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ORIGINAL PAPER

The influence of planning unit characteristics on the efficiency and spatial pattern of systematic conservation planning assessments

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Abstract Systematic conservation planning is a widely used approach for designing protected area systems and ecological networks. This generally involves dividing the planning region into a series of planning units and using computer software to select portfolios of these units that meet specified conservation targets whilst minimising conservation costs. Previous research has shown that changing the size and shape of these planning units can alter the apparent spatial characteristics of the underlying data and thus influence conservation assessment results. However, this may be less problematic when using newer software that can account for additional constraints based on portfolio costs and fragmentation levels. Here we investigate these issues using a dataset from southern Africa and measure the extent to which changing planning unit shape, size and baseline affects the results of conservation planning assessments. We show that using hexagonal planning units instead of squares produces more efficient and less fragmented portfolios and that using larger planning units produces portfolios that are less efficient but more likely to identify the same priority areas. We also show that using real-world constraints in the analysis, based on reducing socio-economic costs and minimising fragmentation levels, reduces the influence of planning unit characteristics on the results and so argue that future studies should adopt a similar approach when investigating factors that influence conservation assessments.

Keywords Systematic conservation planning · Marxan · Reserve selection · Planning units

Introduction

Protected areas (PAs) are a commonly used policy instrument for reducing biodiversity loss (e.g. CBD 2004). One of the most effective approaches for designing these PA networks is systematic conservation planning (Margules and Sarkar 2007), which generally

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involves: (i) developing a list of conservation features, such as important species and habitats; (ii) setting representation targets for how much of each feature should be protected; (iii) sub-dividing the planning region into a number of planning unit polygons; (iv) determining the amount of each feature found in each planning unit; (v) assigning a cost value to each planning unit, based on whichever constraint is relevant to the analysis, e.g. financial value or opportunity costs, and; (iv) using computer software to identify portfolios of these units that meet the representation targets whilst minimising planning unit costs (Moilanen et al. 2009). Thus, planning units are the basis for compiling data on the abundance of conservation features within the planning region. This means that changing the planning unit size, shape or location can alter the apparent spatial pattern of biodiversity (Larsen and Rahbek 2003; Hess et al. 2006; Shriner et al. 2006; Hurlbert and Jetz 2007), thereby affecting which sites are identified as conservation priorities (Stoms 1994; Bassett and Edwards 2003; Rouget 2003; Grand et al. 2007). However, despite this potential impact of planning unit characteristics, there is little formal guidance on the appropriate shape and size of planning units for use in conservation assessments to help identify priority areas.

Such guidance needs to identify which approaches are most efficient, where efficiency is defined as the extent to which priority areas minimise costs whilst also meeting targets, and one source of good evidence comes from previous studies on planning unit size. These show that smaller planning units produce more efficient results, as large units tend to contain superfluous areas that are not needed for target attainment (Larsen and Rahbek 2003; Shriner et al. 2006). This suggests that the minimum size of the planning units should only be limited by computer processing constraints, spatial scale of the underlying distribution data and the implementation of conservation actions (Rouget 2003; Seo et al. 2009; Mills et al. 2010). However, these previous studies were undertaken using software that could not select clusters of planning units and so tend to produce portfolios consisting of a large number of small and isolated PAs (Smith et al. 2010). Such portfolios are less ecologically and economically viable (Balmford et al. 2003; Wiersma and Nudds 2009) and so new conservation planning software packages, such as Marxan and Zonation, were developed to include spatial cost or constraint components in their prioritisation algorithms and so produce less fragmented outputs (Moilanen et al. 2009). Incorporating these spatial aspects produces a trade-off between portfolio efficiency and fragmentation (Stewart and Possingham 2005), and this could potentially weaken the relationship between efficiency and planning unit size found previously (Pressey and Logan 1998; Larsen and Rahbek 2003; Warman et al. 2004; Shriner et al. 2006; Justus et al. 2008).

