An Agent-Based Model of Climate-Induced Agricultural Labor Migration

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Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2013 AAEA Annual Meeting, Washington D.C., August 4-6, 2013

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Abstract: Using an agent-based model, we simulate the climate-induced agricultural labor migration for alternative future climate scenarios. For each agent, the probability of migration is calculated as a function of a set of relevant factors using a logistic regression model. Historical U.S. agricultural employment data was used to calibrate the model. The simulation result showed that larger crop yield reduction induced by climate change tends to generate larger migration flows. Furthermore, we observed that the network effects tend to forecast a larger migration difference between alternative climate scenarios.

INTRODUCTION

Climate change is expected to have negative effects on agriculture in many regions, such as reduced crop productivity (Lobell et al., 2008; Schlenker and Roberts, 2009). Agricultural producers may implement a range of climate change adaptation options, such as irrigation, crop rotation, purchase of agricultural insurance, and migration (McLeman and Smit, 2006; McCarl, 2007).

Empirical approaches have been applied to explore the relationship between the natural environment and human behavior (An, 2012). However, econometric models do not capture the dynamics of coupled human and natural systems at a process level and thus provide an incomplete basis for projecting the adaptive response to climate change into the future. For example, interactions between individuals are omitted.

Agent-Based Model (ABM) provides a process-based representation of real world phenomenon. In an ABM, heterogeneous decision-makers (agents) dynamically interact with each other and their common environment. Previous studies have found that ABMs may capture emergent phenomena in large-scale outcomes as a result of the interactions between heterogeneous agents, thus providing an alternative perspective to empirical approaches (Bonabeau, 2002). ABM has been applied to simulate migration responses to climate change in only a few studies (Hassani-Mahmooei and Parris, 2012; Kniveton et al., 2012). To further explore this emerging approach, we develop an ABM to simulate the effects of climate change on U.S. agricultural labor migration.

LITERATURE REVIEW

In recent decades, off-farm work has become important for U.S. farmers. Mishra et al. (2002) mentioned that the off-farm income share of U.S. farmer household income rose from about 50 percent in 1960s to more than 80 percent in 2000s. Munlak et al. (1997) stated that income difference between agriculture and non-agriculture has positive and significant effect on the rate of off-farm migration. Higher and less uncertain off-farm wage are believed to be the main reason for the increase in off-farm employment (Kilic et al., 2009). Pfeiffer et al. (2009) found that income earned off the farm might be used to help a worker who allocates his/her time in both farm and off-farm works migrate out of the rural sector entirely. Thus we expect that agricultural labor migration may be positively associated with off-farm work and have the similar trend, as they share similar determinants, such as farm productivity and off-farm wage.

Climate change is expected to influence agricultural labor migration, as it reduces crop productivity in many regions (Lobell et al., 2008). For example, Feng et al. (2010) and Feng and Oppenheimer (2012) found that climate-driven changes in crop yields have significant effects on the migration flow from Mexico to the United States. Gray and Mueller (2012) found that flooding only has modest effects on mobility in Bangladesh, while the effects of crop failures likely to be driven by rainfall deficit are stronger. Based on a country-level panel data for sub-Saharan Africa, Marchiori et al. (2012) found that weather anomalies increase internal and international migration through both amenity (direct effect) and economic geography (indirect effect) channels.

Compared to empirical approaches, ABM attempts to simulate the dynamic process of real world by allowing heterogeneous agents to interact with each other and their common environment. ABM has been widely used in many areas, such as land use change (Evans and

Kelley, 2004; Happe et al., 2006) and financial market (Gallegati et al., 2003). Recently, researchers started to use it to simulate climate induced migration. Hassani-Mahmooei and Parris (2012) used an ABM to analyze the effects of climate change on internal migration in Bangladesh. They estimated that between 3 and 10 million people may migrate internally, depending on the severity of the hazards. Kniveton et al. (2012) used an ABM combined with the theory of planned behavior to study how climate influences migration for Burkina Faso. Their simulation results showed emergent pattern in the future climate induced migration flows.

