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Multi-criteria spatial-based modelling for optimal alignment of roadway by-passes in the Tlokweng planning area, Botswana

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ABSTRACT

In this study, Spatial Multi-Criteria Evaluation and the least cost path analysis were applied to find the optimal by-pass road alignment in the Tlokweng Planning Area in Botswana. One-At-a-Time sensitivity analysis and the statistical test for zero proportion were used to investigate the robustness of the entire model. Four alternative by-pass roads were produced stressing economic, environmental, and social suitability as well as trade-offs between the groups. The results showed that the social alternative performs best. Sensitivity analysis and statistical test for zero proportion revealed four criteria as sensitive.

Introduction

A transportation network is imperative for both the development and continued economic sustainability of communities. An often-used approach in determining road alignment in many countries refers to terrain characteristics, such as slope (Yakar and Celik 2014). After selecting several alignments, the economic analysis is performed and the best alignment is then chosen. In some approaches, the planning team also considers social issues besides economic. The environmental impact of the planned road is only assessed after the road alternatives have been developed (Rapaport and Snickars 1999, Belka 2005). The third road planning approach is implementing an environmental impact assessment (EIA) (Shah *et al*. 2010, Swedish Transport Administration 2011, Gonzalez and Enriquez-de-Salamanca 2018), including all social, economic and environmental impacts. This approach helps identify the optimal road alignment as it takes economic, environmental and social criteria into consideration from the start.

Identifying an optimal road alignment represents a spatial problem involving many – usually conflicting – criteria. Spatial Multi-Criteria Evaluation (Spatial MCE) can be applied to solve this dichotomy. It involves combining and transforming geographic (spatial) data into a final output (Malczewski 1999). MCE and Geographical Information

Systems (GIS) have been extensively applied to many problems in different fields since 1990 (Malczewski 2006). One application is transportation, where GIS has been used to solve vehicle-routing problems. However, there are few published papers dealing with the problems of MCE and GIS application in road corridor planning (Rapaport and Snickars 1999, Sadek *et al.* 1999, Belka 2005, Tae-Ho *et al.* 2008, Hala and Hassan 2013, Yakar and Celik 2014, Loganathan and Elangovan 2017, Singh and Singh 2017, Abdallah *et al.* 2019).

Rapaport and Snickars (1999) recognised the importance of introducing the environmental prospective at the beginning of the road planning process in 1999. This was important because Rapaport's research suggested that in order to find the optimal road alignment, the environmental criteria should be considered at the same time as the other criteria usually used in the road planning process, such as economic and technical. However, since his research the introduction of EIA within the GIS-based MCE approach when defining road alignment has been mostly underdeveloped and considered in only few papers (Belka 2005, Hala and Hassan 2013). Another integral part of the spatial MCE approach is sensitivity analysis (SA). The majority of road planning research does not include any (detailed) sensitivity analysis. This is a significant drawback as the robustness of the developed models is not investigated and thus remains unknown.

This paper presents a spatial MCE method which integrates economic, environmental and social criteria using the EIA approach to propose alternatives for by-pass road alignment. The spatial MCE method is based on applying the Analytical Hierarchy Process (AHP) and Weighted Sum (WS), and also implements One-At-a-Time (OAT) sensitivity analysis. A case study in the Tlokweng Planning Area (TPA), Botswana is used to evaluate the method. This is an ideal case study because the current road planning practice in Botswana does not use spatial MCE, allowing the results to be compared. This paper aims to answer the following questions:

- Which by-pass alignments are preferable in respect to economic, environmental and social characteristics of the case study area?
- How much do the results of the proposed spatial MCE approach differ with the by-pass alignments proposed by the 'Tlokweng Development Plan 2025'?
- Which criteria are most sensitive to weight changes?

The final part of this research is developing the automated multicriteria GIS analysis tool to simplify the spatial MCE modelling process, which with slight adjustment would be applicable to other study areas.

Methods

A spatial MCE follows eight steps (Malczewski 1999): *(1) determination of criteria and constraint within each criterion group, (2) criteria standardisation, (3) definition of criteria weights, (4) combining criteria, (5) definition of criteria group weights, (6) combining criteria groups, (7) ranking by-pass solutions and (8) sensitivity analysis*. The entire spatial MCE framework is shown in Figure S1 with a detailed presentation of its eight steps.

Determination of criteria and constraint

Thirteen criteria were defined based on previous work (Rapaport and Snickars 1999, Sadek *et al*. 1999, Belka 2005, Saha *et al*. 2005, Tae-Ho *et al*. 2008, Yakar and Celik 2014, Loganathan and Elangovan 2017, Singh and Singh 2017, Abdallah *et al*. 2019) and the Botswana Road Design Manual; these criteria were classified into the three EIA criteria groups – economic, environmental and social as follows:

- economic (C1-Slope of the terrain, C2-Road-crossing criteria, C3-River-crossing criteria, C4-Flooding areas, C5-Terrain geology, C6-Soil type)
- environmental (C7-Natural protected areas, C8-Major river streams, C9-Surface waters, C10-Ground waters)
- social (C11-Land cover, C12-Air pollution, C13-Noise pollution)

All 13 criteria defined in this study pass through the constraint criterion. Constraint represents Boolean criteria based on binary classifications (1 – true; 0 – false) (Jiang and Eastman 2000). Table S1 presents the 13 defined criteria, constraint criterion and rationale for their inclusion in the road by-pass planning.

