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**Development of an integrated Multi-Objective modelling tool to assess water
and nutrient pressure of agriculture**

Tesis doctoral

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Abstract

The current growth in global population combined with an increasing consumption of natural resources puts increasing pressures on the energy, water and food sectors. Expected populations growth will be also associated with changing consumption habits that would deeply influence food demand all over the globe. More competition for land and water resources will characterize future market and water scarcity will exacerbate the issue under climate change forecast estimation. In this context the concept of Energy-Water-Food Nexus has become the headline for the global research agenda, the reference for sustainable development, and for the identification of new and future management and development strategies. Systematic and objective approaches are essential for understanding and analyse different sectors demands not only at different spatial and temporal scales but also across diversified sectors and under changing local boundary conditions. The challenge is to effectively manage and make optimal use of limited resources to meet future socioeconomic needs. Tools facilitating this analysis are urgently needed in order to develop or to increase the ability to produce analysis and assessments supporting policy measures implementation. These tools and analysis approaches must be capable of identifying the tradeoffs among various and even conflicting sectors, generating cost-effective planning, strategies and policies.

It is within this domain that I wanted to analyse the contribution of multi objective analysis routines combined with biophysical mathematical models in order to provide answers to the various and diversified questions arising from the Nexus approach. This thesis addresses the need for integrated water resources management in European and African countries by exploring the performance of alternative nutrient and water management strategies and developing integrative decision frameworks to improve human and environmental agricultural management tradeoffs. Key agricultural management objectives (crop production, nutrient leaching and runoff, irrigation strategies, etc.) are analyzed and quantified at different scales and under different context and situations. A framework GIS system was developed in order to spatially identify and allocate alternative agricultural and water management practices, by means of the integration of an optimization algorithm and biophysical (EPIC) and hydrological models (SWAT). Different case studies are used to validate the tools and analyze the topic including: 1) an application focused on agricultural food production issue at continental scale in Africa. Based on an integrated biophysical model and a multi-objective evolutionary algorithm efficient irrigation and fertilization management patterns in several African countries are identified 2) an application on the Danube river basin by integrating the hydrological model SWAT and an economic model with a multi-objective evolutionary algorithm to identify Best Management Practices to optimize crop production and water quality in synergy with

waste water treatment plans development strategies, and 3) an application focused on water scarcity issue in the island of Crete for the optimal identification of agricultural irrigation management strategies.

My thesis demonstrates how the integration of biophysical and hydrological model with an optimization framework is an efficient methodology providing answers and alternative solutions for policy makers in evaluating long-term benefit with a long-term perspective based on simulations of crop productivity, water quality and quantity indicators (i.e. concentration of nitrates in surface water and in the leaching, water use and irrigation requirements), when complex scenarios of Best Management Practices are implemented, i.e. reducing fertilizer application and upgrading waste water treatment plants, irrigation and crop spatial allocation. The proposed systematic approach used in this thesis proves to be a powerful tool both for scientists, policy makers and also stakeholders, and could be extended to other models and context.

Resumen

El crecimiento actual de la población mundial combinado con un consumo creciente de recursos naturales aumenta las presiones sobre los sectores de la energía, el agua y el suministro de alimentos. El crecimiento esperado de las poblaciones también estará asociado con cambios en los hábitos de consumo que influirían profundamente en la demanda de alimentos en todo el mundo. Una mayor competencia por la tierra y los recursos hídricos caracterizará el mercado futuro y la escasez de agua exacerbará aun mas la cuestión debido a la estimación del pronóstico del cambio climático. En este contexto, el concepto de Nexus Energía-Agua-Alimentación es fundamental para la agenda global de investigación, la referencia para el desarrollo sostenible y para la identificación de nuevas y futuras estrategias de gestión y desarrollo. Los enfoques sistemáticos y objetivos son esenciales para comprender y analizar las demandas de diferentes sectores, no sólo a diferentes escalas espaciales y temporales, sino también a través de sectores diversificados y bajo condiciones cambiantes locales. El reto consiste en gestionar eficazmente y aprovechar al máximo los recursos limitados para satisfacer las necesidades socioeconómicas futuras. Se necesitan urgentemente herramientas que facilitan estos estudio con el fin de desarrollar o aumentar la capacidad de producir análisis y evaluaciones que apoyen la implementación de medidas de política. Estas herramientas y enfoques de análisis deben ser capaces de identificar las compensaciones entre diversos sectores en conflicto, generando estrategias y políticas rentables en relación a su coste y efectividad.

Es en el contexto del Nexus, donde en esta tesis contribuye mediante la aplicación de técnicas de optimización multi-objetivos integradas con modelos biofísicos. Para ello se aborda la necesidad de una gestión integrada de los recursos hídricos en los países europeos y africanos mediante la exploración del comportamiento de estrategias alternativas de gestión de nutrientes y agua. También, se han desarrollado plataformas integradas de decisión para mejorar los compromisos humanos y ambientales en la gestión agrícola. Los principales objetivos de las buenas prácticas agrícolas (producción de cultivos, lixiviación y escorrentía de nutrientes, estrategias de riego, etc.) se analizan y cuantifican a diferentes escalas y en diferentes contextos y situaciones. Se desarrolló una herramienta GIS para identificar espacialmente y asignar prácticas alternativas de gestión agrícola e hídrico, mediante la integración de un algoritmo de optimización y modelos biofísicos (EPIC) e hidrológicos (SWAT). Se han empleado varios casos de estudio para validar las herramientas y analizar el problema, incluyendo: 1) una aplicación centrada en el problema de la producción de alimentos agrícolas a escala continental en África. Basado en un modelo biofísico integrado y un algoritmo evolutivo multi-objetivo, se identifican los patrones eficientes de gestión del riego y la fertilización en varios países africanos 2) una aplicación en la cuenca del Danubio integrando el modelo hidrológico SWAT y un

modelo económico con un algoritmo evolutivo multi-objetiva para identificar las mejores prácticas de gestión en relación a la producción de cultivos y la calidad del agua, así como explorar las sinergias con las estrategias de desarrollo de planes de tratamiento de aguas residuales y 3) una aplicación centrada en la escasez de agua en la isla de Creta para la identificación óptima de estrategias de gestión agrícola.

La tesis muestra cómo la integración del modelo biofísico e hidrológico con herramientas de optimización es una metodología eficiente que proporciona respuestas y soluciones alternativas que sirven de ayuda a los responsables de la formulación de políticas con las que mejorar la productividad sin penalizar en la calidad ambiental ni los índices de explotación de las aguas. El enfoque sistemático propuesto utilizado en esta tesis resulta ser una poderosa herramienta tanto para los científicos, los responsables de la formulación de políticas como para las partes interesadas, y podría ampliarse a otros modelos y contextos.

List of scientific publications

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1. Pastori, M., Bouraoui, F., Aloe A., **2017**. Modeling the impact of water and nutrient management in African agriculture. *Journal of Water Science* (2017, in press).
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Chapter 1. Introduction

1.1 Background

The current growth in global population combined with an increasing consumption of natural resources puts increasing pressures on the energy, water and food sectors. The global World population is expected to increase by 33% from current level to around 9.7 billion people by 2050 (FAO, 2016; Fao and WWC, 2015; Petersen et al., 2016). Expected populations growth will be also associated with changing consumption habits that would deeply influence food demand all over the globe. More competition for land and water resources will characterize future market and also water scarcity will exacerbate the issue according to climate change forecast estimation. Indeed addition global water demand will likely increase by more than 50% between 2000 and 2050, and water availability for irrigation use is foreseen to decrease (because of less water availability, but also due to high water demands from other competitive sectors) potentially limiting the capacity to produce same production level for several food and feed crops. For example cereals production will have to increase by 50% to satisfy global demand, but will have to compete with a required increase of meat production, that will require much more land and water resources.

Most modern and productive agriculture production is unlikely without external inputs of water and nutrients. Modern agriculture is very closely linked with water availability and in general with the energy sector demanding products dependent on this supply: fertilizers, pesticides, livestock sector, irrigation water, tillage operations are all needed to guarantee a sufficient level of crop production, but all need energy inputs, and in addition their use can be a serious threat to environment.

In this context the concept of Energy-Water-Food Nexus has become the headline for the global research agenda (World Economic Forum, 2011; Zhang and Vesselinov, 2017) and the reference for sustainable development and for the identification of new and future management and development strategies. Under this paradigm (WEF) water, energy and food are critical resources inextricably interrelated (Gold and Webber, 2015; WWAP [United Nations World Water Assessment Programme], 2014) and all policy and administrative decisions, involving one of the three sectors, cannot be effectively developed without considering also other two sectors and relative implications.

Energy-Water-Food Nexus was primarily developed for global analysis, but it can also be applied at local scales: at this level Nexus approach can focus for example for the improvement of water and nutrient use in agriculture production thus allowing to enhance the production and reduce at the same time the impact and the competition with other sectors. Also it may focus on improved water and

natural resources management for the identification of best management practices allowing to optimize different objectives but considering the same target.

Systematic and objective approaches are essential for understanding and analyse different sectors demands not only at different spatial and temporal scales but also across varoius sectors and under changing boundary conditions (landuse, climate changes, etc.).

The continuous increase in food demand, water demands and related sectors will continue to cause augmenting stresses on all the sectors, thus exacerbating the water and shortage at different scales, locally, regionally and nationally as well as at global scale.

The challenge is to effectively manage and make optimal use of limited resources to meet future socioeconomic needs (FAO, 2014a; Howells et al., 2013). Tools facilitating this analysis are urgently needed in order to develop or increase the ability to produce analysis and assessments supporting policy measures implementation. These tools and analysis approaches must be capable of identifying the tradeoffs among various and even conflicting sectors, generating cost-effective planning, strategies and policies (Zhang and Vesselinov, 2017). In addition, the outcomes of such analysis should be clearly transferable and interpretable to effectively inform decision makers and stakeholders.

It is within this domain that I analyse the contribution of multi objective analysis routines combined with mathematical models in order to provide answers to the various and diversified questions arising from Nexus approach.

It is well recognized that computer modelling systems provide an important contribution to the process of integrated management and decision support to identify the appropriate management measures, to optimize the monitoring and sampling programs of the water bodies and to accompany the implementation and evaluation of the measures and their impacts (Lindenschmidt et al., 2007). Distributed models are able to capture the spatial and temporal heterogeneity of environmental factors such as soil, land use, topography, management and climate variables, but they are unable directly to solve water resources management and control problems that require the explanation of a range of available alternatives.

In this regard, decision problems concerning environmental and natural resources management are usually complex or even hyper-complex problems (Brans, 2002). A deep analysis and decision making process requires a high background on environmental, economic and social disciplines. At this point, sometimes it is not easy to develop policies with the agreement of all the policy units involved in the water resources management.

Many researchers have found that optimization algorithms provides an effective tool for water management by adding structure, auditability, transparency and rigour to decisions. Optimization techniques have been widely used in environmental modelling (Jeganathan et al., 2011; J. Nicklow et al., 2010; Recknagel, 2013; Reed et al., 2013) with an increase use of multi-objective approaches. In the case of multi-objective optimization problems, usually there is no unique optimal solution, but there is a set of solutions which are superior to the rest of solutions: these are known as Pareto-optimal or non-dominated solutions (Hans, 1988).

This type of approach has demonstrated great potential for addressing problems in managing conflicting objectives (Ines et al., 2006; Bryan and Crossman, 2008; Higgins et al., 2008; Sadeghi et al., 2009; Meyer et al., 2009; Whittaker et al., 2009; Latinopoulos; 2009). Several authors have combined the use of biophysical and multi-objective programming models (Rabotyagov et al., 2010; Panagopoulos et al., 2012; Panagopoulos et al., 2013; Fernandez-Santos et al. 1993). Pandey and Hardaker (1995) provide an overview of the usefulness of bio-economic modelling for studying the interaction between farm management practices and economic criteria to analyse sustainability of farming systems.

This thesis addresses the need for integrated water resources management in European and African countries by exploring the performance of alternative nutrient and water management strategies and developing integrative decision frameworks to improve human and environmental agricultural management tradeoffs. Key agricultural management objectives (crop production, nutrient leaching and runoff, irrigation strategies, etc.) are analysed and quantified at different scales and under different context and situations. A framework GIS system was developed in order to spatially identify and allocate alternative management practices, by means of the integration of an optimization algorithm and biophysical and hydrological models.

1.2 Objectives and relevance

The goal of this thesis is to develop a modelling system integrating biophysical models with multi-objective evolutionary algorithm optimization techniques in order to perform a multi-objective optimization analysis to dynamically select best management practices by considering different and conflicting objectives;

The specific objectives in line with this general goal are as follows:

- I. Development of an integrated GIS modelling system to simulate and assess the environmental and economic impact of different management practices with specific reference to nutrient losses;
- II. Develop and combine in the system a set of multi-objective optimization techniques in order to dynamically select best management practices by considering different and conflicting objectives;
- III. Evaluation and assessment of the developed tools and methodologies. Application and assessment of the modelling optimization framework (integrating biophysically and hydrological models with multi-objective tools and statistical analysis) with different case studies and more specifically: study of the Pareto-optimal fronts to identify optimal spatial allocation of best agricultural nutrient and water management practices in the studied areas.

In particular different case studies were used to illustrate and analyze the topic:

- A. an application focused on agricultural food production issue at continental scale in Africa; Based on an integrated biophysical model and a multi-objective evolutionary algorithm, we estimated optimal solutions (Pareto front) among agricultural gross margins and nitrates pollution as objectives to identify efficient irrigation and fertilization management patterns in several African countries. This analysis pointed out how the increase of farmer benefit is always related to a higher amount of nitrates losses. Knowledge of these sets of solutions helps decision-makers to choose optimum alternative strategies specifically tailored to each country.
- B. an application on the Danube river basin by integrating the hydrological model SWAT with an economic model to identify Best Management Practices to optimize crop production and water quality in synergy with waste water treatment plans development strategies. We applied a multi-objective, spatially explicit analysis tool, the R-SWAT-DM framework, to search for efficient, spatially-targeted solution of Nitrate abatement in the Upper Danube Basin. The Soil Water Assessment Tool (SWAT) model served as the nonpoint source pollution estimator for current conditions as well as for scenarios with modified agricultural practices and waste water treatment upgrading. A spatially explicit optimization analysis that considered point and diffuse sources of Nitrate was performed to search for strategies that could achieve largest pollution abatement at minimum cost. The set of optimal spatial conservation strategies identified in the Basin indicated that it could be possible to reduce Nitrate loads by more than 50% while simultaneously provide a higher income.

- C. and an application focused on water scarcity issue in the island of Crete for the optimization of irrigation water use; an integrated simulation-optimization framework for optimal identification of agricultural management strategies was developed and applied to the Crete island study area. The framework uses the spatially distributed watershed model Soil and Water Assessment Tool (SWAT) to assess crop yields under current conditions (baseline) as well as under alternative management scenarios for irrigation. The economic module allows evaluating the economic benefit or cost associated to each management strategy, accounting for farmer's net income. One of the most interesting features of the application is that it gives decision makers a good picture of the situation of the study region, allowing exploring from the current state to the maximum improvements that can be achieved by reducing/augmenting water use for all or single crop and for each region of interest. It also provides an evaluation of the costs (or potential income losses) required to afford any conservation strategy (due to political reasons or to environmental constraints).

The methodology is based on objective quantitative data and gives valuable information to decision-makers. It can be easily modified to incorporate additional criteria for inclusion in the optimization process. This type of approach also offers the possibility of integrating in the decision criteria all major concerns of all stakeholder and the final choice of decision-makers may also consider additional factors, such as the socio-economic aspects.

The developed system is not meant to guarantee the implementation of specific optimal solutions, but it provides the data, results and scenarios that feed into political negotiations on the development of sustainable strategies

1.3 Outline

This thesis contains four research chapters (4, 5, 6 and 7), and a concluding chapter (8).

Chapter 2 and 3 deal with the methodological framework and are focused on the description of multi objective optimization and biophysical models used in the thesis.

The last chapter puts the main findings into perspective and elaborates on the further development of the tool.

Chapter 2. MultiObjective Optimization

2.1 MultiObjective Optimization Methodology

The goal of global optimization is to find the best possible elements x^* from a set X according to a set of criteria $F = \{f_1, f_2, \dots, f_n\}$. These criteria are expressed as mathematical functions, the so-called objective functions. A mathematical optimization model consists mainly three basic sets of elements:

- *Objective function*: the objective function defines the measure of effectiveness of the system as a mathematical function of decision variables;
- *Variables and parameters of decision*: the decision variables are the unknowns, or decisions, to be determined by solving the model. The parameters are known values which relate the decision variables with constraints and objective function. The model parameters can be deterministic or probabilistic;
- *Constraints*: to take account of technological, economic and other system, the model should include constraints, implicit or explicit, that restrict decision variables to a range of feasible values.

Figure 2-1 sketches a rough taxonomy of global optimization methods. Generally, optimization algorithms can be divided in two basic classes: deterministic and probabilistic algorithms. Deterministic algorithms are most often used if a clear relation between the characteristics of the possible solutions and their utility for a given problem exists. Then, the search space can efficiently be explored using for example a divide and conquer scheme. If the relation between a solution candidate and its “fitness” are not so obvious or too complicated, or the dimensionality of the search space is very high, it becomes harder to solve a problem deterministically. Trying it would possible result in exhaustive enumeration of the search space, which is not feasible even for relatively small problems.

hand, may only consider those elements of the search space in further computations that have been selected by the heuristic.

An important class of probabilistic, Monte Carlo metaheuristics is Evolutionary Computation (Simon, 2013) . It encompasses all algorithms that are based on a set of multiple solution candidates, called population, which are iteratively refined.

In many practical problems, several optimization criteria need to be satisfied simultaneously. Moreover, it is often not advisable to combine them into a single objective. While it may sometimes happen that a single solution optimizes all of the criteria, the more likely scenario is when one solution is optimal with respect to a single criterion while other solutions are best with respect to the other criteria. The increase of the “goodness” of the solution with respect to one objective will produce a decrease of its “goodness” with respect to the others. While there are no problems in understanding the notion of optimality in single objective problems, multi-objective optimization requires the concept of *Pareto-optimality*.

If a scenario involves an arbitrary optimization problem with M objectives, all of which to be maximized and equally important, a general multi-objective problem can be formulated as follows:

$$\begin{aligned} & \text{maximize} \quad f_m(x), \quad m = 1, 2, \dots, M \\ & \text{subject to:} \quad g_j(x) \geq 0, \quad j = 1, 2, \dots, J \\ & \quad \quad \quad h_k(x) = 0, \quad k = 1, 2, \dots, K \\ & \quad \quad \quad x_i^{(L)} \leq x_i \leq x_i^{(U)} \quad i = 1, 2, \dots, n \end{aligned}$$

where x is a vector of n decision variables: $x = (x_1, x_2, \dots, x_n)^T$. In this case, a Pareto optimal objective vector $f^* = (f_1^*, f_2^*, \dots, f_M^*)$ is such that it does not exist any feasible solution x' , and corresponding objective vector $f' = (f_1', f_2', \dots, f_M') = (f_1(x'), f_2(x'), \dots, f_M(x'))$ such that

$$f_m^* \leq f_m' \text{ for each } m = 1, 2, \dots, M \text{ and } f_j^* < f_j' \text{ for at least one } 1 \leq j \leq M .$$

The reader is referred to (Stadler and Dauer, 1992) and (Stadler, 1988) for extensive discussions of these topics and for the history of multi-objective optimization.

2.2 Pareto Optimality

Pareto efficiency, or *Pareto optimality*, is a concept in economics with applications in engineering and social sciences. The term is named after Vilfredo Pareto (Pareto, 1971) an Italian economist who used the concept in his studies of economic efficiency and income distribution.

In many practical problems, several optimization criteria need to be satisfied simultaneously. Moreover, it is often not advisable to combine them into a single objective. While it may sometimes happen that a single solution optimizes all of the criteria, the more likely scenario is when one solution is optimal with respect to a single criterion while other solutions are best with respect to the other criteria. The increase of the “goodness” of the solution with respect to one objective will produce a decrease of its “goodness” with respect to the others. While there are no problems in understanding the notion of optimality in single objective problems, multi-objective optimization requires the concept of Pareto-optimality.

The solution is said to be Pareto-optimal (belongs to the Pareto-optimal front, or set of solutions) if, with its change not one objective function can be improved without degrading all of the others. All of the solutions that make up a Pareto-optimal front are said to be non dominated, by other solutions. Concepts of the Pareto optimal front, non-dominated and dominated solutions are further explained in Figure 2-2. The axes on Figure 2-2 (F1 = environmental quality and F2 = investment) are two objective functions. Possible solutions for maximization are presented in the F1-F2 plane. Solutions marked with red circles are called *non dominated* and they make up the Pareto-optimal front. Those marked with blue circles are the *dominated* non-Pareto optimal solutions.

A feasible point is considered to be a solution to a multi-objective optimization problem, and is called *Pareto optimal*, when there exist no other feasible point that improves one of the objectives without worsening at least one of the other objectives. The set of these mathematically equivalent point is often referred to as the *Pareto set* or *Pareto front* (red points in the Figure 2-2).

Figure 2-2. Example of efficient (red) and non-efficient (blue) strategies of irrigation and production

2.2.1 Genetic Algorithms (GAs)

Derive their inspiration from the natural process of biological evolution (Goldberg, 1989a). Solutions are encoded into (often binary) strings or chromosomes and the GA operates on a population of these chromosomes. Significant difference between GA and the other global search techniques is that it allows for a parallel search of the space since a population of points is considered at each step instead of just a single point. A solution is represented as a “genome”. The optimization starts with an initial “population” of “genomes”. With each iterative step the “genomes” of the “population” are evaluated with a defined objective function and the “fittest genomes” are chosen to be recombined. The newly generated solutions or “offspring genomes” also are evaluated and the least “fittest genomes” are excluded from the population to maintain the original population size. Process iteratively evolves to the required solution by creation of new and new generations of chromosomes through operations of fitness-based selection and reproduction with crossover and mutation that are fundamentally similar to their natural analogy. A class of GAs comprises probably the most prominent and most popular intelligent algorithms nowadays.

Figure 2-3. General Scheme of the Evolutionary Algorithm

While methods used in the scalarised problem generate a single (local) optimum, the evolutionary optimisation in MOO generates a representation of the complete *Pareto optimal* set. However, the visualization of the Pareto set is impractical for more than 2 (or at most 3) dimensions, thus, for simplicity we consider the local optima convergence.

Evolutionary algorithm optimizers are global optimization methods and scale well to higher dimensional problems. They are robust with respect to noisy evaluation functions, and the handling of evaluation functions which do not yield a sensible result in given period of time is straightforward. The algorithms can easily be adjusted to the problem at hand. Almost any aspect of the algorithm may be changed and customized.

The Multi-Objective Evolutionary Algorithm (MOEA) is capable of dealing efficiently with most of this mathematical function complexities (Udías et al., 2012b). This algorithm applies binary gray encoding (Goldberg, 1989a) for each “chromosome” (optimization string) to represent different management strategies. Each “gene” uses 7 bits to encode the value of each variable, so the total length of the chromosome is 42 bits (6 var x 7 bit/var). The MOEA algorithm evaluates the objective functions fitness based on the outputs of agronomic/hydrologic and economic models as described in the next sections on the thesis.

The initial population is generated randomly if no previous management information is available. The implementation of the algorithm uses the usual procedures of selection (tournament), crossover (single point), and mutation (bit inversion) to generate the new population. It also introduces elitism by maintaining an external population. In each generation, the new solutions that belong to the internal population and are not Pareto dominated by any solution of the external population, are

moved to the external population. If the solutions of the external population are dominated by some of the new solutions, these solutions are deleted from the external population. The external elitist population is simultaneously maintained in order to preserve the best solutions found during the iterative process and to incorporate part of the information in the main population by means of the crossover. Elitism is also included in the recombination process, selecting each of the parents through a fight (tournament), between two randomly-selected chromosomes from the external Pareto set (according to a density criterion) or from the population set (according to a ranking determined through a dominance criterion). Three recombination possibilities are also implemented in the algorithm: crossover of two chromosomes from the external Pareto set, crossover of two chromosomes from the previous population, and crossover of one chromosome from the previous internal population with another from the external elitist population. After a parameter tuning phase, the algorithm gets a set of near-optimal trade-off solutions by using the hypervolume as a valid index of convergence of multi-objective problem (Deb, 2001).

2.3 Biophysical modelling and multi-objective optimization

A comprehensive decision-making framework requires the integration of a biophysical simulation models and a suitable multi-objective optimization technique that is capable of solving complex control problems.

Optimization algorithms have been widely used in environmental modelling (Jeganathan et al., 2011; Meng et al., 2017; J. Nicklow et al., 2010; Recknagel, 2013; Reed et al., 2013) with an increase use of multi-objective approaches. In the case of multi-objective optimization problems, usually there is no unique optimal solution, but there is a set of solutions which are superior to the rest of solutions: these are known as Pareto-optimal or non-dominated solutions (Hans, 1988). This type of approach has great potential for addressing problems in managing conflicting objectives (Bryan and Crossman, 2008; Andrew J Higgins et al., 2008; Ines et al., 2006; Latinopoulos, 2009; Meyer et al., 2009; Sadeghi et al., 2009; Whittaker et al., 2009).

Such approaches can be very useful to support the development of regional spatial land use adaptation strategies. Evolutionary optimization methods such as genetic algorithms (Goldberg, 1989b) are popular in spatial optimization (Ahmadi et al., 2013; Bekele and Nicklow, 2005; Chatterjee, 1997; Goldberg, 1989b; Maringanti et al., 2009; Rodriguez et al., 2011; Zou et al., 2015). The most frequent method of spatial optimization is to link dynamically a watershed simulation model with an optimization algorithm (Ahmadi et al., 2013; Bekele and Nicklow, 2005; Cho et al., 2004; Kalcic et al., 2014a; J. W. Nicklow et al., 2010; Rodriguez et al., 2011), wherein watershed model outputs are used

to estimate the objective functions of the optimization algorithm. Interest has grown in spatial optimization of conservation practices using genetic algorithms and SWAT (e.g., Ahmadi et al., 2013; Bekele and Nicklow, 2005; Maringanti et al., 2011; Rodriguez et al., 2011). Several authors have combined the use of biophysical and multi-objective programming models (Fernandez-Santos et al., 1993; Panagopoulos et al., 2013, 2012; Rabotyagov et al., 2010). Pandey and Hardaker (1995) provide an overview of the usefulness of bio-economic modelling for studying the interaction between farm management practices and economic criteria to analyse sustainability of farming systems. Fernandez-Santos et al. (1993) addressed the nitrate pollution problem in the province of Cordoba, in Spain, using the NTRM crop simulation model and a multi-objective programming model at the farm level. Flichman et al. (1995) used the EPIC biophysical model to generate information on yields and nitrate pollution and a multi-objective bicriterion model, in order to analyse the impacts of the Common Agricultural Policy Reform on nitrate pollution in several European regions. Yang (2011) used a multi-objective optimization model to allocate environmental flows to a restored wetland, by seeking a rational balance among appropriate water allocation for the wetlands, a healthy ecosystem, and optimum economic returns. Bryan and Crossman (2008) developed an optimization-based regional planning approach to identify geographic priorities for unground natural resource management actions that most cost-effectively meet multiple natural resource management objectives. Andrew J. Higgins et al. (2008) applied a multi-objective integer programming model, with objective functions representing biodiversity, water runoff and carbon sequestration. Sadeghi et al. (2009) applied an optimization approach to maximize profits from land use, while minimizing erosion risk. Udias et al., (2007) and Meyer et al. (2009) coupled SWAT (Soil and Water Assessment Tool) with an optimization routine to determine optimum farming system patterns to reduce nitrogen leaching while maintaining income. Similarly, Whittaker et al. (2009) applied SWAT in connection with a Pareto-optimization approach considering profits from land use and chemical pollution from farm production. Latinopoulos (2009) applied optimization to a problem of water and land resource allocation in irrigated agriculture with respect to a series of socio-economic and environmental objectives.

