Innovation Lab for Small Scale Irrigation

Upscaling analysis – from small river basin to country

1. Introduction

The USAID Feed the Future Innovation Laboratory for Small-Scale Irrigation (ILSSI) was formed to undertake research aimed at increasing food production, improving nutrition, accelerating economic development, and protecting the environment in Ethiopia, Tanzania, and Ghana through strategic investments in agricultural development, including small-scale irrigation (SSI).

National statistics show that SSI is not widely practiced in the three ILSSI study countries. Situation analysis of irrigating farmers provides first-hand evidence that SSI offers additional farming opportunity in the dry season and helps generate additional income to improve the welfare of rural households. Moreover, ILSSI's ex-ante analyses of proposed SSI interventions in Ethiopia, Tanzania, and Ghana have indicated that, in general, there is groundwater or surface water available to sustain proposed SSI interventions at the target sites, although knowledge gaps requiring further research and specific constraints on the adoption of SSI (e.g., adverse environmental impacts of SSI, low soil fertility, ineffective management practices, high costs of labor and SSI technologies, irrigation water shortages) were identified. With collected field data, ILSSI has begun refining these results in ex-post analyses, and assessing candidate gaps and constraints and their mitigation. These analyses will ultimately enable ILSSI to recommend optimal SSI solutions at the study sites.

But can SSI interventions be "upscaled" beyond these study sites, at the national level? What is the appropriate investment scale for SSI development across a nation, and which locations within a nation have the greatest investment potential? Using currently available knowledge and data, a variety of modeling tools, and a newly developed methodology for assessing irrigation adoption decisions at the national scale, ILSSI's upscaling analyses will assess the potential for expanding SSI in the project countries, identify specific locations where SSI will be feasible, and evaluate the consequences at the country level for agricultural production, environmental sustainability, and socio-economic outcomes.

In Ethiopia, upscaling analysis is underway and is slated for completion in year four of the ILSSI project. Data collection efforts are underway for upscaling analyses in Tanzania and Ghana, which will begin in year four. This report describes: (i) the data and methodology used in the ILSSI upscaling analyses, including a new, agent-based modeling technique developed by ILSSI for assessing SSI adoption decisions at the national scale; and (ii) the implementation and results, to date, of ILSSI's upscaling analysis in Ethiopia.

2. Data and methodology

While irrigation investment analysis is by no means a novel process, new challenges emerge in assessments at the national scale. For example, in more localized analyses, the prices of crop products used to evaluate the economic costs and benefits of irrigation investment are often taken as exogenous constants. This implies that no consideration is given to the market potential of irrigated crop products. Although this practice is legitimate in analyses at the river-basin scale or at the project level, market potential may act as an important constraint in determining national irrigation adoption potential. For this study, we have developed a new methodology to handle the additional complexities that arise in irrigation adoption analyses at the national level.

This new upscaling framework, shown in figure 1, integrates several modeling tools and biophysical and socioeconomic data to provide spatially disaggregated, quantitative estimates of SSI development potential in the three study countries. The key components of the framework include:

2.1. Pre-suitability analysis

The pre-suitability analysis uses the GIS spatial data analysis tool to score land suitability for irrigation development, based on select environmental criteria. The land suitability scores are used to establish the suitability domain for SSI, an initial estimate of the geographic areas in which irrigation adoption could occur.

2.2. Agent-based model for irrigation expansion simulation

After establishing the suitability domain for SSI, we simulate the process of irrigation technology diffusion. Economic and water balance considerations are introduced into the simulation to refine initial estimates generated in the pre-suitability analysis, and to determine the likely scale and pattern of SSI development across the nation.

This step involves the development of several modeling activities, including an agent-based model (ABM) for simulating irrigation expansion. Agent-based modeling, a class of computational models that has emerged in recent years, provides a bottom-up paradigm for exploring the dynamics of a complex system. These models have been extensively applied to investigate technology diffusion issues (Berger, 2001; Deffuant et al., 2002; Kaufmann et al., 2009). In the context of this study, the application of agent-based modeling techniques allows us to define farmers as autonomous agents and to explicitly evaluate multiple irrigation technology adoption decisions at the farm level. This provides a realistic representation of real-world dynamics, since SSI is regarded as a decentralized irrigation development scheme.

The basic assumptions underlying the development of the ABM are as follows:

(1) Irrigation adoption occurs under social influence (i.e., farmers can learn from their peers) and is also driven by suitability considerations (Foster and Rosenzweig, 1996; Krishnan and Patnam, 2013); therefore, farmers with irrigation technology adopters in their neighborhoods are more likely to adopt the technology, and sites with higher pre-suitability scores tend to be developed first.

(2) A farmer's irrigation adoption decision is also influenced by economic viability and water availability. In the long-run, irrigation adoption must be economically profitable. The prices of irrigated crops in our model are simulated as endogenous variables. Crop prices respond to the increase in crop production that results from irrigation development. Over-adoption will lead to a price crash, which restricts the further expansion of irrigation. Expansion is also constrained by the amount of water resources available for irrigation, a calculation that incorporates considerations of environmental sustainability. Irrigation expansion in a river basin will stop if all water resources presumably allocated for agricultural use are depleted.

A more detailed description of the ABM is provided in the Appendix to this report.

2.3. SWAT

The Soil and Water Assessment Tool, or SWAT (Arnold et al., 1998) is a comprehensive hydrologic and agricultural model with a proven-track record of global application. SWAT is used as a major biophysical modeling tool in the upscaling analysis. The economic cost-benefit and water balance analyses in the ABM require the estimation of irrigated crop yields, irrigation water demand, and water yields of river basins. These variables are estimated using the SWAT model.

2.4. Irrigation and crop production costs input (economic analysis)

This analysis serves as a channel for micro-level knowledge and data to enter the macro-level (upscaling) analysis. Household survey data on existing smallholder farmers are summarized and analyzed to derive nutrient management scenarios and production costs data that characterize SSI production, to inform the SWAT and ABM simulations.

2.5. SPAM

Land cover data is one of key input data sets for the upscaling analysis. SPAM data (as defined and described below) for the three study countries are developed to complement remote sensing based land cover data by providing a more detailed description of the crop production system (e.g., spatial distributions of harvested area, physical area, and yields by crop).

The Spatial Allocation Model, or SPAM (You and Wood, 2006; You, Wood, Wood-Sichra and Wu 2014), is designed to plausibly disaggregate national or sub-national agricultural census data to a fine-resolution grid. SPAM combines a large collection of sub-national production data, satellite imagery of the distribution and intensity of cropland, maps of the share of area currently equipped for irrigation, and data on population density, crop prices, and the biophysical suitability of crop production. The result for each pixel (notionally of any size, but typically ranging from 1 to 100 km^2) is the area and production of each crop produced, split by the shares grown under irrigated, high-input rainfed, and subsistence conditions (each with distinct yield levels).

