Agent-based modeling of crop varieties adoption by farmers

Geographic Information Management and Applications

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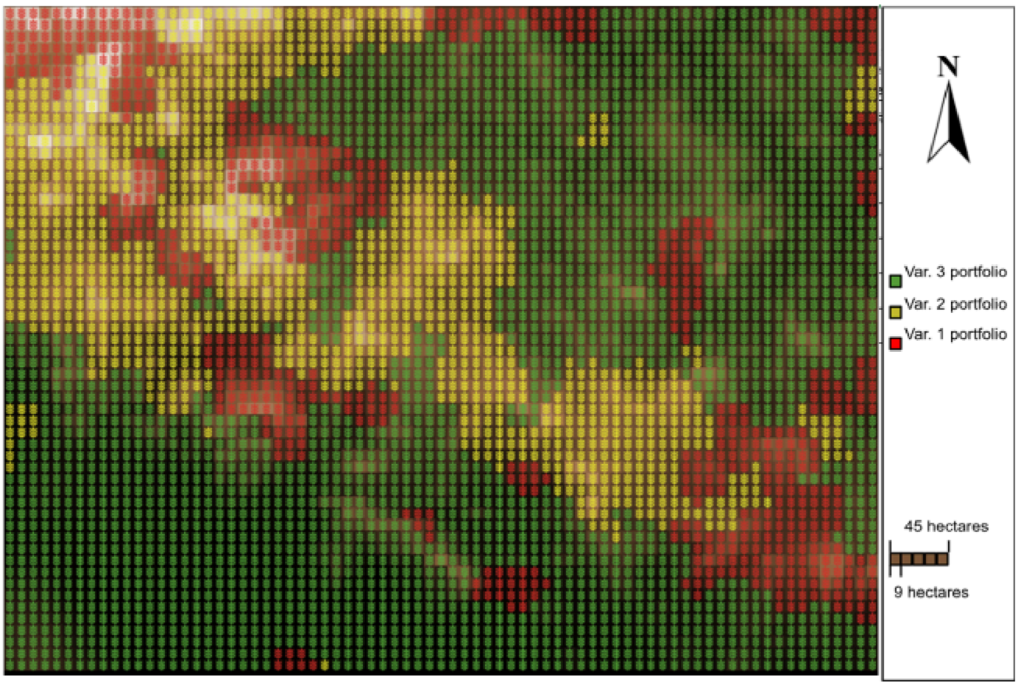

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Abstract

As climate change introduces increasing uncertainties into agricultural practices, farmers will need to adapt their practices to optimally suit local conditions. The study by Brown-Fuentes (2022) provides a new variety of the common bean that is more resistant to heat. This thesis studies how such a new variety would be introduced to the environment and then how it is adopted by the farmers over time. An agent based model (ABM) is created to be able to capture emergent phenomena and spatial patterns of adoption. The decision-making process of the agents (farmers) includes more in-depth social factors than previous projects in this field; the adoption of a new variety is not solely based on its performance but also on social factors such as similarity to neighbors and a personal preference for a certain variety. Incorporating these factors into the decision-making process allows for better insights into what factors increase or decrease the rate of adoption. Model results point to crop performance being the main factor promoting adoption; social and personal factors characterized as similarity to others and a preference for the local crop already known to farmers for generations. This further implies that the introduction of the new variety to farmers should be paired with interventions that further incentivize crop performance maximization to overcome the adverse effects originating from social and personal factors that inhibit adoption.

Table of contents

1. Introduction

To deal with the increasing uncertainties about weather and environmental conditions resulting from climate change, farmers require information on which crop variety is optimally adapted to local conditions, i.e. seed technology. A problem is that this information is often not provided or available to farmers (Fuentes, 2022). Another problem with this is that simply providing information about new seed varieties to the farmers does not necessarily mean that these varieties will be adopted. It is impossible to judge a variety from the seed only; the performance of varieties varies much from season to season and it will only become clear over time by experimenting with it through trials. Farmers need to gain confidence that the variety will work for them, which often means they will try it and compare it with other varieties and gain information from neighbors (Young & Coleman, 1959; Case, 1992). The resulting diffusion process will result in a certain rate of adoption. The relative speed with which an innovation is adopted by members of the population. This rate of adoption, in turn, is influenced by the perceived attributes of the innovation, the type of innovation, the ability of adopters to gain information about the innovation directly or through others, the communication channels through which information about the innovation spreads, which is in turn influenced by the the nature of the social system. Also, adoption is influenced by the extent and type of change agents' promotion efforts. such as introducing a single new variety to farmers directly, or a set of varieties, promoting the sharing of experiences between farmers, providing variety recommendations or organizing demo plots and having farmers discuss new varieties in groups (Rogers, 2010). It is difficult to know what the effects of such interventions are, and usually choices for one approach or another are based on assumptions about the diffusion process. As interventions can involve a mix of different approaches and different approaches may be warranted in different situations, it is important to gain more systematic insights into the diffusion process. So far, most efforts to model the diffusion of crop varieties have used approaches that allow for limited complexity in the interactions between different causal factors that influence the rate of adoption. This leads to insights that are difficult to generalize as they concern only some of the known mechanisms of diffusion (Kiesling, et al., 2012; Berry & Berry, 2018). This research will address this knowledge gap through a characterization of the process of variety diffusion to guide decision-making on the right intervention to use. This characterization should lead to a better insight into the determining factors and make it easier to reason about the extrapolation of findings on relevant interventions to new contexts.

This question can be addressed using simulation modeling. A model can be constructed to provide insights into the process. This model could provide insights into the behavior of the system according to certain theories and hypotheses and also provide insights into the process of adoption. Using this, estimations could be made for the direction and magnitude of the impact of certain interventions in a real-world scenario.

To make the model capable of capturing both economic and social phenomena, it will need to be able to simulate the interactions between farmers and their peers. Agent-based modeling (ABM) is an approach that is able to achieve this by modeling each farmer as an individual agent that bases their decision-making on a combination of their own information and that of their peers, e.g., (close) neighbors. The most relevant point advocating for the use of ABM is that an ABM approach is able to capture aggregate results of behavior at individual level, which may show unexpected collective or emergent behavior (Kiesling, et al., 2012; Githinji, et al., 2023). The model will use simple decision-making rules for agents and investigate how the population adopts a new technology. In addition, ABM is a good way of modeling heterogeneous actors interacting within an environment as shown by the projects making use of ABM in past literature (Brown, et al., 2004; Brown & Robinson, 2006; Matthews, et al., 2007; Schwarz & Ernst, 2009; Kiesling, et al., 2012). These applications show that ABM is able to model complex system behavior based on small heterogeneous interactions which also makes it the method of choice for this research.

Having selected ABM as a modeling method, there are still some issues that require discussion. In ABM, agents act based on the decisions they make and in order to make a decision, agents will go through a decision-making process. The design of the decision-making process will determine what factors agents take into account and how these factors are weighed against one another which is one of the main points of interest for this research. Multiple theories of decision-making exist and the choice of which ones to follow will greatly affect how the process is modeled. This design also greatly influences the complexity of a model, bringing us to the question of how complex the model should be. The goal should be to strive for a model with high performance that is as simple as possible (Tobler, 1970). This logic is in line with the principle of Occam's razor, in that the simplest option to explain a phenomenon should be picked when given a choice, as the simplest explanation is usually the correct one. This means that the model should not be unnecessarily complicated if it doesn’t add to the explanation of the modeled phenomena. The main problem that comes with model building is the inclusion of social factors in the decision-making process as this has not been done in depth in past literature.

1.1 Research question and objectives

There does not yet exist a theory-backed mechanism to make explicit what the impact of interventions would be in an agricultural policy context. And as this model does not yet exist, it brings us to the objective of this research; to gain insights into the impact of interventions by constructing a model that simulates the diffusion of knowledge amongst farmers, keeping in mind not only productivity and yield, but also social factors that play a role in the decision making process. This objective can be reached by answering the following research questions:

1. Which processes play a role in the adoption of a new seed variety and how have these been represented in formal modeling of diffusion processes?
2. What analogue processes have been studied using ABMs that are relevant to variety diffusion?
3. What is a potential implementation of an ABM incorporating main mechanisms of variety diffusion?
4. What insights can be gained from the ABM comparing different intervention methods under different assumptions about the decision-making in the diffusion process and how do these compare to current knowledge about technology adoption?

Research question 1 is focussed on obtaining information from past literature. An ABM has been used before in an agricultural context and insights from these studies can be used to aid the construction of our model and to provide context to our findings.

Research question 2 is concerned with the model’s mechanisms. One of the main mechanisms is the decision-making process of the farmers that can be modeled in accordance to a variety of different theories. In the model, the way of decision-making will be used as a changeable input which will each different affect the output. As shown in the research by Githinji, et al. (2023), the decision-making process can be modeled according to different theories: expected utility theory, prospect theory, bounded rationality theory, theory of planned behavior, and status power theory (Kemper’s theory). In addition to these theories described in the paper by Githinji, et al. (2023), there is also consumat by Jager & Janssen (2012) which takes a slightly different approach. Here agents are characterized as having three needs which they will attempt to satisfy by performing actions. Based on the applications found from research question 1, one of these decision-making theories can be selected as a basis for the decision rules for the agents in our model. Other mechanisms include the calculator of crop performance along with incorporation of a variable environmental factor.

Research question 3 is concerned with the workings of the model. How findings gained from research questions 1 and 2 can be used and combined into a model that incorporates the main mechanisms of innovation diffusion. Part of this research question is also obtaining reasonable parametrizations for the model through experimenting with different scenarios and comparing these results to literature.

Finally, research question 4 relates to interventions that can be implemented during the diffusion process to help reach a certain outcome or to promote a certain type of decision-making. Insights gained from studying these interventions can help with estimating the impact of such interventions in a real world scenario. One aspect for which theoretical expectations exist, is the shape of the adoption curve. This is a visual representation that shows a cumulative view of the adoption of a product or technology, which in our case, is the adoption of new seed varieties. The shape of the adoption curve provides insights into how the technology spreads. A curve that starts at its maximum growth rate and slowly tapers off to an equilibrium is called an R-curve. This curve emerges mainly from nonsocial learning processes. The other, and more common, shape of an adoption curve is the S-curve, starting with a low growth rate that is increased until around the half-way point of the diffusion after which the growth rate starts declining again towards an equilibrium. The S-curve emerges from diffusion with more (biased) social transmission (Henrich, 2001). The adoption curve that emerges will say something about which type of learning was dominant in the adoption process.

To answer the research questions, this thesis first goes into details of innovation diffusion and an ABM approach in the next chapter. Chapter 3 explains the workings of the model and provides the scenarios. Chapter 4 depicts the model results along with some observations. After which the details and links to literature are discussed in chapter 5 along with limitations and possible future research. Finally, the conclusion answers the research questions posed in this chapter.

2. Literature review of innovation diffusion and an ABM approach

This chapter of the thesis discusses and analyzes previous applications of ABM in an agricultural context with a focus on innovation diffusion. First, previous literature on innovation diffusion is discussed to obtain information on what factors are of influence in this process, after which these factors are studied with regards to their application in an ABM context. This will lead to a final conclusion on the methods to use for my model.

2.1 Innovation diffusion

Innovation diffusion is a subject that is often discussed in an agricultural context. This is because, for many developing countries, agriculture is a leading source of employment and generates much of the national income. The productivity of farms in these countries however, is relatively low while adopting modern agricultural technologies that would significantly boost their productivity. While there is no lack in the development of new technologies, there is often a lack of understanding of how these technologies are adopted, and in some cases, why these technologies are not adopted at all. This is where innovation diffusion research comes in to help explain the mechanisms behind adoption and, on the other hand, factors that might reduce the rate of adoption. Studying this will lead to a better understanding of the whole process. A better understanding can, in turn, lead to better policy-making and/or better intervention methods to improve the adoption of new agricultural technologies in developing countries (Doss, 2006).

Doss (2006) writes about limitations of technology adoption in an agricultural context. From his research, three main reasons come forward on why farmers do not adopt improved technologies. The first reason is that farmers are simply unaware of the new technology or unaware of its potential benefits. The second reason is the lack of its availability for these farmers. The third reason is that adopting the new technology might simply not be profitable. This final reason has two potential causes, the first being the complex sets of decisions that farmers have along with the policy environment that could lead to a situation where the new technology is not profitable. Another cause for a lack of profitability could come from the fact that many new agricultural technologies and practices often provide only a little benefit to the individual farmer and that the major benefits are only received on a larger societal scale, and possible only over a longer period (Bell, et al., 2012; Githinji, et al., 2023). In the literature by Orr (2003) and Rogers (2010) they discuss some of the social effects that also play a role in innovation diffusion. An important point is that the decision of an individual to innovate is also influenced by the innovation-decisions of others. This influence could come from the social need of being similar to peers or, on the other hand, the need to outperform them. Through these needs, social effects play a role in innovation diffusion.

To make predictions and gain insights about innovation diffusion, simulation models are constructed in which factors promoting adoption are balanced against factors that could impede adoption, such as the factors described above. Such models can be constructed using different methodologies. Berry & Berry (2018) elaborate on methods of modeling the diffusion of innovation. The first method is through using a traditional top-down diffusion model. Many different diffusion models have been developed, with the main difference being the method of communication and the assumed influences. These models are explained using a multitude of different entities, ranging from defining a whole country as a single entity, to using individual households as entities. However, these models do share some similar characteristics. The first characteristic is that entities learn from each other by borrowing innovations perceived as successful. The second is that entities compete; they adopt policies in an attempt to either gain an advantage over other entities or to make sure that other entities don't gain an advantage over them. Third, there exists national pressure that incentivizes entities to adopt certain policies that are already adopted by others. This logic is also applicable to an agricultural context. For example: farmers will adopt an innovation more quickly if they see their neighbors profiting from it, farmers compete and try to gain the competitive advantage, and finally, farmers also experience national pressure in the form of policies that incentivize them to pursue certain actions or practices.

In addition to diffusion models, Berry & Berry (2018) explain internal determinant models. In contrast to diffusion models explained above, internal determinant models (IDM) focus on internal factors and exclude outside influences such as that from neighbors or a national government. In IDMs the focus lies on political, economic, and social characteristics of the entity itself. In such models, entities optimize their choice based on their individual characteristics without incorporating the influence of the choices that other entities make. Such a model is less relevant for this research as important parts of my model are the social interactions and influences between farmers, which are not really present in an IDM.

