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Using Agent-Based Models to Examine Implications of Introducing Conservation Auctions in Costa Rica:

Overview, Design Concepts, and Details (ODD) Protocol for a Conservation Auction Agent-Based Model (CA-ABM)

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Abstract

The agency responsible for Costa Rica's payment for ecosystem services program (Pagos de Servicios Ambientales, PSA) has been charged with developing mechanisms to increase cost-effectiveness in the forest protection program. One possible mechanism that can be used to achieve this goal is conservation auctions. While a trial run or a pilot auction could be useful in exploring possible auction designs or to identify possible unintended consequences, these options often require significant financial and political support. An alternative way to explore possible auction designs is by simulating participation and conservation outcomes using models, such as an agent-based model (ABM). Using the ODD (overview, design concepts, and details) protocol published in 2006 and updated in 2010, this report describes the structure of an ABM used to examine possible results of introducing a conservation auction to allocate contracts in Costa Rica's PSA forest protection program.

Keywords: Agent-based modeling, conservation auction, informational rents, payment for ecosystem services, strategic behavior.

Introduction

When a government agency plans to introduce a new mechanism into an existing program, a pilot or a trial run can help identify whether that mechanism is properly structured to achieve program objectives and whether there are likely to be any unintended consequences. However, this is not always possible due to funding, legal, or other barriers. As an alternative, models or simulations can be used to explore the implications of the proposed new mechanism. This report describes an agent-based model (ABM) used to predict the results of introducing a conservation auction for allocation of contracts in Costa Rica's payment for ecosystem services (Pagos de Servicios Ambientales, PSA) forest protection program. The ABM uses data on landowners and land enrolled in the program from 2005 to 2014. The first two sections of this report provide brief background information about the PSA forest protection program and ABMs, respectively. The final section presents the CA-ABM, or Conservation Auction ABM, following the ODD (overview, design concepts, and details) protocol framework.

Costa Rica's PSA Forest Protection Program

Established in 1996, the PSA forest protection program pays landowners an annual, per-hectare fee to conserve existing forest on their properties for a given number of years (5 or 10 in different years of the program). In addition to the program's conservation goals, the Costa Rican government would also like the program to contribute to rural development and poverty alleviation, e.g., through payments that make a significant contribution to the income of poor landowners (Ortiz and others 2003).

Over the past 10 years, the PSA program has been modified several times in order to better achieve its environmental and social objectives (James and Sills 2019). Perhaps most notably, forest protection contracts are no longer awarded on a first come, first served basis but are now rated based on environmental and social factors. Theory suggests that the introduction of a conservation procurement auction could further increase the cost-effectiveness of the program in terms of both environmental and social objectives.

Agent-Based Modeling to Examine Possible PSA Program Results

Agent-based models are computation models in which agents (individuals, households, groups, etc.) interact within a closed system. Rather than defining the behavior of individual agents, ABMs consist of purposeful agents who interact over space and time, according to set rules, and whose micro-level interactions create emergent patterns (i.e., increased/decreased forest conservation). In each ABM there are: (i) diverse agents (ii) situated in an interaction structure (iii) whose actions create externalities and can (iv) adapt, evolve, or learn (Page 2005). The bottom-up approach in ABMs allows for the analysis of "evolving systems of autonomous interacting agents" (Tesfatsion 2003); therefore, in ABMs, behaviors of agents emerge and can be observed. The emergence of behavior observed in ABMs helps both predict and understand policy outcomes, by incorporating realistic assumptions about agent behavior, program structure, and timing of micro-level interactions that lead to macro-level patterns.

Unlike previous studies that use simulated data in an ABM to examine the cost-effectiveness of auctions, this model utilizes data from Costa Rica on PSA forest protection contracts that were awarded from 2005 to 2014. Because this ABM is based on the actual joint distribution of property characteristics, the model results provide information about how various auction types and targeting mechanisms would increase or decrease the cost-effectiveness of the program and redistribute participation among landowners who are already participating in the program. One disadvantage of using actual contract data is that the model cannot predict whether auctions will expand the number or the type of landowners who participate in PSA.

There are several variations of the auction model presented in this protocol. The first group of ABMs (Group A) model first price, discriminatory auctions and second price, uniform auctions. Each auction is modeled with three levels of targeting: no targeting, targeting for environmental benefits (EB), and targeting for both environmental and social benefits (EBS). The second group of ABMs (Group B) build on the first price, discriminatory auctions in the first set. Agents in the Group B models are allowed to engage in strategic behavior via learning over repeated auctions. In both sets of ABMs, the model results are used to examine the cost-effectiveness of the program for achieving conservation and participation in the program by disadvantaged landowners. Modeling for the Group A auctions was done in R, using the RStudio interface and the base package. Modeling for the Group B auctions was completed using Repast with an Eclipse interface.