More recently Whittaker et al. (2017) integrated SWAT and an economic model within a hybrid genetic optimization algorithm to analysis the effect of input tax of fertilizers in a watershed in USA to spatial targeting agro-environmental policy decisions. Getahun and Keefer (2016) developed a coupled system based on SWAT, for simulating watershed impacts of several management practices and a cost evaluation model with an optimization genetic algorithm to identify spatially optimized reduction strategies for diffuse source pollution. In the context of biofuel energy production, Lautenbach et al. (2013) integrated SWAT model and a multi-objective genetic algorithm to estimate Pareto optimal solutions for different management strategies.

In several works authors have focused either on using a single objective function for optimization that combines BMP effectiveness with cost (Chatterjee, 1997; Srivastava et al., 2002) or on sequential optimization of effectiveness and cost as separate objective functions (Gitau et al., 2004; T. L. Veith et al., 2004), i.e. constraining one objective function during optimization of the other. In contrast, simultaneous optimization of economic and environmental objectives allows identifying trade-off strategies (Ahmadi et al., 2013; Bekele and Nicklow, 2005; Maringanti et al., 2009; Whittaker et al., 2017).

Chapter 3. Biophysical modelling

This chapter introduces the GISEPIC-AFRICA model framework, the underlying field-scale model EPIC, and the SWAT model which were used in all simulations and analysis for this thesis.

3.1 EPIC model and GIS linkage

3.1.1 GISEPIC-AFRICA framework

GISEPIC-AFRICA is a GIS system integrating the biophysical continuous simulation model EPIC (Williams, 1995) with a spatial geodatabase to simulate nutrient and water cycling as affected by agriculture practices and crop growth at the African continental scale. The loose coupling approach (Huang and Jiang, 2002) was used to link the geodatabase and the EPIC model. The integration is based on the transfer of data between the GIS and the simulation model. This approach was preferred to a tight and full integration to avoid redundant programming and to facilitate the integration with new or other models. The data transfer between the geodatabase and the model is operated by means of a specific tool (dll component) and by the GIS interface. The system (Figure 3-1) is composed of the following components: the EPIC model, the spatial geodatabase, the data transfer component (used for input-output transfer to the GIS) and the GIS interface (for selecting the spatial extent of the simulation). A more detailed and complete description of the system and methodology is given in Pastori et al., 2011.

3.1.2 Most relevant model process

EPIC is a biophysical, continuous, field scale agriculture management model. It simulates crop water requirements and the fate of nutrients and pesticides as affected by farming activities such as timing of agrochemicals application, different tillage, crop types and varieties, crop rotation, irrigation strategies, etc., while providing at the same time a basic farm economic account. The main components can be divided in the following items: hydrology, weather, erosion, nutrients, soil temperature, plant growth, tillage, plant environment control and economics. Complete and detailed information and description of each component are given by Williams et al. (Williams, 1995), while in this paper only a brief description of crop growth and nutrients components is given.

Figure 3-1 Structure of the GISEPIC AFRICA system.

3.1.2.1 Crop growth

A single model is used in EPIC for simulating all crops, both annual and perennial. Annual crops grow from planting to harvest or maturity date, while perennial crops maintain their root systems throughout the year. EPIC uses a daily time step to calculate crop potential growth. Maximum crop yield is based on the radiation use efficiency. The daily potential biomass increase is calculated as:

$$\Delta B_p = 0.001 BE PAR$$

where B_p is the potential biomass production (t/ha), BE is energy to biomass conversion parameter (kg/ha/MJ/m²) function of atmospheric CO₂ level, and PAR is the intercepted photosynthetic active radiation (MJ/m²) estimated based on Beer's law as:

$$PAR = 0.5 RA (1 - EXP^{-0.65 LAI})$$

where RA is the solar radiation (MJ/m²), and LAI is the leaf area index. LAI is calculated daily based on heat units. Heat units (HU) on a particular day are calculated during the phenological development

of the crop as the average daily temperature in excess of the crop base temperature, and the heat unit index (HUI) estimated as the ratio of the cumulative heat unit divided by the potential heat units:

$$HU_i = \max(0, T_{av} - T_b); HUI_i = \frac{\sum_{k=1}^i HU_k}{PHU_j}$$

Where T_{av} is the average daily temperature (°C), T_b is the base crop growth temperature (°C), i is the day, PHU is the potential heat unit for crop j (obtained as the sum of heat units from normal planting to maturity). The yield is calculated as the product of the harvest index and above ground biomass. The harvest index can however be reduced by water stress, or a shortened growing season and it is thus adjusted accordingly.

EPIC adjusts the daily potential growth by constraints including the influence of the following limiting factors: nutrients, water, temperature, aeration and radiation. These stresses can impact not only biomass production, but also root development and yield. A stress is estimated for each of the limiting factor and the actual stress is taken equal to the minimum stress calculated for each of the constraints.

3.1.2.2 Nutrients

EPIC takes into account nitrogen and phosphorus cycles. Five nitrogen pools are considered: active organic, stable organic, fresh organic, nitrate and ammonium pools.

Nitrate losses are related to the processes of leaching, runoff and lateral subsurface and are calculated as a function of flow volumes and nitrate average water concentration. All three process are calculated only for the first top layer, while for the lower layers only leaching and later flow are considered.

Denitrification is considered by the model as an exponential function of temperature, organic carbon, nitrate concentration and soil water content. Denitrification occurs only when the soil water content is 90% of saturation or greater.

The mineralization (transformation from organic to ammonia) is simulated with a modification of the PAPRAN mineralization model (Seligman and Van Keulen, 1981): mineralization can be from fresh organic pool (associated with crop residue and microbial biomass) and from stable organic pool (associated with soil humus). Fresh organic mineralization is mainly governed by C:N and C:P ratios, soil water, temperature and the stage of residue decomposition. For the soil humus pool one stable and one active sub pools are considered and mineralization can occurs only from the active one as a function of organic N mass, soil water and temperature.

Like mineralization, immobilization is calculated with a modification of the PAPRAN model by subtracting the amount of N contained in the crop residue from the amount assimilated by the microorganisms.

Nitrification, the conversion of ammonia to nitrate, is estimated with a first order kinetic rate (Reddy et al., 1979) and is a function of temperature, soil water content and soil pH. Volatilization, the loss of ammonia to the atmosphere, is simulated simultaneously with nitrification as a function of temperature and wind speed, while below surface volatilization is a function of cation exchange capacity and soil temperature.

Crop uptake is a very important process and is estimated using a supply and demand approach. Daily N demand is the product of biomass growth and optimal N concentration in the plant (related to crop stage) while soil supply of N is limited by mass flow of nitrates to the roots.

Fixation of N is important for leguminous crops and is estimated as a fraction of daily plant uptake. It is a function of soil nitrate and water contents and plant growth stage. It decreases linearly below 85% of field capacity to zero at wilting point. EPIC also consider the N contribution from rainfall, as a function of an average N concentration in the rain.

The cycling of organic P is similar to that described for nitrogen with mineralisation occurring from the fresh organic P and organic P associated with humus. Mineral P is divided into a labile P pool, an active mineral pool, and an inactive mineral pool. Fertiliser P is labile at application and then is transferred rapidly to the active mineral pool. The active and stable inorganic P pools are dynamic, and at equilibrium, the stable mineral P pool is assumed to be four times larger than the active mineral P pool (Sharpley and Williams, 1990).

3.1.3 The GEODATABASE for the African continent

A geodatabase was developed to support the application of EPIC for the entire African continent. The geodatabase includes all the data required for EPIC modelling: meteorological daily data, soil profile data, crop distribution and management data, and scenario information. These attributes as well as the model setup are described below.

Considering the resolution of available required datasets (soil, landuse, climate and crop management) a reference spatial modeling unit grid of 15 km x 15 km covering the entire African continent was selected. This resolution is a balanced value between more detailed and coarser data sets. It accounts for landuse, soil and climate variability, which are key elements for nutrient and water dynamics. Entire Africa was thus discretized into 135 000 different grid cells. Each grid cell (SITE) is characterized by uniform topography, soil and climate.

This conceptual model is very useful because it allows performing EPIC simulations based on the mentioned subunits re-aggregating back the results to run unit level: the output in term of environmental and/or economic indicators can be aggregated and weighted in a single value taking

into account crop area. All data were implemented into an object relational data model within the context of the ESRI ArcGIS geodatabase and in a Microsoft SQL Server 2012 environment.

3.1.3.1 The SITE section

This is the core part of the data model as it contains the EPIC spatial simulation run units (Figure 3-2). These units were created in ArcGIS 9.3 using “Fishnet Tool”: the final vector grid is based on a projected space in Lambert Azimuthal Equal Area Projection and has a resolution of 15 km.

Figure 3-2. SITE and simulation unit definition

SITE spatial units are characterized by uniform soil, meteorological and topographic data and for each crop available in the SITE, the management (crop scheduling, soil tillage operations, irrigation practices, fertilization amounts) is also defined.

Soil and topographic data were aggregated to the SITE feature with a spatial analysis as described in the following sections while meteorological data were spatially linked to each site. Finally information on land use and crop distribution were aggregated to each site to obtain agriculture area and crop specific areas.

3.1.3.2 Soil input

The Harmonized World Soil Database (FAO et al., 2009) with a resolution of about 1 km (30 arc seconds) was used to characterize the soils of the SITE units. Over 6 988 different mapping units are present in Africa. The original soil map is based on the concept of Soil Mapping Unit (SMU). For each spatial SMU a list of different soil types is described and characterized in the HWSD database. In order to consider all different soils, a weighted average was calculated at SITE level for each parameter required by EPIC considering the share of presence of the soil type in the SMU. The EPIC model requires information about soil textural composition, porosity, saturated hydraulic conductivity, along with the initial values of the various nitrogen and phosphorus pools.

3.1.3.3 DEM

A global digital elevation model (DEM) with a horizontal grid spacing of 30 arc seconds (FAO, 2009a) was processed to obtain elevation and slope for each grid cell.

3.1.3.4 Land use

The SAGE crop maps (Monfreda et al., 2008) were used to derive a complete landuse dataset for all African countries. SAGE is a detailed database of global landuse describing the area (harvested) and yield of 175 distinct crops for the year 2000 on a 5 min by 5 min (approximately 10 km x 10 km) grid. The data were derived from agricultural surveys collected at the smallest political units available for all the countries (sub-national, usually one or two administrative levels below the national; when these sources are not available, the data refers to FAO national statistics).

3.1.3.5 Meteorological information

Two different datasets were used to derive the daily climate data required by EPIC. The Princeton University Global Meteorological Forcing Dataset for Land Surface Modeling (Sheffield et al., 2006) was constructed by combining a suite of global observation-based datasets with the NCEP/NCAR (National Centers for Environmental Prediction/National Center for Atmospheric Research, (Kalnay et al., 1996) reanalysis. The dataset has a resolution of 1° covering the entire globe (360 x 180 longitude/latitude) and includes the time period extending from 1948 to 2006. The Climatic Research Unit (CRU) monthly dataset covering the period 1961-2006 (New et al., 2002) with a resolution of 10' latitude/longitude was used to downscale the Princeton daily data to a 10' grid. To perform the downscaling, a monthly weighting factor was calculated for each climatic parameter by calculating the long-term monthly average at 10' resolution (CRU) divided by the long-term average of all the CRU grid falling in the corresponding 1° Princeton grid cell. The 1° Princeton daily data were finally multiplied with the 10' weighting factors. The daily climate data includes precipitation, minimum and maximum temperature, wind speed, and solar radiation.

3.1.3.6 Crop management

Crop management is one of the most important sets of input required to run EPIC. It consists of detailed schedules and characteristics of the most common crop operations including sowing, harvesting, tillage, fertilization, and irrigation, for each of the crops used in the EPIC simulations. It was not possible to obtain all management information at the relevant resolution (15 km) for all of Africa. However, management practices (such as fertilization and irrigation practices) can be reasonably considered homogenous at the level of subnational administrative units. For this reason, administrative boundaries provided by FAO (Sub-National Administrative boundaries Level 2 and 3)

(FAO, 2009b) were processed in order to obtain a homogeneous spatial representation of Africa. These administrative units were considered as the reference spatial scale for crop management. The 46 dominant crops in Africa were simulated, and management schemes for each of the crops were derived as described below.

3.1.3.7 *Scheduling dates*

The definition of a sowing date is a key factor because it affects all other management operations (tillage, irrigation, harvest, etc.) and because it will impact crop growth. Planting dates are often estimated on the basis of climate datasets (Waha et al., 2012). This methodology is quite robust even in the case of rainfed agriculture because it allows one to take into account the intra- and inter-annual climatic variability and because the farmers generally base the timing of their sowing on experience driven by past precipitation and temperature conditions. In this study two approaches were used to define the sowing dates according to the geographic location of the site. The potential heat units (PHU) methodology is more appropriate in regions where temperature is the main limiting factor during the growing period and, consequently, it was used in the area above the tropics. This method considers the total number of heat units required to bring a plant to maturity. Heat units are calculated using long-term minimum/maximum temperatures, optimum and minimum plant growing temperatures and the average number of days for the plant to reach maturity. The crop property database provided by Williams (Williams, 1995) and the long-term climate statistics were used to calculate the heat units for each crop.

In the tropical - subtropical regions usually the main limiting factor governing crop sowing is precipitation and consequently, the PHU approach is no longer valid. A different approach based on rain limitation was selected. This approach was originally developed by the Agriculture Hydrology Regional Centre in Niamey and applied in different studies (Genovese et al., 2001; Rojas et al., 2005). The sowing decade (a calendar year is divided into 36 decades) is calculated as the first decade with at least “x” mm of rain followed by 2 decades with at least “x” mm of rainfall. In our study 3 distinct thresholds (x) were used according to different annual averages rainfall (P_{year}):

$x = 10 \text{ mm}$ for regions with $P_{year} < 400 \text{ mm}$;

$x = 20 \text{ mm}$ for regions with $400 \leq P_{year} < 800 \text{ mm}$;

$x = 30 \text{ mm}$ for regions with $P_{year} \geq 800 \text{ mm}$.

All crop management schedules were compared and checked with reported data including crop calendars provided by FAO (FAO, 2012), USDA – FAS Crop Explorer service and EARS (EARS, 2009; USDA, 2009). The limited rain method is less precise than PHU approach because it doesn't consider

crop specific parameters. However a check of the estimated with reported sowing periods suggests that it can be considered a sufficient approximation for the application of the model at the continental scale.

Other relevant crop operation schedules were then evaluated by relating them to the estimated sowing dates. The crop harvesting date was calculated by adding to the sowing date the climatic region specific time to maturity derived from the calculated length of growing period (FAO and IIASA, 2006). A tillage operation was performed three days prior to sowing.

3.1.3.8 Fertilizer management

Fertilization input data were derived from the FAO FERTISTAT database (FAO, 2009c) and complemented by other total fertilizer consumption datasets when required (IFA, 2010). Fertilization data are available at the country level and consequently it was not possible to differentiate fertilization strategies at the sub-national level. The following methodology was thus adopted to derive a spatially detailed fertilization database. First, average annual nitrogen fertilizer consumption data were collected for all countries. Then annual yields and harvested areas were collected for each crop, for each country and for each administrative management unit. These regional crop yield data were then converted into nitrogen yield using crop-specific nitrogen content (Neitsch et al., 2011). Finally, the reported national use of nitrogen was redistributed at an administrative level for each crop based on the regional nitrogen yield. EPIC was then set to run under automatic fertilization with the maximum amount applied for each crop set according to the calculations detailed previously.

3.1.3.9 Water management

The FAO global map of irrigated areas (Siebert et al., 2007, 2006, 2005) was used as the main reference to identify areas where irrigation was considered in the EPIC simulations. This map was selected because it has a resolution of 5' that is compatible with the EPIC SITE dimension, and because it is based on FAO statistics that are the main data source for crop area and distribution. Irrigation reports from FAO were used to identify crops or groups of crops that are irrigated in different countries (FAO, 2005; FAO, 2009e). A table was designed in the database to store all required information: presence of irrigation in the simulation unit (yes if more than 50% of the cropland area is originally mapped as irrigated), the relative percentage of irrigated area, and crop types irrigated. When some discrepancies were observed (rice cultivation in Madagascar not falling in an irrigated area), the Global Irrigated Area Map of the World (Thenkabail et al., 2009) was used to complete the missing information. The Global Irrigated Area Map of the World was developed for year 1999 using multiple satellite sensors and secondary data such as rainfall series, landuse data DEM, and others (see (Thenkabail et al., 2009) for details). The final product is a 10 km resolution map with 28 rainfed and

irrigated crop classes covering the entire globe. EPIC was set to run using the auto-irrigation option. EPIC schedules automatically the irrigation and the amount applied is calculated according to daily plant water stress.

3.2 The Soil and Water Assessment Tool – SWAT

3.2.1 Introduction

The Soil and Water Assessment Tool (SWAT) model has emerged as one of the most widely used hydrological and water quality watershed models worldwide. SWAT is a physically-based, distributed river basin model operating on a daily time step developed by Arnold et al., 1998 for the USDA Agricultural Research Service (ARS). It was developed to predict the impact of land management practices on water, sediment, agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions over long periods of time (Neitsch et al., 2011). Numerous features are implemented in the model to fulfil these objectives.

SWAT requires specific information about weather, soil properties, topography, vegetation, and land management practices in the watershed to directly model the physical processes. These physically based processes comprise in general water movement, sediment transport, crop growth or nutrient cycling. The benefits of this approach are: watersheds with no monitoring data (such as discharge gauges) can be modeled and the relative impact of alternative input data (e.g. changes in climate) on e.g. water quality (NO_3) can be examined. The minimum required data to perform a model run is generally accessible from national authorities. SWAT allows the user to investigate long-term impacts with model runs covering several decades.

Its international use is largely due to its flexible structure that allows it to address different water resource problems, as well as the available complete documentation, supporting software and its open source code that can be adapted by model users for specific applications (Gassman et al., 2007). Because of the large existing literature (J. G. Arnold et al., 2012; Arnold and Fohrer, 2005; Borah and Bera, 2003; Gassman et al., 2014, 2007; Shepherd et al., 1999), only a short description of the model structure and its hydrological and qualitative (sediments and nutrients) components are given herewith. The description will focus on the water and nutrients balances and their key processes within a basin.

Major model components include weather, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management (Arnold et al., 2012; Gassman et al., 2007).

In SWAT, a watershed is divided into multiple subbasins, which are then further subdivided into hydrologic response units (HRUs) that consist in a unique combination of soil, land use/cover and slope. The HRUs are represented as a percentage of the subbasin area and they are not spatially identified, nevertheless they are considered hydrologically isolated. Alternatively, a watershed can be subdivided into only subbasins that are characterized by dominant land use, soil type, and

management. This is often applied in the large scale application (Pagliero et al., 2014; Malagó et al., 2015).

The subbasin is a spatially defined region that comprises a main reach and its contributing area, which is composed by one or more HRUs. The HRUs are ideally connected with tributary channel, a lower order channel, that drain the fluxes in the main reach.

All SWAT model computations are performed at the HRU level (J.G. Arnold et al., 2012). Streamflow, sediment and nutrient loadings from each HRU are aggregated for each subbasin and then routed through the hydrological network (Neitsch et al., 2011). The benefits of HRUs are the increased accuracy in the loading predictions from the subbasin as well as the diversity of plant cover remains in the model at a higher level

3.2.2 Model process

3.2.2.1 The Hydrological component

The hydrological land phase and in-stream phase include the computation of HRU daily water balance and the routing of water in each reach.

The HRU daily water balance solves the change in soil water storage (in mm H₂O) as a function of daily precipitation, surface runoff, evapotranspiration, infiltration in the vadose zone, and baseflow. The conceptualization of SWAT water balance is shown in Figure 3-3 and can be estimated as follow:

$$P = ET + SR + LF + BF + BF_{DA} + DA_{RCHRG} + TLOSS$$

where P is the precipitation (mm), ET is the evapotranspiration (mm), SR is the surface runoff (mm), LF is the lateral flow contribution to stream flow (mm), BF and BF_{DA} are respectively the baseflow contribution to streamflow from shallow and deep aquifer (mm), the DA_{RCHRG} is the amount of water that from the shallow aquifer recharges the deep aquifer, and the TLOSS (not reported in Figure 3-3) is the bed transmission losses (mm) from the main reach or tributary channel.

Figure 3-3. Conceptual SWAT model water balance: P: precipitation; ET, evapotranspiration; BF, baseflow from shallow aquifer; BF_{DA}, baseflow from deep aquifer; INF, infiltration in the soil; LF, Lateral flow; SR, Surface Runoff; DA_{RCHRG}, the deep aquifer recharge; GW_{RCHRG}, the shallow aquifer recharge; WYLD: water yield (Malagó, 2016).

The climatic inputs used in SWAT include daily precipitation (P), maximum and minimum temperature, solar radiation data, relative humidity, and wind speed data. The potential evapotranspiration (PET) was estimated using the Penman-Monteith method (Monteith, 1965) and the actual evapotranspiration (ET) is calculated including the processes of canopy interception, crop transpiration and soil evaporation (Neitsch et al., 2011).

The average air temperature is also used to determine if precipitation should occur as snowfall, while the maximum and minimum temperature inputs are used in the calculation of daily soil and water temperatures.

To account for the increase in precipitation and decrease in temperature with elevation that is typically observed in mountainous regions, SWAT allows implementing the elevation bands (Neitsch et al., 2011).

The total amount of water leaving the HRU (sum of SR, LF and BF) and entering the main channel during the time step is the water yield (WYLD). The accurate estimation of these components is of primary importance when assessing the impact of pollutant transport and for a sustainable water resources use.

SWAT uses two linear reservoirs to partition groundwater into two aquifer systems: a shallow aquifer which contributes baseflow to streams (BF) and a deep aquifer which can also contribute baseflow to streams (BF_{DA}). The remaining portion in the deep aquifer (DA_{RCHRG} - BF_{DA}) can be considered lost from the system. It is noteworthy that in this thesis the contribution of baseflow from deep aquifer was considered negligible. The recharge for a specific day is calculated as a linear function of the daily seepage, the recharge of the previous day and the groundwater delay. Daily seepage includes seepage through the soil profile and through ponds or wetlands and losing streams (tributaries and main channels). All seepage losses are added together and assumed to travel vertically to the aquifer with the same velocity.

The surface runoff (SR, mm) is estimated using the SCS curve number method (USDA Soil Conservation Service, 1972) as modified by Williams (1985) to account for the impact of slope on the curve number. SWAT calculates SR according to the equation:

$$SR = \frac{(P_i - I_a)^2}{(P_i - I_a + S)}$$

where P_i is the precipitation for the day (mm), I_a is the initial abstraction which include surface storage, interception and infiltration prior to runoff (mm), and S is the retention parameter (mm) which is a function of the curve number (CN) for the day.

The peak runoff rate (q_{peak} , m³/s) is calculated with the modified rational formula:

$$q_{peak} = \frac{\alpha \cdot SR \cdot Area}{3.6 \cdot t_{conc}}$$

where Area is the HRU area (km²), t_{conc} is the time of concentration (h), and α is the fraction of daily runoff that occurs during the time of concentration. The time of concentration is calculated with a modified rational method (Chow et al., 1988) as:

$$t_{conc} = t_{ov} + t_{ch}$$

where t_{ov} is the overland flow time and t_{ch} is the channel flow time. The latter is depending on channel length (km), Manning's roughness coefficient of the channel, and channel slope (% or m/m), while the overland flow time is the time that water takes to travel from the furthest point in the subbasin to a stream channel and it is computed as:

$$t_{ov} = \frac{L1^{0.6} \cdot n^{0.6}}{18 \cdot slp^{0.3}}$$

where $L1$ is the average subbasin hillslope length (m), slp is the average subbasin slope (% or m/m), and n is Manning's roughness coefficient.

The lateral flow (LF, mm) occurs whenever the water content of the soil exceeds its water content at field capacity and it is calculated as:

$$LF = 0.024 \left(\frac{2 \cdot SW_{ly,excess} \cdot K_{sat} \cdot slp}{\Theta_d \cdot L1} \right)$$

where $SW_{ly,excess}$ is the drainable volume of water stored in saturated zone of the HRU per unit area (mm), K_{sat} is the saturated hydraulic conductivity (mm/h), Θ_d is the drainable porosity of the soil (mm/mm), and $L1$ is the hillslope length (m).

Multiplying the K_{sat} with slp gives the LF velocity at the HRU outlet (v_{lat} ; Neitsch et al., 2011):

$$v_{lat} = K_{sat} \cdot \sin(\alpha_{hill}) = K_{sat} \cdot \tan(\alpha_{hill}) = K_{sat} \cdot slp$$

where α_{hill} is the HRU gradient (degree). In SWAT it is assumed $\sin(\alpha_{hill}) \sim \tan(\alpha_{hill})$ to simplify the equation, thus slp is equivalent to $\tan(\alpha_{hill})$.

The baseflow (BF) from the shallow aquifer is calculated based on the aquifer recharge (GW_RCHRG, mm H₂O), the deep aquifer recharge (DA_RCHRG, mm H₂O) and the baseflow recession constant (ALPHA_BF, 1/day). Similarly, the baseflow from the deep aquifer (BF_{DA}) depends on the deep aquifer recharge and on the deep-baseflow recession constant (ALPHA_BF_D, 1/day).

3.2.2.2 Crop management and the Best Management Practices (BMPs)

SWAT simulates the land management practices and can incorporate very detailed management information. Management practices are broadly divided into agriculture management, water management and urban areas management.

Some of the agricultural practices include plant growth cycle, timing and quantity of fertilizer, type of tillage, removal of plant biomass, as well as pesticide application.

SWAT uses a single plant growth model to simulate growth and yield of all types of crop. The crop growth is inspired from the Erosion Productivity Impact Calculator (EPIC) model (Williams, 1995) which bases the phenological development of the plant on accumulated heat units which are a function of the minimum and maximum air temperatures. In particular, plant growth is modeled by simulating leaf area development, light interception and conversion of intercepted light into biomass (Jiang et al., 2014). The model calculates the daily accumulated heat units (PHU) and when plant maturity is reached, the plant ceases to transpire and to take up water and nutrients. Then the simulated plant biomass remains stable until the plant is killed or harvested by using a harvest index to define the fraction of dry biomass that is removed as yield. Crop yield is simulated on a dry weight basis.

Water management includes irrigation, tile drainage systems, reservoirs/impounded/depressed areas, water uses, and loading from point sources. Simulation of irrigation can be performed using five alternative water sources: reach, reservoir, shallow aquifer, deep aquifer, or a water body source external to the watershed. The irrigation applications can be simulated on user selected specific dates or with an autoirrigation routine, which activates irrigation events according to a water stress threshold (plant or soil water deficit) (Gassman et al., 2007). Similarly, the fertilization could be applied manually or in automatic way (J.G. Arnold et al., 2012).

For the urban areas, the model estimates the surface runoff with the SCS curve number method or the Green & Ampt equation, while sediment and nutrients are simulated using a linear regression equations developed by the USGS (Tasker and Driver, 1988) or a 'build up/wash off' approach, similar to SWMM-Storm Water Management Model (Huber and Dickinson, 1988). In this thesis the SCS curve number method and the 'build up/wash off' approach were selected.