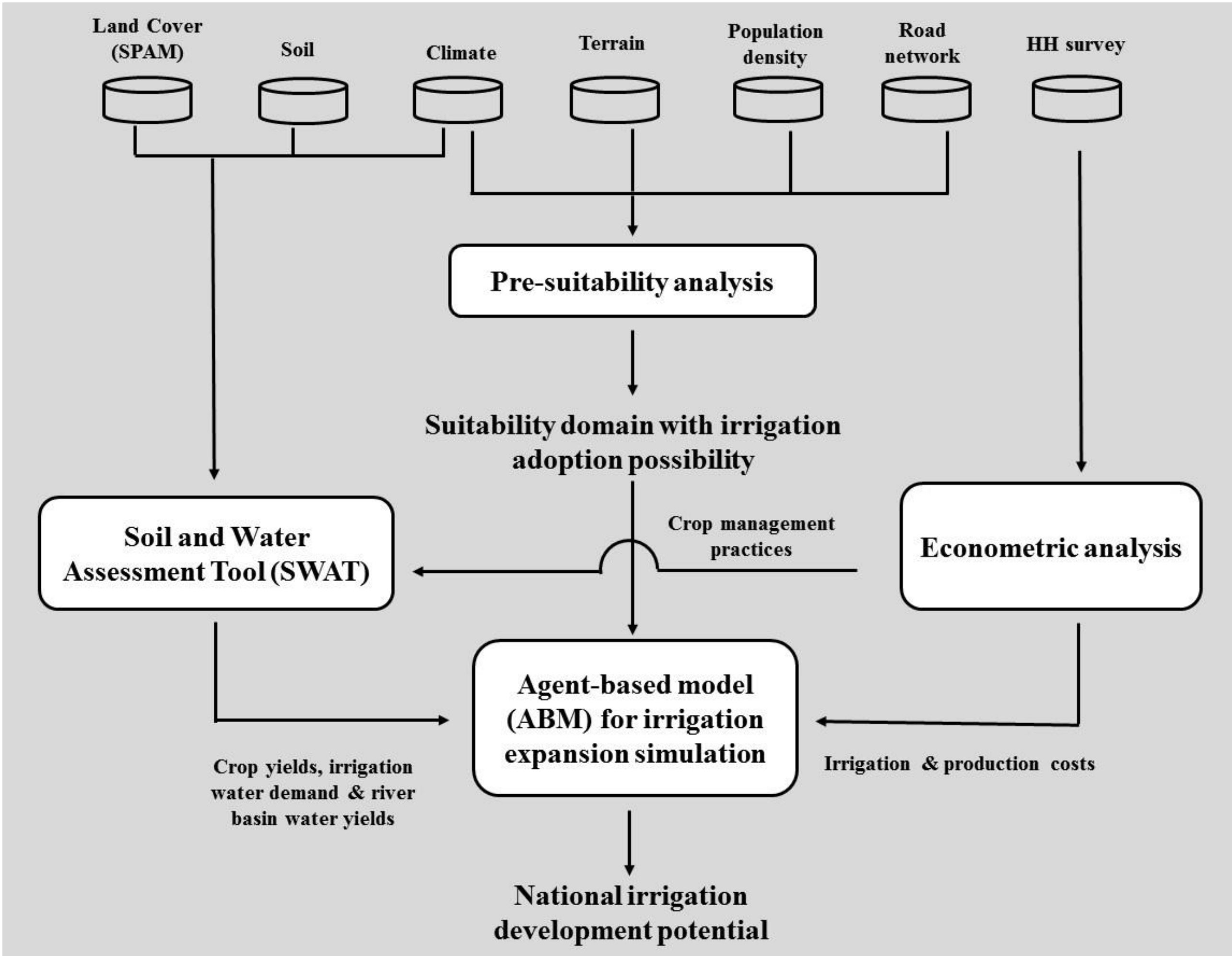

Figure 1. Proposed methodological framework for assessment of national SSI development potential

3. National assessment of SSI development potential for Ethiopia: implementation and draft outputs

3.1. Pre-suitability analysis

Potential land in Ethiopia suitable for SSI was identified using GIS-based Multi-Criteria Evaluation (MCE) techniques. Land suitability was determined by developing and assigning weight to the key factors that affect irrigation potential, using a 1-km grid. These factors were selected based on current literature and expert opinion (Akıncı et al., 2013; Chen et al., 2010; Mendas and Delali, 2012; Worqlul et al., 2015), and included physical land features (land use, soil and slope), climate characteristics (rainfall and evapotranspiration), and market access (proximity to roads and access to market). Factors were weighted using a pair-wise comparison matrix, reclassified, and overlaid to identify the suitable areas for irrigation. Table 1 presents the types of input data used, and their respective sources and spatial resolutions.

Table 1. Source and spatial resolution of data used for the land suitability analysis.

Data	Source	Spatial resol. (m)
Land use	Land use Database of the World (LADA) from the Food and Agriculture Organization (FAO), 2010	10,000
Land use	Spatial Production Allocation Model (SPAM), 2014	1,000
Soil	Africa Soil Information Service (AfSIS), 2015	250
Digital Elevation Model (DEM)	Enhanced Shuttle Land Elevation Data from the United States Geological Survey (USGS), 2000 (released in 2015)	30
Population density	Global Gridded Population Database, 2000	1,000
Road network	Ethiopian Road Authority (ERA), 2006	--
MODIS potential evaporation (mm)	MOD16 Global Terrestrial Evapotranspiration Data Set, 2000 – 2010	1,000
Rainfall (mm/year)	Ethiopian National Meteorological Agency (ENMA), 1996 – 2010	--

Slope and rainfall deficit were found to be the most important factors in assessing suitability for irrigation, followed by population density and soil characteristics. Suitability classes were given weights using equal interval ranging technique. Preliminary suitable land areas were computed using the Weighted Overlay analysis in ArcGIS. The preliminary suitability map shows the location and percentage of irrigable land in each region of Ethiopia (fig. 2). A constraint map with a value of zero and one was used to exclude the unsuitable areas and to optimize with a user-defined threshold number.