There is much less consensus on planning unit shape, with studies using: (i) regular shapes such as squares or hexagons (e.g. Csuti et al. 1997; Cowling et al. 2003); (ii) irregular shapes such as tenure parcels, watersheds or habitat remnants (e.g. Dobson et al. 1997; Roux et al. 2008), or, (iii) a combination of the two (e.g. Smith et al. 2008; Huber et al. 2010). Using irregular planning units can have important advantages: tenure parcels may be more relevant for implementation (Knight et al. 2006) and selecting watersheds and whole habitat patches can facilitate management (Klein et al. 2009; Nel et al. 2009). However, using regular shapes also has advantages because real-world polygons, such as property parcel or administrative boundaries, tend to be relatively large and so it is often more economically efficient and less contentious to identify the important, smaller regular shaped planning units that fall within them (Michael 2003; Matta et al. 2009). It is also generally more appropriate to use regular polygons when dealing with the open ocean or communally managed land, as these are rarely divided up into small administrative units (Smith et al. 2008; Grantham et al. 2011). This is why square and hexagon planning units continue to be used in conservation assessments but there is little work comparing the efficiency of the two alternatives, although hexagon units have a lower perimeter to area ratio and a larger number of edges that may be better for identifying planning unit clusters (Birch et al. 2007).

There is, therefore, a need to investigate the influence of planning unit shape and size when using conservation planning software that can select clusters of planning units. However, such analyses also need to investigate the effects of planning unit cost on such conservation assessments. Past research generally used area as the planning unit cost metric and sought to identify portfolios with the smallest extent to maximize efficiency (Araújo et al. 2002; Carwardine et al. 2007; Linke et al. 2007). However, recent work has shown that metrics based on socio-economic factors, such as land purchase costs or risk of transformation, produce results that are more relevant for implementation (Carwardine et al. 2010). Moreover, these cost values can vary widely between planning units (Naidoo et al. 2006) and so have a large influence on the location of priority conservation areas (Bode et al. 2008; Adams et al. 2010). Any relationships between planning unit characteristics and efficiency may be diminished under these conditions, so there is also a need to determine their importance when using different cost metrics. Here we investigate these issues by measuring the effects of changing planning unit shape, size, baseline coordinates and cost metric on the efficiency, fragmentation levels and locations of priority sites identified by the Marxan conservation planning software.

Methods

Developing the datasets

We used data from the Maputaland Centre of Endemism, a region of 17,000 km^2 that falls within southern Mozambique, eastern South Africa and eastern Swaziland (Fig. 1). A conservation planning system has already been developed for this region and for this analysis we extracted: (i) distribution data on 44 landcover types and 53 species and (ii) a map of agricultural transformation risk, which was based on distance to existing agricultural lands, agricultural potential and combined elevation and slope (Smith et al. 2008). We also used targets that were developed from a previous conservation assessment (Smith et al. 2008).

Producing the planning unit and distribution data

We investigated the impact of planning unit characteristics by undertaking 48 different conservation assessments based on all possible combinations of planning unit shape (square or hexagon), area (25, 100 or 400 ha), cost type (area or agriculture risk) and shift from baseline (0, 100, 250 or 500 m). The planning unit themes were initially created using the Repeating Shape ArcGIS extension (Jenness 2006). This was used to produce three themes consisting of series of hexagons with an area of 25, 100 and 400 ha and three themes consisting of square planning units, also with an area of 25, 100 and 400 ha. Then, we created three more planning unit themes from each of the six original planning unit themes by using the "Move" function in the ArcGIS Editor toolbar to shift each polygon by 100, 250 and 500 m, respectively, in both the *X* and *Y* axis. We used baseline shift as a parameter because the boundaries of square and hexagon planning units can never

