

Draft

Game Approach Application to Measure Farmers' Properties on Adoption: Preliminary Results on Test of Methodology with 10 Farmers in Sepunggur, Muara Bungo, Jambi, Sumatra, Indonesia¹

Desi Ariyadhi Suyamto² x Meine van Noordwijk x Betha Lusiana x Laxman Joshi x Jasnari x Janudianto x Ratna Akiefnawati x Andi Prahmono x Suyitno x Syahril

World Agroforestry Center, Southeast Asia Regional Office, Indonesia

Abstract

Game approaches to measure farmers' properties on adoption: their learning progressiveness, their perception about extension credibility, their prioritisation and their inward information seeking were tested. Ten farmers from rubber landscape of Sepunggur, Muara Bungo, Jambi, Sumatra, Indonesia were invited to play the games. Three of the farmers are the adopters of improved rubber agroforestry system (RAS), which has been promoted by ICRAF since 10 years ago. The results suggest that there are no evidence that learning progressiveness per se can determine whether a farmer is an experimenter (an early adopter) or a conservative (a laggard) in an adoption of newly introduced system. Other properties like farmers' perception about extension credibility, their exposure to extension, their prioritisation, their inward information seeking, their memory recall ability and information availability take significant roles on the overall process of adoption. Effectiveness of information sharing about a new system plays vital role in the adoption process. The results suggest that misinformation or disinformation about a new system can alter the potential adopters to non-adopters. When a new promoted system is still the few among the many, more effective way in information sharing is highly required. Mechanism to activate the early adopters to be the active "messenger" of information may help extension efforts in spreading the knowledge in more effective way. The first task in promoting a new option should be done by shifting the few into the many. Once the new system predominated the community, we can rely on the natural adoption processes for the next phases. Unless, the few will always be threatened by the old many or the new many. Detail description on theoretical framework and data analyses used in this study is presented.

Keywords: *game approach, adoption, learning progressiveness, extension credibility, memory recall ability, prioritisation and inward information seeking*

¹ Funded by: Common Fund for Commodities (CFC)-Improving the Productivity of Rubber Smallholdings through Rubber Agroforestry Systems (CFC/IRSG/11) Project

² Corresponding author, email: d.suyamto@cgiar.org

Table of contents

Abstract	1
Table of contents	2
1. Rationale.....	3
1.1. Learning progressiveness	3
1.2. Extension credibility.....	4
1.3. Prioritisation	5
1.4. Inward information seeking.....	5
2. Methods	6
2.1. Yield prediction game	7
2.2. Seedling selection game	8
2.3. Quiz game.....	9
3. Results	11
3.1. Learning progressiveness (α)	11
3.2. Extension credibility (ε)	16
3.3. “Reliable” α , ε and memory recall ability (r).....	17
3.4. Prioritisation (p)	18
3.5. Inward information seeking (i).....	20
4. Discussion: interpreting the results using a simple conceptual model on adoption	21
4.1. The model.....	21
4.2. Simulation	23
5. Preliminary conclusion.....	25
6. References	26
7. Appendices	26
Appendix 1. Farmers’ predictions and computer realisations in yield prediction game without suggestion using 10 sequential steps.	26
Appendix 2. Farmers’ predictions, computer realisations and suggestions in yield prediction game with suggestion using 10 sequential steps.	27
Appendix 3. Relative values from each option as generated by computer in the seedling selection game and farmers’ allocation fraction. Estimated prioritisation (p) from each farmer and each replicate and its standard error (se) due to fitting procedure were presented in the right column.	28
Appendix 4. Example of questions used for the quiz game.	30
Appendix 5. Twenty permuted random patterns used to shuffle reference datasets.	30

1. Rationale

The study is aimed to measure farmers' properties on adoption using game approach, based on simple theoretical framework as described below. This study is classified as test of methodology (towards test of concept).

1.1. Learning progressiveness

Learning progressiveness is characterised by how much farmers trust the most recent information about actual reward earned from particular option to adjust their expectation about the “benefit” value of that option in the future. In Figure 1, learning progressiveness is defined by the slope of linear equation $y = \alpha \cdot x$, where x is relative difference between the most recent information and previous expectation $([I_{t-1} - E_{t-1}]/E_{t-1})$, while y is relative expectation adjustment $([E_t - E_{t-1}]/E_{t-1})$ taken by farmers. This diagram suggests that rational learning is expected to occur within the first and the third quadrants, when values of x are always responded at the same sign (positive α). Farmers may also behave speculatively, increasing their expectation when the most recent information gives negative signals or the other way around (negative α), as shown by the second and the fourth quadrants of the diagram. Within the rational learning quadrants, farmers may be overconfident of the actual trend, adjusting their expectation more than the trend ($\alpha > 1$).

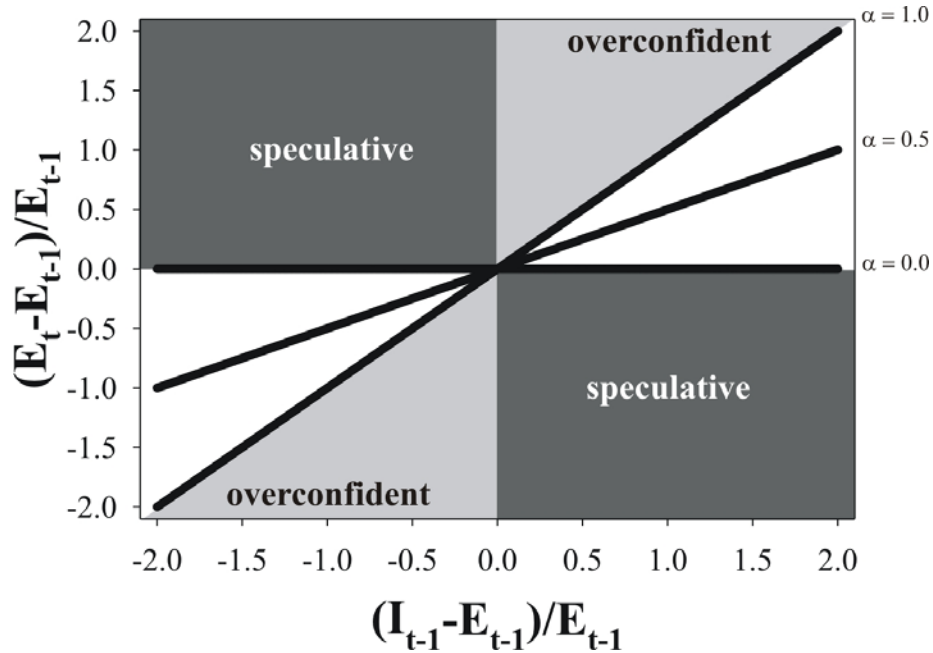


Figure 1. The progressiveness of learning is characterised by α , the slope of linear equation $y = \alpha \cdot x$, where x is relative difference between the most recent information and previous expectation $([I_{t-1} - E_{t-1}]/E_{t-1})$, while y is relative expectation adjustment $([E_t - E_{t-1}]/E_{t-1})$ taken by farmers. Rational learning is shaped by positive α in the first and the third quadrants, while speculative learning is shaped by negative α in the second and the fourth quadrants.

1.2. Extension credibility

Assuming that farmers have specific learning progressiveness (as described in Part 1.1), extension credibility is characterised by how much farmers trust the information about actual reward earned from particular option as delivered by extension agent to adjust their expectation about the “benefit” value of that option in the future. In Figure 2, extension credibility is defined by the slope of linear equation $y = \varepsilon \cdot x$, where x is relative difference between the information from extension agent and previous expectation ($[R_{t-1} - E_{t-1}] / E_{t-1}$) together with assumed learning progressiveness of farmers to the most recent information ($\alpha[I_{t-1} - E_{t-1}] / E_{t-1}$), while y is relative expectation adjustment ($[E_t - E_{t-1}] / E_{t-1}$) taken by farmers. Similar to learning progressiveness diagram, this diagram suggests that rational extension credibility is expected to occur within the first and the third quadrants, when values of x are always responded at the same sign (positive ε). Farmers may also rebel to extension, increasing their expectation when the extension information gives negative signals or the other way around (negative ε), as shown by the second and the fourth quadrants of the diagram. Within the rational extension quadrants, farmers may be overconfident of the extension difference, adjusting their expectation more than the difference ($\varepsilon > 1$).

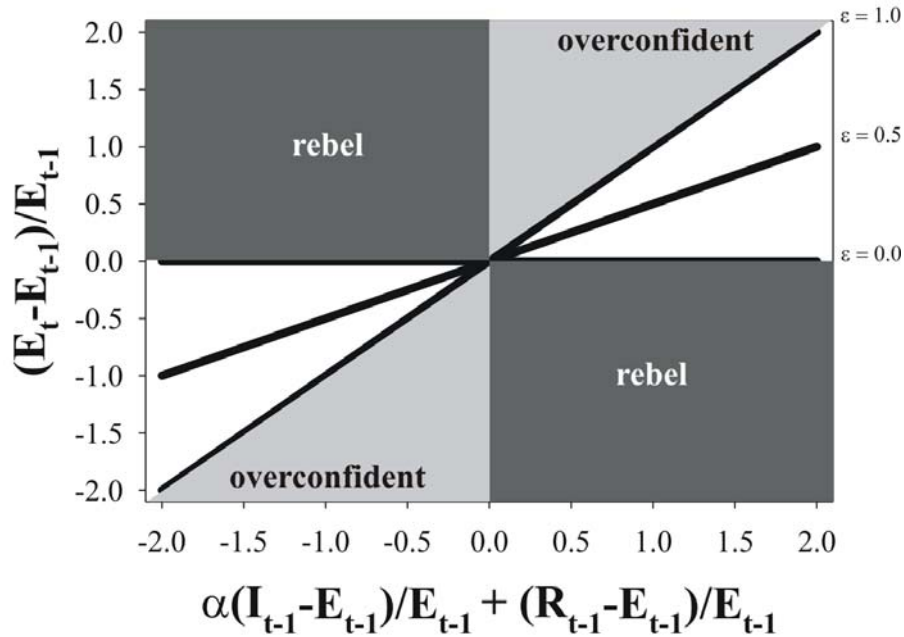


Figure 2. The credibility of extension is characterised by ε , the slope of linear equation $y = \varepsilon \cdot x$, where x is relative difference between the information from extension agent and previous expectation ($[R_{t-1} - E_{t-1}] / E_{t-1}$) together with their assumed learning progressiveness to the most recent information ($\alpha[I_{t-1} - E_{t-1}] / E_{t-1}$), while y is relative expectation adjustment ($[E_t - E_{t-1}] / E_{t-1}$) taken by farmers. Rational extension is shaped by positive ε in the first and the third quadrants, while rebellion is shaped by negative ε in the second and the fourth quadrants.

1.3. Prioritisation

Resource allocation to given number of choices is made by farmers based on relative values of each choice and determined by farmers' prioritisation. In Figure 3, this correlation is simplified using power equation $y=x^p/\sum x^p$, where y is resource allocation fraction to an option, x is its relative value and p is prioritisation degree. At $p=0$, resource is equalised. At $p=1$, resource is allocated proportionally. At $p>1$, resource is allocated more for the best choice.

