Author(s): Eyvindson, Kyle; Öhman, Karin; Nordström, Eva-Maria

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Using uncertain preferential information from stakeholders to assess the acceptability of alternative forest management plans

Kyle Eyvindson[1], Karin Öhman[2], Eva-Maria Nordström[2]

*[1] University of Jyväskylä, Department of Biological and Environmental Science, P.O. Box 35, 40014 University of Jyväskylä Finland kyle.j.eyvindson@jyu.fi

[2] Department of Forest Resource Management, Swedish University of Agricultural Sciences, Umeå, Sweden

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Abstract

In forest management planning, participatory planning processes are often encouraged as a means to acquire relevant information and to enhance the stakeholders' acceptability of alternative plans. This requires the aggregation of the stakeholders' preferences which can be done in a wide variety of manners. The aggregation process strives to reduce the information into a single set of preferences which simplifies the information and allows for the use of discrete decision support tools. Depending on how the preferences are aggregated, a wide range of plan rankings can emerge. While this range of ranking complicates the issue of plan selection, it does highlight the uncertainty involved in aggregating stakeholder preferences. In this study, we suggest an alternative method of deriving rankings for a set of alternative management options. Our proposed method suggests treating acquired preferences as the uncertain elements of a stochastic programming problem and the results provide the decision maker with the acceptability probability for each plan. The method is illustrated with a case of pairwise comparisons from a set of stakeholders representing preferences from different interest groups in a community planning process.

Keywords: Group decision making; pairwise comparisons; stochastic multi-criteria acceptability analysis; stochastic preferences; stochastic programming

1 - Introduction

Forest management planning aims to determine what management activities to implement in a certain forest area at a certain time and is thus a fundamental tool for sustainable forest management since long time horizons and various spatial scales can be considered. Forest planning will be especially important in a biobased economy, where the demand for forest biomass is likely to increase and approaches for sustainable forest management will be absolutely necessary to safeguard not only conditions for sustainable yield but also ecosystem functioning, biodiversity and social values of the forest (UNECE/FAO 2011; Kraxner et al. 2013). Traditionally, forest management planning has been concerned with capturing data and using it in decision support systems and other models to project forest development (Borges et al. 2014). This is however only one aspect of decision making; another equally important aspect is the objectives and preferences of the decision maker(s) (Keeney 1982). Further, in the context of sustainable forest management the importance of not only the actual decision maker's preferences but also stakeholder preferences is highlighted (MCPFE 2003; UN 1992; The Montreal Process 2015). This calls for tools that are able to include different sets of preferences in participatory and group decision making processes.

Multicriteria decision analysis (MCDA) has been used as a means to explicitly include multiple objectives and preferences in forest management planning (Ananda and Herath 2009; Diaz-Balteiro and Romero 2008). MCDA is a collective name for mathematical methods that identify solutions to decision problems with multiple conflicting objectives based on the preferences of the stakeholder(s). The methods were originally developed to support a single decision maker but over the last twenty years MCDA has also been used to involve stakeholders in participatory forest planning (e.g., Ananda & Herath, 2003; Hiltunen et al., 2008; Kangas et al., 2001; Kangas et al., 1996; Nordström et al., 2010; Pykäläinen et al., 2007; Pykäläinen et al., 1999; Sheppard & Meitner, 2005). A critical issue when using MCDA for including stakeholder preferences in participatory planning is the aggregation of preferences (Belton and Pictet 1997; Mendoza and Martins 2006); i.e., how should the preferences from the individual decision makers or stakeholders be elicited and combined to represent what the group as a whole thinks? Individuals may have very different preferences for the objectives or not even the same objectives as others in the group. In some cases there are subgroups of stakeholders with similar views but often it is difficult to state preferences that are representative for the entire stakeholder group. In such situations it could be challenging to find acceptable compromise solutions. One possibility for calculating a compromise solution by aggregating individual preferences is to use numerical aggregation, which means that deliberations and negotiation among stakeholders are to some extent replaced by mathematical methods (e.g., Diaz-Balteiro and Romero 2008; Mendoza and Martins 2006). The advantage of numerical aggregation is that the process is transparent in such way that it is clear what influence each individual has had on the final outcome, but the procedure may in the worst case seem mechanistic and obscure to stakeholders. One of the most commonly used MCDA methods in studies regarding participatory forest planning is the Analytic Hierarchy Process (AHP; Saaty 1990) and varieties of it (Ananda and Herath 2009; Diaz-Balteiro and Romero 2008). This is due to AHP being relatively user-friendly and facilitates stating of preferences by the stakeholder(s) through pairwise comparisons of objectives and alternatives. In studies based on AHP the mean of the individual preferences has commonly been used for aggregation; both the geometric mean and the weighted arithmetic mean have been used (Mendoza and Martins 2006). A number of other aggregation methods have been proposed for AHP and pairwise comparisons in general (e.g., Bryson and Joseph 1999; Cho and Cho 2008; Escobar and Moreno-Jiménez 2007). However, for many of these methods the preferential meaning of the aggregated solutions is not clear and can be debated. This can be a problem when applying the methods in participatory processes, since the aggregation method has to be understandable, equitable, and transparent if outcomes are to be accepted as legitimate by the stakeholders (Munda 2004; Nordström et al. 2009; Sheppard and Meitner 2005). As a response to this, González-Pachón and Romero (2007) developed an extended goal programming approach that can aggregate individual preferences and determine consensus rankings of alternatives based not only on the majority principle, but also for consensus minimizing the disagreement of the most disadvantaged stakeholder and for intermediate consensus balancing the majority and minority perspective. Nordström et al. (2009) applied this aggregation method to a participatory forest planning case involving the preferences of 24 individuals that belonged to four different stakeholder groups with different objectives. However, even though this aggregation method considers the perspective of majority versus minority, it still requires a weight of influence for each stakeholder in the aggregation, like all the previously mentioned aggregation methods. Assigning weights to stakeholders and stakeholder groups is a potentially contentious issue in a participatory process since it concerns power relations between stakeholders.