2.2 An agent-based modeling approach

A newer approach is to look at innovation diffusion through agent-based modeling (ABM). Research by Kiesling, et al. (2012) and Zhang & Vorobeychick (2019) provides some insights of how to use ABMs in the innovation diffusion context. Both papers are quick to state the advantages that ABM brings namely, the simulation is on an individual level which allows the capturing of emergent phenomena which are extremely relevant for diffusion research. Kiesling, et al. (2012) make the distinction between two key elements for ABM: the modeling of consumer adoption behavior and the modeling of social influence. To model consumer adoption behavior one could choose different approaches, the easiest being the use of simple decision rules to determine individual behavior. The rules often take the form of cost optimization or profit maximization equations (Cantono & Silverberg, 2009; Faber, et al., 2010) which carry some explanatory power, but definitely not all. For more explanatory power, social influences need to be added to the equation. While the importance of social factors has been recognized for a while, it still remains one of the points that many researchers state as a limitation of their diffusion models and an area for future research (Kiesling, et al., 2012; Huber, et al., 2018; Zhang & Vorobeychick, 2019; Githinji, et al., 2023; Schimmelpfennig & Muthukrishna, 2023). The ways in which social influences are integrated in diffusion models are inconsistent in literature and it seems like every model makes use of a different method which makes it all the more difficult to compare these methods and determine which is the “best” for a particular application. Constructing these models in a consistent way would make it easier to compare results and to reproduce such models.

To aid comparison of literature, the literature can be split into ABM’s three main elements; agents and social structures, environment, and decision-making / behavior. The following section examines past literature in the light of these three elements, after which the most relevant findings are combined into a section on what should be included in my model.

2.3 Agents and social structures

The first element in an ABM approach is the agents themselves. These are the actors that will make the choices in the model based on influence from either internal or external factors. In most agricultural ABMs, the agents are represented as individual farmers or farmer households (Zhang & Vorobeychick, 2019; Githinji, et al., 2023). Each agent has a predetermined farming area where they can grow certain crops based on the model specifications. In most of these models, agents have a choice in what crop varieties they plant and in what quantity. The details on how these decisions are made is discussed later in the decision-making section. In addition to their crops, agents have individual characteristics and social relations. Individual characteristics are usually represented as certain values that play a role in decision-making, such as a level of risk-aversion or a preference for a certain crop variety for example. These characteristics often differ between agents and make it so that agents experiencing similar outside influences can still reach different decisions, i.e. heterogeneous decision-making. Social relations are usually represented as agents being part of certain networks, or by including the influence neighboring agents exert on each other.

The review by Githinji, et al. (2023) presents Kemper's theory as a way to understand the effect of social relations and as an approach to strengthen ABMs. Kemper's theory includes the effects of social relations to explain how farmers with the same characteristics can end up with different choices. Kemper's theory makes use of social structures called reference groups. These are social groups that the individual agent (farmer) is a part of. These can be thought of as stakeholders influencing the agent to follow their agenda. Following their agenda leads to an increase in status for the individual within the reference group, while different behavior leads to a status decrease or causes the reference group to use power against them. Status could be admiration or rewards for example, while use of power could be a penalty or exclusion of the group. This means that agents will want to please as many of their important reference groups while also avoiding decisions that go against other reference groups' agendas. This could lead to a situation where an agent makes a decision that is suboptimal for performance but pleases as many of their reference groups as possible. While incorporating heterogeneous decision-making in a model is, in theory, beneficial to model performance and realism (Berger, 2001; Huber, et al., 2018), Kemper's theory does have limitations. First comes from determining reference groups; this is very theoretical and would require many assumptions to be made regarding what reference groups agents should belong to. Without a proper way of determining this, Kemper's theory would not be very useful. As said by Githinji, et al. (2023): "Successful use of this theory relies on correctly identifying reference groups, their level of importance, and their preferred land-use options", which are all very difficult to accurately determine within the scope of this thesis, meaning that some alternative approaches have to be considered too.

Another method to represent interactions and influence of a network is the approach taken in the research by Caillault, et al. (2013). While the context of this paper is landscape changes as opposed to variety diffusion, their model explores the influence of different multi-scale incentive networks on farmer decision-making which still provides useful insights in how networks can be represented in an ABM at different scales. They make the distinction between a global network, which represents the influence of public policy on farmer decision-making; a social network which is realized by assigning farmers to one of five associations that influence decisions; and a local network which captures the effect of neighbors' practices. In their research, different scenarios are constructed based on the inclusion of combinations of the three networks. The inclusion of just a local network is found to usually lead to a relatively small amount of heterogeneity. The scenario using only a global network is the only scenario that has a lower heterogeneity. On the contrary, including a combination of global and local networks leads to an outcome with very heterogeneous decision-making by agents. The conclusions should be considered when determining what kind of network to be included in my model.

2.4 Environment

In ABM, the agents reside in an environment which is usually represented as a spatially explicit geographic space. The environment is often represented by a raster grid in which agents can be set as individual cells (Cabrera et al., 2012; Caillault, et al., 2013; Huber et al., 2018). While a grid is not a necessary part of an ABM, it does allow for the inclusion of a spatial component which is very relevant in this context as in geography, all things are related but near things are generally more related than distant things (Tobler, 1970). In addition to being influenced by individual characteristics and social factors, agents are also affected by environmental factors. In an agricultural context, a commonly used environmental factor is the weather or climate that will determine how an agent's crops perform. This weather variable could be determined randomly or via a certain pattern which is chosen in accordance to the purpose of the model. Other environmental factors that are used often in this context are related to the land of the farms themselves, soil type or elevation for example. These factors also influence crop performance and (usually) remain unchanged, as opposed to a weather variable that changes over time. The choice of these factors is based on a real-world area that the model reflects and, depending on the model purpose, different factors can be included or excluded from the environment. This helps to give a more meaningful context to the model outcomes and helps with interpretation of the results as well.

2.5 Decision-making process

Modeling farmers' decision-making regarding the adoption of new seed varieties or practices requires not only an understanding of decision-making on the basis of economic factors and utility, but also with regards to social factors and the utility received from those factors. Literature reviews have found that the focus of models that simulate diffusion in an agricultural context often focus on the economic factors and a deeper investigation of the effects of social factors is often lacking (Kiesling, et al., 2012; Huber, et al., 2018; Githinji, et al., 2023; Schimmelpfennig & Muthukrishna, 2023). An important finding from Huber, et al. (2018) is that there is a need for improved representation of farmers' heterogeneous decision-making. One of the ways this can be done is by considering individual farmer characteristics in the decision-making process. This is in line with the multi-agent spatial approach to model heterogeneous economic behavior and farm-household policy response suggested by Berger (2001). One way to represent heterogeneous agents is as done by Bell, et al. (2012). In their model, each farm (agent) has a certain participation probability which represents their willingness to interact with other agents in the interaction step of the model. Based on this probability, if an agent participates, it exchanges experience (history of yields) with other farms based on their linkage. Heterogeneity between agents is also implemented in this model by (randomly) assigning agents an attitude to risk which will influence how much utility they gain from risky behavior, such as adopting a new practice. Both of these are examples of agent characteristics that can be implemented in a model to further promote heterogeneous decision-making by agents which, in turn, improves the model realism and performance (Berger, 2001; Huber, et al., 2018).

In most agricultural ABMs, agents make decisions on how much of a certain crop they will grow. But in the real world, farmers seldomly grow just a single crop variety. Farmers have a choice in the proportions between the different varieties that they plant, making up their crop portfolio. Which should also be represented in the model. While agricultural diversification is widely used by farmers, the usage of tools that construct risk-reducing portfolios is lacking (Hardaker, et al., 2015). A method to deal with this could be to use the minimum regret model which works as follows: for every scenario, the decision-maker compares the utility of a given portfolio with that of the optimal portfolio for that scenario. The difference is called (opportunity) loss. This loss value is calculated for every scenario and then combined into a regret value, which is then repeated for different portfolios, resulting in a list of portfolios with each assigned a regret value. From this list, the portfolio with the lowest regret value is chosen (van Etten, 2019). A useful characteristic of the minimum regret model is that it can be expanded upon. As opposed to just comparing utility from crop performance from the different portfolios, social factors can also be included in the regret calculation. A potential issue with this method is that it adds complexity to the model and requires each agent to compare a large number of portfolios for each calculation.

The next issue is then how to incorporate these social factors in a formula. The consumat framework aims to do this. Consumat is a generic framework aimed at combining processes that drive human behavior (Jager & Janssen, 2012). A problem with most behavioral models is that the empirical validation and parameterization of the model is time-consuming and it's a question whether all parameters can be empirically measured in a reliable way. However, the consumat approach is more complete and incorporates more factors than other behavioral models that are validated very well. Consumat makes use of three main needs: existence, social, and personality. Existence relates to food, housing, income, etc. referring to the economical dimensions of existence. This need is similar to “gain” used in the Goal Frame Theory (Lindenberg & Steg, 2007) as the consumat bases the agent’s decision of what crop to grow on estimated financial outcome or, if there is no way to sell, based on nutritional value. The social need relates to interactions with others, social status, and belonging to a group. This need relates to decision-making based on being similar, and being superior. The agent’s satisfaction is increased when it’s behavior is similar to that of their peers but also from being superior to peers through means of higher yield or higher financial gain for example. Agents will each have a function balancing between the two. Finally, personality relates to satisfying personal needs. This can be imagined as an ideal situation to which the agent will try to match their behavioral choices. A personality could also be modeled as multi-dimensional, where different personal needs are also accompanied by different weights. Using the consumat approach, decision making of agents will depend on their level of satisfaction and uncertainty. Using these levels will determine how extensive the decision making of an agent will be. Two major rules are: 1) a lower satisfaction will lead to more involvement of an agent to process information on behavioral opportunities, and 2) a larger uncertainty will lead to a larger dependence on the behavior of others in determining ideal behavioral opportunities. In an agricultural context this means that in the case of a low satisfaction, agents will be more triggered to evaluate alternative behavior (different portfolios), and in the case of a large uncertainty, agents will value the behavior of others more in their own decision-making. According to the consumat framework there are four options of how behavioral opportunities are used in the decision-making process:

- Repetition: only the current behavior is considered and the agent will keep behaving this way. If the outcomes are negative, this will lead to a lower satisfaction which will eventually lead the agent to consider alternative behavior.

- Imitation: the behavior performed by peers is considered and the agent will imitate the behavior of successful peers.

- Inquiring: consider all possible behavior performed by other agents, not just that of (nearby) peers.

- Optimizing: all possible options are considered, even those not used by other agents.

The selection of which behavior an agent will perform is based on their satisfaction and uncertainty and if the satisfaction resulting from a certain behavior starts decreasing, agents will consider changing their behavior.

2.6 Summary

Concluding from the literature regarding innovation diffusion, there are a few underlying processes taking part in innovation diffusion that should be incorporated in my model like it has been incorporated in past research. The reasons for the lack of adoption stated by Doss (2006) need to be represented in such a way that is relevant for adoption. This could be in the form of thresholds of a certain value that needs to be reached before a farmer is able to adopt. Berry & Berry (2018) provide a good case for the use of a diffusion model, the three major characteristics of diffusion models align with the goal of representing social influences in the model; which are all factors that are positively related to adoption. These factors can be used as counterbalances to the factors that inhibit adoption as explored by Doss (2006). Additionally, interventions through policies can be represented as pressure coming from a national government that incentivizes the farmers to behave a certain way. While the ABM approach is not always used for diffusion models, its advantages are very much known and are mentioned in many papers (Kiesling, et al., 2012; Zhang & Vorobeychick, 2019; Githinji, et al., 2023) highlighting ABM as the best approach to capture complex phenomena emerging from interactions at an individual level. A final point that comes back often is that, especially in ABMs, the depth and inclusion of social influences is lacking in past literature. This is a knowledge gap that this project can help fill in by focussing specifically on a way to represent social influence and how to balance this against influence coming from economic factors such as performance or profit. From this I conclude that an ABM approach is a useful way of modeling innovation diffusion, and special care should be taken with incorporating social influences in such a model to add realism to the model while keeping it simple and consistent.

With regards to research question 2, the main process relevant to variety diffusion that has been discussed, is the decision-making process. A problem that often comes forwards in past literature is the lack of in-depth representation of social factors within the decision-making process. Most past models focus on economic factors to determine decision-making. The consumat framework by Jager & Janssen (2012) provides a way to incorporate both social and personal factors in the model. This framework assumes that agents strive for maximizing their satisfaction which consists of three needs: existence, social, and personal. In addition to decision-making, the diversification of farmer portfolios is also discussed. Farmers seldomly only grow a single variety of crop (Hardaker, et al., 2015), this has to be represented in the model by having farmers choose from different varieties with different properties and performances.

3. Methodology

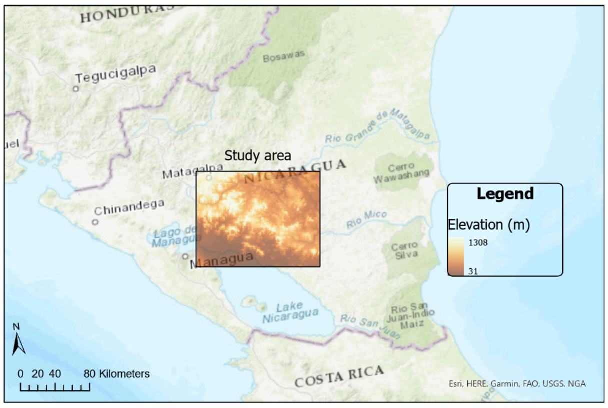
Based on conclusions and insights gained from past literature, a final choice of methods/models was made for what to make use of in this project. This chapter explains a potential implementation of an ABM that incorporates the main mechanisms of innovation diffusion. The implemented model consists of three major elements; agents & social structures, environment, and a decision-making process which are explained separately.

3.1 Case study

Before we can go into the details of the mechanisms and theories used for the model, it is important to explore the context in which the model was created. In the study by Fuentes (2022), data of farm trials across Central America are analyzed. As the model makes use of Fuentes' relative variety performances, it only makes sense to choose one of these regions as the study area so that there is considerable variance in the elevation. The study area of the model is the agricultural valleys of the central western mountains in Nicaragua(*Figure 1*). This area yields the largest part of the national agriculture production of the country and also has enough altitude variability to observe how altitude could affect spatial adoption patterns. This area mostly holds a large number of small farms which suits the purpose of the model of simulating behavior and social interactions of individual agents (farmers). In the model, the grid represents a simplified version of the landscape with an elevation value assigned to each patch. The altitude values are based on the altitude map of the agricultural valley.