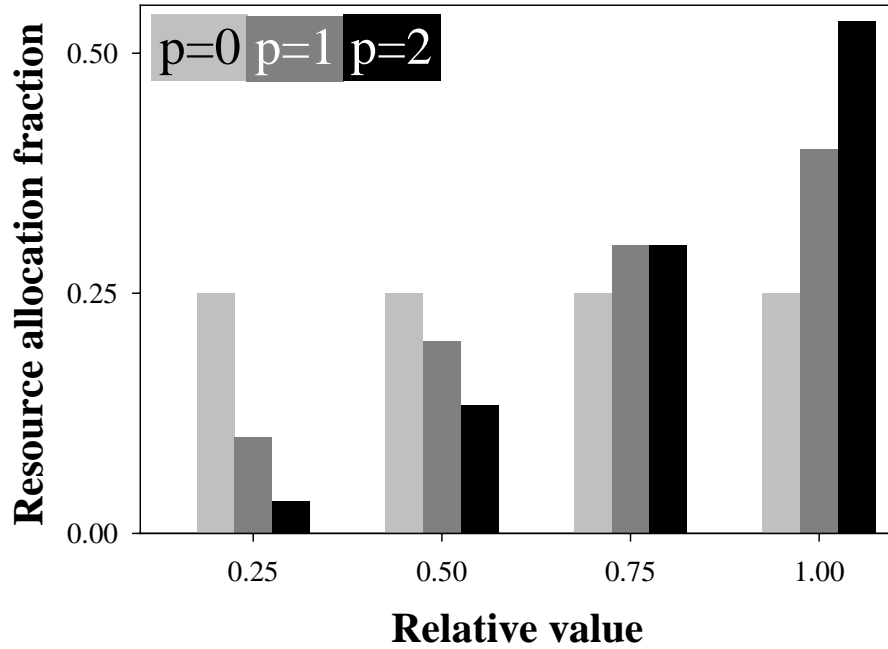


Figure 3. Prioritisation (p) determines how much resource is allocated to given options. At $p=0$, resource is equalised (left grey bar). At $p=1$, resource is allocated proportionally (middle dark grey bar). At $p=2$, resource is allocated more for the best choice (right black bar).

1.4. Inward information seeking

Current theoretical framework assumes that farmers are surrounded by passive sources of information, whose information is provided freely as public goods. Thus, flows of information in a community are determined by how frequent farmers seek information from available sources. Furthermore, connectedness of a community in information sharing is characterised by how frequent majority of farmers seek information from internal sources relative to total information seeking frequency. Figure 4 illustrates three types of farmers in their inward information seeking (i). The blue farmer has $i=1$, the green farmer has $i=0.5$, and the red farmer has $i=0$. When majority of a community has i approaching 1, like the blue farmer has, it implies that the community has very good internal connectedness, a perfect situation to have effective diffusion of information by providing the information internally. When majority of a community has i approaching 0.5, like the green farmer has, it implies that to effectively diffuse information into the community, we have to provide the information from two sources: from internal sources and from external sources. When majority of a community has i approaching 0, like the red farmer has, it implies that to effectively diffuse information into the community, we have to provide the information from external sources, instead of doing it directly from internal sources.

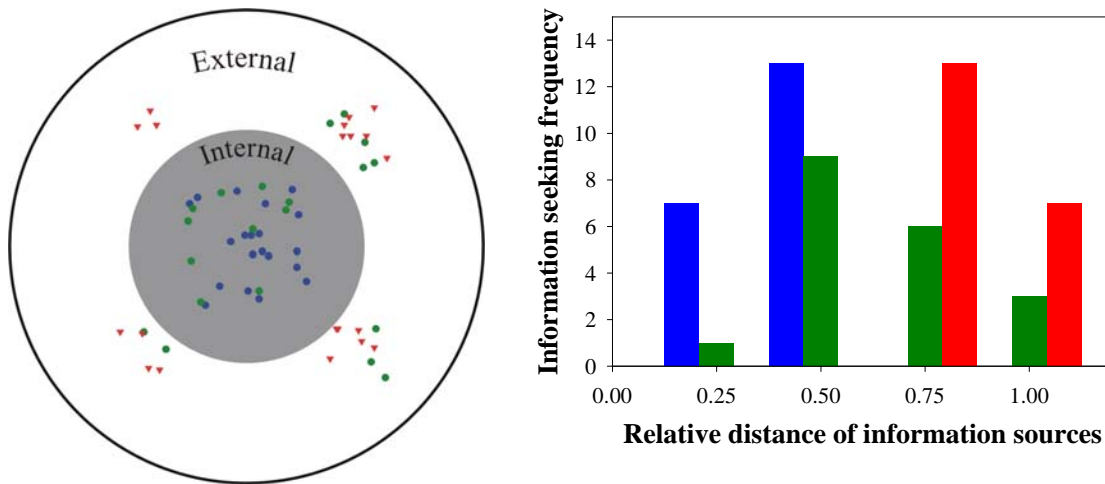


Figure 4. Connectedness of a community in information sharing is characterised by how frequent majority of farmers seek information from internal sources relative to total information seeking frequency. In this case, internal sources of information are defined as sources with relative distance ≤ 0.5 . This diagram illustrates three types of farmers in their inward information seeking (i). The blue farmer has $i=1$, the green farmer has $i=0.5$, and the red farmer has $i=0$.

2. Methods

Simple computer simulation games are developed using NetLogo (Wilensky 1999) to measure farmers' properties affecting adoption. It covers games to measure learning progressiveness (α), extension credibility (ϵ), prioritisation (p), and inward information seeking (i) as described in Part 1.

To test this approach, 10 farmers in Sepunggur, Muara Bungo, Jambi, Sumatra, Indonesia were invited to play the games. The games were conducted from June 28 to July 1, 2006 at ICRAF Muara Bungo Office at individual level (Figure 5). Three of the farmers participated in the game are the adopters of improved rubber agroforestry system (RAS), which has been promoted by ICRAF since 10 years ago. Given that the farmers are adopters or non-adopters, feasibility of the games is judged based on the results.

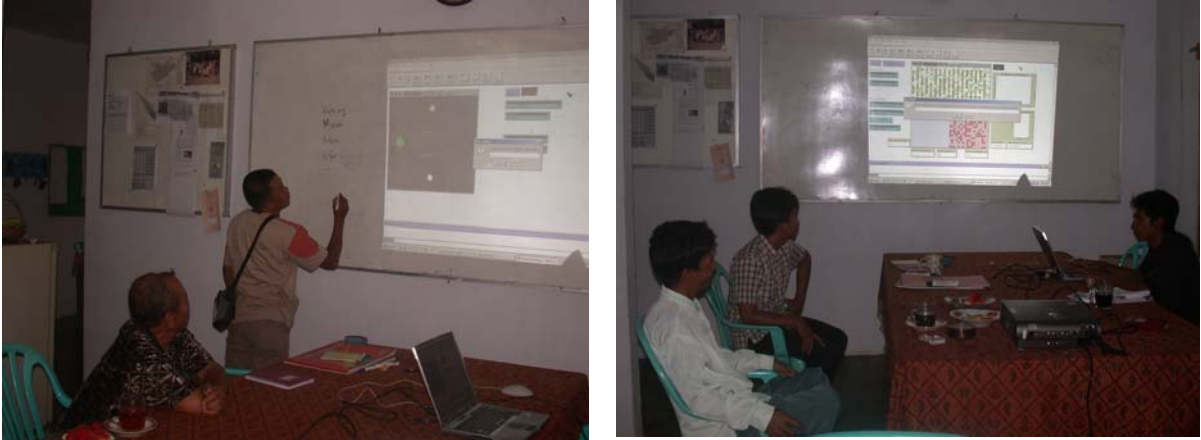


Figure 5. Farmers played the games. Do they behave similarly in real life? (Photos by: Jasnari and Janudianto)

2.1. Yield prediction game

Farmers are asked to predict latex yield for number of sequential steps (Figure 6). Computer generates latex yield based on normal statistic of latex production to represent realisation of the yield. Initial prediction can be made based on farmers' knowledge from their own plot, but the next predictions should be made based on their actual learning in the game. Scoring is made based on prediction accuracy using formula $100 \times (1 - |\text{prediction} - \text{realisation}| / \text{realisation})$, truncated at 0. The game can be set up to provide suggestion for the prediction. The suggestion is made based on realisation time-averaged.

This game is aimed to measure how farmers adjust their prediction to achieve good scores, given the realisation as randomised by computer. At a game setting without suggestion, we expect to measure learning progressiveness (α). At a game setting with suggestion, we expect to measure extension credibility (ϵ).

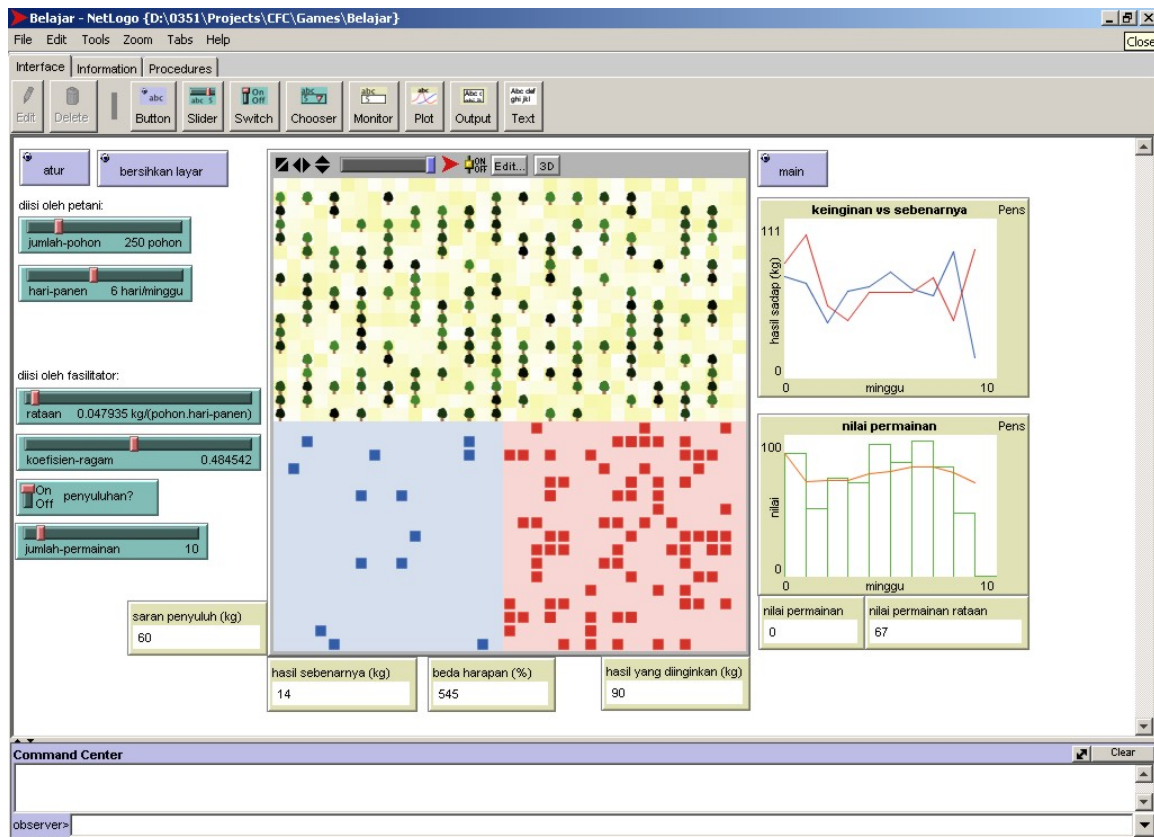


Figure 6. User interface in yield prediction game.

