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Design of an agent-based model to examine population–environment interactions in Nang Rong District, Thailand

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A B S T R A C T

The design of an agent-based model (ABM) is described that integrates Social and Land Use Modules to examine population–environment interactions in a former agricultural frontier in Northeastern Thailand. The ABM is used to assess household income and wealth derived from agricultural production of lowland, rain-fed paddy rice and upland field crops in Nang Rong District as well as remittances returned to the household from family migrants who are engaged in off-farm employment in urban destinations. The ABM is supported by a longitudinal social survey of nearly 10,000 households, a deep satellite image time-series of land use change trajectories, multi-thematic social and ecological data organized within a GIS, and a suite of software modules that integrate data derived from an agricultural cropping system model (DSSAT – Decision Support for Agrotechnology Transfer) and a land suitability model (MAXENT – Maximum Entropy), in addition to multi-dimensional demographic survey data of individuals and households.

The primary modules of the ABM are the Initialization Module, Migration Module, Assets Module, Land Suitability Module, Crop Yield Module, Fertilizer Module, and the Land Use Change Decision Module. The architecture of the ABM is described relative to module function and connectivity through uni-directional or bi-directional links. In general, the Social Modules simulate changes in human population and social networks, as well as changes in population migration and household assets, whereas the Land Use Modules simulate changes in land use types, land suitability, and crop yields. We emphasize the description of the Land Use Modules – the algorithms and interactions between the modules are described relative to the project goals of assessing household income and wealth relative to shifts in land use patterns, household demographics, population migration, social networks, and agricultural activities that collectively occur within a marginalized environment that is subjected to a suite of endogenous and exogenous dynamics.

Introduction

Land Change Science seeks to understand the changing patterns of land use/land cover as a consequence of the complex, multi-thematic, and scale dependent relationships that emanate from human–environment interactions and their dynamics (Rindfuss, Walsh, Turner, Fox, & Mishra, 2004). Invoking theories and practices from across the social, natural, spatial, and computational sciences, Land Change Science seeks to understand pattern–process relations of social and ecological systems and their linked effects through mixed methods approaches. In this study, we develop an agent-based model (ABM) designed to examine land use/land cover change in a former agricultural frontier in Northeastern Thailand that has

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experienced considerable out-migration of young adults to engage in off-farm employment in urban destinations. Rural agricultural households in Nang Rong District receive remittances from the off-farm employment of family members to supplement household income. In addition, remittances serve to diversify risks to household wealth by reducing their reliance on the cultivation of agricultural crops in a region constrained by poor resource endowments and plagued by the vagaries of monsoonal rains. Our ABM, informed through a longitudinal social survey, a satellite image time-series, and GIS coverages of social and ecological factors, integrates population and environment through statistical models, focus group discussions, and spatial simulation methods (Entwisle, Malanson, Rindfuss, & Walsh, 2008; Entwisle, Rindfuss, Walsh, & Page, 2008; Rindfuss, Turner, Entwisle, & Walsh, 2004; Walsh, Entwisle, Rindfuss, & Page, 2006; Walsh, Rindfuss, Prasartkul, Entwisle, & Chamratrithirong, 2005). With an emphasis on 'biocomplexity,' we focus on the interactions within and among ecological systems, physical systems on which they depend, and the human systems with which they interact (Michener et al., 2003; Walsh, Malanson, Messina, Brown, & Mena, 2011; Walsh, Messina, Mena, Malanson, & Page, 2008).

Our ABM is designed to examine household wealth and income by including software modules that account for population migration, household assets, land suitability, agricultural crop yields, fertilizer application, and a Land Use Change Decision Module. We describe each of these modules, with an emphasis on the Land Use Modules, offering context and rationale for their development, and describing the linkages among the modules that reflect population–environment interactions, feedback mechanisms, and adaptive strategies to diversity household risk relative to changing household demographics, environmental settings, agricultural practices, and climate change scenarios. The climate scenarios reflect shifts in the intensity, duration, and onset of floods and droughts and their extension to 'extreme' events in shaping human behavior and altering landscape form and function.

Our model has leveraged the work, for example, by Bousquet, Le Page, Bakam, and Takforyan (2001) in Cameroon, Africa, Manson (2005) in the Yucatan Peninsula of Mexico, Brown, Riolo, Robinson, North, and Rand (2005) in the Great Lakes region of Michigan, Miller et al. (2010) in the Galapagos Islands, and Mena, Walsh, Frizzelle, and Malanson (2011) in the Ecuadorian Amazon. In addition, the work of Sengupta and Bennett (2003) on spatial decision support systems, Evans and Kelley (2004) on multi-scale analysis of household agents, Grimm and Railsback (2005) on the links between ecology and individual-based modeling, Malanson, Zeng, and Walsh (2006a, 2006b) on complexity and characterizing social and ecological ecotones, Clarke, Gazulis, Dietzel, and Goldstein (2007) on land use change models, and Gonzalez, Montes, Rodríguez, and Tapia (2008) on complexity and adaptive systems have offered important design issues for us to consider.

Our ABM has been constructed through data collection campaigns, analyses, and empirical observations that have been conducted over two decades of work in the study area, a longitudinal social survey of nearly 10,000 households across three time periods, an archive of over 35 processed satellite images used to characterize land use/land cover change trajectories, and an interdisciplinary team that extends across the sciences. As such, our ABM benefits from a very large sample size to represent social and ecological factors and to test their linked effects, statistical models and variable coefficients to inform our rules and relationships, disciplinary and interdisciplinary theory to guide our module development, and a large number of sample villages that are sufficiently different to test the robustness of our ABM across different social and ecological conditions and periods.

Research objectives & context

The goal of this paper is to describe the land component of an integrated population–environment agent-based model (ABM) that was developed for Nang Rong District, Northeastern Thailand. We emphasize the processes that are being represented in the model, the algorithms that drive the model, the form of the model, i.e., its general architecture, and the manner in which population and environment are integrated through a base model that is perturbed through climate change scenarios, involving alterations in the typical monsoonal rains that induce droughts, floods, and changes in their onset and intensity. In general, the ABM examines household income and wealth derived from agricultural production of lowland rain-fed paddy rice and upland field crops, primarily cassava and sugarcane, as well as non-agricultural activities associated with remittances sent to rural agricultural households from the off-farm employment of family members working in urban centers, principally, Bangkok, Khorat, and the Eastern Seaboard (Shao, Walsh, Entwisle, & Rindfuss, 2008).

Relying upon a rich and integrated social and ecological data set and a long history of research within the District, the ABM is supported by a longitudinal social survey (1984, 1994, 2000) and a sample of nearly 10,000 households, a deep satellite image time-series that has been classified and enhanced for landscape characterization, and multi-thematic social and ecological data sets organized within a GIS (Crews & Walsh, 2009). In addition, a suite of software modules are developed that integrate data and findings from a cropping system model (DSSAT – Decision Support System for Agrotechnology Transfer) and a land suitability model (MAXENT – Maximum Entropy). Demographic survey data are also used to assess population–environment interactions, the processes that influence them, site conditions and farmer decisions that mitigate or sustain them and modeled outcomes that are derived under uncertainty for a baseline model that is perturbed through scenarios that involve climate change and the adaptive capacity of local farmers and household migrants. Variations in household wealth and income are measured, modeled, and assessed as model outcomes that are generated for annual iterations. These variables are also used as indicators of household vulnerability and resilience to endogenous and exogenous dynamics, such as floods and droughts, as well as market conditions, crop price variations, and soil fertility patterns.

Despite the importance of population to land cover change (Holdren & Ehrlich, 1974), until recently, demography has not been central in research on land use/land cover dynamics and the human dimension. The questions of interest have featured impacts of population on environment rather than vice versa, even though both directions of effect are clearly relevant and endogenously related. Given this, it is not surprising that ecology, geography, and other natural sciences have addressed impacts of population on land use and land cover change (e.g., Allen & Barnes, 1985; Brown & Duh, 2004; Skole, Chomentowski, Salas, & Nobre, 1994; Turner, Geoghegan, & Foster, 2003; Walsh et al., 2008), but demography and the social sciences often have failed to do so (see Pebley, 1998 for a more extensive discussion). Another reason why the population community was not more involved in early research on population and the environment is that data have tended to be unavailable at the appropriate scales and linkages. Fine grain social units, such as individuals and households, do not map well to the spatial units of interest to land change scientists (e.g., pixels and watersheds). Rather, administrative units such as counties, states or provinces, and countries have been the units of observation and analysis in much of the literature on population, land use, and environment (e.g., Allen & Barnes, 1985; Bilsborrow, 1994; Ehrhardt-Martinez, 1998; Grainger, 1993; Lutz & Holm, 1993; Rudel, 1989). Much of this macro level research, using political boundaries and regression approaches, estimates the impact of population size or density on the percent of land in forest at the country level, or possibly at a lower level of aggregation, such as provinces or districts (e.g., Skole et al., 1994). Another stream of research using models and simulations estimates the effects of population variables on land use for broad ecological units in global or regional models. The problem with both sets of macro approaches (the political boundary regression approach and the ecological boundary model simulation approach) is that the role of micro level population processes is largely invisible. While it is true that births and deaths can be assigned to macro units, and people move into and out of them, this is not the level at which decision-making and behavior occurs, or where impacts are necessarily felt. The ecological fallacy (see Robinson, 1950 for the classic statement) of assuming that relationships that exist at higher levels of aggregation also exist at lower levels is a risk. Some approaches using ecological units do not have access to actual data on population and related human behaviors, and are forced to make strong assumptions about such behaviors. This situation has begun to change as more members of the population research community have become actively involved in research linking population processes to land use change in ways that fully utilize the data, tools, and perspectives of the field (e.g., Deane & Gutmann, 2003; Foster, 2005; Foster & Rosenzwei, 2003; Gutmann, Parton, Cunfer, & Burke, 2005; Pan & Bilsborrow, 2005; Rindfuss, Walsh, et al., 2004).