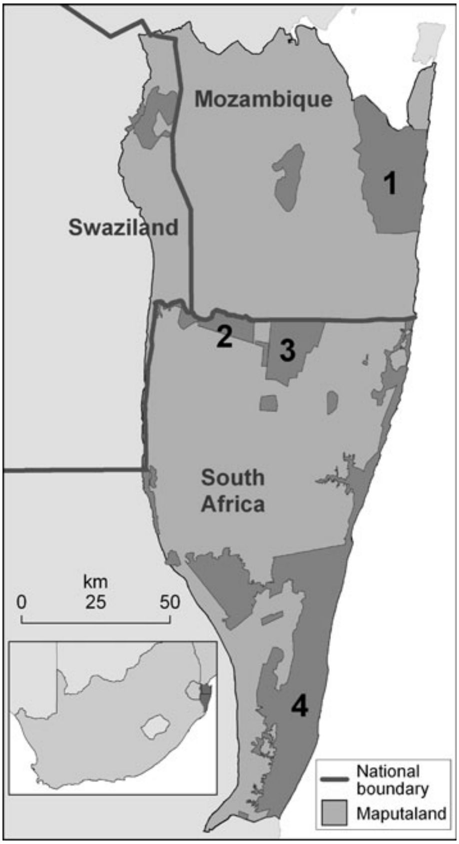

Fig. 1 The protected areas of Maputaland. PAs mentioned in the text are: *1* Maputo Special Reserve, *2* Ndumo Game Reserve, *3* Tembe Elephant Park and *4* iSimangaliso Wetland Park

perfectly coincide, so we wanted to investigate the extent to which any differences in assessment outputs could be due to this lack of overlap.

We next combined each of these 24 themes with the PA theme and clipped them to the Maputaland planning region boundary. This meant that each final planning unit theme consisted of a series of equal sized planning units, other than the PAs and the irregular shaped planning units that neighboured the PAs or the Maputaland boundary. Then, we calculated the two different cost values for each planning unit. The "area cost" metric was simply calculated in ArcGIS by determining the area of each planning unit measured in hectares. The "agriculture cost" metric was calculated by summing the values in the risk of agriculture map using the "Summarize Zones" function in ArcGIS. Finally, we used the same software to calculate the amount of each conservation feature in each planning unit. These data were imported into Marxan using the CLUZ ArcView Extension (Smith 2004).

Marxan analyses

We used the Marxan systematic conservation planning software in this analysis (Ball and Possingham 2000). Marxan uses a simulated annealing approach to select near-optimal portfolios that meet targets whilst minimising the total portfolio cost. This software also allows the user to influence the fragmentation level of each portfolio, where fragmentation is defined as the number of small, isolated patches of planning units (Smith et al. 2010).

Highly fragmented portfolios have a higher boundary edge length (Ball and Possingham 2000), as fewer of their boundaries are shared with other selected planning units. Thus, Marxan calculates the total cost for portfolios that meet all the targets as the combined planning unit costs plus the boundary length cost. In Marxan this boundary length cost is the product of multiplying total edge length by a user-defined boundary length modifier (BLM) value. The user can then adjust the fragmentation levels of the portfolios Marxan identifies 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. The simulated annealing process involves running the software a number of times and producing a near-optimal portfolio per run. Marxan then identifies the "best" portfolio as the one with the lowest cost and produces a "selection frequency" output, which counts the number of times each planning unit appeared as part of the different portfolios (Ball and Possingham 2000).

We set a BLM value of 2.0 for the agricultural cost analyses and 0.35 for the area cost analyses. The BLM value used in the agriculture cost analyses was based on the methods used in a previous analysis (Smith et al. 2008). The BLM value for area cost analyses was scaled so that relative influence of the boundary length cost would be similar to those shown by the agriculture cost analyses. This scaling factor was calculated by dividing the combined area cost by the combined agriculture cost of all the planning units. For each analysis we ran Marxan 200 times, with each run consisting of two million iterations. For each of the 48 analyses we saved the best of the 200 portfolios and the selection frequency output.

Selection frequency comparisons

To compare the selection frequency patterns between the different portfolios, which is one aspect of the spatial patterns of the portfolios identified by Marxan, we intersected the two sets of planning units for each pairwise comparison (Warman et al. 2004). This intersection produced a common set of planning unit subunits and for each subunit we extracted the selection frequency score for the associated planning unit from the two Marxan analyses. Finally, we selected 2,000 subunits at random and measured the correlation between each pair of Marxan selection frequency outputs by calculating the Spearman rank correlation (r_s) using the SPSS 16.0 statistical software (SPSS, Inc, Chicago, Illinois, USA). Initial investigation of these results showed the data were strongly affected by spatial autocorrelation, as some planning units contained few habitats or species and were never selected and some planning units were always needed to meet targets. All attempts to overcome this problem by reducing the sample size were ineffective so when comparing the results we only considered the correlation coefficients, as these are unaffected by autocorrelation (Cliff and Ord 1981). In contrast, significance values are often over-estimated by autocorrelation and so we did not consider these when discussing the results (Balmford et al. 2001).