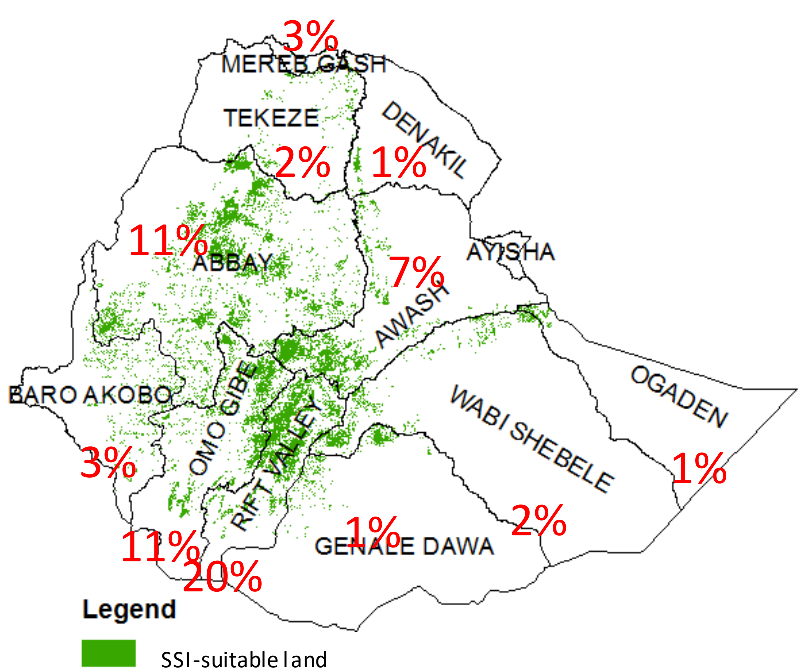

Figure 2. Preliminary suitable land for SSI

Figure 3 indicates the area of suitable land for a variable threshold number. Pixels with a suitability value of greater than 85% were identified as a suitable area. The result indicated thousands of suitable polygons with areas ranging from 1 km^2 to 500 km^2. Nearly 5.3% of the landmass, or approximately 60,025 km^2, is suitable for irrigation.

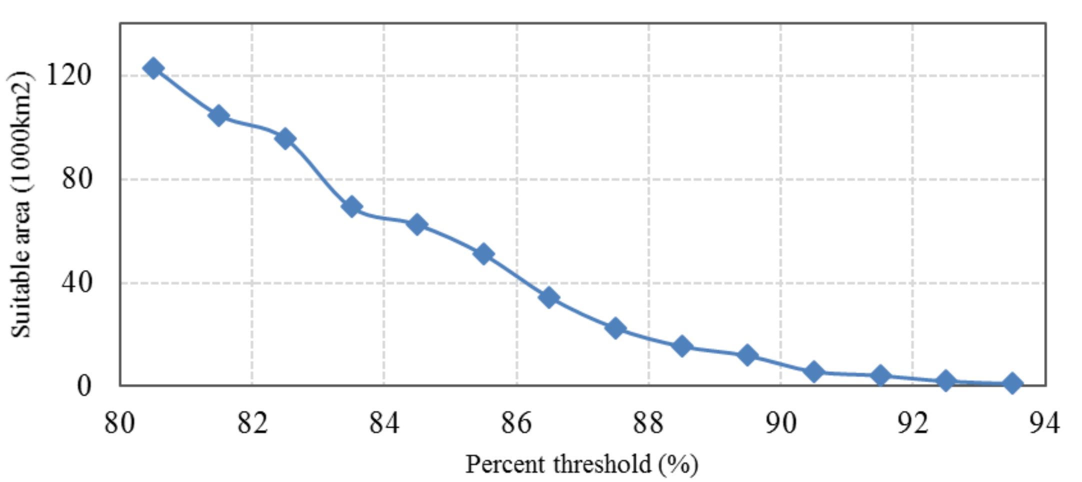

Figure 3. Irrigation-suitable land area at different suitability levels (60,000 km^2 is suitable for a threshold level of 85% and 96,000 km^2 is suitable for a threshold level of 82%)

Suitable land areas were categorized by major river basins. The Abbay (Blue Nile) basin has the largest area of suitable land (21,186 km^2), while the Rift Valley basin has the highest percentage of suitable land (20%).

3.2. SPAM data development

In SPAM data development for Ethiopia, we collected crop statistics on the second sub-national (e.g., district) level for the major crops in Ethiopia for the last decade. To avoid atypical years, we used the 2009-2011 three-year average as our baseline for 2010. For each grid cell, SPAM first provides estimates of suitable irrigated and rainfed areas for each crop, as well as the corresponding potential biophysically attainable yields. The SPAM approach then uses all the various input layers to disaggregate reported sub-national (administrative unit) statistical data on actual crop area and yield, to determine a plausible spatial variation of the baseline (2009-2011 average) production area and yield by pixel, by crop, and by input level (irrigated and rainfed). SPAM databases developed for global or regional study typically have a spatial resolution of 5 arc-minutes, or approximately 10 km at the equator. In this study, the resolution of SPAM data for the three study countries was improved to 1 km.

3.3. Hydrologic and crop simulation

SWAT has been used to estimate different biophysical processes in the ILSSI project. SWAT is a basin-scale, continuous-time model that predicts the impacts of management and climate on water, sediment, and agricultural chemical yields in watersheds (Arnold et al., 2012). SWAT simulates canopy interception of precipitation, partitioning of precipitation, evapotranspiration, subsurface flow, return flow from shallow aquifers, and water distribution between soil layers. It also estimates yields for crops, grasslands, and trees (Luo et al., 2008, Faramarzi et al., 2008, Schuol et al., 2008). SWAT has been used in the ILSSI project to study the impacts of SSI on environmental sustainability.

Different spatial data (e.g., land use and soil) and temporal data are used in the SWAT model for the upscaling activity. The land use data has 30-m resolution and was obtained from the China's Global Land Cover Mapping (Chen et al., 2015). This land use map was combined with the SPAM dataset (HarvestChoice, 2014), which provides detailed crop information for a 1 km-by-1 km grid. The resulting map provides spatially explicit crop information for the agricultural land. Major crops that are cultivated in Ethiopia include teff, sunflower, sorghum, barley, wheat, maize, coffee, cotton, carrot, lentils, and potato. The soil data was obtained from the Africa Soil Information System (AFSIS) and has a spatial resolution of 250 m. The AFSIS data includes grids of soil properties such as sand, silt and clay fractions, coarse fragments, and organic carbon, for a depth of up to six soil layers (Vågen et al., 2010). The information in the AFSIS database was used to generate the SWAT soil database using Saxton and Rawls' (2006) pedo-transfer function. Climate data was obtained from the Ethiopian National Meteorological Agency (ENMA, 2016). Observed climate data includes rainfall and maximum/minimum temperatures for 246 different meteorological stations in Ethiopia. The weather generator was used to fill missing data. Climate data from the synoptic meteorological stations, including rainfall, maximum/minimum temperature, relative humidity, wind speed, and solar radiation, was used to prepare the weather generator. The crop management data was based on experience in the ex-ante and ex-post studies and data obtained from the household survey.

The SWAT model was set up using predefined watersheds of 10 km-by-10 km grid size. Grid-based model development was convenient for sharing model simulations; for example, the grid-based approach helped us to easily integrate results from SWAT with the ABM. The ex-ante and ex-post analyses with the Agricultural Policy/Environment eXtender (APEX) model identified crop parameters for the vegetables. These crop parameters were used in the SWAT model to simulate crop yield.