Best Management Practices (BMPs) are also simulated in SWAT. These conservation practices include cover crops, conservation tillage, residue management, terraces, artificial drainage systems, riparian filtering, and wetlands. Recently the riparian filter strips and the artificial drainage systems algorithms have been updated by SWAT developers/users in order to improve their reliability and replicability at different spatial scale.

White and Arnold (2009) proposed a new routine to simulate the riparian filtering, overcoming some limitations of the previous algorithm, such as the use of the same filtering efficiency for sediment and all nutrients forms. The new routine consists in empirical equations developed from a combination of measured data derived from literature and simulation results of the Vegetative Filter Strip MODel (VFSSMOD) (Muñoz-Carpena et al., 1999). These equations allow calculating the sediment and nutrients reductions based on an empirical runoff reduction (in %), that is only used for this purpose without affecting the water balance.

The subsurface tile drainage is simulated by SWAT using two methods. The first tile drainage algorithm calculates tile flow as a function of a water table depth (wtd), the distance between soil surface and a user defined impervious layer (DEP_IMP), tile depth (DDRAIN) and the time required to drain the soil to field capacity (TDRAIN), as well as the drain tile lag time (GDRAIN) (Du et al., 2005; Green et al., 2006). This method assumes that the tile systems have equidistant tile spacing and size. The second tile drainage algorithm computes tile flow using Hooghoudts (1940) steady state and Kirkham (1957) tile drain equations that are a function of water table depth, tile drain depth, size, and spacing (Moriassi et al., 2013, 2007). Currently, there is a lack of documentation of the Hooghoudt and

Kirkham method and the modified DRAINMOD approach in Neitsch et al., 2011, however details of the theory and practical case studies can be found in Moriasi et al. (2013, 2007).

Scenarios analyses of BMPs application are often performed with SWAT model, albeit only focusing on qualitative benefits (Aouissi et al., 2014; Cerro et al., 2014). However, for policy and management purpose, the investment-cost assessments are an essential task that should be integrated with the environmental analysis. Thus in this thesis, the SWAT model is complemented by a tool for optimal selection of Best Management Practices, BMPs (i.e fertilizer reduction and upgrading of waste water treatment plant), that involves the linkage of SWAT model with economic components.

3.2.2.3 The Qualitative component

The SWAT model distinguishes the nutrient pollution (N, nitrogen and P, phosphorous) from diffuse sources (DS) and from point sources (PS). Diffuse source pollution can be caused by a variety of activities that have no specific point of discharge. For instance, agriculture is a key source of diffuse pollution, but urban land and atmospheric deposition can also be important sources. Conversely, point source pollution comes from one source like an industry or a waste water treatment plant. These sources can lead to several water quality problems, such as the eutrophication phenomena in rivers and reservoirs/lakes. The impact of diffuse sources is reduced in part by the natural retention of soil system and by the effects of the riparian filtering that decrease the amount of diffuse emission (DE) toward the river, as well as the river retention reduces the nutrient load in the rivers coming from both point and nonpoint sources.

Figure 3-4 shows the general conceptualization of nutrients balance by the SWAT model, that however differ for nitrogen and phosphorous as shown in Figure 3-5 and Figure 3-6.

Figure 3-4. Conceptual SWAT model nutrient balance: DS: diffuse sources; PS: Point sources; PLANT_{YR}: nutrients removed with plant yield; Leach: nutrients leaching in the shallow aquifer; DE: diffuse emission; DE_{RF}: diffuse emission after the riparian filtering reduction; Loads: nutrients loads in the output of the Basin (Malagó, 2016).

The transformation and movement of nitrogen and phosphorus from diffuse sources (DS) within an HRU/Subbasins are simulated in SWAT as a function of nutrient cycles consisting of several inorganic and organic pools (Figure 3-4). Within the reach, instead, SWAT adopted a modified version of the QUAL2E model (Brown and Barnwell, 1987) to simulate in-stream nutrient transformations. The sub-components of QUAL2E include models of the biochemical dynamics of algae as chlorophyll-a, dissolved oxygen, carbonaceous oxygen demand and the various chemical forms of nitrogen and phosphorous. Between the HRU/Subbasin and reach, the SWAT riparian filter strips can reduce the diffuse nutrient emission as a function of an empirical reduction of surface runoff, as described in the previous section. In addition, SWAT simulates the nutrient removed by crop harvest (PLANT_{YR} in Figure 3-4, N_{YR} and P_{YR} respectively for nitrogen and phosphorous in Figure 3-5 and Figure 3-6) using a supply-and-demand approach, as well as the nitrate leached (Leach) to the shallow aquifer (Figure 3-5). Instead, the soluble P leaches only from the top 10 mm of the soil into the first soil layer due to its low mobility as shown in Figure 3-6 (Neitsch et al., 2011).

Figure 3-5 shows in details the conceptual SWAT model nitrogen (N) balance. The diffuse sources include the nitrogen fixation by plants (N_{FIX}), the nitrogen deposited on the soil with the precipitation (N_{RAIN}) and the nitrogen applied as fertilizer (N_{APP}). Nitrogen processes simulated in the soil include mineralization, residue decomposition, immobilization, nitrification, ammonia volatilization and denitrification. While in the reach, among the aforementioned processes simulated by QUAL2-E model, the denitrification is not represented and the nitrogen retention is the result of sedimentation and uptake by algae.

SWAT also includes a simple empirical model to predict the trophic status of water bodies, allow the users to define the nutrients settling rates.

In particular, SWAT determines the amount of nitrate lost by denitrification in the soil as following:

$$N_{DENIT,ly} = NO3_{ly} \left(1 - e^{[-CDN \cdot \gamma_{tmp,ly} \cdot SOL_CBN_{ly}]} \right) \text{ if } \gamma_{sw,ly} \geq SDNCO$$

$$N_{DENIT,ly} = 0.0 \text{ if } \gamma_{sw,ly} < SDNCO$$

where ND_{ENIT,ly} is the amount of nitrogen lost through denitrification (kg N/ha), NO3_{ly} is the amount of nitrate in layer *ly* (kg N/ha), CDN is the rate coefficient for denitrification, $\gamma_{tmp,ly}$ is the nutrient cycling temperature factor for layer *ly*, $\gamma_{sw,ly}$ is the nutrient cycling water factor for layer *ly*, SOL_CBN_{ly} is the

amount of organic carbon in the layer l_y (%) and SDNCO is the threshold value of nutrient cycling water factor for denitrification to occur. The default value of CDN is 1.4 and ranged between 0 and 3, while SDNCO is set by default to 1.1.

Nitrate, which is very susceptible to leach, can be lost through surface runoff (SRN), lateral flow (LFN) and percolate out of the soil profile and enter in the shallow aquifer (N_{LEACH}). The amount of nitrate in surface runoff (SRN) is only considered in the top soil layer (10 mm thickness). Amounts of $N-NO_3$ contained in lateral subsurface flow and percolation are estimated as products of the water volume and the average concentration of nitrate in each layer. The organic nitrogen (ORGN) transport with sediment is calculated using a loading function based on the concentration of organic N in the top soil layer, the sediment yield, and the enrichment ratio. The enrichment ratio (ERORGN) is the ratio of the mass of organic nitrogen in the sediment to that in the soil. Nitrate is transported also via tile drainage system (NTILE) and it is obtained multiplying tile flow (m^3/d) by $N-NO_3$ concentration in solution in the layer containing the tile drain and the NPERCO parameter (nitrate percolation coefficient). Nitrate in the shallow aquifer may be lost by biological and chemical denitrification that SWAT simulates using the nitrate half-life parameter. The remaining part can transport to the river with the baseflow (BFN).

Figure 3-6 shows the SWAT conceptualization of the phosphorous (P) balance. SWAT considers as unique form of diffuse source for P the fertilizer application (P_{APP}). The amount of soluble phosphorus removed in runoff (SOLP) is predicted using the labile P concentration in the top 10 mm of the soil, the runoff volume, and a partitioning factor (Neitsch et al., 2011). Sediment transport of P (SEDP) is simulated by a loading function, as described for ORGN, based on an enrichment ratio (ERORGP). As for NTILE, the phosphorous transported via tile drainage system (PTILE) is simulated by SWAT multiplying tile flow (m^3/d) by the phosphorous concentration in the layer with the tile drain and the PHOSKD parameter (phosphorous percolation coefficient) (Moriasi et al., 2013).

Finally, it is noteworthy, that the reduction of pollution due to the riparian filter strips has not impact on NTILE and PTILE, as well as on LFN and BFN (Figure 3-5 and Figure 3-6). In practice, to evaluate the impact of riparian filtering on nutrients diffuse emissions, the model outputs have to be compared with outputs from SWAT simulation in absence of riparian filter.

Figure 3-5. Conceptual SWAT model nitrogen balance: the diffusion sources are represented by the sum of nitrogen applied to the plant biomass via fixation (N_{FIX}), nitrogen transported to the soil with the precipitation (N_{RAIN}) and the nitrogen applied as fertilizer (N_{APP}); N_{PS} is the nitrogen loading to the reach from point sources; the diffusion emissions are the nitrates loading to reach in tile drainage system (N_{TILE}), in lateral flow (N_{LFN}), in surface runoff (N_{SRN}), in baseflow (N_{BFN}) and the organic nitrogen transported with the water yield (N_{ORGN}); $N_{ORGN_{RF}}$ and $N_{SRN_{RF}}$ are respectively the organic nitrogen and nitrates reduced by riparian filtering; N_{LEACH} is the nitrogen leached to aquifer; N_{PYR} , N_{soilR} , N_{aq} , N_{RF} and N_{riverR} are respectively the reduction of nitrogen applied by plant, soil, aquifer, riparian filter strip and river; N_{Load} is the total nitrogen loads at the outlet of the Basin (Malagó, 2016).

Figure 3-6. Conceptual SWAT model phosphorous balance: the diffusion sources are represented by phosphorous applied as fertilizer (P_{APP}); P_{PS} is the phosphorous loading to the reach from point sources; the diffusion emissions are the soluble phosphorous (phosphate) transported in tile drainage system (P_{TILE}) and water yield (P_{SOLP}), the organic phosphorous loading to the reach (P_{ORGP}) and the mineral phosphorous adsorbed to sediment and transported into the reach ($P_{SEDP_{RF}}$);

$SOLP_{RF}$, $ORGN_{RF}$ and $SEDP_{RF}$ are respectively the soluble, organic and mineral phosphorous reduced by riparian filtering; P_{PYR} , P_{soilR} , P_{RF} and P_{riverR} are respectively the reduction of phosphorous applied by plant, soil, riparian filter strip and river; P_{Load} is the total nitrogen loads at the outlet of the Basin (Malagó, 2016).

Chapter 4. Modeling the impact of water and nutrient management in African Agriculture

4.1 Introduction

African agriculture is one of the less productive of the world because of low use of available water resources and of limited fertilizer input (Fleshman, 2006). A large increase in agricultural production is needed to meet increasing food requirements of the growing population of Africa. According to FAO estimates (FAO, 2009d; Godfray et al., 2010b) a general increase of food production by 70 % is expected between 2005 and 2050 and, African countries in particular will have almost to double their average crop production to meet these new needs. African agriculture has enormous potential for growth thanks to its natural resources including water and land, which in many cases are only partially used (Morris et al., 2009). African agriculture will need to invest capital and technology to adapt to the new situation, ensure a proper policy environment and provide adequate training to farmers in order to achieve higher crop yields and ultimately ensure food security (Rosegrant and Cline, 2003).

In Africa, crop production is dominated by rainfed agriculture, representing about 94% of the cultivated area. Most of the irrigated area is concentrated in five countries (You et al., 2010). Increasing irrigation potential could boost agricultural production by at least 50% (You et al., 2010). The African Water Vision for 2025 and the related framework for action suggested a doubling of irrigated area in Africa as a requirement to achieve sufficient crop production goals. The Commission for Africa (Commission for Africa, 2005) called for doubling the investments in irrigation infrastructure. NEPAD (NEPAD, 2003) suggested a new irrigation strategy and water management in Africa as a major instrument of economic and agricultural development. Irrigation will also be a key component of mitigation to combat the potential effects of global warming on crop production.

Lack of fertilization is also a major obstacle to higher crop yield in Africa. About 75% of Africa's agricultural land is degraded and nutrient depletion is a major problem. The average fertilizer application rate is around $20 \text{ kg}\cdot\text{ha}^{-1}$, which is extremely low when compared to the $73 \text{ kg}\cdot\text{ha}^{-1}$ in South America, $135 \text{ kg}\cdot\text{ha}^{-1}$ in East and South East Asia and $206 \text{ kg}\cdot\text{ha}^{-1}$ in the industrialized countries (Fleshman, 2006; Kelly, 2006). This lack of water and nutrients has limited agricultural production in Africa, which is the lowest among all continents (FAOSTAT, 2013; Tittonell and Giller, 2013).

Many studies have focused on crop production at various scales making full use of faster computers, linking biophysical models and Geographical Information Systems (GIS). Biophysical models have proven to be useful tools to perform reliable investigations about the impacts of different

management (and climatic) scenarios and strategies of agricultural production on the environment. GIS are a key component of the spatialization of biophysical crop growth models, despite limitations inherent to the issues of linking various scales: the scale of the biophysical processes simulated, of the available input datasets, of the required output data and that of validation data (Faivre et al., 2009, 2004). However, such integration provides the opportunity of using these biophysical models at regional and continental scales by handling a large amount of geographical data, allowing the assessment of the environmental impact of farming while taking into account soil, climate, and crop management spatial variability.

Different approaches are available in the literature to estimate large-scale crop production ranging from statistical regressions (Neumann et al., 2010) to biophysical (Liu, 2009) and terrestrial biosphere models allowing feedback interactions between crop growth and climate (Berg et al., 2011). GIS-based biophysical models are powerful tools to evaluate crop production as impacted by a full range of drivers (Liu, 2009) and they are frequently used to estimate yield gaps at regional/global levels (Dzanku et al., 2015; van Ittersum et al., 2013).

Different integrated systems of crop growth models and GIS have been developed and applied at global scale. LIU used the EPIC model in a GIS environment (Liu, 2009; Liu et al., 2007) to explore crop water productivity of wheat, maize and rice at a global scale with a resolution of 30' (approximately 55 km). Folberth et al. (2012) used the same model incorporating local management to predict maize yield in Sub-Saharan Africa. Tan and Shibasaki (2003) also used EPIC in a GIS framework (6' grid cell) to simulate at a global scale maize, rice, wheat and soybean production. EPIC has also been used extensively to evaluate the impact of climate change on crop production (Wu et al., 2011). In all these applications the resolution of input datasets was generally not highly detailed (usually larger than 50 km x 50 km) or based on simplified management alternatives. In addition, these applications focused on food crop production, without considering major limiting factors such as water availability and the potential environmental impacts.

However, agriculture has a major environmental impact at a global scale and many studies have shown how agriculture may lead to air, water and soil pollution (Bennett et al., 2001; Burney et al., 2010; Carpenter et al., 1998; Vitousek et al., 2009), loss of biodiversity (Dirzo and Raven, 2003; Hulme et al., 2013), soil degradation and erosion (Hurni et al., 2008; Pimentel et al., 1987), and organic matter and water resources depletion, at the local, regional and global scales. Understanding the potential environmental impacts of an intensification of crop production in Africa is critical in the context of sustainable growth and development. Therefore we think that it is of utmost importance to develop tools allowing a quick assessment of the response of crop production to higher levels of nutrients and water inputs and to evaluate the potential impact of this intensification on the environment.

The aim of this study was to develop a high resolution integrated GIS-biophysical model to estimate water and nutrient requirements of major crop production systems in Africa. We selected the biophysical model EPIC (Williams, 1995) because it simulates crop production under different farming practices and operations including fertilization and irrigation application rates and timing, and because it considers nutrient losses to the environment. In addition, it has been thoroughly evaluated and applied at scales ranging from local to continental (Gassman et al., 2005) and used in global assessments (Liu, 2009; Liu et al., 2008). The model has been applied for irrigation scheduling assessment (Rinaldi, 2001; Wriedt et al., 2009b), climate change studies (Mearns et al., 1999) and biofuels production (Velde et al., 2009). An integrated GIS-EPIC system was applied successfully at the European scale (Bouraoui and Aloe, 2007), laying the grounds for extending it to Africa.

4.2 Material and Methods

A geodatabase was developed to support this application of EPIC for the entire African continent. The geodatabase includes all the data required for EPIC modelling: meteorological daily data, soil profile data, crop distribution and management data, and scenario information. These attributes as well as the model setup are described in the previous section (3.1).

4.2.1 Model validation

The goodness of fit of the validation was assessed using different efficiency criteria and the root mean square error (RMSE) as a measure of errors. Efficiency criteria selected include the coefficient of determination (R^2) and the slope and the intercept of the regression line between the measured and predicted values, a weighted (with the slope) version (wR^2) of the coefficient of determination (as defined in Krause et al., 2005) and the Nash and Sutcliffe (1970) index defined as one minus the sum of the squared differences between the predicted and observed values (normalized by the variance of the observed values). The range of R^2 lies between 0 and 1, where a value of zero means no correlation whereas 1 means that the dispersion of the simulation is equal to that of the observations. More information can be derived by the slope and the intercept of the regression line between the measured and predicted values: for a good agreement, the intercept should be close to 0 and the slope to 1. The weighted wR^2 (Krause et al., 2005) combines the R^2 with the slope of the regression line to overcome the problem that systematic over or under prediction might result in a very high value of the coefficient of determination. The NASH and SUTCLIFFE coefficient of efficiency ranges between $-\infty$ to 1, where 1 indicates a perfect fit while negative values indicate that the mean of observed values is a better predictor than the simulated values.

4.3 Results

EPIC was applied for the five most dominant crops of each SITE cell (15 km x 15 km) for the time period extending from 1980 to 2006. For clarity purposes, we focused our discussion on specific crops critical for food production in Africa. These crops include maize, sorghum, wheat and millet for cereals, cassava for tubers, and banana group for fruits. Cereals are the most important group accounting for 49% of the total cropped area (FAO, 2014b). The most cropped cereals in Africa are maize, sorghum and millet (37% of total area). Root crops and pulses occupy a significant share of the arable land (11% and 9%, respectively), and the most important crops are cassava and beans. Fruits (4%) are less dominant at the continental scale, and the most used is banana (plantain represents 45% of fruit cultivation).

4.3.1 Model validation

The validation focused mostly on crop yield as it is the only reported datum readily available for the entire African continent. The validation was not performed at the site level as no high-resolution measured data were available. Therefore, the validation was performed at the regional level making full use of the available spatial crop yield data. Indeed, it is important to stress that most continental scale studies usually limit the validation exercise to the country level (Liu, 2009; Priya and Shibasaki, 2001; Tan and Shibasaki, 2003). The SAGE raster grids derived by combining national, sub-national census statistics and landuse data (Monfreda et al., 2008) were used as the reference for the regional model validation. Original SAGE grids available at a resolution of 5 minutes were re-aggregated at the administrative level (Monfreda et al., 2008; Ramankutty et al., 2008). The EPIC model was used with no calibration, keeping all default parameters unchanged and a reference long-term average yield was calculated for each crop for the period 1990-2006. The comparisons between the predicted and reported yields for the various crops at national and regional levels are shown in Figure 4-1. The statistical evaluation of the validation of model results obtained by comparing average simulated and average reported yields is given in Table 4-1

The simulated and the reported yields compare well, in particular for cereal. Most crops are well simulated at the country level with a coefficient of determination (R^2) around 0.90, 0.86, 0.67, 0.66, 0.67, 0.57 and 0.51 for maize, wheat, cassava, millet, plantain and sorghum, respectively. For cassava, the R^2 is about 0.17.

Table 4-1. Statistical evaluation of the EPIC model performance for the major simulated crops.

CROP	R ² (gradient - intercept)				wr ²		Nash–Sutcliffe efficiency		RMSE (tons ha ⁻¹)	Av. country Yield (tons ha ⁻¹)		
	Nat.		Sub Nat.		Nat.	Sub Nat.	Nat.	Sub Nat.	Nat.	Sub Nat.	Obs	Sim
Maize	0.9	(0.88-0.46)	0.61	(0.70-0.67)	0.79	0.43	0.92	0.58	0.47	0.8	1.9	2.1
Sorghum	0.5	(0.83-0.68)	0.44	(0.58-1.14)	0.42	0.26	-0.01	-1.3	0.64	0.26	0.9	1.4
Millet	0.6	(0.59-0.35)	0.28	(0.55-0.33)	0.39	0.24	0.53	-0.21	0.21	0.29	0.6	0.7
Wheat	0.8	(0.46-0.57)	0.67	(0.54-0.09)	0.40	0.24	0.6	0.83	1.26	1.14	0.9	1.5
Cassava	0.6	(0.67-2.53)	0.17	(0.47-4.9)	0.45	0.21	0.65	-0.35	1.18	2.19	9	8.7
Plantains	0.5	(0.89-1.07)	0.37*	(0.80-2.02)	0.60	0.35	0.37	-0.27	1.81	3.02	5.8	6.2

However the results are much better when considering only the countries where cassava is one of the dominant crops (Angola, Democratic Republic of Congo, and Mozambique). Indeed when a crop is marginal in a specific country, the yield reported by the FAO might not reflect the national yield, but would be more specific to the location where cassava is grown. At sub-national level, the coefficients of determination are high, indicating that EPIC also captured the regional variations of crop yield (Table 4-1). The R² values are also higher for cereals and lower for cassava at the regional level. The modified R² (WR²) (Krause et al., 2005) values are lower but still high, in particular for cereals. The NASH and SUTCLIFFE coefficient of efficiency is high (close to 1) for maize, wheat and cassava, while it is lower (around 0) for sorghum and for millet, cassava and plantains at sub-national level. Root mean square errors (RMSE) are low both at national and sub-national levels for all crops but wheat. The robustness of the EPIC prediction is also shown by comparing the measured and predicted average yield for most major crops. A significant over-prediction can be noted for sorghum and wheat (Table 4-1).

However, in this study no attempt was done to calibrate the yield. Concerning sorghum, two outliers located in South Africa are affecting negatively the model performance. This over-prediction is probably due to some of the simplification in the management practices and also in part to the accuracy of the reported yield (estimated regional yield). Indeed, as mentioned previously, we used the SAGE data (Monfreda et al., 2008) as a basis for validating the model at the regional scale. However, the regional data in the SAGE database don't always come from reported values but are in many cases estimated. Consequently, there is not always in SAGE a "true" reported regional yield, therefore affecting the regional validation.

We performed an additional validation of the reported yields by comparing the calculated irrigation volume applied with the reported national value. At the country level the amount of simulated irrigation is in general in very good agreement with reported water abstraction for agriculture (FAO, 2014b, 2005). The correlation coefficient between estimated and reported annual water abstraction is around 0.9 (0.05 level of significance). However, EPIC generally tends to under-predict the abstracted water. This is explained by the fact that we only calculated crop water requirements without considering irrigation efficiencies and conveyance losses, which are included in the statistics reported by FAO.

Figure 4-1 Comparison between simulated and reported yields at national (a) and regional (b) level for major crops in Africa.

An important element to consider when evaluating the model is the assessment of its ability to represent the importance of climate parameters and their influence on crop yield and in general on water and nutrient processes and cycles. We analyzed specifically the impact of precipitation on maize yield. In some African countries (Central and Eastern Africa) there is a significant positive correlation between precipitation and the maize yield. For other regions, including North Africa, no linear relation can be found indicating that extra water inputs (irrigation) are controlling maize yield. In southern countries, maize yield tends to exhibit a linear relation with precipitation whereas in central equatorial countries, the yield does not seem to be linked with precipitation. For Africa in general yield seems less correlated with precipitation and other climate variables than in Europe (Velde et al., 2009) and

this can be partially explained by the fact that in many countries agriculture is characterized by low intensity where the main limiting factor is fertilization.

4.3.2 Assessment of agricultural vulnerability of Africa

Crop yields are closely related to the amount of nutrients and water applied and very sensitive to the combination of both factors. The actual fertilizer applications are generally very low in Africa (20 kg·ha⁻¹ average for all crops) and this low input practice is reflected in the crop production, which is the lowest compared with all other continents for all major crops. Insufficient nutrient fertilizers inputs have been identified as a major cause for the extremely low crop production in Africa (Brams, 1971; Folberth et al., 2012; Payne, 2010). Agro-ecosystems with long-term low fertilization inputs can lead to soil nutrient depletion (Weight and Kelly, 1998) and to a loss of soil organic matter and subsequently to a loss of soil functionalities. Cultivation with minimum or no nutrient input can introduce a 30% loss of soil organic matter after 12 years and 66% after 46 years (Weight and Kelly, 1998). To assess the sustainability of current practices, we calculated a nitrogen index defined as the difference between the nitrogen input through fertilization and the nitrogen uptake of the 5 dominant crops (excluding N fixing crops):

$$N_{\text{index}} = \text{FERT } N_{\text{model input}} - N_{\text{model crop uptake}}$$

The index was estimated for each EPIC site and the results are displayed in Figure 4-2. Under current fertilization practices, we predict that only 8 countries have a positive or null nitrogen balance. Egypt is the country where the nitrogen index value (calculated for the 5 dominant crops and including non-fertilized crops) is the highest with an average nitrogen positive excess around 70 kg N·ha⁻¹ while for other northern African countries nitrogen excess ranges between 0 to 10 kg N·ha⁻¹. However, many countries exhibit a negative balance (Figure 4-2). This N deficit indicates a depletion of nitrogen in the soil that will lead in the medium to long term to a decrease of soil fertility.

These negative values of N_{index} reflect an unbalanced crop production and in general a non-efficient management of soil fertility. A consequence of this situation is that many African farmers overcome this problem by abandoning land after few years and deforesting new areas, causing a loss of soil fertility, loss of biodiversity, deforestation and losses of ecosystem services (Achard et al., 2002; Benayas et al., 2010; Carpenter et al., 1998).

N_{index} estimates show negative values in many Sub Saharan Countries with values ranging between -20 to -10 kg N ha⁻¹, values similar to the estimates of nutrient balances (inflows/outflows) in other studies. Weight and Kelly (1998) reported for 38 SSA countries an annual depletion for the period 1980-1990 of nitrogen (22 kg·ha⁻¹), phosphorus (2.5 kg·ha⁻¹) and potassium (15 kg·ha⁻¹). Stoorvogel and Smaling (1998) calculated an annual average nutrient loss for Sub Saharan Countries of 26 kg·ha⁻¹

¹ for the year 2000, while according to other estimates by Bosch et al. (1998) and De Jager et al. (1998) typical value of N balance in central African farms is $-70 \text{ kg N} \cdot \text{ha}^{-1} \cdot \text{yr}^{-1}$. We estimated that more than 80% of the total cropland is characterized by nitrogen crop uptake exceeding the fertilization rate. Similarly, Henao and Baanante (2006) estimated that about 85% of the total cropland in Africa is characterized by high nutrient mining rates.

This index can be considered an efficient indicator of potential soil N mining even though other important aspects were not considered (such as crop residues management, long fallow periods, and other N inputs sources from legume intercropping systems). This indicator clearly shows that actual N fertilizer application rates should be increased to meet crop demand and to allow closing the yield gap without depleting soil fertility. Further, it allows targeting areas where it is possible to close yield gaps while avoiding agricultural expansion into natural ecosystems and clearing more land, thus following a more sustainable path to reach food security (Foley et al., 2011; Ray et al., 2013).

