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RESEARCH ARTICLE

# Optimizing contract allocation for risky conservation tenders

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## Abstract

In the face of a shrinking budget for environmental activities, conservation agencies must design and implement agri-environmental policies that cost-effectively meet the environmental objectives. However, designing such programs is often challenging due to different uncertainties. For example, landholders may be exposed to risks when carrying out conservation projects. To minimise the negative impact of unexpected losses, landholders may require *additional* financial incentives as compensation for undertaking "risky" conservation projects. In such situations, the conservation agency risks over-spending public funds because of prohibitively high opportunity costs from landholders or failing to meet the environmental target. We used analytical and simulation approaches to explore optimal budget allocation in a target-constrained conservation tender. We also compared the performance of the tender with and without own-cost uncertainty. Results showed that as landholders' own-cost uncertainty rises, the conservation agency is forced to allocate more funding to secure the same level of the environmental target. We found that the optimal funding level is sensitive to landholders' competition uncertainty and the magnitude of expected losses.

**Keywords** Bidding theory · Budget allocation · Conservation tenders · Market-based instruments · Own-cost uncertainties · Public expenditure

**JEL Classification** D44 · D81 · D83 · Q57

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## 1 Introduction

Human-induced environmental impact has led to significant investments in designing and implementing agri-environmental programs in many countries. Over the past three decades, market-based policy instruments, such as conservation tenders (CTs); also referred to as conservation procurement auctions or reverse auctions, have been used to address environmental concerns by encouraging conservation, restoration and rehabilitation efforts on private land. Notable programs include the Conservation Reserve Program (CRP) in the US (Reichelderfer and Boggess 1988); the Countryside Stewardship Scheme in the UK (Morris and Young 1997); the Victorian BushTender Biodiversity Trials in Australia (Stoneham et al. 2003); the Challenge Fund Scheme in Scotland; the Grassland Conservation Pilot Tender in Germany (Latacz-Lohmann and Schilizzi 2005); and land use subsidies in developing countries, such as Indonesia and Malawi (Ajayi et al. 2012; Jack 2013).

CTs are multi-unit and multi-winner schemes, allowing the conservation agency to select multiple landholders to deliver numerous environmental outcomes. Therefore, this plays an essential role in providing the conservation agency with useful information about the potential costs of procuring environmental outcomes. For example, in a setting, where landholders have perfect knowledge of their opportunity costs, CTs may induce the landholders to bid closer to their actual costs, thus leading to cost-effective procurement of environmental goods and services (Latacz-Lohmann and Van der Hamsvoort 1997; Cason et al. 2003; Stoneham et al. 2003; Claassen et al. 2008; Glebe 2008). Conversely, when landholders have imperfect knowledge about their opportunity costs or if they are exposed to high risks during the delivery of the environmental goods or services, the potential efficiency gain is likely to erode, thereby reducing the cost-effectiveness of the conservation program. As illustrated in an experimental study by Wichmann et al. (2017), the presence of own-cost uncertainties induces higher bidding levels, potentially leading to lower cost-effectiveness of conservation programs.

The relative lack of cost-effectiveness of agri-environmental payment programs has received attention in government policy documents [e.g., see European Communities Court of Auditors (2015)] as well as in academic literature (e.g., see Zellei 2001; Messer 2006; Matzdorf and Lorenz 2010; Pattanayak et al. 2010; Hanley et al. 2012; Duke et al. 2013; Ansell et al. 2016). Whitten et al. (2003) argue that for market-based instruments to realise their potential efficiency gains, it is important for the conservation agency to carefully design a policy instrument that addresses the design issues, as well as the performance aspects of the instrument. Likewise, Ajayi et al. (2012) suggest the need to have rigorous testing of a given program design at the pilot stage to minimise the impact of information asymmetry between the buyer of environmental goods or services and the service providers. For instance, a carefully designed and tested policy instrument should align the costs of implementing a given conservation program with the social benefits resulting from conservation efforts (Jack et al. 2009; Lundberg et al.

2018). However, in the presence of uncertainties, a conservation agency faces the challenge of a potential mismatch between the cost of procuring a targeted environmental outcome and the benefits expected for society. Thus, the conservation agency risks over-spending public funds, because of prohibitively high expected opportunity costs, or failing to meet the prescribed conservation target due to low participation. Therefore, during the CT program design stage, it becomes important for the conservation agency to account for the uncertainty landholders face ensuring cost-effective allocation of conservation tender contracts.

This study explores the impact of uncertainties on the optimal allocation of contracts for a target-constrained conservation tender. The tender was set in the context of a pollution reduction program, where the conservation agency aimed to achieve a target reduction level of chemical run-off from private agricultural land while minimising the cost of implementing the program. We developed an optimal budget allocation model and then assessed the performance of the tender in a deterministic and a stochastic cost scenario using three performance criteria: (i) budgetary cost-effectiveness (BCE), (ii) economic cost-effectiveness (ECE) and (iii) rent per unit of the environmental benefit (RPU). Numerical simulations were used to answer two main questions: What is the impact of landholders' own-cost uncertainties on the performance of a target-constrained tender? To what extent does rent-seeking behaviour differ between landholders' bidding when they have perfect knowledge of their own-costs (deterministic cost scenario), compared to when they have imperfect knowledge of their own-costs (stochastic cost scenario)? Results from such analysis will be useful in designing more cost-effective conservation tenders.

The remaining part of this paper proceeds as follows: Sect. 2 introduces the model setting. Here we provide the definitions for the analytical model and the optimal bidding model for risk-averse bidders. In Sect. 3 we develop the conservation agency's optimal budget allocation model using a mixed-integer non-linear programming algorithm. Section 4 introduces the simulation scenarios together with the parameter values for the simulation experiment. In Sect. 5 we present our results, followed by discussion and concluding remarks in Sects. 6 and 7, respectively.

## 2 Model setting

Consider a conservation agency that decides to design an agri-environmental program using a target-constrained tender mechanism. The program is meant to encourage landholders to modify their current farming practices (conventional farming technology), by limiting the use of chemical fertilisers (or other chemicals) and adopting a more sustainable and environmentally friendly farming practice (an eco-farming technology).[1] Landholders intending to switch from conventional farming to eco-farming are assumed to have insufficient and unreliable data about the *additional* risks associated with adopting the eco-farming technology. We assumed that

[1] Rolfe et al. (2018) classified this type of conservation tender as "type F". The program involves a modification of current farming practice to a more environmentally friendly practice.

landholders had a lot of time to gain experience with conventional farming (e.g., weather and market changes) but not with the (new) eco-farming technology (technology change risk). As in the case of the Conservation Reserve Program in the USA, the contracts normally last 10–15 years which exposes contract holders to various uncertainties such as an unexpected change in economic conditions, differing product prices and changes in technology that impact the cost of delivering environmental goods (Claassen et al. 2008). Therefore, we modelled the *additional* uncertainty resulting from eco-farming adoption. We also assumed that current farming practices yield optimal profits but negatively affect the environment.

