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An interactive land use transition agent-based model (ILUTABM): Endogenizing human-environment interactions in the Western Missisquoi Watershed

Yushiou Tsai*, Asim Zia, Christopher Koliba, Gabriela Bucini, Justin Guilbert, Brian Beckage

Research on Adaptation to Climate Change, EPSCoR, University of Vermont, Burlington, VT, USA

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ABSTRACT

Forest Transition Theory (FTT) suggests that reforestation may follow deforestation as a result of and interplay between changing social, economic and ecological conditions. We develop a simplistic but empirically data driven land use transition agent-based modeling platform, interactive land use transition agent-based model (ILUTABM), that is able to reproduce the observed land use patterns and link the forest transition to parcel-level heuristic-based land use decisions and ecosystem service (ES). The ILUTABM endogenously links landowners' land use decisions with ecosystem services (ES) provided by the lands by treating both lands and landowners as interacting agents. The ILUTABM simulates both the land use changes resulting from farmers' decision behaviors as well as the recursive effects of changing land uses on farmers' decision behaviors. The ILUTABM is calibrated and validated at 30 m × 30 m spatial resolution using National Land Cover Data (NLCD) 1992, 2001 and 2006 across the western Missisquoi watershed, which is located in the north-eastern US with an estimated area of 283 square kilometers and 312 farmers farming on 16% of the total Missisquoi watershed area. This study hypothesizes that farmers' land use decisions are made primarily based on their summed expected utilities and that impacts of exogenous socio-economic factors, such as natural disasters, public policies and institutional/social reforms, on farmers' expected utilities can significantly influence the land use transitions between agricultural and forested lands. Monte Carlo experiments under six various socio-economic conditions combined with different ES valuation schemes are used to assess the sensitivities of the ILUTABM. Goodness-of-fit measures confirm that the ILUTABM is able to reproduce 62% of the observed land use transitions. However, the spatial patterns of the observed land used transitions are more clustered than the simulated counterparts. We find that, when farmers value food provisioning Ecosystem Services (ES) more than other ES (e.g., soil and water regulation), deforestation is observed. However, when farmers value less food provisioning than other ES or they value food provisioning and other ES equally, the forest transition is observed. The ILUTABM advances the Forest Transition Theory (FTT) framework by endogenizing the interactions of socio-ecological feedbacks and socio-economic factors in a generalizable model that can be calibrated with empirical data.

1. Introduction

Consequences of land use affect food production, freshwater resources, forest resources, regional climate and air quality, and infectious disease (Allan, 2004; Feddema et al., 2005; Foley et al., 2005; Foster et al., 2003). A better understanding of the dynamics in land use and land cover change (LULCC) has been an essential part for modeling coupled natural and human systems aiming at providing insights for designing sustainable strategies and policies. The dynamics of LULCC exhibit (1) interactions of multiple human-induced and natural processes, (2) nonlinearities, (3) legacy and/or path dependence effects (Allan, 2004; Lambin and Meyfroidt, 2010, 2011). These human and natural processes may function at different spatial and/or temporal scales, and they arise from stochastic processes (Allan, 2004; Lambin and Meyfroidt, 2011). A large body of literature concerning human-induced land use can be found (e.g., Aalders and Aitkenhead, 2006; Arsanjani et al., 2013; Claessens et al., 2009; Lippe et al., 2011; Teka et al., 2012; Temme et al.,

* Corresponding author.
E-mail address: yu-shiou.tsai@uvm.edu (Y. Tsai).

