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GeSoN: A Geo-Social Network model applying bounded rationality to farmers in socio-ecological simulations

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Abstract

Agri-ecological environment management is a valuable tool for reducing agricultural impacts on ecosystems. Socio-ecological simulations can support these tools to find better solutions for managing natural resources. Nonetheless, these models are still few and scattered, often stand-alone and usually applicable to a specific context. Here, we present a Formal Model for reproducing the farmer opinion dynamic in a multi-layer geospatial network, focusing on the influence farmers embedded in the same landscape have on each other. The study aims to provide a new tool to integrate complex socio-ecological system simulations incorporating human behaviour and decision-making components, specifically focused on the farmer's social networks and opinion diffusion modelling. The farmers are modelled following the bounded rationality framework and applying the concept of ecological rationality and a bounded confidence opinion dynamic model governs the interaction between agents. The interaction between the agents is governed by an asymmetrical function and involves an explicit role of uncertainty. The model generates a connection between farmers using different criteria and developing a multilayer system where geographical, economic and social aspects are considered. The **G**eo-**S**ocial **N** etwork model (GeSoN) shows promising dynamics and types of behaviour, mainly attributable to the formation of consensus, polarisation and fragmentation amongst the

agents' opinions. Moreover, the GeSoN model presents flexibility and adaptability to be incorporated into more complex simulation systems.

Introduction

Agricultural systems are examples of socio-ecological systems (SESs) (Filatova et al. 2013), inheriting their peculiar characteristics; specifically, the co-existence of social and environmental factors and the inherent complexity (Levin et al. 2013). Thus, when modelling agricultural systems, farmers' behaviour is of paramount importance (Gotts et al. 2019). Crop choice, application of certain agricultural practices and innovation adoption are some of the actions carried out by farmers that affect the economy (Timmer 2002), social sustainability (Janker and Mann 2020) and environmental sustainability (Sabiha et al. 2016) of an agricultural landscape.

In the last decades, a relatively new class of model, the agent-based models (ABMs), has been widely used in modelling SESs (e.g. Kaufmann et al. (2009), Holtz and Pahl-Wostl (2012), Troost et al. (2015)). ABMs are computational models that represent reality, focusing on the atomistic parts of a system (i.e. agents), describing their behaviour and the interactions between them and the environment in a "bottom-up" approach (Murray-Rust et al. 2014). They were first developed for complex theory research (Holland 1996, Lewin 1992 and their popularity throughout academia has increased since then (Macal 2016). When approaching complex socio-ecological systems, such as the agricultural landscape, ABMs can give unique insights thanks to their ability to model complex emerging phenomena (*Kiesling et al. 2012*). Nowadays, models that involve farmers' behaviour are quite numerous (e.g. Guillem et al. (2015), Troost et al. (2015), van Duinen et al. (2016)). Amongst the different facets of farmers' behaviour, studies usually focus on innovation adoption (e.g. *Berger (2001), Deffuant et al. (2002), Kaufmann et al. (2009), Schwarz and Ernst (2009), Sorda et al. (2013)*) and land-use changes (*Murray-Rust et al. 2014, Synes et al. 2019*). Usually, these models apply a behavioural framework to farmers; depending on the chosen framework, they can define a decision-making rule applied to every agent (*Schlüter et al. 2019*). Well-known examples of behavioural frameworks are the Expected Utility Theory (EUT) (Simon 1978, Frank 1989, Monroe 2001), the Prospect Theory framework (*Kahneman and Tversky 1979*) and the Theory of Planned Behaviour (TPB) (*Ajzen 1991*). The behavioural framework influences the set of information that every farmer needs to handle to make a decision. For example, agents' risk aversion may be relevant under the Prospect Theory framework and irrelevant if the theory of planned behaviour framework is applied. Application of the same behavioural framework may also lead to substantially different models.

In most of the frameworks reviewed by *Schlüter et al. (2019)*, the agents' decisions are influenced by their context to a variable extent. This context involves the bio-physical and social environments, including the other agents embedded in the simulation. As clearly pointed out by *Heckbert et al. (2010)*, in complex systems, interactions matter. Hence, in the model regarding the agricultural socio-ecological system, a sophisticated and evolved representation of those interactions, particularly the interactions amongst human agents, should be implemented. Moreover, there is empirical evidence of the influence networks have over farmers' decision-making (*Schneider et al. 2012, Sol et al. 2013, Moschitz et al. 2015*).

While many agricultural systems models have been developed, relatively few studies explicitly account for social interactions (Huber et al. 2018). This study aims to fill this gap by developing a farmers' social networks and opinion diffusion model. This model involves elements of farmers' behaviour and decision-making, focusing on interactions between farmers and their influence on each other. The objective is to formulate a model in the context of SESs that recreates the farmers' social context relevant to the farmers' decision-making process. The model is planned to be part of an ABM of farmers' decision-making; therefore, it is a sub-model, but it can also be used independently to explore network properties.

Theoretical framework

The decision to apply a behavioural framework that exists already and is grounded in theory is generally recommended (Groeneveld et al. 2017, Schlüter et al. 2017). In particular, it facilitates the comparison and re-use of models (Groeneveld et al. 2017), leading to consolidation and improvements of the results (Bell et al. 2015). Moreover, it fosters communication between modellers and enhances theory development. When modelling human behaviour, the most commonly used behavioural framework derives from the Expected Utility Theory (EUT), initially proposed by Bernoulli (1954). This framework's fundamental assumptions are that humans are selfish, have stable and transitive preferences, have an unlimited cognitive capacity to evaluate every behavioural option available and base their decisions exclusively on the utility deriving from those. Being the standard in the economics discipline and being easily formulated mathematically, this framework is prevalent (Schlüter et al. 2017). In contrast, numerous empirical studies refuted the critical assumptions of the EUT in different domains (e.g. Siebenhuner (2000), van den Bergh and Gowdy (2000), Bocquého et al. (2014), Levine et al. (2015)). Consequentially, many other frameworks, mainly from psychology, have been proposed to fill the gap between the EUT and observed human behaviour. Groeneveld et al. (2017), Schlüter et al. (2017) comprehensively describe these frameworks.

