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Considering data uncertainty in the water and sanitation sector: Application to large number of alternatives and criteria

F. Ezbakhe* and A. Pérez-Foguet
Research group on Engineering Sciences and Global Development, Department of Civil and Environmental Engineering, Barcelona School of Civil Engineering (ETSECCPB), Universitat Politècnica de Catalunya
* *e-mail: fatine.ezbakhe@upc.edu*

Abstract: Priority-driven and target-focused management of water and sanitation services is essential to achieve long-term sustainability. However, in the context of water and sanitation, statistical uncertainty is an inevitable feature, as surveys are the primary sources of the information used in the decision making process. Therefore, it needs to be considered to have a greater confidence in the decisions made based on the collected data. Outranking approaches provide an opportunity to handle imprecision and uncertainty characteristic of water management problems. In particular, ELECTRE-III uses pseudo-criteria to consider uncertainty in the decision-maker's preferences, but does not take into account statistical uncertainty. A new interpretation of ELECTRE-III, in which pseudo-criteria are linked to the data uncertainty, is presented in the paper. The modified outranking approach (E3M) is used to evaluate water and sanitation services in Kenya and rank its 338 subdistricts according to their performances on 9 different criteria. E3M proved to be an effective ranking tool, providing a detailed hierarchy between the subdistricts, even when dealing with hundreds of alternatives. However, a quadratic dependence between the number of subdistricts ranked and the computational cost of the method was found, indicating that for larger number of alternatives (order of thousands), the time required would rise to the order of hours. Future work should focus on optimising the method's algorithm and allowing its scalability to thousands of alternatives.

Key words: ELECTRE III; Data uncertainty; Water and Sanitation; Multiple criteria decision-making; Non compensatory

1. INTRODUCTION

Sustainability of water and sanitation services has become a central element in the post-2015 development agenda (Sachs 2012, UN-Water 2014), being now considered fundamental for long-term human and environmental well-being. However, achieving sustainable services can be a complex task, as it concerns all levels of planning (local, regional, global) and contexts (economic, social, environmental) (UNEP 2011). To tackle this complexity, countries have adopted integrated approaches for the management of water and sanitation resources (UN-Water 2012). In addition, to provide more efficient services, countries have developed more decentralised structures (Ribot 2002, Parker and Tsur 2012), shifting decision-making responsibilities to local authorities.

This new way of water and sanitation planning requires improved data systems with robust and reliable information (Medema et al. 2008). Such information can be collected from different sources, from monitoring networks to knowledge-based systems and surveys (Timmerman et al. 2000). In the context of water and sanitation services, household surveys are key sources and consist in standard questions that assess the state of facilities and practices (JMP 2006). As in other types of surveys, the sampling strategy used dictates the reliability of the data (UN 2005) and thus introduces statistical uncertainty in the data. This uncertainty becomes more significant when data is collected at lower administrative levels, as larger samples are needed to cover all smaller areas (Giné-Garriga et al. 2013). Therefore, statistical uncertainty must be considered when data is used to support water and sanitation management decisions.

Multi-criteria decision making provides an opportunity to address uncertainties characteristic of water management problems (e.g. problem formulation, objective identification, preference setting, etc.) (Jakeman et al. 2006, Lerner et al. 2011). Methods based on the outranking approach (i.e.

building outranking relations by pairwise comparison of alternatives) have gained significant interest in the water sector (Roy et al. 1992, Duckstein et al. 1994, Bella et al. 1996, Raju et al. 2000, Trojan and Morais 2012, Kumar et al. 2016). In particular, ELECTRE-III uses pseudo-criteria as means of handling imprecision and uncertainty in the decision-maker's preferences (Roy 1991). However, in the standard ELECTRE-III, the statistical uncertainty related to the data is not considered in the pseudo-criteria. Therefore, a new version of ELECTRE-III is needed to make dealing with data uncertainty less challenging for decision and policy makers. To address this drawback, we proposed a new interpretation of the ELECTRE-III model. In the new approach, denominated as E3M, the pseudo-criteria were linked to statistical uncertainty (i.e. confidence intervals of survey's estimates). E3M proved to be a simple but effective ranking and prioritising tool applicable to a small number of communities. However, outranking methods are considered to be impractical when it is applied to rank more than tens of alternatives (Pereira and Duckstein 1993, Joerin et al. 2001).

