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Multi Criteria Analysis for bioenergy systems assessments

Thomas Buchholz[a,*], Ewald Rametsteiner[b], Timothy A. Volk[a], Valerie A. Luzadis[a]

[a] Department of Forest and Natural Resources Management, State University of New York, College of Environmental Science and Forestry, One Forestry Drive, Syracuse, NY 13210, USA
[b] International Institute for Applied Systems Analysis, Forestry Program, Schloßplatz 1, 2361 Laxenburg, Austria

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ABSTRACT

Sustainable bioenergy systems are, by definition, embedded in social, economic, and environmental contexts and depend on support of many stakeholders with different perspectives. The resulting complexity constitutes a major barrier to the implementation of bioenergy projects. The goal of this paper is to evaluate the potential of Multi Criteria Analysis (MCA) to facilitate the design and implementation of sustainable bioenergy projects. Four MCA tools (*Super Decisions*, *DecideIT*, *Decision Lab*, *NAIADE*) are reviewed for their suitability to assess sustainability of bioenergy systems with a special focus on multi-stakeholder inclusion. The MCA tools are applied using data from a multi-stakeholder bioenergy case study in Uganda. Although contributing to only a part of a comprehensive decision process, MCA can assist in overcoming implementation barriers by (i) structuring the problem, (ii) assisting in the identification of the least robust and/or most uncertain components in bioenergy systems and (iii) integrating stakeholders into the decision process. Applying the four MCA tools to a Ugandan case study resulted in a large variability in outcomes. However, social criteria were consistently identified by all tools as being decisive in making a bioelectricity project viable.

1. Unlocking the potential of bioenergy

The components of a complete bioenergy system include feedstock production, conversion technology, and energy allocation. These processes are each embedded in manifold social, economic, and environmental contexts. The resulting complexity is hard to manage effectively and is often ignored when bioenergy system planning only focuses on a single component of the system. Many different stakeholders with diverse perspectives and training participate in bioenergy systems, including on-the-ground biomass producers, power plant engineers, developers and marketing experts, regulatory agencies, and local communities. The diverse perspectives of these players create barriers that make communication extremely difficult. Moreover, stakeholders come with divergent values on how to assess and make decisions about the best solution to problems that are identified. In addition, bioenergy systems often have high levels of uncertainty and risk that are difficult to quantify because the data available is often limited, incomplete, or inconsistent. As a result, the information used in decision-making around these systems is often subjective and is based on normative values. Therefore an open and transparent participatory process that involves multiple stakeholders, not just experts, is needed to in order for projects to move forward and be sustainable.

Decisions about various components of bioenergy systems are often made solely by 'objective' experts, who focus on finding the optimal solution and applying cost–benefit analysis, while neglecting holistic planning and stakeholder support (Cherni et al., 2007). The amount of data that is used in these decisions is often overwhelming to other stakeholders and they are often sceptical of the result of these approaches. The reasoning behind commonly used reductionistic approaches with little stakeholder involvement, all the while paying lip service to their contribution to the process, is largely due to the need for timely decisions made in a cost-efficient decision process or issues of trust and control. Opinions and perspectives of stakeholders are rarely consulted or they are only sought after the project plans have been completed, and the result is often the failure of a project. Such failures have been described for bioenergy projects in the United Kingdom by Upreti (2004), Upreti and Horst (2004), Upham and Shackley (2007), or Upreti and Horst (2002), who found that 27% of researched bioenergy plants were rejected in the planning stage. In India, Ghosh et al. (2006) describes similar failures, Ghosh et al. (2003) describe a case where 250 small-scale gasifiers for power production run for an average of 160 h only and Ravindranath et al. (2004) describe a case in India where dual fuel mode gasifiers[1] ran for 25% of the time on diesel only, both studies found non-technical reasons for this failure of bioenergy systems, while Munda and Russi (2005) portray comparable constraints for

* Corresponding author. Tel.: +1 315 470 4850; fax: +1 317 470 6934.
E-mail addresses: tsbuchho@syr.edu, thomasbookwood@web.de (T. Buchholz).

[1] Powered by a mix of woodgas and diesel.

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renewable energy projects in Spain. The collapse of many other bioenergy projects is often not analyzed to determine the cause of the failure.

The need to involve stakeholders in bioenergy project development so that they can express their opinions (Giampietro et al., 2006) has been acknowledged (McCormick and Kåberger, 2007). In order to help stakeholders make judgments based on their normative values, technical information and details need to be provided by experts from the various components of the bioenergy system. However, processes to effectively share information and gather stakeholder input around bioenergy systems and assess how it influences the project are not well developed. Apparently, there is a need for tools (i) to apply systems thinking in order to identify all stakeholders involved, (ii) to summarize the vast amounts of information, (iii) to facilitate communication amongst stakeholders and (iv) to include stakeholders in the decision process in a time and cost-efficient process. Such tools could greatly enhance the sustainability of bioenergy systems (see Buchholz et al., 2007; Elghali et al., 2007). Tools based on Multi Criteria Analysis (MCA) have shown potential to guide stakeholders to find and agree on sustainable solutions in a wide range of fields including forest management (e.g. Schmoldt, 2001; Mendoza and Prabu, 2006), or renewable energy systems (Giampietro et al., 2006; Gamboa and Munda, 2007). The goal of this paper is to identify the potential and limitations of selected MCA tools to facilitate the participatory implementation of sustainable bioenergy projects.

The objectives of this paper are to:

- Analyze the suitability of four MCA tools to assess sustainability of bioenergy systems with a special focus on multi-stakeholder inclusion;
- Use data from a multi-stakeholder bioenergy case study in Uganda to assess the effectiveness of these four MCA tools in practice.

2. Multi Criteria Analysis background

MCA can be defined as “formal approaches which seek to take explicit account of multiple criteria in helping individuals and groups explore decisions that matter” (Belton and Stewart, 2002). MCA stands in contrast to single goal optimization and approaches using ‘unifying units’ to offset poor performances of one criterion by good performances of another criterion, as is done by cost–benefit analysis using monetary values assigned to parameters therefore allowing for substitution and compensability between criteria.

MCA methods can be classified as Multi Objective Decision Making (MODM) approaches working with an indefinite set of possible scenarios, and Multi Attribute Decision Making (MADM), suggesting a finite set of scenarios (see Fig. 1). For instance, linear programming follows the MODM approaches starting with a set of principles (e.g. maximizing efficiency, reducing costs) and resulting in an optimized scenario. On the other hand, MADM approaches, which are of concern in this paper, start with a set of scenarios, which are further scrutinized in how well they fit a set of principles. MADM approaches can be further differentiated into (i) value measurement models, (ii) goal, aspiration, and reference-level models, and (iii) outranking models (Belton and Stewart, 2002). Value measurement models assign a numerical score to each scenario, thus ranking scenarios depending on how they score according to a weighted list of criteria. Such approaches follow the Multi Attribute Value Theory (MAVT). The Multi Attribute Utility Theory (MAUT) is perceived as an extension of MAVT, allowing for additional inclusion of uncertainties and risks by assigning utility functions. Goal, aspiration, and reference-level models are goal programming methods where “a mathematical programming algorithm is used to approach these goals as closely as possible” (Belton and Stewart, 2002, p. 105). “In outranking models, the scenarios are compared pair-wise to check which of them is preferred regarding each criterion” (Løken, 2007). After aggregation of the results for each criterion, this approach suggests to what extent the scenarios outrank each other. For a compact overview of MCA methods and classifications see also Mendoza and Martins (2006).