Here, the approach to modelling the farmer's behaviour follows the Bounded Rationality framework (Simon 1955, Simon 1997). Bounded rationality states that, when making decisions, humans (or farmers, in our case) do not set out complex optimisation procedures; instead, they mediate between constraints regarding time, knowledge and cognitive abilities. More specifically, as Jones (2003) explained, four distinct facets concerning the human decision-making must be considered. These are:

1. humans encounter difficulties in evaluating and planning long behavioural sequences, given by their limited, or "bounded", cognitive capacity and the inherent complexity of their environment;
2. people tend to set aspirational levels related to specific goals;
3. they work on goals sequentially and not simultaneously;

4. their search strategy is aimed at satisfaction rather than optimisation.

A vital aspect of the bounded rationality framework is called “ecological rationality” (Gigerenzer and Selten 2001). This concept underlines how decisions are strongly influenced by the environment, intended as the parts of the context, both physical and social, relevant to agents’ goals and needs. According to the bounded rationality framework, the definition of ecological rationality and environment both account for the agent’s context when defining the system’s boundaries in a bottom-up modelling approach aimed at replicating realistic human decision-making. The environment becomes part of the limitations to human-comprehensive rationality (Simon 1997). From another perspective, the ability of individuals to understand and adapt to the environment could determine their success in satisfying their goals (Gigerenzer and Selten 2001).

Modelling approaches

The approach used to model the interaction amongst farmers in this model is the opinion dynamic. This specific branch of the more general social network analysis framework has gained attention for its potential application in social and political science (Sun and Müller 2013). The opinion dynamic studies the evolution of individuals’ views as the result of the interactions between a network of individuals. In other words, it assumes people influence each other, describes the interaction process from an individual point of view and produces results emergent from those interactions, pooled for the population. The seminal works of this discipline are the study conducted by French Jr. (1956) and its revision and formal elaboration by Degroot (1974). Their model, also known as the French-DeGroot model, focuses on consensus and the conditions that lead to a consensus amongst individuals. Since then, many other opinion dynamic models have been developed (e.g. Toscani 2006, Düring and Wolfram 2015, Tian and Wang 2018).

The opinion dynamic approach focuses on the individual elements of the network and requires the specification of several key elements. These are the network identification, the opinions definition and the formulation of an interaction mechanism. The first step in defining the network is to determine whether the network has a specific topology or is completely random and, ultimately, determine who interacts with whom and in which order. The opinions definition involves its mathematical representation; there are two main types. The first type represents opinions as discrete variables; examples are the voter model (Clifford and Sudbury 1973) and the Snajzd model (Sznajd-Weron and Sznajd 2000). The second type models the opinions as continuous variables; usually, the opinion range values lie between 0 and 1. This type includes the *Deffuant* model (*Deffuant et al. 2000*) and the *French-DeGroot* model. The present study belongs to the second type. The interaction mechanism describes how agents respond to the interaction with others. This involves the formula determining the magnitude of the influence and any constraints added to the interaction. The major constraint used in the model presented here is *bounded confidence*. Models developed applying this constraint assume that influence amongst interacting agents does not always occur. This means there is influence during an interaction only when a specific condition regarding the opinions (usually similarity between opinions) is met. Thus, the assumption underlying bounded confidence is that opposite opinions have little or no influence on each other.

The concept of geographical specificity (Namatame and Chen 2016) has been applied to model the links enabling the connection between agents. The geographical specificity must be considered an attribute of the agents that creates higher levels of heterogeneity in the population and ultimately affects the interaction rules by explicitly defining the possible interactions amongst agents. As a result, a multi-layer network was defined following the geographical specificity. Different network configurations were defined with different linking properties, each influencing the same explicit structure where the opinion dynamic takes place. This allows feedback mechanisms to alter the overall network dynamics due to inter- and intra-network interactions. The criteria behind the multi-layer network formation are different. Examples are the physical location and agents' economic attributes. This approach evolves from the random connection formation rule, used in the seminal models of Watts-Stogatz and French-DeGroot and that is a purely mathematical network. Instead, applying economic and social criteria to agents' connections forms a socio-economical network (Namatame and Chen 2016). Other examples of this approach can be found in Chen et al. (2006), Yang et al. (2022) A detailed explanation of this process is given in the Overview of the processes section.

Framing the model

Decisions about what to include or not to include influence the model's flexibility, results and predictive power (Topping et al. 2015). In the modellers' opinion, the processes included in GeSoN were the most relevant in capturing the essential dynamics emerging from the social interaction amongst farmers. Nonetheless, some processes were intentionally left outside the model's system boundaries to maintain an adequate level of model parsimony, simplicity and feasibility. At this stage of development, farmers are the only type of agent represented in the model. In real scenarios, some other entities, like agricultural advisors, food processing industries or institutions, may mediate the interaction amongst farmers and influence the diffusion of innovation. The inclusion of those actors is planned for future developments of the model. Second, although the theoretical approach used in the model accounts for the socio-psychological characteristics of the farmers, the inclusion of every personal psychological sphere is outside the scope of the model. Notably, farmers' emotions were intentionally left outside of the system boundaries. As pointed out by Huber et al. (2018), emotions are rarely included in farmer behaviour models and a more consistent inclusion of these aspects should be considered in future works. Third, the agricultural land market is not taken into consideration. The decision to keep the land market outside the model was taken so as not to over-complicate the model and because of its relatively small effect on determining farmers' social interaction. Fourth, the farmers' position in the landscape is assumed to be located in their farm centre. The location has a major influence on the farmers' social network. Still, farmers' physical movements are not reasonably predicted; therefore, the assumption of the same location between farms and farmers has been made.

An important aspect left outside the model's system boundaries is the other sources of influence affecting farmers' opinions. At this stage of the development of the model, a focus on only the endogenous influence of farmers' opinions best fits the study's aim. Nonetheless, the model structure allows the integration of other sources of influence, like economic and environmental shocks causing a generalised shift in the farmers' opinions, such as their risk aversion.

Overview of the processes

Overview of the components and the connections

The GeSoN model has two main components that are strictly related and work together while representing different aspects of the social context of farmers. These are the farmers' social network and the interaction amongst farmers. The former is the structure that represents the connections between farmers. The latter is the process of interaction between farmers. In the following sections, both components are described in detail. The farmer social network is the process of forming connections between farmers. Different factors, such as the geographical distance between farms, regulate the formation of ties. The Network structure is composed of three distinct layers, forming a multi-criteria web of channels through which farmers interact. The interaction between farmers generates the model influence farmers have on each other when interacting. The influence considers farmers' opinions, like risk aversion or sustainability concerns. The farmer network forms the structure over which the interaction between farmers occurs. Those interactions are not random, but based on neighbourhood. The specific morphology of the landscape and the farmers' characteristics strongly influence the outcome of these interactions and the results of applying the network structure.

