Social network and decision-making of rural land use change

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Abstract

The study explores the role of social networks in influencing farmers' decisions regarding land use changes. Social networks facilitate social learning, information exchange, and collaboration among farmers, which impacts their adoption of new agricultural practices and technologies. The research identifies gaps in existing literature, particularly the lack of complex and dynamic models capturing farmers' decision-making processes. To address this, the study proposes an extended opinion dynamics model, named the asymmetric heterogeneous confidence bound opinion dynamics model (OD-AHC), which simulates farmers' opinion interactions and evolutions over time. This model incorporates factors such as confidence thresholds, farmer characteristics, and network size to reflect real-world complexities. The OD-AHC model is validated through a case study on rural land use change in New Zealand, highlighting its robustness and applicability in understanding and promoting innovation diffusion in agricultural communities.

Keywords:

1. Introduction

Social networks serve as platforms for social learning, information exchange, and collaboration among farmers (Conley & Udry, 2010a). Through interactions with peers, farmers acquire knowledge about new agricultural technologies, market opportunities, and conservation practices, which can shape their attitudes and perceptions towards land use innovations (Deressa et al., 2011). Trusted information sources within social networks increase farmers' confidence in adopting new practices and technologies (Amlaku et al., 2012). Moreover, social networks play a crucial role in shaping social norms and exerting social influence on farmers' behaviour (Pretty & Ward, 2001). Farmers conform to prevailing norms within their social networks regarding sustainable land management practices and environmental stewardship. Positive feedback loops within social networks reinforce these norms and encourage the adoption of land use changes aligned with collective goals and values when a farmer adopts a new land management practice or technology and shares their positive experience with other farmers in the network (Hruska et al., 2017). This sharing leads to more farmers adopting the practice, which in turn encourages even more farmers to do the same, creating a cycle of increasing adoption and reinforcement within the network (Ward & Pede, 2015). Peer pressure and social comparison within social networks may also influence farmers' decisions regarding land use changes (Liu et al., 2018; Rose et al., 2018a). Farmers compare their land management practices with those of their peers and adjust their behaviours to align with perceived social norms or expectations. Positive feedback from peers who have successfully implemented land use changes can encourage others to follow suit, leading to the diffusion of innovations within agricultural communities (Brown et al., 2016; Conley & Udry, 2010b; Egger et al., 2023; Small et al., 2016). Note that negative effects are also expected (H. Xiong et al., 2016). As proposed by H. Xiong et al. (2018) that a negative externality effect in the network can result in fluctuations in the technology diffusion process, leading to a fluctuating diffusion curve rather than a commonly known S-shaped curve.

It is noted that farmers' opinions, beliefs, and attitudes evolve and spread within social networks over time: rather than staying the same, farmers' opinions on land use change evolve with the interactions with other farmers over time (Albizua et al., 2021). However, the complexity and dynamic characteristics of social networks have not been well-studied in the literature on social network effects on farmers' decision-making. One stream of study tends to use simple modelling techniques – a binary or ordinal variable is used to consider the social network effect. In that case, the information used to construct the variables includes whether they talked to other farmers about their land management practices (Miheretu & Yimer, 2017), whether they participated in farmer groups (Jørs et al., 2016), or the number of information sources (a proxy of networks) farmers used to exchange their knowledge about land use change (Kirk et al., 2022a). Another thread of research mainly focuses on the application of spatial models in understanding social networks by capturing the spatial dependencies and interactions among individuals or locations (Kopczewska & Elhorst, 2024; Wu et al., 2022). For example, empirical studies using spatial econometrics models, such as Spatial Autoregressive Models and Spatial Durbin Models, extend traditional regression frameworks and account for spatial correlations as a proxy of social network effects (Kopczewska & Elhorst, 2024; Vega & Elhorst, 2013). Spatial network models integrate spatial and network analysis techniques to study the structure and dynamics of spatially embedded networks, considering both spatial proximity and network ties between nodes (Adiga et al., 2022; Scheider & de Jong, 2022). None of the studies stated above consider the dynamics of interactions and opinion evolution process within social networks, not to mention capturing how the complexity and dynamics affect farmers' decision-making regarding land management practices.

In light of the above gaps in modelling the impact of social networks on farmers' decision-making in the literature, this study aims to build a social network model to capture the complexity and dynamics of farmers' decision-making process – their opinion interactions and evolutions overtime within farmer groups. The theoretical framework of the study is based on the opinion dynamics model which refers to the study of how opinions, beliefs, and attitudes evolve and spread within social networks over time. It involves understanding how individuals' interactions and exchanges of information influence the formation, change, and persistence of opinions within a population (Chacoma & Zanette, 2015a; Gionis et al., 2013). Opinion dynamics models often draw on concepts from social psychology, sociology, and network theory to simulate and analyse the dynamics of opinion formation and diffusion (Anderson & Ye, 2019a; Das et al., 2014; Peralta et al., 2022). One of the foundational theories in opinion dynamics is the "bounded confidence" model, assuming that individuals only update their opinions if they are within a certain threshold of similarity to others in their social networks (Das et al., 2014; Peralta et al., 2022). Through iterative interactions, individuals adjust their opinions towards the average of their peers' opinions, leading to the emergence of consensus or polarisation within the network.

Empirical studies have examined opinion dynamics in various contexts, including political elections, social movements, and consumer behaviour. For example, Centola (2010a) conducted a series of experiments to investigate how individuals' social networks influence their political opinions and voting behaviour. He found that exposure to diverse opinions within social networks can lead to greater tolerance and compromise among individuals with conflicting views. Centola (2010b) and Wan et al. (2018) investigated the dynamics of opinion evolution in online consumer reviews within the e-commerce environment. By using an opinion dynamics model, the study simulated the evolution of opinions of online users, considering factors like social influence, network structure, and the impact of new information on individual opinions. The results showed patterns and mechanisms driving the evolution of opinions in online consumer reviews, shedding light on the underlying processes shaping consumer perceptions and decision-making in e-commerce platforms. Till now, to our best knowledge, the opinion dynamics model has not been used in the context of land use decision-making.

Therefore, the study constructed an extended opinion dynamics model, namely the opinion dynamics model with asymmetric heterogeneous confidence bound (OD-AHC model) to explore how farmers' attitudes towards land use change evolve within agricultural communities. Build on existing social network theory, this model helps improve existing empirical studies based on spatial and social network models to better understand more complex decision-making processes, and the role of opinion interactions over time within different farmer groups. By simulating the interactions and information exchanges within social networks, the study aims to explore the influence factors that affect land use change and identify strategies for promoting behaviour change and innovation diffusion. Adding the influence factors, including confidence threshold, farmers characteristics, convergence parameter, and size of the network (i.e., number of interacted farmers), adds complexity to the basic opinion dynamic model to be more reflective of the real world, hence providing opportunities to apply the extended model in modelling farmers' land use change decision-making. In addition to simulation results, the study applies the OD-AHC model in a case study of rural land use change in New Zealand (NZ), where the results further validate the sound and robustness of the model.

The study makes four key contributions. First, it addresses significant gaps in the existing literature on farmers' land management practices within social networks, modelling the dynamics and complexity in the decision-making process. Second, it advances theoretical understanding by introducing the OD-AHC model, thereby enhancing methodological approaches for modelling opinion dynamics within agricultural communities. Third, by applying the OD-AHC model to a case study of rural land use change in Aotearoa New Zealand (NZ), the study provides empirical validation of the model's soundness and robustness, further enhancing its credibility and applicability in diverse contexts. The results and findings reveal the pathway of how land management practices and innovation diffuse among farmers, thereby bridging the gap between academic research and real-world applications in agricultural land use management.

2. Theoretical Framework

2.1. Opinion Dynamics Models in rural land use decision-making

Opinion dynamics models play a crucial role in understanding the complexities of opinion formation and change in societies. They are valuable tools used in various fields such as sociology, political science, economics, and computer science to understand how opinions, beliefs, and behaviours spread and evolve within a population (Anderson & Ye, 2019b; Simonson, 2022; Uthirapathy & Sandanam, 2023; X. Xiong & Hu, 2012). By modelling individual interactions and aggregating opinions over a network, these models can help researchers understand how factors such as social influence, network structure, and individual attributes impact opinion dynamics, thereby providing insights into the mechanisms underlying the formation and evolution of opinions in a society or group. The importance of opinion dynamics models lies in their ability to inform decision-making processes, policy development, and social interventions. For example, the models can help predict the spread of ideas, identify influential individuals or groups, and suggest strategies for promoting positive change or mitigating the spread of misinformation (Acemoglu & Ozdaglar, 2011; Milli, 2021).

Opinion dynamics models can be grouped into two categories, discrete and continuous models, based on opinion values (Bernardo et al., 2024; Martins, 2008a; Sun & Müller, 2013). Several notable continuous opinion dynamics models have been developed, each contributing to the understanding of public opinion formation and social contagion, including the Deffuant–Weisbuch (DW) model (Deffuant et al., 2000; Weisbuch et al., 2003), the Hegselman-Krause (HK) model (Hegselmann & Krause, 2002), and the CODA model (Martins, 2008b, 2009). The DW and HK models are both examples of bounded-confidence models (Sun & Müller, 2013), characterized by the use of continuous variables to represent opinions and a mechanism where individuals influence each other only when their opinions are sufficiently similar. While these models share this foundational approach, they diverge in their specific opinion update rules. The DW model operates on a one-by-one interaction basis between compatible neighbours[1], whereas the HK model allows for simultaneous interaction among multiple compatible neighbours (Castellano et al., 2009). In contrast, the CODA model presents a hybrid approach, blending elements of bounded-confidence models with binary decision-making. Like its counterparts, actors in the CODA model maintain continuous opinions, but decisions are made in a binary fashion. Notably, agents update their opinions by observing the actions of their peers and adjusting according to Bayesian principles (Martins, 2009).

These foundational models, alongside their subsequent modifications and extensions, have found widespread application in the examination of various phenomena related to public opinion dynamics and social contagion within academic research. In rural land use change environments, continuous opinion dynamics models are more suitable for studying changes in farmers' attitudes towards rural land use changes because they allow for a more detailed representation of opinions. Unlike discrete models, which only consider finite possible opinions (e.g., support or oppose, and change or not change), continuous models represent opinions as continuous variables, allowing for a spectrum of opinions ranging from strong opposition to strong support.

This detailed representation of opinions is important when studying farmers' attitudes towards rural land use changes, as opinions on this topic are likely to be multifaceted and influenced by various factors such as farm and farm characteristics, and economic, environmental, and social considerations (Ligtenberg & Bregt, 2014). Continuous models can capture the complexity of these opinions and how they change over time. Additionally, continuous models can incorporate factors such as social influence and network dynamics, which are important determinants of opinion formation and change in social networks. By considering the interactions between farmers and the influence of their social networks, continuous opinion dynamics models can provide a more realistic depiction of how opinions evolve within farming communities.

[1] Neighbours in the study is not simply neighbours in a geographic space but peers within social networks.

2.2. The model – the asymmetric heterogeneous confidence bound opinion dynamics model

We developed the opinion dynamics model regarding farmers' land use change based on the Deffuant–Weisbuch (DW) model - a classic bounded confidence opinion dynamics model that simulates how opinions evolve in a population through pairwise interactions. The DW model is a continuous opinion dynamic model and hence has the advantage of modelling the complexity of land use decision-making: rather than simply treating farmers' opinions on land use change as discrete options, saying support or not support, and the DW model allows us to use, for example, the propensity of support or not support to represent farmers' opinions on land use change. The model was first proposed by Deffuant et al. (2000), and later refined by Weisbuch et al. (2003). The decision to utilise the DW model as the base model for simulating social influence among farmers was based on its simplicity and intuitive nature. Originally designed to represent farmers' adoption of agro-environmental measures in exchange for financial support, the DW model aligns closely with the specific research inquiries at hand. Its straightforward framework allows for a clear representation of the dynamics involved in the adoption of the land use change process, making it a fitting choice for addressing the research questions in this context.