In the upscaling activity, SWAT is used to provide spatially disaggregated estimates of water availability, irrigation water consumption, and crop yields for different vegetable crops that could be cultivated during the dry season. The vegetable crops selected for simulation include tomato, onion, pepper, cabbage, and potato. These outputs from SWAT are provided to the ABM to optimize crop mix for irrigated crops. Different scenarios will be simulated with the SWAT model to provide diverse information for the ABM. For example, to study the available water and potential for vegetable production at different climatic conditions, outputs are provided for the ABM in the driest and wettest climatic conditions in the record. Because fertilizer application rates also impact vegetable yields, the SWAT model will also simulate maximum and baseline fertilizer rates. The maximum rates are determined based on field research at ILSSI sites, and the baseline rates are obtained from the household survey.

Analysis was performed to assess tomato production potential, available water resources and irrigation water consumption in the driest year on record (1984) in all agricultural fields across the country. Preliminary findings showed that tomato yield can range from less than 1 ton/ha to 2.8 ton/ha (fig. 4a). The available water resources (including surface runoff generation and ground water recharge) across the agricultural fields range from less than 100 mm to over 2000 mm (fig. 4b).

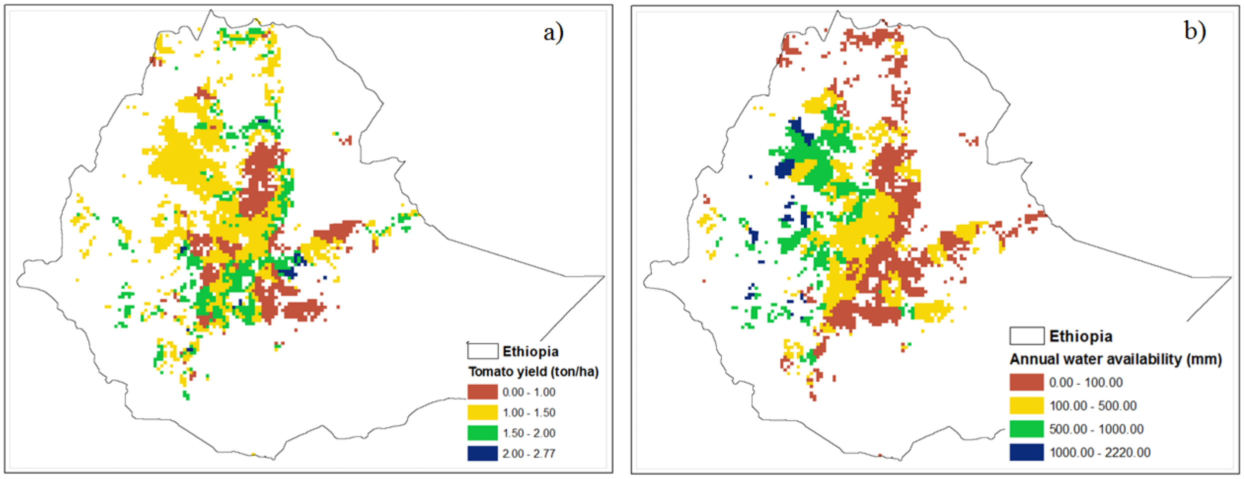

Figure 4. a) Spatial tomato production across agricultural lands, and b) available water resources, including surface runoff generation and groundwater recharge

3.4. Irrigation and crop production costs input

The ABM is used here to assess the impact of SSI technologies on farmers' livelihoods, especially the economic profits from irrigated crops. Part of the input information for the ABM relates to irrigation and other input costs of the irrigated crops. Capital and operational costs that include the costs of each water-lifting technology, fuel, agricultural input and labor, are considered in this study. Data on costs were collected mainly from household surveys conducted by IFPRI, Africa Rising, LIVES-ILRI, and NBDC-IWMI between 2012 and 2015. Information from the surveys includes the costs per hectare (ETB/ha) of fuel, maintenance, seeds, fertilizers (Urea and DAP), and chemicals (pesticides and herbicides), as well as labor required for land preparation, planting, weeding, and harvesting. Four water-lifting technologies were considered in this study: pulley and bucket, rope-and-washer pump, gasoline-motor pump and solar pump. Information collected covered four main agricultural regions of Ethiopia: Amhara, Oromia, Tigray and SNNP. Cost information was provided for six types of cereal/grain crops (maize, teff, wheat, sorghum, millet, and barley), two pulses (beans, peas), groundnuts, and six vegetable crops (tomato, onion, pepper, garlic, cabbage, and lettuce). Information on potato, which can be grown as an irrigated or rain-fed crop, was also included.

3.5 ABM for irrigation expansion analysis

The preliminary results of agent-based modeling for the upscaling of SSI technology in Ethiopia are shown in table 2 and figures 5 and 6. In the analysis, we include vegetable crops (tomatoes, onions, cabbages, peppers and vegetables-other) and pulse and root crops (chickpeas, lentils, and potatoes) as candidate crops for SSI.

As explained above, there are stochastic elements in the ABM, given the need for modeling farmers' irrigation technology adoption decisions. To handle the uncertainty associated with the stochasticity of the agent-based simulation, the model is executed multiple times with varying random seeds to generate multiple realizations of irrigation expansion pathways.

The estimated SSI development potential by region, which is expressed in areas with irrigation adoption potential shown in table 2 and calculated as

$$A_r = \frac{\sum_{i=1}^{N} A_{r,i}}{N} \quad (1)$$

where A_r is the area with SSI adoption potential in region r (ha), $A_{r,i}$ is an estimate for A_r obtained in realization i (ha, aggregated from the pixel-wise estimates for adoption area), and N is the number of total realizations. The economic outcome, or the net revenue from the irrigation development, is also shown in Table 2.

The simulations indicate that the SSI development potential in Ethiopia is about 800,000 ha, mainly in Oromia, Amhara and SNNP. The two regions with the largest SSI development potential (over 300,000 ha per region) are Oromia and Amhara.

Table 2. Estimated SSI adoption potential in Ethiopia

	Vegetables (ha)	Pulses & Root crops (ha)	Total (ha)	Net revenue (million USD/yr)
Affar	55	0	55	0.015
Amhara	200,068	118,102	318,170	92
Benishangul-Gumuz	11,182	419	11,601	2.6
Gambella	320	9	329	0.12
Harari	194	398	592	0.13
SNNP	87,942	41,111	129,053	50
Tigray	9,847	457	10,304	3.2
Oromiya	179,885	150,908	330,793	101
Somali	413	83	496	0.4
Total	489,905	311,487	801,392	249.5

A probability map is constructed to show the adoption probability of SSI in different locations (fig. 5). For each cell on the map, the adoption probability p is calculated as

$$p = \frac{n_{adopt}}{N} \quad (2)$$

where n_{adopt} is the number of realizations in which SSI adoption in the cell occurs, and N is the number of total realizations.

As demonstrated on the map, while adoption of SSI could happen over a vast geographic area, there are a few zones in which successful adoption would most likely occur, such as the Central Rift Valley and areas close to the Lake Tana. We recommend that future endeavors promoting SSI adoption target these areas.

