An agent based analysis of the impacts of land use restriction and network structures on participation in conservation reserve programs

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Abstract: Conservation covenants are a policy tool for biodiversity and environmental conservation on private lands. They are associated with the withdrawal of development rights by the landholder over a particular piece of land in exchange for financial benefits. Previous studies suggest that existing network structure could influence an individual's decision to enrol in conservation programs, but there is a lack of comparative analysis of network types to promote more cost-effective results. In this paper, we develop an agent based simulation model to demonstrate the evolution and impact of future land use restrictions on the enrolment of landholders in conservation covenant programs under different network structure. We observe that the nature of the network has a significant impact on program performance. We obtain a lower response to (and higher cost of) conservation covenanting programs when agents are part of a random matching network compared to other networks options. On the other hand, program costs are lower when agents are part of a local uniform matching network. The outcomes indicate that it might be beneficial for the representations to conduct network analysis the project planning stage to fix their programs more attractive to the landowners.

Key words: Conservation covenants; Land use restrictions; Multi-agent systems; Simulation; Network analysis

JEL classifications: Q24, Q28, D47

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1. Introduction

This study is motivated by the influence of networks and intergenerational spillover effects on landholder participation in conservation covenant programs. Network analysis assumes that agents are interdependent on each other, these interdependencies are manifested through exchange of resource or information, and network structures influence agents' ability to act to any situation (Vance-Borland and Holley 2011). Such flexibility makes network analysis an important tool to understand natural resource management (Bodin and Tengö 2012).

Many of the studies on network have focused on individual elements and structural characteristics of a network. Vance-Borland and Holley (2011), in a review of the literature observed some key network characteristics that could promote sustainable natural resources management, highlighted: groups of people who are densely connected and able to share specific knowledge and work together; diverse sets of groups who can contribute expertise; expert knowledge sharing through existing relationships between groups; and ties to diverse actors to acquire specialized knowledge. While these studies highlighted the importance of networks, formal analysis has been limited by the availability of empirical data and the study of only one or two networks. Comparative studies are relatively rare.

A comparative analysis of different network structures could be useful, as it will help the agencies understand what kind of networks would facilitate their programs, which will enable them to better target their programs. In other words, if the agencies know what kind of network structure exists in the community beforehand and can anticipate the expected response they can tailor their plans. It might also help them to design suitable network intervention programs to make their program more acceptable (Valente 2012).

We contribute to this knowledge gap by comparing different types of networks in the context of landholders' decisions to participate in conservation covenanting programs. The idea of a conservation covenant as a tool for private land conservation efforts was first espoused by William H Whyte in a technical bulletin entitled, '*Securing Open Space for Urban America: Conservation Easements*' (Whyte 1959). Since then conservation covenanting has become a popular policy tool. Conservation covenants are legal contracts signed between individual landholders and conservation agencies (either government or non-government) restricting the use of a particular piece of land for the protection of environmental amenities and services (Kabii and Horwitz 2006).

The trade-offs between immediate financial reward and expected negative impact on future generation due to land use restrictions make conservation covenanting programs an interesting policy mechanism to study the impact of networks. Furthermore, the economic consequences of current and future land-use restrictions under conservation reserve programs have been identified as a major influencing factor in landholders' enrolment decisions. Purvis et al. (1989), for example, found that farmers' willingness to participate in a filter strip program in the United States (US) are influenced by economic factors, including yearly payments and farm opportunity costs. Luzar and Diagne (1999) conducted a survey of wetland owners about their decision to participate in a Wetland Reserve Program. They observed that the number of people living in a household (potential heirs and so the intergenerational economic consequences of their decisions) had an adverse effect on enrolment in the program. Lambert et al. (2007) examined participation in the U.S. Conservation Reserve and Environmental Quality Incentive programs. They found that the characteristics of landholders, as well as the income from their farm business, influenced participation rates in conservation programs. Similarly, in another survey of agriculture landholders in Colorado and Wyoming, Cross et al. (2011) found that family dependence on economic productivity from the land, and future flexibility to use land for livelihood has a negative impact on participation rates in conservation covenants.

This study builds on this body of conservation literature by exploring whether landholders' decisions to engage in conservation reserve programs are influenced by the land use restrictions attached to conservation program, especially when an individual's enrolment decision could be influenced by the group or community outcomes through the network in which they interact. We use agent based simulation techniques[1] to explore the influence of group outcome on engagement in conservation programs as they allow us to consider individuals making decisions, which evolve because of the learnings from the group outcomes, and mimicking better performing sections of the community. It is possible to estimate long-term income at an individual as well as at group level. Agencies are then able to assess the impacts of different conservation programs in terms of payments and land use restrictions (Iftekhar and Tisdell 2015).

We model a hypothetical scenario with a heterogeneous set of landholder agents in which the agents vary in terms of their opportunity costs and quality of land. We use a modified mean-variance utility framework function to model their decision. In the framework two variables: the risk aversion and the future impact aversion variables, capture an agent's sensitivity to a risky option and possible negative consequences to future generation respectively. The simulation begins with randomly generated risk

[1] Agent-based model is a suitable technique to model interactions between individual actors and the environment. The interactions could be both active (where agents are making conscious decisions based on their understanding of underlying processes) and passive (where agents could only react to some information). Both types of behaviours are critical for network analysis Goldstone, R. L. and Janssen, M. A. 2005. Computational models of collective behavior. *Trends in Cognitive Sciences,* 9(9): 424-30..

aversion and future impact aversion variables. With each generation a new set of agents evolve with utility profiles similar to the better performing section of the previous generation. By repeating this process, we generate data to analyze the impact of different networks.

Using an agent-based framework, we compare the performance of a conservation covenant programs under four main types of network structures: uniform matching, small-world, local and randomly matching networks. In a uniform matching network, every agent is connected with each other, whereas in a local matching network only agents within a group (or only with agents of the same type) are connected to each other. The majority of agents in a small-world network are connected within a group, but some could be randomly connected to someone completely outside of the group. Finally, in a random matching network, agents could be randomly connected to agents within or outside the group. Under different network structures individual agents would have different types of neighborhood structure (or group membership), which will influence how the groups evolve.

In order to test the sensitivity of the influence of the network structures we examine the impact of the different networks in two scenarios: different levels of enrollment target and landholder populations with different levels of cost heterogeneity. It might be possible for conservation agencies to set the level of enrollment target as well as target a selected group of landholders with a certain level of cost heterogeneity. Understanding of the impact of different networks therefore will be useful for the agencies. In essence, we ask which types of networks would achieve higher enrollment at lower cost and how cost heterogeneity and enrollment targets influence their cost-effectiveness. While our study is exploratory in nature, it provides some important insight into the potential uptake of long-term conservation contracts under different network structures.

2. Theoretical framework

We present our agent based model in accordance with the Overview, Design concepts, and Details (ODD) protocol of Grimm et al. (2006) (see Appendix A). In this section, we discuss the theoretical framework used in this study, which consists of three sub-models: an individual decision model, a model of the evolution of agent behavior, and a conservation-agency decision model.

2.1. Individual decision model

A landholder's decision to engage in a conservation program has been modeled in terms of an utility maximization framework similar to that used by Rahm and Huffman (1984). We assume that a landholder's choice set is either to participate in one of the conservation programs (four options available with different land use restrictions) or to continue farming. Income from farming is variable, but it does not have any negative consequences for future generations. Income from a conservation payment is certain, but it can impose land use restrictions on future generations depending on program characteristics. The utility function encapsulating these options is based on the standard mean-variance utility function proposed by Freund (1956). Due to its analytical tractability and clear intuitive meaning, the mean-variance preference function has been used extensively to model the farmers' behavior choosing among uncertain prospects (Chavas and Pope 1982, Coyle 1999, Coyle 1992, Janssen et al. 2010). We extend this function to incorporate sensitivity of an agent towards the land use restrictions on future generation. Formally,

$$u_{ik} = \hat{y}_{ik} - 0.5\gamma_i\sigma_{ik}^2 - \delta_i z_k(\hat{y}_{ik} - 0.5\gamma_i\sigma_{ik}^2) \qquad \text{(Equation 1)}$$

Where

u_{ik}	Expected utility of player i from option k
$\hat{y}_{ik}$	Expected income of player i from option k
σ_{ik}^2	Variance of income
γ_i	Risk aversion parameter
δ_i	Future land use restriction sensitivity (impact aversion) parameter
z_k	Level of future land use restriction of option k

In Equation 1, $\hat{y}_{ik}$ measures the expected income from the choice; $0.5\gamma_i\sigma_{ik}^2$ captures the risk sensitivity of the agent in that the higher the variance of income (and/or risk sensitivity parameter) the less utility the agent receives from the option; and $\delta_i z_k\left(\hat{y}_{ik} - 0.5\gamma_i\sigma_{ik}^2\right)$ captures the future land use restriction sensitivity component of the decision[2]. The parameter z_k is a measure of land use restriction imposed on the next generation who inherits the property. For example, if the value of z_k is set at 0.10, the off-spring agent (future generation) who inherits the property would receive 90% of the income from the property, as 10% of the property was locked for conservation by its predecessor and not available for income generation.