We modified the classic DW model and propose the asymmetric heterogeneous confidence bound opinion dynamics model (OD-AHC model) to better model the reality of farmers' opinions change and interactions. While presenting the OD-AHC model regarding farmer interactions and the opinion evolution process, we introduce four influencing factors in the process that may affect the dynamic process of farmers' interactions and exchange of opinions, to be specified in detail as follows in this section. Most importantly, the OD-AHC model is expected address some key limitations of the DW model (will be presented in the following), based on three assumptions:

Assumption One: There are more than two individuals interacted and exchange opinions. Based on the DW model, in each iteration of the model, only two farmers (farmer i and farmer j) are randomly selected to interact with each other. However, this assumption oversimplifies the interaction process and cannot reflect social network connections in the real-world. Hence, in our model, we assume that farmer i (and other farmers) can select more than one farmer as its learning objective to be interacted with at each time and make a weighted evaluation for its opinion update after removing the opinion not located in its confidence region at each time step, partly following the HK model: individuals in the model are presumed to have access to the opinions of all other participants and adjust their own opinions accordingly, averaging over the opinions of all others (Hegselmann & Krause, 2002).

Assumption Two: Individuals have different confidence threshold ε, which defines the difference between the two's opinions on land use change (i.e., individuals' openness to others' opinions), or bounded confidence.

In the DW model, individuals exchange their opinions on land use change based on a tolerance threshold *ε,* Specifically, if the absolute difference in opinions between the two farmers is larger than their tolerance threshold, i.e., $\left|x_i(t) - x_j(t)\right| > \varepsilon$, they do not change their opinions; in contrast, if the difference is smaller than their tolerance threshold, i.e., $|x_i(t) - x_j(t)| < \varepsilon$, they update their opinions towards each other following Equation (1):

$$\begin{cases} x_i(t+1) = x_i(t) + \mu\,[x_j(t) - x_i(t)] \\ x_j(t+1) = x_j(t) + \mu\,[x_i(t) - x_j(t)] \end{cases} \tag{1}$$

where $x_i(t)$ and $x_j(t)$ are the opinions of farmer i and j at time t, and μ is a convergence parameter[2]. In the context of farmers' opinion exchange, both farmer i and j have the same confidence threshold ε, and that is, they hold the same value of seeing how their opinions are different from others. Hence, farmer j is assumed to have the same "shape" of bounded confidence as farmer i shown in Figure 1a (also shown in Equation 1, that the two farmers share the same opinion equation). However, individuals can hardly have the same confidence threshold. Some individuals may be more open-minded and willing to consider different viewpoints, while others may be more closed-minded and resistant to change.

[2] In the context of land use change, the parameter μ is indicative of a farmer's steadfastness. It can be likened to the personality trait of a farmer within the model: when $\mu = 0$, it signifies that a farmer remains unyielding in their opinions, impervious to the influence of social interactions. Conversely, when $\mu = 1$, it indicates that a farmer consistently adopts the opinions of their peers without resistance.

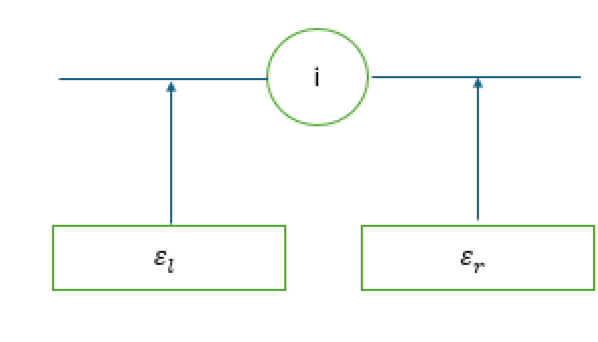
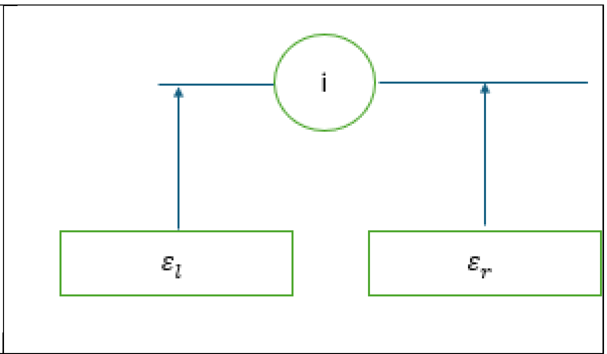
	

Figure 1a. Symmetric bounded confidence for farmer *i*	Figure 1b. Asymmetric bounded confidence for farmer *i*

Figure 1. The comparison of the DW model and the real-world counterpart

Therefore, in the OD-AHC model, each farmer's confidence threshold (ε_i) is assumed to be different and calculated in the following equation:

$$\varepsilon_i = \varepsilon_0 + f(x_i), x_i \in [0,1], \quad (2)$$

where ε_0 is the average degree of open-mindedness of a population, $f(x)$ is a function of *x* to adjust individuals' degree of open-mindedness, and x is a variable to proxy the degree of open-mindedness to upper or lower opinions for farmer *i*. ε_i is determined by *influence factor 1*, ε_0, the average open-mindedness of the farmer community and the open-mindedness function $f(x)$.

Assumption Three: The confidence threshold is symmetric $\varepsilon_l \neq \varepsilon_r$.

The DW model assumes that the confidence threshold is symmetric, which means that if farmer *i*'s opinion is within the confidence threshold of farmer *j*, then agent *j*'s opinion is also within the confidence threshold of *i*. In another world, the threshold interval has the same size for both left and right, i.e. $\varepsilon_l = \varepsilon_r$[3], as shown in Figure 1a. However, individuals may be more open to upper or lower opinions whatever their opinions are (independent asymmetry) (see Figure 1b). In the context of rural land use change, farmer i might be more willing to interact with farmers who have positive attitudes toward land use change, even if the "score" of farmer i's initial opinion on land use change is relatively low, and it could be the same or opposite situation for farmer j. Hence, we assume farmer *i's* confidence threshold is asymmetric and it is dependent on the function $f(x)$, i.e., *influence factor 2*, defined as:

[3] In the context of opinions on land use change, assuming farmer *i's* propensity of making land use changes is 0.3 and *i's* threshold value is 0.1, then I will update options with another farmer *j*, if *j's* propensity of land use change is either 0.4 or 0.2.

$$f(x) = \begin{cases} x * (1 - \varepsilon_0), x \geq 0.5 \\ (1 - x) * (1 - \varepsilon_0), x < 0.5 \end{cases}. \quad (3)$$

More specifically, for each farmer, if $x \geq 0.5$, i.e., the farmer tends to exchange opinions with upper opinions, their confidence threshold is described as:

$$\begin{cases} \varepsilon_l = \varepsilon_0 \\ \varepsilon_r = \varepsilon_0 + x * (1 - \varepsilon_0) \end{cases}, \quad (4)$$

and if $x < 0.5$, i.e., the farmer tends to exchange opinions with lower opinions, their confidence threshold is described as:

$$\begin{cases} \varepsilon_l = \varepsilon_0 + (1 - x) * (1 - \varepsilon_0) \\ \varepsilon_r = \varepsilon_0 \end{cases}. \quad (5)$$

Given the first assumption, the OD-AHC model allows each farmer to interact with more than one farmer and adjust its opinion. Hence, farmer *i's* opinions at the time of $t + 1$ can be expressed as:

$$x_i(t + 1) = x_i(t) + \mu \sum_{k=1}^{m} w_{ik} 1\{A\}(x_k(t) - x_i(t)), \quad (6)$$

where k is the number of randomly chosen farmers to interact with farmer i, $k = (1,2, \ldots, m), m \in N$, N is the sample size, w_{ik} satisfies $\sum_{k=1}^{m} w_{ik} = 1$, and $1\{A\}$ is the indicator function, $A = \{0 < x_k(t) - x_i(t) < \varepsilon_{ir}$ or $0 < x_i(t) - x_k(t) < \varepsilon_{il}\}$, $1\{A\} = 1$ if $\{A\}$ holds, otherwise 0. Simply speaking, assuming eight farmers were randomly chosen for farmer *i* to interact with, of which five farmers were determined to be located in *i's* confidence region, then $w_{ik} = 1/5$. *Influencing factor 3*, *m* is the choice of the number of farmers to be randomly selected for the interaction ($m = 1$ in the DW model given only two individuals are considered in the interaction), which is assumed to affect the formation/changing of each farmer's opinion on land use change. *Influencing factor 4* is μ, the convergence parameter that denotes the degree of farmers' persistence or steadfastness in their opinions. The larger the convergence parameter (i.e., toward 1), the more likely a farmer learns from their peers' opinions on land use change.

2.3. Simulation rules and procedures

Based on the OD-AHC model, we usimulated the influence of the four parameters, i.e., influencing factors described above, on farmers' opinion evolution process with Python 3.11. Specifically, we compare the simulation results of the OD-AHC model to those of the DW model and discuss the impact of influencing factors on social interactions and opinion formulation.

The OD-AHC model simulates the dynamics of opinion formulation in rural land use changes where each farmer has a unique ε and interacts with multiple other farmers. The flowchart in Figure 2 illustrates the rules and procedures of the simulation based on the OD-AHC model, comprising two main parts: ε adjustments and interaction process. First, ε adjustments: At time 0, the value of ε for each farmer is calculated using Equations (2), and (3). Second, interaction process: this process depicted in Figure 3, involves the selection of m farmers, which are then checked one by one to determine if their opinions are close sufficiently close to the target farmer i's opinion. For example, if farmer j's opinion is greater than farmer i's, the difference in their opinions is compared with farmer i's right ε. If the difference is smaller than farmer i's right ε, farmer j is selected to interact with farmer i; otherwise, farmer j is rejected. The same principle applies if farmer j's opinion is smaller than farmer i's, with the only difference in this case is that the difference of the opinions is compared with farmer i's left ε. After the review and selection of farmers to interact with the target farmer i, farmer i' opinion is updated using Equation (6).