One way to avoid aggregation of preferences based on weights of influence is to consider preferences as well as weights of influence as uncertain and use a “backward” approach to assess the acceptability of various alternatives (Kangas et al. 2003). Evaluation of the importance of stochastic elements in a discrete multicriteria decision situation can be done through the use of the stochastic multicriteria acceptability analysis (SMAA) which is a family of methods applied to multicriteria problems with missing or incomplete information. Through stochastic simulation the outcomes are evaluated for random values for objective preferences and weights. Through the use of SMAA, the acceptability of a specific forest plan alternative from a set of alternatives can be evaluated where criteria values and/or preferential information is uncertain (Lahdelma et al. 1998) and it is done through an inverse weight space analysis. A number of SMAA methods have been developed which can utilize a variety of different utility functions and preferential information (Tervonen and Lahdelma 2007). However, to our knowledge only a few applications of SMAA have been used in forest management planning (Kangas et al. 2003; Leskinen et al. 2004).

Understanding the impact of uncertainty in AHP has received some research attention, with a variety of tools being developed to address this issue through different means (see Boender, de Grann & Lootsma 1989; Salo & Hämäläinen 1995; Saaty & Vargas 1987). More recently, Durbach and Calder (2016) examined the potential for a direct link between SMAA and AHP. Through an illustrative example, they highlight how uncertainty can be modelled in AHP and what impacts the uncertainty can have on the outcome of the acceptability analysis. For their case uncertainty was contained within the individual pairwise comparisons, modelled by the decision maker through a defined distribution. The approach suggested by Durbach and Calder (2016) could be applied in participatory planning situations, as the single pairwise comparison matrix can incorporate the difference of opinions of the stakeholders. This is accomplished by including information on the distribution of opinions between each pairwise comparison. While it may be possible for stakeholders to agree on a single pairwise comparison matrix integrating uncertainty, some stakeholders may find it difficult to successfully negotiate their views appropriately into the pairwise comparison matrix. Stakeholders may not feel comfortable making specific comparisons, as they may not have enough knowledge or may be apathetic towards a particular indicator. Thus, rather than requiring stakeholders to make the same pairwise comparisons, methods have been developed to aggregate pairwise comparison matrices with different sets of criteria to be compared (Belton and Stewart 2002; Nordström et al. 2009). The elicitation of preferential information from multiple stakeholders can be interpreted as a source of uncertainty. This preferential uncertainty can be linked with a SMAA approach and can provide ranked evaluation of the alternatives.

The objective of this study is to explore and examine an alternative method of deriving rankings for a discrete set of plan alternatives based on different stakeholder preferences. Our proposed method is built on the extended goal programming approach proposed by González-Pachón and Romero (2007) but suggests treating acquired preferences from the stakeholders as the uncertain elements of a stochastic programming problem. Associated with this is the uncertainty related to the importance of the different stakeholder groups. The approach is applied to the Lycksele case presented by Nordström et al. (2009) as an illustrative example and to make it possible to compare the results with the results based on the original extended goal programming approach. We examine how adjustments to the setting of weights describing the importance of each stakeholder group can impact the acceptability of the alternative solutions.

2 - Materials and Methods

The data to conduct this study relies on a participatory planning case study from an earlier work (Nordström et al. 2009; Nordström et al. 2010). In that study stakeholders' preferences regarding a set of predefined alternative management plans was obtained for an urban forest participatory planning process. Stakeholders were first asked to identify indicators of interest for their stakeholder group, and then each stakeholder was asked to provide pairwise comparisons for this selection of indicators. As a result there are two key data components for this study: first the pairwise comparison data, where each stakeholder provided his/her evaluation of the importance of the selected indicators for their stakeholder group. The second key data component is the results for all of the indicators of interest for each of the alternative forest plans.

Through the case study, we examine multiple ways of incorporating the preferential information obtained from the stakeholders. As the intent is to be a reflection of the original case study, the general structure of method is retained. In this case, there are four stakeholder groups, each with a varying number of representatives and each stakeholder group selected a different set of indicators for the pairwise comparisons. (Timber producers – four representatives; Environmentalists – four representatives; Recreationists – seven representatives; Reindeer herders – one representative). Each group focused their set of indicators according to their expertise and experience (for details readers are referred to figure 1 of Nordström et al 2009). For additional details regarding the data readers are referred to the original source (Nordström et al. 2009).

The key aim of the method proposed in this study is to assist the decision maker with an understanding of how the diversity of opinions both within stakeholder groups and between stakeholder groups impacts the prioritization of the alternative plans. The method proposed uses the uncertainty in the stakeholder opinions and the uncertainty of the importance of stakeholder groups to create a probabilistic ranking for each alternative management plan. We utilize a stochastic goal programming formulation (see Eyvindson and Kangas 2014) of the extended goal programming model (see Romero 2001) to incorporate the uncertainties involved with the stakeholder preferences. For the elements of uncertainty, a discrete representation of the variation is used; this is accomplished by either enumerating all possible cases, or through the use of a Monte Carlo simulation to select a large enough set to approximately represent the variation. In stochastic programming literature this is called the "deterministic equivalent program", which remains a linear programming problem while representing the uncertain elements of interest (Birge and Louveaux 2011). For the case examined here, we use both methods; for the opinions of each stakeholder group we expand all possible permutations for the rankings (set S), and for the importance of each stakeholder group we use the Monte Carlo simulation method to assign a specific weighting (set B).

The model formulated here is rather similar to model 3 of Nordström et al. (2009). The key differentiation is that elements of uncertainty can be incorporated through a discrete representation.

