Assessing land redistribution plans using stochastic multicriteria acceptability analysis

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ABSTRACT

Land consolidation is a primary land management approach that aims to achieve sustainable agricultural development. Land redistribution is a complex decision-making process that involves reallocating land parcels and ownership. Ideally, it involves the production of a number of alternative plans, which can be assessed using multi-criteria decision making (MCDM), to rank alternatives and select the "best" plan based on their performance. Currently, a deterministic approach (D-MCDM) is used for this purpose, which inherently ignores uncertainties and variabilities of both the scores for each criterion as well as the weights assigned to each criterion. Thus, a core research question is: What will be the ranking of alternative land redistribution plans if a stochastic multi-criteria decision-making (S-MCDM) approach is utilised? Hence, we have utilized a specific type of S-MCDM method called Stochastic Multi-criteria Acceptability Analysis (SMAA). SMAA is designed to deal with decision-making problems where there is uncertainty in the criteria weights, performance of alternatives, or both. The SMAA methodology was implemented using an open-source software called JSMAA. The comparison of outputs resulting from deterministic and stochastic MCDM showed different rankings for alternative plans. This suggests that the use of D-MCDM when uncertainties exist can lead to misleading decisions. This finding is important for land consolidation planners, decision-makers, and stakeholders involved in a project, because the "best" plan is one that satisfies the project objectives. Furthermore, other decision-making domains that involve uncertainties should be aware of the use of D-MCDM instead of S-MCDM.

Keywords: Land Consolidation, Land Redistribution, Multicriteria Decision Making, Stochastic Multicriteria Acceptability Analysis, GIS

1. INTRODUCTION

Land consolidation is a primary land management instrument[1] aiming at achieving sustainable rural development, which is strongly supported by international organisations such as FAO[2]. Land consolidation involves land tenure restructuring and the provision of appropriate infrastructure, such as roads and irrigation networks. It aims to reduce land fragmentation[3] and promote agricultural development policies. It also includes broader aims aligned with several Global Goals of the UN 2030 Agenda for Sustainable Development[4]. The most complex process of land consolidation is land reallocation (sometimes referred to as reallotment or reparceling), which can be divided into two sub-processes: land redistribution[5] and land partitioning [5,6].

Land redistribution refers to the process of making decisions about the transfer of land ownership, which typically addresses five key issues in the case of Cyprus. These issues include identifying which landowners will receive property in the new plan and which will not, determining the total area and value of the property each landowner will receive, specifying the number of parcels granted to each landowner, determining the area and land value of each new parcel, and identifying the approximate location of each landowner's new parcels. The process of land redistribution is guided by legislation and related documents, the existing land tenure structure, rules of thumb, landowners' preferences, and the experience of planners. The outcome of this process is a comprehensive plan that consists of land blocks enclosed by roads, with each block containing a set of marks representing the approximate location of new parcels. Each mark is associated with an approximate size, land value, landowner, and other relevant information about the new parcel. From a modelling perspective, this can be considered a multicriteria decision-making problem that involves assessing a discrete number of

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alternative solutions provided by either experts or a system to determine the most advantageous option, which is the focus of this paper.

The process of land partitioning starts with a land redistribution plan, which entails dividing land into smaller parcels in accordance with specific criteria and design constraints. The outcome of this process is a final land consolidation plan that is carried out block by block. This process typically relies on trial and error and is based on legislation, empirical design criteria, geometric constraints, and rules of thumb. The aim is to produce a plan with well-shaped parcels that have access to roads. The land redistribution process assigns each new parcel an approximate area, land value, and location, taking into account constraints such as a minimum parcel size set by legislation as a fundamental principle. Additionally, existing boundaries, such as physical objects like streams, rivers, or fences, should be considered if possible. Other technical constraints include the presence of buildings or other types of construction, which should also be taken into account. In modelling terms, this process can be viewed as a multi-objective optimisation problem subject to a set of constraints that seeks to find the best solution(s) from an infinite number of potential solutions [7,8]. One type of land partitioning is urban land subdivision development, which involves using GIS-based tools to design plots.

Several efforts have been made to automate the preparation of land redistribution plans using various methods and GIS-based technologies. Based on our recent search in bibliographic databases, it seems that all research studies on land redistribution (for land consolation projects) took place from 1990 to 2012. Most of these studies do not separate land redistribution in producing plans or assessing alternative plans. Thus, they treated the procedure as an optimisation process, seeking an optimum solution based on a number of factors and criteria. Specifically, some studies [10,11,12,13,14,15,16] handled the process based on mathematical optimisation; hence, they did not produce a discrete number of alternative solutions to assess them and select the best solution. Hence, they attempt to directly reach an optimum solution through the optimisation process. Similarly, other studies [17,18] have attempted to introduce fuzzy logic based on four reallocation criteria without carrying out a multi-criteria decision-making (MCDM) process and selecting from alternative solutions. Demetriou et al.[5] utilized GIS and Expert Systems to automatically produce a number of alternative land redistribution plans, which then assessed using MCDM using a deterministic approach. Therefore, despite the fact that the land redistribution process inherently involves uncertainties in outputs, no study has treated it using a stochastic multi-criteria decision analysis approach.