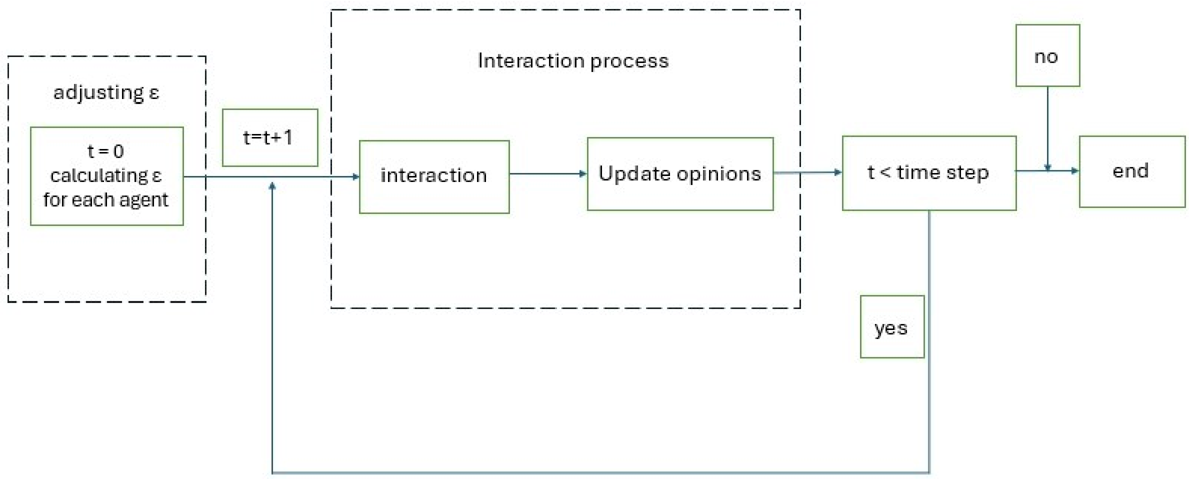


Figure 2. Simulation procedures of social interactions of the OD-AHC model

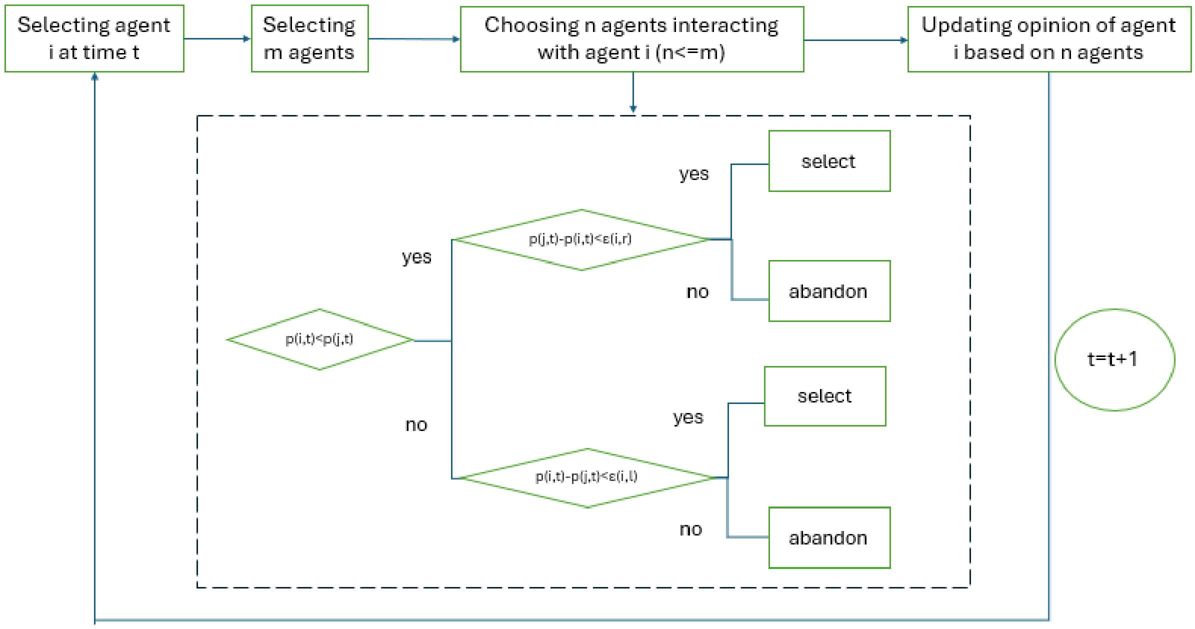


Figure 3. Opinion interaction process of the OD-AHC model

3. Simulation results

Based on the OD-AHCE model, we simulated the opinion evolution process, with a special focus on analysing the four influencing factors as follows. Specifically, the simulation shows the tendency of individuals within a group to align their opinions or viewpoints over time. The convergence phenomenon occurs as people interact and exchange ideas within social groups, leading to a gradual narrowing of differences in opinions and the emergence of a consensus (Bakshy et al., 2015; Xia et al., 2011). Besides showing the simulation results of the OD-AHC model, we also presented the simulation results of the DW model, when appropriate, to discuss the impact of influencing factors on social interactions and opinion formulation.

The confidence threshold ε in the DW model serves as a measure of farmers' open-mindedness, delineating the range within which they are willing to exchange and update opinions. This parameter exerts a significant influence on the opinion formulation process, particularly on the emergence of distinct opinion groups (Bernardo et al., 2021; Wan et al., 2018; Weisbuch et al., 2003; Zhang et al., 2017). Our simulation results, conducted using the DW model, corroborate this assertion. As depicted in Figure 4, an increase in the value of the confidence threshold, ε, corresponds to a reduction in the number of opinion groups. It is important to note that the DW model assumes uniform confidence thresholds across individuals, whereas our OD-AHC model allows for variations by assigning each farmer a unique confidence threshold, ε_i.

Moreover, our model introduces two parameters, ε_0 and x to characterize the level of open-mindedness of farmers. Therefore, we will initially focus on *influencing factor 1* ε_0, to analyse its impact on opinion evolution. Subsequently, we will incorporate the parameter x to investigate how it may alter the dynamics of opinion interactions among farmers.

Influencing Factor 1: ε_0, the average open-mindedness of the farmer community plays a pivotal role in shaping opinion dynamics. Figure 5 illustrates the simulation results highlighting the impact of ε_0 on opinion convergence. It is evident that the average open-mindedness of the farmer community ε_0 significantly influences the opinion evolution process, irrespective of other influencing factors such as $x, m,$ and μ. As depicted in Figure 5, when the initial value of ε_0 is set to 0.1, the farmer community exhibits two divergent opinions, represented by two distinct opinion groups with values ranging around 0.8, and between 0.1 and 0.2 (on the vertical axes). However, as ε_0 increases beyond 0.2, farmers tend to align their opinions, ultimately reaching a consensus. Additionally, a larger value of ε_0, indicating a more open-minded farmer community leads to faster consensus. For instance, the community reaches a consensus by step 30 with $\varepsilon_0 = 0.3$, while the group with $\varepsilon_0 = 0.2$ reaches consensus at step 40. These results underscore the crucial role of initial open-mindedness in facilitating interaction, knowledge exchange, and the emergence of opinion consensus among farmers regarding land use change. A higher initial level of open-mindedness fosters a greater likelihood of collaborative engagement and convergence of opinions among farmers, facilitating agreement faster.

Influencing Factor 2: The asymmetry of a farmer's confidence threshold, denoted by x ($x \in [0,1]$), plays a crucial role in shaping opinion dynamics. In our simulations, we explore two types of distributions of *x: x* follows a uniform distribution and a normal distribution; for each distribution, we further factored in asymmetry in the two distributions. Figure 6 illustrates the simulation results with uniform distributions of x: $x \in [0,0.7]$ representing a left-skewed confidence threshold and $x \in [0.3,1]$ representing a right-skewed confidence threshold[4]. Our findings reveal that the value of *x* significantly influences opinion formulation regarding the opinion convergence values, whilst not affecting the overall convergence trend. First, the convergent trends with either a left- or right-skewed confidence threshold (i.e., $x \in [0,0.7]$ or $x \in [0.3,1]$) are similar to the result shown in Figure 4, where no convergence is reached when

[4] In the previous simulations shown in Figure 3, we assume a symmetric threshold where x follows a uniform distribution between 0 and 1.

$\varepsilon_0 = 0.1$ and x is symmetrically and uniformly distributed between 0 and 1; as the value of ε_0 increases, convergence emerges. Second, a skewed value of x (either left- or right-skewed) determines the opinion values at the convergent point. Specifically, a left-skewed x ($x \in [0,0.7]$), where farmers tend to adopt opinions from those with a lower propensity for land use change, leads opinions to converge at a lower opinion score. For instance, the convergent value is around 0.4 with $\varepsilon_0 = 0.3$ (see Figure 5). Conversely, a right-skewed x ($x \in [0.3,1]$), where farmers exhibit a preference for interacting with individuals with a higher inclination towards land use change, leads opinions to converge at a higher opinion score. For instance, the convergent value is around 0.6 with $\varepsilon_0 = 0.3$ (shown in Figure 6).

Figure 7 presents the simulation results with x following normal distributions. When comparing the results shown in the first column (i.e., $x \sim N(0.5,0.17)$, symmetric) to those of Figure 5, where the confidence threshold is symmetric and x follows a uniform distribution between 0 and 1, there are no clear differences in opinion convergence trend across all three values of ε_0. That is, rather than the distribution of x, it is the initial confidence threshold value that drives the opinion convergent process: farmers' opinions converge as the value of ε_0 increases. It is worth noting that the convergence speed slows down when x follows normal distributions. When examining the asymmetric scenarios, illustrated in the second and third columns of Figure 7, the left- or right-skewed confidence threshold does not influence the overall convergence trend, compared to the symmetric situation (i.e., $x \sim N(0.5,0.17)$). However, a left-skewed confidence threshold leads farmers to achieve consensus at a lower score while a right-skewed helps opinions converge at a higher score through all three values of ε_0. These findings are similar to those we obtained above when x follows a uniform distribution.

The above discussion of influencing factors 1 and 2 provides evidence of the crucial role of the confidence threshold on farmers’ interactions and opinion exchange, which further influences the opinion formulation in two ways: 1) whether or not the farmer community could achieve opinion convergence (consensus) and 2) at what opinion score they reach consensus. The simulation results are consistent with the findings of studies based on the DW model regarding the influence of confidence threshold on opinion evolution (Deffuant et al., 2000; Weisbuch et al., 2003). Moreover, the two influencing factors included in our model capture the complexity of the social network structure regarding its overall open-mindedness of the community and the preference for interacting with either upper or lower opinion-holders, and how that affects opinion formulation. In particular, our results highlight the driving role of the average open-mindedness of the community opinion convergence; meanwhile, the distribution and value of x leads the community to converge at different paces and values.

