Aalto University
School of Business

ROBUST PORTFOLIO MODELING IN ENVIRONMENTAL DECISION MAKING

Case: Peatland Selection

Master's Thesis
Heidi Häyrynen
Aalto University School of Business
Information and Service Management
Spring 2020

Aalto University
School of Business

Aalto University, P.O. BOX 11000, 00076 AALTO
www.aalto.fi

Abstract of master's thesis

Author Heidi Häyrynen	
Title of thesis ROBUST PORTFOLIO MODELING IN ENVIRONMENTAL DECISION MAKING	
Degree Master of Science in Economics and Business Administration	
Degree programme Information and Service Management	
Thesis advisor(s) Juuso Liesiö	
Year of approval 2020 **Number of pages** 72	**Language** English

Abstract

The importance of environmental decision making is growing. Private companies and public organizations are facing decisions involving multiple objectives. In particular, focusing solely on financial objectives is no longer enough but taking into account the environmental, social and political objectives is needed.

The methods used to solve these environmental problems have been based on heuristic approaches. However, these methods lack the capability to provide optimal solutions as most of the environmental decisions are portfolio selection problems. Robust Portfolio Modeling (RPM) is a decision analysis method that combines mathematical optimization in portfolio selection to incomplete preference information. This incomplete information is common in environmental decision making which includes multiple stakeholders with conflicting views. However, RPM has not been applied before to real-life environmental cases.

This thesis will first explore the characteristics of environmental decision making, secondly go through different methods used in environmental decision making and finally apply RPM methodology into peatland selection case. The results of RPM are then compared to the results of the heuristic YODA method previously used in the same peatland selection case.

Results indicate that RPM and YODA select highly different type of peatlands. RPM takes better into account the cumulative effects related to portfolio selection than YODA. Therefore, it is argued that RPM might be suitable for environmental decision making.

Keywords Robust Portfolio Modeling, RPM, Decision analysis, Peatland, Peat production site, Environmental decision making

Aalto-yliopisto
Kauppakorkeakoulu

Aalto-yliopisto, P.O. BOX 11000, 00076 AALTO
www.aalto.fi

Maisterintutkinnon tutkielman tiivistelmä

Tekijä Heidi Häyrynen

Työn nimi ROBUST PORTFOLIO MODELING IN ENVIRONMENTAL DECISION MAKING

Tutkinto Kauppatieteiden maisteri

Koulutusohjelma Tieto- ja palvelujohtaminen

Työn ohjaaja(t) Juuso Liesiö

Hyväksymisvuosi 2020 **Sivumäärä** 72 **Kieli** Englanti

Tiivistelmä

Ympäristöpäätöksenteon merkitys on kasvussa nyky-yhteiskunnassa. Niin yksityiset yritykset kuin julkiset organisaatiot kohtaavat päätöksiä, jotka vaativat syvempää ymmärrystä useammasta perspektiivistä. Enää pelkkä taloudellinen näkökulma ei riitä, vaan myös ympäristöllisiä sekä yhteiskunnallisia vaikutuksia pitää arvioida päätöksenteossa.

Tällä hetkellä monet menetelmät, joilla pyritään ratkaisemaan näitä ympäristöpäätöksiä ovat luonteeltaan heuristisia. Ympäristöpäätökset ovat kuitenkin useimmiten portfolio-ongelmia, jolloin nämä heuristiset mallit eivät onnistu löytämään optimaalista ratkaisua käsillä olevaan ongelmaan. Robusti portfoliomallintaminen (RPM) on päätöksenteon työkalu, joka yhdistää portfoliovalinnan matemaattisen optimoinnin sekä epätäydellisten mieltymysten mallintamisen, mikä on oleellista ympäristöpäätöksenteossa, johon sisältyy useimmiten useita osanottajia ristiriitaisin mieltymyksin. RPM:ää ei ole kuitenkaan vielä laajasti hyödynnetty todellisissa ympäristöpäätöksenteon tapauksissa.

Tämä tutkielma käsittelee aluksi ympäristöpäätöksenteon erityispiirteitä. Tämän jälkeen esitellään joitakin yleisesti käytettyjä päätöksentekomalleja. Lopuksi toteutetaan RPM-mallinnus todelliseen soidenvalintatapaukseen, jossa tietty määrä soita tulisi valjastaa turvetuotantoon samalla minimoiden sen ympäristölliset haittavaikutukset. RPM-mallin tuloksia verrataan heuristiseen YODA-malliin, jota on aiemmin käytetty kyseisen soidenvalintapäätöksen tukemisessa.

Tulokset paljastavat suuria eroja näiden mallien valitsemissa suoportfoliossa. Nämä tulokset myös vahvistavat olettamaa, että RPM voisi soveltua hyvin ympäristöpäätöksenteon haastavampiin sovelluksiin, sillä se kykenee muun muassa ottamaan huomioon portfolioiden kumulatiiviset vaikutukset tehokkaammin kuin heuristinen YODA.

Avainsanat RPM, Portfoliomallintaminen, Epätäydellinen informaatio, Päätöksenteko analyysi, Suot, Turvetuotanto, Ympäristöpäätöksenteko

Acknowledgements

I would like to express my sincere gratitude to my thesis supervisor Juuso Liesiö for his valuable comments and support during this process. He was the first one to introduce me to the interesting world of decision analysis and I have continued to learn under his guidance during my thesis process.

I also wish to thank PORTRIGHT research team for having this opportunity to participate in the project. Special acknowledgment to LUKE for providing me with the data and all the relevant information needed.

Finally, I want to express my gratitude towards my family and friends for their support during my studies and especially during these last months of my thesis process.

Table of Contents

List of Tables

List of Figures

1 Introduction

The importance of environmental decision making has grown in the modern society. Both public organizations and companies are coming across with decisions that require understanding not only the economical but also the sustainable and social consequences of their decisions (Phillips and Bana e Costa, 2007). Actors who do not consider these extended dimensions of consequences are in danger of losing trust as consumers are more informed than ever. Understanding the relationships between these different consequences is important for efficient and open decision making that is acceptable for the public and respects tightened legislations (Antonides, 2017). Hence, there is a growing demand for methods that are able to illustrate the different complex characteristics of environmental decision making (Huang et al. 2012).

Environmental decision problems are commonly in a form where a set of actions is selected based on multiple objectives with certain target levels and limiting constraints (Lahtinen et al. 2017). Currently many companies and public organizations are approaching these decisions without rigorous decision support methods. Instead, they typically use heuristic methods that come with some limitation. For instance, instead of finding the best combination of different actions, these methods find portfolios that are satisfactory but not optimal (Lahtinen et al. 2017). These methods capture compromises and allow stakeholders to set target levels. However, they do not capture the complex connections in resource constraints and value function forms explicitly caused by multiple objectives. This can lead to non-optimal solutions and poor allocation of limited resources. Better results could be achieved by more rigorous methods such as Portfolio decision analysis (PDA) (Salo et al. 2011).

Portfolio decision analysis is a family of methods that helps decision makers to select portfolios from a large set of project alternatives (Salo et al. 2011). These methods have a great potential to fit well for environmental decision making as many of these decisions are actually portfolio selection problems (Lahtinen et al. 2017). PDA aims to select the best combination of different actions, unlike multiple criteria decision analysis (MCDA) methods which can select only one best action candidate. However, the PDA applications in environmental decision making has so far been limited (Lahtinen et al. 2017).

Environmental decision making has a more complex nature than the common application areas of PDA. Environmental decisions need to consider multiple dimensions such as economical, socio-political and environmental risk and their trade-offs (Huang et al. 2011). The environmental decision-making process also includes multiple stakeholders (Vilkkumaa et al. 2014). This increases the risk of conflicting objectives or incomplete information of preferences (Lahtinen et al. 2017). Due to these special characteristics of environmental decision-making, Robust portfolio modelling (RPM) has been selected as the method of interest in this thesis. RPM is a portfolio method that can cope with incomplete preference information efficiently, which makes it attractive method for environmental decision making. The contribution of this thesis is to utilize RPM methodology into a real-life environmental case and to compare its performance to the methods now used on the field.

Hämäläinen (2015) has also noted that simply comparing the end results of different methods is not enough while comparing the superiority of methods. It is also important to understand the underlying risks and biases related the modeling procedure. Thus, it is required to review the suitability of RPM method to the environmental context also with wider context than just concentrating on the end results.

1.1 Research questions

This thesis is done as a part of a research project entitled PORTRIGHT funded by the Academy of Finland. The project team consists researchers from Aalto University School of Business, Finnish Environment Institution (SYKE) and the Natural Resources Institute of Finland (LUKE). LUKE has created their own decision method Your Own Decision Aid (YODA) to help environmental decision making. They have applied YODA on a case of peatland selection. However, YODA is a heuristic in the sense that it is a multicriteria method designed to select one optimal decision alternative whereas the peatland selection problem is a portfolio problem. This leads to the situation that YODA has the same limitations than other heuristic methods in portfolio selection. Therefore, the same peatland selection process is now conducted with portfolio method RPM. The target is to gain insight about how well RPM performs in real-life environmental cases and does it bring additional value to the decision process. Thus, the research questions are:

I. Does Robust Portfolio Modelling (RPM) create additional value for peatland production site selection compared to current methods?

II. What are the benefits and challenges of applying RPM to environmental decision making?

The main objective of this thesis is to evaluate the added value that RPM potentially brings to the real-life environmental decision making. This objective is achieved by comparing the result portfolios of RPM and YODA in the peatland selection case in order to gain insight of the suitability of both processes to the environmental decision-making framework.

The other objective is to gain additional understanding of the challenges that may occur while applying the RPM method to more complex environmental decision-making problems. This information is gained through the modelling phase. The aspects to consider are for example how well the RPM can model the relationships within and among the different aspects of the decision model and whether RPM performs well in situations with highly conflicting stakeholder objectives where one clear decision maker cannot be identified.

1.2 Structure of the thesis

This thesis consists of five chapters containing this introduction. The next chapter will contain the literature review. It starts with the introduction of general environmental decision-making characteristics which is followed by the different decision modeling methods used in the field of operations research. The third chapter will introduce the real-life peatland selection case, description of the original decision method YODA used by LUKE and the data of this thesis. This is followed by the fourth chapter where the actual empirical modeling procedure is done. In this chapter, the model is built and the comparison of the results of RPM and YODA is conducted. Lastly, in the fifth chapter the results to the research questions are interpreted with discussion of the modeling limitations and possibilities of further research.

2 Theoretical background

In this chapter the evolvement of some environmental decision-making theories is presented. First the special characteristics of environmental decision making are discussed. After that the different methods are presented starting from the multiple criteria decision analysis (MCDA) which is mostly used when selecting a single action candidate. This is followed by portfolio modeling (PDA) that selects a set of actions. Lastly RPM methodology is introduced.

The terminology used in this thesis respect the different elements of decision modeling are presented in the Table 1.

Table 1: The terminology used in this thesis

Term	Explanation	Example
Project / Action candidate/Alternative	Options where the selection is conducted	Project A Project B Project C
Criteria	Different aspects based on which the action candidates are evaluated	Price Production time Expected revenue
Preference / Weights	Assessment for the relevant importance of each criterion. Sum up to 1.	0.5x Price 0.2x Production time 0.3x Expected revenue
Objective	The goal of the decision process	Maximize revenue
Constraint	Limitation to the process or criterion	At least 10 000€ of total revenue Can contain Project A or B but not both Production time less than 3 moths
Portfolio	Set of projects	Project A and C selected

2.1 Environmental decision-making characteristics

Looking at the literature, it seems that decision analysis methods have been applied mostly to problems that are related to R&D (Abbassi et al. 2014; Arratia et al. 2016), production (Achillas et al. 2015; Sawik, 2018; Wang et al. 2018) and energy industry (Ender et al. 2010; Lopez and de Almeida 2013). The reasons why decision models have not been applied more for environmental problems varies a lot. Gregory et al. (2012) have identified that these reasons cover following assumptions: decision making with optimization method sounds expensive and time-consuming, the decision process is seen too quantitively and science oriented and also involving different parties with their own relative views of importance requires a lot form the facilitator of this process.

However, the interest in applying optimization models also for environmental decision problems has increased (Huang et al. 2012). Some of the most common managerial decisions related to environmental decision making according to Gregory et al. (2012) are: (1) choosing a single alternative, for example developing a management plan for endangered species, (2) developing system for repeating situations like setting annual harvest levels and (3) project ranking in which for example funds or restorations efforts are prioritized.

Legislation has also affected the increasing interest in environmental decision making in the business world. In Finland both national laws and directives from the European Union are affecting the processes of public and private operators. These legislations cover areas from climate protection to waste and chemical legislation and also soil protection to environmental protection legislation (The Finnish Ministry of the Environment, 2016). There is also legislation about the environmental impact assessment required in some decision-making processes (Finlex, 2017).

Environmental decision making contains the same phases as any decision problem. Thus, the specialties of environmental decision-making affect inside the procedures of each step. According to Kirkwood (1996) the common decision process contains the following five steps:

1) Specifying the objectives and criteria of the decision problem
2) Developing the potential alternatives for the decision problem
3) Determining the performance of each alternative respect each criterion
4) Considering the trade-offs between the criteria
5) Selecting the alternative that performs best regarding the criteria and possible additional constraints

Environmental decision problem are usually portfolio problems (Lahtinen et al. 2017). In these cases, environmental decision problems have usually the same formation than other portfolio decision problems: There is a group of action candidates where to choose the best combination while simultaneously respecting multiple objectives and some constraints (Lahtinen et al. 2017). These objectives and constraints are usually decided at the beginning of the decision process but for example legislation can set some additional constraints for the modeling.

One of the special characteristics of environmental decision-making is its complex nature. Considering the problem in economical perspective is usually enough in standard decision-making. However, in environmental decision making the amount of considered consequences is wider with socio-political, financial and environmental dimensions (Huang et al. 2012; Lahtinen et al. 2017). The decision makers also need to deliberate the different trade-offs between these dimensions as usually a solution that satisfies objectives from all of these dimensions cannot be identified. Some environmental decisions also lack information regarding the consequences of different actions as many results are uncertain (Huang et al. 2012).

Lahtinen et al. (2017) point out that environmental decision-making also includes usually multiple stakeholders with conflicting objectives and preferences. Environmental decision making requires participants with a wide range of backgrounds as the decisions influence politicians, environmentalists, inhabitants and usually producers. Belton and Pictet (1997) also highlight that all of the decision makers cannot be experts respect all dimensions. This seems to be especially true in environmental decisions. It has been acknowledged that the different parties are also more likely to accept the solution if they feel that they have been participating the process (Lerche et al. 2019). However, as the participant group gets more diverse also the objectives and views about how the decision should be made get variation (Webler et al. 2001). There can also rise communicational issues as the stakeholders in environmental decision making have varying backgrounds and knowledge of things (Hämäläinen, 2015).

Environmental decision making also raises strong emotions and positions. This might lead to situations where the big picture and all of the consequences of the decision are not considered by the different parties (Gregory et al. 2012). Some of it can be explained by confirmation bias where all new information is seen to support the decision makers' own strong opinions about the issue in hand (Hämäläinen, 2015). Due to all these presented reasons, the decision process seems to be more complex in environmental decision making than in standard decision-making with a single decision maker.

2.2 Multiple criteria decision analysis

With the help of multiple criteria decision analysis (MCDA) different actions can be evaluated regarding multiple dimensions. MCDA consists of several different methods with different inputs, structures and algorithms to find out the optimal solution (Huang et al. 2012). Based on the literature review by Huang et al. (2011) it seems that the most widely used forms of MCDA are AHP (48%) and MAVT/MAUT methods (16%). Regional distribution however reveals that in Europe MAUT/MAVT is slightly more used than AHP whereas the strong foothold of AHP can be explained by its strong usage in Asia and North America literature as presented in Figure 1.

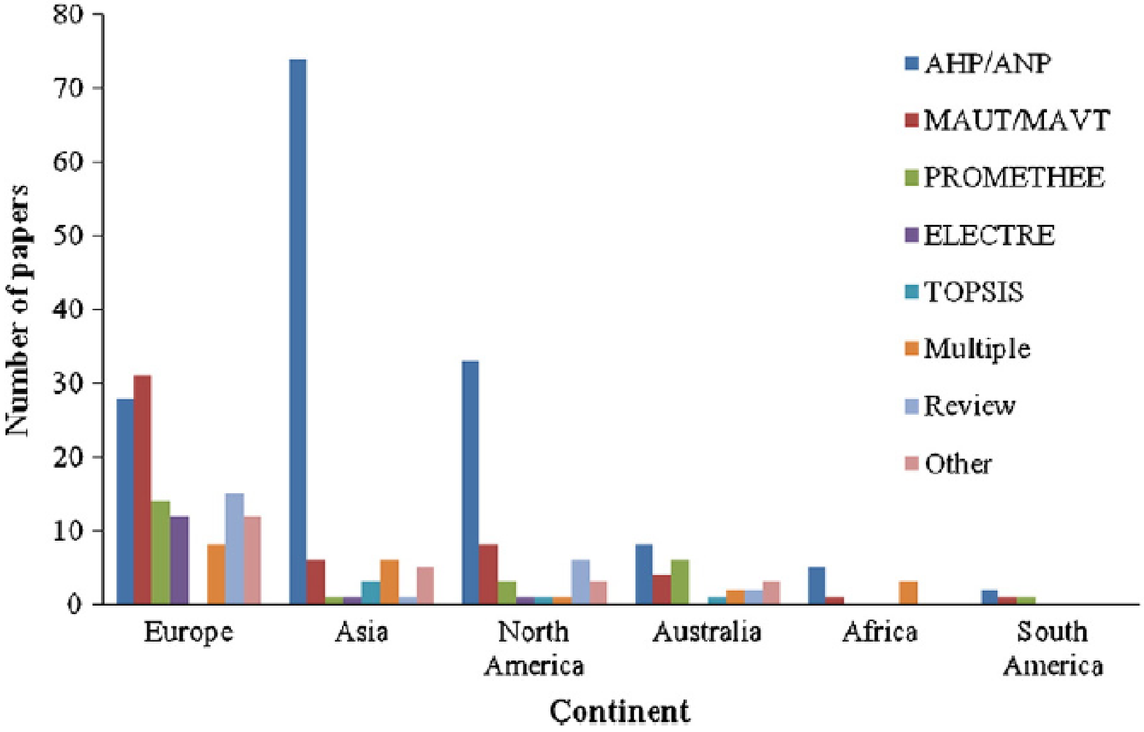


Figure 1. Illustration of regional distribution of different MCDA methods usage (Huang et al. 2011)

2.2.1 MCDA modeling

Saaty developed AHP during the 70s. In AHP the different objectives and criteria are forming a hierarchal tree from where the pairwise comparison in each hierarchal level is conducted (Saaty, 2008). The decision maker is asked how much more important one attribute criterion is respect to another (Huang et al. 2011).

This pairwise comparison procedure has however received critique regarding its breakage of consistency requirements (Barzilai, 1997; Cheng et al. 2002; Stoklasa et al. 2013). This pairwise comparison can lead to situations where decision maker’s choices are not consistent throughout all the objectives and criteria, especially with higher amounts of required comparisons as Saaty’s comparison scale only has values from 1 to 9. Ishizaka and Nemery, (2013) also demonstrated that decision makers can for example state that A is two times more important than B and B is three times more important than C but then A is only four times more important than C even though mathematically is should be six. Due to these critiques towards AHP, it is recommended to use MAVT/MAUT method from the MCDA family if the decision maker is able to construct a utility function (Ishizaka and Nemery, 2013).

Keeney and Raiffa (1976) stated that decision makers preferences can be represented through utility function. This function is usually not known before and it is required to be constructed during the decision process (Ishizaka and Nemery, 2013). MAUT is used when there are uncertainties that effect the criterion values. The decision maker is asked a set of questions to discover the form of the utility function. He or she is introduced with lotteries between uncertain and certain outcomes where these utilities are driven (Keeney and Raiffa, 1976). As uncertainty is playing a big role, the form of the utility function can also tell about the decision makers risk attitudes: concave function tells about risk-aversion and convex for risk-seeking behavior (Ishizaka and Nemery, 2013).

MAVT has mostly the same the principles than MAUT but the decision makers preference values are modeled without uncertainties. The function that captures these decision maker’s preferences is called value function instead of utility function. The form of the function is determined by asking preference questions between two certain outcomes or by comparing preferences respect changes of outcome (Keeney and Raiffa, 1976). In both of the MAUT and MAVT methods the criteria are then mapped through usually an additive function after which the different alternatives can be ranked based on the decision makers values (Ishizaka and Nemery, 2013).

Overall, the use of any MCDA method contains great limitations since the methods have been created to solve only a single optimal action whereas environmental decisions usually contain selection of multiple actions. In practice, this has meant that experts first generate the possible portfolio combinations where the best option has been selected with the MCDA method (Lahtinen et al. 2017). The quality of the model is therefore highly depended on the expert’s ability to identify the right portfolio combinations.