Let us consider a conservation agency that intends to achieve a pre-determined environmental target with a minimum implementation cost. The environmental target is defined as the total amount of chemical reduction, given by the difference between current chemical use and the program's recommended baseline. Suppose the target-constrained tender mechanism has the following setup:

(i) Each eligible bidder is invited to submit a single sealed bid.
(ii) The bids are formulated based on each bidder's expected opportunity cost and the amount of chemical reduction (environmental benefit).
(iii) The conservation agency selects a set of bids that meets the environmental target at a minimum cost.
(iv) The conservation agency uses a discriminatory-price payment mechanism, where winners are paid an amount equal to their submitted bids.

Given the above setup, an illustration of the sequence of events and an outline of the landholders' and conservation agency's decisions are displayed in Fig. 1.

## 2.1 Model definition

Let $N = \{1, 2, ..., n\}$ denote a set of $n$ eligible bidders (landholders). Each landholder, denoted by $i \in N$, is assumed to have private information about his/her farming enterprise. Suppose there exist two income states: (i) a state of high income and (ii) a state of low income. In a state of high income, the realised profit from eco-farming is $\pi_i$. In contrast, in a state of low income, the realised profit from eco-farming is $\pi_i - \omega_i$, where $\omega_i \in (0, \pi_i)$ represents the magnitude of income loss. Landholder $i$'s subjective probability of income loss is given by $q_i \in (0, 1)$.

To begin the analysis, we use the expected utility framework to evaluate a risk-averse landholder's certainty-equivalent profit in the presence of cost uncertainty. The certainty-equivalent profit is given by the difference between the expected profit and the risk premium, where the risk premium represents the maximum amount a risk-averse landholder is willing to pay for protection against a potential loss. The risk premium is conditional on the landholder's degree of risk-aversion and the subjective probability of income loss. This implies that the magnitude of the risk premium will depend on the landholder's utility function and the size of risky alternatives. If landholder $i$'s expected utility function takes the form:

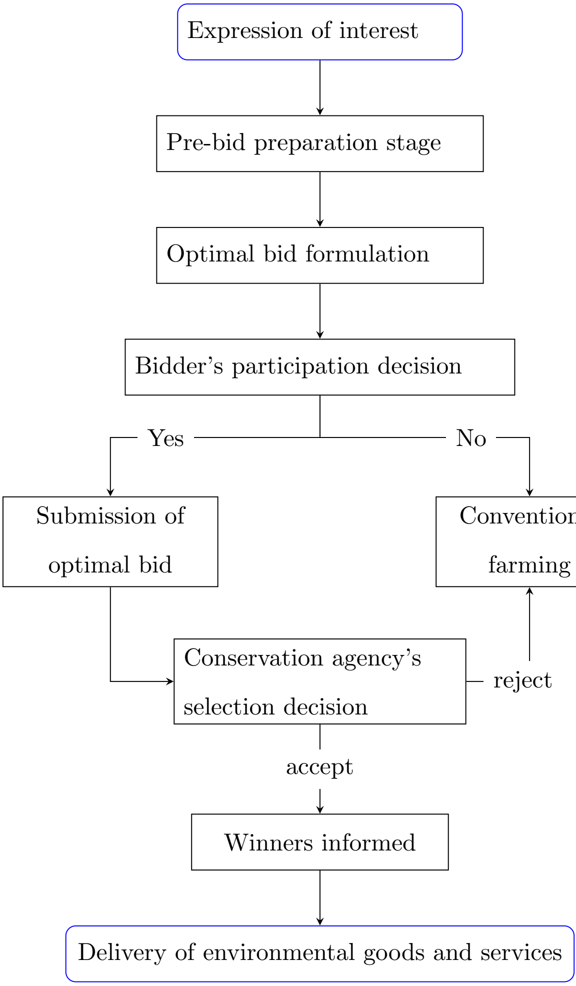


**Fig. 1** Bidders and Conservation agency's decision flowchart illustrating the sequence of events in a target-constrained tender

$$U(x_i) = \begin{cases} \frac{x_i^{1-\rho_i}}{1-\rho_i} & \text{if } \rho_i \neq 1, \\ \ln(x_i) & \text{if } \rho_i = 1, \end{cases} \tag{1}$$

we can define the certainty-equivalent profit corresponding to the expected utility of the risky eco-farming profit as:

$$\pi_{\mathrm{ce}_i} = \begin{cases} \left[ q_i (\pi_i - \omega_i)^{1-\rho_i} + (1-q_i)\, \pi_i^{1-\rho_i} \right]^{\frac{1}{1-\rho_i}} & \text{if } \rho_i \neq 1, \\ (\pi - \omega)^{q_i}\, \pi^{1-q_i} & \text{if } \rho_i = 1. \end{cases} \tag{2}$$

Assume that landholder $i$'s current farming practice (conventional farming) yields a certainty-equivalent profit $\pi_{\mathrm{co}_i} = \pi_{0_i} - r_{0_i}$; where $\pi_{0_i}$ and $r_{0_i}$, respectively, represent the expected profit and the risk premium from conventional farming. The expected opportunity cost ($C_i$) of switching from conventional farming to eco-farming technology is calculated as:

$$\begin{aligned} C_i &= \pi_{\mathrm{co}_i} - \pi_{\mathrm{ce}_i} \\ &= \begin{cases} \pi_{\mathrm{co}_i} - \left[ q_i\,(\pi_i - \omega_i)^{1-\rho_i} + (1-q_i)\,\pi_i^{1-\rho_i} \right]^{\frac{1}{1-\rho_i}} & \text{if } \rho_i \neq 1, \\ \pi_{\mathrm{co}_i} - (\pi - \omega)^{q_i}\,\pi^{1-q_i} & \text{if } \rho_i = 1. \end{cases} \end{aligned} \tag{3}$$

Suppose landholder $i$ uses $C_i$ to formulate his/her bid ($b_i$) to supply the environmental benefit $v_i$. If $v_i$ is independently drawn from a known distribution on the support $[\underline{v}, \overline{v}]$; where $\underline{v}$ and $\overline{v}$, respectively, represent the minimum and maximum environmental benefit in the set $\{v_1, v_2, \dots, v_n\}$, the normalised bid price, $S_i$, for landholder $i$ can be written as:

$$S_i = \frac{b_i}{v_i}, \tag{4}$$

where Eq. (4) represents the average cost, in \$/EB (dollar per unit of environmental benefit), of delivering one unit of $v_i$.