Model:

(1) $$Min\,(1-\lambda)\sum_{b\in B}\sum_{s\in S} D_{bs} + \lambda \sum_{b\in B}\sum_{i\in I}\sum_{j\in J}\sum_{s\in S} w_{bi}\left(n_{bijs} + p_{bijs}\right)$$

Subject to:

(2) $$R^{c}_{bjs} + n_{bijs} - p_{bijs} = R_{ijs}, b \in B, i \in I, j \in J, s \in S$$

(3) $$w_{bi}\left(n_{bijs} + p_{bijs}\right) - D_{bs} \leq 0, b \in B, i \in I, j \in J, s \in S$$

(4) $$1 \leq R^{c}_{bjs} \leq \#J, b \in B, j \in J, s \in S$$

(5) $$\sum_{j \in J} R^{c}_{bjs} = \frac{(\#J + 1)\#J}{2}, b \in B, s \in S$$

(6) $$\lambda \in [0,1]$$

where R^{c}_{bjs} represents the consensus value attached by the group as represented in scenario s for the *j^th^* alternative and the *b^th^* weighting scenario, R_{ijs} is the data for the model, the ordinal rank of the the j^{th} alternative for the i^{th} stakeholder group represented by scenario s, w_{bi} represents the relative importance attached to the i^{th} stakeholder group according to the b^{th} weighting scenario, n_{bijs} and p_{bijs} are the negative and positive deviation variables typically used in goal programming, D_{bs} is the maximum disagreement for each stakeholder group scenario s and each weighting scenario b, I is the set of stakeholder groups, J is the set of alternatives under analysis, $\#J$ is the cardinality (the number of elements) of set J, and λ is a parameter used to control if a majority or minority consensus is preferred, (see González-Pachón and Romero (2007) for a detailed preferential interpretation of this parameter). While λ is not a critical feature for this approach, it can be useful for comparing the range between Archimedean ($\lambda = 1$) and Tchebycheff ($\lambda = 0$) solutions.

This method requires a ranking of the alternatives under consideration. While any type of rankings is acceptable, for this specific example we derived rankings from the pairwise comparison matrices. The matrices can be the individual pairwise comparison matrices, or the set of compromise comparison matrices evaluated for each group. The approach to aggregate the individual pairwise comparison matrices is based on model 1 of Nordström et al. (2009). For each pairwise comparison matrix, a ranking can be developed which applies the concept of maximizing the weighted aggregate of the outcomes, or the concept which minimizes the most displaced result. Thus, for each pairwise comparison matrix, two options for assignment of the rank are possible. The method of calculating the specific rankings is in Phase 2 and Phase 3 of Nordström et al. (2009). The general premise is to calculate the importance of the set of indicators (by evaluating their respective weights), and using these weights to rank the alternative management plans (the methods are explained through a demonstrative code in the supplementary material – S1).

The assignment of weights used to represent the relative importance attached to different stakeholder groups, i.e. (w_{bi}), can be done through a wide variety of ways. The weights can be assumed to be known precisely, partially unknown or completely unknown. If there is knowledge regarding appropriate values for the weights, the information can be incorporated. A wide range of methods are available to include partial and imperfect weighting information into the problem. One simple example is from the application of SMAA (Lahdelma et al.1998), where partial prioritization of weights can be included. A variety of algorithms for assigning weights with preferential information can be found in Tervonen and Lahdelma (2007) and Tervonen et al. (2013).

As a means of summarizing the results, a holistic acceptability index can be used as an interpretation of a rough measure for the overall acceptability of each alternative. The holistic acceptability index is calculated as a weighted sum of rank acceptabilities. This index is calculated through a systematic weighting of alternatives, called meta-weights, and is differentiated from user defined weights. These meta-weights can be used to prioritize the different ranks, and the choice of which meta-weights are to be used will impact the results

(Lahdelma and Salminen 2001). For a description on how to calculate this index, readers are refered to Lahdelma and Salminen (2001).

We examine two potential approaches for utilizing these pairwise comparisons. We can either use the rankings obtained from each individual pairwise comparison as a potential ‘true’ option for the entire stakeholder group, or we can use the rankings obtained from an aggregation of the stakeholder groups individual pairwise comparisons, hereafter called the consensus pairwise comparison matrices. To fully enumerate the potential uncertainty for each case requires a different number of scenarios (set S); the total number of scenarios is calculated with the following equation:

$$\prod_{i \in I} 2c_i \tag{7}$$

where c is the number of pairwise comparisons from stakeholder group i. The number of pairwise comparisons is doubled as we produce two different rankings from the distance metrics in L^p space of 1 and ∞. For the individual pairwise comparisons, there are 2,240 unique scenarios [(4*2)*(4*2)*(7*2)*(1*2)], and for the consensus pairwise comparisons there are 288 unique scenarios [(3*2)*(2*2)*(3*2)*(1*2)] (selecting the non-dominated matrices from table 3 of Nordström et al. 2009). We also examine the extremes of the λ parameter, by setting λ=1 a weighted goal programming formulation is used, and by setting λ= 0 a minimax goal programming formulation is used.

For each of the four different approaches ($\lambda = 1$ or $\lambda = 0$, individual or consensus rankings), four different sets of weights to prioritize the stakeholder groups are used. The first weighting set assumes no preferential information, the second set assumes only a prioritization of the stakeholder groups, the third set assumes a prioritization between the timber producers (with a weight of at least 0.5) and the remaining stakeholder groups, and the fourth set assumes perfect knowledge of the weighting prioritization. The mathematical descriptions are provided in table 1. When evaluating the holistic acceptability index, the centroid weights were used as the meta-weight.

The computational processing was conducted using a computer running a 64 bit version of Window 7, using an Intel® Core ™ i7-4910MQ CPU at 2.9 GHz with 32 MB of RAM. All of the optimizations were performed using the optimization software CPLEX version 12.6.2.

