



An approach for ensuring minimum protected area size in systematic conservation planning

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ABSTRACT

One of the most efficient approaches for designing protected area (PA) networks is to use systematic conservation planning software. A number of software packages are available and all of them include a spatial cost or constraint component in their prioritisation algorithms, which allow the user to determine the level of fragmentation of the final PA system. Many conservation planners want to set minimum PA size thresholds, as small PAs are less viable and more expensive to manage, but this can only be achieved with existing software packages by repeatedly reducing the fragmentation levels of the PA system until every PA meets the threshold. Such an approach is inefficient because it increases the size of every PA, not just the smaller ones. Here we describe MinPatch, a software package developed to overcome this problem by manipulating outputs from the Marxan conservation planning software, so that every PA meets the user-defined size threshold. We then investigate the impacts of this approach with a dataset from the Maputaland Centre of Endemism, and find that using MinPatch to meet the PA thresholds is a much more efficient approach than using Marxan alone. We also show that setting a minimum PA threshold can have important effects on where new PAs are located when compared with Marxan outputs. Based on these results, we recommend that conservation planners use MinPatch whenever they want each PA in a network to meet a minimum size threshold.

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1. Introduction

Many species and habitats are poorly represented by current protected area (PA) systems (Rodrigues et al., 2004; Jenkins and Joppa, 2009), so most countries have pledged to develop representative PA systems as part of their Convention on Biological Diversity commitments (CBD, 2004). One commonly used approach for expanding and modifying PA systems is systematic conservation planning (Moilanen et al., 2009), which involves: (i) developing a list of important conservation features; (ii) setting targets for how much of each of these features should be conserved, and; (iii) undertaking a conservation assessment to identify new priority areas that best meet the targets in combination with any existing PAs. A number of conservation planning software packages have been developed to help with this prioritisation process, with the most commonly used being Marxan, Zonation, ConsNet and C-Plan (Moilanen et al., 2009). Each program uses unique prioritisation algorithms but all of these approaches involve dividing the planning region into a series of user-defined planning units. The software then identifies groups of planning units, referred to as

“portfolios” hereafter, which achieve the targets whilst meeting other specified constraints, such as minimising the combined cost of the planning units. A range of planning unit cost metrics can be used and the efficiency of each portfolio is measured in terms of how well this cost is minimised.

These software packages are also designed to consider the spatial pattern of their results, as networks of many small and isolated PAs are less ecologically viable and more expensive to manage (Cabeza and Moilanen, 2001; Balmford et al., 2003). Previously, the only way to ensure that assessments identified viable PAs was to increase the size of the planning units, but this produces inefficient results because larger planning units tend to contain superfluous habitats that are not needed to meet the targets (Pressey and Logan, 1998). Current software packages overcome this problem by including spatial cost or constraint components in their prioritisation algorithms, which allow the user to determine the level of fragmentation of the final PA system. Thus, analyses can be based on smaller planning units, as long as the software is set to identify clusters of planning units that would make viable PAs. Typically, this involves running the software a number of times and adjusting the emphasis placed on this clustering until the user is satisfied that the resultant reserve system balance the conflicting needs for efficiency and viability.

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Including this spatial component has ensured that conservation planning software produces results with more real-world relevance (Smith et al., 2009). However, the current approach has one major disadvantage that results from the spatial cost or constraint being applied to the whole portfolio. In general, conservation practitioners want to ensure that each PA is above a minimum size, for the reasons of viability and expense mentioned above, although this PA size threshold is generally context specific and based on expert opinion or quantitative studies. At present, the only way to ensure that every PA within a portfolio meets that size threshold is to gradually increase the importance of the spatial component until all the identified PAs are sufficiently large. Unfortunately, this can be a far from efficient approach, as this increases the size of every PA, not just those that are smaller than the threshold. This is an important limitation, as efficiency is a key aspect of systematic conservation planning (Ando et al., 1998; Moilanen, 2008). Here we describe a software package that overcomes this problem by modifying outputs from an existing conservation planning software package, allowing users to specify directly the minimum size of PAs contained within every portfolio.