Criteria standardisation

The criterion maps can be either qualitative (e.g. soil types, vegetation types) or quantitative (e.g. digital elevation model, proximity maps) (Malczewski 1999, Malczewski and Rinner 2015). As different scales of attribute values are involved, criterion maps must be translated into comparable units, known as standardisation of criteria. The decision maker standardisation method, using the scale 1 to 5, was utilised to standardise every criterion (Malczewski and Rinner 2015). A group of 10 experts discussed the criteria and agreed on proper value for standardization. An assigned value of 1 represents the most preferable choice (e.g. least cost), while 5 corresponds to the least preferable (e.g. highest cost). To perform standardisation, every criterion is presented with different classes and then each class is assigned a value from 1 to 5. Table 1 shows the example of standardisation of criterion, C1-Slope. As the slope increases the standardized scale increases. Visualization of standardized criterion C1-Slope is shown in Figure S2.

Table 1. Standardization of C1-Slope.

Slope class (%)	Scale
0–3	1
3–5	2
5–8	3
8–12	4
>12	5

Definition of criteria weight

It is necessary to define the criteria weights used to attribute relative importance of individual criteria. The pairwise comparison matrix for the criteria within every criterion group was determined by a group discussion in which a group of experts gave their opinions before agreeing on the criteria weights. A group of 10 experts (mentioned above) were invited to a meeting to weight the criteria based on a direct method. We used a Delfi (Linstone and Turoff 1975) method, in which experts discussed each criterion and its importance and then agreed on the weight. The consistency of the obtained criteria weights was determined by calculating the consistency ratio (CR). Calculated criteria weights are valid if the CR value is less than 0.10 (Saaty 1980). The consistency ratio was calculated using Equation (1). (Saaty 1980):

$$CR = \frac{CI}{RI} \tag{1}$$

where CI = the consistency index, and RI = the random consistency index value.

Consistency index (CI) was calculated according to Equation (2):

$$CI = \frac{(\lambda max - n)}{(n - 1)} \tag{2}$$

where λmax = principal eigenvalue, and n = number of criteria.

λmax was calculated by Equation (3):

$$\lambda max = \frac{\sum_{i=1}^{n}(Cons_i)}{n} \tag{3}$$

where Consi = elements of consistency vector, and n = number of criteria.

If the computed CR is less than or equal to 0.10 ($CR \leq 0.10$), the degree of consistency is satisfactory. In the case where the CR is equal to 0.0 then perfect consistency has been achieved. If the computed CR is greater than 0.10 ($CR > 0.10$), there is a serious inconsistency and the criteria comparison has to be recalculated; this means that new preference values are assigned and the process is repeated until the CR reaches the required value of being less than 0.10.

Combining criteria

Weighted sum (WS) is used to combine criteria within each criterion group. The formula representing the weighted sum technique is given in Equation (4):

$$A_i = \sum_j w_j x_{ij} \tag{4}$$

where Ai = susceptibility score, Wj = normalised weight determined through AHP, and Xij = criteria value determined through criteria standardisation.

Definition of criteria group weight

Depending on which criterion group is preferable, every group receives twice as much weight than the remaining two criteria groups. Thus, definition of criterion group weights

is specific to giving preference to one group over another, but not the number of criteria within each criterion group. For example, when the economic criterion group is preferable, it receives 50% weight while the remaining two, environmental and social, each receives a weight of 25%. In addition, the fourth solution was also defined, in which every criterion group receives an equal weight of 33.33%. The pairwise comparison matrix was created for each case and CR checked in order to confirm the degree of consistency is satisfactory.

Combining criteria groups

The criteria groups are also combined with WS (Equation (4)) to obtain the final road by-pass solution. Depending on the assigned weight to each criterion group, four solutions are produced: economic, environmental, social and trade-off. The trade-off solution is obtained by giving equal weight to all three criteria groups.

Ranking of solutions

After producing road by-pass solutions, it is necessary to rank them in order to find the solution that performs best. Based on a literature review, the solutions are compared according to the following eight evaluation criteria (Saha *et al*. 2005, Hala and Hassan 2013, Yakar and Celik 2014, Singh and Singh 2017).

- Number of agro land plots crossed (EC1),
- Number of objects demolished (EC2),
- Number of crossings with primary, secondary and tertiary roads (EC3),
- Number of crossings with rivers with 5th, 6th, 7th and 8th stream order (EC4),
- Earth works cut-and-fill (m3) (EC5),
- Total amount of asphalt and rocks used to build a by-pass (m3) (EC6),
- Length of tunnel (metres) (EC7), and
- Length of bridge (metres) (EC8).

To standardise the evaluation criteria, a linear scale transformation method – a maximum score – was applied (Malczewski and Rinner 2015). The formula representing the maximum score method is given in Equation (5):

$$X_{ij'} = 1 - \frac{Xij}{Xj(\max)}$$ (5)

where Xij' = standardised score of the i-th evaluation criterion, Xij = raw value of the i-th evaluation criterion, and Xj(max) = maximum score of the evaluation criteria.

The AHP is used to determine evaluation criteria weights. Finally, WS is utilised to combine the evaluation criteria. Standardisation of evaluation criteria, assigning the weights to these criteria, combining evaluation criteria and ranking solutions are completed using DEFINITE software (Janssen and Herwijnen 1994).

Sensitivity analysis

A sensitivity analysis (SA) for criteria weights helps identify which weights are prone to subjectivity. 'One-At-a-Time' (OAT) sensitivity analysis was applied where only one factor, a criterion weight, is changed to identify what effects it produces on the output. The process was repeated for each factor (Saltelli *et al*. 2004).