An essential stage in developing an ABM is determining the rules of agents' behavior such as how agents interact with each other and their common environment, which can directly influence the simulated outcome. Before simulation, the rules of agents' behavior are usually parameterized by available data (Bianchi et al., 2007). In many cases, the data needed for parameterization is not available, and assumption or calibration-based rules may be used. Therefore, researchers have tried many ways in developing an ABM. An (2012) summarized nine types of decision models as "microeconomic; space theory based; psychological and cognitive; institution-based; experience- or preference-based; participatory; empirical or heuristic rule; evolutionary programming and; assumption and/or calibration-based rule models, which range from highly empirically-based to more process-based." The selection of a specific type of decision model depends on the various factors such as the topic, data availability, the output.

In this study, we developed an ABM to simulate the U.S. agricultural labor migration under alternative future climate scenarios. Our work is different from Kniveton et al. (2012) in that we focus on the agricultural labor migration. Furthermore, while Kniveton et al. (2012) only studied the seasonal migration, we consider both temporary and permanent migration in the model.

METHODOLOGY

Agent-based model

Three key components of our ABM are heterogeneous agents, decision rules, and the network effects between agents. Figure 1 presents the model structure. An agent represents an agricultural producer, who is assumed to be a price-taker and profit-maximizer. At the beginning of each growing season, the agent evaluates the expected crop yield and makes decisions about migration. A lower expected crop yield tends to reduce farm income, and thus raise intention to migrate in order to seek for off-farm work.[1]

We do not compare the returns between farm and off-farm work to exclude migration possibility when farm income is higher than off-farm income. Instead, we assume that all the producers have the possibility of moving even if off-farm income is lower. Therefore we simplify the approach by considering expected crop yield only (implicitly assuming a fixed off-farm income).[2] This assumption should be more realistic than assuming a producer strictly follows profit-maximizing actions, since agricultural producers have many farm options other than migration, and they don't necessarily move when farm income is lower than off-farm income. On the other hand, when farm income is higher than off-farm income, they may still want to migrate due to reasons such as enhancing "the welfare of the children" (Larson and Mundlak, 1997). We also have the assumption that agricultural producers make binary responses about migration, and do not allocate their time between farm and off-farm work. A summary of all the major assumptions are in the Assumptions section.

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[1] Off-farm work may include both rural-to-rural and rural-to-urban migration.
[2] We assume exogenous input and output prices, thus expected crop yield is viewed as a proxy for farm income.

Each agent's migration intention is determined by the following logistic regression model:

$$\ln\left(\frac{P(M_{it})}{1-P(M_{it})}\right) = \beta_0 + \beta_1 Yield_{it} + \sum_{i=2}^{k} \beta_i Ind_{it} \tag{1}$$

where M_{it} denotes agent i's migration intention to move away from the farm during year t,

$Yield_{it}$ denotes the expected crop yield, and Ind_{it} denotes individual characteristics including

gender, age, assets, migration experience, risk attitude, and social networks. Error term is not

included in Eq. 1, since this equation is only used for prediction purpose with β_i calibrated from

other empirical models. In the real world, there are many more factors affecting agent's

migration behavior, however, those are not included in order to simplify the model and also

because data are not available for many of those factors.

The probability of migration intention is assumed to be jointly determined by the factors

listed in Eq. 1. First, it depends on the expected corn yield, for which we use as a proxy for farm

profit. An agent with a lower expected crop yield tends to have a higher intention of migration,

holding everything else constant. The responses of migration to corn yield is obtained from Feng

et al. (2012), who found that the estimated semi-elasticity of emigration with respect to crop

yields is -0.17. While this value is not directly transferable to our model since we are using a

logistic regression, we approximate it by setting a coefficient of corn yield to be -1.85 so that

migration intention will increase about 0.17% when the value of corn yield decreases from 1 to

0.99. Two agents with the same expected crop yield may have different migration intentions, due

to individual characteristics, such as age, gender, assets, and many other observed and

unobserved factors. Age is an important determinant of labor status. It has been found that

younger people are more likely to migrate (Bentham, 1988). Age for each agent was randomly

drawn from the U.S. farmer age distribution generated by Allen (2005). The effect of age on

migration intention is approximated by using the estimated parameter from Cai et al. (2013), who

estimated how age was associated with the odds of planning for migration based on the Gallup