The study by Demetriou et al.[5] revealed the presence of uncertainties in the land redistribution process. In particular, the sensitivity analysis demonstrated that the weights assigned to the criteria are prone to uncertainty as these preferences are subjective and may differ significantly between decision-makers' perceptions. Consequently, the available methods for defining the weights may result in different outcomes. A general finding is that the ranking of alternatives is highly sensitive to the alteration of the weights of the criteria, as also identified by Janssen and Rietveld[19]. Thus, planners should be cognizant of both the weights assigned to each criterion and the weighting method utilised. Additionally, the standardisation process of employing value functions involves considerable subjectivity, as these functions have been defined by experts and the process of assessing them is inherently uncertain. Furthermore, the calculation of the evaluation criteria scores is contingent upon expert systems' solutions and other assumptions, which inherently include uncertainties.

In light of the above, a research challenge is to consider the uncertainties in assessing alternative land redistribution plans through a stochastic multi-criteria decision analysis approach. Consequently, a core research question is: Do stochastic MCDM approaches reach different rankings of alternative plans compared with the ranking resulting from the deterministic MCDM method? The answer is crucial in investigating and ensuring the reliability of the assessment regarding the selection of the best plan, which is input to the next stage, that is, land partitioning (the final stage of a land consolidation plan). Obviously, the answer to the research question is important for land consolidation planers, decision makers, and stakeholders involved in a project, because the "best" plan is that which satisfies the criteria set out better than any other plan, hence the project objectives.

Thus, to answer the research question, the Stochastic Multicriteria Decision-Making (S-MCDM) method was implemented using the same dataset used by Demetriou et. al.[5]. S-MCDM methods are a class of decision-making tools designed to handle situations in which decisions must be made with ambiguities. These methods incorporate randomness or uncertainty in the criteria or decision-making environment, making them suitable for complex decisions where outcomes are not deterministic. S-MCDM methods are particularly useful in fields where decision outcomes are uncertain owing to variability in data, incomplete information, or inherent randomness in the system being analysed. One specific type of S-MCDM method is Stochastic Multi-criteria Acceptability Analysis (SMAA)[20,21], which is designed to deal with decision-making problems where there is uncertainty in the criteria weights, the performance of alternatives, or both. It is a family of methods that helps decision-makers to find acceptable choices without requiring a precise determination of criteria weights or even exact performance values for each alternative.

Based on the above framework, this study is further divided into three sections: the methodology utilised (Section 2), the results of a case study (Section 3), and a summary of the main conclusions (Section 4).

2. MATERIAL AND METHODS

Multi-criteria decision methods (MCDM) are a subfield of decision theory that deal with decision-making problems involving numerous evaluation criteria[24]. These methods are frequently employed to assess alternative solutions based on conflicting criteria [25], and have evolved to provide a set of techniques and procedures for organizing decision problems and evaluating alternative solutions [26,27]. The main objective of MCDM is to facilitate effective decision-making. MCDM utilizes specific definitions, with a criterion being a general term encompassing attributes and objectives. An attribute represents the characteristics of entities in a real-world geographical system, while an objective is a statement regarding the desired state of the system. Options, or alternative courses of action, are evaluated against multiple objectives, with different land redistribution plans being an illustration of alternative options. Malczewski distinguishes two broad categories of MCDM: multi-attribute decision-making (MADM) and multi-objective decision-making (MODM) [26,27].

MODM and MADM are two separate decision-making processes in the field of decision making. MODM involves a continuous search for the optimal solution from a large set of feasible alternatives, which are only implicitly defined. In contrast, MADM entails a selection process between a discrete and limited number of alternatives that are explicitly known and characterized by several attributes. A general MADM model was presented in Malczewski[27], which was utilized by Demetriou et al.[5] in a deterministic model (D-MCDM) that does not account for the uncertainty of both the scores and weights of the criteria used to assess the performance of the examined alternative solutions. However, in practical MCDM scenarios, it is customary to encounter incomplete, imprecise, and uncertain information regarding both the evaluation criteria and the preferences of decision-makers. To tackle this uncertainty, various MCDM approaches have been suggested, including the stochastic multi-criteria acceptability analysis (SMAA) family of methods [28,29], which is employed in this research.