Process description

To better describe the GeSoN structure, the connections between agents are mapped using the network science's concepts of nodes and links. For example, in Fig. 1, the basic features of the GeSoN structure are shown. Farmers and other agents (note that, in the current version of the GeSoN, only farmers are considered) form the nodes distribution. Arrows represent the links between nodes and indicate the connections between agents. Both nodes and links have attributes (or features, characteristics). Nodes' attributes are size, position and the number of connections with other nodes. Links' attributes are direction and strength.

Network structure

The network represents the sum of relevant ties connecting farmers in the same agricultural landscape. These connections resemble the channels through which communication takes place. Amongst all the possible and only partially predictable relationships between farmers, only a few of those are modelled here. Although the farmers' social context involves numerous actors (e.g. their family, agricultural advisors operating in the area and local food industries), in this first development of the GeSoN, the connections between farmers are made only between farmers. In other words, GeSoN does not consider the influence of those actors directly, but leaves the possibility to involve those in future developments. In the past, the network's topology (i.e. the position of the nodes and links between those) was most often separated from sociological questions (Will et al. 2020). Examples are the random network (Erdös and Rényi 1959), the small-world networks (Watts and Strogatz 1998) and scale-free networks (Albert-László and Réka 1999). On the other hand, the network's topology reflects socio-economics phenomena and is highly dependent on the agricultural landscape. Nonetheless, a certain level of stochasticity is incorporated in the formation of the ties. The different criteria forming the links between agents are intended to be separate and interacting layers, each shaping the individuals' social network. Hereafter, the specification of the rationale behind the connection between farmers is given.

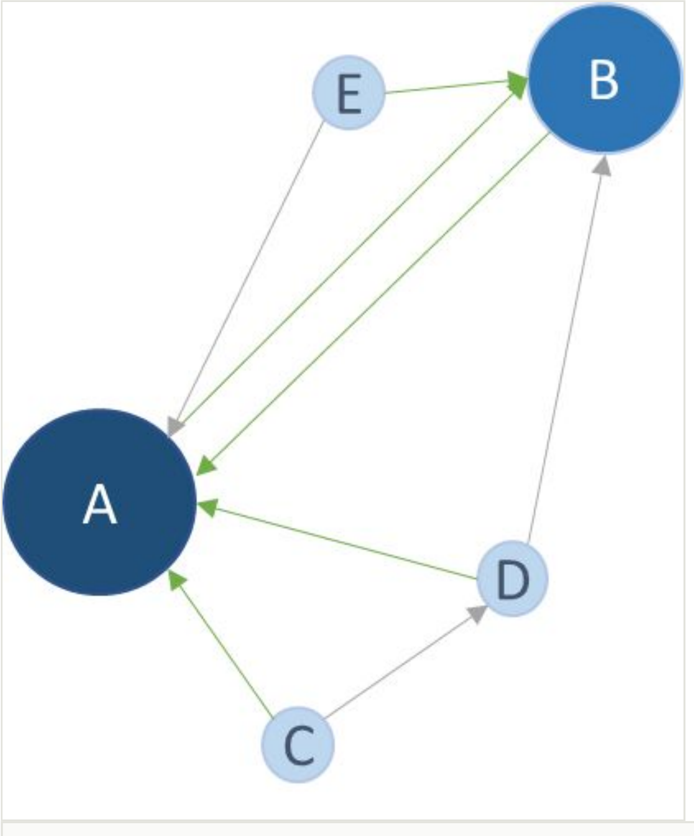

Figure 1. doi

Example of network elements. Coloured dots represent nodes and arrows represent links. The dots' colour, size and position represent the nodes' attributes. The colour and direction of the arrows indicate the strength and direction of the connections.

Ties formation rationale

The ties formation process involves different features, each forming a specific sub-section of the GeSoN. In the first instance (Geographical Network), the geospatial configuration of the landscape is what most influences the network's structure. Farmer agents' primary connections are based on the farms' specific location across the landscape. The basic concept is that, as demonstrated by literature (Neal and Neal 2014, Will et al. 2020), farmers are highly influenced by their peers' behaviour. Physical distance, or proximity, between farmers partially determines their connection. Moreover, the economic size of the farmer also affects the possibility of creating links and larger farms are assumed to influence other farmers more frequently than others. Innovative and more influential farms are usually economically significant (Just and Zilberman 1983, Sunding and Zilberman 2001, Daberkow and McBride 2003). As a second connected parallel network, a set of links is formed to simulate the presence, in a landscape, of groups of cooperating farmers (the Associative network). These can be members of the same cooperative, members of a producer organisation or only similar farmers in terms of agricultural production. The third network set of ties is generated to capture the non-agricultural connections between farmers. These can be various, like friendship or parenthood (the Virtual network). The sub-model section describes these three sets of links in more detail.

Geographical Network

The Geographical Network is the major component of the GeSoN; it represents the influence over the landscape of "nodal" farmers. As described by Poudel et al. (2015), nodal farmers create the highest number of connections with others and, hence, significantly influence the agricultural landscape. The Geographical Network uses a modified gravity model to shape farmer connections. The gravity model is a well-known empirical economic model, originally developed by Newton's law of gravitation (Anderson 2011), first used by Isard (1954) and primarily applied to international trade studies (e.g. Brun et al. (2005), Carrère (2006)). A modified gravity model has been used for three reasons. First, although there is a lack of connection with the economic theory, the gravity model has been proven to have an important explicatory predictive power (Anderson 2011); second, it is a parsimonious model; third has already been applied to ABM regarding farmers network (Yang et al. 2022). The two main assumptions behind the application of this model are: 1) closer farmers are more likely to interact and 2) larger farmers (in terms of farm size) have more influence over their neighbours than smaller farmers. In the Geographical Network, the links between agents are weighted and directional. This means that *Farmer i* can be linked strongly or weakly with *Farmer j*, independent of how *Farmer j* is linked with *Farmer i.* The resulting formula behind the formation of links between farmers under the Geographical Network is:

$$F_{ij} = \frac{M_j}{D_{ij}}$$

where F_ij is the strength of the link that connects *Farmer i* with *Farmer j*. M_j is the *Farmer j* size (note that only the size of *Farmer j* is taken into consideration) and D_ij is the physical distance between *Farmer i* and *Farmer j*, *i.e*. between the two farms. After computing the force connecting them, all farmers have a ranked list of all the other farmers in the landscape, ordered by the force. A graphical example is given in Fig. 2. Note that the ordered list varies amongst farmers; in the example, farmer i has its strongest link with *Farmer j*, while *Farmer j* is linked primarily with *Farmer z*. When the interactions take place, farmers will choose a predetermined number of neighbours from the top part of the ranked list in the same order they are listed. The number of neighbours is one of the state variables of the model.