The model was run in multiple time steps where each time step represents a growing season for the common bean. The central american region has three growing seasons, primera: april - september, postrera: august - december, and apante: november - march. This means that three time steps in the model represent a timespan of one year. The common bean is sensitive to high temperatures, which generally decrease if the elevation goes up. This sensitivity to temperature is captured in the model by making use of the "heat-stress" variable which is calculated for every season based on the elevation of a patch. In the model, three different crop varieties are used which perform differently with either the absence or presence of heat-stress. More details are provided in the environment part below. Nationally, the average farm size in Nicaragua is 9.22 hectares (FAO, 2023). For simplification, this value is rounded to 9 hectares for each farm. As the growing seasons have some overlapping months, farmers cannot use their entire land every season for beans. To keep the model and its calculations simple, I make the assumption that farmers use an equal amount of land each growing season for the common bean. This number is assumed to be 3 hectares which avoids problems in the case of overlapping seasons and it leaves farmers with two to four hectares to use for other crops or livestock. As it is unrealistic to assume that a farmer would dedicate their entire land to one crop variety.

Figure 1: Topographic map of Nicaragua with the study area highlighted along with a smaller elevation map of the study area.



3.2 Agents & social structures

In my model each agent is a single farmer with farmland that is divided among their different crops. As is the case in the real world, farmers will seldomly grow only a single crop variety which is represented in the model by having each agent construct a portfolio of crop varieties. This simply contains the portions of their land that they use for each different crop variety. In addition to their portfolio, farmers have a few other important characteristics. A personal preference for a certain crop variety, and the social groups they belong to. To represent the social factors that come into play when making a decision, the consumat framework was used. In its simplest form, the social structures that agents are part of consist of their nearest neighbors. This is done in accordance with Tobler's law which states that the influence from nearby agents is larger than that of agents further away. As such, farmers receive social satisfaction based on the performance and characteristics of their neighbors.

In this model farmers are static entities in spatial terms; they do not move. Interactions between agents come from observing their neighbors characteristics and their crop performance and adjusting their satisfaction accordingly. Each growing season, farmers make their decision on their portfolio allocation simultaneously and are only able to change it after a growing season is completed.

Plotting the number of farmers that adopt the new crop variety over time provides the adoption curve. The shape of the adoption curve shows something about the relative importance of social- and environmental learning within a diffusion process (Henrich, 2001). The model contains both environmental learning, i.e. looking at individual crop performance, and social learning, i.e. incorporating social factors and the actions of others in the decision-making process. Based on the relative importance of these factors within the decision-making process, the adoption curve should follow a particular shape. Additionally, the model also creates spatial patterns in how agents adopt the new variety, these patterns should reflect how agents act with differing environmental factors.

3.3 Environment

The environment in the model consists of the landscape and the environmental variable. The landscape is a grid where individual cells represent farms with two variables; altitude and heat-stress. Altitude is denoted in meters above sea-level and based on the landscape of Nicaragua; heat-stress is the environmental factor explained below. The environmental factor that is included in the model is meant to represent heat stress on the crops. The study by Fuentes (2022) found the Warm Spell Duration Index (WSDI) to have a significant influence on crop performance and that different crop varieties react differently to different WSDI values. WSDI is derived using daily maximum temperatures and defined as the number of days where, in intervals of at least 6 consecutive days, the daily maximum temperature is higher than the 90th percentile of the temperatures measured in that specific location (ECAD, 2023). In a more simple way, the WSDI is the number of days in a period that the daily max. temperature has been uncharacteristically high for at least 6 days in a row. Another study by van Etten, et al. (2019) also finds heat stress, in the form of maximum temperature at night, to have a significant (negative) effect on crop performance. In the model, heat stress is decided on by a combination of the altitude and a threshold selected from a normal distribution. To determine whether a cell is affected by heat stress, the altitude of the cell is compared to the before-selected threshold. As temperature decreases as altitude gets higher, cells at a higher altitude are less likely to suffer from heat stress. A lower altitude than the threshold value, leads to the cell being affected by heat stress, which then negatively impacts the crop performance. The threshold value is re-selected every growing season to represent the variance of the weather. Additionally, an environmental variance is modeled through the inclusion of a random error-term which is meant to represent unpredictable factors that might further influence the performance of the crops; think of sickness, pests, but also events that could have a positive influence like the lack of sickness or just good weather resulting in a good harvest. This error term is calculated separately for each farmer and results in differences in performance between farmers that might have the same portfolio composition.

The study by Fuentes (2022) also introduces new crop varieties that are adapted to certain climate conditions. In this model, farmers make use of three different varieties of the common bean. Variety 1 is the “old” and local variety that is currently used by most farmers. This variety is adapted relatively well to the local conditions, but its performance suffers under heat-stress. Variety 2 is the risky option. This variety performs best without heat-stress but its performance is severely reduced if heat-stress is present. Finally, variety 3, this variety is one discussed in the study by Fuentes (2022); this variety is resistant to heat-stress and its performance remains equal with both its presence and absence. However, as this is a “new” and unknown variety, its transaction costs are higher which are included in the calculation of crop-performance resulting in a lower performance than the other varieties in the absence of heat-stress.

Table 1: Relative performances of the different crop varieties where crop performance of the yellow variety without heat stress (the highest performance) is taken as a baseline. Each variety is also represented by a color which will be used in the rest of this thesis.

	Crop performance without heat stress	Crop performance with heat stress	Color
Variety 1 (old)	0.7	0.3	Red
Variety 2 (risky)	1	0.1	Yellow
Variety 3 (heat-res.)	0.6	0.6	Green

The most important interaction between agents and the environment comes via crop performance. Crop performance is calculated based on an agent's portfolio; using table 1s relative performances on the basis of the absence or presence of heat stress. The portfolio value for each variety is multiplied by their performance (*Table 1*) to determine the performance per variety. These values are then added together along with the environmental error term, which is a value between -0.2 and 0.2 to make up the “existence satisfaction” which is further used in the decision-making process.

The model is run in multiple time steps with each time step representing a single growing season. Each time step can be divided in three parts:

1) Calculation of heat-threshold

In this step a heat-threshold is selected to determine which patches are affected by heat-stress

2) Calculation of crop performance

As described above

3) Decision-making process

As described below

3.4 Decision-making process

In my model, the decision-making process is based on the consumat framework. One of the most relevant points that came forward from past literature was the lack of investigation towards the effects of social factors on decision-making. To improve on this knowledge gap, my model incorporates both economic and social factors into the decision-making process. Consumat makes a distinction between three different needs for agents: existence, social, and personal. For each of these needs agents receive a certain amount of satisfaction. Their goal is to maximize their total received satisfaction which is a sum of the satisfaction received for each of the needs.

After the satisfaction for a certain portfolio is determined through the consumat framework, farmers compare their satisfaction to that of their neighbors, and if their neighbors have a higher satisfaction, the agent copies their portfolio to use for the next growing season. One of the advantages of using consumat in this situation is that consumat allows for the inclusion of both economic and social factors in a formula that still results in a single satisfaction value associated with a certain portfolio. In this way, portfolios are easily compared based on their total satisfaction.

Before combining the satisfaction from the three consumat needs, these need to be defined first. The “existence need” is represented in the model as crop performance. If the crops perform better, it leads to a higher satisfaction for the agent. The satisfaction received from the “social need” comes from similarity and superiority. Farmers receive satisfaction from being similar to other agents and from being superior to other agents. In my model, superiority is defined as having a higher/better crop performance than other agents. The satisfaction received from superiority is a fixed amount per peer that has a lower crop performance. Similarity is defined in the model as having a similar portfolio to one’s neighbors. A portfolio is considered to be similar to that of neighbors if both portfolios have the largest allocation to the same variety (i.e. if both farmers grow more of the red variety than the other two varieties, their portfolios are considered to be similar). These two satisfaction scores are then combined and used in the calculation as the social need. The final need stated in consumat is the “personal need”. This is defined as personal characteristics that farmers have that bring them satisfaction when met. In my model, the personal need is represented as a preference for one of the three varieties. If the preferred variety is the same as the variety to which a farmer allocated most of their land, they gain satisfaction from their personal need. Otherwise this satisfaction is equal to zero. Together, these three needs make up the satisfaction score which is then used to determine which portfolio a farmer chooses. Below, the satisfaction as formulas used in the model:

$$total\ satifaction_i = existence_s + social_s + personal_s$$

The total satisfaction for portfolio i is equal to the sum of the satisfaction (s) from the three consumat needs; existence, social, and personal.

$$existence_s = crop\ performance_i \times w_e$$

$$crop\ performance_i = performance_{v1} + performance_{v2} + performance_{v3} + \ \varepsilon_i$$

The existence satisfaction is equal to the crop performance multiplied by its weight. Crop performance is equal to the summed performances of all three varieties along with the environmental error term which is randomized separately for each portfolio.

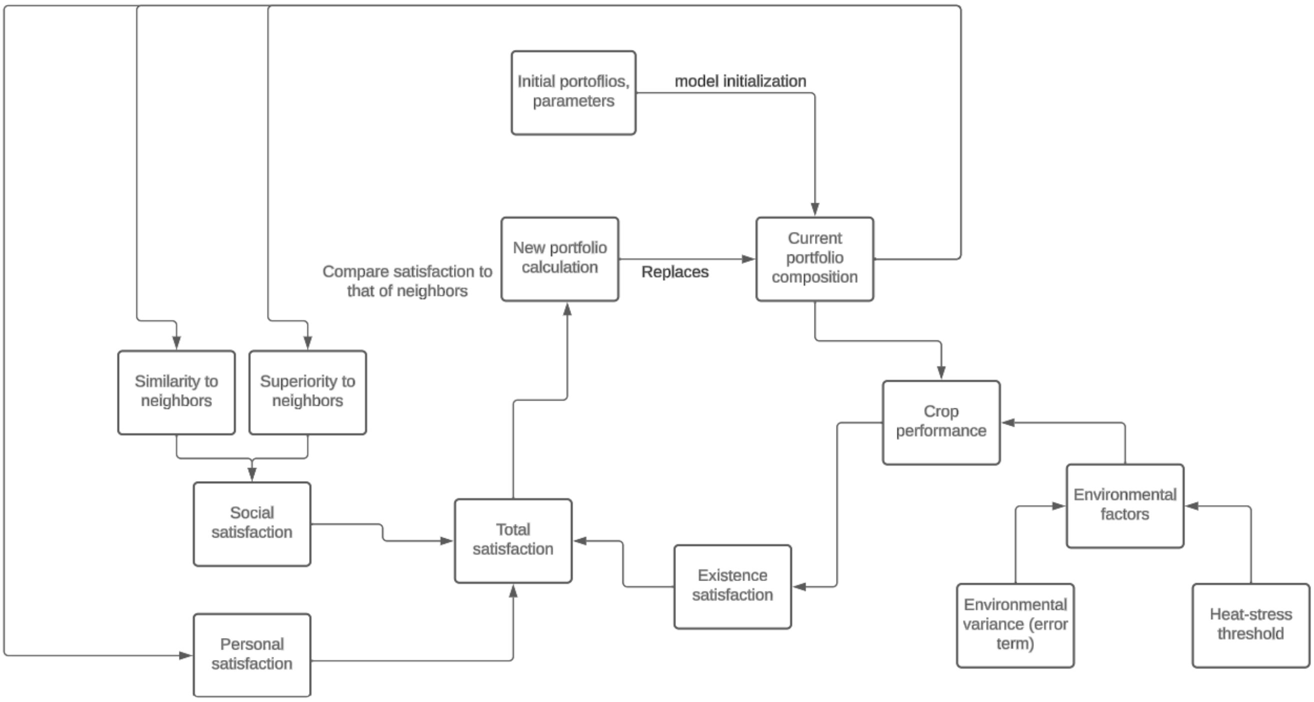
$$social_s = w_s \times (number\ of\ similar\ peers\ \times ssm + number\ of\ inferior\ peers\ \times spm)$$

Social satisfaction comes from the combination of satisfaction from similarity and superiority multiplied by its associated weight. Here ssm = similarity satisfaction measure, and spm = superiority satisfaction measure. ssm and spm are defined beforehand to determine the relative importance of each for the decision-making process.

$$personal_s = w_p\ \times a$$

Personal satisfaction comes from being in line with personal preference. ‘a’ has a value of either 0 or 1 depending on whether the current portfolio matches the personal preference of an agent for a certain crop variety; 0 if not, 1 if it does.

Figure 2: Flow chart of the decision-making process and factors determining the satisfaction of farmers.



3.5 Overview, Design concepts and Details protocol (ODD)

The NetLogo software was used to develop the model and its description follows the ODD protocol designed by Grimm, et al., (2020) to describe agent based models in a comprehensive and reproducible way. Following this framework leads to a description that elaborates on all important parts of the model and that can be compared with other models following the ODD framework more easily.

1. *Purpose and patterns*

The purpose of this model is to investigate how a change in the balance between economic and social influences affects farmer decision-making and consequently, how it affects the diffusion of innovation. In this context it involves the adoption of a new seed variety within an environment.

The model is evaluated on its realism based on the produced results for multiple scenarios and whether these match those found in past literature. The shape of the adoption curve shows something about the relative importance of social- and environmental learning within a diffusion process (Henrich, 2001). The model contains both environmental learning, i.e.

looking at individual crop performance, and social learning, i.e. incorporating social factors and the actions of others in the decision-making process. Based on the relative importance of these factors within the decision-making process, the adoption curve should follow a particular shape. Additionally, the model also creates spatial patterns in how agents adopt the new variety, these patterns should reflect how agents act with differing environmental factors.

2. *Entities and state variables*

Within the model, there are multiple different types of entities.

- ‘Farmers’ (agents/individuals). Each cycle, farmers make a decision on what varieties to plant for the upcoming growing season (portfolio). This decision is based on a combination of economic and social factors, the relative importance of which are decided on beforehand by a decision-making parameter assigning weights to the types of influence. Each farmer has a personal preference for one of the three varieties, reflected as their personality. Additionally, farmers each have a portfolio. The portfolio of a farm is represented as a proportion between the three crop varieties that farmers can choose from. For the first time-step, the portfolio is selected semi-randomly based on scenario parameters, which skews towards farmers assigning larger parts of their portfolio towards a certain variety. Farmers have the option of changing the portfolio each cycle based on their satisfaction (further explained in section 4d).
- ‘Farm’ (spatial unit). Each cell in the environment grid represents a farm of 9 hectares, or 90,000 m2. The environment grid is filled with farms that each have two state variables; altitude and heat stress. Altitude is denoted in meters and is assigned based on an altitude map of the agricultural area in Nicaragua. The altitude remains constant and is used, along with a changing threshold, to determine whether a farm is affected by heat stress. The heat stress variable is a threshold value generated randomly around the mean elevation of the area. This results in each farm being assigned a value of 0 or 1, depicting whether a farm is affected by heat stress; this is then used in the calculation of the crop performance of that specific farm.
- ‘Local network’. This entity represents the relationships that farmers have with their neighbors (Moore neighborhood). Each agent makes up a local network with their neighbors in which they both exert and receive social influence based on similarity and relative performance to each other. Farmers receive satisfaction from having similar portfolios to their neighbors and from having a higher performance than their neighbors.

