MODELLING INDIVIDUAL DECISIONS TO SUPPORT THE EUROPEAN POLICIES RELATED TO AGRICULTURE

Deliverable Report D4.3
Report on extensions of FarmAgriPoliS and CoESM - experimental insights on farmers' response to Agri-Environmental Schemes

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ABBREVIATIONS

AES	Agri-environmental schemes

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EXECUTIVE SUMMARY

Agri-environmental schemes (AES) provide benefits to both farmers and society, but the benefits are often indirect, may only be apparent in the long term, and may be influenced by factors beyond economic incentives, such as individual attitudes and collaboration. The implementation of AES also requires collective action from multiple farms, as an adequate provision of ecosystem services requires a sufficient number of farmers to adopt these alternative uses. The Collective Ecosystem Services model (CoESM) is used to analyze farmers' decisions related to the implementation of flower strips, which provide benefits at both the farm and landscape level. The CoESM incorporates both behavioral and ecological components and was tested through various scenarios. The results showed that the adoption of flower strips was influenced by the value of the crops, risk, and premiums, but that the average gross margins per crop remained similar across scenarios. The model highlights the importance of collective investments in ecosystem services and can be applied to other regions and ecosystem services. In addition, the participatory agent-based model FarmAgriPoliS was used to investigate factors that influence participation in collective AES and to experimentally test certain behavioral assumptions. The results showed that the framing of AES and the payment scheme can affect willingness to participate, and that human decision-making cannot be fully explained by assumptions of rational utility maximization.

As CoESM includes an innovative ecological module that considers interactions with the landscape, it could be used to improve the accuracy of other models in the MIND STEP Model Toolbox. Further, the results of FarmAgriPoliS could be used to create heuristics that more accurately represent human decision-making behavior and to calibrate behavioral modules in other ABMs and IDMs.

1. INTRODUCTION[1]

In the Netherlands, the Dutch government introduced agri-environmental schemes (AES) to support biodiversity conservation and the provision of ecosystem services. Similar approaches are also being discussed in other EU countries. However, the successful implementation of such programs warrants collective implementation (Groeneveld 2018). In other words, an adequate provision of ecosystem services will only happen if enough farmers convert their land to these alternative uses. Nature conservation outcomes in a region, are in the end, a combined result of the individual decisions of farmers in nature conservation (Grashof-Bokdam et al. 2017; Groeneveld 2018; Westerink et al. 2017).

Agri-environmental schemes (AES) provide essential services for the farmer (e.g., water retention, natural pest regulation, pollination; Harrison et al. 2014) but also for society (e.g., aesthetic appreciation, biodiversity conservation; European Union 2013). The benefits from AES are often more indirect compared to traditional farming activities and often only shown in the longer term. Moreover, effective AES measures often require adjustment on landscape levels larger than fields or farms and therefore require collective action of several participating farms in the corresponding region (biosphere). Alternative agricultural activities (e.g. hedgerows, woodlots, flower strips, natural field edges, ditch banks, protected areas for ground nesting) depend on many factors beyond pure economic incentives including individual attitudes, learning, collaboration, compatibility with the business concept of the farm or bureaucratic demands. Therefore, behavioral assumptions are of particular importance when it comes to modelling activities outside the actual economic field of activity of farms.

Task 4.3 aims to provide knowledge on behavioral aspects of modelling AES. We do this by using a two-step methodological approach to investigate the influences of farmers' decision to participate in collective AES. In a first stage the model framework CoESM (Collective Ecosystem Services Management) is used to analyze computer agents' decisions around contributing to ecosystem services (natural pest regulation) beyond the farm level by converting part of their arable land into natural elements (flower strips). In a second stage, experiments with real people will be conducted with the participatory agent-based model FarmAgriPoliS to investigate other possible factors besides economic incentives that influence participation in collective AES and to experimentally test certain behavioral assumptions and characteristics.

[1] Sections of this Deliverable are also part of Deliverable 4.1. This concerns in particular sections from the introduction, the background and the method.

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2. BACKGROUND

In human decision-making, existing neoclassical economic models considering the actors as homo economicus. This utility-maximizing homo economicus is subject to rationality axioms such as completeness, reflexivity and transitivity. However, the axioms of homo economicus are contrasted by empirical findings that human actors behave in systematically different ways than neoclassics would predict. For example, given the same content of the question, the way a question is phrased can have a decisive effect on the outcome of the answer. This is called the "framing effect." The effect can conditionally lead to the fact that e.g. political incentives are perceived, understood and implemented differently, depending on the choice of words and formulation.

Furthermore, it must be assumed that people do not act independently of each other - Especially in agriculture which is characterized by strong spatial interdependencies. However, very few studies on agricultural structural change address spatial interdependencies of neighboring farms: Storm et al. (2015) showed empirically that ignoring spatial interdependencies between farms leads to a substantial overestimation of the effects of direct payments to farms on farm survival. Saint-Cyr et al. (2019) identified various correlations between neighboring farms regarding size and exits from farming. Moreover, they showed that the consideration of these correlations yields different results than pooled estimations. Appel und Balmann (2022) used an exploratory analysis of repeated framed experiments to analyze spatial influences of different behavioral clusters of farm managers on their neighborhood.

These interdependences are further highlighted by the fact that farmers are influenced by their peers when it comes to innovation adoption (Case 1992; Harrington und Reinsel 1995; Holloway et al. 2002; Mzoughi 2011) and therefore also in the implementation of alternative farming practices. An adequate provision of ecosystem services therefore depends on the consideration of these collective dimensions of AES the design of the measures so that enough farmers participate (Groeneveld 2018).