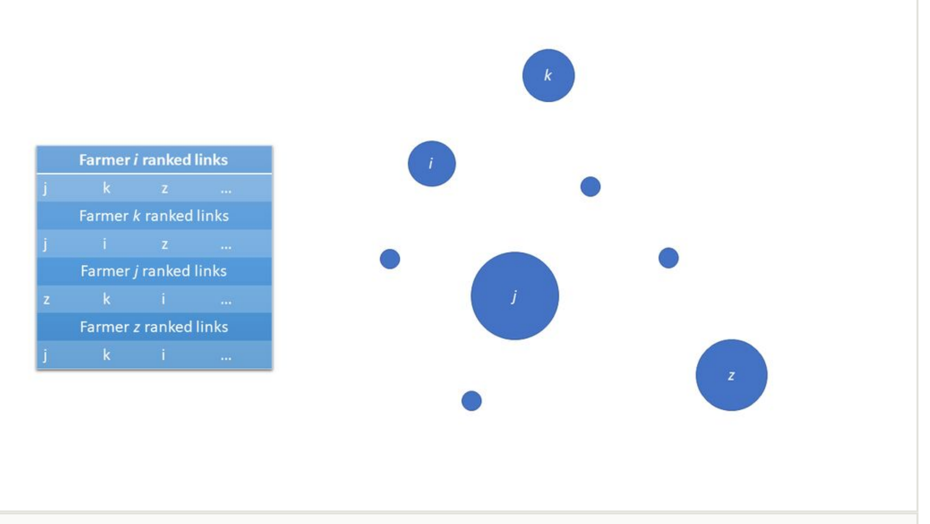

Figure 2. doi

Graphical example of the spatial distribution of farmers and their ranked list of neighbours under the geographical network.

Associative and Virtual Networks

The concept governing the Associative network's formation of ties between farmers is the potential to incorporate information about the farmer's membership of cooperatives, corporations or producer organisations. It is important to add the influence of these types of organisations on the network since farmers are strongly affected in their decision-making by being part of one of these groups (Franks and Mc Gloin 2007). The Associative network is exogenous and predetermined at the beginning of the simulation. If information about farmers' membership to cooperative-like associations is available, scenarios with cooperatives associating similar farmers may give interesting results.The Virtual Network's primary purpose is to incorporate unpredictable connections between farmers. Those can be of various types, like normal friendships, family relationships or social network friendships. This additional layer completes the network structure involving a determined level of stochasticity. As with the Associative network, the Virtual network is exogenous.

Interaction amongst farmers

Once the link between agents is formed, different kinds of information can travel through it. Here we focus on the diffusion of opinions. These are risk aversion and sustainability concerns and form parameters in the farmers' decision-making process. Opinions have been modelled as continuous variables ranging from 0 to 1, with 1 excluded, as proposed by Deffuant et al. (2000) and Hegselmann and Krause (2002). As underlined by Weisbuch et al. (2002), an explicit role of the actor-uncertainty regarding personal opinions is fundamental. Hence, every farmer has his/her personal opinion and a certain level of uncertainty. Uncertainty is modelled as a continuous variable, ranging from 0 to 0.6. A graphical example is given in Fig. 3. The farmer's opinion is the uncertainty's central point or mean value. The values 0 and 1 are the opposite extreme opinions. During the simulation, farmers interact with their neighbours and adjust their opinion according to the neighbours' one. The interaction follows the principle of bounded confidence, which implies that an agent is not influenced by distant positions (Xia et al. 2011). The rationale is that people with similar attitudes are more likely to interact (Neal and Neal 2014) and that there is a lack of understanding between persons with substantially different opinions (Deffuant et al. 2002). The minimum distance, or threshold, to enable the influence of one opinion over the other is represented by the uncertainty associated with the influenced agent's opinion (Weisbuch et al. 2002). Fig. 4 shows when an influence of opinions occurs and when it does not, accordingly to the distance of opinions between agents. In the model, time is discrete and divided into time steps in which the farmers can interact. Every farmer has a list of neighbours, ranked by the force of the link under the geographical network. A certain number of neighbours is taken from this list. To these, other neighbours coming from the other networks may be added. Each farmer then interacts with the chosen neighbours and updates their opinion after interacting with all the selected neighbours. It is important to emphasise that farmers upload their opinions after every other farmer has interacted with their respective neighbours. In this way, it is avoided that the starting order of farmers makes a difference in the results. The magnitude of the influence is controlled by the mobility parameter. The mobility value is fixed for all the agents and set at the beginning of the simulation. The resulting formula controlling the influence is:

$$x_{A,t+1} = x_{A,t} * (1 - \frac{u_A}{(u_A + u_B)} * q) + m_{u_{overlap}} * (\frac{u_A}{(u_A + u_B)} * q) Where: x_{A,t} = Farmer\ A\ opinion, at\ time\ t x_{B,t} = Farmer\ B\ opinion, at\ time\ t u_A = Farmer\ A\ uncertainty u_B = Farmer\ B\ uncertainty u_{overlap} = overlapping\ between\ u_A\ and\ u_B m_{u_{overlap}} = central\ point\ of\ u_{overlap} q = mobility$$

The formula is a weighted mean of the influenced farmer's opinion and the central part of the influencing farmer's shared opinion. The weights given to the two elements are the *mobility* parameter and its inverse, both scaled by a factor indicating the difference in the farmers' uncertainties. This factor results in the influence between farmers with unequal uncertainties being asymmetrical. Thus, when two farmers with high and low uncertainty respectively influence each other, the effect is stronger on the farmer with high uncertainty.

