The Australian Journal of
Agricultural and Resource Economics

Journal of the Australian Agricultural and Resource Economics Society

Australian Journal of Agricultural and Resource Economics, 61, pp. 557–575

How well do conservation auctions perform in achieving landscape-level outcomes? A comparison of auction formats and bid selection criteria*

Md Sayed Iftekhar and Uwe Latacz-Lohmann†

This paper studies the performance of auction design features regarding pricing mechanisms and bid selection criteria for securing wildlife zones across different holdings. We compare two pricing mechanisms: a discriminatory-price auction and a uniform-price ascending auction, and four bid selection criteria on the basis of: total bid, bid-per-value ratio, bid-per-area ratio and a mixed criterion where bids are formed on the basis of cost but they are selected based on the bid-per-value ratio. We develop a best-response group-bidding model for a discriminatory-price auction where bidders form optimal group bids for individual wildlife zones. In the uniform-price ascending auction, individual landholders respond to prices, which are successively raised by the auctioneer and whenever all the landholders from a single zone agree to participate (i.e. the first zone is formed), the auction stops. Based on numerical simulations using a bio-economic model of malleefowl conservation, we observe that the discriminatory-price auction is more cost-effective than the uniform-price ascending auction. However, the budgetary cost-effectiveness of a discriminatory-price auction is sensitive to bidder uncertainty about the number of competing bidder groups and the highest cost of establishing a wildlife zone among these groups. In terms of bid selection, the mixed bid selection criterion performs best. We discuss the policy implications of these findings.

Key words: conservation auction, discriminatory-price auction, environmental service payments, group bidding, landscape auction, uniform-price auction.

1. Introduction

Habitat fragmentation and degradation of the natural environment motivates action to protect nature on private farmland (Michael *et al*. 2014). To achieve better ecological outcomes, often coordinated actions by multiple landholders are required. Improvement in environmental problems like salinity intrusion or nitrate pollution also requires joint actions by multiple landholders.

* Funding from Centre of Excellence for Environmental Decisions (CEED) and UWA Research Collaboration Award are gratefully acknowledged. The authors wish to acknowledge comments from Associate Editor and the anonymous reviewers, which helped in improving the manuscript substantially.

† Md Sayed Iftekhar is at (e-mail: mdsayed.iftekhar@uwa.edu.au) Centre for Environmental Economics & Policy (CEEP), UWA School of Agriculture and Environment, M087, The University of Western Australia (UWA), Crawley, WA, Australia. Uwe Latacz-Lohmann is at Department of Agricultural Economics, University of Kiel, Kiel, Germany.

doi: 10.1111/1467-8489.12226

Establishment of wildlife corridors in fragmented landscape is another area, which requires coordinated actions across multiple holdings (Rolfe *et al.* 2008; Morse *et al.* 2009; Windle *et al.* 2009).

To engage with private landholders, market-based instruments such as conservation auctions (or tenders) have been used in many countries such as Australia, USA and Canada. The Conservation Reserve Program (CRP) of USDA is one of the early programs to use an auction-based mechanism. In Australia, BushTender, EcoTender and the Auction for Landscape Recovery are some prominent examples (Stoneham *et al.* 2003; Whitten *et al.* 2007). There are also some recent examples of testing auction-based mechanisms in developing countries (Jack *et al.* 2009; Ajayi *et al.* 2012). Application of an auction-based mechanism for securing environmental services is attractive as it helps to discover market (supply) prices for nonmarket environmental goods and services. In addition, if the auction is competitive, it can improve the cost-effectiveness of environmental programs. However, the performance of a conservation auction depends on its design.

Most of the work on conservation auction design has focused on standard auctions where bidders submit individual bids to an environmental agency, which then selects bids from the lowest upward until a given budget is exhausted. This is commonly known as a budget-constrained auction where the auctioneer aims to maximise environmental value with a given budget. In a target-constrained auction, by contrast, the agency aims to secure a given environmental target at minimum budgetary cost. In this paper, we study a target-constrained auction where the objective of the agency is to secure a single wildlife zone, which consists of land from multiple holdings. Such an auction would be suitable to capture ecological synergies among different landholdings within a zone. More precisely, we investigate the performance of alternative auction design features (i.e. pricing mechanism and bid selection criteria) for securing wildlife zones across different holdings. In essence, we compare two pricing mechanisms: discriminatory-price and a uniform ascending price, and four bid selection criteria: based on total bid, based on bid-per-value ratio, based on bid-per-area ratio and a mixed criterion where bids are formed on the basis of total cost but the winning bid is selected on the basis of its bid–value ratio. The different bid selection criteria represent scenarios with different amounts of information available to landholders and the agency. We assess the performance of these auction design features against two criteria: budgetary cost-effectiveness and economic cost-effectiveness. The first criterion is concerned with how much the environmental agency has to pay on average to secure one unit of environmental service; the second criterion measures the average farm-level costs of supplying a unit of service. Due to rent seeking behaviour, these two criteria do not always correspond to each other.

Various aspects of landscape-scale auctions have been explored in the literature. For example, Rolfe *et al.* (2009) and Windle *et al.* (2009) studied whether running multiround auctions facilitate the formation of wildlife corridors. The mechanism was designed to achieve landscape connectivity. They observed that most of the connectivity benefits were realised in the first few rounds. Reeson *et al.* (2011) tested the performance of a 'lock in' rule in improving coordination. Banerjee *et al.* (2015) studied whether releasing information about the agency's spatial environmental goals improves auction performance or not. They observed that additional information has a negative impact on the cost-effectiveness of the auction. Recently, Fooks *et al.* (2016) studied the individual and joint effects of network bonuses and spatial targeting. They observed that spatial targeting improves auction outcomes, whereas network bonuses have a negative impact.

The pricing format is a key element of conservation auction design (Hanley *et al.* 2012). The most common pricing format used in conservation auctions is a sealed-bid discriminatory-price mechanism where successful bidders receive their bid. See Latacz-Lohmann and Hamsvoort (1997) for a seminal model of optimal bidding in discriminatory-price auctions with a given budget. In such auctions, rent seeking through bid shading is a common phenomenon. However, a discriminatory-price auction might be easier to understand by the bidders and easier to implement than a uniform-price auction (Brown *et al.* 2011).