SA framework
The main points included in the SA framework are (Chen *et al*. 2010):

(1) The base scenario represents the criteria weights and criteria group weights defined through AHP.
(2) In every criteria group, each criterion weight is changed by 1% (incremental percentage change) within the range −20% to +20% (range percentage change). The base case scenario represents the case where the change is 0%. Thus, the total number of runs for each criterion is 41. Therefore, the total number of model runs in the entire analysis is calculated by Equation (6):

$$Total \ number \ of \ runs = \sum_{i=1}^{n} \sum_{j=1}^{k} \sum_{m=1}^{h} (m)j(i)i \qquad (6)$$

where n = the total number of criteria groups, k = the total number of criteria within a criterion group i, and h = the total number of incremental percentage changes (incremental percentage change is 1% within the range of (−20%, +20%)), representing 41 runs for each criterion j).

(3) When changing the criterion weight by an incremental percentage change within a corresponding criterion group, the additivity constraint applies. This means that the sum of weights for all criteria within a corresponding group is equal to 1.0 at any percentage change. The additivity constraint at any percentage change for all criteria weights within a group is expressed by Equation (7):

$$Wi(m) = \sum_{j=1}^{k} Wi(jm) = 1, m \in (RPCmin, RPCmax), (i = 1 \ \ldots \ 3) \qquad (7)$$

where Wi(m) = the sum of criteria weight within a criterion group i (i = 1–3) at percentage change m, k = the total number of criteria within a criterion group i, Wi(jm) = the weight of criterion j at a percentage change m within a criterion group i, RPCmin = the minimum value of range percentage change – RPC (default is −20%), and RPCmax = the maximum value of range percentage change – RPC (default is +20%).

(4) The weight of a criterion in question at any percentage change within a corresponding group consists of the sum of weight defined through the AHP, base case scenario and percentage change in question by Equation (8):

$$Wi(j, m) = Wi(j, 0) + Wi(j, 0) * m, m \in (RPCmin, RPCmax), (i = 1 \ \ldots \ 3) \qquad (8)$$

where Wi(j, m) = the weight for criterion j for which the weight is changing within a criteria group i, Wi(j, 0) = the weight for base case scenario for criterion j for which the weight is changing within a criteria group i, and m = the percentage change within a criteria group i.

(5) To meet the additivity constraint condition, it is necessary to adjust the weights of other criteria belonging to a corresponding criterion group for which the weight of main criterion is changing. This means that other criteria need to be readjusted in such a way that the sum of all criteria within a group will be equal to 1.0. The criteria within each group are adjusted based on their weights defined for the base case scenario through the AHP by Equation (9):

$$Wi(Cj, m) = (1 - Wi(j, m)) * \frac{Wi(Cj, 0)}{1 - Wi(j, 0)}, m \in (RPCmin, RPCmax), (i = 1 \ldots 3) \quad (9)$$

where Wi(Cj, m) = the adjusted weight for criterion j within a criterion group i at a percentage change m, Wi(j, m) = the weight for criterion j for which the weight is changing within a criterion group i, Wi(Cj, 0) = criterion weight Cj for base case within a criterion group i, and Wi(j, 0) = the base case criterion weight j for which the weight is changing within a criterion group i.

(6) For every iteration performed on every criterion, the total number of cells belonging to each cost value (from 1 to 5) is calculated as well as the transitions happening among the cells (total number of cells that change the cost value in respect to its value defined for the base case scenario).

(7) To investigate the robustness of the entire model the total number of changed cells for every iteration were compared to a critical value X_c indicating if the change in total number of cells is statistically significant. This value is based on the statistical test for zero proportion – the frequentist test (Bradley and Farnsworth 2013). The critical value of X_c is computed by Equation (10):

$$X_c = np_+ + z_a \sqrt{np_+(1 - p_+)} \quad (10)$$

where z_a = 1.645 for significance level a of 0.05, FIND_A_1754010 = the misclassification rate of 0.015, and n = the sample size of 11 343 425 and represents the total number of cells within a cost surface raster dataset.

If the number of changed cells is higher than the computed critical value X_c, then the change in the number of cells is statistically significant. This means that the criterion weight shows sensitivity at the percent change in question.

(8) If the model confirms sensitivity to changes in criterion weight, then the changed cells occurring in the space is visualised. This gives the spatial pattern of criterion weight sensitivity when identifying those cells within a raster dataset that have some degree of uncertainty.

The algorithm to conduct SA has three loops. In the first loop, 41 iterations were performed for a criterion in question. The second loop iterated over every criterion within a corresponding criterion group. Finally, the third loop iterated over every criterion group – economic, environmental and social.

Development of the road planning GIS toolbox

The spatial MCE methodology proposed in this research was automated through the development of a GIS toolbox. The model also incorporated the least-cost path analysis based on Dijkstra's algorithm (Dijkstra 1959) and back-link mechanism (Xu and Lathrop 1994). These were used to produce by-pass road alignments using obtained cost surface raster datasets. The toolbox was created in ModelBuilder, an application of ArcGIS 10.5 software. OAT sensitivity analysis was performed by running a stand-alone Python script that communicated with ArcGIS through ArcPy.

Case study

The study area is the Tlokweng Planning Area (TPA) in Botswana (Figure S3). The total area is 28 389 ha, of which 3 356 ha comprises the built-up area. According to the 2011 census, the TPA has a population of 36 500, which makes it the 13th-largest settlement in Botswana. To the west, TPA shares a border with the nation's capital city, Gaborone. Its proximity to Gaborone makes it a peri-urban settlement with both, urban and rural characteristics. To the south, TPA borders the Republic of South Africa and to the east the Kgatleng District.

