Formation of farmers' pro-environmental behavior: an agent-based simulation based on the theory of planned behavior

Abstract. This study presents an agent-based model based on the theory of planned bebaviour (TPB) to understand how farmers form the intention and behavior of adopting pro-environmental practices. We analyze the three basic factors of TPB and design quantification method including nonlinear programming model and social network model. The model was applied to simulate rice farmers' decisions of the application of slow-release fertilizer (SRF) and the use of nitrogen deep placement (DPN) under different policy scenarios. Our results indicate that agricultural subsidy policy can promote the adoption of both SRF and DPN. However, agricultural carbon trading is efficient for SRF but seems ineffective for DPN.

Keywords: Pro-environmental behavior · Agent-based model · The thoery of planned behavior.

1 Introduction

Sustainable development of agriculture is threatened by nonpoint source pollution. Various protection measures aiming to encourage the adoption of environmentally farming practices are implemented in many countries. However, farmers' participation in agri-environmental programmes is generally low worldwide (Chabé-Ferret & Subervie, 2013). Understanding what drive farmers' participation is crucial to improve the effectiveness of such programmes. Existing studies have shown that farmers' decision-making, especially in changer farming practices is affected by not only economic factors but also social and institutional factors (Bourceret et al., 2022; Sok et al., 2020).

Theory of planned behavior (TPB) (Ajzen, 1991) provides a framework for integrating economic, social and institutional factors into the analysis of behaviors. It has been increasingly used to understand farmers' pro-environmental behaviors. In this study, we developed an agent-based model grounded on TPB to investigate farmers' intention and behavior of adopting pro-environmental practices.

2 Modelling framework

2.1 Theory of planned behavior

According to the TPB, intention is a reliable predictor of actual behavior (Ajzen, 1991). Intention depends on three basic factors: behavior attitude, subjective norm, and perceived behavior control. These factors and their interrelationships (see Fig.1) are clearly defined and formalized (Zhang & Nuttall, 2011).

Behavior attitude In this study, behavior attitude is represented by expected benefits of the technology under consideration, which is a comprehensive measure of perceived value. Integrate the nonlinear programming model to calculate the maximum expected benefits of the different agricultural technologies under the constraints, and then use the expected benefits as an assessment of the behavioral outcomes:

$$\begin{aligned} & a_i^{tech} = \max(P_{tech} - C_{tech}) \\ & s.t. \begin{cases} C_{tech} \leq B_t \\ X_1, X_2, ..., X_k \geq 0 \end{cases} \end{aligned} \tag{1}$$

Where P_{tech} is the expected income of the agriculture activity, calculated according to the Leontief production function. The total cost C_{tech} is bounded with endowment B_t which remained from the last period. $X_1, X_2, ..., X_k$ represent the amount of inputs about each production factor.

Subjective norm We use peer production behavior as a proxy of subjective norm (Schwarz & Ernst, 2009; Zhang & Nuttall, 2011). Following existing studies (Schwarz & Ernst, 2009; Tong et al., 2018; Bourceret et al., 2022), we use descriptive norm in place of subjective norm. A farmer's descriptive norm is measured as the proportion of farmers who adopt the same innovative technology in one's network. Farmer's technology choice is continuously updated during the simulation.

$$s_i^{tech} = \frac{\sum d_{j,t-1}^{tech}}{m(i)} \tag{2}$$

where $m(i)$ is the number of peers in one's social network. $d_{j,t-1}^{tech}$ represents peers' behavior in the social network at last period.