In a uniform-price auction, all winning bidders receive the same pay-off, which is either the lowest rejected bid or the highest accepted bid. There are some examples of the application of uniform-price auctions such as in Canada (Brown *et al.* 2011) and Indonesia (Jack *et al.* 2009). Auction theory has established that truth-telling is the dominant bidding strategy in uniform-price auctions (Cramton 1998). However, this strategy may not always be obvious to the bidders and high-cost bidders may be reluctant to participate in a uniform-price auction (Latacz-Lohmann and Schilizzi 2005). There are some comparative analyses of the price-discriminating and the uniform-pricing formats. For example, Krawczyk *et al.* (2016) studied the role of auction formats in achieving landscape outcomes using laboratory experiments. They observed that the discriminatory-price auction performed better than the uniform-price auction as it allowed better coordination among landholders. However, the studies so far concentrated on behaviour and performance of individual bidders. Without proper analysis, it is hard to tell which pricing method should be applied in a landscape auction, which could involve both group and individual bidding.

Similarly, there is limited discussion on which type of bid selection criteria should be used for a landscape auction. Previously, Iftekhar and Tisdell (2014) compared the performance of net benefit and benefit-cost ratio bid selection criteria in a laboratory experiment setting. They observed that there was not much difference between the two criteria in terms of aggregate outcomes. However, their model assumed that the bidders knew the environmental value of their respective wildlife corridors perfectly. In reality, landholders are more likely to have limited information about the environmental benefits of their lands. It is even more unlikely in a landscape auction where individual landholders have to know the environmental values of the zones they could be part of.

Therefore, we have tested four bid selection criteria: based on (i) total bid; (ii) bid-per-value ratio; (iii) bid-per-area ratio; and (iv) a mixed scenario where bids are formed based on total cost and selected based on bid-per-value ratio. These represent information scenarios. The first selection criterion assumes that landholders do not know the environmental values of the ecological zones and that the agency does not use this information for bid selection either. By contrast, the bid-per-value ratio selection is the most information-intensive criterion: it assumes that both landholders and the agency know the biodiversity value of the individual zones and use this information to form their bids and select the winning bid respectively. The bid-per-area ratio criterion considers land area as a proxy of biodiversity value. Finally, the last criterion reflects the situation where bids are assessed based on the ratio of biodiversity benefit (i.e. a bid-per-value ratio), but landholders are not knowledgeable of the conservation benefits.[1] Contrasting these four selection criteria would inform us as to which types of mechanisms are more sensitive to the availability of environmental value information. Comparing these design features will contribute to the development of more cost-effective and robust landscape auction designs.

To compare the pricing mechanisms and bid selection criteria, we first develop a best-response group-bidding model for a discriminatory-price landscape auction and then conduct simulation experiments to compare different pricing formats and bid selection criteria using a bio-economic model. If a design does not perform well in the simulations, it is highly unlikely that it will perform well in more complex situations, such as in economic experiments or in the field. Simulation experiments make it possible to assess the performance of an auction design under a wide range of scenarios. Outcomes for different design aspects are then systematically compared and evaluated.

2. Conceptual framework

The two auction mechanisms and four bid selection criteria are tested in the context of a landscape conservation program where the objective of the auctioneer is to select an ecological zone (which consists of a certain number of suitable sites from different holdings) at minimum cost. In a discriminatory-price auction, landholders from the same zone form a joint group bid.[2]

[1] We thank the Editor for suggesting this option.

[2] An alternative would have been to allow individual bids to be submitted and potential site synergies to be considered in the bid selection process. However, such a scheme would run the risk of not securing an adequate number of sites and failing to select bid combinations that maximise outcomes including ecological interactions at lowest cost. Further, optimal bidding models for individual bidders, which include the ecological interdependencies among different sites, are not fully developed yet and beyond the scope of this work.

In a uniform-price ascending auction, individual landholders respond to the increasing price offer, and as soon as all the landholders from a zone agree to the program, the auction stops and winning landholders receive the current price. To avoid a multi-unit bidding problem, it is assumed that each landholder can manage only one site and can be part of only a single zone. Under each of the two pricing mechanisms, we test the four bid selection criteria described above: based on total bid (TB); bid–value ratio (BVR); bid–area ratio (BAR); and the mixed scenario (TB-BVR). With BVR selection, the zone with the lowest bid per unit of ecological value is selected. Similarly, under BAR and TB the zones with the lowest bid per area and total bid are selected, respectively. Table 1 presents a summary description of the schemes. These are described in further detail below.

Table 1 Auction mechanisms and bid selection criteria tested in the paper

Pricing mechanisms / Selection criteria	Description
DPA-BVR	Discriminatory-price auction (DPA) where bids are formed based on the cost–value ratio of individual zones and group bids are selected based on the bid–value ratio (BVR) of the offered zones. This is a high-information scenario as it assumes that landholders have information about the conservation value of their sites.
DPA-TB	Discriminatory-price auction where bids are formed based on the total cost of individual zones and group bids are selected based on the total bid (TB) of the offered zones. This represents a low-information scenario.
DPA-BAR	Discriminatory-price auction where bids are formed based on the cost–area ratio of individual zones and group bids are selected based on the bid–area ratio (BAR) of the offered zones. This is moderate-information scenario as knowledge of both size and costs (but not value) are required for bid formation and selection.
DPA-TB-BVR	Discriminatory-price auction where bids are formed based on the total cost of individual zones and group bids are selected based on the bid–value ratio (BVR) of the offered zones. This is an asymmetric-information scenario as the landholder groups do not know the conservation value of their zones, whereas the agency has information on environmental values.
UAA-BVR	Uniform-price ascending auction (UAA) where the price per unit of environmental value is raised gradually, bidders compare with their own site's cost–value ratio and respond positively when the price is higher than their cost–value ratio. The auction stops as soon as a zone could be formed from the willing landholders. This mechanism results in different payments for winning landholders according to the environmental value of their sites.
UAA-TB	Similar process as UAA-BVR, except that the prices are raised per site (irrespective of their value or size) rather than based on bid–value ratio. Winning landholders receive a uniform price irrespective of the value or size of their sites.
UAA-BAR	Similar process as UAA-BVR, except that the prices are raised per area rather than based on bid–value ratio. Winning landholders receive different payments depending on the size of their sites.
UAA-TB-BVR	Similar process as UAA-TB. Since the first formed zone is selected, there is no application of BVR selection.

2.1 Discriminatory-price auction

In a discriminatory-price landscape auction, an optimal group bid is formulated for each ecological zone. The bidding model for DPA-TB is described below.

