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Validation of Agent-based Approach for Simulating the Conversion to Organic Farming

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Background and Purpose: The purpose of this study is to describe the principles of the development of parallel system-dynamics and agent-based models of organic farming for the case of Slovenia. The advantage of agent-based modeling is demonstrated by including geospatial information as an agent attribute. The models were compared by the validation, confirming the appropriate level of similarity.
Design/Methodology/Approach: Both system-dynamics and agent-based modeling approaches were applied. Statistical methods were used in the validation.
Results: The results of the validation confirm the appropriateness of the proposed agent-based model. Introducing additional attributes into the agent-based model provides an important advantage over the system-dynamics model, which serves as the paradigmatic example.
Conclusion: A thorough validation and comparison of the results of the system-dynamics and agent-based models indicates the proper approach to combining the methodologies. This approach is promising, because it enables the modeling of the entire agricultural sector, taking each particular farm into account.

Keywords: *agent-based models; organic farming; system dynamics; validation; multimethod simulation*

1 Introduction

Organic farming has been declared the most viable farming system in terms of sustainability (Rozman et al., 2013) and has been modeled by various approaches (Rozman et al., 2015). The system-dynamics (SD) methodology has been applied by Shi and Gill (2005) for the modeling of ecological agriculture development for Jinshan County (China) and by Rozman et al. (2013) for the modeling the development of organic agriculture in Slovenia. Agent-based modeling (ABM) has emerged as an alternative approach that has become possible with the increased computing power of personal computers. Agent-based modeling is the computational study of social agents as evolving systems of autonomous, interacting agents from the complex adaptive system perspective. ABM researchers are interested in how macro phenomena emerge from micro-level behavior among a heterogeneous set of interacting agents (Holland, 1992).

By using ABM as computational laboratories, one may test in a systematic way different hypotheses related to attributes of the agents, their behavioral rules, the types of interactions, and their effect on stylized macro-level facts of the system (Jansen, 2005). In designing an ABM, the modeler takes a “bottom-up” approach by considering the relevant actors and decisions at the micro level that may produce an observable macro phenomenon (e.g., a system-level outcome). Therefore, the use of ABM to improve our understanding or support the rigorous analysis of potential outcomes of that system (e.g., scenario and policy analysis) requires that ABMs have credible and defensible representations of micro-processes. This require-

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ment raises important questions about available empirical approaches for capturing micro processes and their relative merits (Robinson et al., 2007). Gaube et al. (2009) used ABM in combination with stock-and-flow models for participative analysis of land-use systems in Reichraming (Austria). In this light, Deffuant et al. (2002) presented agent-based simulation of organic-farming conversion in Allier département, where they combined mixed-methods research with integrated ABM to explain land change and economic decision-making in the United States and Mexico.

In this paper, we present the development of an agent-based model for conversion to organic farming and compare it to an SD conversion model. The model will consider only the structure of information spread, i.e. market absorption. We have developed a parallel model, in which the main parameters are set once, and both models apply them. The main topic of the present study is therefore the validation of the proposed ABM model of market absorption. It is important to provide such parallels and validate them, because the library of system dynamics is large, and a methodology for straightforward conversion would be convenient.

2 Methodology: System-dynamics Modeling and Agent-based Modeling

In a previous study (Rozman et al., 2013), we developed a model of organic-farming transition based on SD. Methodologically, SD, ABM and DES (Kljajić et al., 2000) converge as one can observe on the following example. The development of an organic-farming model according to the principles of SD was described in detail in Rozman et al. (2013).

To model the market-absorption process, the following equations can be used to express the two main states:

$$P(t) = P(0) - \int_0^t kC(s)ds \qquad (1)$$

$$C(t) = C(0) + \int_0^t kC(s)ds \qquad (2)$$

where P is potential customers, C is customers, k is concentration of potential customers expressed as $k = P(t)/a$, where a is the size of the potential market, i.e., the number of potential customers, with initial conditions $C(0) = 1$ and $P(0) = a - C(0)$ (Rahmandad & Sterman, 2012). This definition of the model is sufficient for the SD case and is well worked out (Sterman, 2000).