**Definition 2.1** (*Ordered bid prices*) If the conservation agency ranks the bids $\{b_1, b_2, ..., b_n\}$ in an ascending order using a normalised bid price in Eq. (4), the resulting order statistics can be written as $S_{1:n} \leq S_{2:n} \leq \cdots \leq S_{n:n}$; where $S_{1:n}$ and $S_{n:n}$, respectively, denote the smallest and the largest order statistics. Similarly, the realisations of the order statistics, denoted by the lower case $\{s_{1:n}, s_{2:n}, \dots, s_{n:n}\}$ represent the set of observed bid prices. For convenience, we shall use the notation ($r$) to uniquely identify each landholder $i \in N$ and their position $1 \leq r \leq n$ in an ordered set $\{S_{(1)}, S_{(2)}, \dots, S_{(n)}\}$.

### 2.2 Optimal bidding model formulation for a risk-averse landholder

Let each random bid price in the set $\Omega = \{S_1, S_2, \dots, S_n\}$ be independent and identically distributed[2] with a common cumulative distribution function (cdf) $F(s)$, and a probability density function (pdf) $F'(s) = f(s)$, where $s \in \mathfrak{R}^+$. The cumulative distribution function of a bid price, $S_{(r)} : 1 \leq r \leq n$, can be obtained as follows (see Balakrishnan 2007):

$$G_{r:n}(s) = \mathbf{Pr}\{\text{at least } r \text{ random bid prices are} \leq s \text{ and } n - r > s\}, \tag{5a}$$

[2] The independent and identically distributed (IID) assumption can be relaxed by adopting the independent and non-identically distributed (INID) formulation. However, this is beyond the scope of the paper.

$$= \mathbf{Pr}\left\{S_{(1)} \leq s, S_{(2)} \leq s, ..., S_{(m)} \leq s, S_{(m+2)} > s, ..., S_{(n)} > s\right\}, \tag{5b}$$

$$= \sum_{j=r}^{n} \binom{n}{j} \{F(s)\}^{j} \{1 - F(s)\}^{n-j}, s \in \mathfrak{R}^{+}. \tag{5c}$$

Similarly, the corresponding pdf of $S_{(r)}$ is given by:

$$g_{r:n}(s) = \frac{n!}{(r-1)!\,(n-r)!} \{F(s)\}^{r} f(s) \{1 - F(s)\}^{n-r}, s \in \mathfrak{R}^{+}. \tag{6}$$

Consider a landholder with unit cost ($U_r$):

$$U_r = \frac{C_r}{v_r}, \tag{7}$$

where $U_r$ represents the ratio of the expected opportunity cost ($C_r$) to the associated environmental benefit ($v_r$). If the landholder believes that his/her bid price ($s_r$) is in position $1 \leq r \leq n$, the probability that $s_r$ wins the tender is given by the success function:

$$\mathbf{Pr}(\text{win}) = 1 - G_{r:n}(s) \equiv \overline{G}_{r:n}(s). \tag{8}$$

where $\overline{G}_{r:n}(s)$ is defined as Sadegh (2016):

$$\overline{G}_{r:n}(s) = \mathbf{Pr}\left(S_{(r)} > s\right) = \sum_{j=0}^{r-1} \binom{n}{j} F^{j}(s)(1-F)^{n-j}(s). \tag{9}$$

Equation (9) represents the probability that each of the $n - r$ competing landholders submit a bid price amount that is greater than the cutoff bid price.

Suppose that the $r$th landholder applies a bidding strategy $s_r = \beta(U_r)$, where the function $\beta(\cdot)$ is assumed to be an increasing function of the unit cost ($U_r$), and $U_r = \frac{C_r}{v_r}$ denotes the cost for every unit of an environmental benefit $v_r$. The bid price that maximises a risk-averse landholder's expected rent is given by the following profit maximisation problem:

$$\begin{cases} \text{maximise } \left[1 - G_{r:n}(s)\right]\left[s_r - U_r\right], \\ \text{subject to } s_r \geq U_r;\, r \in [\,1, n\,]. \end{cases} \tag{10}$$

The objective function in Eq. (10) denotes the expected unit rent for a risk-averse landholder, where $[1 - G_{r:n}(s)]$ represents the probability of winning the tender, and $\left[s_r - U_r\right]$ represents the unit rent for a risk-averse landholder in position $r$. Note that Eq. (10) depends on landholder's degree of risk aversion.

The constraint imposed on Eq. (10) ensures that the submitted bid price is enough to cover the expected unit cost and represents the participation constraint. That is, the condition under which a risk-averse landholder would find it worthwhile to participate in the tender. We apply this restriction on the equilibrium bidding strategy, because a landholder's net profit will be negative if the submitted bid is below the expected unit cost. Therefore, it is not optimal for a landholder to submit a bid price below their expected unit cost. Differentiating the profit maximisation problem with respect to s and setting the results to zero yields the first order-condition (FOC) (Vukina et al. 2008):

$$
\begin{aligned}
s_r^* &= U_r + \frac{1 - G_{r:n}(s^*)}{g_{r:n}(s^*)}, \\
&= \begin{cases} \dfrac{\pi_{\mathrm{co}_r} - \left[ q_r \left(\pi_r - \omega_r\right)^{1-\rho_r} + \left(1 - q_r\right) \pi_r^{1-\rho_r} \right]^{\frac{1}{1-\rho_r}}}{v_r} + \dfrac{1 - G_{r:n}(s^*)}{g_{r:n}(s^*)} & \text{if } \rho_r \neq 1, \\ \dfrac{\pi_{\mathrm{co}_r} - (\pi - \omega)^{q_r} \, \pi^{1-q_r}}{v_r} + \dfrac{1 - G_{r:n}(s^*)}{g_{r:n}(s^*)} & \text{if } \rho_r = 1, \end{cases}
\end{aligned}
\tag{11}
$$

where Eq. (11) is assumed to be an increasing and twice differentiable function. The first term in (11) represents landholder $r$'s expected opportunity cost of delivering one unit of the environmental benefit $v_r$. The second term implicitly defines landholder $r$'s participation premium; where $g_{r:n}(\cdot)$ denotes the probability density function of the $r^{th}$ order statistic.

Landholders face two types of risks when formulating their optimal bidding strategy. These include: the risk of suffering a winner's curse and the risk of losing the tender. The first risk is captured in the formulation of the expected opportunity cost. The second risk is implicitly captured through the expectation around the number of bidders with bids below the cutoff bid price, reflecting an individual landholder's subjective belief about the competition intensity.

**Definition 2.2** (*A winning bid*) In a target-constrained tender, a given landholder's winning probability is influenced by: the environmental target ($V_T$); the size of the winning group ($m$) and the position of his/her bid price in an ordered set of $n$ landholders. Therefore, a winning bid, $b_r$, identified by its bid price, $S_{(r)}$, meets the following criteria: (i) it is among the lowest bid prices in an ordered set of $n$ landholders; (ii) it is an element of a winning set, which is dependent on an arbitrary cutoff bid price ($\hat{s} \in \Re^+$), i.e., the bid price of the most expensive winner in the winning set; and (iii) the total environmental benefit from the selected landholders must meet the conservation agency's environmental target, i.e., $\sum_{r=1}^{m} v_r \geq V_T$; where $m \leq n$ denotes the number of winning bids.