Overview, Design Concepts, and Details (ODD) Protocol

In 2006, Grimm and others published the ODD protocol to standardize the descriptions of ABMs. The ODD protocol provides a structure for complete model descriptions that facilitates documentation and replication of ABMs. An ODD protocol includes seven sections in sequential order: (1) the purpose of the model, (2) the state variables and scales, (3) an overview of the processing and scheduling implemented in the model, (4) a description of the design concepts,[1] (5) the factors used to initialize the model, (6) a description of the input data, and (7) the submodels used in the model processes (Grimm and others 2006, 2010). The following model description follows the ODD protocol.

1 The design concepts include: (1) a description of the basic principles used in the model; (2) descriptions of emerging and adaptive behavior in agents; (3) the objectives of the agents; (4) the ability of the agents to learn, predict future behavior, sense, and interact with each other; (5) a description of stochastic variables; and (6) what data are being observed and collected from the model.

Purpose

The purpose of this ABM is to explore how auctions could be incorporated into an existing payment for ecosystem services (PES) program and improve understanding of possible implications for cost-effectiveness and equity in participation.

State Variables and Scales

Landowner Agents are the only agent type in this model. Each agent has the following attributes and state variables:

1. Size of their parcel of land
2. Amount of land offered to the PES program
3. Opportunity cost of participation
4. Social Development Index (Índice de Desarrollo Social, IDS[2]) of the district in which the parcel of land is located
5. Environmental benefits of land offered to the program
6. The year in which they participate in the auction

Attributes and state variables are unique to each agent. There are 3,115 total agents in this model, each representing a landowner that owns one parcel of land. When the model is initiated, each agent is aware of their own opportunity cost, the size of their parcel of land, the IDS of their location, and the transaction costs of participating in the PSA program (15 percent of the payment as a fee to the forester or intermediary that creates the management plan that is necessary for being awarded a forest protection contract). In the first price auctions, agents also know the total enrollment cost (opportunity cost plus transaction cost) of the parcel with the highest enrollment cost. As this is a spatially explicit model, agents are also aware of who their neighbors are and who lives in their jurisdiction (canton). Only the program administrator is aware of the exact environmental benefits each parcel of land provides.

Each Landowner Agent is assigned a year in which they can participate in the auction (based on the year they were awarded a PSA forest protection contract). Each time step is 1 year, and there is only one nationwide auction per time step. For each auction type, there are 10 time steps reflecting

2 The IDS is calculated by the Ministry of National Planning and Economic Policy (MIDEPLAN) as a measure of the relative wealth of districts in Costa Rica, with 0 being the lowest and 100 the highest score.