The SMAA method, which was introduced by Lahdelma et al.[30], addresses decision-making issues with multiple criteria when both criteria scores and their weights are uncertain. The core concept behind SMAA involves calculating volumes through a reverse analysis of the weight space to identify the sets of criteria weights that render each option the most favoured. The SMAA employs Monte Carlo simulations to generate descriptive metrics that aid in the decision-making process. Specifically, it uses these simulations to determine the likelihood of each option being the most preferred, its potential ranking, or its classification into categories, thereby facilitating a sensitivity analysis. In addition to the initial SMAA, various adaptations have been developed, including SMAA-2 by Lahdelma and Salminen,[31]. Whereas the original SMAA method focuses on distinguishing between (more or less) acceptable options without considering other rankings, SMAA-2 expands on this by evaluating all possible rankings. This is done by analysing the entire spectrum of weight vectors for each alternative, from the highest to the lowest rank, thereby providing a more comprehensive framework for decision-making. Pelissari et al.[29] have provided general guidelines and a framework for selecting an SMAA variant. In addition, to determine whether the criteria involved in the process are independent or dependent, it is crucial to use different methods. Lahdelma et al.[30] propose two approaches for handling dependent uncertainties in MCDM.

SMAA uses three descriptive measures for decision support: the rank acceptability index, central weight vector, and confidence factor. These measures are computed through Monte Carlo simulation and may contain errors, although the error margins are typically minimal [32]. The acceptability index reflects the proportion of evaluations that make an alternative the most preferred, with values ranging from 0 to 1. A value of 0 indicates that the alternative is never considered the best with the assumed preference model, while a value close to 1 signifies that the alternative is the most suitable solution. The central weight vector is the expected centre of gravity of the favourable first-rank weights for an alternative, representing the preferences of a typical decision maker (DM) supporting that alternative. By presenting the central weight vectors to the DMs, an inverse approach to decision support can also be applied; instead of eliciting preferences and constructing a solution to the problem, the DMs can learn what kind of preferences lead to which actions without providing any preference information[33]. The confidence factor is a measure of the probability that an alternative is preferred, as

indicated by its central weight vector. The main purpose of this assessment is to evaluate the accuracy of the criteria used to distinguish efficient alternatives. Hence, it is recommended to avoid options with low confidence factors and gather more reliable data to make an informed decision if they are deemed attractive. The formulas for calculating the three basic metrics of the SMAA method are expressed as follows (Tervonen[34], Lahdelma and Salminen[31]):
Rank acceptability index (α, RAI):

$$\alpha_i = \int_{w \in W} \delta(i = \arg\max_{j \in A} v_j(w)) f(w) dw, \tag{1}$$

where $v_j(w)$ is the value of alternative j given weight vector w, A is the set of alternatives and $f(w)$ is the probability distribution over the weight space W.

Central weight vector (CWV):

$$cw_i = \frac{1}{\alpha_i} \int_{w \in W_i} w f(w) dw, \tag{2}$$

where W_i is the set of weight vectors that make i the most preferred alternative.

Confidence factor (CF):

$$cf_{ij} = \int_{w \in W_{ij}} f(w) dw, \tag{3}$$

where W_{ij} is the subset of weight vectors where i alternative is preferred over j.

The process of selecting appropriate criteria for this study began with the definition of a hierarchical objective tree based on the goals, aims, and objectives of the land consolidation problem as presented in Demetriou et. al.[5]. This was followed by the formulation of a specific land redistribution objective tree that included the aims, objectives, and corresponding criteria/attributes used to evaluate alternative land redistribution plans. As a result, five criteria were suggested: the mean size (as a percentage change) of the new parcels (C1); the mean parcel concentration coefficient (PCC) (C2); the change (as a percentage) in the number of landowners (C3); the percentage of ownerships that were "completed," which involved reaching the minimum size limit provided by legislation (C4); and the mean landowner satisfaction rate (C5). The two new concepts, PCC and LSR, were introduced by Demetriou et al.,[5]. PCC (C2) for each holding is measured on a scale between -1 and 1, with a value of 0 indicating no change in the dispersion of a holding's parcels before and after land consolidation. A value of +1 signifies "perfect concentration," while -1 represents "worst concentration". LSR serves as an indicator that assesses the level of satisfaction of landowners in relation to the location of their new parcels. This is based on the parcel priority index (PPI) initially proposed by Demetriou et al.[35], which ranks the preferences of landowners with respect to the locations of the new parcels they desire. The calculation of the LSR entails identifying which preferences of each landowner have been fulfilled and assigning a proportional satisfaction rate (known as the partial satisfaction rate, PSR) to each new parcel based on the ranking of the preferences satisfied, with a maximum value of 100%.