Questions about household dynamics and land use are at the heart of an evolving research program on population, land use, and the environment. In the past decade, research has expanded beyond the focus on population growth, deforestation, and agricultural extensification that dominated the earlier literature. Households as a population unit, migration as a component of population change, variability within as well as between major classes of land use (e.g., intensification), and cross-scale interactions have emerged as major foci in the literature (e.g., Brondizio et al., 2002; Fox, Rindfuss, Walsh, & Mishra, 2003; Liu, Daily, Ehrlich, & Luck, 2003; Liu, Ouyang, Tan, Yang, & Zhou, 1999; McCracken et al., 1999; Walsh & Crews-Meyer, 2002; Walsh, Welsh, Evans, Entwisle, & Rindfuss, 1999). Of particular note is a flourishing set of case studies where the social units are individuals or households (for examples, see papers in Entwisle & Stern, 2005; Fox et al., 2003; Liverman, Moran, Rindfuss, & Stern, 1998; Millington, Walsh, & Osborne, 2001; Walsh & Crews-Meyer, 2002; Walsh & McGinnis, 2008).

Much progress has been made with the case study approach (Entwisle & Stern, 2005). However, generalization has been limited. Indeed, a collection of case studies is not necessarily more than that unless comparisons among the cases can be made and generalizations drawn (Entwisle & Stern, 2005; Rindfuss, Turner, et al., 2004; Rindfuss et al., 2008).

The research described here is designed to bridge the gap between case study research and global environmental change. The idea is to take, within a case study, known empirical associations based on statistical analyses, combine them with demographic projections and arithmetic procedures to build a spatially-explicit simulation model that permits the running of 'experiments' where variables that are constant across the site are perturbed in a set of scenario runs. While our data are from one district in Northeastern Thailand, we have data for multiple villages that have distinctly different demographic, social, ecological, and geographic structures. Our model runs are separate by village thus allowing us to systematically compare and contrast model results across multiple villages. The spatial simulation at the heart of the proposed work comes under the broad category of 'agent-based models' (Berger, 2001; Berry, Keil, & Elliott, 2002; Epstein, 1999; Lansing, 2003; Macy & Willer, 2002; Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). The key idea is to project agents individually, but in relation to each other, allowing for feedbacks over time. Households are the primary agents in our simulation, affecting and affected by the behavior of household members, land use on plots, environmental characteristics of the land, and other households in the village. We simulate land use for households with respect to specific, spatially referenced, plots of land. We also allow individuals to marry, out-migrate, remit, return migrate, and of course, to die.

Similarly referencing households as the social unit of analysis and extending the analysis beyond the case study, An, Linderman, Qi, Shortridge, and Liu (2005) examine the impacts of a growing rural population on local forests and the constraints imposed on giant panda habitat. Fuelwood consumption in and around the Wolong Nature Reserve in China is associated with changing household demographics. By tracking the life history of individuals and the dynamics of households, they allow agents to learn about themselves and the implications of their actions, the actions of other agents, and the dynamic environment, as people and environment co-evolve relative to socio-economic and demographic changes as well as natural and anthropogenic forces that shape and re-shape panda habitat. Using individuals, households, and pixels as agents and objects, they develop demographic, landscape, and socio-economic sub-models to study human–environment interactions, with a focus on conservation policy. Also, in a rural region of Queensland, Australia, the decision-making behaviors of individual farmers are examined through an ABM to explore how voluntary mechanisms influence land use changes, associated with the clearing of native vegetation for agricultural development (Valbuena, Bregt, McAlpine, Verburg, & Seabrook, 2010). Compulsory and voluntary intervention mechanisms impact the decisions of farmers, depending upon their ability, i.e., farmer's capacity to take certain actions, and willingness, i.e., the predisposition of a farmer to make decisions, as well as the characteristics of the mechanisms themselves that are part of the agent typology and mediated by local and regional factors. Scenario testing is used to simulate farmers' participation in voluntary mechanisms to restore native vegetation and to address issues of uncertainty related to the future dynamics of human and ecological systems and land use decision-making. Lastly, Brady, Sahrbacher, Kellermann, and Happe (2012) extend an agent-based agricultural policy simulator to examine the consequences of agricultural policy reform on farmers' land use decisions, landscape structure, and ecosystem goods and services in Europe to evaluate the potential environmental impacts of agricultural policy reform on low-intensive agricultural landscapes. The model integrates farms, production activities, investment objects, farm plots, markets, and the political environment, using a suite of state variables associated with each farm-agent in the model. In these examples, and the Nang Rong model described here, the goal is to move beyond case studies to synthesis and process understanding that is achieved through scenario testing, development of conceptual frameworks, integration of household demographics and behavioral shifts on modeled outcomes, and linkages among model components that represent population–environment interactions and feedback mechanisms.

Study area

Nang Rong District is located in Buriram province in Northeastern Thailand, occupying roughly 1300 km^2 in the southwestern portion of the Khorat Plateau (Fig. 1). This region is characterized by marginality, with low soil fertility, poor drainage, and inconsistent monsoonal rains that inhibit agricultural productivity and economic prosperity (Rigg, 1991). Much of the region is ill-suited for agriculture due to irregular topography, persistent erosion, and high soil laterization, salinity, and acidity. Despite the limited natural resource base throughout much of the region, farming is the main household livelihood strategy (Parnwell, 1988), but increasingly off-

Fig. 1. Study area location, Nang Rong District, Northeastern Thailand.

farm employment fuels the wealth and assets of these rural agricultural households. It is common for households to farm 5–10 acres (~3 ha) for subsistence as well as commercial agriculture. Rice production in these seasonally flooded areas returns relatively high yields, although the seasonality and increasing variability of the monsoonal rains are persistent threats to sustainable agriculture (Fuki, 1993; Kaida & Surarerk, 1984). On occasion, upland field crops and lowland, rain-fed paddy rice exploit terrain strata, i.e., middle and high terraces, relatively unsuitable for lowland paddy rice, unless special environmental circumstances and economic opportunities extend cultivation from the normal core areas. Geomorphically, the highlands and the lowlands are connected through a series of undulating natural terraces that serve as areas of environmental transition that bifurcate agricultural activities into lowland paddy rice and upland field crops.

In Northeast Thailand, human interactions with the land have a pronounced legacy that resonates today, albeit in an altered form and fashion. Historically, land was deforested by migrants for subsistence cultivation in the alluvial lowlands. Rice was cultivated through the construction of rain-fed paddies, relying upon retention walls or bunds to manage water levels and flows. Planting was achieved through transplantation from nurseries and broadcast seeding methods. With time, subsistence agriculture was augmented by the commercial cultivation of higher-value rice varietals, such as Jasmine rice. In addition, the uplands were deforested in response to global market demands for a calorie-rich animal feed, i.e., cassava, primarily in Europe. As such, cassava and sugarcane were introduced to the uplands and sustained through relatively large-scale mechanization as individual land parcels coalesced into extensive areas of cultivation (Entwisle, Walsh, Rindfuss, & VanWey, 2005). As a consequence, the landscape mosaic of the uplands changed from one dominated by forest and fragmented by small-scale agriculture to one dominated by extensive areas of field crops and forest fragments.

In addition to the deforestation and agricultural extensification of the uplands, rice cultivation in the lowlands continued to change through the cultivation of lands increasingly remote from nuclear villages and positioned on topographic settings that were less suitable for the cultivation of lowland paddy rice (Entwisle, Walsh, Rindfuss, & Chamratrithirong, 1998). Heavy rice was generally cultivated on wetter sites, whereas Jasmine rice was normally cultivated on drier sites in the agricultural lowlands. Rice farmers periodically, however, would cultivate more marginal lands that were more remote from permanent and semi-permanent water sources and on less productive soils, particularly, when monsoonal rains exceeded normal conditions and/or market opportunities incentivized the cultivation of rice higher on the 3-dimensional topographic gradient that ranged from lower, wetter, and more productive sites, mainly used for paddy rice, to higher, drier, and less productive sites, mainly used for upland field crops, cassava and sugarcane. This change in land use practices occurred as rice farmers 'reached' to higher, traditionally drier, sites and upland farmers 'reached' to lower, traditionally, wetter sites. As a consequence, a transition zone was formed between the 'core' lowland rice growing region and the 'core' cassava- and sugarcane-growing region that periodically transformed the middle and high terraces, topographic settings not optimal for either crop type.

In essence, the land parcels at the opposing ends of the topographic gradient serve as the core areas of the lower, wetter, and more productive rice growing region, and the higher, drier, and less fertile soils serve as the core cassava- and sugarcane-growing region. Cultivation away from these core areas involves marginal or peripheral conditions for lowland rice and upland field crops. Adaptive strategies practiced by household farmers to cultivate crops outside of their core areas include the planting of different crop varietals, altering planting and harvesting schedules and techniques, developing alternate household livelihood strategies that included off-farm employment, integrating market forces and commodity price structures into household decision-making, and integrating the constraints and opportunities associated with climate change and commodity prices on crop choice, agricultural yields, water and land management, and land suitability.

