Miguel, Amblard, Barceló & Madella (eds.) Advances in Computational Social Science and Social Simulation
Barcelona: Autònoma University of Barcelona, 2014, DDD repository <http://ddd.uab.cat/record/125597>

Strategic Interactions and Information Exchange on Networks: An Agent Based Simulation Model of Landowner Behaviour in Conservation Incentive Schemes (Extended Abstract)

Simanti Banerjee

Department of Agricultural Economics, University of Nebraska, Lincoln, USA
Email: sbanerjee4@unl.edu

Savi Maharaj

Computing Science and Mathematics, University of Stirling, Stirling, FK9 4LA, Scotland, UK
Email: savi@cs.stir.ac.uk

Abstract— Starting with data obtained from human-subject experiments to investigate farmers' responses to a conservation incentive scheme, we derive a cognitive model of the farmers' decision-making behaviour, and implement this model within an agent-based simulation of farmers interacting via different types of social network. We find that the outcome of the scheme in early time periods is improved by providing more information to farmers. However, changing the structure of the social network by which the information is provided has no effect.

I. Introduction

THIS abstract contributes to the literature on the use of agent based simulation modeling to study the pattern of land use behaviour on privately owned geographical landscapes, specifically agricultural landscapes. Such landscapes deliver ecosystem services that are beneficial for mankind (Millennium Ecosystem Assessment Report 2005), including food and water provision, flood control, insect pollination services for crop cultivation, water quality maintenance and habitat and biodiversity protection. Land use behaviour pertaining to the provision of these ecosystem services is commonly incentivized with the help of conservation incentive schemes termed Payment for Ecosystem Services (PES) Schemes. These schemes entail financial compensation for private landowners, most commonly farmers, who adopt pro-conservation land uses on their property. The economic rationale behind such funds transfer is that many ecosystem services have public good features, leading to their under-provision by the private agent – thus increase in supply can be potentially affected by making targeted payments to farmers. Another rationale for these payments is that since the ecosystem services provided by the farmers have benefits for society, farmers should be compensated for producing these benefits. Examples of PES schemes include the Stewardship Scheme in the UK (Dobbs and Pretty 2004), the Conservation Reserve Program in the US (Ferris and Siikamäki 2009) and the Pago por Servicios Ambientales (PSA) in Costa Rica (Sanchez-Azofeifa et al. 2007).

In the domain of PES schemes, one issue that has received widespread attention is that adopting the same land use on parcels of neighbouring farms, or on parcels within a given distance of each other, can increase the delivery of many ecosystem services which have positive spatial synergies (Margules and Pressey 2000). The economic literature by Parkhurst et al. (2007), Warziniack et al. (2007), Watzold et al. (2010) and Banerjee et al. (2012 & 2014) has focused on the study of the Agglomeration Bonus (AB) subsidy, that incentivizes such spatially coordinated land use behaviour by neighbouring landowners. The AB is a two-part payment scheme with a base payment and a bonus contingent on spatial coordination of land uses by neighbours. In this format the AB takes the form of a coordination game with multiple Nash equilibria, each corresponding to a particular land use strategy, ranked in terms of their payoffs – under one Nash equilibrium situation, participants make more money than under the other. This is the Pareto efficient equilibrium. However, depending upon the payoffs, the equilibrium selection principle of risk dominance (Harsanyi and Selten 1988) may select equilibria other than the Pareto efficient one, resulting in coordination failure. Previous experimental work has analyzed performance of the AB scheme and coordination failure under various conditions such as repeated interactions with neighbouring farmers, or the possibility of communication before making land use decisions (Parkhurst and Shogren 2007; Warziniack et al 2007).

Banerjee et al. (2012, 2014) focus on behaviour on simple local networks where every farmer has two neighbours whose actions determine whether they receive AB bonus payments or not. Laboratory experiments are used to explore the performance of the AB scheme in achieving cooperation amongst farmers over repeated periods of strategic interaction. In this paper we build upon these experimental results, first by extracting from them a cognitive model of the farmers' decision-making behaviour in response to the scheme, and then by using agent-based simulation to investigate how the performance of the AB scheme is affected by the amount of information available to farmers and the source from which this information is received. Our model adds to the large body of agent-based modelling literature focusing on the study of land use change and decision making under various economic settings as applicable to environmental management and conservation (Berger 2001; Filatova et al.; Ng et al. 2011). We also contribute to the growing body of work on combining agent-based modeling with human-subject experimentation (Duffy 2006).

