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A review of multi-criteria optimization techniques for agricultural land use allocation

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Highlights

- We present a review of optimization techniques for land use allocation problems.
- The review also considers constraint handling for the different methods.
- A structured guideline for selecting appropriate optimization methods is proposed.
- This guideline includes the moment of stakeholder integration and trade-off analysis.

Abstract

Optimal land use allocation with the intention of ecosystem services provision and biodiversity conservation is one of the key challenges in agricultural management. Optimization techniques have been especially prevalent for solving land use problems; however, there is no guideline supporting the selection of an appropriate method. To enhance the applicability of optimization techniques for real-world case studies, this study provides an overview of optimization methods used for targeting land use decisions in agricultural areas. We explore their relative abilities for the integration of stakeholders and the identification of ecosystem service trade-offs since these are especially pertinent to land use planners. Finally, we provide recommendations for the use of the different optimization methods. For example, scalarization methods (e.g., reference point methods, tabu search) are particularly useful for a priori or interactive stakeholder integration; whereas Pareto-based approaches (e.g., evolutionary algorithms) are appropriate for trade-off analyses and a posteriori stakeholder involvement.

***Keywords**:* agricultural land use allocation; multi-criteria decision analysis (MCDA); multi-criteria optimization; stakeholder integration; trade-off analysis; constraint handling

1. Introduction

Humans have been changing landscapes for millennia by converting natural areas for agricultural production and settlement (Delcourt and Delcourt, 1988). As a result, “40 to 50% of the world's land surface had been visibly transformed” for these purposes by the 20th century (Western, 2001). Many of the different land uses are conflicting: for instance, there is agricultural and timber production on one side, competing with space for urban settlements or protected areas on the other side. All these anthropogenic usages impact the provision of ecosystem services (ESS) and therefore directly affect, for example, soil quality as well as water quantities and quality (Fontana et al., 2013). Meanwhile, natural areas provide habitats for wildlife and are especially important for the protection of endangered species (Behrman et al., 2015). Biodiversity loss has been directly linked to land use changes (Sala et al., 2000), and population growth as well as increases of agricultural land use have been labelled the biggest threat to biodiversity and ESS (Behrman et al., 2015).

One way to address biodiversity loss is to integrate ESS into systematic conservation planning (Faith, 2015) and re-allocate land uses in order to support the multifunctionality of landscapes. Sustainable land use allocation therefore seeks to take into account the current and future provision of ESS and biodiversity in order to determine so-called ‘optimal’ land use allocations. In general, land use allocation (also sometimes referred to as land use planning (Stewart et al., 2004)) is a type of resource allocation and can be defined as the process of allocating different activities or uses (e.g., agriculture, residential land, recreational activities, conservation) to particular areal units within a region (Cao et al., 2012). Agricultural land use allocation specifically deals with the allocation of species and activities to areas in agricultural landscapes (Memmah et al., 2015).

Decision support research within the field of natural resources management has relied heavily on multi-criteria decision analysis (MCDA) and its corresponding tools (Mendoza and Martins, 2006). In this paper, we provide a detailed review of MCDA and focus in particular on one branch of MCDA – optimization techniques – since land use allocation problems have been widely formulated as mathematical optimization problems. These problems typically consider multiple, mostly conflicting objectives and aim to minimize the trade-off between them (Liu et al., 2013; Porta et al., 2013). These can include trade-offs between various ESS such as provisioning and regulating services but also between ESS and biodiversity. A trade-off describes the amount that has to be given up of one ESS in order to increase the provision of another (Rodríguez et al., 2006). For example, the intensification of agricultural production may reduce water quality due to a greater use of fertilizers and pesticides and the resulting nonpoint emissions of pollutants from the agricultural fields. The main task is thus to find the right balance between the usage of different ESS.

Solving complex, real-world land use allocation problems remains a key research challenge (Fowler et al., 2015). Additionally, recent applications underline the need for methods that allow for increased stakeholder involvement (Eikelboom et al., 2015; Stewart et al., 2004; Uhde et al., 2015). This is particularly important since “agricultural land use allocation involves many competing actors such as farmers, farmers associations, environmental agencies, land planners and economists” (Memmah et al., 2015). Participatory approaches thus help to find solutions that achieve biophysical objectives but also consider the different perspectives and preferences of various stakeholders (Groot and Rossing, 2011).

Land use allocation problems can greatly differ in their mathematical formulation and therefore require different optimization techniques (see Section 2.2). However, the choice of a technique is often not guided by the characteristics of a problem but depends on the experience of the reseacher in charge or on historical usages (Memmah et al., 2015). While there exist some reviews about MCDA approaches and their applicability particularly in forest management (Mendoza and Martins, 2006; Uhde et al., 2015), current literature lacks guidelines for how to choose the best suitable optimization technique for a particular agricultural land use allocation problem. Therefore, this paper aims to fill this gap by providing a review of current MCDA optimization techniques and their applicability for land use allocation problems; we specifically focus on agricultural landscapes and on studies that aimed to achieve objectives related to ESS and biodiversity.

The following sections provide a review of optimization approaches that have been used in land use management. For an overview, we first classify multi-objective optimization within the broader field of decision support techniques giving an introduction to MCDA. Then, we evaluate different multi-criteria optimization methods in terms of their ability to integrate stakeholder opinions and identify trade-offs between ESS and biodiversity. Furthermore, we mention how constraints can be handled. The suitability of the optimization approaches for different types of land use allocation problems is discussed before we provide a short conclusion and give directions for further research.

2. Solving land use allocation problems with Multi-Criteria Decision Analysis (MCDA)

2.1 An overview of MCDA

MCDA has been widely used to perform mathematical optimization in order to analyze multi-objective decisions and incorporate the varying opinions of decision-makers (Collins et al., 2001). MCDA addresses land allocation problems in a more realistic way than single-objective approaches, since in practice, these problems consist of multiple, conflicting objectives (Antoine et al., 1997), especially when multiple ecosystem services are taken into account (Birkhofer et al., 2015). Furthermore, MCDA methods can combine ecological objectives with social and economic criteria and are able to consider non-market values of ESS. Therefore, they are very popular and frequently used in ecological economics (Fontana et al., 2013; Uhde et al., 2015; van Huylenbroeck, 1997).

Most of the literature classifies multi-criteria optimization either within the broader field of decision support systems (e.g., Myllyviita et al. (2011)) or within MCDA directly (e.g., Aerts et al. (2003)). Therefore, we first provide an overview of the linkage between the two fields and where multi-criteria optimization is set amongst these (see Figure 1).