A group balances net pay-off and acceptance probability: a higher offer promises higher net pay-off but reduces the probability of winning. Each group g therefore faces the problem of determining the optimal offer which maximises their expected net pay-off ($E(\pi_g)$). The group with the lowest offer will be selected. A group's expected net pay-off function is as follows (Li and Zheng 2009):

$$E(\pi_g) = P(b_g(c_g) \leq b_k(c_k), g \neq k) \times [b_g(c_g) - c_g] \tag{1}$$

The first part of the equation defines the probability that bid $b_g(c_g)$ is lower than all other bids, which could also be expressed as $(1 - F(b(c)))^{N-1}$. N is the number of groups competing in the auction. c_g is the participation cost of group g, and $b_g(c_g)$ is a potential bid of group g. $F(b)$ is the cumulative distribution function of bids. Thus, equation 3 becomes

$$E(\pi_g) = \left((1 - F(b(c)))^{N-1}\right) \times [b_g(c_g) - c_g] \tag{2}$$

Maximising the expected profit function (2) with respect to bid and rearranging terms yields the optimal group bid:

$$b_g^* = c_g + \frac{(1 - F(b(c)))^{N-1}}{(N-1)(1 - F(b(c)))^{N-2} f(b(c))} \tag{3}$$

This is a best-response bidding function for individual groups. We denote a group's bidding strategy as function $b(c)$ specifying the optimal bid a group should submit. Since $b(c)$ is strictly increasing and differentiable with respect to c, $F(b(c))$ could be written as $F(c)$. Assume that the costs of all groups are uniformly distributed in the range of $[\underline{c}, \bar{c}]$ which is common knowledge among the bidders. Then, the cumulative distribution function and the probability density function are

$$\begin{aligned} F(b(c)) = F(c) &= \begin{cases} \frac{c_g - \underline{c}}{\bar{c} - \underline{c}} & \text{if} \underline{c} \leq c_g \leq \bar{c} \\ 0 & \text{elsewehere} \end{cases} \\ f(b(c)) = f(c) &= \begin{cases} \frac{1}{\bar{c} - \underline{c}} & \text{if} \underline{c} \leq c_g \leq \bar{c} \\ 0 & \text{elsewehere} \end{cases} \end{aligned} \tag{4}$$

Substituting (4) into (3) yields the best-response bid for group g

$$b_g^* = c_g + \frac{\left(\frac{\bar{c}-c_g}{\bar{c}-\underline{c}}\right)^{N-1}}{(N-1)\left(\frac{\bar{c}-c_g}{\bar{c}-\underline{c}}\right)^{N-2}\left(\frac{1}{\bar{c}-\underline{c}}\right)} \tag{5}$$

Simplifying equation (5)

$$b_g^* = c_g + \frac{\bar{c}-c_g}{N-1} \tag{6}$$

It is clear from (6) that the optimal group-bidding strategy in a price-discriminating auction is one of overbidding: the bid consists of the costs incurred by the group (c_g) and an increment as per the second term in (6). The amount of bid shading depends on the expectations on the number of groups participating in the auction (N) and the highest ($\bar{c}$) cost of participating groups.[3] Further, by taking the partial derivatives of the optimal bid equation $\left(b_g^*\right)$ with respect to expected $\bar{c}$ and N, it is possible to identify the rates of change (or the sensitivity of the optimal bids to the variable of interest):

$$\frac{b_g^*}{\mathrm{d}\bar{c}} = \frac{1}{N-1} \tag{7a}$$

$$\frac{b_g^*}{\mathrm{d}N} = \frac{\bar{c}-c_g}{(N-1)^2} \tag{7b}$$

By comparing (7a) and (7b), we can observe that the optimal bid increases linearly as the expectation on $\bar{c}$ gradually rises, whereas the optimal bid declines nonlinearly as the expectation on the number of participating groups increases. We expect that the cost-effectiveness of the discriminatory-price auction would follow a similar pattern if all the participating groups use the same best-response bidding model. However, these models do not tell us whether a discriminatory-price auction would perform better than an alternative uniform-price ascending auction.

The bidding models for DPA-BVR and DPA-BAR are identical to (5) except that the cost estimates are cost–value and cost–area ratios rather than total costs. Here, we assume that bidders have information about the environmental values and the total area of their zone so that they can calculate the cost–value and cost–area ratios. For DPA-TB-BVR, it is

[3] It is possible that bidders do not know their own costs and values of their sites and zone perfectly. However, we do not model the impact of uncertainty over own cost and values to manage the scope of the paper. Rather, we test the impact of uncertainty with the cost distribution of competitors. Further, we test the impact of not using ecological benefit or area information on auction performance by comparing four bid selection criteria.

assumed that the landholders use their group cost to form best-response bids and the agency selects the most cost-effective bid using the bid–value ratio selection criterion.

2.2 Uniform-price ascending auction

The discriminatory-price auction model is compared to a uniform-price ascending auction (UAA) where the agency starts with a low price and gradually increases its offer. At each level of offer, the landholders indicate whether they wish to participate at that price or not. The auction continues until a zone is formed (i.e. all the landholders belonging to that zone agree to participate in the program). As soon as the first zone is formed, the auction stops and winning landholders receive the current price. We have tested the four price increment rules UAA-TB, UAA-BVR, UAA-BAR and UAA-TB-BVR as described in Table 1.

While the theoretical models presented in equations (5–7b) indicate how the bids in a discriminatory-price auction would change (assuming all the participating bidders and groups are employing the same best-response bidding model) with respect to expectations on the number of groups and costs, they do not inform us about the relative bids (and cost-effectiveness) of a discriminatory-price auction vis-à-vis a uniform-price ascending auction. Therefore, we compare the two pricing mechanisms using a numerical simulation experiment for a particular case study context.

3. A case study application

The above-mentioned auction models are tested in the context of a malleefowl conservation program. Malleefowl (*Leipoa ocellata*) is a large ground-dwelling bird, found in the semi-arid to arid shrublands and low woodlands. A sandy substrate and abundance of leaf litter are required for breeding. In suitable conditions, one to two pairs can be found per site. Malleefowl is listed as vulnerable in the Australian Environment Protection and Biodiversity Conservation Act 1999. Natural predators of malleefowl include fox and feral cats. We have developed the bio-economic model following Nicol and Chadès (2011).

It is assumed that there are 25 landholders who are arranged in five distinct ecological zones; each zone consists of five landholders managing a single site each.[4] Each landholder (i) can protect one site of habitat suitable for malleefowl. The area ($a(i)$) and ecological value ($m(i)$) of a site can vary from one landholder to another. A site can be occupied by malleefowl ($m(i) = 1$) or

[4] For the sake of tractability, the number of zones and landholders has been kept low as the information used to populate the bio-economic model was derived from a limited number of sites. However, subject to the availability of information it is possible to increase the number of zones and landholders. It is also possible to assume different numbers of landholders in each zone.

not ($m(i) = 0$). Following Nicol and Chadès (2011) it is assumed that malleefowl population in individual sites is subject to natural extinction and colonisation. It is assumed that the extinction probability is influenced by predation and other types of stochastic extinction. The probability of extinction due to predation is denoted by $e_{\text{pred}}(i)$ and it is assumed that predation is only caused by fox; that is, $e_{\text{pred}}(i) = e_{\text{fox}}(i)$. $e_{\text{fox}}(i)$ is a function of the time it would require for site extinction, $e_{\text{fox}}(i) = 1/t_{\text{ext}}(i)$. $t_{\text{ext}}(i)$ is a function of the habitat area. The probability of stochastic extinction is defined by $e_{\text{stoch}}(i) = 13/a(i)$. Finally, the probability of extinction is calculated as $e(i) = \min\left(e_{\text{stoch}}(i) + e_{\text{pred}}(i), 1\right)$.