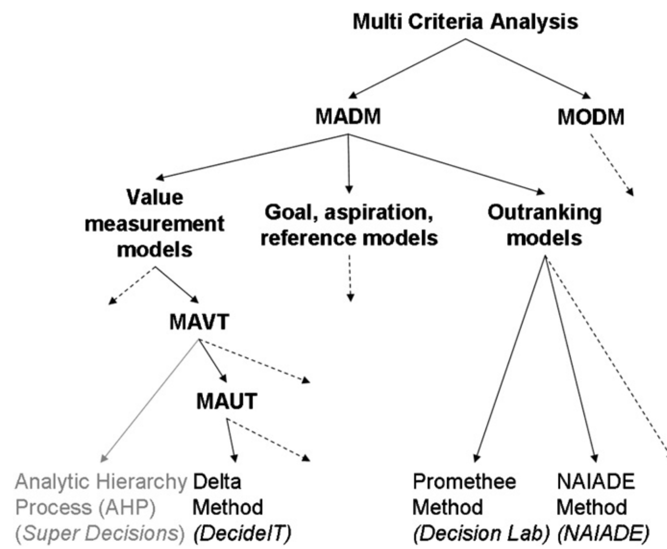

Fig. 1. Classification of MCA methods. Framework is based on Sutter (2003). Note that in the literature many different classifications are used. Dotted arrows indicate existence of other MCA methods not used in this study. Software names are indicated by italics.

MCA has been widely applied in fields related to bioenergy over the past 15 years. For instance, Løken (2007) reviews the use of MCA for energy decisions in general and Munda and Russi (2005) used MCA for comparing renewable and conventional energy options. Other MCA applications come from natural resource management. Mendoza and Prabhu (2005) have built a dynamic forest management system together with communities and evaluated it using MCA. Mendoza and Martins (2006) reviewed MCA applications to natural resource management, while Schmoldt (2001) compiled situations where a specific MCA has been applied to different natural resource management problems. Wolfslehner et al. (2005) applied MCA tools to sustainability assessments using criteria in forest certification processes. In these examples, using MCA proved (i) to be valuable in structuring the problem that needed to be addressed and (ii) involving many stakeholders from different disciplines and perspectives in difficult decision-making situations where facts were uncertain, values were disputed, stakes were high, and decisions needed to be made quickly (Funtowicz and Ravetz, 1993).

3. Material and methods

3.1. Criteria to review MCA tools

To analyze the applicability of the four MCA tools for bioenergy systems assessments, we first scrutinized their structural approach using a set of nine criteria (see Table 1). The criteria

Table 1
Description and justification of criteria used for reviewing MCA tools on their suitability to assess bioenergy systems

Aspects covered		Criteria used for analyzing structural approach of MCA tools	Justification for selection
Stakeholder aspects	1	Stakeholder inclusion in decision-making	Bioenergy is characterized by a high degree of stakeholder involvement and many bioenergy projects were unsuccessful because of a failed stakeholder policy
	2	Application of qualitative data	Qualitative datasets are often seen as the only usable method to assess options in the face of the inherent uncertainty in many decisions and the normative and/or divergent values of stakeholders which are impossible to quantify
Technical aspects	3	Measures to deal with uncertainty	Uncertainty plays a significant role in decision-making and different kinds of uncertainty can be addressed at different stages of a decision process depending on the MCA tool
	4	Inclusion of criteria hierarchies	Hierarchies can help to reduce complexity and make it easier to communicate results and strategies to stakeholders who do not have a technical background in bioenergy
	5	Use of thresholds	Numerically precise thresholds are common in decision tools, and, although they are easy to communicate, they can have significant implications when applied in MCA
Application value	6	Ease of computation	MCA tools can vary considerably with respect to how intuitive the problem structuring, parameter setting, and sensitivity analysis are. Technical user-friendliness is especially important when many stakeholders unfamiliar with MCA are involved
	7	Dynamic reevaluation	MCA is meant as a decision tool to allow engagement in learning cycles which are flexible and adaptive (Gamboa and Munda, 2007), Therefore, it should allow the reevaluation of decisions with new structures, insights, or data
	8	Transparency	MCA applications—especially when many stakeholders are involved—must rely on simple math and intuitive methods to gain acceptance, rather than being perceived as a 'black box'
	9	Communication of decision process and results	A critical feature when applying MCA tools in multi-stakeholder settings is how well they support communication of the decision process and results, e.g. what graphical tools are available to allow their easy comprehension

Table 2
Focus of analysis on tool performance

	Criteria used for assessing MCA tool performance in case study	Justification for selection
1	Assessment and ranking of scenarios	Criteria correspond to steps of MCA application
2	Sensitivity analysis on criteria weighting	
3	Sensitivity analysis on performance of scenarios	

selection was inspired by previous evaluations of MCA tools for their application value (Mendoza and Martins, 2006), structure/methodological review and application value (Wolfslehner et al., 2007), and methodological approaches (Guitouni and Martell, 1998). Criteria for this assessment were supposed to evaluate the methodological implications (e.g. measures to deal with uncertainty), technical aspects (e.g. inclusion of criteria hierarchies), as well as practical application value (e.g. transparency, reevaluation) of the MCA tools analyzed. The nine criteria and their justification are described in Table 1. Criteria were (i) stakeholder inclusion in decision-making, (ii) application of qualitative data, (iii) measures to deal with uncertainty, (iv) inclusion of criteria hierarchies, (v) use of thresholds, (vi) ease of computation, (vii) dynamic reevaluation, (viii) transparency, and (ix) communication of decision process and results (Table 2).

In the second part of our analysis, we applied the four MCA tools to an Ugandan bioenergy case study with an empirical database. Analysis was focused on how the tools performed in practice during (i) assessment and ranking of scenarios, (ii) sensitivity analysis on criteria weighting, and (iii) sensitivity analysis on the performance of the scenarios. We chose these criteria as they correspond to the steps in a decision process at which MCA tools can assist.

3.2. *MCA tools considered*

Table 3 presents an overview on the MCA tools analyzed in this paper. The tools were selected based on the broad acceptance and use of their methodology, their applications in related fields such as renewable energy, natural resource management or participatory assessments, and availability of software.