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2011; Wright and Wimberly, 2013; Zachary, 2013). Generally these studies employ top-down, bottom-up or a combination of both modeling approaches. Top-down models use various combinations of statistical, Markov Chain, system dynamic, and spatial analysis approaches. Bottom-up models employ cellular automata (CA), agent-based models (ABMs) or CA coupled with an ABM (An, 2012). Within a coupled natural-human system, land use decisions reflect trade-offs among household incomes, environmental quality, personal values and risk perceptions. The population of the land use decision makers consists of heterogeneous individuals with respect to income levels, property sizes, current land use management, intrinsic landscape characteristics, perception of public policies and perception of environment degradation. Due to the heterogeneity and the complexity of the interactions among decision makers and potential trade-offs among natural and socio-economic losses and gains, a bottom-up agent-based modeling approach suits the need to identify emergent phenomena that are associated with positive and negative feedbacks (An, 2012; Miller and Page, 2007; North and Macal, 2007). Agent-based modeling is capable of simulating the complex interactions among diverse land use decision makers and the lands they manage to identify emergent macro phenomena and critical points of change. Although advances have been made by these recent LULCC ABMs studies, some challenges still remain. This study addresses two of these challenges: the need to (1) incorporate two way linkages that endogenously couple human behavioral and biophysical processes (An, 2012; Filatova et al., 2013; Matthews et al., 2007) and to (2) calibrate and validate ABMs (National Research Council, 2014; Torrens, 2010) using empirical data. Here we develop an interactive land use transition agent-based model (ILUTABM) in which the landowners' land use decisions, given their expected utilities, are endogenously linked with discrete streams of ecosystem services (ES) affected by the human land use decisions; consequently, streams of ES endogenously impact the landowners' expected utilities, which in turn affect the streams of ES over time. The term "interactive" is given to emphasize the aforementioned dynamics between landowners' expected utilities and the ES provided by their lands, which have been endogenously simulated by the ILUTABM. With this, the ILUTABM adds to the body of literature yet another example of LULCC ABMs equipped with two-way endogenous linkages. The ILUTABM treats both landowners and lands as autonomous agents to endogenously simulate land use transitions driven by the landowners' decision making dynamics. Very few LULCC ABMs consider both landscape and landowners as autonomous agents (Parker et al., 2003), because treating all cells in a grid-based environment as agents can be both computationally inefficient and resulting poor representation of continuous space (Brown et al., 2005). The later limitation can be improved by minimizing the size of land cells. However, when the size of land cells is small, the former limitation can quickly become a heavy burden with an extensive simulation extent in space. Due to these limitations, most of the ABMs simulate landscape changes by cellular automata (CA) and landowners by agent-based modeling. In this study, land cell agents are parameterized based on the National Land Cover Dataset (NLCD) and Census of Agriculture. The use of NLCD restricts the size of a land cell agent to 30 by 30 meter, which is not ideal for approximating representation of continuous natural processes/features such as ecosystem service flows, rivers, soils and so forth. With this significant limitation in mind, we make the assumption that the size of a land cell agent is small enough so that (1) when the model approximates features smaller than a grid cell, artefacts produced by presence of the model grid are considered insignificant; and (2) collective responses, arising from local variation smaller than 30 meter resolution, to non-linear processes in the model can be ignored at watershed scale. An essence of our proposed ILUTABM is that landscape agents have the potential agency, defined as the capacity of individuals to act autonomously, to respond to the feedbacks provided by human agents inside the model. While the modeling of reflexive feedbacks by human agents is a huge challenge, the agency in ecological and biological systems, defined as the ability to adaptively respond to human system feedbacks, could be approximately represented through smaller scale landscape agents. Thereby both landowners' heterogeneous behaviors and natural progression of vegetation dynamics and interactions of the two can be explicitly implemented by modeling both landowners and lands as agents. Few land use agent-based models were parameterized by using both NLCD and Census data that are available across the US. Employing NLCD and Census data allows the framework of the ILUTABM to be applied to where NLCD and Census data are available and then direct comparisons of simulated land use patterns for different study areas can be made.

In this study, agricultural landowners are assumed to be risk neutral. Their perceived financial states are used as a surrogate representing their exhaustive expected utilities. Based on the categories of ES depicted by the Millennium Ecosystem Assessment (2005) and given the context of our study, the ES closely related to landowners' well-being includes provisioning services (food and non-food), supporting services (primary productivity), regulating services (soil erosion/nutrient regulation, groundwater recharge, water purification, pollination and pest control) and cultural services (landscape aesthetics and tourism). Some empirical-based studies have found that generally competition exists between food provision versus non-food provision and regulating services (Hanson et al., 2008; Hou et al., 2014; Schneiders et al., 2012). Therefore, we dichotomize the ES categories defined in the Millennium Ecosystem Assessment (2005) as food provisioning ES (crops and livestock) and other ES (non-food provisioning, supporting, regulating and cultural services). We then construct an ES valuation system that food provisioning ES increases and other ES decreases when land is cultivated compared to natural forests. A general expected utility function is then postulated to combine the effects of food provisioning and other ES on farmers' expected utilities. Two interrelated land use decision heuristics, given landowners' financial states and perceived values of the dichotomized categories of ES, are tested by the ILUTABM. First, non-agricultural lands such as forested, grass/shrub and barren lands are converted to agricultural lands when agricultural landowners' are financially well-off and the food provisioning ES is valued more than that of the other ES (e.g., soil and water regulating). Second, farm lands are abandoned when agricultural landowners are financially stressed, and consequently the abandoned farm lands, if undisturbed for a specific time period, will naturally progress into forested lands. In addition, farm lands are fallow under the circumstance that the farmers are financially well-off but they value other ES more than food provisioning ES. A similar approach has employed by Satake and Rudel (2007). Only their model is purely abstract, and our model is empirically calibrated and validated.

