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Using multi-objective optimization for improving the sustainability of urban development

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Table of Contents

Summary

Urbanization is a global phenomenon observed at unprecedented pace and scale. It is a threat to many ecosystem services and yet it also offers the possibility to shape a sustainable future. The United Nations have defined 11 goals that are intended to make cities and communities sustainable. Reaching these goals is a wicked challenge for decision-makers because the goals are often conflicting and there are many uncertainties and complexities that need to be considered when addressing them.

In order to help decision makers to deal with a wicked challenge, to anticipate and understand the consequences of their actions or even to help them develop a vision for the future, it is often necessary to employ simulation models. A wide variety of modelling and simulation approaches dealing with urban development is available. However, many of them are not very suitable to deal with the wickedness of the problem of reaching the sustainable urban development goals. In particular, they may struggle to deal with the many conflicting objectives involved.

Using a multi-objective optimization approach specifically offers the possibility to account for conflicting objectives. It offers potential solutions to problems that are too complex for humans to solve, and it can be used to derive optimal solutions comprising a vision for a sustainable future. Thus, multi-objective optimization has some interesting properties that could be exploited and used to complement the existing set of modeling approaches used to support decision-making related to sustainable urban development. However, so far the possible applications of multi-objective optimization have rarely been demonstrated to support decision-makers dealing with the wicked challenge of improving the sustainability of urban development.

The aim of this thesis is not only to offer support to decision-makers dealing with the sustainability of urban development, but to demonstrate how multi-objective optimization can be used to support decision-makers for a larger scope of problems related to land-use change and management. The latter is supposed to promote the use of multi-objective optimization in land-use system science. A further step in promoting multi-objective optimization in land-use system science is to present effective algorithms to solve spatially explicit multi-objective optimization problems, which is a prerequisite for applying multi-objective optimization.

I exemplify the use of multi-objective optimization by addressing two goals that are related to sustainable urban development. These two goals (i.e. objectives) are to maximize compact urban development and to minimize the loss of fertile agricultural soils in Swiss municipalities.

In chapter 2, the use of multi-objective optimization will be promoted by showing that there are efficient ways of solving spatially explicit optimization problems. As a strategy for solving the optimization problem I use a so-called genetic algorithm, which is a popular approach when dealing with two objectives. Promoting a wider use of multi-objective optimization approaches, by applying them to answer new research questions and showing possible new applications is achieved in chapters 3, 4 and 5 of this thesis.

In more detail, in **chapter 2** I demonstrate how genetic algorithms (GAs) can be modified in order to solve complex multi-objective optimization problems involving spatial relationships. I used and adapted, the so-called NSGA-II (Non-dominated Sorting Genetic Algorithm – II), for solving the multi-objective problem of minimizing the loss of fertile agricultural soils (i.e., agricultural productivity) due to urban growth and at the same time to maximize compact (i.e. contiguous) urban development. I compared existing modifications of GAs from literature and modifications developed by myself. In order to account for the spatial relationships, I found that it was crucial to include knowledge about how compact urban patterns evolve. In contrast, objectives such as agricultural productivity that do not involve any spatial dependencies (i.e. no neighborhood-relationships are involved) do not need to be dealt with in a special way. This knowledge provides a guideline for future researchers on how to solve multi-objective optimization problems involving spatial relationships.

In **chapter 3**, I show that it is possible to efficiently reduce the loss of agricultural productivity by steering the pattern of urban growth. In a first analysis, I reveal that fertile soils are often found in the vicinity of existing urban areas. This leads to a potential trade-off, as compact (i.e., contiguous) urban development can thus lead to a high loss of fertile soils. In order to protect as much agricultural productivity

(i.e., fertile soils) as possible, decision makers can either resign from having compact urban development or can strive for solutions (i.e. urban patterns) that were obtained in an optimization process. Although using optimization is a difficult and costly approach, my results show that this approach can be used in an efficient manner. Firstly, by comparing simulations of Business As Usual (BAU) urban expansion and urban patterns obtained by multi-objective optimization, I was able to show that there exist some regions for which there is a large difference between BAU and optimal solutions (methodical details on how the BAU urban expansion was modelled can be found in **Appendix 1**.). In order to aid decision makers, I derived a simple rule stating that in regions where high urban growth is anticipated (i.e. many agricultural areas will be converted into urban) the difference between BAU and optimal solutions is large and policy-makers should focus their efforts on steering the pattern of urban development in these regions. Secondly, there are areas of agricultural land that can be converted into urban without losing compactness or the most fertile soils. This knowledge could help policy-makers and planners prioritize areas that can safely be converted to urban without destroying more fertile soils than necessary or without losing more compactness than necessary.

In **chapter 4**, I use multi-objective optimization in order to simulate zoning decisions of urban planners and I exemplify how planning paradigms (in the form of constraints) can be an obstacle in reaching optimal solutions. Although there are many objectives that urban planners need to account for, I am assuming that they focus mainly on reducing the loss of fertile soils and promoting compact urban growth. The planning paradigms that I consider is that zoning is carried out at a local level (i.e. at municipality level) and that a predefined amount of urban zones needs to be created in each municipality. My results show that planning at a local level can be a constraint in reaching more optimal solutions and that cooperation at higher levels is required for an improved protection of agricultural productivity. While the latter is not surprising, I further show that using multi-objective optimization can elucidate whether and how municipalities should cooperate. The two ways in which municipalities can cooperate are (1) that they adapt their preferences in collaboration with other municipalities and (2) that they make agreements on the amounts of urban growth that is permitted in each municipality. The first option for collaboration can be useful if, e.g., two municipalities adapt their preferences, because in one of them a slightly higher loss of compactness can lead to a large gain in agricultural productivity, while in the other one a small increase in the loss of agricultural productivity can lead to a large gain in compactness The second option for collaboration is more effective than the first option, i.e., leading to a stronger reduction of loss of agricultural productivity. However, the second option may require a stronger institutional framework than the first one and may thus also be related to disadvantages.

In **chapter 5**, I use multi-objective optimization to simulate consecutive planning periods in order to come up with recommendations on the length of planning horizons. Again I am relying on the example of allocating urban zones in such a way that compactness of the derived urban patterns is maximal and the loss of agricultural productivity is minimal. In a toy experiment, I prove that due to the non-linear combinatorial nature of the problem of optimally allocating urban zones, short planning horizons may lead to non-optimal solutions. However, in a real-world situation I show that a short planning horizon does not necessarily lead to non-optimal patterns. While these results are interesting, the approach described in chapter 5 is especially valuable for demonstrating a methodology that could be enhanced in order to study in more detail the adequate length of planning horizons depending on the objectives involved and the characteristics of the planning perimeter.

In summary, this thesis shows that multi-objective optimization can complement current urban- and land-use modelling approaches by answering novel questions or questions that remained unanswered so far. The methodological advances presented in chapter 2, 3, 4 and 5 will help future researches to understand whether multi-objective optimization may be an appropriate approach to address their research questions. Pursuing the same purpose, i.e., facilitating researchers with a better understanding on the possibilities and limitations of multi-objective optimization, **chapter 6** discusses a potential taxonomy of optimization approaches for urban and land-use modelling. The same chapter concludes with possible future research directions that build upon results presented in this thesis and with some recommendations concerning sustainable urban development.

Zusammenfassung

Urbanisierung ist ein globales Phänomen, das mit nie dagewesener Geschwindigkeit voranschreitet. Die Urbanisierung ist eine Bedrohung für viele Ökosystemdienstleistungen, aber birgt gleichzeitig auch die Möglichkeit eine nachhaltige Zukunft zu gestalten. Die Vereinten Nationen haben 11 Ziele definiert, deren Erreichung eine Voraussetzung für nachhaltige Städte und Gemeinden darstellt. Diese Ziele zu erreichen ist eine "verzwickte" (engl. wicked) Herausforderung für Entscheidungsträgerinnen, da viele Ziele berücksichtigt werden müssen, die nicht immer miteinander vereinbar sind und ausserdem viele Unsicherheiten einbezogen werden müssen.

Um Entscheidungsträgerinnen bei dieser verziwckten Herausforderung zu unterstützen und um ihnen ein Verständnis über die Konsequenzen ihres Handelns zu erleichtern, ist es hilfreich Modelle zu verwenden, mit denen Ausschnitte der Realität simuliert werden können. Es gibt viele verschiedene Typen von Modellen, die benutzt werden können, um die Prozesse und Konsequenzen von Urbanisierung nachzubilden. Allerdings sind nicht alle davon gut geeignet, um die komplexen und vielfältigen Auswirkungen der Urbanisierung so darzustellen und zu analysieren, dass sie eine geeignete Unterstützung für Entscheidungsträgerinnen darstellen. Insbesondere ist es für viele Modellieransätze schwierig mit unterschiedlichsten Zielen, die zueinander in Konflikt stehen, umzugehen.

Die multikriterielle Optimierung bietet die Möglichkeit unterschiedlichen Zielen, die in Konflikt zueinander stehen, Rechnung zu tragen. Ausserdem können Probleme gelöst werden, die zu komplex sind, als dass der Mensch diese ohne Hilfsmittel lösen könnte. Und nicht zuletzt, ist es möglich optimale Lösungen aufzuzeigen, die eine Vision für eine nachhaltige Zukunft darstellen, die es anzustreben gilt. Die multikriterielle Optimierung hat also Eigenschaften, die geeignet sind, um die Herausforderung einer nachhaltigen Urbanisierung anzugehen und das Repertoire bestehender Modellieransätze zu ergänzen. Allerdings gibt es bisher kaum Studien, die zeigen wie multikriterielle Optimierung genutzt werden kann, um Entscheidungsträger zu unterstützen, die eine nachhaltige Urbanisierung anstreben.

Das Ziel dieser Doktorarbeit ist es nicht nur Entscheidungsträgerinnen relevante Informationen zur nachhaltigen urbanen Entwicklung bereit zu stellen. Es geht dabei vor allem auch darum den Nutzen von multikriterieller Optimierung für ein weites Feld von Problemen, insbesondere für solche, die sich mit Landnutzung und Landmanagement auseinandersetzen, aufzuzeigen. Durch das Aufzeigen dieses Nutzens soll die Anwendung der multikriteriellen Optimierung erleichtert und vorangetrieben werden. Ein weiterer Schritt, um die Anwendung der multikriteriellen Optimierung zu fördern ist es effiziente Algorithmen zu entwickeln, die optimale Lösungen für komplexe räumliche Probleme finden können.

In dieser Doktorarbeit versuche ich zu zeigen, wie multikriterielle Optimierung dazu benutzt werden kann die Ausdehnung von Siedlungsflächen so nachhaltig wie möglich zu gestalten. Eine nachhaltige Gestaltung der Siedlungsentwicklung ist eine enorme Herausforderung die sehr viele sozio-ökonomische und ökologische Ziele berücksichtigen muss. Um beispielhaft zu zeigen, welche Möglichkeiten die multikriterielle Optimierung bietet, fokussiert diese Arbeit auf 2 Zielen bzw. Kriterien, die optimiert werden sollen. Dies sind zum einen eine kompakte Siedlungsentwicklung und zum anderen ein möglichst geringer Verlust von landwirtschaftlich gut geeigneten Flächen. Als Studiengebiet wurden verschiedene Gemeinden im Kanton Zürich in der Schweiz untersucht.

Die Doktorarbeit lässt sich grob gesprochen in zwei unterschiedliche Themengebiete gliedern. In Kapitel 3,4 und 5 geht es darum die multikriterielle Optimierung einem breiten Publikum zugänglich zu Machen, indem gezeigt wird, wie vielfältig das Anwendungsgebiet ist und dass neue Forschungsfragen sowohl aufgeworfen als auch beantwortet werden können. In Kapitel 2, wird es dagegen darum gehen zu zeigen, wie sich Algorithmen gestalten lassen, um multikriterielle Optimierungsprobleme effizient zu lösen. Im folgenden wird ein kurzer Überblick über die einzelnen Kapitel gegeben:

Kapitel 2 handelt davon, wie Genetische Algorithmen angepasst werden können, um komplexe und räumlich explizite multikriterielle Optimierungspprobleme zu lösen. Dabei wurde der sogenannte NSGA II (Non-dominated Sorting Genetic Algorithm – II) verwendet, um ein konkretes Optimierungsproblem zu lösen. Dieses beinhaltete Siedlungsmuster so zu optimieren, dass sie kompakt sind und gleichzeitig einen möglichst geringen Verlust von landwirtschaftlich gut geeigneten Flächen verursachen. Um zu verstehen,

welche Anpassungen im Algorithmus besonders effizient sind, habe ich verschiedene Anpassungen, die in der Literatur dargestellt sind, miteinander verglichen und zusätzlich noch um eigene Ideen ergänzt. Der Vergleich aller unterschiedlichen Methoden hat gezeigt, dass es sich insbesondere lohnt auf die räumlichen Beziehungen der Objekte Rücksicht zu nehmen. Das bedeutet für den hier konkreten Fall, dass vor allem berücksichtigt werden muss, wie kompakte Siedlungsmuster entstehen und weniger darauf eingegangen werden muss, wie der Algorithmus den Verlust von landwirtschaftlich gut geeigneten Flächen minimiert. Dieses Wissen könnte einen wichtigen Anhaltspunkt für das Entwickeln neuer Genetischer Algorithmen darstellen, die dazu in der Lage sein sollen räumliche Optimierungsprobleme effizient zu lösen.

In **Kapitel 3** wird dargestellt, wie der Verlust von landwirtschaftlich gut geeigneten Böden reduziert werden kann, indem das räumliche Muster von Siedlungsausdehnung beeinflusst wird. Dabei wird zunächst gezeigt, dass sich fruchtbare Böden häufig in direkter Nachbarschaft zu bestehendem Siedlungsgebiet befinden. Daher gibt es einen Konflikt zwischen dem Ziel die Siedlungsmuster so kompakt wie möglich zu gestalten und gleichzeitig den Verlust von fruchtbaren Böden zu minimieren. Das bedeutet, dass Entscheidungsträger entweder auf ein kompaktes Siedlungswachstum verzichten können, um den Verlust von fruchtbaren Böden gering zu halten, oder versuchen optimale Lösungen anzustreben, die durch die Anwendung eines Optimierungsalgorithmus erzeugt wurden. Die Anwendung eines solchen Algorithmus kann sehr zeitaufwändig sein und bedarf eines gewissen technischen Vorwissens. Allerdings wird in Kapitel 3 auch gezeigt werden, dass es die Anwendung des Algorithmus häufig nicht nötig ist, da er das Muster des Siedlungswachstums im Vergleich zu einer sogenannten Standardentwicklung, die sich aus der Vergangenheit fortschreibt, nicht immer wesentlich zu verbessern vermag (methodische Details, wie die Standardentwicklung der Siedlungsmuster modelliert wurden finden sich in Appendix 1). Eine einfache Regel, die dabei abgeleitet wurde besagt, dass die Differenz zwischen optimierten Mustern und Standardmustern erst dann besonders gross ist, wenn auch das Siedlungswachstum in dem zu optimierenden Gebiet sehr hoch ist. Neben der Tatsache, dass es sich in manchen Regionen lohnen dürfte optimierte Muster zu erzeugen und in anderen nicht, konnte ausserdem gezeigt werden, dass es bestimmte Flächen gibt, die immer überbaut werden sollten ganz gleich, ob ein Siedlungsmuster erreicht werden soll, dass einen minimalen Verlust an fruchtbaren Böden verursacht oder ein Muster, dass so kompakt wie möglich ist.

In Kapitel 4 werden die Entscheidungen von Raumplanern bezüglich der Ausscheidung von Bauzonen mit Hilfe eines multikriteriellen Optimierungsalgorithmus simuliert. Insbesondere wird dabei veranschaulicht, wie das Festhalten an bestimmten Planungsparadigmen, bzw. die aktuelle Planungspraxis, ein Erreichen optimaler Siedlungsmuster verhindern kann. Erneut steht dabei ein Beispiel im Vordergrund, in welchem es darum geht Siedlungsmuster so kompakt wie möglich zu gestalten und ausserdem den Verlust von fruchtbaren Böden zu minimieren. Die Planungspraxis, welche genauer unter die Lupe genommen wird ist dass Zonierung weltweit und insbesondere auch in der Schweiz meistens auf Ebene der Gemeinden stattfindet. Allerdings könnte eine Ausscheidung von Bauzonen auf einer höheren Ebene, die eine Kooperation von verschiedenen Gemeinden bedingt dabei helfen deutlich mehr fruchtbare Flächen zu schützen. Als mögliche Kooperation zwischen den Gemeinden könnten zwei unterschiedliche Ansätze in Frage kommen. Zum einen kann gezeigt werden, dass es hilfreich ist, wenn Gemeinden ihre Präferenzen untereinander abstimmen. Zum anderen kann es besonders wichtig sein, wenn die Gemeinden miteinander abstimmen, welche Mengen von Bauzonen jede Gemeinde ausscheidet. Beispielsweise gibt es Gemeinden, in denen besonders viele fruchtbare Böden in für eine Überbauung geeigneten Lagen zu finden sind und daher die Menge an Bauzonen in diesen Gemeinden gering gehalten werden sollte. Da einer Gemeinde dadurch jedoch ein wirtschaftlicher Nachteil entstehen kann, sollte eine Abstimmung der Bauzonengrösse gegebenenfalls auch bestimmte finanzielle Kompensationsmechanismen einbeziehen. Während eine Abstimmung der Präferenzen relativ einfach vollzogen werden könnte, bedarf eine Abstimmung der Bauzonengrösse vermutlich eines stärker institutionalisierten Rahmens.

In Kapitel 5 geht es darum mit Hilfe eines multikriteriellen Optimierungsalgorithmus zu zeigen, welches ein optimaler Planungshorizont für die Ausscheidung von Bauzonen sein könnte. Um dies herauszufinden, wurden unterschiedliche Planungshorizonte simuliert und entsprechende Bauzonengrössen gewählt. Für einen kurzen Planungshorizont wurde zunächst eine bestimmte Menge an Bauzonen ausgeschieden und danach wurden diese Bauzonen in einer weiteren Planungsperiode ergänzt. In einem Probeexperiment konnte gezeigt werden, dass die nichtlinearen Eigenschaften des Optimierungsproblems (der Gestaltung kompakter Muster mit minimalen Verlust an fruchtbaren Böden) dazu führen, das sein bei einem kurzen Planungshorizont keine optimalen Muster mehr erreicht werden können. Allerdings konnte diese Schlussfolgerung nicht für ein reales Problem, die Optimierung des Siedlungsmusters in der Gemeinde Uster bestätigt werden. Dort konnten auch bei einem kurzen Planungshorizont immer noch optimale Muster erreicht werden. Die Resultate in Kapitel 5 stellen eine konkrete Information für Entscheidungsträgerinnen zur Verfügung, allerdings geht es hauptsächlich darum eine Methodik aufzuzeigen wie man eine passende Länge des Planungshorizonts definieren kann, die auch in anderen Gebieten der Planung Anwendung finden könnte.

Zusammengefasst wird in dieser Doktorarbeit aufgezeigt, dass die multikriterieller Optimierung bisherige Ansätze zur Modellierung von Landnutzungsystemen bereichert und es erlaubt neue Fragen zu stellen und zu beantworten. Die Kaptiel 2, 3 , 4 und 5 sollen zukünftigen Forschern helfen zu verstehen, ob multikriterielle Optimierung ein geeigneter Ansatz ist, um ihre Forschungsfragen zu beantworten. Dasselbe Ziel verfolgt Kapitel 6, in welchem Grenzen und Möglichkeiten der multikriteriellen Optimierung beleuchtet werden und ausserdem eine vorläufige Gliederung von Optimierungsansätzen zur Modellierung von Landnutzungssystemen dargestellt wird. Ebenfalls in Kapitel 6 werden zukünftige Forschungsfragen aufgeworfen und einige konkrete Schlussfolgerung dargestellt, wie die Nachhaltigkeit urbaner Entwicklung verbessert werden kann.

Chapter 1

1. General Introduction

1.1. Motivation: Sustainable urban development – a wicked problem

Urban growth is an ongoing process and has far-reaching impacts on ecosystems and their services, which are essential for human well-being (Millennium Ecosystem Assessment, 2005, Elmqvist, 2013). The two main reasons for urban growth are a strong increase in urban population (United Nations, 2015) and the increase of urban areas per capita. Thus, urban development expands even in countries with moderate or negative population growth rates (Haase et al., 2013, Pejchar et al., 2015), with Switzerland being no exception to this global trend (ARE, 2014, Jaeger and Schwick, 2014). Seto et al. (2012) forecast that the size of urban land cover will increase by 1.2 million km^2 in 2030, which implies a tripling in size of urban areas compared to 2000 levels. At these rates, it is a major challenge to prevent urban expansion from having a devastating effect on ecosystem services. Developing new methods, approaches and policies that can aid humanity in achieving sustainable urban expansion is thus of great importance.

Achieving sustainable urban expansion can be regarded as a wicked decision-making problem. Wicked problems have several defining properties, which are that (1) a variety of stakeholders and decision makers with conflicting interests and values are involved (Churchman, 1967, Hartmann, 2012, Artmann, 2015), (2) deep uncertainties need to be considered (Walker et al., 2013) and (3) even the formulation of the problem (i.e. the challenge) itself can be contested (Rittel and Webber, 1973).

Because of these properties of wicked problems, Kwakkel et al. (2016) point out that decision making in wicked problem situations should be understood as an argumentative process, in which problem formulation, understanding the functional characteristics of each system and deriving the set of most promising solutions, emerge gradually through a debate process among involved stakeholders.

Deriving the most promising solutions for sustainable futures of urban expansion is an argumentative process, however, it requires the support of scientists using quantitative methods (Haase and Schwarz, 2009, Haase et al., 2014). As the cause and impact of urban expansion are strongly related to the location of the expansion, any quantitative approach will need to take a spatial perspective. Numerous spatially explicit quantitative approaches have been developed to support decision makers in the process of identifying sustainable solutions of urban expansion. Malczewski (2015) divides these approaches into simulation and optimization approaches. He explains that simulation approaches may be characterized as descriptive answering the question "what if" or "what is". Optimization approaches are often considered to be normative, which are mainly concerned with the question "what ought to be". Answering all three of these questions, - "what if", "what is" and "what ought to be", can strongly enhance decision making processes dealing with land-use allocation problems. Dealing with the question "what is" may be necessary in order to understand where we start from and in order to explain actual behaviour of decision-making agents. Addressing the question "what if" may be very useful when dealing with uncertainties and when exploring how varying decisions will influence the future state of a land-use system. Answering the question "what ought to be" may be used in order to judge the efficiency of existing approaches and to provide scientists and policy-makers with a vision about the future.

For example, Nassauer and Corry (2004) argue that normative scenarios encourage policy-makers and scientists to think about the future in a new way, as a tangible goal to explore and to stimulate our imagination. Their study does not only demonstrate that normativity can be extremely helpful when trying to shape a sustainable future, but also that using simulation models can be used to produce normative solutions. While simulation approaches seem to be useful to carry out both, normative and descriptive analysis, there are to my knowledge no examples showing that optimization could not only be used in a normative, but also in a descriptive way. Only answering the question "what ought to be" may, however, not be enough in order to adequately support decision-makers in wicked problem situations.

Nevertheless, the number of studies applying optimization approaches in order to deal with land-use decision-making has been growing over the last years. A main reason for that is the increase in computational power. It allows researchers to use stochastic optimization methods that rely on a large number of iterations and are thus computationally very expensive (Weise, 2011). That allows them to address many optimization problems that could not been solved before. However, although computational power increased and innovative optimization algorithms are available, it is still very challenging to efficiently identify optimal solutions regarding the mostly non-linear combinatorial nature of land-use allocation problems.

In this thesis, I am addressing two major challenges that we need to address if we want to enhance land-use decision-making by using multi-objective optimization. Firstly, how can we use optimization approaches in order to support decision-makers in the argumentative process of shaping sustainable futures of urban development? Secondly, how can we efficiently and successfully solve the optimization problems of sustainable land-use allocation?

Concerning the first challenge, my main goals are to demonstrate that optimization approaches are not inherently normative and can be used to answer the question "what if" (chapter 4 and 5). In addition, I would like to show that a combination of land-use simulation (i.e. the simulation of urban expansion) and land-use optimization can greatly enhance the decision-making process for the wicked challenge of attaining sustainable urban development (chapter 3). In order to address the second challenge, I want to provide guidance to researches on how to design efficient multi-objective optimization algorithms when dealing with land-use allocation problems by analysing and comparing approaches that have been used in the past (chapter 2).

In the remainder of this introduction, I will discuss the different ways in which optimization approaches have been used to assist decision-making processes concerning land-use allocation problems. I will also summarise how different studies have tried to overcome a purely normative use of optimization. To better understand the different optimization approaches, as well as their advantages and disadvantages, I will also present an overview of multi-criteria decision-making approaches used for spatially-explicit analyses as well as a summary of the main algorithms used for multi-objective optimization. Lastly, I will present the case study region in Switzerland and a simplified problem dealing with the sustainability of urban expansion.

1.2. State of the art

1.2.1. Multi-criteria decision making and spatial analysis

The research field of multi-criteria decision analysis (MCDA) provides a suite of methods and approaches to aid decision-makers dealing with complex problems involving conflicting criteria. In case these problems have a spatial nature, MCDA methods are often combined with geographical information systems (GIS). Examples of MCDA methods combined with GIS are weighted sum, ideal points methods, Analytic Hierarchy Process/Analytic Network Process and outranking methods (Malczewski, 2015). More recently, multi-objective optimization methods have been introduced to the field of MCDA (Purshouse et al., 2014, Uhde et al., 2015). While the potential of the abovementioned traditional methods has been demonstrated in many different applications, the potential of multi-objective optimization to facilitate decision-making in land-use planning has not been fully explored and understood yet.

1.2.2. A priori, interactive and a posteriori articulation of preferences

The advantages and disadvantages of multi-objective optimization in MCDA can be explained by detailing on the different MCDA approaches. Most MCDA approaches can be either classified as *a priori*, interactive or *a posteriori*., depending on the moment when stakeholder preferences are included into the process of finding well-suited solutions (Marler and Arora, 2004). Multi-objective optimization is an a posteriori approach.

In the *a priori* approach, the specification of preferences of stakeholders is a prerequisite for identifying and proposing well-suited solutions (e.g. in an optimization process). In interactive approaches, the decision maker's preferences are included progressively during the optimization process. In a posteriori approaches, the search for all optimal solutions is done before the decision maker's preferences are incorporated.

The *a priori*, interactive and *a postiori* MCDA approaches all have advantages and disadvantages. A disadvantage of the weighted sum approach – the most commonly employed *a priori* method - is the difficulty to capture stakeholder preferences in a mathematical model. For example, stakeholders may have a different understanding of what a certain weight implies and are unfamiliar with the possibilities and limitations of the problem beforehand. Furthermore, *a priori* preferential weighting limits the possibility to extract and evaluate trade-offs between conflicting objectives and may be myopic if system dynamics and uncertainties are not well known (Singh et al., 2015). So-called interactive and *a posteriori* approaches may overcome some of these limitations, but they pose new challenges. Interactive approaches give the decision maker the opportunity to interact with the optimization process and to use knowledge about trade-offs and uncertainties when trying to develop and identify a suitable solution. As preferences are included interactively, the search process may be guided towards regions of interest, making it computationally efficient. A potential limitation to the use of interactive methods, however, is the requirement of the decision maker's time and interest to participate in the interactive solution process (Miettinen et al., 2008). A posteriori approaches can overcome some of the difficulties that *a priori* and interactive approaches are facing (Lautenbach et al., 2013, Chikumbo et al., 2014). However, these approaches still attract much less attention than *a priori* approaches. An explanation may not only be that the potential of the *a posteriori* approaches has not been fully demonstrated yet, but, also that their application poses severe challenges. Two of the main challenges include, firstly, finding a set of all optimal solutions within reasonable computation time and, secondly, presenting the results to the decision makers in a meaningful way (Miettinen, 2008). Thus, in order to increase the relevance of a posteriori MCDA methods, it is not only necessary to demonstrate their relevance in decision-making, but also to address the two mentioned challenges.

1.2.3. Approximating the true Pareto Front in land-use allocation problems using evolutionary multi-objective optimization

Multi-objective optimization aims at optimizing more than one objective function simultaneously (Coello et al., 2007). As there is more than one objective, there is no single optimal solution, but a set of optimal solutions called the Pareto Front (PF). Every solution of the PF can only be improved if one objective value is traded off with the value of another objective.

Multi-objective optimization problems can be solved by using either exact methods or heuristics and metaheuristics. An exact method is defined as a method that guarantees to find the true PF, while heuristics or metaheuristics cannot guarantee this. Metaheuristics are used to derive a so-called non-dominated front. This front can be identical to the true Pareto Front, but it may just be an approximation of the true PF. The non-dominated front contains all the dominant solutions that we were able to come up with in an optimization process using a metaheuristic. A solution dominates another solution (assuming that all objectives are to be maximized), if at least one objective value of the dominant solution is higher and all other objective values are at least equally good than the ones of the dominated solutions.

The development of exact methods for solving multi-objective optimization problems is experiencing increasing interest. These methods are however often related to very high computational efforts (Ehrgott et al., 2016). Thus, the use of metaheuristics or of hybrid approaches that combine exact methods and metaheuristics, are often much better suited when dealing with complex multi-objective optimization problems (Coello et al., 2007, Ehrgott and Gandibleux, 2008).

A specific type of metaheuristics are so-called evolutionary algorithms (EAs). EAs have proven to be useful in approximating a set of Pareto-optimal solutions because they can find multiple non-dominated solutions in a single run (Deb, 2001, Coello et al., 2007, Zhou et al., 2011). Furthermore, land-use allocation problems are usually combinatorial and nonlinear. EAs can be very useful when dealing with such problems, whereas more traditional approaches like linear integer programming may fail to find globally optimal solutions within an acceptable amount of time. (Matthews, 2001, Aerts et al., 2003).

A large variety of EAs has been developed for optimization. It has been shown that some EAs perform better than others for a variety of different optimization problems (Tanabe and Oyama, 2017). However, in general there is no algorithm that outperforms the others on all types of problems (Wolpert and Macready, 1997), it is necessary to choose the right algorithm for the problem at hand or to customize the algorithm to a specific problem (Deb et al., 2016).

In studies on land-use allocation, genetic algorithms (GAs) have frequently been used and proven to be very effective (Porta et al., 2013). GAs are a type of evolutionary algorithm and were developed in the 1960's (Holland, 1975) and grew in popularity in the 1980's. The publication of Goldberg (1989) and the rapid increase in available computational power produced a further increase in their popularity. However, it was not until 1999 when they were used for the first time for optimizing multi-objective urban planning and land-use allocation problems (Balling et al., 1999, Feng and Lin, 1999). Since these early applications, several studies have followed using GAs in the context of land-use and spatial planning. The purpose of these studies was mostly to show how the application of GAs could be used to find optimal spatial patterns of land-use and other spatial attributes (e.g. Cao and Ye, 2013, Masoomi et al., 2013).

The procedure of a generic GA includes the following steps (Goldberg, 1989, Konak et al., 2006): initialization, evaluation, selection, crossover/recombination, mutation, and termination (Figure 1). Konak et al. (2006) summarize the properties of many well-known multi-objective GAs, pointing out that these GAs mainly differ in the evaluation and selection process (i.e. by different fitness assignment procedures, elitism, or diversity approaches). While modifications in the evaluation and selection procedures are intended to improve GAs for a wide variety of problems, it is usually left to the user to adapt mutation and crossover operations to improve the performance of the algorithm for specific problems. After initializing and evaluating a population, promising solutions are selected. These solutions are combined using the crossover operator. By iteratively applying the crossover it is expected that good parts of each solution appear more frequently in the population. The mutation operator is intended to increase the diversity in the population which can be crucial for preventing the algorithm to get stuck in a local optima.

Studies trying to improve the performance of existing GAs in land-use allocation problems focus on a variety of challenges. One such challenge is to select values for parameters that are used in the GA. These parameters are population size, crossover, and mutation probabilities as well as a stopping criterion (e.g., number of generations or evaluations). Another challenge – and perhaps the most complicated one – is to adapt the algorithm to the spatial nature of the problem. This usually involves modifying the crossover operator in a meaningful and effective way (e.g. Stewart et al., 2004, Datta et al., 2007, Karakostas and Economou, 2014, Shaygan et al., 2014) and/or adapting the mutation operator (e.g. Cao et al., 2012). Knowledge about the optimization problem may also help finding initial populations that allow the algorithm to quickly converge (Bennett et al., 2004, Lautenbach et al., 2013). In another approach, the GA is parallelized, which has been found to strongly reduce computation time (e.g. Porta et al., 2013, Cao and Ye, 2013). Most of the aforementioned studies use a raster representation of the land-use categories (i.e, of the decision space). Stewart and Janssen (2014) used a vector-based structure that defines the border of each land-use parcel in their study area. A vector-based representation can strongly reduce the number of decision variables and accordingly the computation time. However, a vector-based structure may also complicate a mathematical representation of spatial objectives and require the incorporation of supplementary algorithmic schemes so as to, e.g., account for the location of each land-use parcel relative to its adjacent parcels. Chikumbo et al. (2014) apply a large number of modifications to a GA in order to adapt it to the spatial and many-objective (i.e. 14 objectives) nature of their problem. Such spatial, many-objective problems have hardly been dealt with in in earlier studies using GAs for land-use allocation problems.

Reviewing the literature, I found that most studies focused on a rapid convergence of the search process and that only few studies were concerned with finding a front of non-dominated solutions that are diverse and have the desired spread of front. Yet, decision makers are usually interested to be presented with all possible solutions (Zitzler et al., 2000, Bennett et al., 2004, Karakostas, 2015), so that they can select from a wide spectrum of possible solutions representing a variety of trade-offs. The ultimate challenge of land-use allocation problems is the derivation of a uniformly distributed non-dominated front that includes the extreme cases on all edges of the front and converges towards the true PF as quickly as possible.

There are clearly many different options to improve the performance of GAs in land-use allocation problems. However, these different options are rarely compared, which makes it hard to determine whether

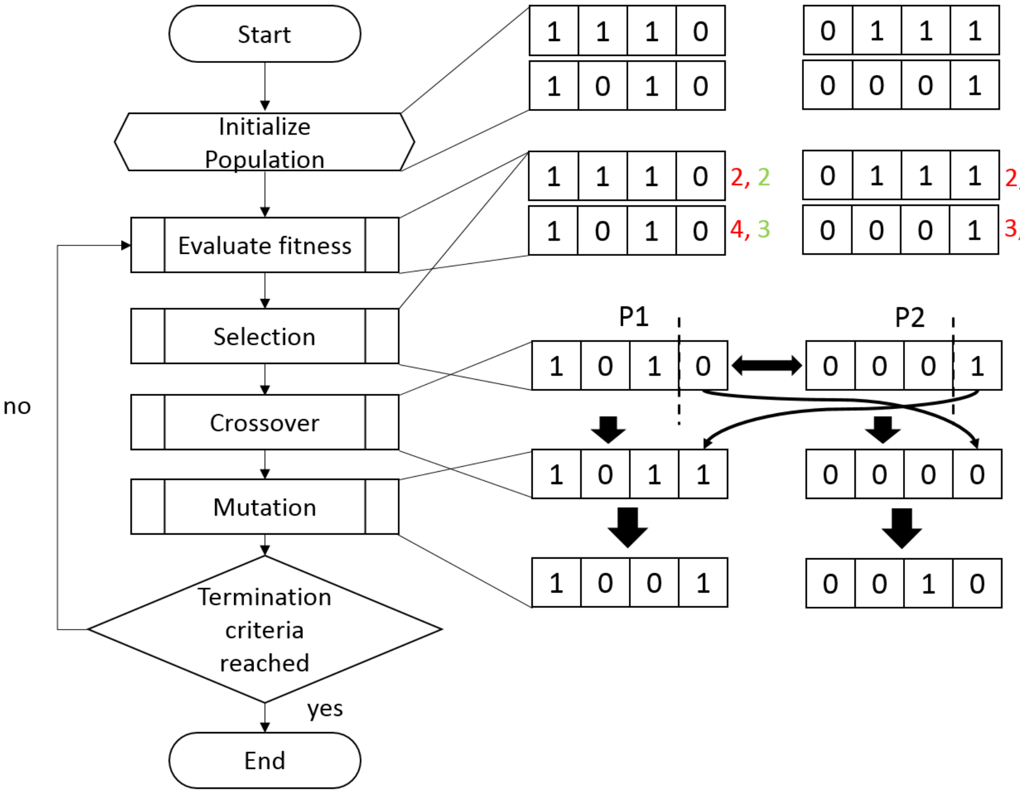

Figure 1: Flow diagram (left) of a genetic algorithm withsimple examples (right)of each step. An individual is represented by four binary variables (1,0). In a first step four individuals are randomly created. This initial population is afterwards evaluated. We assume that there are two objective functions for evaluating the fitness of the individuals. The objective values (here red=objective 1 and green=objective 2) are assigned to each individual. From the whole population of four individuals, the two best ones are selected. These are the parent solutions used in a crossover (i.e., recombination) process. In the crossover, parts of both parents are used to create children. The resulting children are mutated afterwards, i.e., one of the binary variables changes its value.

a specific modification of the algorithm leads to a significantly better performance. Moreover, many studies neglect to provide performance measures and do not discuss whether modifications of the algorithms are problem- or case-study specific or whether they could be useful for a larger set of problems.

1.2.4. Optimization approaches for land-use allocation - beyond normativity

As optimization approaches require the definition of objectives that determine which goals society would like to achieve, such approaches are often defined as normative. However, whether an approach is normative or not, may not only be determined by whether goals are defined or not, because even a descriptive modelling approach will require the definition of objectives, if, e.g., different scenarios are meant to be evaluated. I suggest that there is a degree of normativity inherent to different modelling approaches, which

depends amongst others on the amount of stakeholder involvement and its flexibility to test different assumptions.
Following such a concept of normativity, I argue that the normativity in optimization approaches may be relaxed in different ways. Firstly (1), there are many stages in which stakeholder and decision-makers preferences can be included when using optimization approaches. Secondly (2), results of the optimization process can be analyzed and interpreted with a strongly normative or rather with a descriptive connotation. Thirdly (3), optimization approaches can be combined with more descriptive land-use modelling approaches.

1.2.5. How to include stakeholder and decision-maker preferences when using optimization approaches

Stakeholder preferences may be included before the optimization process (*a priori*), during the optimization process (*interactively*) or after the optimization process (*a posteriori*) (Marler and Arora, 2004, Purshouse et al., 2014). In case preferences are included a priori, there is usually a single or very few optimal solutions presented to the stakeholders and decision-makers (Branke, 2008). Although stakeholders are asked for their preferences at the very beginning of the decision-making process, the results they are confronted with may appear rather abstract or normative and may not be well perceived.

Rather than presenting decision-makers with one or a limited number of solutions, it may be more appreciated when a range of scenarios or solutions is presented from which decision-makers can choose and gain understanding of the decision problem (Miettinen, 2008). Such an *interactive* or *a posteriori* decision-making process may thus be a good possibility to relax the normativity in optimization processes. Due to their complexity, optimization processes may be considered as nontransparent, no matter whether an a priori or an a posteriori process is employed. However, it may be much easier for decision-makers and stakeholders to start a discussion upon advantages and disadvantages of different solutions, if they are provided with a full or at least wide range of solutions in the objective space and the decision space (Miettinen, 2008). In particular, providing them with information on which land use pattern are related to different parts of the solution space could strongly improve the acceptance of optimization in decision support (Chikumbo et al., 2014). In addition, stakeholders might choose their preferences differently if they know the shape of the trade-offs, i.e., the Pareto front. For example, important information can be derived from knee regions; i.e., are parts of the Pareto front presenting the maximal trade-offs between objectives (Das, 1999). Solutions residing in knee regions (Figure 2) are characterized by the fact that a small improvement in an objective will cause a large deterioration in other objectives (Bechikh et al., 2011). Thus, after knowing the knee regions, decision-makers might adapt their preferences in order to get as close as possible towards them.

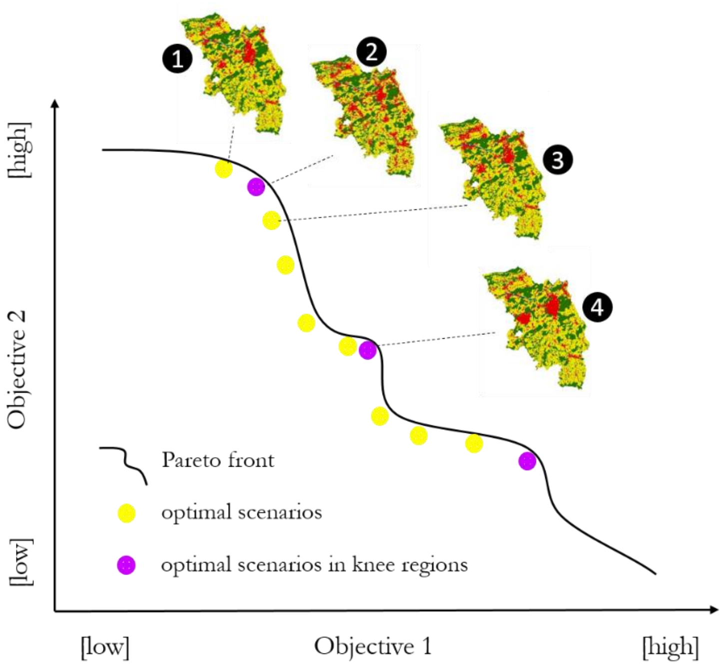

Figure 2: Example of a Pareto front with knee regions. The solutions in the knee-regions may be considered better than other solutions because there is a minimal trade-off between the two objectives. For four solutions the decision-space (i.e., the land-use pattern) has been displayed.

1.2.6. Interpretation of optimization results

The results of an optimization process of land-use patterns may be interpreted and used in very different ways. For example, results could be directly translated into zoning plans and used to delineate protected areas (Watts et al., 2009, Shao et al., 2015). On the other hand, we may derive useful information by analyzing the optimal solution(s). If using multi-objective optimization it may particularly be interesting to analyze what all optimal solutions (i.e. all Pareto optimal solutions) have in common or if there are certain patterns that we can identify. For example, in land-use allocation problems it has been shown that certain land-uses occur regularly at the same locations independently of expressed preferences (Caparros-Midwood et al., 2015, Karakostas, 2017). In addition to an analysis of common features among optimal solutions, it is possible to do a more detailed analysis where we try to understand why there are common features, or in general, what makes solutions optimal. Such an analysis usually involves a post-optimization analysis using data-mining techniques and has been termed innovization (innovation + optimization) by Deb (2013).

1.2.7. Combination of optimization and simulation approaches

Rather than considering optimization approaches merely as a category of land-use modelling approaches, they can also be considered as a complement to the many other existing simulation approaches. Seppelt et al. (2013) described the potential benefits of combining scenario analysis and multi-objective optimization. One such benefit is the possibility to answer the question whether the current land-use system and current political instruments are sufficient to navigate towards optimal land-use patterns. Although not focusing on land-use management, but on marine spatial planning, Lester et al. (2013) argue that of the comparison of management scenario outcomes with optimal solutions can help evaluate whether the optimal solutions are unobtainable due to regulatory or legal constraints. Such results could help guiding institutional changes.

Although combining optimization with scenario-based analysis or current situations is conceptually appealing, only few studies have presented actual experiments in this direction. Matthews et al. (2006), for instance, present a comparison of land-use plans proposed by land-managers and those derived using multi-objective genetic algorithms. Likewise, Mi et al. (2015) show that current land-use patterns can be strongly improved when using a genetic ant colony algorithm for optimal allocation. Polasky et al. (2008) compares landscapes with optimized levels of biodiversity and economic returns with landscapes from 1990, showing that there is a large potential for improvement. Similarly, Nelson et al. (2008) compared landscapes with maximized carbon sequestration and species conservation, with landscapes derived through monetary incentives for landowners. Zhang et al. (2014) find that using a genetic algorithm for optimizing urban growth patterns performs much better than using a cellular automata. This is hardly surprising as the simulations with a cellular automata do not explicitly include optimization, but reflect historical urban growth patterns. Also Hu et al. (2015) presents an approach that takes advantage of the combination of optimization and land-use scenarios. They suggest a combination of multi-objective optimization and scenarios that can be manually designed or using the dynamic land-use change model CLUE-S (Verburg et al., 2002). Other studies suggest the combination of agent-based modelling and optimization approaches (Ligmann-Zielinska and Jankowski, 2010, Yuan et al., 2014, Bone et al., 2011). The latter point out that the combination of bottom-up simulation and top-down optimization may be used to create well-negotiated land-use changes. These negotiated changes may account for the desires (e.g. profit maximization) of agents as well for the objectives, e.g. ecosystem services that are included through the optimization.

1.3. The case of Switzerland

In order to explore how multi-objective optimization can be used to enhance the decision-making process for steering sustainable urban expansion, I focused on a case study area within Switzerland. Although the legal framework as well as the goals for sustainable urban development will be tailored to the Swiss situation, the conclusions I draw from my results are valid for many regions in the world and the proposed methods are applicable to a variety of problem formulations in land-use decision-making.

1.3.1. Sustainable urban expansion

The definition of sustainable urban expansion and particularly the way of reaching sustainable development strongly depends on the regional context (e.g., Sorensen, 2011, Hayati et al., 2010). In general, the sealing of large areas of open land destroys soil functions and associated ecosystem services. In Switzerland, the consumption of the most fertile agricultural soils by urban expansion has been considered a threat to food security and sustainable urban development. These concerns have resulted in an adaptation of the Swiss planning legislation, which now strongly restricts the amount of agricultural available for conversion into urban, and the initiation of a national research program (NRP 68) concerning the resource soil (SNF, 2015).

Besides protecting the best soils, there are of course many other goals that need to be taken into account in Switzerland to achieve a sustainable development of urban areas. Over the last decades many researches have proposed to use compact development as a proxy for sustainable urban development (Ewing and Hamidi, 2015). Although, using this proxy has raised serious concerns (Fischel, 1999, Glaeser and Ward, 2009, McLaughlin, 2012, Addison et al., 2013, Cheshire, 2013, Turner et al., 2014), the compact city has become a leading concept in urban and regional planning (Duany et al., 2000, Haaland and van den Bosch, 2015). This concept includes the promotion of new urban development close to existing development (i.e., contiguous development), but also the increase of housing density in existing urban areas. The compact city concept has had a strong influence in Switzerland. In conclusion, not only reducing the loss of agricultural productivity, but also reaching compact urban development are two major goals of the Swiss planning legislation (Law on Spatial Planning, RPG 2016). Thus, these two goals were formalized into objective functions and used to employ multi-objective optimization for improving the sustainability of urban development, i.e. of urban expansion, in Swiss municipalities.

1.3.2. Land-use policies

Policy instruments used to steer urban development can be broadly classified as regulatory instruments or market-based instruments (Bengston et al., 2004, Nuissl and Schroeter-Schlaack, 2009). In the regulatory approach urban development is often controlled by the setting of growth boundaries or the implementation of so-called zoning, which restricts land use on a defined area (Hirt, 2007). Examples for market-based instruments are taxation (Gihring, 1999) or Transferable Development Rights (TDR; Pruetz and Standridge, 2009, Henger and Bizer, 2010). Land use regulations can help in correcting market failures by accounting for externalities, such as loss of soils and biodiversity (e.g. Fujita, 1989), and can enhance community welfare by increasing housing values (Ihlanfeldt, 2009). However, a growing body of literature suggests that land-use regulations can also have unintended consequences such as negative effects on housing markets, social equity, environmental sustainability and regional economic vitality (McLaughlin, 2012).

Zoning has been in use in Switzerland since the adoption of the Spatial Planning Law in 1980 and is considered the most important instrument for steering the location of new building areas (Gennaio et al., 2009). The decision on where new building zones are allocated is taken by the municipalities. Although zoning has proven to be useful, there is an ongoing debate about using market-based instruments such as Tradable Development Rights (TDR), Levy on Added Value (LAV) and Impact Fees (IF) to steer settlement development (Gmünder, 2010, Gmünder and Müller-Jentsch, 2013, Menghini, 2013).

I would like to point out that there are two fundamentally different ways of formulating optimization problems concerning the allocation of urban areas and other land-use types. These two ways are closely related to the different types of policy instruments that can be used to steer the location of urban development. As pointed out, zoning can be used to control land-use at a particular location. Accordingly, many optimization problems have been formulated in such a way that the whole landscape grid is equivalent to the decision space and the problem to be solved is "what land-use to put where" (e.g. Shao et al., 2015). On the other hand, there are the market-based instruments. These instruments are intended to influence land-use decisions via, e.g., taxes or fees. In this case, the decision-space may be defined by the variable tax and the research goal may be to find the right amount of this tax to maximize certain objectives. Surprisingly, very little attention has been given to these later types of policy instruments in land-use optimizations.

1.4. Summary of research gaps and outline of the thesis

The very general outline of the thesis is that I deal with the multi-objective problem of maximizing compact urban development and minimizing the loss of fertile agricultural soils in municipalities of the canton of Zürich in Switzerland. Relying on this problem I tackle a variety of research gaps that are summarized in the following four paragraphs. In addition, I give a more detailed description of how I proceeded in chapter 2, 3 ,4 and 5 in order to deal with this research gaps.

(I) Lengthy calculations are a major obstacle in using multi-objective optimization (i.e., an a posteriori procedure) in decision-making processes. In most optimizations exercises there is a trade-off between computational effort and quality of the obtained solutions. However, there is the potential to improve multi-objective optimization algorithms in order to reduce this trade-off and reach satisfactory results in acceptable amounts of time.

As my literature review showed, genetic algorithms can be highly suitable for multi-objective optimization, especially if the algorithm is tailored to the problem at hand. Several adaptations to GAs have been proposed in literature, some of which are deemed especially suited for spatial land-use allocation problems. However, these adaptations have hardly been compared to each other and there is a lack of guidelines on the type of adaptation that is suitable for a specific problem. In addition, most studies focused on convergence of the algorithms, while the distribution and spread of the Pareto front was of less interest. Yet maximizing the spread of the Pareto front is important for most applications of multi-objective optimization.

In **chapter 2** of this thesis, I tested which adaptations of genetic algorithms are effective for land-use allocation problems. By comparing many different approaches from the literature, I revealed which guidelines may aid users of genetic algorithms selecting appropriate adaptation approaches. In contrast to many previous studies, I did not only assess the efficiency with which an approach converged, but also the distribution and spread of the Pareto front.

(II) In many studies, it has been shown that optimization approaches are capable of finding solutions that come closer to the optima than those determined by planners or by scenario-based model runs. While it is important to demonstrate that the optimization approaches can help find solutions to complex problems, it may not always be feasible to execute an optimization due to a lack of time and expertise. This raises the question for which problems it is particularly useful to use an optimization approach or when one can better refrain from using an optimization approach. To my knowledge this topic has been fully neglected in the research literature so far.

An argumentative decision-making process strongly involving stakeholders (e.g., using an interactive MCDA approach) is necessary in order to find acceptable and well-balanced solutions. However, such a process can be extremely time-consuming, which may be problematic due to the urgency of the task to steer urban development towards sustainable solutions. In order to allow planners to move ahead with this task, ideally they are provided with "interim urban development scenarios" that would keep open most solutions for the argumentative decision making process. However, such solutions have rarely been provided.

In **chapter 3** I analyzed the differences in loss of fertile agricultural soils between Business As Usual urban expansion and multi-objectively optimized urban expansion. For the purpose of optimizing urban expansion I relied on the findings provided in chapter 2. In order to simulate Business As Usual urban expansion I developed a statistical model, which is described in more detail in Appendix 1.

By comparing BAU and optimal urban expansion in different study areas (i.e, municipalities of Switzerland), I assessed which municipalities have a high potential for reducing the loss of fertile agricultural soils. After that I correlated a variety of variables describing the characteristics of each municipality with the potential for reducing the loss of fertile agricultural soils in each municipality. This step was carried out in order to understand whether it could be possible to predict the benefit (i.e. the potential for reducing the loss of agricultural productivity) of using multi-objective optimization depending on the characteristics of the municipality and the optimization problem. In **chapter 3**, I also analyzed all trade-off solutions obtained when maximizing compactness of urban expansion and reducing the loss of fertile agricultural soils. My intention was to understand why solutions are optimal and what common features they share in order to learn about the problem and potentially enhance decision-making.

(III) Steering urban development towards sustainable solutions happens within a framework of urban planning and policy instruments. Many urban and land-use modelling approaches try to reproduce the rules and constraints of such a framework as detailed as possible. While an exact reproduction has many advantages, e.g. concerning credibility of the model, it may be very difficult to reveal whether there is a constraint in the current policy framework that restrains us from reaching desirable or even visionary solutions. Optimization approaches may be very well suited to design visionary (i.e, optimal) solutions, which can then be compared to solutions found when using constrained optimizations. However, to my knowledge, such comparison of constrained and unconstrained optimizations has not been performed for land-use allocation problems and hardly in other areas where optimizations are applied.

In **chapter 4,** I compared constrained and unconstrained futures of urban development in Switzerland. The constrained situation included separate urban planning in four different municipalities. The unconstrained situation allows the four municipalities to cooperate when they decide on the location for new urban areas. Using multi-objective optimization, I quantify the difference between the constrained and the unconstrained situation on the overall loss of fertile agricultural soils and the compactness of the urban pattern. This quantification may help to decide whether it is worth fostering the cooperation between municipalities (i.e. trying to overcome the constrained situation of separate urban planning).

(IV) Uncertainties about future states of the world complicate the challenge of reaching sustainable urban development. Thus, we are not only seeking to identify decisions that lead us towards the best possible solutions, but also solutions that allow us to reach good (i.e, robust) solutions under a range of uncertainties. There is a growing body of literature dedicated to the identification of robust decisions and solutions. A variety of studies has shown that short-term actions are well-suited to adapt to changing conditions (i.e., uncertainties) and reach robust solutions. However, to my knowledge there are no studies assessing whether short-term actions are capable of reaching optimal solutions. Thus, there is the need to disentangle the trade-offs between short- and long-term actions and give recommendations to decision-makers concerning the right horizon for taking actions.

In **chapter 5,** I tested whether uncertainties about the demand for future urban areas or choosing a too short-planning horizon can prevent decision-makers from reaching optimal solutions. For this purpose, I did consecutive optimization runs, in which results from one run are used as the starting point for a new run. These consecutive optimization runs were carried out for a toy-experiment including only 25 raster cells and a real-world problem, which was represented by the municipality of Uster in Switzerland.