Super Decisions 1.6.0 applies the Analytic Hierarchy Process (AHP) originally developed by Saaty (1980) dealing with proliferation of weapons. Recently the AHP has been widely applied to Natural Resource Management problems (e.g. Schmoldt, 2001). The AHP is based on a pairwise comparison of (a) criteria with regard to an overall goal, and (b) of alternatives against individual criteria and a subsequent ratio scale estimation for each criteria usually using a nine-point scale (for a verbal description of scales see Saaty, 2003, p. 6). This approach allows the use of qualitative criteria as it does not need criteria values. This pairwise comparison has proven extremely intuitive for stakeholders and practical (Kangas and Kangas, 2005). The first step of its application is to build a problem hierarchy that encompasses an overall goal, criteria, and scenario hierarchy. In subsequent steps, criteria are compared using pairwise comparisons to reveal their weights, followed by a pairwise comparison of scenarios within each criterion. The AHP's conceptual base has similarities to the value measurement models following the MAVT, although its origin has been developed independently and follows slightly different assumptions (Belton and Stewart, 2002).

The more recently developed *DecideIT* 2.6 software employs the DELTA method, whose methodology follows the MAUT of the value measurement model (Danielson and Ekenberg, 2007), the driver for its development was to built a decision tool that handles imprecision. It distinguishes itself from other methods within this approach by refraining from precise numerical inputs (although this is also possible) and builds on various degrees of imprecise statements including comparisons to meet conditions of uncertainty. *DecideIT* builds on decision trees, scenarios and criteria are categorized and criteria weights as well as scenario

Table 3
Overview on MCA tools analyzed

	Super decisions	DecideIT	Decision lab	NAIADE
Version	1.6.0	2.6	1.01.0386	2.0
MCA methodology	Analytic hierarchy process	DELTA method	Promethee II	NAIADE approach
MCA classification	Value measurement model	Value measurement model	Outranking model	Outranking model

performances can be defined with various options of imprecise statements. More details on its methodology can be found in (Danielson et al., 2007; Danielson, 2005; Larsson, 2005). The *DecideIT* software is novel and in its beta stage but has been successfully deployed already for various cases ranging from contract formulation to flood management (Danielson et al., 2003).

Decision Lab 1.01.0386 uses the Promethee II method, which has been developed by Brans et al. (1984) as a general decision tool and is categorized as an outranking model. It deploys a decision matrix to evaluate scenarios against a set of criteria. The user can choose preference functions with several threshold function options or crisply define the preference functions. For in-depth information on the Promethee method, see Belton and Stewart (2002). Løken (2007) discusses its use for energy assessments, and Cavallo (2005) applies it to identify sustainable energy options.

The *NAIADE*[2] method and software has been developed by Munda (Joint Research Centre of the European Commission 2006) and can be classified as an outranking method using a pairwise comparison technique for ranking scenarios with an emphasis on imprecise inputs and multi-stakeholder settings. It uses a criteria/scenarios matrix and allows for a range of values from precise, stochastic, or fuzzy numbers or linguistic expressions. Compared with other MCA approaches, *NAIADE* uses for ethical reasons criteria weights as importance coefficients with semantic distance as a measure instead of trade-offs, i.e. bad performance from one criterion cannot be compensated by good performance from another criterion, thus avoiding substitution for badly performing criteria.[3] For a discussion on the theory of such 'composite indicators' or criteria as used in *NAIADE*, see Munda and Nardo (2006).

3.3. Empirical bioenergy case study—Uganda

In this paper, we use the trading centre Kasonga in South-western Uganda as a case study where we apply the MCA tools investigated. Inhabited by about 500 people, the core of Kasonga consists of 36 buildings accommodating various types of businesses and 86 homes associated with the businesses (see Table A1). Businesses operate their own fossil-fuel-powered generators to provide electricity. Faced with restricted electricity supply and high electricity costs, a bioelectricity system, such as a small-scale wood gasification system providing electricity through a mini grid and supplied with wood from sustainable sources, might offer a more sustainable option for Kasonga. As part of a national bioenergy research project, MCA tools were used to design and assess a system that best met stakeholder needs.

The decision process and MCA application followed generally accepted steps of stakeholder identification,[4] participatory modeling of competing scenarios in a workshop setting, criteria selection and weighting, and ranking of scenarios. Nine key stakeholders of Kasonga were invited to two workshops, and eight of them took part in the MCA evaluation. Participants represented the local and national government, NGOs, and gender groups, contributing a wide range of social, economic, and environmental expertise and insight. The objectives of the two workshops were (i) to analyze the current electricity situation and to define a business-as-usual (BAU) scenario, (ii) to introduce the participants to the gasification technology and its financial, social, and environmental implications, (iii) identify criteria against which the competing scenarios would be assessed, and (iv) to get stakeholder input in weighting and ranking of criteria and scenarios. In advance of the workshops a facilitator provided stakeholders with relevant information gathered on fact-finding missions from other parts of Uganda, such as wood consumption of bioelectricity systems, land area required for fuelwood production, local purchasing power, local demand for electricity and additional energy services that can be provided by electricity.

Qualitative models were developed and discussed in a workshop setting. Nineteen topics of concern which were frequently mentioned in the discussions were identified as criteria. Eventually, workshop participants selected 9 criteria out of the original set of 19 that were discussed based on their perceived importance (see Table A2). Criteria selected covered ecological factors (reduced competition for fertile land, reduced pollution), social factors (low training needs, high employment rate, diversity and certainty in ownership and business schemes, low planning and monitoring needs), and economic factors (increased local commerce, high cost efficiency, high supply security).

The MCA evaluation followed the AHP structure of criteria weighting and scenario ranking through pairwise comparisons. The data were collected by means of survey sheets and processed by the *Super Decisions* software. Most criteria were assessed by stakeholders because they were either of purely normative value or their performance was subjective due to a lack of data or inherent uncertainty. Scenarios were rated through pairwise comparisons for each criterion. Only 'employment' and 'cost efficiency' were considered technical criteria and the performance of scenarios for those criteria were quantitatively determined by experts as 'number of jobs created' and 'electricity price in US$/kWh', respectively. The geometric mean was used to aggregate individual weighting and ranking for the final group decision (Zahir, 1999), results were normalized to a scale from 0 to 1 to make performance of scenarios comparable between criteria. Where applicable (*DecideIT*, *Decision Lab*, *NAIADE*) and not otherwise defined, a 10% uncertainty range was considered for criteria weighting and performance of scenarios according to standard practice (Larsson, personal communication, 2007).

[2] Novel Approach to Imprecise Assessment and Decision Environments.

[3] NAIADE ranking methods are "non-compensatory to avoid that bad environmental or social consequences are systematically outperformed by good economic consequences or vice versa, [so that] intensity of preference is not taken into account thus avoiding compensability and allowing for weights being importance coefficients and not trade-offs" (Gamboa and Munda, 2007).