To ensure that the SMAA could be used with reliability for certain data, a correlation matrix was run between all five variable evaluation criteria (based on the original data at the level of parcels and landowners) involved in the SMAA process. Correlation analysis showed a very weak correlation (0.04 to 0.20) between the four variables C1, C2, C4, and C5 and a weak correlation (0.47) between C1 and C3, suggesting the reliability of using SMAA for a particular set of alternative solutions.

In practice, the SMAA methodology was implemented by utilising the open-source software called JSMAA which was implemented in Java and developed by Tervonen34. The standardisation method used in SMAA to convert each criterion on a common scale between 0 and 1 is linear. As noted, this study is a continuation of Demetriou et al.'s5 study, and inevitably, they use the same evaluation criteria and the same alternative land redistribution plans so that outputs will be directly comparable, that is, based on deterministic and stochastic MCDM. The output scores for each alternative were automatically derived from LandSpaCES35 which is a GIS-based land redistribution expert system as part of LACONISS36. Initially, to ensure the best comparison of deterministic and stochastic outputs, the same cases and scenarios examined by Demetriou et al.5. Subsequently, we ran new scenarios (e.g. using different weighting vectors and random distributions) based on the SMAA-2 method to investigate their outputs in terms of ranking alternatives. The discussion of the outputs for both the cases and other scenarios follows

3. CASE STUDY: RESULTS AND DISCUSSION

3.1 The case study area and the outputs of D-MCDM for Cases 1-4

The SMAA was implemented in a real land consolidation project in the Paphos district of Cyprus. The village's administrative boundaries encompassed a total area of 492 hectares of low-lying land, while the consolidated region covered 195 hectares. An example of one of the four land redistribution alternatives is shown in Figure 1, focusing on land blocks 14, 15, and 16 (underlined numbers). Each centroid represents the approximate location of a new parcel, and the number above each centroid refers to the landowner's ID.