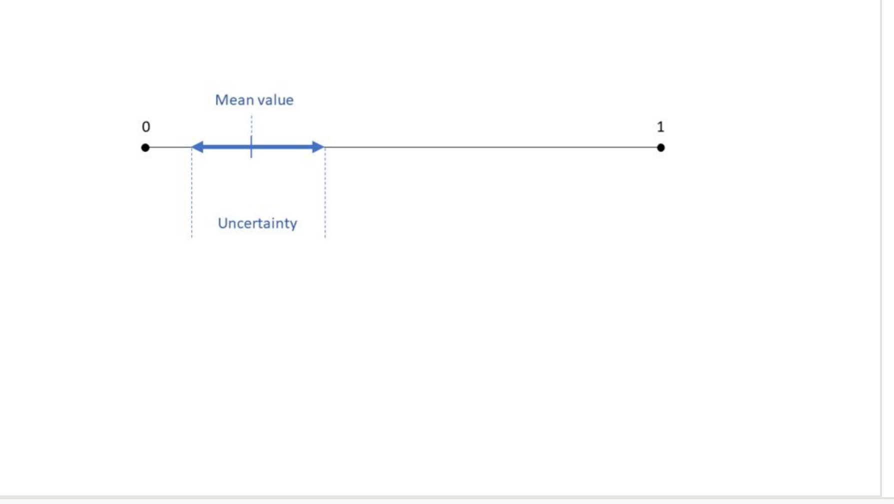

Figure 3. doi

A representation of farmers' personal opinions.

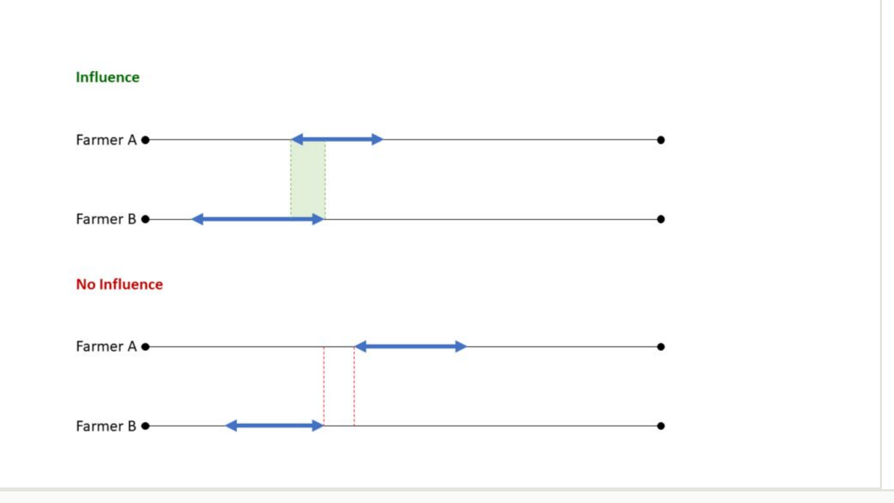

Figure 4. doi

In the upper part, example of similar opinions producing an interaction. In the bottom, example of different opinions not producing an interaction.

Numerical example

Here, we give a numerical example of the interaction between two farmers, say A and B, whose initial opinions are 0.7 and 0.5. Uncertainty is set to 0.4 for Farmer A and 0.2 for Farmer B. Finally, the mobility parameter is set to 0.8. A graphical representation of this specific interaction is given in Fig. 5.

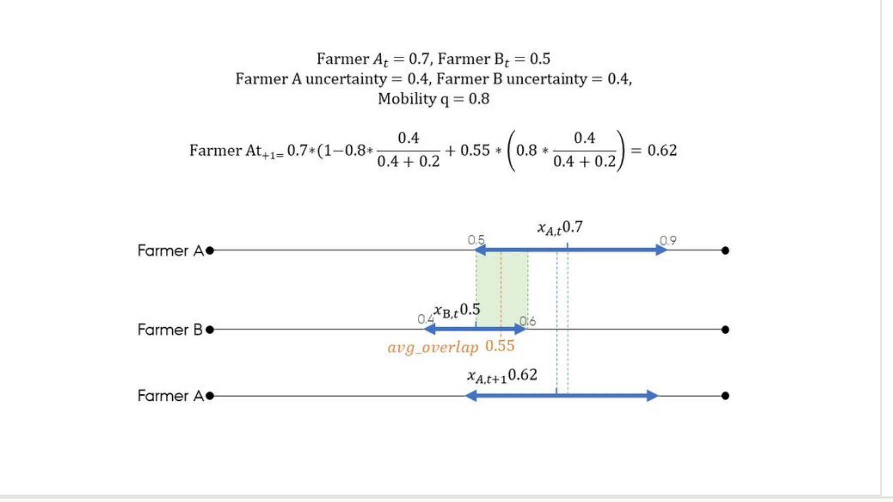

Figure 5. doi

A numerical and graphical representation of the interaction between agents. Farmer A and Farmer B have different opinions (A = 0.7 and B = 0.5). Nonetheless, their uncertainties overlap (green part), so the interaction occurs.

State variables and scales

State variables and scales are shown in Table 1.

Table 1.

State variables and their description.

State Variable	**Description**
Neighbours from the Geographical network	In every round of interaction, the farmers will choose this discrete number of other agents from the ranked list of neighbours given by the Geographical Network.
Neighbours from the Associative Network	In every round of interaction, the farmers will choose this discrete number of other agents from the list of co-associates held by the Associative Network.
Neighbours from the Virtual Network	In every round of interaction, the farmers will choose this discrete number of other agents from the list of friends given by the Virtual Network.
Landscape	The simulated space where farms exist. List of cartesian coordinates associated with the information about the farms' size.
Mobility	A parameter that regulates the convergence of opinions during an interaction. It is a continuous variable bounded between 0 and 1. The value 0 means no convergence and 1 indicates maximum convergence.
Opinions Initial distribution	Farmer's opinion values at the beginning of the simulation. Opinions are continuous variables bounded between 0 and 1.
Uncertainties initial distribution	Farmer's uncertainty values at the beginning of the simulation. Uncertainties are continuous variables bounded between 0 and 0.6.

Network properties and behaviour

A rigorous mathematical analysis and a complete application of the model to a real case scenario are outside the scope of this paper. Nonetheless , some results from the model implementation are shown below to unravel some of its interesting properties.

Visualising the Farmer network

In Fig. 6, a real configuration of farms from a Danish landscape is shown, Himmerland (DK). The dots represent the farms and the size of the dots represents the area covered by each farm. In this landscape, the farms are distributed relatively evenly across the space and there are no particular clusters of large or small farms. Data regarding the farms' location and size have been extracted from the Land Parcel Identification System (LPIS) database for Denmark. LPIS is an IT system based on satellite orthophotos used by the EU to monitor land use and provide farmers with the proper income support. This database is managed at the regional level, making the availability and quality of those data highly region-dependent.The actualisation of the Geographical Network is shown in Fig. 7. Again, the position of the dots represents the actual position of the farms in the landscape and their size represents the actual farm size. The links between the nodes indicate the strongest connections a farmer has. The colour of the dots indicates the number of connections. Hence, dark blue dots indicate farmers strongly embedded in the network, eventually influencing numerous other farmers.