Colonisation probability would depend on the malleefowl condition of other sites and the distance from other sites. The colonisation probability $\theta(i,k)$ between any two sites i and k is calculated as $\theta(i,k) = 0.005e^{-\sqrt{\mathrm{d}(i,k)/5}}$, where $\mathrm{d}(i,k)$ is the distance between site i and k. The closer the sites are the higher probability of recolonisation. So, the total probability of colonisation of an empty site $\varphi(i)$ from all the occupied sites in the landscape can be written as $\varphi(i) = (1 - m(i)) \times \sum_{k,i \neq k} \theta(i,k) \times m(k)$.

Following Nicol and Chadès (2011) and Bode and Brennan (2011), we assume that to improve or to maintain the malleefowl status two management actions can be carried out on each site: fox baiting and malleefowl reintroduction. The effect of fox baiting is removal of 95 per cent fox in the baited area, which decreases the probability of extinction due to predation by 95 per cent (i.e. $e_{\text{pred}}(i) = 0.05 \times e_{\text{fox}}(i)$). Malleefowl re-introduction allows an unoccupied site to become occupied. It is assumed that each attempted re-introduction has a 50 per cent probability of success and that the probability of occupation $o(i)$ increases by 50 per cent if re-introduction is carried out on an empty site; that is, $o(i) = (1 - m(i)) \times 0.50$.

Finally, the expected status of malleefowl for individual sites and a zone after all the processing are

$$
\begin{aligned}
v(i) &= \min(m(i) - e(i) \times m(i) + o(i) \times (1 - m(i)) + \varphi(i), 1) \\
v_g &= \sum_{i,i \in g} v(i)
\end{aligned}
\tag{8}
$$

v_g serves as metric of environmental outcome. We shall refer to it as ecological value in the subsequent analysis.

It is assumed that a fox-baited site will be baited with a density of 7.5 baits per km^2 and baiting is repeated fortnightly to prevent re-infestation by foxes from outside the site during the baiting management period. The total area baited is 1.5 times the size of the site to prevent re-infestation. A bait would cost \$2.07 (inflation adjusted for 2016) including purchase cost of a bait and labour cost to lay the baits (Nicol and Chadès 2011). Therefore, the cost of baiting a site ($c_{\text{bait}}(i)$) for 1 year is: $c_{\text{bait}}(i) = a(i) \times 1.5 \times \$2.07/\text{bait} \times 7.5/\text{sqkm} \times 26/\text{year}$.

Malleefowl re-introduction requires a captive breeding program. They are relatively easy to rear and have been successfully bred in Australian zoos. In suitable habitat conditions, 1–2 breeding pairs per site can be found. So, it is assumed that a re-introduction strategy would involve releasing two breeding pairs per site. Based on Nicol and Chadès (2011) it is assumed that from raising to releasing one animal would cost \$1,498 (adjusted for 2016). The cost of re-introduction ($c_{\text{re-intro}}(i)$) in a site is $c_{\text{re-intro}}(i) = \$1498 \times 2 \times 2 = \$5,992$. Finally, the management cost of a site (i) is $c(i) = c_{\text{bait}}(i) \times m(i) + c_{\text{re-intro}}(i) \times (1 - m(i))$. To fix the management actions, we assume that baiting will be carried out only if the site is occupied and re-introduction will be carried out only if the site is empty. The total management cost of a zone (g) is then $c_g = \sum_{i,i \in g} c(i)$. As such, both benefits and costs will be different for different zones.

4. Simulation experiment

Our main research question relates to the performance of two different auction mechanisms in securing wildlife zones. As observed in equation (6), the optimal bid in discriminatory-price group bidding is sensitive to the number of groups and the highest participation (management) cost among the groups participating in the auction. However, for the sake of completeness we also consider the minimum participation cost among the participating groups. We simulate the performance of discriminatory-price auctions in a scenario where the bidders have perfect knowledge of the number of groups as well as the maximum and the minimum participation costs of the groups submitting an offer in the auction. Further, to test the sensitivity of the performance of the auction to the uncertainty of these parameters, we construct two other scenarios: underestimation (40 per cent lower than the actual values) and overestimation (40 per cent higher than the actual values). We thus compare the discriminatory-price auction with a uniform-price ascending auction in a total of 27 combinations of the above-mentioned variables, that is 3 levels for number of groups × 3 levels for maximum participation cost × 3 levels for minimum participation cost. This will provide us with a comprehensive picture of the performance of the auction mechanisms. We developed our model using the General Algebraic Modeling System (GAMS©).

Due to the stochastic processes involved in the model, 20,000 simulations were conducted for each individual combination. Four steps were carried out. In the first step, following Nicol and Chadès (2011) and Day and Possingham (1995), profiles of individual sites (area, malleefowl status, distance between sites) are randomly generated based on the following uniform distribution: area (100–2700 ha), malleefowl status (0 or 1), distance between sites within a zone (4–5 km) and distance between sites in two separate zones (6–8 km). Ecological values and participation costs are calculated based on the randomly drawn profiles. In the second step, bids are formed following the auction models presented above. In the case of DPA, landholders within a zone form a group and prepare a joint bid based on the respective bid selection criteria. For simplicity, we assume that group bid formation does not involve transaction costs. In the case of UAA, landholders individually participate in the auction. They respond to the auctioneer's offer as per their private information. In the third step, bids are selected based on each of the four bid selection criteria described above. In a discriminatory-price auction, one joint bid is selected, whereas, in a uniform ascending auction, the auction continues until all landholders from a single zone are selected. The auction stops as soon as the first zone is formed. Finally, simulation outcomes are recorded. Then, a new simulation starts repeating the above-mentioned steps.

The results are summarised in terms of two performance indicators:

Budgetary cost-effectiveness (BCE) and Economic cost-effectiveness (ECE). BCE is the ratio of payment and ecological value of the selected zone. The lower the estimate, the better is the performance of the scheme (lower payment per unit of service).
ECE is the ratio of participation cost and ecological value of the selected zone. The lower the estimate, the better is the performance of the scheme as it shows that relatively inexpensive zones with high biodiversity values were selected.