The development of the agent-based model is illustrated in Figure 1, where the information-spread process is considered, which is the basis for the model of organic-farming transition. To begin, we assume that there is only one organic farm in the system (1), which is represented by a red square. If the social factor is set at 3, this farm communicates in one time step with three others (2), which are represented as yellow. One out of the three farm owners who were informed about organic farming

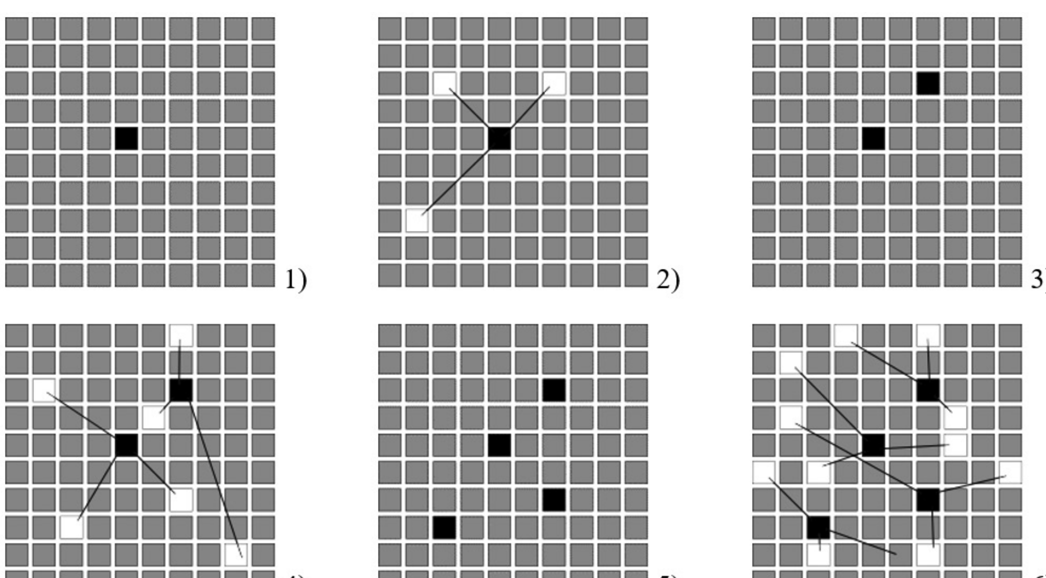

Figure 1: Information spread in an agent-based form

decides to make a transition and is represented by a new red square (3). In the next time step (4), there are two organic farms, each of which communicates with three other, conventional farms. Out of the six newly informed farm owners, represented by yellow, two decide to convert to organic farming. Therefore, four farms have converted (5). The process continues in a similar manner; an increasing number of farm owners are informed (6).

The aforementioned process could be modelled by ABM, which has two states: "Conventional Farm" and "Organic Farm." Figure 2 shows SD and agent-based models of information spread, which influences the transition from conventional to organic farming in parallel. Both models were implemented with AnyLogic software. The left-hand portion of Figure 2 shows the SD model. This is a structure of market absorption in which the transition from conventional farms to organic farms is considered. Two level elements represent the number of each. The transition is determined by the contact rate and the conversion probability. These parameters represent the main influence on the rate of the transition. At the same time, the agent-based approach is modeled runs in parallel; it is shown in the right-hand portion of Figure 2. The model is based on the Bass diffusion agent-based model. As in the SD model, the state chart consists of two states: "Conventional Farm" and "Organic Farm." A transition from conventional to organic farm occurs when "Conventional Farm" receives the message "Convert." This is done in a random manner, which is coded as follows: "sendToRandom("Convert");". The message is conveyed when the contact between two farmers is made and the information about organic farming is exchanged. In our case, the SD and agent-based models are interconnected, and the rate of communication is determined by the set Social Factor and Coefficient of Transition. The code that determines the ABM Contact Rate is coded as follows: "main.ContactRate*main.ConversionProbability".