3 - Results

For each option of conducting the analysis a separate figure has been created to display the probabilities of the rankings for all alternatives portraying all four weighting schemes (Figures 1-4). These figures visually represent the rank probability of each alternative under consideration. A colour gradient from green to red (most acceptable to least acceptable) indicates the ranking of each specific alternative. Those alternatives which are primarily green have a higher probability to be preferred over those alternatives which are primarily red. A summarization of the results is provided by the holistic acceptabilities found in table 2.

From the rank acceptability figures and the holistic acceptability values, the preference for the different alternatives can be seen rather clearly. When timber interests are given a higher importance (as in weights w_2, w_3 and w_4), alternative plan nine is nearly always preferred. This is the case regardless of the distance metric used, or if we rely on either the consensus pairwise comparisons or the original individual pairwise comparisons. When all of the weights are uncertain (w_1), alternative plan four is the most acceptable plan.

4 - Discussion

Sustainable forest management that aims to balance economic, ecological and socio cultural forest values calls for the involvement of multiple stakeholders with a diverse preferences. In this study, we suggest a method of deriving rankings for a set of alternative management plans based on aggregated preferences. Our proposed method suggests treating acquired preferences as the uncertain elements of a stochastic programming problem, while allowing the participants to determine the appropriate level of aggregation to preferential information. For the case examined, uncertainty was viewed as the differing opinions held within a stakeholder group, although any quantification of uncertainty could be used. One benefit of this approach is that aggregation of the input data is not a requirement. This does not mean that preferential information is not aggregated; rather the aggregation of preferential information is conducted through the stochastic process. The result is then a ranking of the alternative plans based on the provided preferential information.

This method is based on an extended goal programming approach, and can produce rankings of the alternatives which maximize overall utility but also a ranking which minimizes the disagreement of the most disadvantaged stakeholder. Through a stochastic approach the rankings are interpreted in terms of acceptability; the probability that a certain alternative will be assigned a certain rank by the stakeholders, given a set of weights. The set of weights used could be completely stochastic (w_1) or even partly stochastic (w_2 or w_3). This choice can be used to avoid the controversial issue of assigning weights to stakeholders in the aggregation of preferences. In a case like the one presented here, where the stakeholders do not state their preferences for all indicators but different stakeholder groups have different indicators, this may be especially useful since weights assigned to the stakeholder groups are very influential and will tip the balance for the resulting consensus ranking in certain directions.

To ease the mathematics of this problem, we assumed that basic rank orderings were aggregated over a set of criteria. This assumption can be relaxed and a method to provide a ranking based on criteria preferences could be directly integrated into the method. The approach to evaluating the appropriate ranks for each individual was based on the earlier work of Nordström et al (2009), and allows for groups to provide preference information which relates specifically to their interests. Alternate methods of ranking alternatives based on multiple criteria could also be integrated into this approach.

A general challenge with MCDA and aggregation methods is in explaining them so stakeholders can understand and trust them. In this case two different sources of uncertainty are included in the analysis; a careful separation between the sources should be highlighted. One source of uncertainty relates to the relative importance of the different stakeholder groups. The method provides a way to allow more flexibility in assigning weighting values. By utilizing specific bounds (such as in table 2) absolute agreement on the importance between groups can be avoided. The other source of uncertainty is with the ranking of the alternatives. In this case, the ranking of the alternatives is based on either the individual pairwise comparison matrix, or the consensus pairwise comparison matrix generated with a specific distance metric. For the individual case, a single stakeholder of each stakeholder group is used to represent the entire group for a specific scenario. For the consensus case, different aggregations of the preferences for the group are used to represent a specific scenario.

By examining the changes in the solutions generated, we can see what effect a reduction in the quantity of uncertainty will have on the outcomes of the process. Moving from the individual pairwise comparisons to the consensus pairwise comparisons can be interpreted as a reduction in the preferential uncertainty. This can be seen as contributing to the improvement of the holistic acceptability for the most preferred alternatives. Alternatively, increasing the detail provided to the stakeholder group weighting scheme is a reduction in the preferential uncertainty. This can be seen when comparing weighting schemes w_2 and w_3, as a rather dramatic improvement in the holistic acceptability occurs (especially when $\lambda=1$).

There are two key differences between the use of the individual and consensus pairwise comparison matrices. The first is with the computational times required to solve the different optimization problems. The number of permutations for the individual comparisons was about 8 times larger than for the consensus comparisons, an expectation can be formed that this will directly correspond to an increase in computation times. With our very limited set of observations, this linear growth in the computational time generally holds with the exception of the cases when using the individual pairwise comparisons with the parameter λ set to 0 (Table 3). This increased time requirement could related to memory requirements exceeded the available RAM for those cases. The second key difference between these pairwise comparison matrices is the loss of some information. This can be seen by comparing the figure created by the different methods (i.e. compare figures 1 & 3, and figures 2 & 4) and between the results found in the holistic acceptabilities table (Table 2). In the figures, the loss of information can be seen as a decrease in the diversity of the rankings for a specific alternative, while in the table it can be seen as increased acceptability for the specific choices. Moving from the individual to consensus matrices the holistic acceptability for the preferred alternatives increases substantially, and in one case, the most preferred option is different (w_2 with λ=0).

The results from this study show that when weights are more certain and timber interests are given a higher importance (as in weight scheme w_2, w_3 and w_4), alternative plan nine (a plan created with focus on timber criteria) is nearly always preferred, and that when weights are uncertain (weight scheme w_1), alternative plan four (a plan with focus on conservation) is the most acceptable plan. This is in line with the results of Nordström et al. (2009) when similar weights were used and the majority principle was applied in the aggregation. Further, when weights are uncertain (w_1), plan one to four (plans focused on conservation criteria) are ranked among the most acceptable plans which is similar to the results of Nordström et al. (2009) when stakeholder groups other than the timber producers are given a higher importance, and especially when aggregation is made according to the minority principle. Thus, in general the aggregation method in this study produces results similar to the results of Nordström et al. (2009) in terms of ranking of alternatives; however, the perspectives on the results and how they are to be interpreted are different in the two studies.