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Chapter 2

Improving the Performance of Genetic Algorithms for Land-Use Allocation Problems

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Abstract

Multi-objective optimization can be used to solve land-use allocation problems dealing with multiple conflicting criteria. In this paper, we show how genetic algorithms can be improved in order to effectively and efficiently solve multi-objective land-use allocation problems. Our focus lies on improving crossover and mutation operators. We tested a large variety of different approaches that were either based on literature or proposed for the first time. We applied them to a land-use allocation problem in Switzerland, including two conflicting criteria: compact urban development and reduction of the loss of agricultural productivity. Our results suggest that a combination of different mutation operators, of which at least one includes spatial heuristics, can help to find well-distributed fronts of non-dominated solutions. These findings provide a benchmark for multi-objective optimization of land-use allocation problems and a promising perspective on how to solve complex spatial planning problems.

1. Introduction

The decision-making process for urban land-use allocation is very complex (Haque and Asami, 2014). As a variety of stakeholders and decision makers with conflicting values are involved, urban land-use allocation can be classified as a wicked problem (Churchman, 1967, Rittel and Webber, 1973, Hartmann, 2012, Artmann, 2015). For example, as good quality soils are often located in areas experiencing large urban growth (Martellozzo et al., 2015), there can be a strong trade-off between reducing the loss of the most fertile agricultural soils and compact urban development (Schwaab et al., 2017).

Planning and decision making in wicked problem situations should be understood as an argumentative process in which problem formulation, understanding the functional characteristics of each system and deriving the set of most promising solutions, emerge gradually through a debate process among involved stakeholders (Kwakkel et al., 2016). To support decision makers in this process, a large variety of tools and approaches has been developed. In the context of urban land-use allocation, these tools and approaches are often referred to as Spatial Decision Support Systems (SDSS; Sugumaran and Degroote, 2011), or as Planning Support Systems (PSS; Geertman et al., 2013).

Most SDSS rely on a combination of methods from the fields of Geographical Information Science (GIS) and Multi-Criteria Decision Analysis (MCDA; Malczewski, 2015). Both fields are constantly evolving by integrating methods from other disciplines. Recently, there have been initiatives to combine MCDA and Evolutionary Multi-criteria Optimization (EMO; Purshouse et al., 2014), in order to support decision makers in the identification of optimal solutions. According to when preferences are incorporated into EMO and MCDA approaches, they can be classified as a priori, interactive or a posteriori decision making approaches. In a priori approaches the decision maker's preferences are incorporated prior to the process of searching for optimal solutions. The weighted sum approach is a commonly employed a priori method. However, it may often be difficult to capture stakeholder preferences in a mathematical model, since every stakeholder may have a different understanding of what a certain weight means and because they do not know possibilities and limitations of the problem beforehand. Another trait of weighted sum approaches is that they cannot trace non-convex regions of the Pareto front (Das and Dennis, 1997). In addition, a priori preferential weighting limits the ability to extract and evaluate trade-offs between conflicting objectives and may be myopic if system dynamics and uncertainties are not well known (Singh et al., 2015). In interactive approaches the decision maker's preferences are included progressively during the optimization process. Interactive approaches give the decision maker the opportunity to interact with a multi-objective optimization process and include knowledge about trade-offs and uncertainties when trying to develop and identify a suitable solution. As preferences are included interactively, the search process may be guided towards regions of interest making it computationally more efficient. However, an important requirement and potential limitation for using interactive methods is that the decision maker must have time and interest in taking part in the interactive solution process (Miettinen et al., 2008). In a posterior approaches the search for all optimal solutions constituting the Pareto front comes before decision maker's preferences are incorporated. A posteriori approaches can overcome some of the difficulties that a priori and interactive approaches are facing (Lautenbach et al., 2013, Chikumbo et al., 2014). However, they pose new challenges. These challenges include finding a set of solutions that are a good representation of the real Pareto Front (PF) within reasonable computation time and presenting the results in a meaningful way to the decision makers (Miettinen, 2008).

Evolutionary Algorithms (EAs) have proven to be useful in finding a set of Pareto-optimal solutions, because they can find multiple non-dominated solutions in a single run (Deb, 2001, Coello et al., 2007, Zhou et al., 2011). In addition they can be very useful when dealing with combinatorial and nonlinear problems, for which more traditional approaches like linear integer programming may fail to find globally optimal solutions within an acceptable amount of time (Matthews, 2001, Aerts et al., 2003). EAs can be described as stochastic optimization methods that share two basic principles which are selection and variation (Zitzler et al., 2004). As they are a stochastic optimization methods, there is no guarantee that EAs converge to the real PF (Deb, 1999). Thus, it is a big challenge to design EAs that converge toward a set of solutions that best approximate the real PF for this class of problems. To design an algorithm that guarantees a rapid convergence and a desired spread of solutions, it is often most appropriate to customize EAs to the problem at hand (Wolpert and Macready, 1997).

Studies using multi-objective optimization algorithms in order to optimally allocate land-use have used different types of meta-heuristics including Genetic Algorithms (GA, Cao and Ye, 2013), Particle Swarm Optimization (Masoomi et al., 2013), Ant Colony Optimization (Liu et al., 2012), Artificial Immune System (Huang et al., 2013), Simulated Annealing (Sante-Riveira et al., 2008, Caparros-Midwood et al., 2015) and Artificial Bee Colony approaches (Yang et al., 2015). In numerous studies GAs have been used and proven to be very effective (Porta et al., 2013). Genetic algorithms were developed in the 1960's (Holland, 1975) and grew in popularity in the 1980's. The publication of Goldberg (1989) and the rapid increase in available computational power produced a further increase in their popularity. However, it was not until 1999 when they were used for the first time for optimizing multi-objective urban planning and land-use allocation problems (Balling et al., 1999, Feng and Lin, 1999). Since these early applications, several studies have followed using GAs in the context of land-use and spatial planning. The purpose of these studies was mostly to show how the application of GAs can be used to find optimal spatial patterns of land-use and other spatial attributes. Many of them also discuss how to increase the performance of the GAs when optimizing spatial patterns.

Genetic Algorithms belong in the family of evolutionary optimization methods, which includes the two basic principles of selection and variation. More precisely the procedure of a generic GA includes the following steps (Goldberg, 1989, Konak et al., 2006): initialization, evaluation, selection, crossover/recombination, mutation, termination (Appendix, Figure 1). Konak et al. (2006) summarize the properties of many well-known multi-objective GAs, pointing out that they mainly differ against their fitness assignment procedure, elitism, or diversity approaches, which are part of the evaluation and selection process. While modifications in the evaluation and selection procedures are intended to improve GAs for a wide variety of problems, it is usually left to the user to adapt mutation and crossover operations to improve the performance of the algorithm for specific problems.

Studies trying to improve the performance of existing GAs in land-use allocation problems focus on a variety of challenges. One challenge is to tune those parameters that are usually not predefined in GAs. These are population size, crossover and mutation probabilities as well as a stopping criterion (e.g. number of generations or evaluations). The most complicated challenges are those that focus on adapting the algorithm to the spatial nature of the problem. That usually involves modifying the crossover operator in a meaningful and effective way (e.g. Stewart et al., 2004, Datta et al., 2007, Karakostas and Economou, 2014, Shaygan et al., 2014) and/or adapting the mutation operator (e.g. Cao et al., 2012). Knowledge about the optimization problem may also help in finding initial populations that allow the algorithm to quickly converge (Bennett et al., 2004, Lautenbach et al., 2013). Another approach has been to parallelize the GA, which can strongly reduce computation time (e.g. Porta et al., 2013, Cao and Ye, 2013). Furthermore, it has been shown that the combination of GAs with MCDA methods or other heuristics can improve the performance of GAs (e.g. Khalili-Damghani et al., 2014, Mi et al., 2015). While most of the aforementioned studies used a grid-based representation of the decision variables, i.e., land-use categories, Stewart and Janssen (2014) use a vector-based structure. A vector-based representation can strongly reduce the number of decision variables and accordingly the computation time. However, a vector-based structure can also complicate a mathematical representation of spatial objectives and may require the incorporation of supplementary algorithmic schemes so as to e.g. account for the relative location of each parcel and adjacencies. Chikumbo et al. (2014) apply a large number of modifications to a GA in order to adapt it to the spatial nature of the problem and to the fact that their problem involves many objectives, which is rarely the case in earlier studies using GAs for land-use allocation problems. Reviewing the literature, we found that most studies focused on a rapid convergence of the search process. However, only few studies were concerned with finding non-dominated solutions which were diverse and had the desired spread, although it can be key to provide decision makers with all possible solutions (Zitzler et al., 2000, Bennett et al., 2004, Karakostas, 2015). The ultimate challenge of land-use allocation problems is the derivation of a uniformly distributed trade-off front that includes the extreme cases on all edges of the PF and converges towards the true PF as quick as possible.

There are clearly many different options to improve the performance of GAs in land-use allocation problems. However, these different options are rarely compared, which makes it hard to determine whether putting effort into the modification of the algorithms pays off with a significant gain in performance. Moreover, many studies neglect to provide performance measures and do not discuss whether modifications of the algorithms could be useful for a larger set of problems or are specific to the optimization problem and case study they have been applied to.

In this study, we modify the nondominated sorting genetic algorithm II (NSGA-II; Deb et al., 2002) applied on a grid-based land-use allocation problem that aims to optimally allocate urban areas on agricultural land. The two objectives we include are to maximize the compact development of urban areas and to minimize the loss of agricultural productivity by reducing the loss of fertile agricultural soils. We test the performance of the algorithm when modifying crossover and mutation operators in various ways. We then propose an efficient modification to the existing NSGA-II procedure for land-use allocation problems. In particular, we elaborate on the development of an efficient mutation process. We present our results showing how modifications in the GA influence convergence, diversity and spread of the obtained non-dominated solutions.

2. Methods

2.1. Problem formulation

Our goal was to optimize the allocation of new urban areas in the municipality of Uster, which is situated in the canton of Zürich in Switzerland. The amount of new urban areas was estimated based on a forecast of the population growth and the residential area per capita (Schwaab et al., 2017). The estimation resulted in a predicted growth of 212 ha of urban area in Uster. As we were working with grid-based spatial data on a hectare-resolution, each agricultural map cell constitutes a candidate urban hectare. Conversion into urban areas was only possible on agricultural land, as forests are strongly protected in Switzerland (Bloetzer, 2004). In summary, the optimization problem was to find the best possible land-use configurations when converting 212 cells out of 1164 agricultural cells into urban cells, among 10^{238} possible solutions. To compare the results obtained for the municipality of Uster with study areas with smaller and larger solution spaces, we also optimized the allocation of urban areas in the municipality of Hedingen and for an area consisting of a combination of four municipalities (i.e., the municipalities Fehraltorf, Pfäffikon, Uster and Volketswil). All municipalities are located in the canton of Zürich. For Hedingen, the solution space was smaller than for Uster, as only 30 new urban hectares had to be allocated on 306 hectares of agricultural land (10^{41} possible solutions). For the combined areas of four municipalities, the solution space was much larger, as 586 hectares out of 3013 hectares had to be chosen (10^{642} possible solutions).

We focused on optimizing two objectives. One of them was to minimize the Loss of Agricultural Productivity (LAP). The other objective was to maximize compactness of urban areas. Compactness was included in a large number of studies optimizing land-use allocation (e.g. Aerts and Heuvelink, 2002, Ligmann-Zielinska et al., 2008). However, it should be noted that compactness is a concept that can be defined and measured in many different ways (Stewart et al., 2004, Ewing and Hamidi, 2015). We decided to calculate the Total Edge Length (TEL) as an indicator which is inversely related to compactness, meaning that a low TEL describes a compact pattern (McGarigal et al., 2012). Reducing the loss of agricultural productivity as well as compact urban development are two important aims of the Swiss planning legislation (Law on Spatial Planning, RPG 2016). As these two aims are causing a strong trade-off (Schwaab et al., 2017), the results from a multi-objective optimization can provide decision-makers with a set of different Pareto optimal options and information about the form of the planning trade-off, which may strongly enhance the decision making process.

As stated by Janssen et al. (2008) there are two types of objectives when optimizing land-use patterns: additive and spatial objectives. According to this categorization additive objectives associate costs or benefits with the allocation of any particular land use to a specific cell, which are then cumulated additively across all cells. Our objective of minimizing the loss of agricultural productivity is calculated as an additive objective. Spatial objectives indicate the extent to which the different land uses are connected, contiguous, or fragmented across the region. Our objective of maximizing the compactness of urban areas is a spatial objective. Note that spatial objectives do not need to be included explicitly. They are inherent to any objective for which the objective value of a specific location depends on its direct or even distant neighbourhood. This will, for example, be the case if including transport related objectives (Balling et al., 1999), heat island effects (Debbage and Shepherd, 2015), water runoff (Zare et al., 2012) or the objective of maximizing biodiversity (Holzkamper and Seppelt, 2007). We adopt the categorization into additive and spatial objectives as it can help understanding land-use allocation problems and may be useful when transferring results from the specific problem investigated in this study to other situations.

Following the notation of Stewart et al. (2004) an additive objective like minimizing the loss of agricultural productivity can be calculated as following:

$$LAP(u) = \frac{1}{A}\sum_{r=1}^{R}\sum_{c=1}^{C}\sum_{k=1}^{K} a_{rck}\, x_{rck} \tag{2.1}$$

where u denotes the specific land-use map expressed in terms of R×C×K binary variables x_{rck} , such that $x_{rck} = 1$ if $u_{rc} = k$, and $x_{rck} = 0$ otherwise, R is the number of rows, C is the number of columns, K is the number of possible LULC categories, a_{rck} is the potential loss of agricultural productivity per cell (i.e., per hectare) and A is the sum of the currently available agricultural productivity (i.e., the sum of all productivity values attributed to all agricultural cells). As many soil functions are irreversibly deteriorated when agricultural areas are partly or completely sealed, we assume that all existing agricultural productivity is lost, when agricultural land is converted into residential land. As an indicator for the loss a_{Srck} in agricultural productivity, we use an existing spatially explicit dataset (Kanton Zürich, 1996). More information on how we calculated agricultural productivity can be found in Schwaab et al. (2017) and in the Appendix, Supplement 1.

Adapting the notation of Aerts et al. (2003) the TEL can be calculated as:

$$TEL(u) = \sum_{r=1}^{R}\sum_{c=1}^{C}\sum_{k=1}^{K}(x_{r+1,c,k} + x_{r,c+1,k} + x_{r-1,c,k} + x_{r,c-1,k}) \tag{2.2}$$

where again u denotes the specific land-use map expressed in terms of R×C×K binary variables x_{rck}. The variables $x_{r+1,c,k}, x_{r,c+1,k}, x_{r-1,c,k}$ and $x_{r,c-1,k}$ are binary variables describing the von Neumann neighbourhood of a centre cell being assigned to a specific land-use (u_{rc}). If a neighbour and the centre are assigned to the same land-use (e.g. $u_{r+1,c} = u_{rc}$), the binary neighbourhood variable is zero (e.g., $x_{r+1,c,k} = 0$). If the neighbour and the center are assigned to different land-uses (e.g, $u_{r+1,c} \neq u_{rc}$), the neighbourhood variable is one (e.g., $x_{r+1,c,k} = 1$).

3. Framework

One of the most commonly applied GAs for multi-objective optimization is the Nondominated Sorting Genetic Algorithm II (NSGA-II) developed by Deb et al. (2002). It has proven to be efficient for a large variety of problems and has been widely used for multi-objective optimization of spatial planning problems. Thus, we used the selection process provided by NSGA-II and tested the performance of modifications in the crossover and mutation operators. We implemented the algorithms using the python framework "Distributed Evolutionary Algorithms in Python" (DEAP) (Fortin et al., 2012).

3.1. Crossover Modifications

The building block hypothesis assumes that GAs are successful in finding good solutions because low order, and highly fit schemata, i.e., building blocks, are sampled, recombined and resampled to form strings of potentially higher fitness (Goldberg, 1989). As Ryerkerk et al. (2012) point out, it is key to the success of GAs to form building blocks and enable these blocks to propagate through successive generations. The genetic algorithm operators must facilitate this process. For example, a suitable crossover operator will tend to avoid the destruction of building blocks (Li et al., 2007).

It has been shown that spatial crossover operators can improve the performance of GAs in two-dimensional or spatial problems (Anderson et al., 1991, Cherba and Punch, 2006, Ryerkerk et al., 2012, Karakostas and Economou, 2014). In general, spatial crossover operators can be either independent of each problem's formulation, i.e. independent of the objective functions and constraints, or incorporate such information (Shaygan et al., 2014). An example for both types of crossover operators is presented by Datta et al. (2007). As problem-specific information is used in the mutation operator (see Section 2.4), we here focus on crossover operators that are independent from the problem formulation. This means that every single cell or block of cells in the landscape grid is exchanged with equal probability. We tested different types of spatial crossover operators and one non-spatial crossover all of which have been used for land-use allocation problems or for spatial problems in general (Figure 1):

1. Uniform crossover (UC): Information is randomly exchanged between individual grid points (Anderson et al., 1991). As a random exchange would yield the same result when encoding the grid as a vector, we define this crossover as non-spatial.
2. Vertical/Horizontal crossover (VC/HC): One random column/row number is generated and the parents are split into two parts along a line indicated by the column/row number.
3. Vertical/Horizontal band crossover (VBC/HBC): Two random row/column numbers are generated, and information inside the vertical/horizontal region of the grid determined by these numbers is exchanged (Anderson et al., 1991).
4. Angle Crossover (AC): The parent grids are split into two halves along a line through the centre of the municipality with a randomly varying angle (adapted from Ryerkerk et al., 2012).
5. Block Crossover (BC): A block is picked out by the random selection of two rows and two columns of parents to be exchanged (Shaygan et al., 2014).

6. Block Uniform Crossover (BUC): Blocks of random shapes and sizes from the parent map are exchanged (Anderson et al., 1991, Karakostas and Economou, 2014).

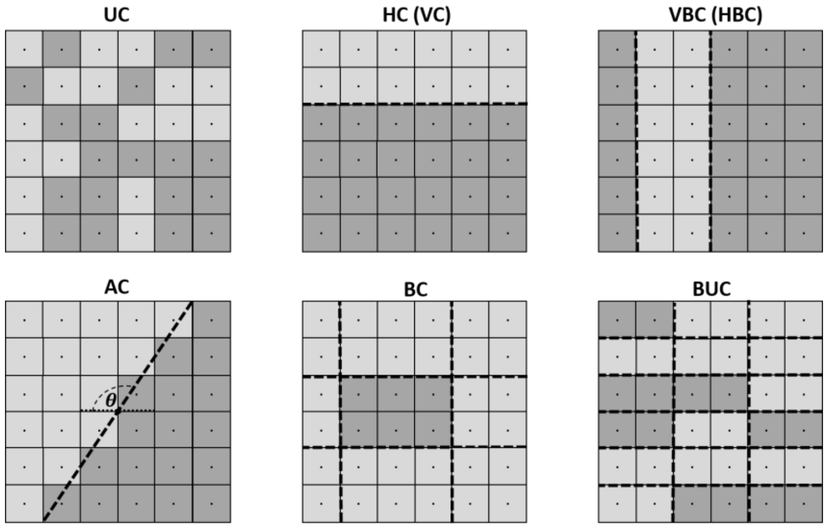

Figure 1: Offspring after recombination. Dark grey areas are genes copied from parent 1 and light grey areas are copies from parent 2.

3.2. Mutation Modifications

The modification of the mutation operator can strongly improve the performance of GAs. We distinguish again between operators that include problem-specific knowledge (biasing the probability that a cell or any other spatial structure takes part in the mutation process) and operators that can be applied as two-dimensional operators to any spatial problem using unbiased uniform probabilities. Henceforth, we will refer to the process of including problem specific information as including heuristics.

Mutation operators that do not include problem-specific knowledge focus on the spatial nature of the problem by mutating not only single cells but also blocks of cells (e.g. Aerts et al., 2005, Cao et al., 2012). The mutation process often needs to include repair mechanisms, as two-dimensional crossover operations usually violate constraints (Yoon and Kim, 2014). For many land-use allocation problems such repair entails the educated increase or reduction of cells allocated to a specific land-use so as to satisfy the imposed constraints on the minimum and maximum area allocated to each spatial entity.

A variety of mutation operators include problem-specific knowledge. However, there are not many examples for spatial problems, in which heuristics were included at the mutation stage. Thus, we will also shortly mention studies when problem-specific knowledge had been included during initialization and crossover (e.g. Karakostas, 2015). Stewart et al. (2004) included heuristics in the initialization stage. They biased the probability of cells being allocated to a certain land-use based on the additive attributes of each cell, the land-use in neighboring cells and the target values for each land-use. Land-use in neighboring cells has also been taken into account in crossover and mutation operators (Datta et al., 2007, Cao et al., 2012).

Inspired by the reviewed literature, we tested a number of different mutation operators and their combinations. In every mutation step we used a repair mechanism to ensure that the number of urban cells was constant. In addition to mutation operators inspired by previous studies, we developed operators that had not been used so far as mutation operators or in a comparable form during initialization or crossover. The tested mutation operators were (Figure 2):

1. Random Repair Mutation (RRM): If the number of urban cells exceeds the predefined fixed number of urban cells, they are randomly selected (uniform distribution) and converted to agriculture until the number of urban cells equals the predefined number. If the number of urban cells is lower than

the predefined number, agricultural cells are randomly selected (uniform distribution) and converted to urban until the demand for urban cells is met.

2. Biased Repair Mutation (BRM): This repair is very similar to the RRM. However, the likelihood of an urban cell being converted into agriculture is inversely proportional to the number of urban cells in its von Neumann neighborhood, i.e., the four cells surrounding the central cell. The likelihood of an agricultural cell being converted into an urban cell is proportional to the number of urban cells in its von Neumann neighborhood.
3. Random Cell Mutation (RCM): One urban cell is randomly selected and converted into agriculture, followed by the random selection of one agricultural cell to be converted into urban.
4. Random Block Mutation (RBM): Random sized blocks are converted into urban. The position of the block is chosen randomly. If part of the area is already urban it remains unchanged. The number of urban cells that remains after subtracting the demand is converted back into agriculture following RRM.
5. Biased Cells Neighborhood Mutation (BCNM): One urban cell is converted into agriculture and one agricultural cell is converted into urban. The likelihood of an urban cell of being chosen for conversion is inversely proportional to the number of urban cells in its von Neumann neighborhood. The likelihood of the agricultural cell being converted into an urban cell is proportional to the number of urban cells in its von Neumann neighborhood.
6. Biased Cells Patch Mutation (BCPM): A contiguous patch of urban cells (according to the von Neumann neighborhood) is removed. The likelihood of a patch being removed is inversely proportional to its size. The number of cells that have been removed are then attached to the boundary of another patch. The likelihood that a patch is selected for the attachment of these new urban areas is proportional to its size. The likelihood for a pixel to be converted at the boundary of the patch is again proportional to the number of surrounding urban neighbors (i.e., cells).
7. Biased Cells Agricultural Productivity Mutation (BCAPM): This mutation is similar to the BCNM mutation. However, instead of biasing the probability of a cell conversion according to neighborhood, it is biased according to the agricultural productivity attributed to each cell.
8. Biased Cells All Mutation (BCAM): This mutation is similar to the BCNM and BCAPM mutation. However, the probability of converting agricultural areas into urban and vice versa does not depend only on the neighborhood or on the agricultural productivity per cell, but on a combination of both.

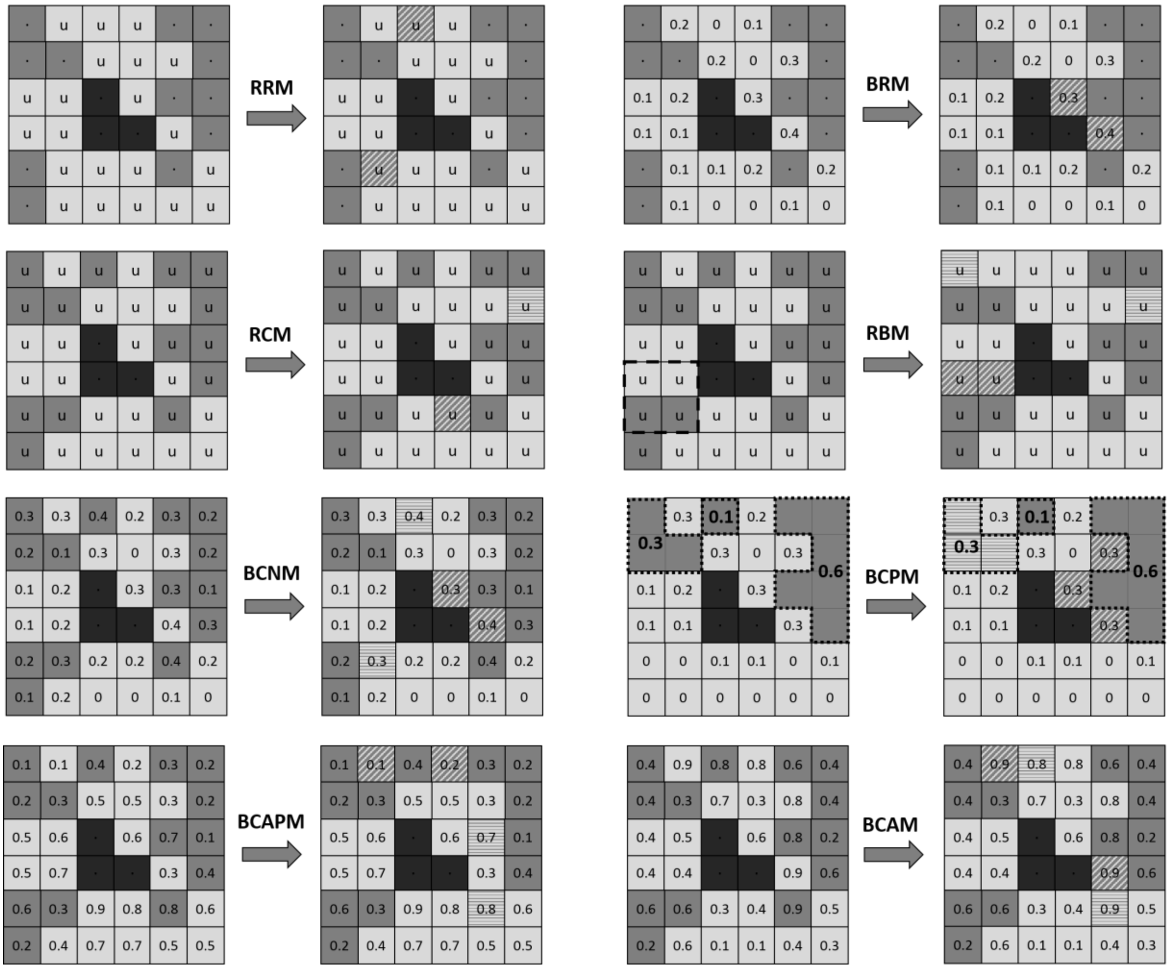

Figure 2: Individuals in the mutation process. The three black cells in the middle represent currently existing urban areas. These remain unchanged throughout the mutation process. Dark grey colored cells represent urban areas of the offspring, i.e, of a land-use pattern that was obtained after recombination. Diagonally striped cells are agricultural cells that are converted into urban during the mutation process. Horizontally striped cells are urban cells that are converted into agricultural cells during mutation. The letter u (="uniform") denotes that there are no probabilities assigned to the different cells. The numbers within agricultural and urban cells show the likelihood for the urban or agricultural cells to be part of the mutation process, i.e., to be converted into each other. The dashed line in the RBM mutation represents the surrounding of a block, which size and location was randomly selected. The dashed line in the BCPM mutation are the borders to all existing urban patches.

3.3. Comparison of the suggested modifications

To test the performance of different crossover operators (Figure 1), we combined each one with the RCM mutation operator. To test the performance of different mutation operators (Figure 2), each mutation operator was combined with the AC crossover. For testing different combined mutation operators, we also combined each of them with the AC crossover. Due to the stochasticity involved in the optimization process, a comparison of different operators requires several runs (e.g. Hadka and Reed, 2013, Karakostas, 2016). In order to compare the mean hypervolumes, we ran the algorithm three times for every operator combination. For two operator combinations we ran the algorithm 30 times. The likelihood for mutation was set to 0.1 for each operator and it was possible for an individual to be mutated several times in one generation (Appendix, Figure 1).

As we do not know the true Pareto optimal solutions for our problem, we assess the performance of the various modifications in crossover and mutation in two different ways. First, we calculated for each run the hypervolume indicator (Zitzler, 1999), which is a measure for the volume of the objective space dominated by a front of non-dominated solutions. Second, we analyze the spread of the front of non-dominated solutions produced with different versions of the algorithm. As a benchmark for the maximal possible spread of the front of non-dominated solutions, we performed separate single-objective optimizations for each objective. For the additive objectives this was a simple task: we ranked the agricultural cells starting with the lowest agricultural productivity values and calculated the sum over the number of cells we wanted to convert from agricultural to urban. To find the optimal value for a spatial objective is in general much more complex. In order to approximate this solution, we used NSGA-II to solve the single objective optimization problem of finding the most compact pattern. We ran the algorithm ten times (every time with a different initial population) to extract an optimal value for compactness, i.e., to find a solution with minimal TEL. In order to determine the variation in results from a single combination of operators, we repeated each simulation three times, using a different random initial population in every run.

To analyze the performance of the algorithms at different stages we ran the optimization process for each combination of operators for 40000 generations and calculated the hypervolume for every generation. For two selected algorithms we calculated 100000 generations. One of them was the algorithm for which we used the RCM mutation, which we call hereafter the "basic" version. The other algorithm was the one for which we used the combined mutation operator RBM_RCM_BRM_BCPM, which we hereafter call the "improved" version of the algorithm. Every time the combined operator RBM_RCM_BRM_BCPM is called, the repair mechanism (BRM) is carried out. The other operators are carried out at a probability of 0.1. This means that none or up to three of the operators (RBM, RCM and BCPM) will be carried out upon one call of the combined operator (Appendix, Figure 1).

To understand the performance differences between the basic and the improved version of the algorithm, we assessed the similarity between land-use patterns along the front of non-dominated solutions. As a measure of similarity, we calculated the amount of congruent urban pixels between all land-use patterns along the front of non-dominated solutions. For example, if all urban areas in two patterns were allocated at the same location, there would be 212 congruent urban pixels. If none of them was at the same location in the two patterns there would be 0 congruent urban pixels.

4. Results

In the municipality of Uster, the solution with the lowest possible loss in agricultural productivity (single-objective minima), caused a loss of 11.1% of the currently available agricultural productivity, as shown by the dashed vertical line in Figure 3 and Figure 4. When testing the genetic algorithm with different crossover operators (in combination with the RCM mutation), we were able to produce non-dominated fronts with a minimal loss of agricultural productivity smaller than 11.3%. The most compact solution we found through single-objective optimization was 85.2km of TEL, as shown by the horizontal dashed line in Figure 3 and Figure 4. The smallest TEL that we found using varying crossover operators was 98km. The solutions at the edges of the fronts varied approximately between 11.2 and 11.3% for loss of agricultural productivity and between 98 and 104km for lowest TEL, as shown by the coloured vertical and horizontal lines in Figure 3. The non-dominated fronts produced when using the different mutation operators (keeping the crossover fixed, using AC) showed more variation in terms of the spreads of the fronts (Figure 4). The edges of the fronts varied approximately between 11.12 and 12% lowest loss of agricultural productivity, represented by the coloured vertical lines in Figure 4. The lowest TELs varied between 88 and 102km (neglecting the RRM and BRM fronts), which is shown by the coloured horizontal lines in Figure 4. Using the mutation operator BCPM in the genetic algorithm, it was possible to reach solutions with a low TEL. However, using the same operator it was not possible to obtain solutions with a loss of agricultural productivity lower than 11.8%. Using the operator BCAPM it was possible to reach solutions with very low loss of agricultural productivity (11.12%), but with compactness not lower than 98km. When combining different mutation operators, we were able to create fronts with the largest spread. The edges of the fronts varied approximately between

11.12 and 11.3% lowest loss of agricultural productivity and between 87 and 92km of lowest edge length (Figure 5).

The largest hypervolumes were reached when using combined mutation operators. All other algorithms we tested, i.e., the ones with single mutation and crossover operators produced fronts with lower hypervolumes (Figure 6). This counts for the hypervolume at generation 40000 and for almost every previous generation. However, when comparing algorithms using different crossover, mutation or combined mutation operators, we found that some algorithms have a higher hypervolume in early generations, but are exceeded by other algorithms in later generations (Appendix, Figure 2, Appendix, Figure 3 and Appendix, Figure 4). The differences between the median hypervolumes of the three runs after 40000 generations when using different combined mutation operators were quite small (Appendix, Figure 2). This indicates that it is more important that there is a least one random mutation operator and at least one mutation operator that includes spatial heuristics, but less important in which form both are included.

We compared NSGA-II when using the basic version of the algorithm (mutation operator: RCM) and when using the improved version (combined mutation operator: RBM_RCM_BRM_BCPM), running each of them for 100000 generations. Between generation 40000 and 100000, both algorithms were able to lower the TEL (Figure 7) by a small amount. The basic algorithm further reduced TEL from 99.4 to 98.2km, while the improved algorithm reduced TEL by a larger amount from 88.4 to 86.6km.

Using the improved algorithm did not only result in a larger spread of the front in comparison to the basic algorithm in the municipality of Uster, but also in the municipality of Hedingen and for the area of the four combined municipalities. The reduction of loss of agricultural productivity and total edge length between the improved and the basic version of the algorithm is smallest in Hedingen, larger in Uster and largest for the four combined municipalities (Appendix, Figure 5, Appendix, Figure 6 and Appendix, Figure 7).

When using the improved algorithm, neighbouring solutions on the non-dominated front, generally have many congruent urban cells, i.e., very similar land-use patterns (Figure 8). However, for the regions of the front with the lowest TEL (patterns with higher IDs in Figure 8), there are solutions which have very similar objective values, but express quite different spatial patterns, i.e., are very different in the decision space. (Figure 8, Appendix, Figure 10 and Appendix, Figure 11). In contrast, the solutions obtained when using the basic algorithm are very similar to each other even for the most compact solutions (Figure 9, Appendix, Figure 12, Appendix, Figure 13).

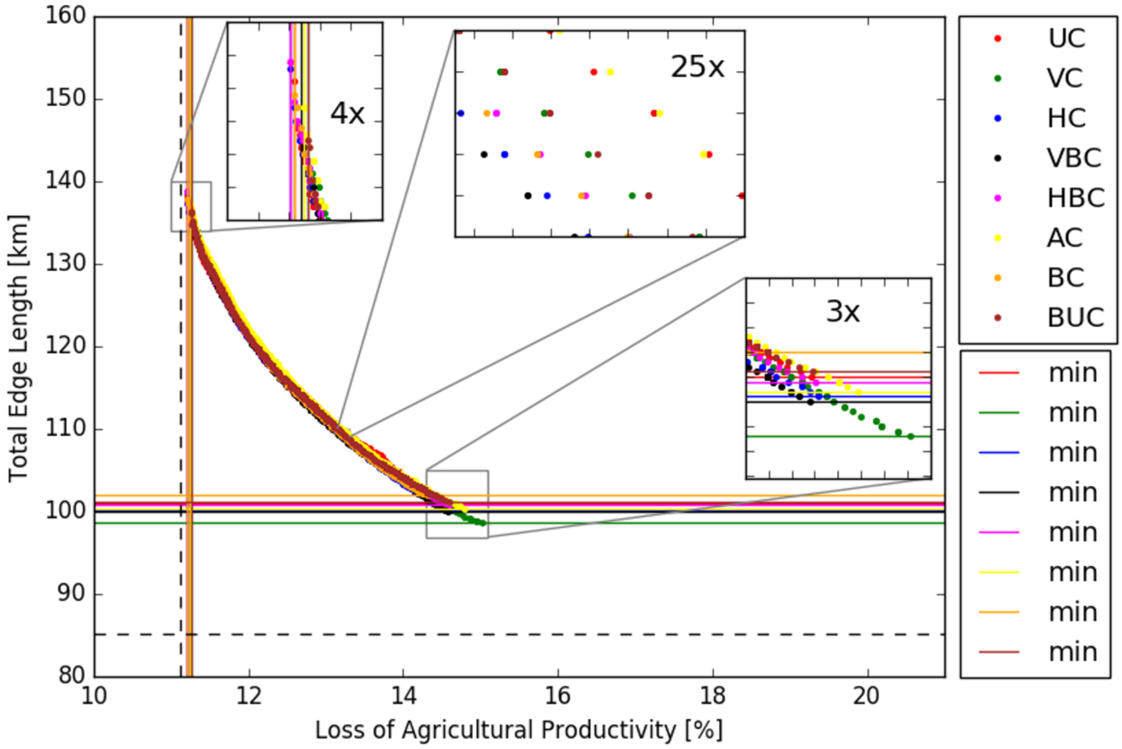

Figure 3: Comparison of different crossover operators. The vertical and horizontal dashed lines show the minimal possible loss of agricultural productivity and the minimal Total Edge Length respectively, obtained by single objective optimization. The colored vertical and horizontal lines show the limits (i.e. the minima) of the non-dominated fronts obtained when using different crossover operators.

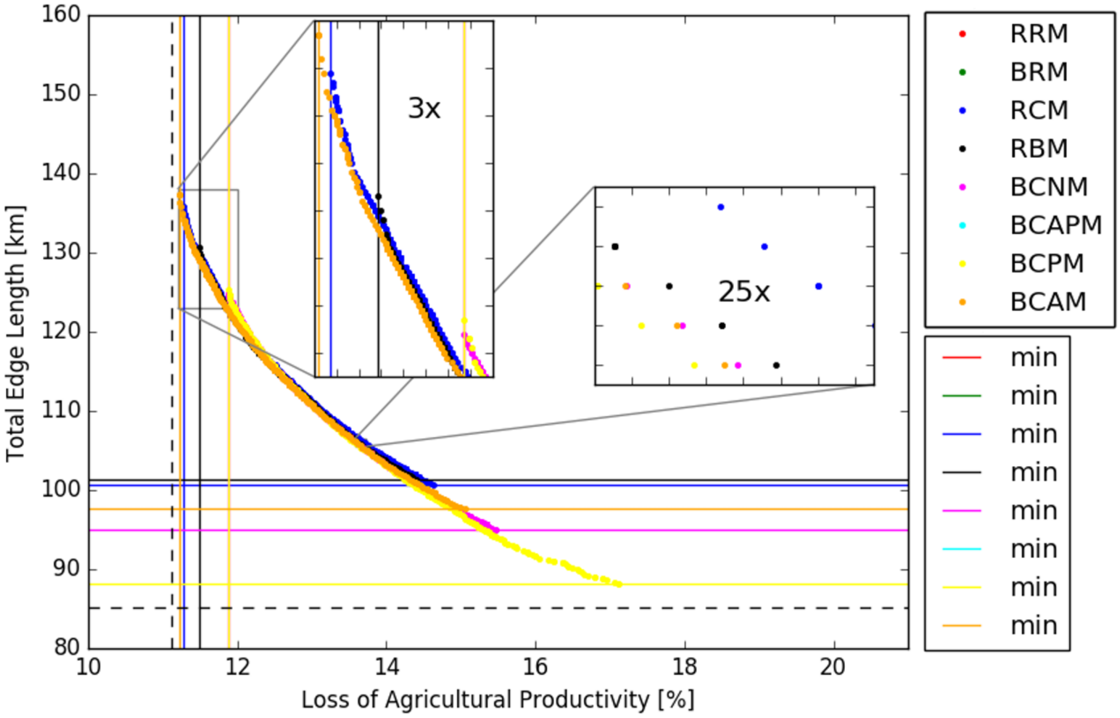

Figure 4: Comparison of different mutation operators. The colored vertical and horizontal lines show the limits (i.e. the minima) of the non-dominated fronts obtained when using different mutation operators in the multi-objective optimization. We do not display colored vertical or horizontal lines for the solutions produced when using the operators RRM and BRM, because using either of these two operators resulted in deterministic behavior of the algorithm and the obtained solutions were clearly inferior to the solutions of the other fronts.

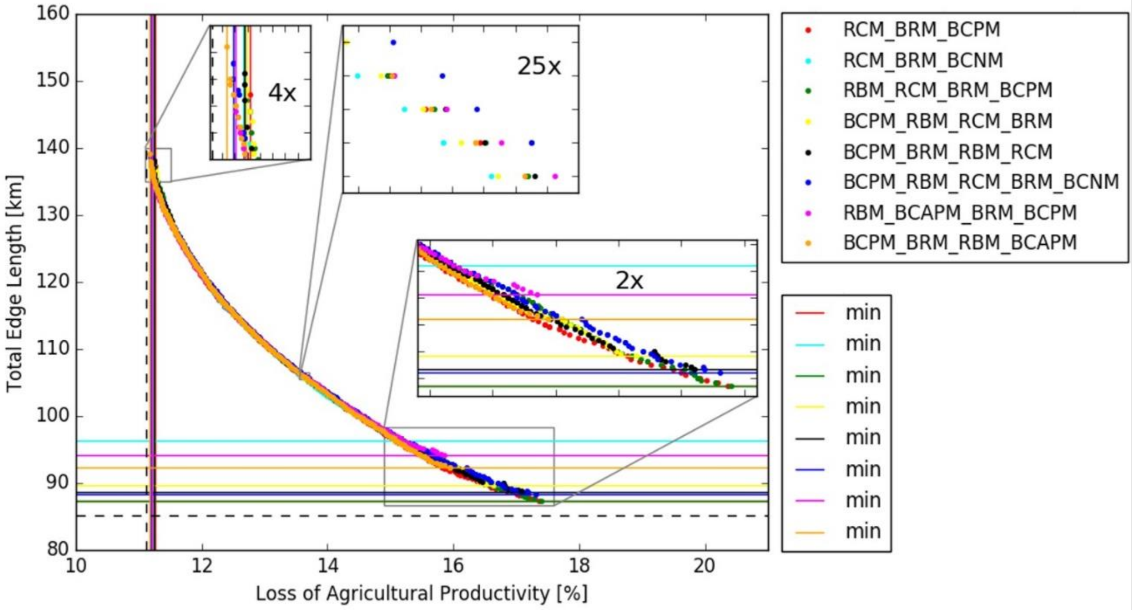

Figure 5: Comparison of combinations of mutation operators. The vertical and horizontal dashed lines show the minimal possible loss of agricultural productivity and the minimal Total Edge Length respectively, obtained by single objective optimization. The colored vertical and horizontal lines show the limits (i.e. the minima) of the non-dominated fronts obtained when using different combinations of mutation operators.

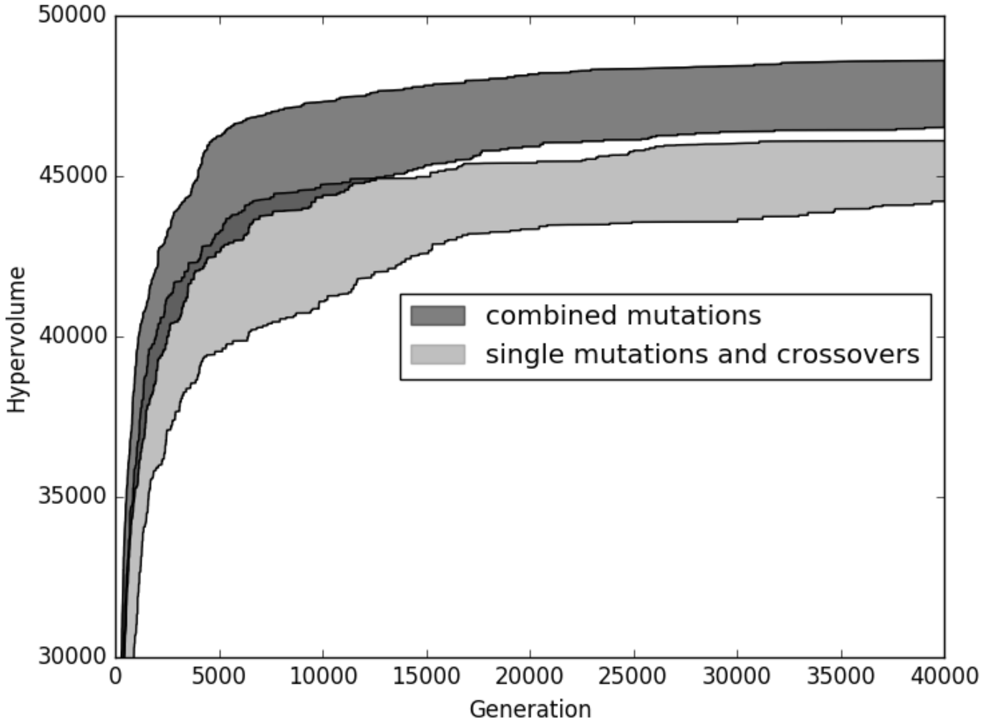

Figure 6: Hypervolumes of all tested algorithms. The grey area includes all hypervolumes from the algorithms using a single mutation or crossover operator and the dark grey area denotes all the hypervolumes when using the combined mutation operators for the optimization.

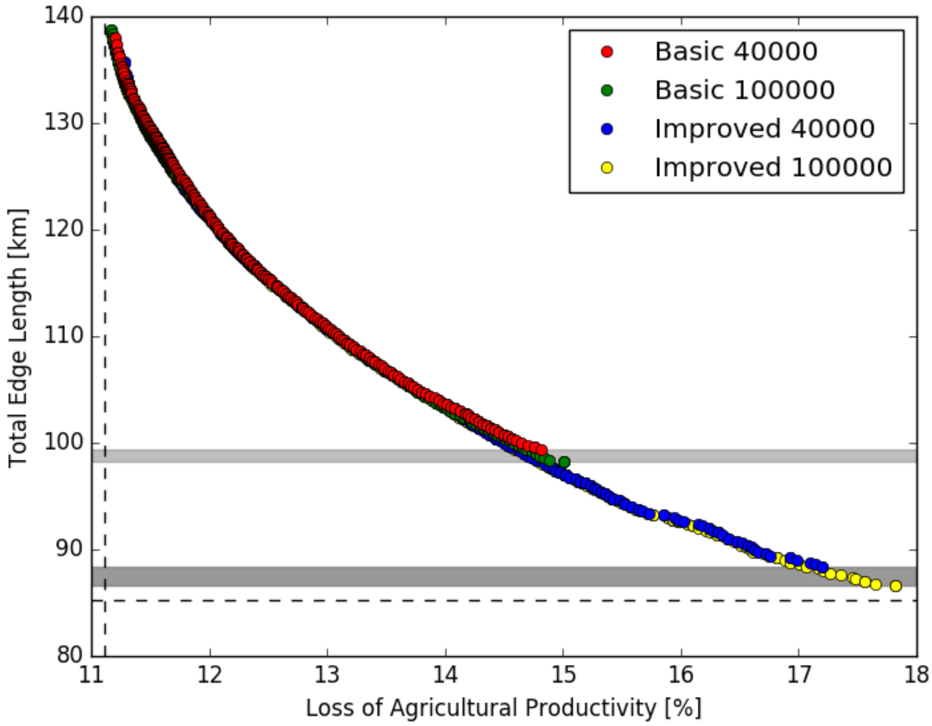

Figure 7: Non-dominated fronts of generation 40000 and 100000 when using the basic version of the genetic algorithm (mutation RCM, crossover AC) and an improved version (mutation: RBM_RCM_BRM_BCPM, crossover: AC). The light grey colored horizontal bar shows the differences in the maximal compactness (i.e., Total Edge Length) of the fronts of the basic algorithm and the dark grey bar shows the differences in maximal compactness of the improved algorithm.

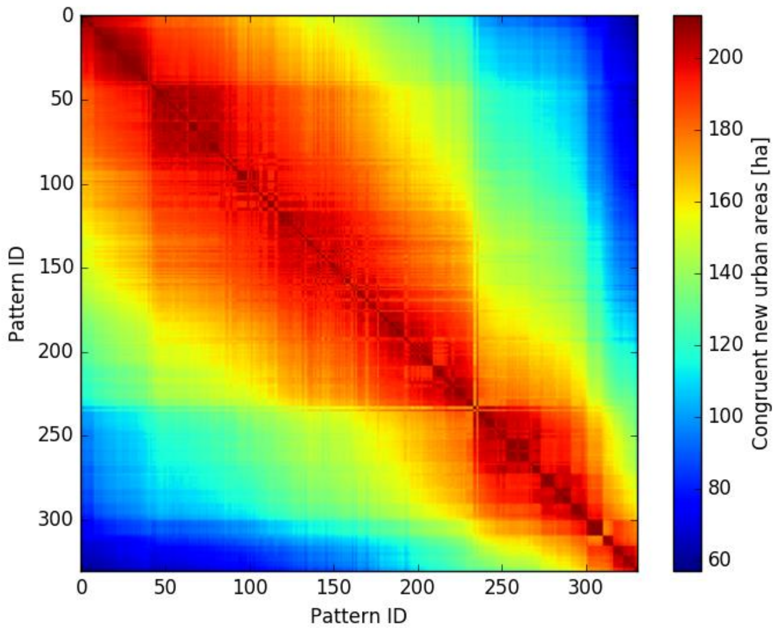

Figure 8: Number of congruent new urban areas calculated for each land-use pattern with every other pattern (solutions obtained when using the improved algorithm).

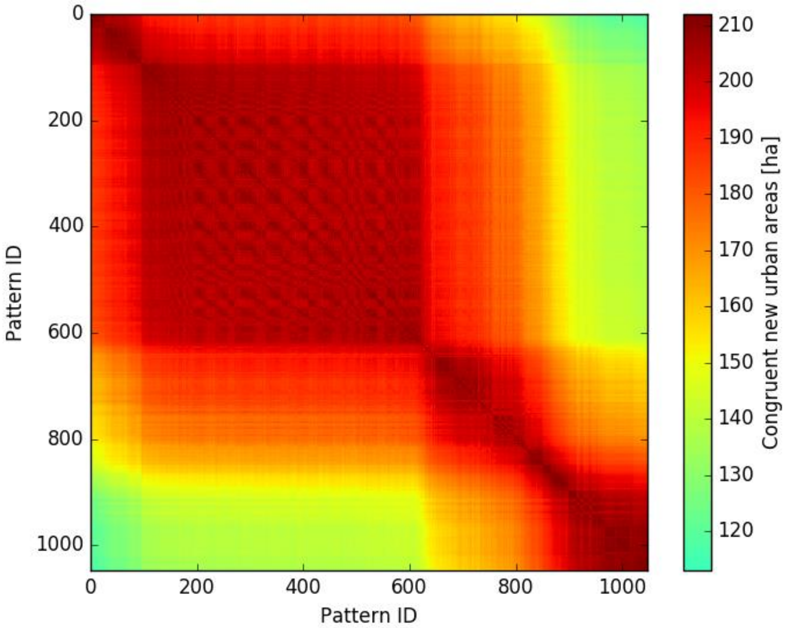

Figure 9: Number of congruent new urban areas calculated for each land-use pattern with every other pattern (solutions obtained when using the basic algorithm).

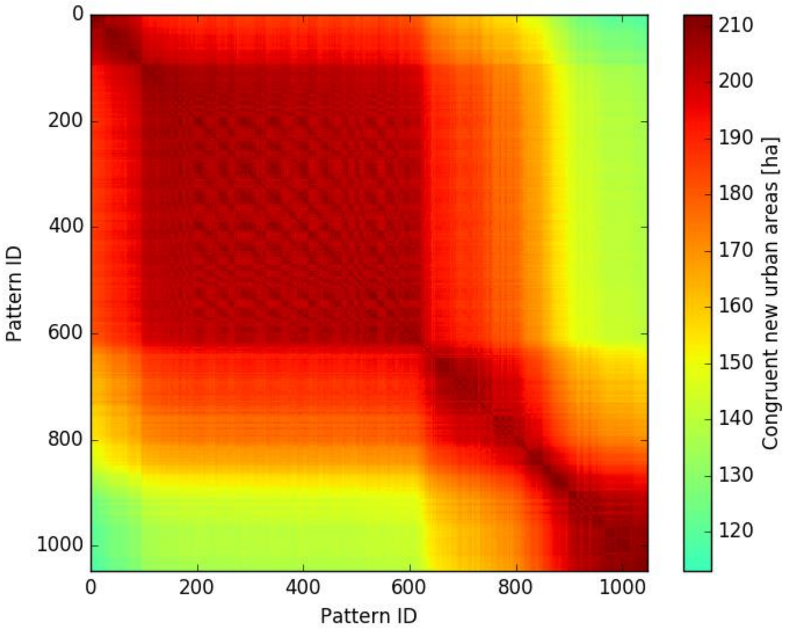

Figure 9: Number of congruent new urban areas calculated for each land-use pattern with every other pattern (solutions obtained when using the basic algorithm).

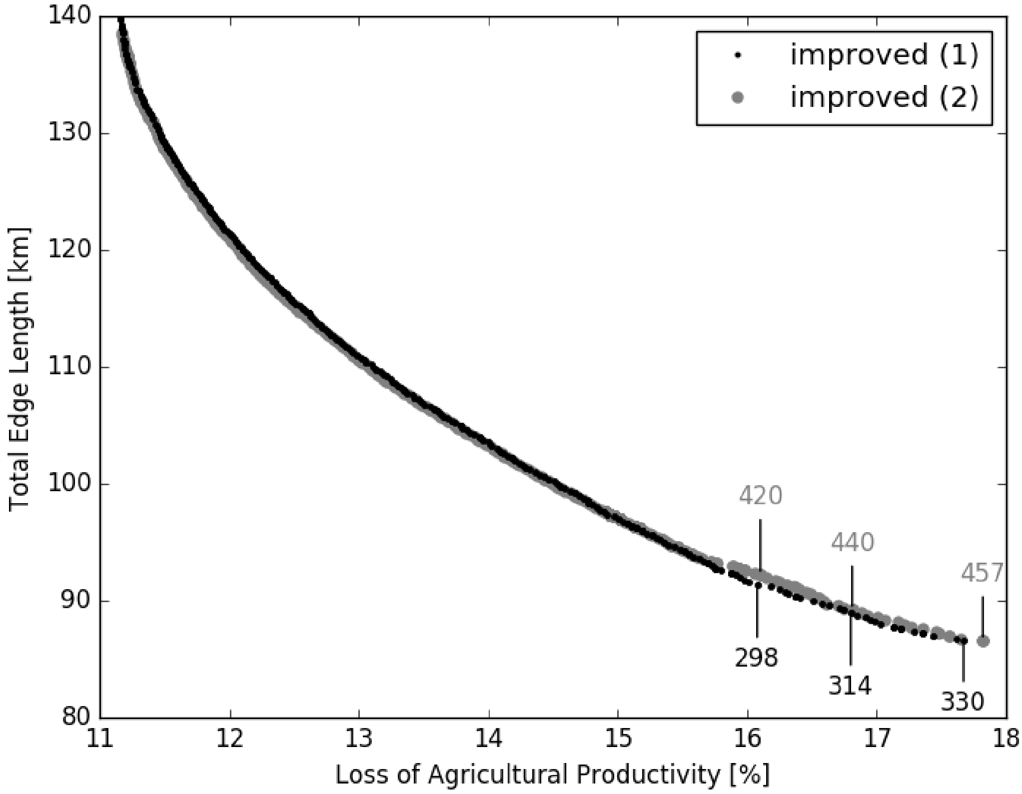

Figure 10: Two non-dominated fronts, obtained after 100000 generations using the same algorithm (combined mutation: RBM_RCM_BRM_BCPM). For each front we selected three solutions for which we display the corresponding land-use patterns (Figure 11).