World Poll. It should be noted that once randomly assigned to an agent, age will remain constant

over time, so that the age distribution does not change during model simulation. Gender also

affects migration behavior. In general, males are more likely to migration than females (Burnam

et al., 1987). Its distribution and relationship with migration are also obtained from Allen (2005)

and Cai et al. (2013). Asset influences both the motivation and ability of migration (Massey et al.,

1998). We randomly assign asset quintiles to agents. Its relationship with migration is also

obtained from Cai et al. (2013).

An agent's risk attitude, migration experience, and other agents' migration behavior

(network effects) also affect the likelihood of migration. Compared to Biondo (2013), who kept

the level of risk attitude constant over time, we allow it to evolve – for an agent who temporarily

migrated last year, the tolerance of risk will increase during this year, while for an agent who did

not migrate last year, the tolerance of risk will decrease this year. We also assume that the agent

can learn from past migration experience – positive or negative migration experience may

influence future migration decisions. The network effect is implemented by assuming that all the

agents live in a two dimensional world, and each agent is influenced by nearby agents. We

assume that agents tend to follow the behavior of nearby agents. For instance, an agent is more

likely to migrate if most of his/her neighbors chose to migrate last year. The network effect also

influences migration decisions in another manner that migrants in the same social network may

be helpful for potential migrants in terms of reducing migration costs and increasing the

likelihood of getting an off-farm job (Chen et al., 2010). However, there is no available data for

the purpose of parameterization for all these three variables – risk attitude, migration experience,

and network effects. Therefore, to calibrate their effects on migration intention, the model was first simulated with these factors varying within a certain range. Then the parameters with the minimum mean squared error between simulated and observed outcome (U.S. farm employment) are chosen to forecast future migration. These three factors are assumed to evolve over time, therefore allowing emergent agent behaviors and outcome.

Overall, our ABM consists of three empirical-based parameters – age, gender, and assets, and three calibration-based parameters – risk attitude, migration experience, and social networks.

Once a final probability of migration intention for each agent is calculated by Eq. 1, we follow the approach of Kniveton (2012) to compare it to a random number uniformly distributed between zero and one. This is to determine whether or not this migration intention will turn into actual migration. If the probability of migration intention is larger than this random number, we assume that this migration intention will turn into actual migration. If it is smaller, we assume that agent will not migrate. Comparing it to a random number is to capture unobserved factors in the real world – a higher intention may not turn into actual migration, while a lower intention may.

We further distinguish temporary and permanent migration. If the probability of migration intention is larger than this random number and the difference is smaller than 0.5, we assume that agents will temporarily migrate; thus they will return to their farms for the next season and evaluate migration decisions under new crop yield expectations and the evolved individual characteristics. If the difference is larger than 0.5, we assume that agents will permanently migrate, and agents will be dropped from the simulation. We assume that three consecutive years of temporary migration will also result in permanent migration. However, the above numbers 0.5 and three are assumption-based – it is arbitrarily selected to capture the

qualitative feature that a stronger migration intention should indicate a higher probability of permanent migration. Although it is possible to calibrate these two numbers by compared simulated and observed outcome, we prefer to keep these numbers as assumption-based, since too many varying parameters will increase the computations demand.

Assumptions

How climate change induces migration is a complex process with multiple channels and interactions, so it is unlikely to develop a comprehensive ABM for it. Thus a challenge in ABM is how to make appropriate assumptions about variable selection and parameterization so that the model is feasible in terms of computational demand, complexity, and performance. Following are some major assumptions in our model:

1. Off-farm work income is not included in the model, while agents may consider off-farm wage and estimate the probability of obtaining an off-farm job (D'Antoni et al., 2012). Furthermore, the off-farm wage may be affected by rural-urban migration. However, the effect may be small as the demand side of the off-farm labor market was not found to be a significant determinant of off-farm work (Kyle, 1990).