This work focused on modifying outputs from Marxan because it is the most widely used conservation planning software package. Marxan uses a simulated annealing approach, which involves running an algorithm many times and identifying a different but near-optimal portfolio each time (Ball and Possingham, 2000). Marxan then identifies the “best” solution, which is the portfolio with the lowest cost, and a “selection frequency” output, which counts the number of times each planning unit appeared in the different portfolios. The combined cost for portfolios that meet all the specified targets is calculated as the total cost of all the planning units plus the boundary cost. The boundary cost is the length of the boundary of the entire systems and it acts as a spatial constraint because fragmented portfolios have more edge. Thus, selecting for less edge will favour portfolios containing larger clusters of planning units. This boundary cost is the product of multiplying total edge length by a user-specified boundary length modifier (BLM) value. Thus, the user can adjust portfolio fragmentation levels by adjusting the BLM value: a higher BLM value increases the relative importance of the boundary cost compared to the planning unit costs, and so produces less fragmented but more extensive portfolios (Ball et al., 2009).

Marxan could be adapted to identify portfolios containing PAs that met a user-defined size threshold, simply by adding a new component to the portfolio cost that penalised portfolios containing smaller PAs. However, measuring cluster size is a relatively time consuming process and would have a very large impact on processing time, as simulated annealing involves recalculating the combined portfolio cost many thousands of times per run. Instead, we have developed an approach that takes the portfolios produced by Marxan and modifies them so that each PA meets a user-defined size threshold. In this article we describe software that uses this new approach and test its effectiveness on an existing dataset from southern Africa. More specifically, we investigate how this new approach affects portfolio efficiency and the spatial pattern of the identified PA systems.

2. Methods

MinPatch for Marxan is a software package written in the Python programming language (Lutz, 2009) and consists of the following stages: (1) it imports a Marxan portfolio and identifies each planning unit cluster, referred to as “PAs” hereafter. It then removes the PAs in this Marxan portfolio that are smaller than a user-defined threshold; (2) it adds entirely new planning unit clusters, referred to as “patches” hereafter, that form the basis of new

PAs of the minimum size until every conservation feature target is met, and; (3) it converts these patches into suitable PAs by removing any superfluous planning units that are not needed to meet the targets, minimise boundary costs or to ensure each PA meets the minimum size threshold. The following gives more details of these stages and then explains how the software was used to process Marxan outputs using a dataset from southern Africa.

2.1. MinPatch algorithm

The user specifies three parameters that are used in MinPatch. The first parameter is the minimum PA size, which should be based on expert opinion or quantitative studies using biological or economic data. The second parameter is the “added patch radius”, which is used in stage (2) to determine the size of planning unit patches added to meet the targets. MinPatch works by adding patches that are larger than the minimum PA size and then removing any superfluous planning units from the portfolio during stage (3). Thus, the added patch radius should be set so that a minimum-sized PA with an elongated shape could fit within a circular patch added by MinPatch: setting a larger patch radius allows ever more elongated PAs to be identified. The third parameter is the BLM value, which is used in stage (3) to determine whether planning units should be removed from the portfolio.

2.1.1. Stage 1: small patch removal

This stage involves removing all PAs that do not meet the minimum size threshold, unless the PA is locked-in to a portfolio because it forms part of the existing PA system.

2.1.2. Stage 2: adding a new patch to the portfolio

This stage consists of the following four steps: (a) Calculate the amount of each conservation feature found within the portfolio and identify the features that have not met their target. Move to stage (3) if all the targets have been met. (b) Produce the “Best-Patch” score for each planning unit based on its suitability to be the centre of a new patch of planning units with the user-specified patch radius, based on equations given in Appendix A. (c) Identify the planning unit with the highest score and then add the patch of planning units with the highest scoring planning unit at its centre. (d) Return to step (a).

This BestPatch score is designed to give high values to planning units that would be at the centre of patches which, if added to the portfolio, would help meet many remaining targets whilst adding little to the planning unit costs (Equation A1 in Appendix A). The BestPatch scoring system does not give higher values for patches that exceed targets because this systematic conservation planning approach is concerned only with meeting targets. In addition, it does not include the costs of planning units that are already in the portfolio and so gives higher scores to new patches that overlap with existing PAs. This increases the likelihood of adding patches that connect to existing PAs and so reduce portfolio fragmentation levels.

2.1.3. Stage 3: simulated whittling

This stage is based on an approach used in the Zonation conservation planning software (Moilanen, 2007) and removes any planning units that are not needed to meet the targets, reduce fragmentation levels or meet the PA size threshold. This consists of the following three steps: (a) Identify all planning units that form the edge of the different patches and that are not locked-in to the portfolio because they are in existing PAs. (b) Calculate the “Low Relevance” score for each planning unit using the system described in Equation A2 in Appendix A. (c) Identify the planning unit

with the lowest score that can be removed from the portfolio without affecting target attainment, reducing PA size below the threshold or increasing the Marxan portfolio cost. If no planning units can be removed then finish, otherwise return to step (a). This Marxan portfolio cost is based on the planning unit cost and the boundary cost, where the latter is calculated as the boundary length multiplied by the BLM value specified by the user as one of the MinPatch parameters. Thus, the user can specify a different BLM value to that used in the original Marxan analysis if they want to produce portfolios that are more or less fragmented than those original outputs.

