQ, 2010). Soil conservation operations were implemented according to Frère (2004) and "*Suivi 2007 du Portrait agroenvironnemental des fermes du Québec*" (BPR, 2008). Soil information was obtained from government soil surveys and studies of the region (Wischmeier et al., 1971; Tabi et al., 1990; Bernard, 1996; USDA-NRCS, 1999; Deslandes et al., 2002). The following mean fertilizer amounts were applied in SWAT and kept constant (unless stated otherwise) throughout all of the simulations.

Table 7.1. Average N and P fertilizer application per crop for the watershed.

	N mineral	N manure	P mineral	P manure	Total N	Total P
Corn	80.0	48.6	7.7	61.4	128.6	69.1
Hay	0	116.4	0	61.0	116.4	61.0
Cereals	78.8	32.2	15.4	35.5	111.0	50.8
Orchard	50.0	0	45.0	0	50.0	45.0
Vegetables	35.0	0	0	0	35.0	0
Switchgrass	0	25.0	0	0	25.0	0
Soybeans	0	0	0	0	0	0
Berries	80	0	40	0	80	40

The daily precipitation and temperature input for the reference period 1971-2000 stemmed from three Environment Canada (EC) meteorological stations: Philipsburg (45.03^{o}N, 73.08^{o}W), Sutton (45.07^{o}N, 72.68^{o}W), and Farnham (45.30^{o}N, 72.90^{o}W).

Although the Pike River is perhaps one of the most instrumented and well-monitored watersheds in Québec, there remain sparse and incomplete datasets for each gauge, especially for water quality. Multiple gauges (Tables 7.1a-b) were thus used to calibrate/validate the SWAT model during various time periods and for different variables. Any missing monthly data for TP and NO_3^--N during the evaluation period was interpolated by Michaud et al. (2004) using FLUX5.0 (Walker, 1998).

Table 7.2a. Measured surface water discharge data available (from CEHQ and IRDA) for calibration and validation of SWAT.

Gauge	Calibration	Validation
Outlet 14	1 Nov 2001 to 31 Oct 2006	1 Nov 2006 to 21 Nov 2011
Outlet 8	1 Nov 2001 to 31 Oct 2006	1 Nov 2006 to 21 Nov 2011
Outlet 4	1 Nov 2001 to 27 Apr 2004	1 Nov 2004 to 1 Nov 2006
Outlet 6	1 Nov 2001 to 27 Apr 2004	1 Nov 2004 to 1 Nov 2006
Outlet 8 (evaluation)		1 Sept 1979 to 21 Nov 2011

Table 7.2b. Measured water quality data for calibration / validation (from MDDEFP and IRDA).

Gauge	Calibration	Validation
Outlet 4	1 Nov 2001 to 1 May 2003	1 Nov 2004 to 1 Nov 2006
Outlet 6	1 Nov 2001 to 1 May 2003	1 Nov 2004 to 1 Nov 2006
Outlet 18 (evaluation)		1 Nov 1979 to 1 Sept 2007

Hydrologic Response Units (HRUs), which form the spatial units of the SWAT model, are based on similar slopes, soil types, and land uses; a total of 2786 HRUs were delineated in this project. All SWAT computations are calculated at the HRU level, based on the water balance equation. Streamflow, sediment and nutrient loadings from each HRU are aggregated at each sub-basin and then routed through the hydrological network (Neitsch et al., 2011). A 5-year warm up period was used for each SWAT simulation in this study.

The Sequential Uncertainty Fitting algorithm (SUFI-2; Abbaspour et al., 2004) was used for calibrating and validating SWAT. The parameters for the calibration were chosen based on a sensitivity analysis of the model. A sequential calibration was carried out for streamflow, sediments, total phosphorus (TP), and nitrate nitrogen (NO_3^--N). The parameter set that best satisfied the objective function was retained for implementation in SWAT.

The Nash-Sutcliffe Efficiency (NSE; Nash and Sutcliffe, 1970) was the primary objective function for calibration/validation, with a minimum criterion value of 0.5. Several other statistical criteria were used to evaluate the model performance (Table 7.3).

Table 7.3. SWAT performance criteria for simulated water quality variables during calibration and validation at the monthly time step.

	Calibration				**Validation**			
	Flow	Sediment	TP	NO_3^--N	Flow	Sediment	TP	NO_3^--N
	Outlet 8	*Outlet 6*			*Outlet 8*	*Outlet 6*		
NSE	0.83	0.16	0.81	0.72	0.78	-0.24	0.16	0.26
RSR	0.55	0.92	0.44	0.53	0.47	1.11	0.92	0.86
Pearson's R	0.91	0.79	0.91	0.90	0.91	0.29	0.45	0.59
R^2	0.84	0.63	0.84	0.82	0.82	0.08	0.20	0.35
PBIAS	7.76	61.24	13.01	16.41	9.77	7.61	17.86	-1.91
Flow NSE	-	0.64	0.64	0.64	-	0.42	0.42	0.42
	Outlet 14	*Outlet 4*			*Outlet 14*	*Outlet 4*		
NSE	0.83	0.66	0.80	0.77	0.75	-1.26	-0.12	0.43
RSR	0.41	0.59	0.45	0.48	0.50	1.60	1.06	0.76
Pearson's R	0.92	0.90	0.93	0.88	0.87	0.35	0.43	0.72
R^2	0.85	0.81	0.86	0.78	0.79	0.13	0.18	0.51
PBIAS	10.39	30.48	15.71	0.38	12.43	-42.64	-5.48	28.35
Flow NSE	-	0.67	0.67	0.67	-	0.49	0.49	0.49

The SWAT model was used to simulate streamflow, sediments, TP and NO_3^--N under historic and under future conditions. The reference simulation represents SWAT run with observed climate data from 1971-2000 and a static land use layer from 1999.

The main steps of this research depicted in Figure 7.2 are to:

i. select climate simulations for 2041-2070 from Regional Climate Models (RCMs), representing a range of future climate variables;
ii. develop land use scenarios based on drivers of land use change as well as on historical land use;
iii. determine the surface water quality resulting from changes in climate and in land use by means of a hydrological water quality model; and
iv. determine the impacts of adaptation strategies and their capacity to mitigate the simulated changes in water quality.

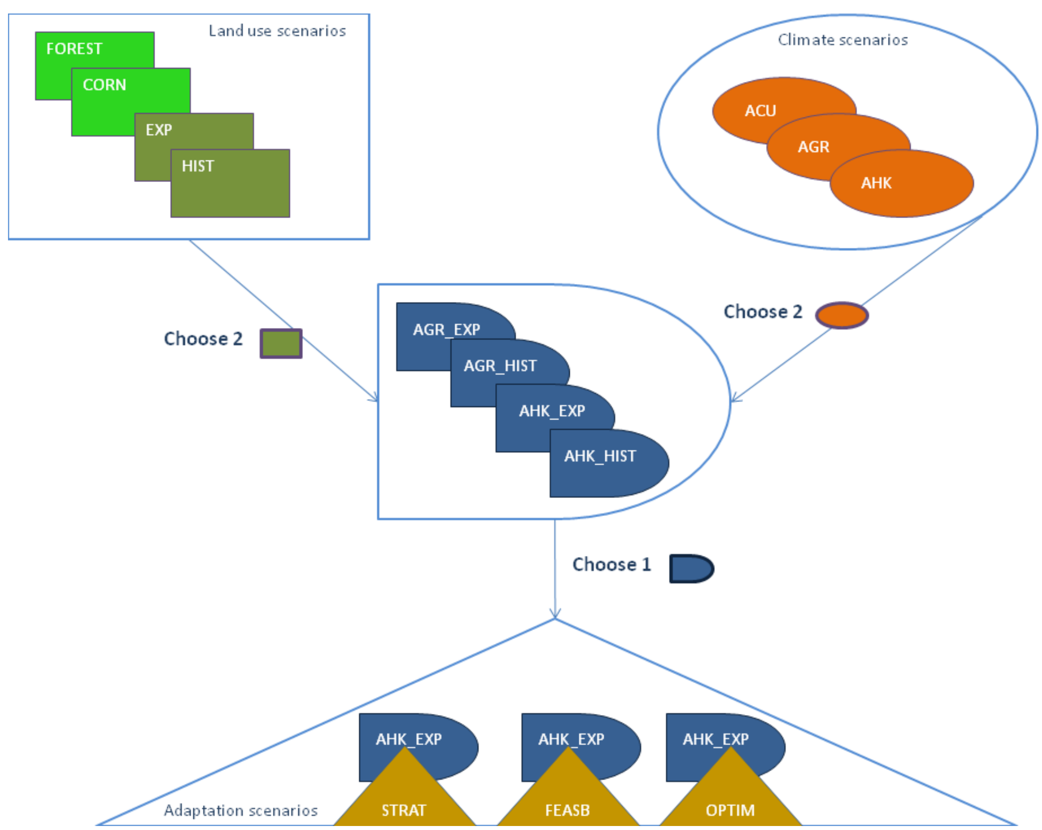


Figure 7.2. Schematic overview of the methodology, depicting that SWAT will be applied to every one of the coloured shapes.

7.3.3. *Future climate change simulations*

In collaboration with the Ouranos Consortium, a suite of climate simulations was selected (Table 7.4), each with a daily time step. The future period 2041-2070, representing the 2050 time horizon, was a medium time horizon chosen because the climate change signal only becomes apparent after 30 years (de Elía et al., 2013). Also, the 2050 horizon is relevant for the land use change scenarios because it is still close enough in the future that management decisions and policy actions remain applicable to the current generation of farmers and stakeholders.

Climate simulations from the RCMs were selected to provide future data because they are dynamically downscaled from Global Climate Models (GCMs) to better represent the physical climate of the mesoscale watershed conditions. Different versions and domains of the Canadian Regional Climate Model (CRCM; Paquin, 2010) were selected, each with a horizontal grid-size mesh of 45 km (true at 60° N). These were piloted by 2 different GCMs. All simulations used the A2 SRES greenhouse gas evolution scenario as developed by IPCC (Nakicenovic et al., 2000). The A2 scenario is a rather pessimistic scenario (but not the most pessimistic) in which expected CO_2 concentrations for the middle of the century are about 575 ppm. Current concentrations of CO_2 have surpassed 400 ppm (Monastersky, 2013).

Table 7.4. Properties of the three climate simulations chosen.

Name of simulation	**Regional Climate Model**	**Piloted by Global Climate Model**	**Regional domain cell*cell**	**SRES**	**Characteristics**
ACU	CRCM4.1.1	CGCM3-4	Québec 112*88	A2	Smallest changes in annual precipitation Largest changes in spring Tmin and Tmax
AGR	CRCM4.2.3	CGCM3-5	Québec 112*88	A2	Smallest changes in 95th percentile of summer precipitation Largest changes in winter Tmin and Tmax
AHI-AHK	CRCM4.2.3	ECHAM5-2	North America 182*174	A2	Greatest changes to annual precipitation Greater changes in 95th percentile of summer and fall precipitation Smallest winter and spring changes in Tmin and Tmax

Since only a limited amount of simulations were run due to resource constraints, the climate simulations were selected based on the sensitivity of SWAT to important climate parameters. Gombault (2012) determined that the changes in minimum and maximum temperatures in winter and in spring, and the changes in total annual precipitation amounts were parameters to which SWAT was sensitive to. As well as extreme precipitation events; therefore changes to the 95th percentiles of precipitation in spring, summer and fall were also included during the selection of the climate simulations.

The cluster analysis method (Houle et al., 2012) enabled climate simulations to be chosen so that the variability of the future changes (with respect to the above defined climate variables) covers approximately 50% of all 16 regional climate simulations available at Ouranos at the time. Thus, the climate simulations selected have different characteristics, and provide a suitable coverage of the available simulations. The values of the climate variables were relevant for the south of Québec.

The three climate simulations chosen were denoted according to their operational name: ACU, AGR and AHI-AHK. In this study, the following codes are used to denote the simulations: ACU, AGR and AHK, respectively.

The CRCM temperature and precipitation data in all of the simulations were bias corrected based on observed station data from Philipsburg, Farnham and Sutton using the “daily translation” method by Mpelasoka and Chiew (2009).

Each sub-basin in SWAT obtains its historic meteorological data from the weather station located nearest to its centroid. For the future climate simulations, data generated from the CRCM from three tiles each at a horizontal resolution of 45 km (true at 60^{o} N) (Plummer et al., 2006) were used to obtain a complete coverage of the Pike River watershed. The bias corrected climate data from each of the CRCM tiles was relegated to the corresponding nearest meteorological station, so that the CRCM tile with centroid [44.80^{o}N, 73.05^{o}W] was allocated to Philipsburg; the CRCM tile with centroid [45.07^{o}N, 72.71^{o}W] was allocated to Sutton; and the CRCM tile with centroid [45.32^{o}N, 73.10^{o}W] was allocated to Farnham.