Best portfolio comparisons

To measure the efficiency of the different portfolios, we used Mann–Whitney U tests to compare the total portfolio area selected and the total planning unit costs. We also used the same tests to measure fragmentation levels based on boundary length cost, number of patches and median area of planning units patches of the 48 different analyses (Pressey and Nicholls 1989). Finally, we measured the pairwise similarity of the best portfolios from each analysis using Jaccard's coefficient to investigate similarities in their spatial pattern (van Jaarsveld et al. 1998; Warman et al. 2004; Shriner et al. 2006). The coefficient is calculated as $A/(A + B + C)$, where A represents planning units present in both portfolios, and B and C represent planning units present in only one of the respective portfolios.

Results

Portfolio efficiency and fragmentation levels

All of the portfolios identified by Marxan met the specified representation targets. Using smaller planning units produced portfolios that were smaller in extent but more fragmented, whereas using hexagonal planning units instead of squares produced portfolios that were smaller in extent and less fragmented (Table 1). Total area selected, boundary length and patch number were generally lower when using the area cost metric but these differences varied, with portfolio efficiency being fairly similar for all the analyses and number of patches differing the most between analyses (Table 1).

Selection frequency comparisons

The correlation between the selection frequency scores of planning unit themes and their shifted versions was generally high, varying between 0.592 and 0.937 (Table 2). Shifting the baseline had the largest impact on analyses with the smallest planning units and some of these correlation values were lower than those found when changing planning unit size, shape or metric cost (compare Table 2 with Tables 3, 4, 5, 6). In addition, correlations were generally high when varying the shape, size or cost metric of planning units, although the lowest correlation was invariably found with the 25-ha planning units (Fig. 2; Tables 3, 4, 5, 6). Varying shape altered the selection frequency of planning units the least (Table 4) and the level of correlation was very consistent when changing the cost metric, with coefficients varying between 0.696 and 0.798 (Table 6), whereas the level of correlation varied the most and was the lowest when varying planning unit size (Table 5). Finally, it is interesting to note that when shape and size varied, the correlation was constantly higher when agriculture was the cost metric (Tables 4, 5).

Best portfolio comparisons

The overlap between best portfolios revealed that hexagonal planning units tended to create a slightly higher overlap than squares, that increasing planning unit size also increases the overlap and that portfolios that used the agriculture cost metric had higher overlap than when using the area cost metric (Fig. 3; Tables 4, 5, 6). In addition, Jaccard's index scores showed that simply shifting the planning units altered the amount of overlap between best portfolios identified by Marxan (Table 3). There were no obvious patterns regarding the influence of increasing shifting distances. Moreover, varying the shape, size or cost metric of planning units produced a Jaccard's overlap index between the best portfolios in the maximum order of 0.695, 0.500 and 0.534, respectively (Tables 4, 5, 6). However, these scores are within the range of values obtained when simply shifting the planning units (Table 3), suggesting that changing shape, size or cost metric had no greater impact than those resulting from changing the planning unit baselines. Despite this,

Table 1 Comparison of portfolio parameters resulting from varying planning unit size, shape and cost metric

	Square			Hexagon		
	25 ha	100 ha	400 ha	25 ha	100 ha	400 ha
Area cost						
Total area selected (%)	47.9*,†	48.8*,†	49.2*,†	47.0*,†	47.4*,†	49.0*,†
Boundary length (km)	6454.5*	2412.9*,†	1220.4*,†	5276.8*,†	2043.7*,†	1069.5*,†
Patch number	404.2*,†	64.9*	12.9†	270.1*,†	54.1*,†	12.3
Median patch size (ha)	0.43*	3.08*,†	16.17*,†	0.37*,†	2.65*	16.57*
Agriculture cost						
Total area selected (%)	51.8*,†	52.1*,†	53.4*,†	50.0*,†	50.7*,†	53.2*,†
Boundary length (km)	6516.0*	2576.6*,†	1314.9*,†	5703.6*,†	2299.3*,†	1181.1*,†
Patch number	432.3*,†	63.7*	12.2*,†	292.0*,†	57.7*,†	12.5*
Median patch size (ha)	0.38*	2.7*,†	14.0*,†	0.34*,†	2.68*	14.97*,†
Total cost	3039889*	3222260*	3275914*	3021458*	3147519*	3262544*