The stakeholder groups have diverging preferences, as is shown in Nordström et al. (2009, Table 4), which results in a somewhat polarized rankings of alternatives. This is also apparent in the resulting rank acceptabilities, especially Figure 1 and 3, which show that alternatives nine to twelve are clearly more preferred by timber producers while alternatives one to four are more acceptable to the other stakeholder groups. Alternatives five to eight (plans which balance competing criteria) seem to be somewhere in between these more strongly preferred alternatives. Possibly, these alternatives have more of a character of compromise than the other alternatives. An interesting way forward could be to generate middle-of-the-road alternatives like this to find improved compromises.

While the method may ease the requirement for consensus building within similar stakeholder groups, the computational requirements to generate a solution can be rather taxing. With no uncertainty included into the weighting scheme (set B), a solution is found very quickly for all of the variations considered (measured in seconds). Incorporating uncertainty into the weighting scheme (through a Monte Carlo process with 1,000 repetitions) causes a rather dramatic increase in the solving time required (between 10 minutes and nearly 6 hours), and the selection of the λ parameter has a very noticeable impact on the computational time required (Table 3). To ease the computational requirements, rather than using all permutations of the pairwise comparisons, a representative selection could be used (i.e. through a Monte Carlo process). The use of this type of simplification will have an impact on the solution quality; however the impact on the solution quality can be evaluated through a variety of tools found in stochastic programming literature (i.e Kleywegt et al. 2001; Bayraksan and Morton 2011).

The method described in this study presents a solution to the contentious issue of aggregation of preferences and provides a constructive principle for interpretation of results. In addition, the participants' preferences are stated through pairwise comparisons which is considered a user friendly method, and participants do not have to evaluate alternatives since this is done automatically with the extended goal programming. These properties make it suitable for group decision making and participatory situations. The results from using the method could assist the decision maker with an understanding of how the diversity of opinions both within stakeholder groups and between stakeholder groups impacts the prioritization of the alternative plans in a participatory planning process.

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Figure 1. Rank acceptabilities for the 12 alternatives when using the individual pairwise comparison matrices and setting λ to 1, for the four weighting schemes.

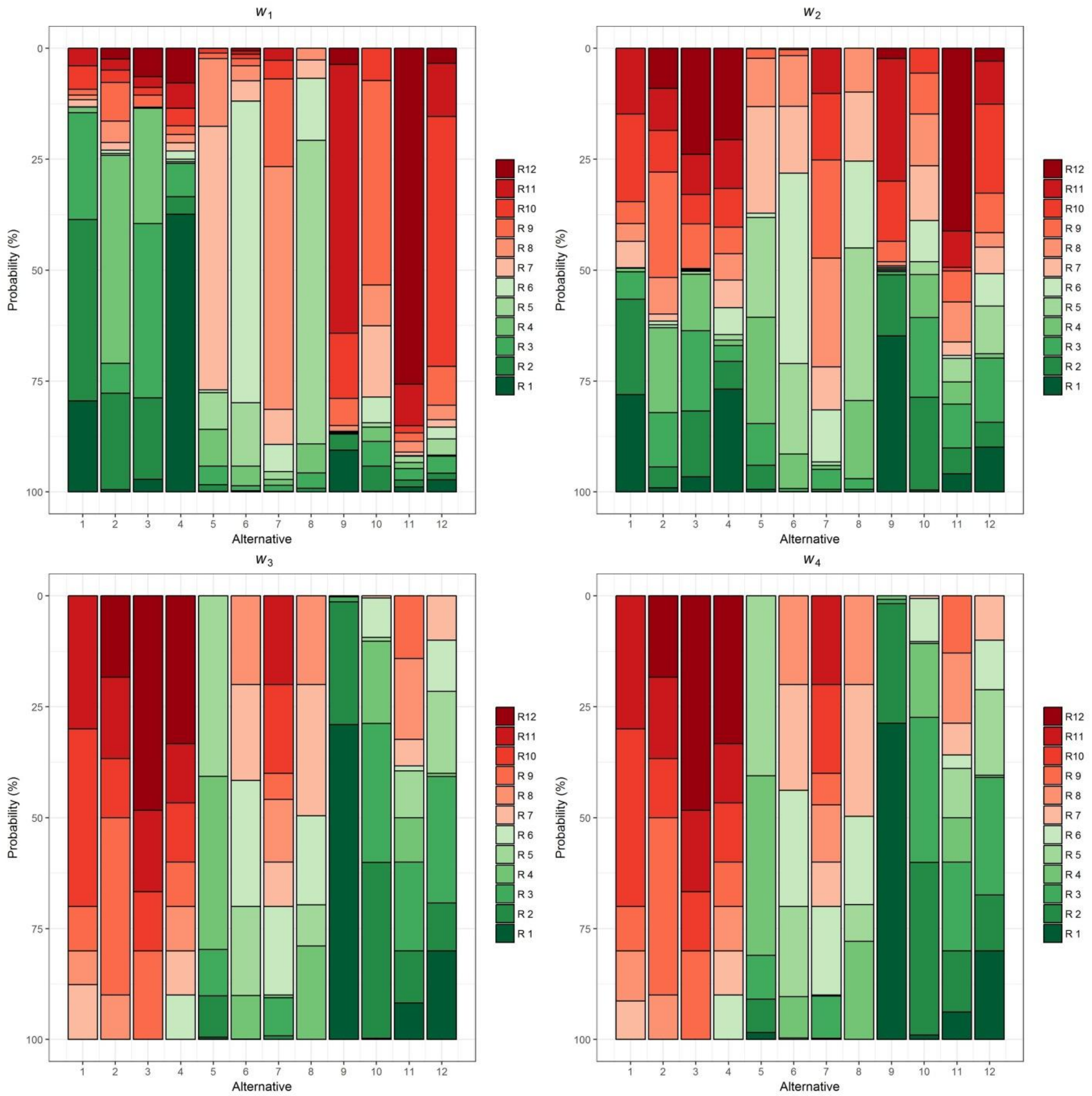

Figure 2. Rank acceptabilities for the 12 alternatives when using the individual pairwise comparison matrices and setting λ to 0, for the four weighting schemes.