Many LULCC ABMs concerning agricultural landowners' land use decisions have adopted the concept that maximizing expected utilities is one of the primary drivers for farmers' land use decisions (Evans and Kelley, 2004; Evans and Kelley, 2008; Evans et al., 2006; Le et al., 2010; Le et al., 2008; Manson, 2005; Manson and Evans, 2007). Although decision makers may not make utility-maximization decisions because they may not always be rational or obtain perfect information (Cohen and Axelrod, 1984; Evans et al., 2006), the utility-maximization concept remains applicable as long as the researchers have made certain assumptions (e.g. most of decision making firms are rational) or modifications to experiment designs (e.g. by employing bounded rationality (Manson and Evans, 2007)). Most of these utility-based LULCC ABMs have used multiple attributes for estimating farmers' expected utilities. These attributes can be grouped into two simple categories: monetary and non-monetary attributes. In this study, instead of employing utility-maximization, we assume that the agricultural landowners follow a heuristic-based decision making process given their perceived expected utilities. A single attribute (i.e., a farmer' perceived financial state) is used as an aggregate proxy variable to represent the expected utility that drives land use decision making. This heuristic based characterization of the expected utility function could be unpacked and disaggregated in future studies, which will however require additional information on farms' production and revenue functions. Other non-economic attributes could also be added in the expected utility function. Presently, we hypothesize that different distributions of landowners' perceived financial states lead to different land use transition trajectories. Exogenous socio-economic factors such as natural disasters, public policies and institutional/social reforms can change landowners' financial states in a specific year. Due to limitation of highly aggregated Census data, a clear stratification scheme for each of the three financial states (i.e., feel good, moderate stress, and major stress) in the initial year is not empirically available. Thus, six Monte Carlo experiments corresponding to six sets of stratification schemes and different exogenous socio-economic factors are developed; and a goodness-of-fit index, the Nash-Sutcliffe efficiency index (NSEI), is used to identify the experiment providing the best fit, which is then considered as Baseline experiment. The values of NSEI of Baseline show that the ILUTABM provides a good fit for the study area. The other five experiments in addition to Baseline are tested by the ILUTABM to assess impacts of different exogenous factors on land use change. Forest Transition Theory (FTT) framework, postulated by Mather (1992) and later refined by Grainger (1995), Rudel et al. (2005) and Lambin and Meyfroidt (2010), suggests that forest cover decreases from its peak to a lowest point and then increases due to an interplay of multiple socio-ecological feedbacks and socio-economic factors. Many studies have found that, given different public policies, institutional frameworks and biophysical attributes, the timing of emergent sustainable land use varies (Frayer et al., 2014; Plieninger et al., 2011; Redo et al., 2012; Yeo and Huang, 2013); moreover, different land use pathways driven by different underlying factors can be observed (Bae et al., 2012; Frayer et al., 2014; Kanianska et al., 2014; Redo et al., 2012; Ribeiro Palacios et al., 2013; Vu et al., 2014; Yeo and Huang, 2013).

A generic agent-based model such as ILUTABM can probe into the complex interactions of multiple non-linear land use transition pathways on different study areas where NLCD and Census data (or equivalences) are available. The ILUTABM is designed as a simulation platform that assesses how land use transitions are driven by a fixed set of socio-ecological feedbacks under various socio-economic conditions shaped by various exogenous factors. At present, the use of the ILUTABM for informing policy design is limited due to its simple framework as discussed in the limitations section (3.4). However we expect that the future extensions of the ILUTABM, in which limitations of the current ILUTABM platform are systematically addressed, could be usable for tailoring or recommending specific policy interventions under various socio-economic conditions for achieving land use policy goals. The present version of the ILUTABM is applied to the western Missisquoi Watershed in northern Vermont, where agricultural landowners are the dominant land use decision makers, to assess the fit of the model in reproducing the observed land use transitions between 1992∼2006. We have found the ILUTABM's endogenously two way linkage between landowners' heuristic-based decision makings given their expected utilities and a simple ES valuation system under Baseline experiment is able to reproduce 62% of the observed land use transitions. Furthermore, two more sets of Monte Carlo experiments under Baseline are conducted to explore the impacts of varying ES on LULCC and the impacts of different assumptions about the time needed for observing mature grass/shrub or forested lands on LULCC.