Our cognitive model combines imitative learning (Eshel et al. 1998) and myopic best response (Morris 2000), along with force of habit (Blume 1993, Kahneman 2003) and a non-specific, time-dependent learning effect. Simulations using this model show that giving farmers more information about other farmers' choices and payoffs leads to higher levels of cooperation during early periods. However, changing the source of that information – whether it comes from local neighbours only or from long-range contacts in a small world network – has no effect on cooperation levels.

II. Methods

A. Experimental data

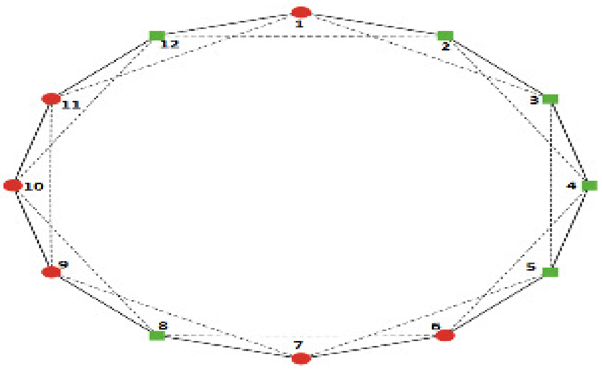

Fig. 1. Network structure in human subject experiments. The geographical network (solid lines) is a ring of 12 farmers. The information network is either a ring (solid lines only) or a ring lattice (solid and broken lines). Squares represent subjects adopting strategy M and circles represent subjects adopting strategy K.

The starting point of our work is data from human subject experiments by Banerjee et al. (2014). These experiments considered networks of 12 subjects representing farmers arranged geographically on a ring, as pictured in Figure 1. Each subject on this network is geographically adjacent to two neighbours, one on the left and one on the right, termed direct neighbours. From a conservation perspective a ring network is useful as it is representative of many geographical landscapes, such as riparian landscapes, but removes potential sources of confounding due to edge effects. Experiments lasted for 30 periods. During a period, each subject was asked to choose between two alternative strategies, M (the "efficient, cooperative" choice) and K (the "inefficient" choice), represented as green squares and red circles, respectively, in the figure. Subjects were provided with a payoff table (Table 1) informing them of the payoffs they would receive for each choice, depending upon the choices of their direct neighbours in the same period. For example, subject 1 in Figure 1 receives a payoff of 60 (the player's choice is K and the neighbours' choices are MM). In each period, subjects are informed of certain other subjects' choices and payoffs in the previous period. In one treatment, this information comes from directly linked neighbours only. In a second treatment, the information also comes from indirect neighbours, who are the direct neighbours of the subject's two direct neighbours on both sides (pictured as broken lines in Fig 1).

Experiments were carried out during 12 sessions (6 for each treatment), with 12 participants at each session. The experimental data (see for example, Figure 4) shows a relatively high initial level of cooperation which declines steadily over time.

Table I.
Payoffs in the Agglomeration Bonus Game

	Direct neighbors' choices		
Landowner choice	MM	MK	KK
M	**90**	50	10
K	60	70	**80**

B. Cognitive model

Many models of human decision making in iterated strategic interactions have been proposed in the literature. Myopic best response (Morris 2000) models cognitively sophisticated agents capable of strategic thinking. In this model, an agent's choice for the current period is the strategy that is the best response to the situation faced in the previous period. So for example, subject 1 in Figure 1 will choose strategy M in the next period, as that is the best response to the situation where both neighbours (subjects 2 and 12) having chosen M previously will do so in the current period as well.

Imitation (Eshel et al. 1998) is an alternative model which requires less cognitive ability on the part of agents. In this model, an agent simply considers the strategies and payoffs of its neighbours from the previous period, and copies the most rewarding strategy in the current period. Force of habit (Blume 1993, Kahneman 2003) is an even simpler model that captures the fact that human beings are cognitively sluggish and tend to repeat the same behaviour even when it might be in their economic interest to change.