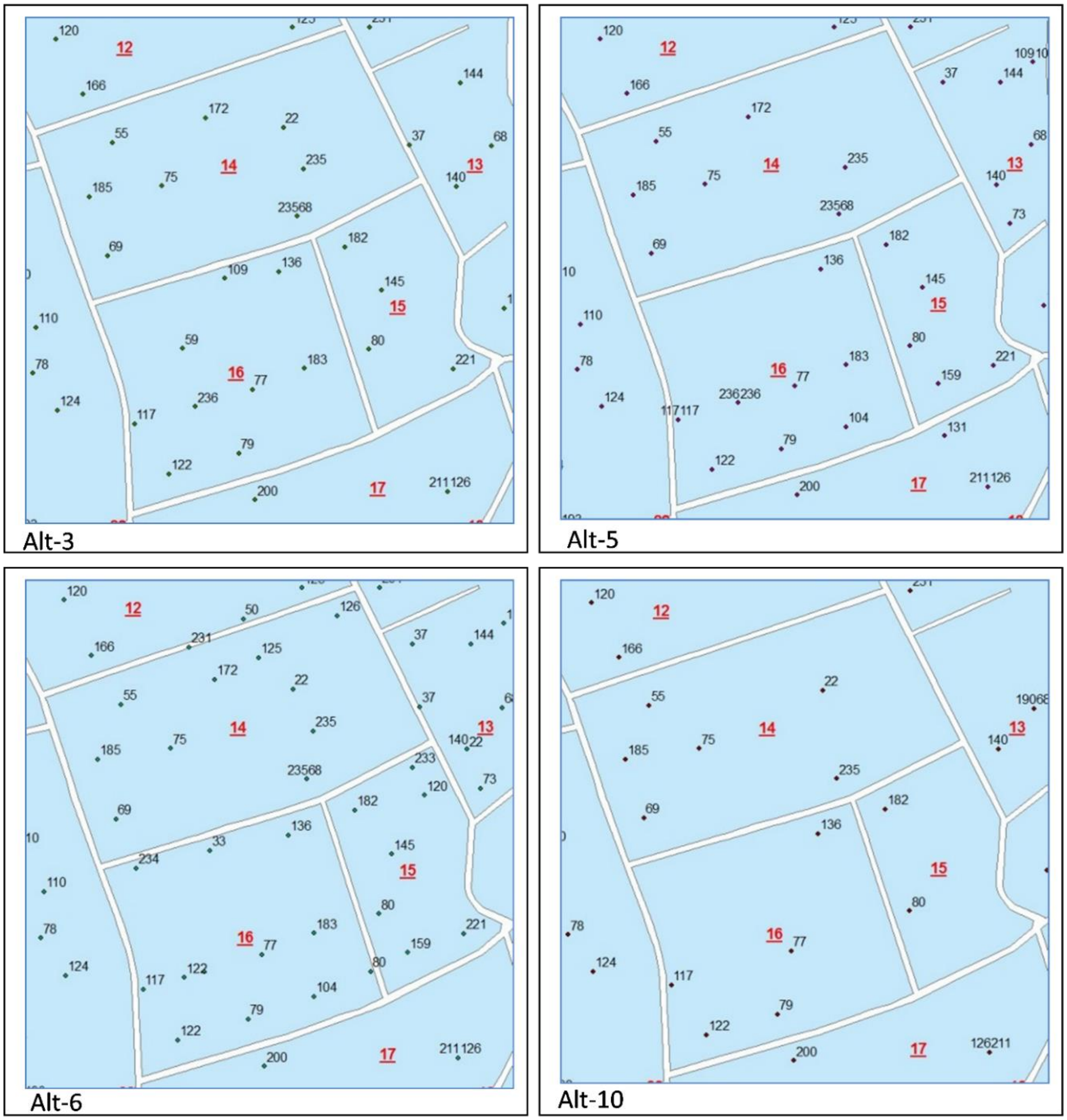

Figure 1: An example of land redistribution alternatives produced by LandSpACES (Demetriou et al.[5])

The D-MCDM method was utilized to evaluate four cases. Each "Case" represents a different weighing set for the five criteria. In Case 1, all five criteria were given equal importance. In Case 2, the weights were assigned to each criterion in descending order of importance: extremely high (score =100), very high (score=80), high (score=60), intermediate (score=40), and moderate (score=30). In contrast, in Case 3, the weights were assigned in ascending order, while in Case 4, they were determined by expert judgment: extremely high, high, high, intermediate, and very high. The ranking of each alternative for each case is illustrated in Figure 2.

Several intriguing discoveries were made, revealing that none of the options consistently outperformed the others in all the scenarios. Specifically, Alternatives 3 and 10 emerged as the top choices in scenarios 1 and 3, and 2 and 4, respectively. However, Alternative 3 demonstrated a more consistent performance across all scenarios than Alternative 10. This was evident, as Alternative 3 secured second place in scenarios where Alternative 10 was ranked first. On the other hand, Alternative 10 exhibited significant variability in its rankings, achieving first, sixth, and ninth positions. This variability makes this the most unreliable option. Interestingly, all other options show a two-position change in their rankings. As a result, Alternative 3 was considered the superior choice because of its stability and ability to maintain balanced performance across all evaluated criteria.

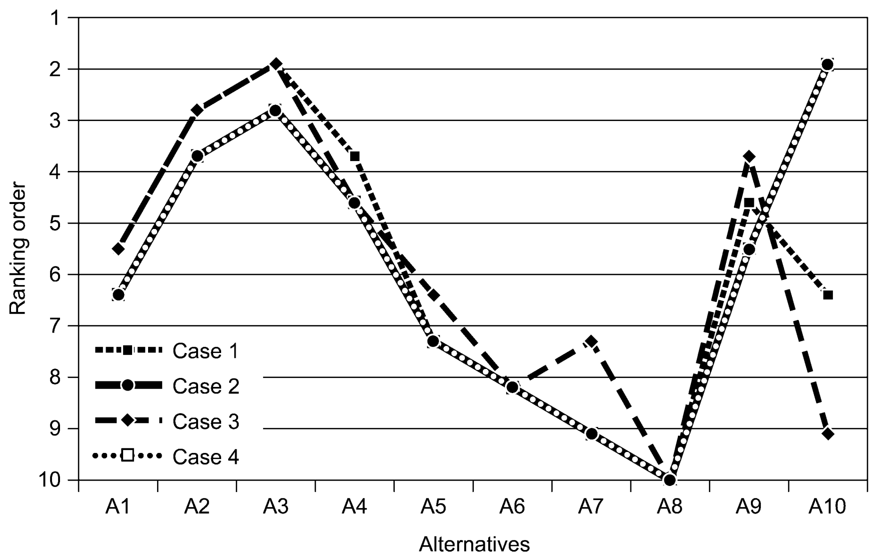

Figure 2: The ranking of alternative land redistribution using D-MCDM (Demetriou et al.[5])

3.2 The outputs of SMAA for Cases 1-4

The SMAA method was ran for Cases 1-4, with the same weights of criteria for each case for comparing the "deterministic" and "stochastic' outputs. To adopt the qualitative weights in SMAA-2, numerical values expressing the same importance were converted appropriately. For all criteria and cases, the normal distribution was used to represent the stochastic perspective of the criteria and ensure common assumptions for the range of criteria scores/values. The evaluation of alternatives using SMAA is based on the aforementioned three metrics: ranked acceptability index (RAI), central weight vector (CWV), and confidence factor (CF), which explained in section 2. The rank acceptability index (RAI) graph and the associated table for all the alternatives are shown in Figure 3. Table 1 presents the potential rankings for each alternative in Cases 1-4. For instance, a ranking of 2nd to 5th indicates that the relevant alternatives have equal possibilities of being ranked between those two positions, as they possess the same or very similar RAI values.