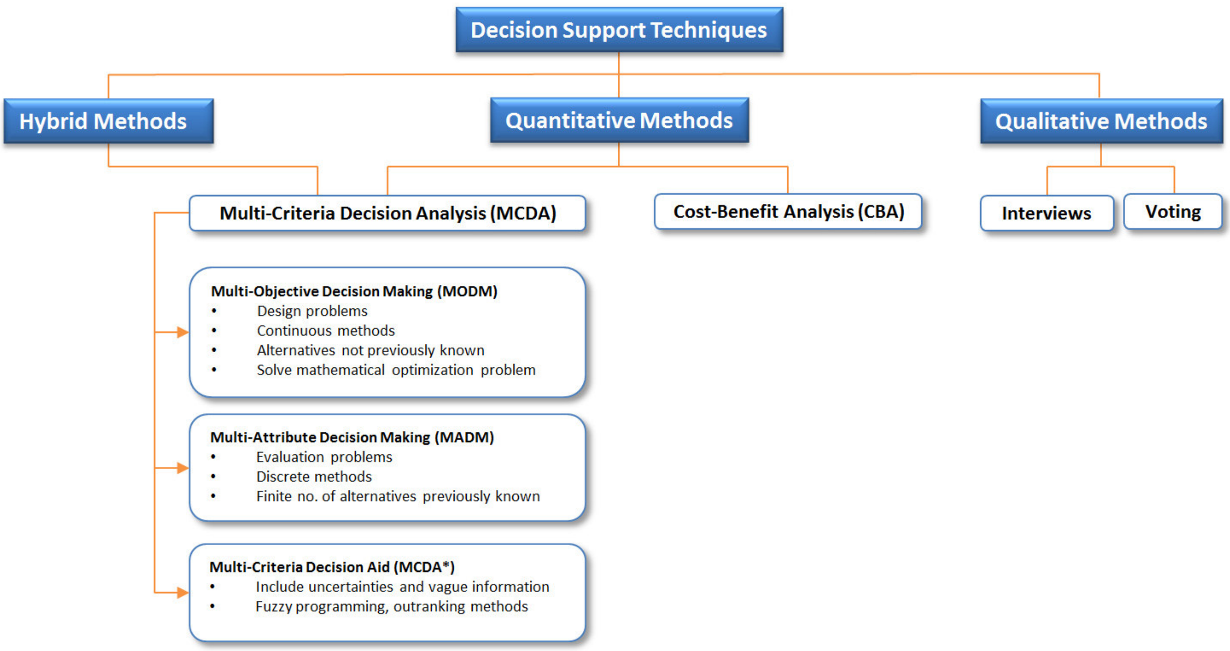

Figure 1 Classification of Multi-Criteria Decision Analysis (MCDA) within the family of decision support techniques.

MCDA is one of many decision support techniques, which can be divided into qualitative, quantitative and hybrid methods. Qualitative methods (e.g., interviews, voting), focus on structuring a problem. They also help to define initial goals and to evaluate stakeholders' opinions (Myllyviita et al., 2011; Uhde et al., 2015). Cost-benefit analysis (CBA) and MCDA – including mathematical optimization techniques – belong to the group of quantitative methods that use numerical information in order to evaluate a number of decision alternatives. Finally, hybrid methods are composed by the combination of different approaches (see Uhde et al. (2015) for an overview of hybrid MCDA methods in forest management).

MCDA methods can be classified in different ways (Mendoza and Martins, 2006). Belton and Stewart (2002) suggest distinguishing three categories: (i) value measurement models, (ii) goal, aspiration or reference level models and (iii) outranking models. Instead, Malczewski (1999) and Zimmermann and Gutsche (1991) distinguish between multi-attribute decision making (MADM) and multi-objective decision making (MODM) (see Figure 1). MADM deals with the evaluation of a finite number of alternatives that are previously known to the decision maker. Therefore, they require discrete MCDA methods. An example of a hybrid combination of MADM techniques can be found in Fontana et al. (2013). The authors evaluated three land use alternatives (i.e., larch meadow, spruce forest and intensive meadow) to determine their ability of providing certain ESS. First, they derived the weights of six ESS with a stakeholder questionnaire and the analytical hierarchy process (AHP) (Saaty, 1988). Later, they applied an outranking method in order to evaluate the different alternatives. More information about MADM techniques like the outranking methods ELECTRE and PROMETHEE, multiattribute utility theory (MAUT) and AHP can be found in Belton and Stewart (2002) and Figueira et al. (2005).

Since land use allocation problems usually include a range of competing objectives, it might often be impossible to create a small set of scenarios that would cover all possible solutions (Bishop, 2013; Groot and Rossing, 2011). Besides, an optimal solution "of sustainable land management might be located 'between' two distinct scenarios" (Seppelt et al., 2013). In this case, the application of design techniques can help to avoid this problem (Aerts and Heuvelink, 2002).

Multi-criteria design problems are of a continuous nature and handled within MODM. Here, alternatives are either not known in advance, or there are so many that the problem cannot be solved with evaluation methods anymore. These problem types can be solved by applying mathematical optimization (Aerts and Heuvelink, 2002; Uhde et al., 2015). The focus of this paper, then, is to provide a detailed review of optimization techniques used in land use allocation which will be given in the following section.

Multi-criteria decision aid (MCDA*) is yet another perspective from which to solve multi-criteria problems and further information can be found in Bana e Costa (1990) and Zimmermann and Gutsche (1991). According to them, the main difference between classical MADM and MODM approaches is that MCDA* also incorporates vague, incomplete, inconsistent and subjective information; also, instead of a single 'optimal' solution, it provides a set of acceptable alternatives. Fuzzy programming and outranking methods such as ELECTRE and PROMETHEE (Figueira et al., 2005) are but a few examples for MCDA* methods.

The classification in Figure 1 must not be seen as strict. There are some approaches that cannot be assigned fully to any of the categories. For example, some MCDA* methods may simultaneously contain portions from MADM and MODM (Zimmermann and Gutsche, 1991). A well-structured overview of MCDA applications in forestry and natural resources management can be found in Mendoza and Martins (2006). Furthermore, Myllyviita et al. (2011) provide a comparative review of studies that used MCDA design techniques, optimization, CBA and hybrid methods in sustainable forest management.

2.2 Optimization methods

The process of land use allocation includes a series of individual steps, which are highlighted in Figure 2 (Belton and Stewart, 2002; Groot and Rossing, 2011; Talbi, 2009). For the optimization, the problem needs to be identified and clearly formulated before it can be modelled. In this context, we identified three important points that should be taken into account:

(i) *Mathematical problem formulation*: objectives, constraints, decision variables and problem type (e.g., linear, non-linear, discrete (e.g., binary), combinatorial, continuous) (Deb, 2001).

(ii) *Desired output/required input*: problem scale (e.g., local, global) (Seppelt et al., 2013), amount and type of available data (e.g., land use maps, information about topography, hydrology, soil quality) and if a trade-off analysis is needed.

(iii) *Stakeholder involvement*: before (a priori), during (interactive) or after (a posteriori) the optimization process (Memmah et al., 2015).