This paper is an extension of the previous work and focuses on the scalability of E3M. The aim is to explore the suitability of the method when dealing with hundreds of administrative subunits. In Section 2, a brief overview of the E3M method and the case study are presented. In Section 3, the uncertainty of the case study's data is analysed. Next, E3M is applied to rank the subdistricts considering this uncertainty, first at a district level (i.e. in each district) and then at a country one (i.e. in all districts conjointly). The paper finished presenting the main conclusions found.

2. METHODS

2.1 New interpretation of ELECTRE-III (E3M)

ELECTRE-III consists of two phases: (i) construction of the outranking relation between each pairs of alternatives and (ii) exploitation of the previous outranking relations to produce an order of all alternatives. In this section, only an overview of the pseudo-criteria is given. The comprehensive description of the method can be found elsewhere (Roy 1978).

When applying ELECTRE III, for each criterion considered (c_i), every alternative is compared to the others in order to assess the outranking relation "alternative *a* is at least as good as alternative *b*" (i.e. *a* outranks *b*). To measure the credibility of this assertion, pseudo-criteria are used, which consist in three threshold values: indifference (q_i), preference (p_i) and veto (v_i). Depending on the difference value between the two alternatives' performances, $g_i(a)$ and $g_i(b)$, four outranking situations can take place: (i) *a* and *b* are considered to be indifferent ($g_i(a)-g_i(b)<q_i$), (ii) *a* is weakly preferred over *b* ($q_i \leq g_i(a)-g_i(b)<p_i$), (iii) *a* is strongly preferred over *b* ($p_i \leq g_i(a)-g_i(b)<v_i$) and (iv) *b* cannot be preferred over *a* ($g_i(a)-g_i(b) \geq v_i$).

These thresholds can be re-interpreted by expressing them in terms of the upper and lower limits of the confidence intervals of the alternatives. Consequently, if alternative *b* falls into the confidence interval of alternative *a*, they cannot be differentiated; but if their intervals do not overlap, alternative *b* can be preferred over *a*. The new definition of the method's thresholds is represented in Figure 1.

The binomial proportion confidence intervals of the alternatives ($p(a)_{upper,i}$ and $p(a)_{lower,i}$) are calculating according to the Clopper-Pearson method (Clopper and Pearson 1934), which is a function of the survey results (number of answers that meet the criterion and total number of answers) and the confidence level α (of 80% in the present study). The method has been implemented in R software (v3.3.1) in a standard laptop (2.6GHz Intel Core i5).

2.2 Case study

In 2006, the Government of Kenya and UNICEF Programme of Cooperation "Acceleration of

Water Supply and Sanitation towards Reaching Kenya's Millennium Development Goals (2006 – 2011)" was launched to increase the access to water and sanitation in 21 rural districts (divided in a total of 338 sub-districts). In 2009, a comprehensive baseline was established to evaluate the impact of this initiative at mid-term. 9 different criteria were assessed: (c1) access to improved water sources (c2) access to improved sanitation facilities, (c3) water quality inspection, (c4) point-of-use water treatment, (c5) water quality, (c6) time used to collect water, (c7) operational status of water source, (c8) individual responsible for collecting water and (c9) domestic water consumption. Data was collected at a household level in each subdistrict. A complete description of the scope and implementation of the survey is detailed elsewhere (Giné-Garriga et al. 2013).

E3M was used to analyse the state of Kenya's subdistricts regarding the 9 water-related criteria. The method was applied to rank these administrative units at a district level (ranking the subdistricts district by district) and country level (ranking all Kenya's subdistricts).

