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INCREASING VOLUNTARY WORKING ENTHUSIASM AMONG POORLY RESOURCED FARMERS BY PROMOTING LABOR AND MARKET EFFICIENCY

Abstract. *Smallholder farming offers few incentives to poorly resourced farmers so they will stay on the land and invest more labor in productivity. We data mined results from a comprehensive household survey to study the decision model about increasing farmers' enthusiasm. Farmers' enthusiasm is a positive voluntary behavior (LIIL, larger investments in labor) that can be described by a range of internal and external factors to the household. Here, we built an agent-based model of farmers' voluntary behavior for farmers from the Central Rift Valley region of Ethiopia. Each virtual agent (farmer) in the model was parameterized using the survey data. We conclude that it is better for the new higher productivity knowledge to improve productivity a single time with a large amount of progress than for it to improve productivity several times with small steps. However, the better strategy for investment in market efficiency is small steps of progress each year over a long time period. There are optimal strategies (integrating the two better strategies) to improve farmers' choice of voluntary LIIL behavior.*

Keywords*: Agent based model, Africa agriculture, Farmer decision making, Voluntary behavior, Agriculture strategy.*

JEL Classification: Q18, C15,C63.

1. Introduction

Farming provides employment and livelihood for over 85 percent of the Ethiopian population, which is the main reason why famines are common under widespread droughts (Devereux, 2000). Rainfall variability and land degradation are the main reasons for the low productivity of agriculture and high food insecurity (Garedew et al., 2009). To improve farming performance, much research has been done on potential land use changes, farming strategies, and investment

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strategies for the Central Rift Valley of Ethiopia (Biazin and Sterk, 2013). However, the lack of incentives for farmers to change their ways by adopting more productive practices has been often considered the cause of the failure of rural development efforts (German et al. 2010).

Here, we researched the incentives required for Ethiopian farmers to voluntarily change and adopt more productive practices and technologies. Considering the farming environment of the Central Rift Valley region, a huge increase in yields could be achieved at a high physical price: much more work, such as planting seed in rows instead of tossing handfuls onto the ground (Johnson, 2014). However, those who are currently farmers did not want to be farmers because of the lower incomes from farming, and the lack of adequate jobs in urban areas made Ethiopian farmers keep their farming jobs (Ambaye, 2015). The government needs strategies to improve the enthusiasm of farmers. Of course, improved agronomies are not easy for farmers in undeveloped countries to adopt (Kumar et al., 2015). In this paper, we look at how to improve the adoption of voluntary LIIL (larger investments in labor) behavior for Ethiopian farmers. Here, voluntary LIIL behavior indicates how farmers voluntarily tried to improve their productivity by learning new agronomies and investing more labor in farming. The voluntary behavior was used as a representation of farmers' enthusiasm. Aarts and van Woerkum (2000) identified compulsion and voluntariness as essential psychological principles of control, whereby voluntary behavior was distinguished according to extrinsic and intrinsic motivation. In voluntary mechanisms (such as learning new agronomies and working hard voluntarily), farmers can decide for themselves whether to do it based solely on their ability and willingness (Siebert et al., 2006; Valbuena, 2010). Farmers' decision-making is not similar, however, because of the diversity in their ability and willingness (Valbuena, 2010). Therefore, it is necessary to study the factors underlying farmers' ability and willingness to participate in voluntary mechanisms and to research the process of farmers' decision-making.

Data analysis methods were used to study the factors and an agent-based simulation was used to research the dynamic decision process in this paper. We used an agent-based model to simulate farmers and link the model to dynamic whole farm models (Li et al., 2015). Meanwhile, many fields of agriculture, such as farmer behavior (Ge et al., 2015) and agricultural strategy (Troost et al., 2015), were studied using agent-based simulations.

2. Agent-based model of decision to undertake voluntary behavior

Valbuena (2010) built a generic conceptual modelling framework to simplify and analyze farmers' decision-making. Farm characteristics were divided into two interrelated components: ability and willingness. Ability and willingness were considered objective and subjective factors, respectively, that affected farmers decisions (Siebert et al., 2006). Group pressure and circumstance were related to changes in voluntary behavior (Aarts and van Woerkum, 2000). Based on these theories, we proposed a decision-making model for the voluntary behavior of

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virtual farmers (Figure 1). Here, voluntary behavior means that a farmer increases the productivity of crops through LIIL behavior.