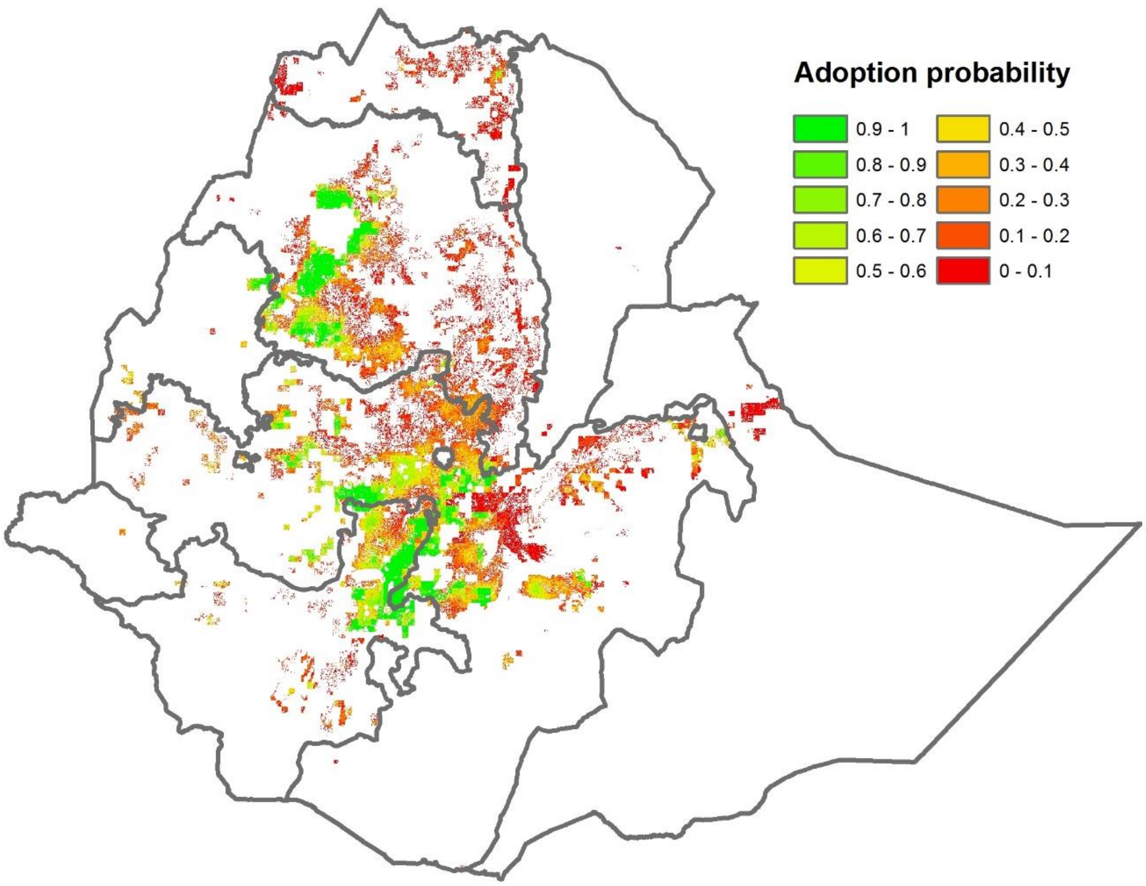

Figure 5. Adoption probability of SSI in Ethiopia

A map showing the river basins that are prone to water scarcity (fig. 6) is constructed in a similar way. In these regions, appropriate institutional arrangements should be made in conjunction with SSI investment activities to reduce negative environmental and socioeconomic consequences of SSI development.