Figure 4-2 Nitrogen index at grid cell level under actual fertilization practices for 5 dominant crops (Marco Pastori et al., 2017).

4.3.3 Irrigation and nutrient requirements for optimal crop production

As highlighted previously, crop production in Africa is limited regionally by the lack of water, and at larger scale by the low input of fertilizers. We propose in the following section to perform a yield gap analysis and to identify for each country the major factor limiting crop growth and calculate nutrient and water requirements to bring production to the optimum level. Yield gap is defined in our study as the difference between potential crop yield under no water and nutrient constraints (Lobell et al., 2009) and the actual yield. Our analysis focuses primarily on the impact of management practices on crop yield. To this end, we set up EPIC to run under two alternative scenarios. The first scenario (SC1) is conservative with respect to water use and is characterized by a maximum (not limited) fertilization strategy. In this scenario the GISEPIC-AFRICA system was set to free auto-fertilization, while irrigation was identical to the baseline. With this configuration the model will apply fertilizer in order to maximize the yield according to crop nitrogen requirements. This scenario is focused on the nitrogen fertilization, which has been identified as the main limitation in restricting yields production, usually more than water availability (Breman et al., 2001). This results in a water-limited potential yield that is a good benchmark for rain-fed agriculture (van Ittersum et al., 2013). The second scenario (SC2) is the “high production potential” with no limitation for both fertilizers and irrigation. This scenario aims at simulating the higher range of potential production of agriculture in Africa under actual land use. Under these conditions crops can always obtain sufficient water and nitrogen when stress occurs. The scenarios were compared with the base scenario representative of current irrigation and fertilization management practices.

The results for both scenarios are given in Table 4-2. For instance for Algeria, unlimited fertilization will result in an increase of crop yield by about 75%, while unlimited fertilizer and water application results in an increase of the yield by 385 (%). Clearly in Algeria, water is the main factor limiting higher production. The comparison between the actual scenario and the “free fertilization” scenario (SC1) highlights that the main limiting factor for agriculture production in Africa can be identified as nutrient fertilization. About 20 countries have their crop production mainly limited by water availability while 32 countries exhibit a nutrient limitation.

Table 4-2. Relative impact of the fertilization and irrigation scenarios on average yields for dominant crops.

COUNTRY	Yield gap (%)			Main crop limitation*	
	SC1-Act.	SC2-Act.	(SC2-SC1)/ SC2	Nitrogen limited	Water limited
Algeria	75	385	4.1		•
Angola	195	372	0.9	•	•
Benin	219	265	0.2	•	
Botswana	97	695	6.2		•
Burkina Faso	284	361	0.3	•	
Burundi	79	314	3.0		•
Cameroon	272	368	0.4	•	
Central African Rep.	179	275	0.5	•	
Chad	195	295	0.5	•	
Congo	49	108	1.2	•	•
Cote d'Ivoire	400	533	0.3	•	
Dem. Rep. of Congo	193	268	0.4	•	
Djibouti	1	1775	1774.0		•
Egypt	0	97	106.8		•
Equatorial Guinea	206	241	0.2	•	
Eritrea	47	385	7.2		•
Ethiopia	149	235	0.6	•	
Gabon	169	229	0.4	•	
Gambia	71	83	0.2	•	
Ghana	308	418	0.4	•	
Guinea	169	250	0.5	•	
Kenya	74	384	4.2		•
Lesotho	88	156	0.8	•	
Liberia	126	167	0.3	•	
Libyan Arab Jam.	58	502	7.7		•
Madagascar	264	356	0.3	•	
Malawi	141	164	0.2	•	

COUNTRY	Yield gap (%)			Main crop limitation*	
	SC1-Act.	SC2-Act.	(SC2-SC1)/ SC2	Nitrogen limited	Water limited
Mali	223	363	0.6	•	
Mauritania	68	454	5.7		•
Morocco	34	451	12.3		•
Mozambique	268	402	0.5	•	
Namibia	153	1021	5.7		•
Niger	170	497	1.9	•	•
Nigeria	256	325	0.3	•	
Rwanda	87	186	1.1	•	•
Senegal	134	219	0.6	•	
Sierra Leone	166	207	0.2	•	
Somalia	190	1023	4.4		•
South Africa	45	229	4.1		•
Sudan	19	75	2.9		•
Swaziland	364	574	0.6	•	
Togo	334	364	0.1	•	
Tunisia	40	183	3.6		•
Uganda	147	436	2.0	•	•
United Rep. of Tanz.	251	391	0.6	•	
Zambia	175	227	0.3	•	
Zimbabwe	76	231	2.0	•	•

* Defined based on the ratio between average yield relative change of SC1 and SC2 scenarios: water limited < 1 and nitrogen limited if > 3

The ratio between the optimal (SC2) and actual nitrogen fertilizer use ranges usually from 1.8 in South Africa to more than 100 in Niger and Uganda. The worst ratio is found in the Democratic Republic of Congo, where the actual nitrogen fertilizer use is less than 0.06 kg·ha⁻¹ while the optimal use is around 60 kg·ha⁻¹ (ratio of more than 1000). In Egypt the ratio is around 0.8, meaning that the reported data by FAO is larger than that calculated by EPIC under the optimal scenario and indicating

an over-fertilization (only case in Africa). The countries that showed the highest potential to increase crop yield included Ivory Coast, Swaziland, Togo, Ghana, Burkina Faso, Cameroon, Mozambique, Madagascar, Nigeria, United Republic of Tanzania, and Mali. They are usually located in rainy regions and are characterized by very low fertilizer inputs under present management.

For water, the ratio between the optimal and actual irrigation volume ranges usually between 0.8 for Sudan and 17 in Ghana, indicating that the volume actually applied is below what is needed for optimal crop growth.

Niger had the highest ratio (around 79) mostly due to the extremely low precipitation (around 150 mm·yr⁻¹) and the absence of irrigation. Egypt, Djibouti, Sudan, Morocco, Tunisia, South Africa, Libya, Mauritania and Eritrea, are characterized by an agriculture production that seems mainly limited by water input.

The potential yield and the calculated nitrogen and water requirements for some major crops are shown in Table 4-3. Maize yield can significantly increase both in North Africa and Sub-Saharan Africa, however with a significant increase of nitrogen application and water application would be needed, in particular in Sub-Saharan Africa. A similar outcome is predicted for all the other major crops. The field gap for maize is significantly larger in Sub-Saharan Africa than in North Africa.

Table 4-3. Required nitrogen and water application rates to bring major crops to optimal yield

		Average yield		N applied		Water applied	
		[tons·ha ⁻¹]		[kg·ha ⁻¹ ·yr ⁻¹]		[mm·ha ⁻¹ ·yr ⁻¹]	
		<i>ACT.</i>	<i>OPT.</i>	<i>ACT.</i>	<i>OPT.</i>	<i>ACT.</i>	<i>OPT.</i>
		<i>SCEN.</i>	<i>SCEN.</i>	<i>SCEN.</i>	<i>SCEN.</i>	<i>SCEN.</i>	<i>SCEN.</i>
Maize	North Africa	6.5	10.4	145.8	267.5	596	915
	Sub-Saharan Africa	1.7	9.6	13.7	335	2	206
Wheat	North Africa	1.5	5.4	65.8	264.7	163	473
	Sub-Saharan Africa	1.2	5.2	27.4	249.3	28	376
Sorghum	North Africa	1.4	6.4	17.5	225.3	31	294
	Sub-Saharan Africa	1.3	7.6	9.9	258.8	2	202
Cassava	Sub-Saharan Africa	8.7	20.5	3.0	102.4	2.8	582
Millet	Sub-Saharan Africa	0.5	2.0	2.4	89	1	307

Increasing crop production is feasible in Africa but clearly with increased economic costs associated with the purchase of nitrogen fertilizers and the price of pumping, irrigation infrastructure, roads, etc. (Mueller et al., 2012) but also increased environmental costs such as additional water abstraction for irrigation. To evaluate the sustainability of the high production scenario (SC2), we calculated at the river basin level (Jenness, 2007) the ratio between the river discharge at the outlet and twice the estimated amount of irrigation water. We used twice the crop water requirements to take into account water required for salt leaching. River discharge was retrieved from Fekete et al., 2002. The ratio gives an indication about the availability of water to satisfy the irrigation requirements at the river basin level. A ratio lower than one indicates that more water than available at the watershed outlet is required to achieve the yield potential, leading to a depletion of water resources. The results for the baseline and the high production scenario are displayed in Figure 4-3. Under current conditions, only a limited number of watersheds are under stress, mostly concentrated in North Africa, Ethiopia, South Africa and Namibia. The Nile River Basin has the highest volume of water use for irrigation and is characterized by a ratio of less than two, indicating some small potential to increase irrigation.

In the high production potential scenario the number of river basins with a ratio less than one increases considerably. The areas under water stress include all North Africa, the Nile river Basin, South Africa (South West Coast, Orange and Limpopo basins). Most of the basins in Central and South East part of Africa can meet the full potential production water requirements without depleting water resources.

The Niger River Basin and the West Coast of Africa are characterized by ratios less than 2 and larger than 1 indicating that irrigation requirements can also be met. However, we did not include in our analysis other water requirements needed to sustain improved access to water, environmental flows, etc. Consequently these basins might be at risk of water stress (Döll et al., 2014; Frija et al., 2014; Schyns and Hoekstra, 2014). In addition, under the high production scenario, increased nutrient losses to the environment can be expected (Fetouani et al., 2008; Fianko et al., 2009; Sall and Vanclooster, 2009). Indeed, we predict that in the high production scenario, nitrate leaching to the aquifer will double, and losses of nitrate in surface runoff will be multiplied by 7, causing additional stress to the environment.

A sustainable intensification of agriculture balancing the quality and quantity of water resources is feasible in Africa, without depleting soil resources while avoiding expansion of agriculture in natural ecosystems.

Figure 4-3. Ratio between the river discharge and irrigation water at river basin level for baseline scenario (left side) and high production scenario (right side).

4.4 Conclusion

African agriculture is one of the least productive in the world because of the small extent of irrigated agriculture and in particular because of the low fertilizer use that is one-tenth of the world average. Consequently, the production gap between Africa and the rest of the world is continuing to rise. In this context African agriculture needs to shift towards a more productive but efficient and sustainable farming. Increasing crop production without agricultural expansion is suggested by many studies and authors as the most sustainable solution (Foley et al., 2011; Godfray et al., 2010a; Hulme et al., 2013; Phalan et al., 2011). However this requires the adoption of strategies and solutions that will not lead to environmental degradation. Using a newly developed and validated tool linking a GIS and the EPIC model, we show that Africa has high potential to increase crop production in order to cope with the increasing demand. We show that in most African countries, the main limiting factor to crop production is nitrogen, while water limitation is restricted to fewer countries. We also show that a mining of soil resources is taking place in many countries in Africa, with the uptake of nitrogen exceeding the inputs. We confirm that irrigation can substantially increase yield in water-rich regions, and that the lack of infrastructure does not allow countries such as those located along the Gulf of Guinea to reach high production levels. Access to fertilizer may not be enough to close yield gaps even in water-rich regions and the adoption of water management strategies is required. On the other

hand, countries such as Northern African countries are mining water resources in many regions and an improved sustainable use of water resources, such as wastewater reuse, will be needed, in particular to cope with climate change (drier and hotter climate). Clearly, these countries will be more vulnerable under climate change with reduced precipitation and increased temperature. We show that yield gaps can be reduced through appropriate nutrient and water management, in particular in Sub-Saharan Africa where the yield gap is larger than in North Africa. However, optimized management strategies considering water availability and water quality are needed in view of a sustainable development. The link of tools such as GIS-EPIC with multi-criteria optimization approaches will play a key role in identifying optimal solutions considering several constraints including social, economic, and environmental factors (M. Pastori et al., 2017). It can be expected that the growth in demand for agricultural commodities, driven by growth in population, per capita incomes and new demands for biofuel, could be met in Africa through sustainable development.

Chapter 5. A Multi-objective approach to evaluate the economic and environmental impacts of alternative water and nutrient management strategies in Africa

5.1 Introduction

As described in previous Chapter in most African countries, the main biophysical factor limiting crop production is nitrogen while water scarcity (including precipitation and irrigation) is the main issue in a more restricted number of countries. Producing more food is feasible in Africa, but it should not be done at the expenses of degrading the environment (The Montpellier Panel, 2013). Even in water rich regions, irrigation has to be managed properly through appropriate infrastructure and efficient technology in order to preserve water resources and to avoid large nutrient losses that may occur through bad practices. For example, increased water abstraction for irrigation could conflict with the demands of water for domestic or industrial use, leading also to adverse ecological effects (Bates et al. 2008). Some countries (mainly Northern Africa) are already mining and overexploiting water resources (Pastori et al., 2011), an issue destined to increase in the context of rising climate stresses including drier and hotter climate and increased variability of the water availability.

Negative impacts of intensive farming on water quality are already reported in several regions of Africa (Fetouani et al., 2008; Fianko et al., 2009; Maherry et al., 2010; Sall and Vanclooster, 2009). This degradation might continue in the near future since the most important increase in reactive nitrogen input over the next decades will occur in tropical African countries, regions that have already shown evidence of high N deposition and that are also an important reserve of biodiversity (Galloway et al., 2008).

Proposed alternatives to achieve higher yields are given by Easterling and Apps (2005). However an uncontrolled intensification could potentially increase adverse agriculture impacts on the environment and lead to new conflicts between different end-users (IPCC, 2007; Schröter et al., 2005). The regional identification of realistic and effective Best Management Practices (BMPs) contributes to a better policy-making procedure (Arabatzis and Manos, 2005; Gómez-Limón and Riesgo, 2004; Manos et al., 2013, 2010, 2007; Pujol et al., 2006; Rizov, 2004; Romero and Rehman, 2003) and minimizes the costs of implementation of the selected strategies while increasing their acceptability by the end-users (Bouraoui and Grizzetti, 2014). However, for a given region (country, basin, etc.) with different farm typologies, soils, climatic conditions and crops the possible number of potential and effective

management practices can increase vastly, and finding the right balance between maximizing crop income, while limiting at the same time environmental (and social) impacts becomes a high complex task. A large number of BMPs are available for implementation from local to national scales. The selection of the optimal set of solutions requires a simultaneous optimization of two or more conflicting criteria.

The aim of this work is to apply for the whole African continent a multi-objective optimization tool to identify trade-off optimum strategies for agricultural land management between profit and environmental impacts in view of helping decision makers to select the optimal solutions according to specific needs and requirements including social, health, economic and environmental priorities. Indeed, decision analysis requires the choice of one alternative among others, a difficult process, especially if the alternatives are non-dominated for a given set of criteria. An alternative is dominant when it is the best solution by considering all decision criteria. Since the decision criteria considered in this study reflect both economic costs as well as environmental status, no single alternative will be dominant because of the potential conflicting nature of the two decision criteria: intensifying agriculture could lead to increase water depletion and degradation and endanger ecological health.

We evaluate two main potentially conflicting objectives including the maximization of farmer's income and the minimization of the environmental impact using the nitrogen leaching loss as a proxy. The main outputs of the analysis are the identification and quantification of trade-off strategies (Pareto frontier curves) between these two potentially conflicting objectives at country level for representative African countries.

The novelty of the study lays in the application of the multi-objective optimization approach at continental scale based on high resolution data (global studies resolution is often larger than 50 km x 50 km) providing a multi-scale tool for identifying at large scale hot spots of mismanagement, and providing at the regional scale detailed optimal sets of sustainable water and fertilizer management strategies. Identified irrigation and fertilization Pareto strategies will help determine the opportunity costs of reducing nitrate pollution, and facilitate the choice of most appropriate management strategies according to stakeholders (farmers, citizens and environment) specific needs at the local and regional scales.

5.2 Methods

Our analysis is based on the combination of the biophysical model EPIC (Williams, 1995) with a multi-objective evolutionary algorithm (Udías et al., 2012b). The model EPIC and the geodatabase developed to support the application for the whole African continent, including all data required by

the model (meteorological daily data, soil data, land use data with crop distribution, and agriculture management information) is described in section 3.1 of the thesis.

A flowchart of the methodological framework is displayed in Figure 5-1. The agricultural management strategies considered in the optimization process are linked to crop fertilization and irrigation schemes (total amount and scheduling). They are the most important factors controlling yield gaps (difference between current and attainable yields for a given region) which are generally very high in several African regions (Mueller et al., 2012). The optimization approach requires the following steps: a) define the set of agriculture management options and their range of variability b) select major crops in each country c) collect information about market price of crops, and cost of water and fertilizer in each country d) define the area (countries) where to perform the analysis e) specify the objective functions for the optimization algorithm.

Figure 5-1. Flow chart of the integrated MOEA-EPIC-GIS methodology.

Maize, sorghum, wheat and barley are the most important cereals crop in Africa, with maize being the most important crop in Central and Southern Africa and wheat being the dominant crop in Northern Africa. So, for our study we applied the integrated tool (EPIC model - MOEA routine) for all these major crops in countries representative of different agricultural systems and environments of the African continent.

Table 5-1. Range of the Decision Variables Considered in All the Analyses.

Parameter	Description	Minimum	Maximum
BIR	Water stress	0	1
VIMX	Maximum annual irrigation (mm)	20	900
ARMX	Maximum irrigation in single application (mm)	50	80
ARMN	Minimum irrigation in single application (mm)	10	60
BFTO	Fertilizer stress	0	1
FMX	Maximum annual fertilization (kg/ha)	200	700

Fertilizer and irrigation strategies control crop yield production at local and global scale (Mueller et al., 2012) and they are directly managed by farmers. Consequently, variables related to fertilization and irrigation were used as model constraints to derive via the Multi-Objective Evolutionary Algorithm (MOEA) alternative management strategies from which the optimal solutions will be selected. Additional constraints (such as a minimum value for crop income or a maximum accepted value for nitrate leaching losses) were not considered not to limit the output information provided to final users. More specifically, for each crop, we considered the total amount of nitrogen fertilizer applied and also different strategies of application (number of applications by cropping season and minimum/maximum amount for each individual application). For irrigated crops, amount and scheduling of total water applied were also variables taken into account (Table 5-1).

The ranges of decision variables to be used via the MOEA to modify EPIC inputs and to perform random simulations are summarized in Table 5-1. The EPIC model was set-up with the auto-fertilization and auto-irrigation options. With this configuration the model schedules automatically the management operations according to daily plant nitrogen and water stresses while respecting the values of variables described in Table 5-1. The plant stress threshold varies from 0 (no stress is considered) to 1 (no stress is allowed thus applications occur as soon as the stress is felt). The model was run for 20 years. For each year, the model calculates the amount of fertilizer and irrigation water to be applied for each crop according to the decision variables (decision triggers), the climatic conditions, and the soil characteristics.

Ranges were set up to the maximum extent allowed by the model for water and fertilizer stress (0 to 1) while maximum constraint values for other parameters were set choosing a reasonable agronomic value. For instance according to statistical data reference average fertilization in Africa is about 20 kg/ha, so we considered a maximum ranging between 200 kg/ha and 700 kg/ha as sufficient to describe a potential increase for all major crops.

5.2.1 The optimization method

It is important to note that, for a given crop, the yield could increase by a factor 2 to 3 with the appropriate application of water and fertilizers. However, this increase is not linear and depends on the interactions between the amounts and timing of application of both fertilizers and irrigation, and on other factors including climate and soil characteristics. Objective functions arising from real world problems do not ensure nice mathematical properties as required by many optimization methodologies (Sarker and Ray, 2009). Thus, we apply a Multi-Objective Evolutionary Algorithm (MOEA) that is capable of dealing efficiently with most of this mathematical function complexities. We have adapted the C-sharp implementation of the MOEA by Udías et al. (2012b). This algorithm applies binary gray encoding (Goldberg, 1989b) for each “chromosome” (optimization string) to represent agronomic strategies (variables of Table 5-1). Each “gene” uses 7 bits to encode the value of each variable, so the total length of the chromosome is 42 bits (6 var x 7 bit/var). The MOEA algorithm evaluates the objective functions fitness based on the outputs of EPIC and the economic model described in the next section.

The initial population is generated randomly if no previous management information is available. The implementation of the algorithm uses the usual procedures of selection (tournament), crossover (single point), and mutation (bit inversion) to generate the new population. It also introduces elitism by maintaining an external population. In each generation, the new solutions that belong to the internal population and are not Pareto dominated by any solution of the external population, are moved to the external population. If the solutions of the external population are dominated by some of the new solutions, these solutions are deleted from the external population. The external elitist population is simultaneously maintained in order to preserve the best solutions found during the iterative process and to incorporate part of the information in the main population by means of the crossover. Elitism is also included in the recombination process, selecting each of the parents through a fight (tournament), between two randomly-selected chromosomes from the external Pareto set (according to a density criterion) or from the population set (according to a ranking determined through a dominance criterion). Three recombination possibilities are also implemented in the algorithm: crossover of two chromosomes from the external Pareto set, crossover of two

chromosomes from the previous population, and crossover of one chromosome from the previous internal population with another from the external elitist population.

After a parameter tuning phase, the algorithm gets a set of near-optimal trade-off solutions with less than 2,000 evaluation of the model (with a population size of 10 and a mutation rate of 3%). Using a higher number of evaluations (tested for a sub sample of the data) proved to introduce a very limited increase in the process performance as indicated by the limited difference (less than 5%) between the two (2,000 vs 20,000 evaluations) resulting hypervolumes. The hypervolume is used as a valid index of convergence of multi-objective problem (Deb, 2001). Since the execution of the EPIC model at continental scale has high computational requirements and the results are an approximation of the real value (both monetary and nitrate leaching), we have considered this level of convergence as an adequate compromise solution.

5.2.1.1 Objective function

Our analysis considered only two objectives since multiplying the number of objectives increases the computational effort and enhances the complexity of interpreting the trade-off solutions curves. The objectives used during the optimization process are defined as follows:

- a) Minimization of the environmental impact of the agricultural strategy. Average nitrate leaching below the root zone is selected as a proxy for the environmental impact, since nitrogen loss from agricultural sources is a major contributor to water quality degradation (Sutton et al., 2011);

$$Nl_{av} = \frac{1}{A(c)} \sum_{i=1}^{N_{cells}} Nl_i * A_i(c)$$

where:

Nl_{av} : nitrate leaching average (kg N/ha);

c : specific crop;

i : is the index of the cells in the country;

N_{cells} : total number of cells in the country;

$A(c)$: total crop area (ha) in the country;

$A_i(c)$: area (ha) of crop c in cell i ;

Nl_i : nitrate leaching in the cell i (kg N/ha).

- b) Maximization of the net income based on crop yield and water and fertilizer costs computed according to the following equation:

$$NI(c) = \sum_{i=1}^{N_{cells}} A_i(c) * [Y_i(c) * SP(c) - WC_i(c) * WP - FC_i(c) * FP]$$

where:

- NI(c): net income (US \$/ha) for the crop *c*;
- $Y_i(c)$: yield average (tons/ha) of crop *c* in cell *i*;
- SP(c): selling price (US \$/tons) for the crop *c* in the country;
- $WC_i(c)$: irrigation water use (m³/ha) for the crop *c* in cell *i*;
- WP: irrigation water cost (US \$/m³) in the country;
- $FC_i(c)$: fertilizer use (kg/ha) for the crop *c* in cell *i*;
- FP: fertilizer cost (US \$/kg) in the country.

5.2.2 Economic Information

The economic analysis was performed considering the potential income deriving from the selling of the crop on the local market and the management costs linked to the different management practices adopted (fertilization and irrigation costs). More specifically, for each crop the selling price was considered homogenous at country level and the average value was calculated from FAO statistical data (FAO, 2014b) using the last 10 years of the simulation period (Table 5-2). We used a 10 year average because the focus of this study was to identify management practices that can be adopted on the long-term. We considered the average price of two important fertilizers commonly used and available on the African market: di-ammonium phosphate (DAP) and urea with an average cost of 1.7 and 0.5 US \$ per kg N ha⁻¹, respectively. A generic cost of 1.1 US \$ per kg N ha⁻¹ was used for all countries. The impact of the fertilizer price will be assessed in a section dedicated to sensitivity analysis.

Having an accurate estimate of the water cost is an important issue when performing a trade-off assessment of cost benefit of alternative management practices. Water cost is variable year by year and depends on many variables such as the availability of water, the type of irrigation applied and the investments cost required to set up the irrigation plant. In our analysis we considered only the operating costs since the focus of the research is on the assessment of different management practices rather than on evaluating the pertinence of developing new irrigation projects.

Table 5-2 .Crop Values, Water and Fertilizer Costs for the Countries Considered in the Analysis.

	Crop Value				Water irrigation cost
	[US \$ tons ⁻¹]				[US \$ 100 mm ⁻¹]
Country	<i>Maize</i>	<i>Wheat</i>	<i>Barley</i>	<i>Sorghum</i>	
Algeria	270	340	210	160	7
Congo DEM	370	n.a.	n.a.	n.a.	9
Ethiopia	180	280	250	230	12
Kenya	310	300	260	270	9
Libya	n.a.	280	250	n.a.	5
Morocco	250	280	220	300	7

The long term average operating water cost for each country (10 year average) was approximated by considering the use of a pump to extract water from the aquifer and/or distribute water in the field. The water cost depends on the diesel cost and the well depth. The method and the equation used for the calculation are described in detail in Hogan et al. (2007), and the calculated prices are given in Table 5-2. The estimated costs are within the range of reported national values (Chohin-Kuper and Strosser, 2008).

5.3 Results

Trade-offs between different objectives are presented as Pareto front solutions that are the final output that end users can use to drive their decision. The Pareto trade-off strategies are calculated for each crop and each country (Figure 5-2 to Figure 5-6). All the selected control variables are related to the fertilization and irrigation operations, so the resulting best management practices will be linked to these two agricultural management aspects.

Figure 5-2. Simulated (grey cross) and Pareto solutions (green dots) obtained when maximizing the economic benefit and minimizing N leaching for barley for one region in Morocco (left) and for maize in one region in Ethiopia (right).

As illustrated in Figure 5-2 the tool runs a large number of management combinations (small grey dots) trying to find the optimal solutions. The cloud of points (solutions) presented in the graph is denser close to the Pareto front because the MOEA iteratively redefines improved sets of management variables to be tested, and determines approximate near-optimum solutions (taking into account the uncertainty of the considered problem) in less than 200 iterations. It can be seen in Figure 5-2 that for barley in Morocco and maize in Ethiopia, the Pareto curves show similar trends with the benefits initially increasing significantly while nitrogen leaching is increasing moderately. After a cut-off point, the Pareto curves show that the production can no longer be increased significantly while nitrogen leaching increases exponentially. This indicates that even with additional fertilizer or irrigation water (in irrigated areas) the yield will not increase significantly (maximum yield reached with the proposed management strategy). In this part of the Pareto curve, the proposed management strategies will lead to a significant increase of nitrogen leaching since the excess fertilizer applied can no longer be taken up by crops.

Figure 5-3. Pareto solutions by country obtained when maximizing the economic benefit and minimizing N leaching for barley. The pixel size represents the magnitude of applied irrigation water.

Figure 5-4. Pareto solutions by country obtained when maximizing the economic benefit and minimizing N leaching for barley. The pixel size represents the magnitude of fertilization input.