The following section explores the impact of cost uncertainty on risk-averse landholders' optimal bidding behaviour.

## 2.3 Sensitivity analysis

### 2.3.1 Impact of probability and magnitude of income loss on optimal bidding behaviour

To test the sensitivity of the optimal bid to the probability of income loss ($q$), we apply the implicit function theorem to the FOC. By differentiating $s_r^*$ with respect to $q_r$ we obtain:

$$\frac{\partial(s_r^*)}{\partial q_r} = -\frac{\frac{\partial U_r}{\partial q_r}\, g(s_r^*)}{-2\,g(s_r^*)\;-\;2\,g'(s_r^*)\,(s_r^* - u_r)} > 0, \tag{12}$$

where $U_r = \begin{cases} \frac{\pi_{\mathrm{co}_r} - \left[q_r\,(\pi_r - \omega_r)^{1-\rho_r} + (1-q_r)\,\pi_r^{1-\rho_r}\right]^{\frac{1}{1-\rho_r}}}{v_r} & \text{if } \rho_r \neq 1, \\ \frac{\pi_{\mathrm{co}_r} - (\pi - \omega)^{q_r}\,\pi^{1-q_r}}{v_r} & \text{if } \rho_r = 1. \end{cases}$

Equation (12) is positive when the numerator is positive and the denominator satisfies the second-order condition (SOC); that is, $-2\,g(s_r^*)\;-\;2\,g'(s_r^*)\,(s_r^* - U_r) < 0$.

Likewise, by differentiating $s_r^*$ with respect to the magnitude of income loss ($\omega_r$) we obtain:

$$\frac{\partial(s_r^*)}{\partial \omega_r} = -\frac{\frac{\partial U_r}{\partial \omega_r}\, g(s_r^*)}{-2\,g(s_r^*)\;-\;2\,g'(s_r^*)\,(s_r^* - U_r)} > 0, \tag{13}$$

where the numerator is positive for any value of $q_r > 0$ and the denominator satisfies SOC $< 0$. Equations (12) and (13) suggest that, as the probability of loss ($q_r$) and magnitude of income loss ($\omega_r$) rise, the opportunity cost of participation increases resulting in a high optimal bid. This is true for all values of $q_r > 0$ and $\omega_r > 0$.

### 2.3.2 Impact of risk aversion parameter on optimal bid

Differentiating the optimal bid with respect to the risk-aversion parameter ($\rho_r$) yields:

$$\frac{\partial(s_r^*)}{\partial \rho_r} = -\frac{\frac{\partial U_r}{\partial \rho_r}\, g(s_r^*)}{-2\,g(s_r^*)\;-\;2\,g'(s_r^*)\,(s_r^* - U_r)}, \tag{14}$$

where the sign $\left[\frac{\partial(s_r^*)}{\partial \rho_r}\right] = \begin{cases} - \text{ if } \frac{\partial U_r}{\partial \rho_r} < 0, \\ + \text{ if } \frac{\partial U_r}{\partial \rho_r} > 0. \end{cases}$

The impact of $\rho_r$ on $s_r^*$ is dependent on the value of $\frac{\partial U_r}{\partial \rho_r}$. The signs − and +, respectively, indicate that the optimal bid is a decreasing and an increasing function of $\rho_r$. There are two types of incentives influencing the optimal bid: the winning bid incentive and loss prevention incentive (Wichmann et al. 2017). In reference to the winning bid incentive, more risk-averse landholders would tender lower bids to increase their chance of winning the tender. In the presence of own-cost uncertainties, landholders may be exposed to ex-post losses if they under-estimate their expected opportunity costs. This is synonymous with the winner's curse phenomenon in the standard auction literature (Thiel 1988). Therefore, the incentive to minimise the negative impact of a loss event results in higher opportunity costs and ultimately higher bidding levels.

## 3 The conservation agency's budget minimisation problem

In Sect. 2, we defined the optimal bidding model for a risk-averse landholder in position $r : 1 \leq r \leq n$. This section aims to assess the impact of cost uncertainty on optimal contract allocation. Let us suppose that the conservation agency has a pre-determined environmental target that is denoted by $V_T$. If all participating landholders follow the same equilibrium bidding strategy illustrated in Eq. (11), the conservation agency's selection decision can be defined as follows:

**Definition 3.1** (*Selection variable*) Let $\{b_1^*, b_2^*, \dots, b_n^*\}$ corresponding to $\{s_1^*, s_2^*, \dots, s_n^*\}$ denote a set of optimal bids from risk-neutral landholders. The conservation agency's selection variable, denoted by a binary variable $x_r$, is such that:

$$x_r = \begin{cases} 1 & \text{if landholder } r \text{ is selected} \\ 0 & \text{otherwise,} \end{cases} \tag{15}$$

where Eq. (15) is dependent on the environmental target ($V_T$). If the conservation agency wishes to achieve $V_T$ with a minimum expenditure, how much will a target-constrained, discriminatory price tender require the conservation agency to pay for $V_T$?

Following the optimisation framework by Messer and Allen (2010), we formulate the conservation agency's selection decision as a budget minimisation problem using a mixed-integer non-linear programming (MINLP) model. The mathematical representation of the problem is summarised as follows:

$$\begin{cases} \text{minimise} & \sum_r s_r^* \, x_r, \\ \text{subject to} & \sum_r v_r \, x_r \geq V_T, \\ & x_r \in \{0, 1\}\,;\, r \in [\,1, n\,]. \end{cases} \tag{16}$$

The objective function in Eq. (16) aims to minimise the expenditure of procuring the environmental target $V_T$. The first constraint in (16) ensures that the total environmental benefit from the selected landholders is at least equal to a pre-determined environmental target. The second constraint indicates that the selection variable $x_r$ is binary. That is, it takes the value of 1 if the bid is selected and 0 if the bid is not selected. After presenting the theoretical setting, in the following section, we provide a numerical example to gain insight into the performance of a target-constrained tender in the presence of landholders' own-cost uncertainties.

# 4 Numerical simulation experiment

## 4.1 Model setup

Let us consider an agri-environmental program that involves implementing chemical management practices. This program aims to reduce chemical run-off from agricultural land by offering incentives to landholders who limit their chemical application rates to the program's proposed baseline. In addition, all eligible landholders must submit a single sealed bid and the payment mechanism follows a discriminatory-pricing tender format. The conservation agency pays each winning landholder an amount equal to their submitted bid. To qualify for this payment, the landholder is required to improve the current chemical management practice and deliver the environmental benefit, $v_{(\cdot)}$, defined as the difference between the current and the proposed chemical application rate. The conservation agency's goal is to procure a pre-defined total chemical reduction $V_T$ from successful landholders while minimising the cost of procurement.