3. *Spatial and Temporal scale*

The model is run in time steps, where each time step represents a full growing season from seed planting to the harvest. There are multiple growing seasons in a year, each around 5 months in length. The landscape of the model consists of 75 X 75 cells which all contain a farmer and their farm. Each cell represents farming land of 9 hectares, resulting in a total area of 50,625 hectares; or about 506 square kilometers. The Moore neighborhood of each cell defines its local network, being the 8 cells around each focal cell.

4. *Process overview and scheduling*

The model is implemented in two procedures, setup and go. Setup initializes a run by clearing all variables from the previous run and resetting the time steps (ticks) to zero. It then creates new agents along with their attributes and networks to set the stage for the next run. The go procedure can be subdivided in a couple of steps:

a. Each farmer receives satisfaction from social, personal, and economic factors.
b. Each farmer determines their portfolio for the upcoming growing season based on decision rules that simulate the decision-making process based on the previously received satisfaction.
c. Portfolio values are updated for each farmer

d. For each farmer, crop performance is calculated and stored to be used as the economic influence for the next decision-making process.
e. Display and file output are updated
f. The simulation clock advances by one and the go process is repeated from step a.

5. Design concepts

a. Basic principles

The basic principles underlying the development of this ABM are:

- To keep the model as simple as possible while retaining explanatory power on the diffusion process
- Agent decision-making is based on the consumat framework (Jager & Janssen, 2012). Each agent has three needs which they try to meet to obtain a high level of satisfaction. The goal of consumat is to represent the influence of both economic and social factors in the decision-making process which aligns with the main purpose of this model as well.
- Agent decision-making is also based on the performance of their neighbors, neighbors with a higher satisfaction are taken as an example and farmers mimic their portfolio with the goal of obtaining a higher satisfaction.

b. Emergence

Emergent properties that are of interest are the spatial patterns emerging in the distribution of the different crop varieties. Heterogeneous environmental factors might lead to divergent behavior between farmers with similar characteristics, while on the other hand, social factors from local networks could incentivize the homogenization of variety choice. The generated distribution is unpredictable and affected by the initial distribution as well as the relative importance of the different factors determining satisfaction (through usage of weights for the three needs).

c. Adaptation

The adaptive behavior of farmers in this model comes from their choice whether to change their portfolio or to keep it the same. And if the choice is made to change the portfolio, what to change it to. The choice of changing their portfolio is based on comparing the received satisfaction of their own portfolio to the satisfaction values of the portfolios of their neighbors. Farmers only consider copying their neighbor’s portfolios if their satisfaction is higher than their own and above a certain threshold. If their own satisfaction is low and none of their neighbors have a higher satisfaction, an agent may “try out” a new portfolio by themselves by changing their portfolio values to include a variety that they do not / barely use. This allows for new portfolios to arise that are not necessarily based on an already existing portfolio. The satisfaction threshold below which farmers will try out a new variety is set at 1.5. The maximum satisfaction from all three needs is equal to 1 meaning that the maximum total obtainable satisfaction for a farmer is equal to 3. The threshold of 1.5 is exactly half of the maximum and this value makes it so that farmers will always try to obtain a satisfaction of at least 1.5 and not remain at a low satisfaction level if all their neighbors happen to have even lower satisfaction values.

The driving factors in the decision-making process are the satisfaction received for each of the three agent needs, consisting of a combination of an economic factor; performance, social factors: similarity and superiority to others, and a personal factor which is a preference for a certain crop variety.

Another important part of the adaptation is the adoption curve. The relative importance of certain factors influencing decision-making can be adjusted which would lead to different spatial patterns and a difference in the adoption curve. Different initial distributions are also studied for their effect on the final outcome of the diffusion process. This was done in the form of simulating different scenarios along with a sensitivity analysis that shows how changes in the starting position and factors affected the final outcome.

d. Objectives

The objective measure used by farmers to decide whether an alternative portfolio is ‘better’ than their current is satisfaction. Farmers receive satisfaction for three needs: existence, social, and personal. The combination of these three makes up the total satisfaction that farmers aim to maximize. This can be formalized into mathematical formulas as elaborated on in the *Decision-making process* section of the methodology section.

e. Learning

Farmers only change their decision-making based on the results of the last growing season and do not store results of multiple previous seasons.

f. Prediction

In this model, farmers make use of a very simple prediction: that the environmental factors for the next time step remain equal. This assumption is used in predicting crop performance to determine the satisfaction gained for the ‘existence need’ for a specific portfolio.

g. Sensing

Farmers are aware of their own state variables and those of their direct neighbors (Moore neighborhood) and use these in the decision-making process. This knowledge is assumed to be accurate and without uncertainty. Farmers are unaware of other farmer’s state variables outside of their direct neighborhood.

h. Interaction

Farmers react to influences from their local network and, in turn, influence other farmers in their local network with their decisions which is the only interaction that happens between farmers.

i. Stochasticity

Stochasticity is used in two separate parts of the model. The first is in the initialization of farmer’s characteristics and their starting portfolio. This has the goal of creating heterogeneous farmers that can react differently to similar situations. Each farmer is randomly assigned a personal preference which brings them satisfaction if they match its conditions. The initial portfolios of farmers are also randomly selected with an increased chance to start with the ‘old’ crop variety. Note: the initial portfolios of farmers follow different rules based on which scenario is chosen.

Stochasticity is also used in the selection of the environmental factor which represents an altitude threshold below which farms experience heat stress, negatively impacting crop performance. The threshold is selected randomly from a normal distribution. In addition to the heat-stress threshold, an error term is also added in the crop performance calculation which represents the unpredictable events associated with agriculture that could positively, or negatively, influence the outcome. Its main purpose is to keep the environmental influence simple to model while making it somewhat plausible by incorporating the variability of the environmental conditions.

j. Collectives

The collectives in the model consist of the local network that each farmer is a part of; consisting of their 8 neighbors (Moore).

k. Observation

The model produces a visual output that reflects spatial patterns of farmer portfolios across the landscape. Summary statistics are also produced and documented on what portfolios farmers choose. Most importantly however, is the output of the plot. The plot shows which varieties are dominant in farmer's portfolios. This is useful for determining how many farmers make use of the green crop variety (variety 3) at the end and during the simulation. The dominance of the red variety can also be seen as its adoption curve, which in turn depicts how well the new variety diffuses across the environment and whether or not this can be noted as a successful diffusion.

6. *Initialization*

There are a couple of factors and values that have to be decided on before the model can be run. These are selected for different purposes and the model has different initializations for different scenarios. For the initialization of the model the following steps should be taken:

- Select values for ssm and spm. These represent the satisfaction farmers receive from social factors. Depending on the purpose of the scenario, these values can be changed relative to one another. If farmers should prioritize similarity, the ssm value can be set higher than the spm. And if farmers should prioritize superiority, the spm value can be set higher than the ssm.
- Next, weights can be assigned to each of the three needs. This is done to offset the balance of influence on decision-making which means that farmers either prefer economic factors (crop performance) or social factors (similarity & superiority) or their personal factor (variety preference).
- Each farmer is also assigned a personal preference as part of their 'personal' need. This promotes heterogeneous decision-making as farmers receive different levels of satisfaction while their other factors might be the same. Farmers are assigned a preference for one of the three varieties which brings them additional satisfaction if the majority of their portfolio is used for this variety.

7. *Input data*

The model uses an external altitude map of Nicaragua to determine the elevation values of the environment. No other additional data sources are used in the model.

8. *Submodels*

The model does not make use of submodels.

3.6 Scenarios

The model was run using five different scenarios. In every scenario, the new heat-resistant (green) variety is introduced to farmers. The method of this introduction is done in three ways; the first method used for scenarios 1 through 3 is random introduction. The weights assigned to the three needs are also experimented with in these scenarios. These assigned weights are determined in the scenario initialization and can represent outside influences on the farmer decision-making process. An example of this could be an intervention in the form of a national policy that subsidies farmers making use of a certain variety, or an intervention that incentivizes farmers to work together, which would increase the weight assigned to the social need for example. Scenarios 4 and 5 use two other methods of variety introduction, elevation-based introduction and clustered introduction respectively. These represent more realistic ways of introduction from which more insights are gained on the effect of different approaches to variety introduction.

Below, the choices made for each of these scenarios are first explained after which the specific parameters for the scenario are listed. Each scenario was run for 30 growing seasons which represents a timespan of about 10 years. This gives the model plenty of time to be able to show spatial patterns and the diffusion of the green variety. As a large part of the setup is semi-random for each of the scenarios, each scenario was run 3 times and averages were taken. These runs are all noted down in the tables per scenario. The shown maps and plot for each scenario is the map from the run, that most closely resembles the average of the runs. Table 2 below contains the parameter values for each scenario. Ssm and spm represent the similarity satisfaction measure and the superiority satisfaction measure respectively. Their values represent the balance between farmers receiving satisfaction from having a similar portfolio to neighbors versus satisfaction from performing better than their neighbors.

*Table 2:*The method of how the green variety is introduced along with the ssm & spm values, and the weights assigned to each of the three needs for all five scenarios.

Parameter	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Green variety introduction	Random	Random	Random	Elevation-based	Clustered
similarity satisfaction measure (ssm)	0.5	0.3	0.7	0.3	0.3
superiority satisfaction measure (spm)	0.5	0.7	0.3	0.7	0.7
existence weight	1.0	1.5	0.8	1.5	1.5
social weight	1.0	0.8	1.5	0.8	0.8
personal weight	1.0	0.8	1.5	0.3	0.3

Scenarios 1, 2, and 3 are meant to familiarize with the workings and mechanisms of the model, as well as analyze the sensitivity of the outcome as several parameters within the model change. These first scenarios make use of randomly setup farmers. Farmers are randomly assigned portfolio values for the three varieties skewed towards a higher value for red variety, i.e. in the starting situation, relatively more farmers have variety 1 as the largest variety in their portfolio.

Scenario 4 and 5 assign the weights in a similar manner to scenario 2 to make the simulation more realistic, where farmers strive for a high crop performance and gain less satisfaction from social factors with an even lower weight assigned to personal satisfaction. In most cases, crop performance of farmers is directly linked to welfare which makes this the prioritized ‘need’ for most farmers. The changes in these scenarios come from the method of introduction of the green variety.

Scenario 1: uses a random green variety introduction, meaning agent portfolios are randomly assigned and skewed towards having a large part of their portfolio dedicated to the red variety. Personalities of farmers (i.e. their preference for a certain variety) are also randomly assigned. The weights for this scenario are all set on equal levels, meaning farmers’ satisfaction of each of the three needs plays an equal role in the decision-making.

Scenario 2: changes the weights around to make farmers prefer crop performance and superiority (spm and existence weight are raised). As crop performance is directly equal to financial gain for most farmers, this weight distribution is more realistic than in scenario 1.

Scenario 3: this scenario changes the weights around to make farmers prefer social and personal satisfaction as opposed to existence. This scenario is meant to investigate the outcome of the diffusion if crop performance is not the most important factor for determining satisfaction. In terms of parameters, this involves increasing social and personal weight and raising the ssm.

Scenario 4: The major change is this scenario comes from the green variety introduction which is done based on the elevation. Farms at a lower elevation are more likely to suffer heat-stress and thus, will profit more from using the new variety, these farmers are also assigned a personality of 3 to match these goals. Not all farmers at low elevation receive a portfolio consisting mainly of the green variety; there is still some randomness involved in the assignment of portfolios. Farmers at higher elevations are still assigned a portfolio randomly but heavily skewed towards the red variety, these farmers are assigned a personality of either 1 or 2, both with a 50% chance.

Scenario 5: uses the same parameters as scenario 4 but introduces the green variety in a different way. In this scenario the green variety is introduced in five small clusters scattered across the environment. This method of introducing a new variety is efficient as the distributors only need to visit a few locations to drop off the green variety (as opposed to the whole environment) (Dennis, et al., 2010; Jawale, 2012). The starting portfolios of farmers outside of these five clusters is still randomly determined, skewed towards the red variety as in the previous scenarios. This scenario can also depict whether and how the green variety spreads across the environment.

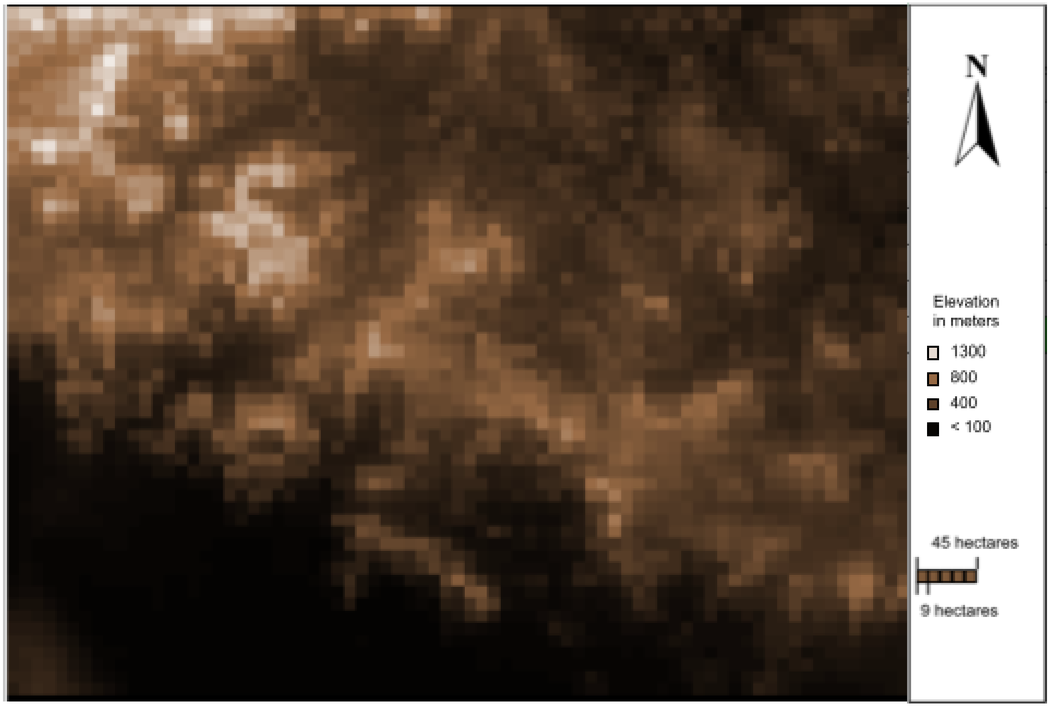
4. Results

In the maps with the model results, farmers are assigned a color based on which variety is the largest in their portfolio. If a farmer mostly makes use of the old red variety they are colored red. If the non heat-resistant yellow variety is largest in the portfolio, the farmer is colored yellow. Finally, a majority of the new heat-resistant green variety in a farmers portfolio results in a green color. These colors are simply used to distinguish between farmers with different portfolios and to depict spatial patterns that emerge in the model outputs. At the end of this chapter, table 8 summarizes the average change of portfolios between the starting and ending situations. Below, the scenarios are first described individually in more detail.