The generated Pareto curves for single crops indicate best management practices specific to the studied area (Figure 5-3 to Figure 5-6). In all African countries the increase of benefit is always related to a higher amount of nitrate losses to the environment. However, substantial variations and different patterns can be observed among the countries. The increase of N leaching per unit income increase varies significantly among countries depending on local climatic and soil conditions (factors that can facilitate or limit nitrogen losses), especially in the case of high productive management practices. For

example, the shape of the barley Pareto front for Algeria and Tunisia (very steep) is very different from that for Kenya and Ethiopia. In Algeria, crop production is nearly optimal under the current management strategies. Barley is irrigated in very limited areas, and crop production is water limited in Tunisia and Algeria (Pastori et al., 2011). Hence, increasing the amount of applied water in irrigated areas will not result in any significant increased income (Figure 5-3). On the other hand, in Tunisia, where the yield of barley could potentiality double, the increase of fertilization and irrigation inputs can lead to an additional production, but with limited benefit because of the high water cost and especially high nitrogen losses (Figure 5-3 and Figure 5-4). In South Africa, crop production is strongly dependent on water availability with large areas being irrigated but with low amounts of fertilizers applied. Thus, increasing nitrogen application will result in higher benefits however with increased nitrogen losses. In South Africa, the increase of benefit is independent from the irrigation amount (amount of water applied is optimal under current management practices for barley). For all countries after a specific tipping point the relation N leaching vs benefit starts to increase much more rapidly.

Figure 5-5. Pareto solutions by country obtained when maximizing the economic benefit and minimizing N leaching for maize. The pixel size represents the magnitude of applied irrigation water.

This steeper slope of the curves indicates that the farmer can gain less net benefit for the same additional net environmental impact or, in other words, that it is necessary to accept a higher pollution to achieve the same amount of economic benefit.

Figure 5-6. Pareto solutions by country obtained when maximizing the economic benefit and minimizing N leaching for maize. The pixel size represents the magnitude of fertilization input.

All previous conclusions can be also extended to other crops. For example in the case of maize (Figure 5-5 and Figure 5-6) we focused the analysis in central and southern countries, where the crop is dominant. Nigeria shows important potential for benefit increase: this partially depends on the crop price that is quite high on the local market (380 US \$ tons in the period 2000-2009), and also on the high water availability (no or very limited irrigation is required) that reduces the management costs required to increase the yield. For all the countries it is possible to identify the value of threshold benefit beyond which the environmental impact starts to increase disproportionately: in the case of South Africa after a benefit of 1300 \$ ha⁻¹ the Pareto curve tends almost to be vertical. In the case of Mozambique the resulting Pareto front is especially steep indicating that any small increase in crop production and so in farmers' benefit is coupled to high nitrogen losses. This specific behaviour is linked to the presence of highly draining soils (arenosols) in this country where the cultivation of maize is both water and nitrogen limited. Yields are higher where water is less limited and, conversely, lower where water availability is limiting crop growth (Tunisia and Algeria). The optimal solutions show a clear linear relationship between yield increase and fertilizer application; for some countries it is also possible to identify the tipping point at which the yield increase becomes more limited (in South Africa, Tunisia and Kenya for barley and Kenya, Congo and Nigeria for maize). Most of the countries are still in a low input production system, and the optimization tool indicates large potential increase of yield while preserving natural resources.

One of the main outcomes of these analyses is that it is possible for each country to identify a specific Pareto front that is closely related to the specific local characteristics of the country, such as climate and soils. In our study we considered generalized average costs that can potentially vary and fluctuate year by year. This variability was not taken into account in this analysis. We tested the impact of varying the input costs in a range +50 –50 % for selected crops and countries. In general no drastic change was observed as illustrated for barley in Morocco (Figure 5-7). The shape of the Pareto front did not change significantly, in particular in the initial linear part of the curve. The most significant difference occurs in the tipping point, which moves to the right at lower costs. In particular, the price of fertilizer shows the largest impact. At the current cost, the tipping point is at around 490 \$/ha. When the price of fertilizer is reduced, the tipping point occurs at a benefit of 550 \$/ha, while when fertilizers become more expensive, the tipping points corresponds to a benefit of 410 \$/ha.

Because the optimization process has a significant stochastic component, each Pareto set comprises a different number of solutions that are distributed not uniformly along the Pareto front. In order to limit this effect in our comparative analysis, we subsampled the original Pareto set distribution to select the same number of points distributed as uniformly as possible. The analysis was performed several times repeating the subsampling process.

Figure 5-7. Pareto solutions obtained in Morocco considering the maximization of the benefit and the minimization of the N leaching for barley for various fertilizers and irrigation costs.

5.4 Discussion

The multi-objective optimization approach applied provides Pareto curves according with one economic (global farmers Income) and one environmental objective (nitrogen leaching below the root zone). For some of the trade-off resulting curves, the solutions are not perfectly distributed along the efficient frontier for some of the executions (even with the best set of the MOEA parameter configuration). This is because the optimization process is stopped after 2000 evaluations (with 10 chromosomes/generation) in order to reduce computation times. However the final trade-off curves are close enough to the Pareto frontier, and they provides accurate optimized solutions.

For instance, the tool can be used by managers to choose optimized solutions for increasing crop production to limit the dependency on crop import. Wheat is one of the major crops in Morocco and accounts for 42 % of the total agricultural harvested area according to FAO statistics. Although the production of wheat in Morocco is one of the highest in Africa and the average yield per ha has increasing in the last years, the production is not yet sufficient to satisfy entirely the local demand, in particular during the periods of lower production (for example, during 2009-2012 period the yield decreased from 2.1 to 1.2 tons/ha). We can observe (Figure 5-8) that the optimal management solutions identified in the Pareto front result in a wide range of economic and environmental outcomes. All the selected solutions are optimal but they have different impact on farmers' income, stakeholders' interests, and environmental impact. For example, the optimal solution identified in the Figure 5-8 (top-left) as optimal-1, is characterized by very low fertilizer input (N input less than 20 kg/ha); while it is very protective for the environment (resulting in a very limited N leaching), it may be not acceptable from a farmer's perspective. The optimal-2 and optimal-3 solutions are characterized by a medium input management, with an average fertilization of 50-70 kg/ha and an irrigation water use of 180 mm and 210 mm, respectively. The high input solution (optimal-4) is characterized by a very high use of fertilizer and water resources (N input 180 kg/ha, irrigation 300 mm/ha/y) that could potentially harm the environment and lead to an overuse of water resources.

Actual management practices are non-optimal with production levels comparable to optimal-1 scenario (corresponding to the lowest benefit for farmers) and moderate nitrogen leaching. As a result, the country has to import high quantities of wheat and other cereals: for example the value of the imported wheat in 2011 was of about 1300 M \$, 70% of Morocco total import value for cereals (FAO, 2014b). The optimization tool indicates the possibility to move towards more profitable yield production while preserving at the same time the environment (limiting nitrate leaching). The "medium input" scenarios (Figure 5-8) show a set of optimal solutions that correspond to a very significant increase of the yield, reaching a potential average production ranging between 2.2 and 3.3

tons/ha/y. Current need for wheat in Morocco is around 9.5 M tons (year 2011 production plus import,(FAO, 2014b)). To be self-sufficient for wheat, an average yield of 3.1 tons/ha would be required considering the total harvest area of 3 M ha. This yield level corresponds to the optimal-3 solution that, notwithstanding a medium/high use of fertilizer and irrigation, is environmentally sustainable and results in higher farmer income.

According to our analysis the increase of nitrogen input is the most adequate solution to increase crop yields in Morocco. Conversely, irrigation does not appear to have a significant potential impact. This is because the area of barley cultivation being actually irrigated is limited (around 4% according to FAOSTAT). Indeed we tested only changing the application rates, not extending the irrigated areas. Nonetheless, increasing irrigation in Morocco is feasible. According to Aquastat (FAO, 2010), an important part of the total Moroccan available water resources ($154.5 \text{ km}^3 \text{ y}^{-1}$) are not yet exploited (the current total water withdrawal is $12.6 \text{ km}^3 \text{ y}^{-1}$).

Figure 5-8. Predicted wheat yields maps for 3 optimal management solutions obtained with the application of the optimization algorithm. The 3 maps correspond to the yellow, blue and red circled symbols in the top-left figure (Pareto solutions for wheat).

Chapter 6. MultiObjective Framework to Identify Efficient Nitrate Reduction Strategies - the case study of the Upper Danube

6.1 Introduction

Nitrogen (N) losses from point (PS) and diffuse sources (NPS) are recognized to be the leading causes of water body impairment throughout Europe (European Environment Agency (EEA), 2005). Despite improvements of water quality in recent years, many aquatic ecosystems in Europe are still at risk of eutrophication from excessive N concentrations (Bouraoui and Grizzetti, 2011; Sutton et al., 2011). Agriculture has been estimated to contribute around 55% of the N loads reaching the European seas while point sources are responsible for around 25% (Grizzetti et al., 2012). The European key policy instrument to protect inland (surface and groundwater), transitional and coastal water resources is the Water Framework Directive (WFD) (European Union, 2000). The European Commission established ecological objectives for all European waters, aiming at more integrated and coherent approach for water protection. The WFD complemented two major pieces of legislations that were put in place in the early 1990's to control the amount of nutrient pollution of European waters, i.e. the Nitrates Directive (European Union, 1991a) and the Urban Waste Water Treatment Directive (European Union, 1991b). The Nitrates Directive regulates the emission of Nitrogen in the form of Nitrate (N-NO_3) from agricultural activities by setting manure application limits, and prescribes the implementation of action programs in Nitrate vulnerable zones. The Urban Waste Water Treatment Directive requires all Member States to implement efficient wastewater treatment and establishes wastewater to undergo at least secondary treatment (C-plants) when discharged into sensitive areas. After 25 years of implementation, many problems linked to high Nitrate concentrations still affect a large number of water bodies in Europe.

Developing efficient management strategies to fulfil the EU legislation requirements needs to consider simultaneously point and diffuse sources of Nitrate. Point source emissions in practice are easy to control as their location and characteristics are well known. Changing the treatment level of a wastewater treatment plant (WWTP) has an immediate effect on the discharged water quality. On the other hand, nonpoint sources are more difficult to control due to their diffuse nature. Furthermore, there is usually a lag time between the implementation of a remedial measure and the environmental response (Schröder et al., 2004).

Management strategies should also consider the location of sources of pollution in order to choose the most appropriate conservation strategies that will achieve the required environmental targets,

while being economically and socially viable. A targeted implementation of Best Management Practices (BMPs) at selected locations in a watershed has been recognized as an effective strategy to improve water quality (Zhen et al., 2004). The state of the art approach is thus to design a local specific BMPs strategy (Cherry et al., 2008). However, this could lead to a multiplication of the implementation of many BMPs in the watershed, without ensuring that the environmental targets at the watershed outlet are achieved (Emerson et al., 2005). Interactions between BMPs may also significantly affect their individual performances at a watershed scale. Harrell and Ranjithan (Harrell et al., 2003) emphasized that a reduced number of management practices could achieve the same outcomes as a multitude of measures implemented throughout the watershed.

Since management practices are usually implemented under a limited budget, costs associated with unnecessary/redundant management actions may jeopardize attainability of designated water quality goals. Consideration of the implementation and maintenance costs of each conservation strategy is essential for the identification of effective management strategies, and to increase the acceptability of the selected measures. Thus a balance has to be achieved between the environmental and economic implications of the many possible conservation strategies. While it is always desirable to implement a BMP that costs the least and gives the most reduction in pollutant load, win-win solutions are few and far in between, and the environmental targets can only be achieved through the appropriate combinations of spatially, temporally and economically tailored sets of conservation measures (Bouraoui and Grizzetti, 2014; Doole et al., 2013). When several management practices are to be considered together across a watershed, the identification of efficient conservation strategies becomes a spatial multi-criteria optimization problem. Spatial optimization of land use and conservation practices under various objective functions/constraints can help sustainably manage limited resources (Ahmadi et al., 2013; Arabi et al., 2006; Doole et al., 2013; Lautenbach et al., 2013; Rodriguez et al., 2011; Srivastava et al., 2002).

The overall goal of this work was to explore potential gains in searching cost-effective solutions to reduce N-NO₃ pollution in the large Upper Danube Basin (132000 km²) by considering both point and diffuse sources. The Basin is characterized by the highest values of N-NO₃ concentration in the surface water in the entire Danube (Tockner et al., 2009), thus Nitrate pollution abatement in the region appears crucial to restore the good ecological status of the Danube River (International Commission for the Protection of the Danube River, 2015). We hypothesize that important reductions of N-NO₃ in the river network can be achieved at affordable cost by applying spatial targeting approaches to identify optimal conservation practice combinations. We used SWAT to simulate point and diffuse N-NO₃ emissions and fate in a watershed. Starting from current basin conditions, we first analyzed the impact of single conservation measures applied uniformly across the region (iterative simulations) to

assess maximum N-NO₃ abatement level that could be reached. We then ran multi-objective, spatially explicit optimization routines to search for solutions that considered several conservation actions in different parts of the Basin.

6.2 Study area

The Upper Danube Basin covers about 132000 km² across Austria, Germany, Czech Republic and Slovakia, extending from the Danube source down to the Gabčíkovo Reservoir near Bratislava (Figure 6-1). The amount of precipitation in the Upper Danube Basin shows a distinct gradient with the altitude. It rises from 650-900 mm/y in the lowland areas to more than 3,000 mm/y in the high mountain exposed to the west and north (Rank et al., 2005). Major landuses within the watershed are forest (38 %) and pastures (18 %) mainly extended in Alpine regions, cropland (34 %) in flat areas, and urban land and water covering approximately 10%. The period of high streamflow is mainly controlled by precipitation and snow melting during late winter and early spring. The mean annual discharge of the Danube at Bratislava, i.e. the Basin outlet, is 2048 m³/s (Pekárová and Onderka, 2016). N-NO₃ is the main component of Nitrogen transported in the Danube River (about 70%; (Tockner et al., 2009)), with mean N-NO₃ concentration around 2.3 mg/L.

Figure 6-1: The Upper Danube watershed with the distribution of the main classes of land cover, main rivers and N-NO₃ annual loads from point sources.

6.3 Methodology

The analysis was conducted with the R-SWAT-DM framework (Udías et al., 2016). R-SWAT-DM is an integrated tool that enables spatially explicit decision-making, helping stakeholders to better understand the main water quality problems and finding the most efficient practices for a given watershed. The framework assesses the economic and water quality impacts of different types/levels of management practices and compares them with the Baseline Scenario (BLS). It applies different BMPs at different location, thus allowing to evaluate their overall impact and search for spatial combinations that are most appropriate to improve the water quality at a minimum cost.

Users can run single or combined simulations of spatially explicit management practices, or iterative simulations whereby all management practices of one type are changed simultaneously step-wise in a fixed range of values. Alternatively, they can also choose to run a multi-objective optimization process. In this case, users should specify the environmental objective, choosing among the available options, the management practices to be considered. Once the simulation and/or optimization process has finished, the user can analyze and compare the management scenario outputs graphically and statistically. The framework can also generate maps with detailed spatial information about a selected scenario.

The framework includes the following main components: (1) a watershed biophysical model (SWAT) for simulating hydrologic and water quality processes under current conditions and management scenarios; (2) an economic module to estimate the monetary value of each management scenario; (3) an optimization engine to search for trade-off management scenarios according to environmental and socioeconomic objectives. The framework can model nutrient reduction measures related to both PS (WWTP upgrading) and NPS (crop fertilization and irrigation strategies).

The steps of the analysis for the Upper Danube Basin were: (1) set up SWAT model to simulate N-NO₃ fluxes under baseline (BLS) and alternative management scenarios; (2) define environmental and economic objectives; (3) apply a multi-objective simulation/optimization tool; (4) perform a sensitivity analysis for the most relevant components of model; and (5) identify optimal spatial allocation of best nutrient management practices.

6.3.1 Biophysical Model Description

SWAT (Neitsch et al., 2011) was used to assess the impact of point sources and land use management practices on N-NO₃ fluxes and on agricultural yields. The SWAT model integrates all relevant eco-hydrological processes including water flow, surface runoff, percolation, lateral flow, groundwater flow, evapotranspiration, transmission losses, nutrients and sediments, vegetation growth, land use, and water management. A detailed description of model is given in chapter 3 of the thesis.

SWAT set-up for the Upper Danube Basin comprised several sources: a) Digital Elevation Map (DEM) of 100×100 m, obtained from the Catchment Characterization Modeling version 2 (CCM2) (Vogt et al., 2007); b) Soil map of 1×1 km, obtained from the Harmonized World Soil Database (HWSD) (FAO et al., 2009; c) Watershed and stream delineation, based on the CCM2 database for continental Europe; d) EFAS-METEO climate data including daily precipitation, temperature, solar radiation, wind speed and relative humidity with spatial resolution of 25 km (Ntegeka et al., 2013) .

A land use map of 1×1 km for year 2000 was built from the combination of databases ((Bartholomé and Belward, 2005; Britz and Witzke, 2008; Klein Goldewijk and van Dreht, 2006; Monfreda et al., 2008)). In the subbasins with dominant arable land, the crops were distributed according to the EUROSTAT (EUROSTAT, 2016a) crop statistics at district level (NUTS 2) using an ad hoc land use assignation routine. The Upper Danube was discretized into 753 subbasins ranging in size from 3 ha to 1011 km^2 , with an average area of 143 km^2 . From the combination of land use, soils and slopes, 822 HRUs were defined, 75 of which were urban areas [45]. Point sources were defined in 533 sub-basins (more than 70% of all subbasins) using the European waste water treatment database WWTPD (European Topic Centre on Islands, 2011) (Figure 6-1). In the SWAT model only one single point source can be defined per subbasin; hence a point source represents all the point sources comprised in the subbasin.

Crop management operations were based on the heat units approach that were calculated at regional level as detailed in Wriedt et al. (Wriedt et al., 2009a). Fertilization was based on outputs from the CAPRI model (Britz and Witzke, 2008). All arable land (291 HRUs) was fertilized, however the main fertilized crops were annual row crops, winter and summer cereals, and managed pastures (Table 6-1). Fertilization management practices (type and schedule) were based on SWAT literature and SWAT database of fertilizers adapted to the European context (Malagó et al., 2015). Figure 6-2 shows the applied fertilization patterns used in the BLS scenario. The irrigated area covers only around 700 km^2 ; the auto irrigation option was selected using the irrigated areas from national statistics. Since the irrigated land in the region was small, irrigation management practices were not further considered in the case study.

The model was calibrated in steps: calibration of crop yields, multi-site calibration of streamflow, and calibration of N-NO₃ at the outlet of the watershed. Annual simulated crop yields for 1995-2009 were calibrated by manually adjusting three parameters (the crop harvest index, HVSTI, and the optimal and minimum plant growth, T_OPT and T_BASE respectively) to match yields reported by EUROSTAT (EUROSTAT, 2016a).

Table 6-1. Upper Danube Baseline Scenario information related to the crop area and quantity of fertilizer. Avg. Observed yields are derived from EUROSTAT (EUROSTAT, 2016a)

<i>Crop Name</i>	<i>CROP id.</i>	<i>n HRU</i>	<i>km²</i>	<i>% Area</i>	Av. Mineral (kg/ha)	Av. Organic (kg/ha)	Av. Simulated Yield (t/ha)	Av. Observed Yield (t/ha)
Generic Agricultural	AGRR	31	8884	17.3	173.3	115.5	6.2	9.1
Fruits	APPL	6	62	0.1	30.5	7.2	34.1	41.0
Barley	BARL	27	6748	13.2	87.8	27.8	5.0	4.8
Pasture	CLVS	27	6715	13.1	40.7	66.7	3.5	NA
Maize Grain	CORN	21	3906	7.6	132.2	126.9	6.9	9.1
Carrot, vegetables	CRRT	7	450	0.9	103.1	4.0	4.6	NA
Silage	CSIL	18	3969	7.7	83.9	321.0	24.2	45.0
Green bean	GRBN	6	584	1.1	1.4	4.1	3.1	2.8
Oats	OATS	11	845	1.6	84.0	39.1	4.0	5.8
Potatoes	POTA	11	1008	2.0	121.1	44.7	26.5	30.0
Rape seed	RAPE	20	1839	3.6	126.7	34.3	2.2	2.7
Rye	RYE	11	835	1.6	60.0	42.2	3.2	3.8
Sugar beat	SGBT	13	982	1.9	143.7	102.5	48.0	64.0
Sorghum	SGHY	18	3058	6.0	24.6	101.6	5.9	5.4
Soybean	SOYB	1	43	0.1	0.0	26.8	0.6	2.4
Sunflower seed	SUNF	6	398	0.8	80.3	24.4	2.9	2.6
Soft wheat	SWHE	11	1135	2.2	132.4	60.2	3.7	5.4
Spring wheat	SWHT	42	9533	18.6	123.9	32.4	4.2	5.7
Grape	TWIN	4	230	0.4	4.2	1.7	6.5	6.4
TOTAL		291	51224	100	55%	45%		

SWAT crop yields were generally well captured, albeit some differences were noticeable for generic agricultural crop, corn, corn silage, and soybean, probably due to very productive crop varieties cultivated in the Basin. However, given that sensitive crop management inputs (Abbaspour et al., 2015) such as planting and harvesting time, fertilizer and irrigation water inputs were generalized for application in the large Basin rather than be locally defined, calibration of crop yields was considered satisfactory.

Monthly streamflow was calibrated in 98 gauged stations for the period 1995-2006, and validated in 150 gauged stations for the period 1995-2009.

Figure 6-2: Map of applied fertilizations in SWAT (kg/ha). NMAN and PMAN: Nitrogen and Phosphorus in manure fertilizer; NMIN and PMIN: nitrogen and phosphorus in mineral fertilizer.

With reference to the calibrated dataset, streamflow simulation at more than 50 % of stations had an average percent bias (PBIAS %, (Moriassi et al., 2007)) of 11% and Nash Sutcliffe efficiency (NSE,(Moriassi et al., 2007)) of 0.57. For the validation dataset, the PBIAS% was satisfactory for more than 60% of gauged stations (average values of 9.7%) and for these the average Nash Sutcliffe was around 0.53. More details about the model setup and the calibration procedure can be found in Malagó et al. (Malagó et al., 2017). Mean monthly N-NO₃ concentration was calibrated manually at the only station for which data was available at the time of the study, i.e. at the watershed outlet for the period 1995-2009, by changing two basin parameters: the denitrification exponential rate coefficient (CDN) was set at 0.6 and the fraction of field capacity water content above which denitrification occurs (SDNCO) was set to 1. After calibration, SWAT N-NO₃ mean concentration at the outlet (2.15 mg/l) was very close to the observation mean (2 mg/l); PBIAS % of monthly N-NO₃ simulation at the outlet was 6.8%. The calibration was validated in other 74 gauging stations in the region that became available at a later stage. SWAT simulated well the monthly N-NO₃ concentrations with performances from very good to satisfactory (PBIAS% <+/- 70% [31]) in about 57% of them (for details see Udias et al., 2016).

6.3.2 Best Management Practices

Two groups of Nitrate Best Management Practices were considered in the work: PS and NPS BMPs. Improved sewage treatment can substantially reduce PS pollution. Primary treatment removes only bulky materials. The more expensive secondary (C-plants) treatment removes also suspended particles and part of the nutrient-rich organic material. The even more expensive tertiary treatment, for instance CN (C-removal + nitrification), CND (C-removal + nitrification + denitrification), or CNDP (C-removal + nitrification + denitrification + Phosphorus removal), which is sporadically implemented, removes also most of the dissolved nutrients. In the Upper Danube Basin, 533 urban and industrial PS were considered, which were modelled as C-plants Waste Water Treatment Plants (WWTP) (Dworak et al., 2008). The WWTP capacity of treatment varied from 9 m³/day to 604500 m³/day, with an average of 8306 m³/day. In this work we considered two possible levels of upgrading WWTP treatment, which achieved removal of a higher percentage of nutrients at higher costs (Table 6-2).

Table 6-2. Cost and nutrients reduction efficiency for each type of WWTP upgrading and the flow.

Upgrade Treatment	coef ₁	coef ₂	Cost (€/m ³)	Nutrient Effic. Remov. (%)		
				NH ₄	NO ₃	PO ₃
No Upgrade (C-plant)	0	0	0	0	0	0
C to CN	0.1115	-0.126	0.1115Q ^{-0.126}	20	20	0
C to CNDP	0.1464	-0.119	0.1464Q ^{-0.119}	55	55	55

(Dworak et al., 2008) Q: capacity of WWTP in m³/day

For NPS, we considered BMPs related to mineral fertilization (Table 6-1). Nitrogen from mineral fertilizer is the major source of N input in EU countries and remains an important cost for the farmers. Mineral fertilization could substantially vary among HRUs, and affected the nutrient losses on one side and the yield crop on the other. It is true that Nitrogen input from manure remains important in regions of high livestock density (European Commission, 2016). However, since the amount of available manure depends on livestock density, a change in manure fertilization would not be realistic without considering a changes in livestock systems. Such analysis was out of the scope of this work. Therefore, in this study livestock density and manure fertilization were kept unchanged from the current situation (BLS).

6.3.3 Environmental Objective

Minimizing pollutant concentration or loads, or alternatively maximizing reduction of pollutant concentration, is a key objective in water pollution control management practices. There is no single

way to assess the water quality in a watershed, especially when water quality is related to the concentration of various contaminants over a period of time in many geographical points. As well, there is no ideal mathematical equation to perform the aggregation of temporal and spatial pollutant concentration values in one single metric that resumes the global quality. Hence, the following three different possibilities for aggregating water quality indicators have been included in the framework.

The average pollutant concentration in all reaches for the whole simulation period.

$$\frac{1}{ns} \frac{1}{nt} \sum_{i=1}^{ns} \sum_{j=1}^{nt} Q_{ij}$$

Where:

nt: number of time-steps in the simulation period.

ns: number of modeled reaches

Q_{ij}: concentration (mg/l) of pollutant in reach “i” and simulation time-step “j”.

The cumulated contaminant: sum of contaminant concentrations in reaches that exceeded an environmentally acceptable threshold

$$\sum_{i=1}^{ns} \sum_{j=1}^{nt} (Q_{ij}) \quad \forall i, j \mid Q_{ij} > Th$$

Where:

Th: threshold that is considered as environmentally acceptable. This can be set according to Water Framework Directive (WFD, (European Union, 2000)) targets or ecological considerations; and the other variables are defined as :

The total load at the watershed outlet:

$$\frac{1}{nt} \sum_{j=1}^{nt} TL_j$$

Where:

TL_j: load of the pollutant exported at the watershed outlet in the simulation period “j”.

6.3.4 Economic Objective

PS and NPS BMPs yield benefits in water quality and wildlife habitats, but their implementation and maintenance come at a cost. On the one hand, agriculture generates economic profit. It is important to consider the impact of BMPs adoption on farmers' revenue. On the other hand, the upgrade of the WWTP is expensive (Table 6-2). A priori, it is not clear where it is more efficient to invest in. The most efficient solution might well be an adequate spatial combination of different BMPs adoption. The economic objective function was defined as:

$$TNI = g_1(x, y | \theta, I, wc, cr, T) - g_2(z | \theta, I, wc, cr, T) - g_1(BLS)$$

Where:

TNI: is the total net income (considering together gross margin of the farmers and cost of the WWTP)

x: denotes decision variables reflecting the quantity and location (HRU) of fertilizer practices.

y: denotes decision variables reflecting the quantity and location (HRU) of irrigation practices.

z: denotes decision variables reflecting the type and location of the WWTP.

g_1 : is the gross margin related with the agricultural production.

g_2 : is the cost related to upgrading the WWTP (additional cost in relation with baseline situation).

T: is the assessment period.

θ : is the vector of calibrated watershed model parameters.