Figure 11: The land-use patterns marked with the grey numbers (420, 440 and 457) correspond to the solutions of the grey front in Figure 10. The land-use patterns marked with the black numbers (298, 314 and 330) belong to solutions of the black front in Figure 10. Red cells: Urban areas, Yellow cells: Agricultural areas, Green Cells: Forest areas, Blue Cells: Water, Black Cells: New Urban areas which were allocated in the optimization process.

5. Discussion

In this paper, we have identified efficient modifications to the existing NSGA-II procedure for a land-use planning problem. We considered a spatial planning problem including two conflicting criteria: compact urban development and reduction of the loss of agricultural productivity (i.e., the loss of fertile agricultural soils). Compact urban development represents a spatial objective, while the reduction of the loss of agricultural productivity represents an additive objective. We show that the genetic algorithm can be hindered from reaching the most compact solutions, which may be due to the fact that these solutions on the non-dominated front are very different in shape from the rest of the non-dominated solutions. The inclusion of heuristics promoting the spatial objective of compact development, enhances the effectiveness of the evolutionary optimization process to develop and promote compact solutions. However, this may prevent the additive objective from reaching the solutions with the lowest loss in soil quality. Thus, we suggest that a combination of different mutation operators, of which at least one includes spatial heuristics, can help to find smooth and widely spread non-dominated fronts.

5.1. Improved performance of modified algorithm

We were able to find non-dominated solutions of urban expansion with minimal loss of agricultural productivity making use of a basic version of NSGA-II, with uniform mutation (RCM) and angle crossover

(AC) as operators. However, using these operators it was not possible to reach the most compact solutions. Biasing the mutation probabilities of the cells, including information about the neighbourhood of each cell, it was possible to reach more compact solutions (mutation operator BCNM). Including information about the patch sizes and the neighbourhood in a more complex mutation operator (BCPM) facilitated the algorithm to reach even more compact solutions. However, this ability of the algorithm to find very good solutions for the spatial objective (i.e., compact urban patterns) was traded-off against the ability to find non-dominated solutions with very low loss of agricultural productivity. Thus, combinations of uniform and biased mutation operators proved to be an efficient way of producing a well-spread front of non-dominated solutions that nearly spanned the complete objective space between the minimal loss of agricultural productivity and the maximal compactness. Biasing the mutation probability (using the mutation operator BCAPM) according to the agricultural productivity that would be destroyed if a specific cell was developed (i.e., increasing the likelihood that an agricultural cell with a low agricultural productivity would be converted into urban), helped to get extremely close to the point of minimal loss of agricultural productivity. However, as the uniform mutation RCM (i.e., agricultural cells being selected for conversion into urban cells with uniform likelihood) already allowed the algorithm to produce non-dominated solutions with very low loss of agricultural productivity, the improvement using the BCAPM mutation operator was very small. In conclusion, there are two ways of designing an algorithm that produces well-spread fronts for the considered objectives. One is to combine uniform mutation and biased mutation including information about neighbourhood and patch sizes, and the other one is to combine both biased mutations, i.e., the one being biased according to neighbourhood and the other one being biased according to agricultural productivity per cell. However, for each of these two possibilities it was necessary to account for the spatial objective by biasing the mutation probabilities. Last but not least, it has to be noted that a mutation operator that includes a combined biased probability (i.e. the weighted sum of the biased probabilities according to both objectives represented by the mutation operator BCAM), barely improves the performance of the algorithm in comparison to the basic version. This underlines the necessity to design separate mutation operators and use them alternately.

5.2. Explaining the improved performance

Following the development of fronts of non-dominated solutions from the initial generations up to the end of the evolutionary optimization process, we observed that the basic algorithm first advances towards solutions in the centre of the front finally obtained (Appendix, Figure 8). The first phase of the search could be described as being dominated by exploitation (visiting those regions of a search space within the neighbourhood of previously visited points), while exploration (visiting entirely new regions of a search space) seems to become more important for later generations. We also showed that solutions constituting the non-dominated front seem to be much more similar to each other in the decision space when they cause a relatively low loss of agricultural productivity than when they are compact and cause a higher loss of agricultural productivity. While it seemed easy for the algorithm to get close to the solution with minimal loss of agricultural productivity, it seemed to almost get stuck at a certain level of compactness, which was far from the highest potential compactness. As the most compact solutions of the basic algorithm, coincide with parts of the front of the improved algorithm, where there is large differences in the spatial patterns, this seems to indicate that the basic algorithm was not able to find solutions that strongly differ in the decision space. A possible explanation could be that it is very difficult for the algorithm to generate new dominant solutions that have a high level of compactness and are very different from the dominant solutions of the current population members in the decision space. However, as our analysis of the similarities in the decision-space (i.e., an analysis of the similarities of the land-use patterns) of the improved version of the algorithm shows, this could be necessary to get close to more compact solutions. The improved version of the algorithm is biased right from the beginning of the search process, so that the non-dominated fronts do not only advance towards the centre of the final front, but tend toward more compact solutions (Appendix, Figure 9). The advantage of the improved algorithm may be twofold. In the beginning of the evolutionary process, there may be a better balance between exploitation and exploration, which is considered a cornerstone for the success of problem solving by search (Crepinsek et al., 2013). The improved algorithm produces much more compact and diverse solutions right from the start. In later generations, when the front cannot advance further in the centre (i.e., in regions with moderate SQL and TEL), but can still advance at its edges, the improved algorithm is able to decrease TEL of the non-dominated front at higher speed than the basic algorithm (Figure 7).

Including heuristics for the spatial objective of reducing TEL, clearly led to an improvement of the algorithm, while the effect of more generic modifications of crossover and mutation operators seem to be less clear. After 40000 generations the differences between different crossover operators we employed were rather marginal. Other studies showed that modifying crossover operators in similar ways improved the performance of genetic algorithms applied to spatial problems (Anderson et al., 1991, Shaygan et al., 2014, Karakostas and Economou, 2014). A possible explanation for this difference is the unique formulation of each study (e.g. Anderson et al. (1991) consider a single objective optimization problem). In addition, these studies ran the algorithms for a lower number of generations. In these stages the performance of the algorithm might depend strongly on how fast the algorithm produces solutions that are close to parts of the true Pareto Front (for example the central parts of the front) and not on whether it was able to generate a well-spread front reaching out to the very far ends of the true Pareto Front.

We found that dividing and recombining the parent maps along vertical lines, in order to generate offspring, produced better results than when dividing and recombining them along horizontal lines (Figure 3). However, this result is most likely not transferable to other study areas as it depends on the spatial distribution of the agricultural productivity per hectare and the existing land-usel pattern, whether a specific direction (e.g. horizontal or vertical) of dividing and recombining the parent maps would be useful. Thus, we also experimented with an Angle Crossover (AC), which is independent of the topographic features. The performance of the Block and the Block Uniform Crossover (BC, BUC) was more or less equally good as the performance of the AC crossover. In the Angle Crossover that we implemented parent solutions were always divided along a line through the centre of the study area. A possible improvement to this approach would be to randomly select points through which a line cuts the parents into two segments.

5.3. Transferability and further improvement of the algorithm

The proposed modifications in the genetic operators can help to improve evolutionary land-use optimization algorithms which include compactness as a spatial objective and one or more additive objectives. We hypothesize that in general spatial objectives pose a larger challenge to solving land-use optimization problems than additive objectives and that any evolutionary algorithm may be strongly improved by including heuristics regarding spatial objectives. This knowledge may also be very helpful when complex environmental models are involved in the optimization process. As these models make every evaluation within the optimization process computationally expensive, it is often suggested to use meta-models. These are models of models, intended to mimic the behaviour of larger, more complex models (Walker et al., 2013). In order to create efficient evolutionary algorithms, it could be a useful strategy to create meta-models that represent the actual more complex model by spatial and additive objectives. As there still remains a gap between the most compact solutions of the non-dominated fronts, obtained when using the improved algorithm, and the maximal possible compactness, we suggest some further modifications. Obviously one solution to improve the current results could be to seed the initial population with the most compact land-use pattern we found, when solving the single objective optimization problem. However, it has to be noted that finding the most compact pattern is a complex optimization problem in itself. For example, the single-objective algorithm converged towards three different patterns within ten different runs, from which we then selected the most compact one (Appendix, Figure 14). Another solution could be to dynamically adapt the biased mutation probabilities which we used in the operators BRM, BCNM and BCPM. Right now, the neighbourhood relationships are calculated one time, after an individual has been passed to the mutation operator. However, every time one cell is converted to urban or agriculture during mutation, the neighbourhood changes, which could be translated into a change of the biased probabilities.

While we have tested a variety of combinations of different operators and parameters that need to be supplied, there remains a huge number of possible parameter and operator combinations. Doing a more extensive and systematic study on these different combinations in order to find possible reinforcements of interacting parameters, could further improve the performance of the algorithm. In addition, it may be useful to dynamically adapt parameters like mutation and crossover probabilities (e.g. Jankowski et al., 2014) or to use self-adaptive mechanisms to find the most suitable operators (e.g. Consoli et al., 2014).

Comparing the improved with the basic algorithm for smaller and larger study areas (Hedingen and four combined municipalities), we observed that the potential for increasing the spread of the obtained solutions increased with increasing amount of agricultural land-use cells and urban cells to be allocated, i.e., more decision variables . This means that the difference between the improved and the basic version of the algorithm increased when the number of possible solutions for this combinatorial optimization problem increased. The gain in performance seems to depend on the number of possible solutions, which is directly related to the size of the study area. As customization usually require time and know-how, it may not always be considered necessary to modify an evolutionary algorithm when dealing with small study areas.

Not surprisingly, it takes more time for the algorithm to converge if the problem is very large. A simple remedy would be to increase the number of generations, which, however, would also increase the computational burden. Another possibility might be to use one algorithm that is able to produce non-dominated solutions with low loss of agricultural productivity (e.g., using mutation RCM or BCAPM) and another algorithm which is able to find compact solutions (e.g., using BCNM or BCPM) and later on combine the two obtained fronts. This may be useful for any optimization problem involving spatial objectives and not only for ones with a particularly large decision space.

Lastly, it should be mentioned that it may be helpful to modify not only mutation and crossover operators, but also the selection process of the genetic algorithm. As we were able to show, two runs with the same algorithm produced almost identical non-dominated fronts in the objective-space (Appendix, Figure 10). However, in the decision space, i.e., the land-use patterns, were in some cases very different from each other (Figure 11). To get as close as possible to the true Pareto Front, there could be two options. First, running the same algorithm a couple of times and then combining the fronts into one front with all dominant solutions (i.e. selecting only the dominant solutions and discarding all the non-dominant ones). Second, instead of preserving the diversity of solutions within in the objective space, accomplished by the so-called crowding distance in NSGA-II (Deb et al., 2002), it may be helpful to also preserve diversity in the decision space. Taking such diversity into account may not only be helpful to get as close as possible to the true Pareto-Front, but may also be used when trying to preserve non-dominant solutions that are close to the Pareto Front in the objective space, but very different in the decision space. This can be very useful, when decision makers want to evaluate a wide range of options (e.g. Kwakkel et al., 2016).

6. Conclusions

We tested different approaches for modifying genetic algorithms in order to improve their performance when applied to a multi-objective land-use allocation problem. These approaches were either derived from literature or were developed by ourselves. To our knowledge this is the first study that compares a large number of different modifications and combinations of crossover and mutation operators. As such, it allows us to provide an overview on what to expect from different modifications and could be very useful for future studies trying to improve the performance of genetic algorithms applied to land-use optimization problems.

By including knowledge about the absolute minima for each objective, we were able to compare different versions of genetic algorithms in a more explicit way than previous studies. Our results suggest that a combination of different mutation operators, of which at least one includes spatial heuristics, can help to find smooth and widely spread non-dominated fronts. Other modifications may result in quick convergence, however, the convergence may be misleading as these algorithms are not able to find a well-spread front. They may converge toward only a specific part of the PF.

Showing how the decision space (i.e., land-use) patterns change along the obtained non-dominated fronts, this is one of the few studies that offers a possible explanation for the different performances of the various approaches for customizing genetic algorithms. When including the spatial objective of creating highly compact land-use patterns, it seems to be difficult for the algorithm to find the most compact solutions on the non-dominated fronts, as these are very different in shape from the rest of the non-dominated solutions.

Anybody who considers using genetic algorithms to produce a front of non-dominated solutions for a land-use allocation problem, will want to know if it is worth customizing the algorithm. By not only applying the genetic algorithms to one fixed size study area, as has been done in previous studies, we were able to show that the differences between a customized and an unmodified genetic algorithm may depend on the number of decision variables involved. The differences seem to increase with an increasing number of decision variables. Thus, especially when trying to optimize large spatial planning entities or when using data with high spatial resolution it may be worthwhile to customize a genetic algorithm.

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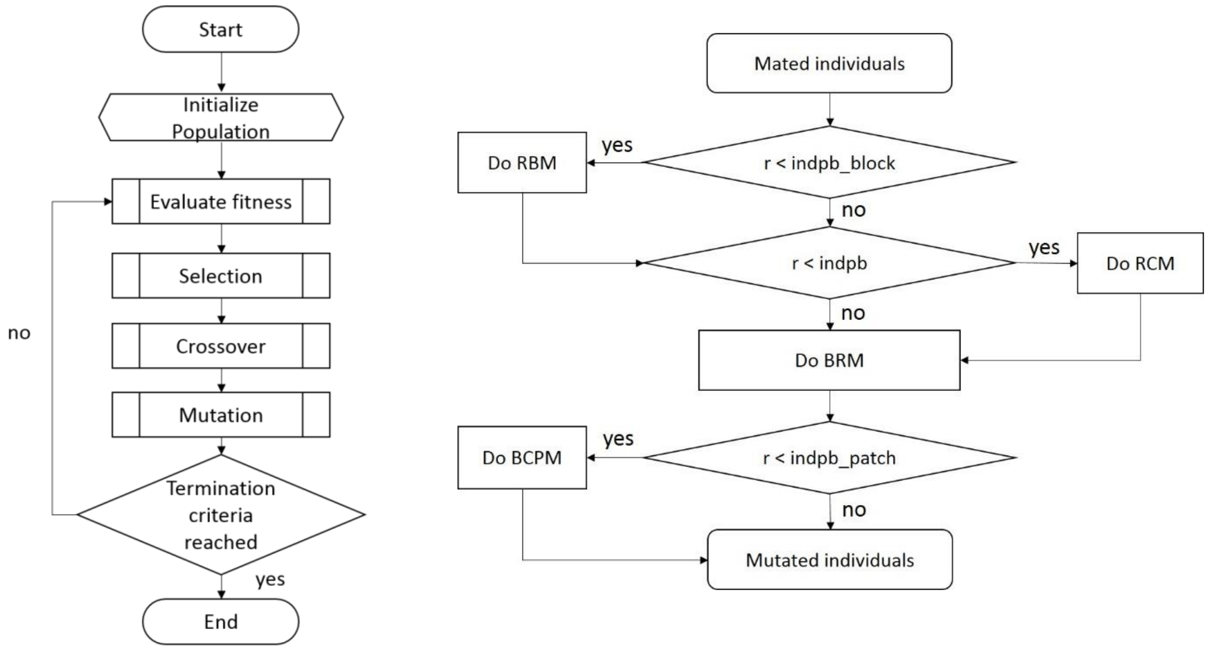
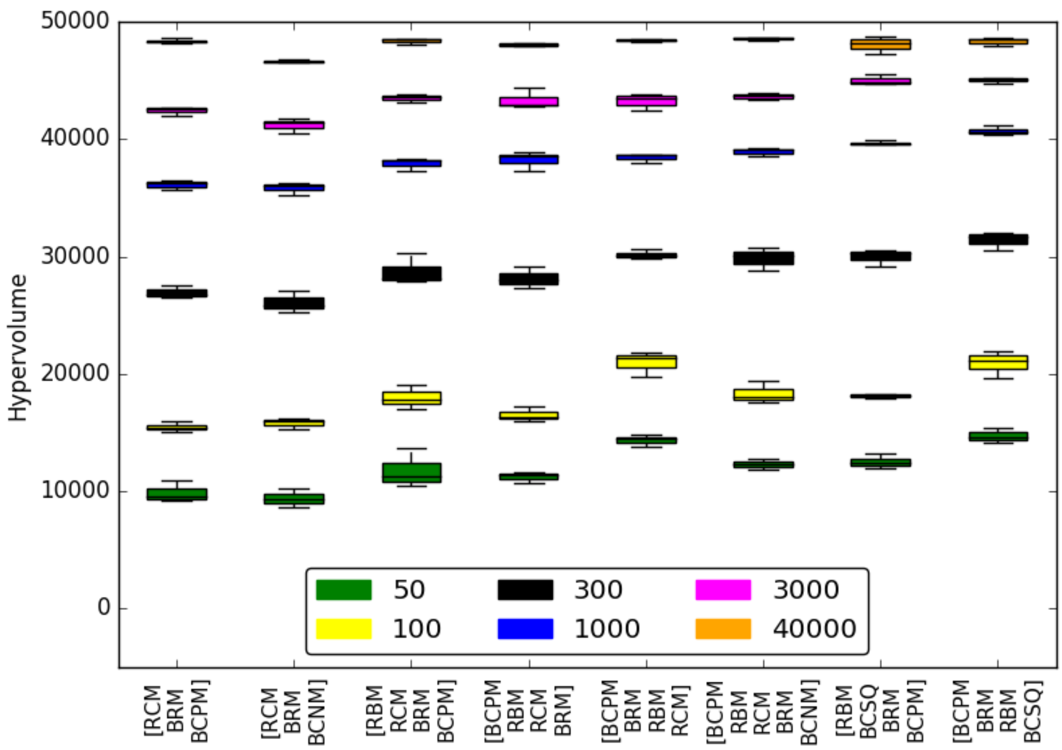
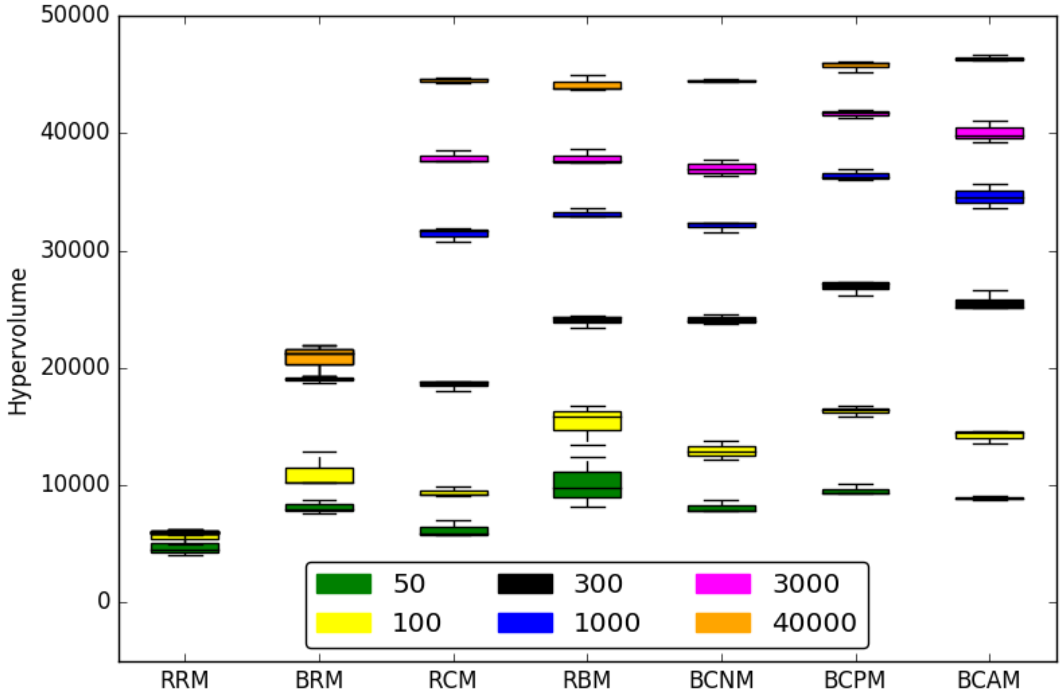
9. Appendix

Appendix, Figure 1: Left: Flow diagram of a generic Genetic Algorithm. Right: Flow diagram of an example for a combined mutation operator. Here we display the combination of four operators: RBM_RCM_BRM_BCPM. The probabilities that the algorithms enter a mutation are called indpb_patch, indpb_block and indpb. Each of them is per default 0.1. A random number between 0 and 1 (r) is selected every time for comparison with the probabilities.

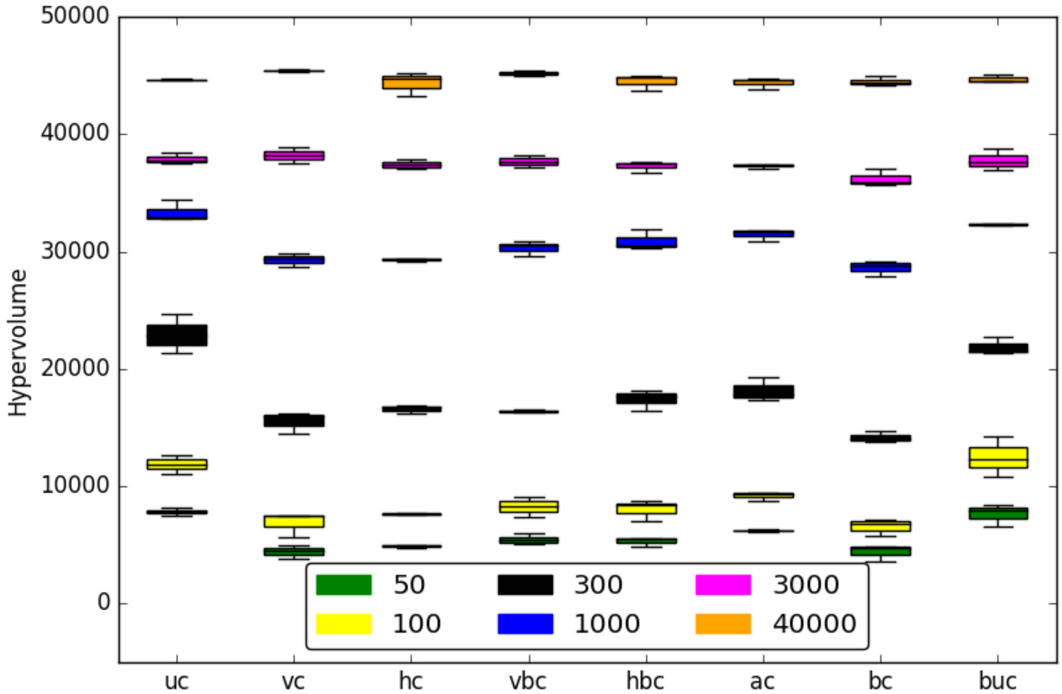




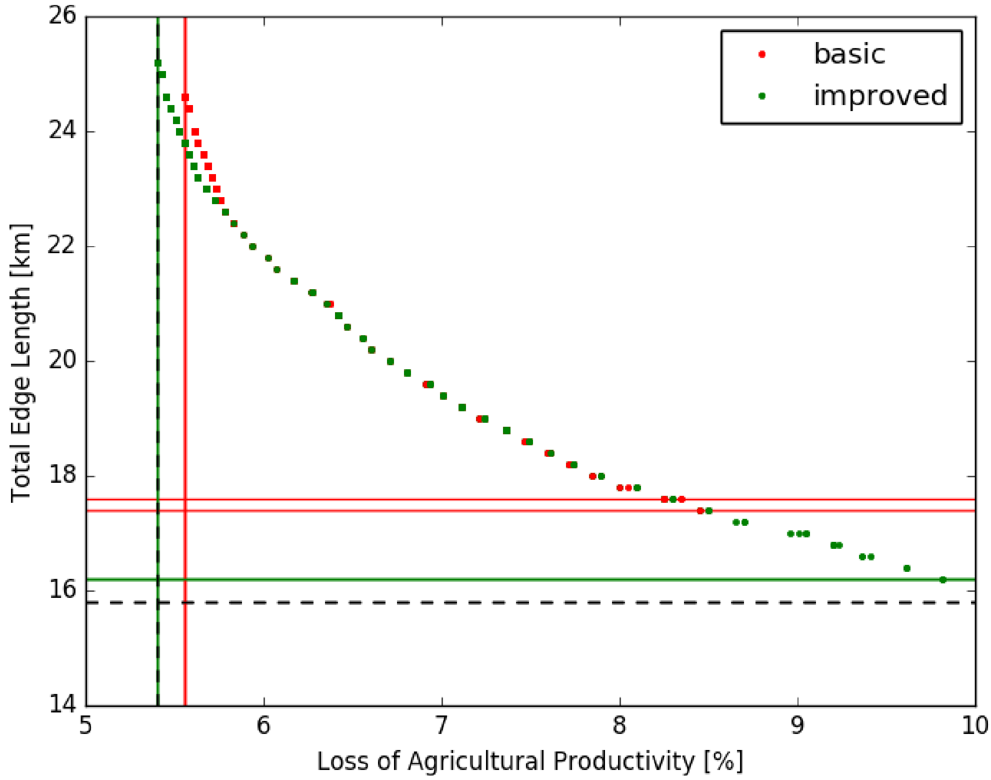
Appendix, Figure 2: Hypervolumes after generation 50, 100, 300, 1000, 3000 and 40000 when using different combined mutation operators in the NSGA-II procedure.



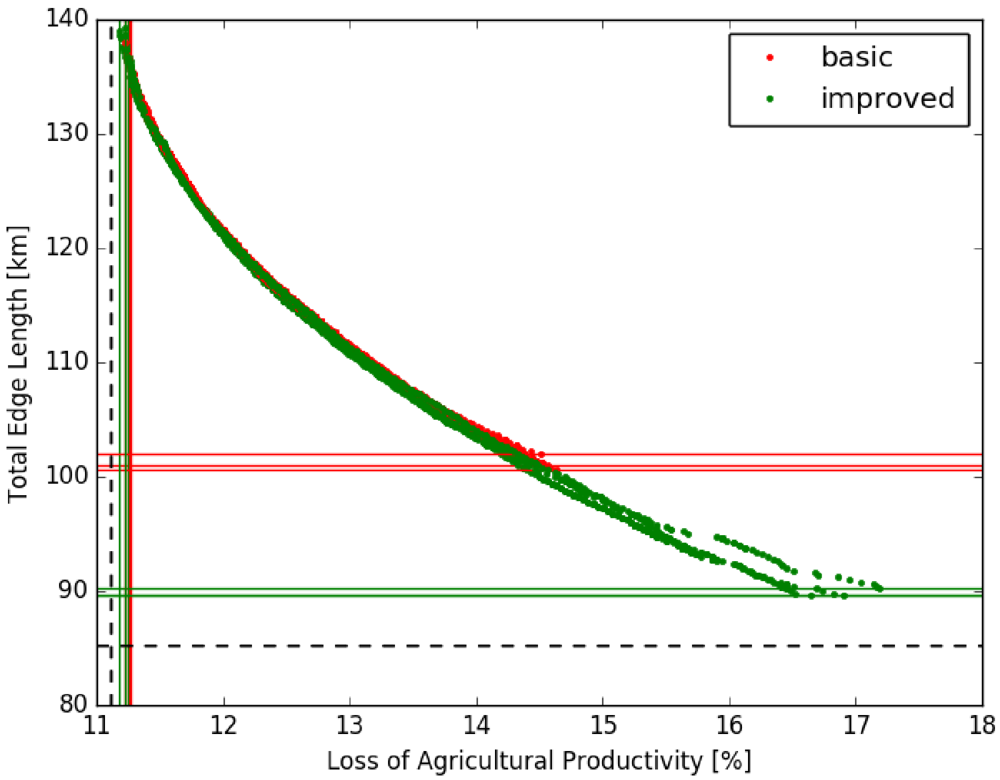
Appendix, Figure 3: Hypervolumes after generation 50, 100, 300, 1000, 3000 and 40000 when using different mutation operators in the NSGA-II procedure.



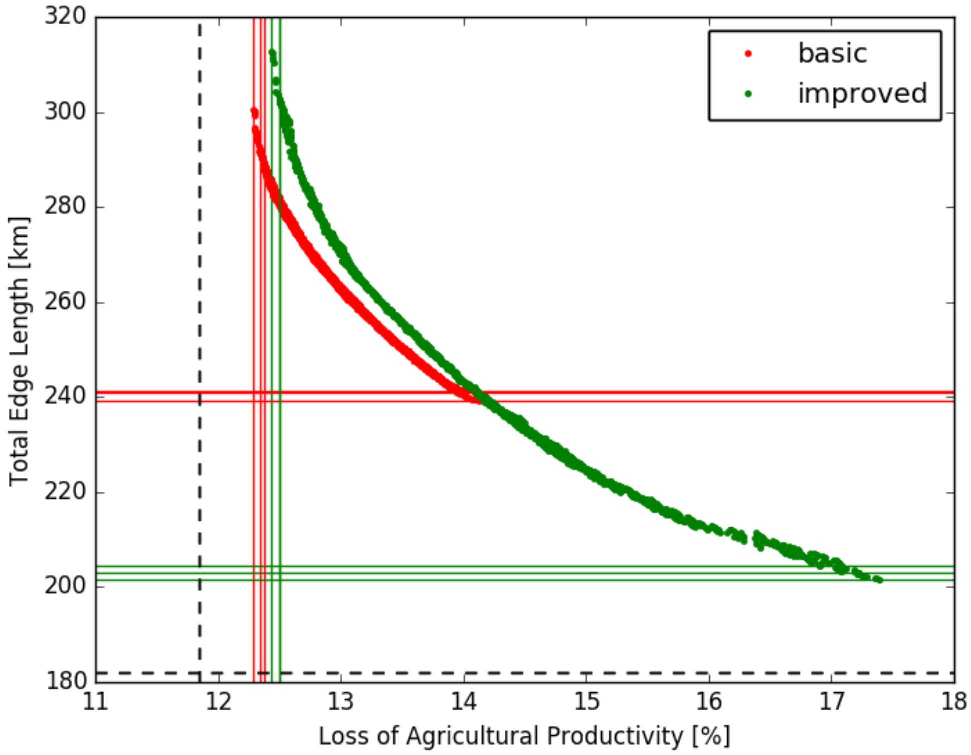
Appendix, Figure 4: Hypervolumes after generation 50, 100, 300, 1000, 3000 and 40000 when using different crossover operators in the NSGA-II procedure.



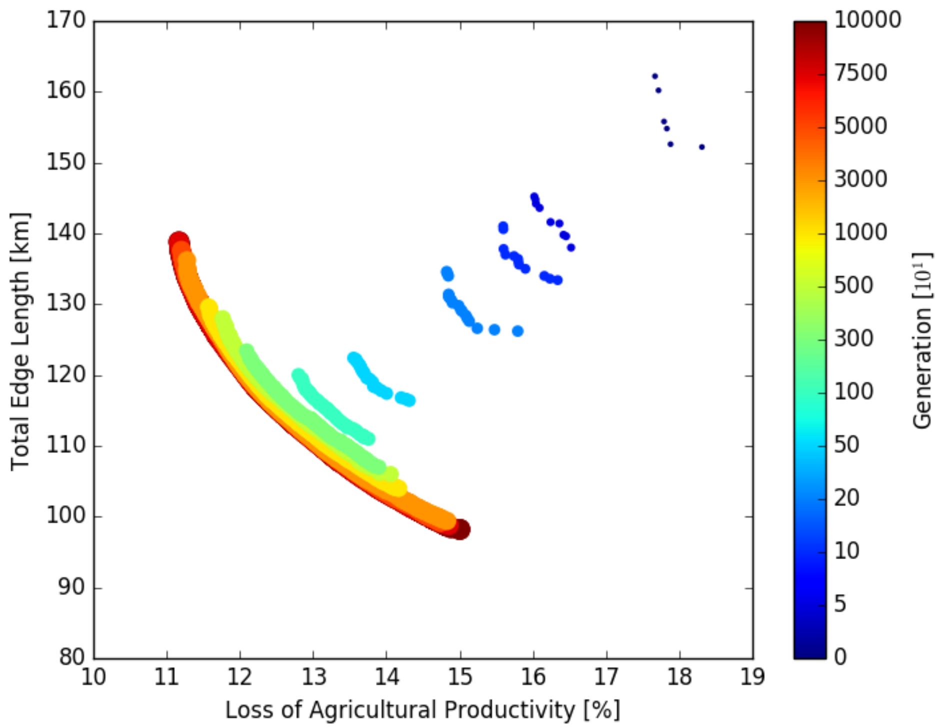
Appendix, Figure 5: Non-dominated fronts obtained when using a basic and an improved algorithm for the municipality "Hedingen".



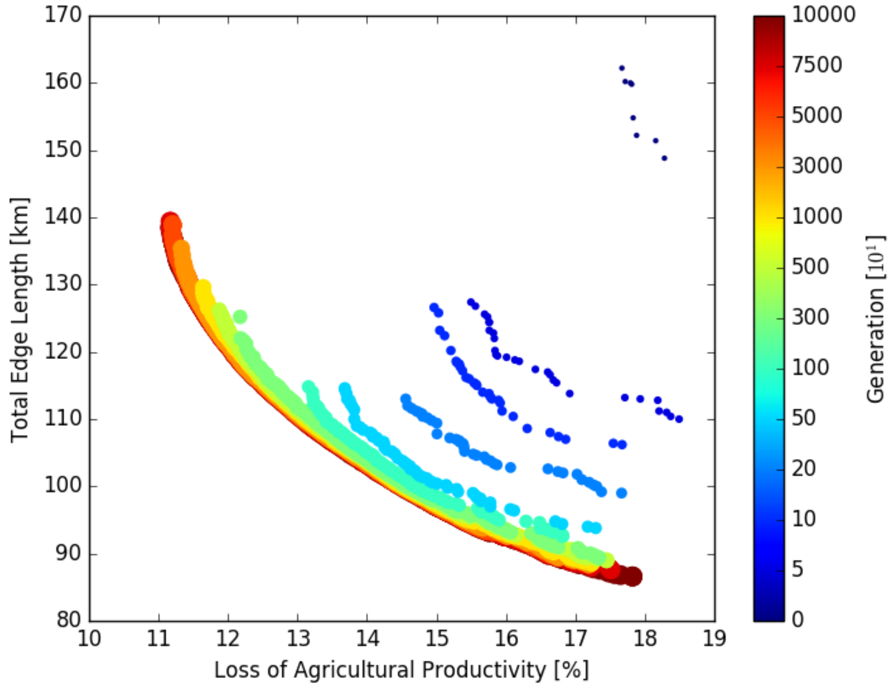
Appendix, Figure 6: Non-dominated fronts obtained when using a basic and an improved algorithm for the municipality "Uster".



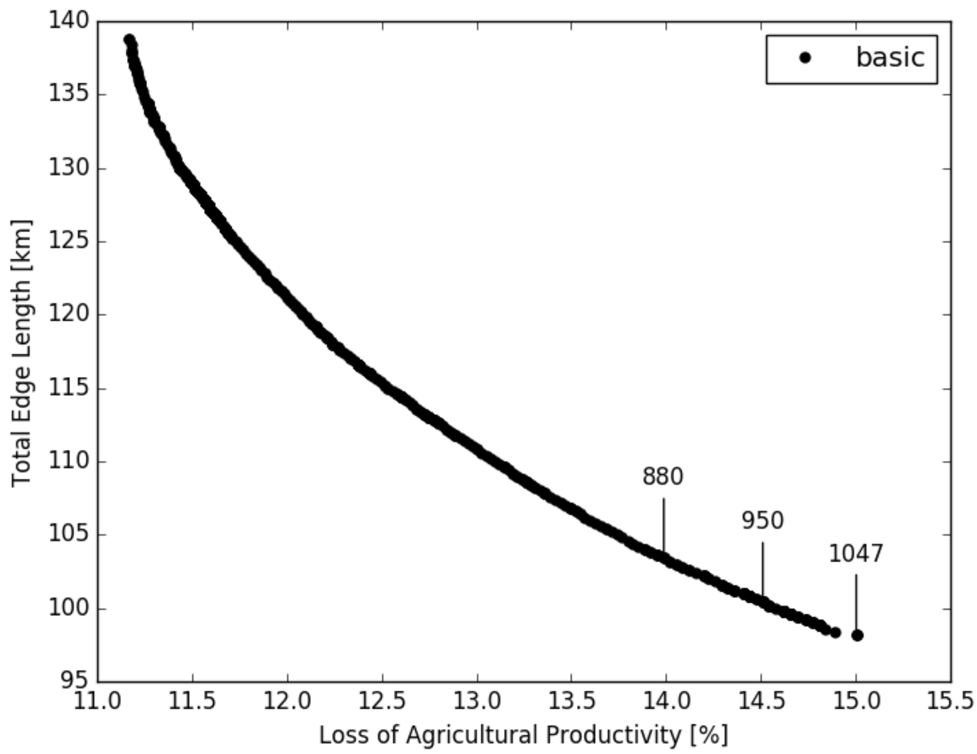
Appendix, Figure 7: Non-dominated fronts obtained when using a basic and an improved algorithm for the area of four combined municipalities.



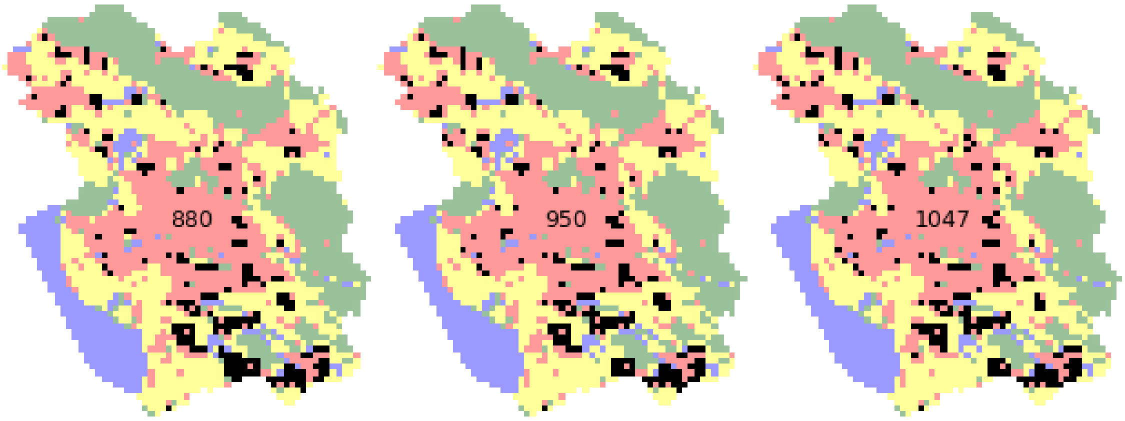
Appendix, Figure 8: Evolution of the non-dominated front for a basic version of the genetic algorithm from generation 0 to generation 10^6. For reasons of improved visualization the size of the dots displaying the non-dominated fronts was increased for larger generations.



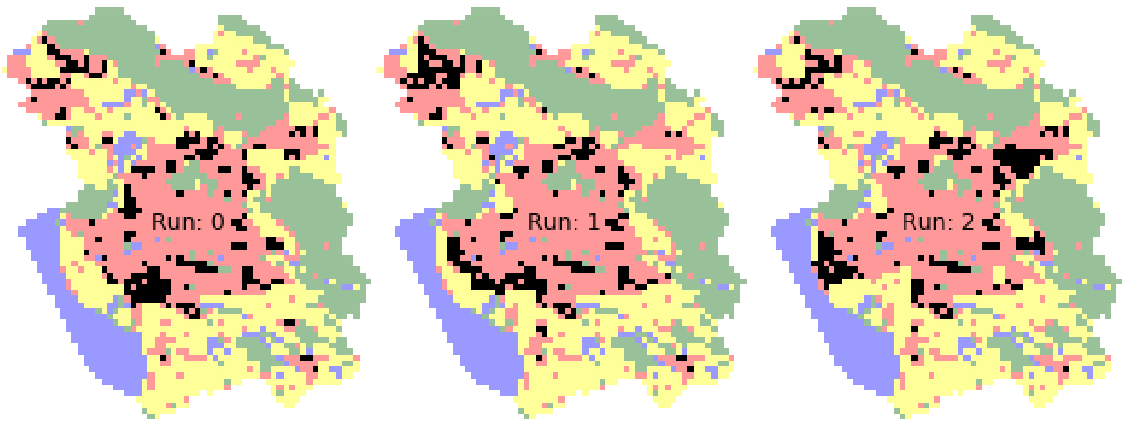
Appendix, Figure 9: Evolution of the non-dominated front for an improved version of the genetic algorithm from generation 0 to generation 100000. For reasons of improved visualization the size of the dots displaying the non-dominated fronts was increased for larger generations.



Appendix, Figure 12: Non-dominated front obtained after 100000 generations using the basic version of the algorithm (mutation: RCM).



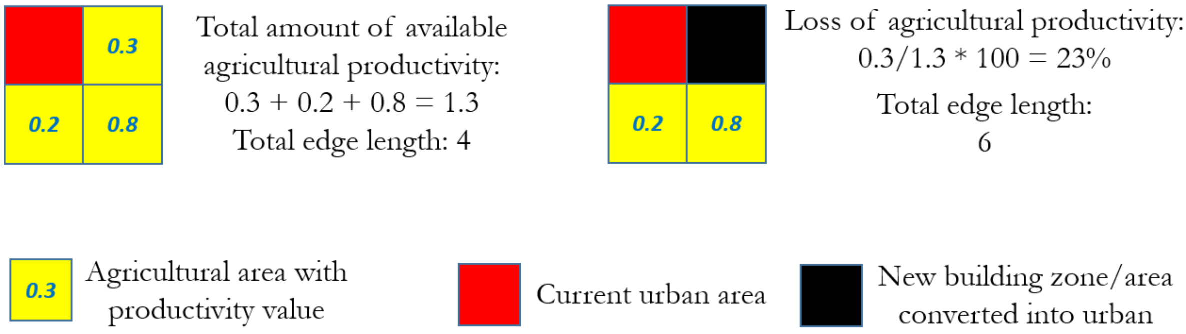
Appendix, Figure 13: The land-use patterns marked with the black numbers (880, 950 and 1047) correspond to the solutions of the front in Appendix, Figure 12. Red cells: Urban areas, Yellow cells: Agricultural areas, Green Cells: Forest areas, Blue Cells: Water, Black Cells: New Urban areas which were allocated in the optimization process.



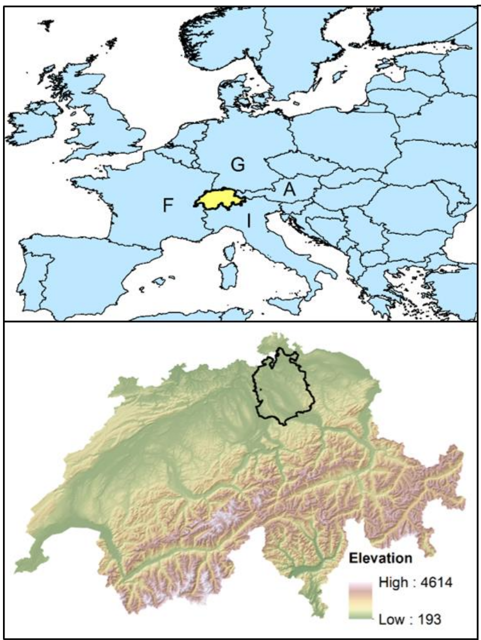
Appendix, Figure 14: Patterns that were obtained when running single objective optimizations (minimizing Total Edge Length). Different runs converged towards different patterns. Here we display three examples. The most compact solution is shown in the left (Run: 0) with 8.52km Total Edge Length, the solution in the center (Run: 1) has a Total Edge Length of 8.64 km and the one on the right (Run:2) has a Total Edge Length of 8.74 km. The loss of agricultural productivity is with approximately 19.2% almost equal for all three of them.

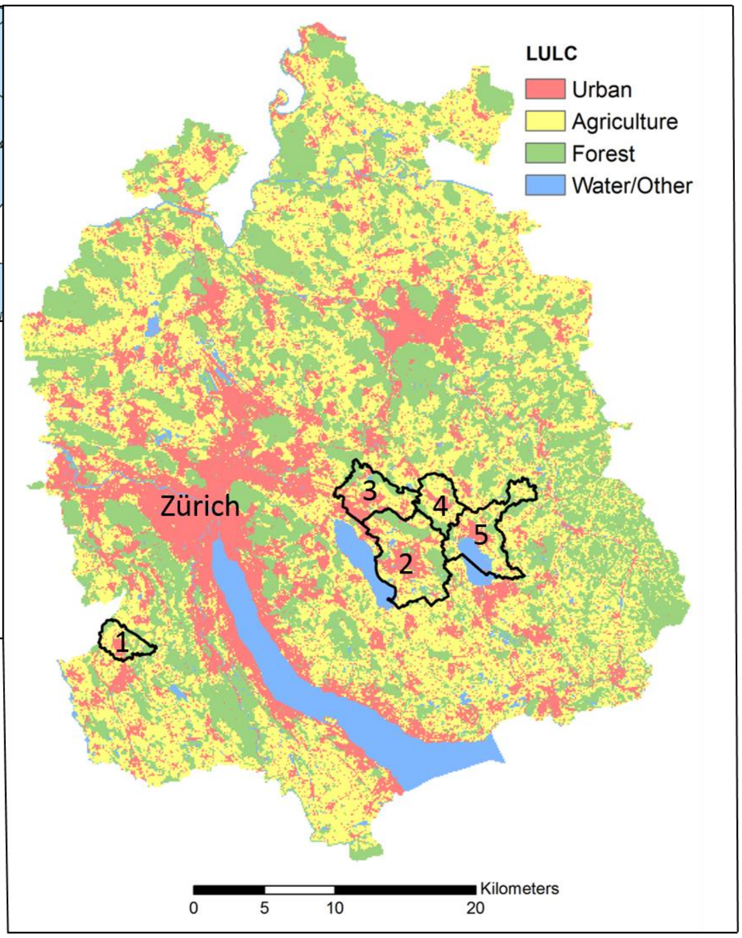
Appendix, Supplement 1: Detailed description on how the loss of agricultural productivity was calculated (adapted from Schwaab et al., 2017).

We restrict the development of urban areas onto areas that had been used agriculturally before. As many soil functions are irreversibly deteriorated when agricultural areas are partly or completely sealed, we assume that all existing agricultural productivity is lost, when agricultural land is converted into residential land. This means that it will be necessary to include a map for potential loss of agricultural productivity resulting from residential development. As an indicator for the loss a_{rck} in agricultural productivity, we use an existing spatially explicit dataset (Kanton Zürich, 1996). The production of this dataset between 1988 and 1996 was carried out by the Swiss Confederation's centre for agricultural research (Agroscope): It involved extensive field work (on average 7 soil profiles per 100 ha), analysis of remote sensing data and the integration of soil data existing at the time (Jäggli et al., 1998). The mapped soil characteristics in combination with climatic variables and slope resulted in a ranking of soils between 1 and 10 according to their agricultural productivity. We used this ranked dataset and slightly modified it. First, we linearly transformed the ranking from 1-10 into 0.1-1. Second, as there was no data on the soil quality available for a few cells, we filled these gaps using an Inverse Distance Interpolation. Although, the ranking of soils from 0.1 to 1 is convenient, these values have to be interpreted with care as they may, for instance, not be linearly related to real-world agricultural production (e.g. defined as the mass of crops produced).

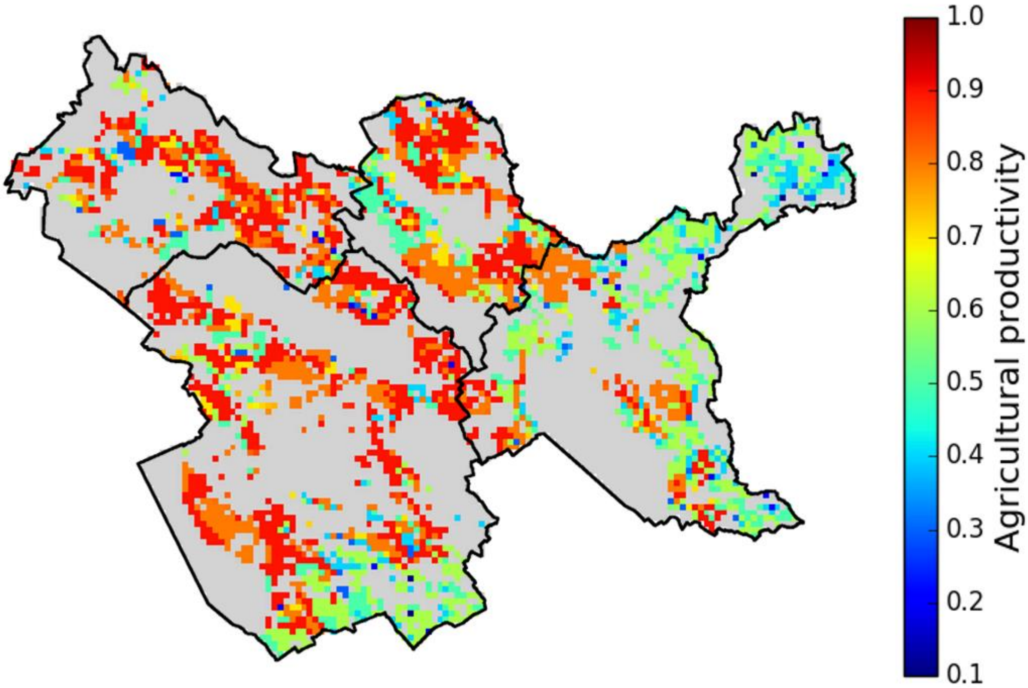


Appendix, Figure 15: Simplified representation of how the two objectives are estimated.

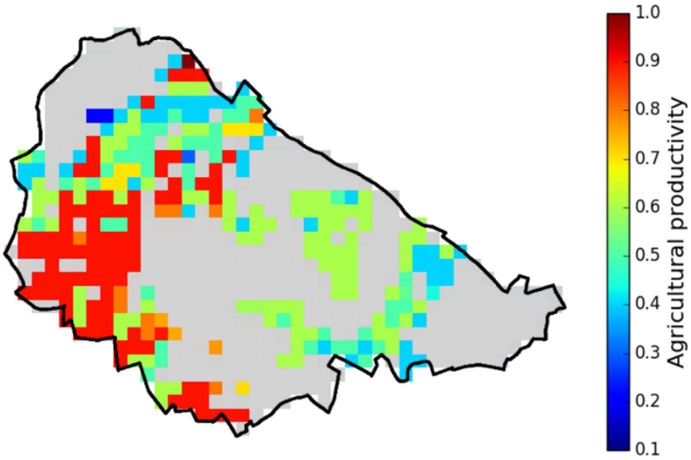




Appendix, Figure 1: Upper Left: Location of Switzerland within Europe (surrounded by France, Germany, Italy and Austria). Lower Left: Location of the canton of Zürich within Switzerland. Right: Location of the case study regions in the canton of Zürich in Switzerland. The city of Zürich is labeled to ease interpretation and orientation. Each number corresponds to a municipality: 1: Hedingen; 2: Uster; 3: Volketswil; 4: Fehraltorf; 5: Pfäffikon.



Appendix, Figure 17: Suitability for agricultural production (agricultural productivity) ranking from 0.1-1 in the area of the four combined municipalities. All non-agricultural areas are grey.



Appendix, Figure 18: Suitability for agricultural production (agricultural productivity) ranking from 0.1-1 in the municipality Hedingen. All non-agricultural areas are grey.

Chapter 3

Reducing the Loss of Agricultural Productivity due to Compact Urban Development in Municipalities of Switzerland

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Computers, Environment and Urban Systems (2017) 65, 162-177

Abstract

Globally urban growth destroys fertile soils and endangers food security. Fertile soils are often located in the vicinity of existing urban areas. Thus, preserving high-quality soils can conflict with the objective of developing compact urban patterns. In this study, we assess the trade-off between compact urban patterns and urban patterns that can help reduce the loss of agricultural productivity by maintaining fertile agricultural soils. We assess the trade-offs for selected municipalities in Switzerland using a multi-objective evolutionary algorithm to create a front of non-dominated solutions. These results are used as a benchmark against which we compare simulations of a Business-As-Usual urban expansion in Switzerland to estimate the potential for reducing the loss of agricultural productivity. By analysing the front of non-dominated solutions, we show that there are areas of open land that can be converted into residential land without trading-off compactness against agricultural productivity. We show that there is a large potential for reducing the loss of agricultural productivity when optimizing the configuration of urban development. This potential strongly varies between municipalities and seems to depend primarily on the amount of demand for new urban land within each municipality. The proposed methodology of using multi-objective optimization, followed by a post-optimality analysis and including results from business-as-usual development can be used to support the decision-making processes in urban planning.

1. Introduction

Urban growth is an ongoing process and has far-reaching impacts on ecosystems and their services, which are essential for human well-being (Millennium Ecosystem Assessment, 2005, Elmqvist, 2013, Dupras and Alam, 2015). The development of urban areas and particularly residential development leads to soil-sealing, which causes an irreversible loss of many soil-functions and their related services (Gregory et al., 2015, Pejchar et al., 2015). As pointed out by Bradbury et al. (2014), the global trend of decreasing average household sizes contrasts with an increase in the average size of homes. Thus, residential development expands even in countries with low or negative population growth rates (Haase et al., 2013, Pejchar et al., 2015), with Switzerland being no exception to this global trend (ARE, 2014, Jaeger and Schwick, 2014). Concerns about negative environmental impacts are caused not only by the amount, but also by the configuration of urban development (e.g. Alberti, 2005).

Undesirable urban growth has often been described as urban sprawl (Galster et al., 2001), while the opposite of sprawl is usually referred to as compactness. It is difficult to clearly define and separate urban sprawl from compact development, as there are many definitions and possible ways of measuring them (Hamidi et al., 2015). However, most defintions and indices include the degree of contiguity, which refers to the state of bordering or being in direct contact with existing development (Ewing and Hamidi, 2015). High contiguity of newly developed areas will in most cases be described as compact, while low contiguity usually corresponds to sprawling development.