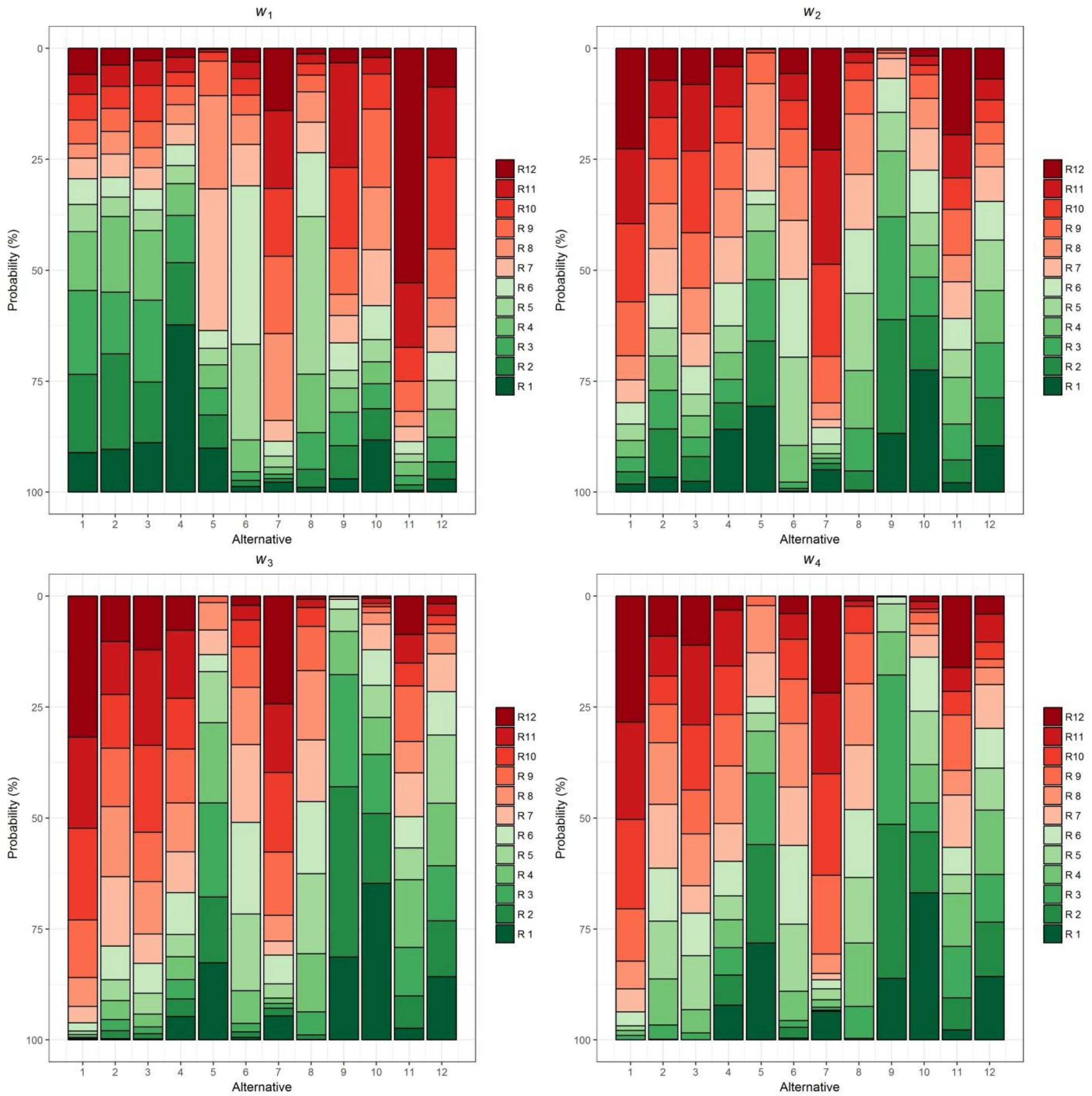

Figure 3. Rank acceptabilities for the 12 alternatives when using the consensus pairwise comparison matrices and setting λ to 1, for the four weighting schemes.