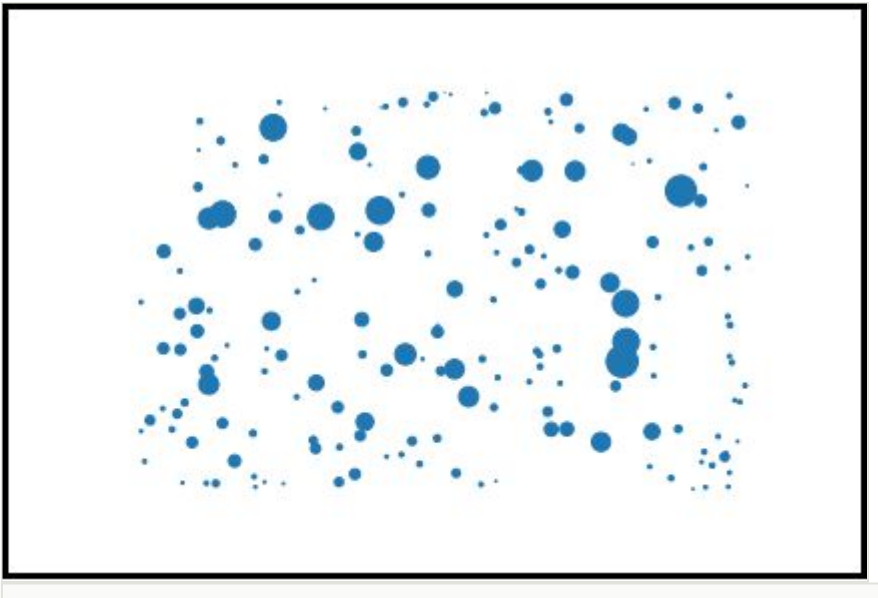

Figure 6. doi

The spatial distribution and size of farms from the Himmerland landscape in Denmark. The dots represent the farms and the size of the dots represents the area covered by each farm.

To provide a less balanced example in terms of farm size and location, we have generated hypothetical landscapes where this information was simulated. Figs 8, 9, 10 show three different examples of the Network implementation over simulated landscapes. The landscapes were produced by forming clusters of farms and with a degree of correlation between farm size and farm location. The resulting network of links differs substantially and, as shown in the next section, will produce different emerging system dynamics.

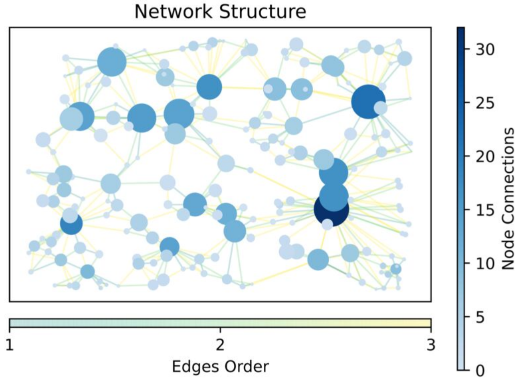

Figure 7. doi

The network structure for the Himmerland (DK) landscape. The links between the nodes indicate the strongest connections a farmer has. Only the top three edges are shown. Edges are coloured differently to indicate the edges' order in strength.

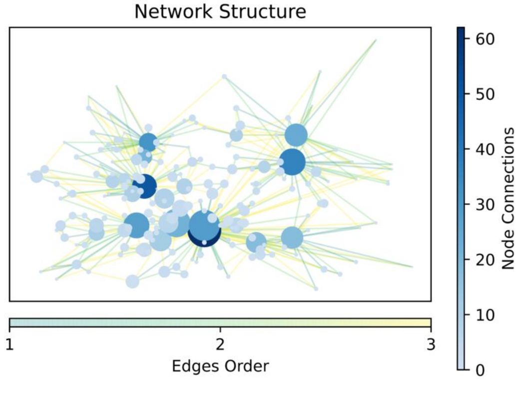

Figure 8. doi

Implementation of the network over a simulated landscape. Here, farms are centred on one cluster and farm size and location are positively correlated. Hence, larger farms are more likely to occupy a central position.

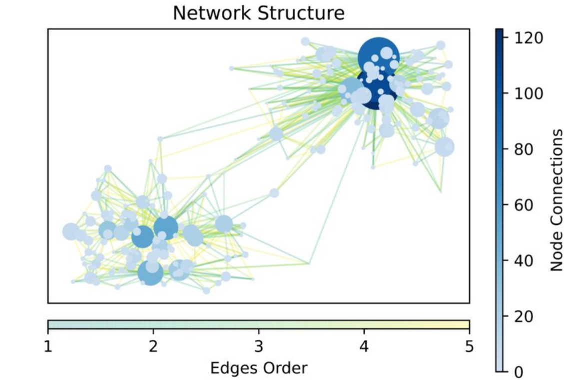

Figure 9. doi

Implementation of the network over a simulated landscape. Here, farms are centred on two clusters and farm size and location are positively correlated. Hence, larger farms are more likely to occupy a central position.

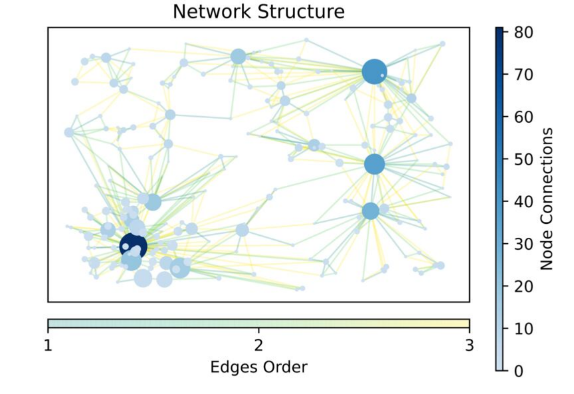

Figure 10. doi

Implementation of the network over a simulated landscape. Here, farms are centred on four clusters of different sizes. Farm size and location are independent.

Visualising the opinion dynamics: consensus, polarisation and fragmentation

We created a prototype implementation of the model in Python to demonstrate its behavioural capabilities. The results below are derived from simulations of real and simulated landscapes and using different network structures.