Our cognitive model combines myopic best response, imitation, and force of habit, together with a period term intended to capture other, non-specific forms of learning over time that might take place (for example, growing apathy or cynicism leading to reduced willingness to cooperate). The model was derived by applying logistic regression to the strategic choices of the human subjects in experiments. The model gives the probability (p) that an agent will choose strategy M in the next period. The model includes three binary predictors, representing whether strategy M is the choice predicted by myopic best response (MBR), imitation (Imit), and force of habit (Habit), respectively. The time period (t) is the final predictor. Table 2 shows the details of the statistical analysis. The estimated regression equation is:

$$log\left(\frac{p}{1-p}\right) = -2.42 + 2.83\,MBR + 0.69Imit + 2.88\,Habit - 0.05t$$

TABLE 2.
STATISTICAL DERIVATION OF THE COGNITIVE MODEL

Random-effects logistic regression
Number of observations: 4176
Number of agents: 144 (exactly 29 observations per group)
Random effects u_i ~ Gaussian
Wald $chi^2(4)$ = 929.18 Prob > chi^2 = 0.00

	Coef	Std Err	z	P > [z]	[95% conf. int.]	
MBR	2.83	0.20	14.16	0.00	2.44	3.22
Imit	0.69	0.17	4.15	0.00	0.36	1.02
Habit	2.88	0.17	17.26	0.00	2.56	3.21
t	-0.05	0.01	-5.39	0.00	-0.07	-0.03
constant	-2.42	0.20	-11.97	0.00	-2.82	-2.03

C. ABM dynamics

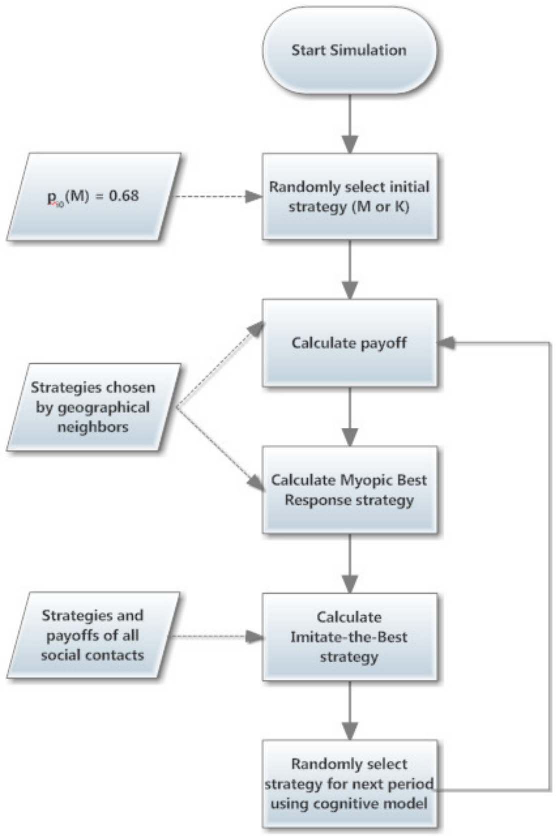

Fig. 2. Flow diagram for a single agent *i*.

Figure 2 illustrates the logic followed by a single agent *i* in the simulation. Initially, the agent will randomly select either strategy M or K, with a probability of 0.68 of choosing M. This probability reflects the proportion of times M was chosen by the experimental subjects in the initial period. The payoffs for the current period are then calculated. The strategies chosen by direct neighbours are examined and used to calculate the myopic best response prediction for the next period. The strategies and outcomes for all social contacts are examined and used to calculate the imitation-based prediction for the next period. Finally, these predictions are fed into the cognitive model equation, yielding a probability $p_{it}(M)$ that agent *i* will select M in the next period *t*, and the agent randomly chooses a strategy according to this probability.

D. Social network treatments

The literature on community natural resource management (Bodin et al. 2009; Prell et al. 2009) suggests that social networks within farming communities play an instrumental role in determining the success of natural resource management initiatives. In our model, the social network acts as the source of information about other farmers' strategic choices and consequent payoffs. We consider the impact of varying two aspects of these social networks 1) the number of social contacts per agent, which determines the amount of information the agent receives, and 2) the topology of the network.