2.2. Seedling selection game

Computer generates four types of fictitious rubber clones with various latex-production, truncated at average production from farmers' plots (Figure 7). Farmers are asked to take a number of seedlings, with a condition that they must select all four clones. This game is aimed to measure how farmers make prioritisation (p) at given number of discrete choices with their relative values.

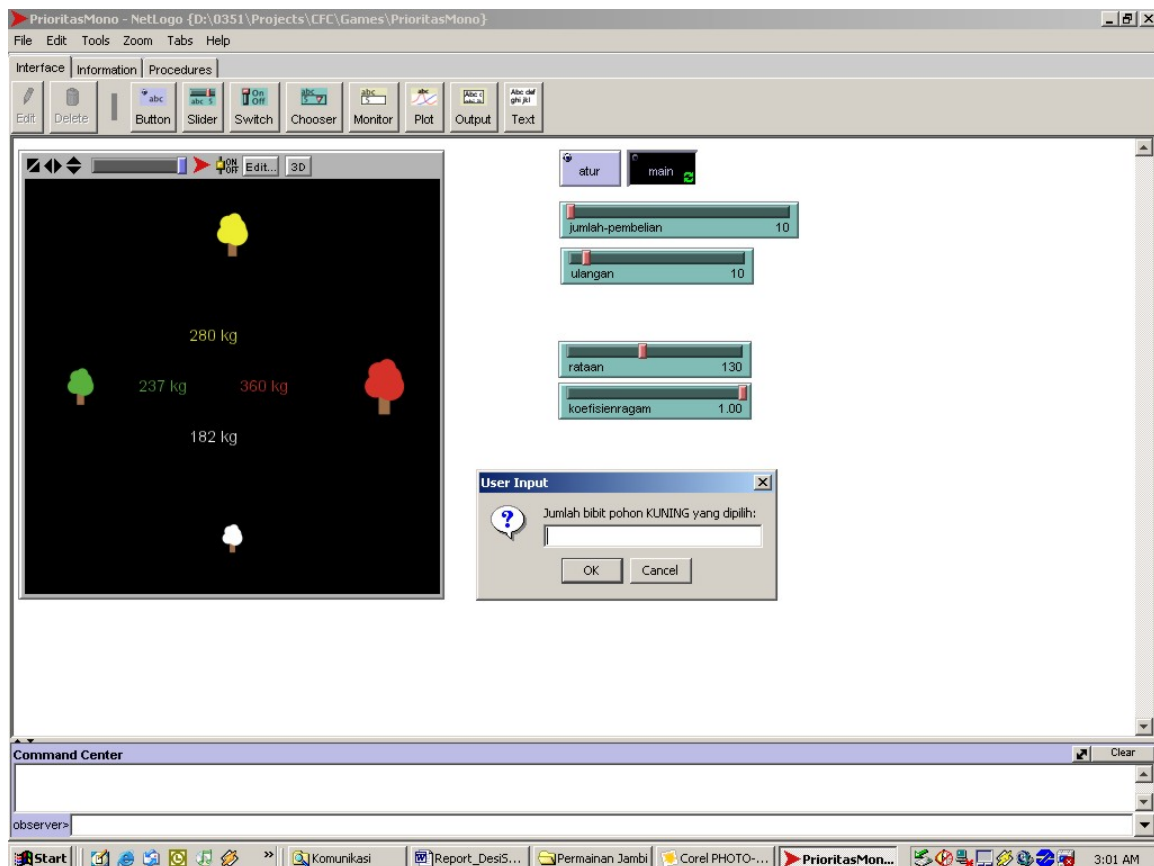


Figure 7. User interface in seedling selection game.

2.3. Quiz game

Farmers are asked to answer a number of questions, where four answer choices are provided (Figure 8). Computer provides a number of information sources that can help farmers to answer the questions when needed. Information provided by the sources is randomised.

The questions range from questions presumably close to farmers' daily life to questions presumably beyond farmers' daily life. Examples of questions are presented in Appendix 4. Sources of information are identified and listed down by farmers prior to the game. Farmers are asked to sort sources of information from the farthest to the nearest. It is aimed to define their boundary: internal or external. Simple method to sort is by making a rescue game. For example, farmers identified researchers, neighbours, television and relatives as their sources of information. Suppose that farmers have a limited carrying capacity of boat to rescue them from flood disaster, whom will they leave at first. After the sources are sorted, relative distance is estimated. For example, we got ascending sorted data as follows: relatives, neighbours, television and researchers, their relative distances are 0.25, 0.5, 0.75 and 1 respectively. Thus, relatives and neighbours are placed within the internal boundary, while television and researchers are placed within the external boundary. To have standard reference, average relative distance from all farmers is used to analyse results from each individual farmer. This game is aimed to measure inward information seeking (i). Parameter i is calculated based on frequency of help seeking with internal sources relative to total frequency of help seeking.

Game Approach Application to Measure Farmers' Properties on Adoption

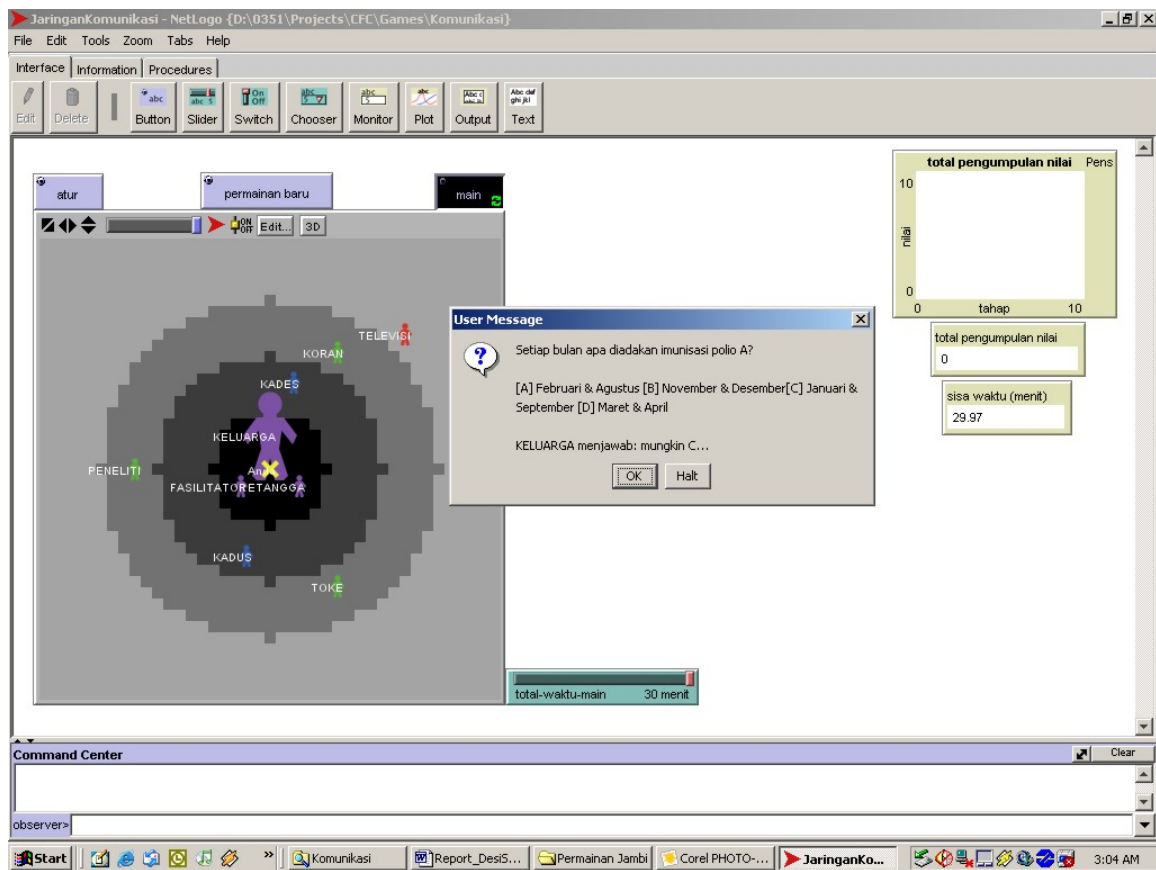


Figure 8. User interface in quiz game.

3. Results

3.1. Learning progressiveness (α)

Farmers played the yield prediction game without suggestion using 10 sequential prediction steps individually. Raw data on farmers' predictions (E) and the computer realisations (I) are presented in Appendix 1. Using the theoretical framework as explained in Part 1.1, these data were plotted to estimate learning progressiveness (α) from their shaped slopes (Figure 9). Results on estimated α are presented in Table 1. These results hold the assumption that farmers use actual realisation as their reference for adjusting their prediction.

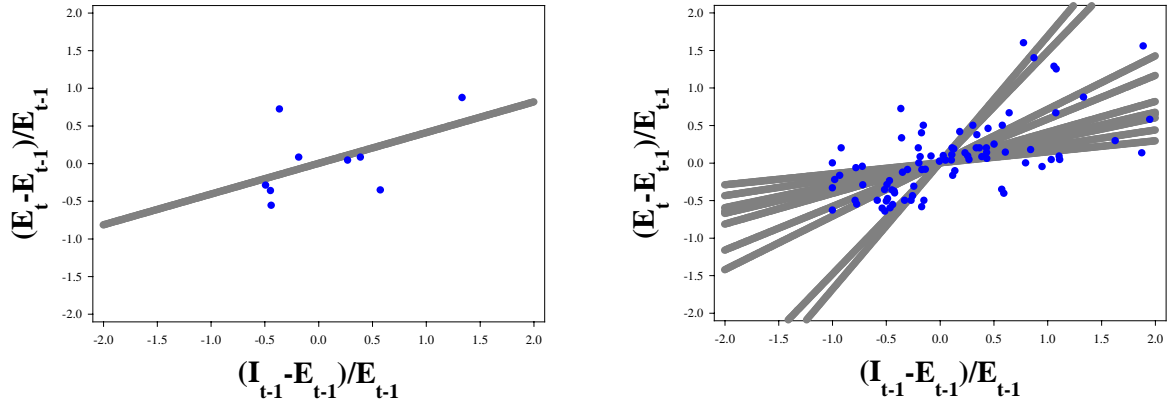


Figure 9. Results on yield prediction game at a setting without suggestion. The left graph shows the result from one respondent (Farmer 01), while the right graph shows the results from all respondents. Learning progressiveness (α) of the respondents was estimated based on the slopes (grey lines). Blue dots are experimental data. E is farmers' predictions, I is computer realisation and t is playing sequence.

Table 1. Learning progressiveness (α) was estimated based on the slope of relative prediction adjustment, assuming that farmers use actual realisation as their reference for adjustment.

	Farmer 01	Farmer 02	Farmer 03	Farmer 04	Farmer 05	Farmer 06	Farmer 07	Farmer 08	Farmer 09	Farmer 10
α	0.41	0.21	0.33	0.24	0.42	1.46	1.62	0.72	0.55	0.34

Further analysis was done to test that at assumed learning progressiveness (α) as estimated in Table 1, farmers adjusted their prediction based only on actual realisation. Thus, relative prediction adjustment based on actual realisation was compared with other references: 2-point, 3-point, 4-point, 5-point moving averages and time-averaged. Comparison was done at the same scale within the first quadrant by looking at the average of responses (Figure 10). Significant differences with actual realisation were determined at confidence level=95% and degree of freedom=104 using least significant difference test. In fact, there is no clear evidence that farmers, at assumed α , adjusted their prediction based only on actual realisation (Table 2). Probability that farmers might also use 2-point, 3-point, 4-point, 5-point moving averages and time-averaged as their reference were 70%, 70%, 70%, 70% and 50% respectively. Overall probability that farmers might also use other references than actual data was 66%. Learning progressiveness (α) resulted by other references are presented in Table 3.