The output of each scenario consists of five parts; a map of the starting situation (*Figure 4)*, a map of the situation after 30 growing seasons (*Figure 5)*, a table with the changes in number of portfolios per variety (*Table 3)*, a plot of the number of portfolios per variety over time (*Figure 6)*, and finally the adoption curve, shown as the average portion of portfolios assigned to the new heat resistant variety (*Figure 7).* The examples given are the figures of scenario 1; section 4.1. Not all of these figures provide results interesting to observe so a few figures have been moved to the appendix and only the discussed figures are included.

A final note before going into detail on the scenarios, is to take note of the elevation map of the area. The color represents the elevation of the area where darker colors represent low elevation and lighter colors represent a higher elevation. The highest concentration of high elevation is in the top left of the map and runs diagonally across the middle. The top right and bottom left areas mostly have a low elevation level (*Figure 3*). This is the basemap on which farmers are created for each of the scenarios.

Figure 3: The elevation map of the study area; the agricultural valley close to the mountains in western Nicaragua. The color of the pixels shows the elevation of each area, light colors represent a high elevation level and darker colors represent a lower elevation level.



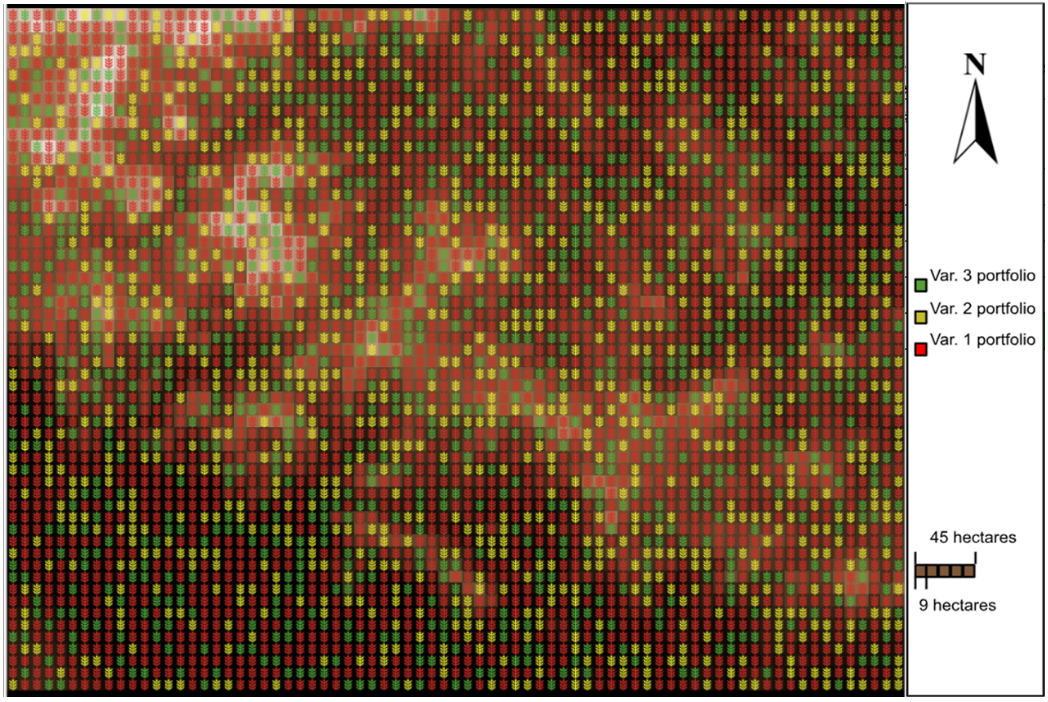
4.1 Scenario 1: Random Introduction - Neutral satisfaction weights

Scenario 1 sees a decreasing trend in red portfolios which are mostly replaced by green portfolios (*Figure 6)*. This is in line with the adoption curve (*Figure 7*). The adoption curve shows a steep rise in the first 20 time steps after which it somewhat balances out. At this point in the simulation, most agents that would profit from adopting the green variety into their portfolio have already done so, i.e. the agents in an area with a high chance of heat stress. The average proportion of the green variety of portfolios seems to balance out at around 0.425 which might seem like a relatively low value considering the number of farmers with a portfolio consisting mostly of the green variety (*Table 3*). This could be explained by reasoning that farmers at a high elevation level (where the risk of heat stress is low) likely make very little use of the green variety as both the yellow and red variety perform better in situations without heat stress.

While not true for all farmers, the spatial pattern mostly represents the elevation map where areas with a high elevation mostly have yellow portfolios and areas with a low elevation, and thus more often under heat stress, tend to have a green portfolio (*Figure 5)*. This is in line with expected values for crop performance, as yellow portfolios perform best at a high elevation where there is a low risk of heat stress, and green portfolios perform best at low elevations where their resistance to heat stress is necessary. Some low elevation areas still contain mostly red portfolios, this can be attributed to both the social and personal factors; as the weights are equal for each of the three needs, the satisfaction gained from similarity along with a personal preference for the red variety leaves these farmers growing the red variety while this does not equal the highest crop performance.

Starting situation

Figure 4: Starting situation for scenario 1 (Run 1). The elevation map in the background is shown by the colors of the cells. The colored plant shapes each represent a farmer with the color showing which of the three varieties is dominant in their portfolio.



Situation after 30 growing seasons

Figure 5: Situation after 30 seasons for scenario 1 (Run 1). The elevation map in the background is shown by the colors of the cells. The colored plant shapes each represent a farmer with the color showing which of the three varieties is dominant in their portfolio.

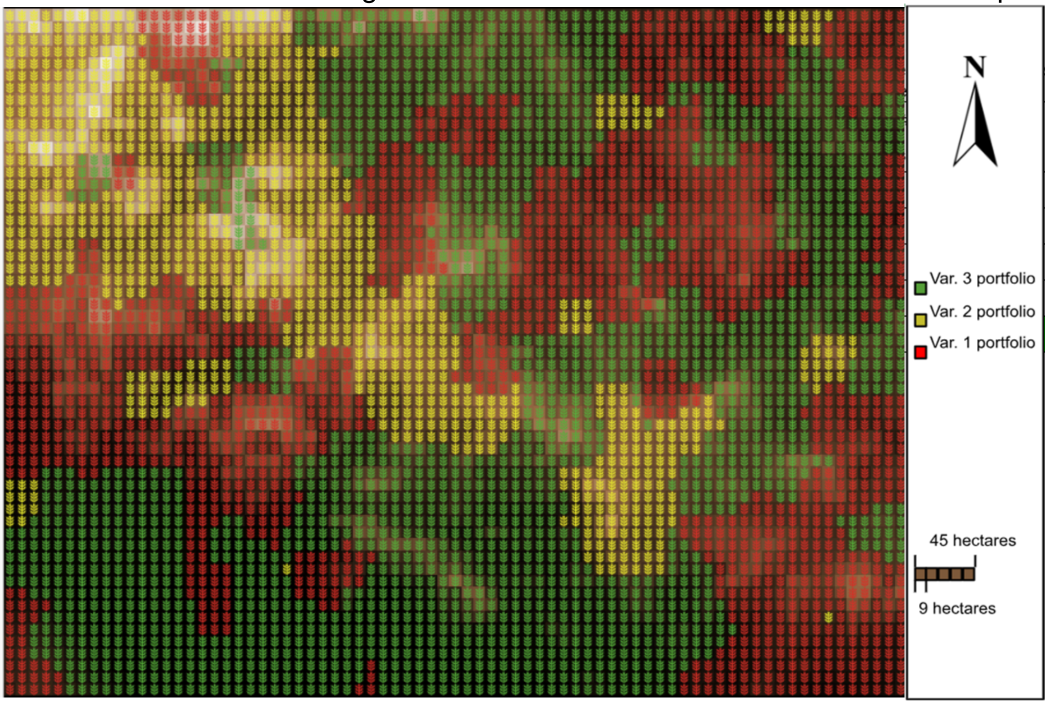


Table 3: farmer statistics for scenario 1 with the number of farmers with each of the three portfolio colors at the start and end of the simulation. Bottom two rows average the numbers of the three runs and depict the average change in number of portfolios per color.

	Starting # red portfolios	Ending # red portfolios	Starting # yellow portfolios	Ending # yellow portfolios	Starting # green portfolios	Ending # green portfolios
Run 1	2459	1465	913	926	903	1884
Run 2	2449	1090	906	1076	921	2109
Run 3	2419	1547	935	1007	921	1721
Average	2442	1367	918	1003	915	1904
Avg. Change		-1075		+85		+989

Figure 6: Plot of farmer portfolios for scenario 1 (Run 1). Each line represents the number of agents with red/yellow/green portfolios over time. Where the colors are assigned the same as in the scenario maps. The green line is not directly related to the adoption curve as the proportions of the green variety could rise within a portfolio while not becoming the largest.

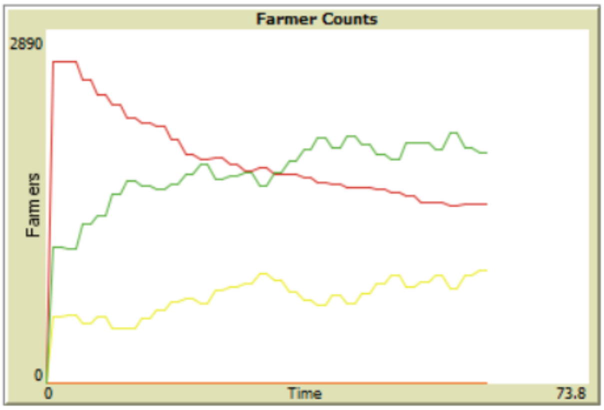
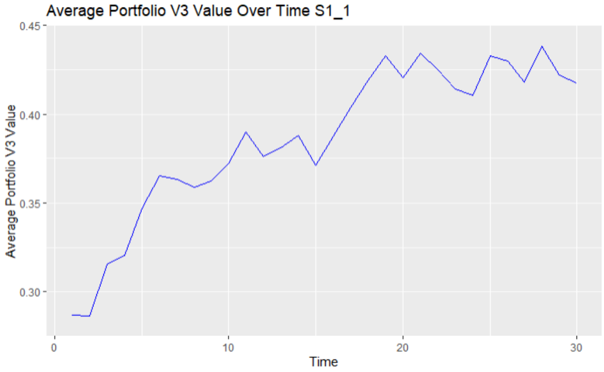


Figure 7: Plot of the average proportion of portfolio assigned to the green variety, over time for scenario 1, run 1.



4.2 Scenario 2: Random Introduction - Existence focused weights

This scenario yields similar results to scenario 1 however, the spatial patterns are more clear in this outcome (*Figure 8*). The higher weight assigned to the 'existence need' makes farmers prefer portfolios with higher crop performance. This means that more farmers swap to either the green or yellow portfolio, both of which are better performing alternatives to the red portfolio. In this scenario the social and personal factors that could withhold farmers from changing away from a red portfolio are weaker which results in a much quicker adoption of the green variety as also shown by the adoption curve (*Figure 9)*. The average value of the green variety in portfolios is above the value of 0.40 already before time step 10. In scenario 1, it took until about time step 17 or 18 to climb above a value of 0.40. In the outcome situation, almost all low elevation areas have farmers with a green portfolio and most high elevation areas have farmers with a yellow portfolio, aside from a few pockets of red portfolios at high elevation as well (*Figure 8)*.

<u>Starting situation:</u> See *Appendix figure 1*

Situation after 30 growing seasons

Figure 8: Situation after 30 seasons for scenario 2 (Run 2). The elevation map in the background is shown by the colors of the cells. The colored plant shapes each represent a farmer with the color showing which of the three varieties is dominant in their portfolio.

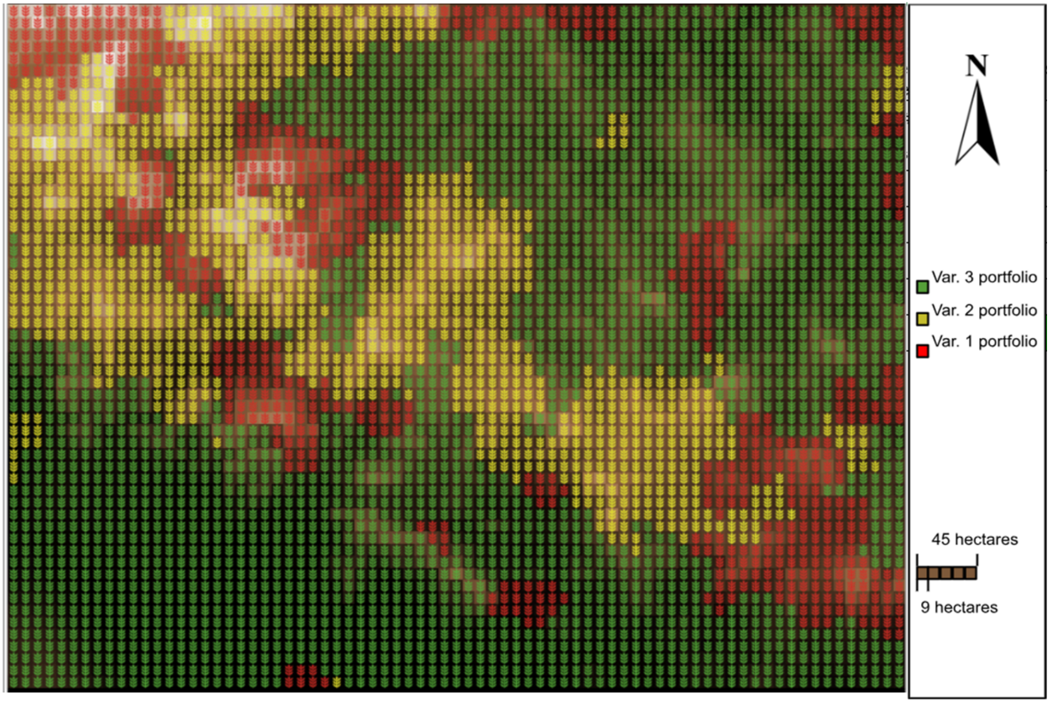
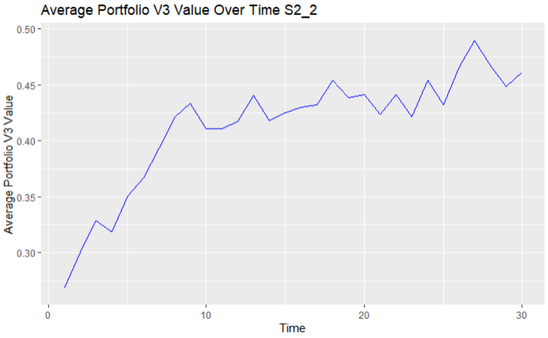


Table 4: farmer statistics for scenario 2 with the number of farmers with each of the three portfolio colors at the start and end of the simulation. Bottom two rows average the numbers of the three runs and depict the average change in number of portfolios per color.