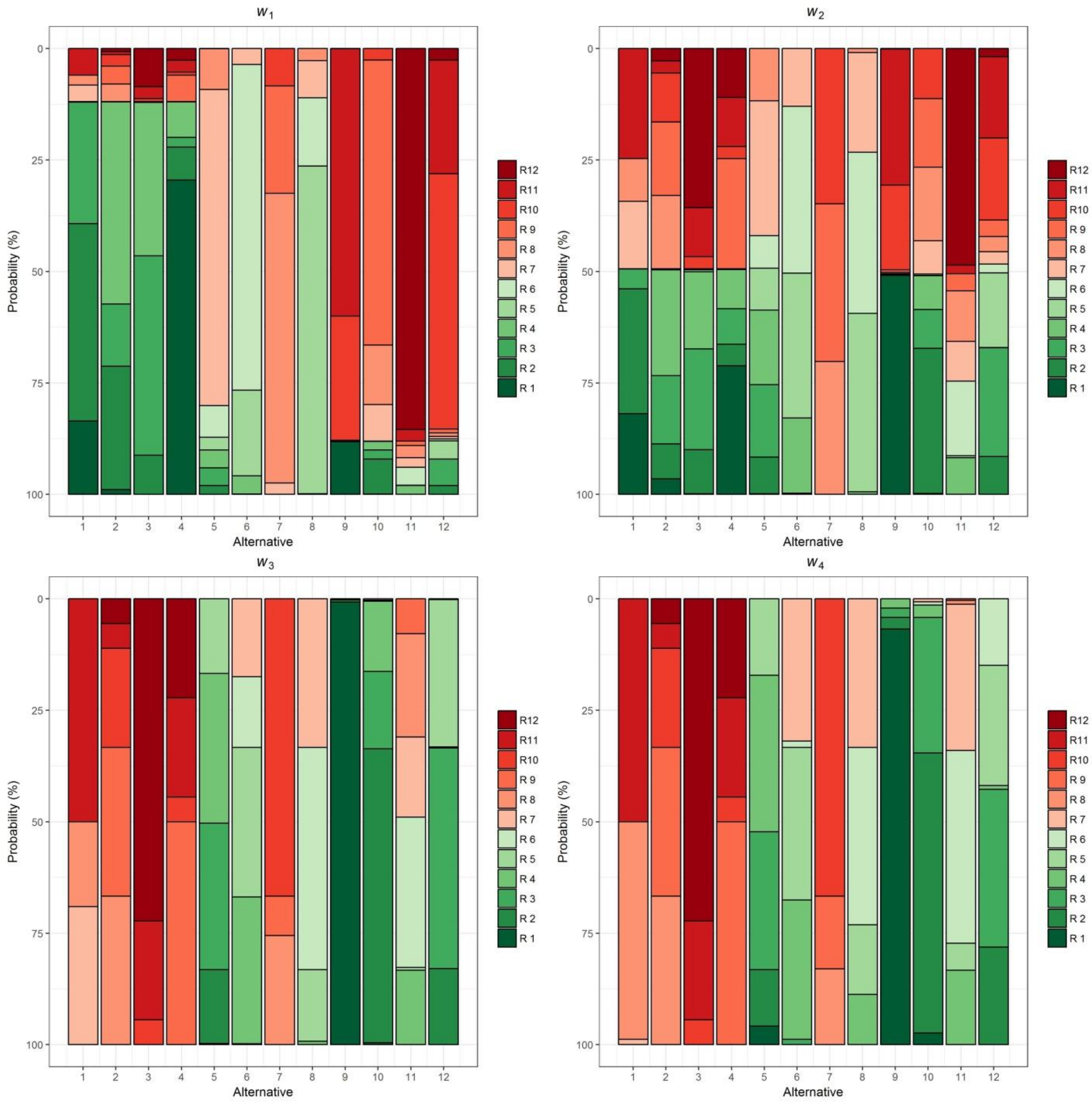

Figure 4. Rank acceptabilities for the 12 alternatives when using the consensus pairwise comparison matrices and setting λ to 0, for the four weighting schemes.