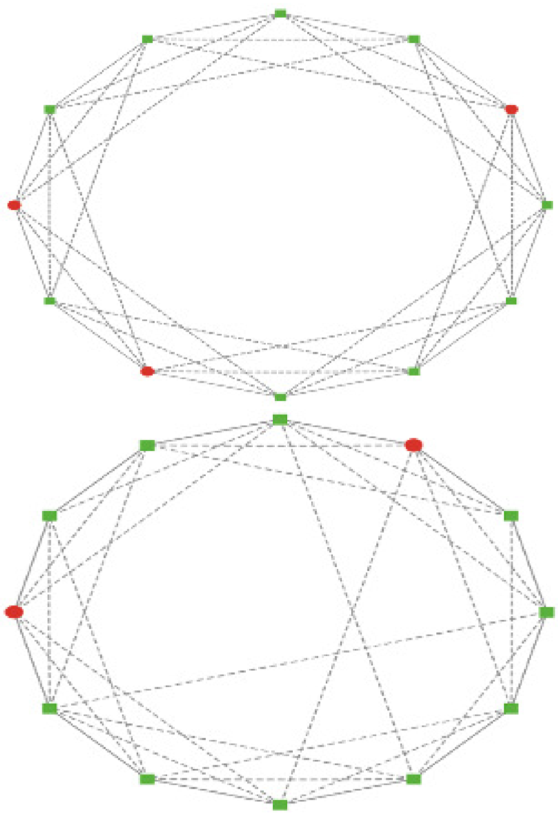

Fig. 3. Geographical network of a ring of 12 farmers with two different social networks. Solid lines represent the geographical network; solid and broken lines represent the social network. Top: regular social network where each agent has exactly 6 local contacts. Bottom: small world social network where each agent has on average 6 contacts which may be local or long-range.

Agents may receive information, not only from their two direct, geographical neighbours, but also from indirect neighbours, a situation referred to as information spillover. To study the impact of the amount of information received, we consider a range of information spillover setups, starting from the minimum setup where an agent's only social contacts are its two geographical/direct neighbours, to one in which the social network is a fully-connected clique. Figure 1 and Figure 3 (top) show two points on this range, illustrating the cases where each agent has, respectively, 4 and 6 social contacts. The social networks in this study are regular networks, of a ring-lattice type, with varying degree.

To study the impact of the network topology, we begin with the regular social networks of the previous stage, and rewire some of the links by replacing them with random links. The effect of rewiring is to replace some local links with long-range links. This reduces the diameter of the network, allowing information to flow more quickly between nodes that are geographically distant. The resulting networks have the small-world property, which has been observed in many real world social networks (Watts and Strogatz, 1998) and has been found to influence the dynamics of many processes that take place on those networks, e.g., epidemic spread and control (Maharaj and Kleczkowski, 2012). By varying the probability of rewiring, we create a range of social networks, from ones with only local links (Figure 3, top), to small world networks (Figure 3, bottom), up to fully random networks. (We note that rewiring, as implemented in our model, may cause links with direct neighbours to be lost, which is arguably unrealistic).

III. Results

A. Comparison of cognitive model with experimental data

Figure 4 shows a comparison of the experimental data with simulations using our cognitive model with the same geographical and social network setups used in the experiments. Here, the information network is a ring lattice, as shown in Figure 1. We also show the results of simulating two simpler cognitive models: pure myopic best response and pure imitation. As the figure shows, neither of the simpler models yields results that resemble the experimental data, therefore it seems likely that the cognitive process employed by experimental subjects is more complicated than either of these. As a measure of model fit we can use the sum of squared differences between the model result and the experimental result at each time step. The imitation model scores 142471 and the myopic best response model scores 23938. Our cognitive model, which combines these simple models with force of habit and a non-specific time-dependent learning effect, captures the behaviour of the experimental subjects better, particularly in the early periods, having the best score (10737). The correspondence between the model and the experimental data is even better in the case of the simple ring network (not shown).

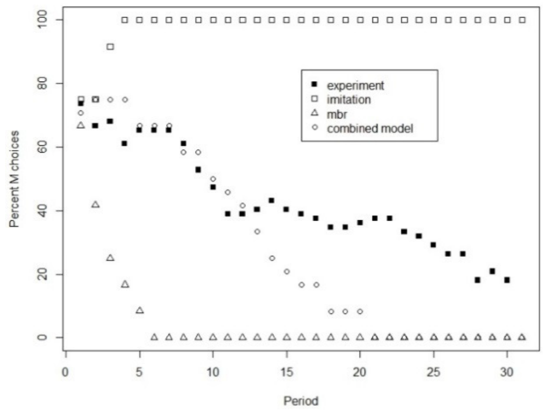

Fig. 4 Comparison of experimental data with simulations of myopic best response, imitation, and the combined model. The figure shows the percentage of cooperation (M choices) by period. The geographical and information networks are as in Figure 1. Simulation results show the median of 1000 replicates. In all cases, the information network is a ring lattice (direct and indirect neighbours) as shown in Figure 1.

