Development of an Agent-Based Model for Weather Forecast Information Exchange in Rural Area of Bahir Dar, Ethiopia

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Abstract: Smallholder farmers in Ethiopia are vulnerable to climate change impacts due to their low adaptive capacity and dependence on rainfed agriculture. Thus, a successful weather forecast system may bring significant economic and social value to the community. The main objectives of this study were to identify the key information exchange agents, understand the information flow path, rank the relative importance of the different information dissemination pathways, and determine weather forecast adoption. We conducted a household survey in five villages of Rim Kebele in Bahir Dar area and found that farmers communicate with four main agents with regard to information exchange. We developed an agent-based model to learn the adoption rates of weather forecast information. Agriculture extension agents were found to be the most influential members of the community. Farmers’ communicating with neighboring village farmers showed higher adoption. Our results show at least twice that improvements in communication network attain higher adoption rates. Radio has also demonstrated positive uptake of information. We also found that forecast accuracy of 70% is sufficient to achieve high adoption rates. Our findings might help decision-makers recognize critical information flow pathways and their relative importance, and identify barriers to disseminating weather forecast information in the community.

Keywords: weather forecast information; dissemination of seasonal forecast; agent-based modeling; climate change

1. Introduction

Water resources management needs improvement to alleviate poverty, food insecurity, and socioeconomic development in Africa [1]. Ethiopia is often considered as East Africa’s water tower [2] within the Blue Nile Basin, which provides about 62% of Nile river flow (50 km³/year) but only utilizes under 1 km³/year. Underuse of its total generated water flows offers potential for additional water resources development and utilization [1]. Climate change is escalating the country’s vulnerability to drought and flood as the temperature increases and rainfall becomes more erratic [3]. Smallholder farmers are sensitive to climate variability and are among the worst hit due to their low adaptive capacity to climate change and dependence on rainfed agriculture [4]. There is a link between rainfall and agricultural productivity in Ethiopia [5]. For this reason, a successful seasonal forecast system may bring significant economic and social value to the rural community of Ethiopia [3]. Seasonal forecasts are suited for rainfed farming systems [6,7] and can improve the livelihoods of farmers in regions of high inter-annual rainfall variability [8,9], improve agricultural productivity [10], and sustain rural competitiveness and development [11,12]. Seasonal forecasts are available for temperature and rainfall in a number of regions developed by National Meteorological Agencies or Services. Each country adjusts these regional forecasts based on their local data to create their own climate forecasts [13]. Followed by frequent droughts during the 1970s and 1980s in Ethiopia, the Ethiopian National
Meteorological Services Agency (NMSA) has developed various seasonal forecasts [3]. This has enabled farmers to have access to weather information to make better farming decisions [14,15]. However, having access to the information is not sufficient. Forecast accuracy and skills are also relatively important to build up trust in weather forecast information. Forecast skill is a measure of prediction accuracy of an observation [16]. This skill of seasonal climate prediction has been improved during recent decades [17,18].

Humans would not be able to confront the complexities of everyday life [19] without trusting each other [20–22]. The concept of trust is vital in communication when the purpose is to convince farmers to adopt weather forecast information [23]. Building farmers’ trust in the seasonal forecast is difficult because of relatively poor and risk-averse farmers who cannot bear the risk of using the “wrong forecast” [24,25]. Lack of trust in the data is a significant barrier to the effective uptake and use of seasonal forecast information which is often ineffectively communicated to the users [26]. The trust that farmers have in a forecast is determined by forecast skill and the status of the communicator in the community [27]. Improved credibility may rely on improved forecasts, better data and better communication from respected sources [28].

Forecast accuracy is the percentage of time that the forecast and actual rainfall are in agreement [28]. In one study, the Ziervogel et al. model [28] simulates a 50-year time series of grain storage under three different cases: when the forecast is correct, when there is no forecast, and for forecast failure. This study shows that poor forecasts can be damaging and lead to a grain deficit. Their study concludes that the forecasts must be correct more than about 60–70% of the time to benefit farmers in South Africa. As forecast skills increase, trust and agricultural income also increase in rainfed dependent communities. This suggests that a failure of weather forecasts over time might cause farmers to lose confidence in the forecasts and this impacts agricultural productivity. A sensitivity analysis of forecast skill indicates that, as forecast skill increased to 70%, the farmers’ net agricultural income and trust in the forecast both increased in Sri Lanka [29]. Stigter [30] considered 70% of weather forecast accuracy a failure, and Berry et al. [31] found that a moderate level of forecast skill, 55–65%, is considered potentially useful for adoption in South America. Changing forecast skills over longer periods of time can affect the adoption of forecasts [32]. If forecast accuracy falls below skill level, e.g., for five or more years, this can hamper the propensity of farmers to adopt and maintain trust. Ash et al. [33] found that forecasts of 70% accuracy are required for users to widely adopt seasonal forecasts in Australia.

On the other hand, it is difficult to assess the impacts of weather forecasts because they are not widely used currently in developing countries [34]. Crop management models have been used to assess the impact of seasonal forecasts [35,36]. Yet assessing the impact of weather forecasts requires the study of complex social and environmental systems.