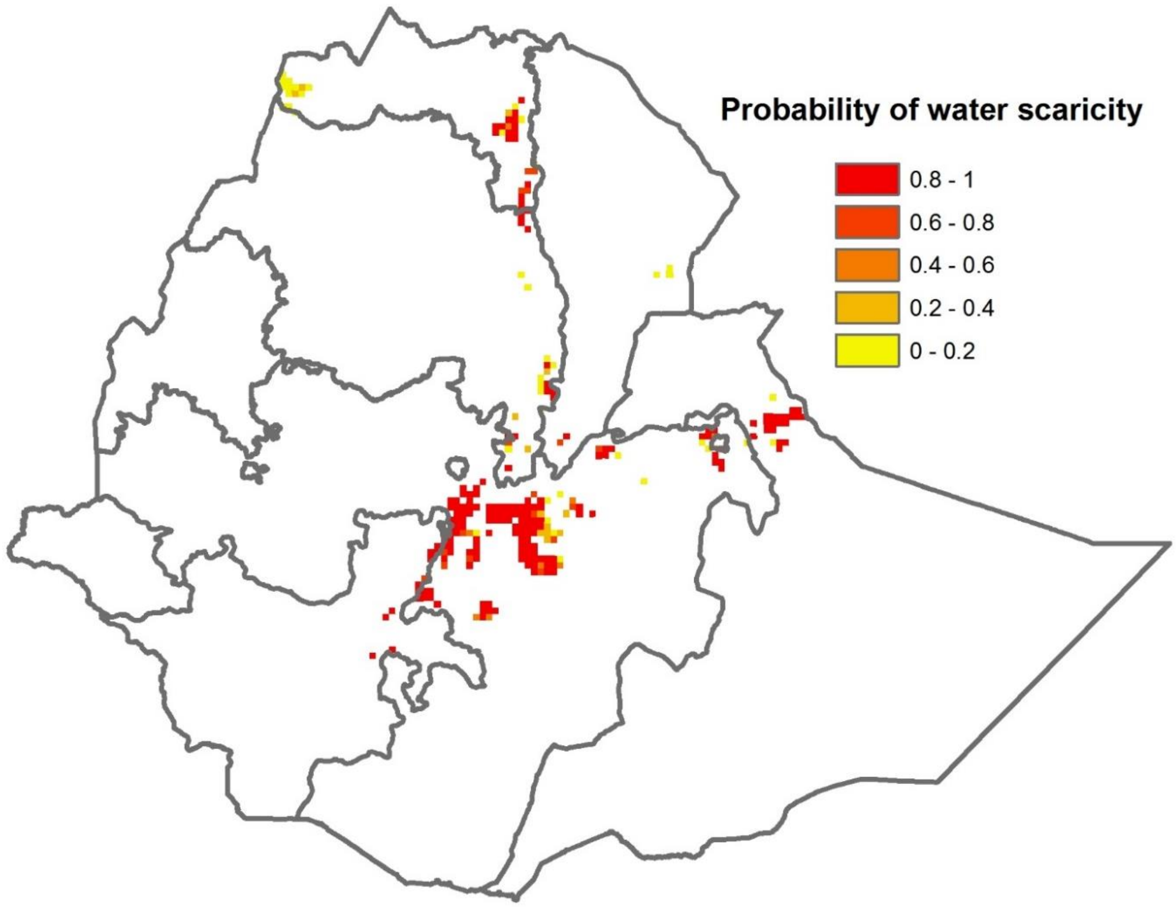

Figure 6. Risk of water scarcity associated with SSI expansion

Finally, the estimated irrigation development potential is sensitive to the irrigation cost figure used in the analysis, and the sensitivity is shown in Table 3. In reality, the small-scale irrigation consists of a collection technologies with varying adoption costs. The cost levels under scenarios accommodated in the sensitivity analysis were specified to approximate three typical situations with different configurations of small-scale irrigation technologies in adoption. The estimated irrigation development potential we already reported above refer to the irrigation development potential in the baseline scenario, in which the irrigation cost was assumed to be $200/ha-yr. This cost level was chosen to reflect the costs associated with the purchase and operation of water lifting devices such as motor pumps. Small-scale irrigation adoption may require construction of certain types of infrastructure in upper stream areas (e.g. small reservoirs and ponds etc.) to provide additional water storage capacities. Under baseline scenario, we assumed that the costs of water infrastructure construction and operation will be financed by governments or NGOs. In high cost scenario, it was assumed that farmers bear all costs of the water infrastructure construction and operation, and a higher irrigation cost $1000/ha-yr was specified to represent the irrigation costs of the whole system. An irrigation cost estimate in the middle range $600/ha-yr was used in the medium-cost scenario under the assumption that costs of constructing and operating water infrastructure will be partially covered by external donors.

According to expected areas with small-scale irrigation development potential shown in Table 2, small-scale irrigation development potential decreases as irrigation costs rises and drops from 0.8 million hectares in baseline scenario to 0.6 million hectares in medium cost scenarios and 0.5 million in high costs scenario. The results of the sensitivity analysis highlight the importance to develop low-cost small-scale irrigation technologies.

Table 3 Estimated small-scale irrigation adoption potential in Ethiopia (ha)-sensitivity

	Baseline	Medium cost	High cost
Affar	55	39	42
Amhara	318,170	224,880	176,468
Benishangul-Gumuz	11,601	11,082	11,069
Gambella	329	255	283
Harari	592	408	323
SNNP	129,053	112,603	101,020
Tigray	10,304	6,408	3,750
Oromiya	330,793	256,988	201,702
Somali	496	459	432
Total	801,392	612,662	494,657

4. Conclusions

Whereas ILSSI's ex ante and ex post analyses of SSI interventions in Ethiopia, Tanzania, and Ghana have focused on specific study sites in the project countries, upscaling analyses will assess the potential for expanding SSI to the national scale, identify specific locations where SSI will be feasible, and evaluate the consequences at the country level for agricultural production, environmental sustainability, and socio-economic outcomes.

The assessment of SSI adoption decisions at a national scale (rather than a more localized level) is complex. For example, whereas analyses at a local level may treat a crop price as constant in cost-benefit evaluations, when SSI investment at a national level is proposed, crop prices must be treated as variable. The upscaling framework that we developed integrates several modeling tools and biophysical and socioeconomic data to provide spatially disaggregated, quantitative estimates of SSI development potential in a target country.

In Ethiopia, upscaling analysis is underway and is slated for completion in year four of the ILSSI project. The pre-suitability analysis for Ethiopia has been completed, and indicated that nearly 5.3% of the landmass in Ethiopia, or approximately 60,025 km^2, is suitable for irrigation. The Abbay (Blue Nile) basin has the largest area of suitable land (21,186 km^2), while the Rift Valley basin has the highest percentage of suitable land (20%).

In the upscaling analysis, we use SWAT to calculate spatially disaggregated estimates of water availability, irrigation water consumption, and irrigated crop yields. These estimates are provided to the ABM for the irrigation expansion simulation. In Ethiopia, SWAT is simulating a variety of potential irrigated, dry-season crops, including tomato, onion, pepper, cabbage, and potato. Preliminary findings show that tomato yield can range from less than 1 ton/ha to 2.8 ton/ha, and that the available water resources (including surface runoff and ground water) across agricultural fields can range from less than 100 mm to over 2000 mm.

The ABM is used to analyze the impact of SSI technologies on farmers' livelihoods, considering irrigation and other input costs of potential irrigated crops. In Ethiopia, we are using the ABM to simulate a variety of candidate crops for SSI, including vegetable crops (tomatoes, onions, cabbages, peppers and vegetables-other) and pulse and root crops (chickpeas, lentils, and potatoes). Preliminary results indicate that SSI development potential in Ethiopia is about 800,000 ha, mainly in Oromia, Amhara and SNNP. Simulations show that, while adoption of SSI could be widespread, SSI adoption is most likely to be successful in select areas as the Central Rift Valley and areas near Lake Tana. We recommend that future endeavors promoting SSI adoption target these areas.

ABM simulations also identified river basins that are prone to water scarcity. In these regions, we recommend that appropriate institutional arrangements be made in conjunction with SSI investment activities, to reduce negative environmental and socioeconomic consequences of SSI development.

APPENDIX A

Applying the ABM to model SSI expansion in Sub-Saharan African countries

The input data for the ABM are shown in table A-1. Additional input parameters required to launch the simulation are shown in table A-2. A list of candidate irrigated crops is identified prior to simulation, and serves as a key assumption underlying the analysis.

Table A-1. Input data for ABM for upscaling analysis on SSI development potential in Ethiopia

Data	Explanations
Pre-suitability for SSI development	1km×1km; derived through GIS-based Multi-Criteria Evaluation (MCE) techniques; the pre-suitability score ranges between 0-100; suitability domain for SSI development is defined by setting a threshold for the pre-suitability score prior to the ABM simulation; SSI adoption only occurs in the delineated suitability domain, or area with suitability score greater than the threshold
SPAM	1km×1km; provide cropping pattern data in base year (2010)
Yields of candidate crops for irrigation	ton/ha; estimated using SWAT model
Irrigation water use intensity of candidate crops for irrigation	m^3 H_2O/ha-yr; estimated using SWAT model
Water yields by subbasin	m^3 H_2O/yr; estimated using SWAT model; subbasin is defined as 10km × 10km grid cell
Initial production by region	ton/yr; used as initial conditions in simulating crop price change; available from CSA survey reports
Initial consumption by region	ton/yr; used as initial conditions in simulating crop price change; disaggregated from national statistics according to population distribution
Initial prices of candidate irrigated crops of by region	$/ton; available from CSA survey reports
Irrigation costs	$/ha-yr: available from household surveys collected in Ethiopia by IFPRI, Africa Rising, LIVES-ILRI and NBDC-IWMI projects
Crop production costs other than irrigation	$/ha-yr: available from household surveys collected in Ethiopia by IFPRI, Africa Rising, LIVES-ILRI and NBDC-IWMI projects

Table A-2. Input parameters

$S_{threshold}$: threshold of land pre-suitability score for irrigation adoption to occur

p_{max}: value of probability p in eq. (AS1-1) corresponding to land pre-suitability score S=100

p_{min}: value of probability p in eq, (AS1-1) corresponding to land pre-suitability score S=$S_{threhshold}$

q_{max}: value of probability q in eq. (AS1-1) corresponding to land pre-suitability score S=100

p_{min}: value of probability q in eq. (AS1-1) corresponding to land pre-suitability score S=$S_{threshold}$

R: radius of neighborhood of influence, km

The proposed ABM runs on a square lattice which consists of 1 km-by-1 km cells. Each cell is viewed as a farm. Farms are autonomous agents. Farm size is estimated as existing rainfed farming area in cells using SPAM data (i.e., we assume irrigation adoption will occur on existing agricultural land).