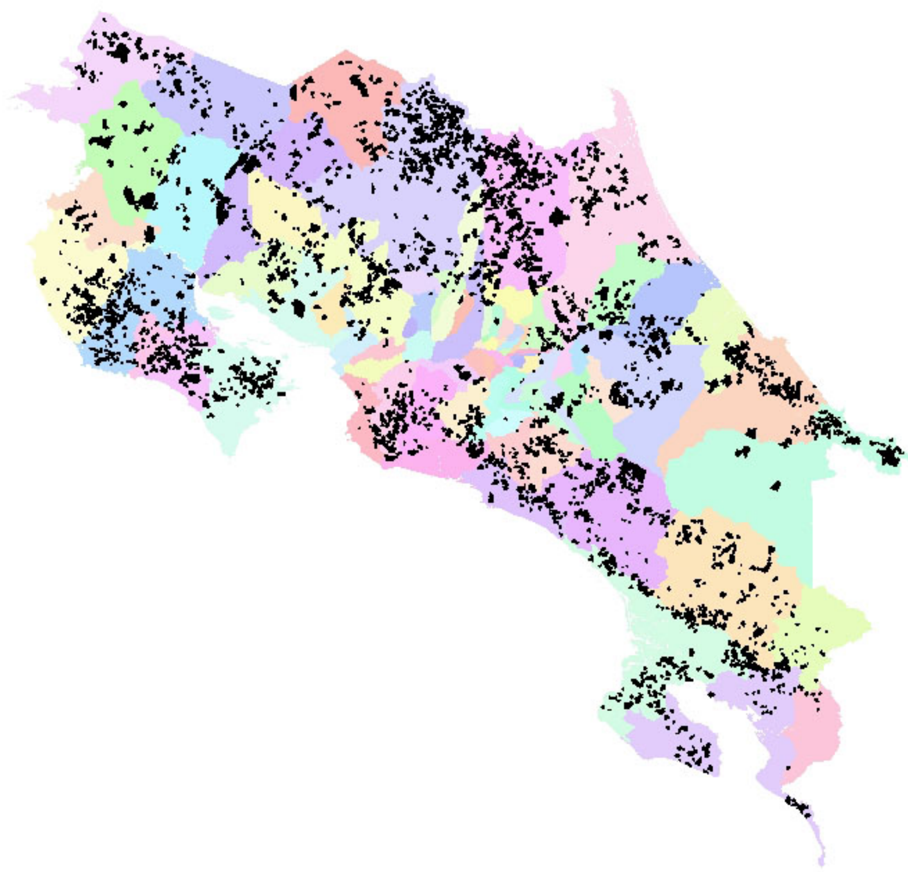

Figure 1—A boundary map of all the cantons in Costa Rica and the location of all properties (marked in black) included in this analysis.

the 10 years of data on landowners who participate in the program. In each time step, participating Landowner Agents submit a bid ($/ha) for a forest protection contract.[3]

The landscape for this model includes all land parcels enrolled in the PSA forest protection program from 2005 to 2014 (shown in fig. 1). Parcels are located in 69 (85.2 percent) of Costa Rica's cantons.

Process Overview and Scheduling

Group A: Schedule for Auction Model—Once each eligible Landowner Agent has determined their bid, all bids are submitted to the nationwide first price auction. Bids are sorted based on the type of targeting and accepted until the budget for contracts is exhausted.

There are three variations of each auction as presented in table 1. In the first price auction, when there is no targeting (FP-NT), bids are sorted in ascending order and accepted until the budget is exhausted. For auctions in which there is targeting of environmental benefits (FP-EB) or both environmental and social benefits (FP-EBS), bids are sorted from the highest to lowest ratio of benefits per dollar, where benefits are defined based on the weights that the implementing agency (Fondo Nacional de Financiamiento Forestal, FONAFIFO) places on environmental and social factors. The bids with the highest benefits per dollar are accepted until the budget is exhausted. Each Landowner Agent is paid their individual bid. The first price auction and the second price auctions are similar in schedule, except that in the second price auctions, Landowner Agents are all paid the same price per hectare. In the first come, first served (FCFS) model, Landowner Agents submit their bid, and the winners (Landowner Agents awarded contracts) are chosen at random. The FCFS model serves as a baseline.

Group B: Schedule for Learning Model—Building on the first price auction models described in the previous section, models in Group B allow Landowner Agents to engage in strategic behavior. There are two learning environments: the independent private values (IPV) environment and the common value (CV) environment. The learning environments differ in terms of with whom Landowner Agents interact and what information is offered. Within each time step, there are three stages (fig. 2). In the first stage, Landowner Agents participating in that year's auction set their initial bid. In the second stage, Landowner Agents have the opportunity to interact with previous auction winners, who provide information about their own winning bids. In the third stage, Landowner Agents determine their final bid based on the information gathered.

Independent Private Values (IPV) Environment—In the IPV learning environment, Landowner Agents participating in the auction gather information from previous auction winners in their canton who submitted winning bids only in the previous year's auction.[4] However, Landowner Agents do not learn the exact amount of winning bids. Instead, previous winners provide a "rough idea" of their winning bid by shading their bid by a random factor drawn from a uniform distribution between -10 and +10 percent. If a Landowner Agent hears of a winning bid that is higher than their optimal bid, this is taken as a signal that the auction can tolerate higher bids. By increasing their bid, the Landowner Agent can increase their informational rent. Therefore, the agent increases their bid calculated in

3 Bidding strategies are detailed in the Submodels section of this report.

4 In the first time step, there are no previous auctions winners, thus these Landowner Agents do not have the opportunity to learn.