2. We assume that there will be no changes in any farm support programs, such as farm subsidies. Although farm programs are likely to have impacts on migration, these changes are hard to be considered in an ABM as they are the decisions made by policymakers and thus it is uncertain about when and how these programs will be implemented.

3. We further assume that crop price is exogenous, that agents' behaviors have no impacts on crop prices. Market price of crops is determined by many factors, such as the price of

other product or import/export amount. Those agricultural producers who may move due to climate change are unlikely to have large impacts on market price, even considering their aggregated production.

4. We assume that agents have perfect information about expected corn yields.

5. We assume that climate change affects agricultural labor migration only through crop yield variations.

6. We do not specify the type of farmers, while farm owners are more likely to work off-farm compared to tenants (Pandit, 2010). However, in our model, the effects of farmer types on migration may be partially captured by risk attitude and migration experience, as the values of these factors varied by farmer types.

7. Agricultural producers are assumed to have binary discrete choice between staying on farm and migration, though they can allocate their time between farm and off-farm works in the real world case. Based on Pfeiffer et al. (2009)'s finding that we mentioned earlier, we expect that agricultural labor migration may be positively associated with off-farm work.

The above assumptions may limit the predictive performance of the model. However, as An (2011) suggested that "until there is greater process-based understanding of human decision-making in the context of natural systems, agent-based modelers should avoid unnecessary complexity through the inclusion of large numbers of trivial details."

Simulation

The ABM simulation is conducted using MATLAB (Mathworks 2012). The model is initialized with 1,000 agents. Each agent is randomly assigned with heterogeneous characteristics, including

crop yield, assets, gender, age, and risk attitudes. Two other factors, migration experience and social networks, are not included in the simulation until the second year, as we assume that they do not exist at the beginning of time. After the calibration process described earlier, we run the simulation for each climate scenario for 100 times and generate a distribution of staying agents.

DATA

The U.S. farm employment data were obtained from the Current Population Survey (CPS) collected by the Bureau of Labor Statistics (BLS). The data used is during the period of 1960-1995. It is the ratio of agricultural employment to total labor force, with the value of the year 1960 adjusted to be 100%.

The predicted average changes for corn yields from Iglesias and Rosenzweig (2010) are used in the simulation model, which are based on the HadCM 3 model assuming greenhouse gas emissions follow the IPCC SRES A1FI, A2A, A2B A2C, B1A, B2A, and B2B scenarios. We only use scenarios A1FI and B2a, as these two projected the maximum and median crop yield reductions among their projections, which are 5.1% and 3.24%, up to the year 2050.

MODEL CALIBRATION AND PRELIMINARY RESULTS

Model Calibration

Figure 2 presents the value of mean squared errors (MSE) for 33,000 set of parameters that were tested. The minimum MSE 0.0038 was found when network parameter is 0.44, experience parameter is 0.32, and risk parameter is 4.4. It should be noted that Figure 2 has an oscillation pattern, indicating that there are some other parameter values that can generate very similar MSE as this minimum one. The calibrated parameters are then implemented in the model to forecast future migration. As there is an unusual and sudden drop of U.S. agricultural labor around the

year 2000, we calibrate the model with the data during the period of 1960-1995 only. Figure 3 shows the calibrated model simulated for 100 times. It is observed that the calibrated model predict the historical trend well.

Preliminary Forecast

After model calibration, we simulate the model for a baseline scenario (no climate change and no yield reduction), and two climate scenarios (A1FI and B2A) which generate different yield reductions in the year 2050 (Iglesias and Rosenzweig, 2010). Figure 4 presents the simulation results of farm employment change over 50 years with alternative climate scenarios, shown in percentage. Taking the result in Figure 4 for just the year 2050, Figure 5 presents the distributions of final farm employment percentage with alternative climate scenarios. It is observed, for the case with network effects implemented, when climate follows the A1F (B2a) scenario, for which yield are forecasted to decrease 5.1% (3.24%) in 50 years, there will be 1.9% (1.2 %) additional people leaving the farm as compared to the baseline scenario. When network effects are not implemented, it will be 1.4% (0.8%) for the A1FI (B2a) scenario. We notice that, for the same climate scenario, there is less migration when network effects are not implemented (Figure 4). Furthermore, the difference between migration projections under alternative climate scenario is larger with network effects implemented (Figure 5). This is consistent with the hypothesis that network effects could generate an emergent outcome. We argue that, when the network effects are implemented, adverse effects of climate change is strengthened as it spreads over the agents. It should be noted that it is not meaningful to interpret the quantitative value of simulated migration as those are sensitive to model calibration and parameterization. Instead, we only have any confidence in the qualitative aspects of the results. We also notice that climate