[4] See e.g. Reed et al. (2006), Mendoza and Prabhu (2000, 2001, 2003), Schmolt and Peterson (2001), Mendoza and Martins (2006), see also Fig. 2.

4. Results and discussion

4.1. Analysis of MCA tools

Table 4 gives an overview of the MCA tools according to the nine criteria against which they were scrutinized followed by an in-depth discussion.

4.1.1. Stakeholder inclusion in decision-making

In a decision assisted by MCA, stakeholders can contribute to various steps in the process: (i) model building and criteria selection, (ii) selection/description of scenarios, (ii) criteria weighting, and/or (iii) scenario ranking. Many applications of MCA tools in stakeholder settings do not mention the inclusion of stakeholders in the first two steps (see criteria selection in Cherni et al., 2007 or Cavallo, 2005), but there are exceptions (e.g. Mendoza and Prabhu, 2005).

Nevertheless, MCA tools are severely restricted in their use for multi-stakeholder applications. Fig. 2 shows the consecutive steps of adaptive multi-stakeholder management cycles largely based on Farley et al. (2005) and Oliver and Twery (1999). Superimposed on this, Fig. 2 shows those steps in the adaptive multi-stakeholder management cycle that are covered by the MCA tools discussed in this paper and which can form a separate cycle, referred to in the following as the MCA cycle. Fig. 2 shows that MCA tools clearly can contribute to only a few steps in the decision process. This figure also shows that MCA tools do not replace the decision on a scenario (step 8) but contribute to structuring up to three decisive steps and overall learning.

Super Decisions is the only tool reviewed that allows for inclusion of stakeholders in the criteria weighting process. Through pairwise comparisons between criteria, individual weights are created for all criteria. *Decision Lab* and *DecideIT* do not offer tools for this step in a decision process but rely on ready-to-use criteria weights or rankings from e.g. an group facilitator or expert, while the *NAIADE* tool works completely without criteria weights. All tools except for *NAIADE* allow for a different ranking of individual opinions (for a *Super Decisions*/AHP application see e.g. Schmoldt and Mendoza, 2001). For instance, more weight can be given to business opinions or minorities (see Giampietro et al., 2006, p. 81). In *Decision Lab*, individual opinions can be compared with each other by assigning scenarios to each opinion. On the other hand, the absence of weights in the *NAIADE* approach makes it an excellent tool for pre-feasibility studies. When there is no input of stakeholders available, this approach offers an objective use of criteria by the 'technical' user. *NAIADE* offers an additional tool for conflict analysis, in which different stakeholder groups can express satisfaction with

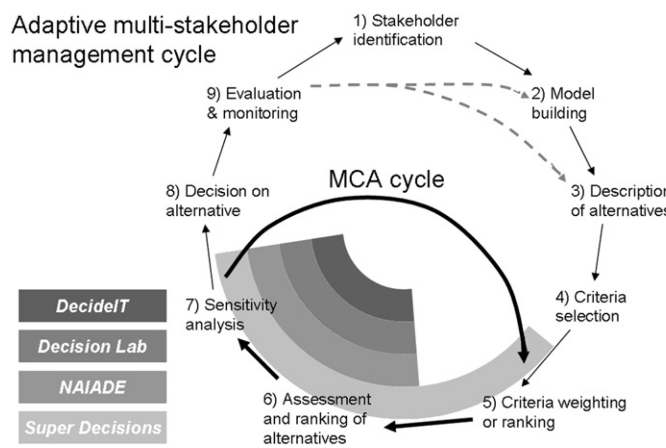

Fig. 2. MCA cycle embedded in an adaptive multi-stakeholder management cycle. Fat arrows indicate embedded MCA cycle. Grey-shaded circle fractions indicate those MCA steps covered by the analyzed MCA tools. The grey dotted arrows indicate optional variations of an adaptive multi-stakeholder management cycle.

Table 4
Nine criteria against which MCA tools were scrutinized

	Super decisions	DecideIT	Decision Lab	NAIADE
Stakeholder inclusion in decision-making	*Very good*; in criteria weighting and assessment of scenarios	*Difficult*; needs external aggregation	*Difficult*; needs external aggregation, group decision analysis possible by assigning scenarios to individual stakeholders	*Difficult*; needs external aggregation, 'Equity' feature allows for identification of groups with similar opinions
Application of qualitative data	*Good*; qualitative scale restricted to points and distances between points	*Not possible*	*Good*; open qualitative scale with restrictions on distances between points	*Very good*; open qualitative scale with many options of variation
Measures to deal with uncertainty	*Difficult*; restricted inclusion of weight preference uncertainty in input stage, only allows preference uncertainty in output stage	*Very good*; all types of uncertainty addressed in input and output stages	*Difficult*; weight preference uncertainty addressed only in output stage, random and probabilistic uncertainty indirectly addressed by scenario analysis	*Very good*; all types of uncertainty addressed in input and output stage
Inclusion of criteria hierarchies	Possible	Possible	Not possible	Not possible
Use of thresholds	*Poor*; no thresholds used, complete substitution of criteria possible	*Good*; optional use of thresholds in the stage of criteria definition and assessment of scenarios	*Very good*; advanced threshold application possible	*Not possible*; no thresholds used, 'semantic weights' prevent complete substitution of criteria
Ease of computation	*Good*; simple to build and assess, hard to apply sensitivity analysis, low 'minimum data requirements'	*Good*; needs inversion if maximization is not the goal, low 'minimum data requirements'	*Very good*; fairly simple in all stages	*Good*; complex when using fuzzy or stochastic data
Dynamic reevaluation	*Difficult*; new data entry, comparison not possible	*Difficult*; new data entry, comparison not possible	*Very good* through scenario comparisons	*Difficult*; new data entry, comparison not possible
Transparency	Very good	Very good	Good	Poor
Communication of decision process and results	Poor	Good	Good	Poor

performance of scenarios and potential coalitions are suggested by means of a 'social impact matrix' resembling decision trees ('Equity' feature, Joint Research Centre of the European Commission, 2006). This tool can be useful to support coalition forming or to identify homogeneity/consensus of decisions.

4.1.2. Application of qualitative data

Super Decisions allows ranking scenarios in a pairwise process on a 1–9-point scale. This arithmetical sequence is fixed in terms of number of points and distances between points, but offers options to use verbal descriptions or graphical visualizations to input ranks. *DecideIT* does not allow for any application of qualitative data and solely relies on numerical data input. *Decision Lab* allows the user to create qualitative scales with no limits in terms of verbal descriptions and ranges. However, the distances between the different decision points cannot be manipulated, i.e. only scales based on arithmetic sequences can be developed. *NAIADE* offers a 1–9-point scale, however, unlike *Super Decisions*, the steps between the points can be manipulated, for example, stepping from 'good' to 'very good' can differ in its relative impact on the decision compared with stepping from 'neutral' to 'good'. The verbal description of the decision points (e.g. good, very good) can also be freely edited by the user, which allows correction for the psychological factors contributing to nonlinearity between decision points, as described by Lootsma (1999).