B. Effect of information

Figure 5 shows the results of increasing the amount of information available to agents. In this figure, simulations are done on regular networks with local social contacts, of the form shown in Figure1 and Figure 3 (top). Our results indicate that given the current adverse payoff structure (whereby there is not much payoff difference between a player and neighbours choosing M or K) on a local network, increasing the information available to agents increases their likelihood of efficient coordination in the short term but does not prevent the inefficient strategy from becoming contagious in the long run. Thus performance of AB-based PES schemes should consider mechanisms to ensure that the efficient outcome can be obtained in the presence of more information even if repeated interaction has a tendency to transition the system to the inefficient outcome.

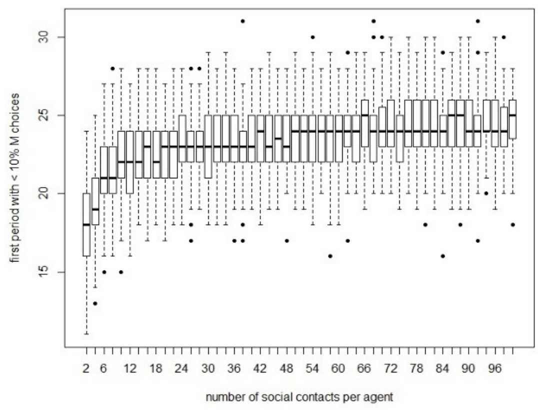

Fig. 5. Number of periods taken for the percentage of M choices to fall to 10% or less, against number of social contacts, in a regular network of 100 nodes with local information. Each box represents 100 replicates. Increasing information leads to greater cooperation in early periods

Surprisingly, introducing long-range, non-local links into the social network has no effect on cooperation. Figure 6 shows typical results. Here, the total number of links in the network is kept fixed at 200 (equivalent to a ring lattice as in Figure 1), but the probability of replacing a local link with a randomly chosen, possibly long-range link, is varied from 0 to 1. The time taken for cooperation to drop below 10% is the same, regardless of the structure of the social network. (Note that the result for the case where there is no rewiring differs slightly from the equivalent case in Figure 5; this appears to be due to stochastic differences between the simulations used in the two figures.)

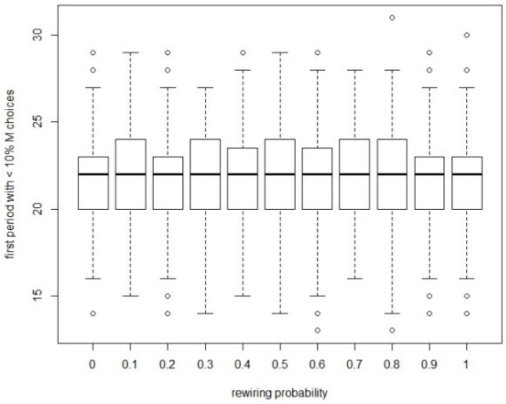

Fig. 6. Number of periods taken for the percentage of M choices to fall to 10% or less, against rewiring probability, in a Watts-Strogatz information network of 100 nodes. Each box represents 100 replicates. Replacing local with long-range information has no effect on cooperation.

IV. Conclusion

We evaluate spatial coordination of agents in an AB scheme when they are arranged on a ring and receive information about others' actions through social networks of varying topologies. We find that additional information and network structure play only a limited role in maintaining efficient coordination over repeated periods of strategic interaction. Future research in this context may thus involve devising and testing different ways of preventing contagion of the inefficient action. One option would be to evaluate agent behaviour when the payoff difference between efficient and inefficient equilibria is much higher than what we consider. Another option is to explore whether information about AB scheme decisions from neighbouring communities can influence agents' to coordinate efficiently. This is important since conservation agencies usually have access to this information that they can make available to farmers at minimal cost. Finally, noting that the network structure does not matter, it would be interesting to use a mean-field mathematical model to simulate behaviour and evaluate AB scheme outcomes.

References

[1] Alós-Ferrer, C., and S. Weidenholzer. 2008. "Contagion and efficiency." Journal of Economic Theory 143 (1): 251-74.