Table 1—Variation in each auction environment, including a description of the optimal bidding strategy for the Landowner Agent, the level of targeting, and how winners are selected

Auction Environment	Optimal bidding strategy	Targeting	Winner selection
Baseline: First Come, First Served	Bid opportunity cost plus transaction costs	No targeting	Random
First Price, Discriminatory	Optimal bid based on opportunity cost, transaction costs, and the opportunity cost of others	No targeting	Lowest dollar per ha
		Environmental benefits targeting	Lowest dollar per environmental benefit score based on the first four factors in the Matrix
		Environmental and social benefits targeting	Lowest dollar per environmental benefit score based on all factors in the Matrix
Second Price, Uniform	Bid opportunity cost plus transaction costs	No targeting	Lowest dollar per ha
		Environmental benefits targeting	Lowest dollar per environmental benefit score based on the first four factors in the Matrix
		Environmental and social benefits targeting	Lowest dollar per environmental benefit score based on all factors in the Matrix

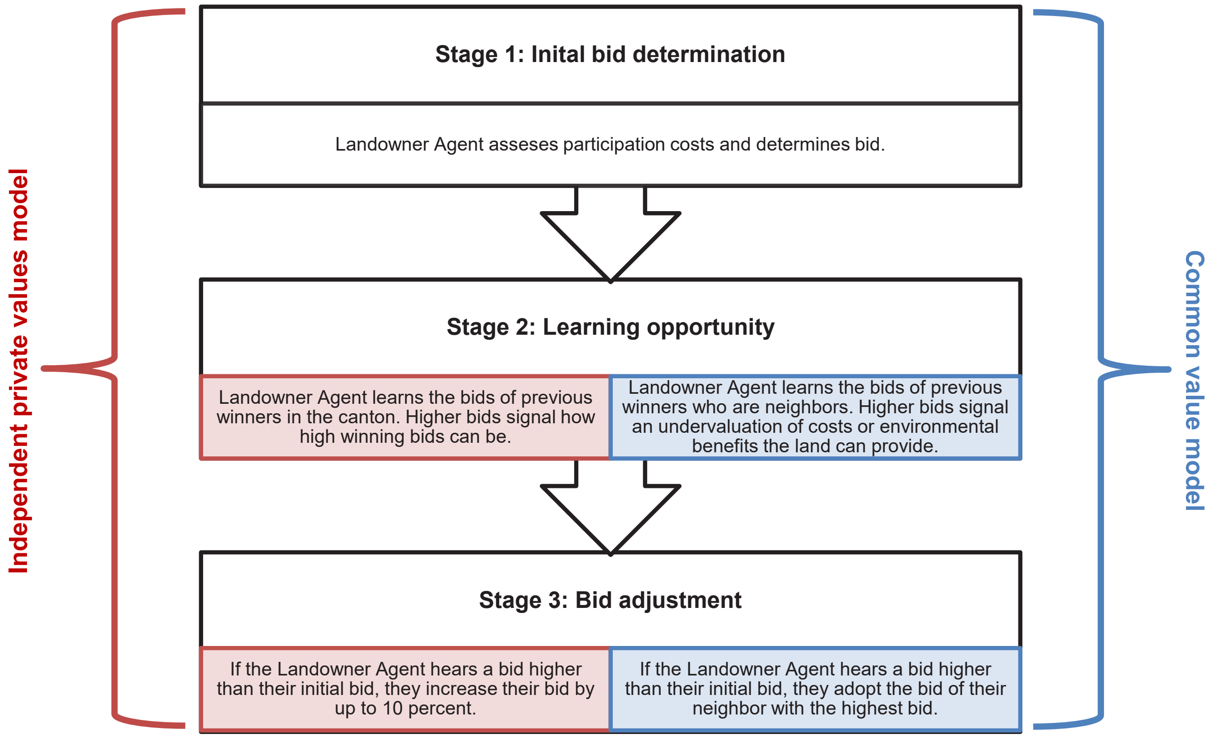

Figure 2—The process and schedule for the independent private values and the common value models of learning.

the first stage by up to 10 percent.[5] In this model, bids are only increased by up to 10 percent to reflect the fact that Landowner Agents know the information they are given may not be accurate and do not want to risk losing the auction. If a Landowner Agent does not have any previous winners in their canton or if they do not hear of any winning bids higher than their initial bid, their bid stays the same. Each Landowner Agent increases their bid only once.

Common Value (CV) Environment—In the CV learning environment, Landowner Agents interact with previous winners who are neighbors. Neighbors share information on their exact winning bids. Landowner Agents are aware the land they are offering in the auction may offer similar environmental benefits as their neighbors' land. If the Landowner Agent hears of a winning bid that is higher than the bid they set in the first stage, this is taken as a signal that their initial valuation is low relative to the actual costs of participating in the program or an undervaluation of the actual environmental benefits their land can provide. Unlike in the IPV learning environment, the Landowner Agent knows their neighbor is providing accurate information about their winning bid. Therefore, the Landowner Agent updates their bid by adopting the bid of the neighbor with the highest winning bid. If the Landowner Agent does not have any neighbors that previously won an auction or if they do not hear of any winning bids higher than their initial bid, their bid stays the same. Landowner Agents are able to update their bids until they reach the highest bid of all their neighbors.