3. METHOD

3.1. Analyzing and modelling human behavior

Alternative approaches for modeling farmers decision making beyond neoclassical economic models, are provided by agent-based models. Agent-based models are flexible with regard to modelling agent behavior. Examples of behavioral approaches range from simple rules to computational intelligence, including learning. Some of these concepts and the modelling process itself are combined with participatory approaches such as companion modelling (Antona et al. 2005). In corresponding modular model frameworks, even several approaches to behavior modelling can be combined with each other (e.g. Huber et al. 2022). A further advantage of using agent-based modelling approaches is that alternative scenarios allow for the analysis of counterfactual developments, which make these models very useful for assessments of (potential) policy measures.

Participatory agent-based models are a specific form of agent-based model. These models involve people either as agents in their models or as translators of the outcomes of simplified role-playing models into computerized agent-based models (cf. Barreteau, O., Le Page, C., D'Aquino, P. 2003). They can be seen as a specific form of framed experimentation(Harrison und List 2004; Fiore et al. 2009; Reutemann et al. 2016) in which the agent-based model provides the context-specific software environments.

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3.2. CoESM - Collective Ecosystem Services Management

We develop a conceptual framework to model farmers' decision-making toward implementing flower strips at the farm level (Figure 1). Individual farmers decide whether to invest in the provision of pest regulation services on their farms by converting arable land into flower strips. The model uses the output data (i.e. gross margin per plot information) from FarmDyn (Britz et al. 2016), and the Agricultural Census in the NOP-ZW region to gather all the necessary data to run the model. As represented in the left box in Figure A1. In each run, farmers decide on the allocation of flower strips in their plots based on their gross margins from the previous year. In the center of figure A1, the dark-colored arrows represent the main model processes. Farmers' gross margins are affected by the pest regulation dynamics and the risk of pest risk. The risk of pest risk depends on the landscape composition which the model updates on every run via the Reilly index represented in the right box in Figure 1. Furthermore, farmers display different decision strategies in selecting their land allocation using the Consumat approach and farmers are characterize by a nature-oriented likelihood, where some farmers are more likely to adopt of flower strips at the farm level than others.

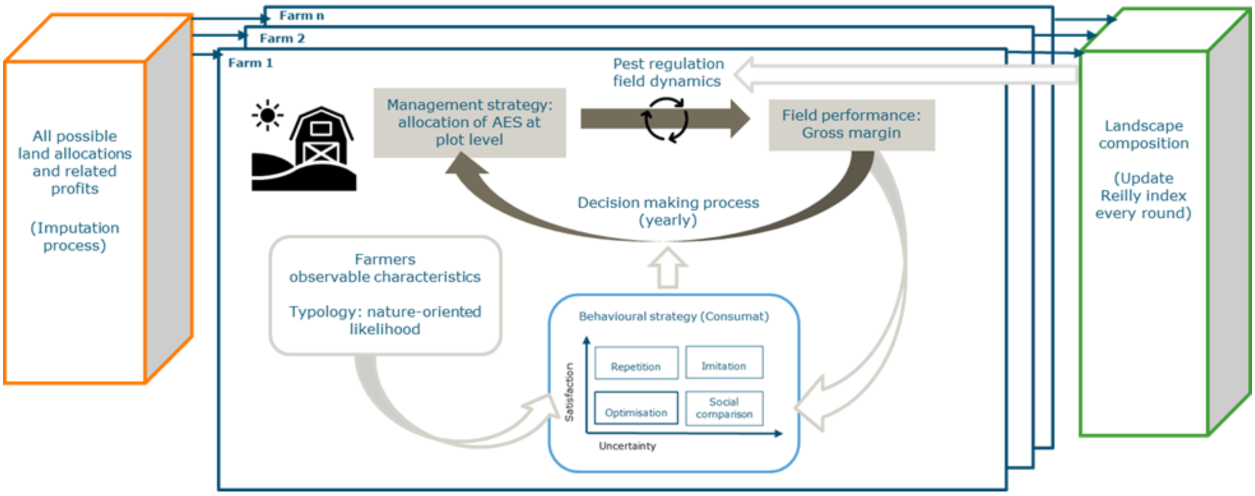

Figure 1. Conceptual framework for the CoESM (Collective Ecosystem Services Management) model. Based on Pacilly et al., 2019. Dark colored arrows represent model processes, and white arrows represent variables and frameworks used as input.

3.2.1. Model output data

The model uses the output data (i.e. gross margin per plot information) from FarmDyn (Britz et al. 2016), and the Agricultural Census in the NOP-ZW region. We create a database containing all possible land allocations and related gross margins as represented in Figure 2. To create this database, we performed an imputation process to account for the missing data and complete a map of the region (Hennen 2009). The imputation process finds a group of farms that have a comparable area and cropping plan, both individual and group, with the farm in the region (Hennen 2009). Correction of individual plots based on groundwater, soil type, and distance from the farm are apply.

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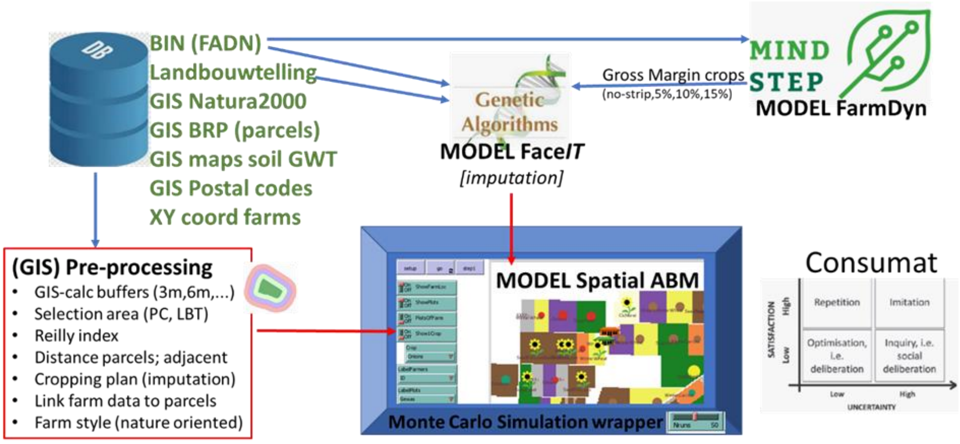

Figure 2. Data processing and inputs for the ABM.