	Starting # red portfolios	Ending # red portfolios	Starting # yellow portfolios	Ending # yellow portfolios	Starting # green portfolios	Ending # green portfolios
Run 1	2939	397	931	589	951	3289
Run 2	2471	686	858	1097	946	2492
Run 3	2444	545	890	1535	941	2195
Average	2618	543	893	1074	946	2659
Avg. Change		-2075		+181		+1713

Figure 9: Plot of the average proportion of portfolio assigned to crop the green variety, over time for scenario 2, run 2.



4.3 Scenario 3: Random Introduction - Social focused weights

The outcome of this scenario shows an opposite trend than the previous two scenarios. Here, the number of red portfolios increase while the other two decrease (*Table 5)*. This can be attributed to the higher weights assigned to both the social and the personal factors. Farmers prefer similarity and their personal preference (which is most likely to be a preference for the red variety) over crop performance. This leads to the emerging spatial patterns not representing the elevation levels as it has in scenario 1 and 2. Despite this, the adoption curve still shows an upwards trend, albeit in a much smaller degree; the maximum value only reaches 0.28 which is considerably lower than in scenario 1 and 2 (*Figure 11)*. In this scenario most farmers have a red portfolio and it is likely to stay that way in future seasons as similarity to neighbors plays a large role in the decision-making process, this scenario also does not lead to interesting spatial patterns emerging (*Figure 10)*.

Starting situation: See *Appendix figure 3*

Situation after 30 growing seasons

Figure 10: Situation after 30 seasons for scenario 3 (Run 1). The elevation map in the background is shown by the colors of the cells. The colored plant shapes each represent a farmer with the color showing which of the three varieties is dominant in their portfolio.

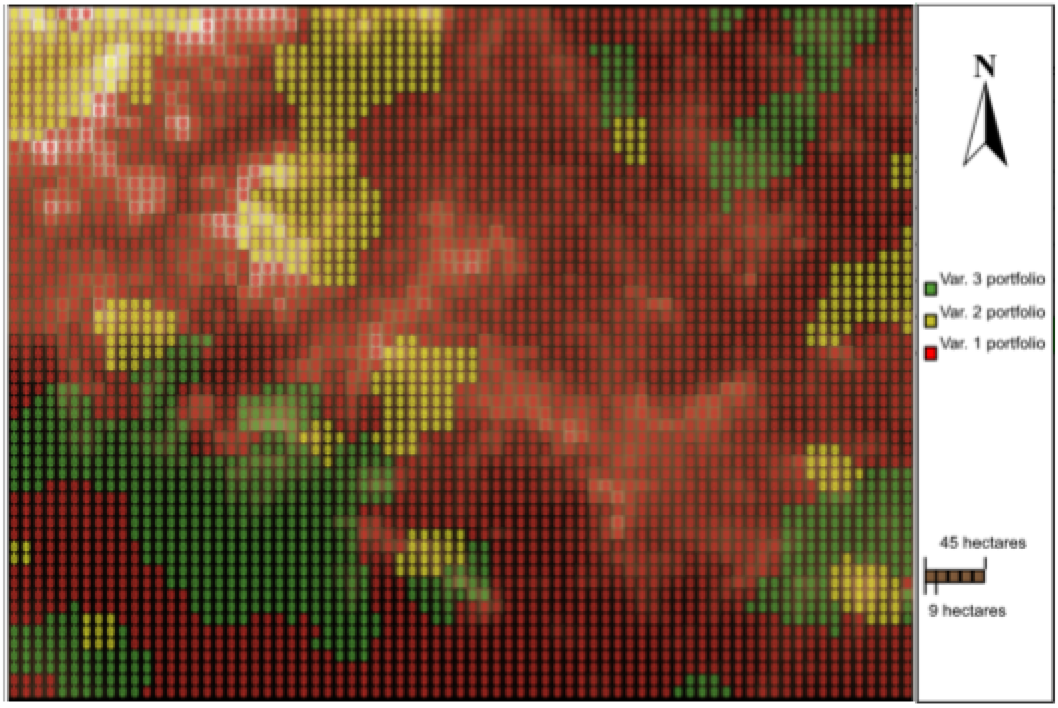
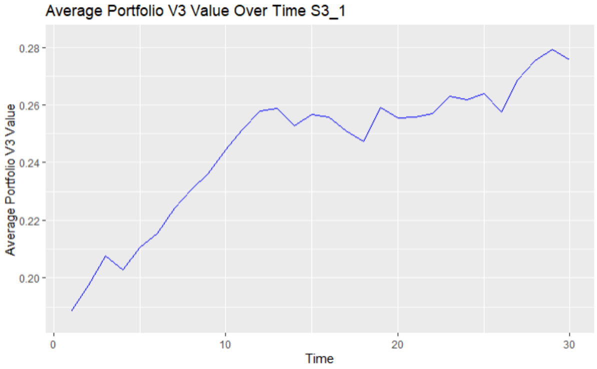


Table 5: farmer statistics for scenario 3 with the number of farmers with each of the three portfolio colors at the start and end of the simulation. Bottom two rows average the numbers of the three runs and depict the average change in number of portfolios per color.

	Starting # red portfolios	Ending # red portfolios	Starting # yellow portfolios	Ending # yellow portfolios	Starting # green portfolios	Ending # green portfolios
Run 1	2469	2971	914	574	892	730
Run 2	2420	2665	916	540	939	1070
Run 3	2461	3032	922	659	892	584
Average	2450	2889	917	591	908	795
Avg. Change		+439		-326		-113

Figure 11: Plot of the average proportion of portfolio assigned to the green variety, over time for scenario 3, run 1.

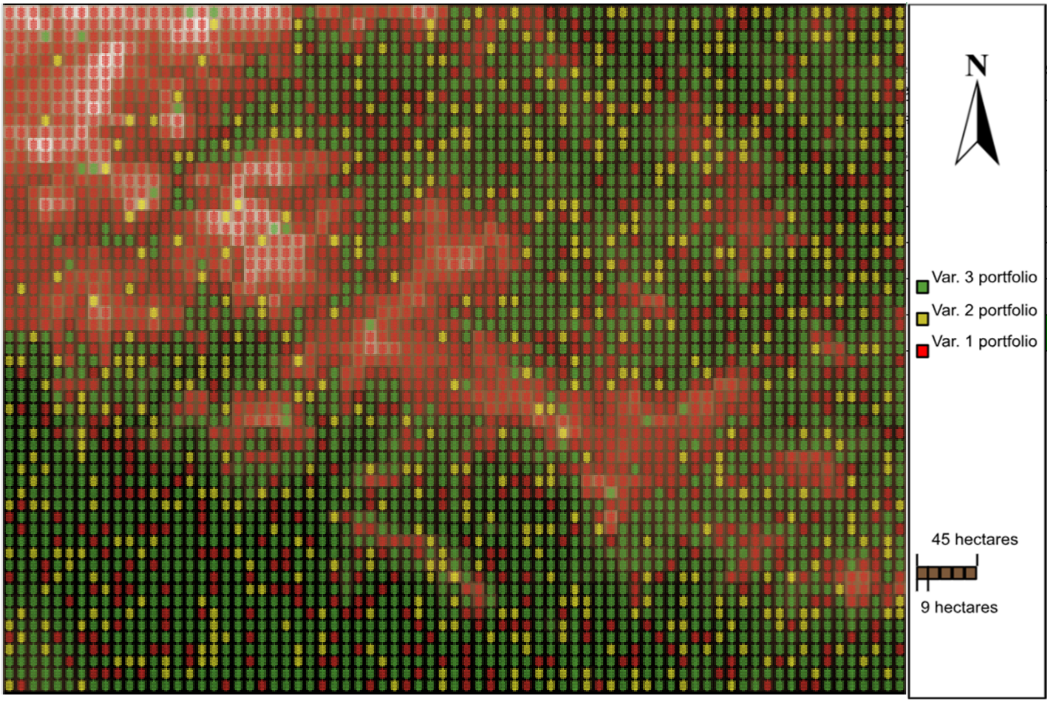


4.4 Scenario 4: Elevation-based introduction

This outcome of this scenario is similar to scenario 2 which partly comes from the similar selection of parameters. The differing factor in this scenario however, is the introduction of the green variety (*Figure 12)*. As crop performance is preferred over the other two needs, the spatial pattern that emerges is again that low elevation areas lead to green portfolios and high elevation to yellow. The starting situation already partly reflected this pattern which leads to the spatial pattern being more pronounced in this scenario than the other two (*Figure 13)*. The adoption curve is shaped differently than in previous scenarios (*Figure 14)*. This can be explained by the method of the green variety introduction. In the starting situation, the spatial pattern that emerged in scenarios 1 and 2 is already mostly in place at the start of this scenario (*Figure 12)*, the average value of the green variety in portfolios is also much higher in this scenario which leaves less potential for change than in the other scenarios.

Starting situation:

Figure 12: Starting situation for scenario 4 (Run 3). The elevation map in the background is shown by the colors of the cells. The colored plant shapes each represent a farmer with the color showing which of the three varieties is dominant in their portfolio.



Situation after 30 growing seasons

Figure 13: Situation after 30 seasons for scenario 4 (Run 3). The elevation map in the background is shown by the colors of the cells. The colored plant shapes each represent a farmer with the color showing which of the three varieties is dominant in their portfolio.

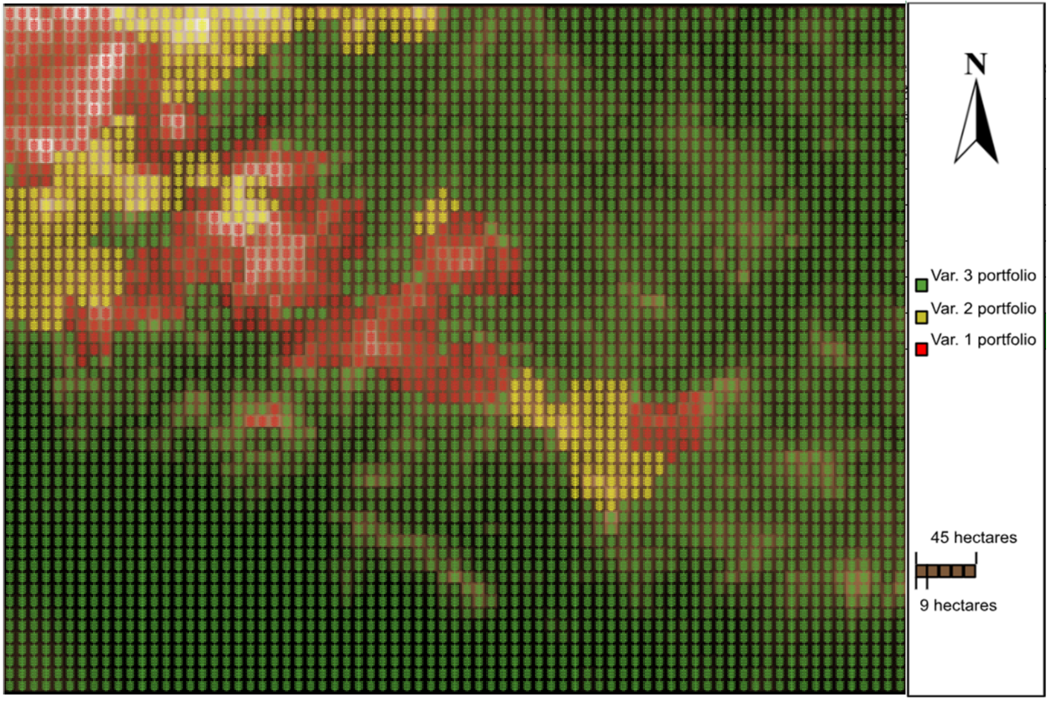
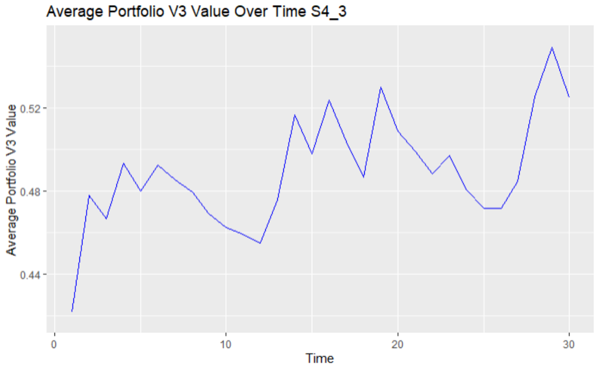


Table 6: farmer statistics for scenario 4 with the number of farmers with each of the three portfolio colors at the start and end of the simulation. Bottom two rows average the numbers of the three runs and depict the average change in number of portfolios per color.

	Starting # red portfolios	Ending # red portfolios	Starting # yellow portfolios	Ending # yellow portfolios	Starting # green portfolios	Ending # green portfolios
Run 1	1605	753	531	284	2139	3238
Run 2	1681	563	516	290	2078	3422
Run 3	1632	560	516	364	2127	3351
Average	1639	625	521	313	2115	3337
Avg. Change		-1014		-208		+1222

Figure 14: Plot of the average proportion of portfolio assigned to crop variety 3, over time for scenario 4, run 3.