To determine the probability of selecting an option which depends on the utilities expected from each of those choices, we use McFadden's (1974, McFadden 1980) multinomial logit model (Equation 2).

$$p_{ik} = e^{u_{ik}} \Big/ \sum_k e^{u_{ik}} \qquad \text{(Equation 2)}$$

Where

p_{ik}	Probability of selecting option k by player i

An agent could select only one option and it will prioritize option k with high relative utility and, as a result, high probability of selection (p_{ik}).

[2] A standard mean-variance utility function does not have this component.

Studies have used a variety of risk aversion parameters. Lien (2002), for example, has estimated the value in the range of $6x10^{-8}$ to $2.022x10^{-6}$ based on a survey (1993-1998) of Norwegian lowland farmers. Similarly, Lien et al. (2011) used a value of $1x10^{-6}$ as the farmer's degree of absolute risk aversion for their optimization. Recently, Monjardino et al. (2013) used the value in the range from 0.0 (risk-neutral) to 0.035 (very risk-averse) for their modeling study on South Australian farms. These estimates are based on a standard mean-variance utility function, with no impact aversion component.

Based on a review of these various methods and estimates, we have randomly generated values for both risk aversion and impact aversion variables for individual agents in the range of 0 to 1 at the start. We then use an applicator dynamic system to model the evolution of these values, which we describe in the following sub-section.

2.2. Model of the evolution of social behaviour

In conjunction with the individual decision model, we use a replicator dynamic system[3] to model the evolution of agent behavior. Let there be N agents ($N = \{1,2 \ldots. , n\}$) in the system. W is the sub-set of agents with payoff in the top-quarter income group[4], i.e.,

$$\mathrm{j} \in \mathrm{W} \text{ if } y_j(t-1) \geq (\bar{y}(t-1) + 0.5(\max y\,(t-1) - \bar{y}(t-1))) \qquad \text{(Equation 3)}$$

Here, $\bar{y}(t-1)$ and $\max y\,(t-1)$ are the average and maximum income of the group in the previous time step. We assume that in each time step a new agent is borne who inherits the property. The new agent is likely to mimic (with 50% probability) the risk and impact aversion profiles of the better fit section of group (i.e., W) if its predecessor received lower payoff than top quarter group earning. In this case, the risk aversion and impact aversion parameters have been randomly generated with a uniform distribution in the range of minimum and maximum values of the better-fit section of the group. Otherwise, the agents will maintain the parameter values as their predecessors. Formally,

[3] Replicator dynamic system is a widely used tool to model biological evolution. It captures all three processes – selection, mutation and reproduction for evolution Brenner, T. 1999. *Modelling learning in economics.* Cheltenham: Edward Elgar. and is thus highly suitable for our study.

[4] This has been used a reference point to identify the better-fit section of the group. It is possible, of course, to use any reference points. Depending on the network structure the extent of the better-fit section for an agent would change.

If $i \notin W$ and $\alpha_i > 0.50$

then

$$\gamma_i(t) = uniform\left(\min \gamma_{j \in W}(t-1), \max \gamma_{j \in W}(t-1)\right)$$

and (Equation 4)

$$\delta_i(t) = uniform\ \left(\min\ \delta_{j \in W}(t-1), \max\ \delta_{j \in W}(t-1)\right)$$

Otherwise

$$\gamma_i(t) = \gamma_i(t-1) \text{ and } \delta_i(t) = \delta_i(t-1)$$

Here α_i is the probability to change strategies. In other words, the probability of a utility profile becoming replicated increases in proportion to the income earned by the agents with that profile.

We further assume that the agents live in a networked environment. An agent gets information from a specified subset of agents who are close by the network (Cassar 2007). Each agent i has s_i neighbours. Given the set S_i of neighbors of agent i, $S_i \subset N, |S_i| = s_i$, specifies an agent's neighborhood structure, the average payoff information the agent receives is calculated by:

$$\bar{y}_i = \frac{\sum_{j \in S_i} y_j}{s_i} \qquad \text{(Equation 5)}$$

In our computational experiments, we test the performances of the conservation programs under four main types of network structures (Corbae and Duffy 2008).

Local network: We assume two variations of the local network.

In the first structure, referred to as the local uniform matching variation (LUM), agents are only connected to their own type (Figure 1a). All agents of the same type are connected to each other. The second structure, referred to as local matching (LM), N agents are arranged in a circle and an agent may only interact with the s_i immediate neighbours. In this way, an agent is connected with the $s_i/2$ immediate agents on the right and the $s_i/2$ immediate agents on the left. In total, there are $\sum_i s_i$ connections. In our example, we presume that agents can interact with just one neighbour on the left and one on the right (Figure 1b).

Random network: Under a random network, each pair of individual agents has equal probability of being connected.

We design two random structures symmetric to the local network structures. In a random local uniform matching (RUM, Figure 1c) network, the total number of connections is set equal to the LUM. In random local matching (RM, Figure 1d) network, the total number of connections set equal to the LM. Yet, in both instances, agents could be linked with others who could be placed anywhere in the circuit.

Small-world networks: In a small-world network, most of the agents are connected to the same group as they would have under a local network. However, some of them could be randomly connected (with very low probability) with other agents who could be far apart in the circle.

We model two small-world network structures: small world local uniform matching (SUM, Figure 1e) network with the total number of connections equal to the LUM and a small world local matching (SM, Figure 1f) network with the total number of connections equal to the LM.

Uniform Matching (UM): This is a global network model where every agent is connected to each other (Figure 1g).

As such, they receive the same information about the community payoffs (i.e., $\bar{y}_i = \bar{y}_j, i \neq j$). We use aggregate outcomes under this network as the performance benchmark (reference network).