7.3.4. *Future land use change scenarios*

Two scenarios of future agricultural land use change were developed with stakeholders by building scenario storylines. Storylines are based on causal relationships within a system that cannot be quantified. Storylines are used to develop qualitative scenarios that reflect assumptions about the drivers of change and that are coherent with available quantitative data. The first scenario was based on historic trends of changes that took place in the watershed (HIST), and the second was based on expert/stakeholder input of potential land use change (EXP).

<u>Land use scenario Historical Trends (HIST)</u>

The HIST scenario examined changes in agricultural land that would occur in the Pike River watershed if farmers continue to do as in the past. Thus, the scenario reflects several factors, including the historic market trends, the past crop insurances available for farmers, and consequent choices of crops that result.

The historic land use trends were projected for the next 30 years by extrapolating the land use changes from 2003-2011. Historical land use in the basin was determined from several digital and stakeholder sources. A 2001 forest cover was obtained from the *Système d'information écoforestière* (available from Québec Ministry of Natural Resources www.mrn.gouv.qc.ca); the spatial distribution of crops in Québec from 2003-2011 stemmed from the *Financière Agricole du Québec* (FADQ, 2011); farm data from 2003 to 2011 collected by MAPAQ (*données d'occupation du sol des fiches d'enregistrement*) was used to complement missing crop data; crop cover for Vermont from 2008 to 2011 stemmed from CropScape (USDA-NASS, available from www.nassgeodata.gmu.edu). The Québec government data had a category of "other agricultural land" which referred to unclassified agricultural land with wide row spacing. There was no specific information available however, so in SWAT it is fertilized according to the same regime as maize.

<u>Land use scenario Expert Guided (EXP)</u>

This scenario was developed from information gathered from farmers and through consultations with stakeholders. A questionnaire was compiled, together with the farmers union, provincial ministries and the local watershed organization (Union des Producteurs Agricoles (UPA), MAPAQ, MDDEFP, OBVBM) regarding why crop changes had taken place historically on the farm, and what factors would bring about a possible change of crops in the future. The questionnaire was answered by two independent groups of farmers; a) farmers with fields located in the Pike River watershed (n=210), and b) agricultural students (n=23) in their third year of the Farm Management and Technology Diploma Program at McGill University, in Ste-Anne-de-Bellevue (Québec).

Further drivers of land use change were considered through a literature review of existing policies, market forces and other drivers. A study on analogous climate (Gagnon et al., 2013) showed the future climate (2050 horizon) in the watershed to be similar to that of the U.S. Corn Belt (Iowa, Illinois, Indiana, Ohio and Pennsylvania). Most of the crops grown in these states are maize and soybean. However, the study also suggests that vegetables, orchards and vineyards will be suitable. Based on all of this information, a storyline of land use change was developed for the next 30 years.

Extreme land use scenarios

In addition to the stakeholder scenarios, two "extreme" scenarios were developed by changing the land use directly in the SWAT model. The extreme scenarios were applied to determine the maximum range of nutrient transport that can be simulated with the current SWAT set-up, and to provide insights in the model behaviour under radical land use changes.

The first extreme scenario (CORN) consisted of the watershed entirely seeded to grain corn, leaving only the urban and water areas intact. The maize is planted on May 12 each year and fertilized with 130 kg N/ha and 66.7 kg P/ha in split applications. These management practices were based on the average rates applied to maize during the calibration and validation periods.

The second extreme scenario (FOREST) consisted of the entire watershed under a mature mixed forest cover; except the urban and water areas. In this scenario, the initial concentration of NO_3^--N in the shallow aquifer parameter (SHALLST_N) was altered. During the calibration, the sections of the watershed that were mostly forested were assigned a value of 25 mg/L, while the sections that were mostly agriculture had a value 72 mg/L. In this scenario, since the land use is forest, the shallow aquifer NO_3^--N was reduced to 25 mg/L.

In both extreme scenarios, only the curve numbers (CN) were adjusted according to the extreme vegetation type. It should be noted that the extreme scenarios were not ideally represented in

SWAT, since the model was initially set-up for the land use of 1999 with its corresponding parameters. Consequently, most of the parameters (e.g. evaporation coefficients, groundwater recharge, snowmelt coefficients, etc.) remained unchanged although they may not be suited to appropriately portray the extreme land uses. We assume that this representation of the extreme scenarios attenuates the amplitude of the corresponding model results.

Spatially distributing the HIST and EXP land use scenarios

To spatially distribute the land areas each year in the HIST and EXP scenarios, the CLUE-S model (Conversion of Land Use and its Effects-Small scale; Verburg et al., 2002) was used. CLUE-S is a dynamic model that draws on empirically quantified relationships (logistic regressions) between the historic driving forces of changing land use patterns (e.g. soil type, distance to market, demographics, etc.) in combination with iterations of land use competition based on user-defined elasticity of change and the logistic regressions. For each storyline, the areas of land use, for every year, were input into CLUE-S which spatially distributed the land uses to yield one raster layer of land use per year.

The coupling of the land use layers from CLUE-S into SWAT was carried out using SWAT2009_LUC (Pai and Saraswat, 2011) which can accept the CLUE-S rasters as input and calculates the changed area fraction of each HRU for each layer (i.e. every year) and transmits this information to SWAT. The SWAT2009_LUC tool maintains physical autocorrelation of soil and slope whenever possible in each sub-basin. The described scenario values were somewhat modified in the coupling process with the SWAT model through SWAT2009_LUC tool (for more details see 7.4.2).

The land use scenarios were developed for a near- to mid-term future (for the next 30 years) because Veldkamp and Fresco (1996) and Verburg et al. (1999) recommend that the “realistic” time horizon for simulating land use change should be limited to no more than 20 to 30 years in the future. Technology, crop varieties and other changes may occur beyond this time period that cannot be captured. Furthermore, the logistic regressions in CLUE-S do not evolve, and hence the assumption that the relationships will remain valid over long periods of time is not realistic.

7.3.5. Determining climate change and land use change impacts on water quality

To determine the combined impacts of both climate change and land use change on the future surface water quality in the Pike River, four simulations were carried out with SWAT consisting of a combination of two climate change simulations and two land use change scenarios.

Therefore, two out of the three climate simulations were chosen with the stakeholders to be combined with the land use scenarios. The SWAT outputs, after being run with each of the climate simulations, were examined and the two simulations that provided the greatest range of difference in the water quality results were chosen. Both of these climate simulations were then run in turn with each of the land use change scenarios (HIST and EXP) in SWAT, to provide four combined scenarios.

In the four combined scenarios, the seeding date of maize was shifted 12 days earlier (Deryng et al., 2011) to account for a warmer climate and an extended growing season; however, harvest dates were maintained. In addition, hay was cut four times instead of three times a year (the manure application remained the same, since we assumed the livestock densities would not increase).

We also assumed that farmers will adapt fertilizer amounts to meet the maximum potential yields. Preliminary SWAT tests showed maize had the greatest response to increased fertilization; other crops did not show a noteworthy response. Thus, for maize, adjusted fertilizer rates were calculated per HRU by taking into account the ratio of historic fertilizer applied per unit biomass of maize obtained per HRU, and applying that ratio to the future (tests showed that an increase of 50% N fertilizer application produced the maximum attainable biomass). The following equation was used to adjust the amounts of fertilizer for maize: $N_{app} = (N_{app}\_hist / Biomass\_hist) \times MaxBiomass\_fut$

where, N_{app} is the amount of adjusted N fertilizer applied; *Napp_hist* is the previous amount of N applied; *Biomass_hist* is the previous mean biomass attained; and *MaxBiomass_fut* is the biomass achieved with the 50% increase in N fertilizer. The same equation was used for calculating new P amounts for maize, but replacing N_{app} with P_{app}.

7.3.6. Adaptation strategies to improve surface water quality

The water management plan (PDE) of the OBVBM defines several actions to improve surface water quality in the basin (e.g. increasing the area under conservation tillage, adding buffer strips, or stabilizing and vegetating river banks) and was conceived as part of Québec's Water Policy. The PDE was used to initiate a discussion with stakeholders (UPA, OBVBM, MAPAQ, and CEHQ) on targeted actions that can be implemented to reduce the vulnerability of the basin to deteriorating water quality under potential future conditions. In this study we considered only strategies related to the management practices of fields and local lands which are physically based and can be modelled in SWAT by adjusting necessary parameters.

Three adaptation scenarios, each comprising a suite of actions for improving water quality were modelled:

<u>Strategic scenario (STRAT)</u>

The STRAT scenario aims to reduce non-point source pollution from the most problematic lands in recent history. The scenario targets a reduction in TP transport from the fields that are most erosion prone and which lose the most TP. In a previous study (Michaud et al., 2007), SWAT was used as a decision support system to define optimal land uses and field management changes that would provide at least a 41% reduction in TP loads into the Missisquoi Bay, and thus achieve an acceptable water quality at the basin outlet.

The aim of the STRAT scenario is to replicate the same management strategies that were most effective in the Michaud et al. (2007) study, but this time with the future climate and agricultural land use changes. This approach allows determining whether these strategies are also effective in light of the potential changes that may take place in the basin.

The following adaptation strategies were implemented based on reconstituting the major elements of scenario #21 in Michaud et al. (2007), which resulted in the most TP reduction (41%) at the outlet:

i. The 10% of cultivated areas (not including hay) most susceptible to TP export (1795 ha) were converted to tall fescue that was not harvested and had no manure application.
ii. Next, soil conservation practices were randomly implemented on 45% of cultivated areas (7875 ha) as follows: maize, soybean, and cereals on soils pertaining to soil hydrological

groups A and B were converted to no-tillage. The same crops on soils pertaining to hydrological group C and D were converted to reduced tillage.

iii. Buffer strips (3 m wide) were implemented on all HRUs adjacent to a stream.

iv. All manure application was incorporated within 24 hours after spreading.

v. A 4% reduction of TP and a 5% reduction in sediment loads at the basin outlet were applied to simulate the implementation of runoff control structures (Hickenbottom inlets).

Feasible scenario (FEASB)

The FEASB scenario implements straightforward management strategies that can be carried out in the short-term by farmers in the watershed. This scenario was developed to implement practices that were the most practical for the agricultural sector to apply immediately, by targeting the "low hanging fruits":

i. On the 10% of cultivated areas (not including hay) which export the most TP (1795 ha), a cover crop was implemented after the harvest as follows: maize was intercropped with rye-grass in June; summer cereals were intercropped with clover in May; and soybean were intercropped with rye cereal in September (after the leaves dropped).

ii. The next most problematic 10% of cultivated areas prone to transport of sediments were taken out of production and converted to switchgrass (1967 ha). Switchgrass was harvested once a year and fertilized with 25 kg/ha of mineral N after harvest in May.

iii. Buffer strips (3 m wide) were implemented on all HRUs adjacent to a river.

Optimistic scenario (OPTIM)

This scenario implements the best knowledge on management strategies to reduce non-point source pollution, including undertaking organic farming on all of the crops:

i. No application of mineral fertilizer was undertaken; only organic fertilizer (swine manure) was applied. This was incorporated within 24 hours after spreading.

ii. Conventional tillage was replaced with reduced tillage on soil hydrological groups C or D, and by no-tillage on soil hydrological groups A and B.

iii. A cover crop (red clover) was seeded after the maize was harvested. After cereals were harvested, alfalfa was seeded in late summer; this was cut 3 times during the following growing season, left over-winter and killed before seeding maize in spring.

iv. All cash crops had the following rotation: maize – soybean - summer cereals - alfalfa.

v. Buffer strips (3 m wide) were implemented in all HRUs that were adjacent to the river.

vi. Agro-forestry (poplars, 20% biomass harvested every 4 years) was undertaken on all slopes greater than 8.5% in the watershed (as determined from the DEM with ArcGIS, which represented 3100 ha.

7.4. Results

The calibration and validation of SWAT were overall acceptable as per Gassman et al. (2007) and Moriasi et al. (2007). The results for streamflow showed a satisfactory SWAT performance (Table 7.3) and the simulation of nutrients were quite satisfactory during the calibration stage; except for the sediment values which were underestimated compared to observed values. The validation of nutrients had a rather poor model performance (although this is not unusual (Gupta et al., 2009), and was attributed to the weaker simulation of streamflow during this period. The SWAT model has rarely been calibrated/validated on all four variables with satisfactory evaluation criteria for all four variables (Gassman et al., 2007).

In the following, the modelled outputs for streamflow, sediment, TP and NO_3^--N are mostly shown as changes in the monthly means of the simulated scenarios compared to the reference simulation in SWAT. The absolute monthly values for the reference simulation are given in Table 7.5. This approach of analyzing changes rather than showing the absolute future values reduces the hydrological model prejudice related to systematic biases in the results. When the absolute values are depicted, they are presented as boxplots and with the reference simulation as a comparison.

Independent t-tests, with a significance level of 0.05, were carried out to determine significant differences of interest between the reference simulation and each modelled simulation.

7.4.1. Climate change impacts on water quality

The future climate simulations for the Pike River basin showed a higher increase in T_{min} than in T_{max}. Generally, the mean monthly T_{min} increase the most for the AGR simulation, and least for the AHK, with the most change occurring from November to March (up to 5.8^{o}C) . The mean monthly T_{max} increases most for the AGR and least for the AHK, with future changes in the range of 1 - 4^{o}C.