The model algorithms are shown in algorithm A1 (for the main model) and algorithms AS1 and AS2 (for the sub-models). Irrigation adoption is modeled as a technology diffusion process. A time step in the main algorithm (A1) represents a growing season. At the beginning of each growing season, sub-model AS1 is used to evaluate the adoption decision of each non-adopting farmer. In the evaluation, a probability indicating a farmer's interest in irrigation adoption is first calculated. The calculation of the probability is based on the epidemic model of technology diffusion (eq. AS1-1). The epidemic model (Griliches, 1957; Mansûeld, 1961; Mansûeld, 1968; Rome, 1977) postulates that social influence is the main factor which drives the diffusion of a technology. The formulation of the eq. AS1-1 follows the Bass model (1969), which is an aggregate technology diffusion model but has been adapted to represent an agent's adoption in an agent-based modeling context (Kiesling et al., 2012). The second term in the equation represents the peer effect, or the influence of adopting farmers in a predefined neighborhood, while the first term reflects the influence of other sources (e.g., agricultural extension services). The size of the neighborhood of influence is defined by input parameter R. We also further assume that are linearly correlated with pre-suitability score (eq. AS1-2 and AS1-3).

Once the farmer is interested in adopting irrigation, the economic viability of the adoption and the water balance of the region in which the farm is located are assessed (eq. AS1-4, AS1-5 and AS1-6) under bounded rationality assumption. In particular, price in eq. AS1-6 refers to the farmer's expected crop price at the end of the growing season. The price expectation is updated adaptively (Hicks 1939; Koyck 1954; Muth 1960; Nerlove 1958) (eq. AS1-7) according to "actual" price in the preceding growing season.

Adoption will occur only if the farmer perceives that irrigated production is economically profitable and irrigation water demand can be fully met. It is further assumed that, if adopted, irrigation will be used to produce crops with the highest economic profitability.

Once a farmer's adoption decisions are revealed, "actual" prices of irrigated crops are estimated according to production under the new irrigation adoption scheme (sub-model 3).

At the end of each growing season, the economic profitability of irrigated production and the water balance of adopting farms are re-evaluated. In the re-evaluation of economic profitability of irrigated crops, expected crop price in eq. AS1-6 is substituted with the "actual" price of the irrigated crop calculated by sub-model 3. If water scarcity occurs in a river basin, due to lack of data to further assess farm's water accessibility, a subset of adopting farms are picked up randomly to remove excess of irrigation water demand. It is assumed that irrigation activities on these farms are restricted by water scarcity, and they suffer a loss equal to capital investment for irrigation. The model tracks the assets of adopting farms, which are calculated as accumulated profits since irrigation adoption. Adopting farms exit irrigation adoption if asset value is less than 0.

In the analysis, the model runs for a sufficient number of time steps until the relative change in the estimated adoption rate is small, or the irrigation expansion stops under the constraints of water availability and when market for irrigated crops is saturated. The adoption pattern is then reported and taken as estimated potential for SSI expansion.

A1 Main model

Initialize simulation; set assets of all farms to zero. At each time step t (t=0, 1, 2, ⋯):

1. For each non-adopting farm in suitability domain, evaluate adoption decision at the beginning of growing season (sub-model 1);
2. Update prices of irrigated crop according to production of irrigated crops under new adoption scheme (sub-model 2); and
3. For each adopting farm, evaluate net revenue using updated crop prices; update farm assets; farm exits irrigation if assets<0.

AS1: Sub-model 1: adoption decision of individual farm

This sub-model is designed to evaluate the adoption decision of an individual farm and determine the crop under irrigation once irrigation is adopted. The decision process represented in the sub-model (described in more detail in Section 2) is illustrated in figure 2.