All of these factors determine the size and complexity of the problem and have an influence on the choice of a suitable optimization method and on computation time. At this point, it should be considered that in the end, the quality of the optimization result does not only depend on the

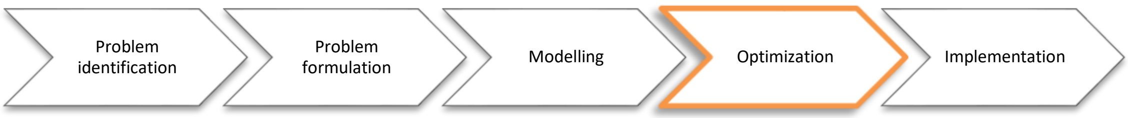

Figure 2 Phases of the land use allocation process. First, the problem itself needs to be identified and clearly formulated before it can be modelled. The model forms the basis of the land use optimization which delivers the results for a possible implementation (Talbi 2009). The focus of this paper lies on the optimization (orange).

performance of the selected algorithm but also on the conceptual design of the optimization problem, particularly if there have been simplifications in the model formulation (Moilanen, 2008). Optimal solutions can then be used by decision makers to inform and support the implementation of new land use strategies.

The selection of optimization methods presented in this section is mainly based on the fact that spatial land use allocation problems are mostly multi-objective combinatorial optimization problems (Porta et al., 2013) that may often be non-linear (Cao et al., 2012; Liu et al., 2016; Memmah et al., 2015). These problems are usually complex and include a large number of alternative solutions requiring high computation times (Porta et al., 2013). Combinatorial problems, as a type of discrete optimization problems, are typically solved by applying local search algorithms such as simulated annealing, tabu search, genetic algorithms and ant colony optimization (Aarts and Lenstra, 2003; Colorni et al., 1996). These and other methods will be presented in the following. In the rare case of a continuous problem formulation, standard methods like the (multi-objective) simplex algorithm (Figueira et al., 2005) can be used for linear problems (see Sadeghi et al. (2009) for an example). But again, if the problem is non-linear, then heuristic optimization methods are needed.

Multi-objective optimization is a useful tool for the evaluation of trade-offs among conflicting objectives. Trade-offs are represented by the Pareto frontier – in some studies, this is also called the efficiency frontier or production possibility frontier (Polasky et al., 2008). The Pareto frontier is a set of optimal solutions to the respective multi-criteria optimization problem. Assuming maximization, a feasible solution to the optimization problem is said to be Pareto optimal if there is no other feasible solution that would increase one of the objective function values without simultaneously decreasing another (Coello Coello et al., 2007). For trade-off analyses it is sometimes necessary to obtain the whole Pareto frontier, particularly for visualization purposes. Therefore, along with the presentation of different optimization algorithms, we will also mention how trade-off curves can be identified. Table A.1 in the Appendix gives a selection of studies from the fields of general and agricultural land use allocation and a few from other research areas. For each study, it also includes information about the moment of stakeholder integration, whether trade-offs were determined and which ESS were taken into account.

One approach for solving multi-objective optimization problems is to define one objective function and add any additional objectives as constraints (ε-constraint method (Ehrgott, 2005)). Then, single-objective algorithms can be applied. For example, van Butsic and Kuemmerle (2015) aimed to maximize agricultural production while minimizing species loss, setting agricultural production as the objective function and target constraints for the species of concern. They determined trade-off curves between agricultural yield and the species' population size by solving the problem multiple times with different targets. Nonetheless, a high variety of multi-objective algorithms is available that can simultaneously account for multiple conflicting objectives. For an overview of multi-objective optimization methods, see Chapter 17 of Figueira et al. (2005). Generally, multi-objective optimization techniques follow two different approaches – scalarization methods and Pareto-based methods (Cao et al., 2012; Madavan, 2002) and these will be outlined below.

2.2.1 Scalarization methods

Scalarization methods combine multiple objective functions into a single-objective scalar function (Miettinen and Mäkelä, 2002). The optimization problem is then solved with a single-objective optimization algorithm which creates a single optimal solution to the optimization problem. Here again, the selection of the algorithm depends on the problem type. For spatial land use allocation problems, heuristics like the greedy algorithm (Cormen, 2007), simulated annealing, genetic algorithms, etc. (Bozorg-Haddad et al., 2017) are usually applicable. There are two main methods to parameterize a problem – either to maximize (or minimize) the weighted sum of all objectives by using weighting coefficients that specify the relative importance of each objective or by using a reference-point-based method (Wierzbicki, 2000).

Weighted-sum approaches provide Pareto-optimal solutions for convex solution sets. The Pareto frontier can be obtained by changing the coefficients of the scalar function and re-solving the problem. Pareto-optimal solutions of non-convex parts, however, cannot be found using this method (for an example, see Caramia and Dell'Olmo (2008)). Kennedy et al. (2016) used a weighted-sum approach in combination with a greedy algorithm based on previous work by Polasky et al. (2008). They optimized three objectives: agricultural production, water quality and biodiversity for a watershed in an agricultural area in southeastern Brazil. By varying the weights of the individual objectives, they obtained trade-off curves between agricultural production and either water quality or biodiversity for different problem settings.

Goal programming (GP) is a reference point method that guides an algorithm, like an evolutionary (Deb and Sundar, 2006) or genetic algorithm (Deb, 1999), for instance, towards a solution that lies in the decision maker's preferred region of the solution space. For this purpose, the decision maker defines goals (i.e., desired values) for each objective. Then, the distance between the goal vector and an attainable vector of the solution space is minimized, and the optimum is a feasible solution that is closest to the goal vector. Defining and striving for a goal seems quite intuitive from a psychological perspective. However, from a mathematical viewpoint, the minimization of a norm (a distance measure) cannot guarantee that the GP algorithm will find a Pareto-optimal solution (Romero, 2014).

Therefore, the more general **reference point** (RP) method has been developed. Instead of using a norm, this approach minimizes a so-called achievement function (Miettinen et al., 2008). If norm minimization is avoided, reference point approaches can obtain the Pareto frontier even for non-convex solution sets when solving the problem multiple times with different reference points (Wierzbicki, 2000).

Stewart and Janssen (2014) used a reference point method in combination with a genetic algorithm in order to solve a non-linear combinatorial optimization problem. The key objectives were the profitability of intensive agriculture, maximization of the visual quality of the landscape (including landscape perception, cultural historic value and recreational value) and maximization of the natural value of the area (including meadow birds, species-rich grasslands and marsh birds). As a result, they generated land use maps that served as a basis for negotiating optimal land use strategies in a case study area in The Netherlands. This paper extends earlier work by Stewart et al. (2004) and Janssen et al. (2008) and forms the basis of work by Eikelboom et al. (2015).