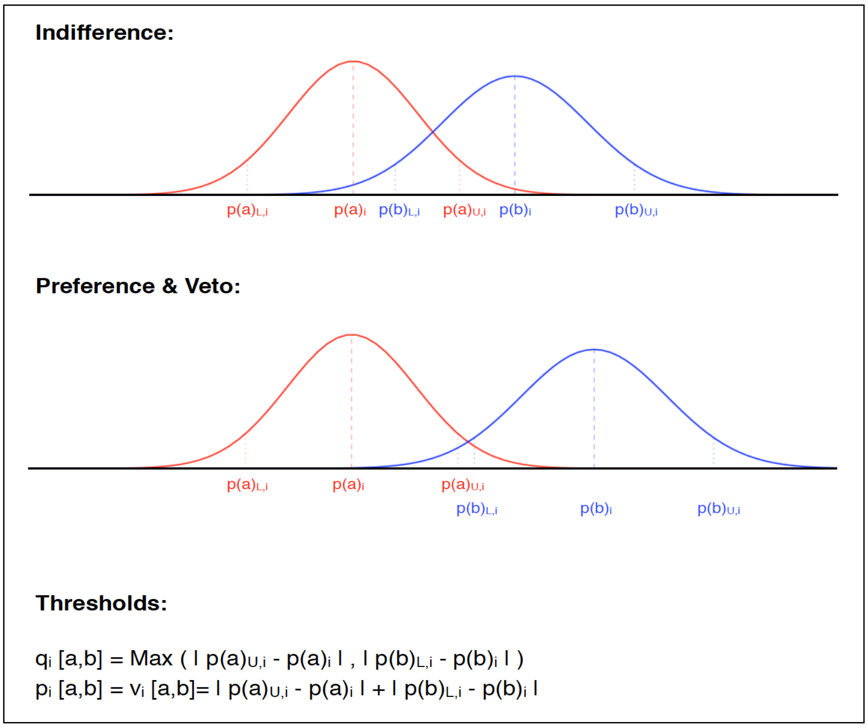

Figure 1. Definition of E3M's thresholds linked to confidence interval of alternatives.

3. RESULTS AND DISCUSSION

In this section, the usefulness of the E3M as a prioritisation and decision-making tool is demonstrated. First, the data's uncertainty is analysed to illustrate the difficulty entailed in its ranking. Next, the method is used to rank the subdistricts at a district level (i.e. applied in each district separately) in order to determine its effectiveness. Finally, the method is used at a country level (i.e. to all districts indistinctly) with the aim of evaluating its suitability for a large number of administrative units.

3.1 Analysis of data uncertainty

Information related to the different water and sanitation criteria was collected at a household level through a structured questionnaire. Values of 0-1 were given to the households depending on whether they met the criterion's condition (1) or not (0). This provided the proportions of households in each of the 338 subdistricts that verified the criterion (p_i), with their respective confidence intervals ($p_{L,i}$, $p_{U,i}$). Figure 2 illustrates these estimates in each district (identified with its enumeration areas, EA) for the criterion of access to improved water sources.