Perceived behavior control External advocacy training and internal accumulation of experience and learning ability are used as alternative measures of perception behavior control. Since measuring the expected benefits of technology already ensures that individuals can produce within their own endowments, endowments and technology costs are no longer considered for perceived behavior control. In each time period, it is assumed that farmers receive sufficient training and information, represented by one. However, differences in farmers' learning opportunities and abilities (μ_i) result in different degrees of knowledge internalization ($p_i^{tech\_cum}$), which accumulate with the simulation. θ_i is the forgotten factor of farmers' experiential knowledge:

$$p_i^{tech} = \mu_i \times 1 + \theta_i p_i^{tech\_cum} \tag{3}$$

Calculation of intention In order to calculate farmers' intention to adopt a given technology, I_i^{tech} , we use a linear function of the three basic factors weighted by their importance in the intention, following Bourceret (2022).

$$I_i^{tech} = \gamma_{att} a_i^{tech} + \gamma_{sn} s_i^{tech} + \gamma_{pbc} p_i^{tech} \tag{4}$$

$$\gamma_{att} + \gamma_{sn} + \gamma_{pbc} = 1 \tag{5}$$

Where a_i is the attitude defined as the perceived satisfaction with the outcome of the behavior, reflected by benefits to some extent. s_i is the subjective norm, which refers to the social pressure people perceive to adopt a particular technology, closely related to the behavior of peers in the farmer's social network. p_i is perceived behavioral control, which is the farmer's perception of their ability to perform a particular behavior. γ_{att}, γ_{sn} and γ_{pbc} weight the effects of the three main factors.

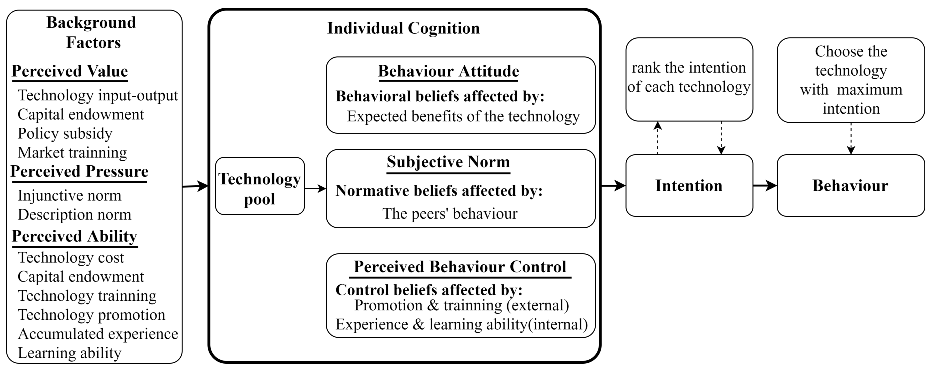

Fig. 1. Conceptual framework

2.2 Agent-based model

Agents The only agent types in this model is farmers. Actually, farmers have the intention to adopt each technology, but the intention varies in degree. Therefore, the ABM calculates and ranks the intention of each technology, and the final decision of farmers depends on the behavior corresponding to the maximum intention (Zhang & Nuttall, 2011; Kniveton & Smith, 2012; Mashhadi & Behdad, 2018).

Behavioral rules We assume that the behavior is the farmer's choice of pro-environmental technologies, which are available from the technology pool. First, it is required to quantify these basic factors of TPB for various technologies. Nonlinear programming model is used to compute the behavior attitude and the subjective norm is calculated by social network model. Next, the intention is composed and weighted by the three basic factors. After that, every agent ranks the intentions of these technologies. Farmer's final choice of technology depends on the maximum intention.

$$B_i = \max\{I_i^1, I_i^2, ..., I_i^n\} \tag{6}$$

Model process and scheduling According to the feedback (see Fig.2), the events that occur in each time will work later. First, the farmer's endowment is updated at the end of each simulation and given to the behavior attitude. Second, farmers' adoption decisions will influence the subjective norm of their peers in the next time through social networks, which is one of the main drivers of the ABM. In addition, the accumulated experience and knowledge will feed back into perceived behavior control in the next time.