Another scalarization approach is **tabu search** (TS), which is usually used in combination with a local search algorithm (Boussaïd et al., 2013). TS was initially developed for single-objective combinatorial optimization problems. The algorithm works on an iterative basis by looking for an improved solution in the neighbourhood of the current solution. In doing so, TS uses a short-term memory (i.e., the tabu list) where recently visited solutions or one or more of their attributes are recorded. All potential new solutions that are on the tabu list cannot be visited again at this stage of the search. This is to avoid endless cycling and prevents the algorithm from getting stuck at a local optimum (Boussaïd et al., 2013). More information about TS can be found in Glover and Laguna (2013). TS can also be applied for multi-objective optimization problems. Qi and Altinakar (2011) used TS in order to optimize agricultural land use with integrated watershed management. They considered three objective functions and combined them into a single-objective function using weights to reflect the relative importance of each objective. Also, Behrman et al. (2015) used weighting while solving their optimization problem with ConsNet (Ciarleglio et al., 2009), which is based on a TS algorithm. In their study, the overall aim was to identify the trade-offs between converting land to switchgrass for biofuel production, agriculture and biodiversity. In order to obtain optimal trade-offs among the objectives, they varied the weights that were applied to each of the three categories. In addition, TS approaches that are not based on scalarization but search directly for the Pareto-optimal set have been developed (Jaeggi et al., 2005). However, these methods have yet to be used in land use optimization.

Simulated annealing (SA) (Kirkpatrick et al., 1983) also applies weighting in order to combine multiple objective functions to a single objective function. Therefore, as with TS methods, trade-offs can be determined by solving the problem multiple times with different weights. The algorithm itself mimics the physical process of heating metal and cooling it again. Starting from an initial solution, SA randomly chooses a new solution in a pre-defined neighbourhood. Temperature is a parameter that is reduced over time. When this temperature parameter is sufficiently high, even solutions that decrease the objective function value can be accepted. This prevents the algorithm from getting trapped in local optima. At lower temperatures, the algorithm accepts only improving new solutions and terminates once a stopping criterion is met. Aerts and Heuvelink (2002) used SA to minimize development costs and compactness costs for the restoration of a mining area in Spain. The algorithm has also been applied for optimizing agricultural land use in Santé-Riveira et al. (2008). Their aim is the optimal allocation of 13 land uses (all different types of crops) in a study area in Spain. All land uses were grouped into five use groups: fodder, cereals, intensive agricultural crops, productive forest and protective woodland. They set the objective function to be a linear combination of three objectives: maximize land suitability for the uses allocated to them, maximize compactness of the total area assigned to a particular use and maximize compactness of the total area assigned to a particular group of uses. The problem was solved for 11 different sets of weights.

2.2.2 Pareto-based methods

Pareto-based methods generate multiple Pareto-optimal solutions simultaneously and are able to provide the whole Pareto frontier as a result of the optimization. There is a wide range of **evolutionary algorithms** (EA), including **genetic algorithms** (GA), which have been used in land use optimization. EAs are inspired by biological evolution. They begin with an initial population of solutions and use concepts such as selection, crossover and mutation in order to create the next generation of solutions. The fitness of a solution evaluates how good it fulfills the problem criteria and determines whether or not it will be selected as a parent for the next generation. The algorithm terminates once a predefined stopping criterion is met (Memmah et al., 2015).

Lautenbach et al. (2013) coupled a watershed model called the Soil and Water Assessment Tool (SWAT) (Arnold and Fohrer, 2005) with the non-dominated sorting genetic algorithm II (NSGA-II) (Deb et al., 2002) in order to analyze trade-offs between bioenergy crop production, food crop production, water quantity and water quality in a case study area in Central Germany. Similarly, Fowler et al. (2015) coupled a multi-objective genetic algorithm from the DAKOTA optimization suite (Adams et al., 2014) with the MODFLOW-FMP2 software (Schmid and Hanson R.T., 2009), which simulates the integrated supply-and-demand components of irrigated agriculture. They optimize the selection of three different crops based on trade-offs between agricultural revenue, water usage and the deviation from actual yield and demand yield for each crop in an artificial study area. In addition to maximizing agricultural profits, Groot et al. (2007) also consider nature conservation and landscape quality by minimizing the loss of nutrients to the environment, maximizing the nature value of fields and borders (i.e., species abundance in grass swards and hedgerows) and maximizing the variation of the landscape (i.e., species presence and hedgerow allocation). They explore the trade-offs between these objectives with an evolutionary strategy algorithm of differential evolution (Storn and Price, 1997) and provide trade-off curves of gross margin with either plant species number, landscape value or nitrogen loss. The underlying data is from a case study area in The Netherlands.

Other EAs that gained much popularity in land use allocation during the last years are **artificial immune systems** (Huang et al., 2012) and particularly **swarm intelligence** (SI) algorithms (see Yang (2014) for an introduction) such as ant colony optimization (Nguyen et al., 2016), the artificial bee colony algorithm (Yang et al., 2015) and particle swarm optimization (PSO) (Liu et al., 2016; Ma et al., 2011). The latter was developed to solve continuous optimization problems. However, Liu et al. (2016) present a method that uses PSO for a binary multi-objective optimization problem. In general, SI algorithms mimic the collective behaviour of single agents in a decentralized and self-organized system. For example, PSO imitates the social behaviour of fish schooling and flocking of birds (Kumar and Minz, 2014).

2.2.3 Hybrid methods

Hybrid optimization approaches combine two or more optimization methods within a single framework to facilitate the search for the Pareto frontier. An example of a hybrid optimization approach applied to the Calapooia River Basin in Oregon, USA can be found in Whittaker et al. (2017). Their approach couples the SWAT watershed model with Data Envelopment Analysis (DEA) (Cooper et al., 2004) – an economic linear optimization model – within a **bilevel optimization** framework that uses NSGA-II. Bilevel optimization problems consist of two nested optimization levels, and each level contains its own set of objectives. In this example, the upper level is a government agency that seeks to maximize the total farm profit of the entire watershed and minimize the nitrogen loading at the watershed's outlet. The lower level consists of farmers that seek to maximize their individual profits using DEA. The two levels are linked because the upper level sets tax rates for the use of nitrogen fertilizer by the lower level, and the lower level's fertilizer use decisions ultimately impact the amount of nitrogen loading that occurs at the watershed's outlet. NSGA-II is used to find the optimal set of tax rates to optimize all objectives at both levels. Whittaker et al. (2017) highlight the Pareto frontier trade-offs for the upper between total accumulated profit of the farmers and nitrogen loading at the watershed's outlet. Other studies, like Bostian et al. (2015) and Barnhart et al. (2017), have utilized a similar methodology to target agri-environmental policy to promote best management practices in order to achieve environmental benefits. According to Memmah et al. (2015) the application of hybrid metaheuristics to land use allocation problems is still rare. Nevertheless, some more examples (e.g., a hybrid PSO) can be found in their study along with general information about the hybridization of algorithms.

Apart from the methods presented above, **fuzzy programming** from the field of Multi-Criteria Decision Aid (see Figure 1) can also be applied to solve land use allocation problems. For an example, we refer to Wang et al. (2004).