4.1.3. Measures to deal with uncertainty

There are several *kinds* of uncertainty occurring in decisions, namely (i) uncertainty of preferences (inconsistent or unclear choices of an individual decision-maker or disagreements between several stakeholders), (ii) uncertainty due to randomness, and (iii) uncertainty caused by imprecision (Mendoza and Martins, 2006). A certain amount of compensation for these uncertainties is possible. For example, methods to tackle the latter two kinds of uncertainty include stochastic or probabilistic approaches, and fuzzy sets, respectively. Additionally, uncertainty can occur at different *stages* of the MCA cycle: At the input stage (ranking or weighting criteria, assessing scenarios; particularly when aggregating individual rankings and assessments) and at the output stage, namely by applying sensitivity analysis. Sensitivity analysis allows determination of the robustness of results by identifying leverage points, i.e. "those places in a system where a small shift can lead to large changes in everything else" (Meadows et al., 1972). In the case of MCA such leverage points can occur at two stages, namely (i) weighting criteria and (ii) assessing scenario performances. At both steps, small changes can significantly alter the ranking of scenarios.

Table 5 gives an overview of the steps of the decision process at which the MCA tools reviewed address uncertainty. The 'inconsistency index' (Saaty, 2003) of *Super Decisions* can be interpreted as measuring uncertainty in individual criteria preferences (step 5 in Fig. 2), this index reveals inconsistencies in the applicants pairwise weighting processes of the criteria. However, uncertainty in weighting criteria—i.e. a range of criteria weights—cannot be included in the further analysis when using *Super Decisions*. Likewise, *Super Decisions* does not allow a range of inputs to describe performance of scenarios; it relies on precise numbers (Kangas and Kangas, 2005). A sensitivity analysis with *Super Decisions* is also difficult to perform because the software analyzes only one criterion at a time, focusing on changes in criteria weights but not on the changing performance of the scenario generated.

In comparison, the *DecideIT* approach offers no tool for uncertainty due to criteria weights but has extensive tools, based on the use of imprecise sets, to deal with random and probabilistic uncertainty in the input stage. On the output side, *DecideIT* has various tools to present uncertainties in the sensitivity analysis. *DecideIT* is the only tool reviewed that allows sensitivity analysis of scenario performances, i.e. how defining changes in scenario performance can alter ranking.

The *Decision Lab* software addresses uncertainty only through sensitivity analysis. *Decision Lab* has tools to check for uncertainties in criteria weights (e.g. using 'walking weights'); checking for uncertainties in performances of scenarios is only indirectly possible by making several runs with different inputs.

The *NAIADE* approach allows for uncertainty by assigning randomness or probabilities to criteria at the input stage. However, on the output stage, the sensitivity analysis provides few options to test the robustness of a decision. Graphical outputs describe how scenarios differed and to what degree depending on their criteria performances. Based on the *NAIADE* methodology, uncertainty due to criteria weighting is not applicable (see Section 3.1).

4.1.4. Inclusion of criteria hierarchies

The manifold interests involved in bioenergy projects often require the creation of criteria hierarchies in order to better organize criteria and manipulate their relative importance. Often, criteria are divided into major principles like 'social', 'economic', and 'ecological'. There is a tendency to restrict criteria to fewer than 10 (see Mendoza and Martins, 2006, which lists many applications with criteria numbers). If more detail is needed for the assessment, further hierarchical levels are often introduced, sorting inputs into levels of principles, criteria, indicators, verifiers (e.g. Oliver and Twery, 1999). Only the methods of *Super Decisions* and *DecideIT* allow for the organization of criteria into such hierarchical structures.

4.1.5. Use of thresholds

In MCA, thresholds play often an important role assessing performances of scenarios using quantitative data. They can give ranges for which scenarios are perceived as the same (indifference

Table 5
Inclusion of uncertainty in weighting criteria and assessing scenarios in the four MCA tools reviewed

	Input stage—uncertainty		Output stage—uncertainty	
	Criteria weighting or ranking	Performance of scenarios	Sensitivity analysis	
			Criteria weighting or ranking	Performance of scenarios
Super Decisions	(X)	0	X	0
DecideIT	(X)	X	X	X
Decision Lab	0	0	X	(X)
NAIADE	n.a.	X	n.a.	X

X—possible; (X)—restricted or possible only indirectly; 0—not possible; n.a.—not applicable.

thresholds) or for which scenarios definitely outrank each other (preference thresholds, see Mendoza and Martins, 2006). A threshold can be a two-edged sword. On the one hand, thresholds are entrancing due to their intuitive logic. However, precise thresholds do often not reflect the whole 'truth' of a complex system, given that they attempt to quantify what are often 'fuzzy' perceptions on the part of human decision-makers and therefore might create false certainties. Legitimacy of thresholds also depends on who set them in the first place.

Thresholds can also be applied to eliminate the risk of absolute substitution of one criterion by another. In basically all MCA approaches, poor performance of one criterion can be compensated by a high performance of another criterion. If a MCA tool—as in the case of *Super Decisions*—does not apply thresholds to prevent extreme trade-offs so total substitution of a poorly performing criterion is possible. For instance, a scenario may outrank all other competing ones because it is by far the most cost-efficient, but at the same time it may create prohibitively large negative impacts to the environment. Therefore, some MCA tools use thresholds rendering a scenario invalid once a threshold for one criterion is violated. *DecideIT* offers the user optional use of thresholds for (i) defining imprecise sets for a criterion and (ii) defining outperformance of one scenario by another. *Decision Lab* allows for an application of thresholds, here thresholds can be defined through percentiles or absolute numbers and thresholds can be set to avoid absolute substitution of one criterion through another. *NAIADE* makes no use of thresholds, however, unlike *Super Decisions*, its methodology prevents absolute criteria compensation (see Section 3.1).

4.1.6. *Ease of computation*

Super Decisions has a straightforward structure, building and assessment framework. Its overall intuitive logic has been widely recognized. The sensitivity analysis, however, is hard to perform, allowing the user to look at only a few dimensions at one time. *DecideIT* has the best user interface of all tools reviewed, offering intuitive tools to structure and define criteria and to perform sensitivity analysis. However, *DecideIT* needs manual conversion of data if minimization instead of maximization of criteria performance is envisaged (for example minimizing water pollution must be framed as maximizing water quality), thus adding another input step for the user. *Decision Lab* also offers a user-friendly interface for structuring the problem and for the data input. Its sensitivity analysis is very user-friendly, offering many perspectives on the problem including 'walking weights' and side-to-side scenario evaluations.

4.1.7. *Dynamic reevaluation*

When reevaluating a decision, *Super Decisions*, *DecideIT*, and *NAIADE* do not allow for direct comparisons between the former and current assessments. In order to do this, the application files of these tools have to be re-structured for another evaluation cycle. Only *Decision Lab* offers direct comparisons between former and new assessments through the scenario analysis in which structures and criteria performances, as well as assessments of scenarios, can be altered and compared with each other directly.