change induced migration flows are likely to be nonlinear (Figure 4), which is consistent with the finding from Kniveton (2012).

CONCLUSION

In this study, we developed and performed a simulation of climate-induced agricultural labor migration using an ABM. The effects of age, gender, and assets were parameterized by a logistic regression based on the Gallup World Poll. The effects of risk attitude, migration experience, and network effects were calibrated by comparing the simulated outcomes with the observed outcomes. As expected, our simulation showed that larger yield reduction induces more agricultural labor to migrate. Furthermore, when network effects are implemented, there are more migrants under the same climate scenario and the difference between migration projections under alternative climate scenario is larger, indicating that ABM may be able to capture some emergent migration patterns induced by network effects.

Although ABM implements the network mechanism as compared to empirical models, it is still rather different from a real world system. Some potentially important factors are not included, such as agricultural support programs and urban wages. For those factors that are included, the approach to parameterization needs to be improved. Due to these limitations, even the model has been calibrated using the observed data, it may not be able to generate a reliable forecast. Thus we should not use the current model to "predict" the effect of climate change on labor migration, but to investigate the effect of key factors and drivers in order to provide insights on system properties.

Climate induced migration is expected to occur with complex interactions through multiple channels. A better understanding of these mechanisms is needed in order to improve

ABM performance. Priorities for research include the functional form of migration determinants

and an improved parameterization approach for each determinant.

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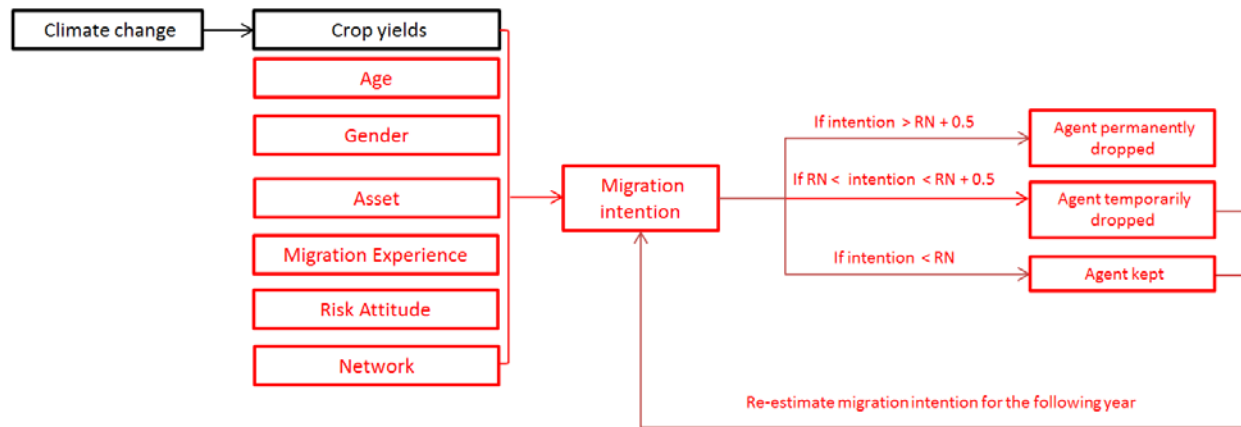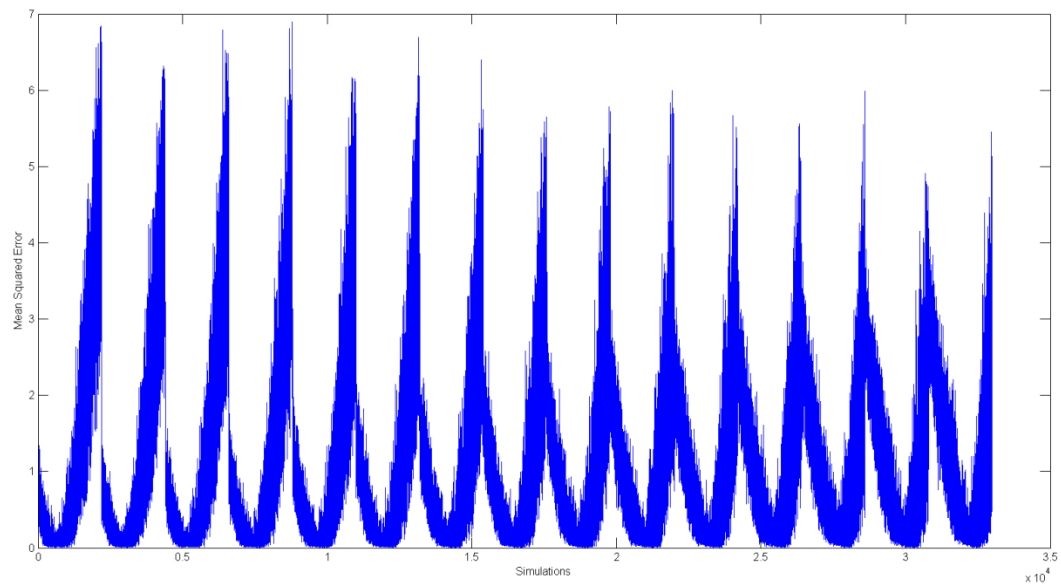
Figure 1. The structure of our ABM.