Data types

Multilevel and multi-dimensional data have been explicitly gathered and extensively processed to examine the interplay between people and environment in Nang Rong District, Northeastern Thailand. Data within the model come from a variety of sources, including demographic surveys, administrative records, hardcopy and digital maps, aerial photography and satellite imagery, and field data geographically referenced using a GPS. Multilevel social data include individuals, households, and villages for a period from 1984 to 2000, while spatial data include raster and files representing, for instance, land use/land cover and vegetation greenness, and vector files, representing, for instance, soil types, agricultural plots, hydrography, roads, village territories, and the district boundary for a period from 1954 to the present. Data are linked, over time, across scales, and across biophysical, social, and spatial domains (Rindfuss et al., 2002, 2007; Rindfuss, Walsh, Mishra, Fox, & Dolcemascolo, 2003; Walsh & Welsh, 2003; Walsh et al., 2005). Further, social network data are spatially referenced for 51 villages, facilitating analyses that treat kinship relationships as an endogenous element in new and innovative way (Entwisle, 2007).

Social survey & demographic data & land use data

There are three levels of social survey data: individual, household, and village. They are used to create and initialize the social agents. Individual agents have unique personal IDs, age, gender, migration status, marriage status, and education. The IDs of the father, mother, and spouse are also included, if there are any. For the household agent, each has a unique household ID, assets, population roster, and centrality. For village agents, each has a unique village ID, distance to nearest village, presence of bus routes, primary school, secondary school, water pumps, vehicles, TVs, and cultivated crop types. The three kinds of agents are linked by Personal ID, Household ID, and Village ID, according to Fig. 2.

The initial data sets are created in text files. Each row in the file contains attribute values for one agent. The initial file is imported into the ABM at the initialization stage to create and populate agent values. Following the creation of the individual agents, the kinship networks are created. The first degree, an individual social network is derived directly from parents and spouse IDs, then the second, third, and fourth social network ties are created through matrix multiplication. These individual social networks are aggregated to the household level through the fourth degree social tie. Fig. 3 shows the hierarchical relationship of kinship networks and the linkage to owned farm parcels by the head of household. Individuals may be connected between households in the same or different villages.

The initial data set for the land portion of the ABM is raster files. The basic unit is the cell that is defined as a row-column feature having a 5-m spatial resolution. Each raster file defines one attributes of the cell. Cells with the same parcel ID and village ID are grouped as a single parcel. The social survey data also defines the ownership and renting behavior between a parcel and a household. If the parcel is owned by a household, this parcel will be linked to the head of the household. If a household splits during the simulation, land owned by the household will also split and a new owner will be linked to the parcel.

Remote sensing imagery & GIS coverages

Numerous spatial data sets, including remotely sensed satellite imagery, and raster and vector GIS data layers, are incorporated as foundational inputs to the ABM. Raster data and rasterized vector

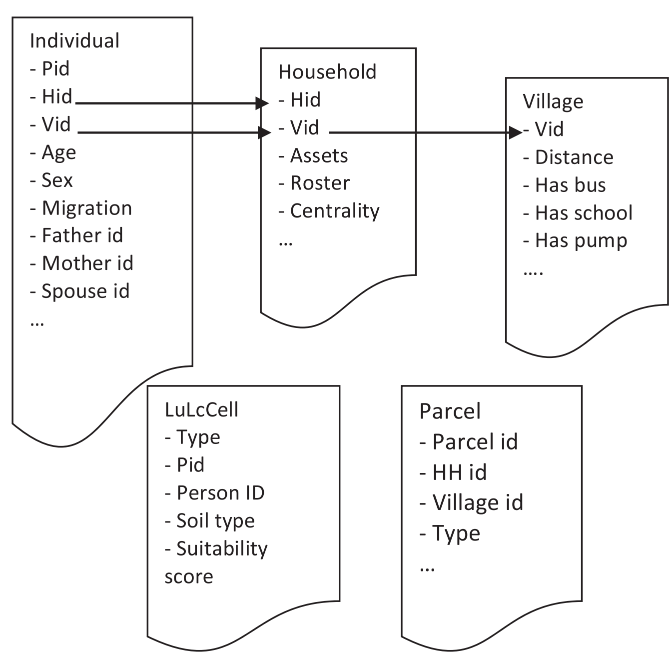

Fig. 2. File links between social agents in the ABM, for example, Hid (Household ID) and Vid (Village ID) as key fields to navigate the relational database.

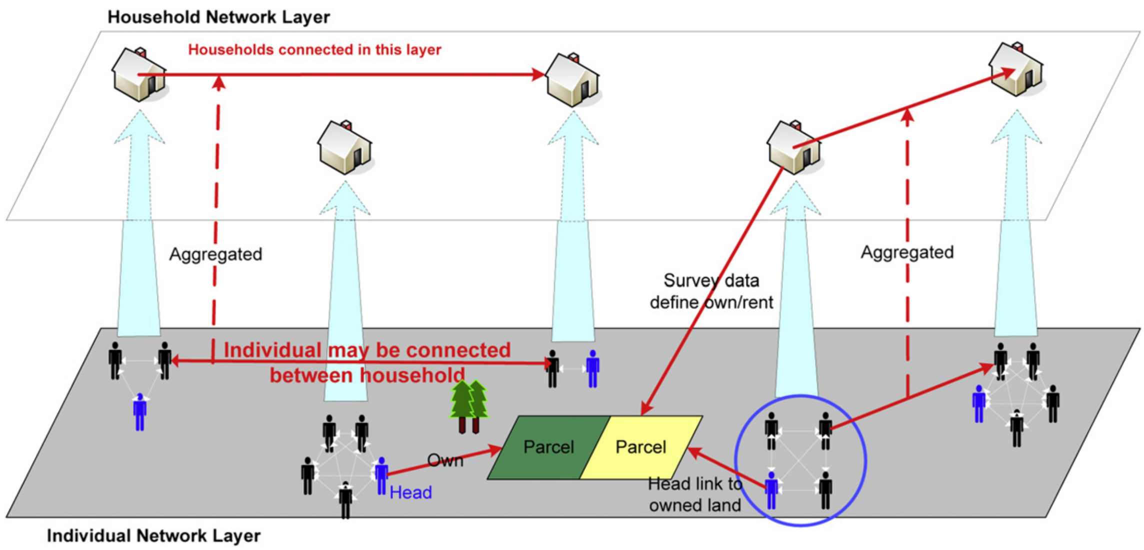

Fig. 3. Schematic of multi-tiered social networks based on available social network data.

data layers are used to establish the background matrix on which modeling activities occur and model outcomes are referenced. In addition, vector data layers and associated tabular attribute data are integrated into the model as key inputs into the creation of model agents.

A December 1999 Landsat Enhanced Thematic Mapper image was classified into primary land use/land cover (LU/LC) types through a hybrid supervised/unsupervised approach (Messina, Crews-Meyer, & Walsh, 2000), The resulting classes of interest – rice, cassava, and sugarcane – were directly included in the model, as well as landscape biomass and greenness characterizations (Walsh, 1999; Walsh, Crawford, Welsh, & Crews-Meyer, 2001). The remaining classes – forest, water, and urban – were aggregated into a 'background' class that was used to delineate exclusion zones for agricultural activities (Walsh et al., 2003).

A Digital Elevation Model (DEM) was created from a 10-m resolution set of contour lines from a collection of 1984, 1:50,000 scale Thai military topographic base maps. In addition, a total of 1373 spot elevations, also collected from the topographic maps, were used to obtain a finer level of detail. The elevation surface was further processed to remove topographic sinks.

Village-level cadastral data exists for each of the modeled villages assessed within the ABM. These parcel boundaries were digitized from hardcopy maps and from data collected during fieldwork in 2000, and subsequently linked to specific households through an innovative land use matching process. Through these linkages for each land parcel, information on household demographics, such as, assets, social networks, and migration, and land use decisions, such as, crop choices and level of fertilizer application, are tied to spatially-explicit locations within Nang Rong District.

As a basis for modeling crop yield and defining land productivity of household land parcels, soil surfaces were generated from a 1974 soil survey conducted by the Thai government. The soils file contains 32 soil series for Nang Rong District, including mixed soil types. Physical and ecological attributes pertaining to texture, organic matter, cation exchange capacity, drainage capacity, and phosphorous and potassium content are included, along with suitability ratings for paddy rice and upland field crops. To reduce and simplify the number of growing conditions used to calculate crop yields, the 32 soil types were reduced to five major soil classes.

Gridded monthly rainfall data from 1900 to 2008 were acquired from the Center for Climatic Research at the University of Delaware. The 'Terrestrial Precipitation: 1900–2008 Gridded Monthly Time Series (Version 2.01)' data set contains monthly precipitation data from a variety of disparate sources, using climatologically aided interpolation and anomaly detection techniques to improve quality and coverage (Nickl, Willmont, Matsuura, & Robeson, 2010). Though created from a variety of sources and including aggregated, interpolated and composited values in many instances, these data sets facilitate a generalized view of the long-term trends in precipitation in Nang Rong District and the immediate vicinity.

The land use for each parcel is initially derived from 'Form 6' (see http://www.cpc.unc.edu/projects/nangrong/data/publicuse_data/public00), a component of our 2000 household social survey in which farmers describe the types of crops grown and other land use/land cover types that occur on their land parcels for 1999–2000 and what they 'anticipated' planting for 2000–2001. Our model includes the primary crop types grown within the District – cassava and sugarcane (upland field crops) and jasmine rice and heavy rice (lowland paddy rice). Several land use types may occur on a single land parcel. In these instances, the calculation of crop yield is computed at the parcel-level for each land use, with the yield then divided according to the number of land uses present on the parcel. In this way, the land uses need not be spatially-explicit within the parcels.