Surveys reveal that national road A12 (Tlokweng road) suffers from serious traffic congestion, especially the section between the Tlokweng built-up area and Gaborone (GIS Plan 2018). It has been acknowledged that through-traffic from the Tlokweng border, particularly heavy trucks on road A12, produces traffic congestion during peak hours (GIS Plan 2018). To improve traffic flow on road A12 and reduce congestion, northern and southern by-passes are proposed in the TPA (Figure S3). The main intention is to divert heavy trucks carrying goods from South Africa to Botswana, Zambia and Namibia via the Tlokweng built-up area.

For the design of the planned by-pass roads (separate from the study of this paper), no spatial MCE method was utilised. The northern and southern by-passes were determined based on the eight planned criteria listed in Table 2.

Table 2. Route selection criteria used for planned solution in TPA.

Planned criteria	Descriptions
PC1-Protection of agricultural lands	The routes will avoid ploughing areas as much as possible.
PC2-Promoting tourism	Proposed route should pass through scenic landscapes.
PC3-Number of road crossings	The route will eliminate expensive traffic interchanges.
PC4-Flood and erosion protection and protection of fragile water courses	Environmental spin-offs from the road will incorporate provision barriers for flood control and protection of fragile water courses.
PC5-Improved border safety	The route will give access for border patrol and control which will improve border safety and security.
PC6-Wildlife and flood protection	Wildlife protection will be achieved by increased anti-poaching activities.
PC7-Physical fire barrier	The proposed routes will represent physical barriers against fire.
PC8-Protection from fuel spillage	Routes will avoid areas with ground water systems.

Data

Spatial data for the study area were available in the format of shapefiles and raster datasets. They were provided by public and private consulting companies (GISPlan, DSM-Department of Survey and Mapping, TLB-Tlokweng Land Board, BPC-Botswana Power Corporation). All datasets were available in a local coordinate reference system for Botswana.

The slope of the terrain was readily available as a raster dataset with cell size 5 × 5 m. Approximately 75% of the area falls between extremely flat and gently undulating slopes (0.2–5.0%). Hilly areas with slopes steeper than 10% were mostly located in the south-western part of the Tlokweng Planning Area (Figure S4).

The existing roads within the Tlokweng study area and data representing the stream size in accordance with the Strahler stream order (Strahler 1964), were available as poly-line feature datasets. Surface and underground water systems as well as the major flood-plains were acquired as polygon feature datasets. Geological and soil conditions with regards to by-pass construction were in the form of polygon feature datasets. Land use and land cover data were available as a combination of raster and polygon feature datasets. Data presenting new urban expansion and economic areas in accordance with spatial growth scenario developed for TPA for year 2025 were obtained as polygon feature datasets.

Results and discussion

By-pass solutions

Four solutions were produced by combining three criteria groups, giving the highest preference to environmental, economic, and social criterion group as well as equal weight (trade-off) to these groups. Depending on which criterion group was preferable, every group received twice as much weight as the remaining two criterion groups. For example, when the economic criterion group was preferable, it received 50% weight while the remaining two, environmental and social, each received a weight of 25%. Because the economic criterion group is preferable, this solution is called the economic solution. The same applies to the environmental and social solutions. The fourth, trade-off solution, represents a combination in which every criterion group receives equal weight of 33.33%. Each solution has 2 by-pass alignments running through southern and northern parts of the study area. The four solutions produced by applying spatial MCE are presented in Figure 1.

For every solution, the least-cost path algorithm was used to produce cost surfaces to place the southern and northern by-pass road alignments. The predicted road alignments exhibit more variation in the south than in northern Tlokweng. This is an indication that the cost surface is more variable in the south and at the same time more stable in the north of the study area. In order to quantify the differences between the solutions, eight evaluation criteria values for each by-pass solution were computed. Table 3 shows the computed values of eight evaluation criteria as a summation of both the northern and southern by-passes for every solution. The values of the evaluation criteria were also computed for the planned solution (Figure S3) and presented in Table 3. The social solution with high social preference mostly protects agricultural lands and existing houses, thus its alignments (s-routes in Figure
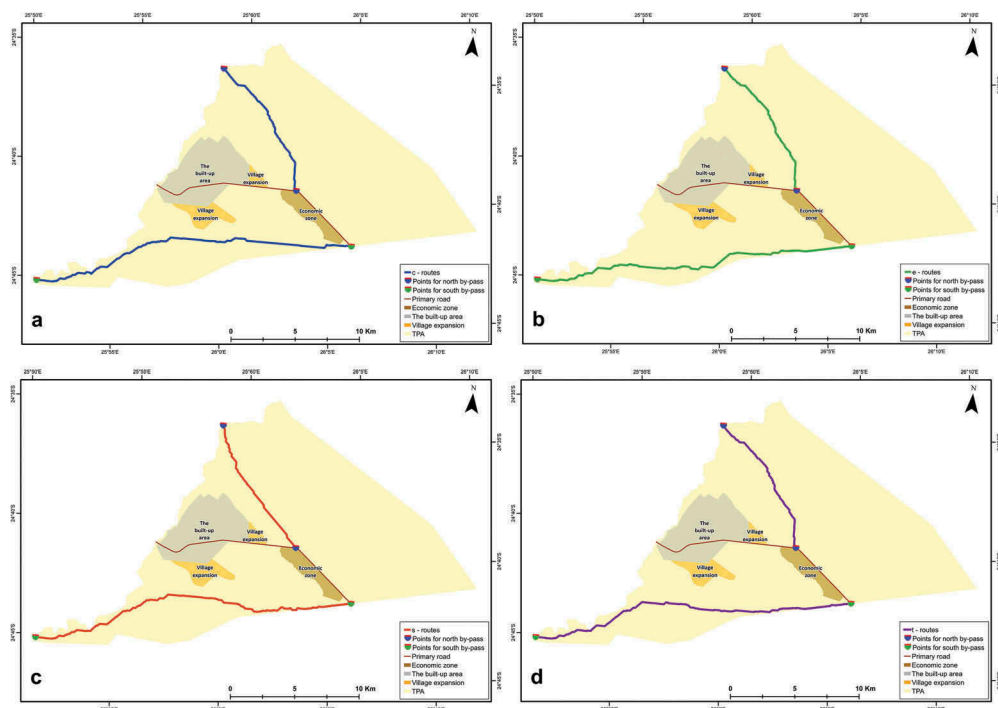
Figure 1. By-pass alignments for: (a) economic solution (c-routes), (b) environmental solution (e – routes), (c) social solution (s – routes), (d) trade-off solution (t – routes).