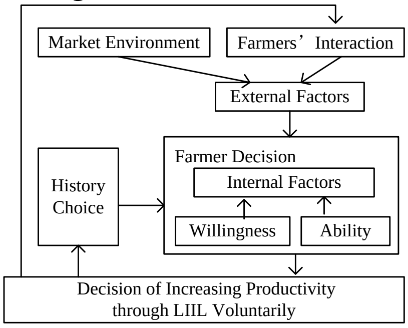

Figure 1. Conceptual framework of farmers' decision model for voluntary LIIL behavior

In the model used in this paper, market environment was considered a circumstance of virtual farmer decision making, and decisions of farmers' friends were proposed to respond to group pressure. The small world model was used as the relationship framework for the virtual farmers. Virtual farmers could influence their friends' decisions through their interactions in the model. Market environment is a parameter (*marketPrice*) that shows the increases in market prices for main crops. The value of "Farmers' Interaction" was calculated by formula (1).

Farmers' interaction = count of farmers choosing voluntary LIIL behavior from friends / total count of friends (1)

For many sociologists, anthropologists and cultural theorists, habits were studied as a factor that influences farmers' behavior (Murdoch and Clark, 1994). We used the historical choices of the farmer as the decision habit in the model. The habit would affect the farmer's decision but not include internal and external factors, as proposed by formula (2).

History choice=times of choosing voluntary LIIL behavior / all decision years (2)

2.1 Willingness

Willingness was considered the combination of subjectively perceived factors that influence a farmer (Siebert et al., 2006). We chose consumption-related variables as factors of willingness and used labor-force-related variables as factors of ability. Socioeconomic factors such as age, income, education and family size significantly determined consumers' willingness to pay (Bett et al., 2013). Education has also been studied to assess farmers' attitude towards the voluntary group marketing of livestock (Kyeyamwa, 2008). Education-related variables were selected in our paper as factors of willingness. Similar to the work of Gailhard and Bojnec (2015), off-farm income was considered a factor of willingness. Table 1 shows the factors for the willingness of virtual farmers' voluntary behavior decision. All variables had a positive correlation with the willingness of virtual farmers.

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Table 1. Factors of willingness for voluntary behavior

Variables Name	Explanation	Classification
education	Education level of farmers	Education related
technology	Technologies used by farmers	Education related
useFertilizersHa	Usage of fertilizers	Education related
consumpEquivalant	Consumption demands	Consumption related
traders	Known of traders	Consumption related
droughtFrequency	Drought frequency	Consumption related
offFarmIncome	Off-farm income	Off-farm income related

Here, we used data from an extensive household survey of 208 households in the Central Rift Valley region (Adami Tulu, Dugda and Meskan) of Ethiopia. The results from the survey have been published elsewhere (Frelat et al., 2016). For ease of analysis, formula (3) was used to conduct normalized processing to the data. x_{new} means the normalized value of x, and x_{max} and x_{min} mean the maximum and minimum values of the variable, respectively.

$$x_{new} = (x - x_{min})/(x_{max} - x_{min}) \tag{3}$$

Using principal component analysis to study the data, three principal components had values larger than 1 and explained more than 50% of the variance (Table 2).

Table 2. Total explained variance of willingness

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.576	22.509	22.509	1.576	22.509	22.509	1.481	21.153	21.153
2	1.188	16.967	39.476	1.188	16.967	39.476	1.264	18.054	39.207
3	1.082	15.459	54.935	1.082	15.459	54.935	1.101	15.728	54.935

Because the first principal component had closer relationships to *education* and *useFertilizersHa*, the paper defined it as "education-based willingness". The second principal component was considered "consumption-based willingness" because of its relationship with *consumpEquivalant*. The third principal component was defined as "environment-based willingness" in the paper.

Table 3. Component score coefficient matrix of willingness

	Component		
	1	2	3
education	0.561	-0.163	0.082
consumpEquivalant	-0.197	0.695	-0.024
traders	0.112	-0.079	0.622
droughtFrequency	-0.055	0.152	0.612
technology	0.182	0.463	0.091
offFarmIncome	0.221	0.225	-0.364
useFertilizersHa	0.485	0.036	-0.013

The component score coefficient matrix was used as a weight for the seven factors when computing farmer's willingness (Table 3). Thus, the three components could be calculated by formulas (4) to (6). Considering the

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significance of the three components for the final results (Table 2), formula (7) was used to calculate the willingness of virtual farmer's voluntary behavior.