Consider a random sample of $n$ eligible landholders in a particular catchment who intend to participate in the agri-environmental program. We assume that each landholder, in the set $\{1, 2, \dots, n\}$, follows the equilibrium bidding strategy as outlined in Eq. (11). To simulate the probability of winning the tender, we need to assume a distribution function for the bid prices in the set $\Omega = \{S_1, S_2, \dots, S_n\}$. Without loss of generality, let us suppose that each random bid price in the set $\Omega$ is independently drawn from a uniformly distributed density function $f(s)$:

$$f(s) = \begin{cases} \frac{1}{\overline{s}-\underline{s}} & \underline{s} \le s \le \overline{s} \\ 0 & \text{otherwise,} \end{cases} \tag{17}$$

defined on a common support $[\underline{s}, \overline{s}]$, where $\underline{s}$ and $\overline{s}$, respectively, represent the minimum and maximum bid price. Now we can write the probability density function of the $r^{th} : r = \{1, 2, \dots, n\}$ order statistic, defined in Eq. (6), as:[3]

$$g_{r:n}(s) = \text{OrderStat}[r, f, n], \tag{18a}$$

$$= \frac{n!(\overline{s}-\underline{s})^{-n}(s-\underline{s})^{r-1}(\overline{s}-s)^{n-r}}{\Gamma(r)\Gamma(n-r+1)}, \tag{18b}$$

where $\Gamma(r)$ and $\Gamma(n-r+1)$ denotes $(r-1)!$ and $(n-r)!$, respectively. Similarly, the cumulative density function of the $r^{th}$ order statistic is given by:

[3] We use Mathematica version 11.1 and OrderStat function in MathStaticav2.72 to derive the symbolic form of the probability density function. See Rose and Smith (2005) for more details.

$$G_{r:n}(s) = \begin{cases} \frac{n! B_{\frac{s-\underline{s}}{\underline{s}-\bar{s}}}(r, n-r+1)}{(r-1)!(n-r)!} & \underline{s} \le s \le \bar{s} \\ 1 & s \ge \bar{s}, \end{cases} \tag{19}$$

where $B_{\frac{s-\underline{s}}{\underline{s}-\bar{s}}}(r, n-r+1)$ denotes the incomplete beta function. Replacing Eqs. (18b) and (19) in (11) we obtain:

$$s_r^* = U_r + \frac{\left(\bar{s}-\underline{s}\right)^n \left(s_r^*-\underline{s}\right)^{1-r} \left(\bar{s}-s_r^*\right)^{r-n} \left(\Gamma(r)(n-r)! - n! B_{\frac{s_r^*-\underline{s}}{\bar{s}-\underline{s}}}(r, n-r+1)\right)}{n!}, \tag{20}$$

where

$$U_r = \begin{cases} \frac{\pi_{\mathrm{co}_r} - \left[ q_r (\pi_i - \omega_r)^{1-\rho_i} + (1-q_r)\, \pi_r^{1-\rho_r} \right]^{\frac{1}{1-\rho_i}}}{v_r} & \text{if } \rho_i \ne 1, \\ \frac{\pi_{\mathrm{co}_r} - (\pi-\omega)^{q_r} \pi^{1-q_r}}{v_r} & \text{if } \rho_i = 1. \end{cases} \tag{21}$$

### 4.2 Model implementation

To implement the model setup introduced in Sect. 4.1, we considered three farming profiles from the study of Latacz-Lohmann and Van der Hamsvoort (1997). Each farming profile had the following attributes and the corresponding values: environmental benefits (Kg N ha$^{-}$1), $v_r \in \{70, 102, 107\}$; net profit from conventional farming technology ($), $\pi_{0_r} \in \{647, 775, 855\}$; and net profit from eco-farming technology ($), $\pi_r \in \{590, 665, 701\}$.

Furthermore, for the purpose of sensitivity analysis, we assumed a sample size of $n = 50$ landholders. The parameter values for landholders' perceived size of winning group $m$ were generated using a uniform distribution over the range $m \in (1, n) : n = 50$. We varied the probability of income loss $q_{(\cdot)}$ over the range 0–40%. To understand the influence of the magnitude of income loss on eco-framing profit, two scenarios were considered for the numerical simulation experiment. First, a deterministic cost scenario, where landholders had perfect knowledge of their opportunity cost of switching from conventional farming to eco-farming technology. Second, a stochastic cost scenario, where the realised profit from eco-farming follows Eq. (2). The magnitude of income loss values $\omega_r$ were randomly generated using a uniform distribution[4] over the range $\omega_r \in (0, \pi_r)$. Although higher values of $q_{(\cdot)}$ and $\omega_{(\cdot)}$ can be used, in our analysis, we have proceeded with the assumption that landholders have an adequate understanding of

[4] Although our analysis focuses on uniformly distributed magnitude of income loss, it is possible to assume other distributions. This will not affect the robustness of our results. In essence, higher magnitude of income loss leads to higher opportunity cost and hence higher optimal bidding level.

the risk they may be exposed to when adopting eco-farming technology. We are assuming the amount at risk is not large enough to jeopardise the landholder's solvency. Overall, higher values of $q_{(\cdot)}$ and $\omega_{(\cdot)}$ lead to increased values of the optimal bidding and optimal budget allocation.

Each landholder, in the set $\{1, 2, ..., n\}$, was randomly assigned a profile with its corresponding parameter values. The analysis was then implemented in two stages within the General Algebraic Modeling System (GAMS v31.1.1) using the SBB Solver. In the first stage, the optimal bid value for each landholder was calculated. In the second stage, the conservation agency's optimal contract allocation model was solved using the results from the first stage. The process was repeated 20,000 times with randomly drawn parameter values to ensure the robustness of the results. Algorithm 4.1 provides a brief outline of the simulation experiment.

**Algorithm 4.1:** Simulation experiment algorithm

1 **Initialise**: number of loops and the total number of participating landholders ($n$).
  loop = 0; $n = 20$
2 **repeat**
3   **Begin** loop
4   Landholder's equilibrium bidding modle formulation
5   **Allocate** each landholder a randomly drawn profile with its corresponding value.
6   **Compute** the opportunity cost and optimal bids for each of the n landholders using Eqs. (3) and (11).
7   Conservation agency's budget minimisation problem
8   **Define** the environmental target ($\mathrm{V_T}$)
9   **Obtain** $\mathrm{v}_r$ and $b_r^*$ from participating landholders.
10   **Compute** bid price scores: $\mathrm{s}_r^* = \frac{b_r^*}{\mathrm{v}_r}$.
11   Let $\mathrm{V} = \sum_r \mathrm{v}_r$.
12   **Partition** $\mathrm{s}_r^*$ into feasible subsets which meet the target constraint i.e., $\mathrm{V} \geq \mathrm{V_T}$.
13   **Search** for best possible solution in the feasible subsets such that the total expenditure, i.e., $\sum_r \mathrm{s}_r^*$ is minimised, otherwise, go to step (12).
14   **Select** the subset corresponding to minimum expenditure.
15   **Return** total number of selected landholders.
16   **Return** optimal budget allocation for the winning landholders, i.e., $\mathrm{B_V} = \sum_{r=1}^{m} b_r^*$.
17   **Return** total environmental benefit provided by the winning landholders, i.e., $\mathrm{V} = \sum_{r=1}^{m} \mathrm{v}_r$.
    **Store** the results in an array
19     loop = loop + 1
20 **until** Loop = 20, 000;
21 **End**