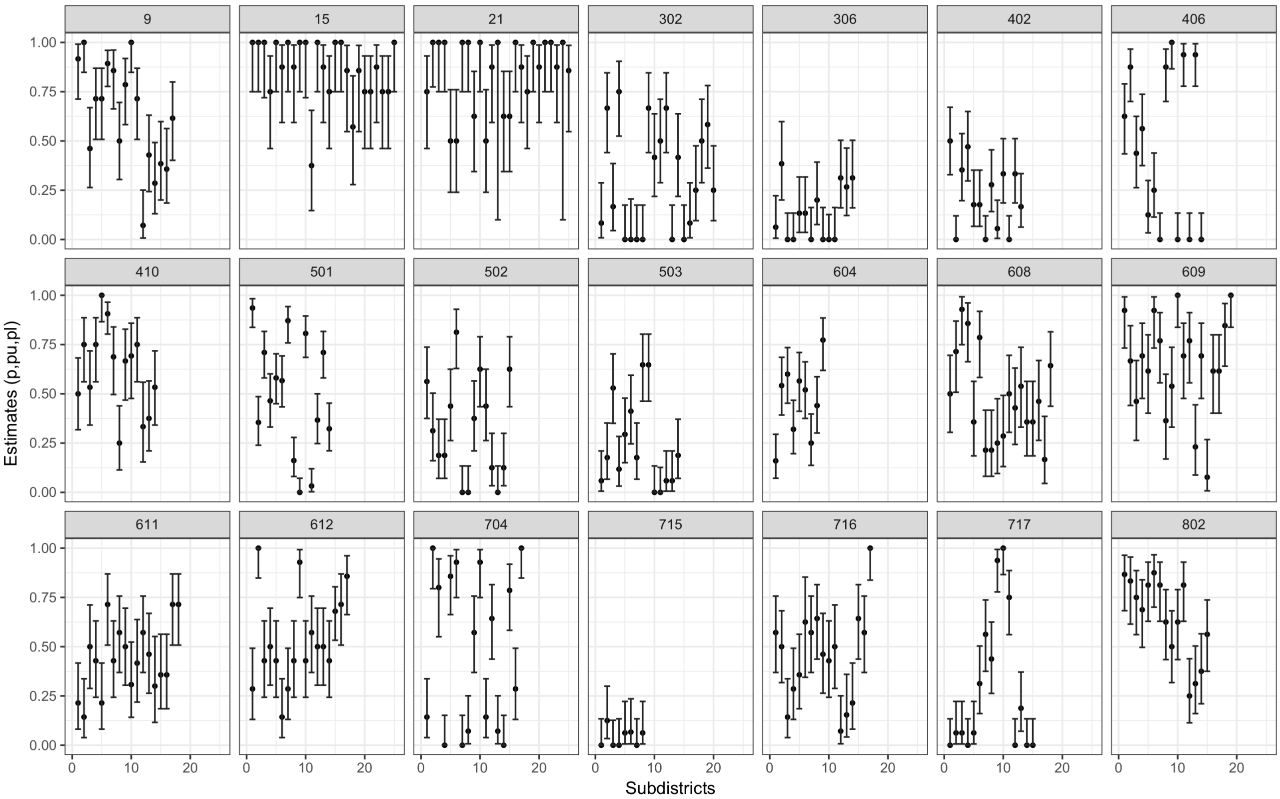

Figure 2. Estimated proportions and confidence intervals of subdistricts (p_i ,$p_{L,i}$, $p_{U,i}$) in the 21 districts for access to improved water sources.

Since small sample sizes were selected for the implementation of local surveys, large lengths of confidence intervals were obtained. As a result, the subdistricts' confidence intervals overlapped, making their ranking a challenging task. It becomes evident that a tool such as E3M, where statistical uncertainty is considered in the analysis, is needed.

3.2 Application of E3M at district level

The E3M method was applied to each one of the 21 rural districts of the Kenyan case study in order to analyse the state of its subdistricts. In each district, the subdistricts were ranked based on their performance regarding the different criteria. At first, only two criteria were considered (c1 and c2), then the outranking tool assessed all criteria. The number of ranks obtained (i.e. the number of positions within the hierarchy) and the ranking effectiveness (i.e. percentage of ranks obtained over the maximum possible, which corresponds to a ranking where each subdistrict is placed in a different position) is presented in Table 1.

When only two criteria were evaluated, E3M was able to provide a detailed ranking of the subdistricts, resulting in most cases in a total of ranks of more than 50% of the maximum possible. This did not happen in just two districts, EA-015 and EA-021, where their 25 subdistricts had a similar performance in terms of access to improved water and sanitation.

When all criteria were considered, the ranking changed in two manners. For most districts, taking more criteria into account entailed a more complete information of the subdistricts conditions, as it was easier to discriminate between them. Consequently, more criteria resulted in more ranks and a higher ranking effectiveness. However, for various districts, the consideration of additional criteria did not help the outranking process. This was the case of EA-604 and EA-612 (which remained the same) and EA-501, EA-503, EA-608, EA-609, EA-611 and EA-716 (which decreased in 1-2 ranks). The drop could be attributed to the fact that their subdistricts' performances were indistinguishable for two pairs of criteria: (i) time used to collect water and individual responsible for the fetching, and (ii) water quality and domestic water consumption. Nevertheless, even in these cases, the ranking effectiveness exceeded 50%.

Table 1. Ranking of sub-districts at district level

District		Nº Sub-districts	Nº Ranks		Ranking effectiveness (%)	
			2 criteria	9 criteria	2 criteria	9 criteria
EA-009	Kitiu	17	9	11	53	65
EA-015	Kieni	25	5	10	20	40
EA-021	Molo	25	10	17	40	68
EA-302	Kwale	20	10	14	50	70
EA-306	Garissa	14	7	12	50	86
EA-402	Isiolo	13	7	10	54	77
EA-406	Tana River	14	8	9	57	64
EA-410	Wajir	14	7	8	50	57
EA-501	Waest Pokot	14	10	9	71	64
EA-502	Turkana	15	11	11	73	73
EA-503	Busia	14	10	9	71	64
EA-604	Kisumu	9	5	5	56	56
EA-608	Bondo	18	12	8	67	44
EA-609	Siaya	19	15	13	79	68
EA-611	Kajiado	18	12	10	67	56
EA-612	Nyando	17	12	12	71	71
EA-704	Rachuonyo	17	10	12	59	71
EA-715	Mwingi	8	4	5	50	63
EA-716	Uasin Gishu	17	11	10	65	59
EA-717	Mandera	15	10	11	67	73
EA-802	Marsabit	15	10	11	67	73