The agent-based model (ABM) has been applied in an array of domains [37], but it is a relatively new approach in agriculture to study farmer-environment relationships and to improve weather forecast assimilation and agricultural productivity. ABM is a computational model that tries to simulate human behavior in order to communicate weather forecasts among users. Agents, households, or other entities interact by a set of logical rules, having unique characteristics for each agent in a confined environment [38]. ABM can facilitate the evaluation of seasonal forecast adoptions by linking social science interests to natural systems [39]. It can also be used to couple crop, climate, and social factors to explore the impact of seasonal forecast use and adaptation strategies [28]. It has been stated [40] that ABM has been proved to be an effective instrument for complex, coupled human/engineered/environmental systems.

The main objectives of this paper are to (1) identify the key information exchange agents, (2) gain an understanding of the key information flow pathways by which the forecast might be disseminated and shared, (3) rank the relative importance of the different pathways, (4) identify barriers to forecast adoption and (5) explore ways to optimize forecast adoption. In this study, an agent-based model was developed based on a field survey of households at the village level to assess the impact of seasonal forecast use by
smallholder farmers in Bahir Dar, Ethiopia. We consider farmers’ initial weather forecast information use and characteristics, their options in reacting to forecasts, and how much they trust weather forecast information.

2. Materials and Methods

2.1. Description of the Study Area

Rim Kebele (a Kebele is the smallest administrative unit in Ethiopia) was chosen for this study, located in Mecha Woreda, West Gojam Zone of Amhara Region, Ethiopia [41] (Figure 1). The choice of Rim Kebele was based on the socio-physical characteristics of the farming systems and the agro-ecological setting. Almost all farmers in Kebele practice rainfed agriculture (Table A1). Rainfed agriculture is the main source of sustenance of 90% of the population in Ethiopia [42].

Figure 1. Location map of Rim Kebele in Ethiopia. Rim Kebele is in the West Gojam Zone of Amhara Region. The study was conducted in 5 sampled villages of Rim Kebele.

Rim Kebele has a total of 18 villages, and for this study the National Science Foundation Partnership for International Research and Education (PIRE) project research team randomly selected five villages with kebele representatives; Angut-Mahal, Cheba-1, KoRim, Sendi, and Dima villages were sampled for this study (Table A1).

2.2. Sampling and Data Collection

PIRE project researchers visited Rim Kebele in 2017, followed by a visit in summer 2018 to pre-test survey questionnaires designed by the project team with four-five farmers. Data collection was discussed with village-level experts and representatives from households. We randomly sampled 100 households from five villages with 20 households each by using local government generated lists of households. Local experts and farmer representatives reviewed the household-level questionnaire prior to in-person interviews with farmers. We conducted survey questionnaires with 100 sampled smallholder farmers in summer 2019.

2.3. Model Development

This study aims to develop an agent-based model based on the household survey to assess the impact of seasonal weather forecast information used by smallholder farmers.
We initially identified 11 types of agents who might communicate weather information in the community during the survey design with local experts. However, survey analysis showed that there are actually four types of agents who are the leading communicators in disseminating and uptaking weather forecast information in the community (Figure 2). Water fathers (berede tebaki), farmer cooperatives, and church priests were thought to be influencers in information dissemination, but were found to be less important in weather communication. The demand for irrigation project experts’ service is less, due to almost all farmers practicing rainfed agriculture (Table A2).

Influential weather information communicators are neighboring farmers, other farmers in the Kebele, agricultural extension workers, and radio. Farmers interact with one another, may trust each other, and act upon the weather information. Agriculture extension workers have higher influence levels in the Kebele compared to other agents (Table 1). Based on the survey reports, there are four extension agent workers in Rim Kebele. They are the Kebele agricultural office head, the Kebele development agent for natural resource management, the Kebele development agent for crop production & management, and the Kebele development agent for animal production & breeding. Our follow-up meetings in 2020 with farmers regarding weather forecast communication found that farmers closely cooperated with agricultural extension workers during the growing season. This explains that extension workers have a high influence among the Kebele farmers.

2.3.1. Conceptual Framework of ABM Development

The purpose of the ABM model is to study the dynamics of information exchange among the agents. We coin “Likelihood to Adopt”, or LTA, a basic unit of measurement in the range of 0 to 100 LTA points for the development that an individual agent gains, holds, or loses during interactions with other agents. It is a measure of an agent’s likelihood that they receive, trust and then adopt weather forecast information. Weather forecast failure reduces agricultural productivity [28,43] and trust in the weather forecast [29]. Thus, forecast skill or accuracy is an important indicator to build up trust and adoption levels in the community. Several authors [30,31,33] have suggested a forecast skill of 55%–70% should be required for wide scale of adoption of weather forecast information. Farmers start to disagree with the information and stop trusting it if it is below this level. Thus, we take an average forecast accuracy threshold of 65% for the model. If forecast accuracy
is above 65%, agents gain LTA points through interactions (Figure A1) or lose points if forecast accuracy is less than 65%.