In summary, some basic findings were identified. Specifically, Alternative 10 ranked 1st in Cases 1, 2, and 4 with RAI values of 0.91, 0.9, and 0.79, respectively. Alternative 10 ranked 2nd in Case 3 with a RAI of 0.28 which is very close to Alternative 6 (and Alternative 7) which ranked first with a RAI of 0.32. Therefore, in Case 3, three alternatives (6, 10, and 7) present very similar results; hence, the same possibilities rank 1st. For all these cases, the CF is the same or very close to the value of the RAI, meaning that the probability of a particular alternative being ranked at a certain position is similar to the RAI values, that is, a high RAI value combined with CF values and vice-versa. In contrast, in all cases, Alternative 8 ranked 10th with RAI values of 0.84, 0.85, 0.52, and 0.61, confirming that it is the worst alternative. The rest of the alternatives, that is, 1, 4, and 9, present similar possibilities (RAI ranges between 0.20 and 0.14) to rank from 2nd to 5th position, and the other alternatives, that is, 2, 3, 5, 6, and 7, ranked in a position between 6th and 9th (except in Case 3, as noted earlier).

Table 1: The potential ranking for each alternative in Cases 1-4

Cases	**Case 1**	**Case 2**	**Case 3**	**Case 4**
Alternatives	**Ranking of Alternatives based on the Rank Acceptability Index (RAI)**			
1	2nd to 5th	2nd to 5th	4th to 5th	2nd to 5th
2	6th to 9th	6th to 9th	6th to 9th	6th to 9th
3	6th to 9th	6th to 9th	6th to 9th	6th to 9th
4	2nd to 5th	2nd to 5th	4th to 5th	2nd to 5th
5	6th to 9th	6th to 9th	6th to 9th	6th to 9th
6	6th to 9th	6th to 9th	1st	6th to 9th
7	6th to 9th	6th to 9th	3th	6th to 9th
8	10th	10th	10th	10th
9	2nd to 5th	2nd to 5th	4th to 5th	2nd to 5th
10	1st	1st	2nd	1st

By comparing these outputs with those derived from the D-MCDM it is concluded a disruptive output in terms of which is the best alternative. Especially, in D-MCDM, Alternative 3 ranked 1st and 2nd and it was judged that "Alternative 3 presents a more stable behavior in all cases than Alternative 10…", while in S-MCDM approach, clearly Alternative 3 ranked in worse positions i.e. between 6th and 9th. In contrast, Alternative 10 which in D-MCDM ranked 1st in Cases 2 and 4 and ranked 6th and 9th in Cases 1 and 3, ranked in S-MCDM as most acceptable in Cases 1, 2, and 4 and ranked 2nd with a small difference from 1st. Thus, Alternative 10 clearly outperformed all the other alternatives using a stochastic approach, and in contrast, Alternative 3 ranked very low. Alternative 2, ranked 2nd and 3rd in D-MCDM and 6th to 9th in S-MCDM. Alternative 8 ranked last in all cases in both approaches, and Alternatives 1, 4, 9 and 5,6,7 were ranked in similar positions in both approaches.