Table 3. Summary table: calculated values of evaluation criteria for each solution.

Evaluation criteria	Economic	Environmental	Social	Trade-off	Planned
EC1-Number of agro land plots crossed	39	31	27	32	37
EC2-Number of objects demolished	40	32	30	38	69
EC3-Number of road crossings (primary, secondary and tertiary roads)	2	2	3	3	2
EC4-Number of river crossings (5th, 6th, 7th and 8th stream order)	8	6	8	8	12
EC5-Earth works cut-and-fill (m3)	780636	2980199	794870	842197	6522557
EC6-Total amount of asphalt and rocks used to build a by-pass (m3)	103824	104272	104238	104269	133446
EC7-Length of tunnel (metres)	0	970	0	0	2100
EC8-Length of bridge (metres)	0	0	0	0	700

1(c)) cross the least amount of agricultural land plots and has the least number of objects demolished, 27 and 30, respectively. The environmental solution with high environmental preference (e-routes in Figure 1(b)) should be diverted from major river systems; thus, the number of river crossings is least for this solution and equals 6. In respect to the economic solution with high economic preference (c-routes in Figure 1(a)), the highest preference is given to slope of the terrain; therefore, an indication of this preference is seen in the least amount of cut-and-fill works (m3) and materials necessary for by-pass building – asphalt and rocks. The trade-off solution (t-routes in Figure 1(d)) assumes equal preference among criteria groups.

The results show that this solution is somewhat between the lowest and highest evaluation criteria values. This is especially evident for evaluation criteria EC1, EC2, EC5 and EC6. The by-pass alignments for the planned solution (Figure S3) were not produced by the spatial MCE method and, therefore, the results significantly differ from the four produced alignments in this study. This is particularly noticeable for evaluation criteria EC5, EC6, EC7 and EC8. In the south, the planned by-pass route follows the border of Botswana with Republic of South Africa, going through hilly areas, thus requiring building tunnels and bridges, which significantly affects the construction cost.

After computing the values of eight evaluation criteria for every solution, it was necessary to rank the solutions. The rankings are presented in Figure 2. The x-axis shows the solutions considered and the y-axis the ranking value. A preference for every solution is shown by bar height – the higher the bar, the better the solution. The best ranked is the social solution followed by trade-off. Evaluation criterion EC1, number of agricultural land plots crossed, mostly contributes to the difference between social and trade-off solution. EC1 receives the highest weight of 0.22 (Figure S1) among evaluation criteria while the agricultural lands in the social solution are highly protected, placing the social solution before others. Further, the results confirm that the environmental solution is ranked lowest among spatial MCE produced by-pass road alignments. Regarding the alternatives produced by the spatial MCE model, the results show that evaluation criteria EC5, EC6, EC7 and EC8 almost equally contribute to the social, trade-off and economic solutions. The
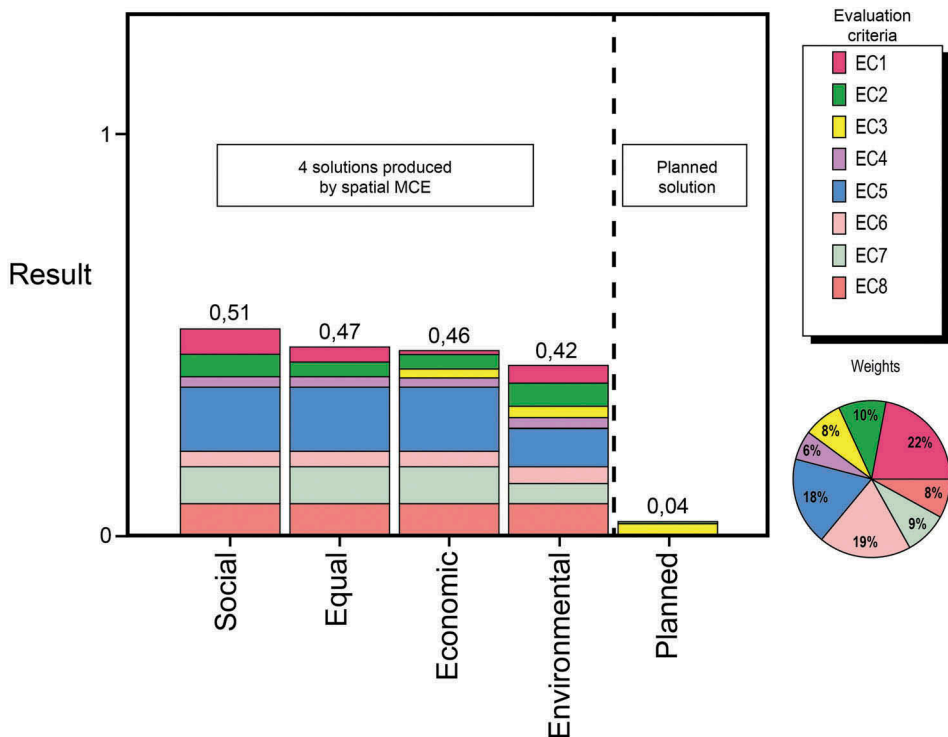

Figure 2. Ranking of the spatial MCE-produced and planned solution.

planned solution defined by a company differs highly from the spatial MCE-produced solutions.