Each value is marked with * if the parameter is significantly different to that for the analysis that was identical apart from using a different planning unit shape, and is marked with † if the parameter is significantly different to that for the analysis that was identical apart from using a different planning unit cost metric (significance is based on Mann–Whitney U-tests where $P < 0.05$). The Total PU cost values are only relevant for the analyses that used the agriculture cost planning unit metric, which explains why this row does not contain any † symbols. These analyses used the planning units that had not been shifted in the X and Y axes

Table 2 Selection frequency correlations (r_s) between portfolios of planning units with the same size, shape and cost metric but where the planning units of one of the pair of portfolios have been shifted by 100, 250 or 500 m in the *X* and *Y* axis

	Area cost			Agriculture cost		
	100 m	250 m	500 m	100 m	250 m	500 m
Hexagon						
25 ha	0.838	0.895	0.642	0.680	0.673	0.592
100 ha	0.930	0.941	0.943	0.925	0.925	0.926
400 ha	0.898	0.884	0.904	0.885	0.896	0.905
Square						
25 ha	0.913	0.915	0.909	0.761	0.890	0.775
100 ha	0.927	0.926	0.937	0.927	0.926	0.937
400 ha	0.857	0.859	0.917	0.873	0.901	0.898

Table 3 Best portfolio overlap between portfolios of planning units with the same size, shape and cost metric but where the planning units of one of the pair of portfolios has been shifted by 100, 250 or 500 m in the *X* and *Y* axis (Jaccard's index = 1 for perfect overlap)

	Area cost			Agriculture cost		
	100 m	250 m	500 m	100 m	250 m	500 m
Hexagon						
25 ha	0.307	0.304	0.271	0.304	0.322	0.300
100 ha	0.392	0.431	0.407	0.459	0.454	0.470
400 ha	0.600	0.637	0.663	0.704	0.656	0.646
Square						
25 ha	0.304	0.297	0.301	0.306	0.317	0.316
100 ha	0.394	0.406	0.406	0.487	0.431	0.445
400 ha	0.650	0.563	0.661	0.625	0.649	0.656

Table 4 Selection frequency correlations (r_s) and best portfolio overlap (Jaccard's index indicated between brackets = 1 for perfect overlap) based on planning units of different shapes

	Area	Agriculture
25-ha squares vs hexagons	0.793 (0.309)	0.882 (0.341)
100-ha squares vs hexagons	0.922 (0.396)	0.925 (0.456)
400-ha squares vs hexagons	0.918 (0.597)	0.919 (0.695)

Table 5 Selection frequency correlations (r_s) and best portfolio overlap (Jaccard's index indicated between brackets = 1 for perfect overlap) based on planning units of different sizes

	Square		Hexagon	
	Area	Agriculture	Area	Agriculture
25 ha vs 100 ha	0.758 (0.323)	0.836 (0.344)	0.827 (0.316)	0.859 (0.351)
25 ha vs 400 ha	0.617 (0.313)	0.695 (0.352)	0.684 (0.315)	0.732 (0.365)
100 ha vs 400 ha	0.838 (0.407)	0.848 (0.500)	0.831 (0.458)	0.861 (0.489)

Table 6 Selection frequency correlations (r_s) and best portfolio overlap (Jaccard's index indicated between brackets = 1 for perfect overlap) based on planning units of different cost metrics

	Square	Hexagon
25-ha area vs agriculture	0.696 (0.299)	0.705 (0.309)
100-ha area vs agriculture	0.775 (0.351)	0.780 (0.395)
400-ha area vs agriculture	0.780 (0.473)	0.798 (0.534)