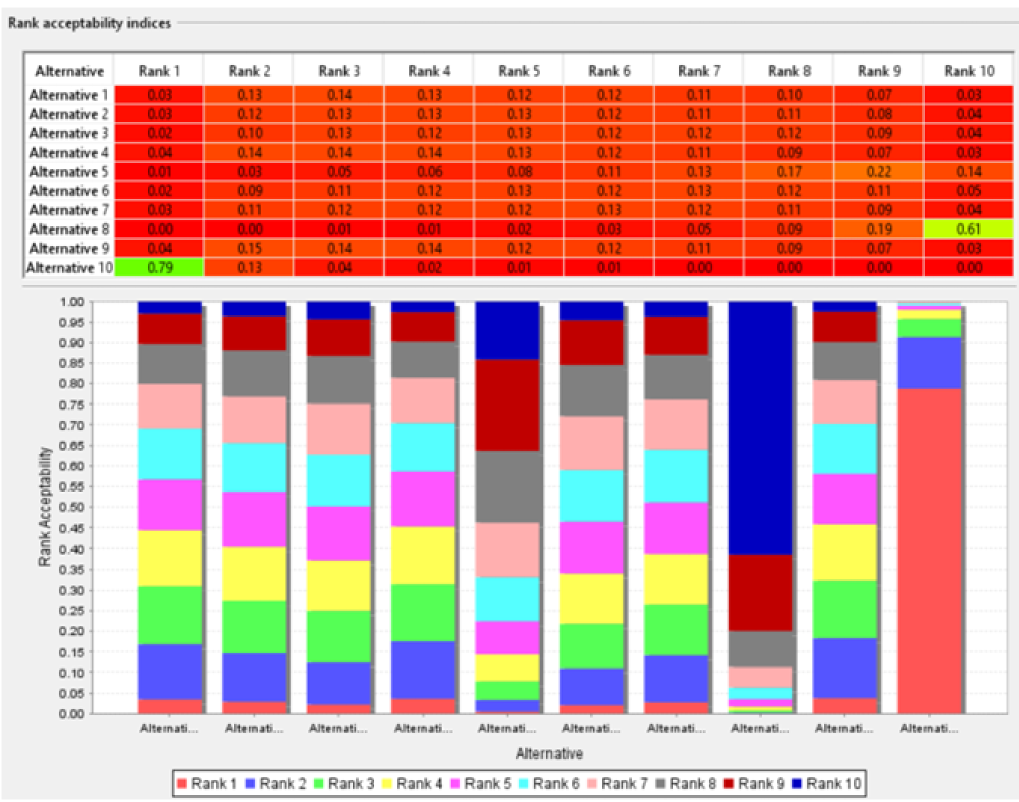

Figure 3: The rank acceptability index (RAI) for all alternatives assessed with SMAA

These outputs set out a critical question about the reliability or ranking of alternative plans using D-MCDM when both the scores of alternatives for various evaluation criteria and weights are prone to uncertainty. Thus, the uncertainty perception pointed out in the initial research is confirmed. Stochastic MCDM explicitly accounts for uncertainty in both the scores of the evaluation criteria and the weights of the criteria. This is more reflective of real-world conditions where data and preferences may not be precisely known. By using probability distributions rather than single-point estimates, stochastic MCDM provides a more nuanced understanding of the potential outcomes and their likelihood.

Although less important, it should be noted that the differentiation of ranking in Case 3 is explained by Demetriou[5] because the criteria are very sensitive in this case. This is because the weighting scheme in Case 3 can be considered as a paradox in terms of the importance of criteria that would normally be assigned by land consolidation experts because the first two and the last two criteria have a significant distance in terms of weighting class. Consequently, a slight change in the weights towards a more reasonable scheme causes a change in the rank order of the alternatives. By contrast, the criteria are much less sensitive for the other three cases because they involve a "sensible" weighting pattern in terms of practice.

3.3 The use of SMAA with five different scenarios

JSMAA software provides the following five random distribution models which can be adopted for criteria variables: Gaussian, LogNormal, LogitNormal, Beta and Discrete. The results in terms of decision making and the evaluation of alternative solutions can vary significantly in different distribution types of stochastic variables used in a model. The type of distribution chosen to represent the stochastic (random) variables in a model can have a profound impact on the model's outputs and the decisions derived from it for several reasons. The type of distribution chosen reflects the analyst's understanding and assumptions regarding the uncertainty inherent in the system being modelled. This choice depends on the nature of the data, existence of empirical distributions of historical or observed data, and adoption of theoretical considerations. Hence, some decision-making variables follow specific distributions, the range and boundaries of data, the existence of extreme values, and computational simplicity. In summary, the selection of stochastic distributions is a critical step that depends on a nuanced understanding of the variables in question, specific context of the decision-making process, and nature of the uncertainties involved. It requires balancing empirical evidence, theoretical considerations, and practical constraints to capture the expected uncertainties and their impact on decision-making outcomes.

Based on these considerations, we selected to use the normal and beta distributions that seemed to fit quite well with the original data for the five evaluation criteria. The Gaussian distribution, also known as the normal distribution, is one of the most important probability distributions in statistics, due to its widespread occurrence in many natural phenomena and its mathematical properties. Beta distribution is a family of continuous probability distributions defined on the interval [0,1], making it particularly useful for modeling random variables that represent probabilities or proportions. Its flexibility in shape makes it suitable for various applications ranging from Bayesian statistics to quality control and project management. The beta distribution is characterised by two positive shape parameters, α and β, which influence the shape of the probability density function (PDF). These parameters allow the beta distribution to take on a variety of shapes, including uniform, U-shaped, J-shaped, or bell-shaped, providing flexibility to model phenomena with different degrees of skewness and kurtosis.

Based on the above background and the direct comparison of outputs (i.e. ranking alternatives 1-10) between D-MCDM and S-MCDM, they were ran the following three scenarios for further investigation of stochastic outputs:

Run 1: All Gaussian random distributions for all criteria with no weights.