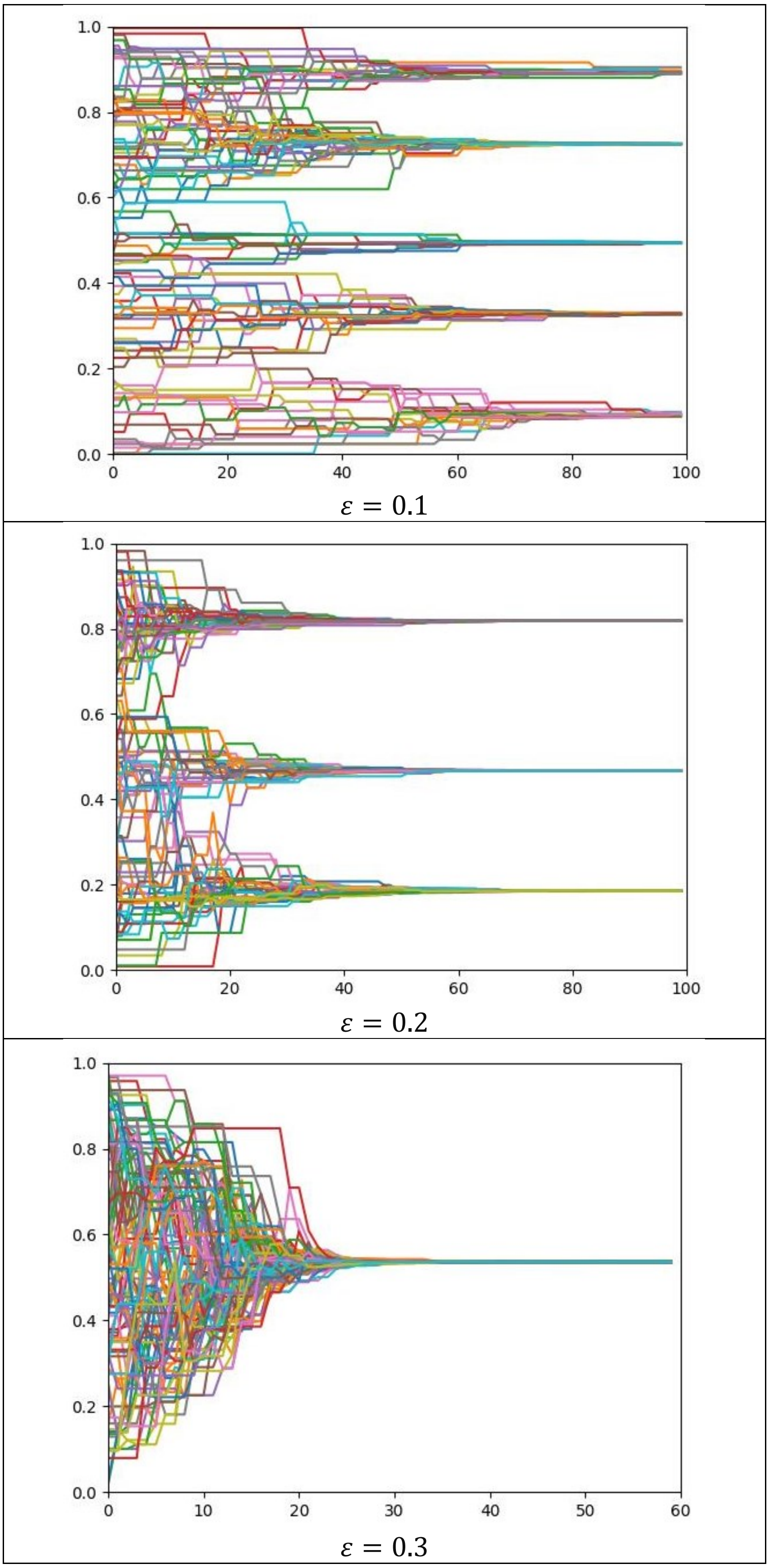
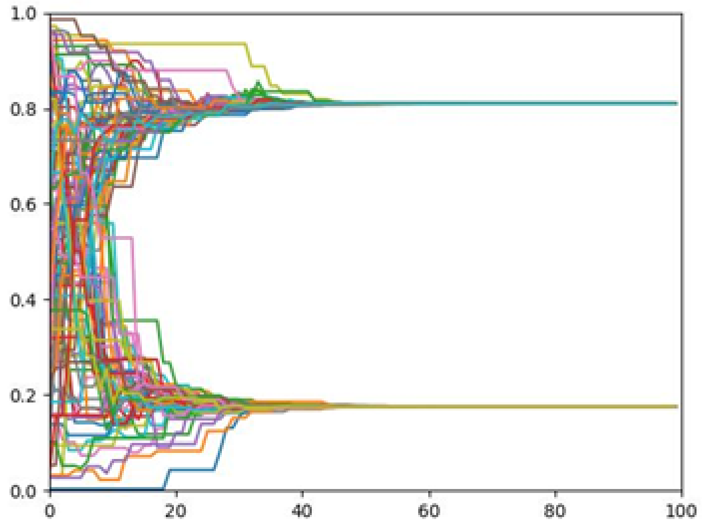
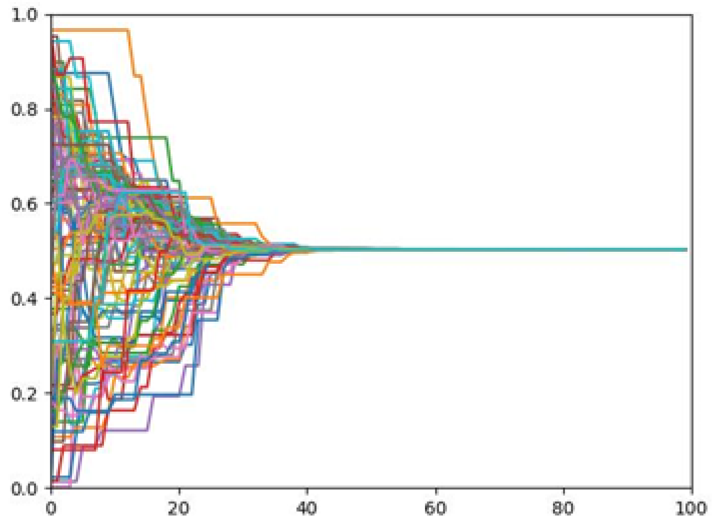


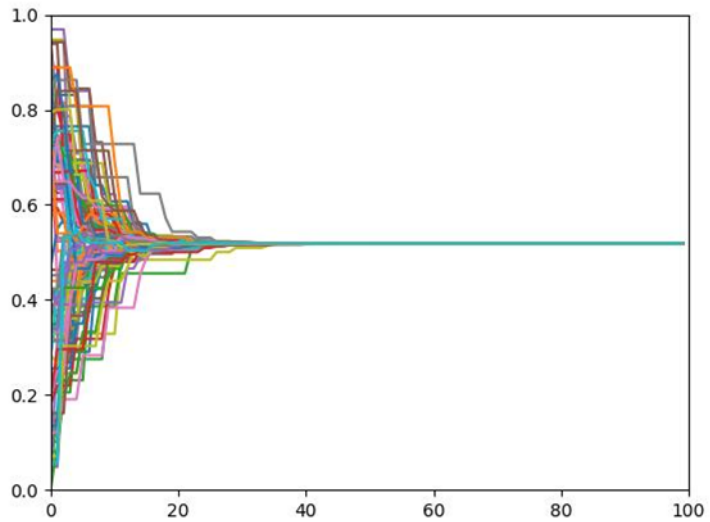
Figure 4. Simulation of opinion convergence based on the DW model given the different values of ε (N=100, steps=100, units=50, m=7, μ=0.5)



$\varepsilon_0 = 0.1$



$\varepsilon_0 = 0.2$



$\varepsilon_0 = 0.3$

Figure 5. Simulation of opinion convergence based on the OD-AHC model given the different values of ε_0 (N=100, steps=100, units=50, m=7, μ=0.5, $x \in [0,1]$ follows a uniform distribution)

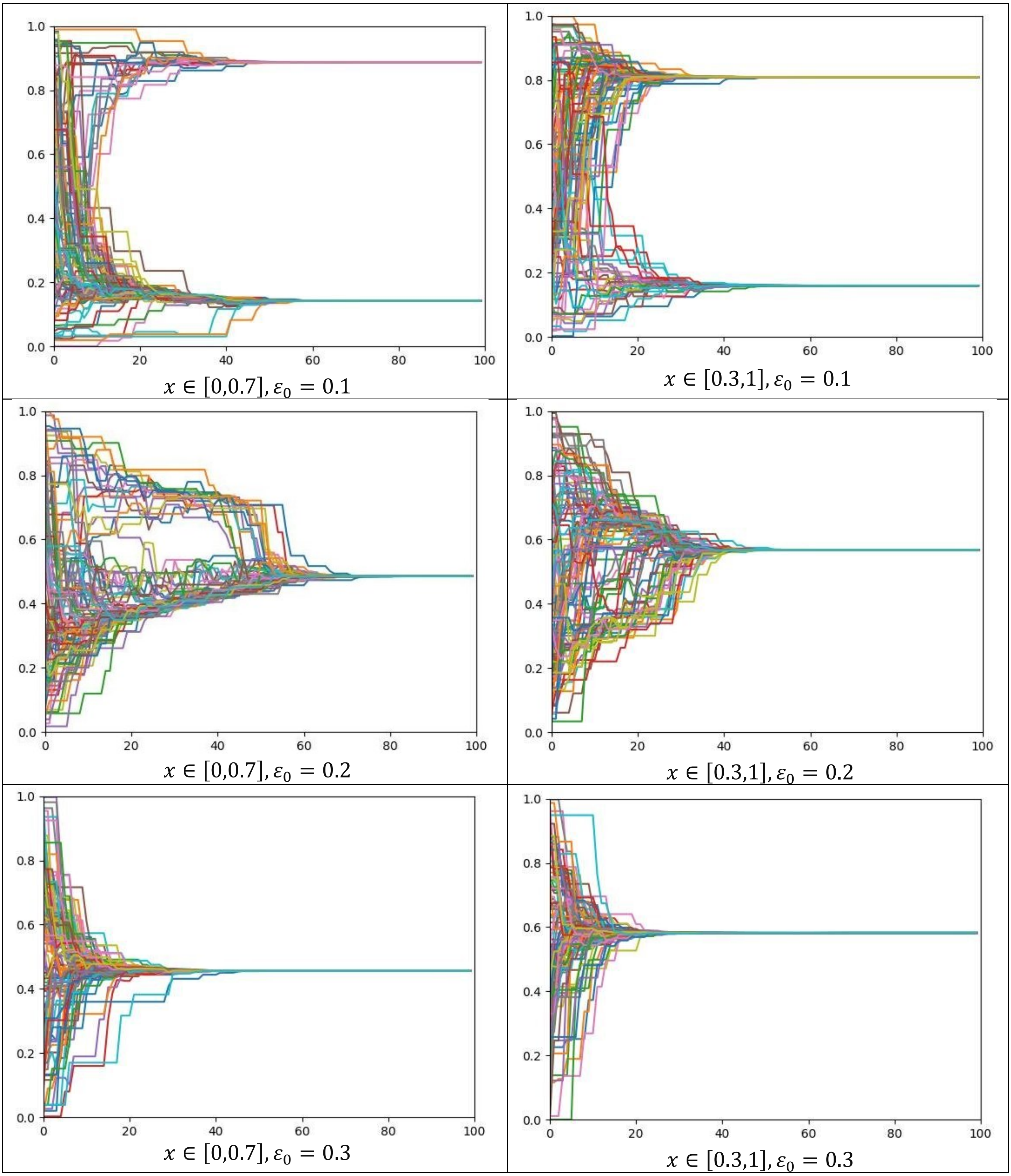
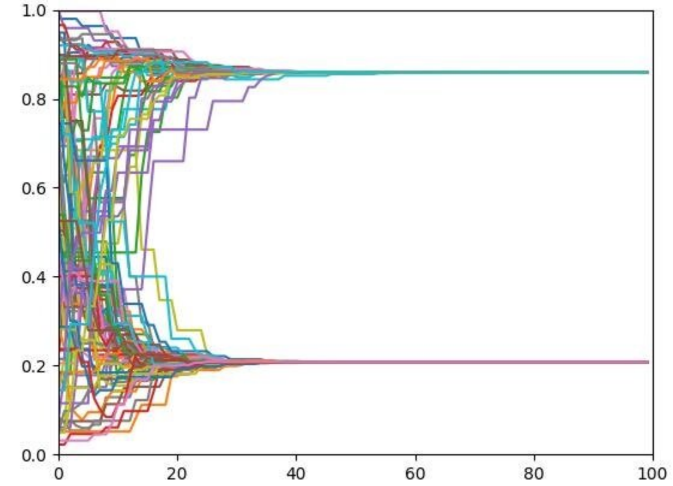
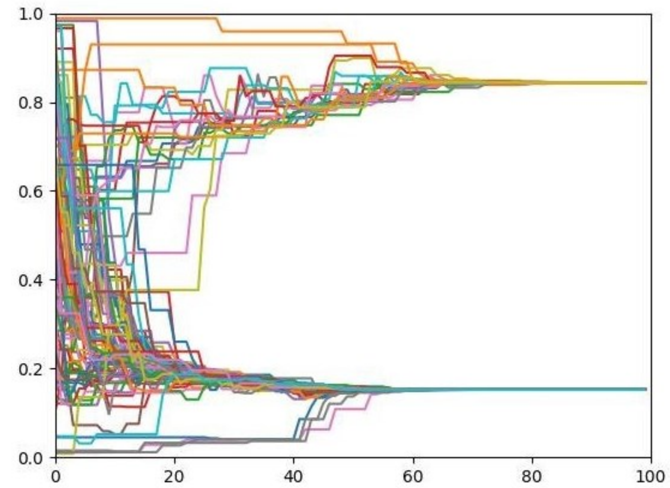