5. Results

Results are presented in the following order. The overall performance of the two pricing mechanisms and the four bid selection criteria are presented. Then the performance of the bid selection criteria separately under each of the two pricing mechanisms, and finally the performance of the discriminatory-price auction when bidders face uncertainty about the number of competing bids and the maximum cost among participating groups. Results for the two measures of auction performance (BCE and ECE) are summarised in Tables 2–5. Pairwise comparisons of means with equal variances tests are used to compare differences between the auction features.

5.1 Performance of auction mechanisms and selection criteria

Table 2 presents mean and median BCE and ECE values for the two auction mechanisms and four selection criteria. It can be seen that overall the discriminatory-price auction (DPA) has outperformed the uniform-price ascending auction (UAA) in terms of both budgetary and economic cost-effectiveness. This means that, compared to the UAA, the DPA selected, on average, higher-value zones that were provided at lower cost. We can further observe from Table 2 that TB-BVR selection has achieved better budgetary cost-effectiveness than the other three mechanisms. However, BVR selection

Table 2 BCE and ECE estimates by auction mechanism and selection criteria

	BCE			ECE		
	Mean	SD	Median	Mean	SD	Median
Auction mechanism						
Discriminatory	8.96	2.39	8.57	7.55	1.70	7.43
Uniform	10.83	2.44	10.79	8.17	1.74	8.14
Selection criteria						
BAR	11.38	3.13	11.04	8.88	1.72	8.89
BVR	9.55	1.79	10.46	7.37	1.50	7.34
TB	9.50	2.38	9.30	7.67	1.71	7.69
TB-BVR	9.14	2.25	8.83	7.50	1.61	7.45
Overall	9.89	2.59	9.63	7.86	1.75	7.81

Note: BCE, payment/ecological value; ECE, participation cost/ecological value. Both BCE and ECE are expressed in \$000 per unit value.

has achieved higher economic cost-effectiveness. Pairwise comparisons of means tests formally confirm (at 1 per cent level of significance) that DPA>UAA for both BCE and ECE, while within the selection criteria TB-BVR>TB>BVR>BAR for BCE and BVR>TB-BVR>TB>BAR for ECE. However, the performance of different selection criteria may be sensitive to the auction mechanism and we should look at more disaggregated levels.

5.2 Performance of bid selection criteria under different auction mechanisms

The first level of disaggregation compares the performance of the bid selection criteria separately under the two auction mechanisms. Pairwise comparisons reveal that under a uniform-price ascending auction, both TB-BVR and TB have performed equally well and significantly better than BVR, and BVR has outperformed BAR in terms of budgetary cost-effectiveness (Table 3). By contrast, under a discriminatory-price auction, TB-BVR has performed significantly better than BVR, which, in turn, has performed significantly better than TB and BAR. Across auction mechanisms and selection criteria combinations, DPA-TB-BVR has performed significantly better than any other combination followed by DPA-BVR and DPA-TB. A TB-BVR selection captures the benefits of information asymmetry, as landholders do not know the conservation values and are thus unable to ask higher prices for high-value zones, whereas, the agency could select the most cost-effective zone based on bid–value information.

In terms of economic efficiency (ECE), by contrast, BVR selection criterion has outperformed the other three criteria under both discriminatory and uniform pricing (Table 4). It should be noted that with BVR selection, group bids are formed based on the cost–value ratio of individual zones. Bid formation under BVR thus harnesses both cost and conservation value information. Such bids reflect the underlying conservation values of the zones better than bids formed under, TB-BVR, BAR or TB selection, and BVR selection is able to select more economically cost-effective zones.

Table 3 Pairwise comparisons of means with equal variances test results for BCE estimates by selection criteria and auction mechanisms

Comparison	Mean difference	SE	Unadjusted t	*P* > *t*	95% CI	
UAA-BVR vs UAA-BAR	−1.219	0.004	−283.300	0.000	−1.228	−1.211
UAA-TB vs UAA-BVR	−0.691	0.004	−160.460	0.000	−0.699	−0.682
UAA-TB vs UAA-BAR	−1.910	0.004	−443.760	0.000	−1.918	−1.902
UAA-TB-BVR vs UAA-BVR	−0.691	0.004	−160.460	0.000	−0.699	−0.682
UAA-TB-BVR vs UAA-BAR	−1.910	0.004	−443.760	0.000	−1.918	−1.902
UAA-TB-BVR vs UAA-TB	0.000	0.004	0.000	1.000	−0.008	0.008
DPA-BVR vs DPA-BAR	−2.448	0.004	−568.790	0.000	−2.457	−2.440
DPA-TB vs DPA-BAR	−1.849	0.004	−429.650	0.000	−1.858	−1.841
DPA-TB vs DPA-BVR	0.599	0.004	139.140	0.000	0.590	0.607
DPA-TB-BVR vs DPA-TB	−0.724	0.004	−168.300	0.000	−0.733	−0.716
DPA-TB-BVR vs DPA-BVR	−0.126	0.004	−29.160	0.000	−0.134	−0.117
DPA-TB-BVR vs DPA-BAR	−2.574	0.004	−597.960	0.000	−2.582	−2.565
DPA-BVR vs UAA-BAR	−3.854	0.004	−895.430	0.000	−3.862	−3.845
DPA-TB vs UAA-BAR	−3.255	0.004	−756.290	0.000	−3.264	−3.247
DPA-TB vs UAA-BVR	−2.036	0.004	−472.990	0.000	−2.044	−2.027
DPA-TB-BVR vs UAA-BAR	−3.979	0.004	−924.590	0.000	−3.988	−3.971
DPA-TB-BVR vs UAA-BVR	−2.760	0.004	−641.290	0.000	−2.769	−2.752
DPA-TB-BVR vs UAA-TB	−2.070	0.004	−480.830	0.000	−2.078	−2.061
UAA-BAR vs DPA-BAR	1.406	0.004	326.640	0.000	1.397	1.414
UAA-BVR vs DPA-BAR	0.187	0.004	43.340	0.000	0.178	0.195
UAA-BVR vs DPA-BVR	2.635	0.004	612.130	0.000	2.626	2.643
UAA-TB vs DPA-BAR	−0.504	0.004	−117.120	0.000	−0.513	−0.496
UAA-TB vs DPA-BVR	1.944	0.004	451.670	0.000	1.936	1.952
UAA-TB vs DPA-TB	1.345	0.004	312.530	0.000	1.337	1.354
UAA-TB-BVR vs DPA-TB-BVR	2.070	0.004	480.830	0.000	2.061	2.078
UAA-TB-BVR vs DPA-BAR	−0.504	0.004	−117.120	0.000	−0.513	−0.496
UAA-TB-BVR vs DPA-BVR	1.944	0.004	451.670	0.000	1.936	1.952
UAA-TB-BVR vs DPA-TB	1.345	0.004	312.530	0.000	1.337	1.354

5.3 Sensitivity of the discriminatory-price auction to bidder uncertainty

The second level of disaggregation concerns the assumptions underlying a DPA. The theoretical model developed in section 2 suggests that DPA bids are sensitive to the expected number of competing bids (i.e. competition intensity) and the maximum cost among the participating groups. The higher the number of groups submitting zone bids, the more competitive is the bidding. The higher the expected maximum cost, the higher the optimal bid.