2. Model framework and application

Several studies have developed a land use agent-based model, either in the form of stand-alone model or within a coupled system. Bithell and Brasington (2009) presented a prototype coupled modeling system to simulate land use change by bringing together three simple process models: an agent-based model of subsistence farming where households and individuals within the households are treated as agents, an individual-based model of forest dynamics, and a spatially explicit hydrological model that predicts distributed soil moisture and basin scale water fluxes. However, in this study by Bithell and Brasington (2009), an agent does not communicate with other agents and past events do not impact an agent's current action. Evans and Kelley (2004) explored a household's land use decisions based on land available, labor allocated among farming, pasture/grazing and off-farm actives, and aesthetics associated with a forested landscape to maximize its utility. A limitation of their model is that it does not include stochastic components. Ng et al. (2011) developed an agent-based model in combination with SWAT (Soil and Water Assessment Tool) to identify factors impacting farmers' decisions on adopting Best Management Practices (BMPs) and corresponding nitrate load reductions. However, Ng et al. (2011) did not collect empirical data on how farmers, individually or aggregated, make decisions on adopting BMPs. Instead, 50 hypothetical farmers were used for modeling the farmers' decisions making. Le et al. (2010, 2008) developed an agent-based modeling system in which both farm households and land parcels are treated as agents that produce utility and biomass respectively. In these two studies, household behaviors are specified for each different livelihood group based on household data by using multivariate statistical analyses. In addition, stochastic components are integrated into determination of the initial households' population and locations, preference of land use choice and other status variables. Although our study also incorporates stochastic processes and empirical data, a more parsimonious farm-level livelihood framework employed by ILUTABM further improves the representation of land use transition agent-based model developed by Le et al. (2010, 2008). In addition, Monte Carlo experiments are used to explore the uncertainties introduced by the ILUTABM and to assess how simulated land use trajectories are affected by different (1) distributions of human agents' initial expected utilities caused by exogenous socio-economic factors, (2) ES valuations, and (3) time periods needed for two of the land use transitions: barren to grass/shrub and grass/shrub to forest.

2.1. Conceptual framework

The framework of the ILUTABM consists of four procedures. The flow chart shown in Fig. 1 illustrates the hierarchical structure of these four procedures in details. The first procedure of the ILUTABM initializes agents and parameters based on 1992 data. Agents of the ILUTABM are categorized into two major types: human agents, who make land use decisions in each time period given their perceived expected utilities; and land grid cell agents, which produce ecosystem services (ES) that affect the human agents' expected utilities. The parameters include the human agents' initial expected utilities, the probabilities of the human agents' annual utility transitions and the probabilities of the annual land use transitions. These landowners' initial expected utilities are generated from triangular distributions in which the parameters are estimated based on the Census of Agriculture. Details of these stochastic processes are illustrated in the following sections.