Table 1. Information flow through agent types.

| Information Flow                          | Neighboring Farmer | Other Farmers | Extension Worker | Media (Radio) | Average |
|-------------------------------------------|--------------------|---------------|------------------|---------------|---------|
| Source of information farmers receive from: | Yes                | 41            | 36               | 50            | 34      | 40.2    |
|                                           | No                 | 59            | 64               | 50            | 66      | 59.8    |
| Level of trust in weather forecast from:  | Not at all         | 59            | 64               | 50            | 67      | 60.0    |
|                                           | somewhat           | 34            | 32               | 24            | 23      | 28.2    |
|                                           | Very much          | 7             | 4                | 15            | 6       | 8.0     |
|                                           | Fully              | 0             | 0                | 11            | 4       | 3.7     |
| How often agents act-upon the forecast information: | Never              | 61            | 64               | 52            | 67      | 61.0    |
|                                           | Twice a year       | 32            | 33               | 40            | 24      | 32.2    |
|                                           | Every month        | 7             | 2                | 7             | 5       | 5.2     |
|                                           | Once a week        | 0             | 1                | 1             | 4       | 1.5     |

2.3.2. Information Flow Path in the ABM Model

An agent receives weather information from four sources: SE—agriculture extension worker, SM—media, SN—nearby neighbors, and SF—other friends, known as “friends” in the community. Trust levels are an important step in model development. TF represents an agent that fully trusts the source of information, TVM, very much trust, and TSM, somewhat trust. The ABM model connects weather forecast accuracy to the trust level of the agent. Agricultural extension workers and radio have an influence on agents gaining or losing LTA points. These get accumulated over a time series, and farmers adopt weather forecast information when their LTA points reach the adoption threshold (Figure 3).

Figure 3. ABM models information flow paths from the source, Sn—neighbors, Sf—other friends in the Kebele, Se—agriculture extension agents and Sm—radio, to agents’ trust levels, Tf—fully trust, Tvm—very much trust and Tsm—somewhat trusts, based on forecast accuracy. Forecast is either true or false. Agriculture extension workers and radio display influence levels and agents gain their LTA points where farmers make decisions at a certain threshold.
2.3.3. Model Calibration

We calculated the probability level of information sources, trust, and adoption levels from the field survey. Since it is impossible to know precisely how much LTAs might be gained from a single interaction, we will use this LTA increase (or decrease) as a calibration parameter. We are able to do this, because we know where each agent gets information from, and how many adoption rates there are from various sources. Each individual agent’s LTA’s increase will be weighted according to their reported trust (Figure 4). ABM sensitivity and trust values were designed based on [44] stratification of trust values (Table 2).

![Figure 4](image-url) Farmers’ interactions result in a gain or loss of LTA points. If a farmer has 0 LTA points, he/she does not trust the weather forecast whereas 100 LTA points is the highest point a farmer might gain from agent interactions. As his LTA points increase, his trust level also builds up until the threshold level, at which he/she adopts weather forecast information to act upon for his/her farming activities.

Table 2. Stratification of trust values.

| Value Range | Label            |
|-------------|------------------|
| 1.0         | Complete trust   |
| >0.9        | Very high trust  |
| 0.75–0.9    | High trust       |
| 0.5–0.75    | High medium trust|
| 0.25–0.5    | Low medium trust |
| 0–0.25      | Low trust        |
| −0.25 to 0  | Low distrust     |
| −0.5 to −0.25 | Low medium distrust |
| −0.75 to −0.5 | High medium distrust |
| −0.9 to −0.75 | High distrust   |
| <−0.9       | Very high distrust|
| −1          | Complete distrust|

2.3.4. Model Sensitivity

It is challenging to quantify how much trust value is exchanged during agents’ communications. Discussion occurs using stratification of trust value, a kind of fuzzy logic of trust, labeling each strata with different trust levels [44]. Thus, ‘very high trust’ > 0.9 places a value of over 90% on how much an agent trusts another agent. Likewise, medium and low trust levels, as well as distrust labels and value ranges, are designated (Table 2).

Based on the stratification of trust values given by Marsh [44], a farmer’s amount of trust in weather forecast information exchange ranges between 0 and 1. The forecast is considered as “true” if accuracy is over 65% or “false” when accuracy is below 65%. Thus, if a farmer has complete trust (1.0) in other agents, then he/she gains all LTA points. If a farmer very much trusts (0.75), or somewhat trusts (0.5), he/she gains 75%, 50% of LTA points, respectively. Similarly, weather forecast failure causes the loss of LTA points in distrust (Table 2). The adoption rate has been chosen based on sensitivity analysis over different LTA points (Figure 5). There is no significant increase over 90 LTA points. Marsh [44] also categorizes > 90’ very high trust’. Thus, based on these two observations, farmers in this model adopt the information at 90 LTA points.