Design Concepts

Basic Principles—The design of CA-ABM draws on the work done by Hailu and Schilizzi (2004) and Hailu and Thoyer (2007) on multi-unit procurement auctions. The design also incorporates insights from Lundberg and others (2018), who constructed an ABM to examine cost-effectiveness gains from a procurement auction compared to a fixed payment scheme in a forest protection PES program. Finally, the design of CA-ABM incorporates basic auction design principles as discussed in the small literature on auctions in allocating contracts for PES programs, including second price, uniform auctions (Jindal and others 2011) and targeting (Ferraro 2008).

The auction mechanisms in CA-ABM are based on auction theory, including the first price optimal bidding strategy discussed by Iftekhar and Latacz-Lohmann (2017) and the second price optimal bidding strategy of Vickrey (1961, 1976).

The learning environments in CA-ABM are based on auction theory and the design of previous ABMs. In the literature on auctions, the independent values model and the common value model have been posited as two alternative ways that agents develop their bids (McAfee and McMillan 1987). In CA-ABM, they inform two possible heuristics used by Landowner Agents to strategically increase their bids. Hailu and Schilizzi (2004) modeled

5 This 10-percent cap is consistent with ABMs presented by Hailu and Schilizzi (2004) and Lundberg and others (2018).

repeated conservation auctions in which agents can learn from their own previous bids, and Lundberg and others (2018) examined the implications of agents learning from neighbors in a conservation auction. Insights from both papers were used to construct the Group B models.

Emergence—The key results of the model, including the types of auction winners (including smallholders or low-IDS landowners) and the characteristics of the land enrolled in the program emerge from the variation in the auction environment and the level of targeting. Each auction environment results in a different optimal bidding strategy for the Landowner Agent. Additionally, each type of targeting results in a different process for selecting winners. These variations are important in the learning environments, as the initial choice of winners determines which Landowner Agents have the opportunity to learn and how many winners they learn from. Thus, micro-level behavior of individual agents allows for the emergence of macro-level changes in the cost-effectiveness of the auction and the distribution of contract winners across auction types and learning environments.

Adaptation—Each Landowner Agent adapts their bidding strategy based on the auction environment (Group A) or learning environment (Group B), as outlined in table 1 and figure 2. Additionally, as the Landowner Agents that are able to participate in the auction in each time step are heterogeneous and bidding strategies vary across auction environments, Landowner Agents in each time step adapt their bid based on their environment.

Objectives—The objective of the Landowner Agent is to maximize informational rents, which requires being selected as an auction winner and receiving a high payment. To do so, Landowner Agents follow the optimal bidding strategy, as outlined in the Submodels section of this report. In the Group B models, Landowner Agents use information from previous winners to strategically set their bids higher, thus increasing informational rents if they win.

Interaction—In the Group A models, Landowner Agents do not interact directly. However, information about the highest opportunity cost of any property in that auction year is known, and this information is used in the optimal bidding strategy. In the Group B models, Landowner Agents have the opportunity to interact directly with past auction winners about winning bid amounts.

Stochasticity—Stochasticity is present in each of the auction environments. For the first come, first served scenario, winners are chosen at random. In each of the first price and the second price auctions, when Landowner Agents submit bids that are tied, one is randomly selected. Stochasticity is also present in the learning environments. In the IPV learning environment, the bids that are shared with the Landowner Agent are shaded by a random factor drawn from a uniform distribution between -10 and +10 percent. Additionally, if the Landowner Agent does learn of a bid that is higher than theirs, they will increase their bid by a random factor drawn from a uniform distribution of up to 10 percent.

Observation—In analyzing the cost-effectiveness of each auction, the total number of hectares, the dollars spent, the environmental benefits gained, and the total informational rents collected by the agents who were awarded contracts are recorded to evaluate cost-effectiveness. To understand the equity of participation in each auction environment, the total number of winners, the number of winners who are smallholders, and the number of winners who are low-IDS landowners are also recorded for each time step.

Initialization

Landowner Agents are initialized and parameterized based on data describing new contracts awarded by the PSA program from 2005 to 2014. Each Landowner Agent owns one parcel with an area of forest that is offered for enrollment in the PSA program (based on number of hectares actually enrolled in the program). The contract data include the size and location of each parcel of land with forest enrolled in the PSA program. Thus, we can identify both the canton in which each parcel is located and any neighboring parcels. Neighbors are defined as parcels with boundaries crossing or touching.