2.1.4. MinPatch outputs

The MinPatch software produces four types of output: (i) the modified version of each Marxan portfolio; (ii) a “patchstats” file that describes the number of PAs, the number of valid PAs, the median PA size and a number of other parameters for each portfolio both before and after it was modified by MinPatch; (iii) the best portfolio, which is the one with the lowest Marxan cost, i.e. the combined planning unit cost plus the total boundary cost; (iv) the selection frequency scores for each planning unit, i.e. the number of times that a planning unit appeared in the different portfolios produced by MinPatch. Outputs (iii) and (iv) are equivalents to those produced by Marxan, although the best portfolio produced by Marxan may not produce the best portfolio identified by MinPatch.

2.2. Updating results from a conservation assessment

To test the use of MinPatch in conservation assessments we used data from the Maputaland Centre of Endemism, a region in southern Africa that falls within Mozambique, South Africa and Swaziland (Smith et al., 2008). This dataset divides Maputaland into 14,861 planning units, consisting of 16 polygons that represent the existing PAs, 13,499 1 km² hexagons and 1346 segments of 1 km² that fill the gaps between the full hexagons and the PAs. We used 44 landcover types and 53 species as conservation features and adopted the targets used in the previous assessment (Smith et al., 2008). We also used the same planning unit cost data, which is based on the modelled risk of each planning unit being cleared for agriculture. We then undertook eight analyses in Marxan, with each analysis consisting of 200 runs and 1 million simulated annealing iterations. The only parameter we varied in these analyses was the BLM value, which was set as 2 in the original Maputaland conservation assessment (Smith et al., 2008). For these eight Marxan analyses we used the following BLM values to provide a broader range: 0.125, 0.25, 0.5, 1, 2, 4, 8 and 16.

We then used MinPatch to modify each of the 200 portfolios produced by Marxan for each of the eight analyses. We specified that every portfolio should be modified so that each PA was at least 10 km², a threshold based on expert opinion, and then set the added patch radius value as 3 km to ensure that the PAs identified by MinPatch would not be overly elongated. The only exception to this specification was for the existing Manguzi Forest Reserve, which has an area of 2.4 km² and was locked-in to all the portfolios (Smith et al., 2008). We set the BLM value used in the simulated whittling stage to be the same as the value used in the respective Marxan analysis. In addition, we ran a ninth analysis in MinPatch that used the portfolios from the Marxan analysis with a BLM of 16 but specified a MinPatch BLM value of 0. This allowed us to investigate how much more efficient the MinPatch results could be if there was no constraint on minimising boundary costs.

We used the MinPatch patchstats file to determine the spatial characteristics of each portfolio before and after it had been modified by MinPatch. We also used the selection frequency outputs to investigate the extent to which the location of PAs identified by MinPatch had changed from those identified by Marxan. We calcu-

lated a “selection frequency change score” value for each planning unit by subtracting its Marxan selection frequency score from the MinPatch selection frequency score. We then grouped the data to identify planning units where the selection frequency change score was positive, i.e. were selected more often by MinPatch, or negative, i.e. were selected more often by Marxan. The original frequency scores were based on the number of portfolios produced by Marxan, ranging between 200 and –200, and we converted these values to percentages.

3. Results

The median area of the portfolios identified by Marxan ranged between 7750 km² for the BLM = 0.125 Marxan analysis and 8601 km² for the BLM = 16 Marxan analysis (Fig. 1; Table 1). Using MinPatch increased the median portfolio area for all of the eight analyses, so that they ranged between 8110 km² for the BLM = 0.125 MinPatch analysis and 8761 km² for the BLM = 16 MinPatch analysis (Table 1). This meant that using MinPatch increased the median portfolio size from between 1.77% for the BLM = 16 analyses and 6.64% for the BLM = 1 analyses (Fig. 1). Increasing the BLM values in Marxan produced portfolios consisting of fewer but larger PA patches, but the percentage of PA patches that met the 10 km² minimum threshold ranged from only 8.2% for the BLM = 0.125 Marxan analysis up to 34.5% for the BLM = 16 Marxan analysis (Table 1; Fig. 2). As expected, all of the PAs in all of the portfolios identified using MinPatch met the 10 km² threshold (Table 1; Fig. 2) and this produced large increases in the median size of the PAs found in each portfolio (Table 1). Comparisons of Marxan and MinPatch portfolios produced with different BLM values showed that, when seeking to produce portfolios containing PAs of a minimum size, it was more efficient to use MinPatch to modify Marxan outputs based on a low BLM value than to run Marxan using a higher BLM value.