2.2.4 Constraint handling

As indicated at the beginning of this section, constraints are an important part of the mathematical formulation of land use allocation problems. They limit the space of feasible solutions by reflecting e.g. environmental, social and political limits, such as the total area that can be allocated to each land use (Stewart and Janssen, 2014), water quality and water demand/supply constraints (Wang et al., 2004), restrictions on nutrient input (Groot et al., 2007) or biodiversity targets (Schröter et al., 2014) to name only a few examples. Handling real-world constraints is one of the most challenging tasks in the optimization process (Michalewicz and Fogel, 2004), especially, since they can increase the computational complexity of a problem. All of the methods presented in this paper support constraints though the way of handling them depends on the algorithm used. The most popular constraint handling method for heuristics is using a penalty function that degrades the fitness value of an infeasible solution (Chehouri et al., 2016). Furthermore, the use of feasibility operators which create feasible-only child solutions (Deb, 2001) and repairing infeasible solutions (Coello Coello et al., 2007) are common methods, too. Linear and quadratic programming generally apply Lagrange multipliers for constraint handling and linear continuous problems can be solved by the simplex algorithm which includes constraint handling (Cavazzuti, 2013). More information about Lagrange multiplier methods can be found in (Bertsekas and Rheinboldt, 2014) and for constraint handling methods for linear and non-linear continuous single-objective problems we refer to (Cottle and Thapa, 2017). Furthermore, Table 1 includes information about constraint handling for the different methods presented in this paper.

3. Stakeholder integration

In order to make land use planning more applicable to real-world problems, stakeholders are increasingly integrated into the decision-making process (Memmah et al., 2015). They can state their interests and ambitions but also provide expert knowledge on current and future developments. This is especially valuable in agricultural areas, since, for example, trends in cultivation techniques, consumer demand but also policies need to be taken into account. Furthermore, stakeholders might provide a deeper insight into the potential of certain areas, which would help to facilitate the decision on where possible land use changes can be implemented. In all cases, it is important to find representative stakeholders first (Harrison and Qureshi, 2000). For example, for agricultural land use allocation problems, there should be a sound combination of people with different backgrounds and point of views, like farmers, conservationists or employees of state ministries (Hauck et al., 2016). This should guarantee a dynamic discussion and prevents the optimization from being biased by too narrow perspectives. However, if the stakeholders cannot agree on “a mutually consistent set of preferences” (Malczewski, 1999), multiple analyses of the problem might be necessary (Malczewski, 1999). Furthermore, important technical terms like, for example, ‘trade-offs’, ‘land sharing/sparing’, etc. and the optimization method applied must be communicated well to the stakeholders in order to create a mutual understanding. Otherwise, there might be misunderstandings or the optimization might look like a ‘black box’, which could create mistrust (Bishop, 2013).

The moment stakeholders are involved in the optimization process has an influence on the problem formulation and affects the choice of a suitable optimization method. Preferences can be included either before (a priori), during (interactively) or after (a posteriori) the optimization. Initially proposed by Cohon and Marks (1975), it is nowadays common practice to classify multi-criteria optimization methods according to these three categories (Coello Coello et al., 2007):

Scalarization is an **a priori** method where the algorithm finds a solution that best meets the stakeholder’s preferences. These are represented by the objective function weights or optimization goals. Examples from the studies presented above are Aerts et al. (2003), Behrman et al. (2015) and Santé-Riveira et al. (2008). However, if scalarization is used to calculate the Pareto-frontier by changing weights/goals like in Kennedy et al. (2016), it is considered as an **a posteriori** approach. Additionally, Pareto-based methods and with them the majority of evolutionary multi-objective algorithms fall into this category (Deb and Köksalan, 2010). These algorithms provide a whole set of Pareto-optimal solutions and, given these alternatives, stakeholders can then select those that fit their preferences best (see, for example, Fowler et al. (2015), Groot et al. (2007) and Lautenbach et al. (2013)). For the case of a posteriori involvement, methods from the field of MADM (Figure 1) can be applied in the selection process. However, a priori and a posteriori approaches do not consider that it might be difficult for the stakeholders to express their preferences analytically and that values can change over time and with growing experience and learning (Coello Coello et al., 2007). Therefore, **interactive** approaches can be favourable. They allow stakeholders to articulate preferences in a progressive way, that is, stakeholders are able to adjust them after each iteration of the optimization. This step-by-step integration of preferences guides the optimization towards the relevant parts of the Pareto-frontier and may help to reduce computational time (Meignan et al., 2015). Such real-time interaction, however, requires short computation times of intermediate solutions (Stewart et al., 2004). This can also be challenging since the computational time to complete a single optimization should preferably be less than a minute (Bishop, 2013; Stewart et al., 2004). Reference point methods and tabu search are popular interactive optimization techniques – see, for example, Stewart and Janssen (2014) and related studies and Qi and Altinakar (2011), but GAs (e.g., Bennett et al. (1999)) can also be used. Wu et al. (2016) present a generic framework for stakeholder integration in combination with multi-objective EAs and illustrate its applicability with a real-world integrated urban water management problem for Adelaide, South Australia.

4. Discussion & Recommendations

In general, most land use allocation problems are very complex and thus hard to solve with optimization techniques. Therefore, scenario analysis might be a better option in some cases (Seppelt and Voinov, 2002). However, working with optimization methods allows the decision maker to evaluate the potential of a landscape by analyzing trade-offs between environmental, social and economic objectives and to assess the efficiency of current land uses (Kennedy et al., 2016). Uhde et al. (2015) recommend optimization techniques particularly for the consideration of provisioning and cultural ESS. For regulating and supporting ESS they suggest a combination of MADM with group decision making or spatial analysis since in practice, their quantification can be difficult.

The moment of stakeholder integration and the decision on whether or not trade-offs need to be identified have a major influence on the choice of a suitable optimization technique. The analysis of biophysical trade-offs requires a high level of objectivity. Certainly, this is not entirely possible in modelling since most models contain some kind of human opinion or experience but stakeholders should (at least) be involved a posteriori. However, if the overall aim is only to allocate land according to the stakeholder's preferences by taking into account the ecological potential of the landscape, then the optimization is rather subjective, and it is reasonable to include stakeholders a priori or interactively and even involve them in the problem formulation. Also, the amount of time that is available for computing solutions should be considered. While interactive methods require solutions within seconds or a few minutes, comparatively slower – and thus perhaps more accurate – algorithms can be used for a priori and a posteriori approaches.For a more detailed discussion of the advantages and disadvantages of a priori, interactive and a posteriori approaches we refer to Coello Coello et al. (2007).

Before we provide guidelines for which of the above presented methods are suitable for different types of land use allocation problems, we need to discuss some of the method's particular strengths and weaknesses, especially in terms of trade-off identification and stakeholder integration. We will begin by comparing scalarization with Pareto-based methods in general; then, we will provide detailed discussion of the methods that fall into these categories.