Input

Data—Data used in this analysis are drawn from two sources: (1) spatial data on PSA forest protection contracts signed from 2005 to 2014 and (2) opportunity cost estimates.

Contract Data—The contract data were collected in 2015. This spatial database created by the Costa Rican Institute of Technology includes information on all new PSA contracts signed from 2005 to 2014 including: the contract number, the specific program that issued the contract, the location of the property, the number of hectares of the property, the number of hectares enrolled in PSA, and a score based on the weights placed on different factors (called the Matrix), as well as the IDS of the district in which the property is located (Aguilar 2015). This spatial database was in turn based on two information systems in the public agency that administers the program: one that manages applications to the program and the other that manages payments (called the Integrated Project Administration System). In each of these time steps, the total budget for contracts is equal to the average value (in USD) of PSA forest protection contracts awarded from 2005 to 2014: $8,091,928.[6] The ABM described in this report is set to reflect real-world conditions in that the program design and the budget can remain the same, even while there is substantial variation in the number of landowners who bid for contracts.

Opportunity Cost—The opportunity cost used in this analysis was constructed by Vega-Araya (2014) under a

6 In reality, FONAFIFO does not pay out the full amount of the contract in the year that it is awarded. For example, with a 5-year contract, 20 percent of the contract value is paid to the landowner in each year. The value presented as the budget is the average of the full value of contracts awarded for each year awarded from 2005 to 2014. In other words, it is the average of how much would be spent each year if FONAFIFO paid the full amount to landowners at the time the contract was awarded.

Table 2—Correlation matrix of the characteristics of the land that will be used in the agent-based model

	Opportunity cost	Farm size	IDS score	Environmental benefits score	Environmental and social benefits score
Opportunity cost	1				
Farm size	-0.034	1			
IDS score	-0.016	-0.066[a]	1		
Environmental benefits score	-0.016[a]	0.051[a]	-0.031	1	
Environmental and social benefits score	-0.066[a]	-0.013	-0.015	0.587	1

[a] Indicates significance at the 1-percent level.
IDS = Índice de Desarrollo Social (Social Development Index).
Source: Aguilar (2015).

contract with FONAFIFO. Vega-Araya (2014) estimated the opportunity cost of participating in PSA based on the productivity of land, accessibility to markets and services, and available infrastructure and public services. The opportunity cost of contracts on properties that fall into more than one opportunity cost zone is an area-weighted average.

Data Description—The CA-ABM utilizes the contract data to create agents, and thus does not rely on assumptions about distributions and correlations to create agents. Perhaps most critically, this means that CA-ABM reflects the actual joint distribution of land characteristics, which is important because a strong correlation between two attributes, such as opportunity cost and the environmental benefits provided, could skew the result of the auctions. However, in the real-world data used for CA-ABM, most of the correlations are small, and only a few are statistically significant (table 2).[7]

A subset of the heterogeneous Landowner Agents are assigned to participate in each step based on the year in which their actual contract was issued. The initial conditions for each time step are presented in table 3, including the number of landowners that participate in the auction and the area of forest for which they submit bids. The first year (t_0) corresponds to the data on PSA contracts issued in 2005.

7 There is a moderate correlation between the EB score and the EBS score. This is expected as the EB score is a part of the EBS score. However, in this analysis, these scores are never used simultaneously.

Table 3—Initial conditions for each time step, where time t_0 = 2005

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Number of participants	375	176	400	442	179	251	362	439	224	267
Number of smallholder participants (≤50 ha)	121	67	144	168	50	97	154	218	127	167
Number of low-IDS participants	164	75	152	152	59	108	154	203	110	124
Total hectares offered	27 335.99	11 718.4	31 619.4	38 808.9	15 593.9	17 560.8	27 704.5	27 101.5	13 002.7	10 933.29
Total environmental benefit offered[a]	26,250	12,890	27,965	31,075	13,285	16,610	24,925	30,285	14,625	16,620
Total environmental and social benefit offered[a]	30,915	15,315	33,085	36,795	15,125	20,115	30,315	37,765	18,900	22,035

[a] Based on the Matrix scoring system for forest protection contracts. See table 5.
IDS = Índice de Desarrollo Social (Social Development Index).
Source: Aguilar (2015).

Submodels

Landowner Bidding Strategy—Each auction offers a 5-year forest protection contract.[8] Each bid submitted by the landowner is the bid per hectare for a 5-year contract.