A comparison of portfolio boundary length produced by Marxan and MinPatch shows that MinPatch boundary lengths were generally smaller with low BLM values, but higher with BLM values of 4 or more (Table 1). The analysis that used the BLM = 16 Marxan portfolios but used a BLM value of 0 in MinPatch produced

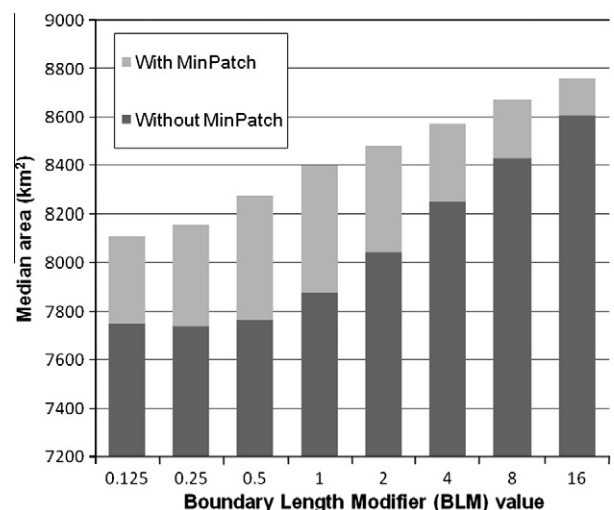


Fig. 1. Median area of the different portfolios produced by Marxan and MinPatch. Each analysis shown involved running Marxan with a particular BLM value and then modifying the outputs in MinPatch using the same BLM value.

Table 1

Details of the 200 portfolios produced for each of the different Marxan and MinPatch analyses. Valid PAs were those that met the 10 km² minimum size threshold.

BLM value	0.125	0.25	0.5	1	2	4	8	16
<i>Marxan portfolios</i>								
Median area (km ²)	7750	7739	7767	7880	8046	8251	8429	8608
Median PA number	424.5	341	232	145	93	57	39	29
Median valid PA number	35	33	29	25	21.5	16	13	10
Median PA area (km ²)	1.0	1.0	1.0	1.0	1.5	2.0	2.0	2.2
Median boundary length (km)	6455	5392	4250	3444	3032	2691	2455	2289
<i>MinPatch portfolios</i>								
Median area (km ²)	8110	8158	8278	8403	8481	8575	8672	8761
Median PA number	26	26	26	24	22	16	14	12
Median valid PA number	26	26	26	24	22	16	14	12
Median PA area (km ²)	15.0	16.5	18.5	20.8	24.0	30.0	33.8	38.9
Median boundary length (km)	4256	3833	3352	3061	2966	2830	2692	2574

portfolios with a median area of 8071 km², which was lower than the BLM = 4 Marxan and BLM = 0.125 MinPatch analysis outputs.

Using MinPatch changed the selection frequency scores of a number of planning units, with the largest increases occurring close to the existing PAs (Fig. 3). The percentage of planning units that increased their scores ranged between 18.3% for the BLM = 16 MinPatch analysis and 32.7% for the BLM = 0.5 MinPatch analysis. The general trend was that as BLM values increased, the total number of planning units with higher scores decreased (Table 2). Similar patterns were seen with planning units that had lower selection frequency scores from MinPatch, although the percentage of planning units that only reduced by 1–25% remained relatively stable (Table 2). The number of planning units that showed no change generally increased with increasing BLM values, nearly doubling over the range of the analyses.

4. Discussion

Conservation planning software is commonly used in systematic assessments to help develop PA systems. The information they provide is only part of the decision making process and the eventual PA system can differ significantly from the initial priority area maps (Knight et al., 2009). However, there are great advantages in producing outputs that reflect the real-world issues faced by conservation practitioners as closely as possible, as it reduces the amount of effort needed to convert the initial priority maps into a form that can guide action on the ground (Smith et al., 2009). Perhaps more importantly, it also builds credibility with stakeholders by producing more realistic results (Smith et al., 2006). Current conservation planning software has done much to build this credibility by responding to user needs and including a number of features, such as accounting for persistence (Game et al., 2008) and management zoning (Watts et al., 2009). In this article we have described a conservation planning software package that adds an important new aspect to portfolio design by ensuring that the identified PAs, or other priority areas, are above a user-defined minimum area threshold. This minimum threshold will vary with context, and can be based on research or expert opinion, but MinPatch provides an efficient approach for incorporating this constraint into PA system design.