Additionally, to leverage the power of ABM, we determine the geographic location of each farm in Slovenia as well as observe the regional distribution of organic farms. This is important for strategic regional planning and other strategic purposes, such as marketing and food processing. For each particular farm, the geolocation was determined and the data was stored in the text file. Initialization of the agents was performed according to the Java programming language code shown in Figure 3, which reads 2,060 posi-

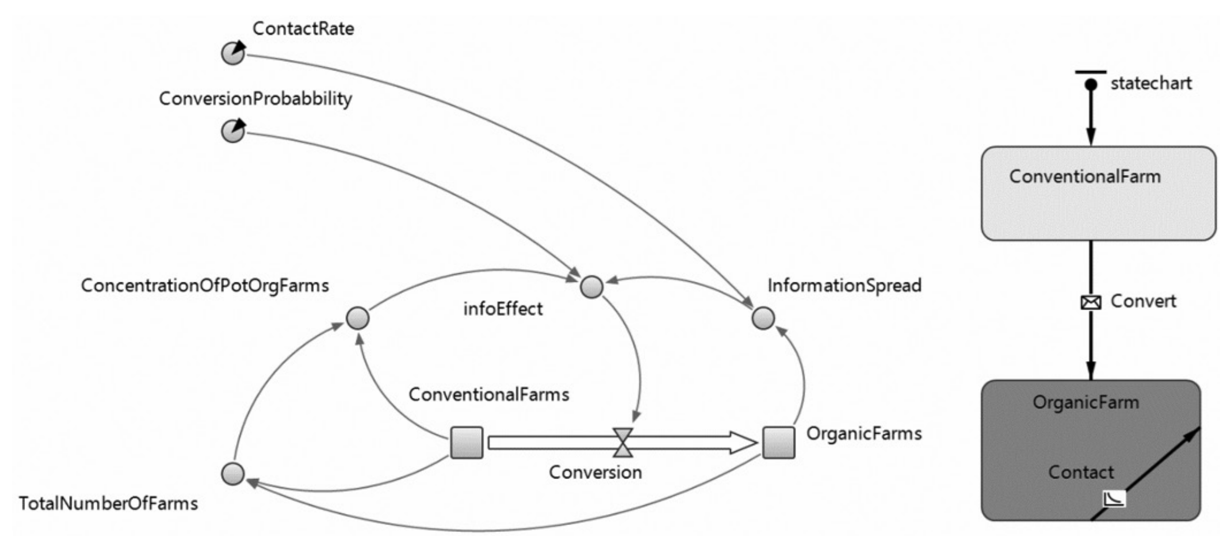

Figure 2: Agent-based model of transition to organic farming; model of information spread

```
for (int i = 0; i < 2060; i++){
        Farm p = add_people();
        p.jumpTo(file.readDouble(), file.readDouble());
        p.oval.setFillColor(gray);
}
deliverToRandomAgentInside("Convert");
```

Figure 3: Initialization code for determination of geospatial agent position; the position of each farm is read from the text file

tions of organic farms from the data file at startup.

The ABM approach is promising because it can model an entire agricultural sector in detail, taking each particular farm into account. At the beginning, one initializes the particular number of agents, in our case 2,060, because this is the number of potential farms for transition. This was the initial situation when the organic-farming policy was implemented. Initially, all the agents are represented by gray, because all the farms are conventional. During the simulation, agents transform from conventional to organic farms; in the graphical view, such agents turn from gray to green (Rozman et al., 2011). This view is extremely important for observation of the concentration of organic or conventional farms in a specific geographic region. The graphical view also contains a graph, where a comparison of the cumulative number of organic farms of the ABM and the ASD model over time is shown.

One can conclude, that an important advantage of the proposed agent-based model is precisely the geographical location of farms. Clearly, the SD model could not provide the user with geolocation information or with any other potential information about the farm. As an example, in our case, the ABM approach shows a high concentration of organic farming in Primorska region, providing decision makers with new information right away. The ABM approach makes it easy to observe the dynamics of the conversion process, which is an important advantage, especially with regard to the concertation of farms in a specific area.

3 Results

The results presented here are twofold. First, we compare the responses of the SD and agent-based models in parallel, and second, we validate the agent-based model, which is done by comparing the results of the two models. Figure 4 shows the results of one simulation run; on the left-hand side, the number of organic farms is shown, whereas the right-hand side presents the conversion rate (farms/month). In both cases, the x-axis represents the time in months. One can observe the difference in response, which is expected, because the agent-based model (red line) depends on probability, whereas the SD model (blue line) is deterministic.