$$educationBasedWillingness = 0.561 * education - 0.197 * consumpEquivalant + 0.112 * traders - 0.055 * droughtFrequency + 0.182 * technology + 0.221 * offFarmIncome + 0.485 * useFertilizersHa \quad (4)$$

$$consumptionBasedWillingness = -0.163 * education + 0.695 * consumpEquivalant - 0.079 * traders + 0.152 * droughtFrequency + 0.463 * technology + 0.225 * offFarmIncome + 0.036 * useFertilizersHa \quad (5)$$

$$environmentBasedWillingness = 0.082 * education - 0.024 * consumpEquivalant + 0.622 * traders + 0.612 * droughtFrequency + 0.091 * technology - 0.364 * offFarmIncome - 0.013 * useFertilizersHa \quad (6)$$

$$willingness = (0.23 * educationBasedWillingness + 0.17 * consumptionBasedWillingness + 0.16 * environmentBasedWillingness)/0.55 \quad (7)$$

This paper used the Kolmogorov–Smirnov (K–S) test to analyze all variables and found that only*consumpEquivalant*had a normal distribution. The other variables' distributions were not Normal, Uniform, Poisson or Exponential. As the value of Asymp. Sig. (2-tailed) was only 0.175, the normal distribution was not used to explain*consumpEquivalant*. The distribution table (Table 4) was used to explain the seven variables related to willingness. The data in Table 4 indicate the probability that the variable's value is in the range of the first line. All values were computed from the survey data. Table 4 was used to generate the attributes of the virtual farmers.

Table 4. Distribution table of the seven variables related to willingness.

Ranges / Variables	[0]	(0, 0.1]	(0.1, 0.2]	(0.2, 0.3]	(0.3, 0.4]	(0.4, 0.5]	(0.5, 0.6]	(0.6, 0.7]	(0.7, 0.8]	(0.8, 0.9]	(0.9, 1]
education	0.38	0.05	0.06	0.09	0.16	0.06	0.06	0.09	0.03	0	0.02
consumpEquivalant	0	0.01	0.14	0.22	0.22	0.23	0.10	0.02	0.03	0.01	0
traders	0.07	0.32	0.38	0.14	0.05	0.01	0.01	0.01	0	0	0.01
droughtFrequency	0.03	0	0.18	0.23	0.28	0	0.12	0.11	0.03	0.01	0
technology	0.13	0	0.26	0	0.33	0	0.16	0.06	0	0.05	0
offFarmIncome	0.22	0.66	0.07	0.02	0.01	0	0	0	0	0	0
useFertilizersHa	0.37	0.51	0.10	0.01	0	0	0	0	0	0	0

2.2 Ability

Ability, in contrast to willingness, referred to the factors that influence the individual farmer, including farm holding and the bio-geographical conditions of the farmland (Siebert et al., 2006). Variables related to age and farm size were considered the ability to influence willingness (Bett et al., 2013). Farmer revenue and age were used to study farmers' risk perception (van Duinen et al., 2015) and to describe farmers' ability in our paper. Labor income was applied as indicators for sustainability of small-size dairy farms (Chand, et al, 2015). Age, experience, property size and herd size were considered to indicate farmers' ability (Greiner,

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2015). Table 5 shows the factors related to the farmers' ability to make voluntary behavior decisions according to previous works.

Table 5. Factors of ability for voluntary behavior

Variables Name	Explanation	Classification
yearsOfGrowingMaize	Experience of growing	Experience related
age	Age	Experience related
totalHouseHoldSize	Household size	Labor related
labourEquivalant	Labor force	Labor related
farmArea	Size of soils	Labor related
fractionOfGoodSoils	Fraction of good soils	Labor related
tropicalLivestockUnits	Units of livestock	Labor related
distanceToOutputMarket	Distance to output market	Location related
distanceToWater	Distance to water	Location related
distanceToFields	Distance to fields	Location related
distanceToSeedMarket	Distance to seed market	Location related
totalLivestockIncome	Livestock income	Financial related
totalCropIncome	Crop income	Financial related
totalAssetValue	Total asset	Financial related

For ease of analysis, formula (3) was used to conduct normalized processing of the data. As the four location-related variables (*distanceToOutputMarket*, *distanceToWater*, *distanceToFields*, *distanceToSeedMarket*) had a negative correlation with farmers' ability, the paper used formula (8) instead of formula (3) for the normalized processing of the four variables.

$$x_{new} = 1 - (x - x_{min})/(x_{max} - x_{min}) \tag{8}$$

Based on normalized survey data, the five principal components had values larger than 1 and explained more than 50% of the variance (Table 6).