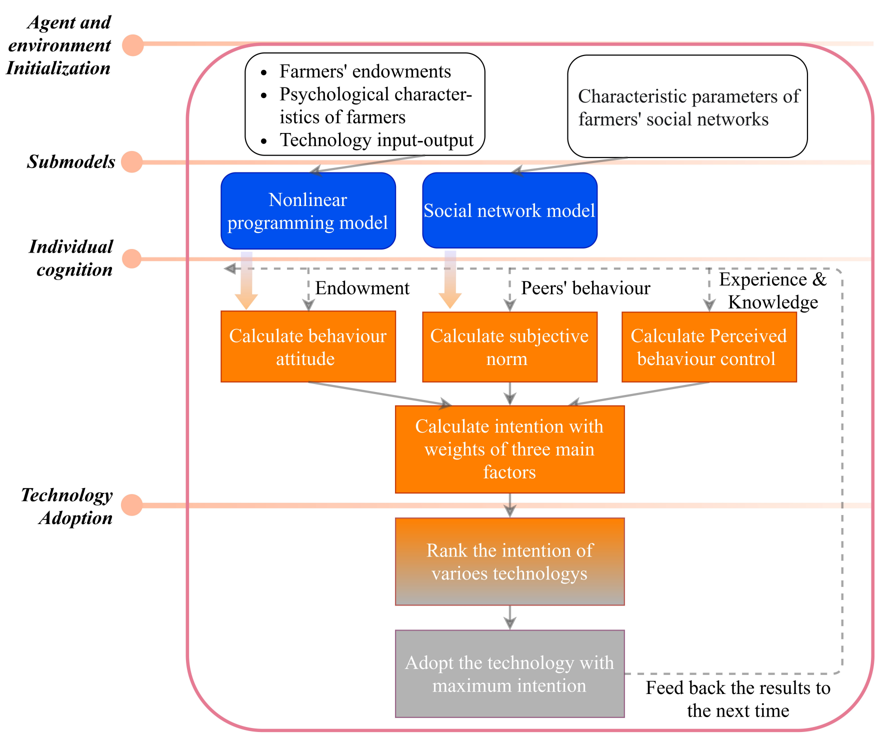

Fig. 2. Overall process and scheduling

3 Preliminary results

We applied the model to simulate farmers' adoption of pro-environmental practices under different polices. The two practices we focused on are nitrogen deep placement (DPN) and the application of slow-release fertilizer (SRF). We use data of 615 agricultural households collected from Hubei Province, China to validate the model.

A sensitivity analysis was performed to further learn the uncertainty of the model and identify key parameters. The results from the Sobol's method based on Latin hypercube sampling with 1014 samples show that weights of the three main factors and two kinds of subsidy ratio are the critical parameters, which are closely related to the farmers' final behavior. In addition, the interaction among the three weights needs to be further explored.

We set up six simulation scenarios consisting of 0% or 70% subsidy for SRF, 0% or 100% subsidy for DPN, and whether farmers participate in carbon market transactions. For SRF, both subsidies and participation in carbon trading programs significantly increase the adoption rate. But there is a little bit different for DPN (see Fig.3), we find that while subsidies could increase adoption, participation in carbon trading may actually decrease adoption.

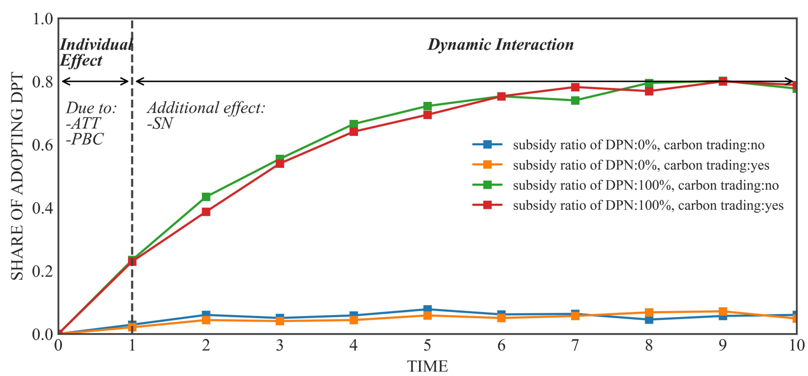

Fig. 3. Adoption of nitrogen deep placement(DPN)

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