ABM models the complex interactions between agents such as nearby neighbors, other farmers in the kebele, agriculture extension workers, and radio.
Each agent’s parameters are calibrated based on survey of monthly and seasonal adoption rates. Each agent is calibrated individually based on individual survey data, and in a group as an average where all agents interact with each other in the modeling environment (Figure 6). We run sensitivity analysis (Figure 5) and model calibration based on survey monthly and seasonal data (Figure 6). We then conducted experiments with various changing variables such as farmer-interaction distance with nearby neighbors, their connection to other farmers, radio influence in the community, weather forecast accuracy, and influence of agriculture extension workers. The number of visits by agriculture extension workers is calculated by varying the interaction distance of the workers.

![Figure 5. Sensitivity analysis of adoption rate.](image)

![Figure 6. Cont.](image)
3. Results and Discussion

A survey determines the demographic characteristics of farmers and the use of weather forecast information among farmers. The age of the household head varies between 20 and 81 years. Questions on education level reveal that 77% of respondents were illiterate. Though 19% of farmers attended school grades 1 through 12 and church school, only 9% of farmers can read and write. The average family size is 5.01 people per household (Table 3). Follow up meetings with farmers were conducted in 2020. Farmers showed interest in using scientific weather forecast information.

Table 3. Demographic characteristics of Kebele.

| Gender of the Household Head | Age of Household Head | Education Level of Household Head | Kebele Households Own | Household Family Size |
|-----------------------------|-----------------------|----------------------------------|-----------------------|----------------------|
| Male                        | 20–30                 | Illiterate                       | Cellphone             | Average 5.01         |
| 31–40                       | 32                    | Read & write                     | TV                    | 0                    |
| 41–50                       | 26                    | Grade 1–12                       | Electricity           | 11                   |
| 51–81                       | 29                    | Church school                    | Radio                 | 66                   |
| Female                      |                       |                                  | Bicycles              | 5                    |
|                             |                       |                                  | Solar lamp            | 72                   |

3.1. Weather Forecast Information and Main Crops

Ethiopia’s climate is geographically diverse [45] and traditionally classified into five climatic zones based on elevation and temperature [46]. Rim Kebele is located at 2000 m elevation [47]. The Kebele is in a “weina dega”—temperature” zone with a mean annual rainfall of 800–1200 mm [48]. There are four seasons in Ethiopia known as the Kiremt, Belg, Bega, and Tsedey. Kiremt or Summer season is the major rainy season that lasts from
June to September [49]. Thus, 72% of Rim Kebele farmers prefer to use weather forecast information for this season and rely on it for their farm activities (Table 4).

Table 4. Seasons in which farmers need weather forecast information.

|                                | Yes | No |
|--------------------------------|-----|----|
| Kiremt/Meher season (Jun–Aug)  | 72  | 28 |
| Belg/Autumn season (Sep–Nov)   | 43  | 57 |
| Bega/Winter season (Dec–Feb)   | 38  | 62 |
| Tsedey/Spring season (Mar–May) | 44  | 56 |

There are other factors that farmers consider when deciding what type of crop to plant, besides weather forecast information. Most of the farmers (72%) consider soil and land condition as important, along with the availability of capital (money) (65%) and farm inputs and resources (60%) (Table 5). However, farmers value scientific weather forecast information. Based on our survey, 72% of farmers are interested in being informed by scientific weather forecasts regarding on-farm activities, and 68% think the use of scientific weather forecasts could help improve their crop yield.

Table 5. Factors to consider when deciding type of crop to plant.

|                                | Yes | No |
|--------------------------------|-----|----|
| Weather forecast               | 55  | 45 |
| Soil/land condition            | 72  | 28 |
| Capital (money) availability   | 65  | 35 |
| Availability of farm inputs/resources | 60  | 40 |
| Availability of labor          | 55  | 45 |
| Family consumption needs       | 56  | 44 |

Survey analysis shows that farmers use traditional forecasting methods over scientific forecasting for land preparation, choosing crop type and variety, determination of planting date and harvest period (Table 6).

Table 6. Farm activities in which farmers use traditional and scientific weather forecast information.

|                                | Traditional | Scientific |
|--------------------------------|-------------|------------|
|                                | Yes | No | Yes | No |
| Land preparation               | 68  | 32 | 21  | 79 |
| Choose what crop type to plant | 54  | 46 | 19  | 81 |
| Choose what crop variety       | 50  | 50 | 21  | 79 |
| Determine planting date        | 71  | 29 | 19  | 81 |
| Determine harvest period       | 69  | 31 | 28  | 72 |
| Pest management                | 49  | 51 | 16  | 84 |
| Weed management                | 47  | 53 | 10  | 90 |

Farmers tend to prefer traditional methods (clouds, wind direction, birds) instead of scientific forecasting (broadcast on the TV, radio, and newspaper). 58% of farmers use wind direction, and 55% use cloud and color of the sky seasonally (1–2 times a year) as traditional forecasting methods. One-third of farmers reported using temperature and humidity. However, fewer farmers use TV and radio for scientific forecasting, and no farmers read the newspaper for information. Hence, TV and newspapers might not be good forecasting dissemination tools in this community. However, the radio can be a useful tool for dissemination since 39% of farmers report listening to the radio for scientific forecast information (Table 7).
Table 7. Farmers forecast methods, sources and frequency of reliance for predicting weather.