Himmerland (DK) scenario

In this scenario, the simulation runs over the Himmerland (DK) real landscape with 190 farmers. The initial opinions are randomly selected from a uniform distribution between the extremes and the mobility parameter is set to 0.5. On the left side of Fig. 11, the opinions' initial distribution and the network structure, the colour of the dots represent the farmers' initial opinions. On the right side of *Fig. 11*, the resulting final condition after 100 time steps is shown. Lastly, Fig. 12 shows the evolution of the opinions throughout the simulation. Here, individuals interact with five neighbours at each time step, all selected from the geographical network. As we can see, the relatively even initial distribution is replaced by a double peak distribution. The more prominent peak is slowly formed during the simulation and is evident from the 60th time step. The smaller peaks are formed early in the simulation and remain stable.

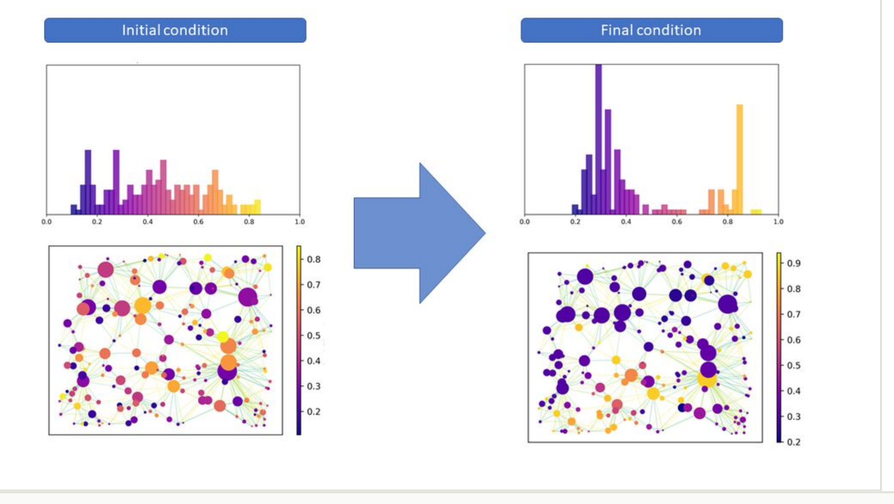

Figure 11. doi

Opinion distribution histogram and network structure. The colour of the dots represents the farmers' initial opinion. On the left side, the initial condition. On the right side, the resulting final condition after 100 time steps.

In this next example shown in Fig. 13, there is a comparison of two simulations where the input values are held constant, except for the network structure. In one, as the above, all neighbours come from the Geographical Network; in the other, all three networks were integrated into the test. Substantially different results emerge from the simulations. The results generated by applying all three networks showed a situation of polarisation of opinions around two values (~ 0.3 and ~ 0.7). In contrast, the results of the application of just the Geographical Network showed consensus around the mean opinion value (~ 0.5). This indicates that the single simple network would give erroneous results if the other networks were active in the real world. It also highlights the importance of considering the limitation of the theoretical representation.

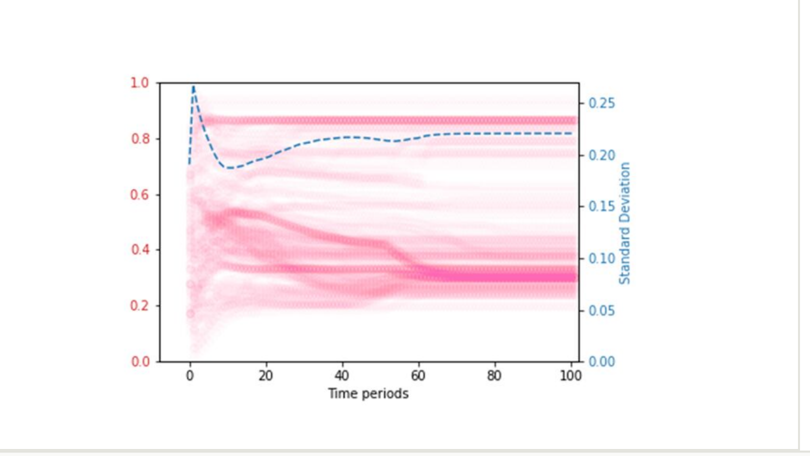

Figure 12. doi

The evolution of opinions during a 100-time-step simulation. The opinions in each time step are shown in pink and the standard deviation of the opinion distribution over time is in blue.

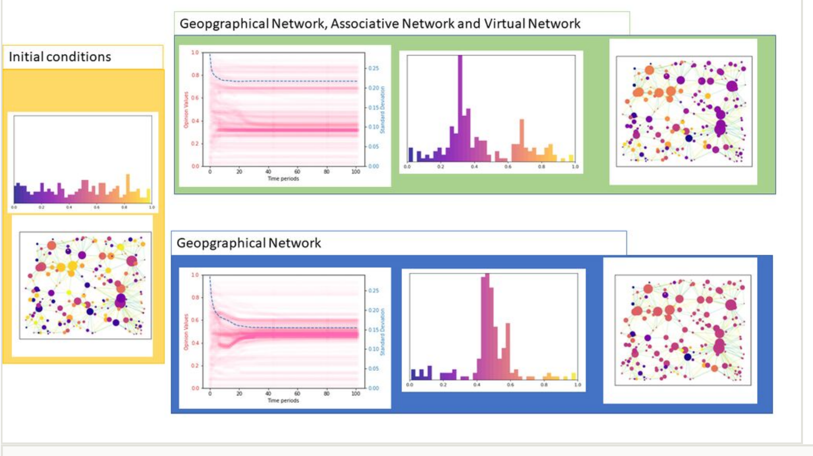

Figure 13. doi

Comparison of two simulations with the same initial conditions and different network structures. In the upper green highlighted result, the result of all three networks. In the lower blue highlighted, the result of only the geographical network.

Simulated landscape

Here, the simulation is carried out with a simulated landscape formed by 214 farmers. The initial opinions were randomly selected from a normal distribution with a mean of 0.5 and a standard deviation of 0.15. The mobility parameter is set to 1, the maximum value. The opinions' initial distribution and the network structure are shown on the left side of Fig. 14, while the final distribution is shown on the right side of Fig. 14. Fig. 15 shows the evolution of the opinions throughout the simulation. This second example shows different emerging dynamics. In the first time steps, two peaks were formed rapidly. The larger peak was around 0.3 opinion value and the smaller is about 0.8 opinion value. Surprisingly, the small peak remains throughout the experiment, but the larger peak drifts towards higher values. This interesting behaviour is given by the peculiar initial value where the spatial configuration plays an important role, as seen by the final spatial distribution of opinions in Fig. 14. The remaining blue cluster in the lower left corner is formed by small farms that likely do not influence surrounding farms and have a very different opinion from the neighbours to be influenced themselves.