2.2.2 MCDA in environmental decision making

The share of environmental applications of MCDA has significantly increased over the last decades (Huang et al. 2011). According to Huang et al. (2011) literature review, many researchers have also reported significant improvements to the decision process and public acceptance after applying MCDA in environmental decision making. Nevertheless, this observation does not imply that MCDA would be the best method for environmental decision making but rather that the decision-making processes function better with than without applied decision support method.

There are numerous examples of environmental applications of multi-criteria methods in the literature. Figure 2 demonstrates the used MCDA method distributions regarding the different types of environmental decision problems based on the research of Huang et al. (2011). These environmental applications have covered topics such as sustainable energy production (Golabi et al. 1981; Lerche et al. 2019), environments rehabilitation processes (Langhans and Lienert, 2016) and forest management (Kurttila et al. 2009; Triviño et al. 2017).

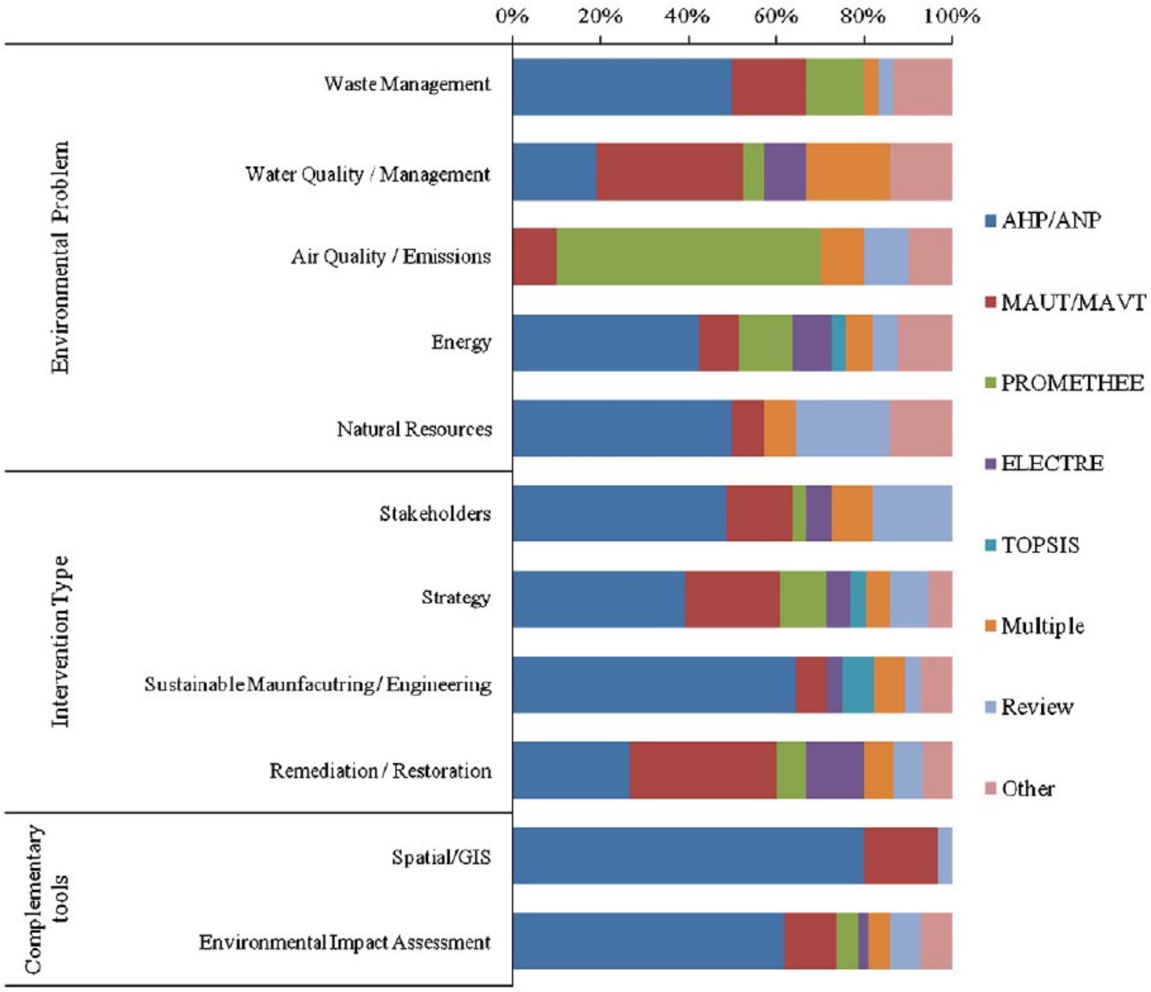


Figure 2. Illustration of different MCDA methods used regarding environmental decision making (Huang et al. 2011)

2.3 Portfolio decision analysis

Portfolio decision analysis (PDA) methods have risen as the solution to the limitations of MCDA. Unlike MCDA, PDA selects an optimal portfolio from a large set of alternative projects (Salo et al. 2011). It combines multi-criteria evaluation and mathematical optimization techniques to find the best combination of actions (Lahtinen et al. 2017). The roots of PDA are in finance (Markowitz, 1952) where investments have required portfolio selection before the notice of other utilization possibilities.

Currently PDA is however widely applied to solve different portfolio problems from diverse fields from R&D project selection (Phillips and Bana e Costa, 2007; Kloeber, 2011; Toppila et al. 2011) to healthcare applications (Kleinmuntz, 2007; Airoldi and Morton, 2011). Numerous applications have also illustrated PDA's ability to perform better resource allocation than before (Salo et al. 2011). The strength of portfolio modeling compared to single choice methods is that it enables to capture the interactions between the alternatives and objectives creating more realistic representation of the problem (Salo et al. 2011).

Phillips and Bana e Costa (2007) argue that the base of selection should be the ratio between the value that the alternative brings compared to its costs, instead just concentrating the value side. However, PDA also outperforms value/cost-ratio based portfolio selection when multiple dimensions need to be evaluated or the budget is fixed to a certain level as the last selected project rarely fills the remaining budget completely leaving value not obtained (Kleinmuntz, 2007). This makes value/cost-ratio unsuitable for complex environmental decision making where the concept of costs is not as central as in traditional business-related decision making.

2.3.1 PDA modeling

As any decision processes also PDA modeling requires decision maker, course of action, information about the available resources and the performance of different alternatives as well as the decision makers preferences among the multiple objectives (Salo et al. 2011). In PDA this information is combined to a value model. Based on value function, the mathematical optimization is conducted which searches the portfolio with highest portfolio value called optimal portfolio. Lahtinen et al. (2017) have illustrated these PDA modeling steppes in Figure 3.

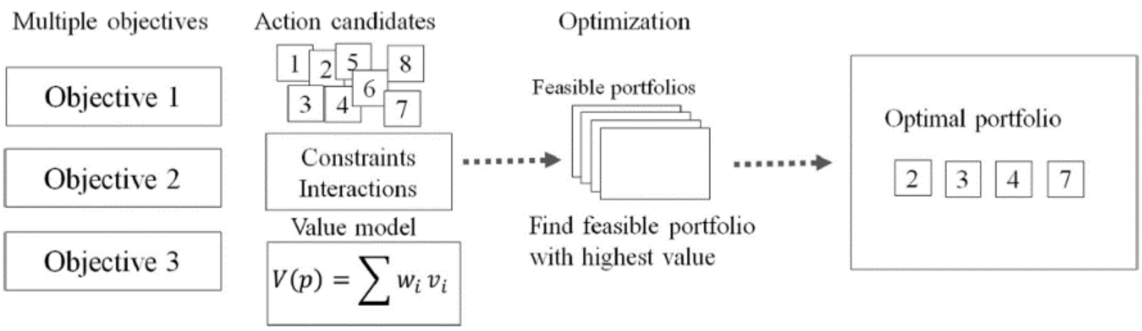


Figure 3. Illustration of portfolio decision analysis process (Lahtinen et al. 2017)

The first step is to identify the objectives and candidates of the process. This can be conducted via two alternative processes: top-down and bottom-up. Top-down is usually used in decision analysis as it starts from the objectives dictated from above and ends with the course of action (Linkov et al. 2014). Bottom-up is instead more used in risk evaluating processes starting from the ground level. However, Lahtinen et al. (2017) see that combining bottom-up to the top-down decision processes would suit well for environmental decision making as the views from the different stakeholders could be taken into account better already early on in the decision process. The portfolio modeling methodology also supports this as it can contain all proposals. This possibility also lowers the risk of path dependencies and other biases in the decision process (Lahtinen et al. 2017).

Next step is to identify the actual value model. Value function is the model's general function that compounds the separate criterion-specific values into a single overall project value of each evaluation candidate (Kirkwood, 1996). These project values are represented by row vectors $x^j = (x_1^j, \dots, x_n^j)$, where x_i^j is the project-specific performance respect criterion *i*. These values are then mapped through the additive multicriteria value function

$$v(x^j) = \sum_{i=1}^{n} w_i v_i(x_i^j), \tag{1}$$

which is a weighted sum of the project's criterion-specific values. Here, w_i is the preference weight of criterion i and $v_i(x_i^j)$ is the criterion-specific value function that maps the performance of each criterion. The overall value of the project j is therefore $v(x^j)$.

The additive function has strict restrictions when it can be applied as preferential independence (PI) is required. The subset of attributes is PI if the preference order of criteria is not dependent on the levels of the other criteria meaning that if $(x_{1,}^1\, x_2') \geq (x_{1,}^2\, x_2')$ then

$(x_{1,}^{1}\, x_{2}'') \geq (x_{1,}^{2}\, x_{2}'')$ for all values of x_2''. At the portfolio level, the same logic also applies. Portfolio is preferential independent when the overall value of a new added project is not dependent on the other projects already at the portfolio (Golabi et al. 1981).

Despite the popularity of additive function, it has been identified that in practice these PI assumptions seldom hold (Liesiö, 2014). Decision makers would want to have more diverse portfolio with nonconstant marginal values in portfolio level (Golabi et al. 1981; Liesiö 2014). In practice this could mean that even though one criterion for example "Biodiversity" is more important for the decision maker than for example "Natural water economy", when the portfolio already has many projects with good "Biodiversity" level the "Natural water" criterion starts to seem more appealing option to complement to portfolio.

Over the years other value function options has also been introduced. Multiplicative function is another traditional value function form which has weaker independence properties than additive function (Dyer and Sarin, 1979). However, in practice it has not been preferred as it requires more parameters to be identified. Some other recent forms of value functions are for example symmetric multilinear criterion-specific portfolio value functions (Liesiö, 2014) and spatial value function (Simon et al. 2014; Harju et al. 2019).

Baseline value is the outcome that the project is assigned if it is not selected. In the additive function equation (1) there is no separate part that processes this phenomenon. In practice this has meant that the value of not doing the project resulted zero among each criterion. Hence, the baseline value has been equivalent for the scores of the worst possible outcome x^0.

According to recent researches this procedure might however lead to incorrect recommendations in portfolio selection setting (Clemen and Smith, 2009; Liesiö and Punkka, 2014). Clemen and Smith (2009) demonstrate in their paper how without baseline value projects containing for example negative monetary outcome and high risk might be selected to the portfolio even though the decision maker would not prefer so. Already Golabi et al. (1981) recognized the importance of baseline value selection even though it was one of the first articles discussing about multicriteria portfolio modeling. According to their research, there can be found a baseline value vector $\underline{x} = (\underline{x_1}, \ldots, \underline{x_n})$ respect each criterion i such that projects with less value than project with baseline performance would not be selected. The equation

$$v(z) = \sum_{j=1}^{m} [z_j v\left(\overline{x^j}\right) + (1 - z_j) v(\underline{x})] = \sum_{j=1}^{m} z_j \left[v\left(\overline{x^j}\right) - v(\underline{x})\right] + m v(\underline{x}) \qquad (2)$$

illustrates how the idea of baseline value is to maximize the added value which the selected project will bring. Here z_i is the binary variable explaining whether the project has been selected or not. If the project is selected its project value $v\left(\overline{x^j}\right)$ is added to sum and otherwise the baseline value $v\left(\underline{x^j}\right)$. The same formal can however also be presented in the difference form on the right (2) which illustrates the added value the project selection brings.

Liesiö and Punkka (2014) developed baseline value assessment even further by introducing a solution to select baseline values that are not included in the original range of criteria called negative baseline value. Hence, the situation where the project with least preferred performance x^0 would still be acceptable, can be taken into account. Liesiö and Punkka (2014) approached this problem by gaining intervals of baseline values instead of fixed values, since it might be challenge to the decision maker to identify a specific vector of baseline values where they are indifferent of implementing or rejecting the project. These two ways to identify the baseline intervals are presented in Table 2.

Table 2: Spesifying baseline intervals according to Liesiö and Punkka (2014)

Rejecting x^0	**Accepting x^0**
Present list of vectors where next option always dominates the next one, starting from the x^0. When decision maker accepts the first project, the interval is calculated from the project values of last rejected and first accepted projects: $v(\$0,'probable',1) \approx 0.133$ $\leq v\left(\underline{x^j}\right) \leq$ $v(\$0,'safe',1) \approx 0.258$	To determine the negative baseline value decision maker is asked would they prefer portfolio of k projects with x^0 (worst performance) or portfolio of *k – 1* projects with *x** (best performance). The *k* is then increased until the decision maker prefers the second option *(k-1 with x*).* Then the rough estimate of baseline interval is therefore [-k, -k +1]: $k'v(x^0) + (m - k')v\left(\underline{x^j}\right) \geq (k' - 1)v(x^*) + \left(m - (k' - 1)\right)v\left(\underline{x^j}\right)$ $\Leftrightarrow$ $0 \geq k' - 1 + v\left(\underline{x^j}\right) \Leftrightarrow v\left(\underline{x^j}\right) \leq -k' + 1$ and $(k' + 1)v(x^0) + (m - (k' + 1)v\left(\underline{x^j}\right) \leq k'v(x^*) + (m - k')v\left(\underline{x^j}\right)$ $\Leftrightarrow$ $0 \leq k' + v\left(\underline{x^j}\right) \Leftrightarrow v\left(\underline{x^j}\right) \geq -k'$

Even though Golabi et al. (1981) and Clemen and Smith (2009) introduced criterion-specific baseline values, recent researches have been supporting one general project level do-nothing baseline value instead (Liesiö and Punkka, 2014; Morton, 2015). According to Liesiö and Punkka's (2014) recommendation, there are two ways to search out the baseline values: 1) determining the interval of project baseline values beforehand or 2) first calculating the potential portfolios and then figuring out the baseline via preference questions of the projects (see also Dou et al. 2019).

One illustrative example of how to select the correct baseline values is from Clemen and Smith (2009). They recommended to think about the status quo level while deciding the criterion-specific baseline values. In their investment example this meant 1) monetary contribution of $0, since there is not cash flow in or out 2) risk free investment, since not doing anything do not add up company's risk and 3) poor fit for strategy, since the business of the financial company is to take risks and gain the monetary rewards from it.

After criterion-specific value functions have been determined only weights which capture the preference information are missing from the value model. Weights are important as they capture the different levels of importance or trade-offs among criteria (Kirkwood, 1996; Tervonen et al. 2017). Correct weight selection is also important as small value changes can have significant effects to the end portfolio depending on the situation (Keisler, 2008). Weights also need to sum up to one (Dyer and Sarin, 1979). Equal weights have also received criticism by their decision quality (Jia et al. 1998; Montibeller and von Winterfeldt, 2015) which highlights the importance of correct weight selection.

After these model building procedures are performed the final optimization phase can be conducted. In this step, some algorithm is used to determine the best combination of projects. After the modeling is completed the final optimal solution portfolio can be presented.

2.3.2 PDA in environmental decision making

PDA has great potential to be suited for environmental decision making as many environmental decisions are portfolio selection problems (Lahtinen et al. 2017). PDA has been used for example to solve decision problems for offshore windfarm locations (Cranmer et al. 2018), costal ecosystems management (Convertino and Valverde, 2013) and nature disaster mitigation (van den Honert, 2016) but wider range of real-life environmental applications have been limited (Lahtinen et al. 2017). These environmental applications already conducted are mostly related to area selection and investment decisions. These are similar applications than in business related decisions but containing environmental perspectives regarding the criteria on which the projects are evaluated.

Environmental perspectives also bring additional challenges while determining the form of the criterion-specific value functions. Multiple decision makers with conflicting interests are common for environmental decisions (Lahtinen et al. 2017). This makes environmental criterion-specific value functions more vulnerable for inaccuracy, since even with traditional decision problems the decision makers value function cannot be modeled precisely (Hu et al. 2018). Montibeller and von Winterfeldt (2015) have studied these motivational and cognitive biases in decision making. Simplified forms such as standardized shapes of criterion-specific value functions have been used to avoid these biases created by the design of the questioning part (Montibeller and von Winterfeldt, 2015). However, Langhans and Lienert (2016) have studied that especially linearity assumption does not hold in environmental decision making around 80% of time.

Environmental decision making also highlights the need for effective group decision making while using PDA. According to Belton and Pictet (1997) group decision making can be divided into three procedures: 1) *sharing* where group acts as one decision maker 2) *aggregating* where individual preferences are combined and 3) *comparing* where additional discussions are conducted based on individual preferences. Especially in aggerating and comparing procedures it is important to verify that the decision makers have similar views of the underlining assumptions of the value functions, for example are bigger or smaller areas more preferred. Belton and Pictet (1997) also argue that actually weights represent the individual's preferences more precisely than value functions and therefore the differences mostly occur in preferential weights and not in criterion-specific functions.

The findings of Belton and Pictet (1997) stress the importance of weight selection in environmental decision making. Assessing the correct weights is dependent on the complexity of the decision problem and number of individuals involved (Keisler, 2008) which are both high in environmental decision making. Montibeller and von Winterfeldt (2015) have also recognized several other biases related to the weight selection process. Some of these can be again debiased by not performing the original questioning protocol.

2.4 Robust portfolio modeling

Robust Portfolio Modelling (RPM) is a form of portfolio decision analysis which can cope with incomplete information (Liesiö et al. 2007). In a real-life setting getting the exact preferences from the decision maker can be a challenge (Jia et al. 1998). The decision makers might be unable or unwilling to answer a long list of questions where the value function forms and weights of the criteria are iterated (Liesiö et al. 2007). RPM was therefore developed to tackle this problem. It uses similar approach as preference programming methods such as PAIRS, where the weights are presented as intervals instead of exact rates (Salo and Hämäläinen, 1992; Mustajoki, 2012). This also lowers the risk of forming incorrect weights especially in situations where single weight values cannot be calculated.

RPM has also been developed even further by combining it with other procedures. Vilkkumaa et al. (2014) have considered how RPM modeling could be applied for a group decision problem where different stakeholders interactively with the model attempt to find acceptable optimal solution. Fliedner and Liesiö (2016) have in turn combined RPM procedure with robust optimization concept in order to create a robust model with adjustable level of conservatism. Liesiö et al. (2008) have also extended the robustness to cover also constraint values and allowing project interdependencies. As with other decision support methods also RPM evolves and new ways of usage are invented.

2.4.1 RPM modeling

The steps of the general RPM modeling process are indicated in Figure 4. The process begins with a similar manner to a general PDA by modelling of the value function and its corresponding weights while respecting the chosen constraints and targets. The difference is the way weights are determined. RPM creates flexibility to the modeling by using incomplete preference information, which is captured with weight preference constraints such as $w_i \geq w_j$, which corresponds to criterion i being more important than criterion j (see also Park and Kim, 1997). However, the decision maker should not be asked direct question is i more preferred than j (Keeney, 1994). Instead the decision maker should use some preference eliciting method to make sure their answers are consistent. One such example is to state does they prefer increase in i from worst to the best level over similar change in j.

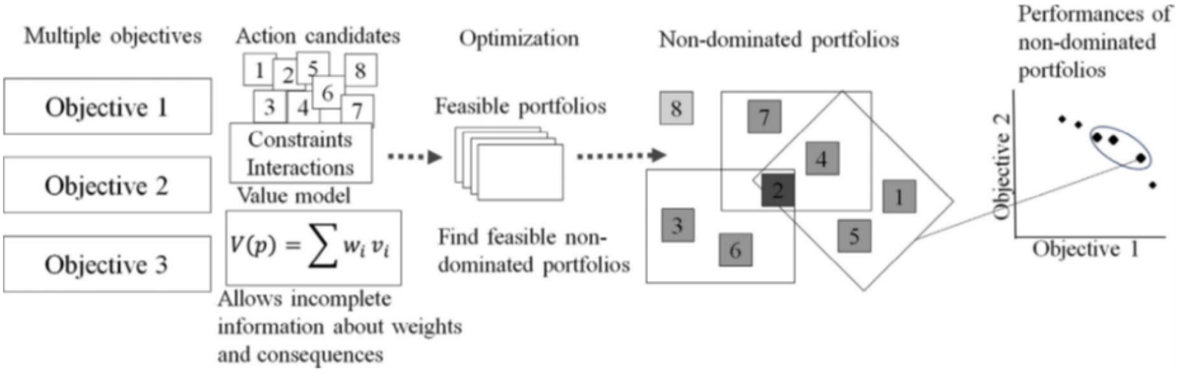


Figure 4. Illustration of portfolio decision analysis process with incomplete information (Lahtinen et al. 2017)

After the problem formation part, the model is optimized using a software which identifies the frontier of non-dominated portfolios. RPM cannot identify one single optimal solution due to the relaxed preference statements. This non-dominated frontier of portfolios is selected by utilizing the regularities of dominance where portfolio is non-dominated if there does not exist another portfolio that is more or equally preferred relative to each criterion (Liesiö et al. 2007).