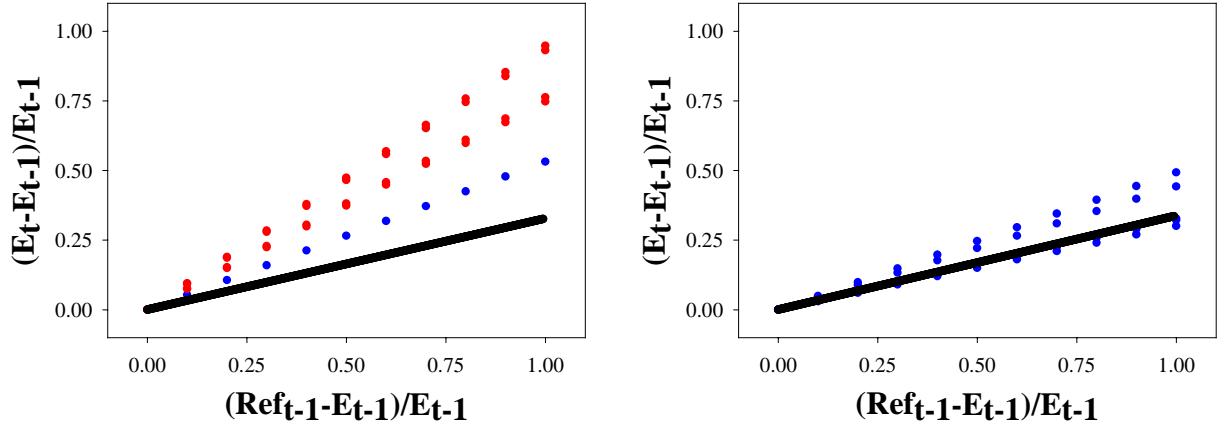


Figure 10. Further analysis was done to test that at assumed learning progressiveness (α) as estimated in Table 1, farmers adjusted their prediction based only on actual realisation. Thus, relative prediction adjustment based on actual realisation was compared with other references: 2-point, 3-point, 4-point, 5-point moving averages and time-averaged. Comparison was done at the same scale within the first quadrant by looking at the average of responses. Black lines represent responses when actual realisation was used as the reference. Blue dots represent other references that resulted no significant difference with the assumption, while red dots represent other references that resulted significant difference with the assumption. The left graph shows results from Farmer 03, where only 2-point moving average was not different with the assumption. The right graph shows results from Farmer 10, where all other references were not different with the assumption. More detail result on difference test is presented in Table 2.

Table 2. Relative prediction adjustment average at various references. Significant differences with actual realisation were determined at confidence level=95% and degree of freedom=104 using least significant difference test. In fact, there is no clear evidence that farmers, at assumed learning progressiveness (α) as estimated in Table 1, adjusted their prediction based only on actual realisation.

	Farmer 01	Farmer 02	Farmer 03	Farmer 04	Farmer 05	Farmer 06	Farmer 07	Farmer 08	Farmer 09	Farmer 10
Actual realisation	0.41	0.21	0.33	0.24	0.42	1.46	1.62	0.72	0.55	0.34
2-point moving average	0.62	0.06*	0.53	0.37	0.46	1.97	2.80*	1.17*	0.86	0.30
3-point moving average	0.84*	0.31	0.95*	0.56*	0.46	1.83	1.78	0.83	0.93	0.44
4-point moving average	0.88*	0.23	0.76*	0.31	0.81*	1.72	1.46	0.87	0.73	0.33
5-point moving average	0.59	0.37*	0.75*	0.28	0.76*	1.74	1.39	0.86	0.86	0.32
Time-averaged	0.89*	0.29	0.93*	0.89*	1.03*	2.14	1.34	1.11	1.53*	0.49
Probability to be different with 5 other references	0.60	0.40	0.80	0.40	0.60	0.00	0.20	0.20	0.20	0.00

Table 3. Learning progressiveness (α) from other references.

α	Farmer 01	Farmer 02	Farmer 03	Farmer 04	Farmer 05	Farmer 06	Farmer 07	Farmer 08	Farmer 09	Farmer 10
2-point moving average	0.62	0.06	0.53	0.37	0.46	1.97	2.80	1.17	0.86	0.30
3-point moving average	0.84	0.31	0.95	0.56	0.46	1.83	1.78	0.83	0.93	0.44
4-point moving average	0.88	0.23	0.76	0.31	0.81	1.72	1.46	0.87	0.73	0.33
5-point moving average	0.59	0.37	0.75	0.28	0.76	1.74	1.39	0.86	0.86	0.32
Time-averaged	0.89	0.29	0.93	0.89	1.03	2.14	1.34	1.11	1.53	0.49

Another analysis was done to test that at assumed learning progressiveness (α), farmers did not adjust their prediction based on random sets. Thus, relative prediction adjustment based on actual realisation was compared with random sets. For that purpose, reference data was permuted following the patterns in Appendix 5. Similar with the previous test, comparison was done at the same scale within the first quadrant by looking at the average of responses (Figure 11). Significant differences with actual realisation were determined at confidence level=95% and degree of freedom=104 using least significant difference test. Among 10 farmers, there was only 1 farmer (Farmer 01) who probably made his prediction randomly, with the probability of predicting randomly = 80% (Table 4). Other farmers seemed not to make their prediction randomly, with probability of predicting randomly ranging from 0% to 10%. These results suggest that most of the farmers did not make prediction on the basis of random sets. Similar tests were also done using 2-point, 3-point, 4-point, 5-point moving averages and time-averaged references. Probabilities to be different with permuted random sets from these references are presented in Table 5. Overall probability that farmers made prediction randomly when they used actual, 2-point, 3-point, 4-point, 5-point moving averages and time-averaged of realisation data as the references were 11%, 14%, 39%, 25%, 33% and 49% respectively.

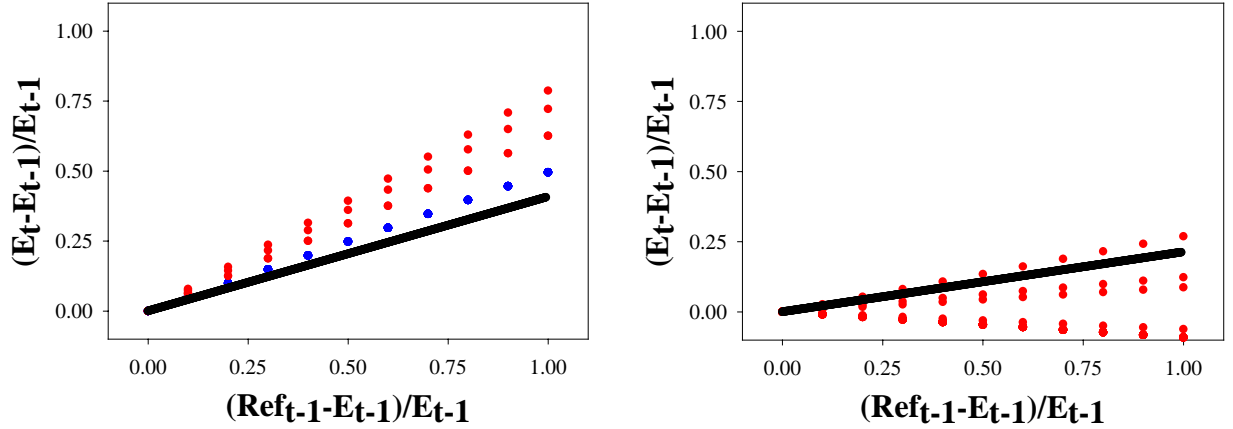


Figure 11. Another analysis was done to test that at assumed learning progressiveness (α), farmers did not adjust their prediction based on random sets. Thus, relative prediction adjustment based on actual realisation was compared with random sets. For that purpose, reference data was permuted following the patterns in Appendix 5. Similar with the previous test, comparison was done at the same scale within the first quadrant by looking at the average of responses (Figure 11). Black lines represent responses when actual realisation was used as the reference. Blue dots represent random permuted references that resulted no significant difference with the assumption, while red dots represent random permuted references that resulted significant difference with the assumption. The left graph shows results from Farmer 01, where only 20% of the random sets were not different with the assumption. The right graph shows results from Farmer 02, where all random references were not different with the assumption. More detail result on difference test is presented in Table 4.

Table 4. Relative prediction adjustment average at 20 permuted random references compared to responses based on actual realisation as the reference. Significant differences with actual realisation were determined at confidence level=95% and degree of freedom=104 using least significant difference test.

	Farmer 01	Farmer 02	Farmer 03	Farmer 04	Farmer 05	Farmer 06	Farmer 07	Farmer 08	Farmer 09	Farmer 10
Actual realisation	0.41	0.21	0.33	0.24	0.42	1.46	1.62	0.72	0.55	0.34
Random 01	0.63*	0.09*	-0.07*	-0.03*	0.29*	1.19	1.20*	0.25*	-0.14*	0.16*
Random 02	0.72*	-0.06*	-0.09*	-0.12*	0.12*	1.56	0.35*	0.01*	0.51	-0.21*
Random 03	0.63*	0.12*	-0.08*	0.10*	0.53*	0.97*	0.24*	0.34*	0.69*	0.08*
Random 04	0.79*	0.27*	-0.43*	0.15*	0.32*	0.98*	0.41*	0.53*	0.45	0.35
Random 05	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 06	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 07	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 08	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 09	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 10	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*

Table 4. Continued.

	Farmer 01	Farmer 02	Farmer 03	Farmer 04	Farmer 05	Farmer 06	Farmer 07	Farmer 08	Farmer 09	Farmer 10
Random 11	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 12	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 13	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 14	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 15	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 16	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 17	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 18	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 19	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Random 20	0.50	-0.09*	-0.15*	0.02*	0.04*	0.77*	0.28*	0.02*	0.24*	0.21*
Probability to be different with permutated random sets, $P(\mu \neq r)$	0.20	1.00	1.00	1.00	1.00	0.90	1.00	1.00	0.90	0.95

Table 5. Probability to be different with permutated random sets, $P(\mu \neq r)$, using 2-point, 3-point, 4-point, 5-point moving averages and time-averaged references.

Probability to be different with permutated random sets, $P(\mu \neq r)$	Farmer 01	Farmer 02	Farmer 03	Farmer 04	Farmer 05	Farmer 06	Farmer 07	Farmer 08	Farmer 09	Farmer 10
2-point moving average	0.80	1.00	1.00	0.90	0.95	1.00	1.00	1.00	0.85	0.15
3-point moving average	0.00	0.95	1.00	1.00	0.20	1.00	0.95	0.10	0.90	0.05
4-point moving average	0.00	0.95	1.00	1.00	0.95	0.85	0.95	0.05	0.85	0.95
5-point moving average	0.00	0.95	1.00	0.95	1.00	0.85	1.00	0.00	0.80	0.15
Time-averaged	0.00	0.15	1.00	0.95	0.15	0.90	0.95	0.05	0.90	0.10

3.2. Extension credibility (ϵ)

Farmers played the yield prediction game at a setting with suggestion using 10 sequential prediction steps individually. Raw data on farmers' predictions (E), the computer realisations (I) and suggestions (R) are presented in Appendix 2. Using the theoretical framework as explained in Part 1.2, these data were plotted to estimate extension credibility (ϵ) from their shaped slopes (Figure 12). To estimate ϵ , data on α from Table 1 and Table 3 were used.