3.2.2. Interaction between agents (behavioral module)

The behavioral unit of the model is based on the Consumat approach (Jager 2000; Jager et al. 2001). The Consumat approach integrates different behavioral aspects of decision making such as theories on human needs, motivational processes, social comparison theory, social learning theory and reasoned action theory (Pacilly et al. 2019). Unlike traditional modelling methods that consider only bounded rationality, the Consumat approach defines more realistic mechanisms to address the choice between different decision strategies (van Duinen et al. 2016), helping to model learning behavior and understanding technology diffusion (Schaat et al. 2017). In the Consumat approach farmers switch between cognitive processes when they experience (un)certainty and (dis)satisfaction, and in this way, facilitates formal modelling (Kangur et al. 2017).

The combination of income satisfaction and level of uncertainty determines which behavior strategy the farmer follows (Figure 3). Following van Jager(2000) and van Duinen et al. (2016), the farmer has experienced high-income satisfaction and a low level of uncertainty; the behavioral approach is to continue with the same strategy as the previous season and choose “repetition”. On the other hand, when the farmer has high-income satisfaction but experiences positive levels of uncertainty, the farmer will seek information in the nearby network and choose to “imitation” the majority decision of the adjacent farmers with strong links. In circumstances where the farmer experiences both high uncertainty and low-income satisfaction, the farmer is encouraged to seek information from a more extensive network of peers and to have chosen for “social comparison”, which intake a broader reference of farmers to imitate their decision. Finally, a combination of a low level of uncertainty and low-income satisfaction triggers the farmer’s individual “optimization” process at the farm level without considering the decisions of other farmers (van Duinen et al. 2016).

Our model uses factual geospatial information of all farms, plots and the crops in each plot in the Noordoostpolder area in Flevoland. We use polygons from geographical information in the Basic Parcel Register to simulate farmers' decisions. Learning is implemented via the Consumat approach. When farmers perceive high uncertainty, they are triggered to look up and learn from peers in the landscape (i.e. heuristic-based agents). They will follow the same decision as most nearby plots (Imitation) or learn from an extended social network (social comparison).

Imitation will then consider the decision of the 10 nearest farmers with the same crop surrounding the plot. Social comparison extends the judgment to the number of farmers with the same crop in the whole polder. More specifically, when more than half of the surrounding plots adopt flower strips,

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farmers will also implement flower strips in their plots. The exception to the rule is given by the farmer's likelihood of adoption based on their individual characteristics, as explained in the prediction session.

Error! Reference source not found. Furthermore, when the farmer strategy is to imitate or social comparison, we apply a farmer-nature oriented likelihood to adopt or not flower strips at the farm level. The likelihood of adoption is expressed in terms of a probability as very likely (0.9), likely (0.7), moderate (0.5), unlikely (0.3), very unlikely (0.1) and determined by farmers' characteristics. The nature orientation is determined per farmer based on the use of resources, company size and intensity (construction plan; number and size of plots)

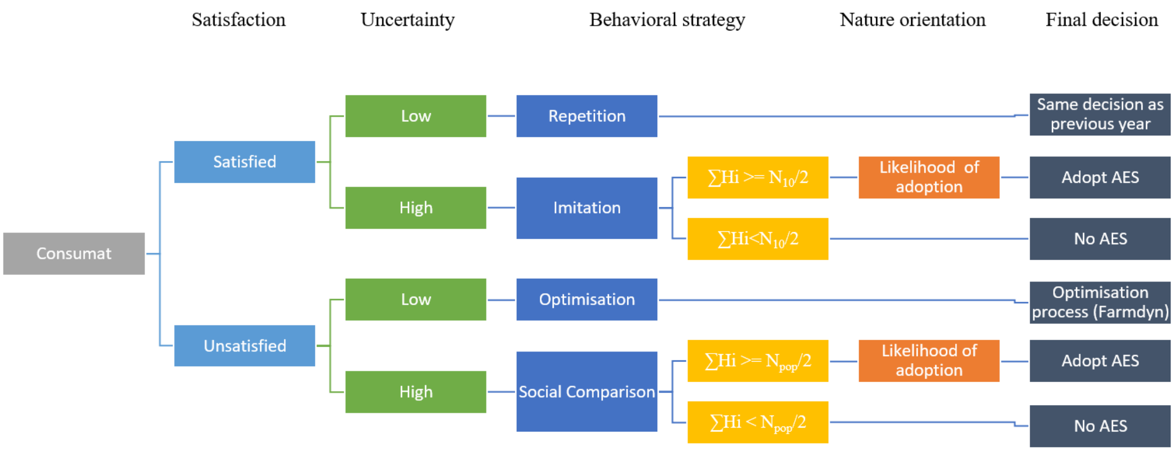

Figure 3. Illustration of assume farmers decision making following the Consumat approach (Jager et al. 2001; Jager 2000)

We assume farmers can see, assess and consider this in their surrounding environment, including other plots with flower strips in the close surrounding (10 nearest plots with the same crop (N_{10})) and in the extended region (entire population of farmers in the Noordoostpolder region (N_{POP})) and the ecosystem services benefits they provide in terms of the risk of pests determined in our model by the Reilly index.