Based on these portfolios in the non-dominated frontier the final action candidates can then be identified. Liesiö et al. (2007) divide these action candidates into three classes according to core index which denotes how often the different candidates have occurred in the different non-dominated portfolio solutions: 1) Core projects are in every portfolio 2) Borderline projects are in some portfolios and 3) Exterior projects that are in none of the portfolios. The final solution should then be a portfolio which includes all of the core projects with some additional best performed borderline projects until the target is fulfilled. Additional information can be used to narrow down the amount of non-dominated portfolios and by that the number of borderline projects (Liesiö et al. 2007). This RPM decision support process is presented in Figure 5. Also, other researchers outside RPM have adopted this class allocation of projects based on the core index values (see: Kurttila et al. 2020).

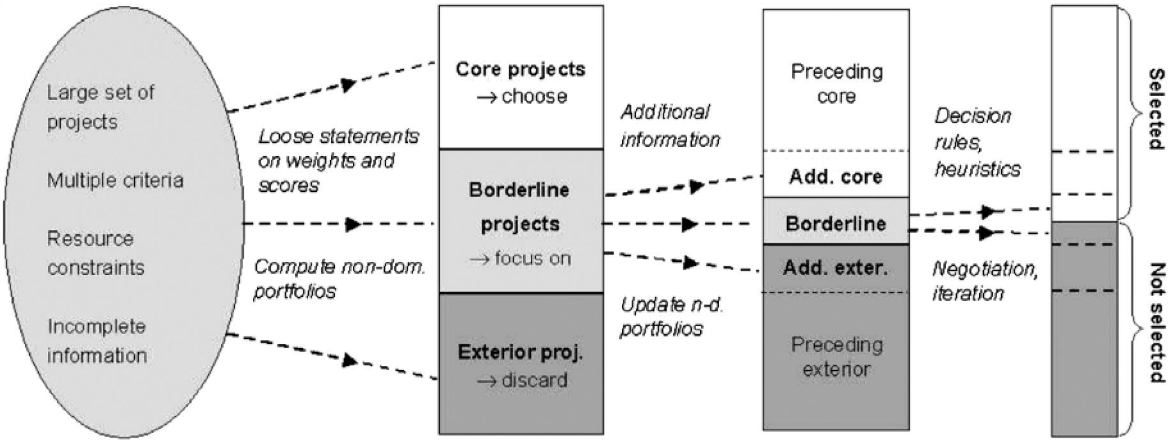


Figure 5. RPM decision support process (Liesiö et al. 2007)

2.4.2 RPM in environmental decision making

Even though RPM is over a decade old method, its environmental applications are minor. Until now the applications of RPM have limited mostly on infrastructure maintenance projects (Liesiö et al. 2007; Mild et al. 2015; Sacco et al. 2019), R&D project selection (Lindstedt et al. 2008) and forestry (Könnölä et al. 2011). Environmental applications where RPM is used to real-life data are therefore lacking from the literature.

Even though the environmental applications of RPM have been limited, it is expected to have a great potential in the field of environmental decision making. In such decisions the data usually cannot perfectly illustrate the impacts of actions as they might be unknown (Lahtinen et al. 2017). The multiple stakeholders and their abilities to give exact preference statements bring also additional uncertainties to the decision process. With RPM method some of these uncertainties included in environmental decision making could be captured with the help of its flexible preference statements.

2.5 Conclusions of the theory

It needs to be noted that these modeling methods cannot provide objective facts about how to solve these environmental decisions (Huesemann, 2002). All decision methods are only reflections of their decision makers preferences and therefore subjective respect to those who are chosen to act as the decision makers to the process. The right selection of stakeholders is therefore crucial to the environmental decision-making processes.

There is a vast number of different methods to help the decision-making process. These decision methods have evolved to comprehend easy-to-use heuristic methods, single decision problems and portfolio selection. The differences of these methods are summarized in Table 3. However, the literature reveals that there is also a gap regarding environmental decision making and its real-life portfolio applications.

Table 3: Summarizing table of the different modeling methods

Method	Solves	Pros	Cons
Heuristic methods	Single decision / portfolio	Easy-to-use, Fast	No optimal allocation of limited resources
MCDA	Single decision	Provides optimal solution	Limitations in portfolio selection applications, Consistency problems (AHP), Time-consuming process
PDA	Portfolio	Provides optimal solution	Time consuming process to get correct function forms and preferences
RPM	Portfolio	Can handle incomplete information, Less time consuming than PDA	No single optimal solution (Provides non-dominated frontier)

3 Case: Peatland selection

Finland is the peatland-richest country in Europe but even here over half of the area is drained mainly for forestry and agricultural purposes (The Finnish Ministry of Environment, 2015). Peatland is a wetland area which is considered as a resource since it provides timber and peat for energy production. It also creates additional value by supporting biodiversity, storing carbon, improving water quality and abatement of floods (Zedler and Kercher, 2005). Peatlands also hold recreational value for the community.

Due to peatland importance, national and regional level planning and environmental permits are required for energy peat production (Kurttila et al. 2020). Especially peatlands containing undrained parts are under close supervision and require extra clearance while planning the usage of the peatland (The Finnish Ministry of Environment, 2015). Lerche et al. (2019) have also identified the importance of higher administrative coordinator in energy production planning since it brings legitimacy to the process.

There are some challenges regarding the peatland selection process. Tolvanen et al. (2013) have researched the trade-offs and conflicting interest among different stakeholders in peatland selection processes. The challenge is that whereas peat production might be good for the economy of the area (Tolvanen et al. 2013) rare ecosystems are destroyed while selecting peatlands to energy production or draining them (Zedler and Kercher, 2005). Consensus is not realistic among all the parties but a compromise solution is achievable (Tolvanen et al. 2013). This is especially important as the participants are more engaged to the decision if they have been participating to the actual process (Lerche et al. 2019)

Peatland selection includes the same challenges as other environmental decision problems. Next will be introduced the context of this peatland selection case. After this background information the process conducted by LUKE’s (Natural Resources Institute of Finland) decision support method YODA is shown. Finally, the gathered data from the YODA process is presented which is used for the empirical part of this thesis.

3.1 Context of the case

During the years of 2010-2018 the Council of the Oulu Region was responsible for conducting the new Regional Master Plan of Northern Ostrobothnia in northern Finland. The regional administrative agencies are in charge of the environmental permits under Finland’s Water Act and Environmental Protection Act (The Finnish Ministry of Environment, 2016).

Therefore, these Master Plans are responsible of setting frameworks for the land usage in the area. Regarding the peatland planning, the council needed to balance between the multitudinous environmental, economical and social objectives.

Related to this planning process, Kurttila et al. (2010) conducted their case study in 2016-2017 regarding which peatlands should be selected to energy peat production. The case study area was Vaala municipality whit area of 1764 km^2. The municipality is presented in Figure 6 with land use information. From this total area 746 km^2 can be classified as peatlands. Also, several peat productions sites and protection areas are located within the boundaries.

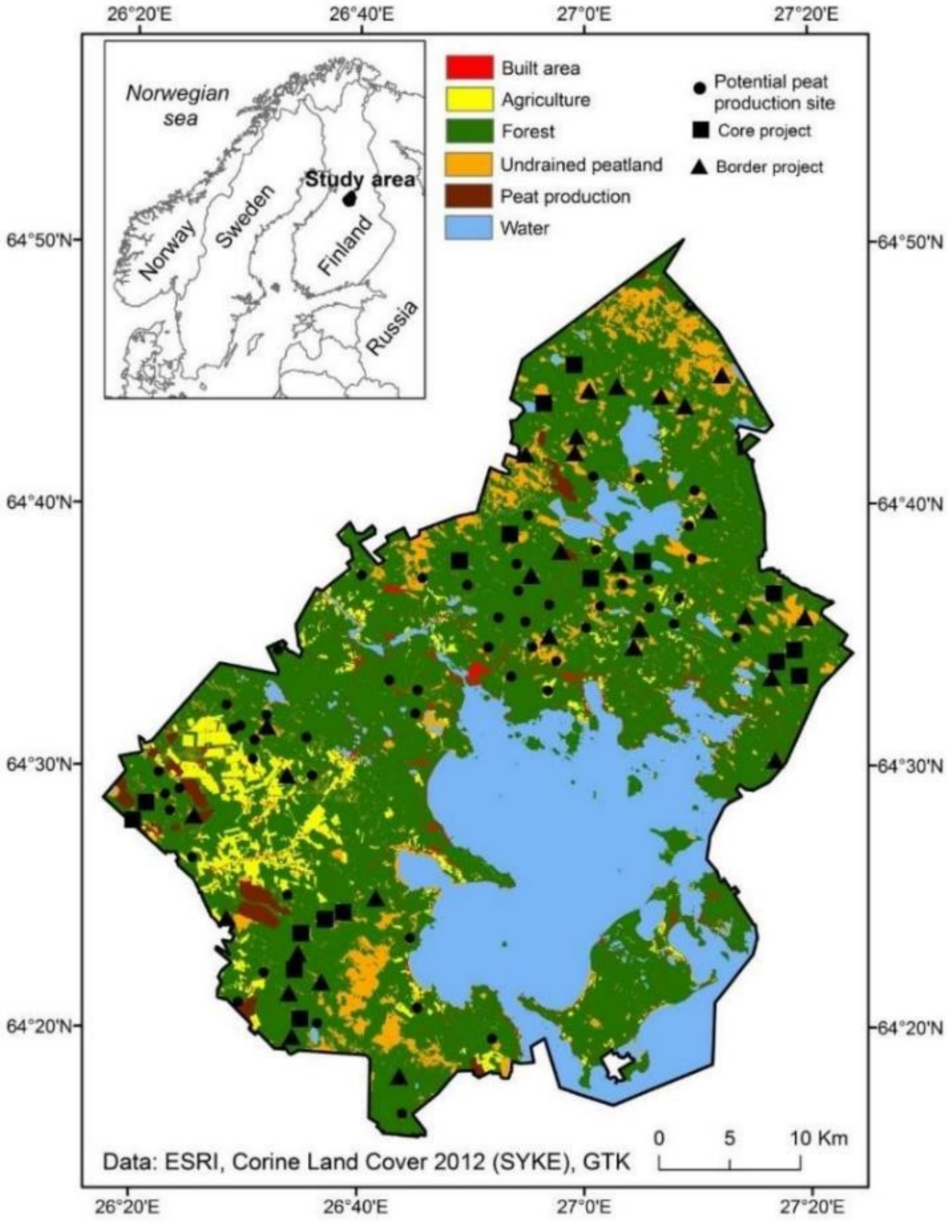


Figure 6. Peatland locations and situation symbols after the second YODA round (Kurttila et al. 2020)

Based on geological researches, Vaala has still plenty not utilized peatland areas with thick-peat which makes them suited for energy peat production. The target level of total area of planned new energy peat production sites should be at least 2000 ha for the Master Plan which was set by The Council of Oulu Region and The Council of Kainuu. However, Kurttila et al. (2020) identify that this is actually about twice the amount that would actually be putted to production as there need to be options. In practice, general public and the house owners can still later on challenge the usage of the selected sites, even though the planning process has already included hearings.

The objective 2000 ha of peatlands are supposed to be selected among 99 peatland candidates identified by the Geological Survey of Finland (GTK). Criteria used for these site identifications were mean peat thickness, which should be over 1.5 meters, and the size of the peatland site basin, which should be over 10 ha. From these 99 candidates a shortlist of 67 most promising candidates was also identified. These 67 peatland areas were selected by setting a minimum 0.5 km level of distances from groundwater and nearest conservation site. The selection of peatlands was then conducted from these candidates.

3.2 Previous YODA method

LUKE has created YODA ("Your Own Decision Aid") to help them in their decision-making processes. YODA is a web-based decision software that employs interactive data visualization. What it does is that by changing acceptance levels of each evaluation criterion some projects are rejected and others accepted by different decision makers. The main idea is to involve all relevant stakeholders and find a commonly acceptable solution with the help of easy to use visualized software. The steps of YODA decision process are the following according to Kurttila et al. (2020):

1. Decision makers define the acceptable threshold values for all of the evaluation criterion in the visual YODA interface.
2. Results of the decision makers can then be obtained. Decision makers should continue changing the acceptance levels until all constraints are met. In this peatland case the portfolio level goal was the total production area of 2000 ha.
3. The results from the different decision makers are then combined. The combined results are divided into core, borderline and exterior projects

according to Liesiö et al. (2007) recommendation. The borderline projects are also divided into two sub-groups: strong borderline projects with for example over 80% of decision makers accepting and weak borderline projects.

4. The combinational results will be formed by selecting all core projects. Since core projects will not satisfy all the constraints also some additional borderline projects need to be selected. The decision of whether a borderline project could be accepted is done based on negotiations of the different decision maker parties.
5. The selected project portfolio of this process will include only projects accepted by all decision makers while respecting all the constraints.

This process of Kurttila et al. (2020) is also illustrated in the Figure 7.

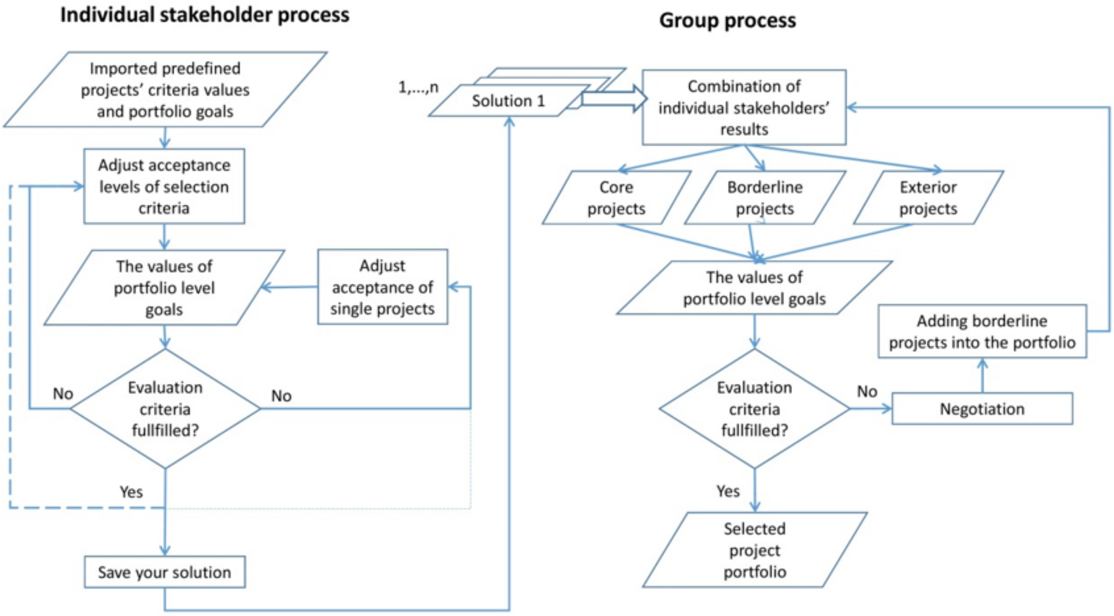


Figure 7. Illustration of YODA process with individual and group level (Kurttila et al. 2020)

The YODA process was done in two rounds during the peatland selection process. On the first round 13 different stakeholders representing regional and national administration, forest owners, conservationists and peat production companies conducted their individual preferences with YODA. However, not a single mutually accepted peatland could be identified. Stakeholders were rejecting too many peatlands as they accepted less than 2000 ha which was the minimum area requirement.

On the second round of the decision making some of the evaluation criteria were changed. Also, this final round included only 4 key stakeholders. As a result, 2400 ha of peatland could be agreed. However, due to later discussions in the land use planning, the final Regional Master Plan included only 1432 ha of peatlands. These results from the two YODA rounds indicate that with too many decision makers YODA cannot perform that well especially if the decision makers do not respect the agreed goals. On the other hand, during the second round with only few participants the stakeholders were able to agree on the needed amount.

Ordinary YODA was created to solve a single decision alternative but Kurttila et al. (2020) have expanded it usage to cover also this portfolio peatland selection process. YODA focus on to find mutual understanding between the decision parties instead of finding the mathematically optimal solution. Tervonen et al. (2017) argue that these kind of practical decision methods that allow iterative project selection and rejection are in a sense heuristic as the current literature does not offer formal methods for such situations.

Even though the stakeholder participation and easy to use visual application of YODA are valued features there are however still some issues in this decision method. First of all, it does not optimize portfolio performance. Instead it relies on the assumption that introducing threshold constraints on the criteria at the individual project level, results in desirable portfolio level performance. This might lead to insufficient allocation of limited resources. It also allows the decision makers to cancel out too many projects as seen in the first round of peatland selection. It has also been noticed that if participants are allowed to obtain their individual results, they are less eager to find a common solution as they have already developed an ownership of their own results (Belton and Pictet, 1997). Lastly YODA compares different portfolios based on their criterion-specific sums even though the criterion-specific performance levels are not always linearly comparable (Lahtinen et al. 2017).

Due to these limitations of YODA method, RPM is applied to the same decision problem. The goal is to see does RPM, which has been discussed more in the current literature, performer significantly better than more heuristic YODA. It is important to identify how much the more time-consuming RPM method can actually improve the results as sometimes a process requiring less resources with a good enough result could be preferred.

3.3 Data

The different peatlands were valued through eleven different criteria from which eight were selected to the final YODA process. These criteria and their definitions are presented in Table 4.

Table 4: Decision criteria of the two YODA rounds (Kurttila et al. 2020)

i	Criterion	Measure	Definition	Range of performance levels	YODA round
1.	*Production area*	*ha*	Area of the potential energy peat production site	11 - 216	1, 2
2.	*Groundwater*	*m*	Distance to the nearest groundwater area	0 - 6383	2
3.	*Settlement*	*m*	Distance to the nearest settlements	0 - 12539	2
4.	*Degradation class*	-	Naturalness class: 0: Irrecoverable changed (in water management and vegetation) 1: Water management changed throughout; vegetation changes clear 2: Both drained and undrained parts 3: Most of the peatland is undrained 4: Some distractions (dikes, roads etc.) at the edges of the peatland but no visible effects to the peatland 5: No distractions for the peatland	0 - 4	1, 2
5.	*Biodiversity*	-	Biodiversity indicator based on: 1) Habitat type 2) Peatland complex type and geomorphological formations 3) Presence of threatened plant and bird species 4) Habitat connectivity 5) Coverage of undrained peatland area 6) Habitat suitability for threatened mire plant site	0.1 – 22.03	1, 2
6.	*Heating*	*Mg gas/m²/year*	Climate-warming effect if energy peat production takes place. Based on CO_2, CH_4 and N_2O	1927 – 4026.8	1, 2
7.	*Phosphor*	*kg/ha*	Phosphor load to the water courses if energy peat production takes place	0.035 – 0.403	1,2
8.	*Estates*	*n*	Number of land owners within the potential peat production project	1 - 27	2
-	*Energy content*	*GWh*	Energy content of peat		1
-	*Monetary value*	*€*	The monetary value of tree stands in the potential peat production project		1
-	*State-owned land*	*%*	Share (%) of state-owned land within the potential peat production project		1

As there were two rounds in the YODA decision process, also the used criteria have evolved during the process. Distance from “Groundwater” and “Settlement” and “Number of estates” have been considered to complement the other criteria better than the original “Energy content”, “Monetary value” and “Percent of stated-owned land”. This change in criteria reflects the shift of focus in the decision problem to consider more environmental aspects and the public of the area instead of the profits of the energy production. This makes the decision on hand to be truly environmental decision problem.

Most of the factors of the criteria calculations are quite logical but some might need some additional explanation. All of the criterion-specific performance levels have been calculated with the help of Geographical Information System (GIS). The “Degradation class” is on the other hand based on the recommended class distributions by The Finnish Ministry of Environment (2015). The areas of consideration in “Biodiversity” are also based on The Finnish Ministry of Environment but the calculations have been conducted by the research group of Kurttila et al. (2020).

There are two main datasets used for the purposes of this thesis: 1) the compilation dataset and 2) the final preference dataset. These datasets are provided by LUKE who were part of the original YODA process. In addition to these, a dataset with the information of the 67 more potential peatlands and also the preferences on the first YODA round were available. However, the final preference dataset was selected as the main source of preference information as 3/8 of the criteria has change between the two YODA rounds leaving the first rounds results disparate. The final recommendation for the Regional Master Plan was also done based on the second YODA round.