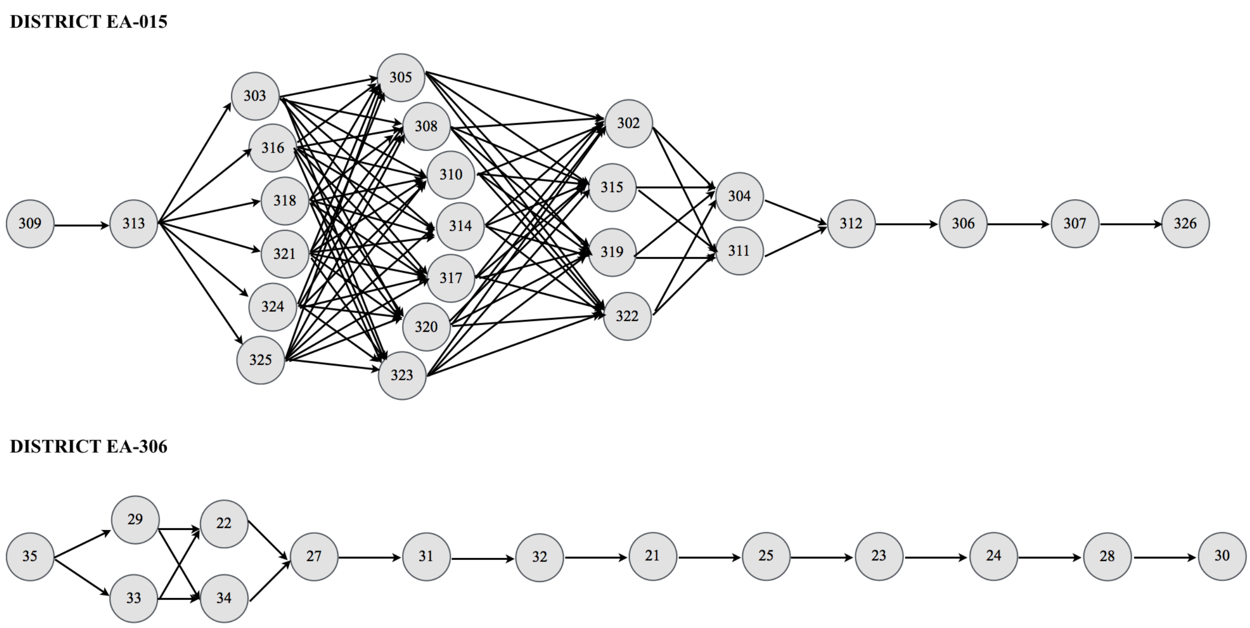

Figure 3. District level ranking in districts EA-015 and EA-306 regarding all criteria.

The difference in ranking effectiveness is illustrated in Figure 3, where districts EA-015 and EA-306 are represented with their ranked subdistricts for all criteria. While E3M provided a poor ranking of subdistrict in EA-015 (its 25 subdistricts were ranked in 10 different positions), for EA-306, the result was more precise (14 subdistricts in 12 ranks). This shows that the effectiveness of E3M for ranking at a district level depends on the data (if subdistricts perform homogeneously, it would be difficult to state that one is better than the others).

3.3 Application of E3M at country level

To determine the suitability of E3M as a prioritisation tool at a country level (with hundreds of administrative subunits), it was applied to all subdistricts jointly. The number of subdistricts evaluated progressively increased (50, 100, 200 and 338) to assess the number of ranks obtained and the computational cost required in each case. At first, only two criteria were considered (access to improved water sources and access to improved sanitation facilities). Then two hygiene-related criteria were added (water quality inspection and point-of-use water treatment). Finally, the analysis was undertaken with all criteria. The results are illustrated in Figure 2.