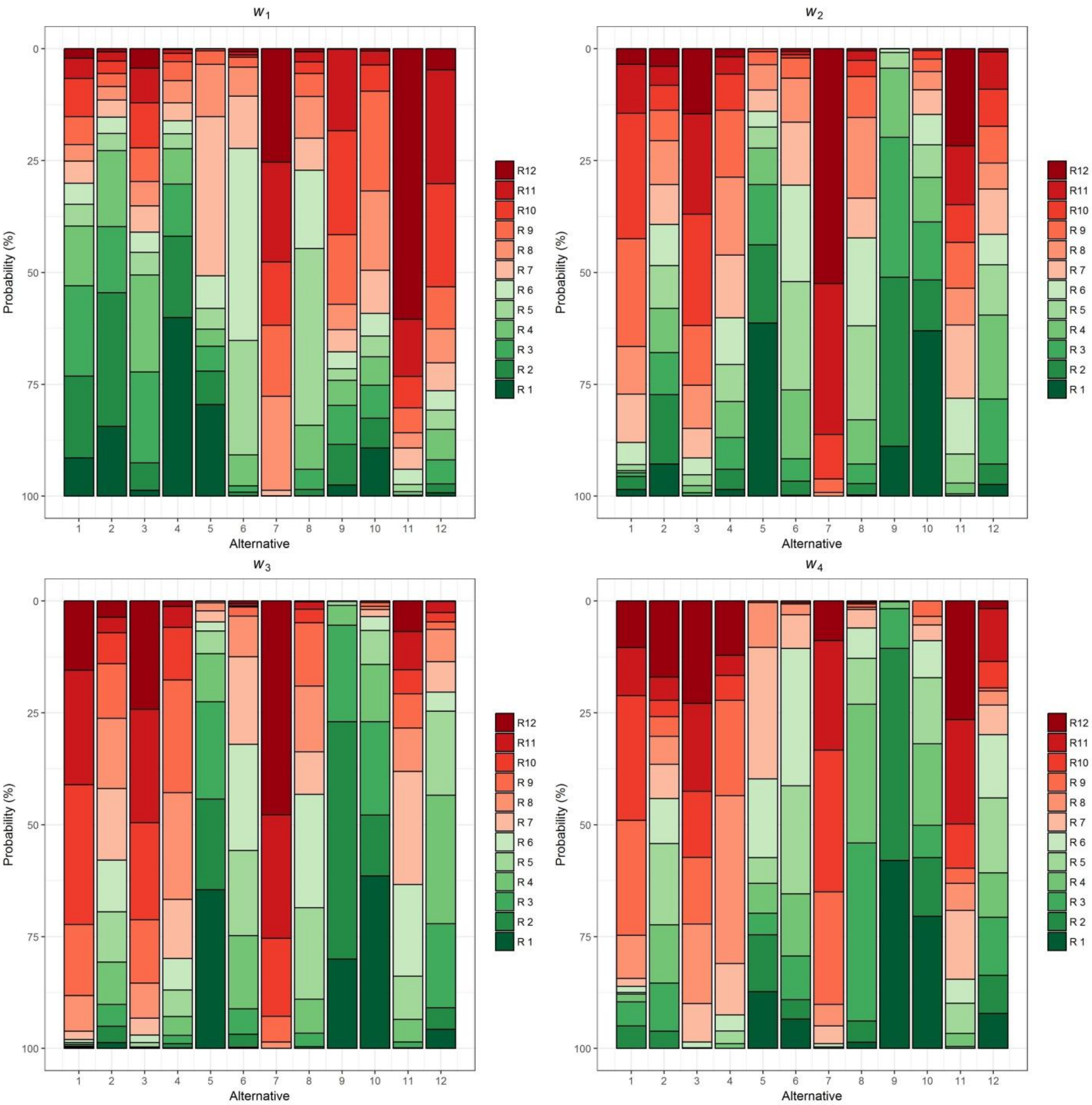

Table 1. A mathematical and linguistic description of the weighting schemes used for the case study.

$w_1 = \left\{ w_1 \in R^n : w_1 \geq 0 \; and \; \sum_{j=1}^{n} w_{1j} = 1 \right\}$	No knowledge regarding the prioritization of the different groups
$w_2 = \left\{ \begin{matrix} w_2 \in R^n : w_2 \geq 0 \; and \; \sum_{j=1}^{n} w_{2j} = 1 \\ and \; w_{21} \geq w_{23} \geq w_{22} \geq w_{24} \end{matrix} \right\}$	Ranked preferences of groups: Timber producers ≥ Recreationalists ≥ Environmentalists ≥ Reindeer herders
$w_3 = \left\{ \begin{matrix} w_3 \in R^n : w_3 \geq 0 \; and \; \sum_{j=1}^{n} w_{3j} = 1 \\ and \; w_{31} \geq 0.5 \end{matrix} \right\}$	Timber producers assigned an importance of over half, no prioritization of remaining groups
$\mathbf{w_4} = \left\{ \begin{matrix} w_{41} = 0.504, w_{42} = 0.170, \\ w_{43} = 0.242, w_{44} = 0.085 \end{matrix} \right\}$	Perfect knowledge regarding the prioritization of the different groups

Table 2. The holistic acceptabilites for the selection of cases, bolded values indicate the maximum values, while underlined indicate the minimum values.

			Alternatives											
			1	2	3	4	5	6	7	8	9	10	11	12
Individual	λ=1	w_1	61.5%	39.3%	45.6%	**71.0%**	22.8%	25.1%	14.9%	30.6%	15.6%	19.1%	5.5%	13.1%
		w_2	43.7%	22.9%	29.5%	35.0%	31.9%	24.9%	14.9%	28.3%	**47.4%**	35.7%	19.6%	30.7%
		w_3	7.8%	6.8%	3.4%	8.0%	40.0%	24.0%	16.3%	24.5%	**90.1%**	52.4%	38.8%	52.3%
		w_4	7.7%	6.8%	3.4%	8.0%	40.1%	23.8%	16.2%	24.5%	**90.1%**	52.6%	38.5%	52.5%
	λ=0	w_1	41.1%	42.9%	41.1%	**59.9%**	32.1%	24.9%	12.4%	30.5%	21.4%	31.4%	7.4%	19.2%
		w_2	13.7%	27.1%	19.0%	32.7%	47.7%	20.7%	12.6%	27.5%	**53.5%**	50.9%	21.6%	37.3%
		w_3	6.1%	15.3%	11.9%	21.7%	51.6%	22.2%	14.6%	24.2%	**63.1%**	61.7%	27.6%	44.2%
		w_4	7.0%	19.0%	14.2%	27.2%	54.2%	20.7%	13.5%	24.0%	**60.2%**	57.3%	25.2%	41.7%
Consensus	λ=1	w_1	61.0%	45.6%	42.1%	**80.4%**	22.2%	26.1%	12.6%	28.5%	15.5%	17.1%	2.7%	10.4%
		w_2	44.0%	30.6%	25.6%	42.6%	32.4%	28.4%	10.0%	25.8%	**51.5%**	35.4%	11.2%	26.7%
		w_3	10.0%	9.6%	1.0%	6.0%	46.3%	30.6%	8.6%	23.7%	**99.7%**	59.6%	22.4%	46.7%
		w_4	8.6%	9.6%	1.0%	6.0%	47.3%	29.9%	8.3%	25.3%	**96.8%**	61.3%	25.3%	44.8%
	λ=0	w_1	41.6%	53.4%	30.3%	**64.8%**	41.7%	25.8%	6.4%	27.1%	22.2%	31.1%	4.5%	15.3%
		w_2	13.7%	35.6%	8.9%	23.6%	**64.7%**	28.2%	2.1%	24.8%	59.5%	60.9%	12.5%	29.8%
		w_3	6.6%	23.2%	6.2%	16.2%	67.0%	28.4%	2.7%	22.8%	**68.3%**	66.8%	18.2%	37.8%
		w_4	13.5%	24.3%	7.5%	12.3%	39.3%	36.6%	7.1%	42.5%	**78.8%**	57.0%	10.2%	35.1%

Table 3. The computational solving time for each case (in seconds)

	Individual λ=1	Individual λ=0	Consensus λ=1	Consensus λ=0
w_1	4,226	20,549	587	1,642
w_2	4,270	20,801	581	1,538
w_3	4,777	20,673	604	1,604
w_4	51	56	8	7

Supplementary Material 1 – Data and code to re-conduct analysis -*Requires CPLEX, R and Python 2.7