Derived climate conditions

To simulate the effects of climatic variability and climate change on rain-fed agricultural productivity, we have developed a climate classification of the monsoonal rains based on the amount and timing of the rains. Using a historical monthly precipitation record from 'Terrestrial Precipitation: 1900–2008 Gridded Monthly Time Series' data set from the Center for Climatic Research at the University of Delaware, we classified nine monsoon scenarios that were used as input for the DSSAT crop yield model. This classification was introduced as a simplification of climate. Within DSSAT, the derived monsoonal conditions correspond to growing seasons of various lengths, while the derived rainfall amounts correspond to different precipitation totals that are distributed as daily rainfall in millimeters.

To determine the type of 'monsoonal' year, we examined the precipitation record from 1900 to 2008 and classified the distribution of amount and timing occurrences on a threshold of one-standard deviation. If the annual amount was greater than one-standard deviation above the mean, the year was coded as 'Wet.' If the annual amount was less than one-standard deviation below the mean, the year was coded as 'Dry.' If the annual rainfall fell within +/− one-standard deviation of the mean, the year was coded as 'Normal.' This method of classifying monsoonal years by the amount of rainfall vs. long-term normal resulted in 17% of the years being 'Wet,' 18% being 'Dry,' and 65% being 'Normal.'

Our characterization of the timing of the monsoon takes into account the fact that the start of the monsoonal year does not fall on any specific data, but instead coincides with the general increase in rainfall over a span of several weeks. Monsoonal timing was classified by identifying the start of the monsoon based on cumulative precipitation in April, May, and June, the normal monsoonal initialization months. If the annual cumulative rainfall in any one of these three months is greater than at least one-standard deviation above the mean, then the monsoon rains have started 'Earlier' than normal. Conversely, if the cumulative rainfall is less than one-standard deviation below the mean, the monsoonal rains are considered to be 'Later' than normal. If the cumulative rainfall is in accordance with the long-term average, with rainfall within +/− one-standard deviation of the mean, monsoonal rains are considered to arrive within a 'Normal' fashion. The resulting classification is shown in Table 1

Only seven of the nine monsoonal scenarios are observed in the historical record; there were no instances in which the monsoon was 'Early' and 'Dry' and none in which it was 'Late' and 'Wet.' In addition to characterizing monsoonal conditions in the historical records, we also created a set of monsoonal conditions that are more extreme than anything in the past 100-years. To do this, we used crop yield data calculated in DSSAT to simulate the effects of severe climate conditions. This produced two drought categories – 'Very Dry with Very Late Rain' and 'Exceptionally Dry with Exceptionally Late Rain' – and two flood categories – 'Very Wet with Very Early Rain' and 'Exceptionally Wet with Exceptionally Early Rain.' The crop yields that were calculated for these categories are based on extrapolating comparisons of the 'Wet/Early' yields and the 'Dry/Late' yields compared to the 'Normal/Normal' yields.

For the scenarios that we use in model simulations, a series of consecutive years within the historical record are selected to correspond to the years within a model run of a given duration (i.e., 25 years). For example, the climate conditions from 1900 to 1924 could be used to determine crop choices and yields during a model run of 25 years. We had more latitude to create hypothetical climate sequences that use monsoonal types (e.g., exceptionally wet/exceptionally early or exceptionally dry/exceptionally late) to mimic unusual or exceptional events. For these scenarios, sequences were created to simulate a stable and unvarying climate, prolonged droughts, prolonged floods, as well as other scenarios that simulate increasing or decreasing variability.

Methods

The land component of the ABM is primarily driven by the Land Use Modules that simulate a variety of biophysical, environmental, and geographic phenomena, such as, land use/land use change, yield calculations for cultivated crops, redistribution of yields among farmers, as well as migrants and farmers who rent the land. As previously noted, there are two distinct, though tightly connected components to the model: the Social Modules and the Land Use Modules that interact with each other through the model parameters.

For sake of simplicity, we focus on the Land Use Modules, and only refer to the Social Modules as factors that affect land use decisions of farmers, and then only in rather simplistic ways, as subsequent papers will more fully describe the Social Modules as the central topic of discussion.

Table 1
Total rainfall vs. monsoonal timing to derive cumulative rainfall.

		Total rainfall		
		Dry	Normal	Wet
Rainfall timing	Early	0 (0%)	5 (4.5%)	12 (10.9%)
	Normal	13 (11.8%)	57 (51.8%)	7 (6.3%)
	Late	7 (6.3%)	9 (8.1%)	0 (0%)

Model introduction

The major modules of the ABM are the Initialization Module, Migration Module, Assets Module, Land Suitability Module, Crop Yield Module, Fertilizer Calculation Module, and the Land Use Change Decision Module. Social statistical models are used to estimate the parameters for the migration and assets modules. The Land Suitability Module is used to generate land suitability scores for the choice of crops types by farming households, and the Crop Yield Module is used to derive crop yields. In addition to the major modules within the ABM, there are a host of secondary Land Use Modules that address specific functions and behaviors related to land use. Each of these modules is graphically described relative to their interconnectivity through single-directional or bi-directional links.

General overview

The model is written in Java, using the Repast *Simphony* development environment. It is comprised of three primary modules, each of which contains several sub-modules that are designed to implement specific thematic elements of the ABM.

The model begins with the Initialization Module and the creation of social agents, land objects, and the importation of various parameters, such as, population migration coefficients and crop yield levels prescribed to soil and terrain settings across the landscape. The initialization process is executed only once at the beginning of the model simulation. When the simulation begins, the model engages the modules related to social actions and behaviors, as well as the modules that determine land use decisions. The model operates on an annual time step, executing the Social and Land Use Modules for each modeled year, and runs are typically for 25 years.

Fig. 4 illustrates the primary modules and their interactions with one another, the model agents, and the Java packages and classes used in the model. The model is initiated in the Main Module that builds the model framework and initializes the agents and rules. The Main Module also contains the functions that generate updates for each annual time step in the model. The other two primary modules are the Social Module that contains all functionality for updating the social network of the model and calculating household assets, and the Landscape Module that contains the model elements that address land use decision-making, crop growth, and crop yield distribution.

There are five types of agents in the model. The Individual, Household, and Village agents are the active social agents that interact with all three primary modules (Fig. 4). The Pixel and Parcel agents are passive agents that interact with the social agents and the Landscape and Main Modules. The Pixel and Parcel agents are passive in that they don't perform any operations on their own, but rather are acted upon by the Household agents.

Within the Landscape Module are four sub-modules that control all aspects of the land use side of the model, as illustrated by the 'green' boxes in Fig. 5. These sub-modules are tightly coupled with

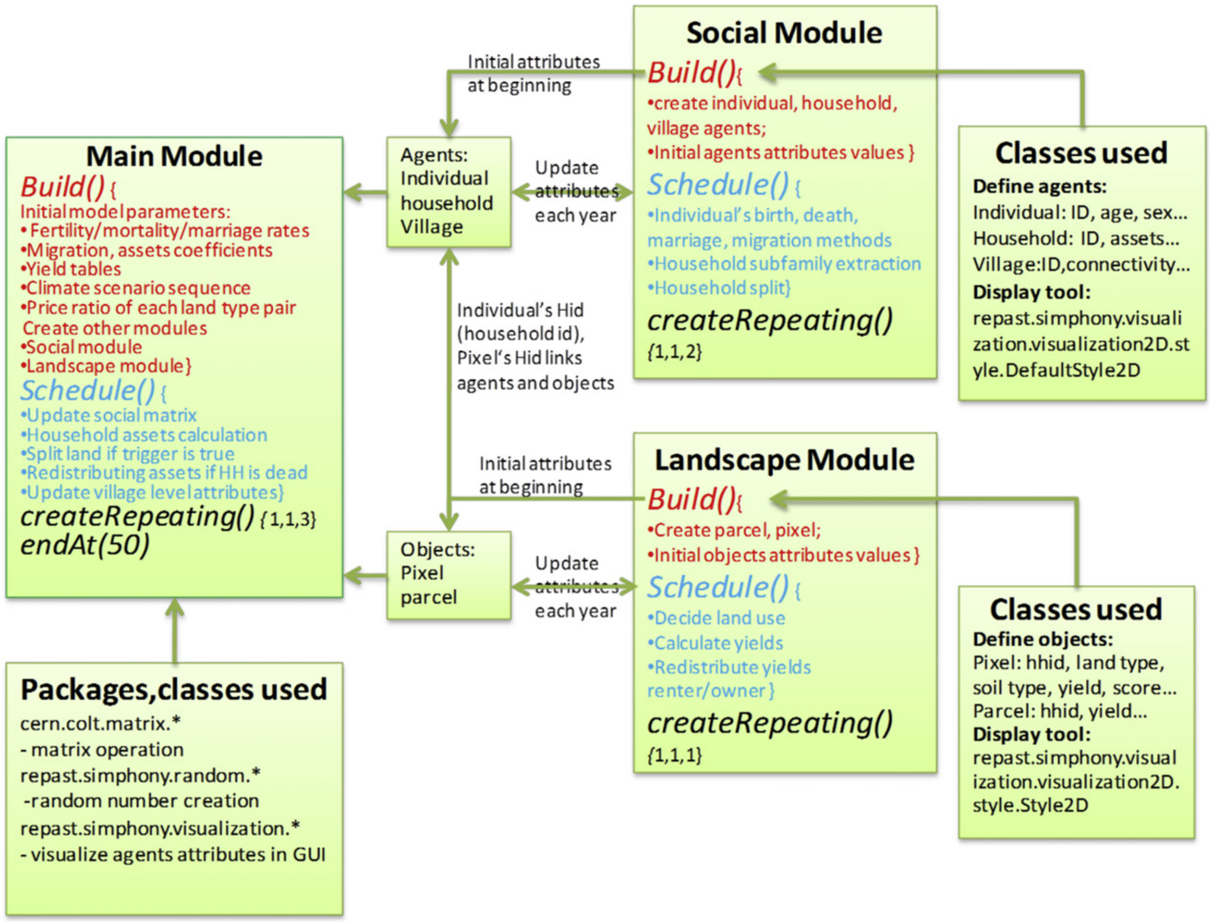

Fig. 4. Primary program modules used in the Nang Rong ABM, with an emphasis on the land component portion of the model.