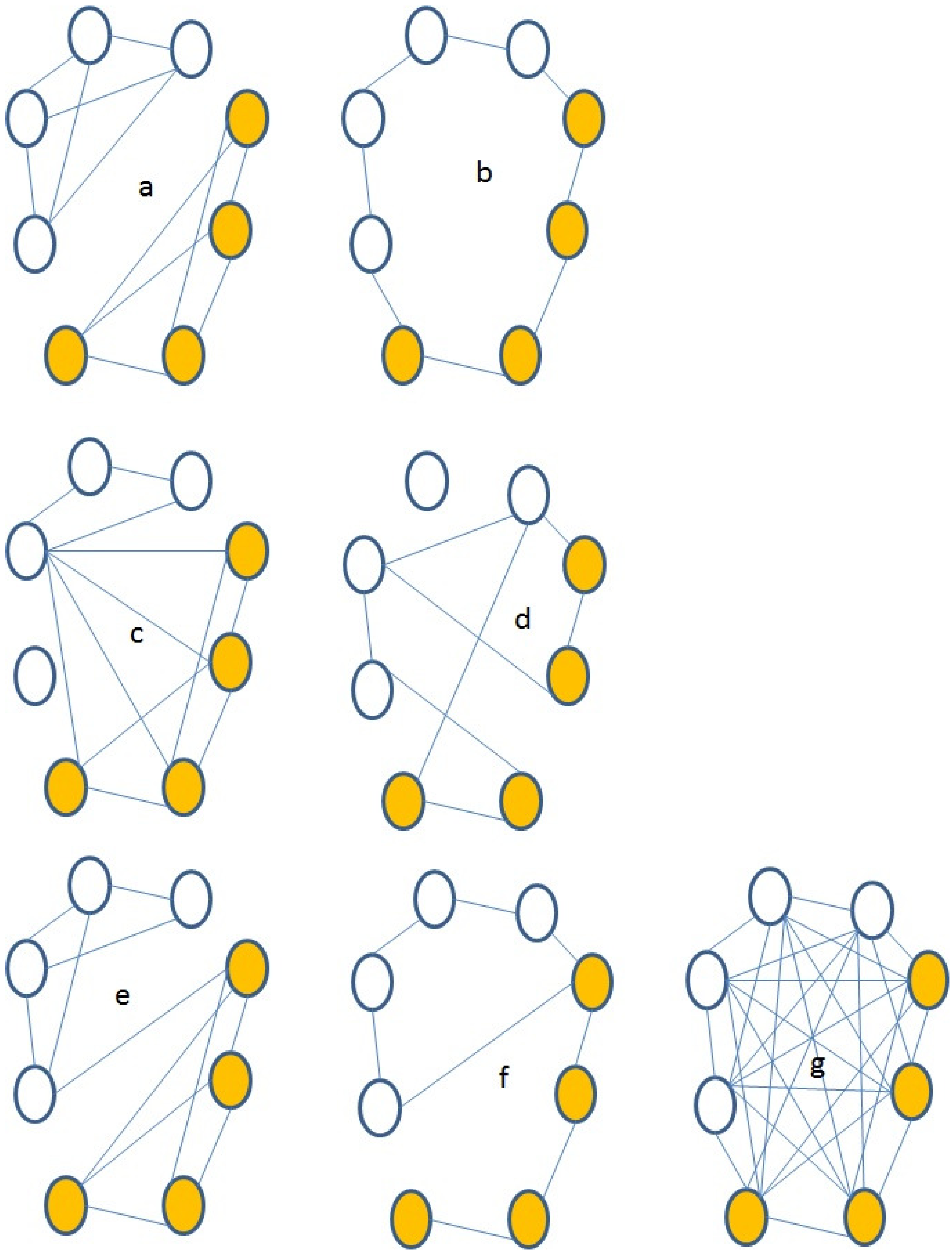


Figure 1: Schematic representation of different network structure: a) LUM, b) LM, c) RLUM, d) RLM, e) SLUM, f) SLM and g) UM

2.3. Conservation agency's decision model

Finally, we use a conservation agency's decision model to test the impact of land use restrictions under a fixed target. Under the fixed target program the agency decides on an enrolment target (ET) at the beginning of the program. In each time step it revises its prices (offers) on different options ($\lambda_k(t)$) depending on the enrolment status in the previous time steps. Agents (landholders) respond to the offer by either participating or not in the program.

In order to model an agency's price revision, we use a two-step optimization procedure. In the first step, a prediction model based on a linear regression system is used to calculate the slope co-efficient (s_k) between offered price and the number of landholders enrolled under each option. This is done by minimizing the squared distance ($e_k(t)^2$) between the observed ($OL_k(t)$) and estimated ($EL_k(t)$) number of landholders enrolled in each time-steps completed so far (i.e., $t \in \acute{T}$):

$$\min \sum_{t \in \acute{T}} e_k(t)^2 \qquad \text{(Equation 6)}$$

Where

$$e_k(t) = OL_k(t) - EL_k(t)$$
$$EL_k(t) = \lambda_k(t) \times z_k \times s_k$$

The derived slope coefficient values (s_k^*) are then used in the second optimization to determine the offer price per enrollment unit under each option k (o_k) to be offered in the next time-step. This is done by minimizing the total expected payment under the program (EP) subject to an expected enrollment (EE) target constraint.

$$\min EP$$

Where

$$EP = \sum_k (s_k^* \times o_k \times z_k) \times o_k$$

(Equation 7)

$$EE = \sum_k (s_k^* \times o_k \times z_k) \times z_k$$

$$EE \geq ET$$

The model minimizes the total expected payment subject to (a) the total expected payment which is a function of the slope co-efficients derived from equation 6, offer for each option (to be determined) and land use restrictions under each option, (b) the expected land to be enrolled (which is also a function of these three factors), and (c) ensuring that the expected area enrolled is not lower than the target. After solving this model the values for expected offers (o_k^*) are obtained, which is then used for setting offers for the next time-step (i.e., $\lambda_k(t+1) = o_k^*$) .

3. Computational experiments

The key features of our computational experiments are described below. We begin by describing the landholder profile. This is accompanied by a description of the simulation scenarios that have been considered. In the last sub-section, we discuss the indicators we use to analyse the results.

3.1. Landholder profile

For our simulations, we assume three different types of populations: homogenous farm income variability (H), increasing farm income variability (I) and declining farm income variability (D). In the H population scenario, farm incomes for all agents are generated from a normal distribution. The mean of the distribution is generated from a uniform random distribution 0.03 to 0.12. The standard deviation of the distribution is generated by multiplying the mean farm income of the agent by the standard deviation multiplier (SDM). The values for SDM are generated from a uniform distribution of 0.05 to 0.95.

In both I and D scenarios, the agent populations consist of four agent types (see Table 1) in equal proportions of the population. The agent types vary in terms of their opportunity costs (variability and mean farm incomes). In the increasing farm income variability scenario, the value of SDM is higher for agent groups with higher expected mean income. In the declining farm income variability scenario the trend is opposite and the value of SDM gradually declines as the mean expected income of the agent group increases.

Table 1: Distribution of opportunity costs (0000 $/Ha) for different agent types

Population	Agent Type	Mean	SDM
H	All	0.03 – 0.12	0.05 – 0.95
I	Group 1	0.03	0.05
	Group 2	0.06	0.35
	Group 3	0.09	0.65
	Group 4	0.12	0.95
D	Group 1	0.03	0.95
	Group 2	0.06	0.65
	Group 3	0.09	0.35
	Group 4	0.12	0.05

In each time step[5], the agency offers four different types of covenant programs with different level of land use restrictions (z_k): 0.05, 0.30, 0.55 and 0.90. Land use restriction set to 0.05 means that if an

[5] To test the impact of covenant programs the network structure is kept fixed between time steps. An alternative would be to allow the network structure to change through time.

agent selects this conservation option its offspring's income will be reduced by 5% as five percent of the productive land will be locked for conservation. Similarly, with 0.30, 0.55 and 0.90 levels the income of the offspring will be reduced by 30%, 55% and 90% respectively.

3.2. Simulation scenarios

Our primary research question relates to the impact of land use restrictions and laterntaive network structures on conservation program success. We have conducted simulation experiments in two main combinations:

- Target X Network simulations: As mentioned in Section 2.2, we consider seven different network types (UM, LUM, LM, RLUM, RLM, SLUM and SLM). The impact of different networks is tested under three enrollment target levels: low (5 conservation units), medium (10 conservation units) and high (15 conservation units). Option conservation units are calculated from the aggregation of covenanted land sets. The enrollment targets cover 28%, 56% and 83% of the maximum supply capacity of the agent population (i.e., if only covenants with highest restriction option (z_k = 0.90) is selected by every agent). We ran these combinations with increasing farm income variability (I) agent population.

- Heterogeneous Cost X Network combinations: It might be possible that the effect of network structure could depend on the underlying distribution of heterogeneity in opportunity costs. Therefore, we tested different network structures for three types of landholders profile as described in section 3.1. We ran these combinations with a medium level (i.e., 10 conservation units) target.

The overall design of the experiment with combination of opportunity costs heterogeneity, program types and network structure is presented in Table 2.

Table 2: Simulation scenarios

Simulation 1: (Network - Target Interactions)	
Enrollment target:	Network:
• 5 conservation units (28% of the maximum supply capacity)	L2, L25, R2, R25, S2, S25
• 10 conservation units (56% of the maximum supply capacity) and	and UM
• 15 conservation units (83% of the maximum supply capacity)	
Simulation 2 (Network - Cost Interactions)	
Landholder Cost profile:	Network:
• Increasing farm income variability (I)	L2, L25, R2, R25, S2, S25
• Homogenous farm income variability (H)	and UM
• Declining farm income variability (D)	

We developed our model using the General Algebraic Modeling System (GAMS©). Due to the stochastic processes involved in the model, we ran 100 simulations for each individual combination.