The advantages and disadvantages of scalarization versus Pareto-based methods first depend on the decision maker's expectation towards the number of optimal solutions that should be determined. Scalarization methods are comparatively easy to implement and efficient if it is sufficient to find only one or a limited number of Pareto-optimal solutions in the preferred regions of the solution space. However, to complete a trade-off analysis, the Pareto frontier needs to be determined by solving the optimization problem multiple times and this can be computationally expensive and time consuming (Janssen et al., 2008). Additionally, scalarization approaches can serve to rapidly find tentative solutions for first discussions (Stewart and Janssen, 2014). Another important factor is the number of objectives within the problem: for more than two objectives, it may be difficult for the stakeholders to interpret visualizations of the Pareto frontier (Deb and Köksalan, 2010). For more than four objectives, even the visualization itself becomes difficult. Therefore, single-solution approaches seem to be more practical. However, representing the whole Pareto frontier can also be advantageous. The whole range of equally optimal solutions comprises much more information than single solutions. This can be, for example, trade-offs and alternative land use options that could have been missed if preferences had been stated in advance. Furthermore, the points of view of multiple stakeholders are reflected better by multiple solutions (Memmah et al., 2015).

4.1 Using scalarization methods

Of the presented methods above, weighted sum is one of the most common and easy-to-use approaches (Bishop, 2013). Nevertheless, it has some major drawbacks: generally, preferences follow a non-linear relationship, but the weighted sum is only a linear approximation of this function. Therefore, it favours unbalanced (i.e., extreme) solutions, although decision makers typically prefer balanced ones (Marler and Arora, 2010). If a weighted sum is used in order to obtain the Pareto frontier, it also has to be considered that most of the land use allocation problems are non-convex problems. This means that the method may not find all Pareto-optimal solutions. Additionally, the weights have to be changed with every optimization run, but here, one has to consider that a uniformly distributed set of weights does not necessarily lead to a uniformly distributed set of Pareto-optimal solutions (Deb, 2001). Furthermore, it should be taken into account that highly correlated objective functions may distort the weighted objective function value and might even hamper convergence (Salmasnia et al., 2013; Steuer, 1989). Marler and Arora (2010) discuss some more aspects that must be taken into account when using the weighted-sum approach for multi-objective optimization problems (e.g., weight-setting). They conclude that alternative methods should be applied if the aim is to depict the Pareto frontier with low computational effort, particularly for non-convex problems, and if complex preferences must be accurately articulated.

If the initial solution is already sufficiently good, simulated annealing can find optimal solutions with comparatively low computational expenses even for non-linear objective functions (Santé-Riveira et al., 2008). SA is therefore a fast and simple method that is more recommendable at an early stage of the land use allocation process (Aerts and Heuvelink, 2002). According to Memmah et al. (2015), SA as well as tabu search perform well for problems with many constraints. Thus, different views of all stakeholders can be taken into account (Qi and Altinakar, 2011). But like SA, TS requires a good initial solution. Otherwise, it may take more iterations and thus more time to achieve an optimal solution. TS and reference point methods are a priori techniques, but, as mentioned before, they are also well-known for interactive stakeholder integration (Meignan et al., 2015; Miettinen et al., 2008).

The benefit of RP methods is that the optimization is guided towards relevant solutions for stakeholders. In contrast to weighted-sum methods, they even promote balanced solutions if achievement functions are applied. The whole approach may seem too subjective for trade-off analyses, but the Pareto frontier can be obtained by varying the aspiration levels, though this can lead to long computation times. Therefore, a Pareto-based method can be more practical for trade-off comparisons.

4.2 Using Pareto-based methods

Methaheuristics (e.g., evolutionary or genetic algorithms) are widely applied in land use allocation. They form the most popular group of algorithms that are able to solve hard combinatorial and non-linear problems (Memmah et al., 2015). Nevertheless, Memmah et al. (2015) also state that the more sophisticated algorithms “have not propagated to the land use optimization community” since the newer methods are not as straightforward as their basic versions.

Population-based algorithms have three main advantages: (i) they are gradient-free, which means that they can deal with complex, non-linear and discontinuous problems; (ii) they are highly explorative, which increases the probability of finding global optima (though there is no guarantee that they actually will be found) and (iii) they can be implemented in a parallel way, which decreases computation time (Yang, 2014). The latter is helpful for problems that consider a high number of generations of a large population, which usually leads to long convergence times. One drawback of population-based algorithms is that parameter tuning is often done by trial-and-error. However, in the context of land use allocation, the main flaw is probably that Pareto dominance is inappropriate for many-objective problems (i.e., problems with more than four objectives (Lautenbach et al., 2013)). The reason for this is that with an increasing number of objectives, the amount of non-dominated solutions increases exponentially, making it more difficult for the algorithm to converge towards the Pareto frontier (Memmah et al., 2015).

For Pareto-based methods, stakeholder integration usually occurs a posteriori. However, there are some exceptions, for example, Porta et al. (2013) maximize a weighted fitness function with a GA, which requires prior weight-setting, and Liu et al. (2016) use PSO with knowledge-informed rules that are partly based on a priori information about stakeholder's preferences. Also, an interactive GA has been applied by Bennett et al. (1999). A summary of the different optimization methods, their particular timing of stakeholder integration and how trade-offs can be identified are all given in Table 1.

In summary, all optimization methods have their individual advantages and disadvantages regarding technical aspects (e.g., complexity of the algorithm and computation time), trade-off identification and stakeholder integration. In some cases, a combination of different approaches (e.g., an EA with local search) or an optimization method with MADM can compensate for the drawbacks of one method and add useful features of another. Thus, hybrid approaches can lead to a more effective and efficient search (Uhde et al., 2015). For example, the bilevel optimization approach used by Whittaker et al. (2017) was able to find better solutions compared to single level or sequential optimization approaches. However, the authors argue that the optimization method is challenging in terms of mathematical requirements (e.g. convexity, continuity, linearity) and computationally expensive, though it is relatively simple to set up for parallel execution.

Table 1 Overview of scalarization and Pareto-based optimization methods used in land use allocation. For every method it is shown when stakeholders are usually integrated. Note, that the classification is not rigid – in some cases, scalarization approaches are handled as a posteriori techniques and Pareto-based methods as interactive or a priori techniques. Furthermore, the table shows how trade-offs can be determined and constraints be handled. The last column gives example studies and their respective contexts (agriculture or land use in general).