There is one key difference with MinPatch when compared to other conservation planning software, as it works by manipulating the outputs of another computer program. Using Marxan to identify initial portfolios has several advantages, as it produces a number of near-optimal portfolios and so allows stakeholders to choose between different outputs (Ball et al., 2009). MinPatch builds on this and so manipulates each Marxan portfolio, maintaining the same level of choice. It also combines the results from these differ-

ent portfolios to produce a new selection frequency score, identifying planning units that are always needed to meet the targets and those that can be swapped for similar planning units elsewhere. The MinPatch outputs produced in this analysis were generally less efficient, adding up to nearly 7% to the portfolio area. However, every one of these portfolios met the minimum PA size threshold and increased the median PA size by between 15 and 21 times.

Moreover, comparisons of efficiency need to be made between analyses to really understand the advantages of this approach. For example, the portfolios for the BLM = 0.125 MinPatch analysis were smaller than the portfolios for the BLM = 4 Marxan analysis, despite the fact that less than one third of the patches produced by the BLM = 4 Marxan analysis met the minimum PA threshold. Thus, using MinPatch to modify Marxan outputs with low BLM values is a more efficient and effective approach than running Marxan with high BLM values for ensuring PAs are all above a minimum size. Moreover, the efficiency of the MinPatch portfolios depends on the BLM value used in the simulated whittling stage. Using a BLM value of 0 to modify the BLM = 16 Marxan outputs meant that the simulated whittling stage removed a large number of planning units from the portfolio. This produced portfolios with a longer boundary length than those produced in the BLM = 16 MinPatch analysis, but the median area of these portfolios was less than even those produced in the BLM = 0.125 MinPatch analysis. Thus, there is scope for producing more efficient portfolios in MinPatch by changing the BLM value.

Using MinPatch also had important effects on the spatial pattern of the PAs identified, as shown by changes in the selection frequency scores of the planning units when compared with the original Marxan results. In general, using MinPatch produced more portfolios with large increases in planning unit selection frequency than large decreases, partly because the MinPatch portfolios tended to contain more planning units. The most dramatic changes occurred with the analyses that used lower BLM values, which was because MinPatch tended to add new PAs in the same locations, so any planning units in these locations that were rarely selected by Marxan would end up with much higher selection frequency scores. In contrast, planning units that were removed by MinPatch from Marxan portfolios were more widely distributed and so the drop in selection frequency was more widespread but less intense. The maps showing these changes highlight the impact that using MinPatch has on the spatial pattern of portfolios and shows that including the minimum PA size constraint can make significant changes to the location of priority conservation areas.

These results suggest that MinPatch should be used whenever conservation practitioners want to produce priority area maps that only contain PAs above a particular size for economic and/or ecological reasons. Setting such a size threshold will often rely on expert opinion but there is already evidence to support such