| Method                          | Never | 1–2 Times a Year | Every Month | 1 Time per Week | Daily |
|---------------------------------|-------|------------------|-------------|-----------------|-------|
| Cloud and color of the sky      | 21    | 55               | 9           | 6               | 9     |
| Wind direction and level        | 26    | 58               | 5           | 2               | 9     |
| Temperature and humidity        | 43    | 41               | 5           | 2               | 9     |
| Indicative birds                | 67    | 31               | 1           | 0               | 1     |
| TV                              | 100   | 0                | 0           | 0               | 0     |
| Radio                           | 67    | 24               | 5           | 4               | 0     |
| Newspaper                       | 100   | 0                | 0           | 0               | 0     |

Around 70% of farmers reported that they need weather forecast on onset and cessation of the rainfall, hail incidence, and dry spells, whereas around 50% or more of farmers reported using the weather forecast for number of rainy days and wind direction. About 45% of farmers need the forecast on rainfall depth and temperature (Table 8).

Table 8. Type of forecast information farmers need for farming activities.

| Information                     | Yes   | No   |
|---------------------------------|-------|------|
| Starting date of rain           | 72    | 28   |
| Ending date of rain             | 71    | 29   |
| Number of rainy days            | 56    | 44   |
| Rainfall amounts (mm)           | 46    | 54   |
| Temperature (low/high)          | 42    | 58   |
| Wind direction                  | 57    | 43   |
| Hail incidence                  | 66    | 34   |
| Dry Spells (days)               | 59    | 41   |

Based on our 2019 survey, smallholder farmers have an average of 0.75 ha of land. 1916 ha (81.8%) of the Kebele land is cultivated through rainfed agriculture, and only about 20 ha is irrigated (Table A1). Maize is the dominant crop, followed by finger millet. 89% of farmers grow maize and 11% finger millet. Farmers who irrigate grow cash crops such as cabbage, tomato, sugarcane, onion, and pepper during Bega season (December–January). Farmers allot 31% of land for cash crops. Most farmers (89%) plant during the 9 May–7 June period. Farmers (86%) prefer to use improved seeds over traditional seeds (11%), and 3% of farmers use both types of seed. Most farmers reported that they did not face pest problems (80%), so they did not use pesticides (88%). Farmers till their land 4–6 times a year. During years when there is a shortage of rainfall, farmers plan the crop later (74%), while 71% reported that they plan earlier in a wet year. 59% of farmers report a decrease of pests during surplus rainfall years. Farmers (79%) store grains for later consumption. If there is an early rain, 92% of farmers plant maize while a smaller number of farmers plant finger millet (6%), wheat (1%), and barley (1%) as their first chosen crop. The second crop would be finger millet (75%) and barley (7%).

The survey indicates that more farmers reported that rainfall and crop yield were normal during 2016–2018. More than half of farmers reported rainfall and crop yield were the same as normal during the last three years (Table 9).

Table 9. Description of rainfall and crop yield in the three years 2016–2018.

| Year              | Much Worse | Worse | Same as Normal | Better | Much Better |
|-------------------|------------|------|----------------|--------|-------------|
| 2018 (2010/11 E.C)| 0/0        | 3/17 | 58/53          | 25/18  | 14/12       |
| 2017 (2009/10 E.C)| 0/0        | 13/12| 63/67          | 21/21  | 3/0         |
| 2016 (2008/09 E.C)| 0/0        | 11/12| 70/73          | 19/15  | 0/0         |
3.2. Baseline Condition

A baseline condition is a process of establishing the initial agent’s communication scenario. Based on the calibrated parameters, we set the following variables for the baseline condition. The average survey adoption rate is 32.5 farmers (Table 1).

For this modeling, average adoption rate per season (28 weeks) is set to be 30 farmers, i.e., 30% of farmers adopt the forecast information (Table 10).

Table 10. List of variables for setting the model baseline condition.

| Agent Type         | Variable                   | Unit         | Baseline Measurement | Adoption Rate per 100 Farmers, Seasonal |
|--------------------|----------------------------|--------------|----------------------|----------------------------------------|
| Number of farmers  | number                     | number       | 100                  | 30                                     |
| Neighboring farmer | interaction radius distance| patch, 45 m  | 15                   | 30                                     |
| Other farmers      | links                      | number       | 5                    | 30                                     |
| Extension worker   | number                     | number       | 4                    | 30                                     |
| Extension worker   | interaction radius distance| patch, 45 m  | 25                   | 30                                     |
| Extension worker   | influence level            | 0–100        | 15                   | 30                                     |
| Extension worker   | speed                      | 0–40         | 10                   | 30                                     |
| Radio              | influence level            | 0–100        | 15                   | 30                                     |

3.3. Experiments

The number of model runs for the experiments is an essential measuring benchmark to assess the outcome quality.