Table 6. Total explained variance of ability

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumu-lative %	Total	% of Variance	Cumu-lative %	Total	% of Variance	Cumu-lative %
1	2.926	20.897	20.897	2.926	20.897	20.897	2.149	15.351	15.351
2	2.059	14.71	35.607	2.059	14.71	35.607	2.11	15.071	30.422
3	1.592	11.373	46.98	1.592	11.373	46.98	1.915	13.677	44.098
4	1.235	8.821	55.8	1.235	8.821	55.8	1.438	10.273	54.371
5	1.025	7.321	63.121	1.025	7.321	63.121	1.225	8.75	63.121

We defined the first principal component as "Labor ability" because of the large weights of *totalHouseHoldSize* and *labourEquivalant*. "Experience ability" was used as the second component. Considering the weights of *totalCropIncome* and *totalAssetValue*, we called the third principal component "Financial ability". "Market convenience ability" and "Field convenience ability" were suggested for the fourth and fifth principal components, respectively, based on the weights of *distanceToOutputMarket*, *distanceToSeedMarket*and *distanceToFields*.

Table 7. Component score coefficient matrix of ability

	Component				
	1	2	3	4	5
yearsOfGrowingMaize	-0.096	0.466	-0.008	-0.052	-0.063
totalHouseHoldSize	0.380	0.054	0.009	0.037	0.218
labourEquivalant	0.333	0.134	0.001	0.109	0.211
farmArea	0.187	-0.045	0.069	0.060	-0.322

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tropicalLivestockUnits	-0.068	0.024	0.257	0.056	-0.260
distanceToOutputMarket	0.081	-0.091	-0.003	0.519	0.241
distanceToWater	-0.354	0.139	0.088	0.051	0.020
distanceToFields	0.092	-0.061	0.040	0.017	0.667
fractionOfGoodSoils	0.162	-0.044	-0.132	0.458	-0.172
totalLivestockIncome	0.214	-0.044	-0.082	0.047	-0.173
totalCropIncome	-0.103	-0.007	0.494	0.000	0.024
totalAssetValue	-0.046	-0.025	0.465	-0.103	0.161
age	-0.082	0.470	-0.025	-0.032	-0.099
distanceToSeedMarket	-0.177	0.087	0.112	0.444	-0.092

Table 7 shows the score coefficient matrix of the five principle components. Based on the data, the paper used formulas (9) to (13) to compute the five components for virtual farmers. Considering the contributions of the five principle components (Table 6), formula (14) was proposed to calculate the ability of virtual farmers.

$$labor\ ability = -0.096 * yearsOfGrowingMaize + 0.38 * totalHouseHoldSize + 0.333 * labourEquivalant + 0.187 * farmArea - 0.068 * tropicalLivestockUnits + 0.081 * distanceToOutputMarket - 0.354 * distanceToWater + 0.092 * distanceToFields + 0.162 * fractionOfGoodSoils + 0.214 * totalLivestockIncome - 0.103 * totalCropIncome - 0.046 * totalAssetValue - 0.082 * age - 0.177 * distanceToSeedMarket \tag{9}$$

$$experience\ ability = 0.466 * yearsOfGrowingMaize + 0.054 * totalHouseHoldSize + 0.134 * labourEquivalant - 0.045 * farmArea + 0.024 * tropicalLivestockUnits - 0.091 * distanceToOutputMarket + 0.139 * distanceToWater - 0.061 * distanceToFields - 0.044 * fractionOfGoodSoils - 0.044 * totalLivestockIncome - 0.007 * totalCropIncome - 0.025 * totalAssetValue + 0.47 * age + 0.087 * distanceToSeedMarket \tag{10}$$

$$financial\ ability = -0.008 * yearsOfGrowingMaize + 0.009 * totalHouseHoldSize + 0.001 * labourEquivalant + 0.069 * farmArea + 0.257 * tropicalLivestockUnits - 0.003 * distanceToOutputMarket + 0.088 * distanceToWater + 0.04 * distanceToFields - 0.132 * fractionOfGoodSoils - 0.082 * totalLivestockIncome + 0.494 * totalCropIncome + 0.465 * totalAssetValue - 0.025 * age + 0.112 * distanceToSeedMarket \tag{11}$$

$$market\ convenience\ ability = -0.052 * yearsOfGrowingMaize + 0.037 * totalHouseHoldSize + 0.109 * labourEquivalant + 0.06 * farmArea + 0.056 * tropicalLivestockUnits + 0.519 * distanceToOutputMarket + 0.051 * distanceToWater + 0.017 * distanceToFields + 0.458 * fractionOfGoodSoils + 0.047 * totalLivestockIncome + 0 *$$

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$totalCropIncome - 0.103 * totalAssetValue - 0.032 * age + 0.444 * distanceToSeedMarket$ (12)

$field\ convenience\ ability = -0.063 * yearsOfGrowingMaize + 0.218 * totalHouseHoldSize + 0.211 * labourEquivalant - 0.322 * farmArea - 0.26 * tropicalLivestockUnits + 0.241 * distanceToOutputMarket + 0.02 * distanceToWater + 0.667 * distanceToFields - 0.172 * fractionOfGoodSoils - 0.173 * totalLivestockIncome + 0.024 * totalCropIncome + 0.161 * totalAssetValue - 0.099 * age - 0.092 * distanceToSeedMarket$ (13)