3.2.3. Changes in the landscape (ecological module)

Overtime, changes in the landscape provide farmers different levels of risk depending on the density of natural elements and flower strips in the surroundings. How the agents affect the landscape and affected by it in model are determine by the Reilly index. The Reilly index measures the share of land used for a certain land-use function in the surroundings of a specific location (Schouten et al. 2013). In other words, the Reilly index calculates the impact of surrounding nature areas on the nearby plots in terms of collective ecosystem services benefits. It considers the proximity and surface of nature, forests and vegetated borders to the plot. The value of the index increases with the area of nature/green density and distance to the plot. This information is then use as an input for the model to assign an individual risk of pest hazard to each plot.

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Figure 4. Example visualization of the Reilly index in the area. Plots with darker shades of red indicate these are less exposed to pest risks because been located near nature elements. On the contrary, plots with lighter red toward white are more exposed to pest threats

3.2.4. Workshop with experts

Our conceptual model has been discussed in a workshop with experts and received good feedback on how the available data is used and assumptions of farmers interaction. We gather a group of relevant policy actors and research advisors from the province of Flevoland and the ministry of agriculture. The objective of the workshop was to present our project to experts and ask input on the used model assumptions and parameters. Furthermore, the outcomes of this session will be used in the follow-up participative workshop with farmers (collective). During this workshop we proposed questions to the audience of experts in order to verify, prioritize and check underlying assumptions and parameters of the model. For this we will make use of participative methods to create interaction and get input in a structured way. In the coming year we will focus on redefining the model and include expert recommendations in the assumptions.

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3.3. FarmAgriPoliS

FarmAgriPoliS (Appel et al. 2018; Appel und Balmann 2019), derived from the ABM AgriPoliS (Happe, K., Kellermann, K., Balmann, A. 2006), provides participants with a software-based environment of a simulated agricultural region. Within FarmAgriPoliS, one farm is managed by a human participant. Their decisions include investments, renting land, off-farm activities and farm exits. The decisions will be made on the one hand against the background of regional conditions, prices and policy uncertainty, and the behavior of competing farms in the region on the other hand. The participant is assumed to manage this farm and to compete with computer-simulated optimizing farm agents that derive their decisions from mixed-integer short-term profit maximization (Appel et al. 2018). Thus, experiments with FarmAgriPoliS provide insights into how human participants behave in these competitive situations compared to computerized optimizing agents as used in AgriPoliS. For Task 4.3 FarmAgriPoliS is extended to allow participants to decide on the participation in collective AES for a specific case study in Germany. The experiments with FarmAgriPoliS will provide insights on how the fact that the payment is dependent on the participation of other farms in the region and the overall framing of collective AES (neutral, economically or ecologically motivated) influences the farmers' willingness to participate in collective AES.

3.3.1. Scenarios

During an experiment with FarmAgriPoliS, participants have from the second simulation year on the option to participate in AES by using part of their pasture extensively for five years. Depending on the scenario they receive either a fixed or collective payment. Collective payment means that the more farms (and therefore the better the environmental effect) the higher the payment (but same expectation value as fixed payment). A further differentiation is done by different formulations of the offered AES: The neutral formulation informs the participant on the extend (5 ha), duration (5 years) and payment (50 €/ ha or 40-60€/ha) of the AES, while the economical framing particularly emphasizes the economic advantage of participation and the ecological framing particularly emphasizes the advantage for the environment.

This results in a total of six scenarios, which differ in terms of payment and framing. (Table 1).

Table 1. Scenarios planned for the experiments with FarmAgriPoliS

Scenario	Payment	Framing	Wording
1	Fixed	Neutral	"Fallowing 5 hectares of grassland for species protection over a period of 5 years is remunerated annually at 50 €/ha."
2	Fixed	Economic	"Participation in an agri-environmental measure with 5 hectares of grassland over a period of 5 years provides you with a payment that is on average significantly higher than the economic land rent for grassland. You will receive €50/ha per year."
3	Fixed	Ecologic	"In the Altmark region, another protected area is to be established for meadow-nesting birds such as the curlew, lapwing and snipe. For this purpose, farms are being sought that will participate in this protected area with 5 hectares of grassland over a period of 5 years. In return you will receive an annual payment of 50 €/ha."
4	Collective	Neutral	"Fallowing 5 hectares of grassland for species protection over a period of 5 years is remunerated annually with 40 €/ha to

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			60 €/ha. The more farms that participate in the region, the higher the payment."
5	Collective	Economic	"Participation in a collective agri-environmental measure with 5 hectares of grassland over a period of 5 years provides you with a payment that is on average significantly higher than the economic land rent for grassland. You receive between 40 €/ha and 60 €/ha per year. The more farms participate in the region, the higher the payment."
6	Collective	Ecologic	"In the Altmark region, another protected area is to be established for meadow-nesting birds such as the curlew, lapwing and snipe is. For this purpose, farms are being sought that will participate in this protected area with 5 hectares of grassland over a period of 5 years. In return, you will receive an annual payment of between 40 €/ha and 60 €/ha. The more farms participate in the region, the higher the payment."

3.3.2. DoE (Pilot)

As a pilot we run the behavioral experiments with 15 participants at the Bernburg University of Applied Sciences. The participants studied agriculture and related subjects. Participants were on average 26.3 years old (SD = 6.67), 40 % were female, 47% already had a Bachelor's degree and practical farming experience (own farm, parents' farm, agricultural apprenticeship etc.).

Participants were randomly assigned to scenarios and each participant had to play up to three different scenarios (drawing from an urn without replacement). Every scenario was also simulated by replacing the respective participant by a computer agent which managed the farm through the standard optimization routines of AgriPoliS with identical initialization. These runs provided benchmarks for comparisons with the respective participant's behavior.

Before the experiments, the participants were introduced to FarmAgriPoliS and were asked to maximize the final equity capital of the farm over the period of twenty rounds (years) in every experiment. They were also informed that they would receive payments contingent on their performance in the experiment. In addition to a fixed show-up fee of 20 euros, subjects received a euro for every two-percent increase in equity capital relative to the computer benchmark; the equity bonus was limited to a maximum of 30 euros per experiment.