We run the model repetitions within a range of 100 to 1000 times. There is a difference between 100–200 model repetitions, but not a significant difference after 200 repeats. (Figure 7). Thus, we chose 200 model repeats for each experiment.

Figure 7. Sensitivity analysis of model run repeats.

3.3.1. Experiment with Varying Farmers Interaction Distance

Farmers’ adoption rate increases proportionally as interaction radius distance increases. They interact at a 15 radius distance at the baseline condition, which is about 700 m, with 30 adoption rates. This simulates a village-wise interaction or mono-village interaction. When inter-village interactions are simulated at about 1200 m (25 distance units), adoption rates increased by about 17%. Higher adoption rates are achieved when farmers interact with other farmers from other neighboring villages (Figure 8).
Studies show farmers learn innovations from each other and share their knowledge with one another through intervillage communications [50]. Farmers Field School (FFS) can be organized and facilitates farmers to reach out to other farmers in other villages for the exchange of ideas. Farmers learn from each other become the main actors to bring new innovations to their villages. Farmers’ information exchanges produced good results in village level interactions in China [51]. In Ethiopia, the FFS organization in Amhara region acted as a platform to learn and link smallholder farmers in order to extend new methods among them [52]. These interactions have an impact on agricultural productivity [53,54].

3.3.2. Experiment with Varying Farmers’ Links to Other Farmers

Farmers are connected to at least five other agents in dissemination of information. Having from five connections to 15 connections results in an increase of 23% in adoption. After that, we did not observe an increase in adoption (Figure 9). Thus, higher adoption rates can be achieved by improving network connections by at least twice compared to baseline conditions. Based on the survey, 63% of respondents have a cellphone, improving ICT support information dissemination in the community. This might be related to rural electrification. According to the International Energy Agency, 26% of Ethiopian rural people have electricity in their households. Ethiopia aims for 100% electrification by 2025 with 35% renewable energy [55]. Our study shows that improving this sector would develop weather forecast dissemination in rural areas.

Figure 8. ABM model experiment with farmers’ interaction radius distance.

Figure 9. ABM model experiment with farmer’s connection links to other farmers.

3.3.3. Experiment Varying the Influence of Radio

Farmers listen to the radio in Kebele. We found that over 60% radio influence improvement is sufficient to achieve high adoption rates in the community (Figure 10).
receives about 40% more visits compared to the baseline condition. Model simulation reveals that, as the extension worker’s interaction radius distance expands, the average number of visits also increases (Figure 11). An increase in visits from an extension agent could improve the productivity of farms and reduce poverty. It is reported that at least one extension worker’s visit to the farmer’s field reduces poverty by 10% [58].

3.3.4. Experiment with Number of Visits from Agricultural Extension Worker

At the baseline condition, the agricultural extension worker interacts with farmers within a radius distance of 900 m. At this distance, a farmer is visited three times at each model step. If an agent increases the interaction distance to 500 m, the average farmer receives about 40% more visits compared to the baseline condition. Model simulation reveals that, as the extension worker’s interaction radius distance expands, the average number of visits also increases (Figure 11). An increase in visits from an extension agent could improve the productivity of farms and reduce poverty. It is reported that at least one extension worker’s visit to the farmer’s field reduces poverty by 10% [58].

3.3.5. Experiment Varying the Extension Workers’ Influence

Likewise, in our research area, extension workers have a greater influence on weather forecast information dissemination in the community. Improving the influence level of extension workers to 30% would result in 27% more adoption rates. Double or triple the influence would improve adoption rates per season by 34–40% (Figure 12). There are 1323 households in Rim Kebele (Table A1). Improving the influence of the agricultural extension worker would result in about 530 smallholder farmers adopting scientific weather

Figure 10. ABM model experiment varying the influence of radio.

There are both local and international radio stations, such as Farm Radio, functioning in the Kebele area. They focus more on teaching crop innovations, but it would also help if they delivered weather forecast information more in Rim Kebele. If mobile phone improves, radio can also be portable via smartphone. Farmers would have access to radio at any location. Improved telecommunication technologies and payment options available for poor people facilitated uptake of mobile phones in developing countries [56]. Rural areas’ mobile users are significantly growing over time in Ethiopia [57].

Figure 11. Average number of visits of agricultural extension worker.

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forecast information. Thus, we found that a 30% influence of agriculture extension worker capacity is enough to reach high adoption rates.

![Image](image-url)

**Figure 12.** Experiment varying the agriculture extension worker’s influence.

Studies confirm that extension agents generate awareness of new agricultural technologies and better adoption rates by smallholder farmers [59]. Studies have shown a positive correlation between access to information and farmers’ behavior in adopting new practices [60,61]. Thus, the more interaction with an extension agent, the more possibility of adoption and higher productivity.

### 3.3.6. Experiment Varying Forecast Accuracy

Weather forecast accuracy is an essential factor in adoption rates. In our simulation, forecast accuracy improvement is positively associated with the number of adoptions.