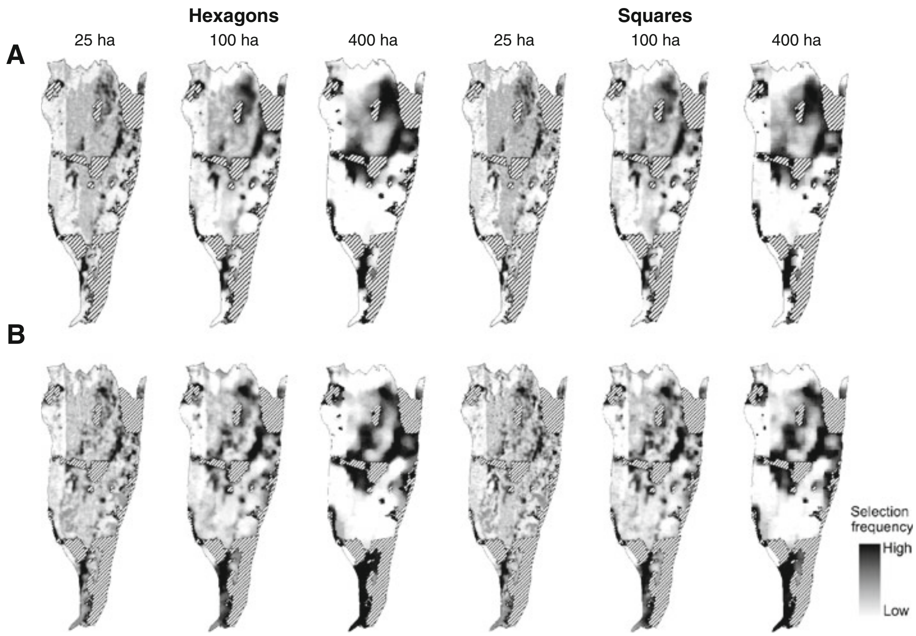

Fig. 2 Selection frequency patterns based on planning units of different shape and size and with cost metrics based on: **a** area and **b** risk of agricultural transformation. These analyses used the planning units that had not been shifted in the *X* and *Y* axes

changing planning unit size produced profound impacts on the overlap, especial when comparing 25 and 400 ha where the overlap reached a minimum of 0.313 (Table 5). Altering the type of cost metric caused little overlap in the best portfolios with smaller and square planning units (Table 6).

Discussion

If systematic conservation assessments are to inform action on the ground then they need to produce results that are relevant for implementation (Smith et al. 2009). There are a number of ways to increase this relevance and these include using real-world cost data and identifying efficient but viable networks of PAs by influencing planning unit clustering. Recently available software packages, such as Marxan, allow such factors to be considered when designing PA networks (Ball and Possingham 2000) and this research is the first to investigate how planning unit characteristics affect portfolio efficiency and fragmentation