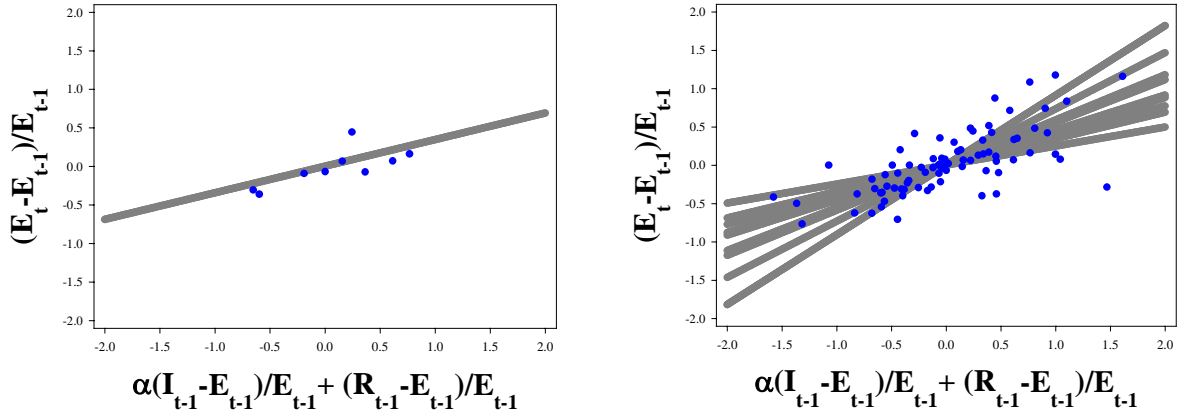


Figure 12. Results on yield prediction game at a setting with suggestion. The left graph shows the result from one respondent (Farmer 01), while the right graph shows the results from all respondents. In this case, both graphs use actual realisation data as the reference. Extension credibility (ϵ) perceived by respondents was estimated based on the slopes (grey lines). Blue dots are experimental data. E is farmers' predictions, I is computer realisation, R is suggestion and t is playing sequence. Data on estimated α from Table 1 and Table 3 were used to estimate ϵ .

Similar procedure as used in Part 1.2 to test that farmers did not make prediction based random sets were also applied, but in this case random sets are permuted random from suggestion data. Results on estimated ϵ using various assumed references and their probabilities to be different with random sets, $P(\mu \neq r)$, are presented in Table 6.

Table 6. Extension credibility (ϵ) was estimated based on the slope of relative prediction adjustment, assuming that farmers use particular reference for adjustment. $P(\mu \neq r)$ indicates probability to be different with permutated random sets of suggestion data.

		Farmer 01	Farmer 02	Farmer 03	Farmer 04	Farmer 05	Farmer 06	Farmer 07	Farmer 08	Farmer 09	Farmer 10
Actual realisation	ϵ	0.36	0.90	0.89	0.71	0.52	0.48	0.26	0.40	0.43	0.71
	$P(\mu \neq r)$	0.15	0.95	0.95	1.00	0.95	1.00	0.05	0.95	0.95	1.00
2-point moving average	ϵ	0.33	1.14	0.87	0.69	0.74	0.52	0.25	0.37	0.35	0.80
	$P(\mu \neq r)$	1.00	0.95	1.00	1.00	1.00	1.00	0.90	0.90	0.95	1.00
3-point moving average	ϵ	0.33	0.90	0.59	0.60	0.82	0.42	0.38	0.49	0.33	0.70
	$P(\mu \neq r)$	1.00	0.95	0.95	0.20	0.95	1.00	0.05	1.00	0.95	1.00
4-point moving average	ϵ	0.38	0.95	0.63	0.74	0.57	0.45	0.40	0.36	0.38	0.72
	$P(\mu \neq r)$	1.00	0.15	1.00	1.00	1.00	1.00	0.95	0.95	0.95	1.00
5-point moving average	ϵ	0.50	0.77	0.61	0.74	0.54	0.45	0.37	0.36	0.35	0.69
	$P(\mu \neq r)$	1.00	0.95	0.95	1.00	1.00	0.95	0.15	0.95	0.95	1.00
Time-averaged	ϵ	0.45	0.94	0.62	0.53	0.56	0.42	0.54	0.45	0.28	0.70
	$P(\mu \neq r)$	1.00	0.95	1.00	1.00	1.00	0.95	1.00	1.00	0.95	1.00

3.3. “Reliable” α , ϵ and memory recall ability (r)

Results from Table 2 suggest that ability of farmers in memory recall varied. Overall probability of not predicting randomly, $P(\mu \neq r)\alpha \times P(\mu \neq r)\epsilon$, as multiplication products of $P(\mu \neq r)$ in Table 4, Table 5 and Table 6 was used in selecting “reliable” α and ϵ to represent farmers’ properties on adoption. Results on $P(\mu \neq r)\alpha \times P(\mu \neq r)\epsilon$ from each individual farmer and from various possible references with regards to their memory recall ability (r) are presented in Table 7.

Table 7. Overall probability of not predicting randomly, $P(\mu \neq r)\alpha \times P(\mu \neq r)\epsilon$.

	Farmer 01	Farmer 02	Farmer 03	Farmer 04	Farmer 05	Farmer 06	Farmer 07	Farmer 08	Farmer 09	Farmer 10
Actual	0.03	0.95	0.95	1.00	0.95	0.90	0.05	0.95	0.86	0.95
2-point moving average	0.80	0.95	1.00	0.90	0.95	1.00	0.90	0.90	0.81	0.15
3-point moving average	0.00	0.90	0.95	0.20	0.19	1.00	0.05	0.10	0.86	0.05
4-point moving average	0.00	0.14	1.00	1.00	0.95	0.85	0.90	0.05	0.81	0.95
5-point moving average	0.00	0.90	0.95	0.95	1.00	0.81	0.15	0.00	0.76	0.15
Time-averaged	0.00	0.14	1.00	0.95	0.15	0.86	0.95	0.05	0.86	0.10

“Reliable” learning progressiveness (α), extension credibility (ϵ) and memory recall ability (r) of each farmer are then selected by optimisation to maximise overall probability of not predicting randomly and to minimise length of memory recall. Table 8 shows that only Farmer 01 and Farmer 07 possibly used 2-step backward in memory recall, while the rest followed the original theoretical framework.

Table 8. “Reliable” learning progressiveness (α), extension credibility (ϵ) and memory recall ability (r) of each farmer, selected by optimisation to maximise overall probability of not predicting randomly, $P(\mu \neq r)\alpha \times P(\mu \neq r)\epsilon$, and to minimise length of memory recall.

	Farmer 01	Farmer 02	Farmer 03	Farmer 04	Farmer 05	Farmer 06	Farmer 07	Farmer 08	Farmer 09	Farmer 10
α	0.62	0.21	0.33	0.24	0.42	1.46	2.80	0.72	0.55	0.34
ϵ	0.33	0.90	0.89	0.71	0.52	0.48	0.25	0.40	0.43	0.71
r	2-point moving average	Actual	Actual	Actual	Actual	Actual	2-point moving average	Actual	Actual	Actual
$P(\mu \neq r)$	0.80	0.95	0.95	1.00	0.95	0.90	0.90	0.95	0.86	0.95

3.4. Prioritisation (p)

Farmers played the seedling selection game for 10 replicates individually. In this game, farmers were asked to select 10 seedlings from 4 given choices. Raw data on farmers' allocation fraction to 4 options with their relative values are presented in Appendix 3. Prioritisation (p) from each farmer and each replicate were estimated using fitting procedure by minimising error, following equation $y = x^p / \sum x^p$, as explained in Part 1.3. Detail data on estimated p and standard error (se) from each farmer and each replicate were also presented in Appendix 3.

Since relative values from each replicate for given farmer are not at the same scale, rescaling was done in order to make general conclusion about prioritisation of each farmer. Rescaling was carried out using estimated p (Appendix 3) to have data on resource allocation fraction at standard relative values: 0.25, 0.50, 0.75 and 1.00. Finally, the overall p of each farmer was estimated using fitting procedure based on average rescaled data on allocation fraction. Grey dots in Figure 13 are original data, blue triangles are rescaled data, and the red squares are the average of rescaled data. Overall p was estimated based on red squares patterns. Results on overall prioritisation of each farmer (p) and its standard error due to fitting (se) were summarised in Table 8.

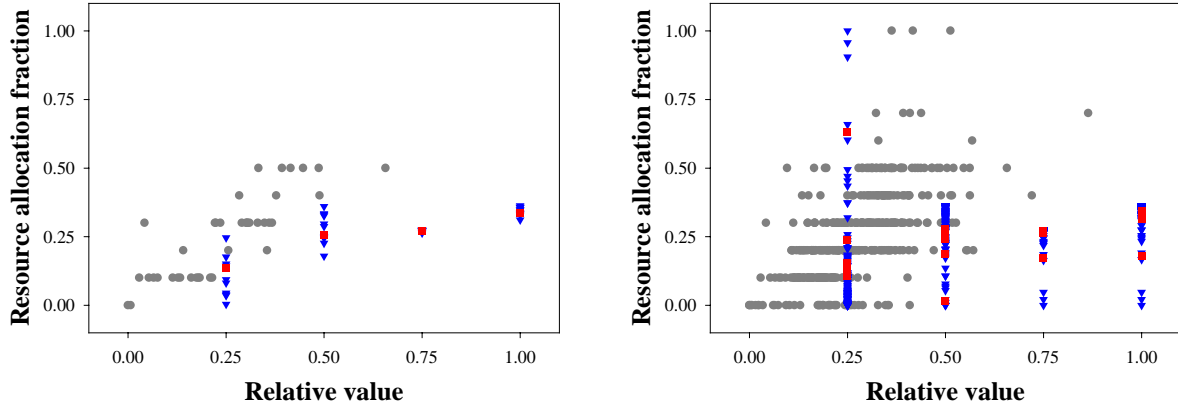


Figure 13. Since relative values from each replicate for given farmer are not at the same scale (grey dots), rescaling was done at standard relative values: 0.25, 0.50, 0.75 and 1.00. Blue triangles are rescaled data and the red squares are the average of rescaled data. Overall p was estimated based on red squares patterns. The left graph shows results from individual farmers (Farmer 01), while the right graph shows results from all farmers.

Table 8. Overall prioritisation (p) of each farmer and standard error (se) due to fitting procedure application to estimate p .

	Farmer 01	Farmer 02	Farmer 03	Farmer 04	Farmer 05	Farmer 06	Farmer 07	Farmer 08	Farmer 09	Farmer 10
p	0.654	0.611	0.713	-0.911	0.202	0.837	0.550	0.713	0.611	0.816
se	0.003	0.002	0.005	0.019	0.001	0.017	0.005	0.005	0.002	0.013

3.5. Inward information seeking (i)

Farmers played the quiz game, answering 10 questions individually. Examples on questions used in the game are shown in Appendix 4. Prior to the game, farmers were asked to sort sources of information based on relative distance. The overall results of this sorting are presented in Figure 14. Boundary was determined by relative distance. When relative distance ≤ 0.50 , information sources were considered as internal sources. Inward information seeking (i) from each farmer was calculated based on frequency of help seeking with internal sources relative to total frequency of help seeking. Table 9 shows detail data from each farmer and estimated i at individual and community levels.