To construct the cost of participation for each Landowner Agent, CA-ABM assumes no discounting.

$$c_i = transaction\ costs_i + (\frac{opportunity\ cost_i}{ha} * 5)$$

$$transaction\ costs_i = \left(\frac{opportunity\ cost_i}{ha} * 5\right) * .15$$

where

c_i = the total cost to the landowner (opportunity cost and transaction cost)
i = index number for individual landowners

First Come, First Served—In the first come, first served environment, Landowner Agents submit bids that cover their opportunity and transaction costs. Each bid is:

$$b_i^* = c_i$$

where

b_i^* = the optimal bidding strategy of the individual landowner

First Price, Discriminatory—Following Iftekhar and Latacz-Lohmann (2017), the optimal bidding strategy used in the first price, discriminatory auction maximizes the Landowner Agent's net payoff by balancing the probability of winning and the size of the payment. The optimal bid is as follows:

$$b_i^* = c_i + \frac{\bar{c} - c_i}{N - 1}$$

where

$\bar{c}$ = the cost of participation for the landowner with the highest costs[9]
N = the number of individuals participating in the auction

Second Price, Uniform—The optimal bidding strategy for a second price, uniform auction is for the Landowner Agent to bid their exact cost for a 5-year contract (opportunity cost plus transaction costs) (Vickrey 1961):

$$b_i^* = c_i$$

8 Although agents are only under contract for 5 years, they do not re-enter the auction as Landowner Agents once their contract has expired. Future work will examine the implications for cost-effectiveness when landowners are able to re-enter the auctions and learn from their own experience. In 2012 and 2013, contracts were actually awarded for 10 years. For simplicity, all contracts awarded in CA-ABM are for 5 years.

9 It is possible that, in a procurement auction, bidders would not have access to information about the costs and values of other bidders. While this uncertainty about other bidders' costs and values is present in the real world, CA-ABM abstracts from this uncertainty in order to focus on the implications of targeting and strategic behavior for auction outcomes.

Learning

Finding Neighbors—In this model, parcels are represented as polygons. Neighbors have polygons that cross or touch. The Polygon Neighbors tool of ArcMap 10.3.1. was used to determine the neighbors of each Landowner Agent. This tool assigned an identification number to each polygon and returned the identification number(s) of neighboring polygons. Table 4 provides summary information on how many neighbor agents are available for interaction. Approximately 52 percent (1,627) of the agents in this model have no neighbors.

Table 4—The number of neighbor agents available for interaction

Number of neighbors	Number of agents
0	1,627
1	929
2	394
3	117
4	38
5	8
6	2

Source: Aguilar (2015).

Figure 3 is a map of land parcels in a section of the canton, Osa. Using this graphic as an example, in the Group B models, the polygon labeled 1 would be able to share information with the polygon labeled 2 and vice versa, as these parcels have boundaries that touch. However, the polygon labeled 5 has no neighbors and therefore has no one to share information with or obtain information from.

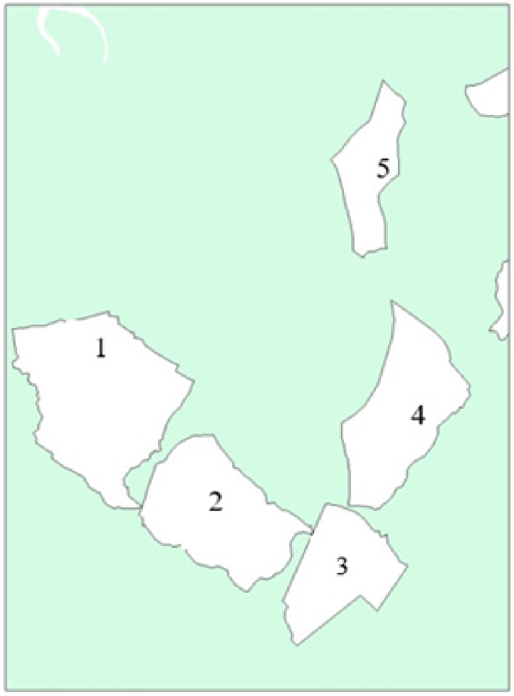

Figure 3—Example of land parcels in a section of the canton, Osa.

Finding Members of Canton—The spatial data used in this analysis include an identification code for the canton in which each parcel is located. Landowner Agents in the IPV learning environment interact with previous auction winners that have the same identification code. Figure 4 is a histogram of the number of agents per canton used in CA-ABM. Of 3,115 total agents, there are only 8 agents who are alone in their cantons.