A 5% improvement of weather forecast accuracy (65–70%) shows a 23% bigger adoption rate. A 15% improvement (65–80%) would increase adoption by 37%. However, a 5% reduction (65–60%) would reduce adoption by 33%. A significant drop in adoption rates is observed with less than 55%. This explains that building farmers’ trust in the weather forecast is challenging due to farmers’ unwillingness to risk using failed forecast [25]. Meteorological agencies should monitor forecast accuracy so as not to decline below 60% at any given time (Figure 13). The main finding is that forecast accuracies of 70% are sufficient to achieve high adoption rates.

![Image](image-url)

**Figure 13.** Experiment varying the accuracy of weather forecast.

### 4. Conclusions

ABM was developed to understand information flow pathways by which weather forecast information might be disseminated among the smallholder farmers in Rim Kebele,
Amhara Region. This enables us to identify and rank different pathways as well as optimize
weather forecast adoption rates. The household survey helped to build and calibrate the
model. Four leading influencers in information communication were identified; nearby
farmers, other farmers in the kebele, agricultural extension workers, and radio. Results
from this study suggest opportunities for engaging agriculture extension workers who have
bigger influences in information dissemination. Their influence can increase adoption rates
by more than 40% per season. Latest forecast information and new agricultural innovations
can be channeled efficiently to smallholder farmers. Capacity building programs to increase
awareness of using extension services appear to be a worthy endowment. Model results
also encourage farmers to interact with neighboring village farmers. Agriculture programs
to involve kebele level interaction of farmers can help disseminate and learn new practices.
Two-thirds of farmers have a cellphone in the kebele. This entails room for improvement
in communication technologies. More information adoption can be attained by improved
farmers’ networks. Radio has also contributed to positive uptake of information. Forecast
accuracy builds farmers’ trust in the community. Results indicate significant improvement
in information uptake with a slight improvement in forecast accuracy. However, reduced
accuracy would lead to a notable decrease in adoption rates. Our study limitations include
the fact that we focused on one Kebele with a sample of 100 households in the Bahirdar area
of the Amhara region. We surveyed smallholder farmers in 2019 and developed our model
based on this year. Additional years of survey would help examine the tendency and future
prospective of use of weather forecast information. Our findings help decision-makers
understand the critical information flow pathways and their relative importance by which
weather forecasts can be disseminated and shared. This might help regional development
programs to identify barriers to the adoption of weather forecast information.

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Appendix A

Description of the research area.
Table A1. List and description of villages in Rim Kebele (Mecha Woreda Agriculture Office, 2017).

| Name of the Village       | Estimated Household Size | Cultivated Land Out of Total Area (%) | Forest Land Out of Total Area (%) | Irrigated Land Out of Cultivated Land (%) | Irrigation User Households Out of Total Households (%) |
|---------------------------|--------------------------|--------------------------------------|----------------------------------|------------------------------------------|------------------------------------------------------|
| 1 Angut—Adis Alem         | 45                       | 81.5                                 | 4.2                              | 0                                        | 0                                                   |
| 2 Angut—Mahal             | 65                       | 76.8                                 | 9.2                              | 0                                        | 0                                                   |
| 3 Shafri                  | 65                       | 81                                   | 4.2                              | 0                                        | 0                                                   |
| 4 Wuren—1                 | 65                       | 81.8                                 | 4.2                              | 0                                        | 0                                                   |
| 5 Wuren—2                 | 60                       | 81.8                                 | 42                               | 0.05                                     | 10                                                  |
| 6 Wuren—3                 | 60                       | 81.8                                 | 4.2                              | 0                                        | 0                                                   |
| 7 Cheba—1                 | 60                       | 81                                   | 4                                | 0.05                                     | 10                                                  |
| 8 Cheba—2                 | 55                       | 81                                   | 4                                | 0                                        | 0                                                   |
| 9 Deber Mender—1          | 55                       | 81                                   | 4                                | 0.05                                     | 10                                                  |
| 10 Deber Mender—2         | 48                       | 81                                   | 4                                | 0                                        | 0                                                   |
| 11 Babo Bate—1            | 45                       | 76.5                                 | 9                                | 0                                        | 0                                                   |
| 12 Babo Bate—2            | 45                       | 77                                   | 9                                | 0                                        | 0                                                   |
| 13 Kuyu                   | 50                       | 81                                   | 4.2                              | 0                                        | 0                                                   |
| 14 Ko Rim                 | 54                       | 82                                   | 4                                | 0                                        | 0                                                   |
| 15 Lay Gult               | 50                       | 82                                   | 4                                | 0                                        | 0                                                   |
| 16 Sendi                  | 54                       | 80                                   | 5                                | 1                                        | 15                                                  |
| 17 Dima                   | 60                       | 81                                   | 5                                | 1                                        | 15                                                  |
| 18 Ketema                 | 387                      | 2                                    | 10                               | 0                                        | 0                                                   |
| **Rim Kebele**            | **1323**                 | **1916 ha (81.8%)**                  | **100 ha (4.2%)**                | **20 ha (0.1%)**                         | **22%**                                              |

Appendix B

Agent-based model development.