The experiments were supplemented by a questionnaire on age, gender, education level, practical experience in agriculture and risk preference of the participants.

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4. RESULTS

4.1. ABM simulation (CoESM)

We present changes for five main outcomes and five different scenarios. The main outcomes for each crop are (1) the gross margin at the end of the simulation, the (2) percentage of plots covered with flower strips. Then, we also present (3) the average gross margin per farm, (4) the average number of plots with flower strips relative to the entire region and (5) the average probability of pest for each simulation. Model outcomes result from a Monte Carlo simulation over 200 runs of 15 years.

We analyze a (1) baseline and compare it with simulations in the absence of the (2) behavioral module and (3) the ecological module, (4) an increase in the Premium per hectare, (5) and a low-risk scenario.

In the absence of the behavioral module (i.e. no implementation of the Consumat), the model restricts farmers from interacting with each other. The decision to adopt or not flower strips is then based on a random draw specified by the likelihood of adoption probabilities. We expect a different distribution of flower strips in the landscape since there are no considerations of low gross margins on farmers' satisfaction and the effect of uncertainty on expected gross margin results.

In the absence of the ecological module (i.e. no implementation of the Reilly index), the model does not consider landscape interactions and the benefits of the ecosystem services. The model assumes a fixed probability of pest risks over time and does not update this probability while the number of flower strips increases in the landscape.

We evaluate the effect of premium changes. We expect a higher premium to lead to farmers applying flower strips in high-value crops. Since we expect from a baseline scenario, farmers may concentrate the flower strips on low-value crops.

Finally, we test a low-risk scenario. The levels of risk in the baseline scenario are very high (on average 88%) because of the real/initial distribution of natural elements in the "Noord-Oost Polder" in Flevoland. We test the effect of reducing the pest risk by shifting the S-curve (Reilly index) and only allowing a maximum risk of 60%. We expect the adoption of flower strips in the plots to decrease with a lower risk.

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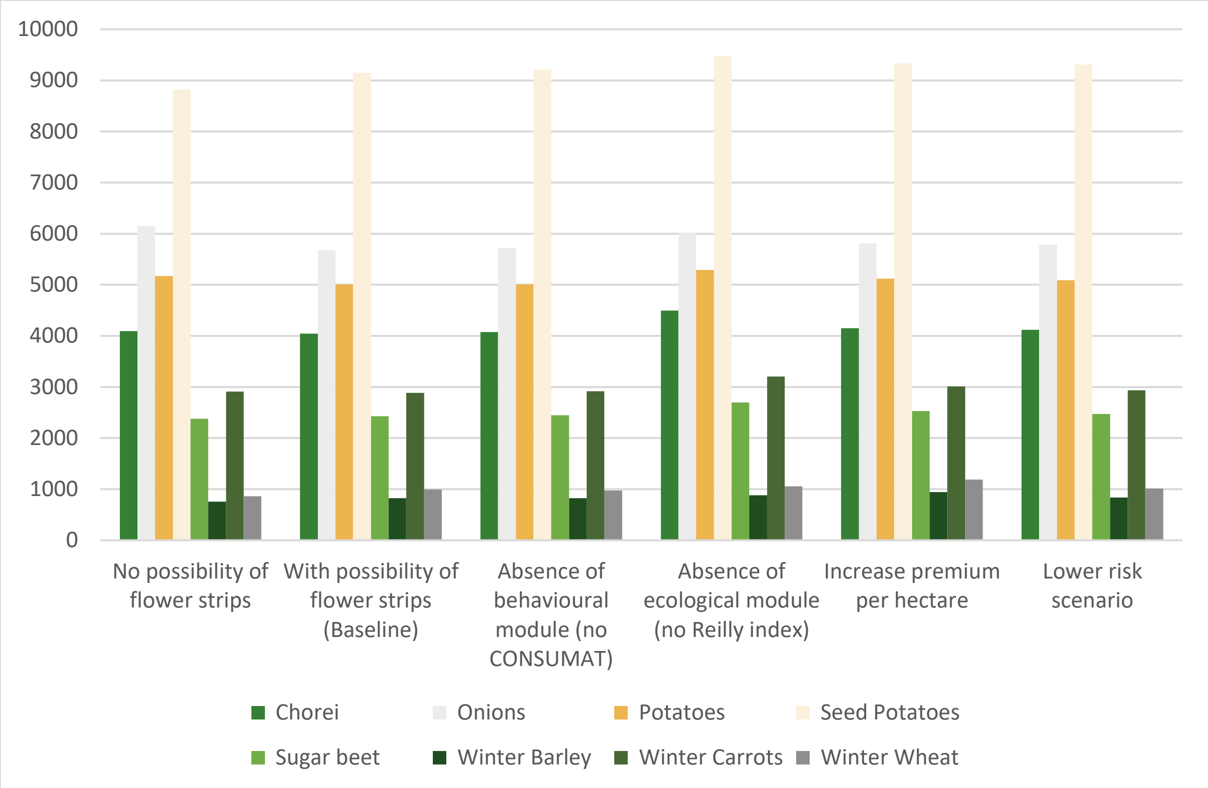

Figure 5. Average gross margin per crop for each scenario. Note: Monte Carlo simulation over 200 runs of 15 years.

Figure 5 shows the results of the average gross margins per crop for each scenario. The gross margins remained very similar between scenarios. Seed potatoes displayed the highest gross margin from the cropping plan, followed by onions and potatoes. Comparatively, crops with the lowest gross margin are winter wheat and barley.