	Method	Stakeholder integration			Trade-off analysis	Notes	Constraint handling	Example [context]
		A priori	*Inter-active*	*A posteriori*				
Scalarization	Weighted Sum	X			• Variation of weights/goals (when used as a posteriori method) • Can be computationally expensive	• For non-convex problems, some parts of the Pareto-frontier cannot be found • Not recommendable, if complex preferences have to be articulated accurately	• Continuous problems: simplex algorithm (linear), Lagrangian Methods, penalty function • See Cottle & Thapa, 2017 • Discrete problems: see Pareto-based methods	• Kennedy et al., 2016 [agriculture] • Polasky et al., 2008 [agriculture]
	Reference Point Methods (incl. Goal Programming)	X	X			• GP might not find Pareto-optimal solutions • RP methods without norm minimization find Pareto-optimal solutions	• See Pareto-based methods	• Stewart & Janssen, 2014 [land use in general] • Stewart et al., 2004 [land use in general] • Janssen et al., 2008 [land use in general] • Eikelboom et al., 2015 [land use in general]
	Tabu Search	X	X				• Add non-feasible solutions to tabu list, penalty function (Coello Coello et al., 2005) • See Pareto-based methods	• Qi & Altinakar, 2011 [agriculture] • Behrman et al., 2015 [agriculture]
	Simulated Annealing	X				• Fast and simple method for an early stage of the land use allocation process	• Penalty function, weight vector in the acceptance criterion (Suman & Kumar, 2006)	• Aerts & Heuvelink, 2002 [restoration] • Santé-Riveira et al., 2008 [agriculture]
Pareto-based	Evolutionary/Genetic Algorithms			X	• Pareto-frontier	• Generally a posteriori, with exceptions (e.g. Porta et al., 2013 – a priori; Bennett et al., 1999 – interactive; Liu, et al., 2016 - a priori) • Can be inappropriate for problems with many objectives (e.g. >4)	• Penalty function, feasibility operators, repair infeasibile solutions • EAs: see Deb, 2001 • SI: see Zeltni & Meshoul, 2016	• Lautenbach et al., 2013 [agriculture] • Fowler et al., 2015 [agriculture] • Groot et al., 2007 [agriculture]
	Swarm Intelligence Algorithms /Artificial Immune Systems			X				• Huang et al., 2012 [land use in general] • Liu et al., 2016 [land use in general] • Ma et al., 2012 [land use in general] • Nguyen et al., 2016 [agriculture] • Yang et al., 2015 [land use in general]

4.3 Recommendations for the method selection

In light of the methods presented and discussed above, a few questions turned out to be essential when selecting an appropriate approach for a land use allocation problem (see Figure 3): *(i) What type of optimization problem is it?* (That is, is it multi-objective, non-linear or combinatorial?) To answer this question, the problem formulation must be clear. In general, one can say that the more objective functions a problem has and the more details are considered, the more complex it will be to solve. This will result in longer run-times, and found solutions might be not as close to optimal as expected. This is because non-convex complex optimization problems can only be solved by (meta-)heuristics which cannot guarantee the finding of the optimal solution(s).

Given a multi-objective optimization problem, it should first be considered whether a trade-off analysis is required *(ii) that is, is it necessary to depict the whole Pareto frontier?* If yes, then *(iii) How many objective functions does the problem have?* If it is many, then *(iv) Can their number be reduced, for example, by combining them or converting some of them to constraints?* Because some population-based algorithms cannot handle many-objective (>4) problems (Lautenbach et al., 2013). If the number of objectives is manageable, then Pareto-based algorithms (e.g., EAs/GAs, SI) with a posteriori stakeholder integration are recommendable. If it is not possible to reduce the number of objectives or no trade-off analysis is required anyway, then the land use planner should choose from the group of a priori and interactive approaches that include all of the scalarization methods. At this point, reference point methods like goal programming but also tabu search are recommendable for interactive stakeholder integration. Scalarization methods also allow the identification of the Pareto frontier, though it may be computationally more expensive than a Pareto-based approach.

Of course, Figure 3 should only serve as a first orientation to the available methods for land use planners. There are methods like hybrid algorithms or the application of knowledge-informed rules that would not fit into this scheme. After all, the suitability of an algorithm is highly dependent on the structure of the optimization problem itself, and since every problem is unique, it is impossible to give a general recommendation that would hold for any kind of optimization problem.

Although decision-support techniques, including optimization, are promising tools for allocating land use, their application is still limited (McIntosh et al., 2011). There are several reasons for this, amongst them a lack of skills and knowledge on the usage of these methods in practice (Volk et al., 2010). Therefore, a strong collaboration between experts (e.g., scientists) and stakeholders/decision makers is needed and even promoted (Hauck et al., 2016). For this, one of the key issues but also challenges is the proper communication of the land use optimization approach and the results to all parties involved in the decision making process (Parker et al., 2002).

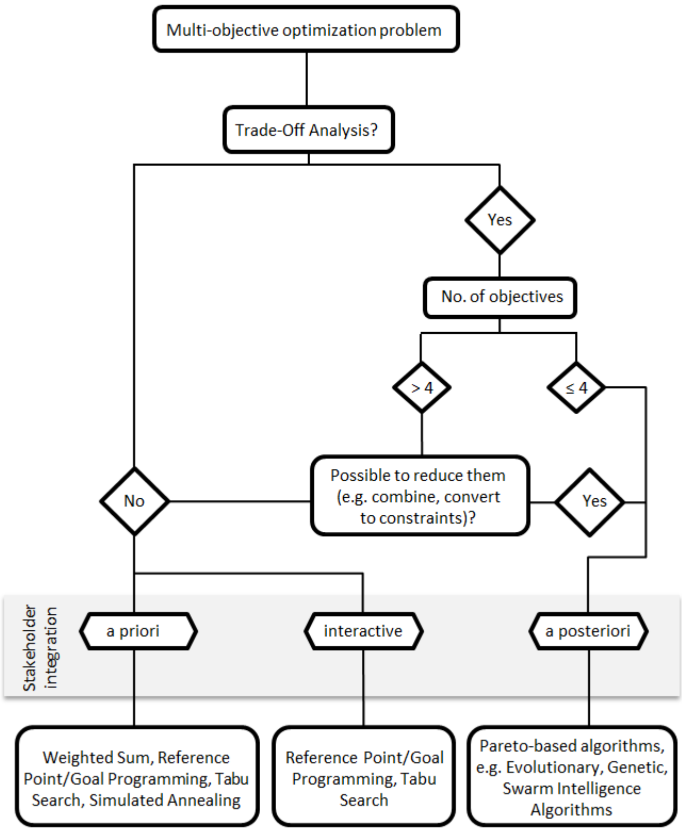

Figure 3 Flowchart of a structured search for suitable optimization methods. The flowchart helps finding an appropriate method for solving a particular multi-objective land use allocation problem. It only serves as a first orientation since there are methods (e.g., hybrids, knowledge-informed rules) that would not fit into this scheme. In case the no. of objectives is >4, trade-offs can still be determined by scalarization methods, though with more computational effort.

5. Conclusion

We presented a review of available optimization techniques that can be useful for agricultural land use allocation. We first classified them within the broader field of decision-support techniques before we presented the methods themselves. We distinguished between scalarization (e.g., weighted sum, RP, TS and SA) and Pareto-based optimization methods (e.g., EAs/GAs, SI algorithms) and illustrated each of them with examples from existing studies. We also highlighted how trade-offs can be identified either, by changing weights/goals and solving the problem iteratively (scalarization approaches) or by determining and analysing the Pareto frontier directly (Pareto-based approaches). Furthermore, we mentioned how constraints can be handled for the different optimization methods and addressed the topic of stakeholder integration (a priori, interactive, a posteriori). In cases where no trade-off analysis is required and the main focus lies on finding optimal land use patterns that best fulfil the stakeholders' preferences, we recommend a priori and particularly interactive approaches. If the identification of trade-offs is of high priority, stakeholders should be involved a posteriori. Also, for problems where it is impossible or not necessary to include stakeholders, a posteriori (i.e., Pareto-based) methods are most suitable.