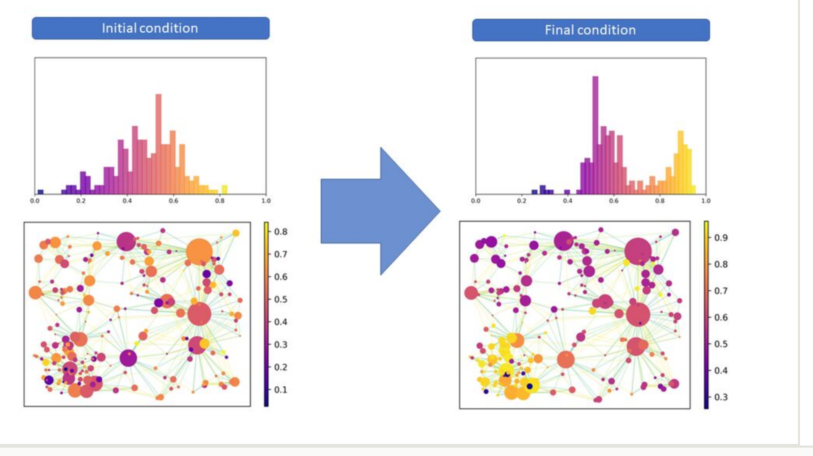

Figure 14. doi

Opinion distribution histogram and network structure. The colour of the dots represents the farmers' initial opinion. On the left side, the initial condition. On the right side, the resulting condition after 100 time steps.

Discussion

Here, we have presented the Formal model of the GeSoN aimed at reproducing the social context that affects farmers' opinions. The model's peculiarity is the conjunction of theoretical aspects regarding the social simulation, mainly based on the opinion dynamics models of bounded confidence (Deffuant et al. 2002), with the bounded rationality behavioural framework (Simon 1997) and the geographical specificity (Namatame and Chen 2016). Moreover, unique to this model is the specification of the equation governing the interaction between farmers through a multifactorial asymmetrical function. Other models apply similar equations, particularly the seminal work of the bounded confidence approach, the Deffuant–Weisbuch model. However, in the case of the Deffuant–Weisbuch model, the formula governing the interaction results is symmetrical. In fact, in their model, the uncertainty is not taken directly into consideration. The multifactorial asymmetrical function has a double consequence. First, farmer interactions are independent, so exchanges are not guaranteed to be mutual. Second, when two farmers interact, the influence one farmer has on the other may have a different magnitude. The asymmetrical function not only allows for the incorporation of actor-uncertainty into the model, but also allows for the possibility of the formation of different “roles” during the simulation in a particular landscape. As already mentioned, farmers with the most connections and low uncertainty will play the role of leaders or “nodal” farmers. The GeSoN shows, since its prototype applications, promising dynamics and types of behaviour. These are mostly attributable to the usual final states reached by the diffusion models, namely consensus, polarisation and fragmentation (Zha et al. 2020). Other models have been tested and showed similar dynamics. Nonetheless, the prototype nature of the dynamics shown by the GeSoN makes it impossible to evaluate the effective similarity, or difference, with other models. Moreover, based on the results of a thorough implementation of the Deffuant model (Gómez-Serrano et al. 2012), models of bounded confidence are demonstrated to be independent and identically distributed non-linear Markov processes, where, as time goes to infinity, opinions converge to a set of clusters. Finally, the results from the prototype of the GeSoN are characterised by non-linearities in the formation of typical consensus and polarisation, indicating the emergence of interesting, complex dynamics. The GeSoN has several limitations. First, the simplicity in the representation of the opinions. Opinions were originally modelled as binary options (e.g. Arthur (1994), Degroot (1974)). With time and during the development of the discipline, this representation has been replaced by continuous variables representing opinions (Deffuant et al. 2000). Nonetheless, this representation ignores the intricacies related to one’s personal opinion. Second, individual opinions are influenced only by neighbours’ opinions. In real scenarios, personal opinions are formed as the sum of different contextual factors (Chacoma and Zanette 2015). To try to overcome this limitation, the GeSoN will be incorporated into a more sophisticated agent-based model. The GeSoN primarily aims at integrating the social network and opinion diffusion in an agent-based model regarding the agricultural socio-ecological system. This will be done using GeSoN as a module of ALMaSS (Topping et al. 2003, Topping 2022). In ALMaSS, various other aspects regarding the farmers’ behaviour and decision-making are modelled using the CONSUMAT as the conceptual framework (Jager and Janssen 2012, Malawska and Topping 2018). Although practical use of the model could arise only after incorporating the model into ALMaSS, the GeSon model has concrete potential to inform policy-makers in defining well-tuned measures. In particular, ex-ante policy analysis could benefit from the model application in predicting farmers' responses to specific policy measures. Farmers' voluntary enrolment measures have considerable importance in the EU agricultural policy framework. Predicting the adoption rate by farmers of these measures is valuable and could lead to higher efficiency and effectiveness. For instance, when allocating the budget for implementing an environmental measure, not precisely foreseeing the adoption by the farmers leads to a sub-optimal allocation. As Barbuto et al. (2017) pointed out, the implications of diffusion and network models for innovators in the marketing domain are also particularly valuable. Finally, a limitation frequently found in this kind of model is to be unable to incorporate, at the same time, social, economic and political unpredictable changes that could strongly influence the farmers’ behaviour, like financial crises, unexpectedly volatile markets and wars. Despite the limitations and the overall simplicity of the GeSoN, implementing it into a more sophisticated agent-based model will lead to rich output, where the different configurations of inputs, the diverse populations of farmers and the different agricultural landscapes will generate complex emergent properties that can inform the real world.

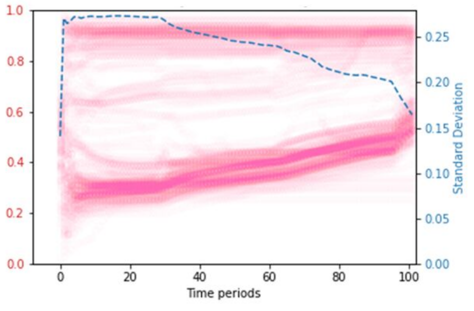

Figure 15. doi

The evolution of opinions during a 100-time-step simulation The opinions in each time step are shown in pink and the standard deviation of the opinion distribution over time is in blue.

Conflicts of interest

The authors have declared that no competing interests exist.
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