The compact city has become a leading concept in urban and regional planning (Duany et al., 2000, Haaland and van den Bosch, 2015). This concept includes the promotion of new urban development close to existing development (i.e., contiguous development), but also the increase of housing density in existing urban areas and the reduction of the amount of open land consumed by built-up land. Although being a leading concept, striving for compact development alone does not automatically imply that the development is sustainable. For example, policies focusing on a reduction of the amount of urban growth, may result in negative consequences for the value of land, welfare and equity (Fischel, 1999, Glaeser and Ward, 2009, McLaughlin, 2012, Addison et al., 2013, Cheshire, 2013, Turner et al., 2014). As Westerink et al. (2013) point out, certain trade-offs in striving for compactness occur especially between environmental and social aspects of sustainability. Although it is often true that the environment will profit from compact development, e.g. concerning biodiversity (McDonald et al., 2008), it remains unclear how agricultural productivity will be affected.

Studies all over the world have shown that fertile soils are often located in areas that are facing high urban growth (Imhoff et al., 1997, EEA, 2006, Afifi et al., 2013, Salvati, 2013, Li et al., 2015, Martellozzo et al., 2015). At the same time, the global loss of fertile soils for agriculture and the resulting loss in food security are major causes of concern (Foley et al., 2011, Gardi et al., 2015, Smith et al., 2016, Hurni et al., 2015). As many soil functions are irreversibly deteriorated when agricultural areas are partly or completely sealed (Burghardt, 2006, EEA, 2006), there is an urgent need for immediate policy efforts.

Many policy efforts that are intended to reduce the loss of agricultural productivity follow the paradigm of compact development. For example, an amendment of the spatial planning legislation in Switzerland forces municipalities to restrict the supply of land available for the construction of residential areas (UVEK, 2014). It is obvious that reducing the amount of sealed land by restricting the supply of land or by providing economic incentives to increase the densities of existing urban areas will reduce the consumption of agricultural soils. However, striving for compaction also means promoting contiguous development of urban areas and may lead to an undesirable situation in which the best sites regarding agricultural productivity are destroyed, because they are located close to existing urban areas. Thus, it may be necessary to not only reduce the amount of new urban areas (i.e., to address land-use composition), but also to control the configuration of urban areas. Yet, no studies to our knowledge have provided evidence for the trade-off between agricultural productivity and compact development, with a focus on the configuration (i.e. contiguity) of urban areas, and discussed the consequences for more sustainable urban planning.

Providing decision makers with information on trade-offs between different objectives in urban planning has been identified as a key challenge when trying to reach sustainable urban development (Haase et al., 2012). Different approaches for identifying trade-offs have been used, many of them focusing on trade-offs between ecosystem services (Bennett et al., 2009, Grêt-Regamey et al., 2013).

To make trade-offs between ecosystem services and multiple other objectives explicit, an increasing number of studies propose the use of a Pareto Front (PF) generated with multi-objective evolutionary algorithms (e.g. Lautenbach et al., 2013, Chikumbo et al., 2014). The PF contains all solutions where the value of one objective can only be improved in trade-off with the value of at least one other objective. The PF of a spatial problem may be presented to decision makers and integrated into decision support tools (Jankowski et al., 2014). While it is clearly useful to confront decision makers with trade-offs, there might be more general knowledge that can be extracted from a PF via the so-called process of innovization (Deb, 2013). Innovization can be defined as an analysis of Pareto-optimal solutions (including data-mining techniques) in order to unveil common properties shared by them as valuable knowledge. Analysing the land-use configurations of the solutions constituting the PF may not only increase the understanding of trade-offs between different objectives, but may also guide decision-makers when trying to improve current land-use policies (Seppelt et al., 2013). As changing current land-use policies by including knowledge from multi-objective optimization can be a complex and time-consuming process (Geertman et al., 2013, Khalili-Damghani et al., 2014), it is important for policymakers to know what potential benefits can be expected from the policy change. However, the quantification of such benefits has been widely neglected in studies proposing the use of multi-objective optimization.

In this study, we assess the trade-offs between compact urban development and maintaining agricultural productivity for selected municipalities in Switzerland using a multi-objective evolutionary algorithm. These results are used as a benchmark against which we compare simulations of the Business-As-Usual (BAU) urban expansion in Switzerland to assess the potential for reducing the loss of agricultural productivity. To understand in which municipalities the potential reduction of agricultural productivity is high, we correlate the potential reduction with different variables describing the characteristics of each municipality. By analysing the Pareto Fronts, we determine whether there are areas of open land that can be converted into residential land without having to trade-off compactness against agricultural productivity.

2. Methods and data

In the following sections we, first, describe the study area. Second, we outline the problem of optimizing the pattern of urban growth and how we solved it. Third, we describe how we modelled BAU allocation of urban areas. Fourth, we explain how we compared the results from BAU simulations and the multi-objective optimization in order to assess the potential for improving the BAU patterns of urban growth. As the main driver of urban growth in Switzerland is the development of new residential areas, we focus on this category of urban growth and do not explicitly consider other types of urban growth (e.g. the development of industrial areas and infrastructure). We use geographical data in a grid-based format to represent the location of land-use and other spatial attributes.

2.1. Study area

Our study sites consist of a selection of municipalities in the Canton of Zurich, Switzerland. From the 168 municipalities in the canton, we first selected the 84 municipalities (50%) which we expected to experience the strongest growth in residential area and which would consequently face a high pressure on agricultural land (Appendix, Figure 1). From this half, we took a stratified sample consisting of 12 municipalities. The sampling was based on the correlation between a variable measuring the proximity to settlement of each cell and a variable indicating agricultural productivity of each cell within a specific municipality (Appendix, Figure 2). Proximity to settlement was calculated as the Euclidean distance from every cell to the next settlement area (Appendix, Figure 3). Spatially explicit data on agricultural productivity was available in the canton of Zürich (Appendix, Figure 4) and will be described in more detail in section 2.2.2.1. A positive correlation between proximity to settlement and agricultural productivity means that most fertile soils are in close distance to existing settlement boundaries, whereas a negative correlation would indicate that the most fertile soils are rather far away from existing settlement boundaries. We selected four municipalities with a relatively strong positive correlation, which were Uster, Dübendorf, Meilen and Hedingen, four other municipalities with moderate correlation, which were Volketswil, Bassersdorf, Oberglatt and Pfäffikon and four additional municipalities with very weak or negative correlation which were Bülach, Nürensdorf, Fehraltdorf and Rümlang (Appendix, Figure 2). To avoid redundancies, some results will be displayed only for the municipality of Uster in the main body of this article. Additional results, including all municipalities, can be found in the Appendix.

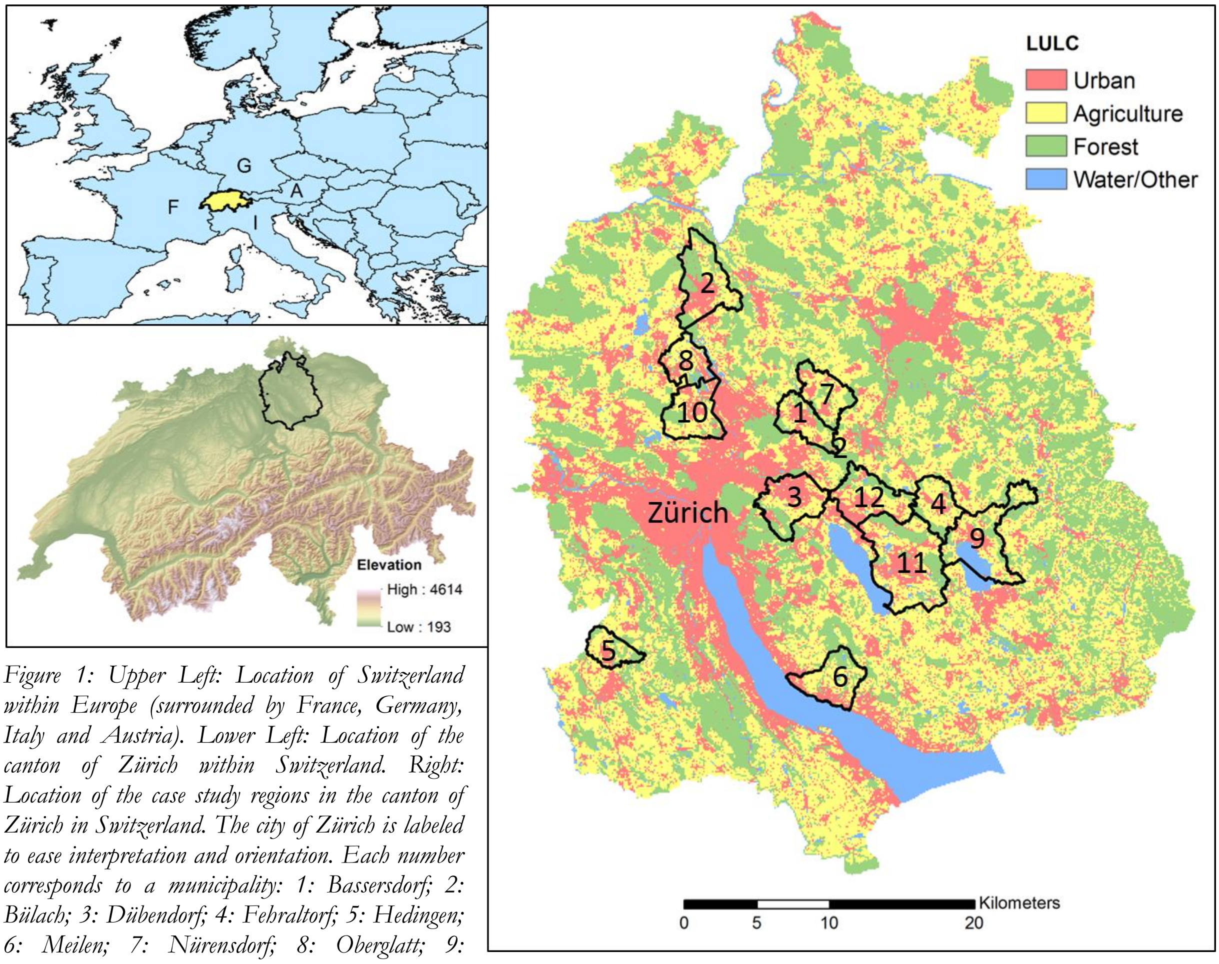

Figure 1: Upper Left: Location of Switzerland within Europe (surrounded by France, Germany, Italy and Austria). Lower Left: Location of the canton of Zürich within Switzerland. Right: Location of the case study regions in the canton of Zürich in Switzerland. The city of Zürich is labeled to ease interpretation and orientation. Each number corresponds to a municipality: 1: Bassersdorf; 2: Bülach; 3: Dübendorf; 4: Fehraltorf; 5: Hedingen; 6: Meilen; 7: Nürensdorf; 8: Oberglatt; 9: Pfäffikon; 10: Rümlang; 11: Uster; 12: Volketswil.

2.2. Multi-objective Optimization

We used an evolutionary algorithm to solve the multi-objective optimization problem. As a result of the optimization process, we produced fronts of non-dominated solutions (NDFs) for every municipality. These fronts are assumed to be very close to the true Pareto Front. However, there is no guarantee that a stochastic optimization algorithms finds the true Pareto Front. Thus, we will henceforth stick to the term non-dominated front when describing the result of the multi-objective optimization process. In the following sections, we will describe the constraints associated with the optimization problem and then present the two conflicting objectives considered in this study. The two objectives were to minimize the loss of agricultural productivity and to maximize the compactness of urban development. After describing the constraints and objectives, we will describe the details of our attempt to solve the optimization problem.

2.2.1. Constraints

We set two constraints in our optimization. First, we used a fixed demand for new residential areas in each municipality (i.e., a fixed amount of agricultural area being converted into residential area), because this work focuses on land-use configuration and not on land-use composition. We defined the demand according to population growth projections and a projected increase of per capita use of residential area (more details are provided in the Appendix, Supplement 2). Second, only raster cells classified as agriculture could be converted to residential area. Forests were excluded from conversion as they are strongly protected in Switzerland (Bloetzer, 2004).

2.2.2. Objectives

We considered two objectives for our study. The first objective was to minimize the loss of agricultural productivity. The second objective was to maximize compactness of the urban area. The cell size of the land-use rasters which we optimised was 1 ha. Janssen et al. (2008) differentiate between two types of objectives when optimizing land-use patterns: additive objectives and spatial objectives. Additive objectives associate costs or benefits with the allocation of any particular land use to a specific cell, which are then accumulated additively across all cells. Spatial objectives indicate the extent to which the different land uses are connected, contiguous, or fragmented across the region. In this study, we calculate the loss of agricultural productivity as an additive objective and compactness as a spatial objective. It is important to highlight that these two objectives are conflicting to each other, thereby facilitating us to find a number of trade-off optimized solutions of the land-use planning problem.

2.2.2.1. Minimizing loss of agricultural productivity

Adapted from Stewart et al. (2004), we formulate this objective in the following way:

$$LAP(u) = \frac{1}{A}\sum_{r=1}^{R}\sum_{c=1}^{C}\sum_{k=1}^{K} a_{rck}\, x_{rck} \tag{3.1}$$

where u denotes the specific land-use map expressed in terms of R×C×K binary variables x_{rck} , such that $x_{rck} = 1$ if $u_{rc} = k$, and $x_{rck} = 0$ otherwise, R is the number of rows, C is the number of columns, K is the number of possible LULC categories, a_{rck} is the potential loss of agricultural productivity and A is the sum of the currently available agricultural productivity. New residential areas can only be built on agricultural land. This means that it will be necessary to include a map for potential loss of agricultural productivity resulting from residential development. As many soil functions are irreversibly deteriorated when agricultural areas are partly or completely sealed, we assume that all existing agricultural productivity is lost, when agricultural land is converted into residential land. As an indicator for the loss a_{Srck} in agricultural productivity, we use an existing spatially explicit dataset (Kanton Zürich, 1996). The production of this dataset between 1988 and 1996 was carried out by the Swiss Confederation's centre for agricultural research (Agroscope): It involved extensive field work (on average 7 soil profiles per 100 ha), analysis of remote sensing data and the integration of soil data existing at the time (Jäggli et al., 1998). The mapped soil characteristics in combination with climatic variables and slope resulted in a ranking of soils between 1 and 10 according to their agricultural productivity. We used this ranked dataset and slightly modified it. First, we linearly transformed the ranking from 1-10 into 0.1-1. Second, as there was no data on the soil quality available for a few cells, we filled these gaps using an Inverse Distance Interpolation. Although, the ranking of soils from 0.1 to 1 is convenient, these values have to be interpreted with care as they may, for instance, not be linearly related to real-world agricultural production (e.g. defined as the mass of crops produced).

2.2.2.2. Maximizing compactness in development

To monitor and describe the development of urban patterns a large variety of landscape and urban sprawl metrics have been developed (Kowe et al., 2015, Ewing and Hamidi, 2015). Studies focusing on multi-objective optimization of urban patterns have usually included one of these metrics in order to maximize compactness (e.g. Aerts and Heuvelink, 2002, Stewart et al., 2004, Ligmann-Zielinska et al., 2008, Masoomi et al., 2013). Here we use the Total Edge Length (TEL) as described by McGarigal et al. (2012) as the measure for compactness. The TEL can be calculated as:

$$TEL = \sum_{k=1}^{m} e_{ik} \tag{3.2}$$

where e_{ik} is the sum over all edge lengths of patches k from the LULC class i (i.e. urban) in terms of the number of cell surfaces (McGarigal et al., 2012). The TEL is inversely related to compactness, meaning that a low TEL corresponds to high compactness. Thus, the objective was to minimize TEL. Adapting the notation of Aerts et al. (2003) the TEL may be reformulated as:

$$TEL(u) = \sum_{r=1}^{R}\sum_{c=1}^{C}\sum_{k=1}^{K}(x_{r+1,c,k} + x_{r,c+1,k} + x_{r-1,c,k} + x_{r,c-1,k}) \tag{3.3}$$

where again u denotes the specific land-use map expressed in terms of R×C×K binary variables x_{rck}. The variables $x_{r+1,c,k}, x_{r,c+1,k}, x_{r-1,c,k}$ and $x_{r,c-1,k}$ are binary variables describing the von Neumann neighbourhood of a centre cell being assigned to a specific land-use (u_{rc}). If a neighbour and the centre are assigned to the same land-use (e.g. $u_{r+1,c} = u_{rc}$), the binary neighbourhood variable is zero (e.g., $x_{r+1,c,k} = 0$). If the neighbour and the center are assigned to different land-uses (e.g, $u_{r+1,c} \neq u_{rc}$), the neighbourhood variable is one (e.g., $x_{r+1,c,k} = 1$).

2.2.3. Evolutionary multi-objective optimization algorithm

To solve our multi-objective optimisation problem, we used the elitist Non-dominated Sorting Genetic Algorithm (NSGA II, Deb et al., 2002), due to its modularity, parameter-less and population approach. We modified the recombination and mutation operators to suit our specific optimisation problem and implemented the algorithm using the python framework "Distributed Evolutionary Algorithms in Python" (DEAP, Fortin et al., 2012). Based on test simulations, we decided to use a population size of 100. At each generation we copied all non-dominated solutions to an external archive while removing all dominated solutions from the archive. To monitor the performance of the optimization process we calculated the hypervolume indicator at each generation (Zitzler, 1999). We terminated the algorithm after 15000 generations. We ran NSGA-II for this large number of generations to obtain a stable non-dominated trade-off front, although the NSGA-II population came close to the final non-dominated front much earlier. The change in hypervolume between generations 10000 and 15000 was smaller than 1% for each municipality.

As demonstrated by Anderson et al. (1991), it can be useful to implement a two-dimensional (also called geographic) crossover, instead of standard one-dimensional crossover operators, for spatial optimization problems (i.e., two-dimensional problems). Our algorithm produced good results when we split the parent solutions into two halves by a line through the centre of the municipality with randomly varying angles (Appendix, Figure 5). A similar approach has been recently applied for a spatial problem by Ryerkerk et al. (2012).

The mutation operator used in this genetic algorithm included three steps: First, either a single cell or patch of varying size was mutated (i.e., converted from agriculture to residential). Second, as the crossover or the first mutation step may violate the constraint of a fixed amount of new residential areas, it was necessary to repair the mutated offspring by either converting agricultural areas to residential or vice versa. In case there were not enough residential areas, the likelihood that an agricultural cell was selected during the repair step and converted into residential, was proportional to the number of urban cells in its von Neumann neighbourhood (i.e., its four-cell neighbourhood). Likewise, if there were too many residential areas, the likelihood for a residential cell to be selected and converted to agriculture, was proportional to the number of neighbouring agricultural cells. Third, we selected one residential patch from all the patches of new residential areas and converted it back to agriculture. The probability of a patch being selected was inversely proportional to its size. The conversion into agricultural cells violated again the constraint of a constant amount of new residential areas. Thus, the amount of cells in the selected patch had to be converted back to residential. For this conversion we selected locations in the direct neighbourhood of an urban patch (i.e., we attached residential areas to existing urban patches). The likelihood for a patch to be selected for attaching of these residential cells was again proportional to the patch size.

2.3. Predicting business-as-usual residential development

We chose a hierarchical modelling approach for predicting BAU residential development by distinguishing between processes at the macro (demand for land use change) and at the micro (spatial allocation of land use change) level similarly to the widely used CLUE-S (Verburg et al., 2002) and other land-use models (Vimal et al., 2012, Meentemeyer et al., 2013). First, we estimated suitability maps for new residential areas at a 1ha resolution across the case study region. Second, we determined the demand for new residential area until 2050. This demand was also used as the fix demand used in the optimization procedure. Third, we used information on the distribution of patch sizes of historic development of residential areas to allocate not only single cells but also a larger number of contiguous cells (i.e., patches). More details on the BAU modelling approach are provided in the Appendix, Supplement 2.

2.4. Estimating the potential reduction of loss of agricultural productivity including varying demands

We base the estimation of the potential reduction of loss of agricultural productivity on a comparison between the loss caused by the BAU and the optimal allocation of residential areas. As there are no single BAU solutions and no single optimal solutions, we facilitated a comparison by calculating a mean loss of agricultural productivity for the BAU solutions and by selecting a loss of productivity assigned to a solution from the NDF that was at least as compact as the most compact BAU solution (Appendix, Supplement 1, Appendix, Figure 6).

We calculated the relative potential reduction of loss of agricultural productivity (PRR) in every municipality. Calculating this potential could reveal, whether and in which municipalities it would be worthwhile initiating policy changes. The factor PRR shows by how much the loss of agricultural productivity can be reduced within each municipality. The potential reduction was calculated for the predicted demand in 2050. In addition, we calculated PRR in the municipality of Uster for demands varying between a minimal demand of 50 new hectares and a maximal demand of 1157 ha of new residential areas, which would cause all available agricultural areas in this municipality to be converted into residential.

It is unlikely that policy- and decision-makers will take information about the potential reduction of loss into consideration, as long as it requires the large effort of modelling BAU and optimal development of residential areas. Thus, we were interested in factors that were correlated to the potential reduction of loss and could hence be used as indicators. One of these factors was the correlation between the two variables “proximity to settlements” (Appendix, Figure 3) and “agricultural productivity” (PROX_AP, Appendix, Figure 4). Two more factors we tested were the demand (DEMAND) for new residential areas and the ratio between the demand for new residential areas and the available amount of agricultural areas (RDA) within each municipality. For a better understanding, why some factors may be more suitable for predicting the potential reduction of loss, we calculated two more factors. These were the mean loss of agricultural productivity per hectare in case of BAU development (L_BAU) and in case of optimal development (L_O). While L_BAU is an indicator on whether the BAU development causes a particularly high or low trade-off between compactness and agricultural productivity, L_O indicates whether the optimal development can be realized with a small trade-off between compactness and agricultural productivity. More details on how the different factors were calculated are provided in the Appendix (Supplement 1).

3. Results

If new residential areas are allocated following the BAU development, agricultural productivity in all 12 municipalities diminishes by 23% in 2050. That means that on average 0.71 agricultural productivity points per hectare of new residential areas are lost. For optimal allocation of residential areas the loss of agricultural productivity can be reduced to 18% over the same time period, i.e., only 0.54 agricultural productivity points per hectare are lost. Summed over all municipalities, equal amounts of loss of agricultural productivity are caused either by 15 km^2 of new residential area under the BAU development or by 19 km^2 of new residential areas optimally allocated (Table 2, exemplified for the municipality of Uster in Figure 6).

The solutions constituting the NDF show a strong trade-off between loss of agricultural productivity and compactness (Table 2). The solutions with the smallest and the largest loss of agricultural productivity were on average related to a difference in compactness of 38%. Solutions for the most and least compact configuration were on average related to a difference in soil quality of 27%.

Although solutions along the non-dominated front differ strongly in both objectives and in the land-use patterns (Appendix, Figure 8, Appendix, Figure 9), there are areas that were selected to be converted into residential in every solution constituting the front. Analysing the fronts of all 12 municipalities, we found that on average 35% of the newly allocated residential cells were always the same, ranging from 3% in the municipality of Hedingen to 58% in the municipality of Oberglatt (Table 1, exemplified for the municipality of Uster in Figure 2). Furthermore, some cells are very frequently selected for residential development, while others hardly occur in the patterns of the non-dominated solutions (Figure 2). Of all agricultural areas potentially convertible into residential areas, an average of 61% are never selected for residential development in any of the non-dominated solutions (Table 2).

The potential reduction of loss of agricultural productivity within each municipality (PRR) ranges from 17% in Volketswil to 39% in Hedingen (Table 1, Appendix, Figure 7). We found that some factors were correlated to the potential reduction of loss, while others were not (Figure 3). The factors L_BAU and PROX_AP were not significantly correlated to PRR. The fact that neither L_BAU nor PROX_AP were correlated to the potential reduction of loss of productivity indicates that the potential for reduction depends on where the NDF is located in the objective space and less on where the BAU solutions are located. Accordingly, we found that L_O was negatively correlated with PRR. While PROX_AP was significantly correlated to L_BAU, it wasn’t significantly correlated to L_O; however, the null hypothesis cannot be strongly rejected (p=0.056). Both, the factor DEMAND and the factor RDA are significantly correlated to PRR and L_O.

The loss of agricultural productivity per hectare of newly allocated residential areas increases for increasing demands if the residential development follows optimal patterns. It slowly decreases with increasing demand for BAU development (Figure 4 a). The relative potential reduction of loss of agricultural productivity is highest for small demands. It almost linearly decreases with increasing demand (Figure 4 b).

From the 66 km² of agricultural land currently existing in the 12 study area municipalities, 15 km² were projected to be converted into residential areas by 2050 (Table 2). Important predictors steering the location of new BAU development are proximity to existing settlements, distance to roads, utility services and public transport (Appendix Table 1). This resulted in new development mainly at the edge of existing settlements (Appendix, Figure 10) and in land-use patterns where the urban areas have been quite compact (i.e., having a low Total Edge Length, Figure 5). A continuation of the current trend and practice of residential development would destroy on average more fertile soils than a random allocation would (Figure 5). This can be explained by the positive correlation between proximity to settlements and agricultural productivity, which we found in 139 out of 168 municipalities in the Canton of Zürich.

The computation time for running the BAU simulations was less than 30 seconds in each municipality. However, to estimate the NDFs for each municipality (involving 15000 generations to calculate each front) took between 30 and 90 minutes, when using a single core. The specifications of the used processor are: Intel(R) Core(TM) i7-4710Q CPU @ 2.50 GHz.

Table 1: Overview of variables calculated for each municipality. ***PROX_AP*** *= Correlation between proximity to settlement and agricultural productivity.* ***AC_1****= Amount of cells always chosen in the patterns of the NDF divided by demand for new residential areas.* ***AC_2*** *= Mean of the sum of congruent residential cells between a deterministic BAU simulation pattern and all patterns constituting the NDF divided by the demand for new residential areas.* ***L_BAU****= Mean reduction of agricultural productivity per hectare for BAU development divided by mean agricultural productivity per hectare in the municipality.* ***L_O*** *= Loss of Agricultural productivity per hectare for optimized development (for the solutions that dominate all BAU development solutions in compactness) divided by mean agricultural productivity per hectare in the municipality.* ***PRR****: Potential Reduction as the difference in loss of agricultural productivity between BAU and optimal allocation of residential areas divided by the loss caused by BAU development in each municipality.* ***DEMAND****: Demand for new residential areas.* ***RDA****: The ratio of demand and available agricultural land within the municipality.*

Municipality	PRR [%]	PROX_AP	L_BAU	L_O	DEMAND	RDA	AC_1 [%]	AC_2 [%]
Hedingen	39	0.49	1.12	0.69	30	0.10	3	39
Dübendorf	23	0.28	1.04	0.80	205	0.42	36	47
Meilen	28	0.26	1.03	0.74	128	0.24	31	36
Uster	31	0.24	1.02	0.71	212	0.18	19	24
Pfäffikon	31	0.15	0.97	0.67	105	0.13	16	37
Bassersdorf	20	0.12	0.97	0.77	82	0.24	46	43
Oberglatt	26	0.1	0.96	0.71	120	0.29	58	26
Volketswil	17	0.08	0.97	0.80	213	0.40	57	41
Bülach	19	0.003	0.97	0.79	201	0.41	57	39
Fehraltorf	32	-0.05	0.95	0.64	56	0.11	18	17
Nürensdorf	36	-0.06	0.97	0.62	62	0.13	37	25
Rümlang	31	-0.06	0.99	0.69	103	0.18	44	33
Average	28	0.13	1.0	0.72	126	0.24	35	34

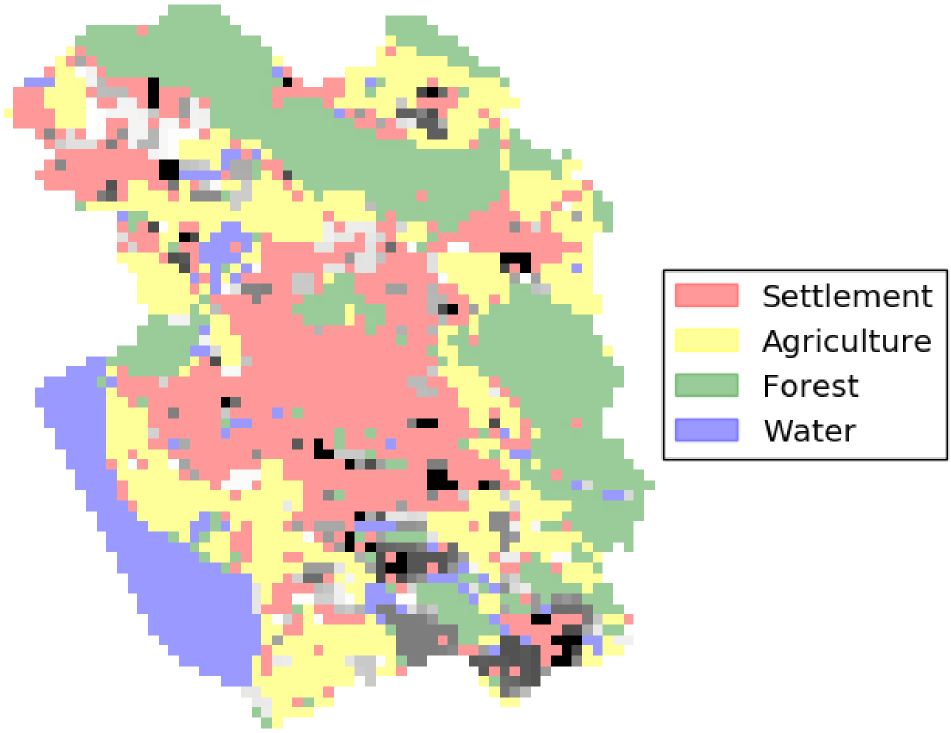

Figure 2: All land-use patterns along the NDF shown in Figure 5 have been analyzed. The frequency with which a raster cell is selected for residential development ranges from white to grey to black, with white being infrequently selected to black being always selected.

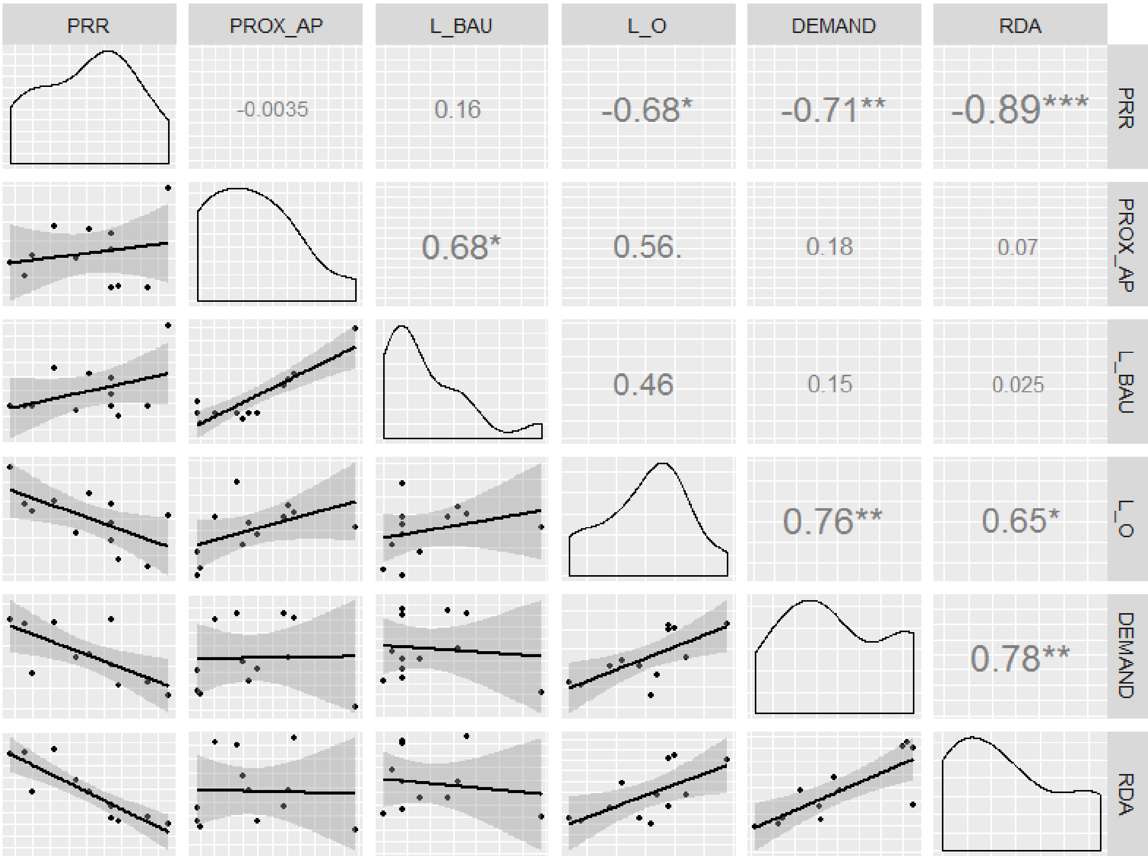

*Figure 3: Pairs plot including all factors displayed in Table 1 (except for AC_1 and AC_2). Below diagonal: Scatterplots and linearly fitted lines with confidence intervals. Diagonal: Density plots. Above diagonal: Spearman correlation coefficients. Significance levels: <0.01 = "***", 0.01<> 0.05 = "**", 0.01<>0.05= "*" ,0.05<> 0.1 = "." , >0.1= " ".*

*Table 2: **PLPA_1**: Mean projected loss of agricultural productivity per hectare in 2050 for stochastic BAU simulations. **PLPA_2**: Mean projected loss of agricultural productivity per hectare in 2050 for an optimized solution that is at least better than the most compact stochastic BAU pattern. **HLLL**: Difference between the NDF solutions with the highest and the lowest loss of agricultural productivity divided by the solution with the highest loss. **HCLC**: Difference between the NDF solutions with the highest and lowest compactness divided by the solution with the lowest compactness **PL_1**: Mean projected loss of agricultural productivity in 2050 for BAU development. **PL_2**: Projected loss of agricultural productivity in 2050 for a solution from the NDF (at least better than the most compact BAU solution). **NC**: Percentage of never chosen cells. **PE**: Point of equal loss in agricultural productivity. Demand allocated in BAU simulation (BAU) and optimally allocated (O) amount/demand of cells.*

	PLPA_1	PLPA_2	HLLL [%]	HCLC [%]	PL_1 [%]	PL_2 [%]	NC [%]	PE	
								BAU [ha]	O [ha]
Hedingen	0.81	0.50	39	33	12	7	78	30	44
Dübendorf	0.77	0.59	27	49	44	34	32	205	256
Meilen	0.68	0.49	35	44	24	17	55	128	169
Uster	0.85	0.59	34	34	19	13	65	212	290
Pfäffikon	0.66	0.45	35	39	12	9	73	105	144
Bassersdorf	0.69	0.55	23	41	23	19	61	82	99
Oberglatt	0.71	0.52	19	40	28	21	59	120	150
Volketswil	0.82	0.68	15	42	39	32	43	213	245
Bülach	0.74	0.60	17	39	40	32	40	201	237
Fehraltorf	0.71	0.48	26	29	10	7	79	56	77
Nürensdorf	0.73	0.47	28	34	12	8	77	62	85
Rümlang	0.77	0.54	23	37	18	12	72	103	140
	MEAN = 0.71	MEAN = 0.54	MEAN = 27	MEAN = 38			MEAN=61	SUM=1517	SUM=1936

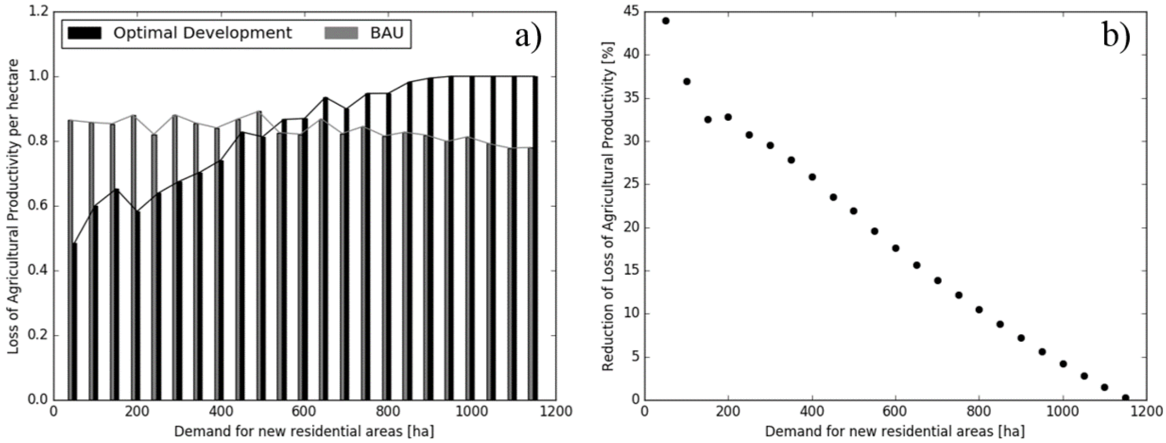

Figure 4 a)-b): Both figures (a-b) were produced for the municipality of Uster. a): Loss of Agricultural productivity per hectare of Optimal and BAU development for increasing demands of new residential areas. b): Potential reduction of Loss of Agricultural Productivity when optimal development replaces BAU development (calculated as the ratio between the difference of loss divided by the loss caused by BAU development).

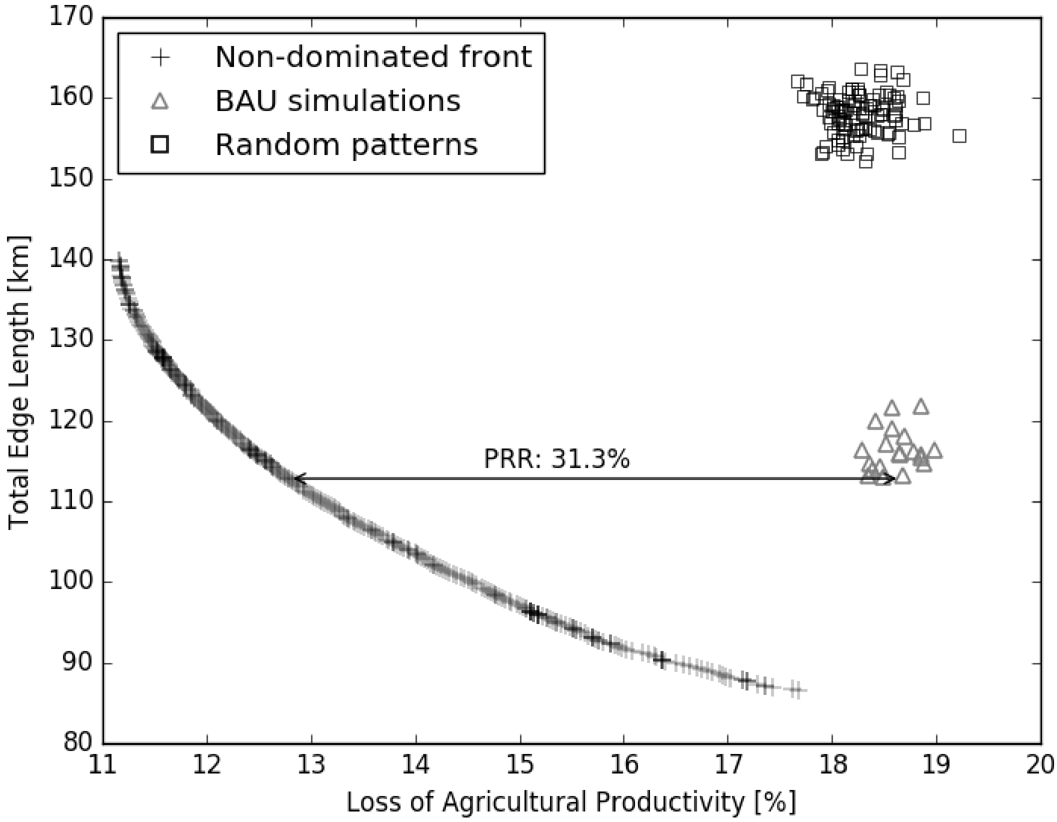

Figure 5: Comparison of objective values of different land-use configurations in the municipality of Uster. Random patterns: 212 residential cells were randomly allocated in 100 simulations. BAU simulations: 212 residential cells were allocated following the Business-As-Usual allocation in 20 simulations (section 2.3). Non-Dominated-Front: 212 pixels were allocated using the evolutionary algorithm (section 2.2.3) The Potential Reduction (PR) of the Soil Quality Loss (SQL) is 31.3%.

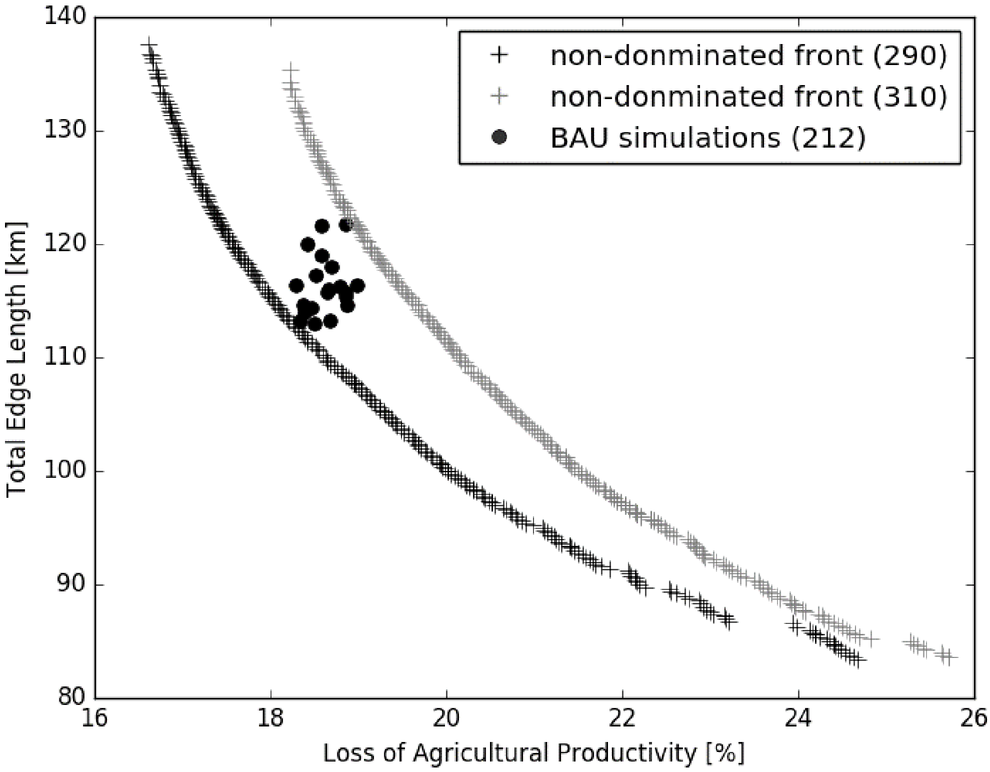

Figure 6: Circular dots represent objective values of BAU scenario simulations for 212 new residential cells. Black cross dots represent the objective values of non-dominated solutions when the land-use pattern is optimized for 290 new residential cells, i.e., yielding more new residential area with better performance on both objectives.. Grey cross dots represent the objective values of non-dominated solutions when the land-use pattern is optimized for 310 new residential cells.

4. Discussion

Our study demonstrates the potential of combining multi-objective optimization and land-use modelling to analyse the trade-offs between compact development and to reduce the loss of agricultural productivity. Using multi-objective optimization we created a set of non-dominated solutions for these two conflicting goals. Analysing the Pareto-optimal solutions in a process of innovization (Deb, 2013), we were able to unveil common patterns of residential development, which may help decision makers in spatial planning to reduce the loss of agricultural productivity. Analysing all 12 municipalities together we were able to show that the potential to improve the current urban development strongly varies, but may be predicted by the demand for new residential areas.

Through modifications of NSGA II, we were able to produce fronts of non-dominated solutions that had a wide and even spread. However, for such a non-smooth and non-linear multi-objective optimization problem, it is difficult to guarantee that the obtained solutions are truly Pareto-optimal. However, the converging behaviour of NSGA-II (Deb et al., 2002) and the converging of all runs are a good indication that the obtained solutions are close to the true Pareto Front.

4.1. Conflict between compact development of residential areas and agricultural productivity

Our analysis shows that fertile soils in the case study region are often close to settlement boundaries and less fertile soils are often more distant from them. This may be explained by the fact that most current settlements originated from smaller agricultural hamlets that were mainly established in or next to fertile areas (Satterthwaite et al., 2010, European Commission, 2012, Martellozzo et al., 2015). Our results further show that current allocation of residential areas (BAU) is likely to be close to existing settlements in the Canton of Zürich. This ensures a compact development of urban areas. However, as there is a positive correlation between proximity to settlements and suitability for agricultural productivity in most municipalities of the Canton, the current development of residential areas can conflict with the goal of reducing the loss of agricultural productivity. Accordingly, the analysis of all 12 municipalities showed that the destruction of agricultural productivity per hectare of new development is higher in municipalities with a high correlation between proximity to settlements and agricultural productivity. This could lead to the conclusion that these municipalities should be prioritized with respect to protecting agricultural productivity. However, while the Business-As-Usual development destroys a lot of good agricultural productivity sites in these municipalities, the potential for improving the pattern does not seem to be higher than in other municipalities.

4.2. Potential reduction of loss of agricultural productivity in different municipalities

The potential to reduce the relative loss of agricultural productivity (PRR) was highest in municipalities with low demand for new residential areas. This can be understood when considering the fact that in every municipality there is a certain amount of areas that are well suited for agricultural productivity and a certain amount that are not. In an attempt to reduce the loss of agricultural productivity, the optimization algorithm selects all areas that can be converted into urban without a high trade-off between compactness and agricultural productivity. When allocating small amounts of new residential areas, the algorithm will mostly be able to select areas that have a relatively low agricultural productivity score. However, when allocating additional residential areas, most areas with a low score will already have been selected and will not be available anymore. Thus, the loss per hectare increases for optimal development, while it stays constant or even slightly decreases for the BAU development. Accordingly the potential to reduce the loss of agricultural productivity will decrease with increasing demand. However, when trying to find out in which municipalities the potential reduction is high, a more suitable indicator than the absolute demand is the ratio between the absolute demand and the amount of agricultural land available for a conversion into residential areas (RDA). This is confirmed by the strong correlation between RDA and PRR (Figure 3). The most appropriate explanation seems to be that the same demands in a small and a large municipality will result in different trade-offs. In small municipalities there will be less areas that can be converted into urban without a high trade-off between compactness and agricultural productivity than in larger municipalities.

The fact that demand (DEMAND) and the ratio between demand and available agricultural land (RDA) were good indicators for the potential reduction of loss of agricultural productivity may be transferable to other land-use allocation problems including other objectives and constraints. If this finding was indeed generalizable it may be a simple indicator that could be used in very different spatial planning contexts. More importantly though, we were able to show that small demands signify that there is a larger potential for optimal configurations. Thus, any policy efforts may be most effective, if they do not only focus either on configuration or demand, but on both. Last but not least, it may be most efficient to initiate policy changes in municipalities with a low ratio between demand and available agricultural land, as we can expect low trade-offs between compactness and loss of agricultural productivity in these municipalities.

4.3. Reducing the loss of Agricultural productivity taking into account the results from the multi-objective optimization

Our analysis of the obtained fronts of non-dominated solutions shows that for every municipality there are certain areas that were chosen to become residential, regardless of the location of a solution on the trade-off front. Such areas within the planning region should become residential no matter how differently the objectives are weighed. In contrast to areas that are always chosen, areas that never occur in the solutions of the obtained NDFs should have higher priority for protection from conversion. Between these extreme cases, there are some areas that are more or less frequently chosen. As has also been shown by Caparros-

Midwood et al. (2015), these are areas where we can expect smaller trade-offs between different objectives. However, it would be misleading to, after a conversion of the always chosen areas, continue with the next most frequently chosen ones, as patterns will be optimal as a whole, but usually not as a combination of different parts of different optimal patterns. Developing the areas common across all NDF patterns for early development, before starting the time-consuming process of decision-making for balancing different preferences, could be a good ad-hoc strategy.

The average loss of agricultural productivity in the BAU simulations is essentially higher than for optimally configured urban growth patterns. Thus, there is large potential for reducing agricultural productivity loss when urban development is led towards optimal configurations. This simple fact allows for a new perspective on how to reduce the loss of agricultural productivity, as many policies mainly focus on a reduction of the overall amount of new built-up area, which may have many negative social and economic consequences. Instead, it could be very useful to actively shape the configuration of residential development. Depending on how much the soil consumption needs to be reduced, it will, however, often be necessary to address both the land-use composition and configuration at the same time.

When discussing potential future development plans with stakeholders and decision-makers, the shape of the obtained NDF can provide important information. It helps decision makers to adapt their preferences, showing them that for a specific non-dominated solution small losses in one objective could result in a large gain in another objective. Last but not least, optimal patterns can be used to develop policy instruments or to identify which combination of policy instruments can be used to reach these patterns. This could be crucial information for decision makers. For example, not all policy instruments may be accepted by the population, which will make some instruments more attractive than others. Choosing the right policy instrument for actively steering land-use configuration may in particular be difficult as there are often many conflicting (e.g. economic) interests of private land-owners.

In some European countries (e.g. Bulgaria, Czech Republic, Slovakia, Poland and the Lombardy Region in Italy) the conversion of agricultural soils into built-up land requires a fee which depends on a couple of factors including the soil quality (European Commission, 2012). As we have observed, current land-use policies and land-use change mechanisms seem to enforce compact urban patterns, which may destroy large amounts of fertile soils. However, in the same way, any policy that focuses on the protection of good agricultural soils may lead to less compact development. Thus, it may be useful to include several fees that depend not only on soil quality, but also on compactness and possibly on other criteria. However, including a fee on compactness is less straightforward than a fee on soil quality, as the level of compactness that a specific area may provide, depends on its neighbourhood, which will change over time. Thus, to successfully implement a fee or any other policy instrument it may be necessary to first optimize the land-use configuration and afterwards to select instruments that can help us to reach optimal configurations. Defining an optimal land-use configuration in a first step and thereafter selecting suitable policy instruments to reach these configurations has another advantage. Fees are directly related to the objectives we want to address. They influence the land-use configuration (i.e., the decision space) in an indirect way. However, knowing an optimal land-use configuration allows us to use instruments that directly influence the land-use configuration and indirectly influence the objectives. For example, we could use zoning regulations or influence the land-use configuration by strengthening public transport in a region that was depicted as being very suitable for residential development by the evolutionary algorithm.

4.4. Compactness or Sprawl?

Our study showed a strong trade-off between compact residential development and maintaining agricultural productivity. Due to this trade-off, our results also show that there is no such thing as one desirable urban form, because preferences for antagonistic objectives (i.e., different weighting schemes) will require different urban forms. This knowledge adds to one of the conclusion of Ewing and Hamidi (2015), who point out that there are no inherently good or bad urban patterns, only good or bad outcomes. Thus, instead of including an objective that explicitly maximizes compactness it would be more appropriate to include objectives that can be directly related to impacts, e.g. on human well-being or objectives that are directly defined by stakeholders. However, this may not always be possible if data and appropriate models are missing. Thus, it may still be appealing to define a desirable urban form in order to simplify planning processes. If the goal is to derive optimal urban forms we again suggest to rely on innovization (Deb, 2013), i.e., analysing Pareto-Optimal solutions to unveil common properties shared by all of them. Innovization may not only be used to define desirable urban forms, but also in order to understand why some areas are suitable for urban development independently from preferences for antagonistic objectives. However, such an analysis may involve more advanced data mining techniques to analyse and understand the multivariate outcome of the multi-objective optimization process.

Last but not least, it has to be mentioned that the configuration of urban areas does not only influence agricultural productivity, but also food processing, distribution and consumption (Seto and Ramankutty, 2016). Thus, an enhanced objective function aiming at food security should not only take into account agricultural productivity, but also the linkages between urban and food systems.

4.5. From Two to Many Objectives

In this study we used two objectives in our multi-objective optimisation. Although compact urban development and reducing the loss of good quality agricultural soils are two important yet conflicting aspects of the political agenda in many countries and particularly in Switzerland, there are many more objectives that could be included in such analyses (e.g. Ligmann-Zielinska et al., 2008, Caparros-Midwood et al., 2015). With regard to the functions and services provided by soils, there are, for instance, many more (possibly conflicting) objectives covering the whole range of soil functions, such as water retention and support for biodiversity (Glaesner et al., 2014). Determining agricultural land suitability can also be considered as a complex optimization problem in itself, requiring the integration of many different criteria. In order to deal with this problem it is possible to use Multi Criteria Decision Analysis approaches together with Geographical Information Systems (GIS, e.g. Mendas and Delali, 2012, Akıncı et al., 2013). These analysis manage to account for many criteria (i.e., objectives), but they usually require a weighing scheme, showing the preferences for the different criteria, in order to capture the multi-objective nature of the problem and translate it into single objective problem. Recent advances show that using, e.g. a GIS-based Logic Scoring of Preference (LSP) method, can be used for handling many criteria, while at the same time being close to human decision making logic (Montgomery et al., 2016). However, if an a posteriori decision-making process is preferred (Marler and Arora, 2004), or the aim is a post-optimality analysis of trade-off solutions, it may be useful to first find all possible solutions and afterwards use a methodology to include stakeholder preferences. It is still computationally challenging to find all possible solutions to multi/many – objective optimization problems within an acceptable amount of time. However, recent extensions of NSGA-II (such as NSGA-III, Deb and Jain (2014)) and other evolutionary multi/many-objective optimisation approaches (such as MOEA/D, Zhang and Li (2007)) exist and have shown to handle as many as 15 objectives. Thus, our two-objective approach can be extended to include other important objectives in our study as a future research. In addition, we aim at integrating the current methodology into a more user-friendly decision support tool. Until now, applying the multi-objective optimization approach we used, requires a good expertise in the field of evolutionary computation.

5. Conclusions

In this study, we have optimized urban patterns including two criteria: compact urban development and reduction of agricultural productivity loss. The suggested modified NSGA-II procedure has been able to find smooth and widely spread trade-off solutions to the problem, thereby providing the decision-makers a wide range of alternative solutions trading-off the two conflicting objectives of the problem.

Analysing the obtained urban patterns of all trade-off solutions exhibits inherent and intelligent sub-strategies which can eventually lead to developing “best practices” principles for the urban planning problem. One such strategy would be to develop all areas, where urban development is optimal no matter how we weight the different objectives.