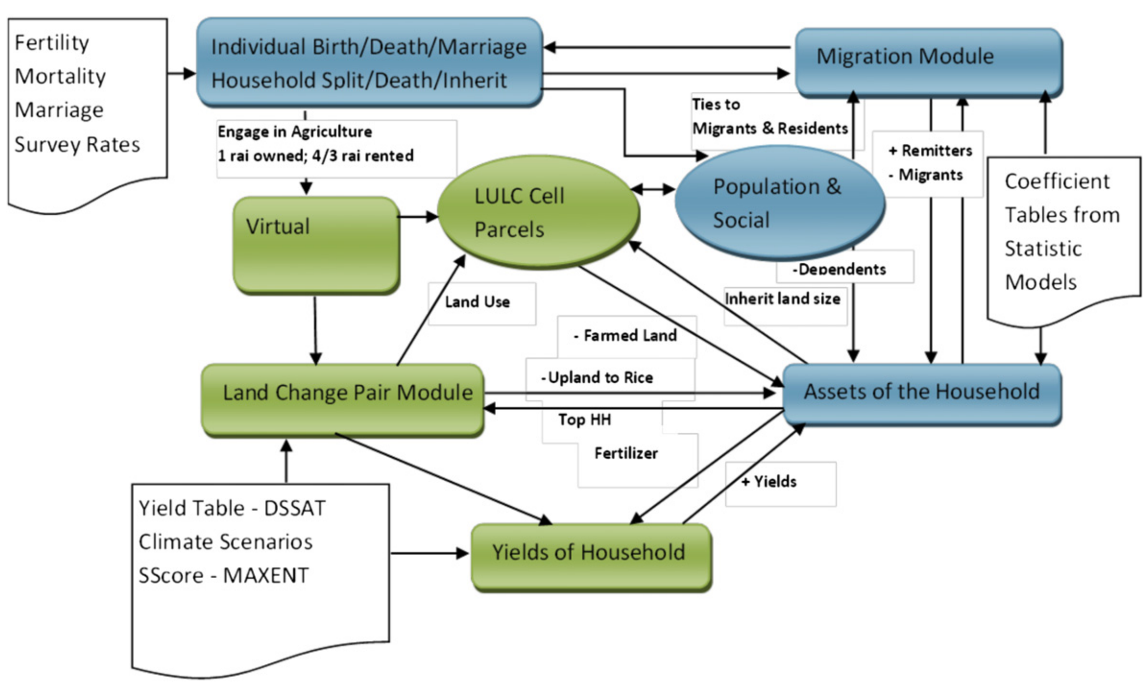

Fig. 5. System operations of the Nang Rong ABM showing selected connectivity and process relationships of the land component portion of the model.

the Social sub-modules, represented by the 'blue' boxes. The parcel size used by the household is determined by the number of individuals in the household. Household assets influence the fertilizer level that determines yield, an important input to the calculation of household assets. Households use owned and rented parcels, and these can be either real parcels, collected during the longitudinal population study, or virtual parcels, created prior to the model run. Virtual parcels are representative of the actual parcels in terms of their size, composition, and distribution across the landscape. The virtual parcels, and all functions that operate on them, are contained within the Virtual sub-module, while the Pixel agents and all of their functions are contained with the LULC Cell Parcels sub-module.

All land use decisions are made within the Land Change Pair sub-module that is informed by decision-making characteristics of a household, a yield table created within DSSAT (see Crop Yield Module – Decision Support System for Agrotechnology Transfer Model section), a pre-specified climate scenario that is based on empirical climate data, three fertilizer amounts, and land suitability scores calculated within MAXENT (see Land Suitability Module – Maximum Entropy Model section) for cells within the household's agricultural parcels. Other than household characteristics, all of the inputs are created *a priori* and generated as lookup tables or arrays, while the parcel suitability scores are based on the intersection of the household's parcel boundaries and the MAXENT values for that particular year. To better inform the decision-making process of households, all agricultural yields are calculated and compared prior to households deciding to switch between crop types, and one land change pair is decided after comparison. At the end of the time step, total yields of all crop types are calculated and input into the Household Assets module to update the annual asset totals. These functions are contained within the Yield sub-module.

The Social Modules simulate changes in human population and social networks as well as changes in population migration and household assets. The Land Use Modules simulate changes in land use types and crop yields. The Social and Land Use Modules interact with each other through the derived parameters. For instance, population change will affect parcel sizes, land inheritance factors, and the subdivision of family farm parcels, while household assets impact the use and amount of fertilizer to increase crop yields and the selection of land use types, as well as the ability of households to negotiate landscape change, such as, the destruction or construction of bunds to encircle rain-fed rice paddies. In addition, yields from crops are important inputs to the Household Assets Module.

When the simulation begins, based on the composition of the household population, various components of the Land Use Modules determine whether a household will engage in agriculture for the initial year of the simulation. If so, the model assesses whether the household has sufficient labor and sufficient land to farm lowland paddy rice or upland field crops. If not, the model identifies a nearby parcel with an appropriate size, derived through the Virtual Parcel Creation Module, for the household to rent, given available wealth, through the Virtual Parcel Selection Method. If engaged in agriculture, the household determines if fertilizer will be used and the appropriate application level, defined by the Fertilizer Calculation Module. In this module, based on the previous year's land use type and household assets, fertilizer costs, application levels, and schedules are determined for a specific crop type through the Land Use Change Decision Module that considers factors, such as, geographic setting, maximum crop yields, and corresponding profit expectations. Various factors affect the decision by households to cultivate a certain crop, such as, soil fertility levels at geographically referenced locations, land suitability scores derived from the Land Suitability Module, and the land price ratio. Based on the land use type, fertilizer level, and amount of land cultivated by the farm household, the Land Use Change Decision Module calculates the yields for each landscape cell by searching the yield table created from the Crop Yield Module that generates yield values based on land use type, soil type, fertility level, and climate conditions. The crop yields are then redistributed to corresponding households based on parcel-specific characteristics, such as, whether the farming household shares, rents, or owns agricultural land parcels. At the conclusion of annual model iterations, changes to the assets of each household are calculated within the Assets Module.

Model environment & agents

There are three data sets that are used to define the environment and to initialize the agents: (1) social survey data that characterizes individual and household agents and links them to their corresponding village that is further described through demographic factors, such as, the number of households in each village and total village population; (2) environmental data that are used to create land objects, including the generation of 5-m resolution raster files to initialize the cell attributes, parcel descriptions to assign parcel attributes that are linked to household demographic and socio-economic conditions, and virtual 'unassigned' land parcels that represent unaccounted or unmatched land parcels that can be rented by households wishing to engage in agriculture, but with insufficient land-holdings; and (3) social and ecological rules or relationships, such as, population patterns and household asset coefficients derived from statistical regression models, human fertility, mortality, and marriage rates derived from social survey data, crop yield data derived from the Crop Yield Module, and land suitability scores for various land use types derived from the Land Suitability Module.

The Social Modules simulate changes in individuals and households, including, for instance, births, deaths, marriages, out-migration, return-migration, household splits, remittances, and inheritance. The Land Use Modules describe land use transitions, crop yields attained for each parcel farmed by the corresponding household, and the redistribution of crop yields based on whether land parcels are rented, shared, or owned by one or multiple households. In addition, at the end of each simulation year, the Assets Module calculates the derived assets for each household based on agricultural yields, off-farm employment and remittances, and social network connections through kinship ties. Land ownership can change as a consequence of land splits through the inheritance of household assets, including exchange of land parcels that may be triggered by household population change, such as mortality.

Land Use Modules

This module achieves a variety of tasks dealing with the initialization of the various Land agents in the model. The Land agents are a fundamental component within the model, and are divided into two main types: Land Use/Land Cover cells ('LULCCells') and Land Parcels. LULCCells are either aggregated to form larger contiguous units, such as land parcels, or they exist as separate entities that are subjected to various modeling activities. As stand-alone agents, LuLcCells have attributes describing land use type, soil type, and land suitability for the various land uses. When aggregated to form Parcel agents, a variety of other attributes are available, such as, yields for land use type, fertilizer application rate, area of the parcel, land suitability score, household identifier, and the listing of owners and renters. The two types of Land agents, LULCCells and Parcels, exist as a series of 15 separate raster files that are engaged in the model to perform the following functions:

- Initialize the modeling environment
- Create cells and aggregation them into land parcels
- Populate the attribute values for cells and parcels
- Connect to social attributes as a means of constructing relationships between households and the parcels that they own or rent

The Land Use Modules are suites of algorithms that simulate processes of land use choice and agricultural production. Each algorithm within the Land Use Modules addresses a specific process, with the inputs and outputs of each algorithm often directly interacting with other land use algorithms and the Social Modules. Below, we briefly describe the central processes in the Land Use Modules.