Since bidders know neither the exact number of bidding groups nor the maximum cost among groups with certainty, they will form expectations about these parameters. In the simulations, bidders' expectations about the number of groups and minimum and maximum zone costs are varied between 0.6 and 1.4. A value of 1.0 means that bidders have perfect knowledge of these parameters. The values 0.6 and 1.4 mean that bidders underestimate or overestimate the values of these parameters by 40 per cent. Such uncertainty

Table 4 Pairwise comparisons of means with equal variances test results for ECE estimates by selection criteria and mechanisms

Comparison	Mean difference	SE	Unadjusted t	$P > t$	95% CI	
UAA-BVR vs UAA-BAR	−0.996	0.003	−324.690	0.000	−1.002	−0.990
UAA-TB vs UAA-BAR	−0.840	0.003	−273.570	0.000	−0.846	−0.834
UAA-TB vs UAA-BVR	0.157	0.003	51.120	0.000	0.151	0.163
UAA-TB-BVR vs UAA-BAR	−0.840	0.003	−273.570	0.000	−0.846	−0.834
UAA-TB-BVR vs UAA-BVR	0.157	0.003	51.120	0.000	0.151	0.163
UAA-TB-BVR vs UAA-TB	0.000	0.003	0.000	1.000	−0.006	0.006
DPA-BVR vs DPA-BAR	−2.023	0.003	−659.060	0.000	−2.029	−2.017
DPA-TB vs DPA-BAR	−1.581	0.003	−515.130	0.000	−1.587	−1.575
DPA-TB vs DPA-BVR	0.442	0.003	143.920	0.000	0.436	0.448
DPA-TB-BVR vs DPA-BAR	−1.918	0.003	−625.100	0.000	−1.924	−1.912
DPA-TB-BVR vs DPA-BVR	0.104	0.003	33.960	0.000	0.098	0.110
DPA-TB-BVR vs DPA-TB	−0.337	0.003	−109.970	0.000	−0.343	−0.331
UAA-BAR vs DPA-BAR	−0.088	0.003	−28.720	0.000	−0.094	−0.082
UAA-BAR vs DPA-BVR	1.934	0.003	630.340	0.000	1.928	1.940
UAA-BAR vs DPA-TB	1.493	0.003	486.410	0.000	1.487	1.499
UAA-BAR vs DPA-TB-BVR	1.830	0.003	596.380	0.000	1.824	1.836
UAA-BVR vs DPA-BAR	−1.085	0.003	−353.410	0.000	−1.091	−1.079
UAA-BVR vs DPA-BVR	0.938	0.003	305.640	0.000	0.932	0.944
UAA-BVR vs DPA-TB	0.496	0.003	161.720	0.000	0.490	0.502
UAA-BVR vs DPA-TB-BVR	0.834	0.003	271.690	0.000	0.828	0.840
UAA-TB vs DPA-BAR	−0.928	0.003	−302.290	0.000	−0.934	−0.922
UAA-TB vs DPA-BVR	1.095	0.003	356.770	0.000	1.089	1.101
UAA-TB vs DPA-TB	0.653	0.003	212.840	0.000	0.647	0.659
UAA-TB vs DPA-TB-BVR	0.991	0.003	322.810	0.000	0.985	0.997
UAA-TB-BVR vs DPA-BAR	−0.928	0.003	−302.290	0.000	−0.934	−0.922
UAA-TB-BVR vs DPA-BVR	1.095	0.003	356.770	0.000	1.089	1.101
UAA-TB-BVR vs DPA-TB	0.653	0.003	212.840	0.000	0.647	0.659
UAA-TB-BVR vs DPA-TB-BVR	0.991	0.003	322.810	0.000	0.985	0.997

may have implications for the relative performance of the two pricing mechanisms.

We can observe from the mean and median values presented in Table 5 that the budgetary cost-effectiveness of a DPA is higher when the groups overestimate the number of bidding groups and underestimate the maximum cost among the participating groups – a situation of perceived high competition intensity. As expected, uncertainty about the minimum cost among the participating groups has no effect on the budgetary cost-effectiveness of a DPA (Table 5). Consistent with theoretical predictions, the budgetary cost-effectiveness of the discriminatory-price auction declines linearly as the expectation on maximum cost moves from underestimation to overestimation. The BCE estimate improves nonlinearly as the expected number of competing bids increases (especially when maximum cost is correctly estimated or is overestimated). When maximum cost is underestimated, changes in the expected number of competing bids do not influence BCE estimates.

Table 5 BCE and ECE estimates of the discriminatory-price auction under uncertainty regarding the number of competing bids and the maximum/minimum costs among bidder groups

	BCE			ECE		
	Mean	SD	Median	Mean	SD	Median
Number of bids						
0.6	9.87	2.82	9.46	7.58	1.71	7.47
1	8.71	2.07	8.43	7.53	1.69	7.41
1.4	8.31	1.88	8.08	7.53	1.69	7.40
Max cost						
0.6	7.65	1.66	7.45	7.52	1.69	7.40
1	8.89	2.00	8.59	7.55	1.70	7.43
1.4	10.35	2.59	9.92	7.57	1.70	7.45
Min cost						
0.6	8.96	2.39	8.57	7.55	1.70	7.43
1	8.96	2.39	8.57	7.55	1.70	7.43
1.4	8.96	2.39	8.57	7.55	1.70	7.43
Overall	9.89	2.59	9.63	7.86	1.75	7.81

Note: BCE, payment/ecological value; ECE, participation cost/ecological value. Both BCE and ECE are expressed in $000 per unit value.

The results also show that there is very low or moderate impact of the three uncertain parameters (number of groups, maximum and minimum group costs) on the *economic* cost-effectiveness of the auction. Recall that the economic cost-effectiveness is calculated as the ratio of participation costs and ecological values and neither of these factors is influenced by the above uncertain parameters.