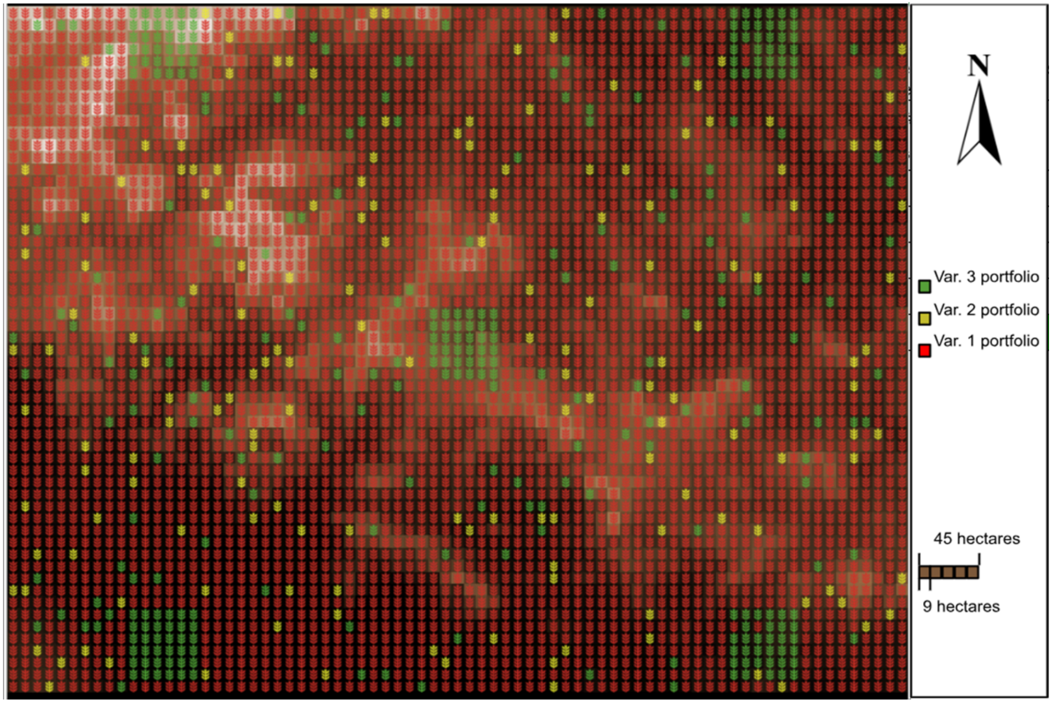


4.5 Scenario 5: Clustered introduction

This scenario has had the lowest number of green portfolios in the starting situation which is still apparent at the end of the simulation. The green portfolios were introduced in 5 clusters at different locations in the environment (*Figure 15)*. The simulation does show an upwards trend for both the yellow and green portfolios which could mean that, over time, the spatial patterns produced are similar to that of scenario 4. It is likely that, in order to reach that point, the simulation must be run for more seasons than 30. This is also in line with the adoption curve for this scenario (*Figure 17*) that, unlike some other scenarios, is still relatively steep after 30 growing seasons. This implies that the number of green portfolios will rise further if the scenario is run for more growing seasons. Additionally, this scenario shows the highest variance of all previously tried scenarios in the amount of green portfolios at the ending situation; ranging from 851 to 2058 which means that the starting portfolios and personalities of the “random” farmers have a greater effect on the outcome in this scenario relative to the others.

Starting situation:

Figure 15: Starting situation for scenario 5 (Run 1). The elevation map in the background is shown by the colors of the cells. The colored plant shapes each represent a farmer with the color showing which of the three varieties is dominant in their portfolio.



Situation after 30 growing seasons

Figure 16: Situation after 30 seasons for scenario 5 (Run 1). The elevation map in the background is shown by the colors of the cells. The colored plant shapes each represent a farmer with the color showing which of the three varieties is dominant in their portfolio.

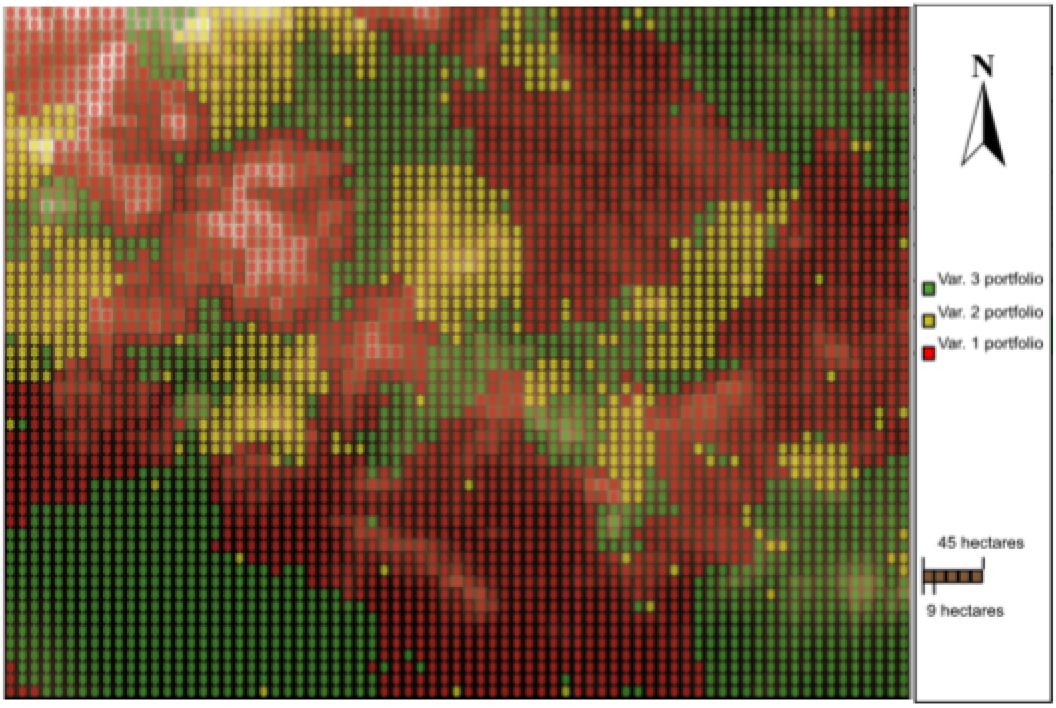
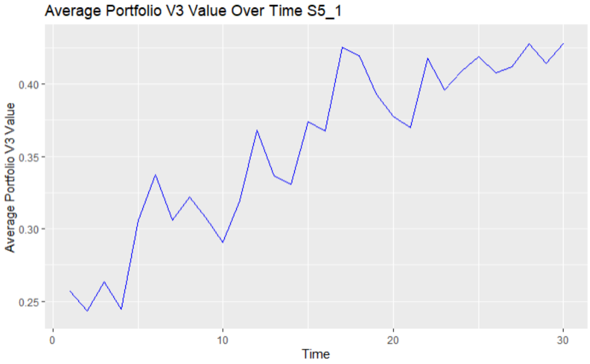


Table 7: farmer statistics for scenario 5 with the number of farmers with each of the three portfolio colors at the start and end of the simulation. Bottom two rows average the numbers of the three runs and depict the average change in number of portfolios per color.

	Starting # red portfolios	Ending # red portfolios	Starting # yellow portfolios	Ending # yellow portfolios	Starting # green portfolios	Ending # green portfolios
Run 1	3788	2186	163	675	324	1414
Run 2	3812	1961	154	256	309	2058
Run 3	3794	2088	167	1336	314	851
Average	3798	2078	161	756	316	1441
Avg. Change		-1720		+595		+1125

Figure 17: Plot of the average proportion of portfolio assigned to crop the green variety, over time for scenario 5, run 1.



4.6 Comparing scenarios

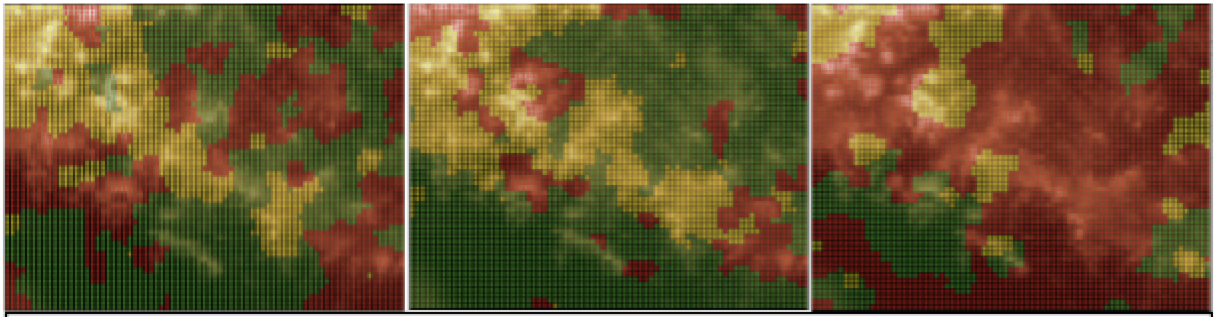
Nearly all scenarios lead to an increase of the number of green portfolios, meaning that, for almost all scenarios, there is a positive rate of adoption; farmers are using the green variety more at the end of the simulation than at the beginning (*Table 8*). This is in line with the adoption curves that show that the average proportion of portfolios assigned to the green variety increases over time meaning that, over time, farmers are adopting the new variety. The rate of adoption differs quite a lot between scenarios. But we can conclude that the scenarios with parameters set towards an economic focus, result in the highest rate of adoption of the green variety.

A comparison of the final situations of scenarios (*Figure 18*) depict a clear spatial pattern for at least three scenario outcomes. This is characterized by a combination of red and yellow portfolios in the high elevation areas and green portfolios in the low elevation areas. Scenario 4 shows this pattern most clearly with only the highest elevation areas being red/yellow and most of the rest of the map with green portfolios and its adoption curve also ends at the highest point of all scenarios (*Figure 19)* which is expected as the starting situation (*Figure 12)* already mostly reflected the spatial pattern shown in Figure 19. The largest contrast with this result comes from scenario 3. In this scenario parameters were selected so social satisfaction was weighed more heavily than the existence satisfaction, meaning that farmers preferred having similar portfolios to neighbors. This led to a situation where the potential gain in crop performance did not outweigh the loss in satisfaction that would come from having a dissimilar portfolio to neighbors.

Table 8: Average change in number of portfolios per variety for each scenario. Nearly all scenarios show a decline in red portfolios and a large rise in uptake of green portfolios.

Scenario	Avg. change in # red portfolios	Avg. change in # yellow portfolios	Avg. change in # green portfolios
Scenario 1	-1075	+85	+989
Scenario 2	-2075	+181	+1713
Scenario 3	+439	-326	-113
Scenario 4	-1014	-208	+1222
Scenario 5	-1720	+595	+1125

Figure 18: Comparison of the scenario maps after 30 growing seasons. Colors representing the respective varieties dominant in farmer's portfolios. The elevation map in the background is shown by the colors of the cells.



Scenario 1	Scenario 2	Scenario 3
Scenario 4	Scenario 5	Elevation Map

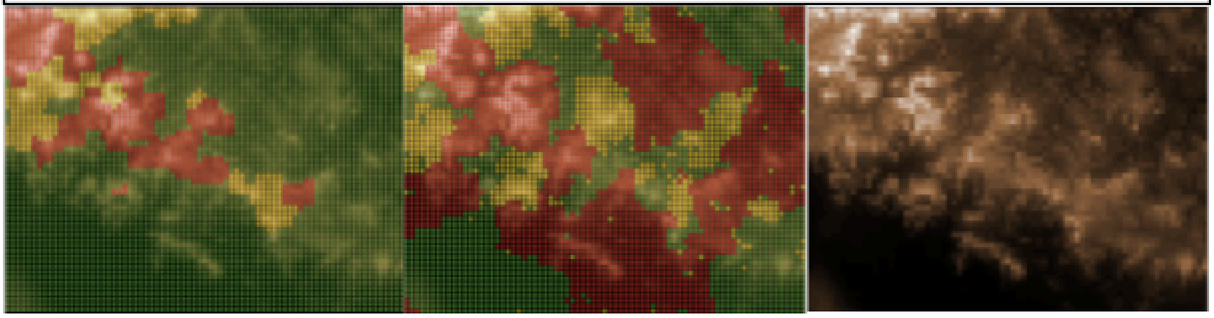
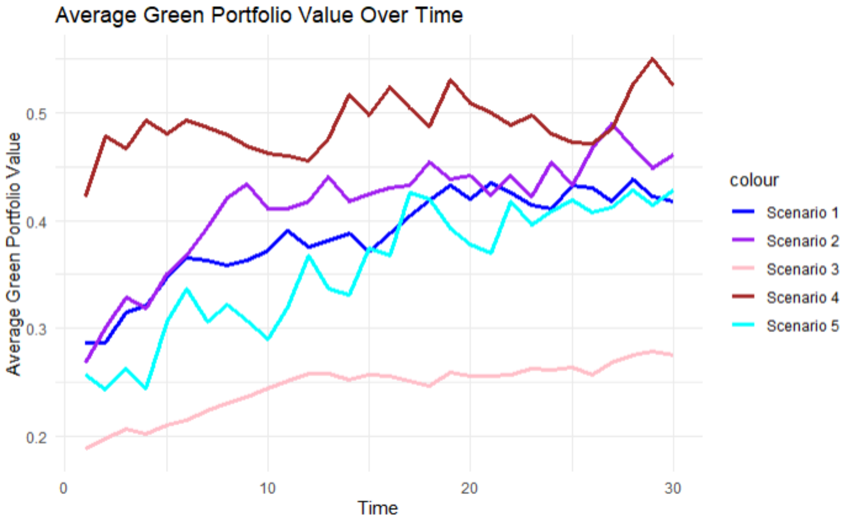


Figure 19: Plot combining the adoption curves of the scenarios showing the average portion of portfolios assigned to the green variety. Scenario 4 keeps the highest value throughout the simulation but also has, by far, the highest starting point. Scenarios 1, 2, show similar paths with steep rise at the start that flattens out later.



5. Discussion

The literature review performed at the start of this thesis brought forward some of the current problems that come with modeling innovation diffusion. One of the main findings is the lack of the inclusion of non-economic factors in decision-making in ABM. That ABM is a relatively newer approach to modeling innovation diffusion is what most authors attribute this lack to. On the other hand, many of these papers have been published before 2020 and since then (and even before then) much has changed in terms of theories and computing capabilities of modeling software. Most previous applications of decision-making in ABMs are based on economic factors but lack depth in other factors, especially when it comes to social factors that could influence decision-making (Kiesling, et al., 2012; Huber, et al., 2018; Githinji, et al., 2023; Schimmelpfennig & Muthukrishna, 2023). The consumat framework by Jager & Janssen (2012) provides a way to tackle this issue; the deconstruction of agent satisfaction into three needs. Agent decision-making is based on the three needs: existence, social, and personal. While these needs are often measured by different metrics, consumat allows for a way to add these types of needs together. In my model each of these needs are quantified in such a way that its value ranges from 0 to 1 which, along with a weight, allows them to be added together and be compared. This results in a model that incorporates more than just crop performance into agent decision-making and can thus, better simulate more complex heterogeneous decision-making among agents (Berger, 2001; Huber, et al., 2018).