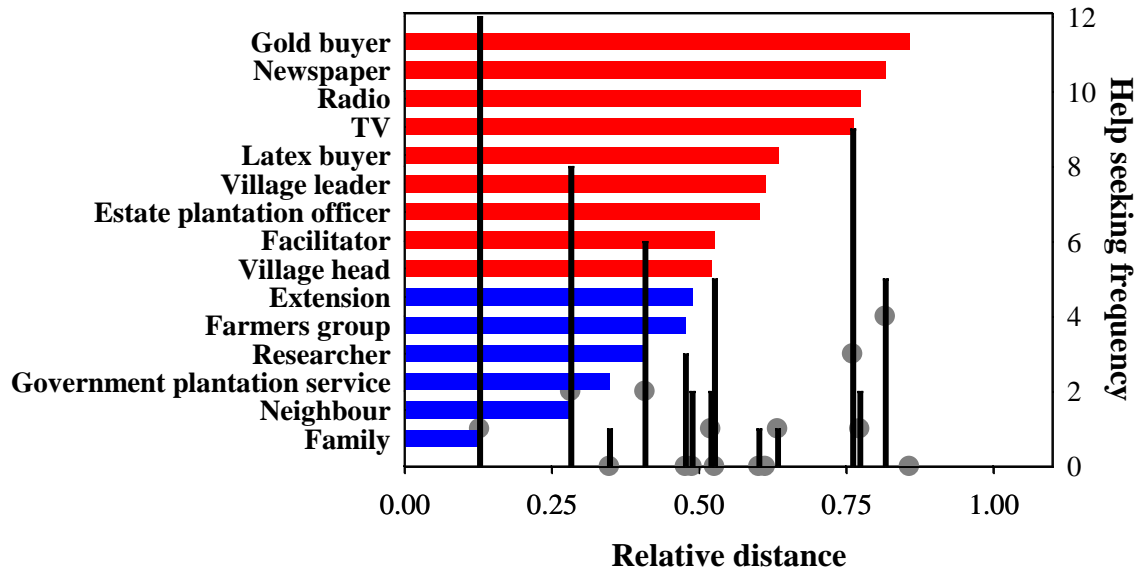


Figure 14. Left y-axis shows sorted sources of information asked by farmers in the quiz game, while x-axis shows their relative distances. The distance was standardised using average from all farmers' sorting results. Boundary was determined by relative distance. When relative distance ≤ 0.50 , information sources were considered as internal sources (blue bars). Inward information seeking (i) from each farmer was calculated based on frequency of help seeking (right y-axis) with internal sources relative to total frequency of help seeking. Black bars show overall frequency of help seeking, while grey circles are individual help seeking frequency from Farmer 05.

Table 9. Frequency of help seeking with information sources at various distances. Relative distance was standardised using average from all farmers' sorting. Grey shaded cells indicate internal boundary.

Source of information	Relative distance	Help seeking frequency									
		Farmer 01	Farmer 02	Farmer 03	Farmer 04	Farmer 05	Farmer 06	Farmer 07	Farmer 08	Farmer 09	Farmer 10
Family	0.13	0	0	0	6	1	1	0	3	0	1
Neighbour	0.28	0	0	0	3	2	1	0	1	0	1
Government plantation service	0.35	0	1	0	0	0	0	0	0	0	0
Researcher	0.41	1	1	0	0	2	0	0	1	0	1
Farmers group	0.48	0	1	0	0	0	1	0	0	0	1
Extension	0.49	0	1	0	0	0	0	0	0	0	1
Village head	0.52	0	1	0	0	1	0	0	0	0	0
Facilitator	0.53	1	1	0	0	0	2	1	0	0	0
Estate plantation officer	0.60	0	0	0	1	0	0	0	0	0	0
Village leader	0.61	0	0	0	0	0	0	0	0	0	0
Latex buyer	0.63	0	0	0	0	1	0	0	0	0	0
TV	0.76	0	1	0	2	3	1	1	0	0	1
Radio	0.77	0	0	0	0	1	0	0	1	0	0
Newspaper	0.82	0	0	0	0	4	1	0	0	0	0
Gold buyer	0.86	0	0	0	0	0	0	0	0	0	0
Individual inward information seeking		0.50	0.57	N/A	0.75	0.33	0.43	0.00	0.83	N/A	0.83
Community inward information seeking		0.56									

4. Discussion: interpreting the results using a simple conceptual model on adoption

4.1. The model

Explanation of the results from the games is discussed in this part using adapted theoretical framework of a simple simulation model on adoption. The adaptation of our theoretical framework from its origin was done through incorporation of memory recall ability (r) of learning agents (*i.e.* farmers) in the model. Moreover, since our purpose is to explore sensible reasons from individual properties, the model was scaled down from community-level into individual-level.

The model was developed using STELLA (Figure 15). In this model, three options of land use systems are provided: the old system, the new system and the alternative system. The old system is a system where many farmers currently adopt it for many years, thus it has reached its maximum performance. The new system is a system that has just been introduced in the community recently, thus there are only few farmers who currently adopt the system and the system is still at early developmental stage. The alternative system is also a new system that has just been introduced in the community. The alternative system differs from the new system with regards to its performance (its benefit value). Therefore, each system is characterised by its maximum performance, its growth rate in its performance and its initial performance.

Farmers use signals from current performance of each system to update their expectation on the benefit values of the system. Information about current system's performance is available either

within internal boundary or within external boundary. If information is available in both boundaries, indicating that the information is available freely as public goods. Farmers compile this information from both boundaries, depending on their inward information-seeking probability (i). This property indicates active information seeking by farmers from passive information sources. Currently, the model has not incorporated active information sources. In constructing the reference for learning, farmers are affected by their ability in memory recall (r). Some farmers may use shorter series of historical data, while others may use longer series in adjusting their current expectation. How much farmers adjust their expectation with regards to the current signals depends on their learning progressiveness (α). Effectiveness of extension to promote a newly introduced system is determined by farmers' exposure to the extension and farmers' perception about extension credibility (ϵ). Finally, farmers allocate their resources based on relative values of each available option and their prioritisation (p). Since the model does not capture limiting factors in adoption due to financial capital, land capital or other physical capitals, simulation results on resource allocation should be interpreted as 'willingness to adopt' or the adoption from knowledge capital point of view.

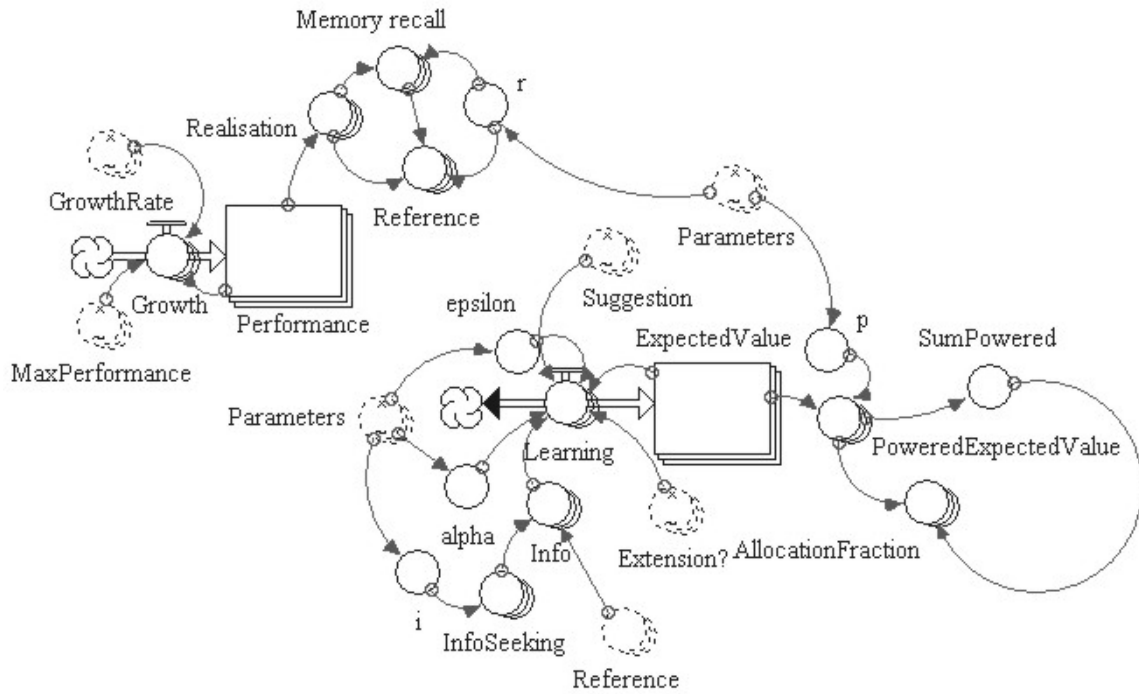


Figure 15. Adapted theoretical framework of the adoption model. In the learning part, the model considers memory recall ability of farmers (r). This adapted model is scaled down from community-level into individual-level.

4.2. Simulation

Parameters resulted by the data analyses as described in Part 3 were used to make simulation (Table 10). For farmers without individual results on prioritisation, p was estimated using community-level average (Farmer 03 and Farmer 09). Additional information is provided to indicate if the farmer is the adopter of improved rubber agroforestry system (RAS) or not. In this case, if farmers are adopters, their exposures to extension in RAS return true.

Table 10. Farmers' properties on adoption used for simulation. Grey shaded cells are the adopters of RAS.

	α	ε	r	p	i	Expose in extension?	Adopter?
Farmer 01	0.62	0.33	2-point moving average	0.65	0.50	TRUE	TRUE
Farmer 02	0.21	0.90	Actual	0.61	0.57	TRUE	TRUE
Farmer 03	0.33	0.89	Actual	0.71	0.56*	TRUE	TRUE
Farmer 04	0.24	0.71	Actual	-0.91	0.75	FALSE	FALSE
Farmer 05	0.42	0.52	Actual	0.20	0.33	FALSE	FALSE
Farmer 06	1.46	0.48	Actual	0.84	0.43	FALSE	FALSE
Farmer 07	2.80	0.25	2-point moving average	0.55	0.00	FALSE	FALSE
Farmer 08	0.72	0.40	Actual	0.71	0.83	FALSE	FALSE
Farmer 09	0.55	0.43	Actual	0.61	0.56*	FALSE	FALSE
Farmer 10	0.34	0.71	Actual	0.82	0.83	FALSE	FALSE

*Community-level

For simulation purpose, the old system and the new system are defined as traditional rubber agroforestry system and improved rubber agroforestry system (RAS) respectively. Alternative systems may represent rubber monoculture plantation systems, oil palm monoculture plantation systems or any other livelihood options that threat the better systems (*e.g.* gold mining, coal mining, logging).

To simulate the 'willingness to adopt' by each farmer, the first simulations were based on two scenarios: (1) if there are only 2 options considered by farmers: the old system and the new system, where the new system performs 50% better than the old system; (2) if there are 3 options considered by farmers: the old system, the new system and the alternative system, where the new system performs 50% better than the old system and the alternative system performs exactly the same as the new system. In both scenarios, information is assumed to be available as public goods in all boundaries.

Table 11 summarises the simulation results in term of resource allocation fraction on the new system at two monitoring points: the first year and the first decade. In this case, Farmer 04 yielded no results, due to its negative p . It is obvious that at the first year after the new system was introduced, the data agree with the model, where farmers who exposed in the extension (Farmer 01, Farmer 02 and Farmer 03) allocated their resources significantly (ranging from 39% to 52%), while others did not allocate their resources to the new option at all. After 10 years, if the performance of the new system from the adopters' plots is recognised by the non-adopters, it should trigger the non-adopters to allocate their resources, as simulated by the model. So, why they did not do it in reality? Is it caused by higher benefit of the alternative systems?