4.1.8. *Transparency*

Super Decisions, based on the AHP method, applies intuitive logic and simple mathematical structure, making it very transparent. The steps in the 1–9-point scale follow easy multiplication rules (e.g. point 2 is twice as desirable as point 1). The *DecideIT* approach also follows a transparent structure and allows for easy analysis because the outputs are given in ranges, which can be easily traced back to the input datasets. Calculations in *Decision Lab* are more complex and the derivations of output graphs are less easily to grasp. The idea of 'semantic weights' in *NAIADE*, which replaces the criteria weights of the other approaches, is less intuitive and makes it difficult to grasp the mathematical concept of the approach. In general, the more heavily a tool draws on qualitative data, the less transparent it ultimately becomes.

4.1.9. *Communication of decision process and results*

All tools tested ultimately produce a single-preference index that accumulates results into a final ranking of scenarios. Such figures are simple, but tend to lose explanatory power. Therefore, additional results like graphs from the sensitivity analysis, impacts of criteria weights on decisions or performance of scenarios with respect to each criterion are important. All tools reviewed lack such explanatory tools to varying degrees. Besides an output matrix, the *Super Decisions* tool offers no output graph other than a column chart visualizing the ranks of the scenarios. *DecideIT* presents results through sensitivity diagrams on how scenarios rank depending on the imprecise sets used in the input stage. *Decision Lab* offers many tools to look at the results from different perspectives: for example, the 'Profiles' function, looking at performance of criteria; 'Multiple comparison', looking at scenario comparisons; 'Walking weights', enabling the user to detect influence of criteria weights on the decision; 'Stability intervals', analyzing the robustness of decisions by means of a numerical matrix; and 'Preference flows', offering insights into the ranking of scenarios. Besides numeric outputs, *NAIADE* allows for a visualization of how much better a selected scenario A performs for each criteria compared with another scenario B (pairwise comparisons). These comparisons are divided into criteria for which scenario A performs much better, better, similar, worse, or much worse than scenario B, accompanied by a 'degree of truth' for such results. Besides this visual output, *NAIADE* graphically displays the ranking of scenarios but gives little support in presenting the sensitivity analysis to laypersons.

4.2. *Application of the MCA tools to the case study*

4.2.1. *Criteria weights and assessment of scenarios*

Table 6 shows criteria weights and scenario performances as determined by the stakeholders (criteria 1–3, 5–7, and 9) and experts (criteria 4 and 8) in the Ugandan bioenergy case study. The dataset were collected using *Super Decisions* (see Section 3.3). The results, as seen in Table 6, were used as input data for the other MCA tools. In five criteria, the fossil-fuel-powered BAU scenario performed best, and in four criteria the bioelectricity scenario performed best. The highest weights were assigned to 'low planning and monitoring needs' and lowest to 'reduced pollution'. All other criteria were weighted in the same general range, with values between 7.6% and 13.4%.

4.2.2. *Ranking of scenarios*

All tools resulted in a final ranking of scenarios using aggregated preference indices. Although the same dataset were used in all the MCA tools, the outcomes differed. Besides the ranking itself, numerical values associated with each rank indicate the robustness of results, i.e. by how much one scenario is preferred over another. For instance, in *Super Decisions* the bioelectricity scenario was perceived as 86% as good as the BAU scenario producing electricity from fossil fuel, indicating a rather narrow preference of the BAU scenario. *DecideIT* ranked the BAU scenario slightly higher than the bioelectricity scenario with the BAU scenario reaching 0.587 and the bioelectricity scenario reaching 0.503 on a scale of 0–1. This coincidentally equates to bioelectricity performing 86% as well as the BAU scenario,

Table 6
Criteria ranked according to their perceived importance and rated scenarios

Sustainability criteria		Intermediate results from *Super Decisions*			
		Weights (%)	Scenario ratings by stakeholders	BAU (fossil fuel)	Bioelectricity
C 1	Reduced competition for fertile land	12.1	1.1 (0.4)	**0.88**	*0.12*
C 2	Reduced pollution	3.7	7.9 (0.88)	*0.12*	**0.88**
C 3	Low training needs	13.4	3.4 (3.5)	**0.62**	*0.38*
C 4	High employment rate	7.6	n.a.	*2*	**9**
C 5	Diversity and certainty in ownership and business schemes	12.6	1.0 (0.4)	**0.89**	*0.11*
C 6	Low planning and monitoring needs	17.9	3.3 (3.3)	**0.63**	*0.37*
C 7	Increased local commerce	10.6	7.4 (1.7)	*0.18*	**0.82**
C 8	High cost efficiency	11.4	n.a.	*0.34–3 (0.5)*[a]	**0.23**
C 9	High supply security	10.7	3.7 (3.1)	*0.41*	**0.59**

For methods used to rate scenarios see section 3.3. Column 'Scenario ratings by stakeholders' shows the geometric mean of stakeholder rankings when comparing the two scenarios on a 1–9 point scale, with 1 favoring strongly the BAU (fossil fuel) scenario and 9 favoring strongly the bioelectricity scenario. Numbers in brackets indicate standard deviations. N.A. indicates that the specific criterion (criterion no. 4 and no. 8) was rated by experts with direct input numbers as displayed in the last two columns of criterion no. 4 and no. 8.
Bold: superior and preferred; in *italics*: inferior.
[a] These values indicate minimum, maximum, and average fossil-fuel-generated electricity costs in US$/kWh (Buchholz and Volk, 2007).

Table 7
MCA tool results: preferred scenarios and criteria preference classification

Tool	Preferred scenario	'Strong preference' criteria	Intermediate criteria	'Weak preference' criteria
Super decisions	BAU	C1, C3, C5, C6	**C2**, **C4**, **C7**	**C8**, **C9**
DecideIT	BAU	C3	**C2**, **C6**, **C9**	C1, **C4**, C5, **C7**, **C8**
Decision Lab	BAU	C1, C3, C5, C6	**C4**, **C7**, **C8**, **C9**	**C2**
NAIADE	Bioelectricity		C4	**C1**, C2, **C3**, **C5**, **C6**, C7, C8, C9

Bold print symbolizes that the inferior scenario performed better in the given criterion. See Table 5 for criteria descriptors.

analogous to the result produced by *Super Decisions*. *Decision Lab* and *NAIADE* calculate an aggregated preference index called 'Φ value' for each scenario, where a positive number indicates above average scenarios and negative values indicate below average scenarios. The higher the absolute value, the more the scenario diverges from a calculated average of all scenarios. *Decision Lab* ranked the BAU scenario first with a Φ value of +0.11. Only *NAIADE* ranked the bioelectricity scenario first with a Φ value of +0.07. In summary, results from the four tools differed slightly, but they all indicated a rather weak preference of one scenario over the other.