I: represents driving forces (i.e. rainfall, temperature, and other environmental factors).

wc: is the unit cost of the implementation the conservation practice.

cr: is the unit price of beneficial products of the conservation practice.

$g_1(BLS)$: is the base line situation gross margin related with the agricultural production.

For the BLS the WWTP cost (the g_2 component) was set to zero. In the following paragraphs the evaluation of the two economic components related to agriculture and to the WWTPs are described.

6.3.4.1 Component related to agriculture

In order to estimate farmer gross margin as affected by the different management strategies, we applied a function based on crop yield, crop price, fertilizer cost, irrigation water cost, standard

operational cost, and specific fixed cost (including seeds cost, tillage operations, machinery, grain drying, labor, etc.). For each alternative BMP, total gross margin was estimated as:

$$g_1^{mp} = \sum_{i=1}^{HRU} \sum_{j=1}^{crop} (Y_{ij}^{mp} * A_{ij} * Up_j - Fc_{ij}^{mp} * Qf_{ij}^{mp} - Qw_{ij}^{mp} * Wc - Oc_j)$$

Where:

g_1^{mp} : agricultural total gross margin for the BMP.

Y_{ij}^{mp} : yield of crop j in HRU i under a BMP.

A_{ij} : area (ha) of crop j in HRU i .

Up_j : unit price (income €/tm) of crop j (Table 3).

Qf_{ij}^{mp} : quantity of fertilizer applied (kg/ha) to crop j in HRU i under a BMP.

Fc_{ij}^{mp} : unit cost of fertilizer (€/kg) of crop j in HRU i under a BMP.

Wc : the water irrigation unit cost (€/mm), constant across HRUs

Qw_{ij}^{mp} : irrigation quantity (mm/ha) for crop j in HRU i under a BMP

Oc_j : operational management cost for the crop j

Crop management costs were assumed constant throughout the simulated period and independent from the annual yield. The average crop yield for the period 1995-2009 of each HRU under management scenarios was assessed with SWAT. Table 6-3 includes the average, minimum and maximum selling price for all crops in the study region, and the operational (fixed) costs, including the labor, machinery. Instead, current European subsidies were not considered in farmers' income.

N, P and K are applied with several fertilizer products (Anhydrous ammonia, Nitrogen solutions 30%, Urea 44-46, Ammonium nitrate, Sulfate of ammonium, super phosphate 20%, etc.) containing different forms and percentages of the elements.

Table 6-3. Upper Danube Crop selling prices, management costs and mean annual simulated crop yields in the period 1995-2009 (dry weight, t/ha). The fixed cost included: total cost of machinery, labor and seed.

Crop Name	CROP id.	Avg Sell. Price. (€/tons) *	Min. Sell. Price. (€/tons) *	Max.Sell. Price (€/tons)*	Fixed Cost (€/ha) *
Generic Agricultural	AGRR	132	88	213	400
Fruits	APPL	381	257	535	5000
Barley	BARL	136	93	206	220
Pasture	CLVS	50			100
Maize Grain	CORN	132	89	221	850
Carrot, vegetables	CRRT	254	117	431	4000
Silage	CSIL	132	89	221	850
Green bean	GRBN	847	495	1190	4000
Oats	OATS	109	70	167	400
Potatoes	POTA	136	70	256	1000
Rape seed	RAPE	269	146	461	220
Rye	RYE	124	67	199	220
Sugar beat	SGBT	38	263	506	1700
Sorghum	SGHY	107	67	188	400
Soybean	SOYB	265	181	467	600
Sunflower seed	SUNF	241	149	396	220
Soft wheat	SWHE	128	82	211	370
Spring wheat	SWHT	128	82	211	370
Grape	TWIN	404	254	698	4000

*Source: Eurostat statistics (EUROSTAT, 2016a).

The total cost of the fertilization was estimated based on the quantity (kg) of elementary N, P and K present in the applied fertilizers. The cost per kg of N P and K was estimated from annual data from 2000 to 2013 [53]. The resulting prices were 1.21 € per kg of Nitrogen, 2.8 € per kg of Phosphorus and 0.97 € per kg of Potassium and the summary cost per fertilizer is showed in Table 6-4.

Table 6-4. Fertilizer prices used for Upper Danube derived from USDA statistics

Fert. Name	Mineral		Organic		Cost (€/kg)
	N (%)	P (%)	N (%)	P (%)	
Elem-N	1	0	0	0	1.21
Elem-P	0	1	0	0	2.8
31-13-00	0.31	0.057	0	0	0.5347
30-15-00	0.3	0.066	0	0	0.5478
28-10-10	0.28	0.044	0	0	0.462
28-03-00	0.28	0.013	0	0	0.3752
25-05-00	0.25	0.022	0	0	0.3641
25-03-00	0.25	0.013	0	0	0.3389
24-06-00	0.24	0.026	0	0	0.3632
22-14-00	0.22	0.062	0	0	0.4398
18-04-00	0.18	0.018	0	0	0.2682
10-28-2000	0.1	0.123	0	0	0.4654
10-20-2020	0.1	0.088	0	0	0.3674
7-7-2000	0.07	0.031	0	0	0.1715
DAIRY-FR	0.007	0.005	0.031	0.003	0

Source: USDA statistics (USDA, 2015)

6.3.4.2 Component related to WWTP

Two upgrading options were considered (Table 6-2): (i) upgrading from C-plants to CN plants (C-removal + nitrification) or (ii) upgrading to CNDP plans (C-removal + nitrification + denitrification + Phosphorus removal). Cost estimates for different upgrading options in municipal wastewater treatment plants for all Danube countries were derived from Dworak et al. (2008), using the cost data reported for Austria. The total wastewater treatment cost includes all investment costs (costs of construction and costs of the mechanical and electrical equipment) as well as all operational costs (labor costs, energy expenses, maintenance costs, chemicals expenses, sludge treatment and disposal costs, and discharge levies). To make investment and operational costs comparable, all investment costs were converted into annual values using a 20-years depreciation horizon and a 5% real interest rate. These costs were available for different sizes of the WWTP, varying from 75 to 150,000 population equivalent. We fitted a power equation to express the cost of the upgrade as a function of the volume of water treated. As a result, the total cost for a WWTP is expressed in €/m³ per year.

For each WWTP scenario the total wastewater treatment cost in the basin was estimated as the sum of the treatment cost for each plant, which was based on the treatment type and the volume of water according to:

$$g_2^{mp} = \sum_{k=1}^{WWTP} \left(365 * Q_k * Coef_1[Y_k] * Q_k^{Coef_2[Y_k]} \right)$$

g_2^{mp} : WWTP upgrading annual cost for the mp water restoration management practices.

Q_k : flow average (m³/day) in PS k .

Y_k : type of upgrade of the k WWTP. 0: no upgrade; 1: upgrade from C to CN; upgrade from C to CNDP

$Coef_1[Y_k]$: coefficient 1 for the Y_k WWTP type of upgrade

$Coef_2[Y_k]$: coefficient 2 for the Y_k WWTP type of upgrade

6.3.5 Multi-Objective Optimization method

A logical approach for targeting PS and NPS pollution control practices should be to propose a multi-objective problem following the next equation:

$$\begin{cases} \text{minimize } \text{Pollutant concentration and/or load}(s) \\ \text{maximize } \text{Global benefit}(s) \end{cases}$$

Under this or other similar approaches, the objective functions are often conflicting and incommensurable. For example, implementation of a large number of conservation practices would likely result in lower pollutant loads, but the cost for implementation and maintenance of these practices would increase. Hence, the optimal solutions for any objective could substantially differ from the optimal solutions for another objective. Multi-objective optimization approaches can determine a set of non-dominated solutions belonging to a Pareto-optimal front. Non-dominated solutions are a set of solutions in the search space that are better than any other solution in one or more objective (Srinivas and Deb, 1994). Any improvement in one objective among Pareto-optimal solutions will essentially result in the degradation of at least another objective (Pareto, 1971).

Since the shape of the objective function cannot be assumed as smooth or differentiable in our management practices application problem, gradient approaches such as quasi-Newton methods cannot be applied (Nocedal and Wright, 1999). Instead, gradient free methods such as evolutionary algorithms are applicable as optimization method. The non-dominated sorting genetic algorithm NSGA-II (Deb, 2001) is among the most commonly used multi-objective global optimization methods

with numerous successful applications in watershed management (Bekele and Nicklow, 2005; Nicklow and Muleta, 2001; Udías et al., 2012b). The procedure starts with an initial population of solutions that are typically generated randomly. The fitness of individual solution in successive generations increases through selection, crossover, and mutation. The procedure stops when a set of predefined termination conditions is met. To run a multi-objective optimization process in the R-SWAT-DM framework, the user should select at least two objectives. Usually at least one refers to the environmental objective, e.g. selecting a constituent of interest and the aggregation metric to be applied. For the economic objective, the user could choose to maximize the total net income, or to minimize the investment in WWTP, or to maximize the gross margin for the farmers.

For the Upper Danube Basin, two objectives were considered. The environmental objective focused on N-NO₃ contamination, because it is the most important issue in the region (International Commission for the Protection of the Danube River., 2009). The aggregation metric was the sum of NO₃ concentration exceeding the WFD threshold of 50 mg/l in all reaches. However, the total N-NO₃ load at the watershed outlet is a key indicator of water quality (International Commission for the Protection of the Danube River, 2015), thus optimization was constrained to not exceed BSL level. The economic objective was based on the total net income.

Figure 6-3: Schematic of the decision variables (chromosome) representing the conservation practices

The multi-objective optimization module simulates individuals of a population as chromosomes (scenarios), which in turn contain genes, i.e. the single units for which conservation can be applied, as their building blocks. Each gene represents a particular set of BMPs (BMP combination) on the chromosome encoding a specific trait. In the Upper Danube Basin, the unit for controlling diffuse pollution was the single HRU. There were 291 fertilized HRU, while we neglected the irrigation option. For point source pollution, the unit was the single WWTP. Therefore, chromosomes for the Upper Danube Basin consisted of 291 HRU + 533 WWTP genes (Figure 6-3).

The NSGA-II results are very sensitive to the operational parameters (population size, number of generations, crossover, and mutation rates) that define the search algorithm. As described in Maringanti et al. (Maringanti et al., 2011), a nonlinear sensitivity analysis where operational

parameters were incremented one at a time was conducted to define the NSGA-II best population size, number of generations, mutations, and crossover probabilities.

6.4 Results and Discussion

The Baseline Scenario (*BLS*) shows the current state of the Upper Danube basin according to the model of SWAT. The simplest analysis that can be performed with the R-SWAT-DM framework is to simulate one single spatially explicit conservation strategy, in order to know its economic and environmental outcomes.

Table 6-5: Short description of the management strategies analyzed.

Strategy	Short description
BLS	Baseline Scenario
SmartFert	Best Iterative fertilization (35% of fertilization reduction)
SmartWWTP	Upgrading all WWTPS to CNDP
SmartG	Combination of SmartFert and SmartWWTP strategies
OptiWWTP1	Selected solution from the Pareto of the optimized WWTP execution
OptiWWTP2	Selected solution from the Pareto (green point in figure 5)
OptiFert	Selected solution from the Pareto of the optimized fertilization execution
OptiG	Optimized simultaneously WWTP and fertilization management
CombinOpti1	Combination of OptiWWTP1 and OptiFert
CombinOpti2	Combination of OptiWWTP1 and OptiFert

Next, results were obtained running the tool to simulate iterative changes in the rate of mineral fertilization applied uniformly in all HRUs (black dots in Figure 6-4). The iterative simulations showed that when starting from a very low rate of mineral fertilizer applied (for all HRUs), a fertilization increase causes low pollution increase while the total net income increases sensibly as crop yields incomes increase more than fertilizer costs. It is possible to identify an optimal fertilization rate (*SmartFert* point in Figure 6-4) corresponding to the maximum total net income. Once this fertilization rate is exceeded, total net income starts to decrease, while pollution continues to increase. Compared to the BLS, the SmartFert strategy corresponds to a reduction of 35% in mineral fertilizer rate applied, and results in an increment of total net income of 75M€ and in a 30% reduction of cumulated N-NO₃

pollution (Table 6-6). SmartFert results are in line with the outcomes of the analysis of statistics and agri-environmental indicators available for the four involved Countries from Eurostat (EUROSTAT, 2016b). These indicators point out a systematic potential surplus of Nitrogen on agricultural land: a surplus of 90, 86, 33, and 30 kg/ha/yr is reported for year 2008 respectively for Germany, Czech Republic, Austria and Slovakia that correspond to 42, 50, 25 and 28 % of total Nitrogen inputs. Surplus numbers are clearly in line with the suggested reduction rates identified in the SmartFert scenario.

Iterative simulations of WWTP consists of upgrading all WWTP by one (to CN; WWTP->1), or two levels (to CNDP, WWTP->2; Figure 6-4). The total cost of upgrading all plants at CN level is 50 M€, and to CNDP level is of 71 M€ (*SmartWWTP*), achieving approximately pollution reductions of 10% and 26%.

The analysis can be done starting from the BLS situation (blue triangles) or from the SmartFert strategy (red squares). Remarkably, the conservation strategy that applies all PS and NPS restoration measures (*SmartG*, in Figure 6-4) may reduce the Nitrogen pollution by nearly 52% with no additional cost, since the increase of agricultural benefits compensates for the cost of upgrading the WWTP (Table 6-6).

However, management outcomes could be substantially improved by applying the multi-objective optimization capabilities of the framework. Focusing only on point source pollution, a first optimization process was run for WWTPs upgrading decision process while keeping fertilization at BLS conditions. In this case, each management strategy was coded as a chromosome of length 553 (one per WWTP). Each WWTP had three possible options: 0 (no upgrade), 1 (upgrade to level CN), or 2 (upgrade to level CNDP). The population size was 60, a crossover probability of 0.9, a mutation probability of 0.1. The optimization process was stopped after 60 generations (3600 evaluations of the model), when the improvement from one generation to the next was negligible (convergence criteria).

Figure 6-4: Comparison between economic (total net income) and environmental objective (N-NO₃ indicator) for iterative simulations. Black dots indicate the strategy of varying the fertilization rate by the same amount in all HRUs. Blue triangles show the strategy of upgrading all WWTPs for the BLS. Red squares show the same strategies applied to the best fertilization strategy (SmartFert). Note that both BLS and SmartFert points are at current WWTP status; WWTP->1: all the plants are upgraded to CN level; WWTP->2: all plants are upgraded to CNDP level.

Table 6-6: Environmental and economic indicator for some of the catchment management strategies tested in the Upper Danube case study.

Strategy	Environmental Indicators						Total Gross Margin	WWTP Cost	Total Income	Total Net Income
Cumulated NO ₃										
Reach > 50 mgN/l			Eq.1	Eq.2	Eq.3					
	(1)	(2)	(3)	(mgN/l)		(M)	(M€)	(M€)	(M€)	(M€)
BLS	1060	78	161	23.98	94671	120	1822.2	0.0	1822.2	0.0
SmartFert	747	51	132	21.23	65618	111	1896.6	0.0	1896.6	75.4
SmartWWTP	809	61	133	20.79	70804	103	1822.2	70.8	1751.4	-70.8
SmartG	549	37	102	18.01	45657	94	1896.5	70.8	1825.7	3.5
OptiWWTP1	821	63	137	21.97	71899	113	1822.2	29.5	1792.7	-29.5
OptiWWTP2	839	63	142	22.35	74472	116	1822.2	15.2	1807.0	-15.2
OptiFert	381	24	83	17.50	32883	103	1926.2	0.0	1926.2	104.0
OptiG	244	12	68	15.71	17908	91	1962.8	48.2	1914.6	92.4
CombinOpti1	242	13	63	16.15	17872	95	1926.2	29.5	1896.7	74.5
CombinOpti2	243	13	63	16.53	19322	99	1926.2	15.2	1911.0	88.8

¹ Notes: Environmental indicators related to reaches: for all reaches during the 15 year simulation period (1) is the number of instances (month-reach cases) when N-NO₃ reach month concentration exceeds the threshold of 50 mg/l; (2) is number of reaches where N-NO₃ month average concentration for the simulation period exceeds the threshold; (3) is number of reaches where N-NO₃ month maximum concentration exceeds the threshold.

Environmental indicator related to concentration: Eq.1: Average N-NO₃ concentration for the simulation period and all reaches; Eq.2: Sum of N-NO₃ concentration in the reaches that exceed the 50mg/l threshold; Eq.3: Total N-NO₃ load at the watershed outlet; Total Income = Total Gross Margin – WWTP Cost.

Figure 6-5: Pareto front of the WWTP optimal upgrade, considering the objectives of minimizing cost and minimizing N-NO₃ concentration, confronted with the all WWTP upgrading strategies to level 1 or 2.

Figure 6-5 shows the WWTPs upgrade Pareto strategies, according to the objectives of minimizing implementation cost and minimizing cumulated N-NO₃ pollution. The *OptiWWTP1* strategy (which cost 29.5M€) could achieve a pollution reduction very similar to upgrading all WWTPs to CNDP level (SmartWWTP, which would costs 71 M€). Moreover, investing only 15.2M€ (*OptiWWTP2* strategy) could achieve a pollution reduction of 21.5%, which is not so far to the 26% reduction achievable by upgrading all WWTPs to CNDP level (SmartWWTP). Both *OptiWWTP1* and *OptiWWTP2* strategies offer a good compromise between economic and environmental objectives. In the *OptiWWTP1*, 77 plants should be upgraded to CN and 180 to CNDP; in *OptiWWTP2* 64 plants should be upgraded to CN and 102 to CNDP. No change would occur for the remaining WWTPs.

The multi-objective optimization can also be carried out for mineral fertilization while maintaining WWTPs at the BLS status. In this case the variables considered were the HRU mineral fertilization rates, so the length of the chromosome was 291 (one variable per fertilized HRU). The fertilization rate variables were continuous, ranging from 0 kg/ha to a maximum equal to the double of the HRU mineral fertilizer applied in the BLS scenario. The population size was 50, the maximum number of evaluations 3000 (60 generations), crossover probability 0.9, and mutation probability of 0.1.

Figure 6-6: Pareto front strategies for the multi-objective fertilization rate (291 HRU) problem (green +), and the Pareto front strategies for the multi-objective fertilization & WWTP (291 HRU + 533 PS; gray x). In both multi-objective processes have been considered as objective the minimization of Total Net Income and of the cumulated NO_3 metric.

The optimization process found fertilization management strategies that were more efficient than the SmartFert strategy for both reducing pollution and increasing the total net income. Figure 6-6 shows the trade-off strategies (green “+”). The Pareto front is slightly sloped, which indicates that it is possible (up to a limit) to improve profitability without significantly increase pollution if adequate local fertilization rates are applied across the region. Among many, we selected one strategy from the Pareto set, labelled *OptiFert* in Figure 6-6. This fertilization strategy provides a total net income increase of 100M€ and a 65% reduction in the N- NO_3 pollution compared to BLS. Compared to SmartFert scenario, it afforded a 50% reduction of pollution.

Finally, a multi-objective optimization run was also performed considering simultaneously all decision variables. In this case, the chromosome length was 824 (291 fertilizations + 533 WWTP). The optimization process was performed with a population size of 80 chromosomes during 50 generations (4000 evaluations), crossover was 0.9 and mutation 0.1. Significant improvements in the total net income with little increase in the N- NO_3 metric were further identified. Among this last Pareto set, we selected one strategy, labeled as *OptiG*. This strategy could achieve N- NO_3 reductions of 81% of BLS and 61% of SmartG strategies, with a total net income of 92M€ higher than the BLS.

Two additional strategies were generated by combining the OptiWWTP1 and OptiWWTP2 with the OptiFert strategy selected from the fertilization only Pareto set (Figure 6-6). We labelled these as

CombinOpti1 and *CombinOpti2* in Table 6-6 (blue points in Figure 6-6). Both strategies yield similar results than OptiG strategy. However, management practices applied in the CombinOpti strategies and in the OptiG are considerably different, especially in terms of WWTP management. In CombinOpti2 102 plants should be upgraded to CNDP level, whereas in OptiG 362 should be upgraded to CNDP level. The implementation cost would raise from 15.2 M€ in CombinOpti2 to 48 M€ in OptiG. However, this higher purification investment in OptiG would be offset by the higher crop revenue achieved by slightly increasing fertilization (and N-NO₃ pollution generated by agriculture). Similarly, the CombinOpti2 and OptiG strategies are very close in terms of objectives (Figure 6-6), but are very different in terms of type and spatial distribution of BMPs that are identified. Hence, the global optimum finds synergies between all types of management alternatives; this example shows the advantage of combining considerations for PS and NPS management at once.

Figure 6-7: Boxplot of reach mean N-NO₃ concentration (mg/l) in the Upper Danube Basin under alternative management strategies.

SmartFert and SmartWWTP strategies respectively reduce fertilizer use or upgrade WWTPs without considering differences in current pollutant concentration status across the reaches. They are quite efficient in decreasing the average N-NO₃ concentration by almost 6 mg/l (see column labelled “eq.1” in Table 6-6). They would also reduce the number of reaches with average N-NO₃ concentration exceeding the 50 mg/l by 50%. However, these strategies do not provide total net income and do not reduce the high average N-NO₃ concentrations in the remaining 50% of polluted reaches (Table 6-6, Figure 6-7).

Conversely, management strategies found by applying the optimization routine (such as OptiG) do consider the location where management is applied. The spatial distribution of monthly average N-NO₃ concentration in the reaches of the Upper Danube Basin is shown in Figure 6-8 for three different management strategies: BLS, SmarFert and OptiG. Where average N-NO₃ pollution is low (i.e. below the WFD threshold of 50 mg/l) in the BLS, there are no significant differences between the three strategies. Conversely, in the reaches where N-NO₃ concentration threshold (50 mg/l) is exceeded, the improvements are important, especially in the OptiG. The number of reaches where on average the threshold is violated is reduced from 78 to 12. OptiG is the only strategy that could reduce the average N-NO₃ concentration of all polluted reaches to less than 70 mg/l (Table 6-6 column labeled as (2)).

Table 6-6 shows the value of several environmental and economic indicators for each of the strategies described above, in which only two objectives have been considered simultaneously: minimizing the cumulated N-NO₃ metric and maximizing the total net income. In a comprehensive decision-making process, the framework could be applied considering simultaneously more than two objectives, for example to account for other pollutants (like PO₃, NH₄, or sediments) or other metrics (or other economic valuation). In these cases, the analysis would be enlarged to a higher number of dimensions (the Pareto set will be a surface instead of one curve).

Biophysical and economic model results are subject to uncertainties. A correct calibration of the biophysical model and a correct estimate of biophysical and economic parameters are essential to minimize the influence of the uncertainties on the decision making process. Simulations and optimizations performed with R-SWAT-DM allow better understanding of the behaviour of the model under different situations.

In addition, the framework allows simple parameter sensitivity analyses to assess which parameters impact the process under study. Figure 6-9 and Figure 6-10 show two parameter sensitivity analyses performed by means of the iterative simulation option. Figure 6-9 shows the effect of variation in the fertilizer price and Figure 6-10 shows the effect of the harvest index coefficient (a SWAT crop parameter that defines the fraction of the total crop biomass removed with the harvest operation) on the final results.

Figure 6-8: Reach average monthly N-NO₃ concentration (mgN/l) for 15 year simulation period in the Upper Danube Basin under three catchment management strategies. Above: BLS; middle: SmartFert; below: OptiG.

Figure 6-9: Sensitivity analysis for the fertilizer prices.

Figure 6-10: Sensitivity analysis for the harvest index coefficient.

As it can be seen, changes in the fertilizer price result in changes of the response curve shape (Figure 6-9), whereas changes in the harvest index coefficient shifts the Pareto fronts to the right or to the left (i.e. the income estimation is sensitive to these parameters) but do not change curve shape (Figure 6-10). In both cases however, the strategy benefits in terms of N-NO₃ pollution remain similar.

6.5 Summary and Conclusion

Although in recent years the Water Framework Directive and the Nitrates Directive have succeeded in achieving some improvement in the nutrient status of many European water bodies, aquatic ecosystems in Europe are still at risk of eutrophication from excessive Nitrogen availability. These risks can be significantly reduced by applying selected BMP efficiently.

An integral simulation-optimization framework (R-SWAT-DM) for optimal allocation of PS and NPS conservation practices was applied to the Upper Danube Basin. The framework uses the spatially distributed watershed model SWAT to assess nonpoint and point source pollution and crop yields under current conditions (baseline) as well as under alternative management scenarios. Management strategies included crop fertilization plans to reduce diffuse pollution and wastewater treatment plant technology upgrading to reduce PS pollution. The economic module allows evaluating the economic benefit or cost associated to each management strategy, accounting for farmers' gross margins and WWTP upgrading investment cost.

For this application in the Upper Danube Basin, we focused on one environmental objective (i.e. minimizing average monthly N-NO₃ concentration exceeding a 50 mg/l threshold) and on one synthetic economic objective (i.e. maximizing the total net income). Efficient strategies that could significantly improve current water quality status were found. Our analysis suggests that a proper management of mineral fertilization can lead to important environmental benefit without affecting farmer economic income. Reducing the mineral fertilization rate by around 35% will allow to obtain a 30% reduction of N-NO₃ concentration in the most polluted river reaches, while concurrently increasing the total net income by 75M€. These results are in line with the outcomes of the EUROSTAT analysis of statistics and agri-environmental indicators of the four Upper Danube Basin main Countries. In this region the high input of organic Nitrogen from manure allows indeed to reduce mineral inputs with limited negative effect on crop yields (assuming a correct management of manure is put in place). In this context, for many crops additional mineral fertilizer inputs would result in slight increases of yields that would not be sufficient to repay the extra fertilization cost or the extra environmental pollution. Over-fertilization is a well-known issue in the Upper Danube, and more generally in all the Danube River Basin (Kunikova, 2013). The fact that farmers may reduce N use and increase their profit is puzzling: a rational farmer should have decided to reduce N use. One explanation could be the lack of information of farmers with respect to best management practices. It could be that local extension services focus more on increasing crop yields than on giving advices to farmers on how to apply N in an efficient way. One policy recommendation could be then to write and disseminate guidelines on

best management practices to farmers. Another policy option could then be to propose farmers some insurance mechanisms to secure their crop yield against the perceived loss in income due to reduced fertilization (Huang et al., 2001) or to redistribute parts of the gains coming from N reduction strategies to the farmers having voluntarily opted to implement actions in the form of subsidies.

Similar reductions in N-NO₃ pollution (measured with the cumulative N-NO₃ metric) could be achieved by upgrading WWTP treatments. The cost of water quality improvements could be relatively low (15M€) if associated to a spatially efficient choice of the WWTPs to be upgraded. The necessity to upgrade WWTPs was recommended by the European Court of Auditors (European Court of Auditors, 2015a) as an effective means to abate urban pollution. Since WWTPs are usually owned by municipalities, a massive program of upgrades raises the issue of funding these investments. One part of the investment cost could be passed through final users but local governments, sometimes for political reasons, may be reluctant to strongly increase water and wastewater prices. Another solution is then to activate the European Regional Development Fund and the Cohesion Fund which are available to Member States in particular for co-financing investments, in particular on UWWTPs upgrade and modernization. In the Danube river basin, an analysis on 28 projects revealed that the EU co-funding has represented on average 62.5% of total expenditures with a minimum of 34% and a maximum of 75% (European Court of Auditors, 2015b). These figures suggest that a significant part of the upgrading cost could be covered through EU co-funding in case a municipality goes for a secondary or a tertiary treatment of waste water.