The compilation dataset contains the criterion-specific information of each of the 99 potential peatland areas. In addition, this dataset also holds the knowledge of which peatlands were selected at the final YODA round and by how many of the participants have agreed. The outcomes of the criterion-specific performances are especially useful when determining the baseline values and scaling the ranges of the criterion-specific value functions. YODA and RPM result comparison is also conducted from these outcomes.

The final preference dataset contains the data from the actual YODA decision process. It illustrates how the four key decision makers have rejected different projects and regarding which criterion the rejection has been done. This information is crucial when forming the preference relations and value function forms of the decision makers as the RPM is conducted only based on data.

Both of the provided datasets were mostly of high quality and did not require much preprocessing. The compilation data was missing one peatland that was a part of the preference dataset. However, as this missing project was rejected by all of the decision makers, it was simply neglected. The preference dataset also showed some inconsistencies of the peatland rejections but this is not a shortcoming of the data itself but illustrates that the decision makers have been able to reject separately some peatlands in addition to the acceptance level monitoring. This however challenges the process of capturing the underlying preferences of the different decision makers.

4 RPM in peatland selection

In the following section, the introduced data is applied to a Robust Portfolio Modeling framework. It will start with elaborating the forms of the value functions. After this the corresponding preferences are identified. Next the modeling phase and results are introduced and finally the RPM solutions are compared against YODA's.

4.1 Value function

In portfolio decision analysis the value function does not only capture decision makers differences among the different criteria but also preferences among different project combinations. Linear-additive function has been selected for the modeling purposes as it is traditional and widely used value function form. As the purpose of this thesis is not to test new value function performance and there are no resources to identify all multilinear function parameters, additive function appears as the best fitted option. Also, all criteria of this peatland selection measure different aspects of the decision problem. It is expected that the decision makers would consider each of these criteria separately from the levels of the others. Therefore, the preference independency axiom of additive function is not discarded.

Here the value function evaluates $m = 99$ peatlands with regard to $n = 8$ criteria indexed $i \in I = \{1, \ldots, n\}$. The performance of project j is represented by row vector $x^j = (x_1^j, \ldots, x_n^j)$, where x_i^j is its performance with respect criterion i. The overall value of project j is given by the additive value function

$$v(x^j) = \sum_{i=1}^{n} w_i v_i(x_i^j), \tag{3}$$

which multiplies the criterion-specific value functions $v_i(x)$ with corresponding weights w_i. Weights capture decision makers preferences of different projects while the values simultaneously respect the rule $\sum_{i=1}^{n} w_i = 1$. The measurement scale is also normalized in each criterion so that the most preferred performance level $v_i(x_i^*) = 1$ and least preferred performance level $v_i(x_i^0) = 0$ (Dyer and Sarin, 1979).

This peatland selection optimization model can be presented as an integer linear programming (ILP) model. The idea is to maximize the overall value of this peatland portfolio selection while satisfying the given minimum level for total area selected for energy production. This results in the optimization problem

$$\sum_{j=1}^{m} v(\underline{x}^{j}) + \max_{z\in\{0,1\}} \left\{ \sum_{j=1}^{m} z_j \left[v\left(\overline{x^{j}}\right) - v(\underline{x}^{j}) \right] \;\middle|\; \sum_{j=1}^{m} x_1^{j} z_j \geq 2000 \right\}, \tag{4}$$

where $\overline{x^j}$ corresponds the project's performance and $\underline{x}^j = (\underline{x}_1^j, \dots, \underline{x}_n^j)$ is the project's baseline performance (i.e. the performance the project is assigned if it is not selected). The binary variable z_j reflects this selection as it is equal to 1 if the project is selected and otherwise 0. The constraint of selecting at least 2000 ha of peatland production area is presented at the right on the equation (4). It is the sum of the production area x_1^j of each project. The binary variable z_j ensures that only the projects that are selected are counted for this constraint production area.

In this thesis the method to figure out baseline values has been selected to be criterion-specific. This is due to the fact that as the weights are already flexible, having flexible baseline values would make the model to be too indefinite. Keeping the status quo reasoning of Clemen and Smith (2009) in mind, the criterion-specific baseline values were determined from the case data. These baseline performances before value function mapping are presented at Table 5.

Table 5: Summary of criterion-spesific baseline performances

x^j	Criterion	Baseline performance $\underline{x_i}$
1	*Production area (ha)*	0
2	*Distance from settlement (m)*	10 000
3	*Distance from groundwater (m)*	15 000
4	*Degradation class (-)*	Current Degradation class
5	*Biodiversity (-)*	Current Biodiversity
6	*Additional heating effect (Mg gas/m²/year)*	0
7	*Additional phosphor effect (kg/ha)*	0
8	*Number of estates near (n)*	0

The baseline performances presented in Table 5 are chosen to represent the situation of not selecting the project. If the peatland is not selected, its corresponding "Production area", additional "Heating" and "Phosphor" effect and "Number of nearby estates" will be zero since there will not be effect from these criteria performances. Applying the same logic, there will not be any changes to the levels of “Degradation class” and “Biodiversity” since the peatlands will stay intact. These criteria will therefore get their corresponding performance values from the data. What comes to the distances from “Settlement” and “Groundwater”, maximum performance is selected as the base value, since without selection the distance will be as far as possible.

4.1.1 Criterion-specific value functions

The specification of criterion-specific value functions requires determining the performance range of each criterion. Table 6 presents the performance range of each criterion obtained from the data and also the selected range for modeling purposes. The determination process for the performance values has differed between criteria. After discussing with experts, it became clear that there are no Finnish level maxima for the performances since the sizes and types of peatlands vary a lot over Finland. Some of the criteria like “Biodiversity” have also been calculated specifically for the Vaala region. “Degradation class” forms an exception as it is based on classification of Finnish Ministry of Environment (2015).

Table 6: Summary of criterion-pesific performances in data and used in modeling

x^j	Criteria	Performance range in data	Performance range used in modeling
1	*Production area (ha)*	11 - 216	0 - 250
2	*Distance from settlement (m)*	0 – 6 383	0 – 10 000
3	*Distance from groundwater (m)*	0 – 12 539	0 – 15 000
4	*Degradation class (-)*	0 - 4	0 - 5
5	*Biodiversity (-)*	0.1 – 22.03	0 - 25
6	*Additional heating effect (Mg gas/m²/year)*	1 927 – 4 027	0 – 5 000
7	*Additional phosphor effect (kg/ha)*	0.03 – 0.40	0 – 0.5
8	*Number of estates near (n)*	1 - 27	0 - 30

Based on the above explanation, the performance range in modeling has been selected mostly based on the values in the provided dataset. However, Morton (2015) demonstrates how adding one more project with higher performance than in the original dataset might change the preference ordering of the projects if the modeling performance levels have been chosen to be equivalent to the extreme performance values in data. Therefore, it is better to have wider range of performance values for the criterion-specific value function modeling. The same logic has been applied for this RPM modeling as the values of performance range has been selected to be greater than the range of original dataset.

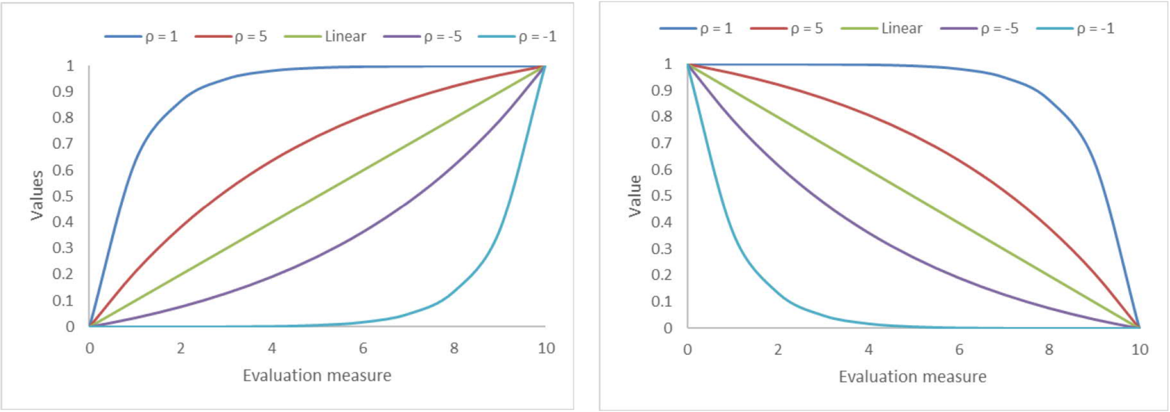
All of the four key decision makers also seemed to exclude projects with similar manner. They determined the acceptance level threshold values by rejecting projects greater than or less than the threshold value depending on each criterion. This similar approach supported the view of using either aggregating or comparing procedures in group decision making from Belton and Pictet (1997). Also, as their research has recognized that differences mostly occur in preferences and not in value function forms, it has been selected to use general criterion-specific value function forms which are aggregated from the individuals' preference data.

Exponential value functions were chosen to capture the criterion-specific values since they allow to conduct sensitivity analyses easily. These value functions are also monotonically increasing. The exponential single dimension value function equations

$$\text{Increasing} \qquad v(x) = \begin{cases} \dfrac{1-e^{\frac{-(x-min)}{\rho}}}{1-e^{\frac{-(max-min)}{\rho}}}, & \rho \neq \infty \\ \dfrac{x-min}{max-min}, & otherwise \end{cases} \qquad (5)$$

$$\text{Decreasing} \qquad v(x) = \begin{cases} \dfrac{1-e^{\frac{-(max-x)}{\rho}}}{1-e^{\frac{-(max-min)}{\rho}}}, & \rho \neq \infty \\ \dfrac{max-x}{max-min}, & otherwise \end{cases} \qquad (6)$$

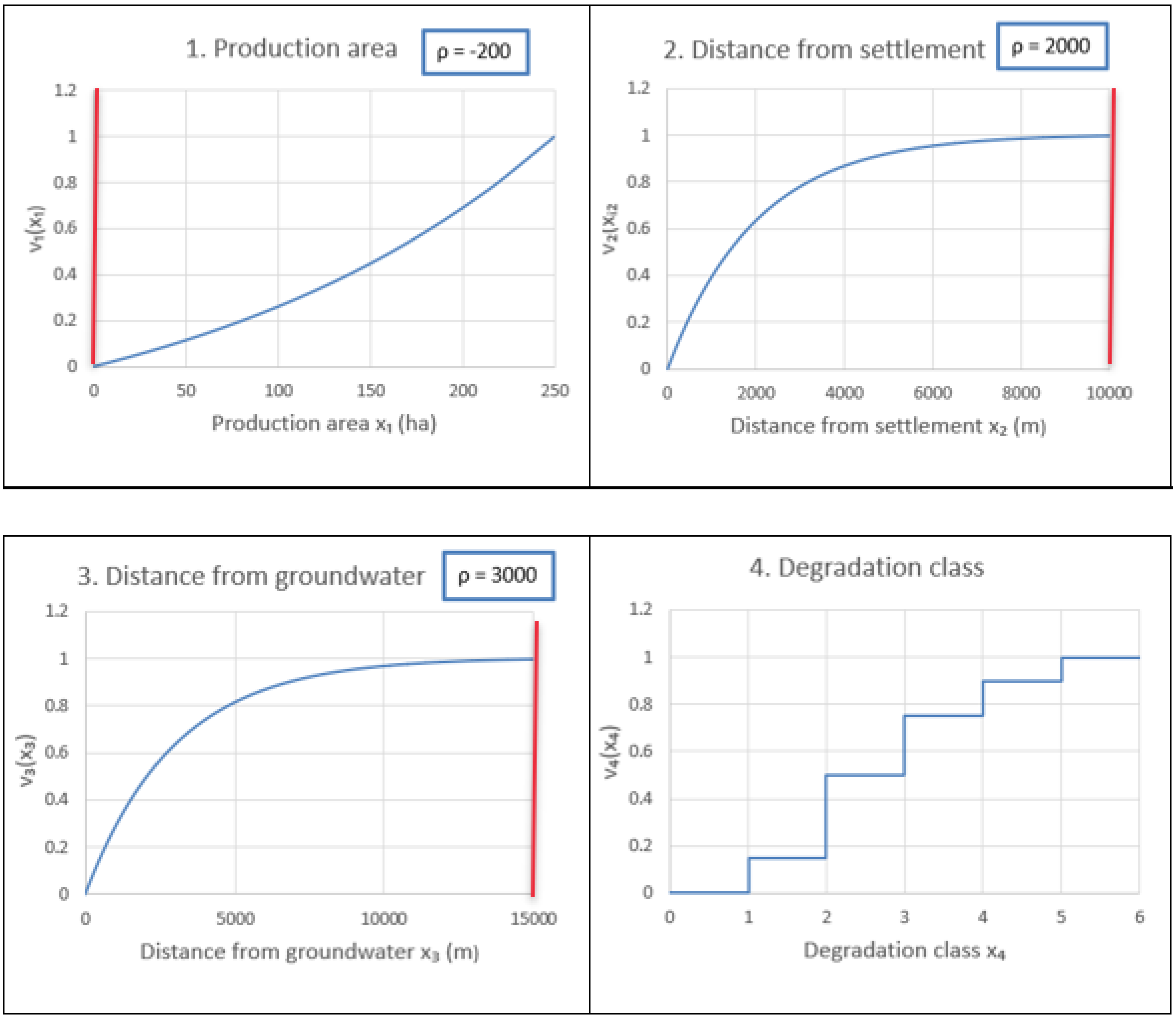
present the general criterion-specific value function form by Kirkwood (1996). By changing the parameter ρ values the form of the function will change from linear to more convex or concave as presented in the Figure 8.



a) Increasing preferences b) Decreasing preferences

Figure 8. Criterion-spesific value function forms

The selected criterion-specific value function forms are presented in Figure 9. The value function for other criteria except for the “Degradation class” are modeled using the exponential single dimension value function by Kirkwood (1996). In the modeling phase, sensitivity analyses are conducted and therefore, these figures are directive forms of the functions. All of the functions are also normalized in a range [0, 1] where least preferred level is $v_i(x^0) = 0$ and most preferred level $v_i(x^*) = 1$ (Dyer and Sarin, 1979).



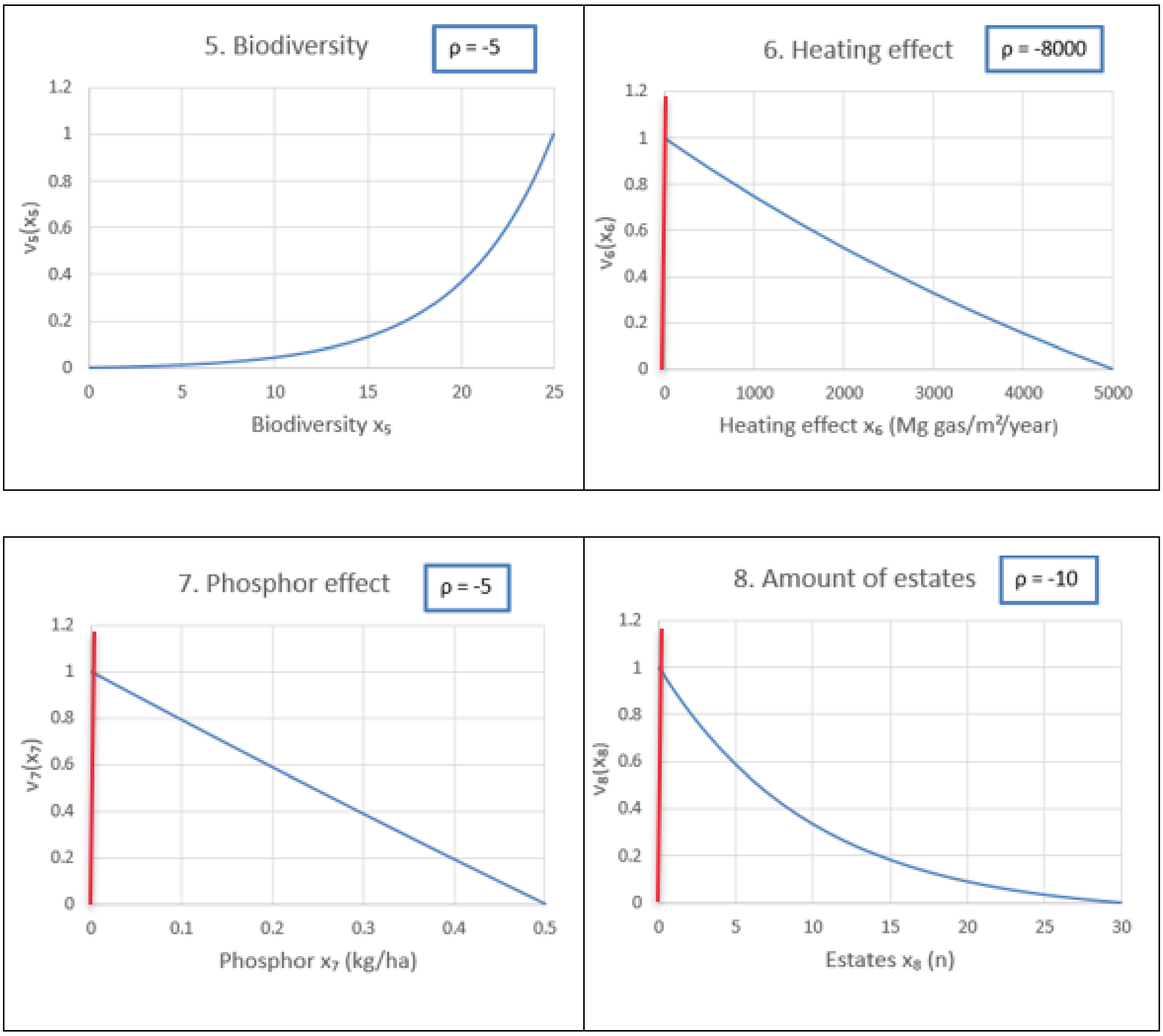


Figure 9. Criterion-spesific value function forms

The functional forms presented in Figure 9 reflect the insights gathered from the preference data. For the "Production area" criterion, smaller areas were more eagerly neglected than larger ones. Regarding criteria "Distance from settlement" and "Distance from groundwater" the 100 meters at the beginning are significantly more valued than the same 100 meters when the distance is already over kilometers. At the end the distance is already far and additional meters would not matter that much anymore. "Degradation class" has only 5 classes where 0-1 and 2-5 are treated as two slightly separate classes according to classification of Finnish Ministry of Environment (2015). In "Biodiversity" it was observed that all performances below 16 were not that valued and therefore further increasing curve is selected. "Heating effect", "Phosphor effect" and "Amount of estates" were all criteria where smaller performance values are more valued and therefore the functions are decreasing.

These criterion-specific value function forms determine that the portfolio level value function is maximised. All criterion-specific value functions perform so that the baseline values are worth more than selected projects' values. These baseline values are presented with red line in Figure 9. In "Degradation class" and "Biodiversity" the baseline values are the projects' corresponding performances as the nature will stay intact, whereas if the project is selected it will lose its value and be assigned $v_i(x^0) = 0$. Therefore, maximizing the portfolio level value function is actually same as minimizing the harmful effect to the environment.

4.1.2 Preferences

After the value function forms are determined the weights representing the decision makers' preferences need to be identified. Correct weight selection is important as they capture the decision makers preferences more precisely than value function forms (Belton and Pictet, 1997). RPM enables incomplete preference information instead fixed values (Liesiö et al. 2007). This makes the result less sensitive to borderline cases where small change in weights could affect to the suggested end-portfolio.

The preference relations of the different decision makers have been identified from the provided final preference dataset. From this dataset the amounts of how many projects a single decision maker has excluded based on certain criterion has been calculated. Based on the results it seems that all four of the decision makers have differing priority orderings, as is typical in environmental decision making. One exception to this is that all four of the decision makers valued high the "Distance from groundwater". However, this was an agreed objective from the preparatory phase (Kurttila et al. 2020) reflecting a common goal for this process.

The weights of RPM are presented as preference relations. Park et al. (1996) have suggested to use dominance-based weak ranking $w_1 \geq \cdots \geq w_n$ to identify the preferences from incomplete information. This notation is also used to illustrate the preference relations of our four decision makers. Based on the selections in the dataset, two alternative preference information rankings are identified. For option 1, aggregating option form Belton and Pictet (1997) is applied. Here the following preference relations have been identified to hold between all of the decision makers at the dataset. In option 2, all of the four decision makers are modeled separately based on their individual excluding options from YODA.