Route difference: spatial MCE-produced solutions and the proposed planned solution

Comparison of the solutions was based on eight evaluation criteria. The results show significant differences between the modelled spatial MCE and planned solution. This is due to the used criteria and applied methodology.

Some criteria are used in both approaches such as protection of agricultural lands (C11) and number of road crossings (C2) (Table S1). On one hand, some criteria quite differ such as promoting tourism with the aim of alignments passing scenic landscape (PC2) (Table 2). Criterion PC2 is especially applicable for the planned south by-pass alignment that follows the Botswana border; on the other hand, this route passes through hilly areas requiring the building of tunnels and bridges which increases construction costs.

Not only were the criteria different, but also the applied methodology. To manipulate criteria for GIS-produced alignments a well-established mathematical structure within spatial MCE is used, such as Saaty's method of pair-wise comparisons and weighted sum (WS). This gives an advantage to this methodology as it brings consistency in the analysis because the criteria are equally evaluated across the study area, without using subjective judgment for the same criteria within the study area.

In addition, the proposed methodology takes into consideration different aspects of the EIA approach, something that is not consider in the proposed planned solution.

This proposed approach is more flexible, as it is not limited to a single solution, which is the case with the planned solution.

Identification of sensitive criteria

Each criterion weight, defined through AHP (base case scenario), is changed by 1% (incremental percent change) within the range of −20% to +20% (range percent change). Thus, SA consists of 533 model iterations. For every iteration, SA results present calculated criteria weights, number of cells in every cost class value (from 1 to 5) and number of cells changed – that is, transitions that happen among different cells. These changes are given with respect to the base case scenario for which the incremental percent change is 0%.

Raster data sets presenting cost surfaces with changed cells are produced through every iteration. This provides insights into the spatial pattern of weight sensitivity, the change in the number of cells and cell transitions as these are identified across the space. Thus, it can be confirmed where these changes are occurring in the space and which criterion is the most sensitive. Based on the statistical test for zero proportion – the frequentist test (Bradley and Farnsworth 2013) – four criteria were identified as sensitive – C3, C7, C9 and C11. For every sensitive criterion, two cost surfaces are shown. The cost surface presenting a base case scenario (0% change) is shown in Figuress 3(a), S5(a), S6(a) and 4(a). The locations where the total number of cell changes is highest are shown with cost surface in Figuress 3(b), S5(b), S6(b) and 4(b).

C1, slope of the terrain, is most responsive to cell changes from a cost value of 4 to a cost value of 3 (Figure 3(b)). This area is located in the southwestern part of the study area within
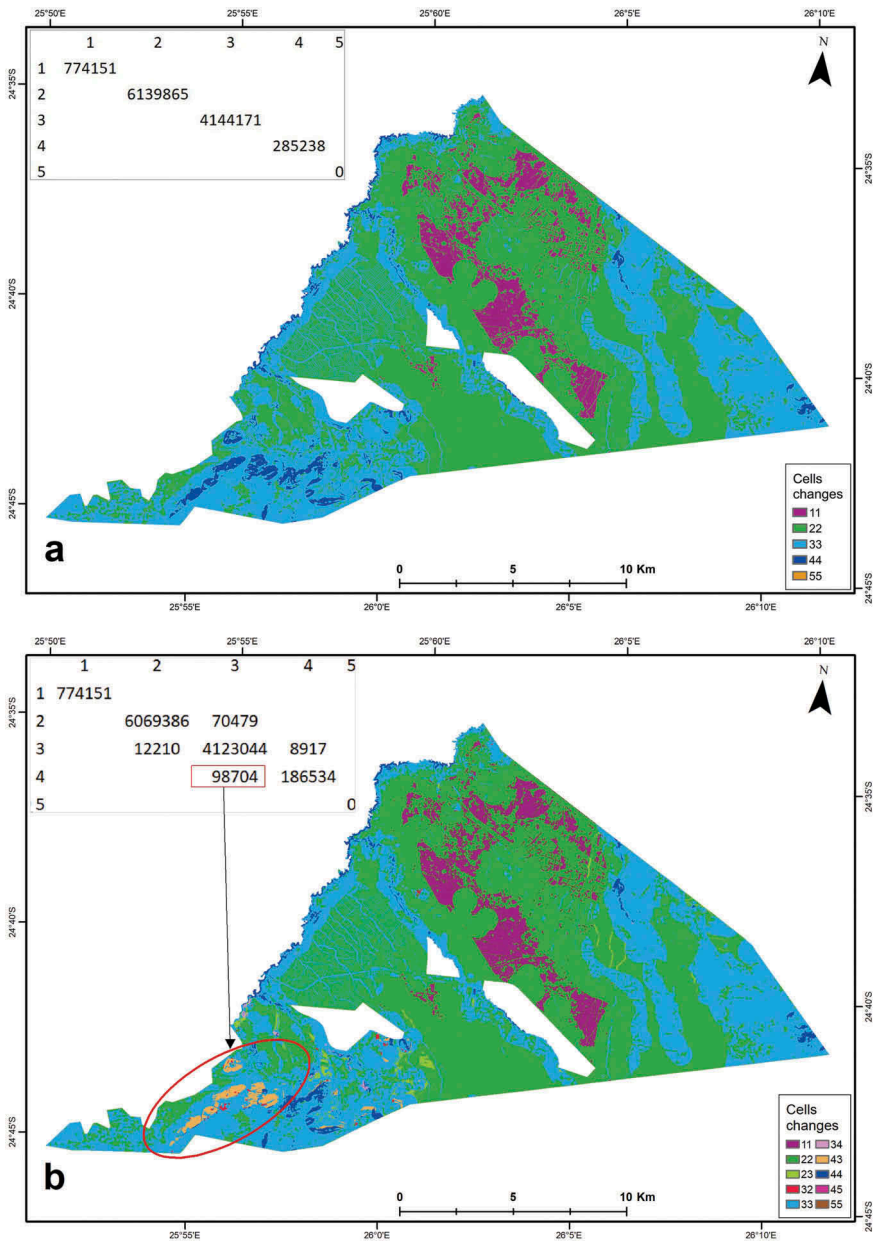
Figure 3. Spatial pattern of weight sensitivity for criterion 1, slope of the terrain: (a) no cells changes – percent change = 0%; (b) highest cell changes – percent change = −20%.