Table 11. Simulated resource allocation fraction on the new system by each farmer at two monitoring points with or without the presence of alternative systems. Grey shaded cells are the adopters of the new promoted system.

Respondents	The first year resource allocation fraction on the new system		Average resource allocation fraction on the new system for the first decade	
	2 options	3 options	2 options	3 options
Farmer 01	0.39	0.39	0.57	0.36
Farmer 02	0.52	0.52	0.49	0.31
Farmer 03	0.47	0.47	0.47	0.29
Farmer 04	N/A due to $p < 0$	N/A due to $p < 0$	N/A due to $p < 0$	N/A due to $p < 0$
Farmer 05	0.00	0.00	0.52	0.34
Farmer 06	0.00	0.00	0.58	0.37
Farmer 07	0.00	0.00	0.41	0.25
Farmer 08	0.00	0.00	0.57	0.36
Farmer 09	0.00	0.00	0.56	0.36
Farmer 10	0.00	0.00	0.57	0.36

To answer above question, sensitivity analyses using scenario 2 were done at 4 values of relative difference between the alternative systems and the new system: 0%, 100%, 200% and 300%. The simulation results were used to estimate elasticity of changes on resource allocation fraction on the new system, as response to changes on relative values of the alternative systems using linear equation. In this case, average resource allocation fraction for the first decade was used. The results are presented in Table 12. It is obvious that to make farmers ignoring the new option at all is at condition where the value of the alternative systems are 6 to 34 times higher than the value of the new system, which is impossible.

Table 12. Estimated elasticity of changes on resource allocation fraction on the new system, as response to changes on the relative values of alternative systems. Grey shaded cells are the adopters of the new promoted system.

Respondents	Slope	Intercept	Intercept/ Slope	R ²
Farmer 01	-0.04	0.35	9	-0.98
Farmer 02	-0.03	0.31	9	-0.99
Farmer 03	-0.03	0.28	9	-0.98
Farmer 04	N/A due to $p < 0$	N/A due to $p < 0$	N/A due to $p < 0$	N/A due to $p < 0$
Farmer 05	-0.01	0.34	34	-0.98
Farmer 06	-0.06	0.36	6	-0.99
Farmer 07	-0.03	0.24	9	-0.97
Farmer 08	-0.04	0.35	8	-0.98
Farmer 09	-0.04	0.35	9	-0.98
Farmer 10	-0.05	0.35	7	-0.98

The only reasonable explanation about why non-adopters were not attracted to adopt the new system a decade after the system was promoted is that they never recognise the current performance (the realisation) of the new system from the adopters. After a decade, the new system was still the few among the many, thus its performance was not fully visible. It is difficult for someone to recognise that few number of their neighbours adopted different technique in their plots among number of many other plots within a complex landscape. In the model, such situation can be simulated so that information about performance of the new system in all boundaries approaches zero (no signals) in every time step.

When farmers could not recognise success stories from the few unless the few exposed the stories to others, thus, to diffuse the knowledge about the new system in more effective way, we should encourage the adopters as active “messengers” of information. Certainly, being a “messenger” means costs for farmers in term of time. But, connecting this issue to rewarding mechanism for

environmental services (*e.g.* RUPES), perhaps the reward can go to farmers who successfully inspire others to adopt environmentally better systems for the landscape.

5. Preliminary conclusion

Things to notice:

- There are no evidence that learning progressiveness (α) per se can determine whether a farmer is an experimenter (an early adopter) or a conservative (a laggard) in an adoption of newly introduced option of a system. Other properties like farmers' perception about extension credibility (ϵ), their exposure to extension, their prioritisation (p), their inward information seeking (i), their memory recall ability (r) and information availability take significant roles on the overall process of adoption. The adoption properties of farmers are in fact independent each other. There is no evidence if low α always corresponds to low r , and so on (see Table 10). Thus, every farmer has the same chance to be the first adopter, no matter what kind of adoption property they have, as long as they recognised the information.
- In fact, effectiveness of information sharing about a new system plays vital role in the adoption process. Misinformation or disinformation about a new system can alter the potential adopters to non-adopters (see Table 10). When a new promoted system is still the few among the many, more effective way in information sharing is highly required. Mechanism to activate the early adopters to be the active messenger of information may help extension efforts in spreading the knowledge in more effective way. The first task in promoting a new option should be done by shifting the few into the many. Once the new system predominated the community, we can rely on the natural adoption processes for the next phases. Unless, the few will always be threatened by the old many or the new many.

Things to extend:

- Farmers may have different ability in memory recall (see Table 2). Actually, applying this parameter from the game-scale into the reality-scale cannot be done directly, like what we applied in Part 4. Not like α , ϵ and p , this parameter is time-scale dependent. Two-point backward in the game does not imply to two-year backward in reality. Thus, it requires other methodologies to measure the scaling rule of memory recall ability.
- To better control the data quality in term of consistency of responses by the farmers, replicate of the same game should be done. If it is impossible due to some reasons, consistency should be checked using other games or other approaches (*e.g.* interview), but with the same purpose.
- Other approaches are required to measure how farmers weigh information from the many compared to how they do it for information from the few. This measure is expected to support explanation of the question in Part 4. Probably, the recognised information is not only affected by how they seek the information and availability of information as such, but also determined by how they select (weigh) the information.
- Conceptual framework of the simulation model at community-level should be adjusted by incorporating varied properties of learning agents. Simplify the community by stratification based on learning progressiveness as such is not feasible.

6. References

Wilensky, U. (1999). NetLogo. <http://ccl.northwestern.edu/netlogo/>. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.

7. Appendices

Appendix 1. Farmers' predictions and computer realisations in yield prediction game without suggestion using 10 sequential steps.

		Playing sequence									
		1	2	3	4	5	6	7	8	9	10
Farmer 01	Prediction	75	48	52	37	24	45	47	81	36	39
	Realisation	41	39	26	58	56	57	30	45	50	46
Farmer 02	Prediction	125	150	200	125	150	100	150	125	125	125
	Realisation	10	96	115	100	0	158	10	224	100	135
Farmer 03	Prediction	52	57	59	45	46	48	80	95	85	90
	Realisation	54	60	31	45	97	100	90	108	122	50
Farmer 04	Prediction	113	103	107	102	93	106	75	85	93	87
	Realisation	94	114	30	71	133	30	92	107	20	62
Farmer 05	Prediction	200	100	120	270	100	95	150	170	200	100
	Realisation	83	134	250	0	195	280	431	313	170	372
Farmer 06	Prediction	500	700	250	600	500	750	300	1000	500	600
	Realisation	414	341	468	671	653	402	724	672	716	526
Farmer 07	Prediction	400	550	2020	800	400	350	800	550	600	850
	Realisation	537	1137	934	586	261	721	606	504	710	433
Farmer 08	Prediction	200	105	120	175	160	200	100	120	200	120
	Realisation	103	169	174	151	240	42	137	197	116	78
Farmer 09	Prediction	130	195	88	225	270	210	125	325	135	175
	Realisation	110	44	254	250	6	335	222	270	355	311
Farmer 10	Prediction	200	200	222	222	242	136	345	222	232	114
	Realisation	0	222	722	468	180	469	167	452	116	301

Appendix 2. Farmers' predictions, computer realisations and suggestions in yield prediction game with suggestion using 10 sequential steps.

		Playing sequence									
		1	2	3	4	5	6	7	8	9	10
Farmer 01	Prediction	47	30	32	29	27	39	27	25	29	31
	Realisation	27	37	24	29	35	7	46	54	65	3
	Suggestion	27	32	29	29	30	27	29	32	32	30
Farmer 02	Prediction	60	125	125	66	100	80	80	77	100	100
	Realisation	100	49	48	132	42	90	78	98	40	146
	Suggestion	100	75	66	82	74	77	77	80	75	82
Farmer 03	Prediction	48	88	40	87	56	105	39	41	47	67
	Realisation	88	25	84	26	104	27	41	42	77	59
	Suggestion	88	56	66	56	65	59	56	55	57	57
Farmer 04	Prediction	85	148	101	103	100	70	79	85	87	88
	Realisation	148	69	96	51	5	116	73	88	89	78
	Suggestion	148	109	104	91	74	81	80	81	82	81
Farmer 05	Prediction	300	354	250	250	150	200	179	160	187	181
	Realisation	324	265	180	73	233	0	154	266	137	92
	Suggestion	324	294	256	210	215	179	176	187	181	172
Farmer 06	Prediction	800	700	800	300	800	500	600	650	700	500
	Realisation	621	1073	415	694	461	463	546	1093	656	566
	Suggestion	621	847	703	701	653	621	610	671	669	659
Farmer 07	Prediction	350	600	300	300	600	350	500	300	700	700
	Realisation	426	265	632	748	133	781	591	925	350	1095
	Suggestion	426	346	441	518	441	497	511	563	539	595
Farmer 08	Prediction	180	42	30	104	80	85	120	94	105	103
	Realisation	42	93	177	66	87	50	147	145	128	204
	Suggestion	42	67	104	94	93	86	94	101	104	114
Farmer 09	Prediction	165	210	311	225	245	200	240	325	95	274
	Realisation	420	156	144	201	48	95	296	283	311	231
	Suggestion	420	288	240	230	194	177	194	205	217	218
Farmer 10	Prediction	157	108	160	216	307	407	272	170	367	331
	Realisation	108	218	321	581	513	364	402	428	796	286
	Suggestion	108	163	216	307	348	351	358	367	415	402

Appendix 3. Relative values from each option as generated by computer in the seedling selection game and farmers' allocation fraction. Estimated prioritisation (p) from each farmer and each replicate and its standard error (se) due to fitting procedure were presented in the right column.