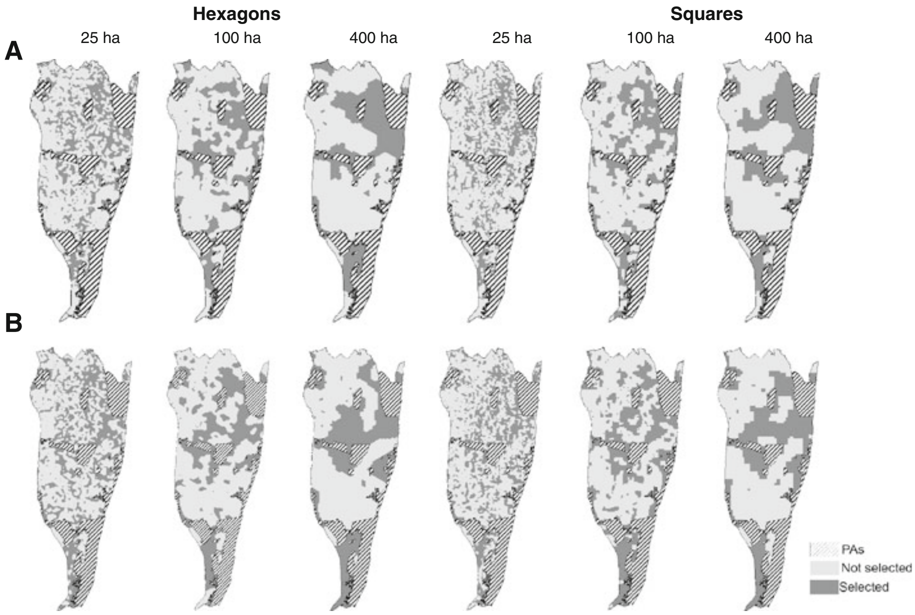

Fig. 3 Best portfolios with planning units of different shape and size and with cost metrics based on: **a** area and **b** risk of agricultural transformation. These analyses used the planning units that had not been shifted in the *X* and *Y* axes

levels within this new conservation planning software context. In this section we will first discuss the methods we used to measure portfolio efficiency and overlap and then discuss how varying planning unit shape, size, baseline and cost affected the efficiency of the results and the spatial location of the priority areas identified.

Metrics for assessing effectiveness

Measuring the ecological, economic, social and political effectiveness of protected area networks is a major challenge in systematic conservation planning (Margules and Pressey 2000; Naidoo et al. 2006), but there are a number of simple metrics that are widely used as surrogates to measure the efficiency and ecologically viability of reserve networks designs (Ando et al. 1998; van Jaarsveld et al. 1998; Erasmus et al. 1999; Warman et al. 2004; Grand et al. 2007; Kark et al. 2009; Grantham et al. 2010; Weeks et al. 2010). Thus, in this study we used total portfolio area and total planning unit cost as a proxy for efficiency, and boundary length, number of patches and median patch size as a proxy for fragmentation levels, which is an aspect of ecological viability (Khan et al. 1997; Chape et al. 2005). These indicators have ecological and economic relevance because highly fragmented portfolios of small PAs are more expensive to manage and less ecologically viable (Moilanen and Wintle 2007; Smith et al. 2010). The correlation results are likely to provide more robust information when comparing portfolios because selection frequency scores in Marxan are based on a number of runs and so are more stable (Carwardine et al. 2007). In contrast, the best portfolios can vary widely if lots of planning units have similar attributes, allowing a great deal of flexibility when identifying portfolios that meet the targets. However, identifying the best portfolio is a key part of the conservation assessment process (Warman et al. 2004) and so we used both measures in our analysis.

Portfolio efficiency

We found that increasing the planning unit size by 16 times, i.e. from 25 to 400 ha, increased the portfolio extent by 1.3 and 1.6% for squares and by 2.0 and 3.2% for hexagons in the area and agriculture cost metrics analyses, respectively. Previous studies also found portfolio efficiency reduced with increasing planning unit size (Pressey and Logan 1998; Larsen and Rahbek 2003; Warman et al. 2004; Shriner et al. 2006; Justus et al. 2008), which arises because large planning units are more likely to contain superfluous sections. However, these previous analyses used software that could not select planning unit clusters and so we compared our results to determine how this affected the efficiency trends. Such comparisons are complicated by the fact that each study used different planning unit sizes and shapes but they show that not accounting for boundary costs produced larger differences. For example when using square planning units, Pressey and Logan (1998) found that increasing the units by 21 times increased portfolio area by approximately 785% and Larsen and Rahbek (2003) found that increasing the units by 8 times increased portfolio area by 115%. In addition, Warman et al. (2004) found that increasing hexagonal planning units by 12.5 times increased portfolio area by 27%. Thus, the effect of using smaller planning units to maximise efficiency seems much less pronounced when using software that identifies portfolios containing planning unit clusters.