$ability = (0.21 * labor\ ability + 0.15 * experience\ ability + 0.11 * financial\ ability + 0.09 * market\ convenience\ ability + 0.07 * field\ convenience\ ability)/0.63$ (14)

The Kolmogorov–Smirnov (K–S) test was used to test the fourteen variables related to ability, and none of variables’ distributions were Normal, Uniform, Poisson or Exponential. Based on the survey data, the distribution values of the fourteen variables are given in Table 8. The values of virtual farmers related to the fourteen variables were generated by the distribution table.

Table 8. Distribution table of factors related to ability

Variables \ Ranges	[0]	(0, 0.1]	(0.1, 0.2]	(0.2, 0.3]	(0.3, 0.4]	(0.4, 0.5]	(0.5, 0.6]	(0.6, 0.7]	(0.7, 0.8]	(0.8, 0.9]	(0.9, 1]
yearsOfGrowingMaize	0	0.16	0.21	0.26	0.11	0.08	0.09	0.05	0.02	0.01	0.01
totalHouseHoldSize	0	0.01	0.05	0.24	0.15	0.31	0.11	0.06	0.02	0.03	0.01
labourEquivalant	0	0.02	0.36	0.21	0.13	0.11	0.07	0.04	0.03	0.01	0.02
farmArea	0.01	0.47	0.30	0.12	0.05	0.02	0	0	0	0	0.01
tropicalLivestockUnits	0.07	0.82	0.02	0	0.04	0.01	0	0	0	0.01	0
distanceToOutputMarket	0	0	0.02	0	0.06	0.01	0.25	0.19	0.08	0.21	0.17
distanceToWater	0	0	0	0	0	0	0.01	0.02	0.01	0.06	0.89
distanceToFields	0	0	0	0	0	0	0.01	0.02	0.04	0.22	0.69
fractionOfGoodSoils	0.53	0	0.02	0.04	0.03	0.05	0.03	0.01	0.01	0.03	0.23
totalLivestockIncome	0.28	0.45	0.18	0.05	0.01	0.01	0	0	0	0	0.01
totalCropIncome	0.15	0.80	0.03	0	0	0	0	0	0	0	0
totalAssetValue	0	0.93	0.02	0.01	0.01	0.01	0	0	0	0.01	0
age	0	0.02	0.12	0.23	0.21	0.12	0.09	0.13	0.05	0.01	0.02
distanceToSeedMarket	0	0	0	0	0	0	0.06	0.07	0.07	0.25	0.53

3. Basic process of the simulation model

The simulation model consists of four main modules: Initialization, Compute Decision Value, Make Decision and Update Income (Figure 2). After the Initialization was performed, the major loop of the four modules was repeated in time (the model's time step was one year). The simulation was stopped by pressing the Stop button on the model interface.

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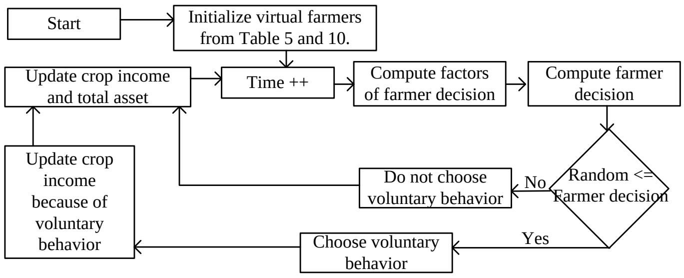

Figure 2. Simulation process of the agent-based model

The Initialization module was based on the distribution values of different variables from the survey data. Each virtual farmer has 21 attributes (7 factors in Table 4 and 14 factors in Table 8). For example, the process of setting a value for *yearsOfGrowingMaize*in Table 8 for a virtual farmer is as follows: (i) generate a random value (such as 0.24) between 0 and 1; (ii) choose the range of (0.1, 0.2] because (0+0.16)<0.24<=(0+0.16+0.21); and(iii) use a random value in the range of (0.1, 0.2] to set *yearsOfGrowingMaize*. Formulas (1) to (14) were used for the module of Compute Decision Value. If a virtual farmer had a larger result from Compute Decision Value, then the farmer had a higher probability of choosing voluntary behavior to increase his productivity.

The process of Make Decision is as follows: (i) generate a random value between 0 and 1; and (ii) if the random value is less than or equal to the value of the farmer's decision, the virtual farmer chooses the voluntary behavior in this year; otherwise, the virtual farmer does not choose the voluntary behavior in this year.