Our study also found that efficient strategies focused on most polluted reaches, whereas water quality was not much improved where N-NO₃ concentrations were already below the threshold of 50 mg/l: in these reaches the upgrade of upstream WWTPs even if combined with the reduction of mineral fertilization in the contributing HRUs did not bring about significant improvements. On the contrary, in most polluted reaches, where the N-NO₃ concentration exceeds the WFD threshold, significant improvements could be achieved through the combined application of the proposed measures. Thus, by effectively exploiting synergies between PS and NPS best management practices, the number of reaches with excessive N-NO₃ concentrations can be reduced from 78 to 12, even with a positive net income (92M€). However, in some reaches where N-NO₃ concentration was most problematic, no combination of the selected measures could reduce N-NO₃ pollution to less than the WFD water quality threshold of 50 mg/l. For these reaches, other strategies, such as reduction of livestock density, different crop rotations, land use changes, irrigation practices, should be contemplated in addition to those considered herein.

The formulation of conservation strategies is under the responsibility of transboundary river basin organizations (such as the International Commission for the Protection of the Danube River for

Danube River Basin) but these organizations need scientific evidence and tools to measure the impact and effectiveness of proposed plans. The decision support system does not guarantee the implementation of the optimal solutions, but it provides the data, results and scenarios that feed into political negotiations on the development of sustainable strategies. If some strategies are not considered feasible or acceptable further constraints may be added in the tool to identify new optimal solutions.

Chapter 7. MultiObjective Framework to Identify Efficient Irrigation Strategies - the case study of a Mediterranean island (Crete)

7.1 Introduction

Water is key resource for sustainable development in most Mediterranean countries, where water scarcity and droughts are a major concern (EEA, 2015). The satisfaction of several and conflicting usages of water resources by maintaining good quantity and quality levels is a big challenge at global scale, but even more in the Mediterranean: water resources are constantly subject to various threats, such as over-exploitation of both surface and groundwater due to increased demographic and economic pressure and variable availability of water due to climatic changes, amongst others (Parry, M.; Canziani, O.; Palutikof, J.; van der Linden, P.; Hanson, 2007; Koutroulis et al., 2013). Agriculture is one of the most demanding water users especially in Greece, where irrigation sector accounts for about 88% of total water abstraction (EUROSTAT, 2016a). The achievement of sustainable water exploitation is a prerequisite of the key target of enhance resource efficiency in Europe as defined within the EU 2020 strategy (EU, 2010) and there is still space for important improvements of water saving in all the dominant sectors, and above all in the agricultural one (EEA, 2012). This target requires the capability to identify cost effective measures and management strategies and their implementation in the Programmes of Measures (PoMs) of the River Basin Management Plans (RBMPs), as designed in the context of the Water Framework Directory (European Union, 2000), is essential for their effectiveness.

The identification and design of such new strategies require the understanding of the water cycle within the basin, the knowledge of different water uses and demands and also their economic and social impact. Hydrological models are a valid tool to analyze such complex problems and they are widely used (refs): between several models the Soil and Water Assessment Tool (SWAT) was selected as it is physically based, it is wide used and applied also in the context of irrigation issue (refs), and it has been specifically adapted to Crete island by Malagò et al. (2016).

The improvement of water management requires an efficient use of water for irrigation, where efficient means to use less water to produce more, or at the same level of productivity. This improvement can be achieved in different ways: by increasing the efficiency of irrigation strategies by

changing technologies, introducing new methods, reducing water losses etc; or by improving water productivity that means by enhancing the resulting outcome of water used for agriculture.

In the case of Crete island we focused on the optimization of water allocation spatially and by crop, as efficient drip irrigation technology is already applied in most of the cropping systems (with olive, vineyards and vegetables). The fact that drip irrigation is so widely adopted is a proof of the importance of an optimal management of water in the island, thus requiring further attention in the context of future increasing demands. In the context of water supply it is also important to consider that water has to be distributed and used both efficiently and equitably (that means that all farmers should have comparable access to water supply to satisfy their local need) but anyway an non-efficient use of water need to be eliminated in the next future. However, this could lead to a multiplication of the implementation of many BMPs in the watershed, without insuring that the treatment targets at the watershed outlet are achieved (Emerson et al., 2005). Interactions between BMPs may also significantly affect their individual performances at a watershed scale. Harrell and Ranjithan (Harrell, Laura and Ranjithan, Ranji, 2003) emphasized that a reduced number of management practices could achieve the same treatment goals as a multitude of measures implemented throughout the watershed.

Evolutionary optimization methods such as genetic algorithms (Goldberg, 1989a) are popular in spatial optimization (Arabi et al., 2006; Chatterjee, 1997; Gitau et al., 2004; Lautenbach et al., 2013; Maringanti et al., 2009; Srivastava et al., 2002; T L Veith et al., 2004). The most popular method of spatial optimization is dynamic linking of a watershed simulation model with an optimization algorithm (Bekele and Nicklow, 2005; Cho et al., 2004; Kalcic et al., 2014b; J. Nicklow et al., 2010) ;among many others), wherein simulation model outputs are used to estimate the objective functions of the optimization algorithm. Interest has grown in spatial optimization of numerous conservation practices using genetic algorithms and SWAT (e.g., (Bekele and Nicklow, 2005; Maringanti et al., 2009)). SWAT is a watershed model commonly used to simulate the impact of land use and land management changes on water quantity and water quality (Arnold et al., 1998). Most of the previous works have focused either on using a single objective function for optimization that combines BMP effectiveness with cost (Chatterjee, 1997; Srivastava et al., 2002) or on sequential optimization of effectiveness and cost as separate objective functions (Gitau et al., 2004; T L Veith et al., 2004), i.e. constraining one objective function during optimization of the other. In addition, most works were conducted in relatively small watersheds or in simplified model representation where the search space for optimal solutions is relatively narrow resulting in efficient implementation of the optimization algorithms.

The overall goal of this work was to develop and apply a simulation/optimization framework to identify cost-effective irrigation management strategies, by maintaining optimal crop productivity. In our study we used the biophysical SWAT model (Neitsch et al., 2011) to simulate crop productivity, water demand, and diffuse nutrient emissions and fate in a watershed. The framework was developed in the open-source programming language R and can be easily used to launch individual or iterative BMPs simulations or search for optimal strategies; it includes advanced plotting, mapping and statistical analysis functionalities to facilitate the interpretation and assessment of the results, and can accommodate alternative simulation/optimization methods.

The objectives of the study were to: (1) set up SWAT model to simulate crop productivity under current and alternative scenarios; (2) integrate a genetic algorithm multi-objective optimization library with the SWAT model and an economic evaluation model; (3) apply the optimization framework on the case of Crete Island in order to identify optimal spatial allocation of best irrigation management practices and (4) potential impact of reduced water availability scenarios.

7.2 Materials and Methods

The R-SWAT-DM is a framework developed to help stakeholders in the selection of BMPs related to nutrients pollution reduction. It includes the following main components: (1) a watershed biophysical model (the Soil and Water Assessment Tool, SWAT;(Arnold et al., 1998)) for simulation of hydrologic and water quality processes under pollution control measures scenarios; (2) a component to link the biophysical model to R; (3) an economic module to estimate the monetary value of each management scenario; (4) an optimization engine to search for trade-off scenarios according to environmental and socioeconomic objectives. The framework can model crop productivity, water and nutrient demands, environmental impact assessment as nutrient losses to surface and groundwater resources.

7.2.1 Study Area

The Island of Crete occupies the southern part of Greece and is the largest island of Greece and the fifth in the Mediterranean, covering an area of 8336 km² (Figure 7-1). The Island of Crete is characterized by a dry semi-humid Mediterranean climate with dry and warm summers and humid and relatively cold winters where mean annual rainfall decreases from west to east and from north to south, but increases with altitude (MEDIWAT, 2013). Annual precipitations are highly variable ranging between 300 mm in coastal areas and 2000 mm in headwaters in White Mountains. For the period 1983-2009, the mean annual precipitation was estimated around 6400 Mm³/y, about which 40% was lost for evapotranspiration, 53% for infiltration and 7% for surface runoff (Malagò et al., 2016). The mean annual temperature ranges from 18.5° in the west to 20° in the south of island and decreases

with altitude. The Island is divided into four administrative prefectures, including from east to west: Lasithi (1810 km²), Heraklion (2626 km²), Rethymno (1487 km²) and Chania (2342 km²).

Figure 7-1: Location of the Crete Island in Europe (insert), and the spatial distribution of elevation (m) and karst areas from geological map.

Crete has about 2870 km² of agriculture land (including managed pasture), about 30% of whole Crete, with more than 1295 km² in Heraklion, and about 3720 km² of pasture (45% of total areas of Crete). The main crops are olives, grapes, and the main vegetables crops are tomatoes, cucumbers, onions, potatoes, watermelons and melons. The demand for irrigation water is high (about 360 Mm³/y), while only 45% (1225 km²) of agricultural land is irrigated. In Heraklion the irrigated area is around 600 km², followed by Lasithi and Chania with around 300 km², while a very small area in Rethymno is irrigated ((Agriculture Statistics of Greece, 2009);Table 7-1). Olives is the dominant crop and as cash crop it plays a very important economic rule for the island. It may be considered a strategic crop in the region also because highly adaptable to dry spells and drought, and able to attain acceptable yield under dry farming.

Table 7-1. Regional distribution of agricultural area (km²) in the Crete Island

Region	Pasture	Agricultural		Olive		Grape	
		All	Irrigated	All	Irrigated	All	Irrigated
Chania	1075	680	266	476	221	20	7
Heraklion	921	1295	592	825	511	195	25
Lasithi	879	433	274	283	235	24	5
Rethymno	844	460	93	256	73	19	3

7.2.2 The agro-hydrological modelling of Crete Island using SWAT

The Soil and Water Assessment Tool model, SWAT, (Arnold et al., 1998) is a semi-distributed, process-based model that simulates the daily water balance, crop yields, sediments, nutrients and pesticide in a basin. A modified version, KSWAT (Karst SWAT) was developed and applied in the Island of Crete by Malagò et al. (Malagò et al., 2016) to simulate streamflow and karst-springs water discharges increasing our knowledge about water resources availability and distribution under different hydrologic conditions.

For this reason, here we provide only a short description of the SWAT and model set up, as well as the calibration/validation procedure related to the hydrological part since the quality part was not object of the study.

SWAT was used to assess the impact of point sources and land use management practices on hydrologic and water quality processes, as well as on agricultural yields. The SWAT model integrates all relevant eco-hydrological processes including water flow, surface runoff, percolation, lateral flow, groundwater flow, evapotranspiration, transmission losses, nutrient transport and turn-over, vegetation growth, land use, and water management. The simulation of watershed hydrology is divided into two main phases: the land phase and the routing phase, which controls the amount of water, sediment, and nutrients into the main stream network. Watersheds are divided into spatially linked subbasins; the subbasins are subdivided into unique hydrological response units (HRUs) with unique soil/land use and slope characteristics. The land phase is solved at HRU level, which determines water flow and nutrient load outputs; these outputs are routed through the subbasin and subsequently, in the water phase, through the stream network till the watershed outlet.

The SWAT model requires pedological, climatological, topographical and land use data. In this study, the subbasins were delineated using the ArcSWAT interface with a Digital Elevation Model of 25 m pixel size (EU-DEM; (Bashfield et al., 2011)). Subbasins and streams were defined using a drainage area threshold of 1000 ha resulting in 352 subbasins with an average area of 19 km² covering 6700 km² (Figure 7-2).

Figure 7-2: Dominant landuse for the SWAT model subbasins in the four Crete Prefectures.

Land cover was derived from a 1 km raster map built from the combination of CAPRI (Britz, 2004), SAGE (Monfreda et al., 2008), HYDE 3 (Klein Goldewijk and van Drecht, 2006) and GLC (Bartholomé and Belward, 2005) for the year 2005. Land use was obtained from the Agriculture statistics of Greece (Agriculture Statistics of Greece, 2009). Soil type and characteristics were defined using a 1 km soil raster map, obtained from the Harmonized World Soil Database (HWSD) (FAO et al., 2009). From the combination of land use, dominant soils, and single slope for each subbasin 502 HRUs (Hydrological Response Units) were defined with an average area of 13 km².

The management practices for each crop included planting, fertilization, irrigation and harvesting. The simulated timing of plant sowing and harvesting were implemented in SWAT through daily heat unit concept. In this study the heat units for each crop were calculated by Bouraoui and Aloe (Bouraoui and Aloe, 2007) using the PHU (Potential Heat Units) program (PHU, 2007), developed at Texas Agricultural Experiment Station.

The amount of manure and mineral fertilization applied were retrieved from the Common Agricultural Policy Regionalized Impact (CAPRI) agro-economic model (Britz and Witzke, 2008).

A manual irrigation was applied selecting the irrigated HRUs for a total irrigated area around 25,000 ha in Chania, 9300 ha in Rethymno, 60,000 ha in Heraklion and 26,000 ha in Lasithi. The total abstractions for irrigation use in each Prefecture was 89 Mm³/y in Chania, 35 Mm³/y in Rethymno, 170 Mm³/y in Heraklion and 66 Mm³/y in Lasithi, respectively. Both irrigated areas and volumes were obtained from the Agriculture statistics of Greece (Agriculture Statistics of Greece, 2009).

The climate data included 69 stations with daily data for precipitation and 21 stations for temperature from 1961 to 2009. Monthly statistics of solar radiation, wind speed and relative humidity were calculated using the pan European high-resolution gridded daily data set EFAS-METEO,

acronym of European Flood Awareness System – METEO (Ntegeka et al., 2012) for 29 stations uniformly distributed over the modeled territory.

The KSWAT developed by Malagò et al. (Malagò et al., 2016) is a combination of an adapted SWAT model and a karst-flow model. The adapted SWAT model has allowed representing the main karst features (i.e. sinkholes and fast infiltration in the soil), while the karst-flow model was enrolled for quantifying the karst spring's discharges. The model KSWAT was applied to the Island of Crete to simulate the daily discharge of 47 springs in the period 1983-2009 and the monthly streamflow in the period 1980-2009. The application of the model required the identification of karst-subbasins based on literature information ("soft data") and the geological map.

As pointed out in Malagò et al. (Malagó, 2016), the calibration procedure involved two steps in sequence: the calibration of annual crop yields and the calibration/validation of streamflow and spring discharges.

Average crop yields were calibrated for the simulation period by considering last available statistics reported (EUROSTAT, 2016a). Comparison of yield productivity for the 2015 from the baseline scenario and Eurostat are reported in Table 7-2. For the calibration and validation of streamflow 15 and 7 gauging stations were used respectively. 19 parameters were chosen for the streamflow calibration as the most sensitive and representative of each hydrological process involved in the calibration, while the discharges of the 47 karst springs were calibrated adjusting 5 parameters that regulate the fluxes in the karst-flow model. More details of the calibration procedure can be found in Malagó et al. (Malagò et al., 2016).

With reference to model results, about 64% of the calibrated gauging streamflow and more than 70% of calibrated springs reached satisfactory PBIAS% (values in the range $\pm 25\%$; (Moriassi et al., 2007). In addition, the recharge areas of each spring were estimated and compared with other studies and the water balance of the whole Crete was estimated in different hydrological conditions.

7.2.3 Best Management Practices

Irrigation as affected by water availability and mineral fertilization strategies were considered in the work. As irrigation methods used in Crete are generally very efficient we used a drip irrigation scheme in SWAT model by considering total volume of water applied as divided in daily application not exceeding 10mm of water. When an increase of irrigation is tested for a crop it is raised the total number of single applications and not the volume of daily applications: this ensure an efficient use of water, even if expensive, but that can be easily or reasonably transferable to Crete reality as very

efficient methods are already put in place and widely used. 47% of the agricultural land is actually irrigated and 86% of this land is currently with olive (other area are cropped with vegetables, grape, citrus and some cereals). Average annual volume applied by crop are reported in Figure 7-3.

Organic fertilization, in general quite limited at least for most of dominant crops in Crete (olive, grape, pasture and grassland, citrus), and was not changed in alternative management strategies design. Mineral fertilization is indeed much handier for farmers and it is also straight linked with costs and agriculture economic productivity assessment. Mineral fertilization was changed only for those crops and regions already fertilized under current management and the total number of applications by year was not modified. Average annual quantities of mineral and organic fertilization applied by crop are reported in Figure 7-3.

Table 7-2. Crete Baseline Scenario information related to the crop area and quantity of fertilizer.
Avg. Observed yields are derived from EUROSTAT – 2016.

Crop Name	CROP id.	Number of HRU	km ²	% Area	Average Mineral Fertilizer (kg/ha)	Average Organic Fertilizer (kg/ha)	Average simulated wet yield (t/ha)	Average Observed Yield (t/ha)	
								Crete	Greece/EU
Pasture	PAST	196	3718	55.8			0.4	na	0.1
Olive	OLIV	101	1840	27.6	3.8	12.6	1.6	1.6 ^a	1.2 / 2.7
Grape	GRAP	27	257	3.9	4.2	13.9	12.6	na	11.5 / 8
Grass	RNGB CLVR	28	217	3.3	1.5	0.1	1.3	na	na
Sorghum	SGHY	14	73	1.1	123.6	0.0	4.9	4.9	3.6
Other Agriculture	AGRR	16	59	0.9	1.5	0.1	0.2	na	na
Potatoes	POTA	11	59	0.9	1.9	52.6	24.8	25.7	27.6
Citrus	CITR	13	58	0.9	8.5	27.7	23.0	na	25.2
Almond	ALMD	12	57	0.9	2.9	9.7	3.1	na	12.5(oils)
Pasture Managed	PASM	4	57	0.9	55.4	15.6	3.1	na	
Tomatoes	TOMA	9	27	0.4	20.9	71.2	18.8	na	37.4(veg.)
Carrots	CRRT	8	25	0.4	12.9	44.0	23.5	na	37.4(veg.)
Watermelons	WMEL	6	22	0.3	17.5	163.4	10.5	na	37.4(veg.)
Green beans	GRBN	6	20	0.3	1.5	8.3	2.0	na	na
Spring wheat	SWHT	4	20	0.3	40.5	40.0	2.6	1.2	2.5
Barley	BARL	4	18	0.3	18.4	14.3	2.4	4.9	2.75
Cucumbers	CUCM	5	13	0.2	17.5	163.4	17.3	na	na
Oats	OATS	5	12	0.2	29.3	17.8	2.6	0.9	
Sunflower	SUNF	6	10	0.1	0.0	0.0	0.1	na	2
Onions	ONIO	4	7	0.1	12.9	44.0	43.7	na	37.4(veg.)
Cereals Grain	GRSG	4	5	0.1	42.6	15.6	2.1	na	2.2
Fruits	APPL	2	5	0.1	2.9	9.7	9.7	na	12.5
Cabbages	CABG	4	5	0.1	12.9	44.0	28.9	na	37.4(veg.)
Alfa Alfa	ALFA	1	2	0.0	1.5	8.3	1.7	na	na
Eggplant	EGGP	1	1	0.0	17.5	163.4	2.9	na	na
Urban Areas	URHD	5	7	0.1					
Water bodies	WATR	3	17	0.3					
Forest	FRST	3	58	0.9					
TOTAL		502	6669	100					

^aPeloponnese area

Figure 7-3: Current management practices for irrigation by crop for all irrigated areas (Baseline condition).

7.2.4 Optimization Objectives

For this study of the Crete Island related to water scarcity under climate change conditions we consider simultaneously two conflicting objectives the irrigation water applied and the farmer's income.

7.2.4.1 Total Irrigation Water

Minimizing the total irrigation water applied is computed by the sum of the water applied to crops in each HRU of the study region:

$$\sum_{i=1}^{ns} \sum_{j=1}^{nt} W_{ij}$$

Where:

nt: number of time-steps in the simulation period.

ns: number of HRU

W_{ij}: irrigation water applied (mm) in HRU "i" and simulation time-step "j".

Alternatively, the objective could be defined as minimizing the total irrigation cost and is computed as follow:

$$\sum_{i=1}^{ns} \sum_{j=1}^{nt} W_{ij} * WCost_{ij}$$

Where:

nt: number of time-steps in the simulation period.

ns: number of HRU

$WCost_{ij}$: water cost (€/m³) in HRU “i” and simulation time-step “j”.

7.2.4.2 Farmers Income

In order to estimate farmer gross margin as affected by the different management strategies, we applied a function based on crop yield, crop price, fertilizer cost, irrigation water cost, standard operational cost, and specific fixed cost (including seeds cost, tillage operations, machinery, grain drying, labor, etc.). For each alternative BMP, total gross margin was estimated as:

$$g_1^{mp} = \sum_{i=1}^{HRU} \sum_{j=1}^{crop} (Y_{ij}^{mp} * A_{ij} * Up_j - Fc_{ij}^{mp} * Qf_{ij}^{mp} - Qw_{ij}^{mp} * Wc - Oc_j)$$

Where:

g_1^{mp} : agricultural total gross margin for the BMP.

Y_{ij}^{mp} : yield of crop j in HRU i under an irrigation pattern

A_{ij} : area (ha) of crop j in HRU i.

Up_j : unit price (income €/tm) of crop j

Qf_{ij}^{mp} : quantity of fertilizer applied (kg/ha) to crop j in HRU i under an irrigation pattern.

Fc_{ij}^{mp} : unit cost of fertilizer (€/kg) of crop j in HRU i under an irrigation pattern.

Wc : the water irrigation unit cost (€/mm), constant across HRUs

Qw_{ij}^{mp} : irrigation quantity (mm/ha) for crop j in HRU i under an irrigation pattern

Oc_j : operational management cost for the crop j

Crop management costs were assumed constant throughout the simulated period and independent from the annual yield. The average crop yield for the period 1990-2010 of each HRU under management scenarios was assessed with SWAT. Table 7-3 includes the average, minimum and maximum selling price for all crops (EUROSTAT, 2016a) in the study region, the operational (fixed) costs (including the labor, machinery, etc.) and the gross margin by crop as reported in 2004 (EUROSTAT, 2016a).

The cost of water per cubic meter can vary greatly between regions, catchment area and even within the same catchment, depending on the management agency and the altitude. In this analysis water cost can range between 0.05 to 0.35 €/m³ (as suggested by Chartzoulakisa (Chartzoulakis et al., 2001) according to the quote (0.01 € if quote < 80m, 0.13 till 160m, 0.35 till 600m and 0.60 for higher quote) and a maximum value of 0.6 is used for very high altitude (> 600 m).

Nutrients N, P and K are applied with several fertilizer products (Anhydrous ammonia, Nitrogen solutions 30%, Urea 44-46, Ammonium nitrate, Sulfate of ammonium, super phosphate 20%, etc.) containing different forms and percentages of the elements.

Table 7-3 Crete crop selling prices, management costs and mean annual simulated crop yields in the period 2000-2014 The fixed cost included: total cost of machinery, labor and seed.

	Avg Sell. Price*	Min. Sell. Price*	Max.Sell. Price*	Fixed Cost **	Gross Margin (rep. 2004) *
Crop category	(€/tons)	(€/tons)	(€/tons)	(€/ha)	(€/tons)
Pasture and grass areas	180*			30	25
Olive	1820	1190	2080	1250	2000 - 3000
Grape	535	400	675	4500	3000
Sorghum and grains	145	135	220	400	255
Citrus	485	200	810	4500	4500
Potatoes	450	312	538	200	6950
Almonds	2227	1417	3083	2400	2100
Tomatoes and vegetables	524	436	645	400	4400
Greenbeans	1558	1015	1976	400	3250
Soft wheat	186	135	235	30	290
Barley	177	137	225	150	280
Apples	607	363	672	3000	2100
* Reported in Eurostat Statistics Database (EUROSTAT, 2016)					
** Fixed cost was estimated based on crop income from reported data – gross margin reported					

The total cost of the fertilization was estimated based on the quantity (kg) of elementary N, P and K present in the applied fertilizers. The cost per kg of N P and K was estimated from annual data from 2000 to 2013 (USDA, 2015). The resulting prices were 1.21 € per Kg of Nitrogen, 2.8 € per Kg of Phosphorus and 0.97 € per Kg of Potassium.

7.2.5 The R-SWAT Decision Making framework

The R-SWAT-DM framework was designed as an integrated decision making tool (Udias et al., 2016). It could assess the economic and water quantity/quality impacts of different types/levels of management practices and compares them with the BLS. It could apply different MPs at different location, thus allowing to evaluate their overall impact and search for spatial combinations that are most appropriate to improve the water availability or quality at a minimum cost. The tool enables spatially explicit decision-making and moves away from blanket policies, helping stakeholders to better understand the main water quality problems and finding the most efficient practices for a given watershed.

The framework was developed in R software. R is an open-source programming language and a free software environment for statistical computing and graphics (Ihaka and Gentleman, 1996; R Core Team, 2011). To date, the large collection of user-contributed R packages containing state-of-the-art functions/algorithms used in many different fields (see e.g. <http://cran.r-project.org/web/views/>) continues to grow exponentially (Fox, 2009). These packages are freely available for public scrutiny, thus resulting in a continuously peer-based quality-control system.

Some of the main advantages of R for the development of the R-SWAT-DM are that it is free and open-source, it benefits from state-of-the-art mathematical/statistical algorithms and data manipulation/visualization techniques, and builds on some R libraries used to modify the SWAT input files or read output files (Zambrano-Bigiarini and Rojas, 2013). Several R libraries allow implementing mono and multi objective optimization techniques (Cortez, 2014).

The framework communicates with the SWAT model through simple ASCII files and/or R wrapper functions, modifying model input files and reading outputs files. Users of the R-SWAT-DM tool need to provide the path where the SWAT model is located and create a folder with files corresponding to the Baseline Scenario (BLS). They must also create a folder with information to build the economic model such as crop prices, water costs, fixed costs.

Users can run single or combined simulations of spatially explicit management practices, or iterative simulations whereby all management practices of one type are changed simultaneously step-wise in a fixed range of values. Alternatively, they can also choose to run a multi-objective optimization process. In this case, users should specify the environmental or water availability objectives, choosing among the available options, the management practices to be considered.

Once the simulation and/or optimization process has finished, the user can analyse and compare the management scenario outputs graphically and statistically. The framework can also generate maps with detailed spatial information about a selected scenario.

7.2.5.1 Multi-Objective Optimization Method

A logical approach for targeting water availability control practices should be to propose a multi-objective problem following the next equation:

$$\begin{cases} \text{minimize Irrigation cost} \\ \text{maximize Global benefit(s)} \end{cases}$$

Under this or other similar approaches, the objective functions are often conflicting and incommensurable. For example, implementation of a large number of conservation practices would likely result in lower pollutant loads, but the cost for implementation and maintenance of these practices would increase. Hence, the optimal solution(s) for each objective could substantially differ from the optimal solution(s) for the other objectives. Multi-objective optimization approaches can determine a set of non-dominated solutions belonging to a Pareto-optimal front. Non-dominated solutions are set of solutions in the search space that are better than any other solution in one or more objective (Srinivas and Deb, 1994). Any improvement in one objective among Pareto-optimal solutions will essentially result in the degradation of at least another objective (Pareto, 1971).