Average yearly precipitation increases for ACU were 66.4 mm; for AGR 98.4 mm; and for AHK 101.9 mm. However, the increases were not evenly distributed throughout the year. Most of the mean monthly precipitation increase took place in March, April, May, November and December. In the months from July to September few differences were simulated, and some precipitation decreases occurred from June to October and from January to February.

Table 7.5. Absolute monthly values for the reference simulation (1971-2000).

Month	**Flow (m^3/s)**	**Sediments (kg/ha)**	**TP (kg/ha)**	**NO_3^--N (kg/ha)**
1	7.84	3.45	0.06	2.05
2	8.34	3.45	0.04	1.57
3	25.66	12.92	0.19	3.50
4	29.10	14.15	0.11	3.00
5	6.85	3.08	0.02	1.31
6	3.73	1.51	0.01	0.77
7	2.54	1.01	0.01	0.38
8	3.10	1.21	0.01	0.65
9	5.18	2.15	0.01	1.42
10	11.48	5.29	0.03	3.09
11	13.15	5.96	0.04	3.52
12	10.70	5.02	0.04	2.95
Annual	9.75	59.21	0.57	24.21

Nutrient loads

The three climate simulations were applied to SWAT, one at a time, in lieu of the observed meteorological data (reference simulation). Due to the greater mean annual precipitation amounts, the climate change simulations increase the mean annual flow (in the order of 1 m^3/s), and the mean annual sediment loads by 27 - 266 Mg/yr. The mean annual TP loads remain for the most part unchanged (0 - 2 Mg/yr increases), however the mean annual NO_3^--N loads increased substantially (152 - 227 Mg/yr). Annual results are presented in Table 7.6.

Table 7.6. Mean annual variables (with standard deviations) for the reference simulation (1971-2000) and for simulations (2041-2070), at the basin outlet.

	Flow (m^3/s)	**Sediments (Mg/yr)**	**TP (Mg/yr)**	**NO_3^--N (Mg/yr)**
Reference	10.6 ±2.1	3740.8 ±885.3	35.5 ±13.2	1530.4 ±289.5
ACU	11.1 ±1.7	3767.4 ±570.3	35.3 ±12.6	1683.3 ±282.7
AGR	11.7 ±1.9	4007.2 ±642.3	37.7 ±12.4	1743.4 ±284.6
AHK	11.5 ±2.2	3843.2 ±784.2	36.3 ±16.8	1757.3 ±293.6
HIST	10.8 ±2.1	3794.1 ±902.9	42.8 ±16.3	1512.1 ±282.3
EXP	10.7 ±2.1	3767.9 ±896.8	41.8 ±16.0	1552.7 ±291.8
AGR_EXP	11.7 ±1.9	4020.8 ±649.3	43.9 ±15.0	1627.3 ±281.5
AGR_HIST	11.8 ±1.9	4042.1 ±656.1	44.3 ±15.0	1589.8 ±268.6
AHK_EXP	11.5 ±2.2	3908.6 ±817.3	41.7 ±19.8	1681.8 ±286.0
AHK_HIST	11.6 ±2.2	3927.8 ±823.2	42.1 ±19.6	1639.7 ±272.2

At the monthly time step, future precipitation from the climate simulations increase in March, April and May. Yet, in all SWAT simulations, the month of April has a statistically significant ($p<0.05$) decrease in streamflow (Table S7.1). This indicates an earlier spring peak flow, shifting from April to March in the future. Overall, there is less snowfall (11 - 13 mm less SWE) in the future, creating less snowpack. The peak flow occurs one month earlier than in the reference simulation (Figure 7.3), and is lower (mean monthly values ranging from 20 – 25 m^3/s in March, instead of almost 30 m^3/s in April).

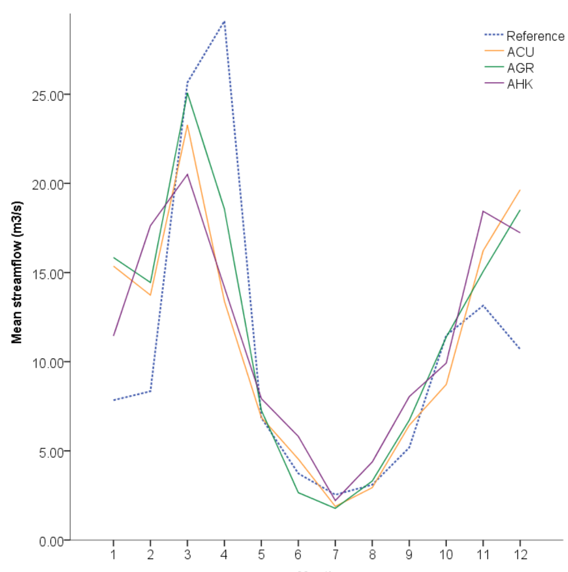


Figure 7.3. SWAT simulated streamflow for the reference simulation (1971-2000) and the future climate simulations (2041-2070).

When the ACU and AGR simulations were applied to SWAT, statistically significant increases in future streamflow of 65% - 102% from December to February were simulated. In AHK, the streamflow in November, December, February and September was statistically significantly higher by 40 to 111%. The greatest increase in streamflow compared to the reference simulation was simulated in the month of February (65% to 111%); the month of April showed the greatest decrease (36% to 54%). During the months from May to September, when the precipitation has the least relative change compared to the reference simulation, few changes to streamflow were simulated to take place in the future.

These results concord well with the *Atlas hydroclimatique du Québec méridional* (CEHQ, 2013). Minor differences (i.e. less infiltration and higher surface runoff volumes in spring and fall) were attributed to the SWAT model having parameters governing sub-surface field drains that reduce surface runoff. Also, the curve number parameter is adjusted in SWAT to accommodate any changes in soil cover and tillage, so that after harvest a higher CN is specified (especially in the absence of plant residues).

Nutrient concentrations

A primary concern is whether the quality of water in the Pike River and its tributaries will exceed the water quality criteria, as per the Québec criteria for surface water quality (MDDEFP, 2002). Therefore nutrient concentrations (which are based on mean monthly nutrient loads together with the mean monthly streamflow volumes) at the basin outlet were examined.

Only in the months of December, January and February was the median concentration of TP negatively impacted by the climate change. The increase in SWAT simulated mean TP loads during these months lead to greater TP concentrations at the outlet for at least one of the simulations, and this despite the increases in mean flow during these months. Whereas in March, the increased future mean flow coupled with mean TP loads similar to the reference simulation, caused future TP concentrations to be reduced. In April, when both the mean streamflow and the mean TP loads were statistically significantly lower, the overall monthly median TP concentration was not affected by the climate simulations. The TP concentrations almost never met the water quality criterion of 0.02 mg/L (only in 2 of 1080 mean monthly values as calculated for 30 years and 3 climate simulations).

For median NO_3^--N concentrations, generally, the months with the highest increase in flow (December, January and February) also had lower concentrations compared to the reference simulation. In April, the median NO_3^--N was slightly higher than the reference, despite the statistically significantly lower streamflow and lower NO_3^--N loads, because NO_3^--N was transported by throughflow. For the remaining months, the variability of NO_3^--N remained within the same range as the reference simulation. The climate change simulations did not alter the fact that the concentrations of NO_3^--N rarely exceeded the water quality criterion of 10 mg/L (in only 8 of 1080 mean monthly values).

7.4.2. Land use change impacts on water quality

Due to the coupling of the CLUE-S raster layers in SWAT with the SWAT2009_LUC tool, some of the desired land use changes did not occur in SWAT as prescribed by CLUE-S. According to the developers of the coupling tool SWAT2009_LUC (Pai and Saraswat, 2011), a 5-10% deviation in the area of land use per sub-basin may occur when HRU thresholds are provided in the model set-up. We found such deviations and also up to 30% for hay in one basin. Even with these divergences, the scenarios represent the closest possible match that could be achieved in the coupling process by using the transfer tool SWAT2009_LUC. Despite its limitations and obvious distortions, this tool ensures that the overall model consistency remains intact and that no re-calibration is required, which would alter the existing model set-up and consequently limit the interpretation of the results. The transferred scenarios still represent plausible pathways of future land use change following the prescribed HIST and EXP storylines (Figure 7.4).

Historically, from 2003 to 2011, the area under agriculture increased from 33740 ha to 34010 ha (0.4%). Soybean area increased the most by 2335 ha (3.7%), while other areas decreased; maize by 549 ha (0.9%), cereal areas by 358 ha (0.6%), forest areas by 315 ha (0.5%), and rangeland by 189 ha (0.3%). The success of recent soybean introduction in Québec is due to its promotion to farmers by the MAPAQ, as well as due to an available market, and to a successful insertion into the crop rotation with maize. The areas of soybean have therefore increased quite rapidly in the past 20 years, and this trend was captured here.

Thus, in the HIST scenario, after 30 years of land use evolution (Table 7.7), forested areas continue to decline (1040 ha; 1.7%) partly at the price of urban expansion. The agricultural land also expands to 35320 ha (56%) as mainly rangeland is cut down (loss of 680 ha; 1.1%) with soybean occupying a dominant role (increase of 4757 ha; 7.5%). Berry and vegetable areas also increase (814 ha; 1.3%). The areas planted to maize are reduced the most by 2568 ha (4.1%). Cereals areas decline (680 ha; 1.1%) as do niche crops such as orchards, switchgrass and other agricultural land ("other ag land" represents unknown agricultural land and is fertilized according to the same regime as maize in SWAT).

Overall in the EXP scenario, after 30 years (Table 7.8), the quantity and distribution of crops alters, but the total agricultural land area remains constant (occupying 54% of the basin). The forested area is protected by a law introduced in 2004 (*Loi sur l'aménagment et l'urbanisme*) and remains stable at 24140 ha (38.2%), as does the area of rangeland 1240 ha (2%). Maize is an important crop (increases by 936 ha; 3.9%), but soybean declines (by 77 ha; 0.4%). Cereal areas increase slightly (by 65 ha; 0.1%). There is more crop diversity due to an increase in new markets driven by the young entrepreneurs. Switchgrass (potential biofuel), vegetables (sweet corn, squash), strawberries and orchards areas increase (cherry replace the apple trees).

Table 7.7. Scenario "Historical Trends Continue" (HIST), percentages of crop areas in the watershed.

	Land use type											
	Other ag land	Orchard	Hay	Forest	Rangeland	Maize	Cereal	Soybean	Vegetables	Urban	Berries	Switchgrass
2011	14.0	1.6	12.8	38.4	2.0	16.7	1.1	5.1	0.4	2.4	0.0	0.2
2040	11.7	1.3	12.1	36.7	0.00	12.4	0.0	16.7	1.6	2.6	0.1	0.1

Table 7.8. Scenario "Expert Guided" (EXP), percentages of crop areas in the watershed.

	Land use type									
	Other ag land	Orchard	Hay	Forest	Rangeland	Maize	Cereal	Soybean	Vegetables	Urban	Switchgrass
2011	14.6	1.6	12.8	38.8	2.0	16.7	1.1	5.1	0.4	2.4	0.2
2040	10.9	1.6	12.1	38.2	2.0	20.6	1.2	5.5	0.6	2.6	0.1