3.3. Performance measures

In order to compare the scenarios we have used the following indicators

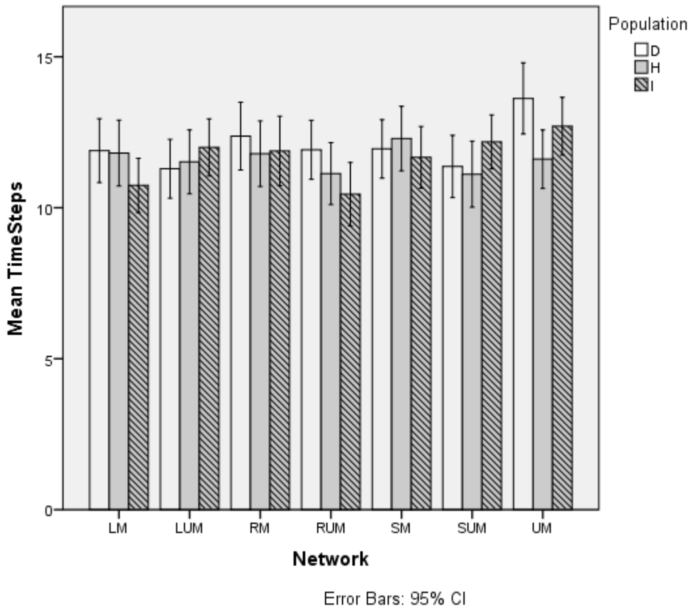
- Speed of convergence: Speed of convergence indicates how quickly different networks could achieve their target under different experimental scenarios. Speed of convergence is an indication of transfer or information under different networks.
- Level of enrolment: Even though we set the agency's target before the start of the program, we consider it is interesting to explore the levels of enrolment achieved by different network under different experimental scenarios. Understandably, under-achievement will indicate failure of the program and over-achievement will indicate wastage of valuable resources.
- Cost of purchase: We measure total costs and unit costs (costs per conservation units enrolled) as estimates for the agency's enrolment costs. The purchase cost has clear implications for government and non-government agencies engaged in conservation programs.
- Income: Average income and enrollment by agents in different groups has been calculated to understand the impact of cost heterogeneity.

4. Results

In this section, we present the results of the experiments. We start with the results for speed of convergence followed by level of enrollment, agency's procurement costs and the distribution of income among different landholder groups.

4.1. Speed of convergence

The average number of time-steps taken in different Cost X Network combinations and Target X Network combinations are presented in Figure 2. We observe that with low and high enrolment targets, more generations are required to arrive at the target level of enrolment. For example, on average it took 36 and 40 time steps respectively, for low and high level of enrollment targets to arrive within the 5 % range of the enrolment target. Whereas, it took 12 time-steps to achieve a medium level enrolment target. The results of a univariate analysis of variance indicate that the level of target has significant impact on the number of time-steps required to achieve expected enrolment targets. Nevertheless, we found no significant impact of networks ($p > 0.10$, Model 1, Table 3).



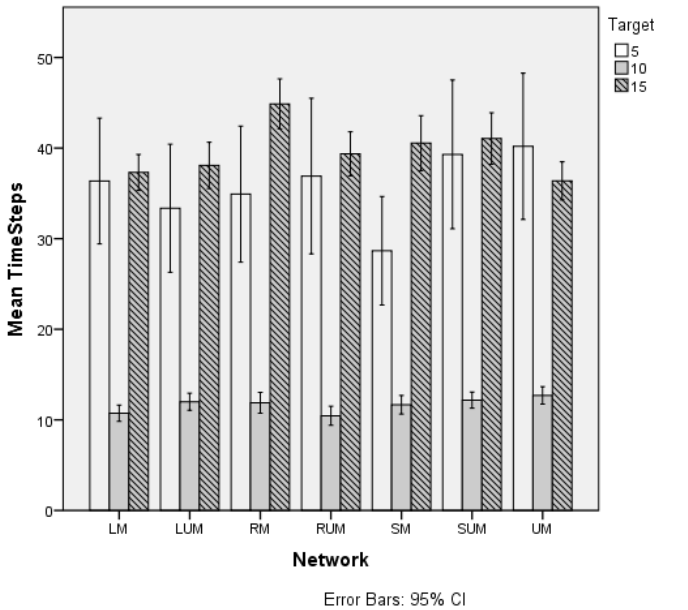


Figure 2: Minimum number of time steps required before the program reaches its target level (within ± 5%) of enrollment under Network - Target Interactions simulations and Network - Cost Interactions simulations.

We found limited variation in the number of time-steps required to achieve enrollment target among different landholder population compositions in Cost X Network simulations (Model 2, Table 3). However, we found no substantial difference in speed of convergence across the various price structures ($p > 0.10$). In contrast, network structure was found to significantly impact on the speed of the convergence. Duncan's range test indicates that UM, RM and SM networks took significantly more time-steps to achieve enrollment targets compared to other networks.

Table 3: ANOVA of the impact of networks, cost heterogeneity levels and level of targets on minimum number of time steps required to secure enrollment target

	Simulation 1: (Network - Target Interactions)					Simulation 2 (Network - Cost Interactions)				
	Type III Sum of Squares	df	Mean Square	F	Sig.	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	335585	20	16779	31	**	936	20	47	2	*
Intercept	1765984	1	1765984	3249	**	291202	1	291202	10765	**
Network	3819	6	637	1		415	6	69	3	*
Cost profiles						85	2	42	2	
Target	321243	2	160621	296	**					
Network * Cost						436	12	36	1	
Network*Target	10523	12	877	2	^					
Error	1130035	2079	5445			56240	2079	27		
Total	3231604	2100				348377	2100			
Corrected Total	1465620	2099				57175	2099			

4.2. Level of enrolment

Enrollment and program features panel regression models took into consideration:

1. Conservation program's enrolment target (represented by dummies for TR5, TR10 and TR15, with TR5 used as the benchmark);
2. Network structure (represented by dummies for UM, LUM, LM, RUM, RM, SUM and SM, with UM used as the reference category); and
3. Cost heterogeneity (represented by dummies for I, D and H, with H as the benchmark)

The results of the target X network simulations are presented in model 1 in Table 4. As expected, the level of purchase is significantly higher for higher levels of targets. Overall, a significantly lower number of conservation units were enrolled under RM network ($\beta_{RM} = -0.041$, $p < 0.05$; Model 1, Table 4) compared to UM network. However, there is no significant difference in the enrollment rate between LM, LUM, RUM, SM and SUM network structures with the UM network as reflected in the main effects ($p > 0.10$). Moreover, the significant interaction effects between networks and targets indicate that the pace of change in enrollment is significantly higher in TR5XUM combinations than any other combinations (except for TR10XLM, TR10XLUM and TR10XRUM).

The results for cost X network simulations are presented in model 1 in Table 5. Overall, there is no significant difference in enrollment under *D* and *I* population compositions with *an H population* ($p > 0.10$). However, in this case, the effect of UM network is even stronger. A significantly lower number of conservation units have been enrolled under RM ($\beta_{RM} = -0.101$, $p < 0.01$; Model 1, Table 5), SM ($\beta_{SM} = -0.044$, $p < 0.05$; Model 1, Table 5) and SUM ($\beta_{SUM} = -0.052$, $p < 0.05$; Model 1, Table 5) networks compared to UM network.

4.3. Total and per unit cost

Figure 3 and 4 graphically show the relationship between average total and per unit costs and cost heterogeneity structure and target levels. The associated regression analysis suggests that with an increase in the level of enrolment targets, the total cost and unit cost increased significantly as shown by the main effects of target levels in the analysis of target X network simulations (models 2 and 3 in Table 4). For example, with medium ($\beta_{TR10} = 8.66$, $p < 0.01$; Model 2, Table 4) and high ($\beta_{TR15} = 43.26$, $p < 0.01$; Model 2, Table 4) demand targets total costs of enrollment are significantly higher than low enrolment target (TR5). Similar trends can be observed for unit costs.

With regard to the main effects, there is no substantial difference between UM and other networks in terms of full costs and per unit cost of purchase for the agency ($p > 0.10$). However, interactions between target level and networks indicate that TR15 X RM combination incurred significantly higher total ($\beta_{TR15XRM} = 1.768$, $p < 0.01$; Model 2, Table 4) and per unit purchase cost ($\beta_{TR15XRM} = 0.174$, $p < 0.01$; Model 3, Table 4) compared to the TR5 X UM combination. On the other hand, TR15 X LUM combination incurred significantly lower total ($\beta_{TR15XLUM} = -2.185$, $p < 0.01$; Model 2, Table 4) and per unit purchase costs ($\beta_{TR15XLUM} = -0.119$, $p < 0.01$; Model 2, Table 4) compared to the TR5 X UM combination.

The positive impact of LUM in reducing total and per unit costs is observed in cost X network simulations presented in Table 5 (models 2 and 3). As shown by the main effects of network structure, LUM network allowed significantly lower total ($\beta LUM = -0.347$, $p < 0.01$; Model 2, Table 5) and per unit costs ($\beta LUM = -0.31$, $p < 0.01$; Model 3, Table 5) compared to UM network. Per unit costs are significantly higher under RM network compared to UM network. There is no significant difference in total and per unit costs under D and I population compositions with an H population ($p > 0.10$).