Engagement in agriculture algorithms

There are two algorithms that dictate a household's ability to engage in agriculture. The first is a confirmation of an adequate supply of household labor for farming, while the second is a check of a minimum area of land for cultivation. The labor requirement for engagement in agriculture is one household member between the ages of 15 and 55. If this requirement is met, the household is eligible to farm during that year. The land requirement for farming and subsistence agriculture, based on empirical work in the District, is one rai per household member if the land is owned and 4/3 rai per person if the land is rented. [Note: a rai is a local unit of land area, equivalent to 1600 m^2 or about 0.40 acres.] In the event that a household does not have enough land to engage in agriculture, the household will be eligible to rent land to accumulate sufficient land area to farm, selecting suitable land parcels through the Virtual Parcel Selection Method.

Virtual Parcel Creation Module

This module imports the background land use raster image, derived from a December 1999 Landsat Enhanced Thematic Mapper (ETM) image that was classified into land use types. In this instance, 'background' refers to the areas in a village's territory that are not occupied by another parcel, and that are within an 'eligible' land use type, rice (jasmine or heavy), sugarcane, or cassava. Once the background territory is defined, the Virtual Parcel Creation Module uses the size distribution of the linked parcels, as defined in the social survey, to create a set of parcels that cover as much of the background area as possible. New parcels are generated until the background area is completely allocated. Though these parcels are referred to as 'virtual,' actual parcels are created in a spatially-explicit location within the raster space for each village.

Virtual Parcel Selection Method

This method determines the size of the 'virtual' parcel that a household will rent, assuming that it does not possess sufficient land to engage in agriculture. The amount of land that a household is able to rent is constrained by the amount of household assets. Households with lower assets can rent smaller sized parcels, while households with higher assets can rent larger parcels. Once it is determined that a household needs to rent land, the virtual parcel pool is searched to find an eligible parcel of the appropriate size.

Virtual Parcel Selection Sub-Method

To more accurately model household dynamics within the ABM, the totality of land that each household uses (i.e., rented or owned) in 2000 was included in the model. Initially, only the parcels that were successfully located and linked to a specific household during the land use matching process in 2000 were included. This resulted in the omission of about 25% of the parcels that were reported as being used. In addition, the problem of omission was widespread, with over 40% of the parcels being unmatched in nearly 20% of the villages.

To reintegrate the missing parcels into the model, for each modeled village, a tabular list of the parcels that were not linked to a household was created. These listings included information, such as, land use type and area. For each missing parcel, the Virtual Parcel Selection Sub-Method, a variation of the Virtual Parcel Creation Method (described above), was used to create a parcel of the appropriate size within the appropriate land use type. Rather than creating an entire set of background parcels, this method only creates the parcels that are specified by an input text file.

Redistribution of yields method

The parcel-level agricultural yields are redistributed among the households that own, rent, or share a parcel. If a household owns a parcel that it uses, it receives 100% of the yield. If a household rents a parcel that it uses, it receives 75% of the yield, with the remaining 25% going to the owner of the parcel. This 75–25% split is based on evidence from qualitative fieldwork in Nang Rong in 2009. Owners can either be real, existing in the roster of households and collecting yield payments from renters, or they can be 'virtual,' existing only as a mechanism for the payment of rent. Any parcel that is shared is treated independently and proportionally administered by each household that uses it. For instance, if two households use a parcel, each household farms 50% of the parcel, and collects yields from that portion of the parcel.

Migration Module

This module is implemented after the human fertility and mortality modules. The Migration Module changes the migration status for an individual who is between 10 and 29 years old. People outside of the 10–29 year old age range don't migrate in this context. If an individual is a resident of a study village, he/she has the opportunity to migrate to an alternate locale. If the individual is a migrant, he/she has the chance to return to the village. The module implements a migration equation that is created by a regression model from the 1994 and 2000 household surveys. Annualized migration and return rates are obtained from a renormalization of the resulting regression based on the 6-year range. The equation has various coefficients including village-level variables, such as, population, connectivity, migration prevalence, household-level variables, such as, centrality and assets, and individual level variables including ties to migrants and residents, marital status, and age.

When an individual aged 10–29 is assessed for migration, the module calculates a probability of migration based on the individual, household, and village attributes for each individual. A random number is generated and compared to the probability of migration. If the probability is larger than the random number, the individual will migrate. If not, the individual will remain in the village.

Asset Module

The Assets Module is executed at the end of each year after all individual activities and land change decisions have been made. The Asset Module calculates the asset change for each household for the year by considering money derived from crop yields and remittances, costs of fertilizer, living cost, and costs of any land conversion between lowland paddy rice, i.e., Jasmine rice vs. Heavy rice, and upland field crops, i.e., cassava. The coefficients for this equation are derived from price and cost data for Northeastern Thailand. The equation is as follows:

$$\begin{aligned}\mathrm{Change\,in\,Assets} = {} & 3.8\,\mathrm{kg\,jasmine\,rice} + 4.0\,\mathrm{kg\,heavy\,rice}\\ & + 0.70\,\mathrm{kg\,cassava} + 0.40\,\mathrm{sugar\,cane}\\ & + 12{,}000{*}\#\mathrm{of\,migrants\,remitting}\\ & - 340{*}\#\mathrm{rai\,rice\,land\,fertilized}\\ & - 1000{*}\#\mathrm{rai\,cassava\,land\,fertilized}\\ & - 1800{*}\#\mathrm{people\,in\,household}\\ & - 3000{*}\#\mathrm{migrants\,living\,away\,from\,household}\\ & - 600{*}\#\mathrm{rai\,converted\,to\,rice\,land}\\ & - 650{*}\#\mathrm{rai\,converted\,to\,cassava\,or\,sugar\,land}\end{aligned}$$

Crop Yield Module – Decision Support System for Agrotechnology Transfer Model

If a household engages in agriculture in a given year, for each of its plots, it must first choose the crop to plant. This choice is modeled based on probabilities calculated through MAXENT. If land changes from an upland crop, cassava or sugarcane, to Jasmine or Heavy rice, the assets calculator includes a cost for the land transformation to an alternate land use.

The crop yield for each plot is calculated by alternate methods. In deciding how to calculate the plot-level crop yields, a number of different methods were evaluated for appropriateness, effectiveness, and ease of implementation. The first approach was to use empirical data with crop yield calculated as a function of household and village characteristics. For example, if a land parcel is used for rice, its yield is hypothesized to be the consequence of parcel characteristics, household labor and resources, and village characteristics, per the following equation:

$$Y_{pjvt} = \lambda_{0pjv} + \sum_{q}^{Q} \lambda_{qpjv} X_{qpjvt-1} + \sum_{l}^{L} \lambda_{ljv} X_{ljvt-1} + \sum_{s}^{S} \lambda_{sv} X_{svt-1}$$

where Y is the agricultural yield in ms/ha, for plot p of household j of village v at time t. The plot variables include crop suitability, location, size, and application of chemical fertilizer, pesticides, and/or herbicides. The household-level variables include the number of plots farmed by the household, agricultural assets, and the number of household members between the ages of 13 and 55. The village-level variables are the percent of households using chemical fertilizers, pesticides, and herbicides, and village location relative to Nang Rong town, the central market and administrative town within Nang Rong District. The coefficients for the land use equation are based on a continuous regression model using our social survey data from 2000 that includes plot-level information.

This approach, however, did not include differences in climate (timing or amount of precipitation) or planting methods and techniques. To provide this inclusion, the Decision Support System for Agrotechnology Transfer (DSSAT; Jones, Osborn, & Briffa, 2001) shell was used for calculating yields. DSSAT provides a framework for controlling a variety of inputs, such as, climate and soils, as well as on-farm choices, such as, the timing and method of planting for a wide array of crop types. The DSSAT platform was previously used to examine rice, cassava, and sugarcane in Thailand (Cheyglinted, Ranamukhaarachchi, & Singh, 2001; Piewthongngam, Pathumnakul, & Setthanan, 2009). For Nang Rong District, the relevant crop models in DSSAT are CERES-rice for rice, GUMCAS (Matthews & Hunt, 1994) for cassava, and CANEGRO (Inman-Bamber, 1995) for sugarcane.

Running models in DSSAT require the use of several inputs that are generated and managed within a GIS. For soils, information from the Thai Government is used that categorizes soils throughout the study area, relative to their physical and ecological characteristics. These data describe 32 soil series for Nang Rong District, including mixed types. Attribute information pertaining to texture, organic matter, cation exchange capacity, drainage, and phosphorous and potassium content are included, along with suitability ratings for paddy rice and upland crops. For some of the mixed types, since their quantification was missing, the average of the designated types is used to arrive at a reasonable approximation. For example, for the Tha Uten/Korat series, the soil texture descriptions of Tha Uten and Korat are averaged.

DSSAT models also require specific parameters for relations of plant growth, size, and yield. These parameters are set in DSSAT's shell through the choice of cultivar. For sugarcane, we use one of the cultivar choices, Geoff's Fav that is grown in Isan, the broader region of Northeastern Thailand that includes Nang Rong District. For cassava, we use a weighted combination of four cultivars to represent the Rayon variety, based on cross-breeding background (Rojanaridpiched et al., 1998). For rice, we determined the coefficients for KDML 105, the white jasmine rice grown ubiquitously throughout Thailand. The other commonly used type of rice is a more traditional 'heavy' or 'big seed' rice whose characteristics are approximated and coefficients adjusted by using data from the Rice Decision Support System Project (http://www.mcc.cmu.ac.th/research/DSSARM/ThaiRice/ricevalid.html). For all crops, the choice of cultivar is an important factor since yields and market prices vary greatly among varieties.