Figure 2. Mean square errors with varying parameters for social networks, migration experience, and risk attitude. We calibrate the model by selecting the set of parameters with minimum mean square error.
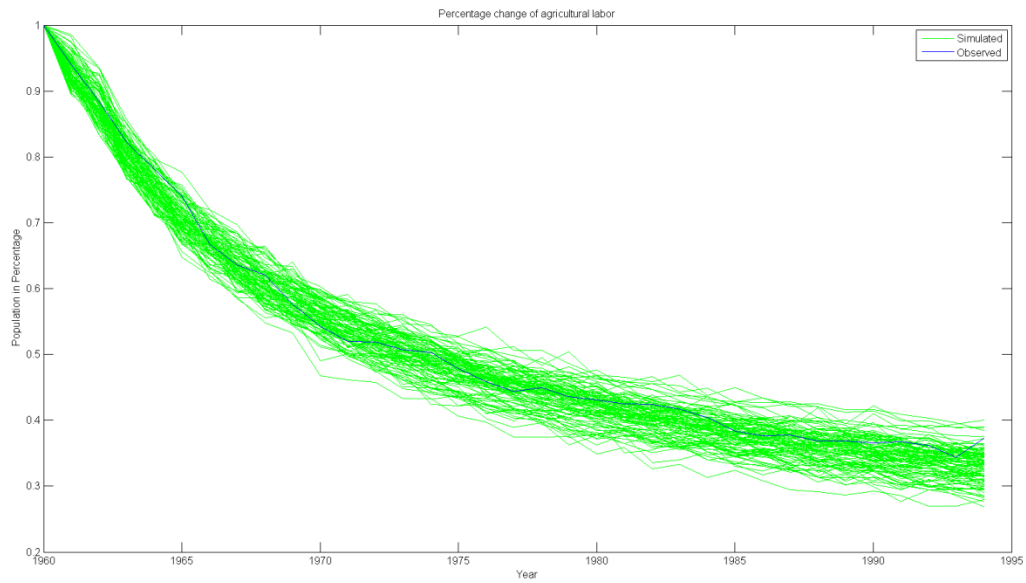
Figure 3. Historical U.S. agricultural employment and 100 simulations generated by the calibrated model.
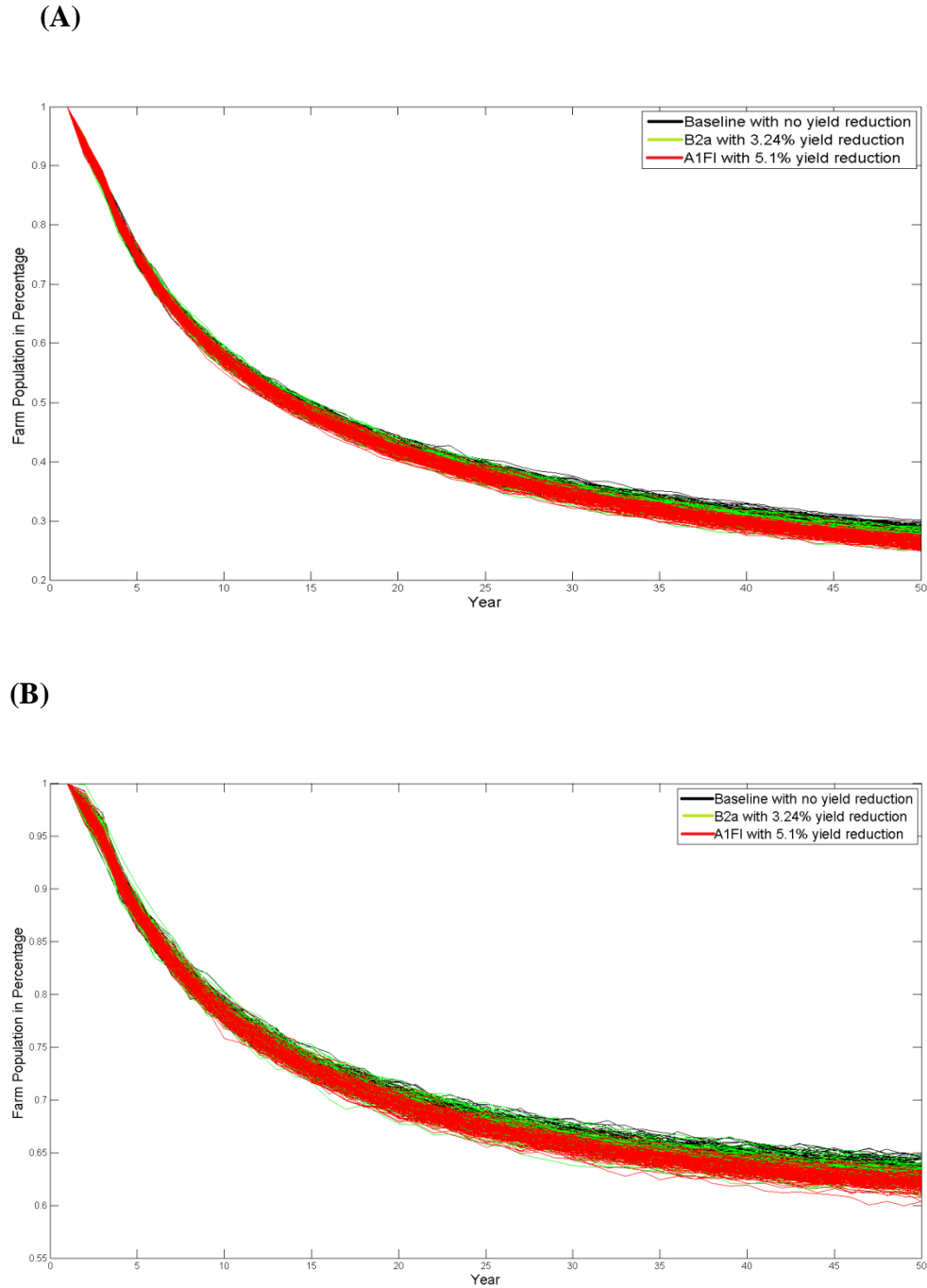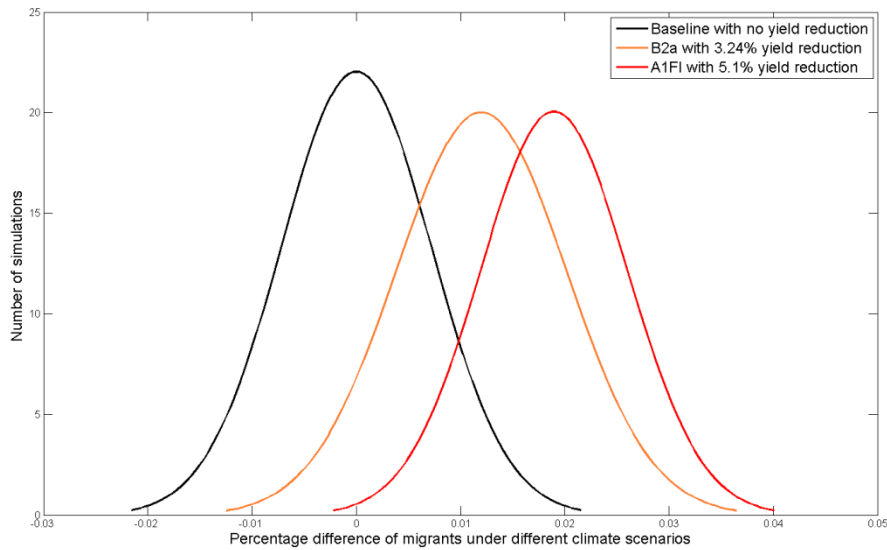
(A)