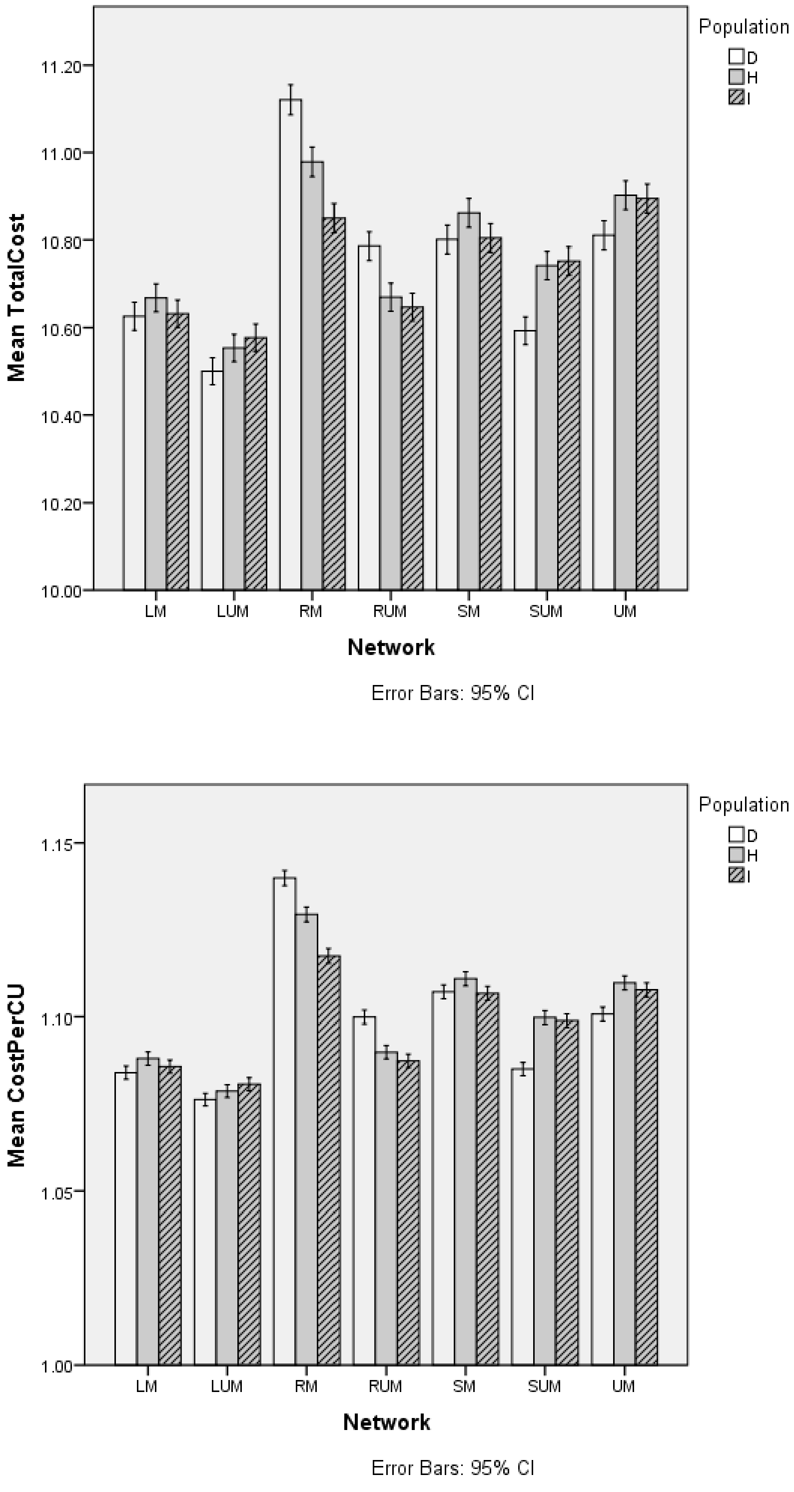
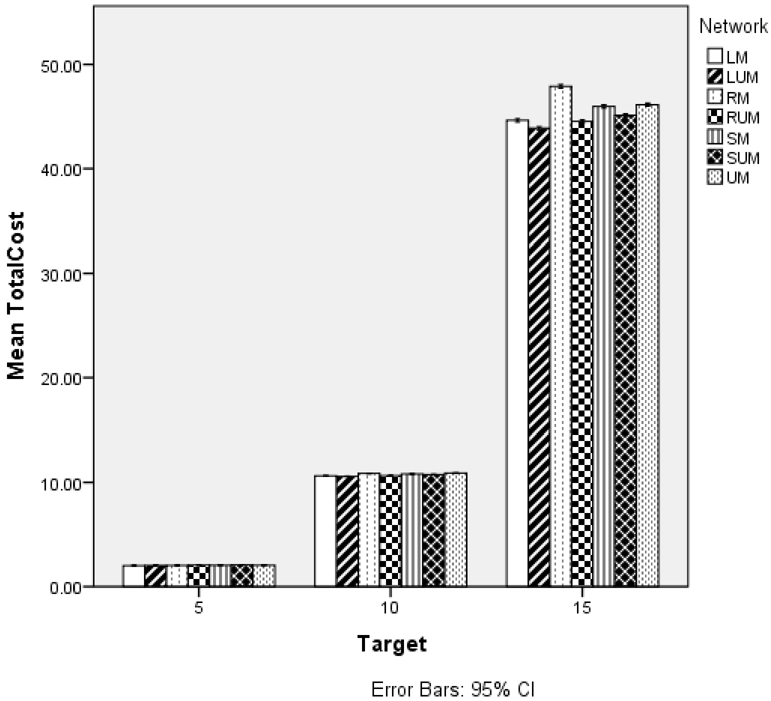


Figure 3: Average total cost and cost per unit of conservation unit enrolment by network and cost heterogeneity compositions under Network - Cost Interactions simulations.



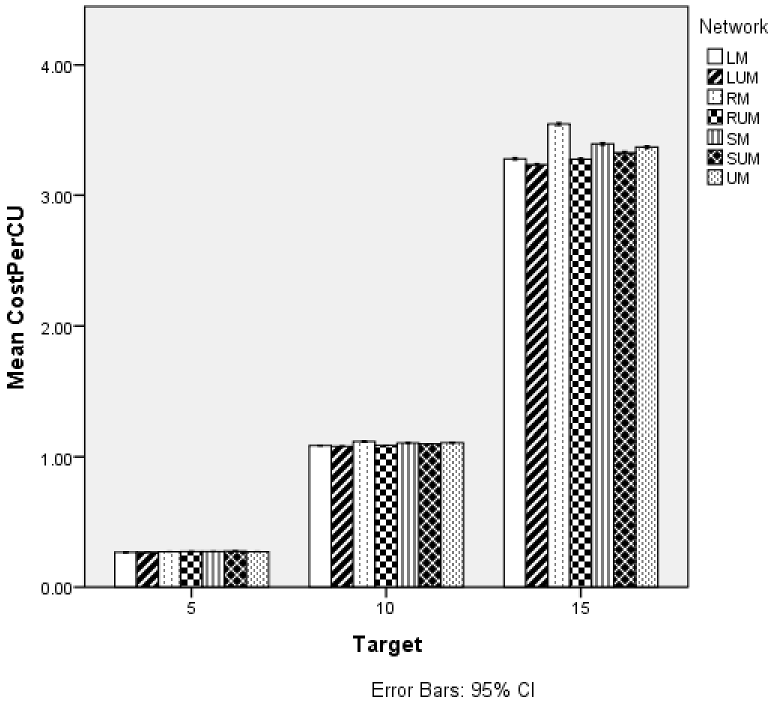


Figure 4: Average total cost and cost per unit of conservation unit enrolment by network and enrolment target under Network - Target Interactions.

Table 4: Panel regression model with AR (1) disturbances. Numbers of conservation unit enrolled, total cost and cost per unit of conservation unit enrolled with enrolment target and network structure.

	Model 1 (Conservation Units enrolled)		Model 2 (Total Cost)		Model 3 (Cost per conservation unit enrolled)	
	Coefficient	P	Coefficient	P	Coefficient	P
Level of target						
TR10	2.255	**	8.662	**	0.773	**
TR15	5.886	**	43.259	**	2.884	**
Network						
LM	-0.015		-0.036		-0.004	
LUM	0.005		-0.007		0.001	
RM	-0.041	*	-0.011		-0.001	
RUM	-0.006		0.014		0.002	
SM	-0.019		0.002		0.002	
SUM	0.016		0.031		0.003	
Target X Network						
TR10 X LM	-0.020		-0.214		-0.014	
TR10 X LUM	-0.045		-0.295		-0.024	
TR10 X RM	-0.080	**	-0.027		0.013	
TR10 X RUM	-0.032		-0.256		-0.016	
TR10 X SM	-0.047	^	-0.085		-0.002	
TR10 X SUM	-0.063	*	-0.172		-0.010	
TR15 X LM	-0.062	*	-1.440	**	-0.075	*
TR15 X LUM	-0.118	**	-2.185	**	-0.119	**
TR15 X RM	-0.142	**	1.768	**	0.174	**
TR15 X RUM	-0.091	**	-1.578	**	-0.084	*
TR15 X SM	-0.127	**	-0.140		0.027	
TR15 X SUM	-0.139	**	-1.025	**	-0.040	
Constant	7.45	**	2.08	**	0.29	**
Wald	625128.83	**	226243.24	**	86870.72	
R-sq:	0.71		0.86		0.89	
No. of observations	525000		525000		525000	

Note: Here, TR5 and UM are the reference categories. "**", "*" and "^" refer to significance at 1%, 5% and 10% level of significance respectively

Table 5: Panel regression model with AR (1) disturbances. Numbers of conservation unit enrolled, total cost and cost per unit of conservation unit enrolled with population composition and network structure.