Furthermore, land use allocation usually occurs at a regional or local scale where ESS should be addressed (Uhde et al., 2015). Nevertheless, optimal solutions might look different if linkages to other regions were considered (e.g., trade or animal migration) (van Butsic and Kuemmerle, 2015). Also, optimal solutions will depend on scale – for example, the allocation of certain crops could look completely different at a local scale compared to a national or even global level. However, large-scale studies are difficult to conduct and cannot capture the details of small-scale studies. Ultimately, implementations of global solutions are likely to fail since there is no world institution for land management.

To date, most of the agricultural land use allocation studies have focused on economic trade-offs between ESS use (e.g., crop production) and ESS provision (e.g., water provisioning, water quality, soil erosion) (Fowler et al., 2015; Groot et al., 2012; Sadeghi et al., 2009). Only few studies explicitly included biodiversity trade-offs, like Groot et al. (2007), Groot et al. (2018) or Kennedy et al. (2016) (see also Table A.1 in the Appendix). On the other hand, systematic conservation planning creates areas that protect species and habitats, but it does not consider biodiversity protection on 'working lands' (Polasky et al., 2008). This substantiates the impression that there is optimal land use allocation as a distinct objective and biodiversity protection as another. Also, Macfadyen et al. (2012) argue that from focusing only on either biodiversity conservation or ESS management, "it does not follow that… [this] will provide reciprocal benefits of the kind we should be seeking in land-use decision-making". Therefore, a stronger collaboration between both research areas is needed to determine economically efficient land use patterns that are ecologically sustainable and protect biodiversity at the same time. A first step has been done by including the ESS concept in conservation planning, though this is still "a fairly new practice" (Schröter and Remme, 2015).

In this context, mathematical optimization offers powerful and flexible methods that allow for the integration of biophysical and biodiversity models. Here, a clear (mathematical) formulation and specification of the optimization problem is necessary and forms a mutual basis for decision makers and stakeholders for discussing land use solutions. At the same time, it makes problem understanding and repeatability for other case studies much easier. This is particularly important since some methods from related fields like spatial conservation prioritization or spatial forest planning could also be used in agricultural land use allocation and vice versa. After all, conservation prioritization as well as forest planning handle similar optimization problems (Kurttila, 2001, 2001; Mendoza and Martins, 2006; Moilanen and Wilson, 2009).

However, in the end it should be clear that mathematical land use optimization as well as any other MCDA technique is only a tool to support decision making (Stewart et al., 2004), and none of them provides a completely objective analysis that always leads to the 'right answer' (Belton and Stewart, 2002). For future research, the development of hybrid methods that combine different optimization algorithms or integrate other MCDA techniques along with the use of parallelization techniques and participatory approaches are seen as most relevant (Memmah et al., 2015; Uhde et al., 2015). Particularly for a priori stakeholder integration, the application of knowledge-informed rules can improve the finding of efficient and effective land use solutions (Liu et al., 2016). Future research should aim at the integration of changing climatic conditions (Klein et al., 2013) and uncertainties (Malczewski and Rinner, 2015) into optimization frameworks.

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Appendix

Table A.1 A selection of studies from the research fields of general and agricultural land use allocation and examples from other related areas. All studies used mathematical optimization. The table indicates the optimization method used, when stakeholders were included, whether trade-offs were determined and which ecosystem services (including biodiversity) were considered. For studies where ES were not mentioned explicitly we translated considered land use types into the respective ES (e.g., "forest" to "forest-related ES").

Reference	Stakeholder			Optimization Method							Trade-offs	Ecosystem Services								
	a priori	interactive	a posteriori	Reference point	Evolutionary/Genetic Algorithm	Particle Swarm Optimization	Ant Colony Optimization	Simulated Annealing	Tabu Search	Other		Agricultural production	Water	Soil/erosion	Forest-related ES	Wildlife/nature	Carbon sequestration/storage	Recreation/cultural value	Other	Biodiversity
Land use in general																				
Cao et al. (2012)	•			•	•														•	
Eikelboom et al. (2015)		•		•	•							•	•	•		•				
Huang et al. (2012)			•							•	•	•								
Janssen et al. (2008)		•		•	•							•	•			•		•		
Liu et al. (2013)			•			•						•	•			•			•	
Liu et al. (2016)	•					•						•			•					
Ma et al. (2011)			•			•						•	•		•					
Porta et al. (2013)	•				•							•			•	•				
Stewart et al. (2004)		•		•	•							•	•			•		•		
Stewart and Janssen (2014)		•		•	•							•						•		•
Wang et al. (2004)		•								•	•	•	•	•	•			•	•	
Yang et al. (2015)	•									•		•	•		•					
Agriculture																				
Antoine et al. (1997)		•		•								•		•						
Behrman et al. (2015)	•								•			•								•
Bekele and Nicklow (2005)			•		•						•	•	•							
Bennett et al. (1999)		•			•							•		•		•				
Bostian et al. (2015)			•		•						•	•	•							
Chikumbo et al. (2012)	•		•	•	•						•	•	•	•	•		•			

Fowler et al. (2015)			•		•						•	•	•							
Groot et al. (2007)			•		•						•	•		•						•
Groot et al. (2012)			•		•						•	•		•						
Groot et al. (2018)			•		•						•	•	•						•	•
Kennedy et al. (2016)			•							•	•	•	•							•
Klein et al. (2013)			•		•						•	•	•	•						
Lautenbach et al. (2013)			•		•						•	•	•							
Lu and van Ittersum (2004)			•							•	•	•		•						
Mishra et al. (2014)	•			•						•		•	•							
Nguyen et al. (2016)			•				•					•	•							
Polasky et al. (2008)			•							•	•	•			•					•
Qi and Altinakar (2011)		•							•			•	•	•						
Sadeghi et al. (2009)			•							•	•	•		•						
Santé-Riveira et al. (2008)	•							•				•			•					
Seppelt and Voinov (2002)			•		•							•	•	•						
Shaygan et al. (2014)			•		•							•		•						
van Butsic and Kuemmerle (2015)										•	•	•								•
Whittaker et al. (2017)			•		•					•	•	•	•							
Other (e.g. conservation planning, forestry, restoration, watershed management)																				
Aerts and Heuvelink (2002)	•							•					•		•				•	
Arabi et al. (2006)			•		•						•		•	•						
Keller et al. (2015)	•									•				•			•		•	•
Rabotyagov et al. (2010)			•		•						•	•	•							
Randhir and Shriver (2009)	•									•	•		•							
Schröter et al. (2014)			•					•			•				•	•	•	•		•