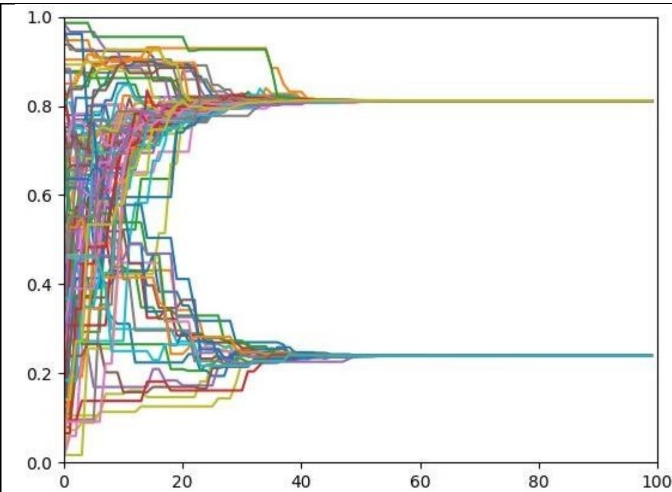
Figure 6. Simulation of opinion convergence based on the OD-AHC model given two uniform distributions of x and ε_0 values ((N=100, steps=100, units=50, m=7, μ=0.5).



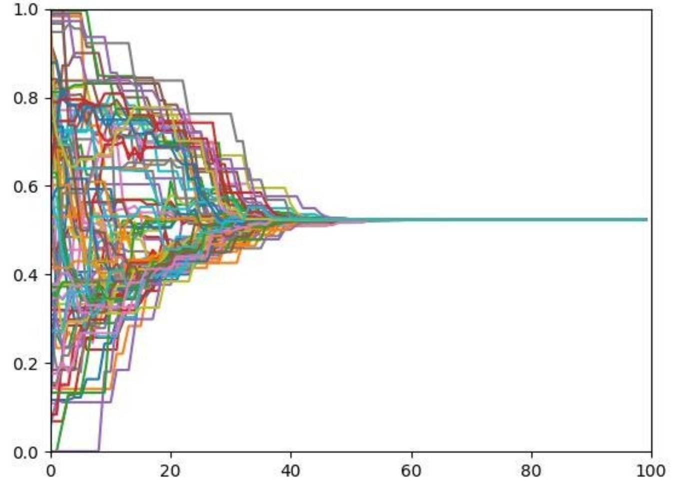
$x \sim N(0.5, 0.17), \varepsilon_0 = 0.1$



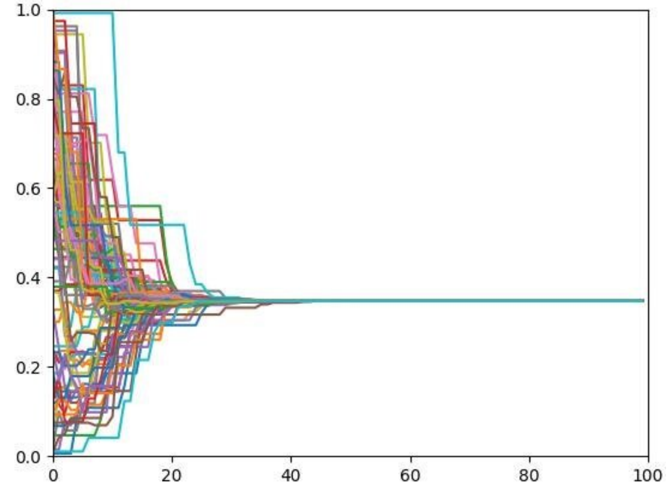
$x \sim N(0.3, 0.17), \varepsilon_0 = 0.1$



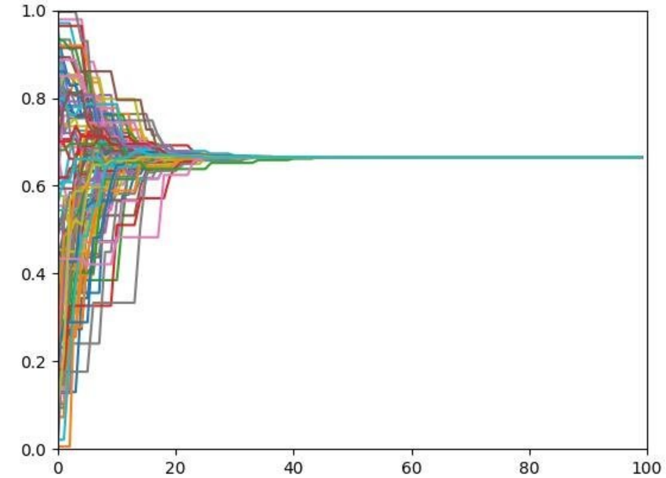
$x \sim N(0.7, 0.17), \varepsilon_0 = 0.1$



$x \sim N(0.5, 0.17), \varepsilon_0 = 0.2$



$x \sim N(0.3, 0.17), \varepsilon_0 = 0.2$



$x \sim N(0.7, 0.17), \varepsilon_0 = 0.2$

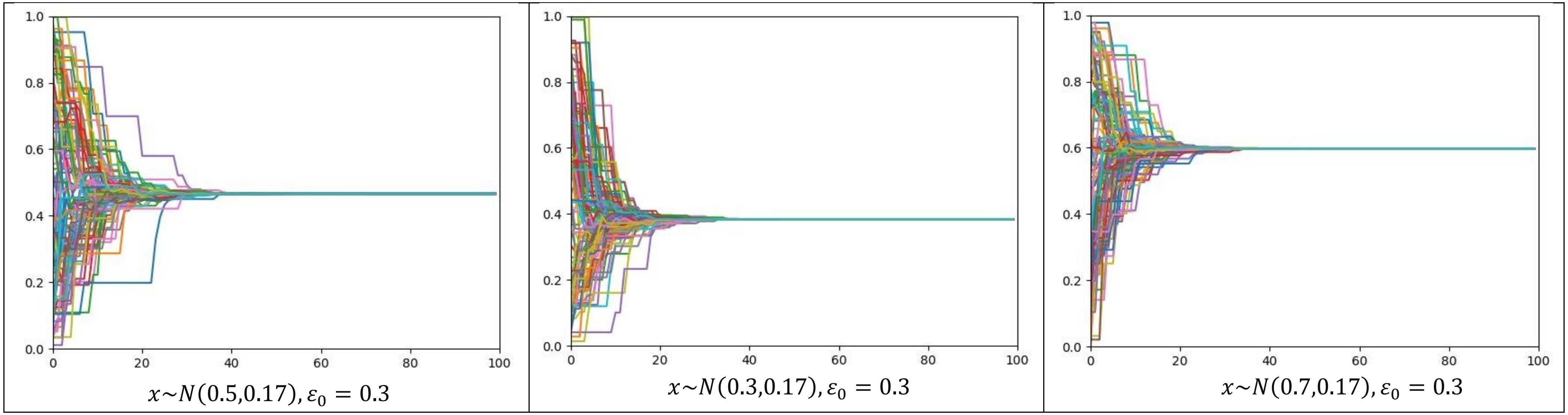
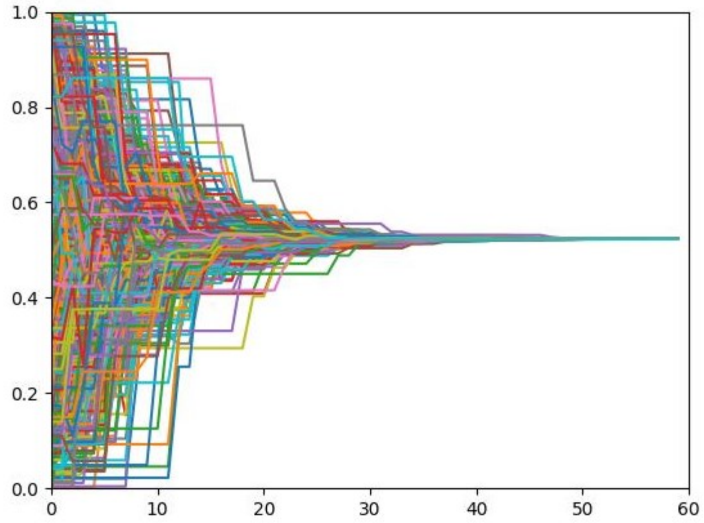


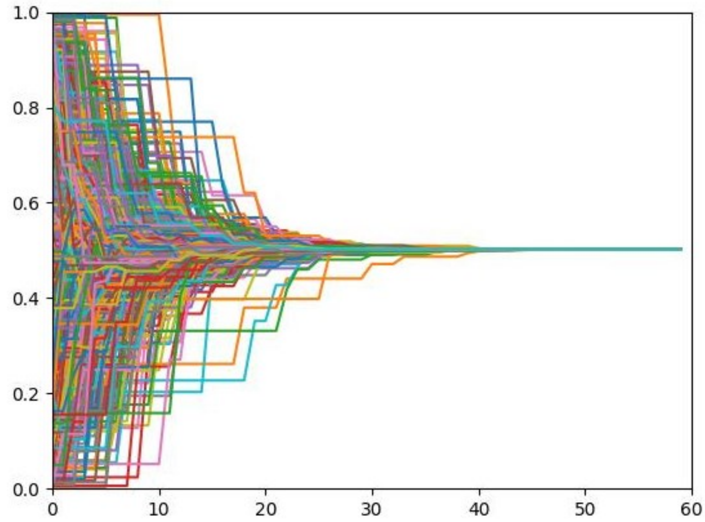
Figure 7. Simulation of opinion convergence based on the OD-AHC model with x follows normal distributions and ε_0 values ((N=100, steps=100, units=50, m=7, μ=0.5)

Influencing Factor 3: m, the number of randomly selected farmers to interact with farmer i. Compared to the DW model, where only one individual is randomly selected to interact with farmer i, in the OD-AHC model, we assume each farmer can interact with *m* farmers. The simulation results presented in Figure 8 show how different values of *m* may affect farmers' opinion exchange and formulation. In our simulations, we have chosen three values for *m*: $m = 3, m = 6$, and $m = 9$. We found that as *m* increases, convergence time decreases. Our results show that convergence starts at step 48, 40, 35 for $m = 3, m = 6$, and $m = 9$, respectively.