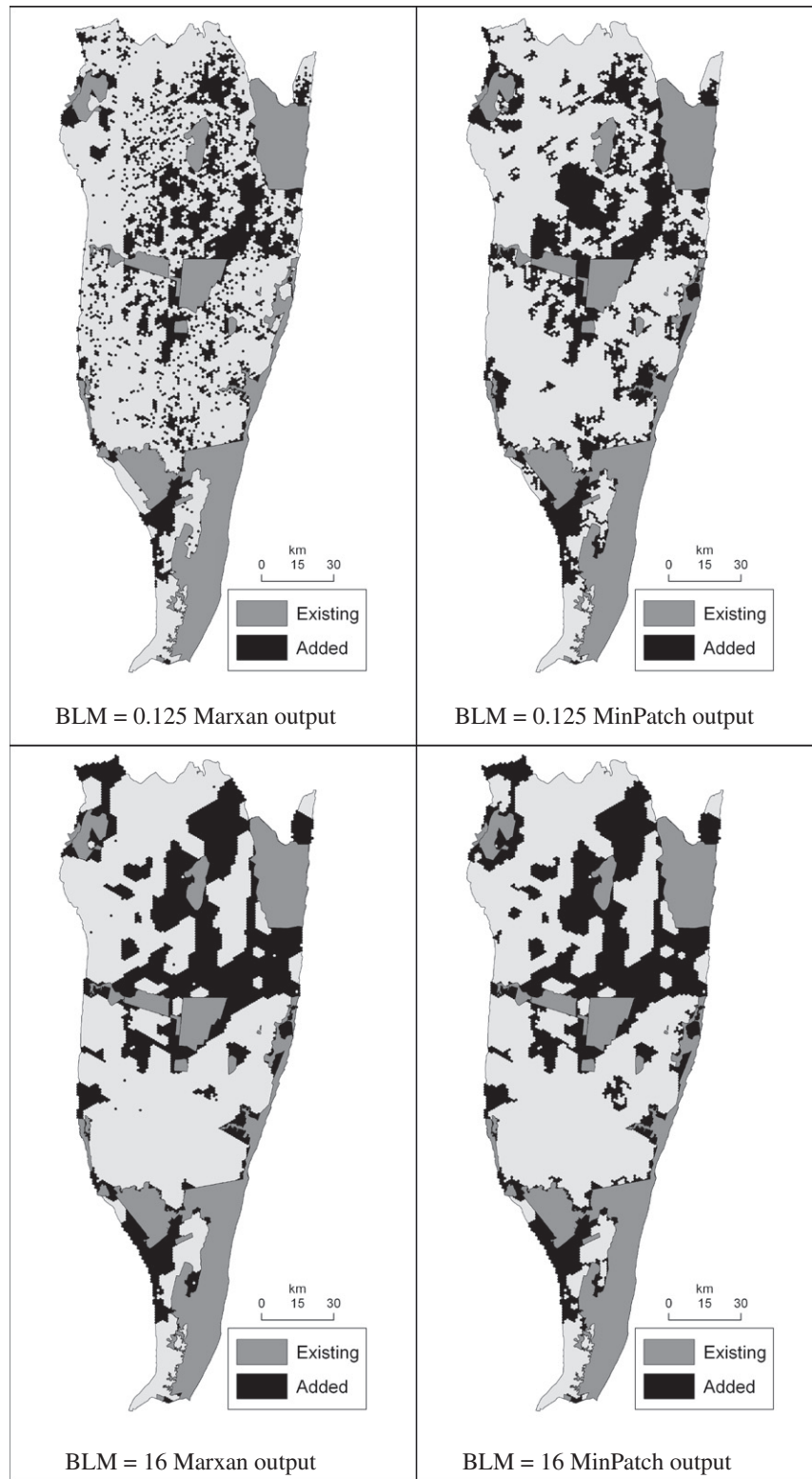


Fig. 2. Best portfolios produced by Marxan, based on two different BLM values, and the results of updating them using MinPatch. Existing PAs are shown in grey and planning units that were added to the portfolio by Marxan or MinPatch are shown in black.

decisions from studies of population size (Burgman et al., 2001), ecological disturbance (Leroux et al., 2007) and management costs (Balmford et al., 2003). Moreover, several priority setting exercises have already set such criteria (e.g. described in Klein et al., 2008) and this is likely to increase in the future. Thus, we would argue

that the MinPatch approach should be widely adopted, especially as it could be applied to outputs from a range of conservation planning software packages. Such developments could also include a number of changes to help produce more viable portfolios. In particular, the simulated whittling component could be improved to