hilly terrain. Regarding C7, naturally protected areas, and C9, surface waters, the results show that these are most responsive to cell changes from cost value of 3 to a cost value of 2 situated along Maratadiba, and Notwane rivers (Figure S5(b) and S6(b)). The most sensitive criterion C11, land cover, shows quite high sensitivity with the total number of changed cells that is over 2 million (Figure 4(b)). Changing the total number of cells for each cost class
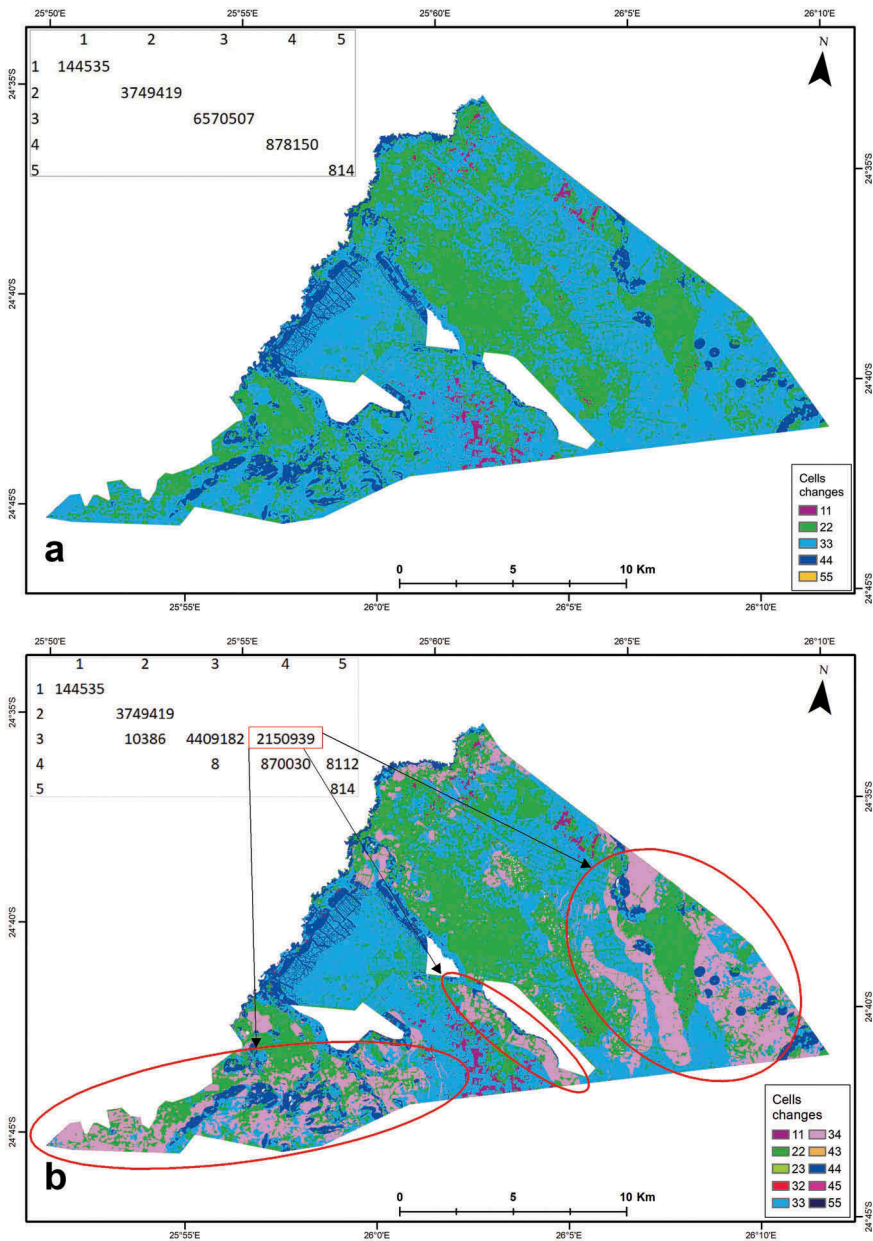
Figure 4. Spatial pattern of weight sensitivity for criterion 11, land cover: (a) no cells changes – percent change = 0%; (b) highest cell changes – percent change = +20%.