To validate the results from the agent-based model, thorough validation was performed. The SD and the agent-

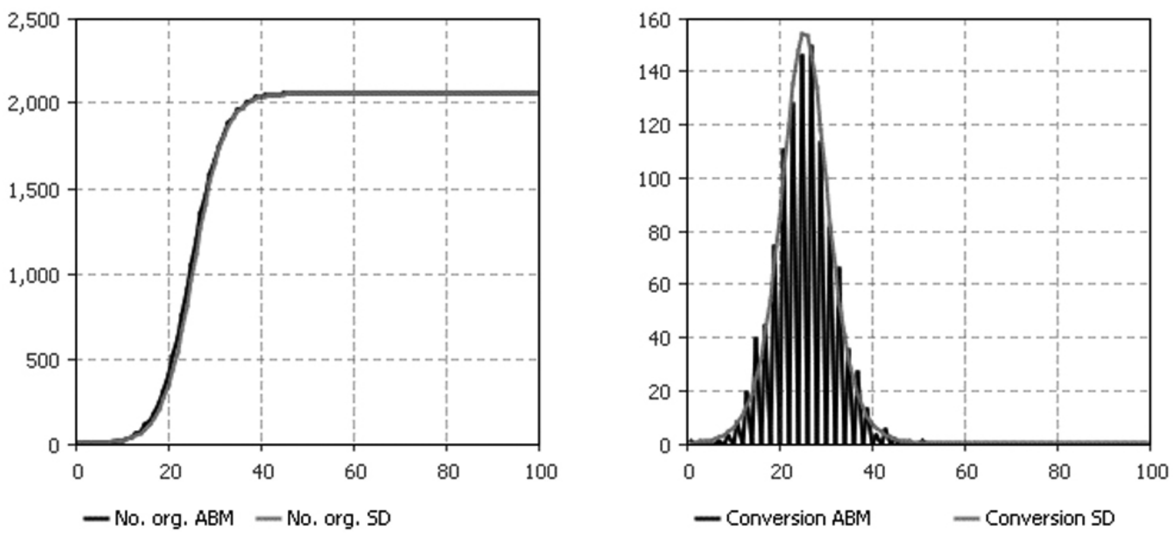

Figure 4: Comparison of the responses of the system-dynamics model (gray line) and agent-based model (black line). Left: cumulative number of organic farms, Right: conversion rate (farms/month). In both cases, x-axis represents the time in months

Table 1: Simulation scenarios and the parameters' values

Scenario	Contact Rate	Conversion Probability
SC1	1	0.1
SC2	2	0.1
SC3	3	0.1
SC4	1	0.3

based models were compared in different scenarios by setting different values for the model parameters defined in Table 1. Here, we change the Contact Rate and Conversion Probability which determine the behavior of both models. The Contact Rate represents the intensity of the organic-farming-initiative spread, whereas the Conversion Probability represents the degree to which the farmers actually intend to perform the transition from conventional to organic farming.

For each of the defined scenarios, five simulation runs were conducted to obtain the averages of the agent-based model. As noted, ABM has a probabilistic character; therefore, certain statistical postprocessing tasks should be completed, an undertaking that inevitably accompanies multiple simulation runs. To illustrate the results, Figure 5 shows five simulation runs for scenario SC1. The graph shows the dynamics of the conversion rate over time. Results are stochastic, giving slightly different responses each time, but the overall response has a distinct characteristic: the conversion rate is low at the beginning, but it gradually increases and, in the end, gradually decreases as the number of organic farms saturates towards their maximum capacity of 2060 farms.