We have explored the impact of bidder uncertainty on budgetary cost-effectiveness further by systematically varying and combining the uncertain parameters that affect the performance of the DPA under different selection criteria. Figure 1 presents the results of this exercise. The figure displays the difference in median BCE and ECE estimates between the DPA and UAA auction mechanisms for individual combinations of number of competing bids and maximum cost among bidder groups.[5] Negative numbers indicate better performance by DPA. It is clear from the figure that the discriminatory-price auction is outperformed by the uniform-price auction only when bidders underestimate the number of competing bids but overestimate maximum zone cost (such as 0.60/1.40) under all selection criteria – a situation of perceived low bidding competition. Otherwise, discriminatory pricing consistently outperforms the uniform-price auction or at least performs equally well.

[5] We do not show the corresponding ECE estimates in Figure 1 since these are insensitive to these parameters.

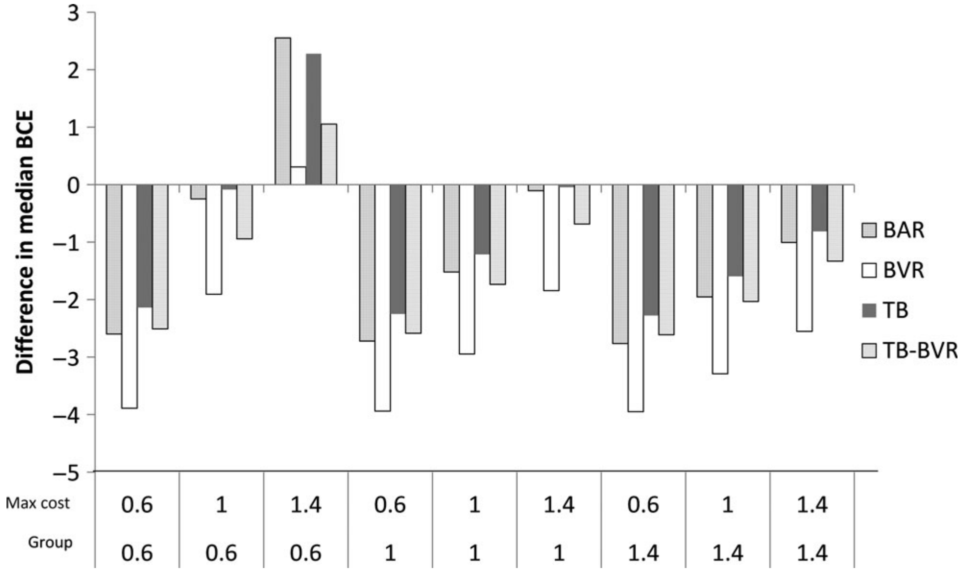

Figure 1 Difference in median BCE between discriminatory and uniform-price auctions for different combinations of expected number of competing bids and estimated zone costs under the four bid selection criteria. Negative values indicate superior performance of the discriminatory-price auction.

6. Discussion

This paper has analysed the performance of discriminatory and uniform pricing in the context of a landscape auction where it is possible to allow group bidding as well as individual bidding. We have compared the performance of these two pricing mechanisms under four bid formation and selection models, which require different amounts of information regarding conservation values of the zones offered for wildlife management. To the best of our knowledge, this aspect has not previously been explored in the literature.

Based on a best-response model of group bidding, we have simulated and compared the cost-effectiveness of a discriminatory-price and a uniform-price ascending auction in a particular context (conservation of malleefowl), which requires a joint effort of multiple landholders. We have observed that the discriminatory-price auction outperforms the uniform-price auction as a mechanism to establish ecological zones across different holdings. This finding conforms well to the literature. There is evidence of superior performance of the discriminatory pricing rule in conservation auctions in general. For example, Windle and Rolfe (2008) observed that a price-discriminating auction was 30 per cent more cost-efficient than a uniform-price grant mechanism in an auction in Australia. Similar results were obtained by Deng and Xu (2015) for a case study in China. Cason and Gangadharan (2005) compared the outcome properties of uniform versus discriminatory-price auctions for reducing nonpoint source pollution. They found that although overbidding was more pronounced in the discriminatory-price auction, the discriminatory format had superior overall market performance.

However, the relative performance of a discriminatory-price landscape auction is sensitive to the bidders' uncertainty about the number of competing groups and the highest conservation cost among the groups participating in the auction. When bidders underestimate competition intensity (i.e. low number of participating groups and low maximum conservation costs), a discriminatory-price auction may be outperformed by a uniform-price ascending auction. These findings are well in line with theoretical observations made by Latacz-Lohmann and Hamsvoort (1997). Other experimental studies have found similar results (Cummings *et al.* 2004). Further, and in line with theoretical predictions, the simulation results show that the budgetary cost-effectiveness of a discriminatory-price auction is completely insensitive to bidder uncertainty about the *lowest* conservation cost among the groups submitting a bid. From an agency perspective, it seems that it is more cost-effective if bidders underestimate the maximum cost and overestimate the number of bids. However, it does not matter whether bidders know the 'true' minimum costs or not.

In reality, several additional factors could influence the relative performance of the two pricing mechanisms. For example, in the simulations, it has been assumed that the cost of group bid formation in a discriminatory-price auction is zero. If we change this assumption to a more realistic assumption of costly information collection and group formation, the relative cost advantages of a discriminatory-price auction could quickly erode. In this situation, running a uniform-price ascending auction might be more cost-effective. There are several additional advantages of a uniform-price ascending auction. First, truth-telling is a dominant property in a uniform-price ascending auction. Second, the uniform-price auction does not require bidders to have information on the maximum cost of establishing individual ecological zones. Therefore, the uniform-price auction is less information-intensive and could be administratively easier to run.

Our results also highlight the necessity to carefully consider bid selection. We observed that the performance of the TB-BVR selection criteria has performed best in terms of budgetary cost-effectiveness. Recall that in TB-BVR scenario the landholders do not know the environmental values of wildlife zones and they cannot use this information to form their bids. However, agencies could use environmental value information to select the most cost-effective bid. This finding is in line with Banerjee *et al.* (2015) who investigated whether releasing information about the agency's spatial environmental goals improves auction performance. They found that additional information has a negative impact on the budgetary cost-effectiveness of the auction. In terms of economic cost-effectiveness, by contrast, BVR selection has outperformed the other three criteria under both discriminatory and uniform pricing. Environmental agencies should therefore apply BVR selection (and communicate environmental value information to bidders) if it is interested in maximising *economic* cost-effectiveness.