I. Consensus preference information

$w_3 \geq w_1, w_2, w_4, w_6, w_7, w_8$

$w_2 \geq w_8$

II. Decision maker specific preference information

$DM1$: $w_3 \geq w_6 \geq w_1, w_2 \geq w_4 \geq w_5, w_7, w_8$

$DM2$: $w_3 \geq w_1 \geq w_7 \geq w_2 \geq w_8 \geq w_5 \geq w_4, w_6$

$DM3$: $w_3 \geq w_4 \geq w_2 \geq w_8 \geq w_7 \geq w_5 \geq w_1, w_6$

$DM4$: $w_5 \geq w_3 \geq w_4 \geq w_6 \geq w_7 \geq w_2 \geq w_1 \geq w_8$

The logic of having these two preference models is the following. Similar to criterion-specific value functions, weights perform a significant role in environmental decision making. According to Belton and Pictet (1997) weights reflect the individual preferences more precisely than value function forms. Therefore, it is important to compare the results between common preferences and individual preferences so that no core preference relations are lost especially when conflicting preferences are possible. On the other hand, Vilkkumaa et al. (2014) remark that sometimes individual modeling might not find a suitable solution even though it might be preferred approach. They recommend to use both individual and combined preference models in order to be able to solve these stalemate situations. This result motivates the use of the consensus preference model.

4.2 Modeling

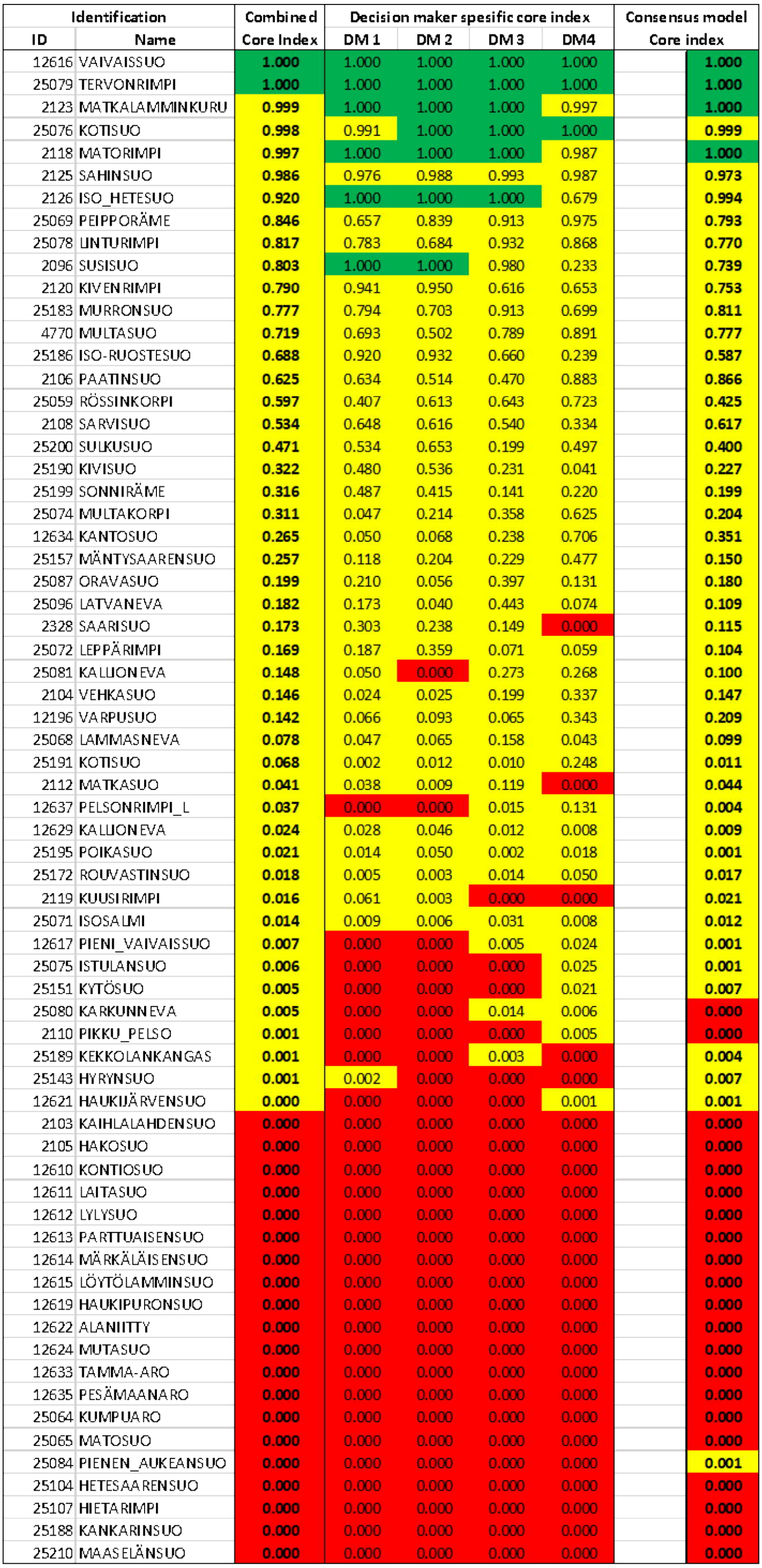
RPM Decisions software is a portfolio decision analysis software that can cope with incomplete preference information (Liesiö et al. 2007, 2008; see also Lahtinen et al. 2017). This Java based decision software can identify all non-dominated portfolios up to 100 projects depending on the complexity of the rest of the model. In addition, the software is provided with an approximate algorithm which can solve most of the non-dominated portfolios even with larger project amounts. For the purposes of this thesis the approximate algorithm was the main solver used as it gives satisfactory results with faster computation. The exact solver was tested but the running times were considerably longer, causing memory errors. For further details of the RPM software see http://rpm.aalto.fi.

The input of this RPM software is in spreadsheet form. The entered values of each portfolio are in the difference form between the criterion-specific value function value and baseline value as presented in equation (4). The “Production area” is the only criterion with positive difference values where others present the negative effects if the peatland is selected. Due to this, the overall portfolio values are also negative. The feasibility constraint’s lower bound is 2000 ha of production area as stated in the case description. Finally, the preference orders are given in interval-valued weight statements, e.g. $w_3 - w_1 > 0$ represents the preference that criterion 3 is more important than criterion 1.

4.3 RPM results

According to Vilkkumaa et al. (2014) it is advisable to first try to recognize all the non-dominated portfolio options that are common to all decision makers in individual modeling level. In Figure 10 the modeling results of the shortlist of 67 peatlands are presented. We refer to the decision maker specific preference models as a **combined model** and the model with consensus preference as a **consensus model**. In combined model the decision maker specific preferences are combined to a combined core index which is the average of the decision makers individual core index values. There are only two peatlands that are core projects to all of the four decision makers which indicates that at least these should be chosen to the end portfolio. Surprisingly despite the conflicting interests of the four decision makers preferences, the core index is mostly in similar level in each decision makers list. This indicates that some projects are seen more appealing regarding their starting performance despite the differences in criterion preferences.

However, there might have been a situation where these common non-dominated portfolios could not have been easily identified. In those situation Vilkkumaa et al. (2014) recommend to use the consensus group preferences for modeling. As the combined model could already identify some common projects from the decision maker specific preferences, the consensus model was conducted here merely for comparison. In Figure 10 it is seen that this consensus model has also selected mostly the same peatlands than the combined model from the decision maker specific models. This gives the legitimacy to the received results.



Identification		Combined	Decision maker spesific core index				Consensus model
ID	Name	Core Index	DM 1	DM 2	DM 3	DM4	Core index
12616	VAIVAISSUO	1.000	1.000	1.000	1.000	1.000	1.000
25079	TERVONRIMPI	1.000	1.000	1.000	1.000	1.000	1.000
2123	MATKALAMMINKURU	0.999	1.000	1.000	1.000	0.997	1.000
25076	KOTISUO	0.998	0.991	1.000	1.000	1.000	0.999
2118	MATORIMPI	0.997	1.000	1.000	1.000	0.987	1.000
2125	SAHINSUO	0.986	0.976	0.988	0.993	0.987	0.973
2126	ISO_HETESUO	0.920	1.000	1.000	1.000	0.679	0.994
25069	PEIPPORÄME	0.846	0.657	0.839	0.913	0.975	0.793
25078	LINTURIMPI	0.817	0.783	0.684	0.932	0.868	0.770
2096	SUSISUO	0.803	1.000	1.000	0.980	0.233	0.739
2120	KIVENRIMPI	0.790	0.941	0.950	0.616	0.653	0.753
25183	MURRONSUO	0.777	0.794	0.703	0.913	0.699	0.811
4770	MULTASUO	0.719	0.693	0.502	0.789	0.891	0.777
25186	ISO-RUOSTESUO	0.688	0.920	0.932	0.660	0.239	0.587
2106	PAATINSUO	0.625	0.634	0.514	0.470	0.883	0.866
25059	RÖSSINKORPI	0.597	0.407	0.613	0.643	0.723	0.425
2108	SARVISUO	0.534	0.648	0.616	0.540	0.334	0.617
25200	SULKUSUO	0.471	0.534	0.653	0.199	0.497	0.400
25190	KIVISUO	0.322	0.480	0.536	0.231	0.041	0.227
25199	SONNIRÄME	0.316	0.487	0.415	0.141	0.220	0.199
25074	MULTAKORPI	0.311	0.047	0.214	0.358	0.625	0.204
12634	KANTOSUO	0.265	0.050	0.068	0.238	0.706	0.351
25157	MÄNTYSAARENSUO	0.257	0.118	0.204	0.229	0.477	0.150
25087	ORAVASUO	0.199	0.210	0.056	0.397	0.131	0.180
25096	LATVANEVA	0.182	0.173	0.040	0.443	0.074	0.109
2328	SAARISUO	0.173	0.303	0.238	0.149	0.000	0.115
25072	LEPPÄRIMPI	0.169	0.187	0.359	0.071	0.059	0.104
25081	KALLIONEVA	0.148	0.050	0.000	0.273	0.268	0.100
2104	VEHKASUO	0.146	0.024	0.025	0.199	0.337	0.147
12196	VARPUSUO	0.142	0.066	0.093	0.065	0.343	0.209
25068	LAMMASNEVA	0.078	0.047	0.065	0.158	0.043	0.099
25191	KOTISUO	0.068	0.002	0.012	0.010	0.248	0.011
2112	MATKASUO	0.041	0.038	0.009	0.119	0.000	0.044
12637	PELSONRIMPI_L	0.037	0.000	0.000	0.015	0.131	0.004
12629	KALLIONEVA	0.024	0.028	0.046	0.012	0.008	0.009
25195	POIKASUO	0.021	0.014	0.050	0.002	0.018	0.001
25172	ROUVASTINSUO	0.018	0.005	0.003	0.014	0.050	0.017
2119	KUUSIRIMPI	0.016	0.061	0.003	0.000	0.000	0.021
25071	ISOSALMI	0.014	0.009	0.006	0.031	0.008	0.012
12617	PIENI_VAIVAISSUO	0.007	0.000	0.000	0.005	0.024	0.001
25075	ISTULANSUO	0.006	0.000	0.000	0.000	0.025	0.001
25151	KYTÖSUO	0.005	0.000	0.000	0.000	0.021	0.007
25080	KARKUNNEVA	0.005	0.000	0.000	0.014	0.006	0.000
2110	PIKKU_PELSO	0.001	0.000	0.000	0.000	0.005	0.000
25189	KEKKOLANKANGAS	0.001	0.000	0.000	0.003	0.000	0.004
25143	HYRYNSUO	0.001	0.002	0.000	0.000	0.000	0.007
12621	HAUKIJÄRVENSUO	0.000	0.000	0.000	0.000	0.001	0.001
2103	KAIHLALAHDENSUO	0.000	0.000	0.000	0.000	0.000	0.000
2105	HAKOSUO	0.000	0.000	0.000	0.000	0.000	0.000
12610	KONTIOSUO	0.000	0.000	0.000	0.000	0.000	0.000
12611	LAITASUO	0.000	0.000	0.000	0.000	0.000	0.000
12612	LYLYSUO	0.000	0.000	0.000	0.000	0.000	0.000
12613	PARTTUAISENSUO	0.000	0.000	0.000	0.000	0.000	0.000
12614	MÄRKÄLÄISENSUO	0.000	0.000	0.000	0.000	0.000	0.000
12615	LÖYTÖLAMMINSUO	0.000	0.000	0.000	0.000	0.000	0.000
12619	HAUKIPURONSUO	0.000	0.000	0.000	0.000	0.000	0.000
12622	ALANIITTY	0.000	0.000	0.000	0.000	0.000	0.000
12624	MUTASUO	0.000	0.000	0.000	0.000	0.000	0.000
12633	TAMMA-ARO	0.000	0.000	0.000	0.000	0.000	0.000
12635	PESÄMAANARO	0.000	0.000	0.000	0.000	0.000	0.000
25064	KUMPUARO	0.000	0.000	0.000	0.000	0.000	0.000
25065	MATOSUO	0.000	0.000	0.000	0.000	0.000	0.000
25084	PIENEN_AUKEANSUO	0.000	0.000	0.000	0.000	0.000	0.001
25104	HETESAARENSUO	0.000	0.000	0.000	0.000	0.000	0.000
25107	HIETARIMPI	0.000	0.000	0.000	0.000	0.000	0.000
25188	KANKARINSUO	0.000	0.000	0.000	0.000	0.000	0.000
25210	MAASELÄNSUO	0.000	0.000	0.000	0.000	0.000	0.000

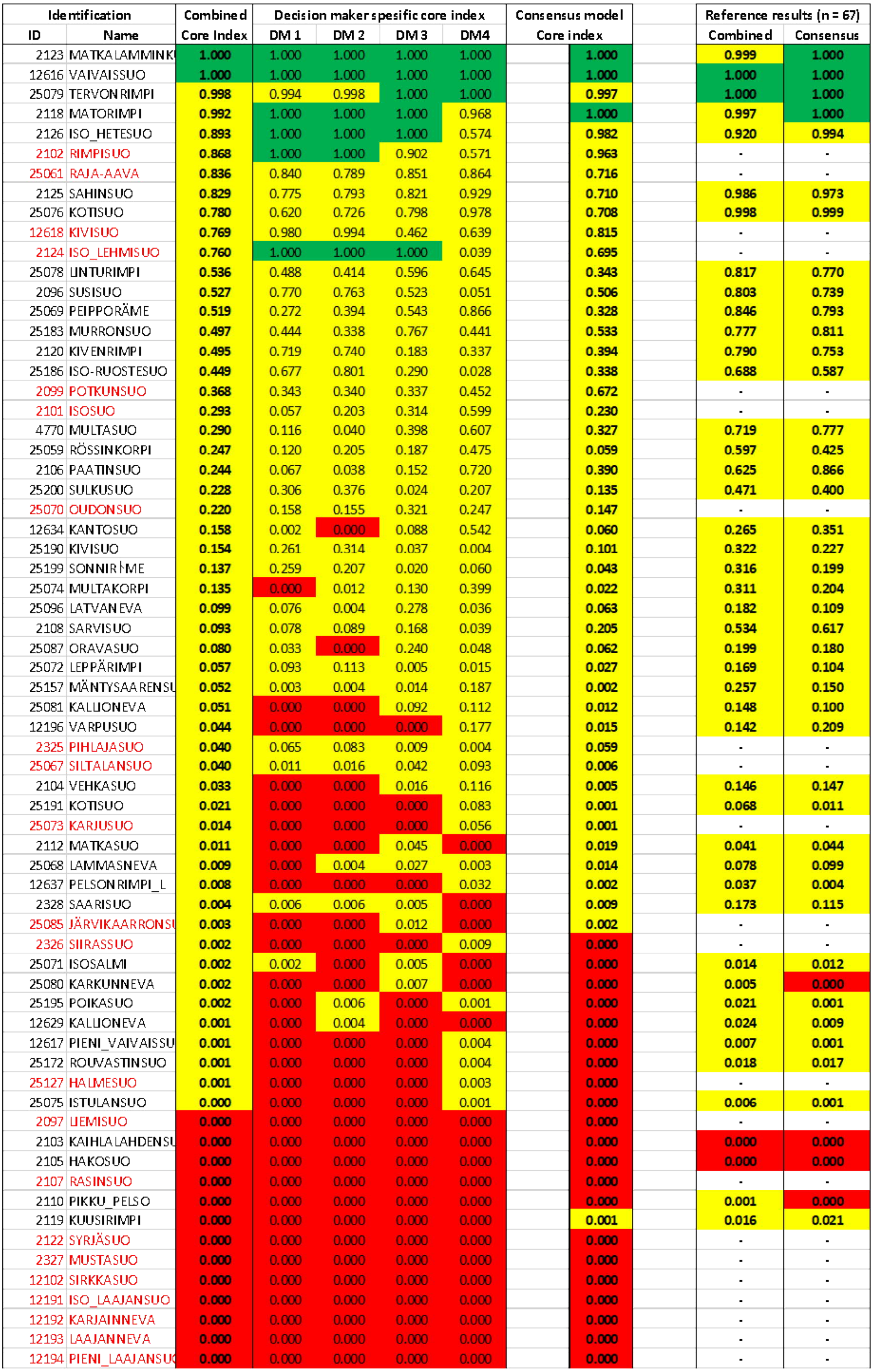
Figure 10. Core index illustartion of the 67 peatland candidates

In order to examine the stability of these results, sensitivity analyses were conducted. The uncertainties and inaccuracies associated with the model building and preference modeling are often underestimated (Bertsch et al. 2007). Sensitivity analyses can however capture these properties by illustrating the effects to the end portfolio by having small changes in weights and value function forms (Kirkwood, 1996). During the modeling several diverse models with slightly different inputs were tested to verify the result.

These sensitivity analyses illustrated the main focus areas of modelling. The main effects seemed to be related to whether the model was conducted via the decision maker specific preferences or via consensus preferences. Also, the change from peatland project lists of 67 to 99 candidate showed differences to the end portfolios. Therefore, in addition to the 67 peatland candidates, these models were also conducted with the original dataset containing all of the 99 peatland candidates. Not all from these 99 peatlands respect the constraints of having the 0.5 km minimum distance from groundwater and nearest conservation site. However, the decision makers were able to choose from all of these peatlands in the second YODA round where they were able to constrain only the distance from the groundwater but not the conservation site. For example, peatland with ID number 2102 was selected to the production in YODA even though it is not a project candidate in the shortlist of 67 peatlands. Therefore, it is important to conduct the same modeling procedure also for the whole dataset so that potential peatlands are not ignored.

Conducting the RPM with all 99 peatlands showed some significant effects to the project selection. In Figure 11 the peatland ID's missing from the 67 peatland candidate dataset are presented in red. Even though many of these new peatlands ended up at the end of the core index listing, some were performing surprisingly well being core projects of some decision maker specific models. This indicates that these highly potential peatlands should be taken back into consideration.

There are also some other differences between the core indexes of the results of 67 and 99 peatland candidate lists. The core index values are generally smaller with 99 peatlands than in the 67-peatlands modeling. This is most likely due to the grown set of project candidates were to choose which leads to a situation that more different portfolio combinations are available. There are also slight chances on the ordering of borderline projects. However, the core indexes between the combined model and consensus model are quite similar despite some small exceptions.