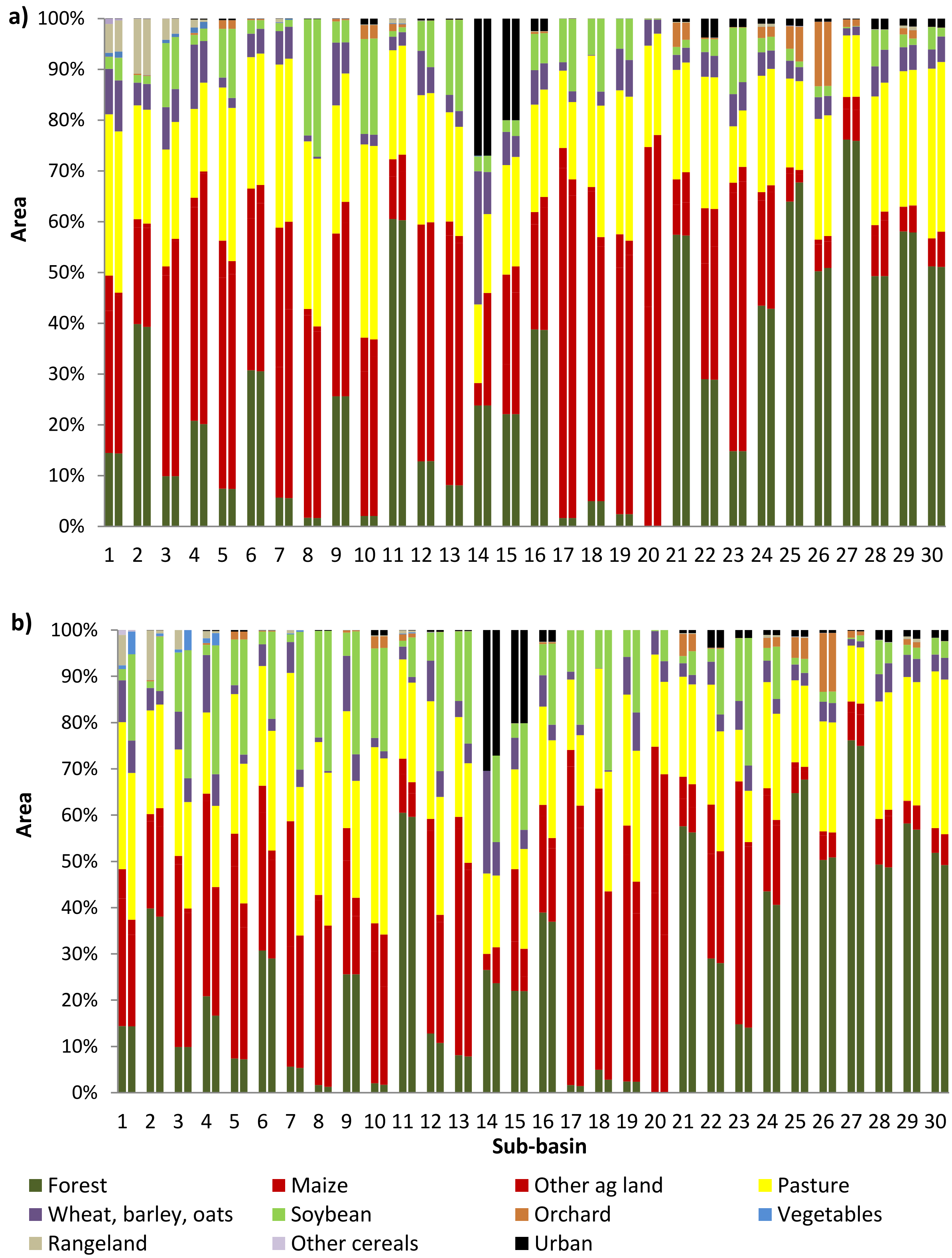


Figure 7.4. Land use change per sub-basin for a) EXP scenario and b) HIST scenario. Bars on the left in each sub-basin represent Year 1, and bars on the right represent Year 30 of simulation.

Nutrient loads

The mean annual streamflow from the land use scenarios compared to the reference simulation was not greatly impacted. Although the land use changes brought about an increase in mean annual sediment and TP loads, it was not statistically significant due to the high standard deviations. There was no statistically significant change in mean annual NO_3^--N loads.

The mean monthly streamflow, sediments, TP and NO_3^--N loads were also not statistically significantly different from the reference simulation (Table S7.2). The cumulative land use changes in both scenarios led to, on average, no alternations in the water quality at the outlet of the basin.

Nutrient concentrations

For both land use scenarios, the simulated in-stream concentrations of nutrients were similar to the reference simulation, and were not statistically significantly different in any of the months. The water quality criterion for TP was not met in the land use simulations (Figure 7.5); the mean monthly values were always above 0.02 mg/L. On the other hand, the mean monthly values for the water quality criterion of 10 mg/L for NO_3^--N was only exceeded once in January by each of the land use change scenarios (Figure 7.6).

Extreme scenarios

Maize has a row-spacing of 75 cm and also has shallow roots; both these factors are conducive to surface sealing, surface runoff, rill erosion and low infiltration. Thus, for the CORN scenario, the mean streamflow was higher almost every month compared to the reference simulation. Only in August and September was lower streamflow simulated because these months have less baseflow (aquifer recharge) available to sustain the summer low flows due to low groundwater recharge (similar model results were found by Schilling et al. (2008) when 93% of a macroscale watershed in Iowa was planted to maize).

Compared to the reference simulation, the CORN scenario has high variability and statistically significantly higher mean TP concentrations from January to April (Figure 7.5), when the soil is bare and prone to surface runoff from snowmelt. Due to the high mean monthly streamflow, in March and April the TP concentrations attained 0.02 mg/L a few times because of the increased flow diluting the TP loads.

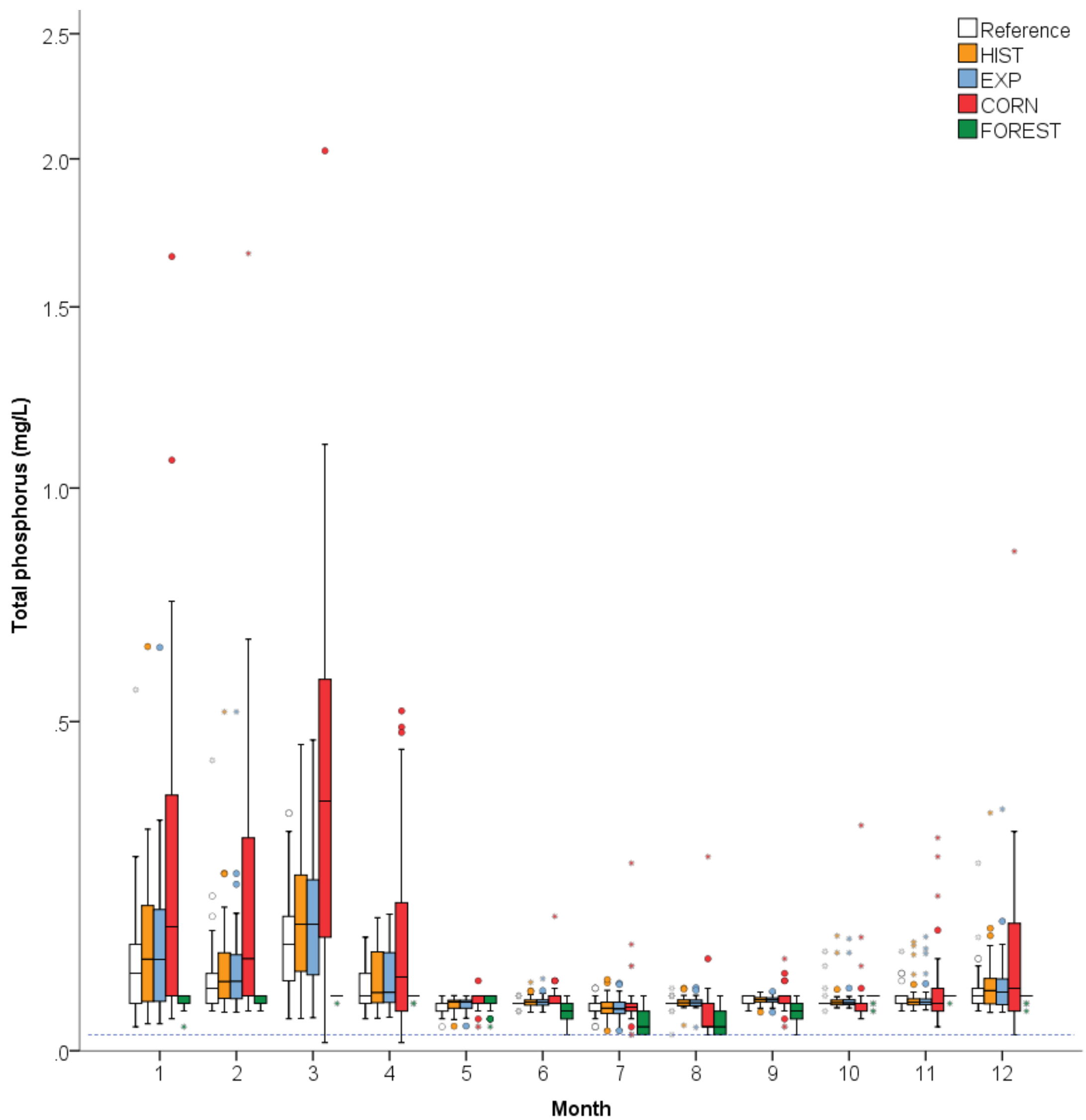


Figure 7.5. Concentration of SWAT simulated TP (mg/L, exponential scale) at the basin outlet for the land use change scenarios (2041-2070; coloured boxes), compared to the reference simulation (white boxes). The dotted line is the water quality criterion of 0.02 mg/L.

The mean concentration of NO_3^--N exceeds the water quality criterion of 10 mg/L often in the CORN scenario (Figure 7.6), this was not surprising since the area of maize cropland has been strongly correlated to nitrogen and phosphorus amounts in surrounding water bodies (Donner, 2003).

The FOREST scenario always has lower mean monthly streamflow compared to the reference simulation, with the July to September period being statistically significantly lower due to less runoff**.** Empirically, forested land cover has more interception and deeper roots to allow for more infiltration and deeper seepage than other land uses. Trees also consume more water than crops, lowering the streamflow (Bosch and Hewlett, 1982; Farley et al., 2005).

The mean monthly FOREST scenario values were able to attain the water quality criterion of TP concentrations of 0.02 mg/L in 8 months out of the 30 years. This is influenced and limited by the SWAT model set-up, and the result would likely change if the model was calibrated for a forest scenario. For example, the SWAT parameter which dictates the concentration of P in the groundwater (GWSOLP) was not changed (re-calibrated) from the original set-up with agricultural land.

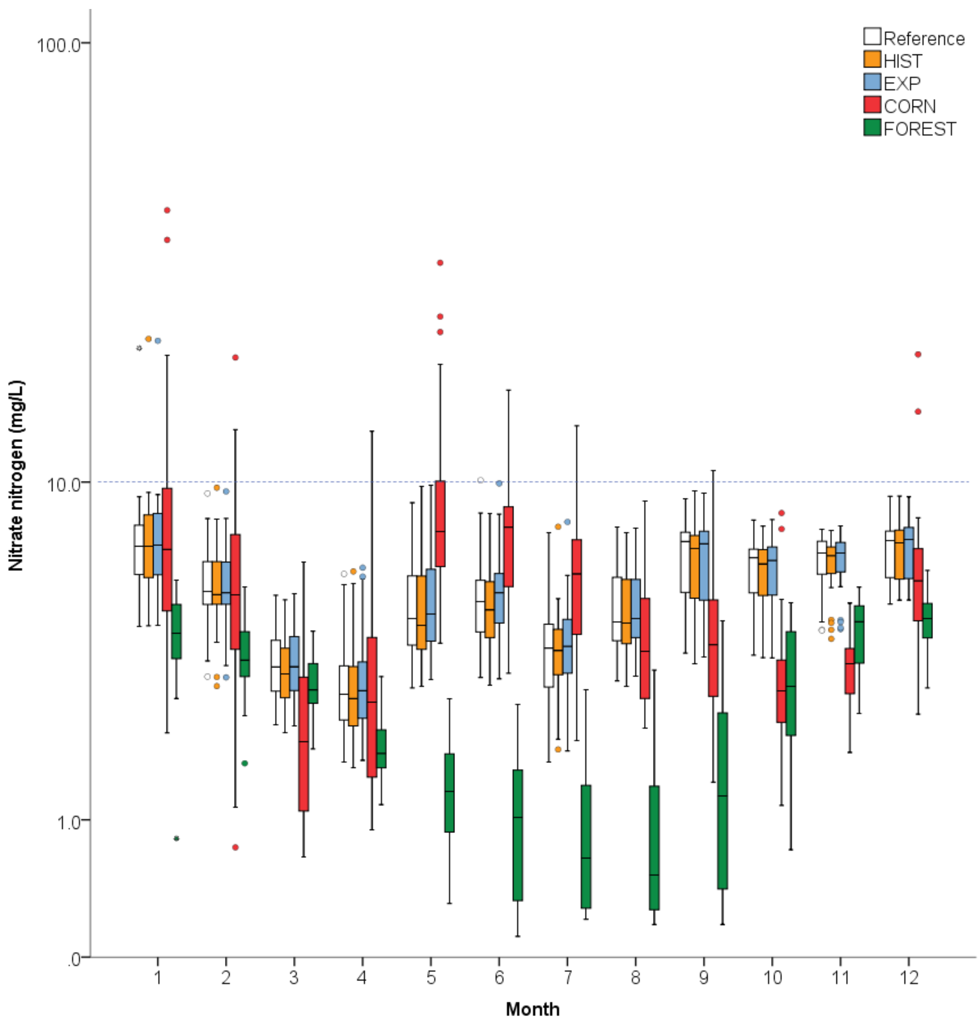


Figure 7.6. Concentration of SWAT simulated NO_3^--N (mg/L, exponential scale) at the basin outlet for the land use change scenarios (2041-2070; coloured boxes), compared to the reference simulation (white boxes). The dotted line is the water quality criterion of 10.0 mg/L.

7.4.3. Combined climate and land use change impacts on water quality

The climate simulations ACU and AGR showed similar impacts on water quality in the watershed, although AGR tended to simulate the lowest changes in streamflow and in nutrient concentrations. On the other hand, AHK simulated the most opposing results for sediment and nutrient transport (i.e. it set the upper boundaries of change), especially in the winter and spring months. Therefore, in consultation with the stakeholders it was agreed to retain the AGR and AHK simulations as they provided the lower and upper limits, respectively, of nutrient transport. The AGR and AHK climate simulations were thus in turn combined with each of the two land use change scenarios (HIST and EXP), to provide the four combined scenarios: AGR_EXP; AGR_HIST; AHK_EXP; AHK_HIST.