## 5 Results

The results obtained from the numerical simulation experiment are presented as follows: we begin with a comparative analysis of the overall performance of a hypothetical conservation tender program across a deterministic and a stochastic cost scenario. In the deterministic cost scenario, landholders are assumed to have perfect knowledge of the cost of adopting the recommended chemical management practice. Therefore, the landholders only face the winning bid uncertainty; that is, the risk of losing the tender if the submitted bid is higher than the cutoff bid price. In the stochastic cost scenario, the landholders are assumed to have imperfect knowledge of the cost of delivering the environmental benefit. This scenario differs from the former, because the landholders face both the winning bid and own-cost uncertainty.

The conservation agency assesses the performance of the tender using three indicators: (i) budgetary cost-effectiveness (BCE), (ii) economic cost-effectiveness (ECE) and (iii) rent per unit of the environmental benefit (RPU). Following Schilizzi and Latacz-Lohmann (2007), BCE is defined as the ratio between the conservation agency's total expected expenditure and the total environmental benefit from the winning landholders, that is, the payment per unit of chemical reduction. The total expected expenditure is based on the assumption that all the landholders follow the same equilibrium bidding strategy as defined in Eq. (11). ECE is defined as the ratio between the winning landholders' expected opportunity cost and the total environmental benefit from the winning landholders. Finally, RPU is defined as the ratio between the winning landholders' expected rent or bid mark-up and the total environmental benefit from the winning landholders; alternatively, the difference between BCE and ECE. For all three performance indicators, lower values indicate better tender performance. In addition, we explore the impact of own-cost uncertainty components, i.e., the probability of income loss $q_r$ and the magnitude of income loss $\omega_r$, on the three performance indicators of the stochastic cost scenario.

### 5.1 Overall performance of a target-constrained tender mechanism

The summary statistics in Table 1 shows that, on average, the tender achieved greater cost-effective contracting across budgetary and economic cost-effectiveness performance indicators (BCE and ECE, respectively). That is, when landholders had known costs (Panel A) than when the costs were uncertain (Panel B). Conversely, landholders with known costs extracted higher rents than landholders with uncertain costs (compare RPU performance indicators in Panel A and B). These findings are consistent with an experimental study by Cason et al. (2003) and Banerjee and Conte (2018), which found increased rent-seeking when landholders accessed environmental quality information related to their bids. More information on environmental quality in their work is analogous, in our work, to a reduction in uncertainty of landholder's own-costs.

To understand the extent to which the performance indicators differ between the baseline (deterministic cost) and stochastic cost scenarios, we computed the

**Table 1** Summary statistics of the numerical simulation experiment

| | Mean | SD | Median | 1Q | 3Q | IQR |
|---|---|---|---|---|---|---|
| Panel A: deterministic cost scenario: baseline | | | | | | |
| Performance indicators ($/EB) | | | | | | |
| Budgetary cost-effectiveness (BCE) | 2.49 | 0.59 | 2.44 | 2.01 | 2.92 | 0.91 |
| Economic cost-effectiveness (ECE) | 0.98 | 0.03 | 0.98 | 0.96 | 1.00 | 0.04 |
| Rent per unit of the environmental benefit (RPU) | 1.50 | 0.59 | 1.46 | 1.03 | 1.94 | 0.91 |
| Target-constrained tender outcome | | | | | | |
| Number of winners | 23.8 | 7.0 | 24.0 | 18.0 | 30.0 | 12.0 |
| Total environmental benefit $\sum_{r=1}^{m} v_r$ | 2506.3 | 726.7 | 2512.0 | 1876.0 | 3129.0 | 1253.0 |
| Panel B: Stochastic Cost Scenario | | | | | | |
| Performance indicators ($/EB) | | | | | | |
| Budgetary cost-effectiveness (BCE) | 3.03 (↑ 21.7%)[a] | 0.72 | 2.98 | 2.49 | 3.49 | 1.00 |
| Economic cost-effectiveness (ECE) | 1.80 (↑ 83.7%)[a] | 0.69 | 1.64 | 1.28 | 2.13 | 0.86 |
| Rent per unit of the environmental benefit (RPU) | 1.22 (↓ 18.7%)[a] | 0.51 | 1.15 | 0.82 | 1.56 | 0.74 |
| Target-constrained tender outcome | | | | | | |
| Number of winners | 23.4 | 7.1 | 23.0 | 17.0 | 29.0 | 12.0 |
| Total environmental benefit $\sum_{r=1}^{m} v_r$ | 2505.6 | 726.8 | 2512.0 | 1876.0 | 3129.0 | 1253.0 |

*SD* standard deviation, *1Q* first quartile, *3Q* third quartile, *IQR* inter-quartile range

[a] % change relative to the deterministic cost scenario; $/EB represents dollar per unit of the environmental benefit

relative change in the mean expenditure. Over the 20,000 simulations, results from pairwise comparison reveal a significant mean difference (at $p$ value $< 0.001$) between the performance indicator values of the deterministic cost and stochastic cost scenarios. Taking Panel A of Table 1 as our baseline, we observe a 21.7% rise in BCE indicator and an 83.7% rise in ECE indicator for landholders with stochastic cost (see Panel B). Higher (that is worse) values of BCE and ECE in the stochastic cost scenario is due to the impact of the subjective probability of income loss $q_{r\in 1:n}$ and magnitude of income loss $\omega_{r\in 1:n}$. By contrast, we observe an 18.7% reduction in the average rent (RPU) for the stochastic cost scenario. Landholders in the deterministic cost scenario have lower opportunity costs than landholders in the stochastic cost scenario, which provides increased possibilities to seek greater rent.