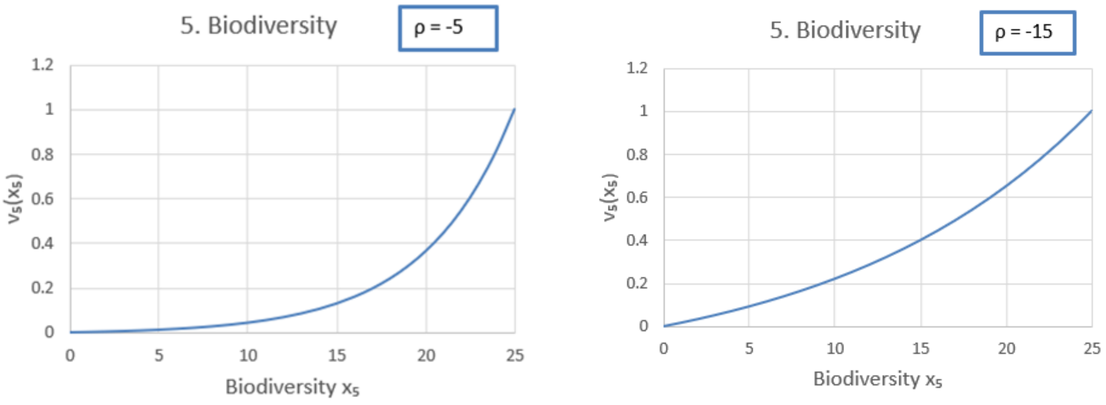


Identification		Combined	Decision maker spesific core index				Consensus model	Reference results (n = 67)	
ID	Name	Core Index	DM 1	DM 2	DM 3	DM4	Core index	Combined	Consensus
2123	MATKALAMMINK	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000
12616	VAIVAISSUO	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
25079	TERVONRIMPI	0.998	0.994	0.998	1.000	1.000	0.997	1.000	1.000
2118	MATORIMPI	0.992	1.000	1.000	1.000	0.968	1.000	0.997	1.000
2126	ISO_HETESUO	0.893	1.000	1.000	1.000	0.574	0.982	0.920	0.994
2102	RIMPISUO	0.868	1.000	1.000	0.902	0.571	0.963	-	-
25061	RAJA-AAVA	0.836	0.840	0.789	0.851	0.864	0.716	-	-
2125	SAHINSUO	0.829	0.775	0.793	0.821	0.929	0.710	0.986	0.973
25076	KOTISUO	0.780	0.620	0.726	0.798	0.978	0.708	0.998	0.999
12618	KIVISUO	0.769	0.980	0.994	0.462	0.639	0.815	-	-
2124	ISO_LEHMISUO	0.760	1.000	1.000	1.000	0.039	0.695	-	-
25078	LINTURIMPI	0.536	0.488	0.414	0.596	0.645	0.343	0.817	0.770
2096	SUSISUO	0.527	0.770	0.763	0.523	0.051	0.506	0.803	0.739
25069	PEIPPORÄME	0.519	0.272	0.394	0.543	0.866	0.328	0.846	0.793
25183	MURRONSUO	0.497	0.444	0.338	0.767	0.441	0.533	0.777	0.811
2120	KIVENRIMPI	0.495	0.719	0.740	0.183	0.337	0.394	0.790	0.753
25186	ISO-RUOSTESUO	0.449	0.677	0.801	0.290	0.028	0.338	0.688	0.587
2099	POTKUNSUO	0.368	0.343	0.340	0.337	0.452	0.672	-	-
2101	ISOSUO	0.293	0.057	0.203	0.314	0.599	0.230	-	-
4770	MULTASUO	0.290	0.116	0.040	0.398	0.607	0.327	0.719	0.777
25059	RÖSSINKORPI	0.247	0.120	0.205	0.187	0.475	0.059	0.597	0.425
2106	PAATINSUO	0.244	0.067	0.038	0.152	0.720	0.390	0.625	0.866
25200	SULKUSUO	0.228	0.306	0.376	0.024	0.207	0.135	0.471	0.400
25070	OUDONSUO	0.220	0.158	0.155	0.321	0.247	0.147	-	-
12634	KANTOSUO	0.158	0.002	0.000	0.088	0.542	0.060	0.265	0.351
25190	KIVISUO	0.154	0.261	0.314	0.037	0.004	0.101	0.322	0.227
25199	SONNIR¦ME	0.137	0.259	0.207	0.020	0.060	0.043	0.316	0.199
25074	MULTAKORPI	0.135	0.000	0.012	0.130	0.399	0.022	0.311	0.204
25096	LATVANEVA	0.099	0.076	0.004	0.278	0.036	0.063	0.182	0.109
2108	SARVISUO	0.093	0.078	0.089	0.168	0.039	0.205	0.534	0.617
25087	ORAVASUO	0.080	0.033	0.000	0.240	0.048	0.062	0.199	0.180
25072	LEPPÄRIMPI	0.057	0.093	0.113	0.005	0.015	0.027	0.169	0.104
25157	MÄNTYSAARENSU	0.052	0.003	0.004	0.014	0.187	0.002	0.257	0.150
25081	KALLIONEVA	0.051	0.000	0.000	0.092	0.112	0.012	0.148	0.100
12196	VARPUSUO	0.044	0.000	0.000	0.000	0.177	0.015	0.142	0.209
2325	PIHLAJASUO	0.040	0.065	0.083	0.009	0.004	0.059	-	-
25067	SILTALANSUO	0.040	0.011	0.016	0.042	0.093	0.006	-	-
2104	VEHKASUO	0.033	0.000	0.000	0.016	0.116	0.005	0.146	0.147
25191	KOTISUO	0.021	0.000	0.000	0.000	0.083	0.001	0.068	0.011
25073	KARJUSUO	0.014	0.000	0.000	0.000	0.056	0.001	-	-
2112	MATKASUO	0.011	0.000	0.000	0.045	0.000	0.019	0.041	0.044
25068	LAMMASNEVA	0.009	0.000	0.004	0.027	0.003	0.014	0.078	0.099
12637	PELSONRIMPI_L	0.008	0.000	0.000	0.000	0.032	0.002	0.037	0.004
2328	SAARISUO	0.004	0.006	0.006	0.005	0.000	0.009	0.173	0.115
25085	JÄRVIKAARRONS	0.003	0.000	0.000	0.012	0.000	0.002	-	-
2326	SIIRASSUO	0.002	0.000	0.000	0.000	0.009	0.000	-	-
25071	ISOSALMI	0.002	0.002	0.000	0.005	0.000	0.000	0.014	0.012
25080	KARKUNNEVA	0.002	0.000	0.000	0.007	0.000	0.000	0.005	0.000
25195	POIKASUO	0.002	0.000	0.006	0.000	0.001	0.000	0.021	0.001
12629	KALLIONEVA	0.001	0.000	0.004	0.000	0.000	0.000	0.024	0.009
12617	PIENI_VAIVAISSU	0.001	0.000	0.000	0.000	0.004	0.000	0.007	0.001
25172	ROUVASTINSUO	0.001	0.000	0.000	0.000	0.004	0.000	0.018	0.017
25127	HALMESUO	0.001	0.000	0.000	0.000	0.003	0.000	-	-
25075	ISTULANSUO	0.000	0.000	0.000	0.000	0.001	0.000	0.006	0.001
2097	LIEMISUO	0.000	0.000	0.000	0.000	0.000	0.000	-	-
2103	KAIHLALAHDENSU	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2105	HAKOSUO	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2107	RASINSUO	0.000	0.000	0.000	0.000	0.000	0.000	-	-
2110	PIKKU_PELSO	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000
2119	KUUSIRIMPI	0.000	0.000	0.000	0.000	0.000	0.001	0.016	0.021
2122	SYRJÄSUO	0.000	0.000	0.000	0.000	0.000	0.000	-	-
2327	MUSTASUO	0.000	0.000	0.000	0.000	0.000	0.000	-	-
12102	SIRKKASUO	0.000	0.000	0.000	0.000	0.000	0.000	-	-
12191	ISO_LAAJANSUO	0.000	0.000	0.000	0.000	0.000	0.000	-	-
12192	KARJAINNEVA	0.000	0.000	0.000	0.000	0.000	0.000	-	-
12193	LAAJANNEVA	0.000	0.000	0.000	0.000	0.000	0.000	-	-
12194	PIENI_LAAJANSU	0.000	0.000	0.000	0.000	0.000	0.000	-	-

Figure 11. Core index illustartion of the peatlands with best scores from the 99 peatland candidates Reference results corresponds to the core indexes from 67 peatland candidate modeling (see Figure 10)

Grouping of the preference statements was also performed with some of the models. It was noticed that especially the preferences of decision maker #1 had four clearly separate groups where criterion 3 was much more important than others, criteria 6, 1 and 2 where moderately important, criterion 4 had small importance and criteria 5, 7 and 8 were not their interest. Therefore, despite the original $w_6 \geq w_1, w_2$ preference statement, it was seen that grouping these together would most likely reflect the decision maker's preferences more accuracy and diminishing the risk of statistical error in the data. Grouping possibilities were also investigated with regard to the other preference statements but not as clear groups could be identified. Some of these preference groupings had slight effects but mostly the same peatland projects were risen from the optimization. The same result was also contracted when using stronger weight differences, for example forcing the "Groundwater distance" to be at least three times more important than the rest criteria, even though this procedure was expected empathize the main criterion. Excluding the "Production area" from the value function did not either have significant effect to the solved portfolios. Therefore, it was left to the model as it was a criterion also in YODA method.

Sensitivity analysis was also conducted with regard to the value function forms. During this process it was acknowledged that the that original value function for criterion "Biodiversity" might not have been suitably chosen. It was blurring the biodiversity differences of the projects as most of the projects had less than 15 performance on "Biodiversity" but the original curve was only starting to rise by then. A value function with a slightly lower curvature was seen to perform better in the modeling purposes as it brought differences of "Biodiversity" better in sight. This new "Biodiversity" value function, presented in Figure 12, was used in calculating the core indexes above in Figure 10 and Figure 11. Changing the other value function forms did not have mentionable effects to the results.



a) Original curve b) New curve

Figure 12. Value functions of biodiversity

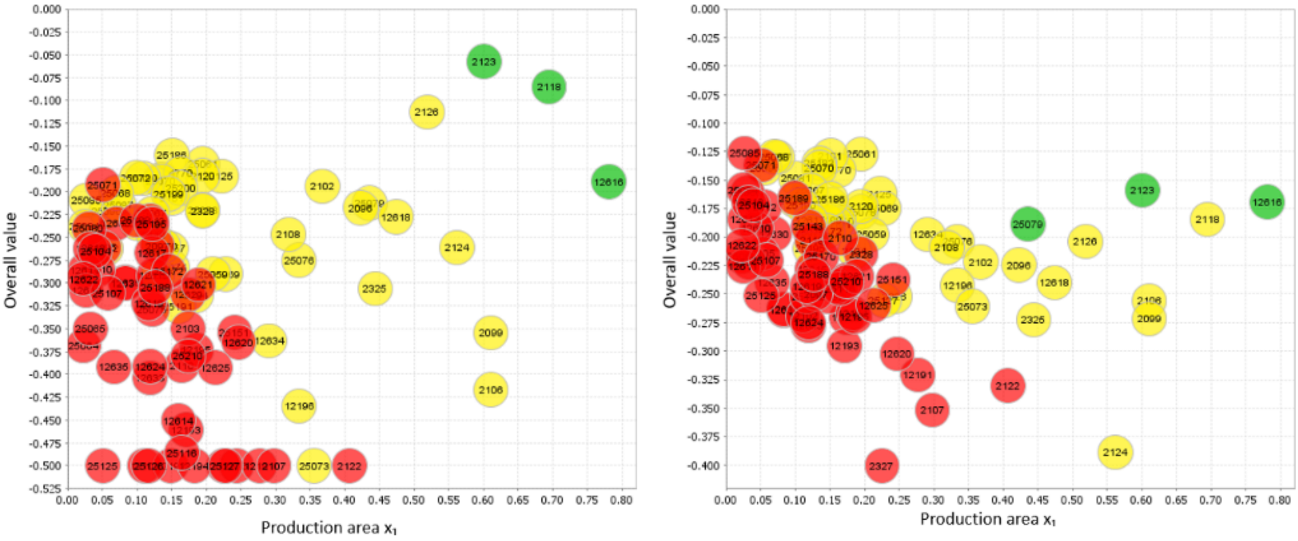
Based on these results the recommendation of project selection should be conducted. According to the logic of RPM, all core projects should be included in the final portfolio or otherwise it will be dominated by other portfolios (Liesiö et al. 2007). However, similar theoretical justification of borderline project selection is not available. Mild et al. (2015) have recommended to use these core indexes with a heuristic approach as a guidance and starting point of the project selection. According to them choosing the projects with highest core index values until the constraint is met approximately maximizes the correct choices of projects. This however requires that all of the non-dominated portfolios are seen as equally attractive choices. In the combined model the average of core indexes cannot be used in this heuristic by itself. Instead, the projects that have earned high scores from all of the decision makers are taken into consideration. However, in a real-time decision-making process, the different decision makers would have had the opportunity to discuss the best compromises around these borderline projects.

The model dependent solution proposals are presented in Table 7. All these portfolios required 14 to 16 different project candidates to meet the 2000 ha objective from the original case. From these different portfolios the total number of eight projects were same in all of the portfolios which are bolded in the Table 7. The red projects in Table 7 are also the projects that were not included in the 67 peatland lists.

Table 7: Selected projects of main RPM models

Combined model m=67	Consensus model m=67	Combined model m=99	Consensus model m=99
2096	2096	2099	2096
2106	2106	2102	2099
2108	2108	**2118**	2102
2118	**2118**	2120	**2118**
2120	2120	**2123**	**2123**
2123	**2123**	**2125**	2124
2125	**2125**	**2126**	**2125**
2126	**2126**	**12616**	**2126**
4770	4770	12618	**12616**
12616	**12616**	25059	12618
25059	25069	25061	25061
25069	**25076**	25069	**25076**
25076	25078	**25076**	**25079**
25078	**25079**	25078	**25183**
25079	**25183**	**25079**	
25183	25186	**25183**	

Throughout the data it is seen that decision maker #4 has divergent preferences from the others as she was emphasizing more the environmental effects such as “Biodiversity”. The other three decision makers have much more similar preferences which is seen from their closer core index values. From the 67-project lists, there is only one difference in the final selection of consensus and combined models. In the consensus model project 25186 got slightly better core index value than project 25059. However, decision maker #4 had significantly lower core index value for project 25186 than for project 25059 which had more similar core index values among all decision makers. Also, the same phenomenon is seen even more strongly with all of the 99 peatlands where project 2124 was a core project for all the other decision makers except decision maker #4 who had a core index value of only 0.039. This vast difference is explained by the biodiversity performance which was the highest of all the projects in peatland 2024. Decision maker #4 was also the only one whose RPM solutions did not show strong dependencies of a project’s overall value on its performance on criterion “Production area”. This is illustrated in Figure 13 where production area is presented on horizontal axel and overall value in vertical one. None of the other criteria evaluations revealed such visible dependencies.



a) Consensus model

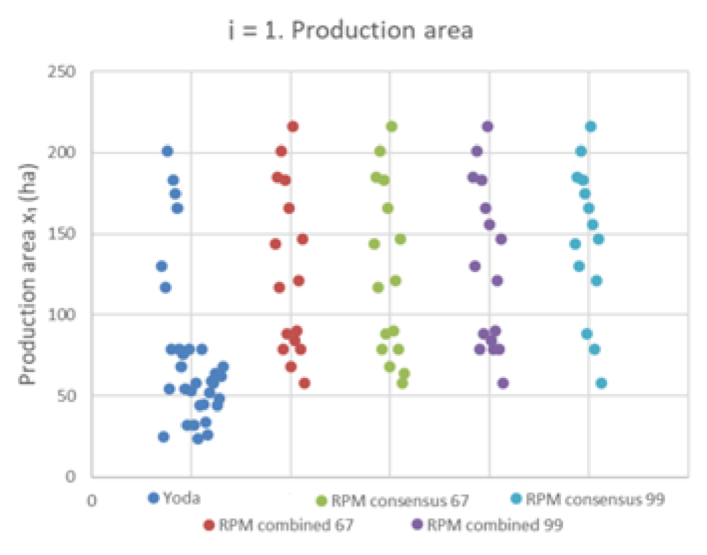
b) DM4

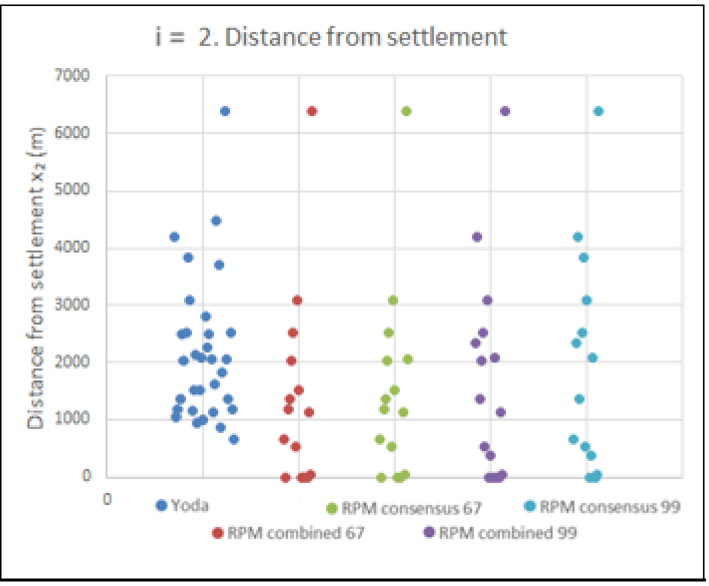
Figure 13. Project performance dependencies on "Production area"

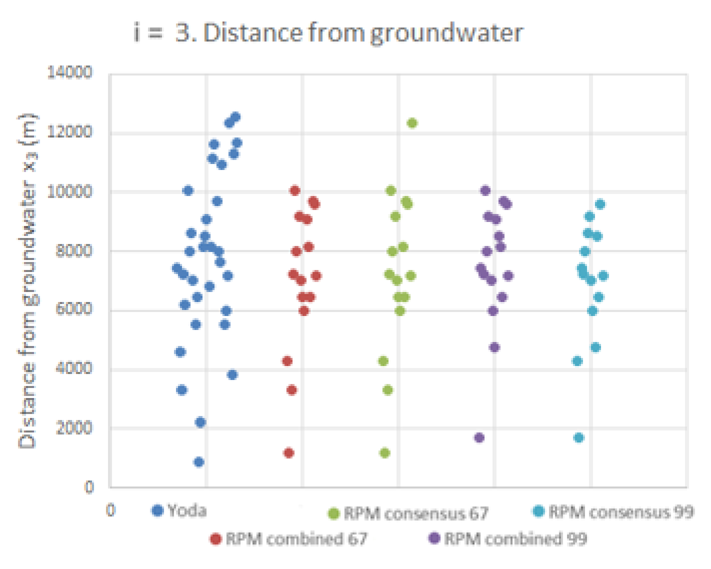
4.4 Comparison of RPM and YODA results

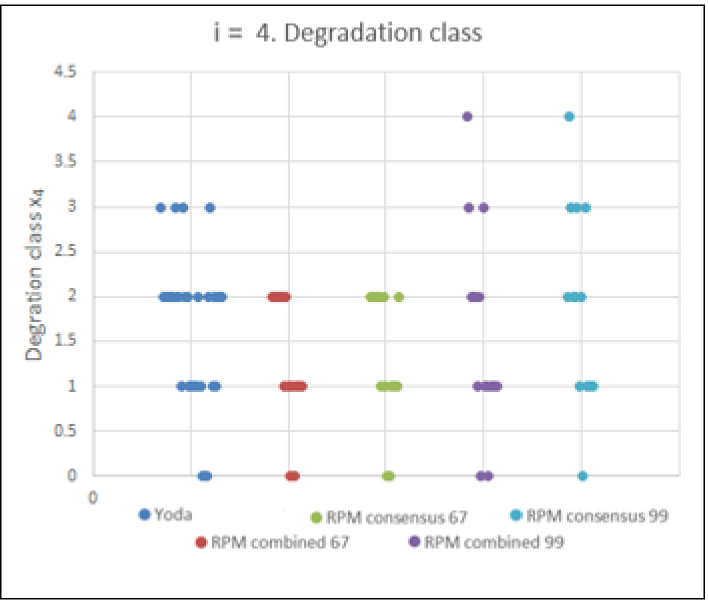
The results of RPM and YODA differ with regard to the peatlands that they recommend to apply to the Regional Master Plan. Peatland 21616 was the only project candidate that was a core project of all of the main RPM models conducted. However, it is not included to the production plan of YODA. From the main four projects identified in RPM only two were among the 32 projects of YODA solution. Similarly, only half of the eight peatlands common in all of RPM final solutions were included in YODA. On the other hand, the solution of YODA has included multiple peatlands that performed poorly in the RPM model. Four of the YODA peatlands were exterior projects in all RPM main models. In addition to this, YODA recommended the selection of 11 borderline projects with core indices lower than 0.2 in all the main RPM models.

The differences in the solutions of these two methods is examined next. The portfolio solutions are compared with respect to their performance on each criterion. The performance of projects regarding each criterion are presented in Figure 14. It illustrates how YODA has selected much smaller peatlands whereas RPM has been more focused on selecting fewer projects with greater area. Other noticeable differences are in the distances. Projects from YODA are with safe zone to the settlement whereas RPM has also selected projects near inhabitation. This also reflects to greater amounts of estates near. YODA model has similarly selected more projects with longer distance from groundwater than RPM. The phosphor level investigation also reveals that RPM projects seems to have slightly less emissions than the peatlands of YODA has.