<u>Nutrient loads</u>

Compared to the reference simulation, the mean annual streamflow increased by approximately 1 m^3/s. The mean sediment, TP and NO_3^--N loads were not statistically significantly different than the reference simulation possibly because the inter-annual variability was high (Table 7.6).

For the most part, the changes in mean monthly streamflow were positive compared to the reference simulation (Table S7.3). February showed the greatest relative increase (by 115%) and April the greatest decrease (by -51%), this was comparable to results obtained with the climate simulations alone. The climate change scenarios were driving the mean streamflow changes because the combined simulations, showed very similar results to the climate simulations alone.

The changes to mean monthly TP loads were also mainly driven by the climate change simulations. However the months with statistically significant changes were not necessarily the same as when climate change alone was simulated. For example, the change in mean TP load for AGR_EXP was statistically significantly higher in December (0.03 kg/ha) than the reference simulation, whereas the change in mean TP load in the AGR simulation alone, and in the EXP simulation alone, were not statistically significant in December.

The mean monthly changes in the NO_3^--N loads behaved similarly to the climate change simulations alone, yet there were differences. For example, the mean load for AHK_EXP had a statistically significantly higher mean change (0.48 kg/ha) in June, which was not the case with the AHK or with the EXP alone, which both had lower, statistically insignificant, changes (0.36

kg/ha and 0.05 kg/ha, respectively). Overall, the AHK_EXP scenario simultated the highest increases in mean NO_3^--N loads.

In the four simulations of the combined climate and land use change scenarios the outcomes demonstrate there is not a simple additive effect of the two changes on mean sediments, TP and NO_3^--N loads. To illustrate this point, two months were selected from the AHK_EXP scenario where statistically significant changes were noticed (Table 7.9). The compounded impacts were not the same as adding the mean climate change to the mean land use change: during some months the impacts were less, and during other months greater than the sum.

Table 7.9. Example of absolute changes in streamflow, sediment, TP, and NO_3^--N for the climate change scenario (AHK), the land use change scenario (EXP), and the combined effect scenario (AHK_EXP), for April and December, with respect to the reference simulation (1971-2000).

	Mean monthly changes for April				**Mean monthly changes for December**			
Scenario	Flow (m^3/s)	Sediment (kg/ha)	TP (kg/ha)	NO_3^- N (kg/ha)	Flow (m^3/s)	Sediment (kg/ha)	TP (kg/ha)	NO_3^- N (kg/ha)
AHK	-14.93	-7.92	-0.07	-1.23	6.53	2.90	0.02	1.41
EXP	0.19	0.13	0.02	0.10	0.05	0.02	0.01	0.04
AHK_EXP	-14.89	-7.78	-0.07	-1.25	6.54	3.06	0.03	1.07

Nutrient concentrations

Regarding the nutrient concentrations at the outlet, due to the increased streamflows and absolute nutrient loads during the months of January and February, the median monthly values for TP were higher in the four scenarios than in the reference simulation (Figure 7.7). In March, April, and June they were lower, yet none of the scenarios could respect the water quality criterion of 0.02 mg/L. This is in contrast to the climate change simulations only, when the criterion was met twice (in the 1080 months).

The mean monthly NO_3^--N concentrations from September to March and in May were lower than for the reference simulation, but for the remaining months they were higher. Overall, there was more variability in the future scenarios (Figure 7.8) so that the mean monthly values exceeded the water quality criterion of 10 mg/L, 13 times in 30 years (for the climate change simulations only, this was exceeded 7 times and for the land use changes scenarios only it was exceeded twice out of 1080 months).

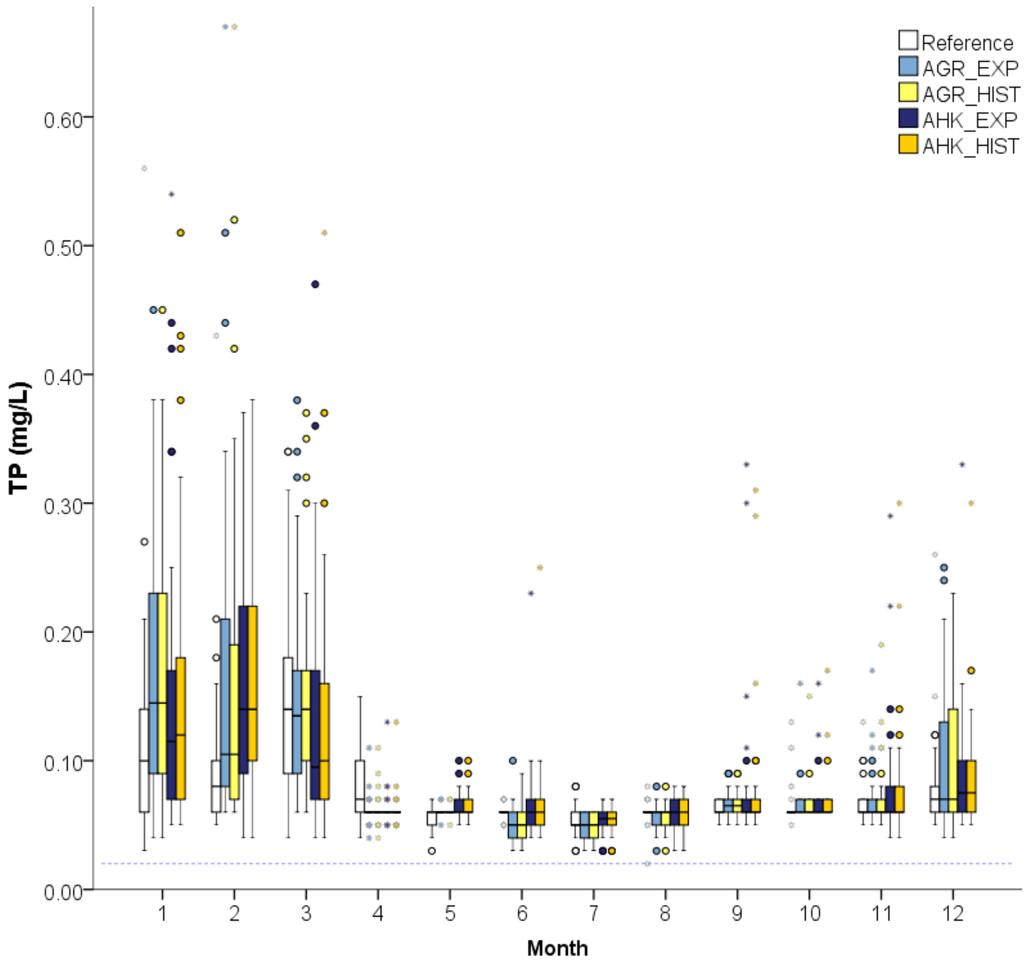


Figure 7.7. Concentration of SWAT simulated TP (mg/L), at the basin outlet for the climate change simulations combined with land use change scenarios, representing the period 2041-2070 (coloured boxes), compared to the reference simulation (white boxes). The dotted line is the water quality criterion of 0.02 mg/L.

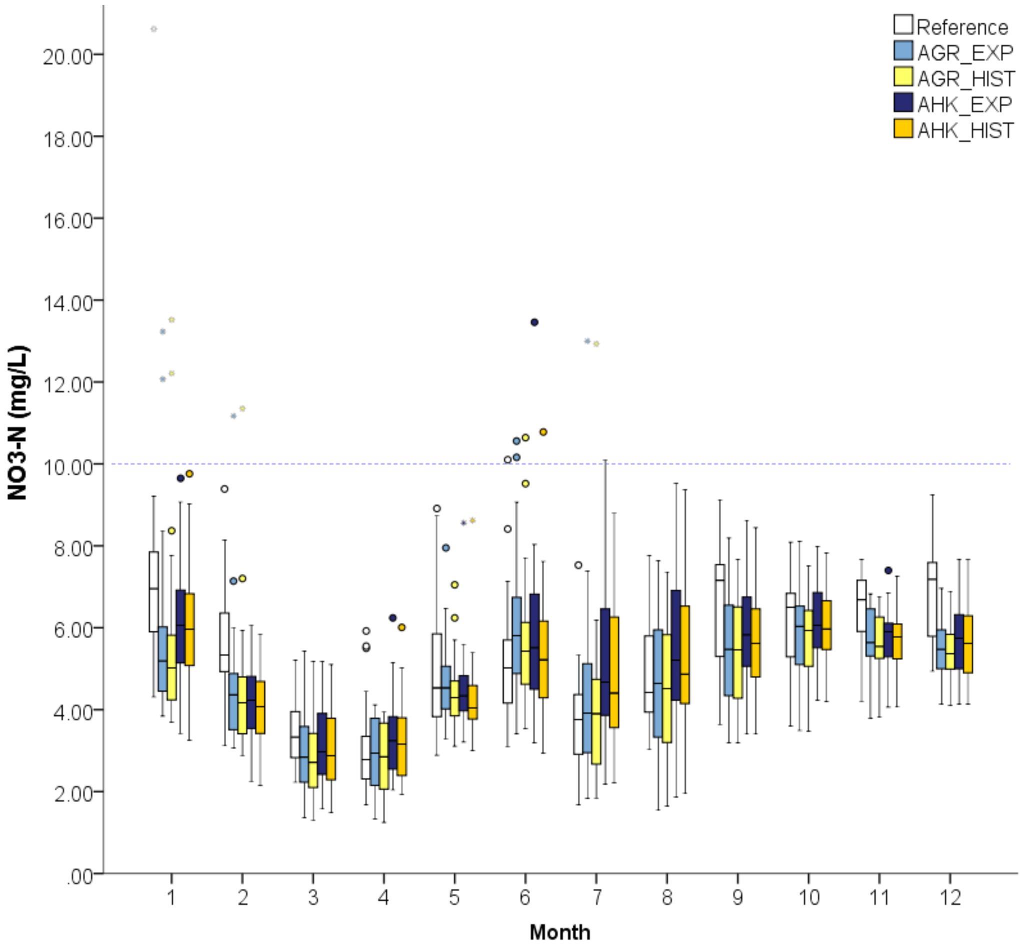


Figure 7.8. Concentration of SWAT simulated NO_3^--N (mg/L), at the basin outlet for the climate change simulations combined with land use change scenarios, representing the period 2041-2070 (coloured boxes), compared to the reference simulation (white boxes). The dotted line is the water quality criterion of 10.0 mg/L.

7.4.4. Water quality as a result of implementing adaptation strategies

The AHK climate demonstrated the greatest sediment and nutrient load exportation changes compared to the reference simulation, and therefore represented the "worst case scenario" from the climate simulations. The monthly AHK_EXP scenario simulation results confirmed the greatest impacts on nutrients, especially for nitrate, and strengthened the argument that this was a "worse" scenario for impacting water quality than the other three combined scenarios. Thus, the AHK_EXP scenario was selected as the new baseline scenario and was run with and without adaptation strategies to determine the effectiveness of the best management practices to mitigate the impacts of the simulated climate and land use change in the basin.

Nutrient loads

Figure 7.9A represents the AHK_EXP scenario (without adaptation strategies) and shows that the most TP (the class 1.21 - 2.00 kg/ha) is exported from around the Bedford area and the agriculturally most intensive lands to the west of Bedford. The sub-basin in the east, straddling the Québec-Vermont border, is mainly forested with patches of grain corn, orchards and hay, but is prone to TP transport because it has some of the steepest slopes (average of 5%) in the basin.

The mean annual sediment loads were only statistically significantly reduced in the OPTIM scenario, by 62%. The improvements in mean annual TP loads were statistically significant for all three adaptation scenarios. Compared to the original AHK_EXP run, the added STRAT adaptation scenario reduced mean annual TP loads at the outlet by 32%; the FEASB scenario by 26% and the OPTIM scenario by 47%. The NO_3^--N loads were not statistically significantly reduced (Table 9).

Figure 7.9B shows that the STRAT scenario effectively targeted the critical sub-basins with high TP transport, and did not affect sub-basins with relatively low TP loads. The greatest reductions (class 0.81 - 1.20 kg/ha) were achieved in the agriculturally most intensive sub-basin near Bedford, and in the sub-basin with steep slopes in the forested area. This scenario also had an additional TP reduction mechanism implemented at the basin outlet, to mimic runoff control structures, which is not observable in Figure 7.9B.

The FEASB scenario (Figure 7.9C) showed strong reductions in TP loads in the critical sub-basin around Bedford. Smaller reductions (class 0.41 - 0.80 kg/ha) were evident in 5 other sub-basins with high TP loads in the AHK_EXP scenario, however not all of the critical sub-basins exporting TP were targeted.

The OPTIM scenario (Figure 7.9D) achieved the largest of all modelled TP reductions (class 1.21 - 1.60 kg/ha) in the sub-basin containing the town of Bedford. It also achieved reductions in TP from a much larger area in the whole watershed, due to its all-encompassing strategies.