To perform the validation for n data points, the following measures, expressed in Eqs. 3–9, were computed to compare the results of the SD and agent-based models: determination coefficient r^2, mean absolute percent error (MAPE), mean square error (MSE), root mean square error (RMSE), correction (bias) component of the MSE U^M, variation component of the MSE U^S, and covariation component of the MSE U^C (Oliva, 1995). For all scenarios, n is set to 101 (initial time step plus 100 months).

$$r^2 = \left(\frac{\frac{1}{n}\sum_{t=1}^{n} S_t A_t - \overline{S}\,\overline{A}}{S_S S_A} \right)^2 \qquad (3)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{S_t - A_t}{A_t} \right| \qquad (4)$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n} \left(S_t - A_t \right)^2 \qquad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} \left(S_t - A_t \right)^2} \qquad (6)$$

$$U^M = \frac{\left(\overline{S} - \overline{A} \right)^2}{MSE} \qquad (7)$$

$$U^S = \frac{\left(S_S - S_A \right)^2}{MSE} \qquad (8)$$

$$U^C = \frac{2\left(1-r\right) S_S S_A}{MSE} \qquad (9)$$

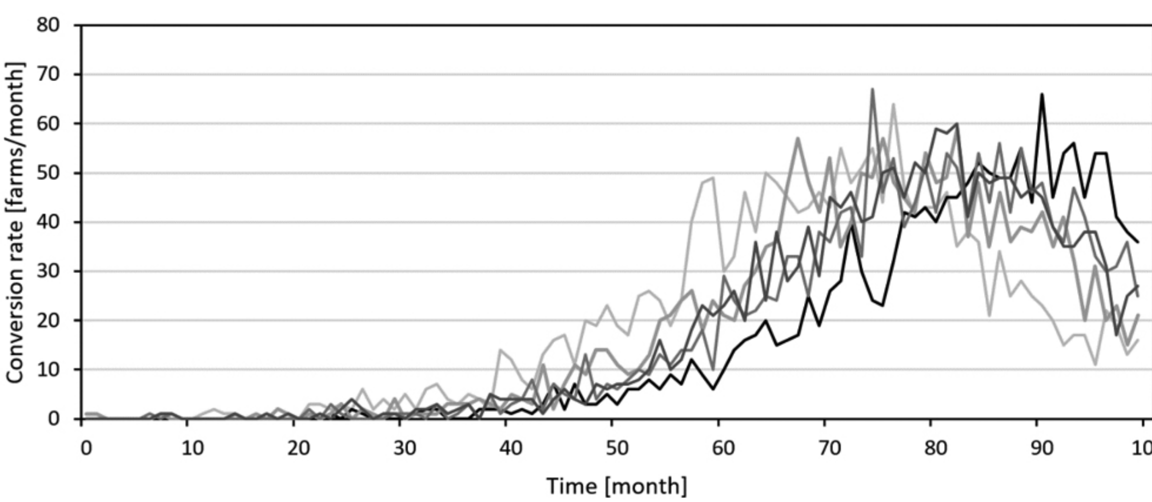

Figure 5: Example of five runs (different gray lines) of the agent-based model for scenario SC 1

where S_t and A_t represent the number of farms in the SD and agent-based models at time *t*, respectively. $\overline{S}$ and $\overline{A}$ represent the mean of the time series of the SD and agent-based models, respectively, and S_S and S_A represent their respective standard deviations.

Table 2 shows the results of five simulation runs of the model for Scenario 1 with the parameters Contact Rate and Conversion Probability set to 1 and 0.1, respectively. There are five columns representing the values of validation statistical measures. The last column shows the average value of measures. In this case, we can observe an r^2 value of 0.982, which indicates a high correlation between the models. MAPE is below 1%. U^M has the highest value, indicating that deviation from average is most influential. A low value of U^S indicates that deviation is more in tune with SD results and an even better result is provided with covariation U^C. Similar results can be found in Table 3, Table 4 and Table 5 for scenarios 2, 3 and 4, respectively.

By examining several parameter combinations and thorough validation with the statistical measures, we find that the lowest r^2 value is 0.957 and the highest MAPE value is 0.34%, across all scenarios. From these results, we can conclude that the SD and agent-based models can be treated as equal and that the agent-based model could be used in further development of organic farming modeling. The validation results by themselves define the general approach to ABM validation when transitioning from SD.