Our results show that we can find compact urban patterns that strongly reduce the loss of agricultural productivity. However, these patterns may be very different from the patterns emerging through business-as-usual development and reaching them may require severe changes of current land-use policies. To effectively reduce the loss of agricultural productivity, policy changes have to influence both, the future amount of open-land being converted into urban and the configuration of future urban areas. The potential of reducing the loss of agricultural productivity within a municipality is likely to be high if the demand for new residential areas is low.

The multi-objective optimization methodology, a subsequent post-optimality analysis and including results from business-as-usual development, which we demonstrated in this paper, should attract attention from urban planners and our future efforts will be spent on working with real decision-makers to develop a more pragmatic urban planning and decision-making methodology.

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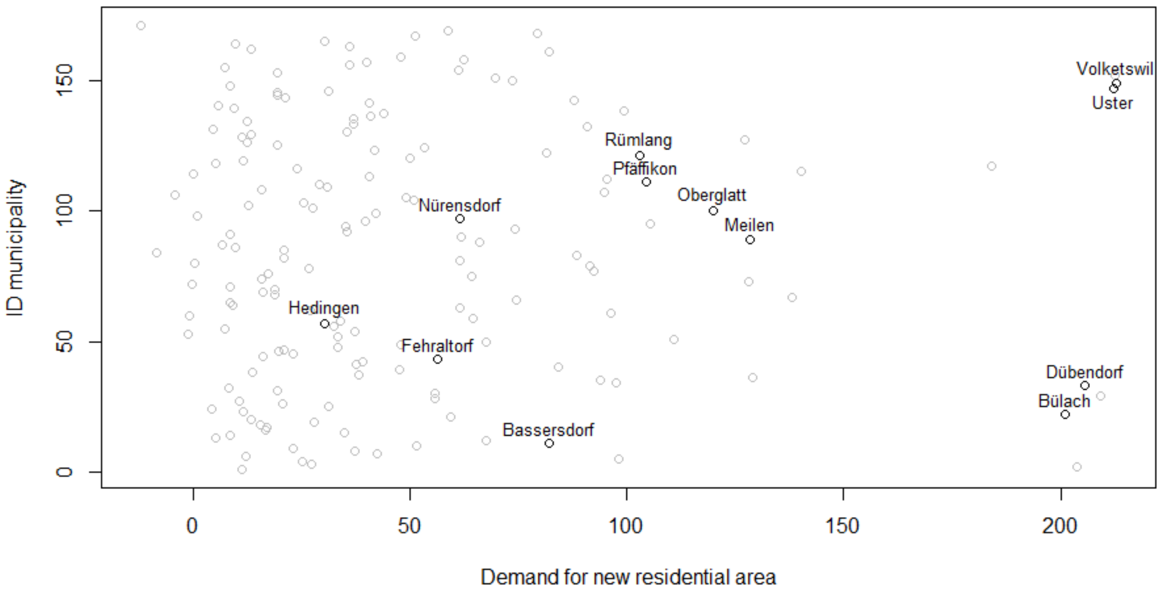
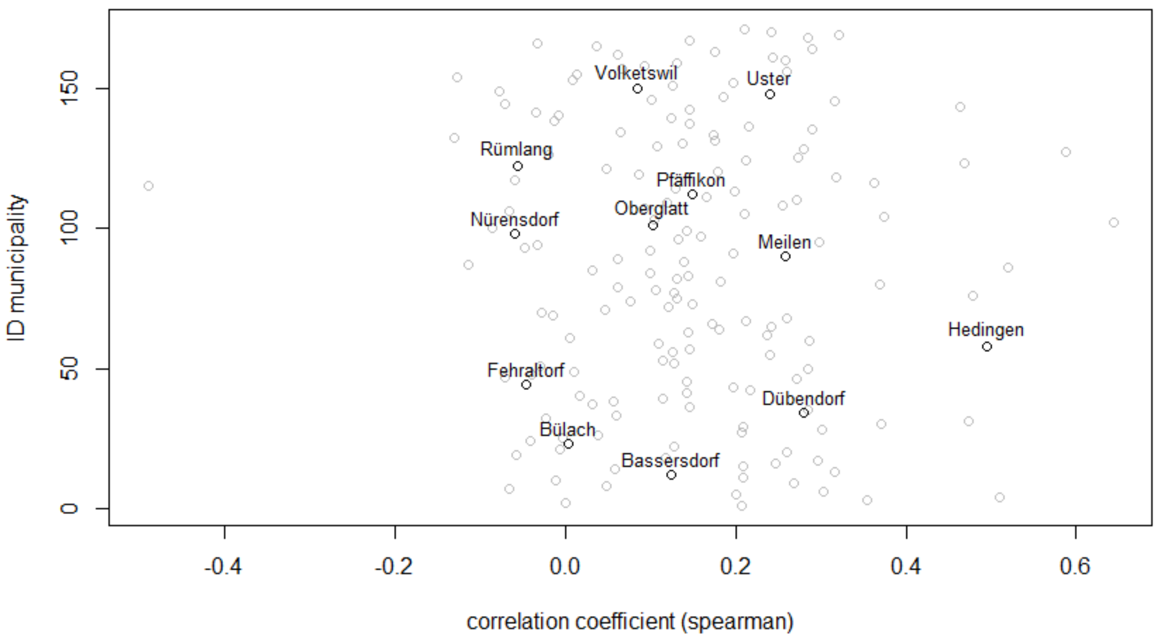
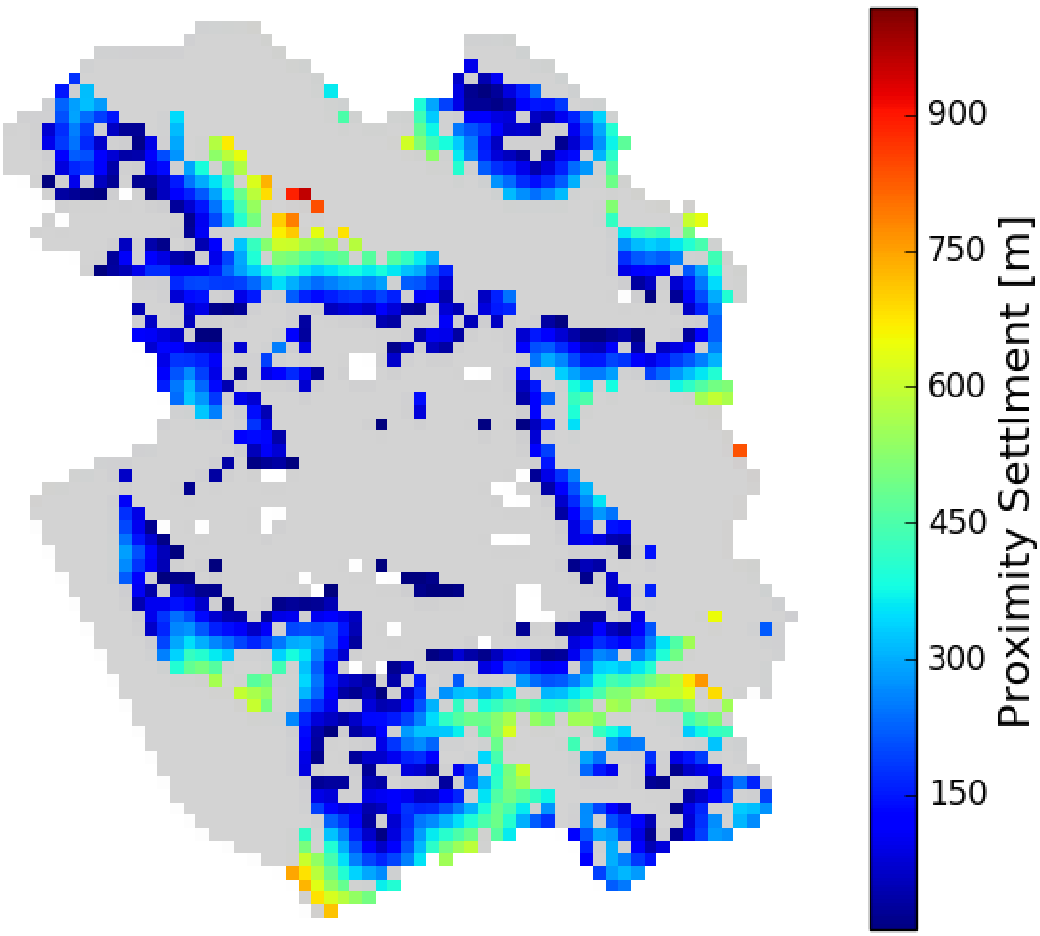
8. Appendix



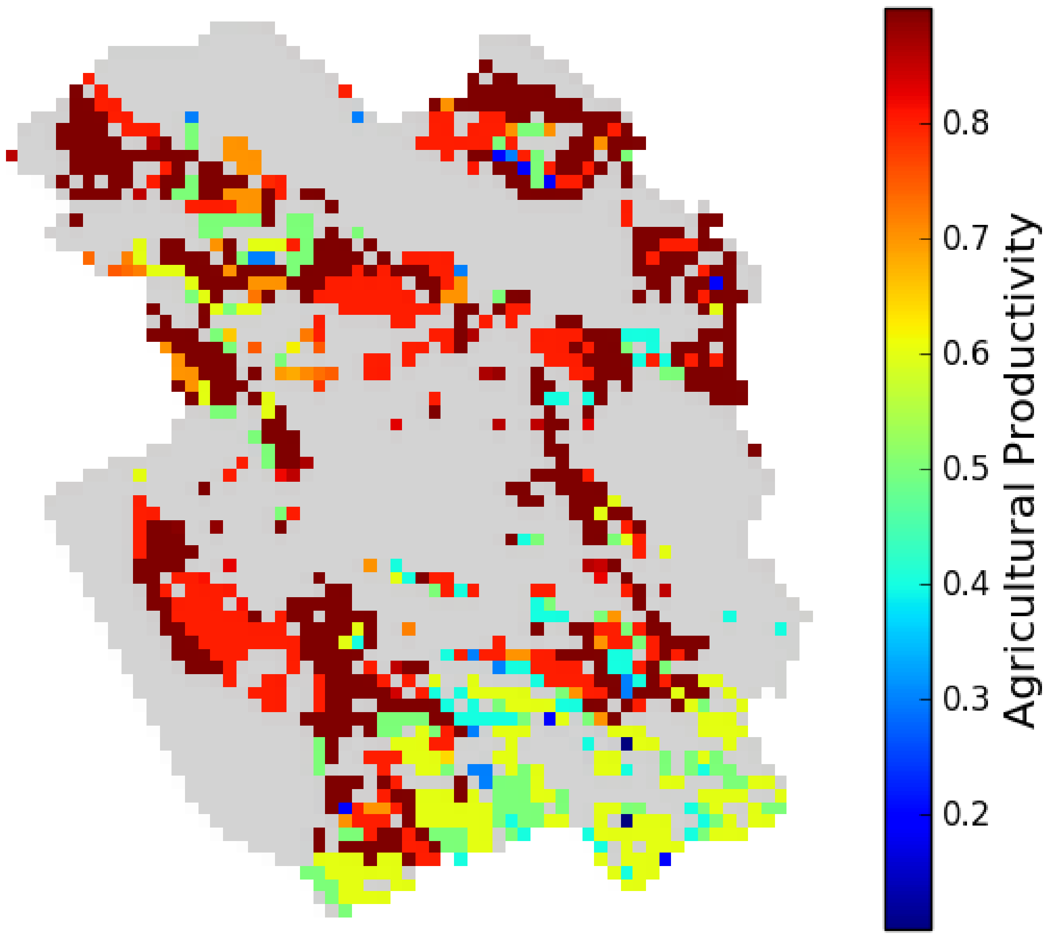
Appendix, Figure 1: Grey dots: Demand for new residential area for every municipality in the canton of Zürich. Black dots with labels: Municipalities which were selected as part of the study area.



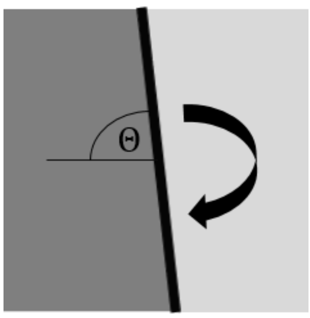
Appendix, Figure 2: Grey dots: Correlation coefficients for the correlation between proximity to settlement and agricultural productivity in every municipality in the canton of Zürich. Black dots with labels: Municipalities which were selected as part of the study area.



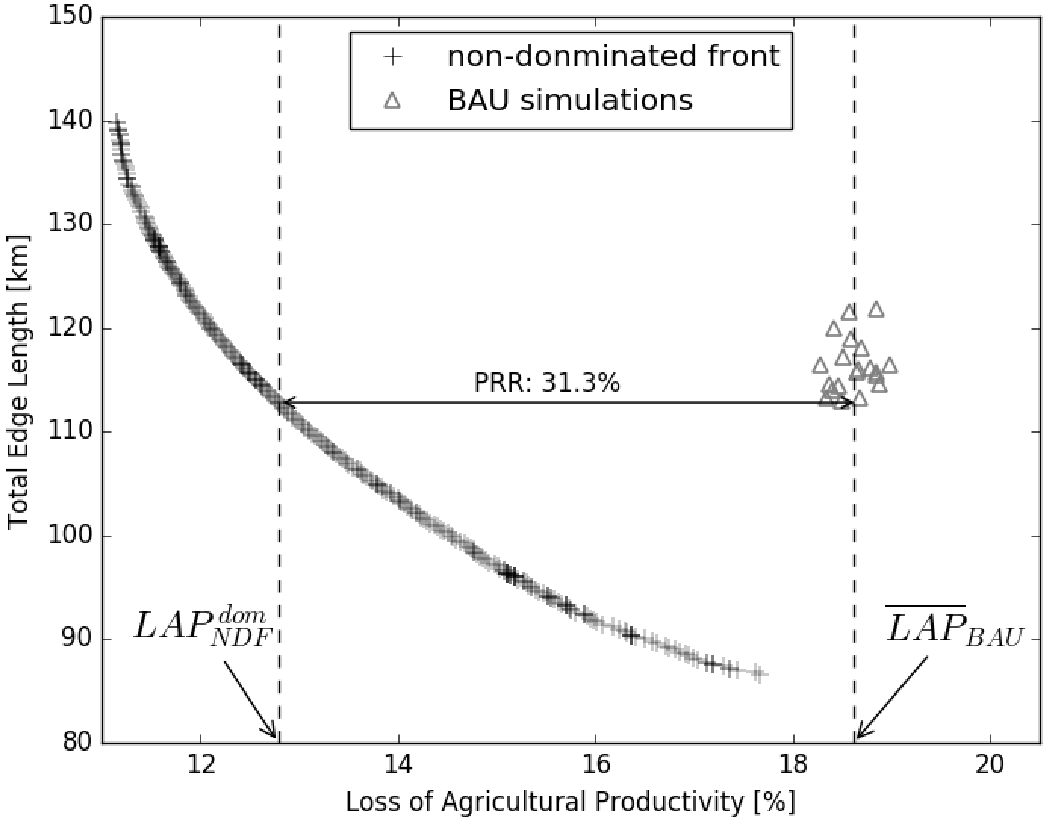
Appendix, Figure 3: Proximity to settlement in the municipality of Uster - calculated as the Euclidean distance from the edge of settlement patches. The definition of settlement patches is derived from the topographical landscape model of Switzerland (VECTOR 25), excluding detached buildings (e.g. farms).



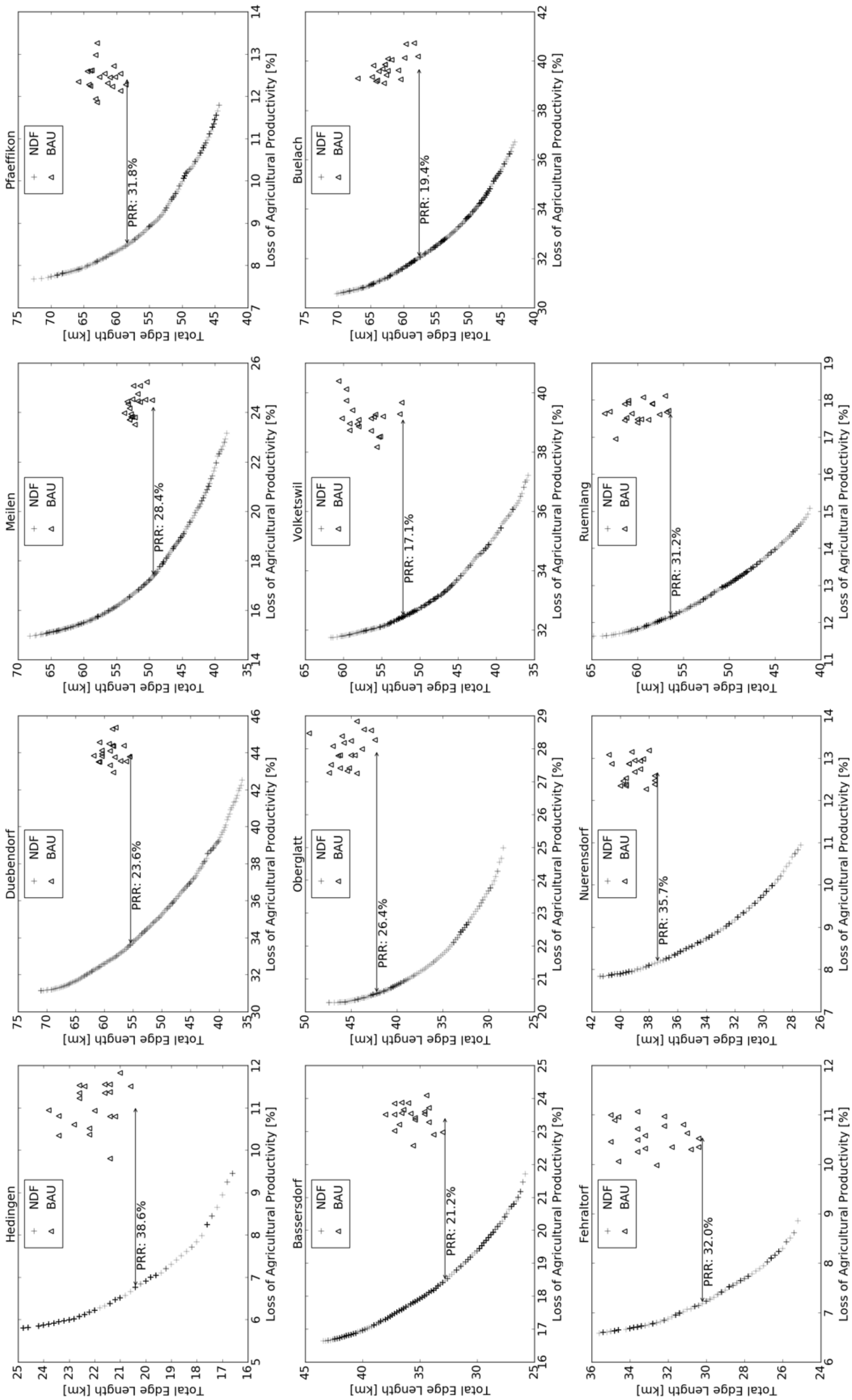
Appendix, Figure 4: Agricultural productivity ranked between 0.1 and 0.9 in the municipality of Uster. All non-agricultural areas are grey.



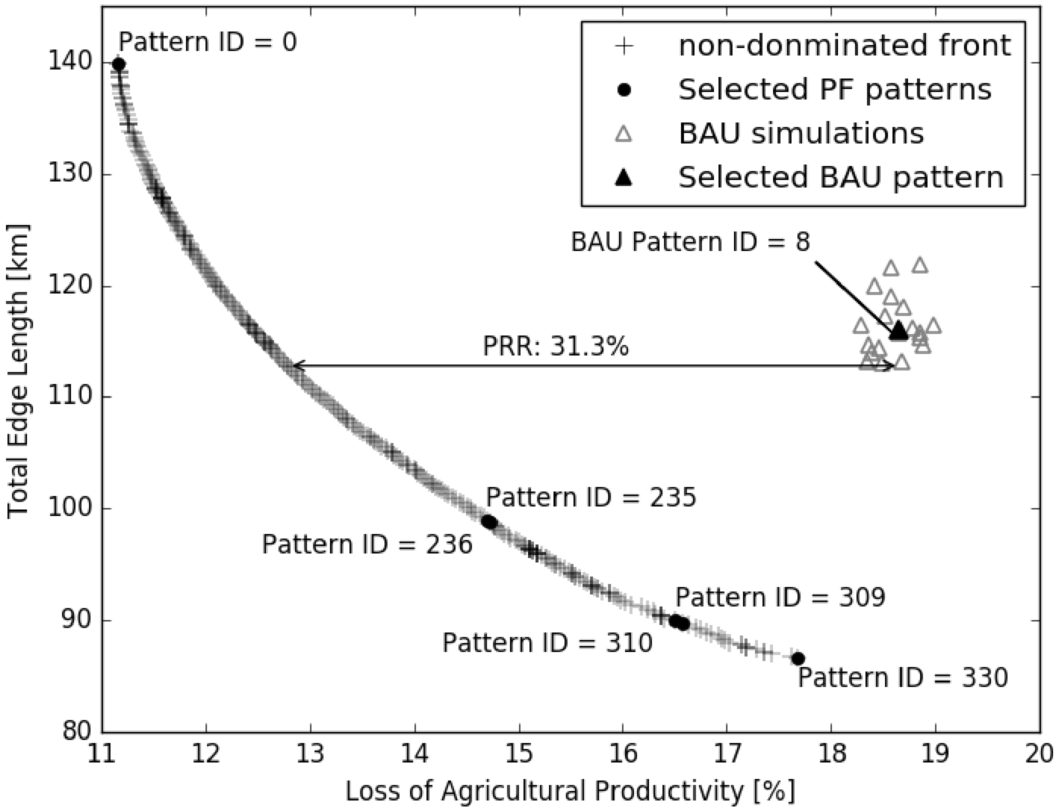
Appendix, Figure 5: Crossover bisecting landscape into two halves. Angle Θ between the border of the two segments and a horizontal line varies randomly between 0° and 180°.



Appendix, Figure 6: Graphical illustration of the variables $\overline{LAP}_{BAU}$ *and* LAP_{NDF}^{dom}.

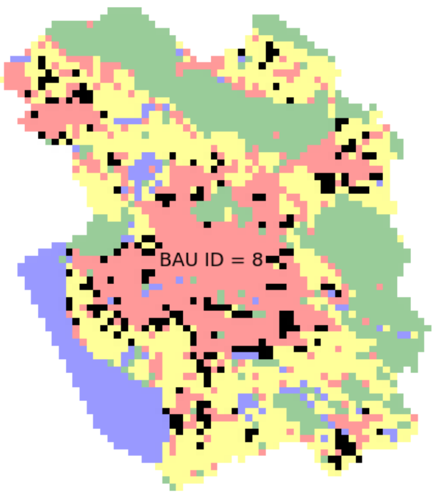


Appendix, Figure 7: Non-dominated fronts of optimized development of residential areas and Business-As-Usual development of residential areas for each municipality.



Appendix, Figure 8: NDF and the results from the BAU simulations in the municipality of Uster. The patterns of selected solutions (indicated as Pattern ID = 0, 235, 236, 309, 310, 330) are shown in the Appendix, Figure 9. The pattern of a selected solution of the BAU simulations (BAU Pattern ID=8) is also shown in the Appendix, Figure 10. The Potential Reduction (PR) in loss of agricultural production is shown as the percentage in difference between the mean loss of agricultural production in the BAU simulations and a solution at the NDF that dominates all BAU solutions in compactness.

Appendix, Figure 9: Solutions constituting the Pareto Front (selected Pattern ID 0, 235, 236, 309, 310 and 330, see Appendix, Figure 8). Black = 212 ha of residential areas allocated in the optimization process. Red = Settlement (2009). Yellow = Agricultural areas (2009). Green = Forest (2009). Blue = Water (2009).



Appendix, Figure 10: Simulated BAU development of residential areas until 2050 (selected BAU Pattern ID = 8, see Appendix, Figure 8). Black = new residential areas, Red = Settlement (2009). Yellow = Agricultural areas (2009). Green = Forest (2009). Blue = Water (2009).

*Appendix Table 1: Column1: Tested explanatory variables. Column 2: Regression coefficients. Column 3: Standard errors. Column 4: P-values (based on a likelihood ratio test (test statistic: Chi-square) when comparing the full model with reduced versions, i.e., dropping one variable at a time). Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1. Column 5: Type of variable, either categorical or continuous. Column 6: First aid transformations applied to the explanatory variables (Appendix, Supplement 2). Column 7: Independent effects calculated based on hierarchical partitioning (Appendix, Supplement 2).*

Explanatory Variable	Coef.	Std. err.	P (>Chi)	Type	First aid	Inde-pendent effects
Intercept	-4.67	208.29	-			-
Utility Services (US)	0.19	0.05	0.00***	Continuous	Log	11.1
Slope (SLOPE) Slope2 Slope3 Slope4 Slope5	 0.24 0.37 0.42 1.0	 0.11 0.18 0.33 1.10	0.07.	Categorical	-	1.2
Motorway Access [MA]	-	-	-	Continuous	Log	-
Public Transport (PT) PT1 PT2 PT3 PT4 PT5 PT6	 1.02 1.12 1.62 1.64 1.78 1.73	 0.24 0.19 0.19 0.21 0.27 0.41	0.00***	Factor	-	15.4
Distance to big Rivers (DR) DR1	-	-	-	Factor	-	-
View (VIEW)	-	-	-	Continuous	arcsin	-
Noise (NOISE)	-0.02	0.01	0.02*	Continuous	-	3.0
Aspect (ASP) Asp2	 -0.17	 0.09	0.07.	Factor	-	1.8
Distance to big lakes (DBL) Dbl2 Dbl3 Dbl4 Dbl5	 -0.96 -1.18 -1.32 -0.98	 1.07 1.04 1.04 1.04	0.06.	Factor	-	2.7
Distance to medium size lakes (DML)	-	-	-	Factor		-
Distance to small lakes (DSL)	-	-	-	Factor		-
Distance to public green space (DPGS)	-	-	-	Factor	-	-
Distance to high voltage power line (DHVPL)	-	-	-	Factor	-	-
Proximity (Distance) to settlements (DS)	-0.79	0.03	0.00***	Continuous	-	35.7
Distance to roads category 01 (DR1)	-0.04	0.02	0.14			3.0
Distance to roads category 02 (DR2)	-0.33	0.02	0.00***			20.2
Distance to roads category 03 (DR3)	-0.10	0.02	0.00***			2.3
Tax (TAX)	-	-	-	Numeric	-	-
Mean global radiation (MGR)	-	-	-	Numeric	-	-

Municipality Typology (MT)			0.00***	Factor	-	3.3
MT1	6.27	208.29				
MT2	6.86	208.29				
MT3	7.18	208.29				
MT4	6.48	208.29				
MT5	6.45	208.29				
MT6	7.37	208.29				
MT7	6.88	208.29				
MT8	6.96	208.29				

Appendix Table 2: Description of the explanatory variables in Appendix Table 1.

Predictor Variable	Description
Utility Services (US)	Amount of utility services within a distance of 1000 m. Utility services were calculated based on the census of enterprises in Switzerland (Swiss Federal Statistical Office (BFS) Geostat, 2008) and classified according to Altwegg (2014).
Slope (SLOPE)	Slope, 5 categories [in percent]: 0:10->1; 10:20->2, 20:30->3, 30:50->4, >50->5
Motorway Access [MA]	Path distance to motorway access.
Public Transport	Quality of public transport, 6 categories from very good to not existent based on estimations of the office of transport of the canton of Zürich (Kanton Zürich, 2017).
Distance to big Rivers (DR)	Distance to large rivers lower or higher than 100m, 2 categories.
View (VIEW)	Percentage of area that can be seen within a radius of 5 km.
Noise (NOISE)	Noise from aircrafts, streets and railways.
Aspect (ASP)	Aspect, 2 categories: South - North
Distance to big lakes (DBL)	Distance [in m] to big lakes (> 50 ha), 5 categories: <100~1, 100:500~2, 500:2000~3, 2000:6000~4, >6000~5
Distance to medium size lakes (DML)	Distance to medium size lakes (> 2 ha , < 50 ha), 5 categories
Distance to small lakes (DSL)	Distance to small lakes (< 2 ha), 5 categories
Distance to public green space (DPGS)	Distance to public parks, sports facilities and cemeteries.
Distance to high voltage power line (DHVPL)	Distance to high voltage power line lower or higher than 150 m, 2 categories.
Distance to settlements (DS)	Distance to settlements.
Distance to roads 01 (DR1)	Distance to roads being more than 6 m wide.
Distance to roads 02 (DR2)	Distance to roads being 4 m wide.
Distance to roads 03 (DR3)	Distance to roads being 3 m wide.
Tax (TAX)	Average tax burden per municipality.
Mean global radiation (MGR)	Mean global radiation.

Typology of municipalities (TM)	Typology of municipalities, 22 categories (Schuler and Joye, 2007). English translation of the original classes: (1) Large centres, (2) Medium-sized centres, (3) Small centres, (4) Periphery centres, (5) Rich municipalities, (6) Touristic municipalities, (7) Semi touristic municipalities, (8) Municipalities with large amount of public institutions and collective households, (9) Municipalities with high levels of employment in metropolitan regions, (10) Suburban municipalities in metropolitan regions, (11) Periurban municipalities in metropolitan regions, (12) Municipalities with high levels of employment in non-metropolitan regions, (13) Suburban municipalities in non-metropolitan regions, (14) Periurban municipalities in non-metropolitan regions, (15) Commuter municipality with high increase in population, (16) Commuter municipality with low increase in population, (17) Industrial tertiary municipalities, (18) Industrial Municipalities, (19) Agro-industrial municipalities, (20) Agricultural an tertiary municipalities, (21) Agricultural municipalities, (22) Municipalities with strongly decreasing population

Appendix, Supplement 1: Factors that were calculated for every municipality.

$$\overline{LAP}_{BAU_g} = \frac{1}{n}\sum_{k}^{n} LAP_{BAU_{g_k}} \tag{4}$$

$$PR_g = LAP_{NDF_g}^{dom} - \overline{LAP}_{BAU_g} \tag{5}$$

$$PRR_g = \frac{PR_g}{\overline{LAP}_{BAU_g}} \tag{6}$$

$$L\_BAU_g = \overline{LAP}_{BAU_g} \tag{7}$$

$$L\_O_g = \frac{LAP_{NDF_g}^{dom}}{\frac{1}{a}\sum_i^a LAP_{g_i}} \tag{8}$$

$$PROX\_AP_g = \frac{\sum_{i=1}^{a}(PROX_{g_i} - \frac{1}{a}\sum_i^a PROX_{g_i})(LAP_{g_i} - \frac{1}{a}\sum_i^a LAP_{g_i})}{\sqrt{\sum_{i=1}^{a}\left(PROX_{g_i} - \frac{1}{a}\sum_i^a PROX_{g_i}\right)^2}\sqrt{\sum_i^a\left(LAP_{g_i} - \frac{1}{a}\sum_i^a LAP_{g_i}\right)^2}} \tag{9}$$

Variables:

n	number of BAU simulations for every municipality (i.e, 20)
m	number of selected municipalities (i.e., 12)
a	number of agricultural cells in the selected municiaplity
LAP	Loss of Agricultural Productivity
BAU	Business-As-Usual
NDF	Front of non-dominated solutions
g	municipality
LAP^{dom}	LAP value of the solution with minimal LAP selected from the part of the NDF that dominates all BAU solutions.

Appendix, Supplement 2: BAU modelling approach.

The suitability map (i.e., the likelihood of new agricultural areas being converted into residential areas) was based on a logistic regression model calibrated using information on previous land-use/land-cover (LULC) changes in the Canton of Zürich as a response variable, which were derived from differences in the Swiss area statistics between 1997 and 2009 (Humbel, 2009). A binary response variable was created by reclassifying the LULC classes for agricultural land that remained agricultural land (no change) and agricultural land that changed to residential area (change). As predictor variables, we tested a range of biophysical and socio-economic factors that may have a significant influence on residential location choice (Schirmer et al., 2014). According to exploratory data analysis and the rules of thumb provided by Mosteller and Tukey (1977) we employed several first-aid transformations to some of the predictor variables (Appendix Table 1).

In total there were 172883 observations available (171681 no change events and 1202 change events). According to King and Zeng (2001) it can be useful to apply so-called endogenous stratified sampling when one of the values in a binary response variable is underrepresented. We thus randomly selected 10803 events from all no-change observations. All change observations were used. Based on that sample, we calculated the logistic regression parameters using a classical maximum likelihood estimation (McCullagh and Nelder, 1989) and reduced the amount of predictor variables using stepwise backward selection based on the Akaike Information Criterion (AIC Sakamoto et al., 1986).

In order to determine how many hectares of new settlements had to be allocated, we had to quantify the demand for new residential areas. The demand until 2050 was estimated based on forecasts of population growth and the residential area per capita in every municipality, which is an approach that has been widely use in the literature (Hoymann, 2011, Arsanjani et al., 2013). For population forecasts, we used data on population development between 1981 and 2014 in every municipality and an automated process for time series forecasting relying on ARIMA models (Hyndman and Khandakar, 2008). The area per capita was estimated by dividing the sum of residential areas in every municipality (based on the Swiss area statistics 2004/2009) with the average population from 2004-2009. We assumed that the area per capita increases linearly at the same rate as it did between 1985 and 2009.

In the final step of our model, new residential areas were allocated to the raster cells in our study area. Raster cells that were converted into residential areas were selected based on the following analysis steps. First, we selected from all the existing agricultural areas single cells (seeds) and we drew a potential patch size for the new building site. The likelihood for a certain patch size to be drawn was derived from the distribution of sizes of new patches according to changes in the Swiss area statistics between 1979/85 and 2004/09. This approach is a simple adaptation of the approach proposed by Meentemeyer et al. (2013) and follows the idea of pattern-oriented modelling (Grimm and Railsback, 2012). Second, selected seeds and neighbouring cells (in case the selected patch size was larger than one) were converted to the LULC class "residential" until the selected patch size was reached. For selecting neighbouring cells we searched for agricultural cells in the Moore neighbourhood of the seeds (or the most recently allocated cell) and randomly selected one of these cells for allocation. Selection of seeds and patch sizes was implemented as a stochastic process. Thus, every simulation of the model produced different land-use configurations and accordingly different objective values.

Chapter 4

Using multi-objective optimization to secure fertile soils across municipalities

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In Preparation

Abstract

Globally, large amounts of agricultural land are transformed to urban land, which has far-reaching impacts on the soil's capacity for agricultural production. In order to protect fertile agricultural land and guarantee food security in regions that are strongly affected by urban growth, it is crucial to use and design appropriate policy instruments. In Switzerland, as well as in many other countries worldwide, one of the most important instruments for steering urban development is zoning. Zoning regulations are usually implemented at local governance levels and have proven to effectively account for externalities. Although a local zoning implementation may be useful in many contexts, it may not be appropriate for protecting agricultural soils. In order to determine whether zoning across municipalities could lead to a better protection of fertile agricultural soils, we developed an innovative approach based on multi-objective optimization. Using this approach we were able to quantify the trade-off between reducing the loss of agricultural productivity and obtaining compact urban development patterns for a local and a regional zoning scenario. We showed that cooperation between municipalities is useful at two different stages in the decision-making process. Firstly, municipalities should cooperate when they define their environmental and socio-economic development goals and how they rank their preferences concerning different goals. Secondly, municipalities should cooperate when deciding on how much agricultural land is allowed to be converted into urban land. These results are valuable in two different respects. Firstly, they allow decision-makers to understand if regional zoning may significantly reduce the loss of agricultural productivity and should thus be favoured over local zoning. Secondly, understanding which possibilities of cooperation there are (i.e. at which stage and to which extent) may help decision-makers to frame and institutionalize cooperation between municipalities in the right way.

1. Introduction

Urbanization is a global phenomenon and a threat to many ecosystem services and the soil's capacity for agricultural production (Millennium Ecosystem Assessment, 2005, FAO and ITPS, 2015b). These impacts are largely irreversible on human time scales (Gregory et al., 2015, Amundson et al., 2015). According to Seto et al. (2012) urban land cover will increase by 1.2 million km² between 2000 and 2030, which means that urban areas will nearly triple in size. The large increase in urban land caused can be explained by an increasing population and an increasing per capita demand for floor-area (Angel et al., 2011, Bradbury et al., 2014).

Although urban expansion is observed at unprecedented pace (Seto et al., 2012), it may have a relatively small effect on the total area of available cropland, as cropland covers more than 12% of the Earth's ice-free terrestrial surface and urban land less than 3% (Ramankutty et al., 2008). Thus, the loss of cropland due to urban expansion is sometimes considered more of a regional problem with possible global implications (Seto and Ramankutty, 2016, FAO and ITPS, 2015a). According to the FAO and ITPS (2015b) land take and soil sealing are the greatest threat to soil functions in Europe and Eurasia. In Switzerland, urban areas increased by 23.4 % between 1985 and 2009, which caused a more than 5 % loss of agricultural land in the same period (Bundesamt für Statistik, 2013).

Concerns about food security are not only caused by the total amount of urban expansion (Gardi et al., 2015), but also by the fact the most fertile soils are often located in areas facing high urban growth (Imhoff et al., 1997, EEA, 2006, Afifi et al., 2013, Salvati, 2013, Li et al., 2015, Martellozzo et al., 2015). Schwaab et al. (2017b) have shown that there is trade-off between compact (i.e., contiguous) development of urban areas and the reduction of the loss of fertile agricultural soils in many municipalities in Switzerland. In other words, compact development of settlements and cities is usually accompanied by an important loss of agricultural productivity. As the compact city has become a leading concept in urban planning worldwide (Duany et al., 2000, Haaland and van den Bosch, 2015) and also in Switzerland (Rudolf et al., 2017), many fertile agricultural soils may disappear or deteriorate not just because of the amount of urban expansion, but also because of the form and location of urban expansion.

In order to protect fertile agricultural land and guarantee food security in regions that are strongly affected by urban growth, it is crucial to use and design appropriate policy instruments. Policy instruments used to steer urban development can be broadly classified as regulatory or incentive-based instruments (Bengston et al., 2004, Nuissl and Schroeter-Schlaack, 2009). Examples of incentive-based instruments are tradable development rights or taxation. In the regulatory approach, urban development is often controlled by the setting of growth boundaries or the implementation of so-called zoning, which restricts certain land use to a defined area (Hirt, 2007). Zoning is one of the most important instruments for steering urban development worldwide (Light, 1999, Hirt, 2013). Although different forms of zoning exist, zoning regulations are most commonly implemented by local governments at the municipal level.

The implementation of zoning rules at the local level has proven to be effective. However, it may be questioned whether an implementation at a larger scale could also be useful or even more effective when it comes to the protection of fertile soils. Mainly focusing on economic and socio-political aspects, Slack and Bird (2013) summarize the advantages of local governance structures as being efficient, responsive and accountable, whereas the advantages of higher-level governance structures are the general advantages related to economies of scale, the ability to account for externalities and a higher capacity to deliver and coordinate services. In conclusion, answering the question which governance structure is the most useful, is not straightforward and will always be context-specific.

For restructuring governance at the municipality level, one possible option is the amalgamation of municipalities. This leads to a very strong transfer of administrative power. Compared to amalgamation, there may be better options for restructuring governance, as has been shown by Slack and Bird (2013). Such options involve inter-municipal cooperation, which may rely on generic cooperative agreements with a wide scope of intervention, but without any delegation of powers or supra-municipal authorities, which rely on the constitution of a supra-municipal tier of government to which functions are delegated (OECD, 2014).

In Switzerland, zoning has been in use since the adoption of the Spatial Planning Law in 1980 and is considered the most important instrument for steering the location of new building areas (Gennaio et al., 2009). The decision on building zones allocation is taken by the municipalities. However, according to article 15 of the federal spatial planning law, which entered into force in May 2014, municipalities are obliged to collaborate on zoning decisions. Yet, we are not aware of any examples of such collaboration between municipalities. A reason for this lack could be that it is unclear which form of cooperation across municipalities would be effective and appropriate. Another reason may be the lack of knowledge on the benefits of higher-level planning. For instance, the protection of fertile soils could potentially benefit from higher-level planning, but evidence to support or disprove this hypothesis has yet to be provided.

In order to quantify the impact of different planning levels and forms of cooperation, computer-based modelling can be helpful. In general, the impact of policy changes on land-use/land-cover changes (LULCC), e.g. a shift from local to regional zoning, can be estimated using land-use change models, of which there exist a large variety(Verburg et al., 2004, Silva and Wu, 2012). Zoning may be introduced into these models either as a driver or as a constraint (e.g. Geneletti, 2013). The aforementioned models are usually concerned with the impact of zoning on land-use change and not with a sustainable or optimal allocation of zones. For optimally allocating zones a variety of spatial planning support tools has been developed. These tools involve, e.g., multi-criteria decision making (e.g. Grêt-Regamey et al., 2016) or evolutionary algorithms that perform a multi-objective optimization to find optimal solutions for the allocation of zones (Liu et al., 2012, Shao et al., 2015). In the latter studies, the results of optimisations provide decision-makers with normative solutions. These normative solutions can provide decision-makers with a perspective on which solutions they could possibly reach are can thus strongly enhance decision-making. However, (multi-)objective optimization may not only be used as a normative tool, but also in order to mimic fully rational behaviour. This may be the behaviour of planning agents at local or regional levels and may allow to simulate the effect of a change in governance structure.

In this study, we will analyse whether zoning decisions at a regional level can better protect agricultural productivity (i.e., the most fertile soils) than zoning decisions at a local level. To quantify the differences in agricultural productivity between local and regional zoning, we use a multi-objective optimization algorithm for allocating building zones. We optimize two objectives: (i) maximal compactness of urban areas and (ii) minimal loss of agricultural productivity. First, we optimize zoning locations within the administrative boundary of four separate municipalities. Second, we optimize zoning locations for the aggregated area of the four municipalities. In order to compare the two different scenarios (i.e., local vs. regional zoning), we develop a method for quantifying the loss in agricultural productivity. We use the two terms local and municipal as well as the two terms regional and supra-municipal interchangeably.

2. Methods and data

2.1. Study area

Our study sites consist of four municipalities (i.e. Fehraltorf, Pfäffikon, Uster and Volketswil) in the canton of Zürich, Switzerland. The region consists of a mix of towns and villages, agricultural land and forests (Figure 1). The populations of these four municipalities are predicted to grow strongly in the coming decades (a growth of 15-30% between 2015 and 2035), mainly due to their proximity to the city of Zürich, resulting in a strong increase in residential area. The expected strong increase in residential area will mainly be at the expense of large amounts of agricultural land, since forests are highly protected in Switzerland (Bloetzer, 2004). The four municipalities are neighbours to each other and may thus be potential candidates for a supra-municipal planning strategy of allocating building zones in order to protect agricultural productivity.

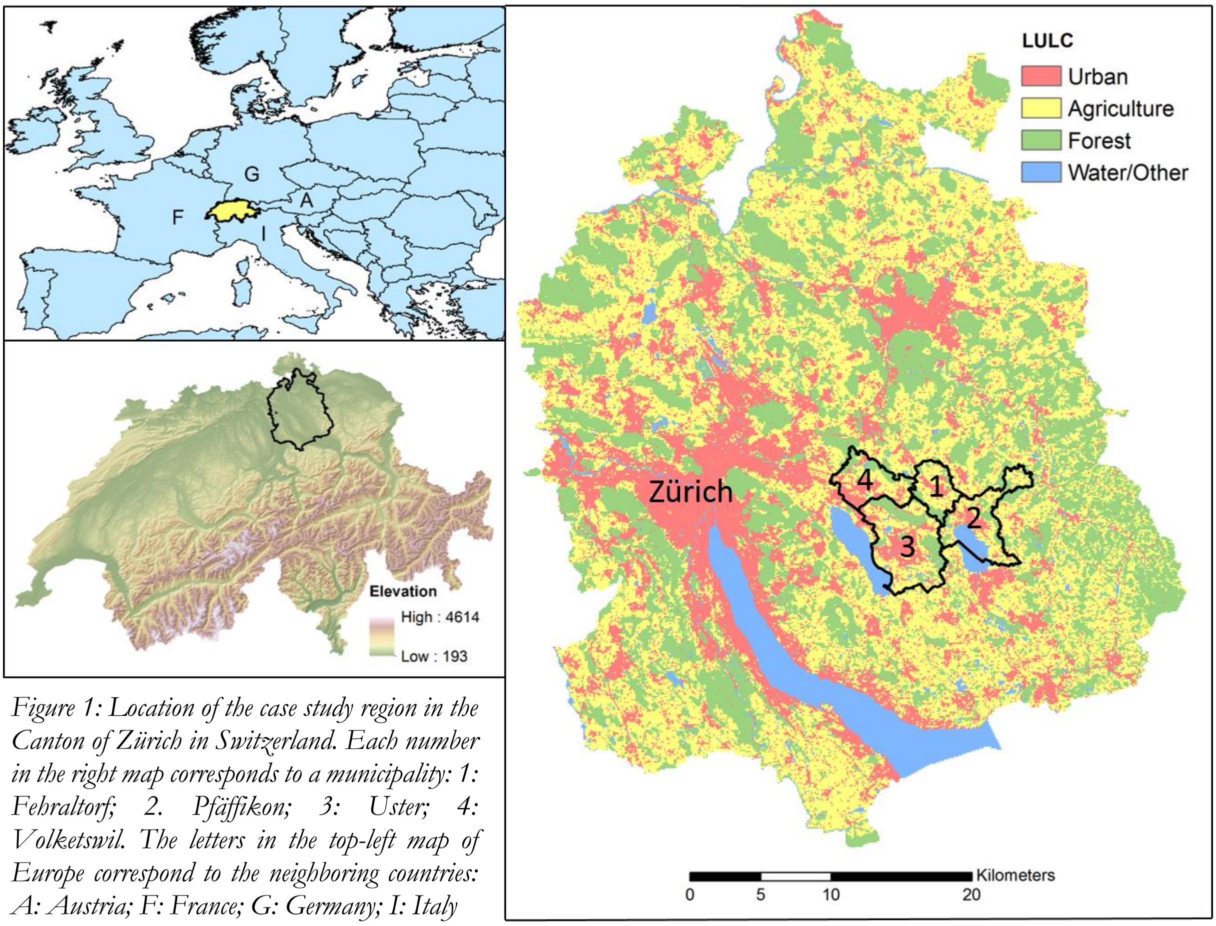

Figure 1: Location of the case study region in the Canton of Zürich in Switzerland. Each number in the right map corresponds to a municipality: 1: Fehraltorf; 2. Pfäffikon; 3: Uster; 4: Volketswil. The letters in the top-left map of Europe correspond to the neighboring countries: A: Austria; F: France; G: Germany; I: Italy

2.2. Local and regional zoning

We define local zoning as the allocation of building zones at a municipal level, whereas with regional zoning building zones allocation is at a supra-municipal level. Although the Swiss law on spatial planning requires municipalities to plan across administrative boundaries, the actual planning practice has focused on the allocation of new building zones at the municipality level. With zoning at the local level, every municipality takes into account the future demand for new residential areas and accordingly allocates the necessary amount of new building zones at specified locations (UVEK, 2014). The demand for building zones can be approximated by using forecasts on population growth and the average per capita residential area of a person (more details in Supplement A 1). This demand we refer to as the externally defined demand. If there is planning at a supra-municipal level, we assume that the total demand for new building zones is the sum of the demands that were calculated for each municipality. In local zoning the demand for new building areas is an external factor, whereas in regional zoning the urban growth per municipality can be actively regulated by the municipalities involved. The optimal urban growth (in terms of minimal loss of agricultural productivity and maximal compactness of the urban pattern) per municipality can be inferred from the non-dominated front (henceforth referred to as the optimal urban growth) produced in the multi-objective optimization process (section 2.3).

2.3. Simulating the zoning process using multi-objective optimization

The decision-making process leading to the allocation of building zones is complex and usually involves a variety of stakeholders with diverging interests (Fischel, 2015). We decided to use multi-objective optimization to simulate the process of allocating building zones for two reasons. 1.) Planners usually have to weight various goals against each other when distributing building zones. Two important criteria for selecting new zones in Switzerland are settlement compactness and minimal loss of fertile soils (Law on Spatial Planning, RPG 2016). As has been shown by Schwaab et al. (2017b), there is often a trade-off between these criteria. Since we do not know the outcome of the decision-making process, i.e., the expressed preferences and the weighing of the two criteria, multi-objective optimization provides the possibility to compare many different potential solutions. 2.) The optimization process can be understood and used as a mimicking of fully rational planners that try to find the best solutions under given conditions.

The aim of multi-objective optimization is to find the so-called Pareto Front, which contains all Pareto optimal solutions. A solution is Pareto optimal if the value of one objective can only be improved in trade-off with the value of at least one other objective (Pareto, 1896). We are using a stochastic optimization algorithm (i.e. an evolutionary algorithm) to approximate the solutions to the optimization problem as there are not exact methods to solve the multi-objective optimization problem formulated in this study (e.g. Aerts et al., 2003). As we are only approximating the set of optimal solutions, there is no guarantee that the true Pareto Front is found. Thus, in this study we will mostly speak of the non-dominated front, which expresses the fact that the solutions obtained with the used algorithm may not be truly Pareto optimal, but are at least not dominated by any other solution that we evaluated.

We considered two objectives for the optimization. The first objective was to minimize the loss of agricultural productivity. The second objective was to maximize compactness of the urban area. To calculate the loss of agricultural productivity we used a raster map of the suitability of land for agricultural production (Kanton Zürich, 2012). The raster map has a 100 m spatial resolution and was initially produced in 1998 and was updated in 2012. In this map, the suitability for agricultural production mainly depends on the soil characteristics, but also on climatic indicators and the topography (Jäggli et al., 1998). As many soil functions are irreversibly deteriorated when agricultural areas are partly or completely sealed (e.g. Burghardt, 2006), we assume that all existing agricultural productivity is lost, when agricultural land is converted into urban land. Accordingly, the loss of agricultural productivity was calculated by dividing the sum of the lost agricultural productivity (i.e. all areas converted to urban) by the total amount of available agricultural productivity (Figure 2). To maximize compactness we calculated the total edge length of all urban cells. Edges were either counted when they were in neighbourhood to any other LULC class than urban or when there was no information about the LULC class in the direct neighbourhood (e.g., at the edge of the LULC map, Figure 2).

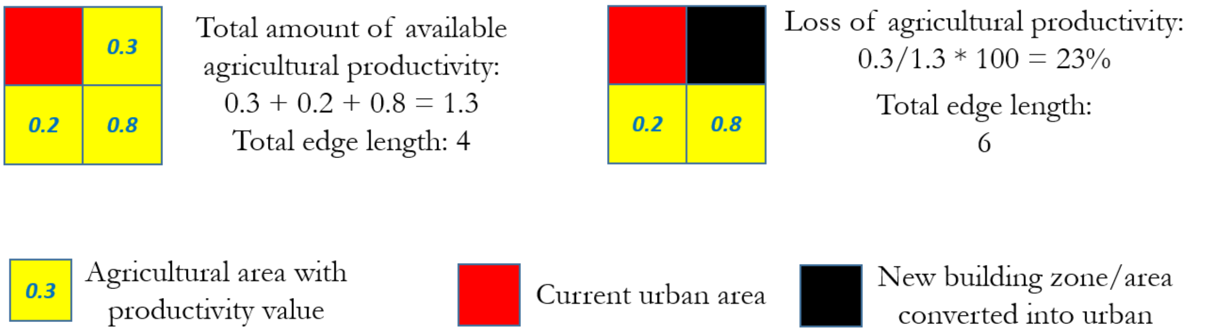

Figure 2: Simplified representation of how the two objectives are calculated.

To solve the multi-objective optimisation problem of maximizing compactness while minimizing the loss of agricultural productivity, we used the elitist Non-dominated Sorting Genetic Algorithm (NSGA II, Deb et al., 2002). We chose this algorithm because of its modularity, freedom from parameters and population approach. We modified the recombination and mutation operators to suit our specific optimisation problem and implemented the algorithm using the python framework "Distributed Evolutionary Algorithms in Python" (DEAP, Fortin et al., 2012). For more information on genetic algorithms, we refer to Goldberg (1989) and Deb (2002).

Modifications of the crossover and mutation operators were mainly used to account for the spatial nature of the problem. For the crossover we split the parent solutions into two halves by a line through the centre of the municipality with randomly varying angles, which is similar to an approach that has recently been applied for a spatial optimisation problem (Ryerkerk et al., 2012). The mutation process used in our modified genetic algorithm was basically a combination of uniform and biased mutation operators. For biasing the likelihood of an agricultural cell to be converted into urban, we included heuristics in order to find the most compact urban patterns (further details of this approach can be found in Schwaab et al. (2017b) and Schwaab et al. (2017a).

Based on test simulations, we decided to use a population size of 100. At each generation we copied all non-dominated solutions to an external archive while removing all dominated solutions from the archive. To monitor the performance of the optimization process, we calculated the hypervolume indicator at each generation (Zitzler, 1999). We terminated the algorithm after 15,000 generations for the local zoning simulations and after 60,000 generations for the regional zoning simulations. For the regional zoning simulations, more generations were necessary due to the relatively high number of possible solutions compared to local zoning simulations. For example, in the municipality of Uster there are 1164 ha of agricultural land, which can be selected for 212 ha of new urban areas, which results in approximately 10^{238} possible solutions. For the four combined municipalities, the agricultural area amounts to 3013 ha and there are 586 ha of urban land to be allocated, which results in 10^{642} possible solutions.

2.4. Comparison of local and regional zoning

To simulate local and regional zoning, we used largely the same multi-objective optimization algorithm. However, for local zoning optimisations, we allocated the number of building zones for each municipality independently. This meant to run the optimization four times, allocating 56ha of building zones for the municipality of Fehraltorf, 105 ha for Pfäffikon, 212 ha for Uster and 213 ha for Volketswil. For the regional zoning optimizations the demand was the sum of these four demands. Thus, for regional zoning, we ran the optimization one time and allocated 586 ha of building zones within the region.

Whereas, the local zoning simulations result in four different non-dominated fronts (i.e. one for each municipality/each optimization run), the regional zoning simulation results in one front. To facilitate a comparison of local and regional planning we had to combine the fronts from the local zoning. For this purpose, we selected 11 or 12 solutions (depending on the municipality) from each of the four non-dominated fronts. Each of the selected solutions was indexed, starting from 1 for the solution with the lowest loss in agricultural productivity, until reaching 11 or 12 for the most compact solution. The selected solutions are approximately equally distributed across the non-dominated front (more details on the process of selecting solutions from each front can be found in Supplement A 2 and Figure A 2). We took the sum of all possible combinations of the selected solutions, which show the compactness and the loss of agricultural productivity summed up for all four municipalities. This way the objective values could be compared between the local and regional zoning simulations.