Figure 6 displays the percentage of plots covered with flower strips for each crop. We compare the different scenarios to the baseline scenario. First, without a behavioral module, we observe more variability in the distribution of flower strips amongst crops compared to the baseline scenario, where flower strips are adopted mainly in low-value crops. As hypothesized above, the Consumat approach trigger farmers' satisfaction and uncertainty based on low gross margins. Therefore, farmers are more likely to compare each other and adopt flower strips in low-value crops (baseline). Second, in the absence of the ecological module (i.e. no implementation of the Reilly index), we also observe more variability in the distribution of flower strips amongst crops compared to the baseline scenario. By not implementing the Reilly index, the model considers a static high level of risk over time, which triggers uncertainty in all crops, not only low-value ones. Third, an increased premium per hectare increases the adoption of flower strips, especially in low-value crops (sugar beet, winter barley, winter carrots and winter wheat). Finally, a lower-risk scenario slightly increases the adoption of flower strips in low-value crops. Still, it does not seem to have a large effect compared to the baseline scenario.

Figure 7 shows the overall average gross margins per hectare per farm (cropping plan) do not change much between scenarios. The number of plots with flower strips increases the most in a high-premium scenario. As expected, the probability of pests is the highest in the absence of ecological benefits consideration.

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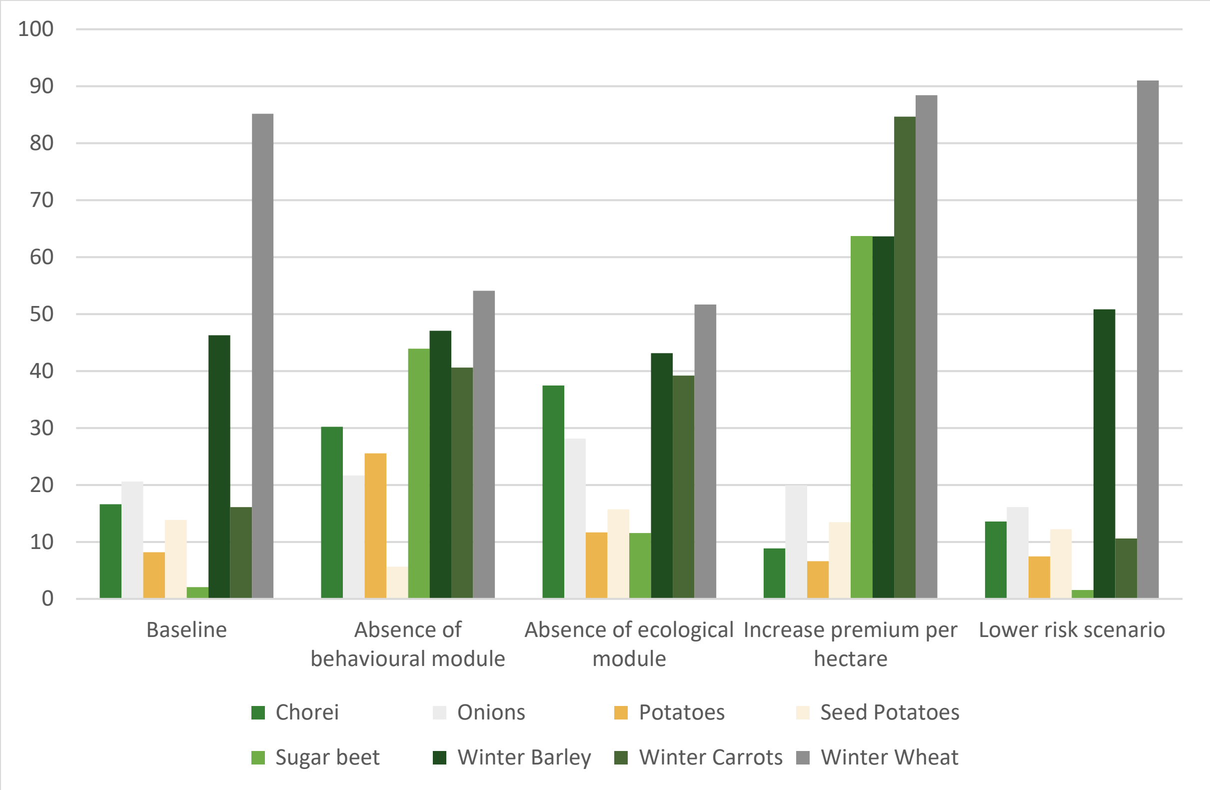

Figure 6. Percentage of plots covered with flower strips for each crop. Note: Monte Carlo simulation over 200 runs of 15 years.