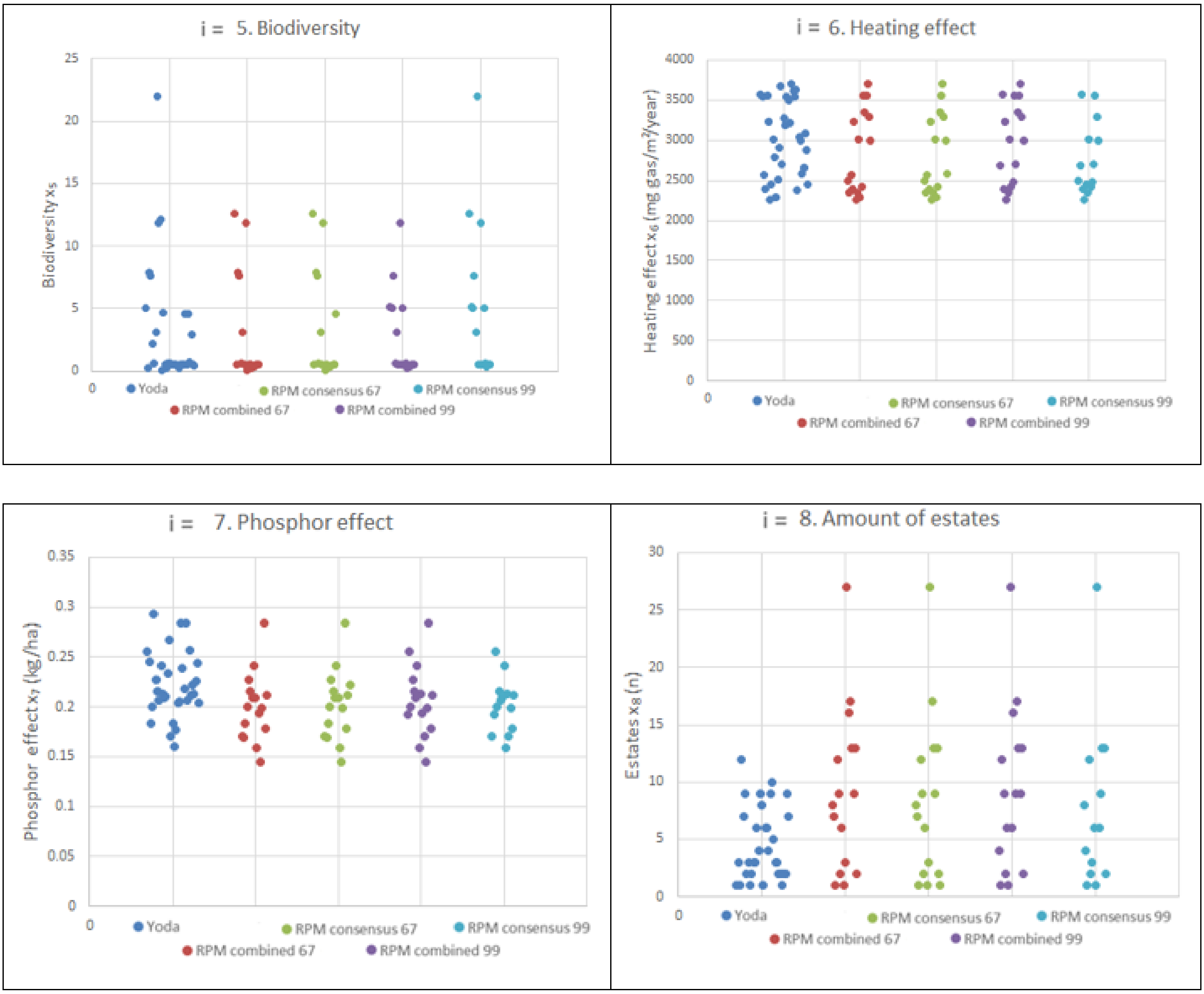


Figure 14. Criterion-spesific comparison of YODA and RPM models

In addition to the project performance comparison, also the cumulative effects of the projects were calculated. The criterion-specific sums and averages of the portfolios are presented in Table 8 and 9. The greater amount of selected production area is seen throughout the Table 8 where YODA portfolio has gained much larger cumulative performance than the RPM portfolios. While taking the averages of the portfolio performances the differences diminish between YODA and RPM solutions. However, it is important to note that not all of these performance criteria are additive. For example, two peatlands with “Degradation class” performances of one are having much less value than one peatland with “Degradation class” performance of two. Also, the average performances are not representing comparable impacts to the environment as there are vast differences in production areas and number of projects chosen.

Table 8: Sum of selected projects' criterion-specific performances

i (min/max)	Criterion (Measure)	YODA	RPM combined model (m= 67)	RPM consensus model (m=67)	RPM combined model (m=99)	RPM consensus model (m=99)
1 (~2000)	Production area (ha)	2 368	2 026	2 006	2 062	2 049
2 (max)	Settlement (m)	69 461	20 426	22 480	26 071	27 390
3 (max)	Groundwater (m)	247 749	113 017	116 254	120 206	96 061
4 (min)	Degradation class (-)	53	21	22	25	26
5 (min)	Biodiversity (-)	98.2	48.1	52.1	42.7	75.6
6 (min)	Heating (Mg gas/m²/year)	96 709	45 811	44 831	47 549	38 651
7 (min)	Phosphor (kg/ha)	7.1	3.2	3.2	3.3	2.8
8 (min)	Estates (n)	146	146	131	147	107

Table 9: Averages of selected projects' criterion-specific performances

i (min/max)	Criterion (Measure)	YODA	RPM combined model (m=67)	RPM consensus model (m=67)	RPM combined model (m=99)	RPM consensus model (m=99)
1 (~2000)	Production area (ha)	74	127	126	129	146
2 (max)	Settlement (m)	2 171	1 277	1 405	1 629	1 956
3 (max)	Groundwater (m)	7 742	7 064	7 266	7 513	6 862
4 (min)	Degradation class (-)	1.7	1.3	1.4	1.6	1.9
5 (min)	Biodiversity (-)	3.1	3	3.3	2.7	5.4
6 (min)	Heating (Mg gas/m²/year)	3 022	2 863	2 802	2 972	2 761
7 (min)	Phosphor (kg/ha)	0.22	0.2	0.2	0.21	0.2
8 (min)	Estates (n)	4.6	9.1	8.2	9.2	7.6

As there is some variation in the total amount of selected peatlands in each model, the effects are also presented in Table 10 divided by this total area. However, these performances suffer also from the same lack of additive form of some criteria as the previous calculations. This procedure was still conducted in order to diminish the possible comparison errors depended on the different sizes of final portfolios but still be possible to illustrate the effect differences of YODA and RPM models. The environmentally interesting and more additive criterions like the "Heating" and "Phosphor" effects reveal that RPM portfolios are having much less emissions per hectare of peat production. It also seems that less biodiversity is lost in RPM solutions.

Table 10: Sum of selected projects' criterion-specific performances divided by the total area

i (min/max)	*Criterion (Measure)*	*YODA*	*RPM combined model (m=67)*	*RPM consensus model (m=67)*	*RPM combined model (m=99)*	*RPM consensus model (m=99)*
1 (~2000)	Production area (ha)	1	1	1	1	1
2 (max)	Settlement (m)	29	10	11	13	13
3 (max)	Groundwater (m)	105	56	58	58	47
4 (min)	Degradation class (-)	0.022	0.01	0.011	0.012	0.013
5 (min)	Biodiversity (-)	0.041	0.024	0.026	0.021	0.037
6 (min)	Heating (Mg gas/m²/year)	40.8	22.6	22.3	23.1	18.9
7 (min)	Phosphor (kg/ha)	0.003	0.002	0.002	0.002	0.001
8 (min)	Estates (n)	0.062	0.072	0.065	0.071	0.052

These findings suggest that there is some variation in the results of these two models. However, the evaluation of their results should be done regarding the aspects what the decision makers actually value. In the "Settlement" and "Groundwater" perspective YODA was actually choosing projects with longer distances. The actual environmental effects such as "Biodiversity", "Heating" and "Phosphor" effects however backs up the usage of RPM. As YODA selects more smaller projects it's performance regarding these cumulative criteria increases even though project placement interpretation does not show it.

5 Conclusions and discussion

This section is divided into three parts. In the first sub-section the results are discussed regarding the two research questions stated at the beginning. After this the limitations of this thesis are brought up. Finally, possible future research areas are presented.

5.1 Interpreting results

The two research questions of the thesis were:

I. Does Robust Portfolio Modelling (RPM) create additional value for peatland production site selection compared to current methods?

II. What are the benefits and challenges of applying RPM to environmental decision making?

Regarding the first objective to figure out the potential of RPM in environmental decision-making respect current methods, the literature is quite limited. The applications of RPM have been limited mostly to infrastructure maintenance projects (Liesiö et al. 2007; Mild et al. 2015; Sacco et al. 2019). Based on literature the portfolio environmental problems solved with portfolio method PDA are mostly area selection (Cranmer et al. 2018) and investment decisions (Van den Honert, 2016). These problem types are already familiar from the more business-oriented applications of RPM. The difference should be that in environmental decision making the perspectives of the different criteria of the model are taking into account environmental perspectives and not focusing on solely business perspectives and finance.

Based on the literature RPM was expected to bring additional value to the environmental decision processes. Still many organizations rely on more heuristic methods. It has been stated that heuristics can find sufficiently good solution but not optimal resulting in a poor allocation of limited resources (Lahtinen et al. 2017). Decision methods such as MCDA, PDA and RPM can therefore perform better as they utilize mathematical optimization and decision makers preferences to the project selection (Liesiö et al. 2007; Salo et al. 2011; Lahtinen et al. 2017).

In the empirical part of the thesis, these expectations were tested by applying RPM decision making to a same real-life peatland selection data previously used by YODA method. YODA is in a sense an example of a heuristic method used in the organizations as it is a decision method that is created for a single level selection whereas peatland selection is a portfolio problem. Therefore, YODA is lacking the perspectives to find the best combination and is focusing on finding separate acceptable projects.

The empirical part was conducted according to ethical research standards. It was done by trying to avoid the Hammer and Nail syndrome where every problem (i.e. nail) is seen to be a problem to be solved according to a certain method (i.e. hammer) the modeler is accustomed to (Hämäläinen, 2015). Therefore, even though RPM was expected to perform better this was not a result that was tried to be gotten from the modeling results. The RPM modeling was conducted with certain sensitivity analyses and the results were presented before any comparison was done. This procedure was done in order to make sure that the RPM models are not optimized to perform better than YODA but to represent the actual preferences of the decision makers as good as possible.

The findings of the empirical part were however slightly surprising. Even though RPM portfolios overall result was seemed to perform better regarding the most environmental aspects such as “Biodiversity” and “Heating” and “Phosphor” effects, some of the criteria were not performing as much better as expected. Even with RPM models that emphasized the decision makers’ main goals, which were “Distance from groundwater” in most of the cases, the results stayed similar. From the selected project placement maps (Figure 14) it seems that most of the projects were performing in quite similar levels. YODA solutions even had longer distances from groundwater and settlement than RPM models.

The final portfolio obtained from YODA and RPM also differed a lot between each other. The decision makers in YODA have agreed on projects with smaller areas whereas RPM has selected the large peatlands into production. The explanation behind this vast difference is most likely in the different decision process. The YODA method allows decision makers to set limitations to different criterion-specific performances. However, these performances are not scaled with respect to their production area. This leads to a situation where the decision makers reject projects with for example high “Biodiversity” or “Heating effect” performances even though their relative effect would have been smaller than with smaller peatlands. As RPM uses mathematical optimization, it takes better into account these relative performance effects related to the production area leading to much better result regarding cumulative criteria.

Hämäläinen (2015) also points out that accuracy is not the only thing that matters when comparing methods as other features are also important. These other features to be evaluated are for example models performance in communication and learning experience (Hämäläinen, 2015). In this perspective YODA could be seen more intuitive to users as it has a visual interface and easy-to-understand operational model with acceptance level changes. It is also important to evaluate methods regarding their complexity and time requirements. Sufficiently good results from a heuristic method could be seen as better than a procedure that requires much time and effort to obtain the optimal solution. The answer to the first research question is not therefore unambiguous but some main observations are highlighted here.

(Q1) Does Robust Portfolio Modelling (RPM) create additional value for peatland production site selection compared to current methods?

(A1) The conducted Robust Portfolio Modeling (RPM) reveals that it has great potential in environmental decision making. It was able to select a combination of projects that had much smaller negative effect to the environment respect each hectare in most of the evaluated criteria. RPM's ability to detect the cumulative effects in portfolio level is especially important in environmental decisions which is a feature that most heuristic methods lack.

On the other hand, it still needs to be considered what is the additional value that RPM brings with solution closer to optimal compared to the more heuristic methods. RPM could not find a solution that would perform better according to all criteria as YODA was identifying projects with longer distances from groundwater and settlement. There are also other dimensions that need to be evaluated such as the communicativeness of results and time requirements of the modeling.

Based on the comprehensive evaluation it cannot be said that RPM would be a superior choice with regard to all of these dimensions even though it has shown to be a well-performing option for the peatland production site selection.

The second research question addresses the different benefits and challenges of applying RPM into environmental decision making. Environmental decisions have many special characteristics that need to be taken into account compared to traditional business decisions. As real-life environmental applications of RPM have not been conducted before, literature regarding this issue is missing.

Many of the features of RPM seem to support environmental decision-making possibilities. RPM can include multiple criteria and constraint statements (Liesiö et al. 2007). This makes it an appealing method to solve environmental decisions as they usually require that the problem is evaluated through multiple dimensions including environmental, financial, social and political (Huang et al. 2012; Lahtinen et al. 2017). Environmental decision-making is also highly legislated (The Finnish Ministry of the Environment, 2016) where these additional requirements can also be modeled through constraints. In the peatland selection case of LUKE, the minimum requirement of selected area was set by The Council of Oulu Region and The Council of Kainuu. The other criterion level dimensions were environmental with “Heating” and “Phosphor” effects, “Groundwater distance”, “Biodiversity” and “Degradation class” performance. Also, social aspects were valued through the “Distance from settlement” and “Number of estates” near the production sites. RPM would have enabled even more criteria if other aspects would have been wanted to be included to the decision-making process.

Lahtinen et al. (2017) have identified that most of the environmental decisions are actually portfolio problems. However, many of the methods used, such as some heuristics and MCDA’s, are created to solve single selection problems. This leads to inefficient result portfolios and non-optimal use of resources (Lahtinen et al. 2017). RPM is however part of portfolio modelling family which is therefore able to address the problem as a whole which can also be seen in the highly differing results of RPM and YODA project selection. RPM was evaluating the projects as portfolios with cumulative effects whereas YODA was evaluating them as separate projects.

Other benefit of RPM is its flexible preference statements which can handle incomplete information of preferences. What makes RPM more appealing method to environmental decision making than other portfolio methods, is its capability to relax the strict preference statements. Liesiö et al. (2007, 2008) created RPM to cope with preference statements that are based on dominances of Park et al. (1996). This forms weight intervals that are less risky for modeling errors than strict weight values in traditional PDA methods. In the peatland selection case of this thesis this was especially beneficial as there would have not been a way to get exact preference statements from the decision makers. These more relaxed preference statements also gave additional flexibility for the modeling and increased the acceptance that the actual preference would be somewhere between the given intervals.

One of the biggest challenges of environmental decision making is the multiple stakeholders and their conflicting views (Vilkkumaa et al. 2014; Lahtinen et al. 2017). RPM is meant to be used by a single decision maker. If there are multiple stakeholders, they should be able to form general consensus opinions, what Belton and Pictet (1997) refer as sharing, and based on those opinions the RPM model could be then conducted. However, it has been noted that stakeholders are more likely to accept the result if they have felt being participating the decision-making process which encourages to use joint combined processes (Villkumaa et al. 2014; Lerche et al. 2019). As RPM does not provide interface that could participate all stakeholders, it can be seen as a shortcoming of this modeling procedure.

At this peatland selection case both models of consensus preferences and combined preferences of the stakeholder specific models were used. Even though Liesiö et al. (2007) do not consider how the borderline projects of RPM should be evaluated, these core index values can still guide the selection process in a single decision maker setting. The same logic can also be expanded to cover the group decision making process where the projects with high core index values from all of the stakeholders should be selected to the final portfolio. With this kind of approach this challenge of group decision making of RPM could therefore be overcome at some level.

Hämäläinen (2015) also pointed out the importance of communication and learning in method comparison. RPM can also be used to communicate the result with its visual interfaces presented in Appendix A. Vilkkumaa et al. (2014) have recommend that the core and exterior projects should be highlighted in group RPM modeling so that in the final negotiation the discussion is moderated to cover the borderline projects. The clear color code of green, yellow and red of RPM software are more intuitive than just bare numbers. However, RPM does not give visible explanations why certain projects have been selected and others not. The YODA method for example can tell that peatland 2125 was rejected due to its too short groundwater distance. As RPM lacks such explanation, the different stakeholders might see it harder to accept the results conducted in such a black box.

Gregory et al. (2012) have also identified that managers are reluctant to use decision models due to their expectations of high price, time and effort requirements. These same problems can also be seen as the challenges of RPM. The model formation is time consuming and challenging process in RPM which needs a facilitator that knows the right questions for value function and preference statement creation. RPM also requires a separate software which need to be learned to use and get access to. YODA, on the other hand, is intuitive and easy to use visual interface where different stakeholders can just change the acceptance levels of the performance values to limit which project to choose and which to reject (Kurttila et al. 2020). Other heuristic methods can also seem more appealing to the managers that want fast and easy solutions. RPM is also not yet widely used in the environmental decision making and this unknowability can be seen as a challenge to get the position in environmental decision-making field.

As seen here, there are many benefits but also challenges of applying RPM to environmental decisions. In order to get a better understanding of these characteristics, the main results to this research question are presented here.

(Q2) What are the benefits and challenges of applying RPM to environmental decision making?

(A2) The benefits of RPM in environmental decision making are mostly related the method’s capabilities. RPM is a method that can include multiple criteria and constraints from vide range of perspectives required in environmental decision making. It can also include more flexible preference statements which pros in processes including multiple stakeholders with conflicting views. RPM is also portfolio method which ensures that the problems are evaluated as a whole taken into account also the cumulative effects of project selection. RPM software also provides visual illustrations of the solutions.

RPM has also some challenges regarding environmental decision making. Firstly, it is not developed as a group decision method even though its use can be expanded to cover this aspect as well. Also, even though RPM provides visual interface it cannot explain the reasons behind certain project rejections. This might have effects on the acceptance of the result. Finally, RPM is much more time-consuming process that requires special software and facilitator that is familiar with decision analysis and value function forming than easy-using heuristic methods. This might made it less appealing even though it would perform better than its alternatives.

5.2 Limitations

The RPM procedure conducted in this thesis has some limitations. The greatest limitation is that the modeling is done purely based on data. The forms of value functions and preference rations could have been different if asked directly from decision makers according to the normal RPM procedure. Data also limits other effective modeling perspective that could have been applied to the modeling related to baselines (Liesiö and Punkka, 2014) or value function forming (Liesiö, 2014). The RPM software can also interpret only linear-additive value functions leaving possibilities of other value functions forms outside this thesis scope.

The same performance values and criteria of the YODA method were used to conduct the RPM. This ensures that results are comparable but at the same time the author recognizes that the eight criteria provided might not be the most suitable. For example, "Degradation class" and "Biodiversity" are based on quite similar calculations and the criteria values have moderate correlation.

The data from YODA method has also created some challenges for the modeling of the preference statements in RPM. In YODA the decision makers have been able to reject individual projects in addition to the acceptance level changes. This has allowed inconsistencies in the decision makers' preferences as the performance acceptance level constraints have not been the only rejection rule and other aspects than the presented eight criteria could have had an effect. This challenges the preference modeling and value function forming for the RPM as sometimes there are no clear reasons to been seen why some peatlands are selected and others are not. Therefore, the RPM models used here can have their shortcomings.

The use of same value function forms for all decision makers can also cause limitations to the model accuracy. Langhans and Lienert (2016) do always recommend the real value function forming procedure instead of this kind of direct value function determination. These consensus value functions diminish the decision maker specific effects. Therefore, even though forming only one set of value functions from the data was seen as the best option, as no interactions with the decision makers were possible, the normal value function forming could have brought more conclusive results.

Montibeller and von Winterfeldt (2015) have also identified multiple cognitive and motivational biases in decision processes. Even though RPM modeling has been conducted using data instead of people who are vulnerable for biases, these might have affected the result. The data used is from YODA method which might be more vulnerable for biases listed by Montibeller and von Winterfeldt (2015). YODA could include for example conservatism as the decision makers are not experts regarding each criterion but still, they might have strong opinions and set strict performance boundaries. From the data of YODA, it is not possible to identify which amount of project rejections are based on actual preference weights of each criterion. Some might be only reflecting that the performance values of the data were not that good which have led to multiple discards even though the criterion itself were not that important to the decision maker. These affects to the data which has been used as the base of this RPM modeling procedure causing possible inaccuracies.

Finally, it also needs to be noted that the author is not an expert regarding peatlands, energy production or the environmental effects the selection would bring. This might have caused some inaccuracies on the criterion-specific modeling. Luckily the performance values of criteria were provided from LUKE which lowers the effects of such possible limitations.

5.3 Future research

The main contribution of this thesis is that it covers a topic that has not been discussed before in literature. The results show that RPM has potential to answer to the challenges of environmental decision making. Still real-life environmental applications of RPM are missing. An interesting future research topic would be to conduct RPM simultaneously with another method to see how RPM would perform if process would have been made right from the start including decision maker interviews and not just applied based on data. This comparison could also be conducted with other more widely used decision analysis methods as YODA is only one Finnish based example of a method used in the field.

This thesis also overcomes the challenge of group decision making by applying RPM respect decision maker specific preferences on combined model and also consensus model. This reveals potential to even further develop the practices of group usage of RPM.

In the practical perspective, this thesis has shown that RPM could have potential to be used in environmental decision making also in real-life cases. However, more literature for the topic could stronger its placement in the field. Therefore, there is a demand to apply RPM to other environmental decision-making settings in addition to site selection in order to see its true potential with wider environmental context.