For the planting date, we derive monsoon scenarios from existing weather records to approximate the variable planting dates for the two rice varieties. We use three monsoonal initiation scenarios – 'Early,' 'Normal,' and 'Late.' For cassava, the planting date is set at late spring (June 1), which is the usual time in Nang Rong District. For sugarcane, we include a spring (April 1) planting date in the model. For the planting method for rice, we originally calculated yields for seedling transplantation, following a 5 cm ('one thumb') deep planting of rice seedlings, spaced every 20 cm. Eventually, however, we settled on the broadcast seeding of dry seed at comparable resulting plant density, since this method has largely replaced the more labor intensive transplantation from nursery stock in Nang Rong District as a consequence of the out-migration of young adults to cities for off-farm employment, generally leaving the very young and the very old in rural households throughout Nang Rong District. For fertilization of rice, we based our parameters on qualitative interviews that we conducted in Nang Rong District in 2009. Accordingly, we use a rate of 50 kg/rai of fertilizer that is commonly used for rice cultivation throughout Nang Rong District. It is common for one-half of the fertilizer to be applied just before planting, and the remaining one-half applied when the rice begins to develop grain.

We developed three scenarios for fertilizing rice: no fertilizer, only fertilizing applied at planting (25 kg/rai), and two fertilizer applications of 25 kg/rai each. These strategies are assigned to households based on their assets and the number of remitting household members. The timing of the second fertilization was adjusted through trial runs in DSSAT, using daily output so the daily onset of grain development can be seen. We use a common second fertilization time of 90 days after planting for jasmine rice, and 34 days after planting for heavy rice, which maximized yield in most conditions, though the onset of grain varied somewhat among different soil and monsoonal conditions. Fertilization effects are not included in the GUMCAS and CANEGRO models in DSSAT. To match the potential for fertilization effects linked to assets for cassava, we developed multipliers of 1.22 and 1.29 for the basic yield output for low and high fertilizations based on empirical results (Boonseng, Santisopasri, Soommart, & Paerayakrato, 1999). For harvesting dates, both KDML 105 (jasmine rice), and JAYA (heavy rice) are set at 180 days after planting; cassava and sugarcane were set at one year. Both cassava and sugarcane can continue to grow beyond one year, with the actual harvest timing largely dependent on local market prices. Since the model runs at one-year intervals, we used one-year harvest schedules to coincide with the time step of the ABM.

The structure of the table was fixed once it was sorted by fertilizer level, land use type, climate, and soil type. There are a total of 405 rows in the table (5 soil types × 9 climates × 3 cultivars × 3 fertilizer levels). Based on the various land use and soil types for the cells that comprise the study area, household's fertilizer level and current climate, the row in the yield array is found through the following equation:

$$\begin{aligned}\text{Row} = {} & \text{nitrogen value} \times \text{constant-nitrogen}(135) + \text{LULC value} \\ & \times \text{constant-LULC}(45) + \text{climate value} \\ & \times \text{constant-climate}(5) + \text{soil value} \times \text{constant-soil}\end{aligned}$$

For sugarcane, the only difference compared to cassava is the soil type input. As such, the equation to calculate the row is the same, but the constant will differ according to the soil type.

Land Suitability Module

The choice of which crop to grow is a complex decision based on natural, social, and economic conditions. To capture the suitability of the natural environment for crops in the model, we used the species distribution model MAXENT (Phillips, Anderson, & Schapire, 2006; Phillips, Dudík, & Schapire, 2004; Phillips et al., 2009). The MAXENT Model predicts species distributions based on observed species presences and geographic environmental data using the concept of maximum entropy in which the distribution of a species is found that has the least variability (closest to uniform), given environmental constraints. MAXENT has been found to be among the most robust and best performing species distribution models (Elith et al., 2006). The outputs of MAXENT include a map of species presence likelihood that we have adapted as crop suitability (Elith et al., 2011). Since the MAXENT model only considers individual species, we derive relative crop suitability by comparing the individual suitability scores (see later section).

As described in Heumann, Walsh, and McDaniel (2011), we model crop suitability of the three major crops in Nang Rong – jasmine rice, heavy rice, and cassava based on topography (a proxy for hydrology), soil class, and solar radiation during the growing season. Assessment of the MAXENT model shows that the crop–environment relationships conformed to expectation – rice is grown in richer soils in the lowlands, while cassava is grown on poorer soils in the highlands. The model also could predict crop locations accurately based on the Receiver Operating Characteristic and an examination of the output suitability maps with validation crop locations (Pontius & Schneider, 2001).

Land Use Change Decision Module

The Land Use Change Decision Module examines each household and parcel that is owned, rented, or shared by the household. There are four land types considered: jasmine rice, heavy rice, cassava, and sugarcane. For each parcel, three-land change pairs CC_i are calculated and one pair is chosen as the land change decision for the land parcel for the year. The Land Use Change Decision Module is based on the following equation:

$$CC_i = \text{Base}*\text{Suitability}*\text{Income}*\text{Assets}*(\text{Risk}*\text{GeogNbr}*\text{SocNbr})$$

where each variable is as follows:

- CC_i: The chance of change for a given parcel
- Base: Constant constraint on land use change
- Suitability: The ratio of crop suitability between the current and potential crop
- Income: The expected income from a new crop vs. the existing crop
- Assets: The threshold of assets for a change to occur
- Risk: The willingness of a household to change
- GeogNbr: An indicator of the geographic neighbors of the parcel
- SocNbr: An indicator of the social neighbors of the parcel

In the Land Use Change Decision Module, each variable is implemented according to the following steps:

- The base value is set at 0.2 for all villages and does not change during the simulation. This value is set by finding the amount of land use change in Nang Rong through satellite change pairs. Thus, the base value is a semi-empirical constraint coefficient on land use change.
- Suitability is a cell level value that does not change after initialization, once created from the Land Suitability Module.
  - The Zone value is the ratio of a potential new crop's suitability compared to the crop's suitability. If a potential crop is more suitable than the current crop, the chance of change increases and vice versa.
  - The suitability values for sugarcane are the same as cassava. Since land change is based on parcel-level values, the zone value of each parcel is calculated as the average of its cell's values. If a parcel split occurs, the parcel's zone value will be updated.
- Income is calculated for each parcel each year as:
  - income $= l*(P_{to}*Y_{to}/P_{from}*Y_{from})^2$, if the change pair is within the same terrain

    where: P is crop price, Y is crop yield, to and from indicate the potential and current crops, respectively, and l is the land conversion coefficient set to 0.5 for conversion between upland and lowland crops to reflect the cost of land conversion, and set to 1 in all other cases.
  - The ratio of P_{to}/P_{from} is set to 1 for all types currently. The yield of 'to' land type and yield of 'from' land type are calculated from the yield table for each year, based on climate and household fertilizer levels for that year. Price can be used to introduce economic change into land use decision-making.
- Assets are a threshold condition that is set to 1 or 0. This factor is designed to account for the ability of a household to afford the labor intensive costs of creating or destroying rice bunds. If the change pair is between an upland use and a lowland use, and if the household's assets are greater than the median assets in the village, then assets are set to '1'. If these conditions are not met, then the assets are set to '0'. If the change pair is between the two varieties of rice or upland crops, then the assets will always be set to '1'.
- Risk, GeogNbr, and SocNbr are social factors that will be incorporated into the model in the future versions. Risk describes the likelihood of a household to engage in higher risk decisions. GeogNbr and SocNbr are factors that allow for social diffusion of land use change based on geographic neighbors or

social networks. In other words, these factors increase the likelihood of converting to a new crop, if geographic neighbors or family kin are growing a specific crop type.

If the total of the three CC_i values is less than 1, the chance to keep the present land type is 1 − total CC_i. Based on these four change pair risks, a random number is drawn to choose one of the risk pairs. If the total of the three CC_i is greater than 1, then it is assumed that the chance of keeping the same crop type is 0 and the three CC_i values are scaled from 0 to 1. A random number is drawn to choose one of the change pairs. In this instance, the current land use type will always be changed. In summary, the Land Use Change module performs as follows:

- Decide whether or not the household engages in agriculture
- Decide the household's level of fertilizer application
- If necessary, locate a suitable virtual parcel for the household
- Count the total area of each land use type
- Call the Land Use Change Decision Module to determine the land use change pair for each parcel owned or rented by each household
  - The Land Use Change Decision Module then calculates three pairs of CC_i values. The following algorithm is used to decide how to select one change pair for a given year:
- After determining the *change to* type, all pixels within the parcel will be changed to the *change to* land use type
- Count the total area of each land use type after the land use type change
- Calculate the change percentage:
  - (Δjasmine + Δheavy + Δcassava + Δsugar)/total area
- Continue with the remaining components in the Land Use Module

Selected model outputs

Using the processes described above, a host of outcomes can be generated through the Land Modules. For instance, Fig. 6 shows total agricultural yields for a sample village generated for a monsoonal flood scenario that extends from year 10 through year 17 of the simulation period. The 'solid red line' shows the total yield for sugarcane, whereas the 'dashed red lines' indicate one-standard deviation from the mean yield; the 'solid blue line' shows the total yield for cassava, whereas the 'dashed blue lines' indicate one-standard deviation from the mean yield; and the 'solid green line' shows the total yield of lowland paddy rice, whereas the 'dashed green lines' indicate one-standard deviation from the mean yield.