Table 7 shows the preferred scenarios and the criteria assessments as computed by each MCA tool. All tools allow criteria to be sorted into those with a strong preference for one scenario and those with weaker or no preference for one of the scenarios. 'Weak preference' criteria as shown in the last three columns[5] in Table 7 were those criteria in which both scenarios ranked fairly equal. This categorization of criteria into strong, intermediate, and weak preference criteria implies that a small change affecting a 'strong preference' criterion—all other things being equal—does not change preference for one scenario. However, such a small change affecting a 'weak preference' or 'intermediate preference' criterion might change overall rating of scenarios. The categorization in weak, intermediate, and strong preference criteria does not indicate which scenario performs better regarding a specific criterion. A scenario that was inferior in the overall ranking can still hold 'strong preference' criteria in which it outranked the superior scenario. Therefore, bold print symbolizes that the inferior scenario performed better in the given criterion.

All 'strong preference' criteria were in favor of the preferred scenario as computed by the MCA tools. However, the different tools categorized individual criteria differently. For instance, the criteria C1, C3, C5, and C6 occur in all three categories: strong, intermediate, and weak. These differences originate in how criteria weights, the performance of scenarios within each criterion, and uncertainties attached to each criterion are included in the sensitivity analysis. While *Super Decisions* and *Decision Lab* base the sensitivity analysis of the criteria on criterion weights only—i.e. what change in criteria weight is needed to change ranking of scenarios—*DecideIT* and *NAIADE* perform sensitivity analysis for criteria holistically, including both criteria weights[6] and criteria performances of the different scenarios.

4.2.3. *Insights gained by stakeholders and MCA facilitators*

There was an overwhelming feedback from stakeholders that the MCA process and especially the qualitative modeling part helped greatly in understanding the energy systems of their community, i.e. which aspects and sub-systems are involved in their current condition and a potential biopower system, how aspect differ in priorities, and which additional stakeholders would need to be included in future decisions. It was also noted that the confrontation with one's own weights of criteria and those of other stakeholders creates another layer of insights in their community structure. From the MCA facilitator's perspective, a decisive insight was the limitations the applied

[5] Only the *NAIADE* tool uses a similar categorization. In the case of the other MCA tools, criteria were categorized based on the performance of the sensitivity analysis (*Super Decisions*), 'normalized weights' (*DecideIT*), and the 'stability intervals" (*Decision Lab*).

[6] Using 'semantic' weights in the case of *NAIADE* (see Section 3.1).

MCA tools actually have in communicating the results to the stakeholders.

5. Conclusions

Three major conclusions can be drawn from this study:

(1) Different tools may give different results.
The MCA tools used in this study all focus on different steps of a decision process and differ widely in their mathematical methods and structure. Their results and insights are affected by their design. Compared with the other three tools, the strengths of *Super Decisions* lay in covering the additional step of 'Criteria weighting and ranking'. Not only did this step prove to be intuitive and easily accepted by stakeholders, but the dataset generated could also readily be used as input for the other MCA tools applied. *DecideIT* offers good options to assess scenarios and has strong sensitivity analysis. *NAIADE* offers many options for assessing scenarios but has very limited options for sensitivity analysis. Results from the case study support the views of Guitouni and Martell (1998), Kangas and Kangas (2005), and Løken (2007); namely, which one should apply more than just one MCA tool to a problem in order to cross check results and to look at the problem from many different angles or to select the most appropriate tool for a given problem. See also Mendoza and Martins (2006) and Belton and Stewart (2002) for an in-depth discussion supporting the combination of MCA tools to accommodate different MCA paradigms and different comfort levels of stakeholders with specific MCA tools.
The tools varied considerably in how they ranked criteria in those with strong preference for one scenario and others with weak preferences. It might be useful to first identify key criteria as those with high and/or uncertain weighting (e.g. using *Super Decisions* and *Decision Lab*), and secondly identify those with high uncertainties (e.g. using *DecideIT* and *NAIADE*). This approach sensitizes the users for the underlying complexity of the problem. For instance, if the goal is to make the rankings of scenarios more robust, MCA can be used to separate key criteria with high weights and/or high uncertainty (leverage points) from insensitive criteria, and efforts can be concentrated on those key criteria. If one's goal is to reverse a ranking, MCA can help to determine those criteria least favorable for the inferior scenario, and those criteria can be specifically addressed.

(2) The results of the analysis show that social criteria, not costs, play a key role in making bioelectricity systems viable for a rural community in Uganda.
Cost differences, which are often used as a decisive criterion for energy planning (e.g. cost–benefit analysis), played only a minor role in the MCA results (e.g. criteria weight for 'high cost efficiency' was only 11.4%) although scenarios differed considerably 0.23 US$/kWh for bioelectricity vs. 0.34 US$/kWh for electricity from fossil fuel). In comparison, social criteria (low training needs, high employment rate, diversity and certainty in ownership and business schemes, low planning and monitoring needs) received higher weights, favored the BAU scenario, and were decisive in the final rankings of scenarios. For instance, workshop participants articulated concerns about sustainable management of fuelwood supply and the lack of knowledge on running and managing a biopower and grid system. If one aims to make bioenergy competitive with conventional power production systems in rural communities in Uganda, these results imply that resources should be focused on improving bioenergy's performance with respect to these social criteria.

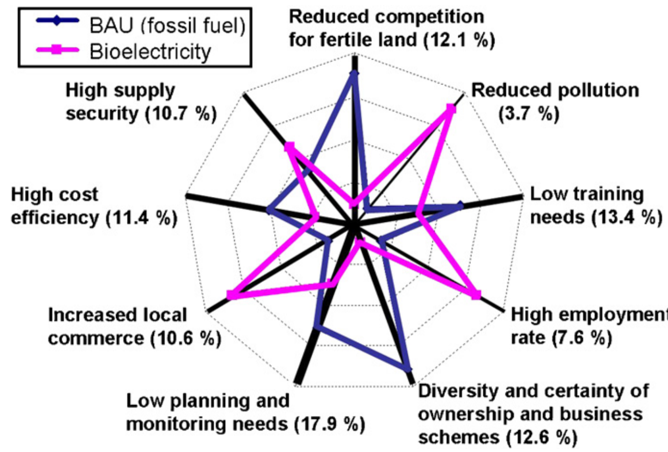

Fig. 3. Scenarios from the Ugandan case study depicted in a radar graph with input data from Table 6. Goal is to maximize criteria performance, i.e. the more a scenario scores towards the outer cycle of the graph for a given criterion, the more it is preferred. Axis strength reflects weight of the respective criterion, a thin axis corresponds with a low criterion weight. Criteria weights (see Table 6) are displayed in brackets.