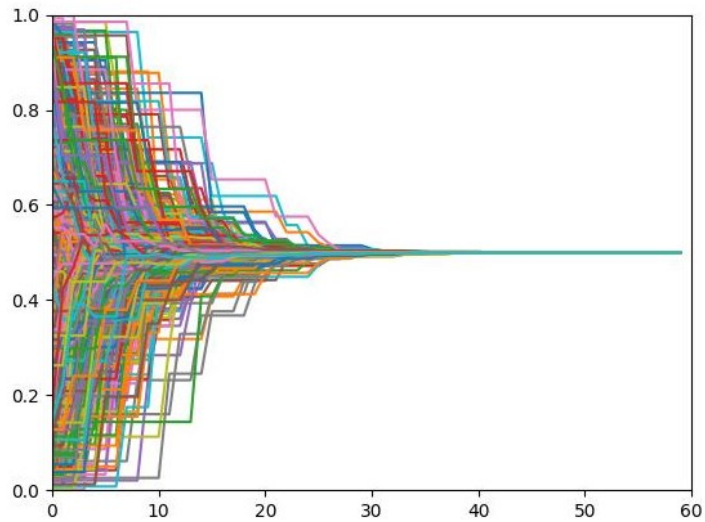
Influencing Factor 4: μ, the convergence parameter that denotes the degree of farmers' persistence or steadfastness in their opinions. Given the different values of μ, the simulation results show that μ has an impact on the time required for opinion formation (see Figure 9). As μ increases, the speed of opinion formation increases. For example, farmers reach a consensus by step 40 with $\mu = 0.5$, whilst they only achieve consensus at 80 with $\mu = 0.2$. The finding is consistent with previous studies on the impact of convergence parameter on opinion formulation using the DW model (Chacoma & Zanette, 2015b; Deffuant et al., 2000; Gavrilets et al., 2016).



$m = 3$

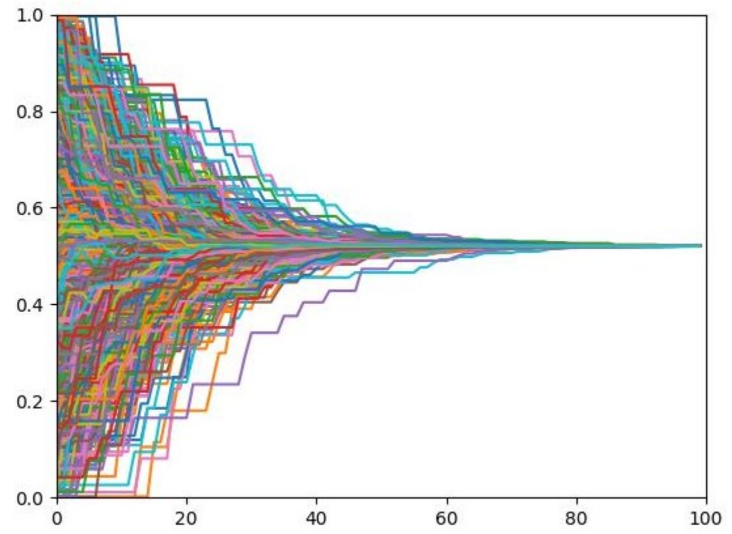


$m = 6$

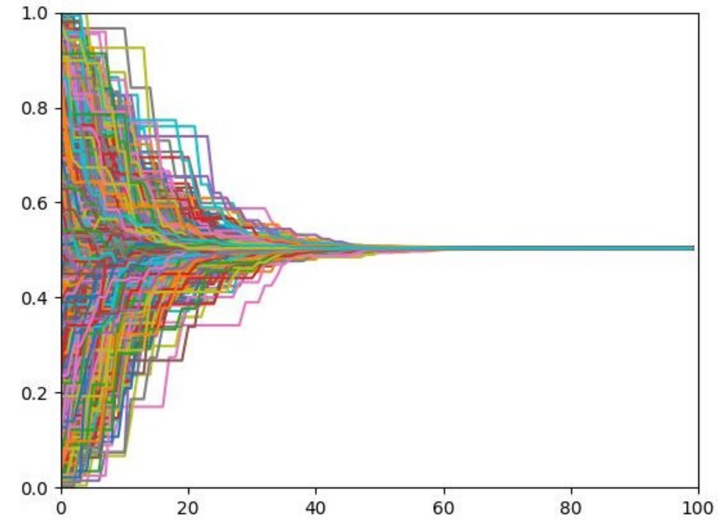


$m = 9$

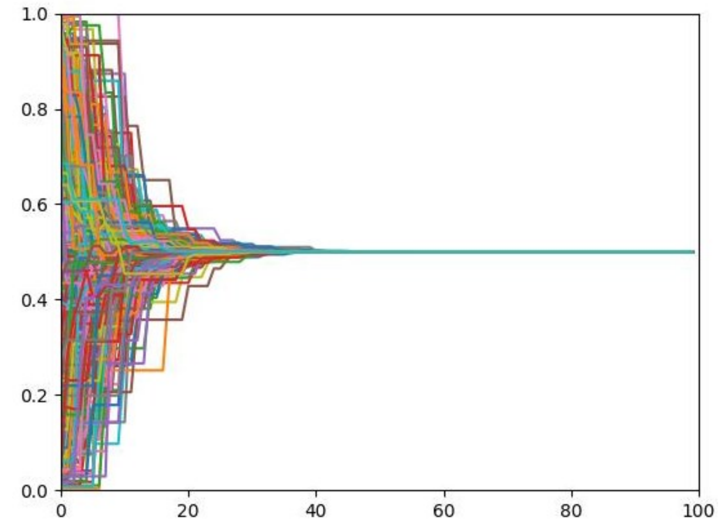
Figure 8. Simulation of opinion convergence based on the OD-AHC model given the different values of m (N=100, steps=100, units=50, $\varepsilon_0 = 0.4$, μ=0.5, $x \in [0,1]$ follows a uniform distribution)



$\mu = 0.2$



$\mu = 0.3$



$\mu = 0.5$

Figure 9. Simulation of opinion convergence based on the OD-AHC model given the different values of μ (N=1000, steps=100, units=500, $\varepsilon_0 = 0.4, m = 7$, $x \in [0,1]$ follows a uniform distribution)

4. Case study – Rural land use change in New Zealand

4.1. Context of the case study

The agricultural landscape of New Zealand (NZ) exhibits remarkable diversity, owing to its maritime temperate climate, fertile soil, and abundant water resources, which support a range of pastoral, horticultural, and arable farming activities. Over centuries, human interventions and environmental factors have shaped significant transformations in the rural landscape. Early settlers-initiated landscape modifications through deforestation to establish agricultural land, marking the inception of successive land use changes. In the early 20th century, intensification of land use emerged in response to agricultural demands, followed by subsequent phases driven by shifts in global markets and the removal of agricultural subsidies in the late 1980s. Notably, the rapid expansion of dairy farming has contributed significantly to NZ's export earnings and economic growth. However, this expansion has raised concerns about environmental sustainability, evident in nitrogen leaching, water quality decline, and greenhouse gas emissions from livestock. Recent years have seen shifts in land use patterns, including a decrease in dairy farming and an increase in horticultural land use, reflecting efforts to balance economic gains with environmental preservation. The government's target to double agricultural export value by 2025 adds pressure on landowners and managers to navigate various challenges, from domestic regulatory requirements to global sustainability concerns. Understanding recent rural land use changes is crucial for addressing these challenges and transitioning towards a more sustainable agricultural economy. Land use changes are influenced by a complex interplay of natural environmental factors, human activities, and farmer decision-making processes. Farmers, as key stakeholders, respond differently to various factors based on their individual characteristics, values, and demographics, thereby shaping the rural landscape in diverse ways.

Besides relying on the heterogeneity of farm-level land-use strategies, farmers' decisions regarding land use are significantly influenced by their peers within social networks. These peer interactions provide opportunities for knowledge exchange, facilitating learning about innovative practices and enabling farmers to assess the experiences of their peers, thus shaping their attitudes and behaviours towards land use innovations (Kirk et al., 2022b; Wood et al., 2014). Despite recognizing the pivotal role of social networks in farmers' decision-making processes, research in NZ has been limited in its examination of these effects. Existing studies have often adopted simplistic methodologies: some simply treated social network effects as exogenous variables (e.g., size of the social network and number of information sources) that affect farmer decisions (Small et al., 2016); others employed spatial econometrics models to model social network effects as spatial dependence based on cross-sectional analysis (Yang & Sharp, 2017; Yang & Wang, 2023). However, these approaches overlook the dynamic nature of social interactions among farmers and fail to capture the complexities of how these interactions influence land management practices. Thus, address these limitations by applying the OD-AHC model within the context of rural land use change in NZ. specifically, the objectives are threefold:

1) to validate the OD-AHC model using real-world data from NZ.

2) to gain insights into understanding the complexity and dynamics of social interactions within the farmer community and their impact on opinions regarding land use change over time.

3) to provide policy recommendations regarding the incorporation of social network interactions into land use change decision-making processes.

4.2. Data and variables

The sample data utilised in the case study are sourced from the 2021 Sustainable Rural Development Monitor (SRDM), a national internet-based survey conducted in New Zealand (NZ). This comprehensive survey comprises 182 questions covering various aspects including demographic information, farmers' values, objectives, future plans, rural land use change, and farm management practices. In addressing the challenge of data consistency and quality, the SRDM employs several strategies. Firstly, it has been conducted biennially since 2013, ensuring the consistent collection of farm-level data across all 16 regions in NZ. Secondly, the sample is drawn from membership lists of various agricultural institutions and organizations, ensuring the representation of diverse farming populations. These organizations include Beef + Sheep New Zealand, the Farm Forestry Association, Federated Farmers, the Foundation for Arable Research, Horticulture New Zealand, New Zealand Wine, the QEII Charitable Trust, and Rural Women. Additionally, samples are drawn from previous SRDM participants to monitor changes in farmer behaviours and their influence on decision-making over time. The survey is distributed via email through the National Animal Identification and Tracing database, allowing respondents flexibility in completing the questionnaire and thereby enhancing response rates.

The dataset comprises a total of 6674 observations, consisting of 2769 commercial farmers and 3905 lifestyle farmers. For the analysis of land use change, only commercial farmer respondents were included, resulting in a final sample size of 2014 after data cleansing. Within this final sample, 652 farmers are classified as sheep/beef industry participants, 350 as dairy industry participants, 177 as horticulture and cropping industry participants, and 835 as 'others'. The 'others' category encompasses farmers from smaller industries such as deer, pig, poultry, forestry, farm-based tourism, and beekeeping, and those who did not provide industry information. In the final dataset, each type of farmer is represented as a dummy variable, with the 'others' column dropped to avoid the dummy variable trap.

Based on the OD-AHC model presented in section 3, two variables are included in the study. First, the initial opinion values regarding farmers' opinions on land use change are based on the results of the machine learning network model, the artificial network model (ANN)[5]. In particular, the results of the ANN model provides a series of probabilities of farmers' land use change potential dependent on the farm and farmer characteristics; the values of the probabilities are in good shape, as a continuous variable ranging between zero and one, to act as a proxy of farmers' initial opinions on land use change without considering any social network effects. Figure 10 shows the distribution of farmers' initial opinions on land use change. It is clearly shown that the distribution curve is a left-skewed bell, with an average value of 0.22 and a standard deviation of 0.11. That is, the average propensity of land use change in the NZ farmer community is 0.22.