	Model 1 (Conservation Units enrolled)		Model 2 (Total Cost)		Model 3 (Cost per conservation unit enrolled)	
	Coefficient	P	Coefficient	P	Coefficient	P
Cost heterogeneity level						
D	-0.005		-0.091		-0.009	
I	0.010		-0.008		-0.002	
Network						
LM	-0.013		-0.233	*	-0.021	*
LUM	-0.033		-0.347	**	-0.031	**
RM	-0.101	**	0.077		0.020	*
RUM	-0.032		-0.231	*	-0.019	*
SM	-0.044	*	-0.041		0.001	
SUM	-0.052	^	-0.160		-0.010	
Cost X Network						
D X LM	-0.001		0.048		0.005	
D X LUM	-0.020		0.036		0.006	
D X RM	0.035		0.230		0.018	
D X RUM	0.020		0.207		0.018	
D X SM	-0.013		0.031		0.005	
D X SUM	0.002		-0.058		-0.006	
I X LM	-0.022		-0.029		0.000	
I X LUM	-0.007		0.031		0.004	
I X RM	-0.021		-0.122		-0.010	
I X RUM	-0.006		-0.016		0.000	
I X SM	-0.022		-0.049		-0.002	
I X SUM	0.005		0.017		0.001	
Constant	9.696	**	10.887	**	1.105	**
Wald	91.980	**	74.660	**	122.240	**
R-sq:	0.000		0.003		0.010	
No. of observations	525000		525000		525000	

Note: Here, H and UM are the reference categories. "**", "*" and "^" refer to significance at 1%, 5% and 10% level of significance respectively

4.4. Enrolment and income by different groups

To understand the distribution of enrolment and income we examined the cost X network simulations. The average number of conservation units enrolled and the income received per agent by agent type have been plotted in Figures 5 and 6 respectively. We observe that agents from the last group (with higher expected mean income and lower variation) enrolled in covenanting program at a lower rate (i.e., has remained engaged in farming activity) than other groups in both I and D population scenarios. Even though the differences in enrollment by different groups are small, Wilcoxon signed rank test indicates that they are significantly different (Table 6). The last group faces lower income variability than other groups and hence gain lower utility from joining a conservation program. As a consequence, they also suffer less from land use restrictions. Both of these factors contribute in their higher average income than any other groups (Table 7).

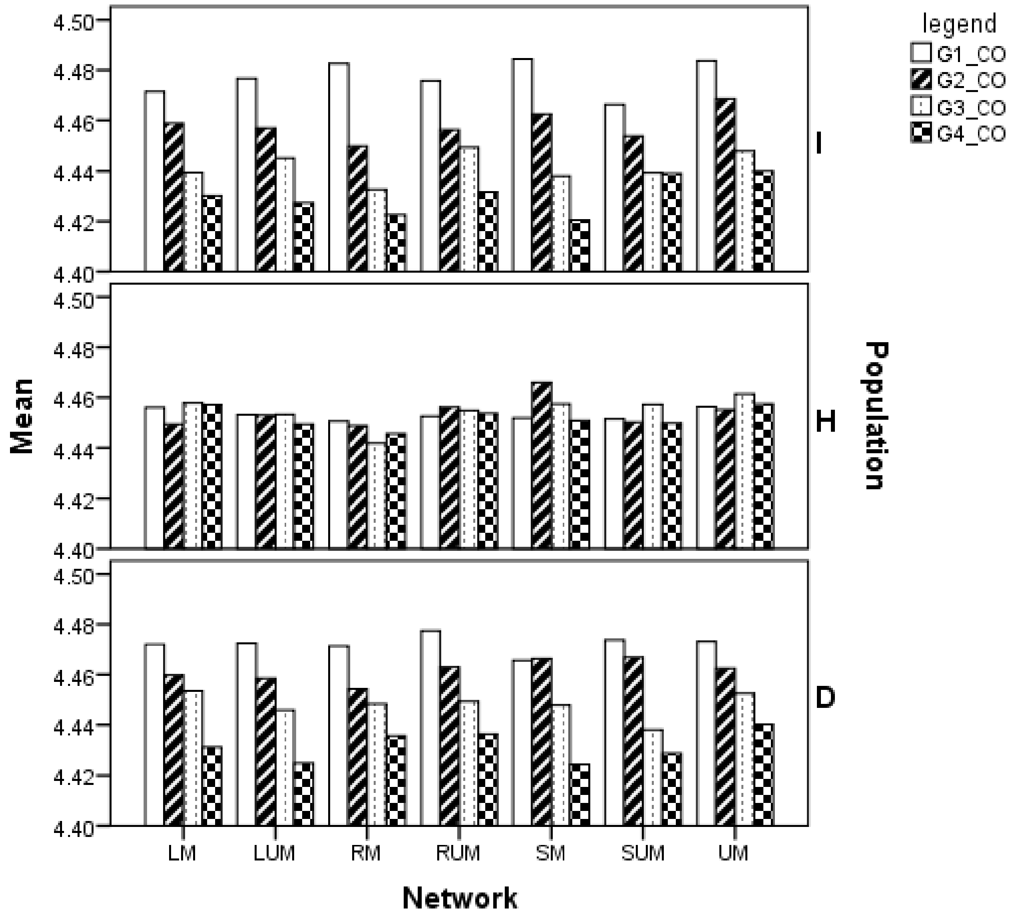


Figure 5: Average enrollment in conservation program by individual agents in different groups of landholders for different networks in Network - Cost Interactions simulations.

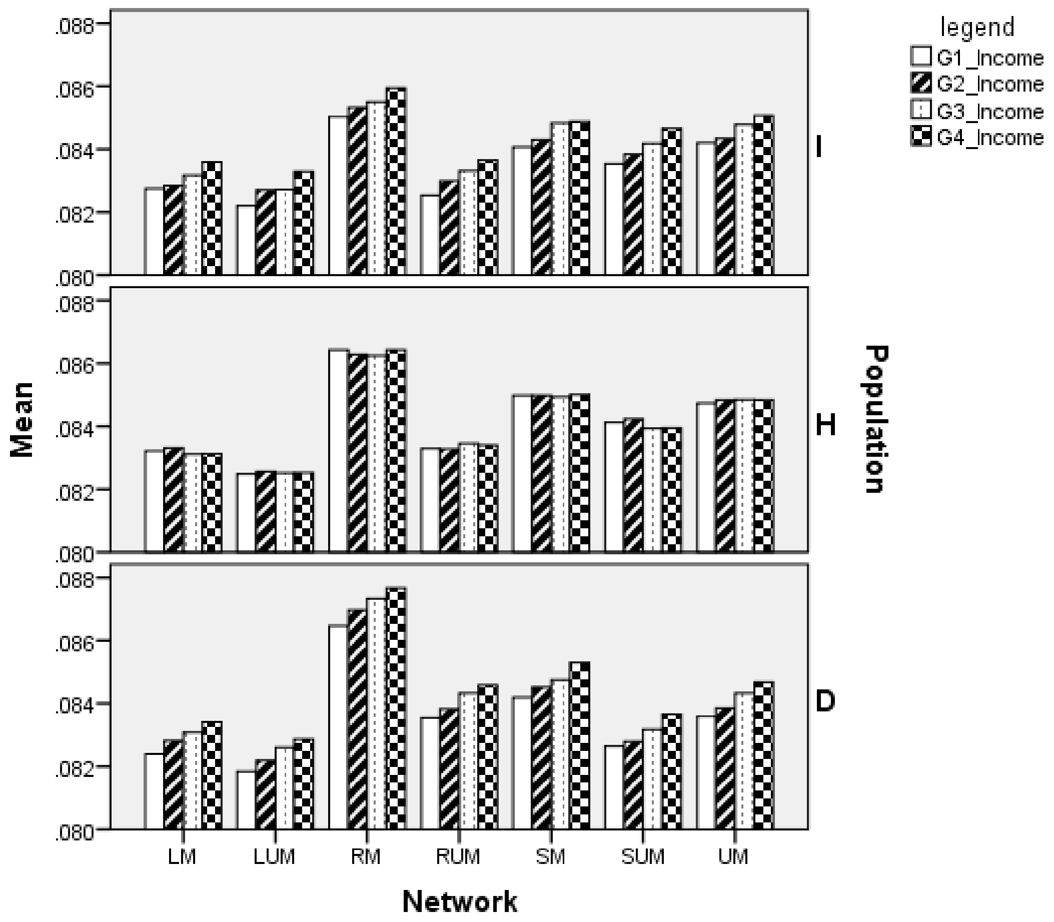


Figure 6: Average total income received by individual agents in different groups of landholders for different networks in Network - Cost Interactions simulations.