The greatest and most statistically significant reductions were achieved with OPTIM, in which TP loads were statistically significantly reduced in 3 months of the year (February, March and

December) by up to 0.08 kg/ha (Table S7.4). The STRAT scenario was also effective at statistically significantly reducing mean TP loads in February and March by up to 0.06 kg/ha. Both of these scenarios targeted the cropland most prone to phosphorus export. The results reflect the efficiency of focusing on “hot spots” also under climate change conditions.

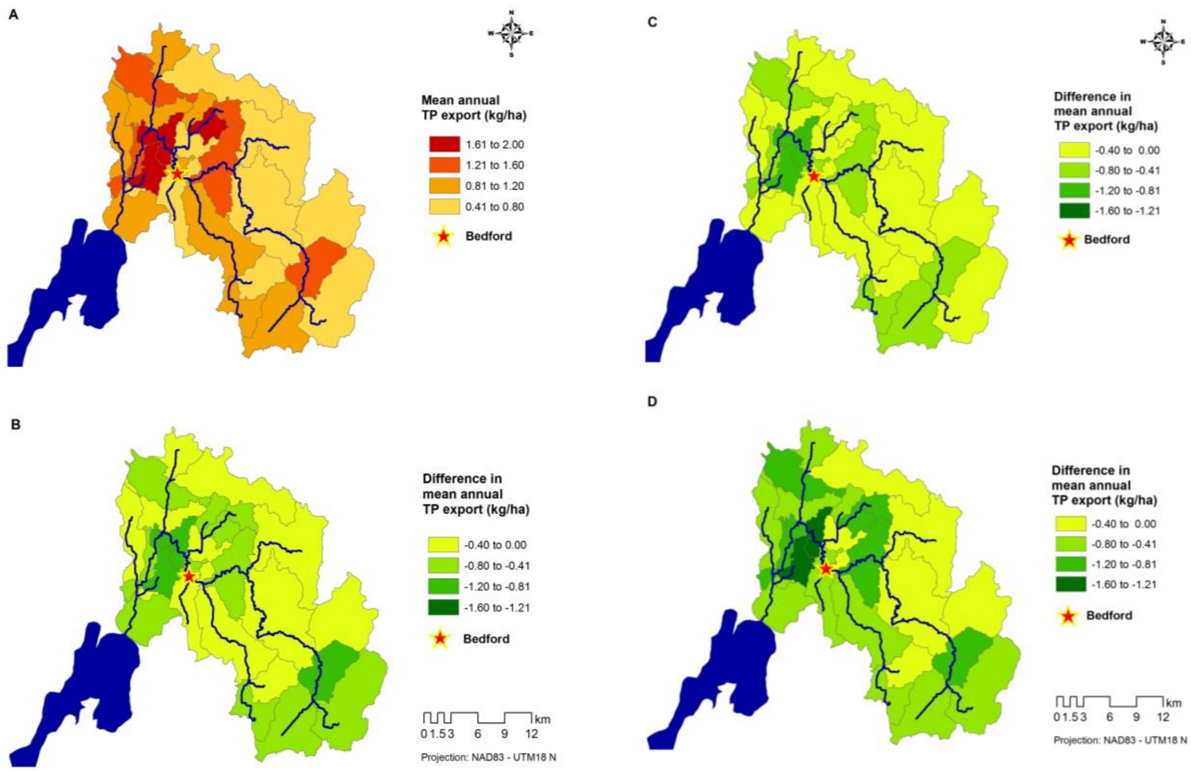


Figure 7.9. A) Mean annual TP export from the AHK_EXP scenario. Reduction in TP loads due to adaptation strategies based on **B)** STRAT scenario; **C)** FEASB scenario; **D)** OPTIM scenario.

Nutrient concentrations

All three adaptation scenarios were able to decrease the mean monthly TP concentrations at the outlet of the basin and despite being combined with the worst case scenario of climate change and land use change combination (AHK_EXP), they even improved concentrations to lower levels than in the reference simulation in three months (January, March, April), and restored them to similar levels as in the reference simulation in six further months (May, August-November). However, the 0.02 mg/L criterion was not achieved by the STRAT or FEASB scenarios, and only rarely (twice) by the OPTIM scenario (Figure 7.10).

Despite the high variability in some months, the median NO_3^--N concentrations in the STRAT and FEASB scenarios were almost always reduced (Figure 7.11). The three adaptation scenarios improved the mean monthly NO_3^--N concentrations in five months compared to AHK_EXP without adaptations, and even to levels lower than those in the reference simulation in eight months (January-March, May, September-December). The improvements were the result of the cover crops being planted after the fall harvest of maize and cereals. However, with FEASB, in June and July just before the planting of cover crops the median NO_3^--N was higher than in the AHK_EXP scenario which was attributed to the fertilization of the switchgrass after harvesting in May.

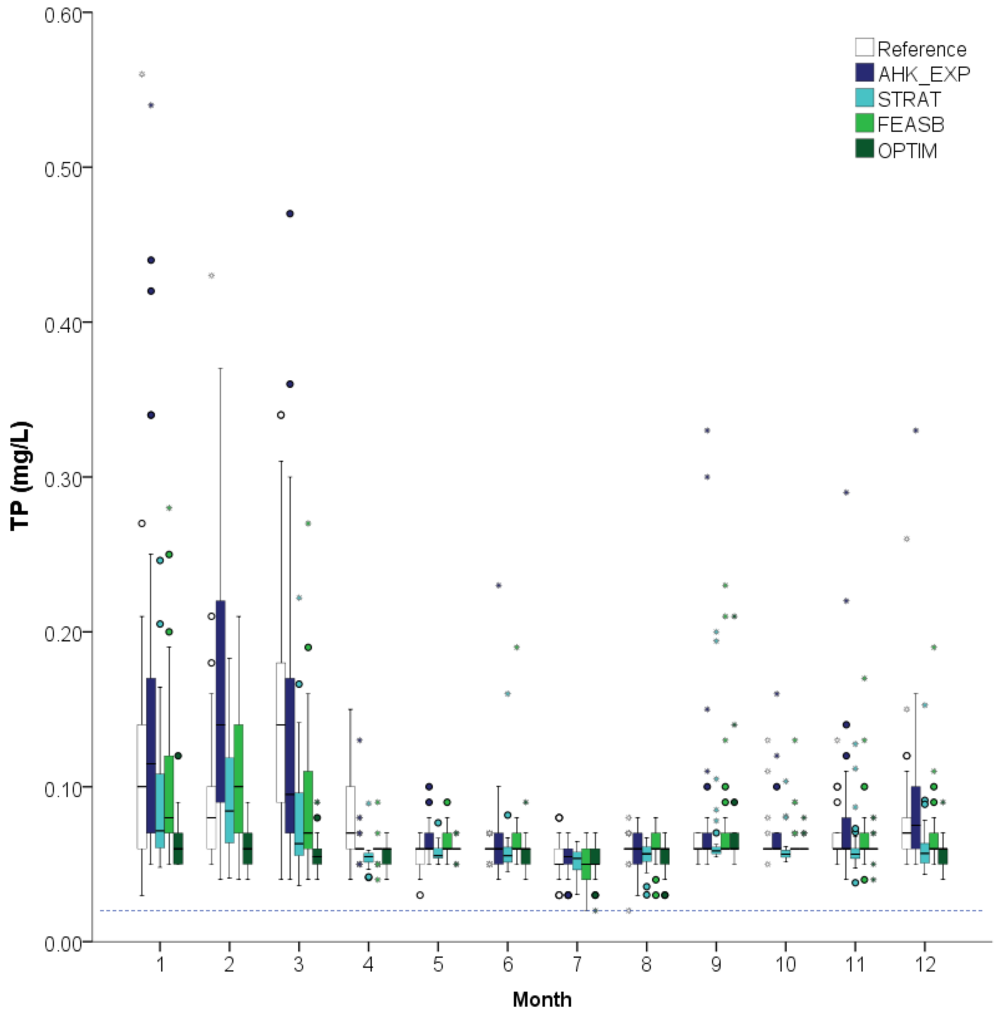


Figure 7.10. Simulated mean monthly TP (mg/L) at the basin outlet for the reference simulation (white boxes), climate and land use change AHK_EXP scenario (dark blue boxes), and the AHK_EXP with adaptation scenarios (green boxes). The dotted line is the water quality criterion of 0.02 mg/L.

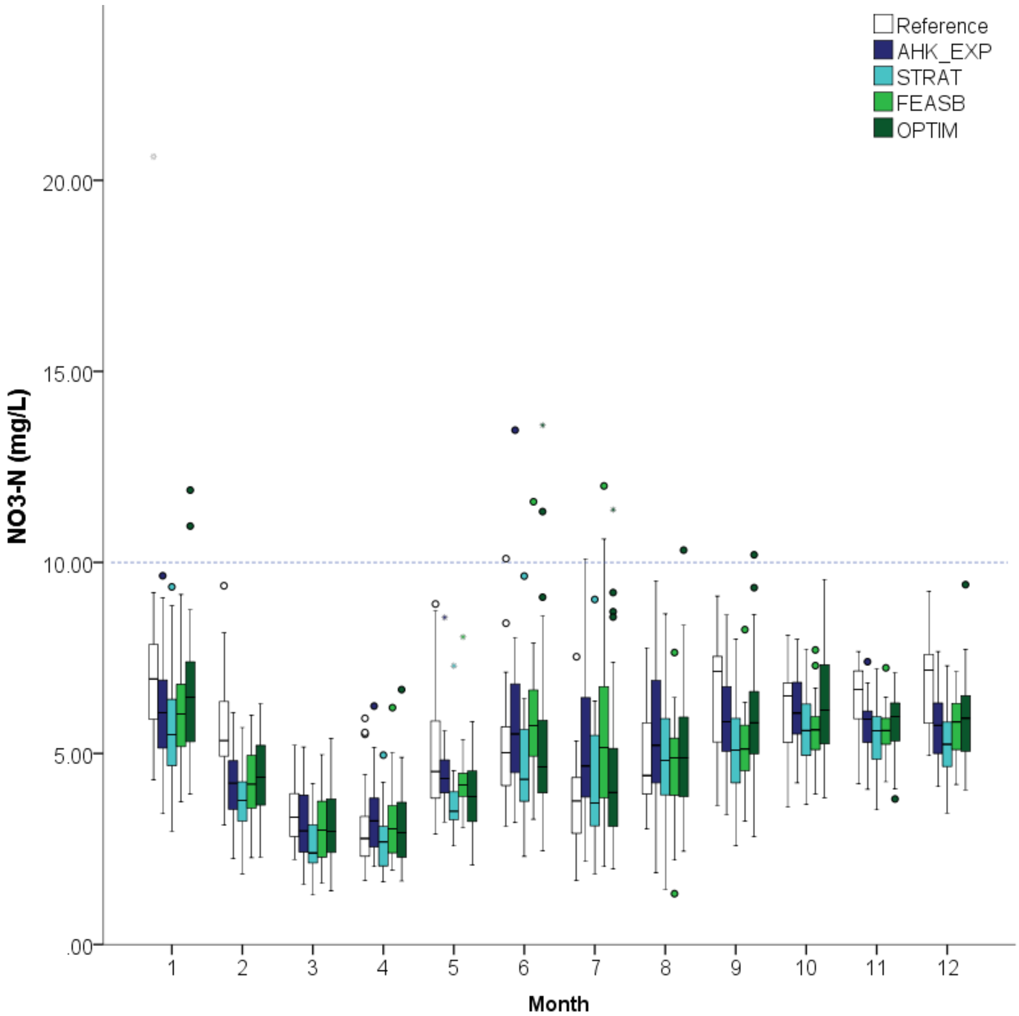


Figure 7.11. Simulated NO_3^--N (mg/L) at the basin outlet for the reference simulation (white boxes), climate and land use change AHK_EXP scenario (dark blue boxes), and the AHK_EXP with adaptation scenarios (green boxes). The dotted line is the water quality criterion of 10.0 mg/L.

The water quality criterion of 10.0 mg/L was respected by the STRAT scenario, but was exceeded 3 times in the FEASB and 7 times in the OPTIM scenario during the 30 years of simulation. In OPTIM, the NO_3^--N values show more outliers than the other scenarios, which is a function of only swine manure being applied to the crops in this scenario. The ratio of the P:N in the swine manure applied was almost 1:3 and as the P values were used to calculate the required fertilizer amounts for each crop, the N was over-applied. Hence, there is relatively more nitrogen than necessary for crop uptake in the basin.

7.5. Discussion

Running SWAT with the future climate simulations caused increases in TP concentrations at the basin outlet to take place predominantly in winter. This was due to the combined effect of higher TP loads stemming from the fields and the greater runoff. Mineral P (particulate P) is transported mainly by surface runoff, and is also highly correlated to suspended solids (Michaud and Laverdière, 2004). Greater precipitation amounts in these months makes TP prone to surface transport. Future warmer surface air temperatures affect certain important hydrological processes, such as snowmelt. This impacts the transport of TP since TP is driven by surface runoff, including snowmelt. Under future climate conditions, the largest decrease in TP concentration was simulated to take place in April, mainly due to the lower mean TP loads transported by the lower mean streamflow, compared to the reference simulation.