The updated Income module was not the same for the virtual farmers who did or did not choose the voluntary behavior. The farmers who chose voluntary behavior had additional incomes compared with the farmers who did not choose voluntary behavior. The value of the additional income was the same for the result of the voluntary behavior. At the end of each year, virtual farmers updated their crop incomes and total assets according to the results for the year. The model assumed that the crop income and total assets of the virtual farmer remained stable if the market price was not changed and the voluntary behavior was not chosen. Thus, only market price and voluntary behavior could affect the income and assets of virtual farmers. All of the other factors in Table 4 and 10 were not changed after beginning the simulation.

4. Validity of the simulation model

The values of most variables were set according to Table 4 and 8. The weights of internal factor, external factor and history choice could not be determined using the survey data. Thus, the basic values of market increase and contribution of voluntary behavior were designed in the model.

Because we surveyed 203 households in the Central Rift Valley, this paper defined 203 virtual farmers in the simulation model. Since the small world model was used for the relationships of virtual farmers, the paper set the value of average

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connections for virtual farmers first. Based on the survey data, the average household size was 6.95, and the average kinship was 21.9. Thus, the average number of connections in the simulation was 3 (21.9/6.95=3.15). AnyLogic 6 Professional was used to build the model, and we also tested many values for weights of different factors and found a group of significant weights, as shown in Figure 3.

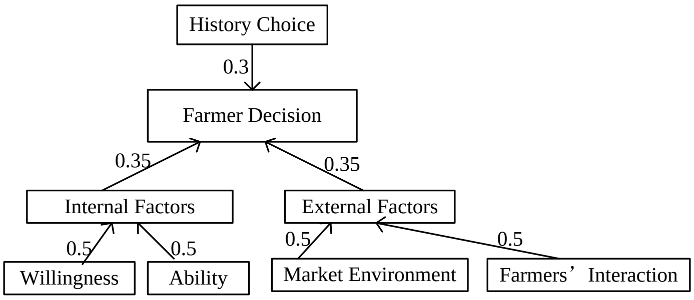

Figure 3. Weights of factors

Different decisions of farmers based on Figure 3 would cause different yields in the model. If the model kept the market prices stable, the increase of crop yields was the same as that observed for crop income. This paper used the increased data of Ethiopia's main crop yields to show the validity of weights in Figure 3. Considering the 2014 report on area and production of major crops (http://www.csa.gov.et/), it is found that the increase in yield was approximately 7% for main crops in Ethiopia from 2011 to 2014. All experiments in this paper were simulated five times, and error bars are shown in the following figures.

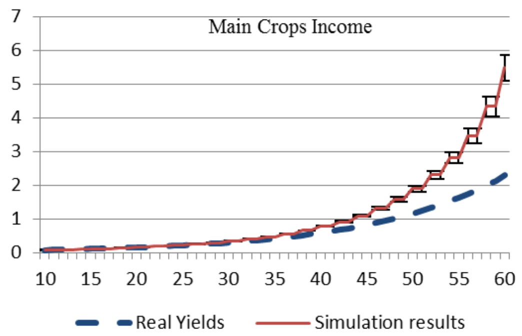

Figure 4. Comparison of increases between simulation and real world

It was found that the simulation could reach a stable status after 10 years of simulation. The group of virtual farmers changed to another status after 40 years. The stable period of the group was between approximately 10 and 40 years. The period from 10 to 30 years was thus used as the research period in this paper because of the stable status. Figure 4 shows that the increase in yields (average increase of farmers) from 10 to 30 years was similar to that observed in the real world (7% increase). This means that the simulation model is valid for at least 10

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to 30 years. All experiments presented below were studied in this simulation period.

5. Scenarios

Louhichi and Paloma (2014) proposed three support policies to improve agricultural yields: (i) increasing the support of agricultural inputs, training and mechanization; (ii) facilitating the use of new agronomy; and (iii) improving the infrastructure and other aspects. Based on previous studies, we proposed scenarios considering the two most important factors: Efficiency of Voluntary Behavior and Efficiency of Market. Here, Efficiency of Voluntary Behavior means how many farmers' income could be increased by choosing voluntary behavior each year. The government could invest in higher labor force efficiency knowledge (such as new agronomy, crops, or rotation schedules) to improve the efficiency of voluntary LIIL behavior. After receiving the knowledge training, an example farmer in Ethiopia would have a yield of 5.5 to 6 tons per acre compared with the previous yield of approximately .8 to 1 ton per acre (Johnson, 2014). We assumed that there were seven types of increase in the farmers' yields in this scenario to show the influence of training. Efficiency of Market means that the government (or some organizations) invests in the infrastructural construction of the market. The prices of crops could be increased by this investment (e.g., roads, auction). The scenarios included the following:

(i) Scenario of Voluntary Behavior Efficiency: The efficiency of voluntary behavior was increased by 1% to 5%, with a step of 1%, after 10 years. In this scenario, 1% means that the value increased by 1% per year. Two other experiments for this scenario were designed: (a) A farmer could obtain double yields only one time, even if he chose voluntary behavior many times (+100% only once). (b) A farmer could obtain double yields if he chose voluntary behavior (+100% multiple times).