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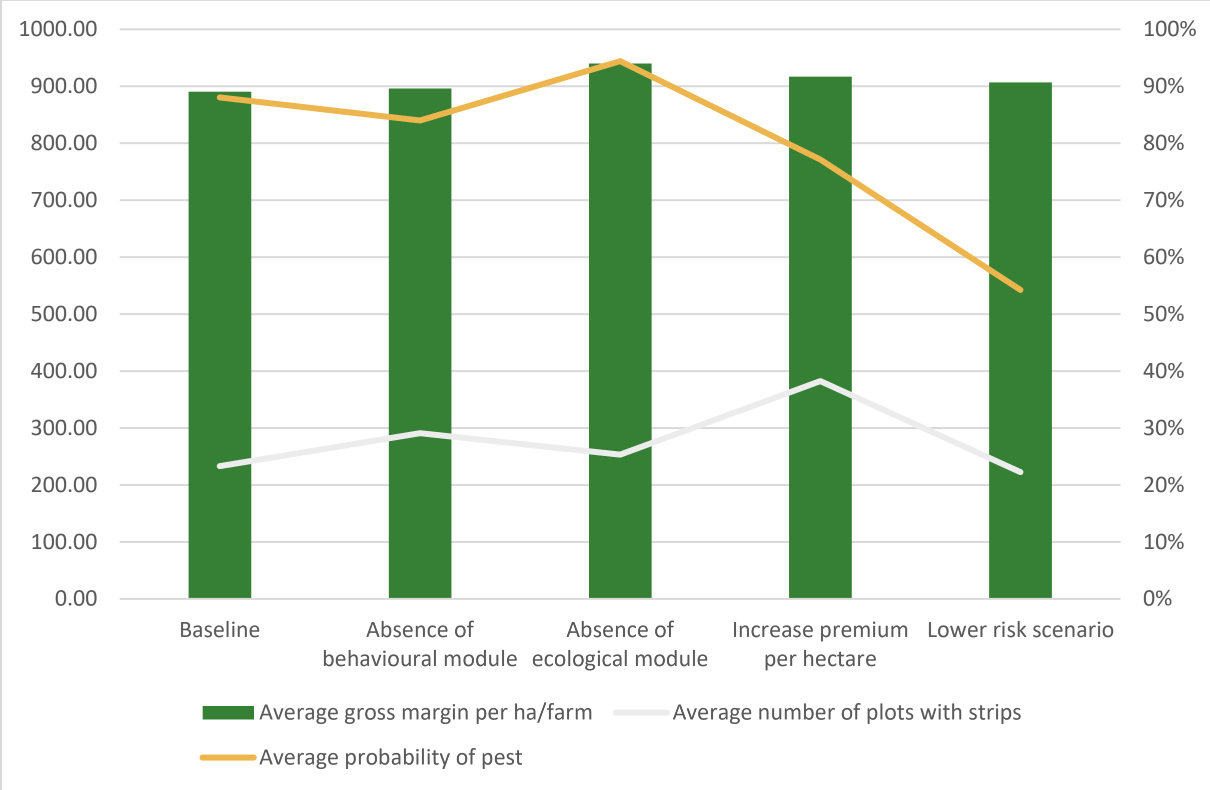

Figure 7. Average gross margins per farm (cropping plan), the number of plots with flower strips and the probability of pest. Note: Monte Carlo simulation over 200 runs of 15 years.

4.1.1. Conclusion

The Collective Ecosystem Services model (CoESM) is a tool used to analyze how farmers in the Noordoostpolder area of the Netherlands make decisions related to the implementation of flower strips, which provide benefits at both the farm and landscape level. The CoESM is an Agent-Based Model (ABM) that incorporates both behavioral and ecological components to understand how farmers interact and contribute to nature transition initiatives in Europe. The model was tested through various scenarios, including a baseline scenario, the absence of the behavioral or ecological modules, changes in premiums for flower strips, and a low-risk scenario. The results of the model showed that while the average gross margins per crop remained similar across scenarios, the adoption of flower strips was influenced by the value of the crops, risk, and premiums. The model highlights the importance of collective investments in ecosystem services and can be applied to other regions and ecosystem services with additional model calibration and the exploration of different assumptions, such as policies and subsidies.

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4.2. Behavioral experiments (FarmAgriPoliS)

Table 2. Contingency table with runs, absolute participation in AES, absolute and average decisions per scenario and refusal rate

Scenario	Runs	Absolute participation in AES		Decisions per scenario	Ø Decisions per run and scenario	Rejectionrate (RR)
		participation	participation			
	n	n	n	n	n	%
1	6,00	16,00	18,00	34,00	5,67	112,50
2	4,00	11,00	16,00	27,00	6,75	145,45
3	7,00	24,00	12,00	36,00	5,14	50,00
4	7,00	25,00	7,00	32,00	4,57	28,00
5	9,00	32,00	10,00	42,00	4,67	31,25
6	8,00	21,00	36,00	57,00	7,13	171,43
∑	**41,00**	**129,00**	**99,00**	**228,00**	**N/A**	**N/A**

In total, data sets of 41 experiments with 228 decision situations are available for the analysis (Table 2). We logged the decisions of the participants and various indicators for the participants' farm as well as of all other computer farms, such as farm investments, land rentals, farm sizes, financial results, rents paid etc. As we have these data for every farm, we can reconstruct each single simulation run in detail and aggregate the farms' data to observe regional patterns as well.

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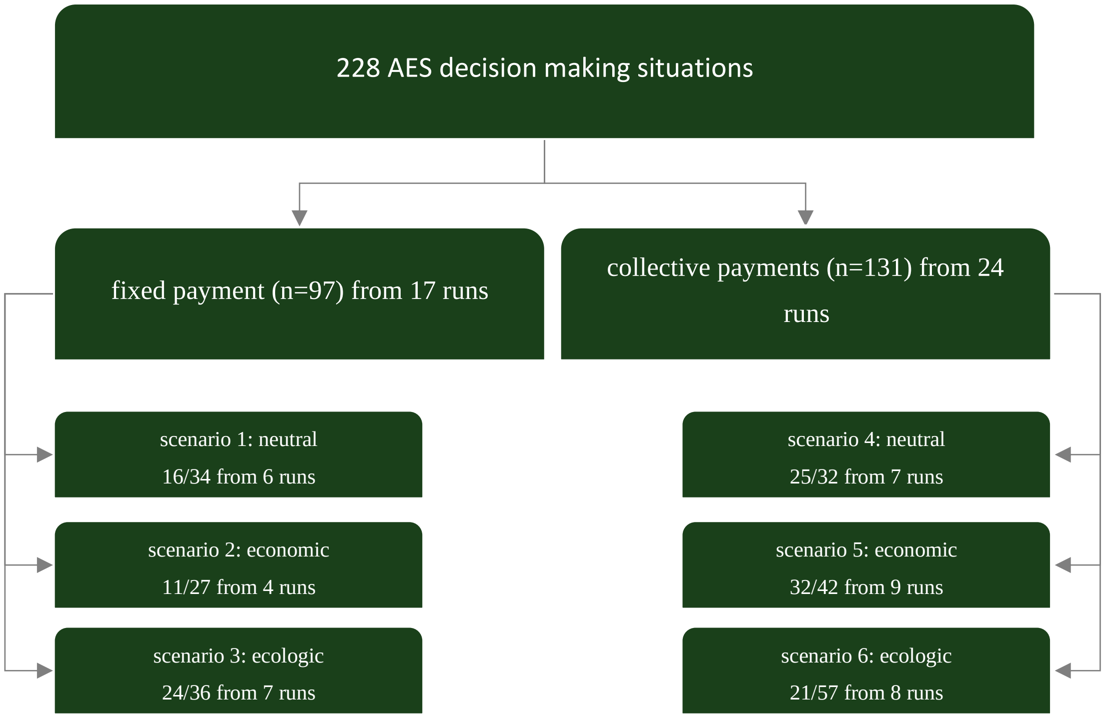

Figure 8. Structure diagram of the six scenarios with the absolute frequencies of the runs and the absolute and relative participation in agri-environmental measures per scenario.