In addition, we observe higher dispersion in the average ECE for the stochastic cost scenario compared to the deterministic cost scenario, with an inter-quartile range (IQR) of 0.86 ($/EB) and 0.04 ($/EB), respectively. Recall that in the stochastic cost scenario, the dispersion in the ECE indicator is due to a random draw of different farm enterprise types (i.e., low, medium and high values); as well as own-cost uncertainty variables (i.e., $q_{r\in 1:n}$ and $\omega_{r\in 1:n}$). In contrast, in the deterministic cost scenario, the variation is only influenced by a random draw of different farm enterprises. The values for both BCE and RPU indicators are highly dispersed in both deterministic and stochastic cost scenarios (see IQR in Panel A

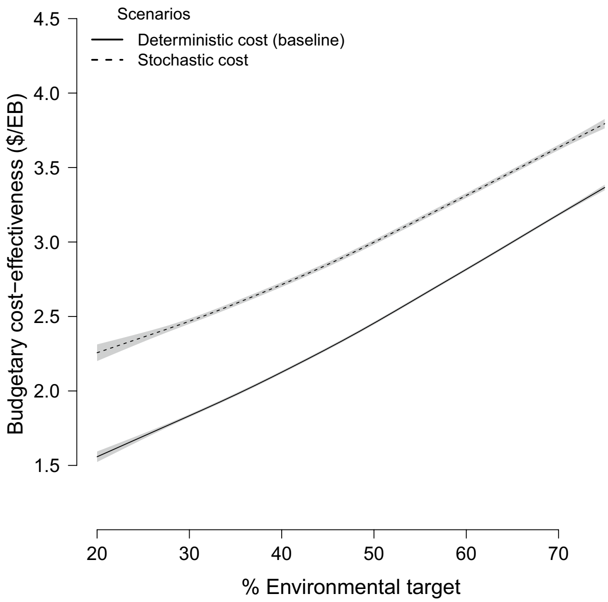


**Fig. 2** Association between the average budgetary cost-effectiveness and the environmental target across the deterministic and stochastic cost scenarios. $/EB represents $ per unit of environmental benefit

and B of Table. 1) as the random drawing of different farming enterprises and the expected number of winners ($m$) influence the values for both BCE and RPU.

We now explore the association between the environmental target and BCE performance indicator across the stochastic cost and the deterministic cost scenario. There are two sources of uncertainties in the stochastic cost scenario: own-cost and winning bid uncertainties. Conversely, the deterministic cost scenario has only one type of uncertainty: the winning bid uncertainty. From Fig. 2 we see that, on average, the BCE performance indicator for both deterministic and stochastic cost scenarios deteriorate with a higher environmental target. As the demand for the environmental target rises, more costly landholders also get selected, leading to a rise in the BCE indicator. However, at all levels of the environmental target, the average BCE for landholders with the deterministic cost is lower than that of landholders with stochastic costs. These results suggest that the conservation agency could achieve cost-effective contract allocation when landholders fully know their cost of delivering environmental goods or services.

Figure 3 highlights the relationship between the landholders' expected selection rate ($\frac{m}{n}$) and the proportion of the expenditure going to rent. We see that as $\frac{m}{n}$ increases (i.e., a less competitive tender), the share of the total expenditure going to rents rises. The trend is evident in both deterministic and stochastic cost scenarios. However, for a given level of the expected selection rate, there is a significant difference in the average RPU indicator between the two scenarios, with a greater difference observed as the expected selection rate rises.

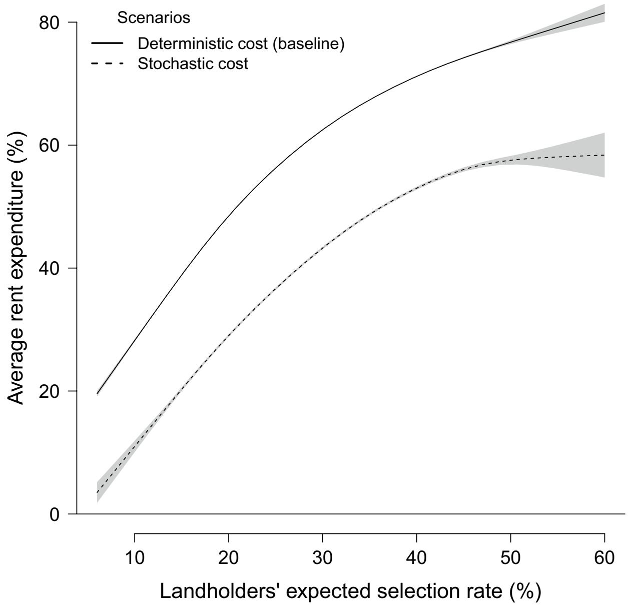


**Fig. 3** Relationship between the proportion of optimal budget allocated to rent and the landholders' expected selection rate, ($\frac{m}{n}$); where $m$ and $n$, respectively, denote landholders' expected number of winners and the total number of eligible landholder

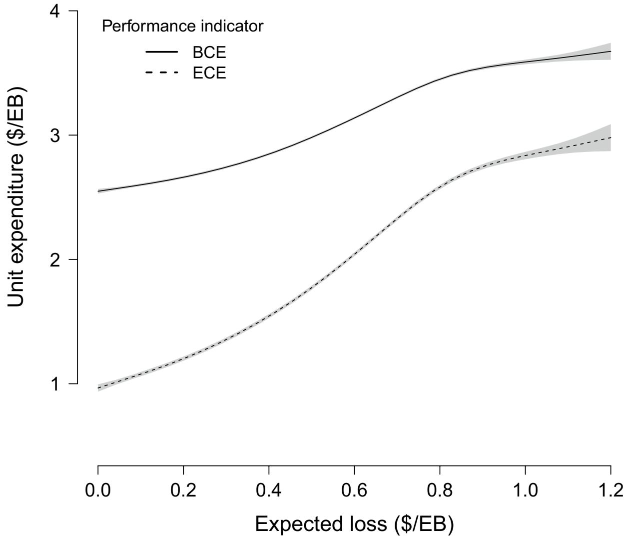


**Fig. 4** Effect of the expected loss on BCE and ECE (budgetary and economic cost-effectiveness). The gap between BCE and ECE represents the average rent (RPU). EB represents environmental benefit. The estimated smooth curves were fitted using **'gam'** package in R

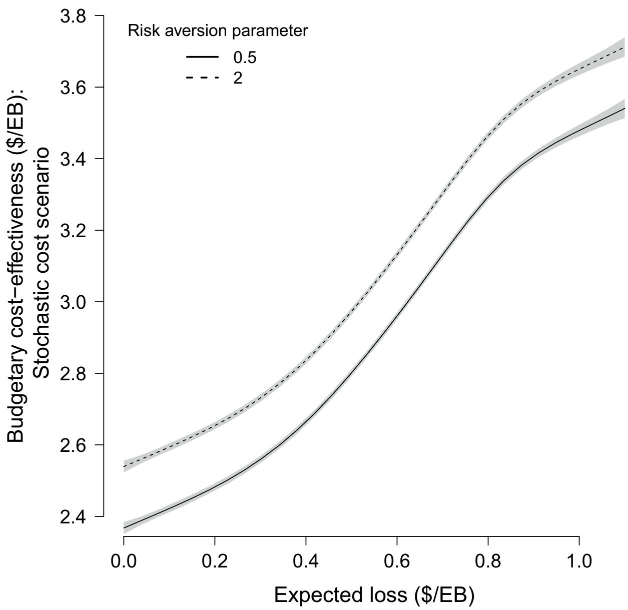


**Fig. 5** Effect of expected loss on budgetary cost-effectiveness at various risk aversion levels. EB represents environmental benefit. The estimated smooth curves were fitted using **'gam'** package in R

### 5.2 Impact of own cost uncertainty variables on the performance indicators

Let us now consider the sensitivity of the performance indicators in relation to landholders' own-cost uncertainty variables, i.e., the subjective probability of income loss ($q_{r\in 1:n}$) and the magnitude of income loss ($\omega_{r\in 1:n}$). Figure 4 plots the interaction between $q_{r\in 1:n}$ and $\omega_{r\in 1:n}$ in the form of expected loss. As shown by the summed effect model in Fig. 4, both values for BCE and ECE increase monotonically with higher expected losses. The reasoning behind this observation is that as the bidders' probability of experiencing a loss event increases, their expected opportunity costs also rise, leading to higher optimal bids. We also see that the presence of higher expected losses causes landholders to extract less rent, leading to a smaller gap between BCE and ECE. The implication is that high-risk landholders would bid closer to their expected opportunity costs, thereby extracting lesser rents.