Table 6. Pairwise comparison between enrollment by different groups in different cost heterogeneity and network scenarios with two-sided Wilcoxon Signed Rank test: z-statistics

Cost heterogeneity	Network	G2:G1	G3: G1	G4: G1	G3: G2	G4: G2	G4: G3
D	LM	-2.02*	-2.88**	-6.63**	-1.03	-4.58**	-3.49**
	LUM	-2.22*	-4.16**	-7.53**	-1.91^	-5.39**	-3.43**
	RM	-2.82**	-3.54**	-5.47**	-0.93	-2.80**	-2.15*
	RUM	-2.41*	-4.51**	-6.61**	-2.02*	-4.29**	-2.17*
	SM	-0.03	-2.94**	-6.60**	-2.96**	-6.76**	-3.78**
	SUM	-1.08	-5.79**	-7.46**	-4.47**	-6.12**	-1.49
	UM	-1.61	-3.28**	-5.15**	-1.64	-3.49**	-2.06*
H	LM	-1.07	-0.41	-0.03	-1.47	-1.23	-0.26
	LUM	-0.18	-0.01	-0.74	-0.08	-0.61	-0.64
	RM	-0.18	-1.26	-0.75	-1.15	-0.65	-0.53
	RUM	-0.52	-0.40	-0.15	-0.11	-0.38	-0.22
	SM	-2.28*	-1.05	-0.22	-1.32	-2.32*	-1.12
	SUM	-0.16	-0.94	-0.14	-1.06	-0.07	-0.96
	UM	-0.17	-0.93	-0.21	-1.04	-0.23	-0.67
I	LM	-2.11*	-5.11**	-6.66**	-2.98**	-4.68**	-1.53
	LUM	-2.98**	-4.86**	-7.76**	-1.84^	-4.70**	-2.95**
	RM	-5.15**	-7.90**	-9.47**	-2.68**	-4.20**	-1.38
	RUM	-3.20**	-4.42**	-6.96**	-1.11	-3.92**	-2.73**
	SM	-3.52**	-7.46**	-10.10**	-3.87**	-6.71**	-2.76**
	SUM	-2.03*	-4.35**	-4.44**	-2.25*	-2.29*	-0.09
	UM	-2.43*	-5.63**	-7.06**	-3.13**	-4.49**	-1.31

Note: "**", "*" and "^" refer to significance at 1%, 5% and 10% level of significance respectively

Table 7. Pairwise comparison between average income per agent by different groups in different cost heterogeneity and network scenarios with two-sided Wilcoxon Signed Rank test: z-statistics

Network	Cost heterogeneity	G2:G1	G3: G1	G4: G1	G3: G2	G4: G2	G4: G3
LM	D	-1.45	-2.24*	-3.08**	-0.79	-2.02*	-1.04
	H	-0.49	-0.37	-0.06	-0.52	-0.66	-0.14
	I	-0.47	-1.58	-2.77**	-1.10	-2.37*	-1.30
LUM	D	-1.63	-2.53**	-3.64**	-1.10	-2.34*	-1.24
	H	-0.25	-0.52	-0.15	-0.10	-0.18	-0.03
	I	-1.75^	-1.67	-3.67**	-0.40	-1.92^	-2.21*
RM	D	-1.71^	-2.54**	-3.39**	-1.31	-1.86^	-0.67
	H	-0.69	-0.80	-0.21	-0.19	-0.41	-0.81
	I	-0.62	-1.30	-2.96**	-0.21	-1.90^	-1.44
RUM	D	-1.07	-2.18*	-3.30**	-1.53	-2.28*	-0.98
	H	-0.23	-0.54	-0.54	-0.47	-0.40	-0.17
	I	-1.71^	-2.83**	-3.92**	-0.94	-2.22*	-1.41
SM	D	-1.10	-1.32	-3.38**	-0.86	-2.56**	-1.85^
	H	-0.54	-0.16	-0.08	-0.29	-0.16	-0.45
	I	-0.52	-2.36*	-2.54**	-1.54	-2.22*	-0.47
SUM	D	-0.35	-2.20*	-3.54**	-1.19	-2.58**	-1.73^
	H	-0.57	-0.79	-0.49	-0.87	-0.98	-0.14
	I	-0.90	-2.24*	-3.65**	-1.10	-2.66**	-1.56
UM	D	-1.15	-2.50**	-3.39**	-1.54	-2.64**	-1.06
	H	-0.60	-0.20	-0.40	-0.04	-0.04	-0.09
	I	-0.47	-1.57	-2.94**	-1.72^	-2.02*	-1.01

Note: "**", "*" and "^" refer to significance at 1%, 5% and 10% level of significance respectively

5. Discussion

In this paper, we studied the impact of network structure on the enrolment rate in a conservation program. The influence of networks is manifested in terms of inter-generational impacts of conservation programs. Based on a stylized agent based model we have explored the impact changes in network structures have on the performance of conservation covenanting programs. Given our model set up, we asked with which network structure, it is possible to achieve conservation outcomes at lowest cost and how their cost-effectiveness vary with enrollment target and farm income variability.

We observed that under the local uniform matching (LUM) network the total and per unit cost of enrollment were lowest. In this network, agents are connected only with the agents within their own group. Therefore, every agent within a group received the same signal about the performance benchmark of the previous generation. The differences in agents' income in a network of similar type of agents are more influenced by their decision to enrol in covenanting program and received a certain payment, rather than from the differences in their expected income due to their type differences. Consequently, under local uniform matching networks the cost is significantly lower.

We found higher costs to a conservation covenanting program when agents are part of a random matching network compared to other networks. Under a random matching network, an agent has fewer connections than under UM, LUM and SUM. They have the same number of connections as LM and SM, but under RM an agent could be randomly connected to any agent in the population. Thus, individual agents are more likely to be influenced by a smaller number of agents who could come from any part of the whole network. If a low farm income agent is partnered with a high farm income agent, its offspring is likely to adopt the utility profile of the high farm income agents. However, high farm income agents are less likely to enrol in covenanting programs (unless the payment is sufficiently high). As a result, the agency has to increase the offers to secure its enrollment target.

Results from our analysis also show that land use restrictions have a significant negative effect on the level of enrolment in conservation programs. Our results are supported by the findings of many studies including Cross et al. (2011) and Lambert et al. (2007). In our model, the evolution of agent behavior plays a significant role as the agency has to increase its offer gradually as the time progresses before a stable point is reached. Such increases in enrolment costs are necessary, due to the negative reinforcement as agents with particular type of utility function enrolling in conservation programs impose some land use restrictions on its future generation, which in turn makes its offspring have lower income (or fitness) and less probability of being successful. As a consequence, the utility profile has less probability of being successful and propagates.

Enrolment rates could be influenced by enrollment target and farm income variability. We found a non-linear increase in program cost as the enrollment target is increased. This is related to the supply and demand ratio as the target is gradually increased more expensive lands are brought under conservation, which of course required higher payments. Similar observations have been made for an auction based conservation program by Iftekhar et al. (2014). The results from both our increasing and declining farm income variability scenarios confirmed that the high variable income landholders could improve their income (on average) by participating in a conservation program. Similar observations have been made by Armsworth et al. (2012). Based on a survey of the participating farmers in the Agri-Environment Schemes (AES) in northern England, they observed that once enrolled, many farmers relied on the payment from the schemes to compensate for the variability in the farm income. Therefore, it might be possible to increase enrolment rate (at lower cost) by targeting a select group of landholders facing highly variable farming income.