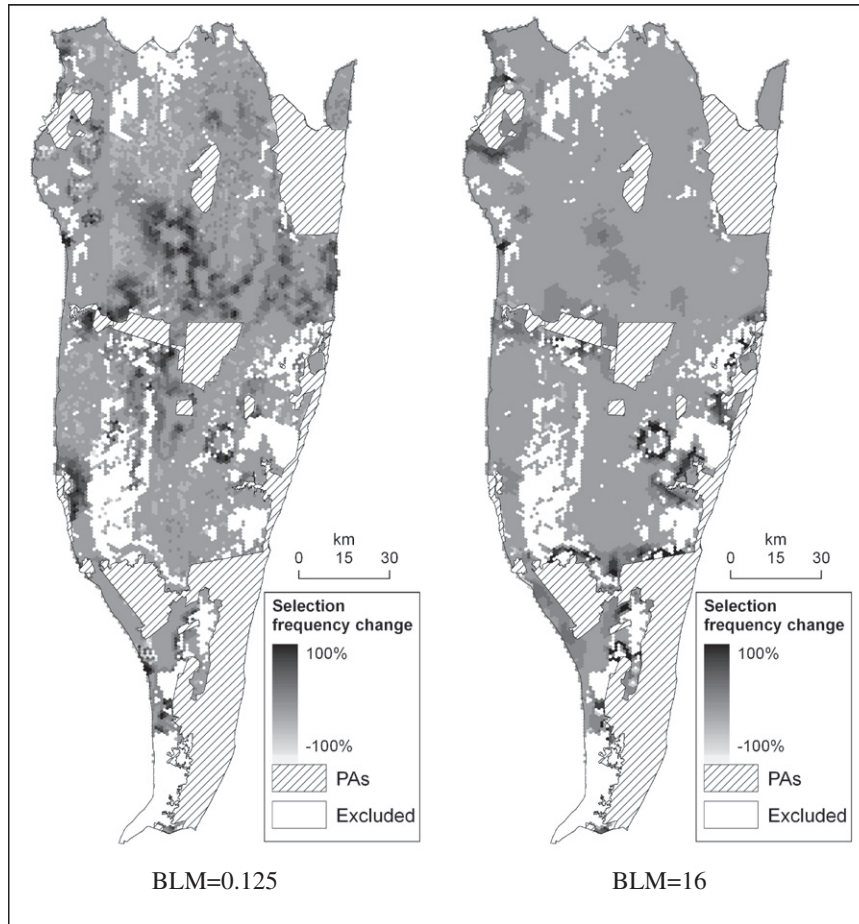


Fig. 3. Planning unit selection frequency score change for portfolios produced using two different BLM values. The planning units with the highest change values (100%) appeared in every MinPatch portfolio and none of the Marxan portfolios.

Table 2
Percentage of planning units with selection frequency change scores based on comparisons between the Marxan and MinPatch outputs.

BLM value	0.125	0.25	0.5	1	2	4	8	16
<i>Selection frequency change</i>								
≥75%	0.85	3.11	3.50	2.88	2.03	1.70	1.55	1.41
25–75%	9.67	10.49	8.44	7.38	6.71	5.64	4.52	3.77
0–25%	18.13	15.05	20.74	16.74	15.67	15.42	14.65	13.10
0%	15.32	17.91	14.19	21.24	22.94	27.32	28.72	27.83
0% to –25%	49.52	51.20	51.94	51.02	51.86	48.96	49.49	52.71
–25% to –75%	5.94	2.03	1.03	0.56	0.63	0.80	0.92	1.01
≤–75%	0.44	0.08	0.04	0.04	0.03	0.02	0.02	0.05

remove larger patches of unneeded planning units, as the current approach removes planning units one-by-one and can often identify PAs with jagged edges. There is also scope for using this approach to ensure that portfolios meet minimum patch or population size thresholds for key species, as well as PAs. This would allow the production of fine-scale priority area maps that support the requirements of wide-ranging species, meet targets for other species and habitat types and minimise planning unit costs.

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Appendix A

A.1. Equation A1 – calculating the best patch score

A.1.1. Calculate the amount of unprotected feature in the patch

$$u_{jp} = \sum_{i=1}^m y_i a_{ij}$$

where m is the total number of planning units, a_{ij} is the amount of feature j in planning unit i , and y_i is a control variable that indicates

if the pu is in the patch (y_i is 1 if the pu unprotected and in the patch)

A.1.2. Calculate the feature shortfall

$$s_j = t_j - \sum_{i=1}^m a_{ij}x_i$$

where t_j = target amount for feature j , x_i is a control variable to say if the planning unit is protected, a_{ij} is the amount of feature j in planning unit i

A.1.3. Calculate the patch cost

$$\text{Patch cost } (C_p) = \sum_{i=1}^m y_i c_i$$

where m is the total number of planning units, c_i is the cost of planning unit i , y_i is a control variable that indicates if the pu is in the patch (y_i is 1 if the pu is unprotected and in the patch)

A.1.4. Calculate the final score

$$\text{Final score} = \frac{\sum_{j=1}^n \frac{u_j p}{s_j}}{C_p}$$

where n is the total number of features

A.2. Equation A2 – calculating the simulated whittling score

$$\text{Simulated whittling score} = \sum_{j=1}^n \left(a_{ij} / \sum_{i=1}^m a_{ij}x_i - t_j \right)$$

See above for notation.