[2] Banerjee, S, A.M. Kwasnica and J.S. Shortle. 2012, 3.Agglomeration Bonus in Small and Large Local Networks: A Laboratory Examination of Spatial Coordination. *Ecological Economics,* 84, pp. 142 – 152,

[3] Banerjee, S, F.P. deVries, N. Hanley and D. van Soest. 2014. The Impact of Information Provision on Agglomeration Bonus Performance: An Experimental Study on Local Networks. *American Journal of Agricultural Economics*, forthcoming

[4] Berger, Thomas. 2001. "Agent-based Spatial Models Applied to Agriculture: A Simulation Tool for Technology Diffusion, Resource use Changes and Policy Analysis." Agricultural Economics 25 (2-3): 245-260.

[5] Berninghaus, S.K., K.M. Ehrhart, C. Keser. 2002. "Conventions and local interaction structures: experimental evidence." *Games and Economic Behavior* 39 (2): 177-205.

[6] Blume, L. E. 1993. "The statistical mechanics of strategic interaction." *Games and Economic Behavior* 5 (3): 387-424

[7] Bodin, O. and B.I. Crona. 2009. "The role of social networks in natural resource governance: What relational patterns make a difference?" *Global Environmental Change* 19: 366 - 374

[8] Dobbs T.L and J.N. Pretty. 2004. Agri-Environmental Stewardship Schemes and "Multifunctionality". Applied Economic Perspectives & Policy, 26(2), 220-237.

[9] Duffy, J. 2006. "Agent-Based Models and Human Subject Experiments". In *Handbook of Computational Economics*, Testfatsion L and Judd KL (eds.), Elsevier, edition 1, 2(2).

[10] Eshel, I., Samuelson, L., Shaked, A., 1998. Altruists, egoists, and hooligans in a local interaction model. The American Economic Review 88, 157–179.

[11] Ferris J, and Siikamäki J. 2009. "Conservation reserve program and wetland reserve program: Primary land retirement programs for promoting farmland conservation." RFF Backgrounder, Resources for the Future.

[12] Filatova, Tatiana, Alexey Voinov, and Anne van der Veen. 2011. "Land Market Mechanisms for Preservation of Space for Coastal Ecosystems: An Agent-Based Analysis." Environmental Modelling & Software 26 (2): 179-190.

[13] Harsanyi, J. C., and R. Selten. 1988. "A general theory of equilibrium selection in games." MIT Press Books, Cambridge, USA.

[14] Millenium Ecosystem Assessment, 2005. http://www.maweb.org

[15] Keser, C., K. Ehrhart and S.K. Berninghaus. 1998. " Coordination and local interaction: experimental evidence." *Economics Letters* 58(3): 269-275

[16] Kahneman, D. 2003. "Maps of bounded rationality: Psychology for behavioural economics." The American Economic Review 93 (5): 1449-75.

[17] Maharaj, S and Kleczkowski, A (2012). Controlling epidemic spread by social distancing: do it well or not at all. BMC Public Health 08/2012; 12(1):679.

[18] Margules, C. R., and R. L. Pressey. 2000. "Systematic conservation planning." Nature 405 (6783): 243-53.

[19] Morris,S. Contagion, Rev. Econ. Stud. 67 (2000) 57–78.

[20] Ng, Tze Ling, J. Wayland Eheart, Ximing Cai, and John B. Braden. 2011. "An Agent-Based Model of Farmer Decision-Making and Water Quality Impacts at the Watershed Scale Under Markets for Carbon Allowances and a Second-Generation Biofuel Crop." Water Resources Research 47 (9): - W09519.

[21] Parkhurst, G. M., and J. F. Shogren. 2007. "Spatial incentives to coordinate contiguous habitat." *Ecological Economics* 64 (2): 344-55.Prell, C., K. Hubacek and M. Reed. 2009. "Stakeholder Analysis and Social Network Analysis in Natural Resource Management". *Society and Natural Resources* 22: 501-518.

[22] Sánchez-Azofeifa, G. A., Pfaff, A., Robalino, J. A. and Boomhower, J. P. (2007), Costa Rica's Payment for Environmental Services Program: Intention, Implementation, and Impact. *Conservation Biology*, 21: 1165–1173.

[23] Warziniack, T., J. F. Shogren, and G. Parkhurst. 2007. "Creating contiguous forest habitat: An experimental examination on incentives and communication." *Journal of Forest Economics* 13 (2–3) (8/6): 191-207.

[24] Watts, D. J. and Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature*, 393.