4 Conclusions

The process of transition from conventional to organic farming is complex, incorporating different entities, relations, and regional specifics. The previously applied SD approach to organic farming modeling (Rozman et al., 2013) has been improved by the application of the ABM approach, which enables us to develop models with greater accuracy. It is our intention to model each particular farm in Slovenia as an agent with its unique characteristics. The present study represents an important intermediate step in our effort; it clearly outlines the similarities in SD and ABM methodology, and its results demonstrate that the ABM approach is suitable for the challenging modeling task.

The SD and ABM methodologies are quite different. The ABM is less pre-prepared, because the variety of agents' interactions and attributes is much richer than in the SD approach. To develop adequate models, it is important to be well acquainted with basic principles of ABM. For the SD modeler, it is important to have a good "Rosetta stone" in order to correctly transcribe the main SD principles into the language of ABM. The future of modeling will certainly be in hybrid or multidomain (multimethod) modeling, in which SD, ABM, and discrete-event simulation are integrated. In our case, the advantage of the ABM approach is demonstrated by incorporating the geographical information system component, declaring the geographical location of each farm and revealing important geospatial information about the regional concentration of farms. Therefore, there are many reasons to transform models to ABM in addition to the increased computer power that has enabled the development of relatively large ABM models.

It is important to validate rigorously in the carving of the SD–ABM Rosetta stone, because the ABM models may be quite complex from the programming point of view and, on the other side, SD models are very well validated.

We believe our contribution to this important topic will help modelers further develop good SD–ABM relationships and merge the approaches appropriately.

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Table 2: Validation of Scenario 1 (Contact Rate is 1 and Conversion Probability is 0.1)

Measure	Run 1	Run 2	Run 3	Run 4	Run 5	Average
r^2	0.989	0.946	0.999	0.986	0.990	0.982
MAPE	0.388	0.572	0.177	0.327	0.235	0.340
MSE	15465.886	92841.638	1876.977	23250.744	14744.608	29635.971
RMSE	124.362	304.699	43.324	152.482	121.427	149.259
U^M	0.527	0.465	0.499	0.492	0.487	0.494
U^S	0.158	0.365	0.289	0.295	0.251	0.272
U^C	0.315	0.170	0.212	0.213	0.262	0.234

Table 3: Validation of Scenario 2 (Contact Rate is 2 and Conversion Probability is 0.1)

Measure	Run 1	Run 2	Run 3	Run 4	Run 5	Average
r^2	0.989	0.988	0.969	0.932	0.985	0.972
MAPE	0.388	0.128	0.449	0.312	0.179	0.291
MSE	15465.886	14046.094	35657.427	83490.845	17970.980	33326.246
RMSE	124.362	118.516	188.832	288.948	134.056	170.943
U^M	0.527	0.282	0.306	0.316	0.310	0.348
U^S	0.158	0.012	0.031	0.007	0.008	0.043
U^C	0.315	0.706	0.663	0.677	0.682	0.608

Table 4: Validation of Scenario 3 (Contact Rate is 3 and Conversion Probability is 0.1)

Measure	Run 1	Run 2	Run 3	Run 4	Run 5	Average
r^2	0.990	0.922	0.984	0.910	0.979	0.957
MAPE	0.222	0.737	0.138	0.254	0.124	0.295
MSE	8984.011	68848.186	14833.077	91788.603	19841.957	40859.167
RMSE	94.784	262.389	121.791	302.966	140.861	184.558
U^M	0.218	0.204	0.193	0.210	0.198	0.204
U^S	0.095	0.102	0.061	0.056	0.059	0.075
U^C	0.688	0.694	0.746	0.734	0.743	0.721

Table 5: Validation of Scenario 4 (Contact Rate is 1 and Conversion Probability is 0.3)

Measure	Run 1	Run 2	Run 3	Run 4	Run 5	Average
r^2	1.000	0.987	0.996	1.000	0.997	0.996
MAPE	0.035	0.199	0.073	0.110	0.068	0.097
MSE	38.488	11932.703	3669.380	278.900	2225.930	3629.080
RMSE	6.204	109.237	60.575	16.700	47.180	47.979
U^M	0.004	0.204	0.175	0.213	0.200	0.159
U^S	0.204	0.093	0.069	0.035	0.028	0.086
U^C	0.792	0.704	0.756	0.751	0.772	0.755

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