After comparing the objective values for the regional and the local simulations, we compared the amount of agricultural areas converted into urban areas for the regional and the local zoning simulations. For the regional zoning simulations, the amount of agricultural areas converted into urban areas for every municipality was implicitly determined by the optimization process and depended on the preference between compactness and the reduction of loss of agricultural productivity (i.e., on the location on the non-dominated front). We inferred the amount of new urban area per municipality for each solution at the non-dominated front, in order to understand how the amount of urban area determined by the optimization process differed from the amount predicted by the population growth model.

In addition to the comparison of the local and the regional zoning simulations, we analysed in more detail the differences of the local solutions. For this purpose we calculated the standard deviation of the index combinations of the local solutions. The index of each solution is a measure for the location on the non-dominated front. Thus the standard deviation of the combination of the four indices is an indicator for the similarity of the solutions in terms of loss of agricultural productivity and compactness.

3. Results

3.1. Local vs regional zoning

3.1.1. Form of Cooperation: Consultation on preferences

For the local zoning simulations, there were 19,008 possible solutions. From these solutions, only approximately 1.2% were dominant, while the other 98.8% of the solutions were not (Figure 4). This means there were combinations of solutions that were optimal at the regional level, however, most of them were not. The difference between the objective values of the dominated (non-optimal) and the dominant (optimal) solutions was often small. However, there were solutions that caused a loss in agricultural productivity that is about 10% higher than the loss of a dominant solution with a very similar level of compactness (Figure 4). If municipalities decided independently from each other about the allocation of new building zones (i.e. local zoning simulations) ,the solution were found to be non-optimal compared to the regional zoning simulations. This meant that the level of compactness was lower and the loss of agricultural productivity higher than necessary.

Our results show that the standard deviation of the indices of the combined single optimized solutions were lower for dominant solutions than for dominated solutions (Figure 5). In other words, we found that most of the dominant solutions were obtained, when combining solutions from similar parts (i.e., with a similar level of compactness or loss of agricultural productivity) of each of the four fronts. This means that it is more likely that the solution will be optimal or closer to optimal when the preferences of the municipalities are similar. If all municipalities select a rather compact solution or all of them select a solution with a low loss of agricultural productivity, it is more likely that the solution is optimal than when the municipalities have distinct preferences (e.g. some prefer strong reduction of loss of agricultural productivity while others prefer a compact solution). For example, when Fehraltorf selects solution 8, Pfäffikon selects solution 8, Uster selects solution 7 and Volketswil selects solution 9, the overall solution becomes dominant (Figure 4). The standard deviation of this index combination is approximately 0.7. If the municipalities select, e.g., the solutions 1 (Fehraltforf), 4 (Pfäffikon), 12 (Uster) and 12 (Volketswil), the overall solution is non-dominant (Figure 4) and the standard deviation is approximately 4.9. However, while the likelihood that the overall solutions are dominant is higher, if municipalities have the same or similar preferences, there is no guarantee that these solutions will be dominant. For example, the overall solution composed of the solutions 8 (Fehraltorf), 8 (Pfäffikon), 8 (Uster), and 8 (Volketswil) is non-dominant.

3.1.2. Form of Cooperation: Consultation on the amount of growth and preferences

When simultaneously optimizing the area of the four combined municipalities (i.e. the regional zoning simulation), the loss of agricultural productivity triggered by the allocation of new building zones varies between 19 % and 12 % depending on the level of compactness (Figure 4). The loss of agricultural productivity in the local zoning scenario varies between 20 % and 15 % (Figure 4). This means that the loss of agricultural productivity in the regional scenario for equally compact solutions is relative to the loss in the local scenario approximately 12 % to18 % lower.

Zoning at a regional level clearly has the potential to achieve more compact development that results in less loss in agricultural productivity than zoning decisions at local level. However, optimally distributing building zones at the regional level means that the optimal urban growth in each municipality can differ from the externally defined demand. While the externally defined demand amounts to 105 in the municipality Pfäffikon, the optimal urban growth varies approximately between 200 and 330 (Figure 8). Externally defined demands in Uster and Volketswil are mostly higher than the optimal urban growth and in Fehraltorf the externally defined demand is approximately equal to the optimal urban growth. The optimal urban growth in Pfäffikon is highest, because there are a lot of agricultural areas with a soil quality lower than that in the other three municipalities. However, the optimal urban growth strongly varies in each municipality depending on the preferences (i.e., the location on the non-dominated front). For compact solutions, the amount of urban growth attributed to the municipality of Fehraltorf strongly decreases, while it clearly increases in Uster and Volketswil. This means that there seems to be a relatively small trade-off between compactness and the loss of soil quality in the municipalities Uster and Volketswil.

4. Discussion

4.1. Local or regional zoning?

The quantification of a local and a regional zoning scenario could help decision makers to decide whether to shifting planning practices from a local approach to a regional approach is worthwhile. Comparing the local and the regional zoning front, it can be argued that the question whether a change in planning practices is worthwhile, depends on the preferences of the municipalities. When reducing the loss of agricultural productivity is given a much higher preference than maintaining compact urban development, the difference in loss of agricultural productivity between the local and the regional zoning scenario, i.e., the scenario in which the form of cooperation involves an agreement on the amount of urban growth, adds up to more than 18%. If compactness is much more important than the loss of agricultural productivity, the gain in compactness will be less than 7%. On the one hand, a strong focus on reducing the loss of agricultural productivity, can thus be more beneficial than a focus on compactness and a motivation to initiate a change from local to regional zoning. On the other hand, if compactness is of high importance, even a small gain in compactness may be considered sufficient to changing planning practices.

4.2. Form of cooperation

We have shown results for two possible forms of cooperation, which could help decision makers to decide for one of the forms. If the cooperating municipalities would cooperate when deciding on the amount of urban growth in each municipality the loss of agricultural productivity can be much stronger reduced than when they are cooperating concerning their preferences. However, cooperating on the amount of growth may involve higher transaction costs (Buitelaar, 2007) than when they are cooperating concerning their preferences. In particular, the cooperation of urban growth may require some form of compensation for municipalities that accept to reduce growth stronger than others.

The form of cooperation also relates to the question on the administrative and legal framework of cooperation. While the cooperation on preferences may be well organized relying on cooperative agreements without any delegation of powers to supra-municipal authorities, the cooperation on urban growth may require a strong transfer of administrative power from the local level to a higher level authority.

4.3. Advantages and disadvantages of using multi-objective optimization to model local and regional zoning

The proposed modelling approach relied on an evolutionary algorithm for solving a multi-objective optimization problem. It quantifies and compares the outcome of a constrained and an unconstrained multi-objective optimization problem. Advantages and disadvantages of this approach are best explored when comparing them to other modelling approaches that can be used to investigate whether cooperation between municipalities is useful in order to protect high quality agricultural soils and guarantee compact urban patterns.

First, we compare optimization approaches with approaches that are not based on optimization. There is a very large variety of models that can be used to estimate land-use change or more specifically urban growth, which can be categorized in several ways (Silva and Wu, 2012). We will limit our discussion to the differences between our optimization approach and two main categories of land-use models which are so-called deductive and inductive approaches (Overmars et al., 2007). Inductive approaches can be described as empirical and being based on observations. These models are usually calibrated using historic data of land-use, which was thus shaped and influenced by the historic socio-economic and political situations. Thus, with inductive approaches it is often difficult to show how non-existing or hypothetical socio-economic or political conditions will affect land-use and spatial planning in the future. An inductive model calibrated using historic data on zoning, is thus not suitable to show how spatial planners can adapt to new conditions. Deductive models that are rather theoretical and process-based may be more useful when simulating future developments under changing conditions. However, while some authors propose that zoning is a result of economic processes (e.g. Pogodzinski and Sass, 1994), spatial planners undoubtedly play a strong and active role in the allocation of new zones as most land-use regulations are specifically designed to account for externalities (Fujita, 1989, Ihlanfeldt, 2009). In contrast to inductive and deductive approaches, using an optimization approach allowed us to mimic a rational planner who tries to optimally allocate resources and is able to adapt to new conditions such as a change from municipal to supra-municipal zoning. While the inductive and deductive approaches aim to model and understand land-use in a truthful way and answer the question how it could or will be, the optimization approach may be considered normative and focussed on answering the question how it should be. It should also be mentioned that a genetic algorithm is able to find optimal solutions for this very complex combinatorial problem we dealt with in this study. In reality, spatial planners may not be fully rational, but bounded rational. This means that they could be limited in the number of options that they can evaluate. Thus, instead of selecting an optimal solution they may rely on heuristics or saticficing (i.e. valuating options until a one is found that is expected to satisfy) when selecting a solution (Schlüter et al. 2017).

Second, we compare multi- and single-objective optimization. Before using single-objective optimization, it is necessary to assess the preferences of stakeholders *a priori* or to translate all objectives into a single objective with a common metric (Marler and Arora, 2004, Miettinen, 2008). After this step a constrained and an unconstrained optimization can be performed and it is possible to decide whether it is worth it removing the constraint. To find a common metric for all objectives may be impossible and determining preferences can be a time-consuming and complex process. These two steps are not necessary, if the decision whether or not it is worth to remove a constraint is based on a multi-objective optimization. As we discussed before (chapter 3.1.2), removing of a constraint can be done depending on an *a posteriori* assessment of preferences of stakeholders that had been provided with the Pareto Fronts of the constrained and the unconstrained optimization problem. However, if a constraint does not cause large differences between the unconstrained and the constrained Pareto Fronts, we can safely conclude that it is not worth removing the constraint without *a posteriori* assessment of stakeholder preferences. This information is important as it can prevent wasting time on a complex decision-making process.

Performing a multi-objective optimization with an *a posteriori* assessment of stakeholder preferences, can also have other advantages and disadvantages. On the one hand, exploring the whole decision space can be computationally challenging and can thus also lead to a lengthy analysis process, as is the case with an *a priori* stakeholder involvement (Purshouse et al., 2014). On the other hand, *a posteriori* decision-making can have the advantage of providing information about the form of the non-dominated front. From this form one can derive the severity of a trade-off between objectives at a specific location in the decision-space, i.e., the rate of change in one objective that is associated with a certain change in another objective. Such information can influence the decision-makers' preferences as a slight decline in one objective can cause a large increase in another objective (Das, 1999).

For future applications the current modelling approach could be extended by including more than two objectives. For example, further objectives in Switzerland may be the preservation of biodiversity (FOEN, 2012) and the reduction of CO_2 emissions caused by land-use change (FOEN, 2017). In addition, it could be verified if the two trade-off fronts are in general closer together for compact solutions than for the ones with lower loss in soil quality, or if this is just the case in the selected study area.

As already mentioned, using an evolutionary algorithm for optimization cannot guarantee finding the true Pareto front. However, the convergence of the hypervolume indicates that we were close to the true Pareto front. Further convergence of the simulated front with the true front may be possible by increasing the number of generations. However, the improvement of the front is expected to be minor, whereas the computational expense strongly increases (Schwaab et al., 2017b).

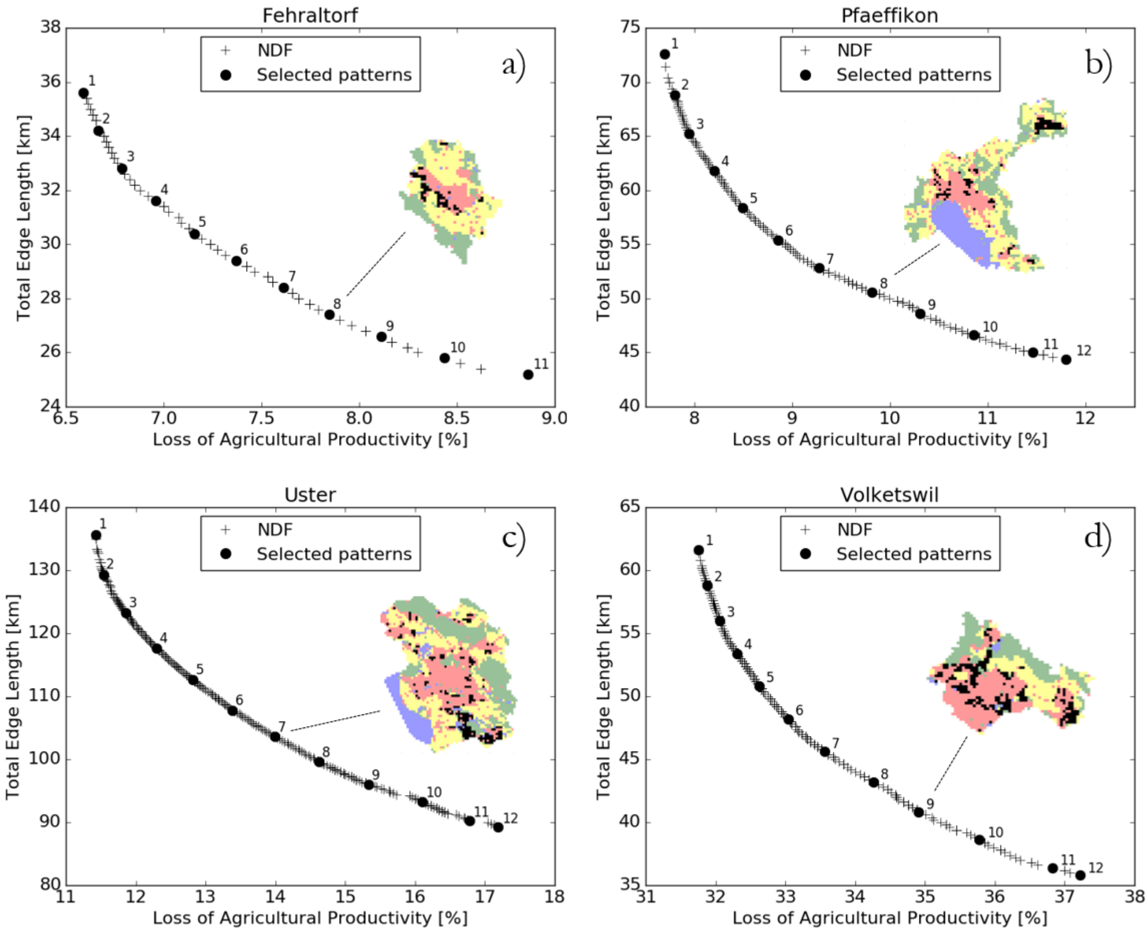

Figure 3: Non-dominated fronts (NDFs) obtained when optimizing the urban patterns in each municipality. The selected patterns were indexed starting with the solution on the upper-left end of the front. These solutions were later used for recombination and producing the local zoning scenarios shown in Figure 4. As an example for the decision space (i.e. the land-use pattern), we show a land-use pattern of one of the solutions in each municipality. The map colours define the different land-use classes: Black = new building zones (allocated in the optimization process), Red = existing urban areas, Yellow = agriculture, Green = forest, Blue = water/other.

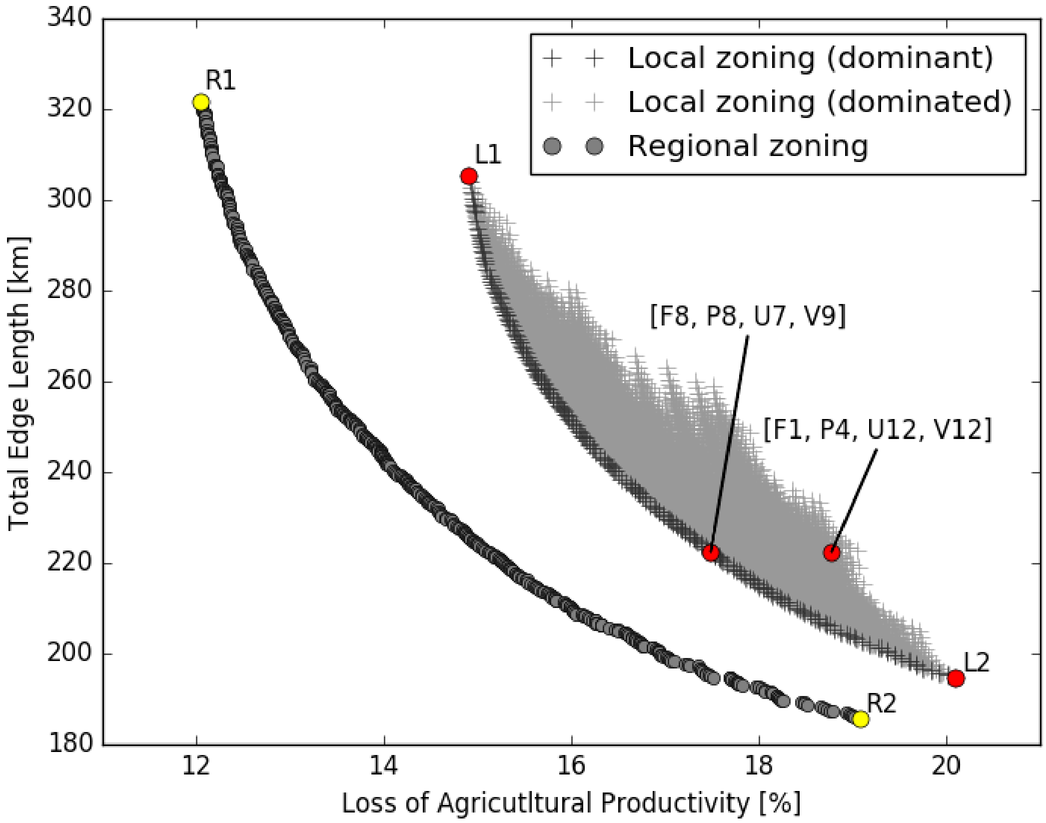

Figure 4: Comparison of regional and local zoning in the solution space. The decision space (land-use patterns) of the highlighted solutions are shown in Figure 6 and Figure 7. The solution with the lowest loss in agricultural productivity in the regional scenario (R 1) and the lowest loss in the local scenario (L1), as well as a comparison of the most compact solution of the regional (R 2) and the local scenario (L 2) are shown in Figure 7. A comparison of a dominant and a dominated solution of the local scenario are shown in Figure 6.

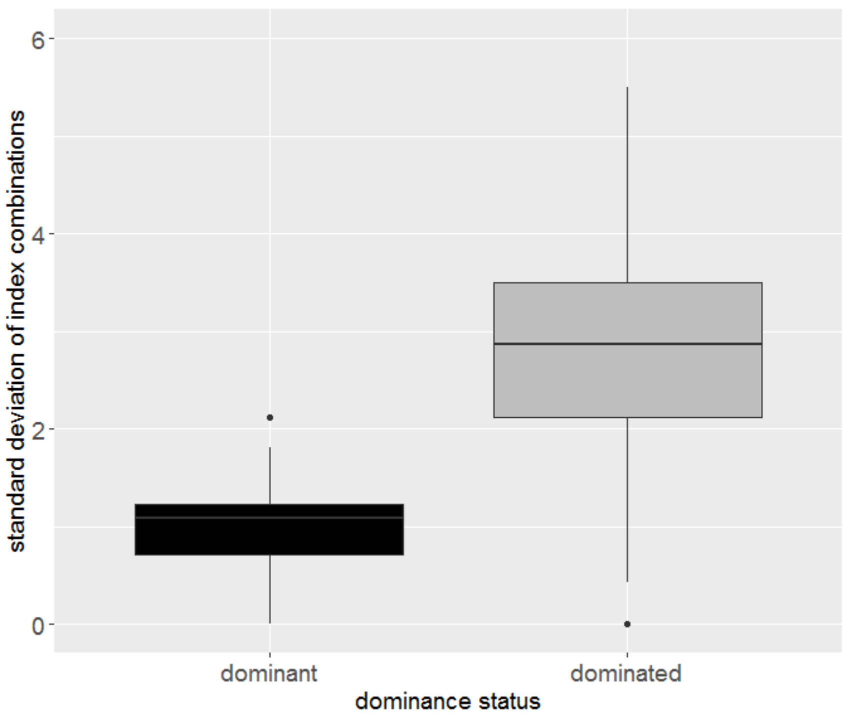

Figure 5: Boxplot showing the standard deviations of the index combinations of all dominant and all dominated solutions.

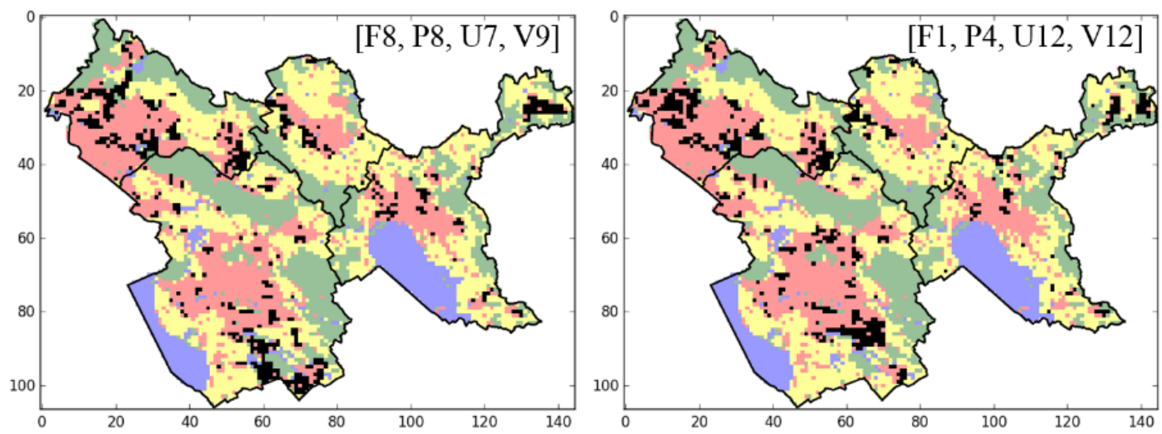

Figure 6: Decision space of a dominant (left) and a dominated solution (right). The two solutions are also displayed in the objective space (Figure 4). Black = new building zones (allocated in the optimization process), Red = existing urban areas, Yellow = agriculture, Green = forest, Blue = water/other.

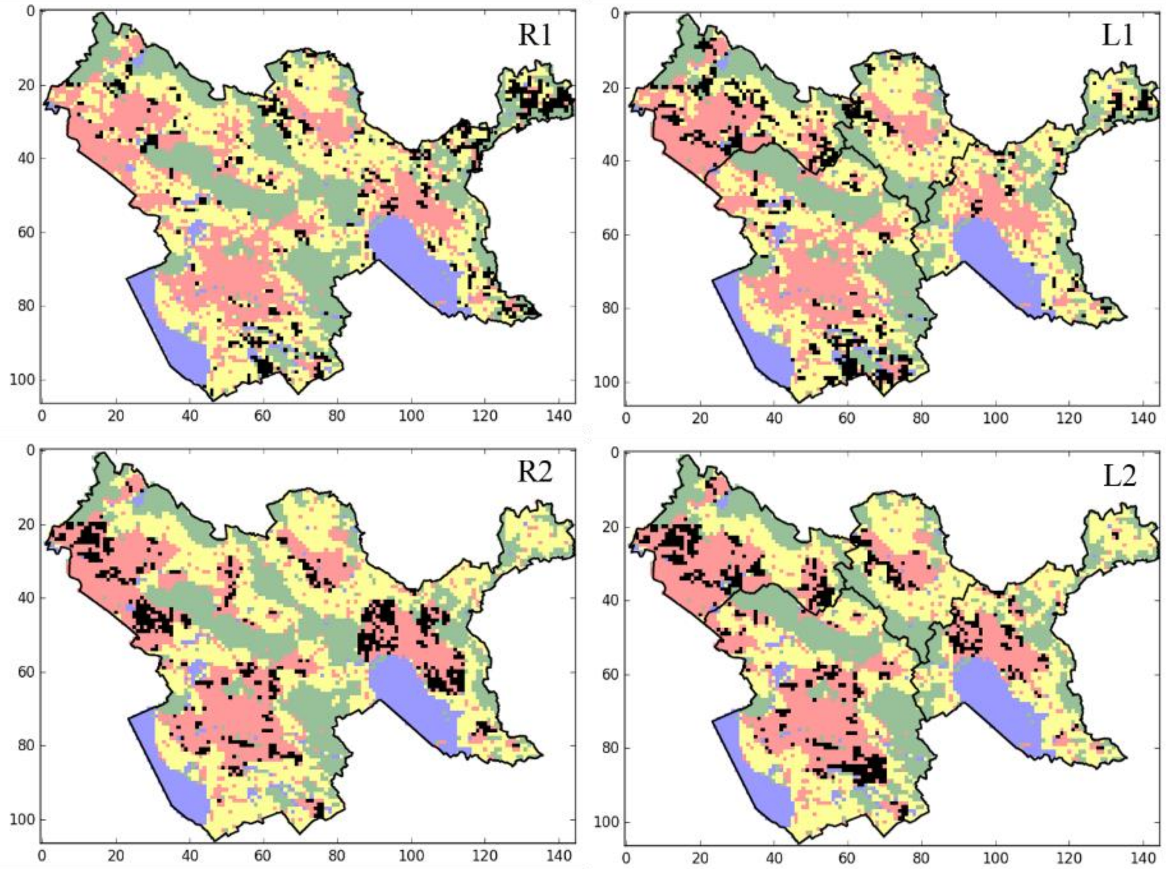

Figure 7: Decision space (i.e., land-use patterns) for two regional and two local zoning scenario solutions. The solutions are also displayed in the objective space (Figure 4). Black = new building zones (allocated in the optimization process), Red = existing urban areas, Yellow = agriculture, Green = forest, Blue = water/other.

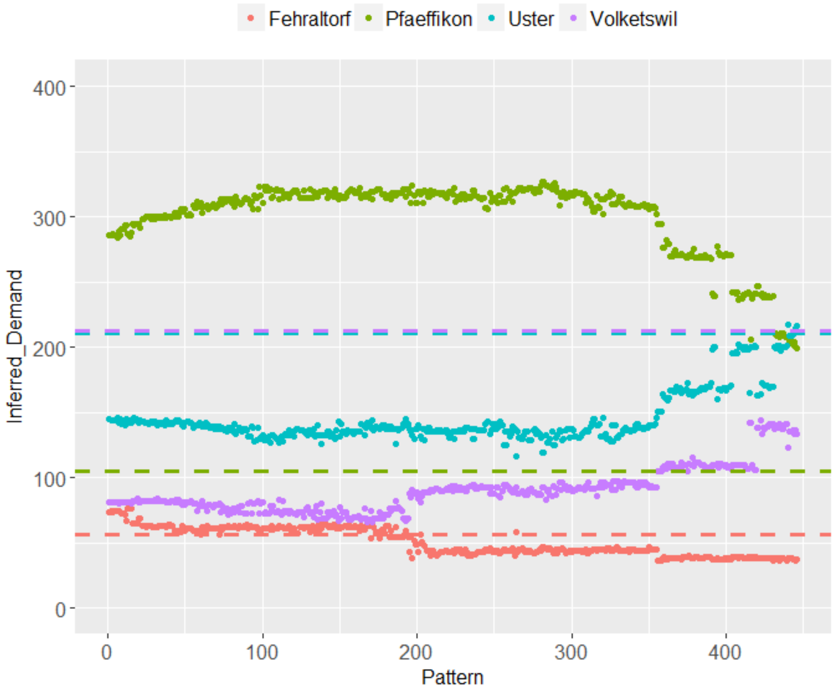

Figure 8: The dashed lines show the externally defined demand in every municipality (Fehraltorf 56, Pfäffikon 105, Uster 212, Volketswil 213). The dots show the demands (i.e., the amount of urban growth) inferred from the solutions constituting the non-dominated front of the regional zoning simulation.

5. Conclusion

We developed a multi-objective optimization approach to explore the potential benefits of a regional zoning in comparison to local zoning(i.e. the current zoning practice in Switzerland). Using this approach we were able to quantify the loss of agricultural productivity and compact urban development for the two types of zoning under many different preferences for these two variables.

Whether it is worthwhile to promote regional zoning opposed to local zoning, depends on stakeholder preferences. As the non-dominated fronts for local and regional zoning are relatively close together for compact solutions, it may not be considered beneficial to change the current zoning practices. However, if reducing the loss of agricultural productivity is the main preference, the big difference between the regional and the local zoning simulations suggests that it could be worthwhile to initiate changes in zoning policies.

We showed that the cooperation between different municipalities, which is required for regional zoning, is useful at two different stages in the decision-making process. First, municipalities should cooperate when they determine their preferences concerning the reduction of loss of agricultural productivity and compactness. If preferences are not synchronised between municipalities for regional zoning, the best achievable land-use solution (i.e. with minimal loss in soil quality and maximum compact development) is considerably worse than when the municipalities agree on the preferences. In addition, if the municipalities choose similar preferences there is a higher likelihood that the overall solution is preferable (i.e., dominant). Second, municipalities should cooperate when deciding on how much agricultural area they allow for conversion into urban. If every municipality separately defines how much agricultural area should be converted to residential based on the demand for new urban areas, the result is likely to be non-optimal from a regional planning perspective. However, with regional planning, the amount of growth per municipality again strongly depends on the decision-makers' preferences between compactness and reduction of loss of soil quality.

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7. Appendix

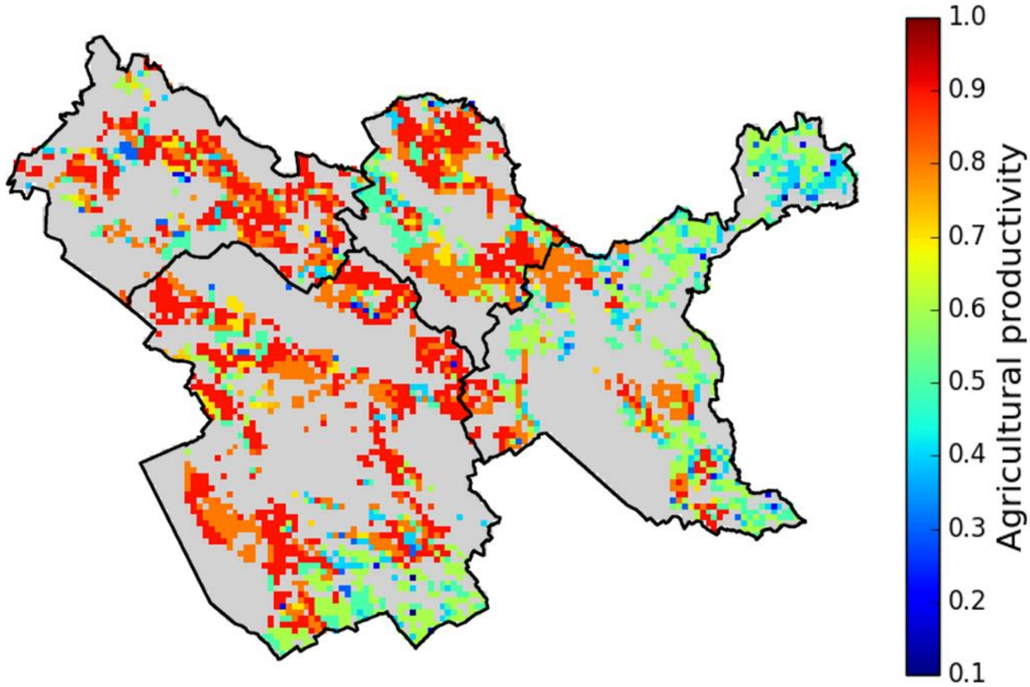

Figure A 1Soil Quality for agricultural production scaled from 0.1-1 in all four municipalities. All non-agricultural areas are grey.

Supplement A 1: Demand for building zones (i.e. residential areas).

In order to determine how many hectares of new building zones had to be allocated per municipality, we had to quantify the demand for new residential areas. The demand until 2050 was estimated based on forecasts of population growth and the residential area per capita in every municipality, which is an approach that has been widely use in the literature (Hoymann, 2011, Arsanjani et al., 2013). For population forecasts, we used data on population development between 1981 and 2014 in every municipality and an automated process for time series forecasting relying on ARIMA models (Hyndman and Khandakar, 2008). The area per capita was estimated by dividing the sum of residential areas in every municipality (based on the Swiss area statistics 2004/2009) with the average population from 2004-2009. We assumed that the area per capita increases linearly at the same rate as it did between 1985 and 2009.

Supplement A 2: Selecting solutions from the non-dominated fronts.

To select solutions from the non-dominated front of each municipality, we first normalized the objective space by dividing the objective values of each solution by the maximal values of objective 1 and 2 (i.e., total edge length and loss in agricultural productivity). After that we calculated the distance (d) between the first solution on the front (i.e., the upper-left solution) and the last solution on the front (i.e, the lower left solution). We divided this distance by 10, which resulted in the step distance (d_{step}, Figure A 2). The step-distance was then used in an iterative process to select solutions on the front. Starting with the first solution on the front, we then selected the solution that was approximately at a distance of d_{step} to this first solution (i.e., closest to the edge of a circle with radius d_{step} and centred around the first solution). The newly selected solution was then used to select the next solution on the front, and so forth until reaching the end of the non-dominated front. As the last step may not fall together with the last solution on the front, it happened that the last two selected solutions were very close together.

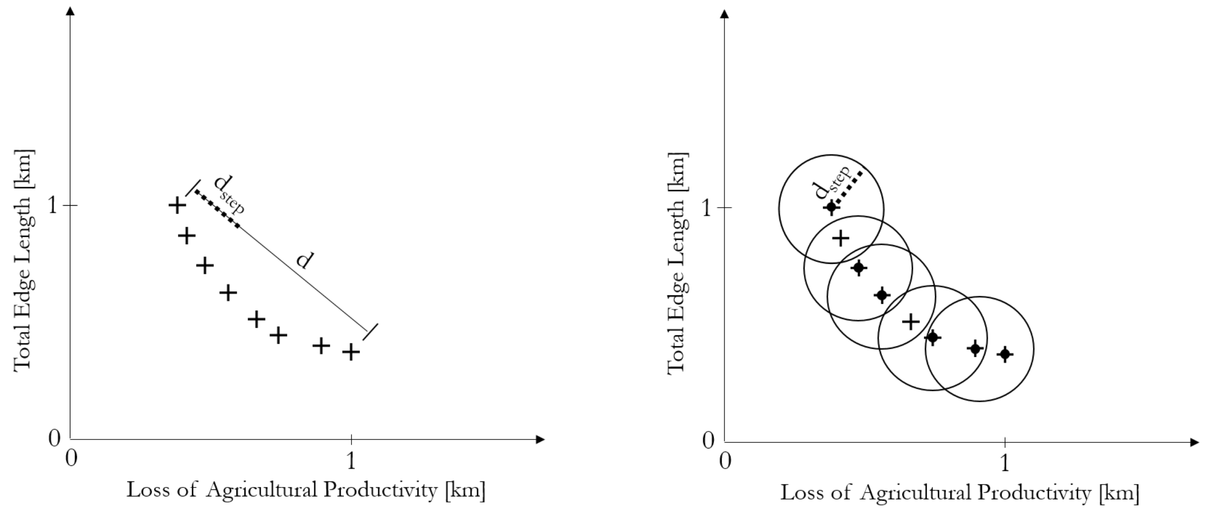

Figure A 2: Example of how approximately equally distanced solutions from the non-dominated fronts were selected.

Chapter 5

How to choose the right planning horizon? Using multi-objective optimization to support urban planning

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Abstract

To be useful to urban planners, urban models need to deliver plausible futures. However, the complexity of urban processes and related uncertainties make it difficult not only for urban planners, but also for urban models, to deliver plausible futures. Such uncertainties may for example involve population growth and the preferences of different stakeholders, which may change over time. In addition, urban planning outcomes are multi-dimensional and usually there are many trade-offs involved. To account for uncertainties in a multi-dimensional context we propose a modelling approach based on multi-objective optimization. We applied this approach in an artificial experiment and to a city in Switzerland accounting for two objectives. These were to preserve high-quality agricultural soils and to guarantee compact city development. As the most productive soils are often located close to existing urban areas, these two objectives are strongly conflicting and can cause a large trade-off. Our methodological approach involved two steps. First, in an artificial experiment, we demonstrated that uncertainties related to population growth or choosing a wrong planning horizon can prevent planners from reaching optimal solutions. We then tested the results from the artificial experiment for a real-world problem, which was the city of Uster in Switzerland. As the real-world problem was very complex, we used a metaheuristic for solving the multi-objective optimization problem of allocating new urban areas in all possible ways that would protect the most fertile soils and guarantee the compactness of the urban patterns. The used metaheuristic was the genetic algorithm NSGA-II. In order to account for the spatial nature of the optimization problem, we used a modified version of the original algorithm. After this, we ran the modified NSGA-II many times in order to create several Pareto Fronts for different planning horizons or if including uncertainties in population growth. We show that despite uncertainties and even when choosing a short planning horizon we may still be able to reach optimal urban patterns in a distant future, which is surprising as we are dealing with a highly non-linear combinatorial problem. In conclusion, the methodology we developed could help urban and spatial planners to identify the right planning horizon for a large variety of urban and spatial planning problems. In addition, the results from the multi-objective optimization can be used to improve interactive decision-making processes. By not only presenting a limited number of scenarios, but a whole range of different Pareto-optimal trade-off solutions to the decision-makers, they may be able to choose an efficient solution that fits their preferences very well.

1. Introduction

Globally large amounts of agriculture land are converted into urban areas, which has far-reaching impacts on ecosystem services and the soil's capacity for agricultural production (FAO and ITPS, 2015). To reduce these impacts, it is possible either to reduce the amount of open land that is converted into urban or to find urban patterns that are less detrimental to the environment. If the amount of agricultural areas being converted into urban is reduced, this clearly diminishes the environmental impact. However, it may be much more difficult to identify urban patterns that best preserve good quality agricultural soils and at the same time account for economic objectives like reducing infrastructure costs.

Urban planners are facing the difficulty of designating agricultural land to the future development of urban sites - a process usually called zoning. Designing sustainable zoning plans is a wicked decision-making challenge because a variety of stakeholders and decision makers with conflicting values are involved (Artmann, 2015), deep uncertainties need to be considered (Walker et al., 2013) and even the formulation of the problem itself can be contested (Rittel and Webber, 1973). Because of these properties of wicked problems, Kwakkel et al. (2016) point out that decision making in wicked problem situations should be understood as an argumentative process.

To support urban planners and decision-makers in the argumentative process of finding sustainable solutions for urban growth, a large variety of quantitative tools and approaches has been developed. Malczewski (2015) divides these approaches into simulation and optimization approaches. He explains that simulation approaches may be characterized as descriptive and that optimization approaches are often considered to be normative. In short, normative approaches are concerned with the question "what ought to be", while descriptive models rather reflect decision-making agents and processes for answering the question "what if" or "what is".

A variety of studies has proposed to use multi-objective optimization in order to support decision-makers in urban planning (e.g. Haque and Asami, 2014, Caparros-Midwood et al., 2015, Schwaab et al., 2017). The aim of multi-objective optimization is to create many trade-off solution, i.e., a set of Pareto optimal solutions, so that stakeholders and decision-makers can select one of them according to their preferences. Providing optimal trade-off solutions to stakeholders and decision-makers is a normative approach, which can be very helpful as it allows them to explore many potential solutions and balance their preferences well. However, a purely normative approach may not be sufficient in order to thoroughly support decision-makers in wicked problem situations where an argumentative process is essential. We argue that multi-objective optimization offers a large spectrum of methodological approaches and applications. Instead of only answering the question "what ought to be" it may as well be possible to answer the questions "what if" and in particular to show how we may deal with uncertainties related to the challenge of reaching sustainable urban growth.

In this study, we provide the reader with a novel approach on how to use multi-objective optimization. We demonstrate in which way multi-objective optimization may help us to deal with the problem of uncertain demands for new urban areas and the problem of choosing the right planning-horizon, when proposing optimal allocation of new urban zones. In order to show this, we formulate the bi-objective problem of maximizing compact urban development while minimizing the loss of good quality agricultural soils, which are two important aims of the Swiss planning legislation. In order to analyze whether short or long-term planning may be more useful considering uncertainties in the demand for new urban areas, we apply a stepwise optimization process, which we explain in detail.

2. Methods

2.1. Problem formulation

Our goal was to optimize the allocation of new urban areas for a small artificial landscape and in the municipality of Uster, which is situated in the canton of Zürich in Switzerland. We focused on optimizing two objectives. One was to minimize the loss of agricultural soil quality. The other was to maximize compactness of urban areas. As a first constraint, urban areas were only allowed to be built on agricultural land and not on other areas (e.g. forests). Second, the amount (i.e. demand) of urban areas to be allocated was fixed.

The soil quality loss (SQL) was calculated as following (notation adapted from Stewart et al. (2004)):

$$SQL(u) = \frac{1}{S}\sum_{r=1}^{R}\sum_{c=1}^{C}\sum_{k=1}^{K} s_{rck}\, x_{rck} \tag{5.1}$$

where u denotes the specific land-use map expressed in terms of R×C×K binary variables x_{rck} , such that $x_{rck} = 1$ if $u_{rc} = k$, and $x_{rck} = 0$ otherwise, R is the number of rows, C is the number of columns, K is the number of possible LULC categories (i.e., in this study: urban or agriculture), s_{rck} is the potential loss of soil quality and S is the sum of the currently available agricultural soil quality. For more details on how the soil quality loss has been calculated please refer to Schwaab et al. (2017).

We decided to calculate the Total Edge Length (TEL) as an indicator for compactness. The TEL is inversely related to compactness, meaning that a low TEL describes a compact pattern (McGarigal et al., 2012). The TEL was calculated as (notation adapted from Aerts et al. (2003):

$$TEL(u) = \sum_{r=1}^{R}\sum_{c=1}^{C}\sum_{k=1}^{K}\begin{pmatrix} x_{r+1,c,k} + x_{r,c+1,k} \\ +x_{r-1,c,k} + x_{r,c-1,k} \end{pmatrix} \tag{5.2}$$

where u denotes the specific land-use map expressed in terms of R×C×K binary variables x_{rck}. The variables $x_{r+1,c,k}$, $x_{r-1,c,k}$, $x_{r,c+1,k}$ and $x_{r,c-1,k}$ are binary variables describing the von Neumann neighbourhood of a centre cell being assigned to a specific land-use (u_{rc}). If a neighbour and the centre are assigned to the same land-use (e.g. $u_{r+1,c} = u_{rc}$), the binary neighbourhood variable is zero (e.g., $x_{r+1,c,k} = 0$). If the neighbour and the center are assigned to different land-uses (e.g, $u_{r+1,c} \neq u_{rc}$), the neighbourhood variable is one (e.g., $x_{r+1,c,k} = 1$).

2.2. Algorithm

To solve our multi-objective optimization problem, we used the elitist Non-dominated Sorting Genetic Algorithm (NSGA II, Deb et al., 2002). We modified the recombination and mutation operators to suit our specific optimization problem and implemented the algorithm based on the python framework "Distributed Evolutionary Algorithms in Python" (DEAP, Fortin et al., 2012).

Modifications of the recombination and mutation operators were mainly used to account for the spatial nature of the problem. For the recombination we split the parent solutions into two halves by a line through the center of the municipality with randomly varying angles, which is similar to an approach that has been recently applied for a spatial problem (Ryerkerk et al., 2012). The mutation process used in this genetic algorithm was basically a combination of uniform and biased mutation operators. More details on the modification of crossover and mutation operators can be found in Schwaab et al. (2017). To monitor the performance of the optimization process we calculated the hypervolume indicator at each iteration (Zitzler, 1999).

2.3. Comparison of short- and long-term planning

To simulate short- and long-term planning, we used identical genetic algorithms. However, we defined different demands for new urban areas and instead of running the algorithm one time in the long-term case, we applied a stepwise optimization procedure to simulate short-term planning. For both short- and long-term planning, the optimization started based on the land-use pattern in 2010. For the stepwise short-term planning process, we optimized the allocation of new building zones from 2010 until 2030. From the obtained non-dominated front we selected one pattern, which we assumed to be the development path chosen by the decision-makers (i.e., the preference according to the two objectives considered). This pattern was then used as the new starting pattern for the optimization from 2030 until 2050. For each solution (i.e. pattern) that we selected from the non-dominated front created for 2030, we created a new non-dominated front in 2050 (i.e. several 2030-2050 fronts). For the long-term planning process, we ran the genetic algorithm only one time and produced one font for the year 2050 (i.e. one 2010 – 2050 front) as there was only one starting pattern, which is the one from 2010 based on the Swiss Area Statistics (Humbel, 2009). The demand for new urban areas between 2010 and 2050 was estimated based on population forecasts and data about the urban area per capita.

Both, the population forecast as well as the prediction of the future urban area per capita were highly uncertain. As urban planners will try to avoid oversized building zones they may choose a very conservative demand estimate. To account for this, we predicted the demand until 2050 using the lower 95% boundary of the confidence interval of the population forecast instead of the median forecast. The resulting demand was 174 ha of new urban areas instead of 212 ha. However, we would like to know if this more conservative demand estimate would prevent reaching optimal urban patterns if the demand turns out to be higher. Thus we also extended that run from the 174 ha solution by adding 38 ha of additional demand, to reach the demand of 212 ha, which was the demand if using the median population growth prediction until 2050. Note that this experiment was equivalent to the comparison of short- and long-term planning described in the previous paragraph. However, the time periods would be slightly different here. Using the lower demand (based on the lower 95% confidence interval boundary) in the optimization process would correspond to short-term planning from 2010 to approximately 2043. From 2043 to 2050 the difference in the demand (212-174 = 38 ha) has to be added to reach the full demand through 2050.

3. Results and Discussion

3.1. Toy Experiment

Short-term urban planning can result in non-optimal solutions in comparison to long-term planning (Figure 1). This can happen due to the non-linear combinatorial nature of the problem. As our simplified experiment showed, there are two ways of detecting whether short-term planning does result in non-optimal solutions when considering a longer time horizon. First, it is possible to analyze the non-dominated solutions resulting from short- and long-term planning in the objective space. If there is a gap between solutions on these fronts (Figure 1 b), it is most likely that short-term planning (i.e., the optimization split into two smaller parts) is not able to produce optimal solutions in the long run. Second, if the non-dominated solutions reveal differences in the decision space, this will most likely also mean that the short-term planning has resulted in non-optimal solutions. This would mean that the final urban patterns look different (as was the case in our example in 2050, Figure 1 a).

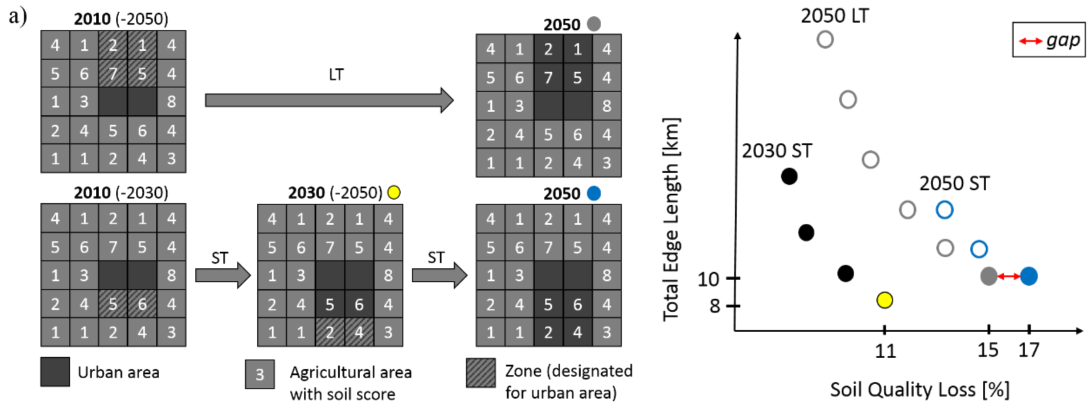

Figure 1 a),b): Toy experiment. In 2010 there are two urban cells and 23 agricultural cells. We aim at finding the most compact solution in 2050 with the lowest loss in soil quality (numbers in cells represent soil quality). This corresponds to a solution at the bottom-right of a front of non-dominated solutions. For example, the Total Edge Length for the pattern marked with the grey dot would be 10 (including the two edges at the upper end of the pattern). The loss of soil quality would be 2+1+7+5 = 15. To exemplify long-term planning (LT), we designate four agricultural cells to future urban areas (zoning area in the upper left pattern). By 2050, these zoned areas are becoming urban (upper right pattern). In the short-term (ST) planning case, we first only designate 2 cells to future urban use. The most compact solution with the lowest loss in soil quality causes a loss of 11 soil points and a Total Edge Length of 8 (lower left pattern). By 2030, the designated zones are converted into urban and 2 new cells are designated for urban areas (lower central pattern). By 2050, these two zones turn into urban, which causes a Total Edge Length of 10 and a Soil Quality Loss of 17 since 2010.

3.2. Real-world application

In contrast to the toy problem situation above, we found that short-term planning didn't result in non-optimal solutions when optimizing the urban pattern in the municipality of Uster in Switzerland. First, there was no gap between the fronts produced in the optimization process simulating long-term planning and the fronts produced in the optimization process simulating short-term planning (Figure 2). Second, the most compact patterns resulting from the simulations until 2050 (adding to land-use map in 2010 two times 106 new urban cells (short-term planning) and adding 212 new urban cells (long-term planning) are very similar and both contain the pattern found when simulating short-term planning until 2030 (Figure 3).

The fact that short-term planning didn't result in non-optimal solutions means that urban planners could be recommended to develop a zoning plan for 2030 first and afterwards to create a second plan for 2050. If they would instead do the zoning for 2050 (starting in 2010), they might designate too many agricultural cells to future urban areas (oversized zones) because the demand for urban areas may have been overestimated. However, urban planners will try to avoid oversized zones because they often result in unforeseen and non-optimal urban patterns, as the actual allocation of urban areas within zones is strongly driven by economic factors and does usually not account for externalities (Holcombe and Williams, 2012).

The simulation of the short-term planning reveals that a chosen preference, expressed as the weight for the two objectives, strongly determines which solution we are able to reach in the long run (Figure 2 a, Figure 4 a). Selecting a preference early (Figure 2 a) will allow us to reach a wider range of solutions than when selecting the preference in a later stage (Figure 4 a). This could mean that if there is uncertainty about the right preferences, short-term planning may be more reasonable, as an early adjustment in preferences may have a larger effect than later adjustments.

Interestingly, we found that two patterns having almost the same objective values showed quite some differences in the decision space (i.e., in the land-use patterns). While most of the 212 urban cells allocated in the two optimization runs (short- and long-term simulation) were at the same location, more than 30 of them were found at different locations (comparison of pattern 441 and 336). Instead of preserving the diversity of solutions within in the objective space, accomplished by the so-called crowding distance in NSGA-II (Deb et al., 2002), it may be helpful to also preserve diversity in the decision space. Taking such diversity into account may not only be helpful to get as close as possible to the true Pareto-Front, but may also be used when trying to preserve non-dominant solutions that are close to the Pareto Front in the objective space, but very different in the decision space. This can be very useful, when decision makers want to evaluate a wide range of options (e.g. Kwakkel et al., 2016).

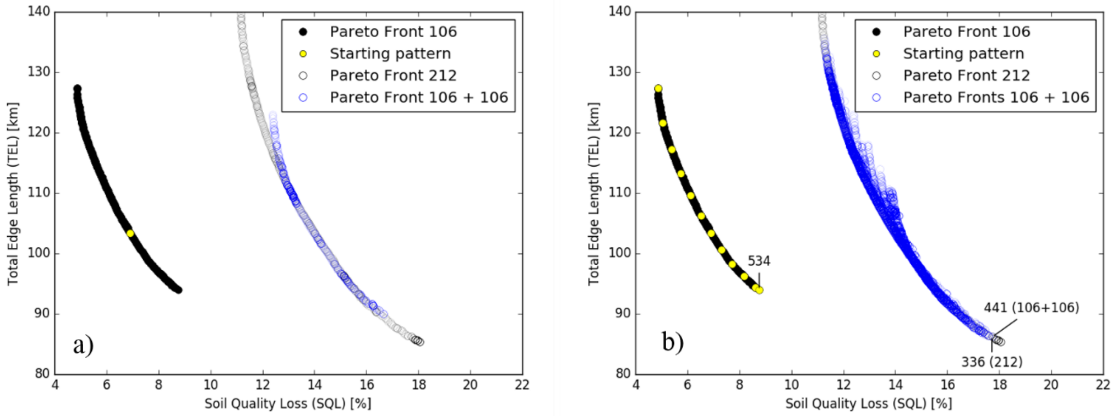

Figure 2 a),b): a) The figure shows 3 non-dominated fronts. Two of them represent the short term-planning process (black dots with fill, blue dots without fill color) while one of them represents the long-term planning (grey dots without fill color). Short term planning involved one optimization run placing 106 new urban areas (which corresponds approximately to the year 2030) onto the current land-use map (from 2010). After that, one pattern from the front of non-dominated solutions was selected (yellow dot) and again 106 new urban areas were placed onto this land-use pattern. In total there were 212 new urban areas. For the long-term planning process, 212 new urban areas were allocated in one single optimization run. b) In total the figure shows 14 non-dominated fronts. Each yellow dot represents a land-use pattern that was used as a starting point for an optimization run (short-term planning process). Each blue front is a result from the optimization process based on one of the starting patterns. The front produced for long-term planning until 2050 is largely invisible as it is mostly covered by the 12 blue fronts. The most compact pattern in the year 2030 (pattern 534), the most compact one in 2050 for short-term planning (pattern 441) and the most compact pattern of long-term planning (pattern 336) are shown in Figure 3.

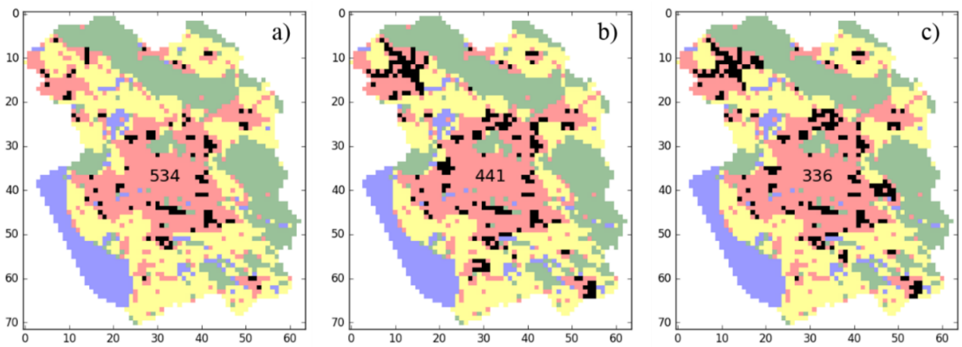

Figure 3 a)-c): Red cells: Urban areas; Yellow cells: Agricultural areas; Green Cells: Forest areas, Blue Cells: Water; Black Cells: New Urban areas which were allocated in the optimization process. a) Pattern 534. Most compact pattern when 106 new urban areas are added in the optimization process (short-term planning) to the current land-use in the year 2010. b) Pattern 441. Most compact pattern when 106 new urban cells are added to pattern 534. c) Pattern 336. Most compact pattern, when 212 new urban cells are added to the current land-use in the year 2010.