(B)

Figure 4. Agricultural labor for the next 50 years for three climate scenarios (taking the year 2000 as baseline year). The farm population in the first year has been adjusted to be 100%. Corn yield is projected to reduce by 3.24% for B2a scenario and 5.1% for A1FI scenario in 50 years. Each climate scenario has been simulated for 10,000 times – there are 100 curves for each climate scenario and each curve is the average of 100 simulations. (A) with network effects. (B) without network effects.
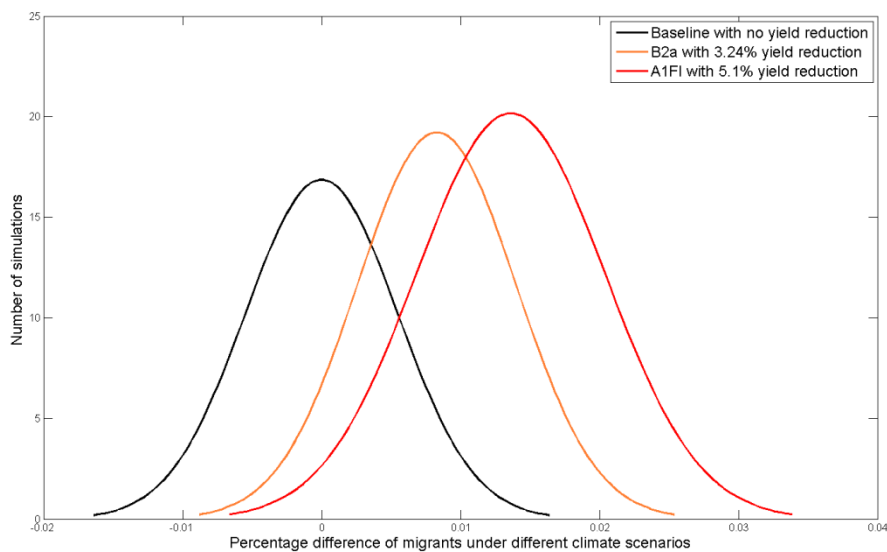
(A)

(B)

Figure 5. Normal distributions of agricultural labor forecast in the year 2050 for three climate scenarios. It is the result of the fiftieth year from Figure 4, while it is now presented as distribution curve. The curve for baseline scenario is adjusted to have a mean of zero. Corn yield is projected to reduce by 3.24% for B2a scenario and 5.1% for A1FI scenario in 50 years. Each normal distribution curve is generated from histogram of 100 forecasts, and each of the forecasts is the average of 100 simulations. (A) with network effects. (B) without network effects.