Run 2: All Gaussian random distributions for all criteria with equal weights.

Run 3: Various distributions (three Gaussian and two beta distributions) with no weight.

Each scenario represents the utilization of varying random distributions, such as Gaussian or beta distributions, and distinct weighting sets, including equal weights or no weights. Consequently, scenarios differ from the prior terms "Case," which alludes to different weighting sets. It should be also noted that, the term "no weights" differs from using equal weights, as it does not imply equal importance for all criteria. Instead, it indicates unknown or unspecified criteria importance. The method examines how each alternative performs across all possible weight combinations, rather than assuming equal weights for all criteria. The goal is to assess each alternative's ranking robustness without committing to a specific weighting scheme. In SMAA, when no specific weights are provided, the method does not default to equal weights. Instead, it considers all possible weight combinations that meet certain conditions, such as non-negativity and summing to one. This involves generating random or systematically varying weight vectors from a weight space, often through Monte Carlo simulations or other sampling techniques. These vectors represent different sets of preferences a decision-maker might have. By evaluating each alternative across this spectrum of possible weights, SMAA calculates the acceptability index (the probability of an alternative being the most preferred) and other relevant metrics without requiring the decision-maker to specify weights. The results and findings are summarised as follows:

Runs 1- 3: Alternative 10 ranked 1^{st} in all three runs, with an RAI 0.71 (with CF 0.99), 0.91 (with CF 0.91), 0.58 (with CF 0.84), respectively. Also, in all runs Alternative 8 ranked last i.e. 10^{th} with RAI 0.69 (with CF 0.99), 0.84 (with CF 1.0) and 0.36 (with CF 0.84). The rest of the alternatives, that is, 6 and 7, present similar possibilities (RAI ranges between 0.15 to 0.22) to rank 2^{nd} or 3rd position, Alternatives 2 and 3 ranked in a position between 4^{th} and 6^{th}, and all the other alternatives ranked between 7^{th} and 9^{th} for all three runs. Alternative 3, which, as mentioned above, was judged as the best in past research could ranked 4^{th} or 5^{th} with very low RAI. This confirms again that uncertainty can alter the ranking and, hence, the decision making about which alternative to follow to satisfy project objectives in the best way.

A new question arose: "what would happen in terms of ranking alternatives, if the best alternative i.e. 10 removed from the evaluation process?". The rationale for eliminating the top-performing alternative, which plainly ranked first and significantly exceeded all the others, was to ascertain whether another alternative would likewise considerably outperform all the others in the absence of Alt-10. Thus, they were run another 2 scenarios:

Run 4: All Gaussian random distributions for all criteria with no weights, while removed Alternative 10

Run 5: Various distributions (3 Gaussian and 2 beta) with no weights, while removed Alternative 10

In both cases, Alternative 6 seems (RAI 0.21,0.23) to be slightly better than 7 (0.18,0.20) with CF 0.48 and 0.36 respectively. The remaining alternatives had considerably lower RAIs. Therefore, although Alternative 10 was removed, none of the other alternatives seemed the best, and Alternative 6 did not considerably outperform the others, as Alternative 10 in the previous analysis. In addition, CF is quite low (0.48), indicating that the probability that Alternative 6 is ranked as the best is in the middle of the confidence scale.

4. CONCLUSIONS

The comparison of outputs regarding the assessment of alternative land redistribution plans between deterministic and stochastic MCDM showed critical differences in the outputs. In particular, the best alternative land redistribution plan resulting from S-MCDM is different from the best alternative based on the D-MCDM approach. In this regard, it should be noted that the best alternative derived from the D-MCDM is ranked quite low with the S-MCDM. In addition, there is considerable differentiation in the ranking of the other alternatives between the two approaches. These outputs set out a critical question about the reliability or ranking of alternative plans using D-MCDM when both the scores of alternatives for various evaluation criteria and weights are prone to uncertainty. Thus, the uncertainty perception pointed out in the initial research is confirmed. Clearly, the stochastic approach explicitly accounts for uncertainty in both the scores of the evaluation criteria and criteria weights. This is more reflective of real-world conditions where data and preferences may not be precisely known. By using probability distributions rather than single-point estimates, stochastic modelling provides a more nuanced understanding of the potential outcomes and their likelihood. This suggests that the use of D-MCDM when uncertainties exist can lead to misleading decisions with socioeconomic consequences for a land consolidation plan. This finding is important for land consolidation planners, decision-makers, and stakeholders involved in a project because the "best" plan is one that better satisfies the project objectives. Furthermore, other decision-making domains that involve uncertainties should be aware of the use of D-MCDM instead of S-MCDM.

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