For the simulated NO_3^--N concentrations, a decrease was simulated at the outlet when streamflow was higher than in the reference simulation (i.e. in January), and an increase in mean NO_3^--N concentration took place when streamflow was lower, as was the case in April. Nitrate is water soluble and thus easily dissolved and transported by water. In all of the scenarios simulated in SWAT, NO_3^--N outputs were more variable than TP which is an indication of NO_3^--N being more labile since it is conveyed by several hydrological pathways (infiltration, seepage, percolation, groundwater flow, surface runoff). Therefore, it is a nutrient that is more sensitive to hydrological changes in the basin.

The agricultural landscape in Québec evolves in a world of perpetual change. Hence, it is futile to forecast, with any precision, an exact portrait of its future progression within the next 20 to 40 years. Nevertheless, it is possible to extract trends, preferences, tendencies, and even driving factors which will strongly influence the direction of changes that may take place in the agricultural sector. The land use scenarios portray two possible future agricultural trajectories in the Pike River watershed for the near- to mid-term future. Most changes revolved around changing crop quantities and types, and are considered to be subtle changes.

The two land use change scenarios impacted the TP loads by a greater magnitude than they did the NO_3^--N loads. Furthermore, the months in which TP loads were increased due to land use change were of the same order of magnitude as increases due to climate simulations. Yet, no statistically significant differences were detected compared to the reference simulation because of the high variability. The impacts of the land use scenarios on the NO_3^--N loads were roughly 10 times less than with the climate change simulations alone. Altering crops necessitate a new fertilizer regime being implemented in the basin that involves variations in the amounts and in the timing of N and P applications to correspond to the new crop configuration needs. Crops determine the nutrient input amounts required in the basin, by proxy of fertilization rates, whereas the movement and the transformation of nutrients are governed by the climate.

The paths of land use changes followed subtle alterations of the crop quantities and types (leaving the forest and urban areas mostly unchanged), and the water quality was not improved or deteriorated to any significant extent by the HIST and EXP land use change scenarios alone. However, the extreme “all corn” and “all forest” land use scenarios showed that the water quality could be greatly impacted by more radical land use changes.

When combining our climate change simulation with the described (subtle) land use change scenarios in the SWAT model, the impacts to water quality were mostly driven by the climate change scenarios. However, the combined impacts of climate and land use change showed a non-linear behavior on surface water quality, which is consistent with results found for climate and land use change impacts on streamflow in other studies (e.g. Wang et al., 2013). Non-linear processes and dynamic feedbacks made the direction of change non predictable. Thus, it is imperative to study climate and land use changes together since examining them separately will not provide an accurate portrayal of the potential scope of hydrological impacts that may occur.

The implementation of adaptation strategies that focus on agricultural management in the basin are a form of land use change, based on managing crops and cover practices. In the future, a longer growing season will provide more flexibility for implementing management practices at the field level, such as inter-cropping or fall seeding of a green manure. The STRAT and FEASB scenarios focused on removing agriculture from the 10% of land most vulnerable to non-point source pollution transport. This was an effective strategy to significantly reduce mean annual TP loads by approximately 10 (±4) Mg compared to the climate and land use change scenario AHK_EXP. The OPTIM scenario, on the other hand, implemented best management practices to the whole watershed, and was more effective at reducing the overall mean annual sediment (2400 (±200) Mg) and TP loads (20 (±4) Mg) in the watershed compared to the AHK_EXP scenario. An important reason for this decrease was also because the agricultural land on slopes >9% was converted to poplars.

Overall, the adaptation strategies modelled were able to maintain water quality at concentrations that are currently observed. They also, however, improved the quality during several months of the year. Our combined climate and land use change scenarios showed that most of the TP was transported during snowmelt in February and March. Two of the adaptation scenarios (OPTIM and STRAT) demonstrated the ability to significantly reduce TP transport during the months when snowmelt and high runoff amounts contribute to the most non-point source pollution, showing again that a targeted approach, as well as a holistic approach of implementing adaptation managements can be effective.

During three months of the year, the mean monthly TP concentrations in all of the adaptation scenarios were lower than in the reference simulation. Yet, the water quality criterion for TP (0.02 mg/L) was extremely difficult to attain in light of climate and land use change. This finding is comparable to that of Bosch et al. (2014) who found a combination of no-till, cover crops and buffer strips were able to offset the impacts of climate change in the Lake Erie region, but not to improve water quality beyond concentration observed historically. Even major measures, such as those in the OPTIM scenario - although highly effective - were not able to achieve this goal. The difficulty of attaining the TP criterion may be due to the parameter denoting the concentration of soluble P in the groundwater (GWSOLP), which was fixed at 0.08 mg/L and surely provided a limitation to decreasing the mean TP concentration in the surface water. There is some indication of this observed in the FOREST scenario. Future work should examine the effects of reducing this parameter value. Perhaps a SWAT set-up with calibrated parameters to such adaptation practices would provide different results.

The adaptation scenarios are effective at reducing the median monthly concentrations of NO_3^--N in the watershed on the whole, except when manure is applied as the only fertilizer (even then, the water quality criterion of 10.0 mg NO_3^--N /L was only rarely exceeded). During eight months, the mean monthly concentrations of NO_3^--N in all of the adaptation scenarios were below that of the reference simulation.

Like with all modelling studies, our results would be misleading without recognizing some of the inherent limitations of this study. The modelling uncertainties due to applying climate simulations in hydrological models are manifold (Wilby, 2005; Poulin et al., 2011). One possibility of accounting for some of the uncertainty is by using an ensemble of climate models (Harvey, 1997; Meehl, 2007). Using only three future climate simulations is not sufficient to represent the variability in the climate system and to determine the full range of potential impacts, yet we attempted to increase variability in the simulations by selecting runs that reflect a broad representation of climate variables that SWAT is most sensitive to. The three climate simulations here covered approximately 50% of the climate variability from the 16 regional climate models that were available at Ouranos.

The land use scenarios were developed as an evolving trend over 30 years (starting with a land use representation of 2011), which can be interpreted as representing a time horizon of the 2020s. This is significantly closer than the 2050 horizon of the climate scenarios. By applying a near-term land use scenario to a mid-term climate horizon, the land use changes may be regarded as conservative trajectories of change, and hence may not manifest themselves very prominently amongst other changes in the basin. However, they are only scenarios of possible change (i.e. not specific predictions), and in the absence of more realistic scenarios for a longer-term future, we consider these scenarios to also be a plausible proxy for a more distant time frame in which land use may change within a similar range.

Although best management practices can be modelled in SWAT, they have not been validated for the Pike River site due to a lack of field data. Thus, it is uncertain if the modifications to the parameters, based on expert judgment and literature, are entirely justified and effective for the watershed.

We recommend water quality data be collected in the watershed at least once a week (several times per month) throughout the year, and ensure samples are obtained from multiple outlets in the watershed. Applying controlled standards is also necessary to improve the calibration and validation of the water quality component of the hydrological model. Increasing the length of all data series will help draw links between hydrology, land use and climate change. In addition to water quality data, actual land use information (and the corresponding management practices) is needed to test the adequacy of the model simulations to portray the observed changes.

7.6. Conclusions

Climate change impacts do not consistently increase the concentrations of nutrients at the outlet of the watershed, compared to the reference simulation. The months in which median TP concentrations increased the most are in winter except during snowmelt the increased streamflow cause the TP median concentrations to be lower than in the reference simulation. Achieving a good water quality concentration of 0.02 mg/L for TP was not possible under climate change conditions. Overall, the water quality criterion of 10 mg NO_3^--N /L was respected.

Although the land use changes increased TP loads in winter and spring months by the same magnitude as the increases observed with the climate simulations alone, the results of the land use driven increases were not statistically different than in the reference simulation. The land use change simulations caused up to 10 times less NO_3^--N loads being transported from the land, than the climate change scenarios. The possible conservative land use changes in the two scenarios caused the water quality not to be significantly impacted by agricultural land use change alone. The extreme, all forested and all maize, scenarios did impact water quality and indicated a broader range for possible changes to be modelled.

According to the four investigated scenarios of combined climate and land use change, the simulated impacts on surface water quality in the Pike River by 2041-2070 led to a degradation of water at the outlet, of similar range to the climate change simulations alone. However, we recommend examining both changes simultaneously since the direction and the magnitude are not predictable from the individual changes alone.

Field level adaptation strategies can be highly effective to improve surface water quality compared to the reference simulation. The critical period of snowmelt was also effectively targeted. During mostly winter, the mean monthly TP concentrations in all of the adaptation scenarios were lower than in the reference simulation. During most of the year, except summer, the mean monthly concentrations of NO_3^--N in all of the adaptation scenarios were below that of the reference simulation. Considering that Québec has agreed to reduce TP loads transported into the Missisquoi Bay by 38.9 Mg/yr (LCBP, 2013) from three watersheds (Pike River (41% of area); Missisquoi River (48% of area); and Rock River (11% of area); OBVBM, 2011a), these strategies only provide a partial contribution towards achieving this reduction in light of the possible future changes that may occur in the basin.

The reductions achieved will depend on the types of management strategies carried out. Targeting the 10% of land most prone to erosion and P loss by taking it out of agricultural production is an effective option for reducing sediment and nutrient loads. However, implementing wide-reaching practices (e.g. buffer strips, cover crops, crop rotations, agroforestry on steep slopes) reduces TP transport almost twice as much and the amount of sediment transported by up to 7 times. Despite the significant reductions by the adaptation scenarios in the TP concentrations, the water quality criterion of 0.02 mg/L for TP was not consistently attained. Yet, mean monthly NO_3^--N concentrations rarely exceeded 10.0 mg/L for all adaptation scenarios.

7.S. Supplemental Material

Table S7.1. Absolute changes in mean streamflow, sediment and nutrients for the watershed due to future climate simulations (2041-2070), compared with the reference simulation (1971-2000). Green boxes denote a statistically significant change ($p<0.05$).

	Month	Flow (m3/s)	Sediments (kg/ha)	Total P (kg/ha)	NO_3^--N (kg/ha)
ACU	1	7.51	3.58	0.04	1.56
	2	5.39	2.30	0.03	0.73
	3	-2.39	-2.04	-0.06	-0.62
	4	-15.72	-7.91	-0.07	-1.31
	5	0.02	0.02	0.00	-0.07
	6	0.81	0.29	0.01	0.12
	7	-0.65	-0.32	0.00	-0.08
	8	-0.16	-0.06	0.00	0.02
	9	1.25	0.64	0.00	0.21
	10	-2.76	-1.32	0.00	-0.68
	11	3.07	1.38	0.01	0.72
	12	8.94	3.86	0.05	1.81
AGR	1	8.00	3.78	0.05	1.53
	2	6.10	2.67	0.05	0.87
	3	-0.60	-1.00	-0.03	-0.45
	4	-10.54	-5.89	-0.06	-0.97
	5	0.42	0.18	0.00	0.08
	6	-1.08	-0.50	0.00	-0.19
	7	-0.77	-0.36	0.00	-0.10
	8	0.21	0.12	0.00	0.14
	9	1.53	0.73	0.00	0.34
	10	-0.10	0.09	0.00	0.06
	11	1.91	0.71	0.01	0.36
	12	7.81	3.69	0.03	1.70
AHK	1	3.60	1.82	0.03	0.71
	2	9.29	4.12	0.06	1.30
	3	-5.16	-3.46	-0.09	-0.88
	4	-14.93	-7.92	-0.07	-1.23
	5	1.08	0.46	0.01	0.11
	6	2.08	0.84	0.01	0.36
	7	-0.33	-0.25	0.00	-0.02
	8	1.28	0.55	0.00	0.31
	9	2.85	1.35	0.02	0.63
	10	-1.56	-0.91	0.00	-0.35
	11	5.29	2.13	0.02	1.24
	12	6.53	2.90	0.02	1.41

Table S7.2. Absolute changes in mean streamflow, mean sediment and mean nutrients for the watershed due to land use scenarios, compared with the reference simulation (1971-2000). Green boxes denote a statistically significant change ($p<0.05$).

	Month	Flow (m^3/s)	Sediments (kg/ha)	Total P (kg/ha)	NO_3^--N (kg/ha)
HIST	1	0.06	0.03	0.01	0.00
	2	0.09	0.02	0.01	-0.02
	3	0.55	0.35	0.06	-0.08
	4	0.43	0.27	0.02	-0.03
	5	0.02	0.01	0.00	-0.03
	6	0.10	0.05	0.00	-0.02
	7	0.22	0.10	0.00	0.03
	8	0.05	0.02	0.00	0.00
	9	-0.11	-0.05	0.00	-0.05
	10	-0.04	-0.02	0.00	-0.06
	11	0.05	0.02	0.00	-0.04
	12	0.10	0.04	0.01	0.01
EXP	1	0.03	0.02	0.01	0.03
	2	0.05	0.02	0.01	0.01
	3	0.28	0.18	0.05	0.06
	4	0.19	0.13	0.02	0.10
	5	0.03	0.01	0.00	0.05
	6	0.08	0.04	0.00	0.05
	7	0.13	0.05	0.00	0.04
	8	0.01	0.01	0.00	0.00
	9	-0.12	-0.05	0.00	-0.04
	10	0.01	0.00	0.00	0.00
	11	0.02	0.01	0.00	0.01
	12	0.05	0.02	0.01	0.04

Table S7.3. Absolute changes in mean streamflow, sediment and nutrients for the watershed due to climate and land use change scenarios (2041-2070) compared with the reference simulation (1971-2000). Green boxes denote a statistically significant change ($p<0.05$).