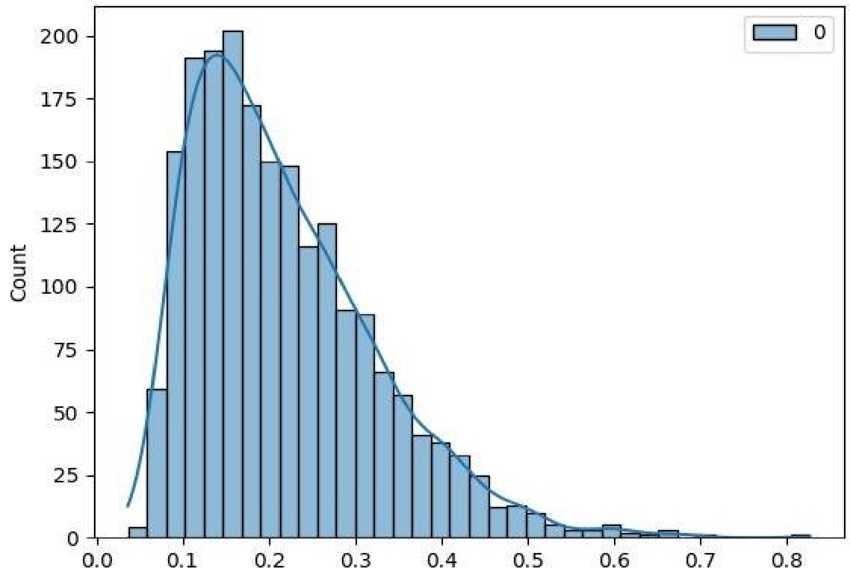


Figure 10. The distribution of farmers' initial opinion values on land use change.

[5] Details of the ANN results were presented in NZARES ECR Section 2023: Wang, L., Renwick, A., Dynes, R., Thomas, S., (2023) "Factors affecting rural land use change in New Zealand: empirical analysis using neural network method". Paper presented at the NZARES-NZAE Early Career Workshop (Post-Graduate Awards Winner). 6th Sep. 2023, Online.

In addition, the *influencing factor 2* $x, x \in [0,1]$ stated in Section 3.2 is to proxy the degree of open-mindedness to upper or lower opinions. Here we used the question about whether a farmer is willing to try something new6 to construct x, which follows the literature that "willingness to try new things" is a key factor that influences their business competitiveness and decision-making (Rose et al., 2018b). The variable was standardised to between 0 and 1, with a mean of 0.51 and a standard deviation of 0.25. As shown in Figure 11, most farmers (over 700) are relatively "neutral" to the question of trying something new - in the middle of strongly disagree and strongly agree. Also, the shape of the distribution curve is seemingly symmetric, but it does not follow either uniform or normal distribution.

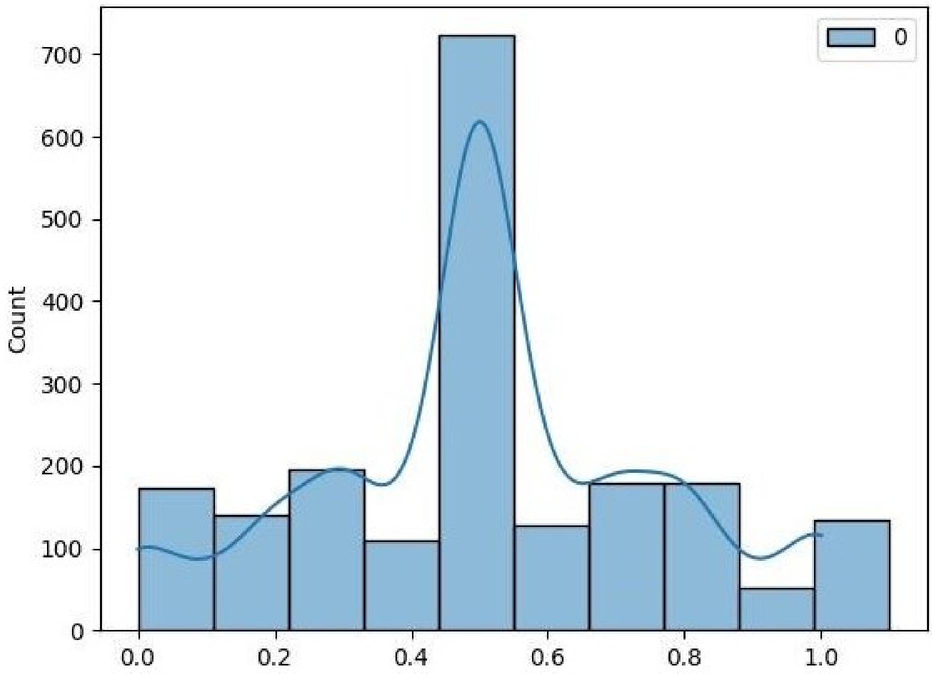


Figure 11. The distribution of whether farmers are willing to try something new.

4.3. Results and discussion

We used the information about the land use change intentions of farmers in NZ to conduct the empirical analysis based on Equations (3) – (6) shown in the previous section. Additionally, we test the opinion formulation process based on various initial open-mindedness values, i.e., $\varepsilon_0 = 0.2, \varepsilon_0 = 0.3$, and $\varepsilon_0 = 0.4$, as well as different numbers of potentially connected farmers m, with $m = 12$, and $m = 16$. Note that, according to the study of (Brown & Roper, 2017), NZ

[6] The Question is "Q123 I am/we are generally **one of the first** in {District x} to **try something new**. Select number from 0 to 10. 0: Strongly disagree -10: Strongly agree".

farmers tend to have about average 9 connections to chat about their farming practices. The analysis results are shown in the following Figures.

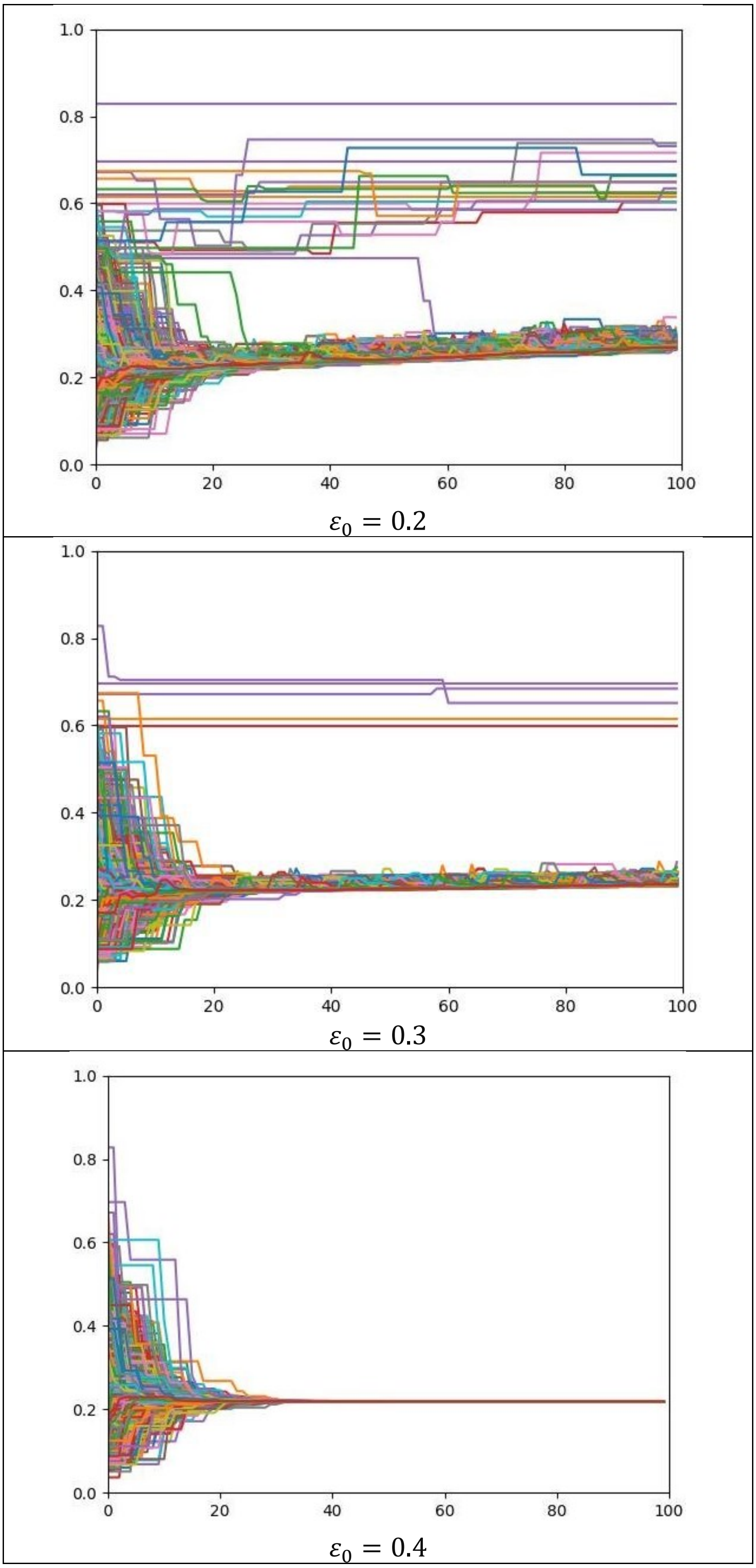


Figure 12. Simulation of opinion convergence on land use change of NZ farmers based on the OD-AHC model given the different values of ε_0 (N=2769, steps=100, units=50, m=9, μ=0.5, $x \sim N(0.51, 0.25)$

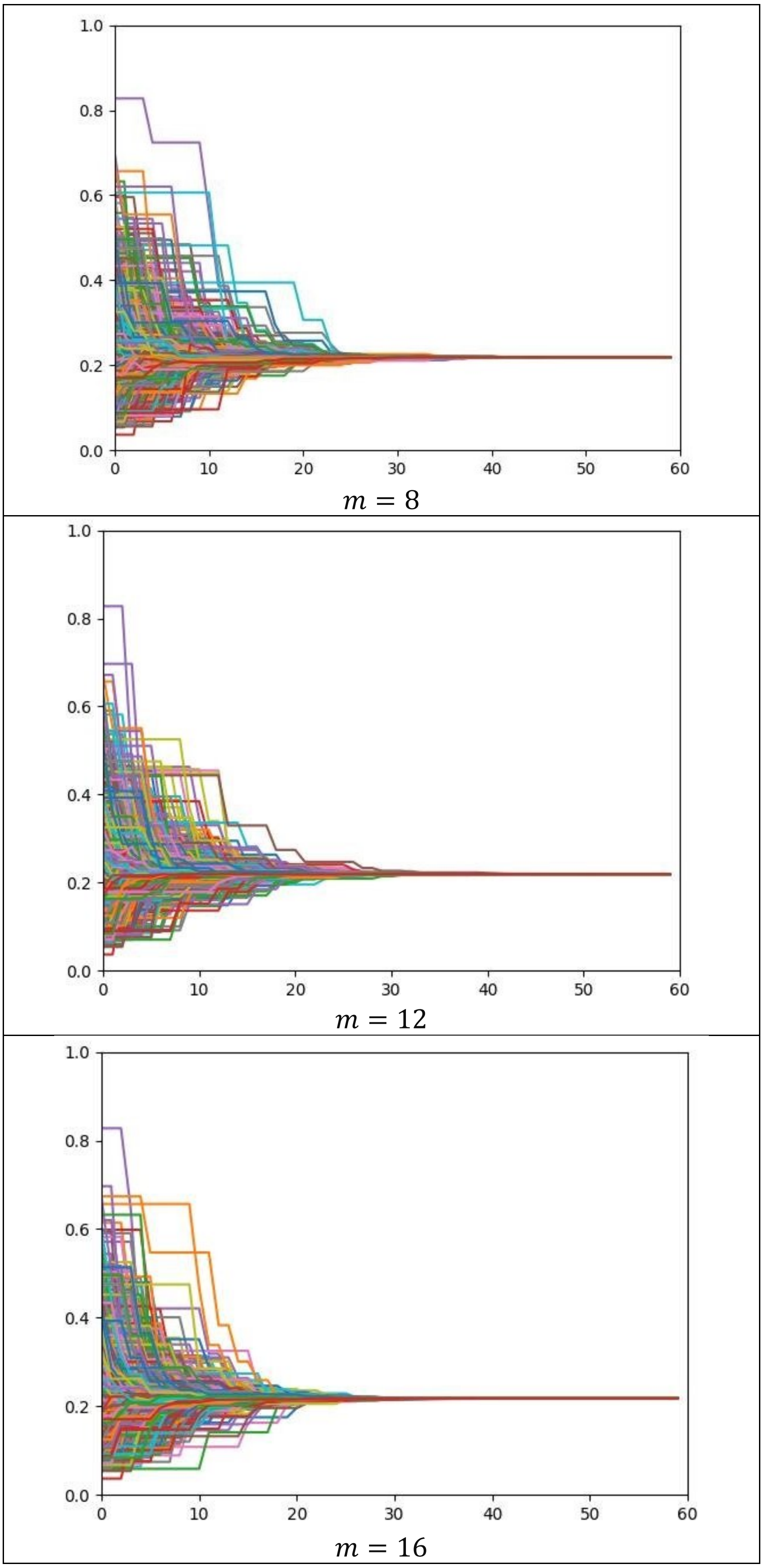


Figure 13. Simulation of opinion convergence on land use change of NZ farmers based on the OD-AHC model given the different values m (N=2764, steps=60, units=50, $\varepsilon_0 = 0.4$, μ=0.5, $x \in [0,1]$)