Lastly, RPM could also be applied for more complex environmental applications. The peatland selection conducted in this thesis did not contain strong interactions between the different criteria or wider collection of constraints that limits the project selections. RPM however has expected capabilities to deal with much more complicated models. Thus, in addition to the different kind of environmental problems, RPM could be also applied to more complex settings to see its performance.

References

Abbasi M., Ashrafi M. & Sharifi Tashnizi E. (2014). “Selecting balanced portfolios of R&D projects with interdependencies: A Cross-Entropy based methodology”. *Technovation*, January 2014, vol.34, No.1, p.54-63

Achillas C., Aidonis D., Iakovou E., Thymianidis M & Tzetzis D. (2015). “A methodological framework for the inclusion of modern additive manufacturing into the production portfolio of a focused factory”. *Journal of Manufacturing Systems*, October 2015, vol.37, p.328-339

Airoldi N. & Morton A. (2011). Portfolio Decision Analysis for Population HeFalth. In A. Salo, J. Keisler, & A. Morton (Eds.), Portfolio decision analysis: Improved methods for resource allocation. New York: Springer

Antonides G. (2017). “Sustainable consumer behaviour: A collection of empirical studies”. *Sustainability*, September 2017, Vol.9, No.10

Arratia M, Lopez I., Schaeffer S. & Cruz-Reyes L. (2016). “Static R&D project portfolio selection in public organizations”. *Decision Support Systems*, April 2016, Vol.84, p.53-63

Barzilai J. (1997). “Deriving weights from pairwise comparison matrices”. *Journal of the Operational Research Society*, December 1997, Vol.48, No.12, p.1226-1232

Belton V. & Pictet J. (1997) “A Framework for Group Decision Using a MCDA Model: Sharing, Aggregating or Comparing Individual Information?”. *Journal of Decision Systems*, January 1997, Vol.6, No.3, p.283-303

Bertsch V., Treitz M., Geldermann J. & Rentz O. (2007). “Sensitivity analyses in multi-attribute decision support for off-site nuclear emergency and recovery management”. *International Journal of Energy Sector Management*, May 2007, Vol.1, No.4, p.342-365

Cheng E., Li H. & Ho D. (2002). “Analytic hierarchy process (AHP): A defective tool when used improperly”. *Measuring Business Excellence*, December 2002, Vol.6, No.4

Clemen, R. T. & Smith, J. E. (2009) “On the Choice of Baselines in Multiattribute Portfolio Analysis: A Cautionary Note”. *Decision Analysis*, Vol.6, No. 4, p.256-262

Convertino, M. & Valverde, L. J. (2013) “Portfolio Decision Analysis Framework for Value-Focused Ecosystem Management”, *Plos One,* June 2013, Vol. 8, No. 6

Cranmer, A., Baker, E., Liesiö, J. & Salo, A. (2018) "A portfolio model for siting offshore wind farms with economic and environmental objectives". *European Journal of Operational Research*, May 2018, Vol. 267, No. 1, p. 304-314

Dou, Y., Zhou, Z., Xu, X. & Lu, Y. (2019) "System portfolio selection with decision-making preference baseline value for system of systems construction". *Expert Systems With Applications*, June 2019, Vol.123, p. 345-356

Dyer J. (2016) "Multiattribute Utility Theory (MAUT)". In: Greco S., Ehrgott M., Figueira J. (eds) "Multiple Criteria Decision Analysis". *International Series in Operations Research & Management Science*, vol 233. Springer, New York, NY

Dyer J. & Sarin R. (1979) "Measurable Multiattribute Value Functions". *Operations Research*, July-August 1979, Vol 27, p. 810-822

Ender T., Murphy J. & Haynes C. (2010). "A Framework for Portfolio Management of Renewable Hybrid Energy Sources". *IEEE Systems Journal,* September 2010, Vol.4, No.3, p.295-302

Finlex (2017). Online. Available at: www.finlex.fi/fi/laki/ajantasa/2017/20170252, [4.2.2020].

Fliedner T. & Liesiö J. (2016). "Adjustable robustness for multi-attribute project portfolio selection". *European Journal of Operational Research*, August 2016, Vol.252, No.3, p.931-946

Golabi, K., Kirkwood, C. & Sicherman, A. (1981). "Selecting a Portfolio of Solar Energy Projects Using Multiattribute Preference Theory". *Management Science,* February 1981, Vol.27, No. 2, p.174

Gregory, R., Failing, L., Harstone, M., Long, G., McDaniels, T. & Ohlson, D. (2012). "Structured Decision Making: A Practical Guide to Environmental Management Choices". Wiley-Blackwell, Oxford, p. 299

Harju M., Liesiö J. & Virtanen K. (2019). "Spatial multi-attribute decision analysis: Axiomatic foundations and incomplete preference information". *European Journal of Operational Research,* May 2019, Vol.275, No.1, p. 167-181

Hu J., Bansal M. & Mehrotra S. (2018) "Robust decision making using a general utility set". *European Journal of Operational Research*, September 2018, Vol. 269, No.2, p.699-714

Huang, I., Keisler, J. & Linkov, I. (2011) "Multi-criteria decision analysis in environmental sciences: Ten years of applications and trends". *Science of the Total Environment*, Vol.409, No. 19, p. 3578-3594

Huesemann M. (2002). “The inherent biases in environmental research and their effects on public policy”. *Futures*, Vol.34, No.7, p.621-633

Hämäläinen R. (2015). “Behavioural issues in environmental modelling - The missing Perspective”. *Environmental Modelling and Software*, November 2015, Vol.73, p.244-253

Ishizaka A. & Nemery P. (2013). “Multi-Criteria Decision Analysis: Methods and Software”. John Wiley & Sons, Inc, Chichester, United Kingdom, p. 296

Jia J., Fischer G. & Dyer J. (1998). “Attribute Weighting Methods and Decision Quality in the Presence of Response Error: A Simulation Study”. *Journal of Behavioral Decision Making*, June 1998, Vol.11, No.2, p.85-105

Keeney R. (1994). “Using Values in Operations Research”. *Operations Research*, Vol.42, No.5, p.793-813

Keeney R. & Raiffa H. (1976). “Decisions with multiple objectives: preferences and value tradeoffs”. Wiley, New York, p.569

Keisler J. (2008) “The Value of Assessing Weights in Multi-criteria Portfolio Decision Analysis”. *Journal of Multi ‐Criteria Decision Analysis*, September 2008, Vol.15, No.5-6, p.111-123

Kirkwood C. (1996) “Strategic decision making: multiobjective decision analysis with spreadsheets”. Duxbury Press, Belmont, Canada, p. 345

Kleinmuntz, D. (2007). Resource Allocation Decisions. In: Edwards, W., Miles, R., von Winterfeldt, D. (Eds.), Advances in Decision Analysis: from Foundations to Applications. Cambridge University Press, New York, p. 400–418.

Kloeber J. (2011). Current and Cutting Edge Methods of Portfolio Decision Analysis in Pharmaceutical R&D. In A. Salo, J. Keisler, & A. Morton (Eds.), Portfolio decision analysis: Improved methods for resource allocation. New York: Springer

Kurttila M., Haara A., Juutinen A., Karhu J., Ojanen P., Pykäläinen J., Saarimaa M., Tarvainen O., Sarkkola S. & Tolvainen A. (2020) ”Applying multi-criteria project portfolio tool in selecting energy peat production areas”. Manuscript submitted for publication.

Kurttila M., Muinonen E., Leskinen P, Kilpeläinen H. & Pykäläinen J. (2009). ” An approach for examining the effects of preferential uncertainty on the contents of forest management plan at stand and holding level”. *European Journal of Forest Research*, Vol.128, No.1, p.37-50

Könnölä T., Salo A. & Brummer V. (2011) “Foresight for European coordination: developing national priorities for the Forest-Based Sector Technology Platform”. *International Journal of Technology Management*, Vol 54, No. 4, p. 438-459

Lahtinen, T. J., Hämäläinen, R. P. & Liesiö, J. (2017) “Portfolio decision analysis methods in environmental decision making”. *Environmental Modelling and Software*, August 2017, Vol.94, p.73-86

Langhans S. & Lienert J. (2016) “Four Common Simplifications of Multi-Criteria Decision Analysis do not hold for River Rehabilitation”. *Plos one*, March 2016, Vol11, No.3

Lerche N., Wilkens I., Schmehl M., Eigner-Thiel S. & Geldermann J. (2019). “Using methods of Multi-Criteria Decision Making to provide decision support concerning local bioenergy projects”. *Socio-Economic Planning Sciences,* December 2019, Vol.68

Liesiö, J., Mild, P. & Salo, A. (2007) “Preference programming for robust portfolio modelling and project selection”. *European Journal of Operational Research*, Vol.181, No. 3, p.1488-1505

Liesiö J., Mild P. & Salo A. (2008) “Robust portfolio modeling with incomplete cost information and project interdependencies”. *European Journal of Operational Research*, Vol.190(3), p.679-695

Liesiö, J. & Punkka A. (2014) “Baseline value specification and sensitivity analysis in multiattribute project portfolio selection”. *European Journal of Operational Research*, September 2014, Vol.237, No. 3, p.946-956

Lindstedt M., Liesiö J. & Salo A. (2008). “Participatory development of a strategic product portfolio in a telecommunication company”. *International Journal of Technology Management*, Vol 42, No.3, p 250 - 266

Linkov I., Anklam E., Collier Z., DiMase D. & Renn O. (2014). “Risk-based standards: integrating top–down and bottom–up approaches”. *Environment Systems and Decisions*, Vol.34, No.1, p.134-137

Lopez Y. & de Almeida A. (2013). “A multicriteria decision model for selecting a portfolio of oil and gas exploration projects”. *Pesquisa Operacional*, December 2013, vol.33, No.3, p.417-441

Markowitz H. (1952). “Portfolio selection”. *Journal of Finance*, March 1952, Vol.7, No.1, p.77-91

Mild, P., Liesiö, J. & Salo, A. (2015). “Selecting infrastructure maintenance projects with Robust Portfolio Modeling”. *Decision Support Systems*, September 2015, Vol.77, p.21-30

Montibeller G. & von Winterfeldt D. (2015). “Cognitive and Motivational Biases in Decision and Risk Analysis”. *Risk Analysis*, July 2015, Vol. 35, No.7, p. 1230-1251

Morton, A. (2015) “Measurement issues in the evaluation of projects in a project portfolio”. *European Journal of Operational Research*, September 2015, Vol.245, No. 3, p.789-796

Mustajoki J. (2012). “Effects of imprecise weighting in hierarchical preference programming”. *European Journal of Operational Research*, Vol.218, No.1, p.193-201

Park K. & Kim S. (1997). “Tools for interactive multiattribute decisionmaking with incompletely identified information”. *European Journal of Operational Research*, Vol.98, No.1, p.111-123

Park K., Kim S. & Yoon W. (1996). “An Extended Model for Establishing Dominance in Multiattribute Decisionmaking”. *Journal of the Operational Research Society*, November 1996, Vol.47, No.11, p.1415-1420

Phillips L. & Bana e Costa C. (2007). “Transparent prioritisation, budgeting and resource allocation with multi-criteria decision analysis and decision conferencing”. *Annals of Operations Research*, Vol.154, No.1, p.51-68

Saaty, T. (2008) “Decision making with the analytic hierarchy process”. *International Journal of Services Sciences*, Vol. 1, No. 1, p.83–98.

Sacco, T., Compare, M., Zio, E. & Sansavini, G. (2019) “Portfolio decision analysis for risk-based maintenance of gas networks”. *Journal of Loss Prevention in the Process Industries,* July 2019, Vol.60, p.269-281

Salo A. & Hämäläinen R. (1992). “Preference Assessment by Imprecise Ratio Statements”. *Operations Research*, Vol.40, No.6, p.1053-1061

Salo, A., Keisler, J. & Morton, A. (2011) ” Portfolio Decision Analysis - Improved Methods for Resource Allocation”. Springer, New York, p. 409

Sawik T. (2018). “Selection of a dynamic supply portfolio under delay and disruption risks”. *International Journal of Production Research*, January 2018, Vol.56, No.1-2, p.760-782

Simon J., Kirkwood C. & Keller L. (2014) ” Decision Analysis with Geographically Varying Outcomes: Preference Models and Illustrative Applications”. *Operations Research*, Vol. 62, No.1, p.182-194

Stoklasa J., Jandová V. & Talasová J. (2013). ”Weak consistency in Saaty’s AHP – evaluating creative work outcomes of Czech art collages”. *Neural Network World*, vol.23, No.1, p.61-77

Tervonen T., Liesiö J. & Salo A. (2017) ”Modeling project preferences in multiattribute portfolio decision analysis”. *European Journal of Operational Research,* November 2017, Vol.263, No.1, p.225-239

The Finnish Ministry of Environment (2015). “Suot ja turvemaat maakuntakaavoituksessa”. *Suomen ympäristö,* Vol. 5

The Finnish Ministry of Environment (2016). Online. Available: https://www.ym.fi/en-US/The_environment/Legislation_and_instructions [4.2.2020]

Tolvanen A., Juutinen A. & Svento R. (2013) ” Preferences of Local People for the Use of Peatlands: the Case of the Richest Peatland Region in Finland”. *Ecology and Society*, Vol.18, No.2

Toppila, A., Liesiö, J., & Salo, A. (2011). A resource allocation model for R&D investments –A case study in telecommunication standardization. In A. Salo, J. Keisler, & A. Morton (Eds.), Portfolio decision analysis: Improved methods for resource allocation. New York: Springer

Triviño M., Pohjanmies T., Mazziotta A., Juutinen A., Podkopaev D., Le Tortorec E. & Mönkkönen M. (2017). ” Optimizing management to enhance multifunctionality in a boreal forest landscape”. *Journal of Applied Ecology*, February 2017, Vol.54, No.1, p.61-70

van Den Honert, R. C. (2016) “Improving Decision Making about Natural Disaster Mitigation Funding in Australia—A Framework”. *Resources,* September 2016, Vol.5, No.3, p.28

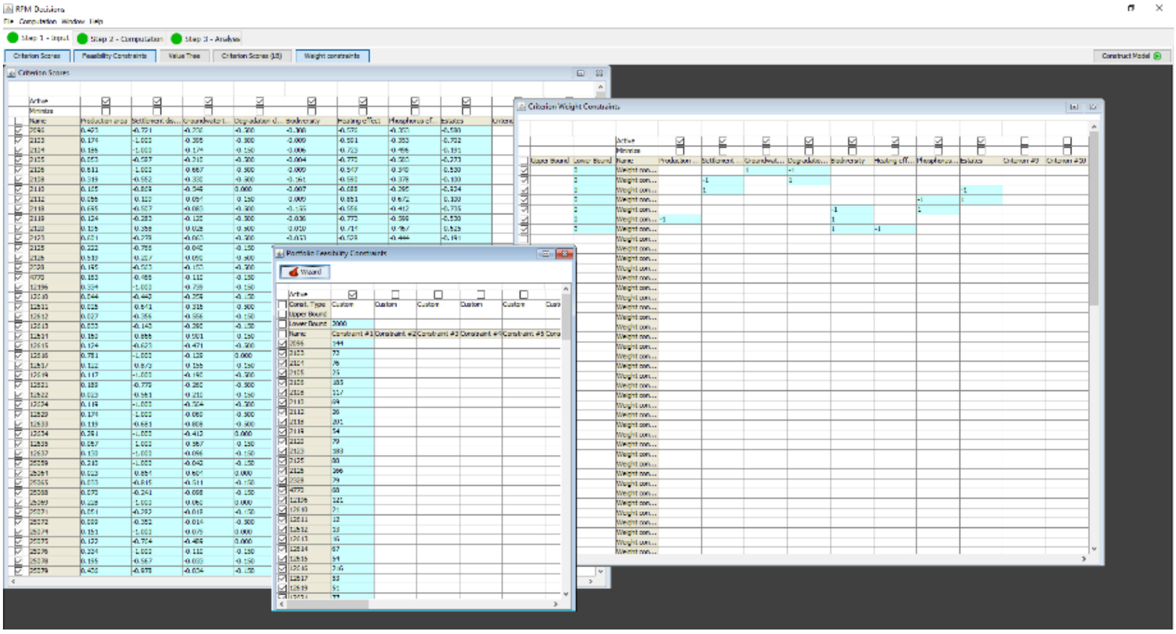
Vilkkumaa E., Salo A. & Liesiö J. (2014). ”Multicriteria Portfolio Modeling for the Development of Shared Action Agendas”. *Group Decision and Negotiation*, Vol. 23, No.1, p.49-70

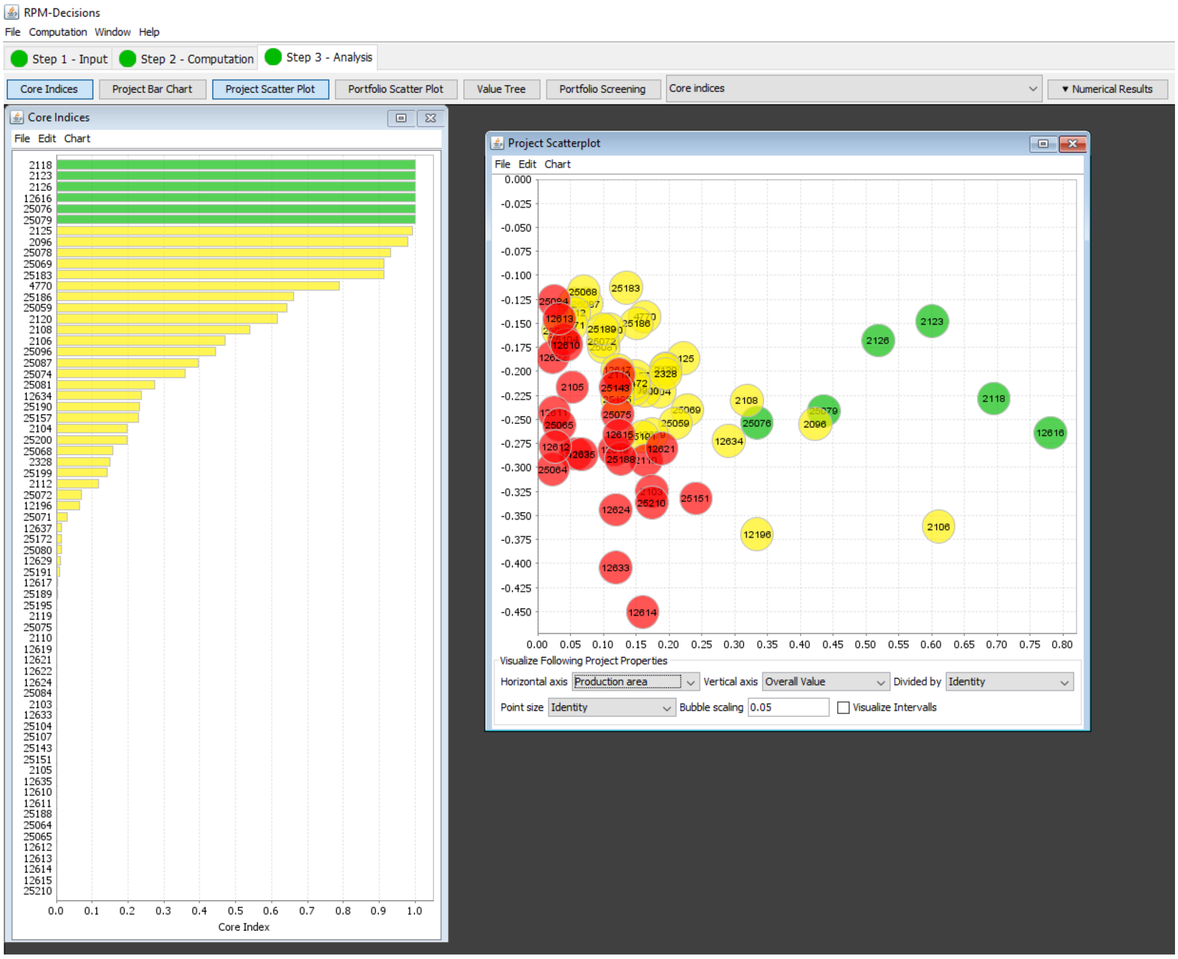
Wang K., Nguyen P., Wu S. & Xue J. (2018). “Technology portfolio adoption considering capacity planning under demand and technology uncertainty”. *Journal of Manufacturing Systems*, April 2018, Vo.47, p.1-11

Webler T., Tuler S. & Krueger R. (2001). “What Is a Good Public Participation Process? Five Perspectives from the Public”. *Environmental Management,* Vol.27, No.3, p.435-450

Zedler J. & Kercher S. (2005). "WETLAND RESOURCES: Status, Trends, Ecosystem Services, and Restorability". *Annual Review of Environment and Resources*, Vol.30, p.39-74

Appendix A: RPM software interfaces





Visualize Following Project Properties

Horizontal axis: Production area
Vertical axis: Overall Value
Divided by: Identity
Point size: Identity
Bubble scaling: 0.05
☐ Visualize Intervals