Finally, some comments on the limitations and future extensions are in order as our findings are specific to the case study of malleefowl conservation. First, we considered only one type of value distribution (where costs, area and ecological values are highly correlated), so the main results are applicable to our case study. It would be worthwhile to test a different example where there is a less strong (or even negative) relationship between area and ecological values. This could help to separate the performance of the selection criteria more clearly. Second, we did not study the impact of rent sharing among group members on the performance of a discriminatory-price auction. Similarly, we did not study the impact of own-cost or own-value uncertainty since we assumed these factors were perfectly known. Finally, as mentioned before, group bid formation can be costly and it could vary by group size. Based on field observations, it is possible to get an idea of the transaction costs of forming group bids. That would definitely change the cost-effectiveness performance of a discriminatory-price auction. All these issues should be explored further to cross-validate our findings.

References

Ajayi, O.C., Jack, B.K. and Leimona, B. (2012). Auction design for the private provision of public goods in developing countries: Lessons from payments for environmental services in Malawi and Indonesia, *World Development* 40, 1213–1223.

Banerjee, S., Kwasnica, A.M. and Shortle, J.S. (2015). Information and auction performance: a laboratory study of conservation auctions for spatially contiguous land management, *Environmental and Resource Economics* 61(3), 409–431.

Bode, M. and Brennan, K.E. (2011). Using population viability analysis to guide research and conservation actions for Australia's threatened malleefowl *Leipoa ocellata*, *Oryx* 45, 513–521.

Brown, L.K., Troutt, E., Edwards, C., Gray, B. and Hu, W. (2011). A uniform price auction for conservation easements in the Canadian prairies, *Environmental and Resource Economics* 50, 49–60.

Cason, T.N. and Gangadharan, L. (2005). A laboratory comparison of uniform and discriminative price auctions for reducing non-point source pollution, *Land Economics* 81, 51.

Cramton, P. (1998). Ascending auctions, *European Economic Review* 42, 745–756.

Cummings, R.G., Holt, C.A. and Laury, S.K. (2004). Using laboratory experiments for policymaking: An example from the Georgia irrigation reduction auction, *Journal of Policy Analysis and Management* 23, 341–363.

Day, J.R. and Possingham, H.P. (1995). A stochastic metapopulation model with variability in patch size and position, *Theoretical Population Biology* 48, 333–360.

Deng, X. and Xu, Z. (2015). Green auctions and reduction of information rents in payments for environmental services: An experimental investigation in Sunan County, Northwestern China, *PLoS ONE* 10, e0118978.

Fooks, J.R., Higgins, N., Messer, K.D., Duke, J.M., Hellerstein, D. and Lynch, L. (2016). Conserving spatially explicit benefits in ecosystem service markets: Experimental tests of network bonuses and spatial targeting, *American Journal of Agricultural Economicsaav* 061, 061–021.

Hanley, N., Banerjee, S., Lennox, G.D. and Armsworth, P.R. (2012). How should we incentivize private landowners to 'produce' more biodiversity?, *Oxford Review of Economic Policy* 28, 93–113.

Iftekhar, M. and Tisdell, J. (2014). Wildlife corridor market design: An experimental analysis of the impact of project selection criteria and bidding flexibility, *Ecological Economics* 104, 50–60.

Jack, B.K., Leimona, B. and Ferraro, P.J. (2009). A revealed preference approach to estimating supply curves for ecosystem services: Use of auctions to set payments for soil erosion control in Indonesia, *Conservation Biology* 23, 359–367.

Krawczyk, M., Bartczak, A., Hanley, N. and Stenger, A. (2016). Buying spatially-coordinated ecosystem services: An experiment on the role of auction format and communication, *Ecological Economics* 124, 36–48.

Latacz-Lohmann, U. and Hamsvoort, C.V.D. (1997). Auctioning conservation contracts: A theoretical analysis and an application, *American Journal of Agricultural Economics* 79, 407–418.

Latacz-Lohmann, U. and Schilizzi, S. (2005). Auctions for conservation contracts: A review of the theoretical & empirical literature, *Project Report (Project No: UKL/001/05)*. Scottish Executive Environment and Rural Affairs Department, Edinburgh, 101 pp.

Li, T. and Zheng, X. (2009). Entry and competition effects in first-price auctions: Theory and evidence from procurement auctions, *The Review of Economic Studies* 76, 1397–1429.

Michael, D.R., Wood, J.T., Crane, M., Montague-Drake, R. and Lindenmayer, D.B. (2014). How effective are agri-environment schemes for protecting and improving herpetofaunal diversity in Australian endangered woodland ecosystems?, *Journal of Applied Ecology* 51, 494–504.

Morse, W.C., Schedlbauer, J.L., Sesnie, S.E., Finegan, B., Harvey, C.A., Hollenhorst, S.J., Kavanagh, K.L., Stoian, D. and Wulfhorst, J. (2009). Consequences of environmental service payments for forest retention and recruitment in a Costa Rican biological corridor, *Ecology and Society* 14, 23.

Nicol, S. and Chadès, I. (2011). Beyond stochastic dynamic programming: a heuristic sampling method for optimizing conservation decisions in very large state spaces, *Methods in Ecology and Evolution* 2, 221–228.

Reeson, A.F., Rodriguez, L.C., Whitten, S.M., Williams, K., Nolles, K., Windle, J. and Rolfe, J. (2011). Adapting auctions for the provision of ecosystem services at the landscape scale, *Ecological Economics* 70, 1621–1627.

Rolfe, J., McCosker, J. and Windle, J. (2008). Identifying the incentives that graziers in central-western Queensland need to manage land for conservation outcomes, *Rangeland Journal* 30, 297–303.

Rolfe, J., Windle, J. and McCosker, J. (2009). Testing and implementing the use of multiple bidding rounds in conservation auctions: A case study application, *Canadian Journal of Agricultural Economics-Revue Canadienne D Agroeconomie* 57, 287–303.

Stoneham, G., Chaudhri, V., Ha, A. and Strappazzon, L. (2003). Auctions for conservation contracts: an empirical examination of Victoria's BushTender trial, *The Australian Journal of Agricultural and Resource Economics* 47, 477–500.

Whitten, S., Gorddard, R., Knight, A., Reeson, A. and Stevens, D. (2007). *Designing and testing an outcome focused conservation auction: evidence from a field trial targeting ground nesting birds*. CSIRO, Canberra, 19 pp.

Windle, J. and Rolfe, J. (2008). Exploring the efficiencies of using competitive tenders over fixed price grants to protect biodiversity in Australian rangelands, *Land Use Policy* 25, 388–398.

Windle, J., Rolfe, J., McCosker, J. and Lingard, A. (2009). A conservation auction for landscape linkage in the southern Desert Uplands, *Queensland, Rangeland Journal* 31, 127–135.