(ii) Scenario of Market Efficiency: The net income of main crops on the market was increased by 1% to 5%, with a step of 1%, after 10 years. Another experiment for this scenario was to increase the net income of main crops to double in the 10th year and then remain stable in the simulation (+100% at 10 years).

(iii) Scenario of Voluntary Behavior and Market Efficiency: The efficiency of voluntary behavior and the net income of main crops were increased by 1% to 5%, with a simultaneous step of 1%, after 10 years. It was also supposed that net income was increased by 1% and that farmers could obtain double yields only one time (+100% only once). This experiment was defined as "+1%+100% only once".

6. Simulation results

Based on the valid model, the model was first used to study the scenario of Voluntary Behavior Efficiency. The baseline in the following figures refers to the valid model without any adjustment. The main crops' incomes (average value of all virtual farmers) are shown in Figure 5(a). If the additional yield of voluntary behavior increased by 1% per year (Yield 1% in Figure 5(a)), the average incomes could be increased accordingly, with small values. If farmers could get double

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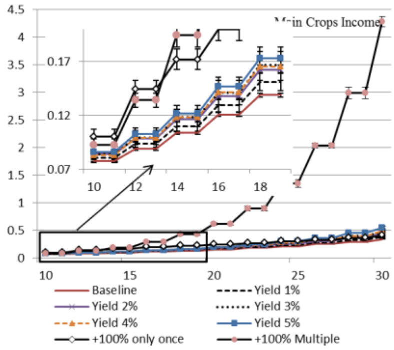
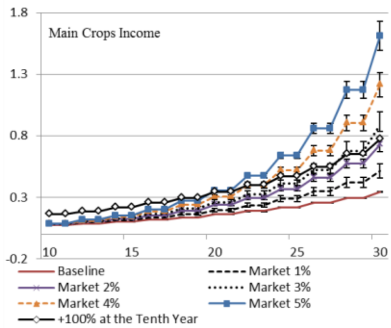
yields with voluntary behavior (+100% multiple), the virtual group would obtain the maximum profits. Meanwhile, the income of experiment (a) was similar to that of experiment (b) in the first five years.

As the count of farmers with voluntary behavior exhibits a large fluctuation in the simulation, we compared the change of the first and last five years of the simulation (Table 9). If we increased the efficiency (yield) of voluntary behavior, more virtual farmers would choose voluntary behavior compared with Baseline. The best way was the last experiment (+100% multiple), but it is difficult to realize in reality. It is possible to train farmers with new agronomy or new crops to increase their yield in Ethiopia, as shown by the experiment of +100% only once.



(a) scenario i.



(b) scenario ii.

Figure 5. Main crop income (average) in scenario i and ii

Table 9. Average counts of voluntary farmers in the first scenario

	10^{th} to 15^{th}	25^{th} to 30^{th}	Increase
baseline	68.68	69.2	1%
+1%	68.76	72.64	6%
+2%	66.76	72.04	8%
+3%	69.6	71.96	3%
+4%	65.6	71.64	9%
+5%	70.28	74.04	5%
+100%only once	66.48	73.88	11%
+100%multiple	63.96	82.12	28%

The results of Scenario (ii) are shown in Figure 5(b) and Table 10. If we increased the market price by 100% in the 10th year (Experiment +100% at 10 years), the virtual group would get the best result from the 10th to 20th years in the simulation. After 20 years in the simulation, the increase of voluntary farmers was the worst for the experiment of +100% at 10 years. To realize the experiment of +100% at 10 years in practice, many investments would be used by the 10th year. For the experiment with an increase of 1% in each year (Market 1% in Figure 5(b)), fewer investments were needed each year in the real world.