Winner Selection—The first price, discriminatory auction pays the winning Landowner Agent the price they bid for the number of forest hectares that they offer. When there is no targeting, bids are sorted in ascending order. Bids are accepted until the budget is exhausted. In auctions with targeting, the score is based on the Matrix (table 5). To determine a score for the environmental benefits (EB) generated by conserving forest on a given parcel, the first four factors of the Matrix are summed. The environmental benefits with social benefits (EBS) score is obtained by summing all factors of the Matrix. As an example, consider Landowner A who owns a farm (or parcel) of ≤50 hectares (25 points) in a Conservation Gap (85 points) located in a low-IDS district area (10 points). In an auction with EB targeting, Landowner A will be assigned 85 points. In an auction with EBS targeting, Landowner A will have 120 points.

In the auction with EB targeting, bids are converted to a ratio of environmental benefit per dollar (EB/$) and sorted from highest to lowest. Bids are accepted until the budget is exhausted by payments of the bid times the number of hectares offered by each landowner. In the final auction, bids are converted to ratios of the environmental and social benefits per dollar (EBS/$). In all auctions, when there is a tie in bids, winners are chosen at random.

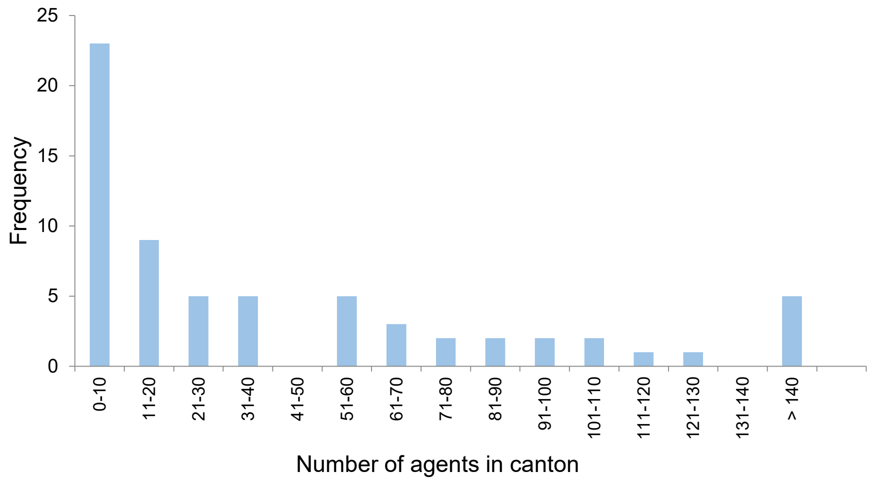

Table 5—Matrix scoring system used for forest protection contracts starting in 2012

Criteria	Priorities	Points
1	Forests on farms located in areas defined in the Conservation Gaps within Indigenous Territories of the country.	85
2	Forests on farms located within the officially established Biological Corridors. Forests that protect water resources or where the importance of protecting the forest is evident.	80
3	Forests on farms located within Protected Areas that have not been bought or expropriated by the State.	75
4	Forests outside any of the above priorities.	55
I	Forests in the Forest Protection modality complying with the provisions of the above points, which have signed contracts for payment of ecosystem services in previous years, provided they meet other requirements.	10 additional
II	Forests in farms located in districts with <40 on the IDS.	10 additional
III	Forests in any of the above priorities, with application to enter the PSA where the size of the farm is ≤50 ha.	25 additional

Acknowledgments

The author would like to thank Liv Lundberg and Martin Persson for their assistance in the formation of this model. The author would also like to acknowledge Erin Sills, Emily Berglund, and Elizabeth Ramsey for their useful feedback during the manuscript review process.

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The agency responsible for Costa Rica's payment for ecosystem services (PES) program (Pagos de Servicios Ambientales, PSA) has been charged with developing mechanisms to increase cost-effectiveness in the forest protection program. One possible mechanism that can be used to achieve this goal is conservation auctions. While a trial run or a pilot auction could be useful in exploring possible auction designs or to identify possible unintended consequences, these options often require significant financial and political support. An alternative way to explore possible auction designs is by simulating participation and conservation outcomes using models, such as an agent-based model (ABM). Using the ODD (overview, design concepts, and details) protocol published in 2006 and updated in 2010, this report describes the structure of an ABM used to examine possible results of introducing a conservation auction to allocate contracts in Costa Rica's PSA forest protection program.

Keywords: Agent-based modeling, conservation auction, informational rents, payment for ecosystem services, strategic behavior.

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