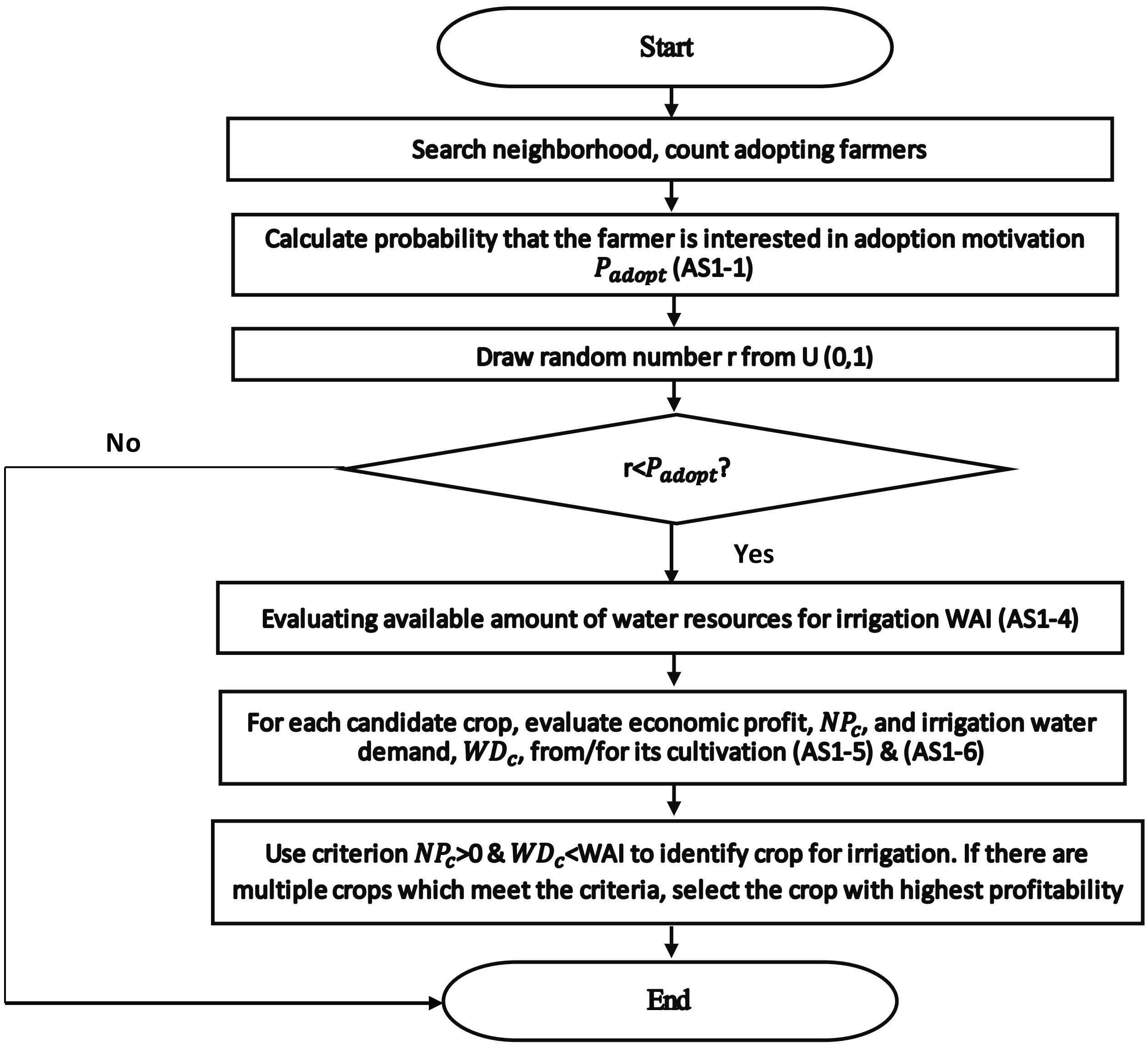

Figure 2. Farmer's decision process for SSI adoption

The probability indicating a farmer's interest in irrigation adoption P_{adopt} is calculated as

$$P_{adopt} = p + q\,\frac{I}{I_{total}} \tag{AS1-1}$$

where p is the probability that the farmer becomes interested in adoption under independent external influence, such as influence from agricultural extensions; q is a probability which characterizes the influence from peers in a predefined neighboring area; I is the number of farms in the predefined neighboring area who have already adopted irrigation, and I_{total} is the size of neighborhood.

p and q in eq. AS-1 are calculated monotonically increasing function of pre-suitability score.

$$p = p_{min} + \frac{p_{max} - p_{min}}{100 - S_{threshold}} \cdot (S - S_{threhsold}) \tag{AS1-2}$$

and

$$q = q_{min} + \frac{q_{max} - q_{min}}{100 - S_{threshold}} \cdot (S - S_{threhsold}) \tag{AS1-3}$$

where S is the pre-suitability score for irrigation adoption of the farm, $S_{threshold}$ is the threshold of pre-suitability score for irrigation adoption to occur, p_{max} and q_{max} are values of p and q corresponding to maximum value of pre-suitability score (100), and p_{min} and q_{min} are values of p and q corresponding to threshold value of pre-suitability score.

The amount of water resources available for irrigation, WAI (m^3 H_2O/yr), is calculated as

$$WAI = WY - \sum_i w_i \cdot A_i \tag{AS1-4}$$

where WY is annual water yield in the river basin in which the farm is located (m^3 H_2O/yr), A_i is the irrigated area in farms that have already adopted irrigation and belong to the same river basin (ha), and w_i is the irrigation water use intensity (m^3 H_2O/ha-yr) on those farms.

The water demand for each candidate irrigated crop, WD_c (m^3 H_2O/yr), is calculated as

$$WD_c = w_c \cdot A \tag{AS1-5}$$

where w_c is irrigation water use intensity (m^3 H_2O/ha-yr) for crop c and A is farm size (ha).

The economic profit of cultivating each candidate irrigated crop, NP_c($/yr-ha), is evaluated as

$$NP_c = p_c^e \cdot y_c - C_{irr} - C_{other} \tag{AS1-6}$$

where p_c^e is the farmers' price expectation for crop c ($/ton), y_c is the yield of the irrigated crop (ton/ha-yr), C_{irr} is irrigation costs ($/ha-yr), and C_{other} is the crop production of other components ($/ha-yr).

The price expectation is formed by

$$p_c^e = p_{c,-1}^e + (1 - \lambda)(p_{c,-1} - p_{c,-1}^e) \tag{AS1-7}$$

where $p_{c,-1}^e$ is the expected price in the last growing season ($/ton), $p_{c,-1}$ is the "actual" price in the last growing season ($/ton), and $(1 - \lambda)$ is the forecasting adjustment factor: price expectation will not change if $\lambda = 1$, and $p_c^e = p_{c,-1}$ if $\lambda = 0$. λ is drawn as a random number from uniform distribution between 0 and 1, U(0,1), to reflect the heterogeneity in the farmer's price expectation.

AS2: Sub-model 2: crop price change simulation

The algorithm used in this sub-model to simulate crop price change under the influence of irrigation adoption is modified from the Dynamic Research EvaluAtion for Management (DREAM) model (Wood et al., 2008). 12 regional markets are defined in the sub-model, including 11 domestic regional markets (corresponding to 11 administrative regions) in Ethiopia and an additional market representing the "Rest Of World" (ROW).

For each region, a linear demand function is specified

$$C_{rt} = \gamma_r + \delta_r P_{rt} \quad \text{(AS2-1)}$$

where C_{rt} is quantity of irrigated crop under simulation being consumed in region r at time step t (ton/yr), and P_r is the price of the irrigated crop at time step t ($/ton). The slope and intercepts of the linear demand function are determined using initial crop production and initial crop price at t=0 and price elasticity of demand in region r, η_r (<0)

$$\delta_r = \eta_r C_{r0}/P_{r0} \quad \text{(AS2-2)}$$

$$\gamma_r = (1 - \eta_r)/C_{r0} \quad \text{(AS2-3)}$$

It is assumed that the prices in regional markets can be calculated as

$$P_{rt} = (1 + \upsilon_r)P_t \quad \text{(AS2-4)}$$

where υ_r is the market margin between region r and the market equilibrium price P_t. Since total production across all regional markets are equal to total consumption

$$\sum_r Q_{rt} = \sum_r C_{rt} \quad \forall t \quad \text{(AS2-5)}$$

(where Q_{rt} is the production of irrigated crop in region r (ton/yr), the market margins can be estimated as

$$\upsilon_r = \frac{P_{r0}}{P_0} - 1 \quad \text{(AS2-6)}$$

where

$$P_0 = \frac{\sum_r Q_{r0} - \sum_r \gamma_{r0}}{\sum_r \delta_{r0}} \quad \text{(AS2-7)}$$

The crop price in region r and at time step t is calculated using eq. AS2-4, where

$$P_t = \frac{\sum_r (Q_{r0} + \Delta Q_{rt}) - \sum_r \gamma_{r0}}{\sum_r \delta_{r0}} \quad \text{(AS2-8)}$$

and ΔQ_{rt} in AS2-8 denotes increased crop production (ton/yr) in region r and is calculated by summing up all irrigated production in cells in region r

$$\Delta Q_{rt} = \sum_{(i,j)\in r} (y_{(i,j),c} \cdot A_{(i,j),c}) \quad \text{(AS2-9)}$$

where cell/farm are indexed by its row number i and column number j in lattice, $y_{(i,j),c}$ is crop yield in cell/farm (i,j) (ton/ha-yr), and $A_{(i,j),c}$ is the farm size or the area of irrigated crop in cell/farm (i,j) (ha).

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