We also found that using hexagons produced more efficient results when compared with squares, and this improvement ranged between 0.2 and 1.8% reductions in portfolio extent. This is because hexagons can be arranged in a more spatially compact manner and so need fewer superfluous planning units to form patches containing the important conservation features (Culver et al. 2004; Birch 2006; White and Kiester 2008). Using hexagons also generally produced portfolios that consisted of fewer smaller patches and there were similar trends when using larger planning units. Thus, there is an apparent trade-off between efficiency and viability and it could be argued that planning unit size should be selected to strike a balance between efficient but fragmented and less efficient but more viable portfolios made up of larger PAs (Shriner et al. 2006; Mills et al. 2010). However, such a conclusion ignores the fact that some planning units are likely to contain transformed habitats, such as agricultural land or human settlements, that would not be included in any PA system and that larger planning units are more likely to contain these unsuitable areas. Therefore, we would argue that it is better to use small, hexagonal planning units to maximise efficiency and then reduce their fragmentation levels by increasing the boundary length cost through the BLM value or other methods (Smith et al. 2010).

Best portfolio and selection frequency comparisons

Two factors make it difficult to compare the spatial patterns of the priority sites identified in the different portfolios. First, increasing planning unit size reduces flexibility because larger planning units tend to contain more of each conservation feature and so become relatively more important for meeting targets (Larsen and Rahbek 2003). This is shown by our results, where Jaccard's Index scores and selection frequency correlation scores were always higher when using 400 ha planning units when compared to 25 ha planning units. Similar results were found by Shriner et al. (2006) where overlap increased as planning unit size increased.

The second factor is more profound, as previous studies have shown that altering the planning unit boundaries can have a large influence on the spatial pattern of portfolios (Margules et al. 1988; Csuti et al. 1997; Pressey and Logan 1998; Bassett and Edwards

2003; Warman et al. 2004; Hess et al. 2006). This makes investigating the impact of planning unit shape difficult, as any differences could simply result from the planning units not overlapping perfectly and so having different baselines. We investigated this by measuring the impact of shifting the planning unit baselines and found that this could produce large differences in the resultant portfolios. For example, the correlation between the selection frequency scores was only 0.592 when comparing results from using 25 ha hexagons with the agriculture cost metric with those from an analysis that was identical apart from shifting the planning units by 500 m in the *X* and *Y* axis (Table 2). However, this result was the most extreme, with correlation coefficients closer to 0.9 for most analyses based on larger planning units with smaller baseline shifts. Moreover, despite these differences, all of the portfolios tended to identify areas in the south and western of Maputo Special Reserve, west of the iSimangaliso Wetland Park and neighbouring Tembe National Park and Ndumo Game Reserve (Figs. 1, 2, 3).

Comparisons between analyses based on different cost metrics are more straightforward, as these use identical sets of planning units. These showed a robust trend, which is that correlation coefficients were always higher when using the agriculture cost metric. This result confirms earlier work showing that the type of planning unit cost metric can have a large influence on conservation assessment results (Naidoo et al. 2006; Bode et al. 2008; Adams et al. 2010). Such variation in costs leads to a reduction in flexibility, as planning units with equal biodiversity value may differ in the cost of including them in the portfolio. In such cases, Marxan will preferentially select the cheaper planning units and so priority areas tend to be identified in the same location (Carwardine et al. 2010), reducing the influence of planning unit shape or size. However, this effect of planning unit cost metric was less pronounced when using larger planning units, which was because increasing planning unit size also reduces flexibility (Larsen and Rahbek 2003; Shriner et al. 2006) and so some high cost units always had to be selected to meet the targets.

Conclusion

Conservation assessments should be designed to best inform action on the ground (Smith et al. 2009), so the choice of planning unit should account for tenure patterns and proposed implementation strategies. However, there are many occasions where using regular shaped polygons is the most appropriate and our results show that using small, hexagonal planning units will produce more efficient results. In some cases this efficiency will produce portfolios containing smaller, more isolated PAs but this problem is better overcome by increasing boundary length costs rather than using larger planning units. We also found that the spatial pattern of the portfolios can be far from robust and that changing parameters, such as planning unit baseline, shape and size can produce quite different results. This was especially the case when using smaller planning units, although in most cases there were some areas that were frequently selected, even if the exact locations differed. Finally, we found that using a socio-economic planning unit cost metric and applying constraints to reduce portfolio fragmentation reduced the influence of planning unit characteristics on assessment results. This echoes previous studies which found that using real-world cost and constraint data often produces more robust results (Bode et al. 2008; Carwardine et al. 2010) and so future studies on the factors that influence conservation assessments should include such data.

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