Table A2. Full list of agents and information flow: source, trust, and 'act upon'.

| Agent Types                     | Source   | Trust          | Act Upon       |
|---------------------------------|----------|----------------|----------------|
|                                 | Yes      | No             | Not            | Some | Very | Fully | Never | Season | Month | Week |
| Neighboring farmers             | 41       | 59             | 59             | 34   | 7    | 0     | 61    | 32     | 7     | 0    |
| Other farmers in the kebele     | 36       | 64             | 64             | 32   | 4    | 0     | 64    | 33     | 2     | 1    |
| Relatives outside of the kebele | 22       | 78             | 78             | 21   | 0    | 1     | 78    | 21     | 1     | 0    |
| Church Priest                   | 9        | 91             | 91             | 5    | 4    | 0     | 91    | 8      | 1     | 0    |
| Water Father                    | 1        | 99             | 99             | 1    | 0    | 0     | 99    | 1      | 0     | 0    |
| Agriculture extension worker    | 30       | 50             | 50             | 24   | 15   | 11    | 52    | 40     | 7     | 1    |
| Irrigation projects expert      | 1        | 99             | 99             | 1    | 0    | 0     | 99    | 1      | 0     | 0    |
| Farmer cooperative member       | 2        | 98             | 98             | 2    | 0    | 0     | 98    | 0      | 2     | 0    |
| Radio                           | 34       | 66             | 67             | 23   | 6    | 4     | 67    | 24     | 5     | 4    |
| Newspaper                       | 0        | 100            | 100            | 0    | 0    | 0     | 100   | 0      | 0     | 0    |
| Television                      | 0        | 100            | 100            | 0    | 0    | 0     | 100   | 0      | 0     | 0    |
Appendix B.1. Agents’ Environment and Interaction with the Neighboring Farmer

Social networks play an important role in farmers’ learning and adopting new agricultural technologies [62]. Many studies show that farmers get involved in diverse learning processes by experimenting in their own plots before adopting or learning from the performances of neighbors, friends, and relatives [63]. The farmer agent interacts with the neighboring farmers within his/her predetermined distance radius (Figure A2).

Figure A2. Horizontal and vertical distances of the kebele. Unit radius distance of the farmer to interact with other nearby neighbors is 45 m. Farmers interact with other agents based on their interaction radius distance. Distance measurement calculates the distance between the agents and allows the setting of the farmer’s interaction radius distance with other agents.

If the farmer agent’s interaction distance is small and no other farmers are in his/her range, an agent cannot communicate with other agents and does not gain any LTA points. As agent’s interaction distance radius increases, the agent captures more farmers into his/her communication radius (Figure A3). If the weather forecast is accurate the farmer looks for the closest farmer who has a maximum amount of LTA points and gains that agent’s LTA points based on the trust level. If the weather forecast fails, the farmer loses his/her LTA points based on the trust level.

Figure A3. Farmer agents with smaller and bigger radius of interaction. Farmer agents interact with nearby neighboring farmers within his/her radius of interaction and gains or loses LTA point based on trust levels.

Appendix B.2. Agents’ Interaction through Networks

Information and communication technologies’ (ICT) use has been increasing globally [64]. Researchers found ICT-supported dissemination would be most effective in conveying relevant weather information for farmers [65]. In our research in Kebele, 63% of farmers own cell phones. This shows that they can communicate about the weather forecast and share information through phone calls. Our assumption is that farmers call other farmers at a distance for information (Figure A4).
Figure A5. Agriculture extension workers brings weather information into the community for efficient dissemination. This improves radius of interaction, influence level and speed. Increasing their radius of interaction, they involve and influence more farmers.

ABM program, Netlogo 5.3.1, was used to build a virtual Kebele environment where smallholder farm households are located on a geographically referenced platform. This platform is positioned on grids known as “patches” that expand into “x” horizontal...
(3.87 km) and “y” vertical distances (2.52 km). The area of the kebele is 9.75 km². The distance is measured in patches, equal to 45 m (Figure A2).

Per modeling characteristics, an agriculture extension agent has a radius distance of interaction, measured in patches (each patch = 45 m) and influence level. The influence level measures the extension worker’s capacity to effectively deliver weather information among the farmers (Figure A5). Extension workers might have higher or lower influence levels regarding weather forecast information on farmers.

Appendix B.4. Influence of Media in Weather Forecast Dissemination

Radio is an important medium to convey weather information to rural households. The Ethiopian National Meteorological Services Agency (NMSA) has been broadcasting weather forecast information through media since 1951. Daily weather forecasts are read by a radio announcer every morning and made in three local languages: Amharic, Oromigna, and Tigrigna [71]. However, ineffective broadcasting was also reported due to the poor relevance of weather forecast contents to farming needs [72,73]. Based on our survey, 34% of Kebele farmers reported listening to the radio for weather information (Table 2). In the modeling environment, we assume farmers listen to the radio to receive information and share it with other agents in the community.

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