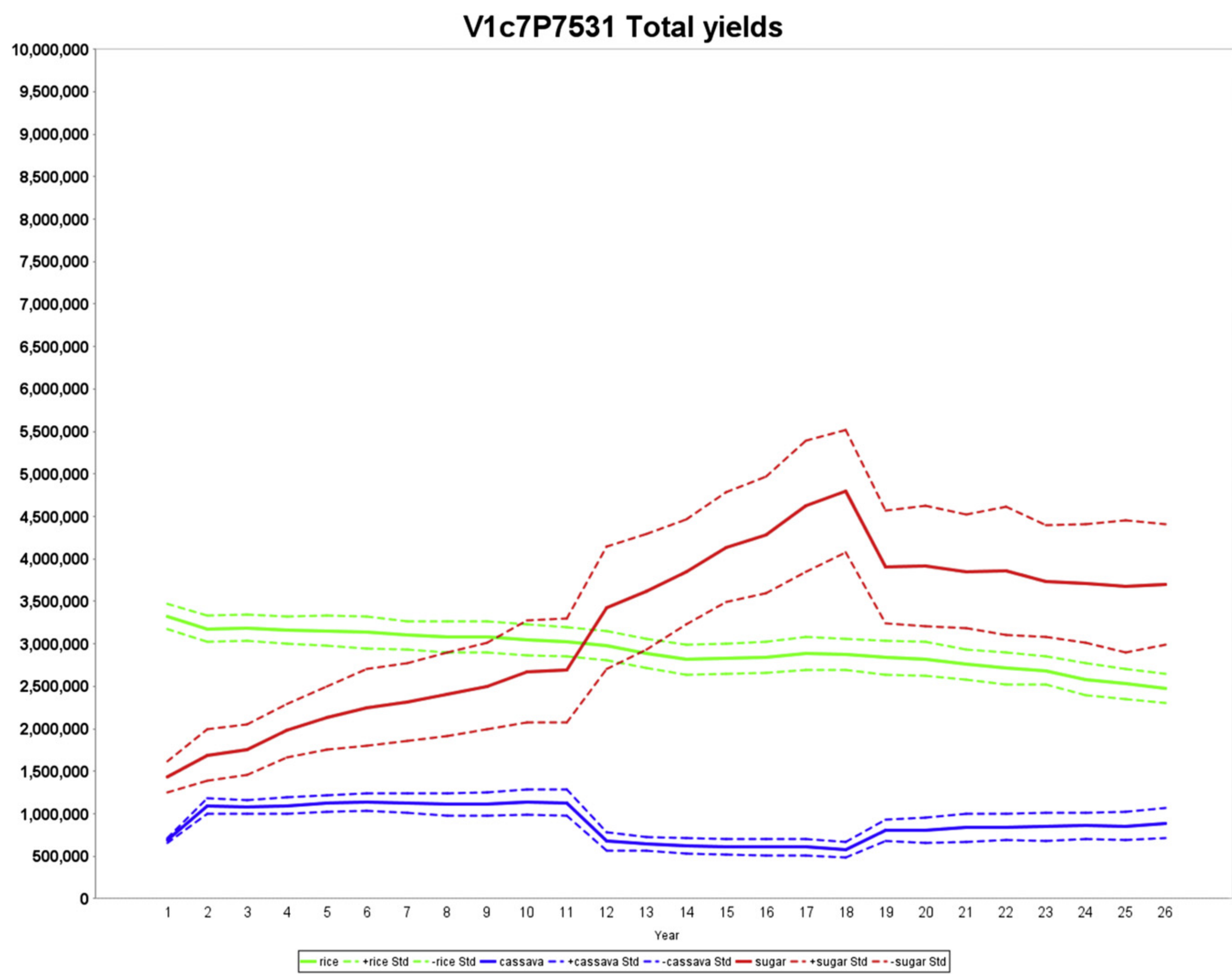

Fig. 6. Model run of total agricultural yields for a sample village (Village 1) running with a climate scenario of 7 consecutive years of monsoonal flood (years 10–17): red is the yield for sugarcane, blue is the yield of cassava, an upland field crop, and green is the yield of lowland paddy rice. One-standard deviation from the mean yield is represented as dashed lines on either side of the mean for each crop type.

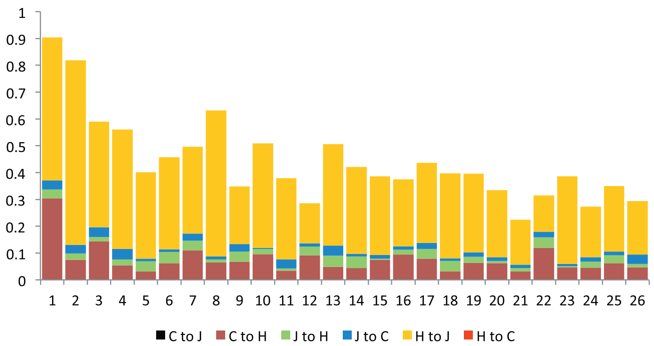

Fig. 7. Model run of percent land cover/land use change for a sample village (Village 1) running with a normal climate: "C" represents upland cassava, "J" represents jasmine rice, and "H" represents heavy rice.

For upland sugarcane, the imposition of monsoonal floods in years 10–17 generates higher yields in the upland areas that are topographically protected from the pooling of water in lowland areas. Even after the monsoonal floods have ended in year 18, relatively high and consistent yields of sugarcane persist. Cassava yields, the blue lines, are relatively depressed by the imposed period of monsoonal floods in years 10–17, as tuber crops cultivated in very wet areas generally rot in the field. This has been empirically observed and also confirmed through interviews of farmers who have described circumstances in which they occasionally extend the cultivation of cassava too far down the topographic-moisture gradient during normal climate conditions and, as in this case, monsoonal rains alter the normal landscape conditions making it too wet for the cultivation of cassava.

Lastly, Fig. 7 shows the percent land use/land cover change for a sample village under normal climate conditions for the simulation period – 'C' represents cassava, 'J' represents jasmine rice, and 'H' represents heavy rice. Most of the change occurs from heavy rice to jasmine rice and from cassava to heavy rice, with lesser amounts of change occurring from jasmine rice to heavy rice and jasmine rice to cassava. Cassava is an upland field crop, whereas jasmine and heavy rice are varietals of lowland paddy rice. Jasmine rice is normally cultivated in wetter lowland conditions, whereas heavy rice prefers drier lowland conditions. As a consequence, heavy rice is often cultivated on middle and upper terraces that can also support upland field crops under certain moisture conditions, vs. the alluvial plains and low terraces where jasmine rice is normally cultivated. In relatively dry periods, even associated with a normal climate, heavy rice often replaces jasmine rice to accommodate local terrain conditions and drier than normal geographic settings.

Conclusions

The ABM that we developed for Rang Rong District, Northeastern Thailand explicitly links people and environment through Social and Land Modules that include an Initialization Module, Migration Module, Assets Module, Land Suitability Module, Crop Yield Module, Fertilizer Module, and the Land Use Change Decision Module. These Social and Land Modules are constructed as a suite of spatially-explicit, object-oriented programs. We use the 'Repast' platform and JAVA programming, because Repast provides a tool kit that is advanced, flexible, allows us to develop the experiments that we need, and has a large user community that allows us to take advantage of ongoing developments (North, Collier, & Vos, 2006).

The primary goals of developing the ABM were to examine population–environment interactions as well as social and ecological dynamics by addressing important pattern–process relations that feature the accumulation (or loss) of household wealth and income derived from agricultural production of lowland paddy rice and upland field crops as well as from remittances earned through off-farm employment by family members working in urban destinations. Our ABM, therefore, was designed to analyze individual villages for a variety of climate scenarios. Nang Rong District contains a relatively large number of villages that are geographically arrayed across a varied three-dimensional landscape that is strongly influenced by geomorphic settings, particularly, soil characteristics, drainage patterns, and moisture conditions, that afford considerable variability to examine social-ecological interactions and the impact of imposed climate variation on crop yields, land suitability, human behavior, migration patterns, and the accumulation of household wealth.

Farmers who live and work in Nang Rong are well aware of the vagaries of climate and its impact on agricultural production (Blaikie & Brookfield, 1987). The ecological marginality of Northeastern Thailand has necessitated that farmers learned to cope with floods, droughts, and variations in the arrival, departure, and intensity of these extreme events (Parnwell, 1988; Rigg, 1991). In other words, marginality and climate variability are more the rule rather than the exception to life in Nang Rong District, Northeastern Thailand (Kaida & Surarerk, 1984). To minimize economic and social disruptions, farmers have adopted a risk diversification strategy that involves the cultivation of lowland paddy rice as well as upland field crops in less than ideal settings (Ellis, 1998, 2000). Having access to different land types with varying environmental conditions is an adaptive strategy to life in a marginal and inconsistent ecological setting.

Among the central strategies practiced by farm households living in rural Nang Rong District is the reliance on off-farm employment of young adults in construction, manufacturing, and domestic employment in Bangkok, the Eastern Seaboard, and in provincial Central Cities, like Khorat and Buriram. The sending of remittances to rural kinship households in Nang Rong District, as part of a diversified household livelihood strategy, offers additional income beyond what can be generated through agriculture. In addition, households employ alternate ecological strategies in the use of chemical fertilizers, timing and amount of their application, and choice of crop types for particular topographic settings. The interactions of social-ecological factors is further mitigated by the changing household demographics, labor and market conditions, and climate change, most notably associated with the changing pattern of monsoonal rains, i.e., their timing and amount as well as the onset, severity, and persistence of floods and droughts.

Because of the size and complexity of our ABM, we have focused our description primarily on the Land portion of the integrated Social-Land Use ABM. We have included only those parts of the Social Modules that were essential to understand the processes being represented in the Land Modules and the nature of their interactions. Subsequent papers will detail the Social Modules and define key links to the Land Modules as well as discuss specific model runs linked to climate scenarios and the behavior of farmers under uncertainty.

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