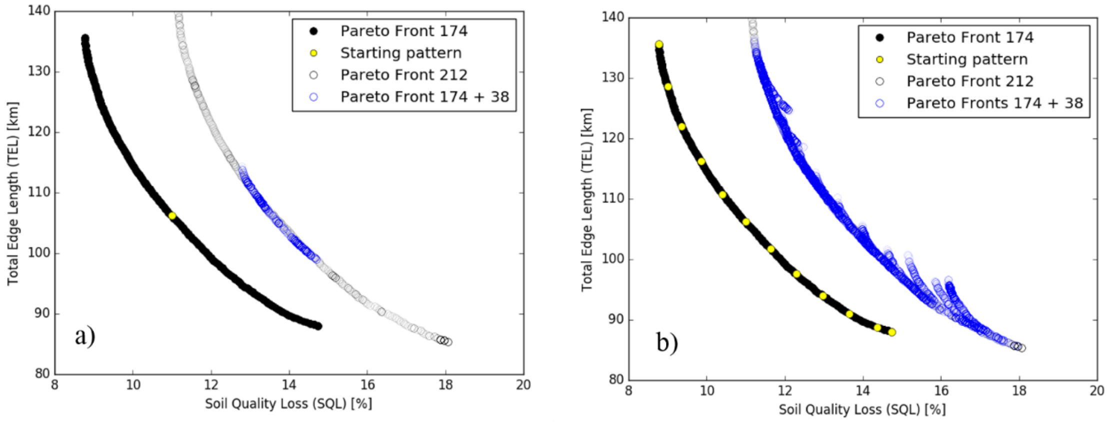

Figure 4 a), b): a) The figure shows 3 non-dominated fronts. Two of them represent the planning process when first using a conservative demand estimate of 174 ha (black dots with fill) and afterwards adding 38 ha more of urban areas (blue dots without fill color). This could also be interpreted as a short-term planning process (2010-2043-2050). The third front was produced for the median demand prediction and corresponds to the long-term planning until 2050 (grey dots without fill). b) In total the figure shows 14 non-dominated fronts. Each yellow dot represents a land-use pattern that was used as a starting point for an optimization run (conservative scenario/ short-term planning process). Each blue front is a result from the optimization process based on one of the starting patterns. The front produced for the median demand estimate (or long-term planning until 2050) is largely invisible as it is covered by the blue fronts.

3.3. Comparison of toy experiment and real-world application

The toy experiment showed that a short-term planning process can be problematic if it prevents finding an optimal solution on the longer run. However, the real-world application showed that this doesn't necessarily have to be the case. It will depend on the spatial pattern of the current land-use and the spatial pattern of the soil quality, whether a short- or a long-term planning process is recommendable. In order to be able to give a more generalizable recommendation to urban planners, it would thus be necessary to apply our analysis to a large variety of different municipalities.

Building on this work, future analysis could address the question whether it is possible to identify a minimum length of the planning periods with which it would still be possible to find the best solutions in comparison to a long-term planning period (i.e., for the longer run). In addition, it could be necessary to formulate the whole problem in a more dynamic approach (Zhiqiong and Bojin, 2010), as urban planners may not only want to identify the best possible solutions at a defined point in time but also find good solutions applicable over a period of time.

4. Conclusions

In this paper, we have shown that multi-objective optimization can be used to support urban planners in choosing the right planning horizon. The presented methodological approach and results show that multi-objective optimization can be more useful than just providing decision-makers with optimal solutions for complex problems. We believe that demonstrating innovative approaches of how to use multi-objective optimization has the potential to enhance decision-making processes and will foster the application of multi-objective optimization in the area of urban modelling and planning.

In a concrete example using multi-objective optimization we showed that short-term planning would be recommended for the urban planning problem in the municipality of Uster in Switzerland. However, it depends on the spatial pattern of the current land-use and the spatial distribution of the soil quality, whether a short- or a long-term planning process is recommendable. Building on this work, future analysis could address the question whether it is possible to identify a minimum length of the planning periods with which it would still be possible to find the best solutions in comparison to a long-term planning period. The methodology we developed could help planners to identify the right planning horizons for a large variety of spatial planning problems.

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Chapter 6

6. Synthesis

6.1. The use of optimisation in land-use decision-making.

6.1.1. Using multi-objective optimization in innovative ways

The use of multi-objective optimization for supporting land-use allocation decision-making has been rather one-sided. Most applications were limited to the formulation of an optimization problem, the estimation of a set of non-dominated solutions (i.e., the Pareto-optimal set) and, in some cases, to a post-optimality analysis of the non-dominated solutions. In this thesis, I explored three new ways of using multi-objective optimization in support of decision-making processes that are intended to promote sustainable urban growth.

(1) By comparing a non-dominated front with simulations of Business As Usual (BAU) development of urban growth in several Swiss municipalities I was able to determine where potential improvement of the BAU development was highest. This knowledge can allow decision makers to focus their efforts on regions where a change in planning practice or policies can have a high impact. The approach of comparing optimization results with BAU scenarios may not only be applicable to land-use decision-making, but also to other decision-making problems that have an influence on a globally defined goal.
(2) The comparison of two optimization runs, of which one includes a constraint that the other does not, can be used to quantify the effect of the constraint. Applied to a land-use allocation problem, I showed that this approach can help decision-makers to determine whether it is worth to put effort into the relaxation of a constraint or not.
(3) Multi-objective optimization can be used in a dynamic way in order to explore robust pathways of land-use development. Taking into account the temporal dimension in optimization problems is a complex task. I presented an approach to simulate successional land-use decision steps. In this approach I used the solutions form a non-dominated front obtained in an optimization run as starting points for the next optimization run. This allowed me to show which planning horizon may yield optimal and robust results. In addition, I was able to show how the selection of preferences in an early stage of decision-making strongly limits the possible future states that can be reached.

6.1.2. Promoting the use of multi-objective optimization

In a series of analyses, I demonstrated that there is a high potential for using multi-objective optimization to improve decision-making processes related to sustainable land-use and urban development. I believe that demonstrating this potential will increase the use of multi-objective optimization. However, despite the presented advances, there are still many unexplored potential applications of multi-objective optimizations to improve decision-making. In order to further promote the use of multi-objective optimization it is necessary to provide software packages that simplify the use of multi-objective optimization. Although such packages are increasingly becoming available (e.g. Hadka et al., 2015), using multi-objective optimization still requires a fairly large amount of programming skills and know-how.

In addition to lowering the technical barrier of using multi-objective optimization, there is also the need to clarify in which ways optimization approaches can add to and be distinguished from other land-use modelling approaches. In my opinion, this lack of clarity arises from literature on the use of optimizations. A first cause of confusion regarding the use of optimizations is that the two perspectives on using optimization are hardly discussed in a holistic manner. From a perspective often found in MCDA literature, optimization is a normative approach that provides us with solutions showing "what ought to be" (Malczewski 2015). From a perspective found in literature about the simulation of socio-ecological systems, optimization is a way to model the ability of agents to select an optimal solution considering goals like utility maximization (Chen et al., 2010, Schlüter et al., 2017). Embracing both views will help researchers and decision-makers to better understand and interpret the results obtained in an optimization process. Secondly, I believe that literature often neglects the distinction between the optimization procedure itself (i.e., how we are solving the problem) and the formulation of the problem (i.e., the formulation of the objectives and constraints). Readers of studies using (multi-objective) optimization might often get the impression that there is just one possible way of formulating a specific problem and that this problem is exactly the one that should be optimized. However, a wealth of information can also be obtained by varying the problem formulation (e.g., by varying constraints or even objectives), yet such analyses are rarely performed for land-use allocation problems.

6.1.3. Simulation vs. optimization: an example with tradable development rights.

The conclusions presented in the previous paragraphs have some implications for approaches that suggest or demonstrate the combination of scenario analysis (i.e., using simulation models) and optimization (Ligmann-Zielinska and Jankowski, 2010, Seppelt et al., 2013, Hu et al., 2015, Schwaab et al., 2017). A main purpose of such a comparison is to assess whether and why the results from scenarios are inferior to those from optimizations. However, it may be extremely difficult to determine whether this is the case, because a) constraints are usually different between the simulation model and the optimization, b) the simulation implicitly and inherently addresses other (or more/less) objectives than the optimization, or (c) the simulation model is simply not able (and surely not designed) to derive optimal solutions for a complex problem.

With the following example, I will show that the comparison of simulation results (including scenarios) and optimization results may not be straightforward. Results obtained from the optimization of land-use patterns were compared with those obtained when running an economic model which reflected a land-use system in which trade of development rights steers the development of new urban areas (Appendix 1: On the impact of zoning- and market-based policy instruments on settlement configuration and ecosystem services in Switzerland). The basic mechanism behind tradable development rights (TDR) is that landowners, who own a specific amount of development rights, can trade these rights among each other. If landowners try to maximize their profits, the ones who own very valuable land (e.g., because it is close to a lake or the central business district etc.) will try to buy development rights, while landowners that possess less attractive land will try to sell development rights (Pruetz and Standridge, 2009). The result of this trading process is that the likelihood of urban development at a certain location will be approximately proportional to that location's land-price.

In order to develop TDR model in Switzerland, I used data on property prices of single family homes in the canton of Zürich in Switzerland and fitted a hedonic model. I used this model in order to estimate land-prices for every cell of a 1 ha raster grid in the canton of Zürich. (more details are provided in Appendix 1: On the impact of zoning- and market-based policy instruments on settlement configuration and ecosystem services in Switzerland). Subsequently I allocated urban land, based on the assumption that the likelihood of cell being converted into urban would depend on the land-price (i.e. the higher the price the higher the likelihood for conversion).

In order to steer the location of development in a TDR system, it is possible to charge fees that are proportional to certain locational attributes. Using a grid-based representation of the land-use system, I included a fee that was proportional to the agricultural soil quality of every cell ("soil fee") and a fee that was inversely proportional to the number of urban cells in the neighborhood of every cell ("sprawl fee"). These fees had an influence on land-prices, which in turn had an influence on the likelihood of urban development. I ran several simulations using the economic TDR model using different scenarios, which were simply based on varying the two fees that were charged.

As expected, I found that a high soil fee led to a relatively low loss of good quality agricultural soils, while a high sprawl fee resulted in compact urban development. However, none of the scenario outcomes came close to those in the Pareto Front obtained through multi-objective optimization of the land-use pattern (Figure 2). The reasons for the difference between the front and the scenarios can be twofold. Firstly, there is no explicit optimization process in the simulation of the TDR system. The TDR model follows predefined rules, but there are no previously and explicitly defined objectives (i.e. goals) that the model tries to reach. The implemented fees are of course intended to make the urban pattern more compact and to reduce the loss of fertile soils, however, it remains unknown whether maximally compact patterns and a minimal loss of fertile soils was indeed reached. Secondly, there is an inherent objective in the TDR system, which is that land-owners maximize their profits. This means that there is actually a third implicit objective, in addition to the two that are influenced by the fees (i.e., minimizing Total Edge Length indicating the degree of compactness/sprawl and minimizing Soil Quality Loss). Thus the differences in the objective space between the simulation and the optimization results may have resulted from a trade-off between the objective of maximizing landowner profits and those of reaching compact development with a low loss of soil quality.

There are two options to disentangle the two possible explanations for the differences between optimal results and scenario results. (1) A first option is to compare results in which a land-use pattern was directly optimized (i.e., the land-use pattern is the decision space) to results from the simulation model in which input parameters were optimized (i.e., the fees in the previously described case). The difference between the two resulting fronts of non-dominated solutions can then be attributed to the effect of the inherent objective (i.e., profit maximization) in the simulation model (Figure 2, compare green front and blue front). The difference between the scenarios developed with varying fees in the TDR model and the front obtained when optimizing the TDR model (i.e. when optimizing the amount of fees according to the two objectives), reflects the differences that are caused if there is no agent or algorithm involved that can solve a complex non-linear problem. (2) A second option would be to not only look at the objective space in two dimensions, but to include profit maximization as third objective, which so far only had been considered implicitly. This would help to understand the trade-offs between the three objectives and would paint a clearer picture of the differences between the optimization and simulation results.

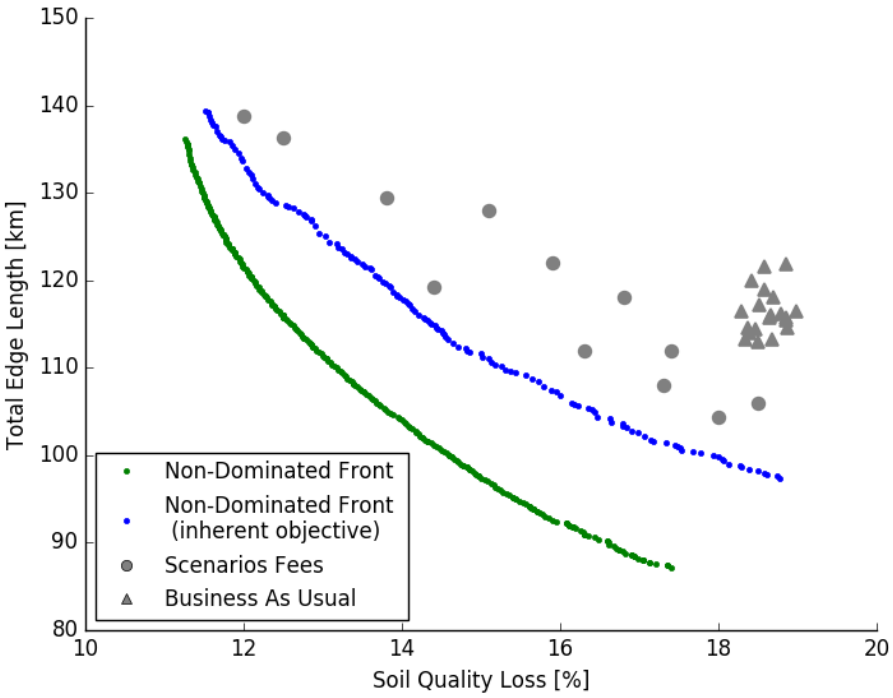

Figure 5: Comparison of non-dominated solutions and scenarios obtained by simulation. The green non-dominated front represents optimal solutions that were obtained by optimizing the land-use patterns. There were hardly any constraints involved in this optimization process. The blue front was obtained when optimizing the TDR model (i.e., optimizing the fee parameters) and the grey round dots were produced by simulating the TDR system including varying fees.

The example of comparing solutions from a multi-objective optimization and an economic simulation model, shows that any approach comparing the results of simulation models to those of optimization models needs to be carefully designed. In addition, it may often not be a comparison between simulations (i.e. scenarios) and optimization that we should strive for, but rather a comparison of optimizations, which differ in their formulating of objectives and constraints. So far, the very few approaches that combined optimization and simulation seemed to have been motivated by the mere possibility of doing this (e.g. because two models were available) and not by the possibility of answering a challenging question.

In order to help researches design experiments involving optimizations, I will outline a taxonomy of different approaches using optimization and/or simulation in the following chapter. In addition, I will point out what questions can be answered with each type of approaches. With this information, the focus of optimization research will hopefully shift from purely methodological (i.e. "what is possible" and "how is it possible") to a more purpose oriented point of view.

6.1.4. Optimization in combination with simulation – a taxonomy

Optimization and simulation are very broad categories of modelling approaches. In my taxonomy, I will address optimization and simulation models in a very general sense. This means that I define an optimization approach as an approach in which goals (i.e. objectives) are explicitly defined and there is an optimization algorithm involved that is used to solve the optimization problem (i.e., maximize/minimize the objectives under given constraints). In a simulation model there is no explicit definition of objectives. A simulation model is based on rules that determine the behavior and outcome of every simulation run. This definition of simulation and optimization is useful for illustrating the possibilities to combine optimization and simulation, however, it does not always allow a clear distinction between optimization and simulation as the following paragraphs will show.

(1) **Optimization within agent-based simulation:** Optimization procedures may be used in models to represent the decisions of rational actors (Schlüter et al., 2017). For example, there are models simulating land-use changes of farmers that try to maximize (i.e., optimize) their profits, e.g., by deciding which areas and which crop they want to cultivate (e.g. Briner et al., 2012) or by deciding whether they sell their land for housing development (e.g. Magliocca et al., 2015). These models may be used to explore different scenarios and to get a better understanding of the influence of the decisions or actions of rational land-owners on the functioning of the land-use system.

(2) **Coupled optimization and simulation:** With the term "coupled", I indicate that both types of modelling approaches are linked dynamically. To my knowledge, there is only one example in literature where a comparable approach has been used in a planning context. Li et al. (2011) used such an approach to find an optimal path for an expressway in a region of China. They coupled a cellular automata (as simulation model) for simulating urban development and an ant colony algorithm (as meta-heuristic for the optimization) to find the optimal path and showed that their approach increased the performance in comparison to a decoupled method.
One motivation behind this approach may be to model land-use changes as realistic as possible and investigate on the dynamics of the whole land-use systems. Undeniably many land-use systems, could be described as systems in which rational actors try to optimally react to changing conditions in the land-use system. Their reaction will in turn have an influence on the system itself. In addition, providing simulation results as additional information to a rational actor could be interpreted as the attempt to overcome the bounded rationality that a decision-maker is often facing.

(3) Simulation within optimization: With simulation within optimization, I refer to integrated models in which either the objective functions or the constraints in the optimization include the simulation of land-use changes. This means that the objective functions in this approach may depend on the land-use pattern, whereas the decision space is defined through variables other than land-use categories. For example, the decision-space may be defined by the amount of subsidies provided to farmers. Depending on this amount farmers will change their behavior, which will in turn have an influence on the overall land-use pattern. Thus, using a simulation within optimization could be used in order to find out which amount of subsidies would yield the most desirable land-use pattern. If the land-use pattern is regarded as a collective objective and not a personal objective, then this type of models can be used to assess how individual actions can lead to collective goals.
To my knowledge there are no studies that use simulation models, e.g., an agent-based model, in order to derive land-use patterns within an optimization process. The main reasons for that may be that land-use models are often quite complex and running them is related to high computational costs. This means that it can be very difficult to find optimal solutions, as meta-heuristics usually require a high amount of function evaluations.
It should be clear though, that "simulation within optimization" can be considered as a somewhat artificial category, because any objective or constraint formulation could be described as a model and used for simulation. Accordingly, every optimization could be regarded as "simulation within optimization".

(4) **Constrained vs. unconstrained optimization:** Using constraint vs. unconstraint optimization is an approach that may be used in order to find out how a specific constraint influences the overall result of an optimization. Constraints can refer to, for instance, land-use rules or regulations, but also to cultural or environmental constraints. The category "constraint vs. unconstraint optimization" also cannot be clearly separated from the previously described approaches. It can, for example, include "simulation within optimization". Nevertheless, I would like to introduce constraint vs. unconstraint optimization as a separate category, because it clearly goes beyond a normative approach of optimization.
Constrained vs. unconstrained optimization may also be interpreted as an attempt to reach visionary or ideal solutions. Visionary solutions may be obtained in an unconstraint optimization. A

constraint optimization may, e.g., represent the current system which is implicitly or explicitly related to many different constraints.

To my knowledge, this category of models has hardly been used in literature, but an example of such an approach has been given in chapter 4 of this thesis. In this example, I contrasted the loss of agricultural productivity when urban expansion was planned intra-municipal (i.e. constrained optimization) with that when planning was supra-municipal (unconstrained optimization). With multi-objective optimization, this resulted in two different Pareto-fronts. The distance between these fronts provided interesting information about how limiting the constraint of intra-municipal planning is.

(5) **Coupled optimization:** Coupled optimization may refer to a coupling of the same optimization process (i.e. based on the same problem formulation) or to the coupling of different optimization processes (i.e. different problem formulations) over time. Instead of running the optimization process one time and trying to obtain a solution for a predefined period of time, the optimization process may be coupled by iteratively running the optimization process several times for shorter periods, whereby the results of the last run are the starting point of the next run. The purpose of such an approach may be to represent the influence of the temporal dimension on the results of an optimization as has been demonstrated in chapter 5 of this thesis. Instead of talking of coupled optimization, this could also be referred to as specific type of dynamic optimization.

The purpose of coupling different optimization approaches can also be to set the boundary conditions to a dynamic process. In this case, usually one optimization process will be used to define the constraints of another optimization process. Coupling two different optimization approaches in such a way has been termed bi-level optimization (Sinha et al., 2017). Although the term "bi-level" implies that two optimization problems are considered, in theory several problems could be considered. For illustration I will shortly introduce a toll-setting problem as a classic example of bi-level optimization. The overall objective of this problem is to maximize the revenue raised from tolls set on some roads in a road network. There are two optimization problems involved. The network manager's goal is to maximize revenue which is a function of the amount of toll and the traffic flow. At the same time, there are road users that try to minimize the cost of their travel, which is a function of the toll and the time associated with taking a certain route. If the toll is very high a lot of road users may decide to avoid the toll route. Thus the first optimization problem depends (or contains) the second one and running the optimizations one after the other can result in an optimal amount of toll that maximizes the revenue of the road network.

(6) **Simulation vs. Optimization:** Instead of coupling optimization and simulation approaches, it is also possible to simply compare the results obtained from separate simulation and optimization models. However, as I already discussed in chapter 6 (section 6.1.3), there may be difficulties in comparing simulation approaches (i.e. scenarios analysis) and optimization approaches, as it may be very hard to reveal the reasons for differences in results. Nevertheless, a comparison of results from optimization and simulation can provide useful information. Such a comparison can, for instance, provide an indication as to whether to use optimization or not. Even though the problem may be extremely complex, we might be able to come up with a decent solution with simulations (i.e, selecting the right scenarios/parameters) instead of using an optimization approach. If optimization only produces marginally better solutions than simulation, it can be argued that the relatively small benefit of optimization does not weigh up against its large effort and high computational costs. However, it would still be necessary to compare simulation and optimization at least in some cases to come with a rule that defines whether it is necessary to employ optimization or not, as has been shown in chapter 3.

The presented taxonomy is an attempt to categorize some of the possibilities and applications of optimizations. The taxonomy is not exhaustive, but may provide important information to researchers considering the use of optimization potentially in combination with simulation.

6.2. Challenges and research gaps

This thesis revealed some innovative approaches of using multi-objective optimization in land-use allocation problems. In the following, I will discuss how future work may build upon the findings of this thesis. Furthermore, I will point out which methodological advances from the fields of multi- and single-objective optimization have not made their way into the field of land-use modelling yet.

One of the toughest challenges in the application of optimizations is still to develop methods that allow us to efficiently solve optimization problems. In this thesis, I have shown that including heuristics into an evolutionary optimization process can be very useful in order to deal with spatial objectives (chapter 2). Although this finding may be important for future applications, it needs to be verified in a broader context. So far I only included one spatial objective (i.e. maximizing compactness of the urban pattern) and one additive objective (i.e. minimizing the loss of agricultural productivity by reducing the loss of the most fertile soils). To substantiate the claim that spatial objectives can be optimized efficiently by including heuristics, further spatial objectives should be included and investigated.

In this thesis, I presented different possibilities on how to support decision-makers using multi-objective optimization. The results of this thesis have been used to inform a Swiss panel of decision-makers that is in charge of improving the soil protection in Switzerland. The results were well-perceived and are likely to have an influence on soil policies. However, I did not systematically analyze how the results could be used and prepared in order to have a maximum effect in decision-making. Although I started to introduce my results to decision-makers, my work remains largely theoretical. This is actually a more general problem: Very few studies on multi-objective optimization have actually been used to inform real decision-making processes (Chikumbo et al., 2014). Up until now most studies have focused on the technical aspects of formulating and solving multi-objective optimization problems (e.g. Porta et al., 2013). The reason for focusing on this aspect may be that multi-objective optimization mainly evolved in the field of engineering where problems were often well-defined and the main challenge was indeed to mathematically or computationally solve the problem. However, in wicked problems situations, which are encountered in land-use allocation problems, a strong involvement of stakeholders and decision-makers is required. Thus, it is, for instance, essential to understand in which form decision-makers would use information obtained through multi-objective optimization and at which stages of the decision-making process the information could be included. In particular, it is necessary to develop adequate post-optimality analysis methods, in order to present the optimization results in a meaningful way to decision-makers. Post-optimality analysis may for example include the use of data-mining techniques in order to analyze the properties of optimal solutions and in order to find appropriate ways of visualizing the results which are often multi-dimensional.

Three approaches in multi- and single-objective optimization that have been hardly explored yet in land-use allocation problems are dynamic optimization, bi-level optimization and meta-modelling. In order to introduce these approaches, it is clearly necessary to use available methods and knowledge gained in other fields to adequately model and optimize land-use systems.

<u>Dynamic optimization:</u> While static representation of land-use systems might sometimes be a useful approximation of the reality, it is much more adequate to account for the dynamics. However, to my knowledge, there is only one study that tried to capture the dynamics of land-use systems (Chikumbo et al., 2014) and many research gaps remain. For example, it remains unclear how to evaluate temporally varying objectives or how to detect pathways of optimal land-use change.

<u>Bi-level optimization:</u> I am not aware of any studies using bi-level optimization concerning land-use allocation problems. However, there is an example provided in a similar field addressing the problem of agricultural management. Whittaker et al. (2017) show that incentives, in the form of taxes or fees, implemented on an upper level will have a strong impact on decisions at a lower level. Their example can be easily transferred to the field of land-use allocation problems. On the upper level, there may be an environmental agency or a government implementing a fee in order to better protect ecosystem services. At a lower level, this fee will influence the decisions of land-owners that try to maximize their profits. In order to find out, which fee is ideal to protect ecosystem services and at the same time allows for economic growth both levels need to be optimized.

<u>Meta-modelling</u>: Meta-models are models of models and can be described as the attempt to reproduce the functioning of complex models in order to calculate faster than the original model (Jin, 2011). This is

particularly important, when using evolutionary computational methods that rely on high number of function evaluations (i.e. models runs) in order to find optimal solutions. Many objective functions related to land-use allocation problems may be extremely complex and computationally expensive. In particular, agent based models can require high computational costs (Matthews et al., 2007), but also large data models, such as hydrological and climate models (Lautenbach et al., 2013, Davin et al., 2011), usually require lengthy computations. Thus, using meta-models may be an important step towards improving the optimization of land-use allocation problems.

As I have shown and discussed in this thesis, the fields of land system science and spatial planning can strongly benefit from using methods from the field of multi-objective optimization. However, this is no one-way relationship. The field of land-use system science poses problems that are very case specific, comprise of difficult non-linear combinatorial relationships and are of a wicked nature. These attributes not only pose severe challenges to the decision-making processes, but also to the design of multi-objective optimizations. A good collaboration between scientists, land managers and decision-makers can reveal research gaps and may boost innovation in the development of multi-objective optimization methods and the development of adequate post-optimality analysis.

6.3. Implications for sustainable urban growth

In this thesis, I have proposed multi-objective optimization as an approach to facilitate sustainable urban development. As sustainable urban growth is a wicked challenge, involving many different objectives and uncertainties, decision-makers need to enter an argumentative process. This process can only be successful if the argumentative process is supported with sound quantitative information. Thus, my focus was to provide information that could be useful for decision-makers who are steering urban growth patterns.

Using multi-objective optimization was useful to derive and illustrate the trade-off related to compact urban development and urban development that minimizes the loss of fertile agricultural soils. Illustrating this trade-off can help decision-makers to get a better understanding of the consequences of their actions and prevent them from taking short-sighted measures that, for instance, strongly favor compact urban development while neglecting the protection of fertile soils. Decision-makers will eventually have to opt for a solution that reflects their preferences in terms of compactness and loss of fertile soils. This solution may not be Pareto-optimal, i.e., it can be improved either in terms of compactness or in terms of loss of fertile agricultural soils or even in both. However, I presented some approaches that can help decision-makers to reach Pareto-optimal solutions. Firstly, I showed that it is worth analyzing all Pareto-optimal trade-off solutions in order to find common patterns amongst these solutions. If there are common patterns, these can essentially simplify the task of striving for Pareto-optimal solutions. Secondly, I showed that Pareto-optimal solutions can only be reached if the right planning horizon is chosen. Thirdly, I was able to show that steering urban growth patterns can help to strongly reduce the loss of fertile agricultural soils. However, I also showed that the potential of reducing the loss of fertile soils is only high, if the amount of urban growth is low. Thus, decision-makers should not only be concerned with the pattern of urban growth, but should at the same time find ways to reduce the total amount of urban expansion. The latter can for instance be achieved with urban densification (Martellozzo et al., 2015).

In summary, this thesis provides innovative methodologies that are intended to be applicable to many problems related to land system sciences and decision-making processes. However, I hope that the more concrete results in this thesis, will ultimately help decision-makers in Switzerland and in other countries to improve the sustainability of urban development.

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Appendix 1

On the impact of zoning- and market-based policy instruments on settlement configuration and ecosystem services in Switzerland

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Abstract

Globally large areas of unsealed land are converted into settlement, which has far-reaching impacts on ecosystems and the availability of the scarce resource land. Switzerland is no exception of that global trend. To reduce the negative impact of settlement development a range of policy instruments is available, however, it is a very complex task to assess the impact of different instruments. In order to support policy makers we developed a modelling framework to assess the impact of two potential policy instruments, one based on zoning and the other one based on market mechanisms. The assessment evaluated the effects of the policy instruments on the development of residential areas as well as the effects of emerging settlement patterns on ecosystem services and biodiversity in a canton in Switzerland. The modelling framework for simulating future development consists of three steps. First, we estimated the suitability for new development of residential areas in a spatially explicit way. As an indicator for the locations that would be suitable for residential development when zoning is employed, we calibrated a logistic regression model using remote sensing data on historic development of residential areas in Switzerland. As an indicator of the suitability of residential development under market mechanisms, we calibrated a hedonic model using data on prices of single-family homes. In a second step, we estimated future demand of new residential areas. In the third step we allocated new residential areas until the demand was met, based on the spatial suitability derived for the two different instruments. Our results indicate that a regulatory framework based on zoning might be advantageous if the goal is to reduce the negative effects of settlement growth on the provision of pollination, groundwater recharge and the connectivity of ecosystems. If aiming at an increase of plant species richness and a reduction in the loss of carbon stocks and good quality soils for agricultural production it may be of advantage to create incentives embedded in a market driven policy environment. However, we observed local variations in the impact of the two policy instruments. The variations show that on a municipal level one of the two instruments could be clearly preferable as it deteriorates less ecosystem services than the other instrument not only for particular ecosystem services but for all of them. In summary, our results aid policy makers in their decision whether they should employ market-based policies or regulatory policies including zoning.

1. Introduction

Globally large areas of unsealed land are converted into settlement, which has far-reaching impacts on ecosystems and the availability of the scarce resource land (Millennium Ecosystem Assessment, 2005, Elmqvist, 2013). Switzerland is no exception of that global trend (Price et al., 2015). To reduce these impacts policy makers can either reduce the demand for settlement areas or foster land-use patterns that minimize ecological, environmental and sociological impacts (Nuissl et al., 2009). This is a complex task due to the large number of possible land-use configurations as well as complex interactions and trade-offs between manifold objectives (Haase et al., 2014). Thus, policy makers call for scientific support in order to deal with these complexities and to anticipate the possible consequences of optional land-use policy decisions (Helming et al., 2011).

Boosted by the Millenium Ecosystem Assessment (2005) and TEEB (2010) the concept of ecosystem service (ES) has been promoted for reducing the human-induced deterioration of nature. Although intended to support the development of policies and instruments that integrate social, economic and ecological perspectives (Seppelt et al., 2011), it remains challenging to actually integrate ES into decision making (de Groot et al., 2010). Oftentimes ESs are external factors that are unintendedly influenced by policy measures having an impact on land-use change. Modelling the impact of land-use policies on changes in land use/land cover (LULC) and on ES and biodiversity, can help policy and decision makers to anticipate the consequences of their decisions (Lauf et al., 2014). However, inevitable trade-offs among ESs can make it difficult to provide clear policy advice (Lawler et al., 2014).

Policy instruments used to steer urban development can be broadly classified as regulatory or as instruments that are referred to as incentive or market-based (Bengston et al., 2004, Nuissl and Schroeter-Schlaack, 2009). In the regulatory approach urban development is often controlled by the setting of growth boundaries or the implementation of so-called zoning, which restricts land use on a defined area (Hirt, 2007). Examples for market-based instruments are taxation (Gihring, 1999) or Transferable Development Rights (TDR; Pruetz and Standridge, 2009, Henger and Bizer, 2010). Land use regulations can help in correcting market failures by accounting for externalities, such as loss of soils and biodiversity (e.g. Fujita, 1989), and can enhance community welfare by increasing housing values (Ihlanfeldt, 2009). However, a growing body of literature suggests that land-use regulations can also have unintended consequences such as negative effects on housing markets, social equity, environmental sustainability and regional economic vitality (McLaughlin, 2012). Although policies being either based on regulations or on market forces may have a very different impact on ESs, we are not aware of any scientific studies that spatially explicitly compared the potential impacts of such policies on ESs.

As urban sprawl continues across Switzerland (Jaeger and Schwick, 2014), securing ESs will require the understanding of the effectiveness of policies on steering settlement expansion and related loss in ESs. A wide range of modelling approaches is available to predict spatially explicit land-use change (Verburg et al., 2004, Koomen, 2007, Silva and Wu, 2012). Empirical approaches use historic data of urban development and a variety of biophysical and socio-economic variables to predict future developments based on statistical models such as logistic regression (e.g. Hu and Lo, 2007, Arsanjani et al., 2013a) or support vector machines (Rienow and Goetzke, 2014) to allocate land use change at the micro level – in addition a model at macro scale predicts the demand for the different land use classes. Spatially explicit economic modelling of land-use change (e.g. Bockstael, 1996, Lubowski, 2002) in contrast, is a rather process oriented approach (Irwin and Geoghegan, 2001) that can be considered deductive in comparison to the inductive logistic regression approach (Overmars et al., 2007). An advantage of this approach is that it allows to simulate the effects of future policies that modify the net returns to landowners (Lawler et al., 2014). As shown by Koomen et al. (2015) both approaches are suitable to predict land-use change and a combination of both can further improve model performance. Here, it is our aim to exploit both statistical modelling and spatially explicit economic modelling to identify impacts of two different policies on urban development configurations and ESs.

We compare the effects of a zoning (Zoning Driven - ZD) and a Market Driven (MD) policy instrument on the development of residential areas focusing on the effects of the two instruments on the land-use configuration. Zoning has been in use in Switzerland since the adoption of the Spatial Planning Law in 1980. Although zoning has been included in spatially explicit land-use models mainly as a constraint or has been subject to studies on multi-objective optimization or multi-criteria decision-making (Geneletti, 2013, Liu et al., 2012, Altwegg, 2014), we are not aware of any studies trying to spatially explicitly model the outcome of current zoning practices. However, an explicit modelling is necessary, if we aim to predict future settlement development under a zoning policy. To model market-based instruments and make spatially explicit predictions it is necessary to include measures of net return to the land-owner (Plantinga and Lewis, 2014). To derive probabilities of land-use conversion being based on net-returns econometric models have been calibrated using data on land-use transitions which are interpreted as the choices of land-owners to develop their land or to not develop (Bockstael, 1996, Lubowski et al., 2006, Lewis and Plantinga, 2007). Although these models may be suitable for the United States, we have to assume that they are not well suited to model market-based instruments in Europe and particularly in Switzerland, where zoning regulations may be more dominant and have a very strong influence on land-prices and the decision of land-owners (Beatley, 2000, Gennaio et al., 2009, Gmünder et al., 2015).

The comparison of the ZD and MD policy instrument builds on three methodical steps: First, we analyse empirical data on historic land-use and property prices in order to determine the likely location of new residential areas when land-use is governed by either zoning or market mechanisms. Second, we present a modelling framework including two spatially explicit models to simulate the development of residential areas based on these two instruments. Third, we link the different land-use configurations emerging from simulations of both instruments to the provision of ESs. The obtained results are further used to discuss potential benefits and drawbacks of the two presented policies and the modelling framework.

2. Methods and data

2.1. Study Area

The study area is the canton of Bern located in Switzerland (cf. Figure 1), which covers an area of approximately 6000 km². The canton of Bern reflects many characteristics of the Swiss landscape and Switzerland's socio-economic structure, including Alpine regions and lowlands as well as urban centres, small agricultural and touristic municipalities. The total population of the canton is approximately 1 million people, of which almost 140,000 live in its capital Bern.

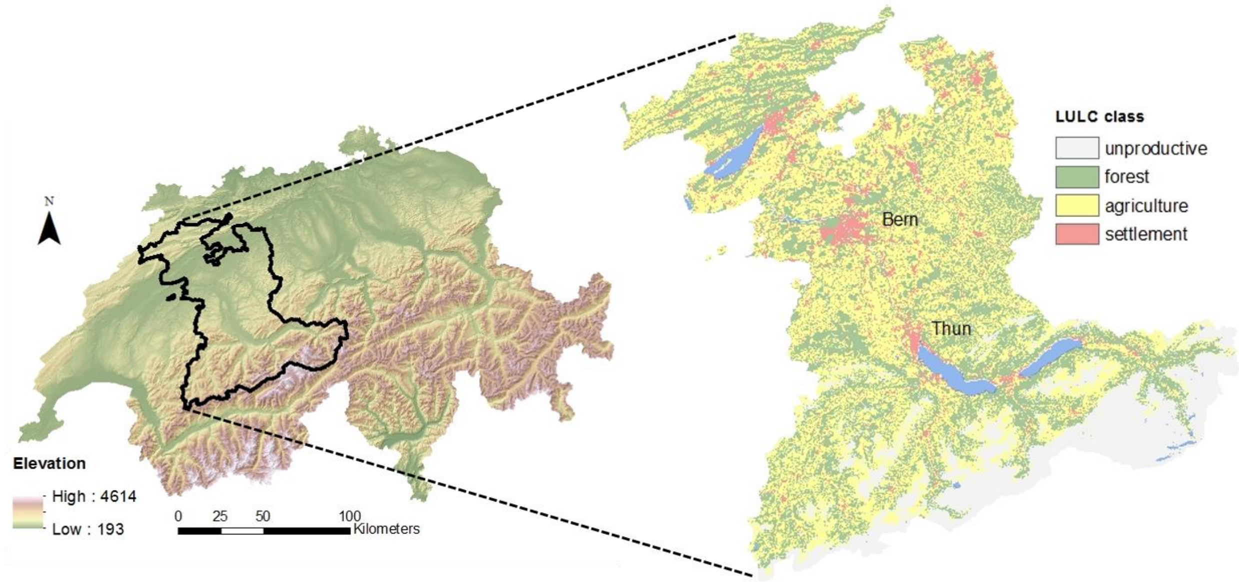


Figure 1: Location of the case study region in Switzerland and distribution of current land use in the region. Two important cities in the canton are labeled to ease interpretation and orientation.

2.2. Land-use change modelling

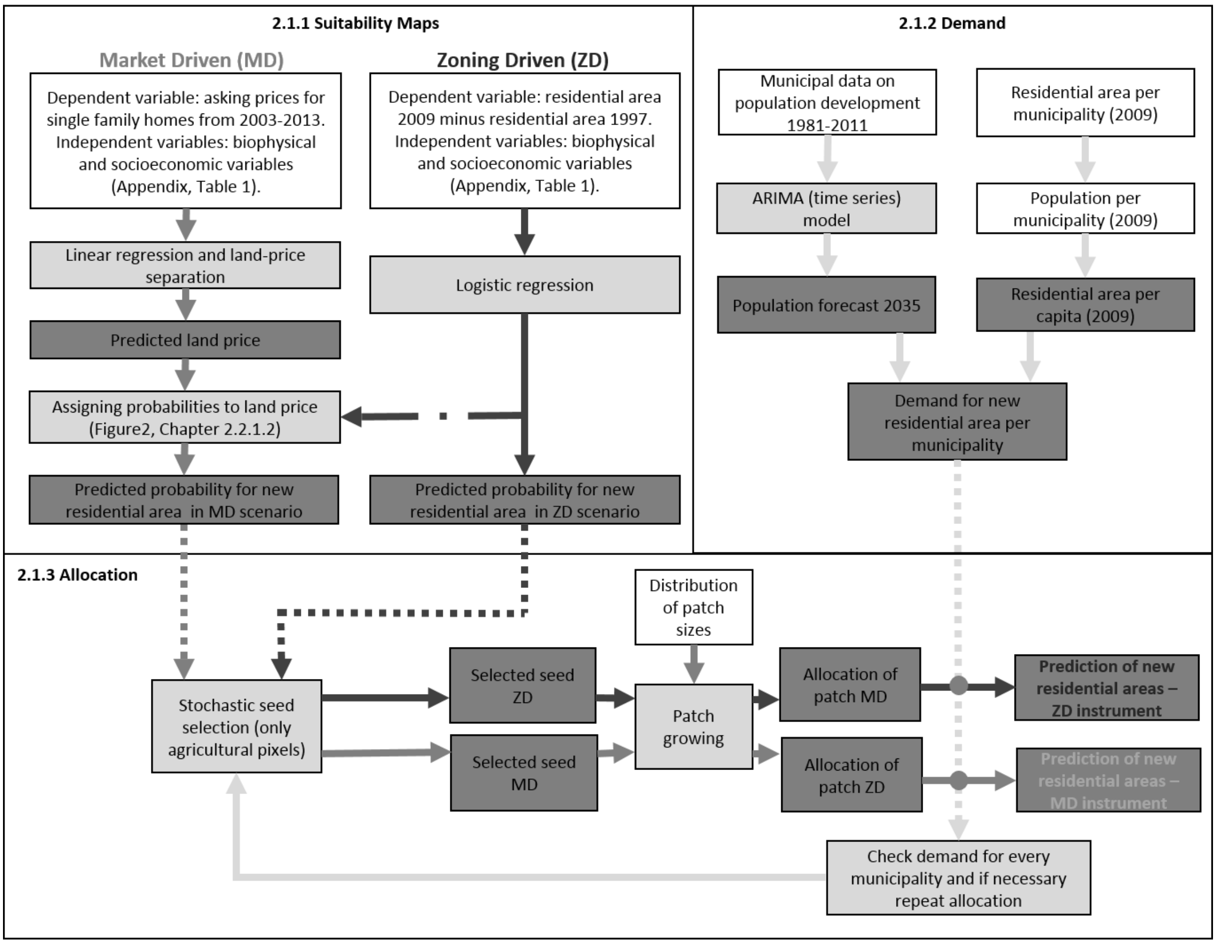


Figure 2: Modelling framework for simulating the development of residential area expansion. White boxes = input, light grey boxes = model steps and dark grey boxes = (intermediary) results. Dark grey and black arrows show the flow for the two different models and light grey arrows indicate workflows that are the same for both models.

To simulate the growth of residential areas relying on zoning or on market mechanisms in the Canton of Bern, we used the modelling framework shown in Figure 2. The modelling approach is hierarchical in that it distinguishes between processes at the macro (demand for land use change) and at the micro (spatial allocation of land use change) level similar to the widely used CLUE-S (Verburg et al., 2002) and other land-use models (Vimal et al., 2012, Meentemeyer et al., 2013). First, we estimated suitability maps for new residential settlement areas at a 1ha resolution across the case study region. Second, we determined the demand for new residential area based on population forecasts and the average residential area per capita for each community. Third, we used information on the distribution of patch sizes of historic development of residential areas. If patch size was larger than one hectare, we allocated new residential areas around the seed selected for development until the selected size or the overall demand was met. Although both, the ZD and MD development of residential areas were assumed to be driven by similar processes at the macro level, different suitability maps were used to allocate land use similar to the approach used by Koomen et al. (2015). For the MD model, the likelihood of new settlement was mainly determined by predicted land prices which were calculated based on a hedonic model including variables like utility services, slope and distance to big lakes as important predictors (chapter 2.2.1.2). The likelihood of new settlement areas in the ZD model was estimated based on a logistic regression model fitted to the historic development of settlement development with distance to settlement, distance to roads and utility services as the most important predictors (chapter 2.2.1.1).

2.2.1. Modelling the development of new residential areas

2.2.1.1. Modelling residential development for the ZD instrument

The suitability of land for establishing new residential areas in the ZD model was based on a logistic regression model calibrated using information on previous land-use/land-cover (LULC) changes as a response variable, which were derived from differences in the Swiss area statistics between 1997 and 2009 (Humbel, 2009). As historic and contemporary development of residential areas in Switzerland is strongly influenced by zoning (Gennaio et al., 2009, Supplement 4) and only around 2 percent of new residential areas are located outside of designated building zones (Hornung et al., 2011), modelling historic development of residential areas in Switzerland effectively results in modelling ZD development.

A binary response variable was created by reclassifying the LULC classes to agricultural land that stayed agricultural land (no change) and agricultural land that changed to residential area (change) (cf. Appendix Table 4). As predictor variables, we tested a range of biophysical and socio-economic factors (Table 1) that have a significant influence on residential location choice according to Schirmer et al. (2014). In addition, we included the provisioning of a number of ESs as predictor variables in the model to test whether these have had a significant influence on historic residential development in the Canton of Bern. According to exploratory data analysis and the rules of thumb provided by Mosteller and Tukey (1977) we employed several first-aid transformations to some of the predictor variables (Appendix Table 2).

In total there are 256,185 observations available (255,247 no change events and 938 change events). According to (King and Zeng, 2001) it can be useful to apply so-called endogenous stratified sampling when one of the values in a binary response variable is underrepresented. We selected all observations that indicated change and selected randomly from all no-change observations (10,642 events). Based on that sample, we calculated the logistic regression parameters using a classical maximum likelihood estimation (McCullagh and Nelder, 1989) and reduced the amount of predictor variables using stepwise backward selection based on the Aikaike Information Criterion (AIC; Sakamoto et al., 1986). The correlogram of the residuals of the reduced model indicated spatial autocorrelation, which was confirmed by a Moran's I test (p-value: 0.02). To account for the spatial autocorrelation we used Spatial Eigenvector Mapping relying on the function "ME" in the R-package spdep (Bivand et al., 2008, Dray et al., 2006, Griffith and Peres-Neto, 2006). While the Moran's I test was not significant anymore after including the Moran Eigenvectors in the model calibration (p-value: 0.1), the effect on the parameter estimates and their significance was negligible. Thus, we used the previously selected model to predict the suitability for new residential areas.

2.2.1.2. Modelling residential development for the MD instrument

In the MD model, we used spatially explicit predictions of land prices in current or potential residential areas in order to derive a suitability map. Using these land prices as a single indicator for the spatially explicit suitability of residential areas involved a couple of assumptions. First, we assumed that a farmer (i.e. landowner) would develop or sell a land parcel where it generates the greatest present discounted value of net returns minus conversion costs. Second, we assumed that spatial variation of conversion costs were small in comparison to the variation of land prices for potential residential development and could therefore be neglected. Third, agricultural land prices, i.e. net returns from agricultural land use in Switzerland do not vary much within a region and are very small (less than 10 CHF/m², (Gmünder et al., 2011)) in comparison to the net returns from developed land (median values in different regions of the canton of Bern rank between 70 and 930 CHF/m², Wüest & Partner AG (2014)). Therefore, we assumed that their effect on the location of new residential areas would be very small and could also be neglected. Not including agricultural net returns means that in our model there is no threshold (i.e. land-price) below which landowners would not develop or sell their land, as net returns from development were smaller than returns from agricultural use. However, the demand for developed land in the MD model was treated as finite and determined by population growth. Forth, while a developer intending to buy and develop land is per se indifferent as to where she would buy land, if we assume that the market prices of the land tend to even out the expected net returns, the likelihood for selling and buying will follow the land price pattern because more added value can be divided between seller and buyer.

In a first step of the MD model, we estimated land prices relying on a spatially explicit hedonic model and the separation of property prices into land-price and building price. The response variable for this model was derived from real estate data provided by the private company Meta-Sys AG (Sager, 2014). This company collects pricing data from advertised real estate together with additional information from online platforms, deletes double counts (identical offers) and performs geocoding via Google Earth. From this dataset, we selected prices of single-family homes (n = 5343; Appendix Table 3) and linearly regressed them against the predictor variables that have been used in the ZD model (Table 1). As in the ZD model, we also tested for the significance of ES in explaining the land price. Predictor variables were selected using again stepwise backward selection based on the Aikaike Information Criterion (AIC). For categorical predictors we made sure that only those predictors were maintained that had more than seven observations per factor level (Van Voorhis and Morgan, 2007). The fitted model was used to predict property prices. To calculate land prices we used the so-called construction cost method (Diewert et al., 2015). Using this method, we assumed that the land price can be calculated by subtracting the price of the building, hereafter called structure, from the property price (more details in Appendix, Supplement 1). The consulting company Wüest & Partner AG provided prices for average construction costs in 2014 in Switzerland (Appendix Table 3).

In the ZD model, our response variable to derive the suitability map included the information on where residential zones were located and the information which parcels have actually been developed. Thus, we were able to directly infer the probability for new residential development in the ZD model based on the fitted logistic regression model. In the MD model, we derived the suitability map from price information. Prices contain the information of the location preferences of potential future residents, but they do not include the information, where houses will actually be built. We were able to infer land-price differences (i.e. household preferences) in the MD model but not the likelihood of new developments, which depends on many unknown factors. For example, landowners may be unwilling to sell their land, although it would be economically reasonable. In addition, the likelihood of selling land will depend on the negotiation between landowners (sellers) and developers (buyers), which will not always be successful. If a landowner is willing to sell unattractive land for a very low price it may become profitable for a developer to buy and develop this land instead of developing land with more desirable amenities. In general, this means that there is an empirical gap between land prices and the likelihood for new residential areas. Instead of trying to somehow translate land prices into probabilities (e.g. via a linear transformation), we chose an alternative approach in which we considered the ranking of land prices as robust. In other words we assumed that the mean likelihood that houses will be built on a certain plot is always higher for a higher ranked pixel than for a lower ranked pixel when establishing a ranking based on land prices. However, the differences in these mean likelihoods are unknown. Thus, as a proxy we used the ranked allocation probabilities from the ZD model and assigned them to the ranked land prices (Figure 2, Figure 3). By using the same allocation probabilities, but different rankings, we focused on the effect of the regression predictor variables on the location of new residential areas in the two models and reduced the effect of uncertainties related to the gap between land price and the probability of a parcel to be developed. To determine the influence of the probability distributions on our results, we performed a sensitivity analysis using different distributions of allocation probabilities. To produce different distributions, we raised the probabilities from the ZD model to a given power (Meentemeyer et al., 2013) and used these transformed distributions for both models (Appendix Figure 1). Transforming the distributions with an exponent higher than 1 means that the ranking of pixels according to the suitability map is less strictly followed (i.e. the configuration becomes more random). Transforming the distributions with an exponent lower than 1 means that the ranking of the pixels is more strictly followed and an exponent of one corresponds to no transformation.

2.2.2. Modelling demand for new residential area

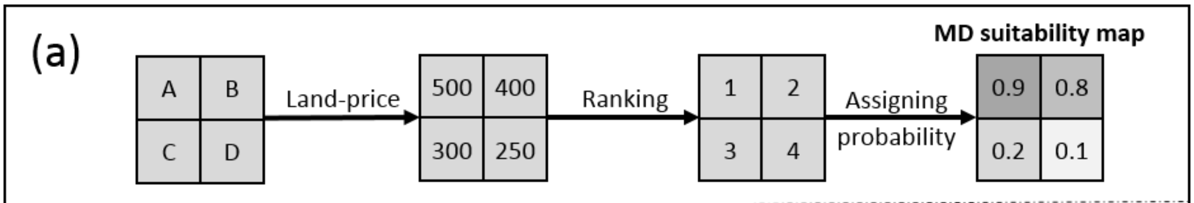
In order to determine how many hectares of new settlements had to be allocated, the demand for new residential areas had to be quantified. This demand was estimated based on forecasts of population growth and the demand for residential area per capita in every municipality (e.g. Hoymann, 2011, Arsanjani et al., 2013b). For population forecasts, we used data on population development between 1981 and 2011 in every municipality and an automated process for time series forecasting relying on ARIMA models (Hyndman and Khandakar, 2008). The area per capita was estimated by dividing the sum of residential areas in every municipality (based on the Swiss area statistics 2004/2009) with the average population from 2004-2009. Since we exclusively focused on the configuration of land-use and not on the composition, we defined an equal demand for both models, which was 1977 hectares of new residential area.

2.2.3. Allocation of new residential areas

In the final step of our modelling framework (Figure 1), new residential areas were allocated to the raster cells in our study area. Raster cells that were converted into residential areas were selected based on the following analysis steps (Figure 2). First, we excluded those raster cells that were classified as conservation areas as well as forests, which are strongly protected in Switzerland and very unlikely to be converted to residential areas (Bloetzer, 2004). Second, we selected from all the existing agricultural areas single pixels (seeds) and we drew a potential patch size for the new building site. Third, selected seeds and neighbouring pixels (in case the selected patch size was larger than one) were converted to the LULC class "residential" until the selected patch size was reached. For selecting neighbouring pixels we searched for agricultural pixels in the Moore neighbourhood of the seeds (or the most recently allocated pixel) and randomly selected one of these pixels for allocation.

In order to realistically predict the patch sizes of new residential areas, we followed the idea of pattern-oriented modelling (Grimm and Railsback, 2012) by trying to match observed patterns. The likelihood for a certain patch size to be drawn was derived from the distribution of sizes of new patches according to changes in the Swiss area statistics between 1979/85 and 2004/09. This approach is less precise but similar to the approach proposed by Meentemeyer et al. (2013).

Selection of seeds and patch sizes was implemented as a stochastic process. Thus, every simulation of the two models will produce different land-use configurations and accordingly different losses in ESs. To be able to compare ZD and MD model in a robust way, we simulated every model 100 times and compared the outputs.



(b)

Four agricultural pixels for potential development	Land-price (MD) [CHF/m²]	Predicted probability (ZD)	Ranking according to land-price (MD)	Ranking according to predicted probability (ZD)	Allocation probability (MD)	Allocation probability (ZD)
A	500	0.8	1	2	0.9	0.8
B	400	0.9	2	1	0.8	0.9
C	300	0.2	3	3	0.2	0.2
D	250	0.1	4	4	0.1	0.1

Figure 3: Allocation probabilities assigned to potential residential areas in the MD model shown by a hypothetical example for a municipality with only four pixels for potential development. (a) Spatially explicit representation of the assignment of probabilities. Every pixel within a municipality is ranked and afterwards a probability is assigned to every pixel. b) Differences between the two models: In the ZD model the predicted probability (from the logistic regression) equals the ZD allocation probability. In the MD model the allocation probabilities of the ZD model are ranked according to the suitability in the MD model (i.e. according to land-price).