The plots shown in the result section show the change of farmer portfolios over time (Figures 2, 4, 6, 8, 10, these plots only account for which variety is the largest in portfolios and does not tell us much about the average usage of the green variety over time. A better plot to represent the adoption curve as described by Henrich (2001) plots the average green variety presence in portfolios over time (as in Figures 3, 5, 7, 9, 11. The shape of this line can further be related to the type of learning dominant in adoption of the new variety. An R-shaped curve implies that the major factor determining adoption is economic (the 'existence need' in the model) and an S-shaped curve implies that the adoption is more based on a social factor and the behavior of other agents. Scenarios 1 through 3 depict an R-shaped adoption curve. As mentioned above, this implies that the major factor determining the rate of adoption is economic. While this does not exactly align with observations from Henrich (2001) it can be reasoned why this is the case. The starting situation in the scenarios is that most farmers have a portfolio where the red variety is dominant and their personal preference is also the red variety. This means that both social and personal factors incentivize farmers to keep the red variety the largest in their portfolio. This means that most of the pressure towards adopting the green variety has to come from the 'existence need'; the economic factor which would explain the shape of the adoption curve, which I have characterized as the overall average proportion of the green variety in portfolios.

Research question 4 is more concerned with the actual outcomes of the model and how changes in parameters lead to changes in the outcome and the adoption of the new variety. One of the main findings is the spatial pattern that comes forward in all scenarios where the 'existence need' weight is set higher than the weights of social and personal needs. This spatial pattern is one where farmers choose between either the yellow variety or the green variety based on their elevation, and thus based on their perceived chance of heat stress; areas with a low elevation tend to be affected by heat stress more often leading to farmers preferring the green variety which is resistant to the heat. Areas with a high elevation tend to be affected less often which leads to farmers dedicating their portfolio mostly to the yellow variety, which has the best performance out of the three varieties if there is no heat stress. Only in the scenarios where a higher weight was assigned to social and personal factors did we not see the spatial pattern described above. From this we can deduce that making the 'existence need' the most important determinant of satisfaction will lead to the environment having the highest crop performance globally. According to Henrich (2001), innovation diffusion with an adoption curve like observed in the scenarios, implies that the majority of reasons for adoption do not come from social factors. This in turn tells us that interventions with the goal of increasing overall crop yield/performance should focus on making sure that farmers receive the most satisfaction from economic gain. One way this could be done is by providing a subsidy to farmers that allocate most of their agricultural land to growing the “new” crop variety. This will lead to an additional gain of satisfaction from crop performance that could help overcome factors that would normally slow or stop the adoption of a new variety such as the lack of information, availability, profitability of this new variety, or even the stubbornness of farmers that have grown a certain variety for generations (Doss, 2006). In the model this stubbornness is represented by most farmers having a personality of 1 which means that they will only receive satisfaction from the personal factor if they mostly grow the red variety. As seen in the scenarios, assigning higher weights to crop performance, and possibly even increasing this crop performance outright through subsidies or improved availability, will lead to a higher adoption of the new variety.

5.1 Limitations and future research

One of the main limitations of the model is one that is relevant for most simulation models; that it shows a simplified version of reality. In order to keep the creation and interpretation of the model doable, assumptions and simplifications have to be made. Actions can be taken to reduce the possible bias or to account for some of the factors excluded from the model. In my model, crop performance is determined by the presence (or absence) of heat stress along with a random error term meant to capture some of the variance from excluded factors. Heat stress is determined by a random threshold regarding the elevation, while in reality, there are many changeable conditions that determine whether or not a crop suffers from this (Fuentes, 2022). In addition, heat stress is assumed to be either 0 or 1; the model makes no distinction between different levels of stress. Another assumption is that farmers only belong to one social group consisting of their direct neighbors. Other farmers that are not direct neighbors do not exert direct influence, while this is unlikely to be the case in a real world scenario. Further simplifications and assumptions include the lack of other location-based variance that are linked to elevation; if the heat stress variable remains equal, a variety is assumed to have equal performance at altitudes of 300 meters and 2000 meters. My model uses the consumat framework to incorporate social factors in ABM decision-making; only this single method has been explored within the agricultural context. Future research could make use of multiple different frameworks that go in-depth with social factors and compare how the choice of framework affects the outcome and possibly come up with a metric to determine which method is the most realistic/plausible.

6. Conclusion

Past literature on ABMs in innovation diffusion showed the main knowledge gap to be the inclusion of social factors in the decision-making process. The Consumat framework (Jager & Janssen, 2012) is an approach to deal with this issue by basing agent decision-making on satisfaction from three factors, one of which is the social factor. The study presented in this thesis shows a possible implementation of a spatial multi-agent approach that provides interesting insights in modeling the behavior and response of heterogeneous farmers to changes in incentives, which can originate from policy changes or methods of how the innovation is introduced to the population. One of its main features being the consumat-based decision-making process of agents. Another feature is the environmental factors modeled as heat stress; this introduces more variety into the model with regards to crop performance and allows for spatial patterns to emerge from the simulation.

Running the model in accordance to five different scenarios provided useful insights into the diffusion and adoption of a new crop variety; in nearly all scenarios, a spatial pattern emerges that is in line with the elevation map of the area. Farmers in low elevation areas tend to adopt the heat resistant variety while farmers in high elevation tend to grow the yellow and red varieties that only perform better in the absence of heat stress. Scenario 5 showed that usage of a clustered introduction method for the new variety achieves a similar trend as random introduction but that it would likely take longer to diffuse to all farmers that would profit from this. This however, is the most realistic and efficient method of introduction of the scenarios because relatively few seeds of the new variety are needed and these only have to be delivered at five locations. Based on the size of the study area, more clusters of introduction can be used if necessary. The introduction of the new variety to farmers should be paired with interventions that further incentivize crop performance maximization to overcome the adverse effects originating from social and personal factors that inhibit adoption. These can be defined as farmer stubbornness that they prefer the old crop variety that they are already familiar with. Additionally, satisfaction gained from similarity to neighbors further lessens the incentive for farmers to be the first one to try out a new variety. The path of implementing decision-making taken in this thesis could also be used in different ABM contexts, and expanding ABMs to include more in-depth social factors could further help move ABMs towards a more realistic representation of innovation diffusion dynamics.

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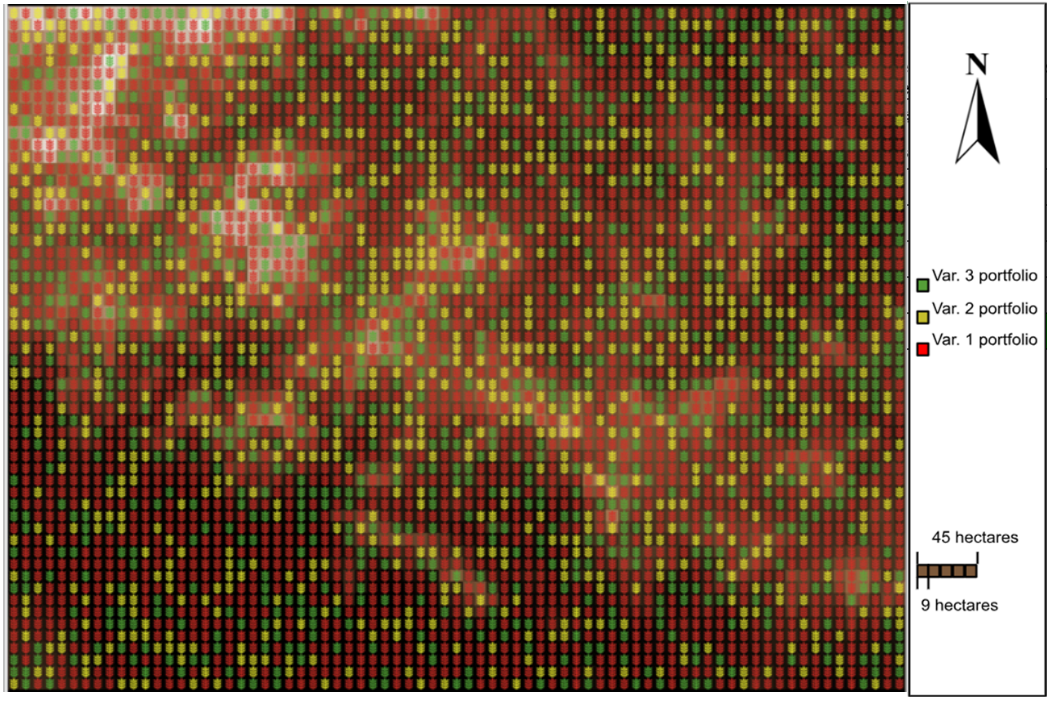
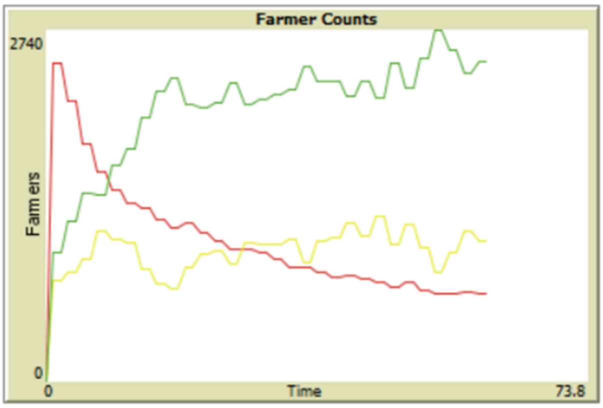
8. Appendix

8.1 *Scenario 2 Figures*

Appendix Figure 1: Starting situation for scenario 2 (Run 2). The elevation map in the background is shown by the colors of the cells. The colored plant shapes each represent a farmer with the color showing which of the three varieties is dominant in their portfolio.

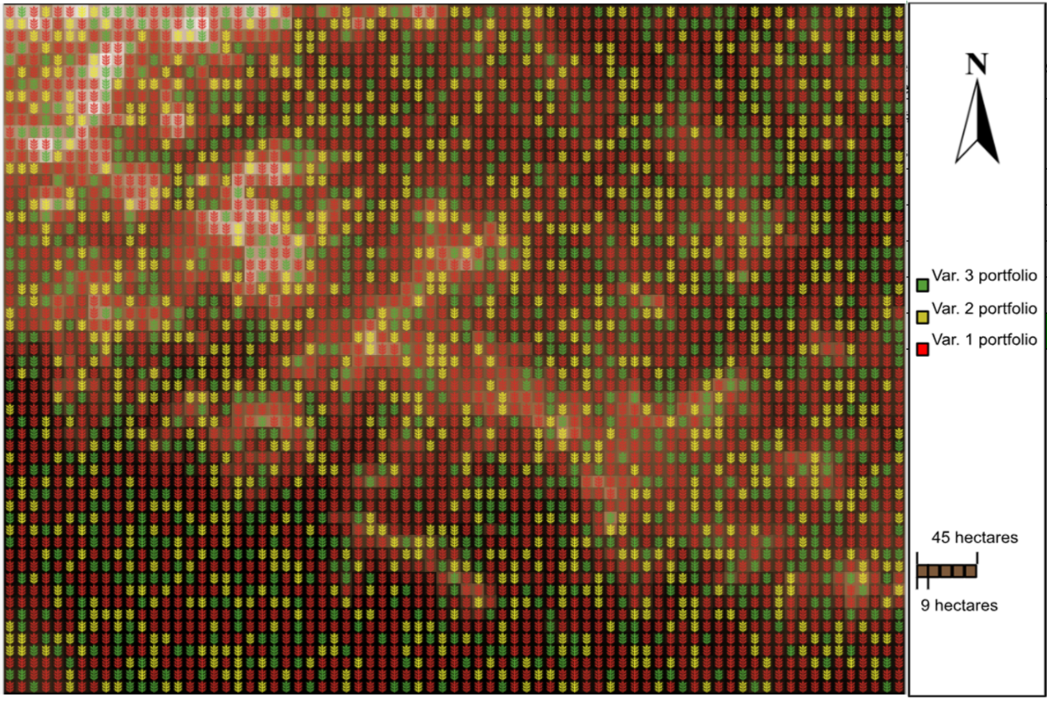


Appendix Figure 2: Plot of farmer portfolios for scenario 2 (Run 2). Each line represents the number of agents with said portfolio over time. Where the colors are assigned the same as in the scenario maps.

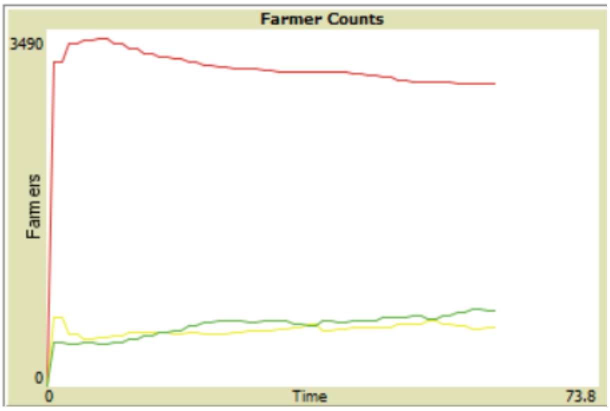


8.2 *Scenario 3 Figures*

Appendix Figure 3: Starting situation for scenario 3 (Run 1). The elevation map in the background is shown by the colors of the cells. The colored plant shapes each represent a farmer with the color showing which of the three varieties is dominant in their portfolio.

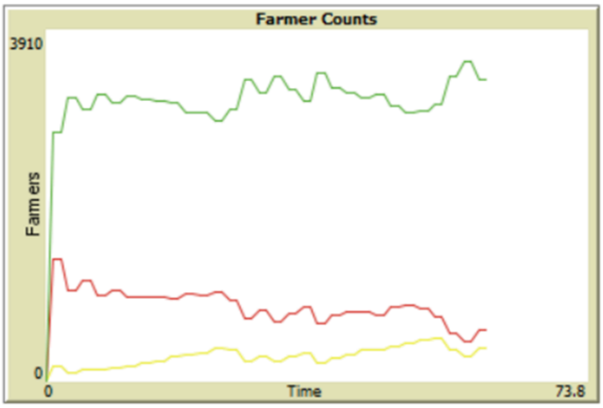


Appendix Figure 4: Plot of farmer portfolios for scenario 3 (Run 1). Each line represents the number of agents with said portfolio over time. Where the colors are assigned the same as in the scenario maps.



8.3 *Scenario 4 Figures*

Appendix Figure 5: Plot of farmer portfolios for scenario 4 (Run 3). Each line represents the number of agents with said portfolio over time. Where the colors are assigned the same as in the scenario maps.



8.4 *Scenario 5 Figures*

Appendix Figure 6: Plot of farmer portfolios for scenario 5 (Run 1). Each line represents the number of agents with said portfolio over time. Where the colors are assigned the same as in the scenario maps.