Respondents	Replicate	Relative value allocation fraction								p	se
		Option A		Option B		Option C		Option D			
Farmer 01	1	0.39	0.50	0.14	0.20	0.21	0.10	0.26	0.20	1.663	0.010
	2	0.13	0.10	0.24	0.30	0.33	0.30	0.31	0.30	0.943	0.003
	3	0.01	0.00	0.28	0.40	0.35	0.30	0.37	0.30	0.575	0.008
	4	0.03	0.10	0.36	0.30	0.31	0.30	0.30	0.30	0.449	0.000
	5	0.04	0.30	0.49	0.40	0.35	0.20	0.11	0.10	0.168	0.023
	6	0.00	0.00	0.38	0.40	0.17	0.10	0.45	0.50	1.600	0.000
	7	0.22	0.30	0.18	0.10	0.18	0.10	0.41	0.50	1.501	0.007
	8	0.05	0.10	0.66	0.50	0.22	0.30	0.07	0.10	0.612	0.001
	9	0.22	0.10	0.29	0.30	0.16	0.10	0.33	0.50	3.254	0.002
	10	0.08	0.10	0.49	0.50	0.13	0.10	0.30	0.30	1.047	0.001
Farmer 02	1	0.18	0.20	0.45	0.30	0.25	0.30	0.11	0.20	0.322	0.001
	2	0.12	0.20	0.30	0.30	0.32	0.30	0.25	0.20	0.449	0.002
	3	0.37	0.30	0.34	0.30	0.37	0.20	0.29	0.20	0.773	0.004
	4	0.15	0.20	0.21	0.30	0.36	0.30	0.27	0.20	0.301	0.004
	5	0.15	0.10	0.29	0.40	0.24	0.20	0.32	0.30	1.557	0.006
	6	0.49	0.30	0.32	0.20	0.52	0.30	0.16	0.20	0.418	0.001
	7	0.11	0.10	0.35	0.40	0.27	0.30	0.27	0.20	1.386	0.003
	8	0.15	0.10	0.36	0.40	0.27	0.30	0.22	0.20	1.438	0.001
	9	0.23	0.30	0.22	0.20	0.09	0.10	0.46	0.40	0.758	0.002
	10	0.19	0.20	0.25	0.30	0.34	0.40	0.22	0.10	1.649	0.007
Farmer 03	1	0.18	0.20	0.19	0.20	0.41	0.40	0.23	0.20	0.939	0.001
	2	0.30	0.10	0.17	0.10	0.36	0.50	0.17	0.30	1.190	0.040
	3	0.19	0.30	0.13	0.20	0.36	0.20	0.51	0.30	0.128	0.004
	4	0.33	0.00	0.25	0.00	0.06	0.00	0.36	1.00	102.400	0.000
	5	0.14	0.20	0.35	0.20	0.08	0.10	0.42	0.50	0.855	0.016
	6	0.72	0.40	0.26	0.20	0.42	0.20	0.31	0.20	0.814	0.002
	7	0.14	0.10	0.19	0.00	0.41	0.70	0.26	0.20	2.911	0.005
	8	0.34	0.20	0.03	0.00	0.39	0.70	0.24	0.10	7.486	0.005
	9	0.27	0.20	0.39	0.40	0.17	0.20	0.17	0.20	0.891	0.003
	10	0.32	0.40	0.17	0.10	0.34	0.30	0.16	0.20	1.138	0.007
Farmer 04	1	0.20	0.20	0.40	0.10	0.20	0.20	0.19	0.50	-16.115	0.007
	2	0.29	0.30	0.22	0.20	0.30	0.20	0.20	0.30	-0.220	0.005
	3	0.56	0.20	0.57	0.20	0.18	0.20	0.25	0.40	-0.224	0.013
	4	0.31	0.30	0.28	0.30	0.25	0.10	0.17	0.30	-0.068	0.015
	5	0.27	0.20	0.20	0.30	0.25	0.20	0.29	0.30	-0.437	0.005
	6	0.47	0.20	0.20	0.20	0.56	0.40	0.24	0.20	0.606	0.007
	7	0.21	0.20	0.28	0.20	0.37	0.20	0.13	0.40	-0.828	0.003
	8	0.20	0.20	0.36	0.30	0.26	0.10	0.18	0.40	-0.542	0.023
	9	0.36	0.20	0.15	0.30	0.34	0.20	0.15	0.30	-0.478	0.000
	10	0.10	0.50	0.24	0.10	0.31	0.20	0.35	0.20	-0.991	0.008
Farmer 05	1	0.20	0.10	0.36	0.40	0.11	0.30	0.33	0.20	0.209	0.024
	2	0.28	0.10	0.21	0.20	0.20	0.50	0.32	0.20	-2.736	0.022
	3	0.52	0.40	0.16	0.10	0.41	0.20	0.43	0.30	1.491	0.003
	4	0.34	0.40	0.34	0.20	0.16	0.20	0.16	0.20	0.538	0.01
	5	0.32	0.30	0.34	0.20	0.15	0.40	0.19	0.10	-0.386	0.023
	6	0.39	0.30	0.39	0.20	0.21	0.10	0.40	0.40	1.966	0.009
	7	0.19	0.10	0.33	0.40	0.23	0.20	0.25	0.30	1.948	0.003
	8	0.33	0.40	0.28	0.30	0.16	0.10	0.23	0.20	1.907	0.000
	9	0.11	0.20	0.45	0.30	0.11	0.20	0.33	0.30	0.306	0.002
	10	0.23	0.20	0.18	0.10	0.13	0.20	0.47	0.50	1.127	0.006

Appendix 3. Continued.

Respondents	Replicate	Relative value				allocation fraction				p	se
		Option A		Option B		Option C		Option D			
Farmer 06	1	0.36	0.50	0.25	0.00	0.00	0.00	0.39	0.50	4.417	0.011
	2	0.42	1.00	0.02	0.00	0.22	0.00	0.35	0.00	51.200	0.000
	3	0.35	0.00	0.41	0.40	0.02	0.00	0.57	0.60	2.851	0.025
	4	0.17	0.00	0.32	0.50	0.48	0.50	0.02	0.00	1.349	0.027
	5	0.24	0.00	0.25	0.30	0.32	0.70	0.19	0.00	6.085	0.018
	6	0.50	0.50	0.18	0.00	0.36	0.00	0.47	0.50	5.892	0.012
	7	0.31	0.50	0.20	0.00	0.21	0.00	0.28	0.50	5.094	0.021
	8	0.19	0.00	0.33	0.60	0.18	0.00	0.30	0.40	5.595	0.002
	9	0.22	0.00	0.12	0.00	0.37	0.50	0.30	0.50	2.753	0.029
	10	0.34	0.50	0.26	0.00	0.06	0.00	0.34	0.50	51.200	0.000
Farmer 07	1	0.22	0.30	0.21	0.00	0.13	0.00	0.44	0.70	2.324	0.022
	2	0.21	0.30	0.27	0.40	0.30	0.30	0.22	0.00	1.982	0.034
	3	0.38	0.30	0.36	0.20	0.39	0.30	0.25	0.20	0.897	0.003
	4	0.10	0.00	0.28	0.00	0.31	0.50	0.30	0.50	14.95	0.022
	5	0.29	0.50	0.17	0.50	0.29	0.00	0.26	0.00	-2.124	0.091
	6	0.86	0.70	0.27	0.00	0.18	0.10	0.55	0.20	2.518	0.005
	7	0.18	0.20	0.18	0.00	0.34	0.40	0.30	0.40	2.095	0.013
	8	0.20	0.20	0.26	0.30	0.34	0.40	0.20	0.10	1.724	0.004
	9	0.41	0.00	0.07	0.00	0.51	1.00	0.00	0.00	51.2	0.000
	10	0.35	0.50	0.09	0.00	0.36	0.50	0.20	0.00	5.192	0.002
Farmer 08	1	0.22	0.20	0.39	0.30	0.26	0.30	0.13	0.20	0.418	0.002
	2	0.16	0.20	0.11	0.10	0.56	0.50	0.16	0.20	0.810	0.001
	3	0.53	0.30	0.43	0.30	0.22	0.10	0.35	0.30	0.884	0.005
	4	0.21	0.20	0.34	0.40	0.14	0.10	0.31	0.30	1.468	0.001
	5	0.40	0.40	0.13	0.10	0.24	0.30	0.23	0.20	1.059	0.003
	6	0.34	0.30	0.18	0.10	0.31	0.20	0.51	0.40	1.212	0.002
	7	0.19	0.10	0.35	0.40	0.23	0.30	0.23	0.20	1.535	0.006
	8	0.16	0.20	0.44	0.40	0.24	0.30	0.16	0.10	0.863	0.005
	9	0.32	0.40	0.31	0.40	0.18	0.10	0.19	0.10	2.571	0.000
	10	0.33	0.40	0.12	0.10	0.22	0.10	0.34	0.40	2.278	0.004
Farmer 09	1	0.29	0.30	0.20	0.20	0.14	0.20	0.37	0.30	0.509	0.001
	2	0.22	0.30	0.19	0.20	0.19	0.10	0.41	0.40	1.009	0.007
	3	0.35	0.30	0.39	0.30	0.19	0.10	0.41	0.30	1.324	0.001
	4	0.15	0.10	0.17	0.30	0.14	0.10	0.55	0.50	0.870	0.010
	5	0.27	0.30	0.34	0.40	0.13	0.10	0.26	0.20	1.637	0.002
	6	0.16	0.20	0.41	0.30	0.28	0.20	0.31	0.30	0.485	0.002
	7	0.25	0.20	0.36	0.40	0.26	0.20	0.13	0.20	0.930	0.006
	8	0.14	0.20	0.16	0.20	0.37	0.30	0.33	0.30	0.468	0.000
	9	0.16	0.10	0.21	0.10	0.26	0.40	0.37	0.40	1.477	0.015
	10	0.11	0.20	0.24	0.30	0.30	0.20	0.35	0.30	0.242	0.004
Farmer 10	1	0.24	0.20	0.11	0.10	0.26	0.20	0.39	0.50	1.767	0.002
	2	0.22	0.10	0.15	0.10	0.29	0.30	0.35	0.50	2.693	0.002
	3	0.15	0.10	0.25	0.20	0.44	0.50	0.31	0.20	1.785	0.003
	4	0.33	0.50	0.22	0.20	0.18	0.10	0.28	0.20	2.817	0.006
	5	0.20	0.20	0.19	0.10	0.24	0.20	0.36	0.50	2.050	0.002
	6	0.38	0.20	0.52	0.50	0.30	0.20	0.18	0.10	1.848	0.003
	7	0.13	0.10	0.24	0.20	0.31	0.50	0.32	0.20	1.400	0.025
	8	0.17	0.20	0.43	0.50	0.12	0.10	0.28	0.20	1.273	0.005
	9	0.39	0.50	0.12	0.10	0.26	0.20	0.23	0.20	1.735	0.002
	10	0.21	0.10	0.26	0.20	0.29	0.50	0.24	0.20	5.604	0.003

Appendix 4. Example of questions used for the quiz game.

1. How much is the price of sugar per kg nowadays in your area?
2. How much is the price of kerosene per l nowadays in your area?
3. How much is the price of RRIC100 per seedling nowadays in your area?
4. How much is the price of “*kaki tiga*”(local rubber) per seedling nowadays in your area?
5. How much is the price of urea per kg nowadays in your area?
6. Which months are the months for polio immunisation?
7. Who is the elected *bupati* of Bungo?
8. Do clonal rubbers have higher yield than local rubbers?
9. Are clonal rubbers easier to fall than local rubbers?
10. Which one is not rubber disease?
11. Who is the founder of electrical lamp?
12. In which island is Lore Lindu located?
13. What is the cause of tsunami?
14. What is the raw material to produce turpentine?
15. What does make airplane fly?
16. From where is *degung* originated?
17. From where is *talempong* originated?
18. What is the name of international research centre in agroforestry?
19. What is the name of research centre for rubber in Palembang?
20. What is the name of famous tire company?

Appendix 5. Twenty permuted random patterns used to shuffle reference datasets.

Data	Permuted random																			
	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8	Set 9	Set 10	Set 11	Set 12	Set 13	Set 14	Set 15	Set 16	Set 17	Set 18	Set 19	Set 20
A	A	B	C	D	E	F	G	H	I	J	A	C	E	G	I	B	D	F	H	J
B	C	D	E	F	G	H	I	J	A	B	E	G	I	A	C	F	H	J	B	D
C	E	F	G	H	I	J	A	B	C	D	I	B	B	E	G	J	B	D	F	H
D	G	H	I	J	A	B	C	D	E	F	D	F	F	J	B	C	G	I	A	A
E	I	J	A	B	C	D	E	F	G	H	H	I	A	D	F	G	A	C	E	E
F	J	A	B	C	D	E	F	G	H	I	J	A	C	F	H	I	C	E	G	G
G	H	I	J	A	B	C	D	E	F	G	F	H	H	B	D	E	I	A	C	C
H	F	G	H	I	J	A	B	C	D	E	B	D	D	H	J	A	E	G	I	I
I	D	E	F	G	H	I	J	A	B	C	G	J	J	C	E	H	J	B	D	F
J	B	C	D	E	F	G	H	I	J	A	C	E	G	I	A	D	F	H	J	B