While our results are based on a stylized example, our findings lead to several possible policy suggestions for covenanting programs, like the U.S. Conservation Reserve Program. Our results demonstrate that the rate of uptake would depend on the network structure. In a random matching network, the enrolment in conservation programs could be low and the agency might have to invest more to secure its enrolment target. On the other hand, in a local uniform matching network, the acceptability of the program could be higher and it can be implemented at a lower cost. Thus, targeting small tightly knit groups could be more cost effective for conservation covenanting programs. As part of the project evaluation and design, it might be beneficial to carry out similar type of comparative analysis on the potential uptake of a program given the existing network structure of the target community to understand which types of programs would be more suitable and how the make the programs more attractive to the landholders.

Further research could extend the current model. It is possible to include public and private benefits from conservation covenanting in individual landholder's decision-making framework. It could be informative to explore other social benefits such as the possibilities that due to higher adoption of conservation programs more people might be attracted to live in the place. These issues will be explored further in future research.

References

Armsworth, P. R., Acs, S., Dallimer, M., Gaston, K. J., Hanley, N., and Wilson, P. 2012. The cost of policy simplification in conservation incentive programs. *Ecology Letters,* 15: 406 - 14.

Bodin, Ö. and Tengö, M. 2012. Disentangling intangible social–ecological systems. *Global Environmental Change,* 22(2): 430-39.

Brenner, T. 1999. *Modelling learning in economics.* Cheltenham: Edward Elgar.

Cassar, A. 2007. Coordination and cooperation in local, random and small world networks: Experimental evidence. *Games and Economic Behavior,* 58(2): 209-30.

Chavas, J.-P. and Pope, R. 1982. Hedging and production decisions under a linear mean-variance preference function. *Western Journal of Agricultural Economics,* 7(1): 99 -110.

Corbae, D. and Duffy, J. 2008. Experiments with network formation. *Games and Economic Behavior,* 64(1): 81-120.

Coyle, B. T. 1992. Risk aversion and price risk in duality models of production: a linear mean-variance approach. *American Journal of Agricultural Economics,* 74(4): 849-59.

--- 1999. Risk aversion and yield uncertainty in duality models of production: a mean-variance approach. *American Journal of Agricultural Economics,* 81(3): 553-67.

Cross, J. E., Keske, C. M., Lacy, M. G., Hoag, D. L. K., and Bastian, C. T. 2011. Adoption of conservation easements among agricultural landowners in Colorado and Wyoming: The role of economic dependence and sense of place. *Landscape and Urban Planning,* 101(1): 75–83.

Freund, R. J. 1956. The introduction of risk into a programming model. *Econometrica: Journal of the Econometric Society,* 24(3): 253-63.

Goldstone, R. L. and Janssen, M. A. 2005. Computational models of collective behavior. *Trends in Cognitive Sciences,* 9(9): 424-30.

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S. K., and Huse, G. 2006. A standard protocol for describing individual-based and agent-based models. *Ecological Modelling,* 198(1): 115-26.

Iftekhar, M., Hailu, A., and Lindner, R. 2014. Does it pay to increase competition in combinatorial conservation auctions? *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie,* 62: 411–33.

Iftekhar, M. S. and Tisdell, J. G. 2015. An agent based analysis of combinatorial bidding for spatially targeted multi-objective environmental programs. *Environmental and Resource Economics*: 1-22.

Janssen, S., Louhichi, K., Kanellopoulos, A., Zander, P., Flichman, G., Hengsdijk, H., Meuter, E., Andersen, E., Belhouchette, H., and Blanco, M. 2010. A generic bio-economic farm model for environmental and economic assessment of agricultural systems. *Environmental Management,* 46(6): 862-77.

Kabii, T. and Horwitz, P. 2006. A review of landholder motivations and determinants for participation in conservation covenanting programmes. *Environmental Conservation,* 33(01): 11-20.

Lambert, D. M., Sullivan, P., Claassen, R., and Foreman, L. 2007. Profiles of US farm households adopting conservation-compatible practices. *Land Use Policy,* 24(1): 72-88.

Lien, G. 2002. Non-parametric estimation of decision makers' risk aversion. *Agricultural Economics,* 27(1): 75-83.

Lien, G., Hardaker, J. B., van Asseldonk, M. A., and Richardson, J. W. 2011. Risk programming analysis with imperfect information. *Annals of Operations Research,* 190(1): 311-23.

Luzar, E. J. and Diagne, A. 1999. Participation in the next generation of agriculture conservation programs: the role of environmental attitudes. *Journal of Socio-Economics,* 28(3): 335-49.

McFadden, D. 1974. The measurement of urban travel demand. *Journal of Public Economics,* 3(4): 303-28.

--- 1980. Econometric models for probabilistic choice among products. *Journal of Business,* 53(3): 13-29.

Monjardino, M., McBeath, T., Brennan, L., and Llewellyn, R. 2013. Are farmers in low-rainfall cropping regions under-fertilising with nitrogen? A risk analysis. *Agricultural Systems,* 116: 37-51.

Purvis, A., Hoehn, J. P., Sorenson, V. L., and Pierce, F. J. 1989. Farmers' response to a filter strip program: results from a contingent valuation survey. *Journal of Soil and Water Conservation,* 44(5): 501-04.

Rahm, M. R. and Huffman, W. E. 1984. The adoption of reduced tillage: the role of human capital and other variables. *American Journal of Agricultural Economics,* 66(4): 405-13.

Valente, T. W. 2012. Network interventions. *Science,* 337(6090): 49-53.

Vance‐Borland, K. and Holley, J. 2011. Conservation stakeholder network mapping, analysis, and weaving. *Conservation Letters,* 4(4): 278-88.

Whyte, W. H. 1959. 'Securing open space for urban America: conservation easements.' in *Securing open space for urban America: conservation easements*. New York City: Urban Land Institute.

Appendix A. The Overview, Design concepts, and Details (ODD) Protocol

Purpose

This model has been developed to analyze the effect of social networks, farm income variability and conservation program characteristics (such as level of targets) on enrolment and conservation payments.

Entities, state variables, and scales

In our model, agents are individual landholders, characterized by the state variables: risk aversion parameters, impact aversion parameters, and opportunity costs deciding on signing conservation contracts with a central agency.

Process overview and scheduling

In our model the following steps are followed:

In the first time step, a population of landholder agents was generated and their risk aversion and impact aversion parameter values were randomly assigned. The risk aversion and impact aversion parameters determine their utility profiles. Depending on their utility profile they engaged in the program with maximum expected utility. The opportunity cost of enrolment in terms of forgone farm income was randomly drawn from a normal distribution for each agent as described in Table 1.

Once the individual agents' decisions were made, the state of nature was realized, and farm and conservation payment income was released. If an agent's previous generation entered into a conservation contract the offspring's income was reduced in proportion to the land use restrictions imposed under the program.

In the following time steps, a new set of agents with updated utility function inherits the properties. The agent's strategy was such that an offspring mimicked its predecessor's utility profile if its predecessor's income was within the top-quarter income group at a previous time $(t-1)$. Otherwise, the agent mimicked the more successful members (with income in the top quarter of the network) of the network.

This process was repeated through 250 time steps or generations.

Design concepts

Emergence: In the conceptualization of the design emergent phenomena includes nonlinearity in the effects of individual's utility function on enrolment and convergence of the total number of landholder engaged.

Adaptation: The society adapts as a whole as in each time steps individual agents mimic successful agents from the previous generation.

Objective: Agents' objective is to maximize their utility from land use.

Interaction: Agents can perceive average income of the better-fit section of the network at previous time steps. They also receive information about the distribution of the risk aversion and impact aversion parameter values for the better-fit section of the group.

Learning: The society as a whole effectively learns from previous generations and as such exhibits an evolution.

Sensing: Agents know their own status (characterized by their state variables) on which their utility function is based.

Stochasticity: In the first time step, the parameter values for individual agents' utility functions are randomly generated. In each time step, the income from farming is also randomly generated.

Observation: The following observations over time were recorded for model analysis: 1) Number of landholders of different types engaged in different conservation programs and farming; 2) Price paid for different types of covenants; and 3) Income per agent for different options and for different agent types.

Initialization

A total of 20 agents were created for each simulation. Agents' characteristics were randomly initialized. In the first time step, the values of risk aversion and impact aversion parameters for individual landholders were randomly generated from a uniform distribution of 0 to 1. The initial prices for options with different land use restrictions were also randomly generated in the range of 0 to 1. An agent's network structure is pre-determined at the beginning of a simulation.

Input data

The model does not use input data to represent time-varying processes.

Sub-models

Our model consists of three sub-models

- Individual agent's decision model
- Model of the evolution of social behavior
- Conservation agency's decision model

The details of the models are presented in section 2.