References

- Ando, A., Camm, J., Polasky, S., Solow, A., 1998. Species distributions, land values, and efficient conservation. *Science* 279, 2126–2128.
- Ball, I., Possingham, H., 2000. *Marxan (v1.8.2) – Marine Reserve Design using Spatially Explicit Annealing*. University of Queensland, Brisbane, Australia.
- Ball, I., Possingham, H., Watts, M.E., 2009. *Marxan and relatives: software for spatial conservation prioritization*. In: Moilanen, A., Wilson, K.A., Possingham, H. (Eds.), *Spatial Conservation Prioritization: Quantitative Methods and Computational Tools*. Oxford University Press, Oxford, pp. 185–195.
- Balmford, A., Gaston, K.J., Blyth, S., James, A., Kapos, V., 2003. Global variation in terrestrial conservation costs, conservation benefits, and unmet conservation needs. *Proceedings of the National Academy of Sciences of the United States of America* 100, 1046–1050.
- Burgman, M.A., Possingham, H.P., Lynch, A.J.J., Keith, D.A., McCarthy, M.A., Hopper, S.D., Drury, W.L., Passioura, J.A., Devries, R.J., 2001. A method for setting the size of plant conservation target areas. *Conservation Biology* 15, 603–616.
- Cabeza, M., Moilanen, A., 2001. Design of reserve networks and the persistence of biodiversity. *Trends in Ecology & Evolution* 16, 242–248.
- CBD, 2004. COP 7 Decision VII/28.
- Game, E.T., Watts, M.E., Wooldridge, S., Possingham, H.P., 2008. Planning for persistence in marine reserves: a question of catastrophic importance. *Ecological Applications* 18, 670–680.
- Jenkins, C.N., Joppa, L., 2009. Expansion of the global terrestrial protected area system. *Biological Conservation* 142, 2166–2174.
- Klein, C.J., Steinback, C., Scholz, A., Possingham, H., 2008. Effectiveness of marine reserve networks in representing biodiversity and minimizing impact to fishermen: a comparison of two approaches used in California. *Conservation Letters* 1, 44–51.
- Knight, A.T., Cowling, R.M., Possingham, H.P., Wilson, K.A., 2009. From theory to practice: designing and situating spatial prioritisation tools for implementing conservation action. In: Moilanen, A., Possingham, H.P., Wilson, K.A. (Eds.), *Spatial Conservation Prioritization: Quantitative Methods and Computational Tools*. Oxford University Press, Oxford, United Kingdom, pp. 249–259.
- Leroux, S.J., Schmiegelow, F.K.A., Lessard, R.B., Cumming, S.G., 2007. Minimum dynamic reserves: a framework for determining reserve size in ecosystems structured by large disturbances. *Biological Conservation* 138, 464–473.
- Lutz, M., 2009. *Learning Python*, fourth ed. O'Reilly Media, Sebastopol, USA.
- Moilanen, A., 2007. Landscape Zonation, benefit functions and target-based planning: unifying reserve selection strategies. *Biological Conservation* 134, 571–579.
- Moilanen, A., 2008. Generalized complementarity and mapping of the concepts of systematic conservation planning. *Conservation Biology* 22, 1655–1658.
- Moilanen, A., Wilson, K.A., Possingham, H. (Eds.), 2009. *Spatial Conservation Prioritization: Quantitative Methods and Computational Tools*. Oxford University Press, Oxford.
- Pressey, R.L., Logan, V.S., 1998. Size of selection units for future reserves and its influence on actual vs targeted representation of features: a case study in western New South Wales. *Biological Conservation* 85, 305–319.
- Rodrigues, A.S.L., Andelman, S.J., Bakarr, M.I., Boitani, L., Brooks, T.M., Cowling, R.M., Fishpool, L.D.C., da Fonseca, G.A.B., Gaston, K.J., Hoffmann, M., Long, J.S., Marquet, P.A., Pilgrim, J.D., Pressey, R.L., Schipper, J., Sechrest, W., Stuart, S.N., Underhill, L.G., Waller, R.W., Watts, M.E.J., Yan, X., 2004. Effectiveness of the global protected area network in representing species diversity. *Nature* 428, 640–643.
- Smith, R.J., Goodman, P.S., Matthews, W.S., 2006. Systematic conservation planning: a review of perceived limitations and an illustration of the benefits, using a case study from Maputaland, South Africa. *Oryx* 40, 400–410.
- Smith, R.J., Easton, J., Nhancale, B.A., Armstrong, A.J., Culverwell, J., Dlamini, S.D., Goodman, P.S., Loffler, L., Matthews, W.S., Monadjem, A., Mulqueeny, C.M., Ngwenya, P., Ntumi, C.P., Soto, B., Leader-Williams, N., 2008. Designing a transfrontier conservation landscape for the Maputaland centre of endemism using biodiversity, economic and threat data. *Biological Conservation* 141, 2127–2138.
- Smith, R.J., Verissimo, D., Leader-Williams, N., Cowling, R.M., Knight, A.T., 2009. Let the locals lead. *Nature* 462, 280–281.
- Watts, M.E., Ball, I.R., Stewart, R.S., Klein, C.J., Wilson, K., Steinback, C., Lourival, R., Kircher, L., Possingham, H.P., 2009. *Marxan with zones: software for optimal conservation based land- and sea-use zoning*. *Environmental Modelling & Software* 24, 1513–1521.