2.3. Ecosystem services and biodiversity modelling and mapping

The effectiveness of the selected spatial planning instruments to support the provision of ES was assessed by quantifying the differences in ES between the current situation and the development pattern predicted under the MD and ZD development with the help of the two models. We focused on ESs that can be categorized as provisioning or regulating (Millennium Ecosystem Assessment, 2005, TEEB, 2010). As biodiversity supports the production of many ESs, we also assessed changes in biodiversity (MEA, 2005). Several indicators were used to assess ESs and biodiversity (Table 1). The different ES indicators were either based on national and cantonal datasets or were estimated using statistical and process-based models, as described in more detail in the supplement material .

As an indicator for the ES food we used a soil map containing information on the soil quality with respect to agricultural production on cultivated land (Swiss Federal Statistical Office (BFS) GEOSTAT, 2012). The soil quality is organized in five classes that depend on pedological and topographic criteria.

Table 1: Indicators used to assess ESs and biodiversity.

ES	Indicators
Food	**SQ** - Soil quality for food production
Climate regulation	**CA** - Net carbon stocks
Drinking water supply	**GR** - Groundwater recharge
	PW - Proximity to protected areas in drinking water catchments
Pollination	**PO** - Pollination supply/demand
Biodiverstiy	**PR** - Plant species richness
	WL – Connectivity Wetlands
	DL - Connectivity Dry Grasslands
	EL – Connectivity Extensively used open land
	CO - Wildlife corridors

2.4. Comparison of the market-driven and zoning-driven residential development

The MD and ZD instrument were compared by analysing the importance of different predictor variables when explaining historic growth patterns of residential areas and property prices and by evaluating the simulations of both instruments regarding the provisioning of ESs. The importance of different predictor variables was tested based on hierarchical partitioning using the function hier.part in R (Chevan and Sutherland, 1991, Mac Nally, 2000). For this comparison, we only selected those predictor variables that were important in determining the suitability for new residential areas within every municipality (Appendix Table 1). As we assumed equal demands for every municipality, major differences between the impact of the ZD and the MD instrument in our results will mostly be related to these variables. Although not selected as a predictor in the two models, we included the variable public transport in the hierarchical partitioning. Applying this selection meant in case of the MD model omitting variables that are independent of location (e.g. age of the house and surface of the property) and variables that explain price differences between the municipalities (e.g. tax and municipality typology). This selection assured that we did not test the importance of more than nine variables in each model as recommended by Olea et al. (2010). The change in ES was calculated across the region in comparison to the status quo similar to Geneletti (2013). These changes are sometimes rather small when comparing land-use scenarios with equal composition, i.e. the same demand for new residential areas, as in our study. However, since the stochastic allocation of settlements was repeated 100 times for each of the two policy instruments simulated, we were able to determine whether the mean differences between them were significantly different or not. For this purpose we used a Wilcoxon signed rank-tests. In addition to calculating ES for the whole canton we compared ES in every municipality.

3. Results

3.1. Drivers of residential development

The explanatory variables that were retained after selecting the models for the prediction of the suitability maps differ between the MD and the ZD model (Table 2, Appendix Figure 1). In both models, the variables distance to utility services, slope, view, aspect and distance to big lakes were selected. The suitability in the ZD model also depended on distance to settlements and distance to roads. For the MD model distance to large rivers, noise, taxes, mean global radiation and municipality typology were selected additionally. Coefficients of determination indicate a decent fit for both models. The adjusted R^2 for the MD model (i.e. fitting property prices) was 0.63. The Nagelkerke/Cragg and Uhler's pseudo R^2 for the logistic regression (i.e. in the zoning driven model) was 0.68.

The results of the hierarchical partitioning showed for the selected variables that distance to settlement and distance to roads had the highest independent effect when explaining historic transitions from agricultural to residential land-use (Table 2). The most important variables for explaining historic land-prices were, according to the independent effects, distance to utility services, slope and distance to big rivers. The variables slope, view, aspect and distance to lake showed a higher independent effect for the land price than for historic transitions from agricultural to residential land. The ES indicators were not significant except for net carbon stocks in the case of the ZD model and for plant species richness in case of the MD model. However, these two indicators were not selected as predictors (details in chapter 0).

3.2. Comparison of zoning-driven and market-driven development patterns

We found that both, market driven and zoning driven development patterns caused a decrease in the supply of all ESs and biodiversity indicators, except for plant species richness. The mean differences in ES loss were significant for the two development patterns, except for proximity to water protection zones (Figure 4). However, none of the two instruments consistently resulted in a lower decrease for a certain ES if we analysed the patterns on a regional scale. In some municipalities ESs are more negatively affected by the MD development and in others more negatively by the ZD development Figure 5. The ZD development, compared to the MD development, caused higher loss of plant species richness, soil quality and carbon stocks. In contrast, the MD development resulted in a higher loss for the ES indicators pollination, wildlife corridors, groundwater recharge, proximity to water protection zones and connectivity of extensively used agricultural land, dry grasslands and wetlands (Figure 4). The loss of the ESs and biodiversity indicators pollination, soil quality for food production, wildlife corridors and connectivity of extensively used agricultural land, dry grasslands and wetlands showed a large variation within the 100 simulations for every policy instrument (Figure 4). Plant species richness, proximity to water protection zones, carbon stocks and groundwater recharge showed only a low variance within the simulations (Figure 4). The difference between the two development patterns was very small for carbon stocks and groundwater recharge. Plant species richness was the only ES indicator that increased in comparison to the status quo.

3.3. Sensitivity analysis

The sensitivity analysis indicated that the differences in ESs between the two instruments (MD and ZD) changed for different allocation probabilities (Appendix Figure 1). However, the sign of the differences was hardly affected by the use of different allocation distributions. In other words, irrespective of the allocation probabilities used, the ZD instrument mostly caused a higher loss in plant species richness, soil quality for food production and carbon stocks, while the MD instrument mostly caused a higher loss in pollination, groundwater recharge, wildlife corridors and in the connectivity of wetlands, dry grasslands and extensively used open land.

*Table 2: Variables selected for the MD and ZD model together with independent effects derived from hierarchical partitioning. Variables selected as predictors for the suitability maps are marked with an x. *The variable Public Transport was not selected as a predictor in the two models, but tested in the hierarchical partitioning.*

Predictor Variable	Selected for final model		Independent effects (hierarchical partitioning)	
	MD	ZD	MD [%]	ZD [%]
Utility Services (US)	X	X	22.2	13.2
Slope (SLOPE)	X	X	16.6	2.5
Public Transport (PT)	-	-	22.8*	12.8*
Distance to large Rivers (DR)	X	-	4.3	-
View (VIEW)	X	X	9.9	2.9
Noise (NOISE)	X	-	3.1	-
Aspect (ASP)	X	X	6.2	0.7
Distance to Big Lakes (DBL)	X	X	14.8	1.4
Distance to High Voltage Power Line (DHVPL)	-	-	-	-
Distance to Settlements (DS)	-	X	-	39.0
Distance to Roads 02 (DR2)	-	X	-	14.5
Distance to Roads 03 (DR3)	-	X	-	13.0

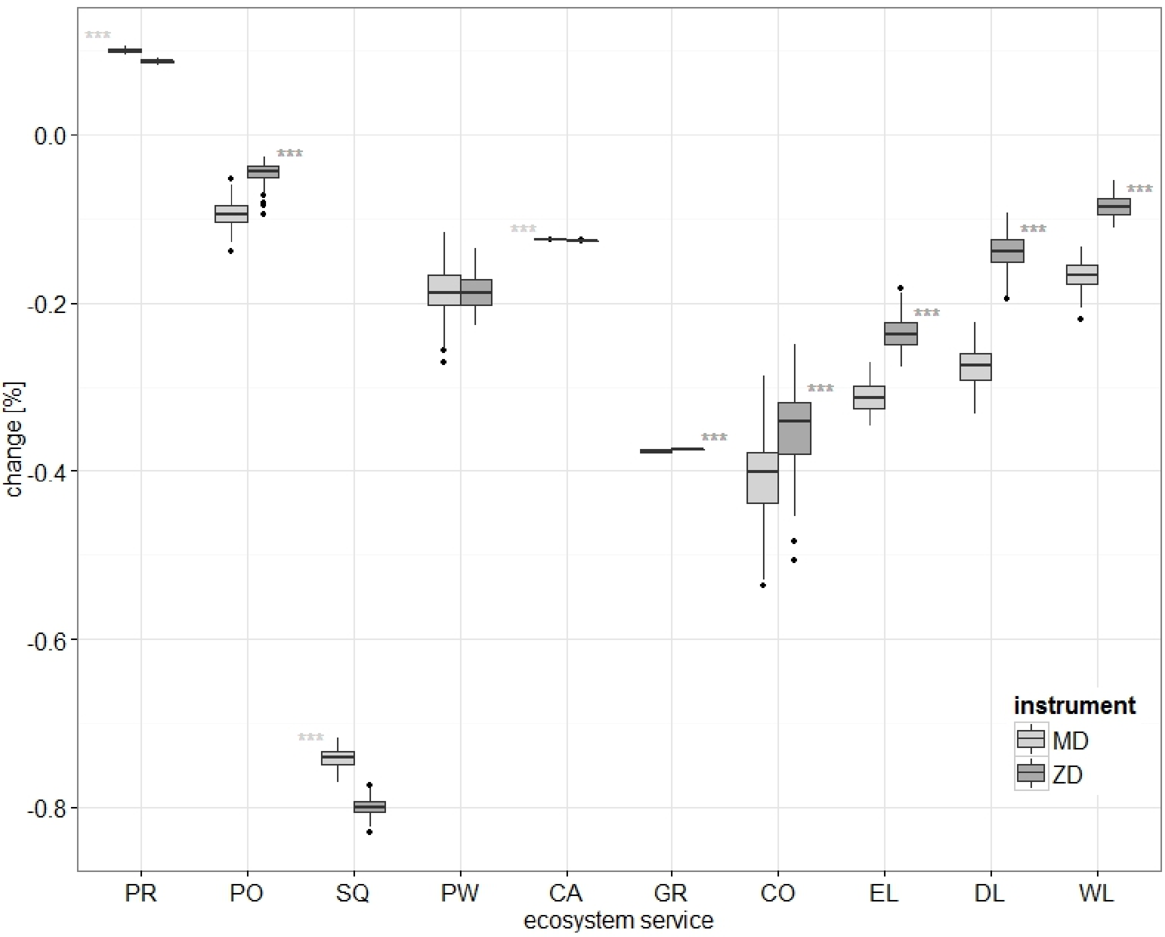
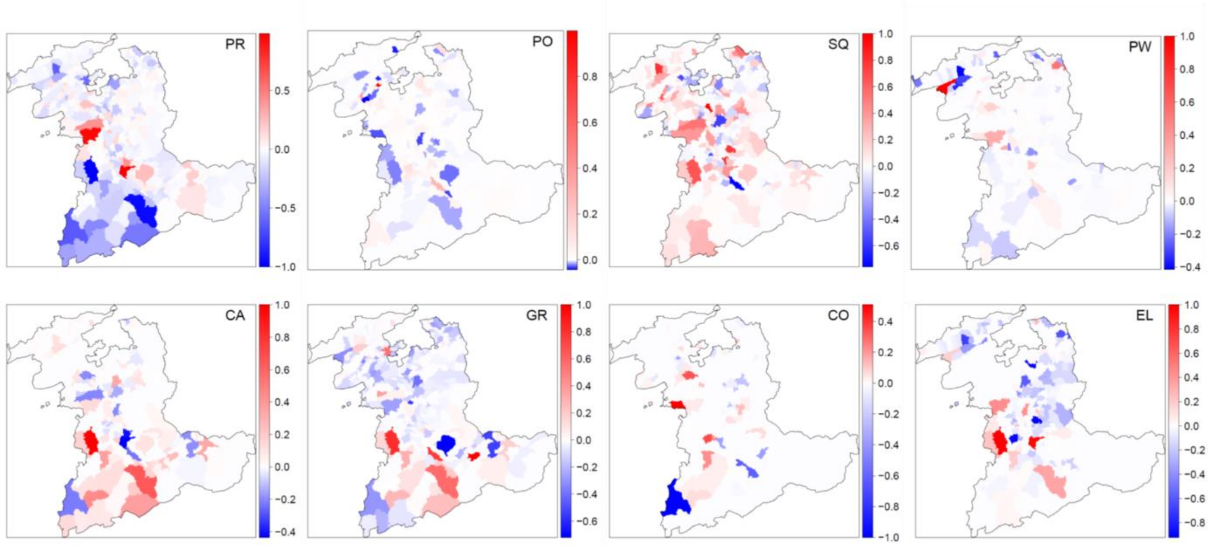


*Figure 4: Boxplots showing percentage change for every ecosystem service in comparison to the status quo (100 randomized simulations for ZD and 100 randomized simulations for MD development). Stars indicate significance level: *** significant at 0.01. SQ - Soil quality for food production; CA - Net carbon stocks; GR - Groundwater recharge; PW - Proximity to protected areas in drinking water catchments; PO - Pollination supply/demand; PR - Plant species richness; WL – Connectivity Wetlands; DL - Connectivity Dry Grasslands; EL – Connectivity Extensively used open land; CO - Wildlife corridors*



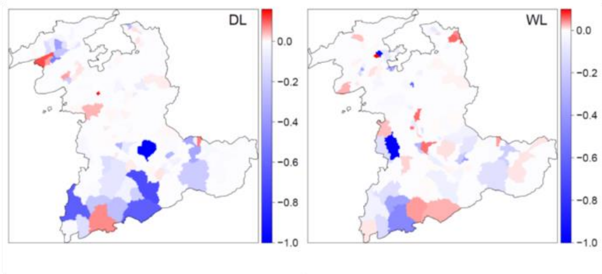


Figure 2: Municipalities in which ESs and biodiversity indicators (average values of 100 simulations) are lower for the MD development than for the ZD development are colored in red. Municipalities in which the difference between the two developments is very small or zero are colored in white. Municipalities that are colored in red are characterized by a smaller loss in ESs or biodiversity in the MD development.

4. Discussion

4.1. Results supporting policy makers

The modelling framework developed in this paper allowed us to compare the ESs provision under two generalised policy instruments focussed on steering residential development via zoning or market mechanisms. We point at three major findings of this study which may support policy makers in their decision making, in particular, when they are in the stage of deciding between market-based land-use policies or regulatory policies including zoning: (1) In general, results showed that each policy instrument was beneficial for a different set of ESs. Policies aiming at reducing the negative effects of settlement growth on the provision of pollination, groundwater recharge and the connectivity of ecosystems may be well embedded in a regulatory framework such as zoning. For policies focussed on increasing plant species richness and a reduction in the loss of carbon stocks and good quality soils it could be beneficial to create incentives embedded in a market driven policy environment. (2) The impact of the two policy instruments varied locally. For most municipalities, no policy instrument was consistently better at preserving ESs than the other instrument. However, there are a number of municipalities in which nine or even ten (out of ten) ES indicators were higher under the zoning driven development. Particularly in these municipalities zoning regulations should be preferred for preserving ESs. Contrastingly, in several other municipalities seven (and in one case eight) ES indicators were higher under the market driven development. A characterisation of the regions that performed better in one of the two development scenarios lies beyond the scope of this study. However, a preliminary visual inspection of our results indicated that the market driven development performed better in the higher populated municipalities, while the zoning driven development performed better in small municipalities. (3) While the different land-use configurations of the two development scenarios caused high differences for some ESs (e.g. soil quality for food production), others hardly seemed to be affected (e.g. groundwater recharge; Figure 4). This shows that some ESs could be very vulnerable to a shift from zoning to market driven land-use policies or vice versa. For the ESs that were less affected by the configuration differences, it could be more important to focus on the question of how much land is developed under the two development scenarios rather than to question where land is developed. This is related to the question of how effective specific market and zoning driven instruments are in reducing the overall demand for newly developed residential areas (i.e. an aspect that is left out of consideration in this study).

4.2. Locations chosen for residential development applying the two instruments

By calibrating the two instruments, i.e. land-use models, to the historic development of residential areas and property prices (i.e. prices of single-family homes) we tried to capture two different processes underlying location choice when ZD or MD instruments are used. Historic development was mainly driven by zoning in Switzerland. Thus, it mainly reflects the choices of local governments when allocating new building zones (i.e. designated residential areas). Differences in prices of single-family homes at different locations partly reflect households' preferences for location amenities. According to our results and a large amount of literature on hedonic models (e.g. Baranzini and Schaerer, 2011, Crespo and Gret-Regamey, 2012) people's preferences are, amongst others, to live on south facing slopes, close to big lakes and in areas with a nice view. We found that these drivers were far less important for the zoning driven development. According to the independent effects of the variables it seems more important for local governments to allocate residential areas close to existing settlements and roads. This seems reasonable, as local governments will try to keep the costs for land-development (infrastructure etc.) low. However, the zoning process is complex and local governments may as well account for people's housing preferences in order to attract new residents. It has to be noted that the hierarchical partitioning facilitates a comparison of the importance of the predictor variables, however, it should not be confounded with the importance of the predictor variables in the finally selected regression models. In addition, it should be mentioned that we used hierarchical partitioning for only seven predictor variables in the market driven model, although we included a total of 17 predictors. Integrating all variables could affect the independent effects that we found, due to collinearities with the omitted variables.

Although the differences in the importance (i.e. the independent effects) of the predictors between the two regression models can be reasonably well explained, they have to be interpreted with care. Both, location choices derived from actual development of residential areas and land-prices derived from actual property prices (i.e. location preferences of residents) were not independent from each other. The importance (i.e. independent effects) of predictor variables in the zoning driven model were derived from data indicating where residential development actually took place. Within zones destined for residential development it have probably been land prices which determined the locations of new residential areas. Thus, also in the zoning driven model, people's preferences probably have had an influence on the importance of the predictor variables. A major limitation when deriving land prices, was that our response variable (property prices) used for calibrating the hedonic model was not independent of zoning and cannot fully reflect land development costs (e.g. for infrastructure), because we used property prices from houses that were mainly built in designated building zones for which local governments committed to partly bear development costs. Distance to settlement and distance to roads would most likely become significant in the market driven model if it was possible to eliminate the influence of zoning on prices and the differences between the suitability maps of the two models would decrease.

When calculating the suitability map in the market driven model (i.e. land-prices), predictor variables that explained price differences between municipalities (e.g. tax and municipality typology) were found to be significant. However, these variables were not significant when generating the suitability map for the zoning driven model. A possible explanation for this finding is that the response variable in the market driven model (property prices) reflects both demand and supply for new housing and thus differences between municipalities (Waddell et al., 2003). In Switzerland building zones tend to be oversized particularly in small and agricultural municipalities (ARE, 2012). This corresponds to a high supply of land available for development and may result in lower land-prices than in metropolitan areas, where the land in the few remaining building zones are in high demand. This explanation is confirmed by our finding showing that the variable "municipality types" caused higher land-prices in centres and metropolitan areas than in agricultural municipalities (Appendix Table 2). By defining the demand for new residential areas for every municipality we avoided the difficulty of predicting how specific market-based instruments or specific shaping of zoning regulations would influence the inter-municipal demand. However, we were thus limited to the analysis of the intra-municipal land-use configurations.

4.3. Land-use modelling framework

The presented land-use modelling framework, which is in some respects similar to the FUTURES model (Meentemeyer et al., 2013), offers the flexibility to model and compare the effect of both, zoning regulations and market-based mechanisms. Many parameters that determine the location of new residential areas were calibrated using empirical datasets. Although this can be regarded as beneficial for the realism of the model, it can make it more difficult to model the effects of new policy instruments. Including more process based modules that rely on economic theory and/or explicitly model the behaviour of actors in the housing market may extend the frameworks' ability to simulate counterfactual land-use policies. Including such modules could ease trade-offs that are often encountered when trying to empirically calibrate and model land-use patterns and at the same time modelling underlying processes that generate these patterns (Irwin and Wrenn, 2014).

Although it may be beneficial to include process-based modules into the modelling framework, it will be essential to calibrate as many parameters as possible. Since zoning regulations are usually employed by local or regional governments it is necessary to find a way to translate their choices of allocating residential zones into a suitability map. We argue that this would be possible using data on historic or current zoning plans or if zoning strongly regulated the development of new residential areas in the past, using data on historic land-use transitions as we did. If the location of historic residential development is mainly determined by zoning, it may be also appropriate to calibrate the distribution of allocation probabilities and the distribution of patch sizes using data on historic land-use change. When market-based instruments are used, we assume that the decisions of land-owners, which seek to maximize their profit, would shape settlement development. Thus, a suitability map being based on land prices, derived using a hedonic model, seems to be a useful approach. However, as historic settlement development was in Switzerland mainly a result of zoning, it is not possible to calibrate the distribution of allocation probabilities and patch sizes in the market-driven model. As our sensitivity analysis shows, different allocation probabilities may not change whether one of the two instruments is favourable regarding a particular ecosystem service or biodiversity indicator. However, instead of relying on a sensitivity analysis it may be possible to determine the relationship between land prices and allocation probabilities making use of agent-based models that explicitly model land and housing markets (Magliocca et al., 2015, Filatova, 2015). The calibration of the patch size distribution to the current and historic land-use changes might be approximately valid for both models as the reduction of infrastructure costs may be a goal of both, the local municipality and potential developers of land.

In general, the use of our modelling framework is not restricted to the way we formulated the policy instruments but could be extended to implement more realistic and more specific land-use policy instruments. It could be useful to for example integrate impact fees and analyze Transferable Development Rights (TDR) (Gyourko, 1991, Johnston and Madison, 1997). Impact fees could e.g. be introduced as a fee proportionate to a parcel's distance from existing settlements and roads. As an impact fee would lower the net return to a landowner when developing a parcel and assuming that in a competitive market land prices are equal to the discounted sum of expected net returns obtained by allocating the land to its most profitable use (Plantinga et al., 2002), the impact fee could be implemented by modifying the suitability map (i.e. land-price) in the market driven model (cf. Figure 2). Such a modification could require an explicit estimation of net returns, which may be based on the hedonic land-price predictions and conversion costs, the latter of which would increase if an impact fee is introduced. Such a modification of land prices, i.e. net returns, would be crucial for implementing any sort of economic incentives into the market driven model. The instrument transferable development rights may be well based on the market-driven model, if we assume that buying development rights and developing a parcel would be more likely, i.e. more profitable, if the land-price of the potentially developed parcel is high. An implementation of market-based instruments like impact fees and TDR often will not fully replace zoning regulations and, as already mentioned, will mainly steer the development of parcels within zones. Thus, it seems reasonable to connect both models in order to get more realistic predictions. It may be particularly useful to combine the two models in a dynamic way as land prices are obviously influenced by regulations (e.g. Kok et al., 2014). The hedonic model used to predict land prices is a snapshot of a market at one point in time conditioned on the distribution of land of various sorts and the distribution of buyers with different incomes and preferences (Bockstael, 1996). Thus, not only zoning regulations but any change in market conditions will have an impact on the hedonic price estimation, which causes high uncertainties when using the model to simulate settlement development for long time horizons.

4.4. Provision of ESs

We assessed changes in the provision of several ESs to determine the environmental impact of two different policy instruments, an approach that has been used in several other studies (cf. Martinez-Harms et al., 2015). As in many other studies, the ESs and biodiversity indicators used in this study were calculated in a static way and were not dynamically adapted to an evolving land-use configuration, with the exception of the two indicators pollination and plant species richness. Static calculations may not always provide consistent results on the effects of land management and land-use change as has been discussed by Sturck et al. (2015). In our study, for example, important areas for the connectivity of ecosystems were defined for the current land-use configuration and assumed to deteriorate if residential development takes place on these areas. This approach does not account for the fact that some areas may become more important for connectivity if others are lost. In addition, we were not always able to calibrate the effect of the development of residential areas on the deterioration of ESs or biodiversity. For example, we were not able to calibrate the habitat quality for wild-bees of different land-use classes in Switzerland. However, in case of pollination and for most other ESs an exact calibration would rather influence the quantity of deterioration and not the difference between the two instruments in ESs provision which will be more robust.

All ESs and biodiversity indicators, except for plant species richness, decreased for both instruments. The loss in ESs caused by the growth of residential areas did not exceed 1% of the current provision of ESs (Figure 4). This loss appears to be small, however, we assumed that the increase of residential areas would be very moderate amounting to only 0.8% of all agriculturally used land in the canton of Bern in 2009. This means that for example, the loss of soil quality is almost proportional to the increase in residential areas and that neither of the two instruments was effectively reducing this loss. It seems that either ESs have to be explicitly included into land-use policies or that land consumptions has to be strongly reduced, which confirms the findings of Lawler et al. (2014) who argue that policy interventions need to be aggressive to significantly alter underlying land-use change trends and shift the trajectory of ecosystem service provision. The increase of plant species richness is not surprising as cities serve as habitat for many alien as well as native species (Kuhn et al., 2004, Wania et al., 2006). We found higher plant species richness evaluating the simulations of the market driven instrument but at the same time a stronger disturbance of the ecological connectivity for this instrument. This shows that none of the two instruments can be easily attributed to a higher biodiversity and highlights the importance of using a combination of biodiversity indicators to assess different potential impacts of settlement development on biodiversity.

The fact that most of the ESs were not identified as important drivers for the development of residential areas in the regression models, indicates that they have not played an important role in defining property prices or building zones. Only net carbon stocks was selected as a predictor in the model explaining historic residential development (zoning driven model) and plant species richness was selected in the land-price model (market driven model). However, we included neither net carbon stocks nor plant species richness in the final models. We are not aware of any guidelines or laws that promote the consideration of loss in carbon stocks when zoning decisions are made. Thus, we suppose that the significance can be attributed to collinearity with other potentially missing predictor variables. For the same reason, plant species richness might have been selected in the market driven model. In fact, one could argue that households would prefer high plant species richness in their neighbourhood. However, the regression coefficient we found was negative, which would mean that prices are higher where there is low plant species richness. This doesn't seem to be reasonable as environmental amenities tend to raise prices (Gibbons et al., 2014).

5. Conclusion

The locations chosen for residential development when zoning is employed differ from locations that would be chosen when market mechanisms, i.e. the preferences of residents, determine the location of new residential areas. Although zoning would allow local governments to account for loss in ecosystem services and biodiversity when choosing new zones for residential area, they do not seem to ingrate them sufficiently. Our results indicate that it is most important for local governments to reduce infrastructure costs, i.e. chose locations close to existing settlements and roads. For residents on the other hand, it seems most important to choose locations that guarantee a good view, are close to big lakes and to utility services.

Our results may support policy makers, in particular, when deciding whether they would like to employ market-based policies or regulatory policies including zoning. If aiming at reducing the negative effects of settlement growth on the provision of pollination, groundwater recharge and the connectivity of ecosystems, choosing a regulatory framework relying on zoning may be advantageous. If aiming at an increase of plant species richness and a reduction in the loss of carbon stocks and good quality soils for agricultural production it may be of advantage to create incentives embedded in a market driven policy environment. However, the impact of the two policy instruments varies locally, which means that some municipalities would be recommended to rely on zoning and others on market mechanisms.

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Appendix

Appendix Table 1: Description of predictor variables

Predictor Variable	Description
Utility Services (US)	Amount of utility services within a distance of 1000 m. Utility services were calculated based on the census of enterprises in Switzerland (Swiss Federal Statistical Office (BFS) Geostat, 2008) and classified according to Altwegg (2014).
Slope (SLOPE)	Slope, 5 categories [in percent]: 0:10->1; 10:20->2, 20:30->3, 30:50->4, >50->5
Motorway Access [MA]	Path distance to motorway access.
Public Transport	Quality of public transport, 6 categories from very good to not existent.
Distance to large Rivers (DR)	Distance to large rivers lower or higher than 100m, 2 categories.
View (VIEW)	Percentage of area that can be seen within a radius of 5 km.
Noise (NOISE)	Noise from aircrafts, streets and railways.
Aspect (ASP)	Aspect, 2 categories: South - North
Distance to big lakes (DBL)	Distance [in m] to big lakes (> 50 ha), 5 categories: <100~1, 100:500~2, 500:2000~3, 2000:6000~4, >6000~5
Distance to medium size lakes (DML)	Distance to medium size lakes (> 2 ha , < 50 ha), 5 categories
Distance to small lakes (DSL)	Distance to small lakes (< 2 ha), 5 categories
Distance to public green space (DPGS)	Distance to public parks, sports facilities and cemeteries.
Distance to high voltage power line (DHVPL)	Distance to high voltage power line lower or higher than 150 m, 2 categories.
Distance to settlements (DS)	Distance to settlements.
Distance to roads 01 (DR1)	Distance to roads being more than 6 m wide.
Distance to roads 02 (DR2)	Distance to roads being 4 m wide.
Distance to roads 03 (DR3)	Distance to roads being 3 m wide.
Tax (TAX)	Average tax burden per municipality.
Mean global radiation (MGR)	Mean global radiation.
Typology of municipalities (TM)	Typology of municipalities, 22 categories (Schuler and Joye, 2007). English translation of the original classes: (1) Large centres, (2) Medium-sized centres, (3) Small centres, (4) Periphery centres, (5) Rich municipalities, (6) Touristic municipalities, (7) Semi touristic municipalities, (8) Municipalities with large amount of public institutions and collective households, (9) Municipalities with high levels of employment in metropolitan regions, (10) Suburban municipalities in metropolitan regions, (11) Periurban municipalities in metropolitan regions, (12) Municipalities with high levels of employment in non-metropolitan regions, (13) Suburban municipalities in non-metropolitan

	regions, (14) Periurban municipalities in non-metropolitan regions, (15) Commuter municipality with high increase in population, (16) Commuter municipality with low increase in population, (17) Industrial tertiary municipalities, (18) Industrial Municipalities, (19) Agro-industrial municipalities, (20) Agricultural an tertiary municipalities, (21) Agricultural municipalities, (22) Municipalities with strongly decreasing population
Quarter	Quarter in which the property has been offered for sale.
Number of Rooms (NR)	Number of Rooms.
Balcony (BA)	6 categories: -1 unknown , 1 average balcony, 2 small balcony, 3 large balcony, 4 terrace, 5 rooftop terrace
View specified for property (VIEW_SP)	View specified for every property in the advertisement, 6 categories: -1 unknown, 1 average view, 2 mountain view, 3 lake view, 4 lake and mountain, 5 other view
Stove (STOVE)	2 categories: 1 no stove, 2 stove
Parking 1 (P1)	4 categories: -1 unknown, 0 no parking, 1 parking available, 2 uncovered parking available
Parking (P2)	3 categories: -1 unknown, 0 garage not available, 1 garage available
Age (AGE1)	Age of the house (linear term).
Age (AGE2)	Age of the house (quadratic term).
Surface property (SP)	Property surface.
Surface living area (SLA)	Surface living area.
Soil quality (SQ)	Soil quality for food production, 5 categories: low, medium, high, very high, unusable
Net carbon stocks (CA)	Net carbon stocks [t/ha]
Groundwater recharge (GR)	Groundwater recharge [l/ha]
Proximity water catchments (PW)	Proximity to protected areas in drinking water catchments
Pollination (PO)	Pollination supply/demand
Plant species richness (PR)	Amount of Plant species
Connectivity Extensively used open land (EL)	Connectivity Extensively used open land, 2 categories: pixel is important for connectivity, pixel is not important
Connectivity Dry Grasslands (DL)	Connectivity Dry Grasslands, 2 categories: pixel is important for connectivity, pixel is not important
Connectivity Wetlands (WL)	Connectivity Wetlands, 2 categories: pixel is important for connectivity, pixel is not important
Wildlife corridors (CO)	Wildlife corridors (CO) , 2 categories: pixel is important for connectivity, pixel is not important

*Appendix Table 2: Predictor variables. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1. Type: Numeric=Continuous, Factor=Discrete*

Explanatory Variable	ZD			MD			Type	First aid
	Coef.	Std. err.	P (Chisq)	Coef.	Std. err.	P (F)		

Intercept	4.4	0.76	-	9.44	0.14	-		
Utility Services (US)	0.12	0.05	0.03*	0.04	0.004	0.00***	Numeric	Log
Slope (SLOPE)			0.00***			0.07.	Factor	-
Slope2	0.11	0.14		-0.012	0.01			
Slope3	0.83	0.17		-0.0003	0.01			
Slope4	0.15	0.23		-0.05	0.02			
Slope5	0.20	0.55		-0.02	0.04			
Motorway Access [MA]	-	-	-	-	-	-	Numeric	Log
Public Transport	-	-	-	-	-	-	Factor	-
Distance to big Rivers (DR)	-	-	-			0.00***	Factor	-
DR1				-0.07	0.02			
View (VIEW)	1.16	0.46	0.01*	0.16	0.04	0.00***	Numeric	arcsi n
Noise (NOISE)	-	-	-	-0.003	0.0005		Numeric	-
Aspect (ASP)			0.01*			0.06.	Factor	-
Asp2	-0.31	0.11		-0.015	0.008			
Distance to big lakes (DBL)			0.04*			0.00***	Factor	-
Dbl2	-2.10	0.76		-0.12	0.04			
Dbl3	-1.93	0.74		-0.24	0.04			
Dbl4	-1.70	0.71		-0.24	0.04			
Dbl5	-1.93	0.71		-0.27	0.04			
Distance to medium size lakes (DML)	-	-	-	-	-	-	Factor	
Distance to small lakes (DSL)	-	-	-	-	-	-	Factor	
Distance to public green space (DPGS)	-	-	-	-	-	-	Factor	-
Distance to high voltage power line (DHVPL)	-	-	-	-	-	-	Factor	-
Distance to settlements (DS)	-0.96	0.04	0.00***	-	-	-	Numeric	-
Distance to roads category 01 (DR1)	-	-	-	-	-	-		
Distance to roads category 02 (DR2)	-0.21	0.02	0.00***	-	-	-		
Distance to roads category 03 (DR3)	-0.23	0.02	0.00***	-	-	-		
Tax (TAX)	-	-	-	-0.19	0.03		Numeric	-
Mean global radiation (MGR)	-	-	-	0.02	0.002	0.00***	Numeric	-
Municipality Typology (MT)	-	-	-			0.00***	Factor	-
MT2	-	-	-	-0.29	0.03			
MT3	-	-	-	-0.33	0.03			
MT4	-	-	-	-0.40	0.04			
MT5	-	-	-	-0.02	0.04			
MT6	-	-	-	-0.23	0.04			
MT7	-	-	-	-0.45	0.04			
MT8	-	-	-	-0.39	0.04			
MT9	-	-	-	-0.17	0.03			
MT10	-	-	-	-0.18	0.04			
MT11	-	-	-	-0.16	0.03			

MT12	-	-	-	-0.35	0.03			
MT13	-	-	-	-0.36	0.03			
MT14	-	-	-	-0.36	0.03			
MT15	-	-	-	-0.41	0.03			
MT16	-	-	-	-0.33	0.04			
MT17	-	-	-	-0.40	0.03			
MT18	-	-	-	-0.51	0.04			
MT19	-	-	-	-0.45	0.03			
MT20	-	-	-	-0.37	0.03			
MT21	-	-	-	-0.46	0.04			
MT22	-	-	-	-0.74	0.11			
Quarters (QU)	-	-	-			0.00***	Factor	-
2004_Q2	-	-	-	-0.08	0.04			
2004_Q3	-	-	-	-0.01	0.05			
2004_Q4	-	-	-	-0.07	0.04			
2005_Q1	-	-	-	-0.08	0.04			
2005_Q2	-	-	-	0.009	0.04			
2005_Q3	-	-	-	-0.02	0.04			
2005_Q4	-	-	-	-0.04	0.04			
2006_Q1	-	-	-	-0.02	0.05			
2006_Q2	-	-	-	-0.01	0.04			
2006_Q3	-	-	-	-0.00	0.04			
2006_Q4	-	-	-	-0.04	0.04			
2007_Q1	-	-	-	-0.02	0.04			
2007_Q2	-	-	-	-0.02	0.04			
2007_Q3	-	-	-	-0.02	0.04			
2007_Q4	-	-	-	0.01	0.04			
2008_Q1	-	-	-	0.03	0.04			
2008_Q2	-	-	-	0.04	0.04			
2008_Q3	-	-	-	-0.005	0.03			
2008_Q4	-	-	-	0.02	0.04			
2009_Q1	-	-	-	0.01	0.04			
2009_Q2	-	-	-	-0.01	0.04			
2009_Q3	-	-	-	-0.001	0.04			
2009_Q4	-	-	-	0.01	0.04			
2010_Q1	-	-	-	0.05	0.04			
2010_Q2	-	-	-	0.09	0.04			
2010_Q3	-	-	-	0.03	0.04			
2010_Q4	-	-	-	0.06	0.04			
2011_Q1	-	-	-	0.06	0.04			
2011_Q2	-	-	-	0.03	0.04			
2011_Q3	-	-	-	0.08	0.04			
2011_Q4	-	-	-	0.12	0.04			
2012_Q1	-	-	-	0.06	0.04			
2012_Q2	-	-	-	0.13	0.04			
2012_Q3	-	-	-	0.11	0.04			
2012_Q4	-	-	-	0.06	0.04			
2013_Q1	-	-	-	0.10	0.04			
2013_Q2	-	-	-	0.13	0.04			
2013_Q3	-	-	-	0.16	0.04			
2013_Q4	-	-	-	0.08	0.04			
Number of Rooms (NR)	-	-	-	0.02	0.003	0.00***	Numeric	-
Balcony (BA)	-	-	-			0.00***	Factor	-
BA1				0.01	0.009			
BA2				-0.04	0.08			
BA3				0.04	0.03			

BA4 BA5				0.05 0.08	0.01 0.03			
View specified for property (VIEW_SP) VIEW_SP1 VIEW_SP2 VIEW_SP3 VIEW_SP4 VIEW_SP5	-	-	-	 0.02 0.04 0.07 0.09 0.05	 0.01 0.01 0.02 0.05 0.02	0.00***	Factor	-
Stove (STOVE)	-	-	-	0.03	0.009	0.002**	Factor	-
Parking 1 (P1)	-	-	-	-	-	-	Factor	-
Parking 2 (P2) P2_1 P2_2	-	-	-	 -0.03 0.03	 0.04 0.009	0.00***	Factor	-
Age (AGE1)	-	-	-	0.08	0.009	0.00***	Numeric	Log
Age (AGE2)	-	-	-	-0.03	0.002	0.00***	Numeric	Log
Surface property (SP)	-	-	-	0.21	0.008	0.00***	Numeric	Log
Surface living area (SLA)	-	-	-	0.54	0.02	0.00***	Numeric	Log
Soil quality (SQ)	-	-	-	-	-	-	Numeric	-
Net carbon stocks (CA)	-	-	-	-	-	-	Numeric	-
Groundwater recharge (GR)	-	-	-	-	-	-	Numeric	-
Proximity water catchments (PW)	-	-	-	-	-	-	Numeric	log
Pollination (PO)	-	-	-	-	-	-	Numeric	-
Plant species richness (PR)	-	-	-	-	-	-	Numeric	-
Connectivity Extensively used open land (EL)	-	-	-	-	-	-	Factor	-
Connectivity Dry Grasslands (DL)	-	-	-	-	-	-	Factor	-
Connectivity Wetlands (WL)	-	-	-	-	-	-	Factor	-
Wildlife corridors (CO)	-	-	-	-	-	-	Factor	-

Appendix Table 3: Swiss average of construction costs in 2014.

Building quality	Construction cost single family home (CHF per m^3)	Construction cost dwelling (CHF per m^2)
1	550	2700
2	688	3350
3	825	4000
4	963	4650
5	1100	5300

Appendix Table 4: Classification of Swiss area statistics (ASCH97, ASCH04).

Aggregated class	Area in 2009 [ha]	Classes from Swiss land use statistics
Building areas	20846	One- and two-family houses (3), Surroundings of one- and two-family houses (4), Terraced houses (5), Surroundings of terraced houses (6), Blocks of flats (7), Surroundings of blocks of flats (8)
Other settlement and urban areas	20351	1-2, 9-36
Agricultural areas	253746	Intensive orchards (37), Field fruit trees (38), Vineyards, 39, Horticulture, 40, Arable land, 41, Meadows, 42, Farm pastures, 43, Brush meadows and farm pastures, 44, Alpine meadows, 45, Favorable alpine pastures, 46, Brush alpine pastures, 47, Rocky alpine pastures, 48, Sheep pastures, 49
Wooded areas	186720	50-60
Unproductive	114277	61-72

Appendix, Supplement 1: Separation of property prices into land and structure.

The property price decomposition using the construction cost method relies on the assumption that the total market value of a property is the sum of the value of the structure (i.e. the buildings) and the value of the land (Diewert et al., 2011):

$$V_P = V_L + V_S \tag{1}$$

$$V_P = p_L L + p_S S \tag{2}$$

, where V_P is the total value of the property, V_L is the value of the land, V_S is the value of the structure, S is the floor space area of the structure, L is the area of the land that the structure sits on and p_S and p_L are the prices of a unit of S and L respectively. Equation (1) solved for p_L:

$$p_L = \frac{V_P - p_S S}{L} \tag{3}$$

To illustrate that the variables are spatially (s) and temporally (t) dependent we rewrite equation (3):

$$p_L(s,t) = \frac{(V_P(s,t) - p_S(s,t)S(s,t)}{L(s,t)} \tag{4}$$

Assuming that floor space area *S* and area of the land *L* are constant over time, that the price of a structural unit is constant over space and that we are interested in the land price at one point in time (t'), equation (3) simplifies to:

$$p_L(s,t') = \frac{(V_P(s,t') - p_S(t')S(s)}{L(s)} \tag{5}$$

To estimate the property value *Vp* on a regular grid we use a hedonic model. Predicting the property price at every location for a fixed floor space area (single family home) and a fixed lot size further simplifies matters (*L(s)* and *S(s)* can be replaced by *L* and *S*).

Appendix, Supplement 2: Description of biodiversity and ecosystem services indicators.

We chose net carbon stocks as an indicator for climate regulation. The stocks were calculated as the differences between the stocks of agricultural land and settlement following the chapter Land Use, Land Use Change and Forestry (LULUCF) of the Swiss Greenhouse Gas Inventory 1990-2012 (Heldstab et al., 2012), which is based on the Good Practice Guidance of the IPCC (IPCC, 2003). Carbon stocks of agricultural land were calculated as the sum of soil stocks and biomass taking into account that agricultural management and soil types vary with elevation (Leifeld et al., 2005, Bolliger et al., 2008). For carbon stocks in residential areas, we assumed that 50% of the soil carbon stock of the previous land use category would be lost. Furthermore, biomass was calculated as an average of the biomass given for different settlement classes by Mathys and Thürig (2010).

We used two indicators to assess the impact of the instruments on water supply: groundwater recharge and proximity to protected areas in drinking water catchments. Data on groundwater recharge was provided by the Swiss Federal Research Institute WSL and were based on the hydrological model PREVAH (PREecipitation-Runoff-EVApotranspiration HRU Model) which was developed to suit conditions in mountain environments (Viviroli et al., 2009). The model has been extensively calibrated using discharge data (Schattan et al., 2013, Speich et al., 2015) and information on snow (Jorg-Hess et al., 2014). Proximity to drinking water abstraction was mapped by calculating the distance to areas protected for water abstraction and assigning a high ES level to close by areas and a low level to distant areas (Altwegg, 2014).

Pollination supply and demand were calculated based on the distance between potential pollinator habitat and cropland with crops that require or benefit from pollination (Lautenbach et al., 2011, Gret-Regamey et al., 2014). The visitation probability as a function of that distance was calculated based on the results of Ricketts (2008). More details on the model and datasets included can be found in the Appendix, Supplement 3).

To assess the influence of the ZD and MD instrument on biodiversity we used several indicators. These included regional and supra-regional wildlife corridors and the connectivity of extensively used agricultural open land, dry grasslands and wetlands. These indicators were provided as maps by the Swiss Federal Office for the Environment (FOEN) and are intended to provide information about the location of important wildlife habitats and areas important for the connectivity of these habitats (Berthoud et al., 2004). As a further indicator we calculated plant richness. Adapting the approach of Wohlgemuth et al. (2008) we used data of the Swiss federal Biodiversity Monitoring (BDM) (Plattner et al., 2004) to fit a Poisson Generalized Linear Model (GLM) and predict vascular plant species richness (Appendix, Supplement 4).

Appendix, Supplement 3: Pollination model and data used to calculate demand and supply.

Demand for pollination was estimated using data on agricultural production for each municipality, which was obtained from the Swiss agricultural information system GELAN - Gesamtlösung EDV Landwirtschaft und Natur (2013). The GELAN data includes information on the amount of land that is used to cultivate specific crops in each municipality. To transform the data on the amount of land into a production price we first multiplied it with crop yield per unit area (Agristat, 2013) and after that with crop specific production prices per unit weight in Switzerland in 2014 provided by the Swiss Federal Statistical Office. Since the crop categories of yield and production price data did not always correspond to each other, we aggregated a few categories. We then downscaled the data to a 1ha resolution with the help of the Swiss Area Statistics (Humbel, 2009). However, in the Swiss Area Statistics there are not as many specific crop classes as there are provided by GELAN. Thus, we aggregated different crops and fruits into several general classes and then assigned them to the Swiss Area Statistics classes. The dependence of crops on natural pollination was based on Klein et al. (2007).

Appendix Table 5:

	Habitat quality	
Land-use	Inside	Edge
Settlement	0.0001	0.0001
Intensively Used	0.0001	0.0001
Extensively Used	0.1	0.1
Forest	0.0001	0.7
Other	0.0001	0.0001

Appendix, Supplement 4: Description of Plant species richness model calibrated parameters.

Adapting the approach of Wohlgemuth et al. (2008) we used data of the Swiss federal Biodiversity Monitoring (BDM) (Plattner et al., 2004) to fit a Poisson Generalized Linear Model (GLM) and predict vascular plant species richness. The BDM provides data on the number of vascular plant species for 474 systematically on a national grid sampled quadratic plots (1 km^2). As predictor variables we used topographic and environmental variables as well as landscape metrics. For model selection we followed the procedure described by Wohlgemuth et al. (2008), which included removing strongly correlated variables (<0.9) and selecting variables according to the highest AIC until the change in explained deviance was less than 1%. The final model included seven variables and explained 74.6% of the deviance.

Variable	Coefficient	SE	P-Value
Intercept	5.35e+00	1.39e-02	0.00***
Percentage Bare Land	-8.06e-01	2.67e-02	0.00***
Shannon Diversity Index	2.73e-01	1.17e-02	0.00***
Percentage Lake	-5.15e-01	3.81e-02	0.00***
Standard Deviation Elevation	1.20e-03	6.10e-05	0.00***
Mean Elevation	-1.34e-04	8.31e-06	0.00***
Calcareous Substrate	7.77e-02	7.85e-03	0.00***
Aspect North	-1.08e-01	1.74e-02	0.01**

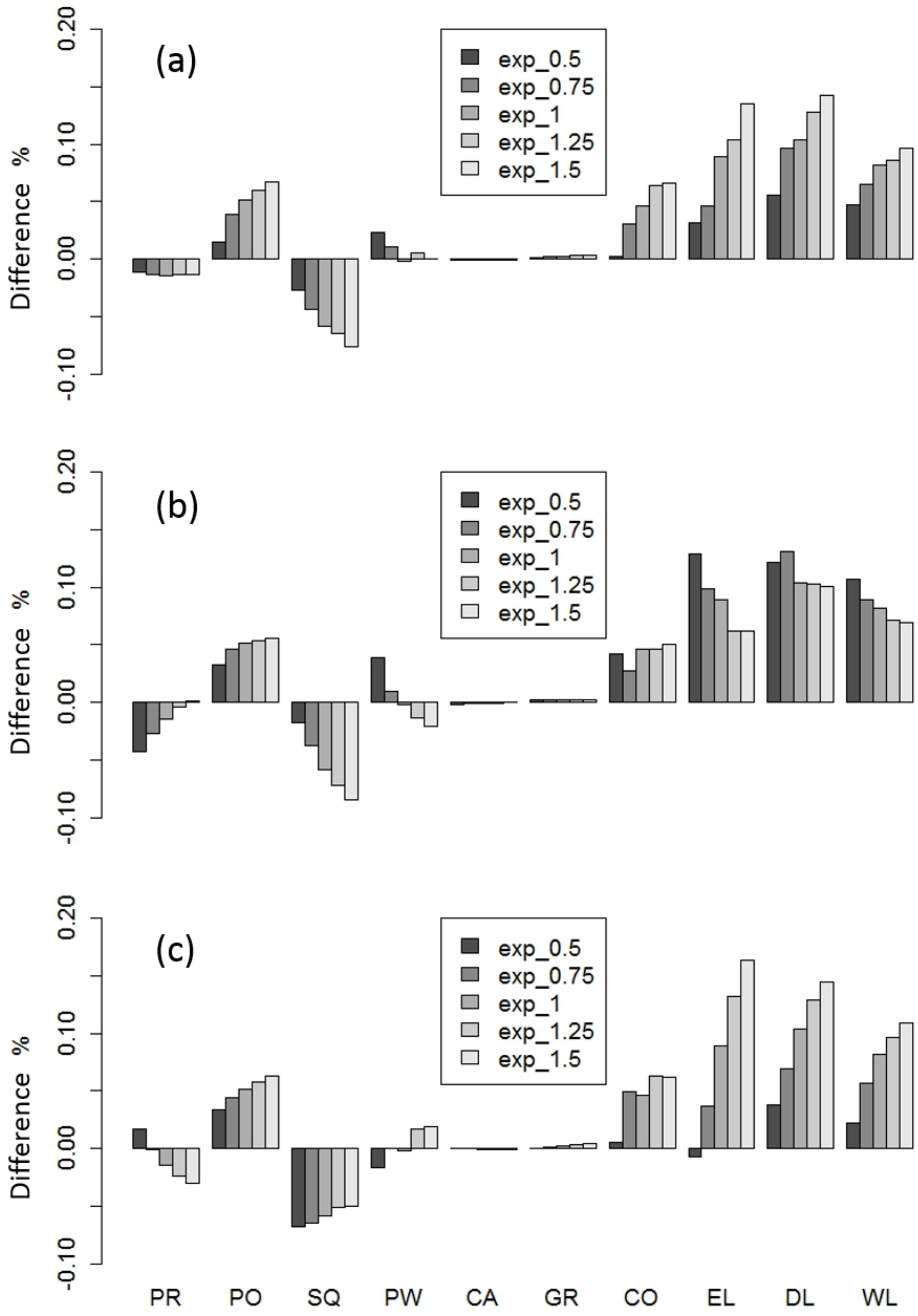
Appendix Table 6: Dependency level of crops in the canton of Bern

GELAN category)	Yield [t/are]	Price [CHF/t]	Dependency	Area Statistics Class
Horse bean	25.7	641	0.09	Arable land
Other berries	126	750	0.49*	Horticulture
Other orchards	302	1080	0.65	Intensive Orchards
Bramble	175	750	0.49	Horticulture
Cassis	97	750	0.25	Horticulture
Annual berries	126	750	0.49*	Horticulture
Peas	34	638	0.05	Arable land
Strawberries	175	6214	0.25	Horticulture
Blueberries	42	750	0.65	Gartenbau (Horticulture)
Raspberry	112	750	0.65	Horticulture
Field fruit trees	306.5	980	0.65	Field fruit trees
Currant	159	750	0.25	Horticulture
Flax	26.5	1101	0.05	Arable land
Lentils	29.7	641	0.09	Arable land
Lupines	29.5	641	0.09	Aarable land
Apples	332	980	0.65	Intensive Orchards
Pear	281	1181	0.65	Intensive Orchards
Stone fruits	160	3030	0.65	Intensive Orchards
Oil sqash	359.9	1101	0.95	Arable land
Soya	25.2	960	0.25	Arable land
Raspberry	112	750	0.65	Horticulture
Rapeseed	32.5	1095	0.45	Arable land
Sunflower	21.8	1183	0.25	Arable land
Gooseberries	158	750	0.49	Horticulture
Rapeseed	32.5	1095	0.45	Arable land

* mean value of berries (Strawberry, Currants, Raspberries, Blueberries, Cranberries)

** value of the more general class pulses

Appendix Figure 1: Results of the sensitivity analysis. Allocation distributions are transformed via the exponents 0.5, 0.75, 1, 1.25, 1.5. Exponent 1 is equal to the reference instrument used for calculating differences in ecosystem services. (a) Median differences between the ecosystem services of both developments (MD and ZD) for transformed allocation distributions used for both instruments. (b) Median differences between the ZD reference instrument and transformed MD instrument. (c) Median differences between the MD reference instrument and the transformed ZD instrument. SQ - Soil quality for food production; CA - Net carbon stocks; GR - Groundwater recharge; PW - Proximity to protected areas in drinking water catchments; PO - Pollination supply/demand; PR - Plant species richness; WL – Connectivity Wetlands; DL - Connectivity Dry Grasslands; EL – Connectivity Extensively used open land; CO - Wildlife corridors



Appendix, Supplement 5: Zoning development.

To test whether residential development and allocation of building zones followed the same mechanisms, which would be a strong indicator that the location of residential development is determined by the choice of zoning locations, we used data on zoning plans in the canton of Bern from 2012, 2002 and from 1965-1980. Zoning plans in 2002 were digitally available and provided from the Administrative Office for Spatial Planning - AGR (Amt für Gemeinden und Raumordnung). Zoning plans of different years for every municipality, i.e. from a period between 1969 and 1987, were also provided by the AGR but had to be digitized since they were only available as paper maps.

We created new binary variables reflecting change in zoning between 1969/1987 to 2012 and for changes in zoning between 2002 to 2012. If new zones occurred they were reclassified as “change” (1) and if there was no change in comparison to previous zoning plans we reclassified them as “no change” (0). To analyze the independent effects of the same predictor variables that have been used to calibrate the zoning and the market driven scenario, we used hierarchical partitioning. Our results indicate that the variables show very similar independent effects for the two dependent variables reflecting the change in zoning and for the variable reflecting the change in actual residential development between 1997 and 2009 (Appendix Table 7).

Appendix Table 7: Independent effects found for different dependent variables using hierarchical partitioning.

Predictor Variable	Independent effects (hierarchical partitioning)		
	Residential Development between 1997-2009	Building Zones 2002-2012	Building Zones 1969/1987*-2012
Utility Services (US)	13.2	11.2	9.0
Slope (SLOPE)	2.5	4.3	3.1
Public Transport (PT)	12.8	14.5	10.4
View (VIEW)	2.9	0.3	0.4
Aspect (ASP)	0.7	1.0	0.3
Distance to Big Lakes (DBL)	1.4	1.3	0.5
Distance to Settlements (DS)	39.0	37.3	51.6
Distance to Roads 02 (DR2)	14.5	20.1	13.5
Distance to Roads 03 (DR3)	13.0	10.0	11.2