(3) MCA can assist in stakeholder integration and communication of complex decisions.
MCA's greatest strength might lie in its ability to integrate normative judgments (e.g. stakeholder opinion) and technical expertise (e.g. quantitative data). The MCA tools analyzed can help to communicate this analysis. However, all of the tools analyzed lacked good visualization options to present results in multi-stakeholder settings. For instance, radar graphs (see e.g. Giampietro et al., 2006; Gomiero and Giampietro, 2005) depicting several scenarios and their performance for several criteria in one graph would assist greatly in communicating results. Fig. 3 suggests a radar graph design depicting the Ugandan case study created separately from the MCA tools analyzed. Acknowledging the rather restricted options provided by conventional MCA approaches to include stakeholders in the decision process, as discussed earlier and shown in Fig. 2, Munda developed the concept of embedding MCA in a bigger framework called Social Multi Criteria Evaluation (SMCE, Munda, 2004). This approach follows in principle the decision steps shown in Fig. 2 but the whole decision cycle is embedded in a coherent method for policy assessments. Such approaches are promising to increase stakeholder inclusion in the decision-making process and needs further attention. In summary, MCA can contribute to a better management of stakeholder inclusion in decision processes when embedded in a broader participatory decision framework as its sole application does not fulfil stakeholder participation goals.

It is clear from a methodological perspective, as well as from application to our case study, which MCA tools can contribute to sustainability assessments of bioenergy systems. However, constraints and concerns remain. For instance, the MCA tools investigated in this paper differed in ranking the scenarios according to their preference when applied to the case study. Furthermore, this case study was limited in terms of number of stakeholders involved, geographic scale, number of possible scenarios, and duration of the decision process. Therefore, in using MCA for sustainability assessments of bioenergy systems, whether in the evaluation of existing projects or in designing new projects, four issues should be further explored:

- MCA tools should also be applied to more sophisticated case studies, with more scenarios, a larger scale, and more stakeholders. The inclusion of more stakeholders allows meaningful analysis when grouping individual preferences, like those of businesspeople, environmental NGOs, gender groups, minorities, etc. Instead of comparing bioenergy systems with fossil-fuel-based systems, MCA might best be used to differentiate among different approaches to implementing bioenergy systems.
- With the use of more case studies, a framework has to be developed for presenting the entire decision process. In our case study, for instance, the results of MCA were not presented to the stakeholders. This decisive step—how stakeholders accept the aggregated[7] criteria weights and rankings of scenarios—needs more focus not only from researchers but also from MCA tool developers, in order to provide more output options for visualizing results.
- Stakeholders freely choosing criteria upon which a sustainability assessment is based, as in the case study, seemed to work well. Many standard criteria discussed on an international scale for bioenergy sustainability assessments were intuitively chosen. However, there is a need for a set of proven and widely accepted criteria from which stakeholders and decision-makers can choose and build upon for more elaborate bioenergy systems larger in scale. There is already a wide array of criteria developed that could be of significance for sustainability assessments of bioenergy systems, but no set that is universally accepted. Many are covered in Buchholz et al. (2008, in prep.), the International Energy Agency (2007), Verdonk et al. (2007), Bioenergy Wiki (2007), Cramer et al. (2006), Lewandowski and Faaij (2006), Dam et al. (2006), Reijnders (2006), Fritsche et al. (2006), Jürgens and Best (2005), Smeets et al. (2005), Mog (2004), or Volk et al. (2004).
- Social criteria were of high importance for the ranking of scenarios and, in most cases, favored the BAU scenario. To make bioenergy competitive, it might be useful to have a research focus in exploring and optimizing its social implications.

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Appendix A

See Tables A1 and A2 for description of energy scenarios for the Kasonga case study and criteria used in the Ugandan case study, respectively.

[7] Using e.g. the geometric mean of individual stakeholder ranking and weightings which can considerably divert from this aggregated mean value (see also Section 3.3).

Table A1
Description of energy scenarios for the Kasonga case study

The *BAU scenario* comprises current use of 8 privately owned gasoline and diesel powered generators with an individual capacity ranging between 0.7 and 10 kW providing electricity to the governmental administration buildings, NGO offices, and businesses of Kasonga. The electricity provided is used in cinemas, barber shops, metal workshops, cell phone charging stations, administration (computer equipment, communication). Expenditures mostly vary between 0.34 and 3 US$/kWh with an average around 0.5 US$/kWh. Expenditures for gasoline to power generators can consume up to 80% of a business's revenues. Light is provided by candles and kerosene lights with an average cost of 0.11–0.17 US$/night and room. Taking electricity and lightning expenditures into account, the businesses, administration, and homes of Kasonga spend between US$ 220 and 310 per week for energy services. Total installed capacity is 16 kW provided by 7 generators individually owned by the consumers (business and administration). It is estimated that in total 2 jobs are created for maintaining these generators.

The *bioelectricity scenario* consists of a 10 kW wood gasifier and appliances, a mini-grid connecting all consumers with the producer, and the fuelwood supply chain. The design of the system relies on the assumption that all businesses operating currently with generators and the administrative buildings will be connected to the grid. Compared to the BAU, the bioelectricity scenario considers additional electricity demand from homes which have currently no access to electricity for lighting and small appliances (e.g. radios) and a higher load factor for the installed capacity compared to the BAU scenario. Electricity costs are estimated at 0.23 US$/kWh delivered which is economically competitive with fossil-fuel-powered electricity and substitute sources of energy (kerosene lamps, candles). Expenditures for fuelwood are estimated to be around 700 US$ per year or 0.03 US$/kWh. Fuelwood providers are local farmers. Land area demand for supplying the fuelwood is estimated around 3–14 ha depending on site productivity, conversion efficiency of the gasifier, and electricity demand. To assure a sustainable fuelwood supply, a community-based tree plantation scheme has to be introduced, and a substantial knowledge and material transfer to the community must occur to assure economic and technical viability. It is assumed that the bioelectricity scenario creates 9 jobs, including technical services to operate the gasifier and grid, fuelwood supply chain, and overall management.

Table A2
Description of criteria used in the Ugandan case study

Assessment criteria	How important are the following aspects
Ecological criteria	
Reduced competition for fertile land	Availability of land for additional fuelwood production, particularly competition with protected lands, land for food and fiber production, and forests.
Reduced pollution	Impacts on air quality, soil, and hydrological cycles
Social criteria	
Low training needs	Educational and capacity building activities. Need for training from outside the community.
High employment rate	Numbers of jobs are created by electricity production.
Diversity and certainty in ownership and business schemes	Regulating ownership and control of equipment. Logistics schemes for the firewood supply chain. Supporting establishment of individual woodlots.
Low planning and monitoring needs	Ensuring a sustainable wood supply. Setting up a scheme needed to keep machinery running.
Economic criteria	
Increased local commerce	Financial flows within the community and money exchange with the outside community.
High cost efficiency	Cost of electricity per kWh. Initial investment costs for gasifier vs. generators.
High supply security	Security of supply of firewood vs. gasoline, kerosene, and diesel. Stability of prices.

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