Since the shape of the objective function cannot be assumed as smooth or differentiable in our management practices application problem, gradient approaches such as quasi-Newton methods cannot be applied (Nocedal and Wright, 1999). Instead, gradient free methods such as evolutionary algorithms are applicable as optimization method. After testing some of the R libraries that implement multi-objective algorithms, we finally integrated the *nsga2R* package (Tsou, 2013) in the R-SWAT-DM because in the test it behaved slightly better than other methods (with a lower number of evaluations of the objective function) and its implementation was appropriate to include some modifications. The *nsga2R* package implements the non-dominated sorting genetic algorithm NSGA-II (Deb, 2001) which is among the most commonly used multi-objective global optimization methods with numerous successful applications in watershed management (Bekele and Nicklow, 2005; “Identifying Efficient Nitrate Reduction Strategies in the Upper Danube,” 2016; Nicklow and Muleta, 2001; Udías et al., 2012a). The procedure starts with an initial population of solutions that are typically generated randomly. The fitness of individual solution in successive generations increases through selection, crossover, and mutation. The procedure stops when a set of predefined termination conditions is met.

For the multi-objective optimization in the Crete Island case study, we considered simultaneously two objectives: one is related with water availability (minimize water quantity of water cost) and the other is the economical objective (maximize total net income).

The multi-objective optimization module simulates individuals of a population as chromosomes (scenarios), which in turn contain genes as their building blocks (Figure 7-4). Each gene represents a particular set of irrigation BMPs (BMP combination) on the chromosome encoding a specific trait. In this study, three management scales were considered, leading to different number of chromosomes (decision variables):

- Approach 1: agricultural management is defined per crop, independently by its spatial location (14 decision variables, one for each crop).
- Approach 2: agricultural management is defined per irrigated irrigated HRU (97 decision variables).
- Approach 3: agricultural management is defined per crop but must be homogenous in each administrative prefecture (Chania, Heraklion, Rethimno and Lasithi; 56 decision variables, one for each crop in each prefecture).

Figure 7-4: Schematic of the decision variables (chromosome) representing the irrigation practices for the three spatial decision level approaches considered

The NSGA-II results are very sensitive to the operational parameters that define the search algorithm. In order to search effectively for near-optimal solutions, best NSGA-II operational parameters, such as population size, number of generations, crossover, and mutation rates, need to be estimated. This task was performed by using a nonlinear sensitivity analysis (Maringanti et al., 2009), in which different values of the NSGA-II operational parameters were incremented one at a time at the end of the final generation using different population sizes, numbers of generations, mutations, and crossover probabilities.

7.3 Results and Discussions

Olive is a cash crop of great importance for Crete island and may be considered a strategic crop in all Mediterranean area because it can be considered quite highly adaptable to expected future dryer conditions and limited water availability. Nevertheless, olive crop produces higher yields with high rainfall and/or irrigation water (Iniesta et al., 2009; Martínez-Cob and Faci, 2010; Moriana et al., 2003; Palese et al., 2010; Palomo et al., 2002) and therefore its relation with water resources availability is a crucial aspect to be carefully considered.

In Crete olive is the dominant crop both for its distribution (about 64% of arable area) and for its economic importance (about 44% of total agricultural crop value production). Other important crops for Crete agricultural economy are vegetables (27%), grape (5%), citrus (4%) and other fruits (7%) and potatoes (4%) (Figure 7-5). Moreover olive is the most irrigated crop in Crete as it accounts for about 86% of total irrigated land.

Figure 7-5: Crete annual crop value production M€ - Eurostat (5 years avg.) vs Baseline

We focused our analysis on alternative irrigation practices in order to assess if it possible to maintain or improve the total agriculture crop benefit, reducing the irrigation water use and/or adapting to a reduced future water availability. The R-SWAT-DM framework was so applied in order to analyze different scenarios of increased/reduced irrigation for several crop and regions in the Crete island. The tool searches new management strategies, starting from the Baseline Scenario (BLS) implanted in SWAT and based on the current situation as described in previous section of this paper.

A preliminary analysis was performed simulating predefined iterative changes in the rate of irrigation water applied in all HRUs starting from the BLS values (dark blue dots in Figure 7-6). Each point is the result of an increase or decrease of 5% in the amount of irrigation water applied with

respect to the previous iterative point. The iterative simulations showed that the crop benefit increases with the applied irrigation volume. At low irrigation rates (left part of the curve, crop benefit below 600 M€), a 5% irrigation increase produces a more than proportional crop benefit increase, because at these rates, crops are very reactive to water applications. Instead, near the baseline (both left and right side), 5% changes in irrigation rates generate a less than proportional change in crop benefit: at these irrigation rates, crop water stress is generally low, and crop productivity is near its potential. The slope of the curve to the right of the BLS point (irrigation increment) has a different shape. This is because we introduced a maximum limit of water that can be applied to each crop in each HRU to avoid very high unsustainable irrigation schemes (Figure 7-6).

Figure 7-6: Pareto front strategies according to the minimum irrigation cost and maximum crop benefit objectives. The red and green Pareto correspond at the efficient strategies considering respectively the crop irrigation rate and the HRU irrigation rate respectively as unit/levels of decision/management. The blue light Pareto correspond to the efficient strategies considering the crop irrigation rate as unit of decision in each of the four Crete regions. The blue dark point corresponds to the iterative irrigation rate variation of the BLS.

Figure 7-6 shows the Pareto fronts that minimize water cost (directly linked to irrigation water use) vs total crop benefit for the three management decision levels (decisions per crop, per HRU and crop/prefecture combinations), in comparison with the baseline (BLS) conditions. The management strategies identified in the three Pareto fronts are all more efficient than the BLS iterative irrigation strategies. The most efficient strategies occur when the spatial management decision units are smaller (*Approach 2, HRU level*). However, implementation of management solutions identified with this

approach requires a large effort and high operational complexity, as each farmer should be required to adopt different strategies depending on field location. On the other side, solutions identified with the *Approach 1* (crop level) are less efficient in water saving, but they can be implemented very easily, as the same crop solution is valid everywhere, and strategies can be transferred locally with less practical and political difficulties.

The *Approach 3* (crop management by prefecture) can be identified as a balanced compromise between searching for efficient water saving solutions but reducing implementation difficulties. Adoption of efficient solutions tailored per prefecture can also ensure simplicity of knowledge transfer, and equal treatments among farmers' communities.

Table 7-4: Short description of the management strategies analysed.

Strategy	Identified solution	Short description
Current	BLS	Baseline Scenario
<i>Approach 1</i>	1.A	Same Benefit than BLS minimizing irrigation at crop management resolution
<i>Approach 1</i>	1.E	Same Irrigation Cost than BLS maximazing Benefit at crop management resolution
<i>Approach 2</i>	2.B	Same Benefit than BLS minimizing irrigation at HRU management resolution
<i>Approach 2</i>	2.D	Point coming from the same Pareto frontier than B but close to the highest benefit
<i>Approach 3</i>	3.C	Same Benefit than BLS minimizing irrigation at crop management resolution by region

In order to analyse in more details different optimal solution for each Pareto front, we compared some targets solutions to the baseline management (Table 7-4, Figure 7-6). Strategies "1.A", "2.B" and "3.C" are efficient solutions identified in the three decision approaches that have similar crop benefit than "BLS". In addition, point "1.E" is an irrigation strategy that potentially allows increasing farmers' benefit while maintaining the current water irrigation use. Finally, point "2.D" was arbitrarily selected from the *Approach 3* (by HRU) Pareto front as an example of management strategy that potentially allows achieving a very high crop benefit (increasing it by 15%) while reducing irrigation water use compared with the baseline.

Solution "1.A" (by crop) is very simple and it is mainly characterized by a reduction of water irrigation use for olive crop (by 36 %; Table 7-5), and would result in 84 Mm³ of water saving and about 26M€ avoided cost. According to SWAT simulations, the large reduction of the irrigation in olive would entail a reduction of olive production of about 11% (from 85.5 to 75.7 thousand tons per year, Table 7-6) corresponding approximately to 24M€ loss of olive crop benefit, with a net saving of 2M€. For other crops, the "1.A" strategy envisage increases or decreases of irrigation rates, which are in some

cases noticeable, but generally with a small impact on total income because of the much smaller cultivated areas. With this strategy, it would be possible to reduce the total water cost by almost a third (31.6 % reduction of total irrigation volume, 90 Mm³) without losing crop profits.

Table 7-5: Crop rates variation from the BLS to the A water scarcity strategy

STR	Pota	Oliv	Toma	Grsg	Almd	Grbn	Barl	Citr	Grap	Oats	Swht	Sghy	Onio	Crrt
A	88%	-36%	-20	-90	86	34	-76	72	88	-90	-70	-90	-44%	6%
E	84%	10%	20	20%	44%	10%	-54	-28	88%	-90	30%	-90%	-48%	80%

By comparing cost and income for Baseline (BLS) and 1.A solution (Table 7-6) it can be appreciated an important difference both of crop income of 26.9M€ (663.0-635.9) and of irrigation cost of 27.8M€ (83.9-56.1), which denote the great importance of olive in the agriculture sector of Crete.

Solution 2.B could potentially reduce current irrigation cost by about 80% (and 70% of irrigation volume; amounting to 199 Mm³) by maintaining at the same time the current benefit. This impressive reduction could be achieved by modifying irrigation in each HRU. Also in this case, most of the water savings occur in olive crop HRUs that accounted for 77% (180Mm³) of water reduction achieved under this strategy. The importance of olive to potential water saving is because it is the most extensively used and irrigated crop in the island, so that even small reductions can permit important savings, and because it is sometime over-irrigated in regions where water availability is higher.

Table 7-6: Economic indicator for some of the irrigation management strategies tested in the Crete Island case study.

Crop Product.			Irrigation				Income	Crop Benef.	
	Irr.	Irr. Oliv	Av.	Tot.	Tot. Oliv	Tot. Cost	Irr.	Irr.	Tot.
Strategy	10 ³ xT	10 ³ xT	(mm/ha)	(Mm ³)	(Mm ³)	(M€)	(M€)	(M€)	(M€)
BLS	154.3	85.5	229.1	283.0	234.9	83.9	663.0	412.3	626.2
1.A	146.8	75.7	156.6	193.4	150.7	56.1	635.9	413.0	626.9
3.C	144.1	72.3	109.5	135.2	102.6	35.2	614.6	412.6	626.5
2.B	136.3	69.2	68.3	84.4	54.6	17.7	594.7	410.2	624.1
2.D	161.4	89.9	123.6	152.7	115.2	34.9	709.1	507.4	721.3
1.E	160.1	87.5	231.7	286.1	243.6	83.8	694.3	443.7	657.6

Mean Irrig.: for the HRU irrigated; Mean Irrig: for the HRU irrigated; Irr. Crop Income: for the HRU irrigated (with all crops is 1141Me); Tot. Cop Benefic: including irrigated and non-irrigated HRU

Differences in irrigation volumes, crop yields, and total benefit for each crop and scenario can be appreciated in Figure 7-7, Figure 7-8, Figure 7-9).

Figure 7-7 shows the importance in the study area of the irrigation volume applied in olive compared with all other crops. Also, the high reductions in total irrigation volume that can be achieved with strategies "1.A", "2.B" and also for "3.C" and "2.D" in comparison to the Baseline (BLS), are evident. Figure 7-8 shows a relatively small variation in the total crops production under the different management solutions: the reduction for olive production is always the largest, up to 15% for solution "3.C". In terms of benefit (Figure 7-9), the loss for olive is important in solutions 1.A, 2.B and 3.C, but it is compensated by an increase of benefit generated by other crops, mainly grape (GRAP), vegetables (TOMA), and potatoes (POTA).

Figure 7-7: Total irrigation by crop for the six selected strategies.

Figure 7-8: Total production by crop in irrigated HRU for the six selected solutions.

With solution “1.E” the total irrigation cost is not changed, but modifying irrigation volumes by crop could increase the benefit by 7% (around 30M€). According to this strategy, the irrigation rate in olive should increase by about 10% (Table 7-5). In force of the maximum HRU irrigation rate threshold imposed in the model, in the HRUs that already receive very high irrigation rates under current management the increase does not occur, whereas irrigation rates are increased in the HRUs where current water use is below the allowed maximum. This is why the Pareto front changes shape with higher irrigations than point 1.E, because the crop approach is partially constrained by the applied threshold.

This aspect could also be appreciated in the dot plot of Figure 7-10, looking at solutions of the “BLS” and for “1.E” strategy. In all HRUs where the irrigation rates in olive is already high (550 mm), no variation of irrigation rate is applied. The total irrigation water use for olive crop changes from 234.9 Mm³ (“BLS”) to 243.6 (less than 4% increase) in this solution (Figure 7-7, Table 7-6)

Figure 7-9: Total benefit in irrigated HRU by crop for the six selected strategies.

Strategy “2.D” reduces the irrigation cost of about 58 % and brings an increase of the global crop benefit of about 15% respect to “BLS” (Table 7-6). The most important contribution for the benefit increase come from olive crop (see Figure 7-9), for which an important reduction of water costs is linked with a limited reduction of crop yields.

Strategies “2.B” and “2.D” are a clear example of exploiting the capacity of olive to produce good yields under limited water stress. Albeit limited, individual olive producers can legitimately consider unacceptable these crop production losses. This is a complex political problem where various stakeholders should convene on if, where, and how to implement solutions that ask some farmers to

reduce water use while allowing others to increase it for an overall larger community benefit. Clearly, compensation systems should be considered in this type of solutions.

Figure 7-10: Dot plot for irrigation quantity used for olive in each HRU for different strategies.

Figure 7-11: Total irrigation by region for the six selected strategies.

Finally, “3.C” strategy (Figure 7-6 and Table 7-6) has been selected from the Pareto front of the crop by prefecture approach. While maintaining the same benefit of the Baseline solution (same condition that we use to select 1.A and 2.B strategies), solution “3.C” could achieve a 53 M€ (60%) reduction of irrigation cost and a 148 Mm³ (52%) reduction of irrigation volume. The reduction in water volume in olive would amount to 132 Mm³ (90%). The prefecture of Heraklion has the largest

irrigated agricultural area (592 km², Table 7-1) followed by Lasithi and Chania (274 and 266 km² respectively), and Rethymno (93 km²). However, water irrigation use in Chania is almost double that in Lasithi, and almost eight times that of Rethymno (Figure 7-11): this is partially explained by the fact that there is more olive in Chania than in Lasithi and Rethymno, but most probably this is also linked with the higher water availability in Chania (46% of Crete), compared to Heraklion (25%), Rethymno (20%) and Lasithi (9%). In Chania, annual irrigation rates are high (Figure 7-11): indeed, most of the HRU points with high annual irrigation values for olive belong to Chania (black spots in Figure 7-10).

Figure 7-12: Total benefit in irrigated HRU by region for the six selected strategies.

Figure 7-13: Wet Crop yield by region for the selected strategies for olive (left) and grape (right)

Looking at the solutions that reduce water uses (strategies B, C and D in Figure 7-11), the reductions of irrigation rates are very different across prefectures: the irrigation reduction in Chania is the most important (nearly 85% for strategies B and C in comparison with the BLS). At the opposite, the application of strategy “C” (crop optimization by prefecture) would require a slightly increase of the irrigation volumes in Rethymno region (Figure 7-11), the poorest region in water availability.

It has to be stressed that global benefit preservation (table 6) can be acceptable at global scale but not at local scale because in Lasithi strategies “A” and “B” bring reduction (

Figure 7-12). It must also be considered that preservation of benefits is mainly due to a reduction of water cost (26.9 M€ for strategy “A” and 49 M€ for strategy “C”) but imply similar reductions of global gross income for some crops (table 6): 27.8M€ for strategy “A” and 48.7 M€ for strategy “B”, in both cases about 95% of the Income reduction correspond to olive .

The average annual olive yield (Figure 7-13 left) varies considerably across prefectures (for the baseline it is about 2.5-2.7 tons/ha in Chania and Heraklion and 1.6-1.8 tons/ha in Lasithi and Rethymno), and it is quite sensitive to irrigation volumes used under different scenarios in all the regions (Figure 7-13 left). Also for grape, yields variability as affected by different water irrigation scenarios is evident in all the four prefectures (Figure 7-13 right). Olive and grape sensitivity to irrigation is more than sufficient to generate important benefits for crop production to offset the irrigation costs in several scenarios and regions.

The “3.C” strategy reduces quite significantly the yield of olive in the region of Lasithi (Figure 7-13 left) while increasing the yield of grape (Figure 7-13 right) and the combination of these factors together with the reduced cost for less water use allow to achieve the same benefit of baseline.

Overall, the optimization process is able to identify solutions allowing to achieve important reduction in water use by preserving total agriculture benefits and production by compensating losses that may occur for some crops in some regions with gains for other crops more productive in other prefectures.

7.4 Summary and Conclusions

The achievement of sustainable water exploitation is a prerequisite of the key target of enhance resource efficiency in Europe as defined within the EU 2020 strategy (EU, 2010) and there is still space for important improvements of water saving in all the dominant sectors, and above all in the agricultural one (EEA, 2012). This target requires the capability to identify cost effective measures and management strategies and their implementation in the Programmes of Measures (PoMs) of the River Basin Management Plans (RBMPs), as designed in the context of the Water Framework Directory (European Union, 2000) , is essential for their effectiveness. This issue is particular crucial in the Mediterranean region and above all in agricultural areas such as Crete island.

An integral simulation-optimization framework (R-SWAT-DM) for optimal identification of agricultural management strategies was developed and applied to the Crete island study area. The

framework uses the spatially distributed watershed model Soil and Water Assessment Tool (SWAT) to assess crop yields under current conditions (baseline) as well as under alternative management scenarios for irrigation. The economic module allows evaluating the economic benefit or cost associated to each management strategy, accounting for farmer's net income.

For this application in Crete, we focused on one environmental objective (i.e. minimizing total water use for irrigation) and on one synthetic economic objective (i.e. maximizing the global net income, based on water cost saving and crop selling prices). Taking into account simultaneously these two dimensions required to implement a multi-objective analysis. In Crete, efficient strategies that could significantly reduce global irrigation water demand were identified.

In this application, three levels of different spatial resolution were analyzed in order to point out different levels of integration of optimal solutions. Standard solution for each crop at global scale can be easily identified but more efficient solutions can be identified by searching for site specific strategies linked not just to crop type, but also to specific local condition (of the HRU management unit). The first approach (*Approach 1: "by crop"*) allow to identify very quickly which crops would be more impacted by reduced water irrigation input, and to pick out changes of irrigation patterns (for example increasing water for one crop and reducing for another). The second approach (*Approach 2: "by HRU"*) allows to find locally specific optimized strategies specifically tailored for each crop according to its location. The third approach is a combination of the two and it works with an approach "by crop" but at sub-regional level (in this analysis the sub-regional level is equal to the four prefecture in which Crete is divided) thus trying to get the most positive aspects of both approaches (simplicity and facility of implementation form one side and geospatial relevance from the other side).

The analysis suggests that more efficient management of water can be achieved without losing the current agricultural production and benefit. A crop approach would result in reducing water irrigation volume by around 32% (90 Mm³). With the more local HRU approach the possible reduction of water irrigation use could amount to about 70% (199 Mm³). In both cases, the highest irrigation reduction (and crop production) would be in olive: this is because olive is less sensitive to water stress than other dominant crops (vegetables and grapes) in the island such as vegetables and grape. Despite its water stress resistance, olive quantitative and qualitative production depends on suitable irrigated management. The reduction of irrigation could potentially bring larger yield losses in dry years, an aspect that was not fully considered in this analysis. Thus the use of irrigation in olive is justified.

The intermediate approach (solution strategy 3.C) was particularly interesting as it allowed identifying locally relevant solutions for each crop and prefecture. An optimal water saving scheme would call for irrigation to be drastically reduced in olive and grapes of Chania (87%) and Lasithi (72%),

slightly reduced in Heraklion (27%) and increased in Rethymno (13%). The net result of this reallocation of water would entail a 7% income reduction (same benefit) for a 52% water saving (148 Mm³).

One of the most interesting features of the proposed framework is its flexibility and the possibility to identify several optimal management strategies. Different, equally optimal, solutions can be identified at the scale of interest of different stakeholders: for example a national manager could be more interested in solutions under crop approach that can be more easily implemented, while a farmer would be more interested in more locally relevant solutions (HRU approach), and a water management agency could be interested in crop-by-prefecture approaches.

The projected impact of the water stress on crop yields should be verified in the field. Also, transferability of water across catchments should be verified. However, the large potential water savings highlighted in the analysis indicate that despite limitations of the study, cost-effective optimal irrigation should be searched and implemented in water scarce regions, such as the Mediterranean area.

Chapter 8. Conclusion

8.1 Concluding remarks

The research topic of the thesis was motivated by the need to provide answers to the various and diverse questions arising from Nexus approach and specifically to develop tools and methods to effectively manage and make optimal use of limited resources in order to meet future socioeconomic needs. In this context, I analysed the contribution of multi-objective analysis routines combined with biophysical mathematical models.

For such purposes, the main objective of this thesis was to develop a spatially explicit framework in order to spatially identify and allocate alternative management practices, by means of the integration of an optimization algorithm and biophysical and hydrological models.

Several case studies were analyzed in order to demonstrate the capability of the system in different context: i) in the case of African continental context the biophysical EPIC model was selected as this model is particular adapted to estimate crop yields production as affected by different management strategies and to assess nutrient and water crop requirements, and integrated within a multi objective framework; ii) in the European context a multi objective framework was developed by integrating the hydrological model SWAT, in order to better analyze tradeoff between crop agriculture productivity and water environmental quality and quantity issues at river basin scale. These newly developed integrated tools were used in the following applications:

- I. Using a newly developed and validated tool linking a GIS and the EPIC model, we show that Africa has high potential to increase crop production in order to cope with the increasing demand. I show that in most African countries, the main limiting factor to crop production is nitrogen, while water limitation is restricted to fewer countries. I also show that a mining of soil resources is taking place in many countries in Africa, with the uptake of nitrogen exceeding the inputs. I confirm that irrigation can substantially increase yield in water-rich regions, and that the lack of infrastructure does not allow countries such as those located along the Gulf of Guinea to reach high production levels. On the other hand, countries such as Northern African countries are mining water resources in many regions and an improved sustainable use of water resources, such as wastewater reuse, will be needed, in particular to cope with climate change (drier and hotter climate). I show that yield gaps can be reduced through appropriate nutrient and water management, in particular in Sub-Saharan Africa where the

yield gap is larger than in North Africa. However, optimized management strategies considering water availability and water quality are needed in view of a sustainable development. The link of tools such as GIS-EPIC with multi-criteria optimization approaches was identified as a key step in identifying optimal solutions considering several constraints including social, economic, and environmental factors and for this reason the system was linked with a multi-objective algorithm.

- II. a multi-objective optimization tool was developed integrating the GISEPIC system for the whole Africa. It was applied to identify trade-off optimum strategies for agricultural land management between profit and environmental impacts in view of helping decision makers to select the optimal solutions according to specific needs and requirements including social, health, economic and environmental priorities. I evaluated two main potentially conflicting objectives including the maximization of farmer's income and the minimization of the environmental impact using the nitrogen leaching loss as a proxy. The novelty of the study lays in the application of the multi-objective optimization approach at continental scale based on high resolution data (global studies resolution is often larger than 50 km x 50 km) providing a multi-scale tool for identifying at large scale hot spots of mismanagement, and providing at the regional scale detailed optimal sets of sustainable water and fertilizer management strategies. The tool provides an effective and practical system to simulate and analyse the impact of several management strategies on crop productivity, water use, fertilizer needs, farmers income, environmental impact, etc.: identified Pareto strategies (for example for irrigation and fertilization) will help determine the opportunity costs of reducing nitrate pollution, and facilitate the choice of most appropriate management strategies according to stakeholders (farmers, citizens and environment) specific needs at the local and regional scales.
- III. An integral simulation-optimization framework (R-SWAT-DM) for optimal allocation of PS and NPS conservation practices was successfully developed and applied to the Upper Danube Basin. The framework uses the spatially distributed watershed model SWAT to assess nonpoint and point source pollution and crop yields under current conditions (baseline) as well as under alternative management scenarios. Management strategies included crop fertilization plans to reduce diffuse pollution and wastewater treatment plant technology upgrading to reduce PS pollution. The economic module allows evaluating the economic benefit or cost associated to each management strategy, accounting for farmers' gross margins and WWTP upgrading investment cost. The analysis demonstrated that a proper

management of mineral fertilization can lead to important environmental benefit without affecting farmer economic income. Reducing the mineral fertilization rate by around 35% will allow to obtain a 30% reduction of N-NO₃ concentration in the most polluted river reaches, while concurrently increasing the total net income. The framework can also be used to demonstrate how similar reductions in N-NO₃ pollution (measured with the cumulative N-NO₃ metric) could be achieved by upgrading WWTP treatments.

- IV. The R-SWAT framework (R-SWAT-DM) was also used in another case study aimed at the identification of cost-effective irrigation management strategies, by maintaining optimal crop productivity in a Mediterranean island (Crete). One of the most interesting features of the R-SWAT-DM framework demonstrated in this analysis is that it gives decision makers a good picture of the situation of the study region, allowing exploring from the current state to the maximum improvements that can be achieved by reducing/augmenting water use for all or single crop and for each region of interest (in this analysis I proposed an optimization at the level of the four prefecture of Crete, but different levels of aggregation are possible and easily implementable. It also provides an evaluation of the costs (or potential income losses) required to afford any conservation strategy (due to political reasons or to environmental constraints). The visualization tools included in the framework help to identify crops and regions where most of the changes need to be implemented. The tool provides Pareto optimal strategies, especially useful in the definition of the improvements that can be expected and for the identification of trade-offs between environmental and economic objectives

In conclusion the thesis demonstrated how the integration of biophysical and hydrological model with an optimization framework is an efficient methodology providing answers and alternative solutions for policy makers in evaluating long-term benefit with a long-term perspective based on simulations of crop productivity, water quality and quantity indicators (i.e. concentrations of nitrates in surface water and in the leaching, water use and irrigation requirements), when complex scenarios of BMPs are implemented, i.e. reducing fertilizer application and upgrading WWTPs, irrigation spatial and crop allocation. Furthermore, the visualization tools included in the framework help quickly to identify crops and regions where most of the changes need to be implemented.

The proposed systematic approach has shown to be a powerful tool both for scientists, policy makers and also stakeholders, and could be extended to other models and context.

8.2 Recommendation for future research and outlook

Concerning the development and application of the EPIC model in the African continent it has to stressed how in this context crop yield productivity is much more controlled by crop stresses if compared with high productive agriculture in Europe and in general in developed countries. In EPIC (and also in SWAT) nutrient (N) and water stresses are normally considered as the main limiting factors affecting crop productivity: adequate consideration of those and other stresses is very important above all when projecting crop yields in future years. For instance phosphorous and micronutrients limitation, weeds pest damage and post-harvest losses are example of potential sources of stress and damages that may lead to important yields losses and thus requiring attention for more specific analysis on future trends on crop production in the context of food security and Water Food Nexus approach.

The accuracy of model outputs largely depends on the quality of input data, and although the validation has shown that model EPIC performed well in simulating crop yields at national and sub-national level, the application of such system at more local scale requires a specific validation and setup of model with input data with higher spatial resolution data.

There is a wide range of possible future enlargement of assessment that can be performed with the developed tools both at African continental scale (EPIC) that at river basin level (R-SWAT), mainly linked with the identification of best management practices (BMP) for fertilizer and irrigation use and in for the optimal management of water resources preserving their quantity and quality. More specifically the inclusion of other crop management strategies such as crop rotations is an important further step to be considered. Also, the inclusion of climate change scenarios analysis for the identification of specific mitigation option is an important future opportunity for the application of the developed systems.

The developed tool is integrating currently the two models EPIC and SWAT, but it is open to further development and can accommodate the inclusion of new optimization libraries and models when needed. The possibility to include other models is an important issue, as it will allow to compare outputs from different models and increase the reliability and transferability of optimal solutions identified. An additional step will be the inclusion of energy model as well.

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