As shown Figure 8, 228 decision situations could be evaluated from the collected data. The random assignment of participants to the scenarios results in 17 scenarios with a constant payment and 24 scenarios with a collective payment. Per scenario, the participants faced an average of 5.56 decision situations regarding participation in AES. The seemingly small number of decision situations is due to the fact that the duration of the AES is five simulation years and participants are not allowed to participate in more than one at a time. But it is possible to invest again after the termination of the participation. Thus, in a run of 19 simulation years, participants make four decisions while continuously participating in AES. Illiquidity or abandonment may result in fewer than four decision situations in a run. If participation in the proposed AES is refused in a simulation year, the decision to (not-) participate is again requested in the following simulation year.

For further analysis the rate of rejection (RR) to participate in AES is calculated as given in Equation 1.

Equation 1: Rejectionrate (RR) in AES within the scenario i in percent

$$RRi = \frac{absolute\ rejection\ to\ participate\ in\ AES\ in\ scenario\ i}{absolute\ participation\ in\ AES\ in\ scenario\ i} * 100$$

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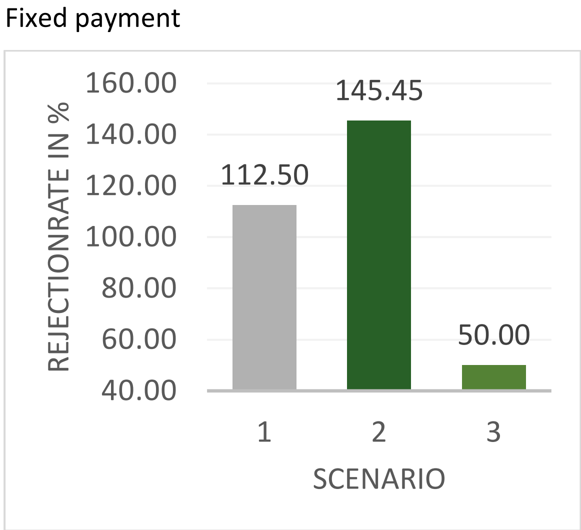

Figure 9. Rejectionrate (RR) per scenario in %

Figure 9 shows that the average rejection rate of 102.65% within the fixed payment is higher than that of 76.89% for the collective payment. AES were particularly rejected by participants who received neutral and economically motivated formulations. AES with ecologic framing had a rejection rate of only 50% at constant payment. In the case of collective payments this is reversed: the neutral and economic framed AES are rejected in 28 % and 31,25% while ecologic framed AES exceed these RR by a factor of (RR=171.43 %).

A Chi² independence test (Table 1) shows that overall the "scenario" and "participation in AES" are stochastically dependent on each other while no stochastic dependence can be demonstrated between the first and second, and the fourth and fifth scenarios.

Table 3. p-values of different sets of scenarios resulting from Chi²-tests

Chi2-test for different sets of scenarios	p-value
1+2+3+4+5+6	0.00
1+2+3 4+5+6	0.09 0.00
1+2 4+5	0.62 0.84
1+3 2+3 4+6 5+6	0.10 0.04 0.00 0.00
1+2+4+5 3+6	0.00 0.01

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4.2.1. Conclusion

In the neoclassic assumption of a homo economicus neither the framing nor the payment (given that the collective payment has the same expected value as the fixed payment) would have an effect. In the experiments with FarmAgriPoliS, however, we found that the different framings (partially) affects willingness to participate in the AES: Within the same payment scheme, an indiscriminately reaction of the participants can be found for neutral and economic framings while participants reacted significantly different in scenarios with ecologic framing. Thus, we can conclude that there is a framing effect. A further finding is that this effect is opposite for the different payment schemes. Both, the payment scheme and the framing affect the behavior of the participants and they cannot be considered independent of each other.

5. OPPORTUNITIES AND INTERFACES WITH THE MIND STEP MODEL TOOLBOX

The Collective Ecosystem Services model (CoESM) provides insights into how farm agents make decisions related to the adoption of ecosystem services through the implementation of agri-environmental schemes (AES). These insights are based on factors such as gross margins and the comparison of these margins between farms. The CoESM also includes an innovative ecological module that considers interactions with the landscape, which can improve the accuracy of other models in the MIND STEP Model Toolbox.

In addition, the results of experiments with the participatory agent-based model FarmAgriPoliS can provide a more comprehensive understanding of individual farmer decision-making. These results reveal that human decision-making cannot be fully explained by the assumptions of rational utility maximization alone, as the behavior of human participants in FarmAgriPoliS deviated significantly from these assumptions (see also Appel und Balmann 2019). If carried out on a larger sample, FarmAgriPoliS could even be used to quantify the deviations in human decision-making behavior from the actions of computerized agents. These results could be used to create heuristics that more accurately represent human decision-making behavior. In the context of the MIND STEP Model Toolbox, the results of participatory ABMs like FarmAgriPoliS could be used to calibrate behavioral modules in other ABMs and IDMs.

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