through 41 iterations for criterion C11, land cover, is shown in Figure S7. This criterion is most responsive to cell changes from a cost value of 3 to a cost value of 4 starting with an incremental percent change of +8%. The number of cells with cost values of 1, 2 and 5 remain quite stable through iterations. C11, land cover, receives the most weight of 0.70 among all criteria (Figure S1), making this criterion the most sensitive. Thus, it has a high influence on the evaluation results within a social criterion group.
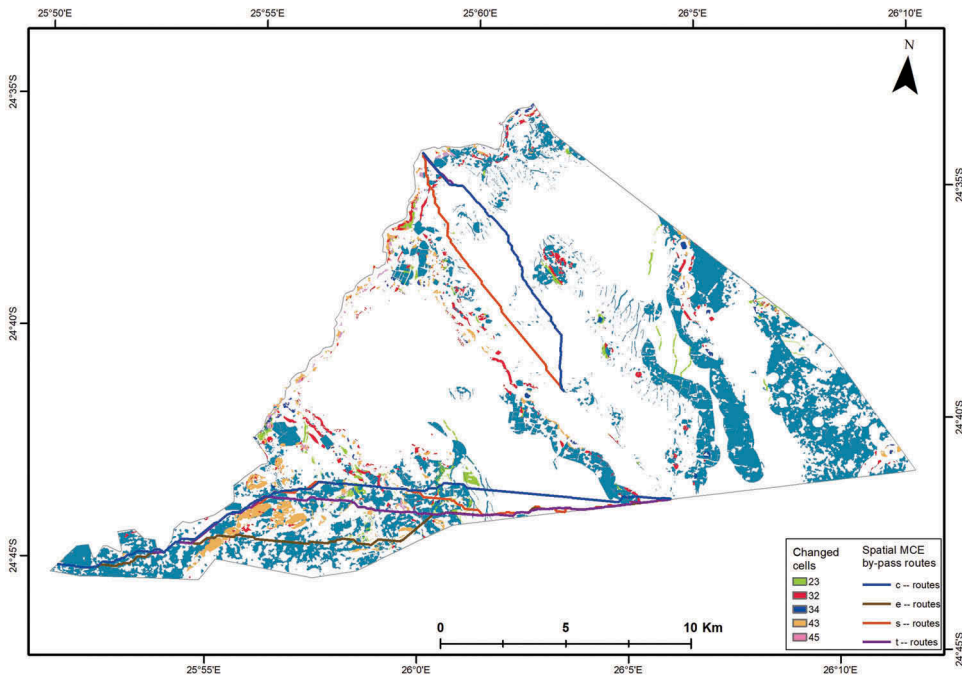
Figure 5. Spatial sensitivity within the Tlokweng Planning Area (TPA).

All the areas within the TPA where the highest cell changes occur are shown in Figure 5. Despite some criteria being sensitive to weight changes, the north area where the by-pass alignments are located proved relatively stable from the SA investigation. Thus, the results derived from the base-case scenario can be used to analyse the consequences of building the by-pass road in this area. On the other hand, the SA analysis confirmed sensitivity within the study area where southern by-pass roads are located. This spatial sensitivity is mostly driven by only one criterion C11, land cover, revealing that this criterion will mostly affect the solutions within the social criterion group.

Conclusion

In this study, the spatial MCE approach was applied as an integrated part of an environmental impact assessment (EIA) to determine optimal by-pass alignments in the Tlokweng Planning area in Botswana. Also, One-At-a-Time (OAT) sensitivity analysis was applied to identify sensitive criteria. The latter has not been studied much in spatial MCE.

The spatial MCE model produces four solutions – economic, environmental, social and trade-off – when combing three criteria groups – economic, environmental and social. Although this study focuses on four solutions, the adapted methodology can be used to test different solutions within TPA and help practitioners reach reliable decisions. The model is flexible in several aspects. It allows defining criteria standardisation, its weights, and criteria group weights as well as combing criteria and criterion groups in different ways. It is not limited to producing by-pass alignments between the points used in this analysis as it also enables changing the locations between which the road alignments

should be produced. The model is practical to use and produces results quickly. Not only does the model save time, it ensures errors are avoided that could have happened otherwise. Results for spatial MCE produced solutions are quite different to the planned solution proposed by the 'Tlokweng Development Plan 2025' mainly because they have not considered and optimized all social, economic and environmental factors, while designing the roads.

OAT sensitivity analysis and the statistical test for zero proportion were carried out in order to determine the robustness of the entire model. This analysis helps identifying criteria sensitive to weight changes. Besides presenting OAT results as the number of changed cells for produced cost surfaces, the OAT results were also shown spatially. This way, more insights were obtained about the stability of the output results. OAT was completed using a standalone Python script; It is flexible and can be run to test different scenarios.

Based on eight evaluation criteria, the main findings from this study suggest that the social solution performs the best. Evaluation criterion EC1, number of agricultural land plots crossed, mostly contributes to this solution being placed first. OAT sensitivity analysis confirms four criteria as sensitive, of which C11, land cover, displayed the greatest sensitivity affecting by-pass alternatives for the social solution. The model became sensitive at +8% of this criterion weight change.

The final spatial MCE model for the Tlokweng Planning area in Botswana could serve as a base for planning and determining road alignments. However, with slight adjustment and depending on prevailing criteria, it could be used for the same purpose in other study areas. In addition, the model could find application not only in road planning, but also in other research areas such as urban planning, site selection, natural hazards, etc.

Disclosure statement

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