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Table 10. Average counts of voluntary farmers in the second scenario

	10^{th} to 15^{th}	25^{th} to 30^{th}	Increase
baseline	68.68	69.2	1%
+1%	67.56	74.76	11%
+2%	69.08	74.24	7%
+3%	70.72	78.16	11%
+4%	71.56	84.68	18%
+5%	71.92	79.52	11%
+100%at 10^{th}	70.24	74.12	6%

Scenario (iii) studied the integration of Scenarios (i) and (ii). Market & Yield 1% in Figure 7 indicates that the market price and yield of crops were increased 1% per year. The experiment of "+1%+100% only once" was the lowest cost project, if we want to realize Scenario (iii) in Ethiopia. It was found that farmers could get the maximum profits in the first years of the simulation. The experiment was better than Baseline and Market & Yield 1%, even in the last year of simulation. The increase in virtual farmers choosing voluntary behavior was better than obtained in most of the experiments (Table 11).

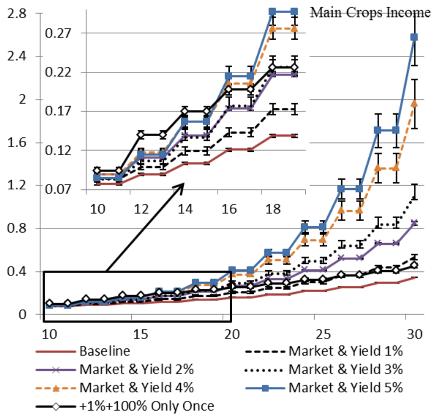

Figure 7. Main crop income (average) of the third scenario

Table 11. Average count of voluntary farmers in the third scenario

	10^{th} to 15^{th}	25^{th} to 30^{th}	Increase
baseline	68.68	69.2	1%
+1%	66.2	75.04	13%
+2%	67.56	78.56	16%
+3%	71.48	76.28	7%
+4%	70.48	78.28	11%
+5%	68	83.88	23%
+1%+100%only once	66.8	75.28	13%

7. Discussion

The paper modeled farmers in the Central Rift Valley of Ethiopia with agent-based simulation. In contrast to the previous works that used one variable to

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describe farmers' ability or willingness (Valbuena, 2010; Siebert et al., 2006), we used seven and fourteen factors to describe farmers' ability and willingness. The results showed that virtual farmers had many of the same attributes with farmers in the real world. Louhichi and Paloma (2014) found that the policy would influence farm productivity and boost household income. The results (Figures 7, 8, and 9) showed that the average income was influenced by different scenarios. The cumulative effects of individual farmer's decisions affected the resulting incomes at the group level (Morgan and Daigneault, 2015). The results of Scenario (ii) showed the cumulative effects of farmers' decision on voluntary behavior. The results of Scenario (i) and (iii) showed the cumulative effects of voluntary behavior and market prices. Kumar et al. (2015) proposed that it was difficult for the adoption behavior to improve the use of technologies in developing countries. The results (Tables 11, 12, and 13) indicated that fewer farmers chose voluntary behavior, even if doing so would benefit these farmers. The voluntary adoption of new agronomy was influenced by a farm's many factors (Gachango et al., 2015). Most farmers would not change their attitudes about voluntary behavior according to different conditions (changed efficiency of behavior and market) in our paper too. Yazdanpanah et al. (2015) revealed that farmers' voluntary behavior was influenced by self-efficacy and behavioural outcome expectancy. The results of our paper showed that a higher crop income will increase the probability of choosing voluntary behavior. Meanwhile, virtual farmers with more assets (high self-efficacy) had higher probabilities of choosing the voluntary behavior.

8. Conclusion and future research

Agent-based simulation was used to determine the working enthusiasm of farmers in the Central Rift Valley. We can draw the following four conclusions based on the model. (i) Education level, consumption requirement, and drought frequency were the most important factors for farmers' willingness to choose voluntary behavior. Farmers' ability to choose voluntary behavior was affected mostly by the years of experience, age, household labor forces, household income and assets, and distance to market and fields. (ii) To increase the number of farmers with voluntary LIIL behavior, it was better that the new knowledge (such as agronomy, crops, or rotation schedules) improve productivity one time with a large step than for it to improve productivity many times with small steps. (iii) Long periods of increase (1% per year, lower investment) in market infrastructure had more significance to farmers in terms of choosing voluntary behavior than did a one-time bigger investment (higher investment in the first year). (iv) The results of using better strategies in Scenarios (ii) and (iii) at the same time were smaller than a simple sum of using the two strategies separately. Of course, the results of integrating the two better strategies simultaneously were better than the results of implementing only one strategy if there was a large enough budget. The government should invest in the better strategy in Scenarios (ii) or (iii) separately if they do not have enough funding.

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The proposed approach has room for improvement, namely, the need to account for real-world situations (different rural environments). The influence of dynamic crops' prices is another topic for future research. Thus, the current work can serve as a first step in the further development in the field of enhancing farmers' working enthusiasm.

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