### 5.3 Impact of risk aversion parameter on budgetary cost-effectiveness

The relationship between landholder's risk aversion ($\rho_{r\in 1:n}$) and budgetary cost-effectiveness (BCE) is presented in Fig. 5. We observe that the BCE performance indicator for a tender with more risk-averse landholders (compare $\rho_r = 2$ and $\rho_r = 0.5$) deteriorates as the expected loss rises. This is a result of an increased chance of suffering the winner's curse, leading to a rise in landholders' expected opportunity costs and the optimal bids. These findings suggest that by mitigating risks, particularly for landholders with greater downside risk, the conservation agency may encourage lower optimal bidding behaviour, thereby increasing the cost-effectiveness of the tender.

## 6 Discussion

Conservation agencies are continually challenged by the difficulties that exist when implementing conservation tenders. These challenges include: (i) informational asymmetry, which may lead to landholders' attempting to obtain more rent (Cason et al. 2003; Hanley et al. 2012; Arnold et al. 2013; Conte and Griffin 2019; ii) the risk of over-spending public funds when landholders are exposed to high-cost variability; and (iii) low participation rates among landholders due to their perception of risks involved in delivering environmental goods or services (Rolfe et al. 2018). Landholders are often hesitant to participate in conservation tenders, because they are uncertain whether the compensation they receive will be sufficient to cover the cost of delivering environmental goods or services. In particular, the cost of providing the environmental goods or services can be more expensive than initially anticipated. Consequently, landholders may find it in their interest not to participate in programs that are likely to expose them to risks that could ultimately jeopardise their farming enterprise. Alternatively, they may demand higher payments from the conservation agency to ensure that "winning" the tender does not result in unexpectedly high costs of implementation and thus private financial losses.

This study set out to explore the impact of own-cost uncertainty on the performance of a target-constrained tender using three indicators: (i) budgetary cost-effectiveness (BCE), (ii) economic cost-effectiveness (ECE) and (iii) rent per unit of the environmental benefit (RPU). We compared the performance of the target-constrained across two scenarios: a deterministic and a stochastic cost scenario. The first scenario, which was our baseline case, investigated the performance of a target-constrained tender, where landholders were assumed to have perfect knowledge of their opportunity costs. The second scenario investigated the performance of a risky target-constrained tender, where landholders faced own-cost uncertainties. Here landholders were assumed to have imperfect knowledge of their opportunity costs. To assess the impact of own-cost uncertainties on the conservation agency's optimal budget allocation, we considered two main factors: (i) the probability of income loss $q_{(\cdot)}$ and (ii) the magnitude of income loss $\omega_{(\cdot)}$. In addition, we also considered landholders' expected selection rate $\frac{m}{n}$. The eligible number of landholders ($n$) was held constant in both scenarios.

Our results reveal that the conservation agency achieved more cost-effective contracting when landholders had certain opportunity costs than when the opportunity costs were uncertain. That is to say, the optimal budget allocated to the program was low in the deterministic cost scenario, because the landholders tendered low bids. Our study also revealed a positive association between the first two performance indicators (i.e., BCE and ECE) and the expected loss, defined as the product between the probability of income loss and the magnitude of income loss. As the landholders' subjective belief about experiencing a loss event increases, their expected opportunity costs also rise, leading to higher optimal bids. These results are consistent with the experimental study by Wichmann et al. (2017), which found that bidders tendered higher bids in the presence of cost-risk.

With regards to the landholders' expected selection rate ($\frac{m}{n}$), we observed, in both deterministic and stochastic cost scenarios, higher rent-seeking among bidders with higher values of $\frac{m}{n}$. That is to say, a greater proportion of the total expenditure was used to pay rents in a tender with a lower competition intensity. Consistent with the literature (see, e.g., Marion 2007), this study found that landholders with lower opportunity costs sought more rent; than landholders with higher opportunity costs who tendered bids that were relatively close to their expected opportunity costs.

## 7 Conclusions

Engaging private landholders in agri-environmental programs plays a significant role in addressing the environmental concerns resulting from human-induced activities. Therefore, the conservation agency needs to design and implement cost-effective agri-environmental policies that meet the environmental objectives at a minimum implementation cost. However, in the presence of cost uncertainties, minimising the cost of procuring a given environmental target poses a challenge to the conservation agency for various reasons. The landholders can be exposed to cost variability when delivering environmental goods or services. Consequently, they may require additional incentives as compensation for undertaking conservation projects. In such situations, the conservation agency runs the risk of over-spending public funds to achieve a given conservation target. This study contributes to the conservation auction literature by developing an optimal budget allocation model for a target-constrained tender. In addition, it explores the impact of landholders' own-cost uncertainties on the level of the optimal budget, or equivalently, since the environmental target is pre-determined, on the efficiency with which the optimal budget is spent. We found that when the costs of delivering environmental goods or services are known, the optimal budget allocation is significantly lower than when the costs are uncertain.

These results suggest that there is value for the conservation agency to reduce uncertainty around landholders' own costs. This could have two implications. First, applied to a specific conservation program, the approach could inform the conservation agency on the optimal level of investment in information gathering and sharing with the landholders. Second, by providing a risk mitigation tool such as an insurance mechanism, the conservation agency may help minimise the impact of landholders' own-cost uncertainty on the inefficiency with which the tender budget is allocated, leading to better performance of conservation tenders.

A possible extension to this study would be to analyse the performance of the tender in the presence of bidders' participation uncertainty. Depending on (i) when own-cost uncertainty is resolved relative to when costs are incurred or (ii) whether the land use decision is reversible, some of the uncertainty may be mitigated by the option to exit a contract in the event of a negative shock. For instance, this will be true in a contract with annual payments, where a landholder makes repeated annual decisions about participating in the program. In such a case, when the payoffs from participation fall below the payoffs from exiting, the landholder may choose to exit provided that there is no penalty. This generates some option value and makes the contract more attractive, all else equal (see Oliva et al. 2020).

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