As shown in Figure 12, given a relatively small ε_0 (i.e., the farmer community is less open-minded), saying $\varepsilon_0 = 0.2$, farmers' opinions on land use change vary from centring between 0.2 and 0.3 to various branches between 0.5 and 0.8. However, as the value of ε_0 increases, farmers gradually reach a consensus, which is consistent with the simulation results shown in Section 3.2. In addition, the real-world data with real initial opinion values and preference for upper or lower opinions has added complexity and noise to the opinion formulation process. Whilst the overall open-mindedness of the network ε_0 determines whether opinion convergence can be achieved, the initial opinion value, in our case the probability of conducting land use change determines the convergence value – farmers may agree to make changes in land use practices but at a relatively low probability. Note that the distribution of x does not follow the distributions we assumed in the simulation, and hence it may add noises to the opinion formulation process shown in Figure 12. However, it does not affect the ultimate convergence of farmer group opinions on land use change, which is consistent with the simulation results that the distribution of x may influence the opinion convergence value (dependent on the symmetric or asymmetric characteristics) but not the overall convergence trend. Similar to the simulation results shown in Figure 7, the speed of opinion convergence is dependent on the number of farmers who have potentially interacted with an individual farmer (see Figure 13).

5. Discussion and Conclusion

5.1. Findings from the simulation results and empirical analysis

The simulation and empirical analysis conducted in this study have yielded several key findings regarding the dynamics of opinion formation and land use change in the agricultural landscape of New Zealand. By utilizing the OD-AHC model and data from the Sustainable Rural Development Monitor (SRDM) survey, this study has illuminated the intricate interplay between social interactions, individual characteristics, and land management decisions among farmers. Through simulation experimentation and model validation, several key findings have emerged.

First, social networks exert a significant influence on farmers' decision-making processes regarding land use. Traditionally, land management decisions have been portrayed as individualistic endeavours, largely overlooking the impact of peer interactions and knowledge exchange within farming communities. However, this study reveals that farmers' attitudes and behaviours towards land use innovations are shaped not only by personal factors but also by the opinions and experiences shared within their social networks. Through peer interactions, farmers gain insights into innovative practices, assess the experiences of their peers, and ultimately adjust their land management strategies accordingly.

Second, the OD-AHC model effectively captures the complexity of social interactions within farmer communities and simulates the process of opinion formation and land use change. One of the primary objectives of this study was to validate the OD-AHC model using real-world data from New Zealand. The model's ability to capture the complexity and dynamics of social interactions within the farmer community was demonstrated through empirical analysis. By incorporating variables such as initial opinion values and the degree of open-mindedness, the model effectively simulates the process of opinion formation and land use change. The results align with theoretical expectations, demonstrating the model's validity in representing the nuanced interactions among farmers.

Third, influencing factors such as open-mindedness, connectivity within social networks, and the asymmetry of confidence thresholds play crucial roles in shaping the speed and extent of opinion convergence among farmers. The study highlights several influencing factors that contribute to opinion convergence among farmers. These factors include the average open-mindedness of the farmer community (ε_0), the asymmetry of farmers' confidence thresholds (x), the number of potentially connected farmers (m), and the convergence parameter (μ). Through simulation and empirical analysis, it was observed that variations in these factors significantly affect the speed and extent of opinion convergence. For instance, higher levels of open-mindedness and increased connectivity within social networks expedite the consensus-building process among farmers.

5.2. Contributions

This study contributes to the understanding of social network effects on land use change decision-making in several ways. First, it provides empirical evidence of the influence of social networks on farmers' attitudes and behaviours towards land management practices, challenging traditional notions of individualistic decision-making. Second. by validating the OD-AHC model using real-world data, the study demonstrates the model's utility in capturing the nuanced interactions among farmers and simulating opinion formation processes. Last, the exploration of influencing factors offers insights into the mechanisms driving opinion convergence within farmer communities, enhancing our understanding of the dynamics of social interactions in land use decision-making.

5.3. Implications for Policy and Practice

The findings of this study have important implications for policy formulation and practice. Understanding the dynamics of social interactions and their impact on land use decisions has important implications for policy formulation and resource management. By recognizing the pivotal role of social networks in influencing farmers' attitudes and behaviours, policymakers can design interventions that promote knowledge exchange, collaboration, and the adoption of sustainable land management practices. For instance, policymakers can leverage social networks as channels for promoting knowledge exchange, collaboration, and the adoption of sustainable land management practices. Additionally, the findings highlight the importance of tailored approaches that account for the heterogeneity of farmer communities and their specific contextual factors.

5.4. Concluding Remarks and Suggestions for Future Research

In conclusion, this study enhances our understanding of the complex interplay between social networks and land use decisions. Moving forward, several avenues for future research merit consideration. Longitudinal studies could provide insights into the evolution of social networks and land management practices over time, offering a more comprehensive understanding of dynamics. Incorporating qualitative methods such as interviews or focus groups could enrich our understanding of the underlying mechanisms driving farmers' decision-making processes. Exploring the potential of novel technologies, such as social media platforms, to facilitate knowledge exchange and collaboration among farmers warrants further investigation. By addressing these research gaps, future studies can build upon the findings of this study and contribute to the advancement of knowledge in the field of social network effects on land use change decision-making.

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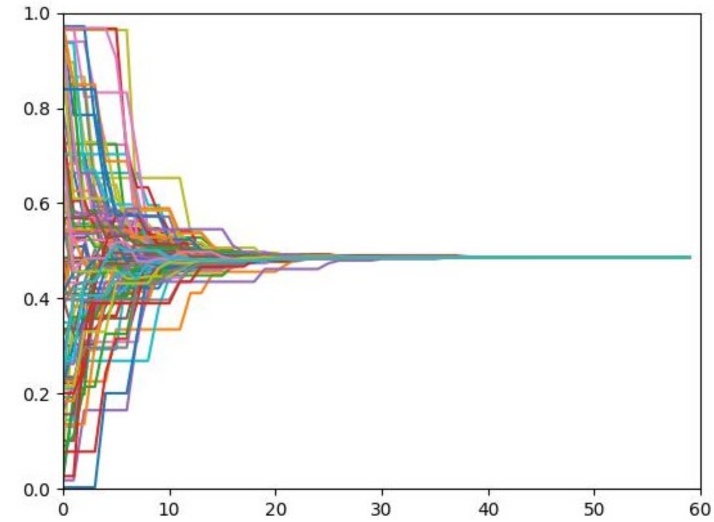
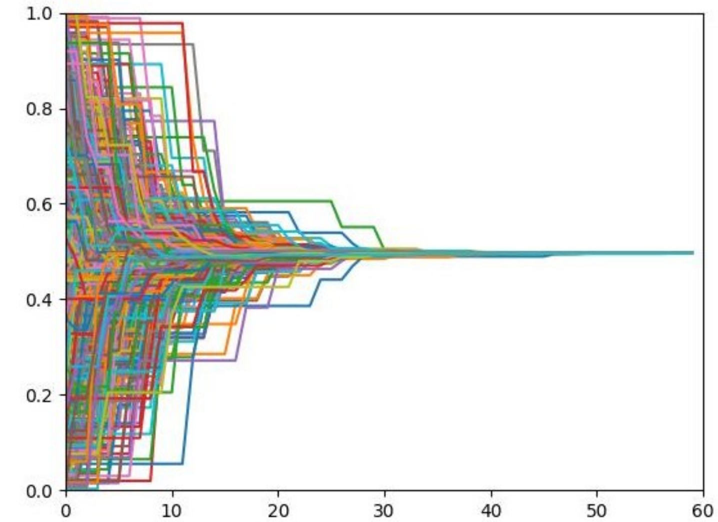
Appendix

In addition to analysing the impact of the four influencing factors on opnion formulation, we attempted to conduct a robust check to examine whether or not different sample size might affect opnion formulation. The simulation results are presented in Figure A1. The results show that the sample size *N* may have an influence on the speed of opnion formulation, where a smaller community (e.g., *N*=100) could reach consensus faster than a larger community (e.g., *N*=2000). However, the influence is not significant large, as the small community with 100 farmers reaches consensus at step 26 and the larger community with 2000 farmers reaches consensus at step 33.



$N = 100$



$N = 1000$

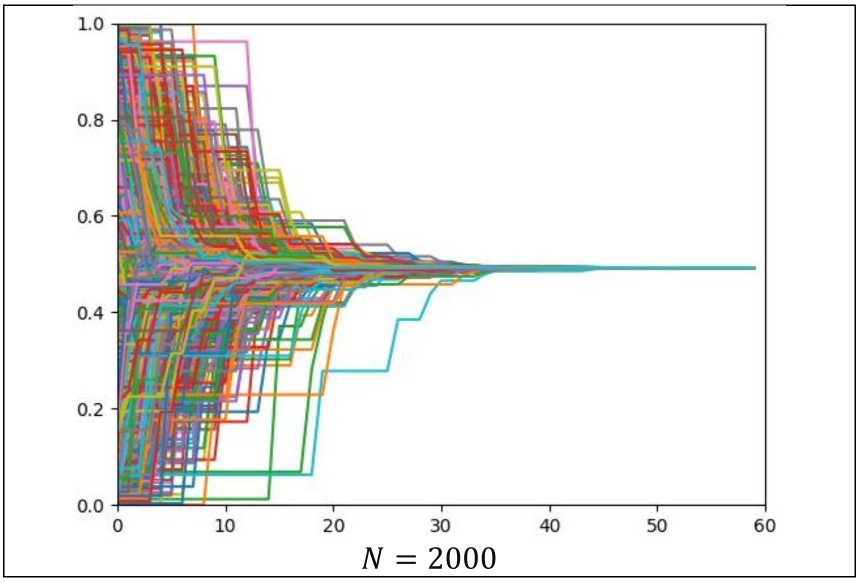


Figure A1. Simulation of opinion convergence based on the OD-AHC model given the different values of *N* (steps=60, units=500, $\varepsilon_0 = 0.4, \mu = 0.5, m = 7,\ x \in [0,1]$ follows a uniform distribution)