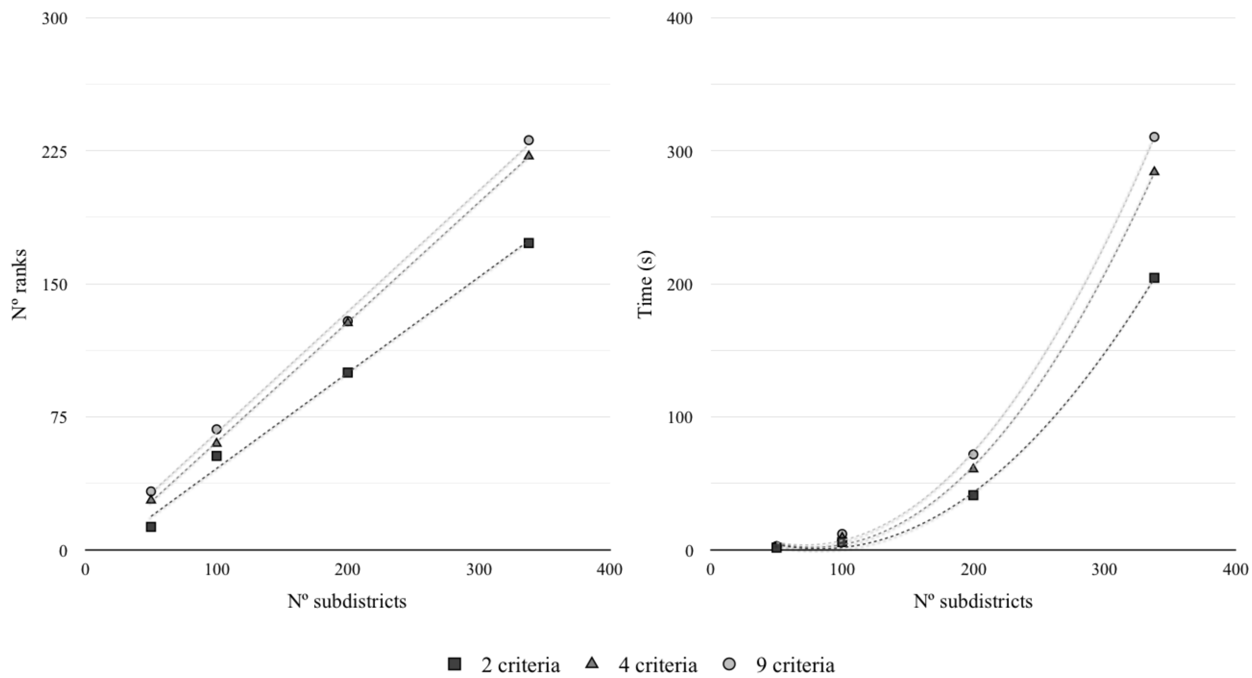

Figure 4. Ranking of sub-districts at country level.

The number of ranks obtained increased linearly with the number of subdistricts evaluated, for all groups of criteria (R^2 value of 0.9938, 0.9999 and 0.9983, respectively). However, it did not translate in an linear increase of ranking effectiveness. For the two criteria evaluation, E3M ranked the 50, 100, 200 and 338 subdistricts in 13, 53, 100 and 173, respectively. Except the first increase in the number of subdistricts (i.e. from 50 to 100), in which the effectiveness increased from 26 to 53%, in the rest it remained constant. The same happened when considering four and nine criteria. The reason of this lied in the data: since many subdistricts performed similarly, it was not possible to conclude that their performances were different.

On the other hand, the time required to execute E3M algorithm followed a second order polynomial function (R^2 value of 0.9989, 0.9991 and 0.9993 with 2, 4 and 9 criteria, respectively). The method's outranking algorithm performs loops of n x n x m, being n the number of subdistricts and m the number of criteria considered. Therefore, it performs n^2 operations. Doubling the input amount of subdistricts increases the number of operations by a factor of four, which explains the quadratic time dependence. It can be thus concluded that E3M is suitable when dealing with hundreds of alternatives.

4. CONCLUSIONS

Statistical uncertainty is an inevitable feature of water and sanitation services management, as surveys are the primary sources of the information used in the decision making process. Sampling strategies lead to high levels of uncertainty present in the data, which complicates its use for prioritisation and targeting purposes. Therefore, to measure water and sanitation services and identify those sector areas and communities most in need, statistical uncertainty needs to be considered.

The paper employs a new version of the outranking method ELECTRE-III, E3M, in which pseudo-criteria are expressed in terms of estimates' confidence intervals. The method was used to rank Kenya's 338 subdistricts in regards to their performance on 9 water and sanitation related criteria. The subdistricts were ranked first at a district level (i.e. district by district). E3M provided an effective ranking of the administrative subunits, being able to establish a detailed hierarchy between the subdistricts. Then, a country level analysis was selected (i.e. to all districts indistinctly), in which 50, 100, 200 and 338 subdistricts were compared. The number of ranking positions and the computational time used was analysed. The first followed a linear increase with number of subdistricts, showing that E3M remained effective even when ranking hundreds of units. On the other hand, the computational time presented a quadratic increase. For a larger number of alternatives (order of thousands), the method's time shoots to the order of hours.

Consequently, this modified ELECTRE-III approach was found effective at taken statistical uncertainty into account in prioritisation and ranking tasks, even when the number of administrative units to be evaluated was hundreds. However, with 1,000 or 2,000 subdistricts, the method is expected to have an impractical computational cost of 1 and 4.4 hours, respectively. Future work should focus on optimising the algorithm to decrease its time complexity and allow its scalability to thousands of alternatives.

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