	Month	Flow (m3/s)	Sediments (kg/ha)	Total P (kg/ha)	NO_3^--N (kg/ha)
AGR_EXP	1	8.07	3.82	0.07	1.32
	2	6.21	2.72	0.07	0.73
	3	-0.38	-0.86	0.01	-0.61
	4	-10.49	-5.85	-0.06	-1.01
	5	0.44	0.19	0.00	0.15
	6	-1.20	-0.54	0.00	-0.16
	7	-1.19	-0.53	-0.01	-0.16
	8	0.00	0.05	0.00	0.10
	9	1.71	0.81	0.01	0.17
	10	0.05	0.18	0.00	-0.28
	11	1.95	0.73	0.01	-0.04
	12	7.85	3.72	0.04	1.32
AGR_HIST	1	8.18	3.89	0.07	1.26
	2	6.31	2.74	0.07	0.67
	3	-0.14	-0.72	0.01	-0.72
	4	-10.39	-5.81	-0.06	-1.07
	5	0.46	0.19	0.00	0.07
	6	-1.16	-0.53	0.00	-0.19
	7	-1.16	-0.52	-0.01	-0.16
	8	0.02	0.05	0.00	0.09
	9	1.71	0.81	0.01	0.13
	10	0.01	0.15	0.00	-0.33
	11	2.01	0.76	0.01	-0.07
	12	7.95	3.76	0.04	1.28
AHK_EXP	1	3.66	1.93	0.05	0.57
	2	9.40	4.18	0.09	1.14
	3	-5.01	-3.32	-0.06	-0.99
	4	-14.89	-7.78	-0.07	-1.25
	5	1.10	0.48	0.01	0.19
	6	2.02	0.89	0.01	0.48
	7	-0.40	-0.27	0.00	0.09
	8	1.08	0.54	0.00	0.39
	9	2.98	1.46	0.02	0.54
	10	-1.44	-0.72	0.00	-0.60
	11	5.30	2.20	0.03	0.76
	12	6.54	3.06	0.03	1.07
AHK_HIST	1	3.73	1.96	0.05	0.52
	2	9.52	4.23	0.09	1.06
	3	-4.81	-3.25	-0.06	-1.09
	4	-14.84	-7.77	-0.07	-1.30
	5	1.10	0.49	0.01	0.09
	6	2.08	0.92	0.01	0.41
	7	-0.35	-0.24	0.00	0.08
	8	1.10	0.55	0.00	0.37
	9	2.97	1.45	0.02	0.49
	10	-1.49	-0.74	0.00	-0.65
	11	5.36	2.24	0.03	0.72
	12	6.62	3.10	0.03	1.03

Table S7.4. Values of absolute changes in mean streamflow, mean sediment and mean nutrient loads (2041-2070) at the basin outlet, for AHK_EXP with STRAT, FEASB and OPTIM adaptation strategies, compared to AHK_EXP without adaptation strategies. Green boxes denote a statistically significant change ($p<0.05$).

Scenario	Month	Flow (m3/s)	Sediments (kg/ha)	Total P (kg/ha)	NO_3^--N (kg/ha)
STRAT	1	0.33	-0.51	-0.05	-0.16
	2	0.35	-0.42	-0.06	-0.27
	3	0.63	-0.56	-0.05	-0.36
	4	0.83	-0.49	0	-0.24
	5	0.72	-0.10	0	-0.17
	6	0.37	-0.17	0	-0.13
	7	0.30	0.03	0	-0.01
	8	0.18	-0.17	0	0.01
	9	0.66	-0.08	-0.01	-0.03
	10	0.56	-0.45	0	-0.05
	11	0.57	-0.97	-0.01	-0.15
	12	0.45	-1.47	-0.02	-0.23
FEASB	1	0.08	-0.18	-0.04	0
	2	0.06	-0.10	-0.05	-0.01
	3	0.10	-0.17	-0.04	-0.07
	4	0.07	-0.26	0	-0.09
	5	0.06	-0.08	0	-0.05
	6	0.16	-0.06	0	0.12
	7	-0.38	-0.15	0	-0.02
	8	-0.17	-0.08	0	-0.19
	9	0.17	-0.03	-0.01	-0.23
	10	0.06	-0.25	0	-0.16
	11	0.04	-0.27	-0.01	-0.11
	12	0	-0.42	-0.02	-0.02
OPTIM	1	0.32	-2.73	-0.07	0.22
	2	0.28	-3.56	-0.08	0.17
	3	0.55	-5.57	-0.08	0.03
	4	0.56	-4.25	-0.01	-0.06
	5	0.20	-2.41	0	-0.19
	6	-0.24	-1.35	-0.01	-0.16
	7	-0.17	-0.48	0	-0.04
	8	-0.42	-1.19	0	-0.10
	9	-0.90	-2.20	-0.01	-0.16
	10	-1.06	-2.87	-0.01	-0.24
	11	-0.62	-5.82	-0.02	-0.11
	12	-0.21	-5.90	-0.03	0.09

8. SUMMARY, CONCLUSIONS & AREAS OF FURTHER RESEARCH

In this thesis, I have shown the potential impacts of future climate change, both alone and combined with agricultural land use scenarios on the surface water quality to the 2050 time horizon in two mesoscale watersheds located in temperate, mid-latitude regions. The first general conclusion is that overall the quality of surface water simulated in both watersheds will be deteriorated in the future. The second general conclusion is that simulated adaptation management strategies at the farm level are able to mitigate the combined impacts of climate and land use change, and also can improve the quality of surface water compared to the in-stream nutrient concentrations modelled in the reference simulation.

Specifically, the suite of climate change simulations deteriorated annual surface water quality in both watersheds. The range of the impacts on nutrient loads was greater for the Altmühl River, where decreases as well as increases in mean annual loads for TP as well as NO_3^--N were simulated. In the Pike River, mean annual loads only increased under the climate change simulations. This may be because in the Altmühl River, seven climate simulations were applied, compared to three in the Pike River. However, the mean annual increases were of the same magnitude in both basins (up to 2 Mg/yr for TP; and 220 Mg/yr for NO_3^--N). The in-stream nutrient concentrations of TP and NO_3^--N were not improved under climate change simulations in either basin, so that the “good” water quality criteria for TP in both basins remained surpassed in all months.

The land use change scenarios were developed using a scenario storyline approach. The farmer scenario was based on driving factors of crop change that were obtained from farmer responses to a questionnaire. This scenario development was considered to be a bottom-up approach, while the agricultural policy driven scenario utilized a top-down approach of desired outcomes from a government perspective. These approaches provided two contrasting scenarios for each watershed. The third land use change scenario in each basin was a business-as-usual scenario in which historic land use change trends were extrapolated into the future. When the three land use change scenarios were applied in turn to the hydrological model, in the respective watersheds, they were not significantly different from each other in terms of their impacts on surface water quality, so that each land use change scenario was comparable in terms of the impact on sediment, TP and NO_3^--N loads.

However, regional differences appeared when the land use change scenarios were applied with climate change simulations to the hydrological model. In the Altmühl River, when land use change was simulated with climate change simulations, a further deterioration of water quality occurred whereby mean annual loads increased 3 fold for NO_3^--N and 8 fold for TP, compared to when climate change was simulated alone. The period from May to November was particularly vulnerable to higher nutrient loads. The extent to which water quality is impacted appears to be strongly dependent on the amount of maize area that changes in a basin. Future research should verify and quantify this statement.

In the Pike River, the land use change scenarios applied alone to the hydrological model caused mean annual NO_3^--N loads to be impacted 10 fold less than climate change alone, whereas mean annual TP loads were impacted by the same magnitude as climate change. When the land use scenarios were applied with the climate change simulations in the Pike River, the climate change simulations dominated the impacts to water quality; the period from December to February had significantly higher loads in the future scenarios.

Although the watersheds were physically and climatologically similar, the hydrological outputs were different when the land use change scenarios were simulated with the climate change simulations. This is partly because after coupling with the hydrological model, the land use change impacts were proportionally greater in the Altmühl River; in the farmer scenario of land use change, the maize area increases 4 times more than in the Pike River. The inference is that land use change can be an important influence on water quality, depending on the magnitude of change taking place. Land uses ascertain the quantities and spatial distribution of nutrients in a basin, whereby the climate change simulations establish the process and the timing of their transportation into water bodies.

In both watersheds, it was determined that the combined interaction between climate change and land use change in the hydrological model are unique and non-linear. Thus, the combined effects need to be examined in concert to determine the full extent of impacts that may occur to water quality in a basin since the direction and the magnitude are not predictable from the individual changes alone.

Adaptations implemented at the field level can counter the impacts of climate change and land use change and were effective at reducing simulated nutrient loads. However, only one combination of climate change and land use change was scrutinized in which the adaptation strategies were effective at reducing the overall mean annual sediment (by 2400 (±200) Mg), TP (20 (±4) Mg) and NO_3^--N (110 (±70 Mg) loads in the watershed, during winter mostly. The adaptation strategies that improved water quality the most were targeted towards applying wide-reaching practices (e.g. buffer strips, cover crops, crop rotations, agroforestry on steep slopes) and were able to reduce the amount of sediment transported by up to 7 times and the amount of TP transported by up to 2 times.

For each of the adaptation scenarios, the mean monthly TP concentrations were lower than in those simulated in the reference simulation, yet the 0.02 mg/L water criterion for TP was still exceeded. During most months of the year, except during summer, the mean monthly concentrations of NO_3^--N in all of the adaptation scenarios were below that of the reference simulation, and therefore within the good water quality criterion of 11 mg NO_3^--N/L. A limitation of the research is that the adaptation management strategies implemented in the hydrological model lack corresponding measured/observed data to verify if they actually reduce nutrient concentrations to the extent simulated. Collecting data at the field level under a variety of farm practices is therefore imperative to conduct and to validate these types of studies.

Including uncertainties from calibrating a hydrological modelling is important information for decision-makers. For the Altmühl River, the parameter non-uniqueness was included with the climate change simulations. Integrating both of these uncertainties provides a more accurate global indication of the uncertainty on account of the hydrological model and the climate simulations, thus I recommend undertaking this type of uncertainty reporting routinely. The next step for reporting an even more complete range of uncertainty will be to add the non-unique parameters to the climate change simulations combined with the land use change scenarios.

The calibration of the hydrological model in each watershed was comparable and acceptable for all variables. The hydrological framework methodology outlined in this research appears suitable at identifying the impacts of future climate and land use changes in a watershed and can be applied to other basins, provided the necessary data are available to run the model. However, there remain limitations to reliably predicting water quality in the future with such an approach.

The hydrological model was calibrated to the best of our ability using multiple gauges in each watershed, as well as with years of historic data for the calibration periods. This provides some confidence that the SWAT model is able to simulate water quality for the watershed also with other sets of climate and land use input data. However, our understanding of bio-physical and natural processes is limited and under future conditions, parameter values not yet observed historically (out of the model range) may occur and the hydrological model may react in a non-cohesive, unrealistic manner. Also, the climate simulations themselves may not be truthful predictions of future climates to come and therefore we cannot be certain the results simulated will be as reported here.

In closing, this research provides insights into impacts to surface water quality under given scenarios. The approach of questioning farmers helped to understand the local drivers of land use change and gain awareness of their decision making processes. A main challenge remains on how to quantify such qualitative information gained. Developing scenarios of land use change from storylines is an effective means to explore several futures (which should not be interpreted as predictions), but the difficulty in scenario development is the unknown. For example, farmers will take advantage of new technologies and new opportunities (i.e. with respect to emerging markets) but these are difficult to include in scenarios, as future developments in that direction are simply unknown.

The application of multiple models is useful to examine synergetic relationships that are not necessarily available to investigate when using one model alone, however the approach leads to uncertainty that is propagated and accumulated through the modelling chain. While there is no direct way to reduce this uncertainty, it is important to report as much uncertainty as possible during the modelling exercise. This means the outputs will have a larger range, but they reflect the possibility that the results could lie anywhere in this range. Further research should entail applying a suite of hydrological models using parameter non-uniqueness to provide an even greater global indication of the uncertainty.

The uncertainty in the reported outcomes is therefore correspondingly high, and the results must be interpreted with caution. I have applied available tools that were current and most suitable to provide some indication of the direction and the magnitude in which surface water quality may be impacted by future changes in two mesoscale agricultural river basins.

9. REFERENCES

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