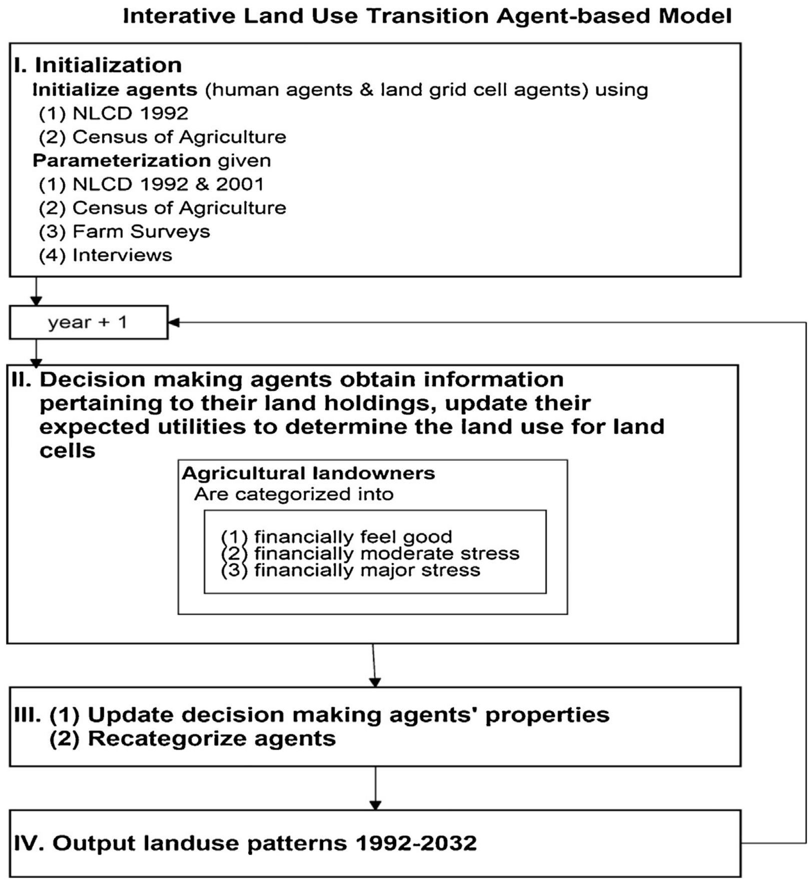

Fig. 1. Framework of the interactive land use transition agent-based model (ILUTABM).

The second procedure of the ILUTABM collects information relating to ES produced from landowners' landholdings to evaluate the landowners' expected utilities for the current year. The landowners' expected utilities positively correlate with ES gained from managing their lands. The landowners expect values of ES provided by their landholdings to change corresponding to a land use transition. Given the level of the landowners' expected utilities, different land use decisions are made. Here the landowners are categorized as: financially feel good, financially moderate stress, and financially major stress. Applicability of this underlying mechanism of translating ES into landowners' expected utilities is provided in Section 2.3. The third procedure of the ILUTABM updates both the human and the land cell agents' properties and then re-categorize these agents based on their current properties. The last procedure of the ILUTABM outputs simulated land use patterns of every year from 1992 to 2032.

2.2. Study area

The framework of the ILUTABM is implemented to simulate the dynamics of the landowners' decision making and land use patterns in the western Missisquoi Watershed (Fig. 2), where the majority of the land use decision makers are agricultural landowners and the agricultural runoff is considered a primary P and N contributor causing the water quality degradation of the Missisquoi Bay (Gaddis et al., 2010; Ghebremichael et al., 2010; Medalie et al., 2012; Michaud and Laverdiere, 2004). A better understanding of land use transition dynamics for the watershed is essential for two reasons. First, it improves representations of modeling efforts on the fate and transport of P and N within the watershed and bay. Second, it facilitates land use planning aimed for mitigating erosion and non-point source agricultural runoff, which reduces the nutrient loads entering the bay.

2.3. Land cell agents

A land cell agent of the ILUTABM is defined as a land grid cell of 30 by 30 meter. A land cell agent at a given year has three attributes: land use type, landownership, and farmers' perceived values for two types of ecosystem services (ES): food provisioning (crops and livestock) and other ES (non-food provisioning, supporting, regulating and cultural services). These attributes are homogenous within a land cell, which is a significant limitation of this model, but heterogeneously distributed across the land cells. The western Missisquoi Watershed consists of approximately 0.3 million land cell agents. A total of seven land use types can be observed in any given year within the watershed: open water (class code $\iota = 1$), urban ($\iota = 2$), barren ($\iota = 3$), forest ($\iota = 4$), grass/shrub ($\iota = 5$), agriculture ($\iota = 6$) and wetlands ($\iota = 7$). These seven land use types are consistent with the eight-class land use classification system of the National Land Cover Dataset 1992/2001 Retrofit Land Cover Change Product (NLCD 1992/2001 Retrofit). This study uses the NLCD eight-class classification system instead of the NLCD in their original and finer classifications, because the mapping scheme used to produce NLCD 1992 is different than that for NLCD 2001 and 2006, direct comparisons among NLCD 1992, 2001 and 2006 in their original classifications are not advisable. Instead, the NLCD eight-class system, which has been used to retrofit the NLCD 1992, is a consistent classification system across all NLCD products to allow direct comparisons among the NLCD 1992, 2001 and 2006. The retrofitted

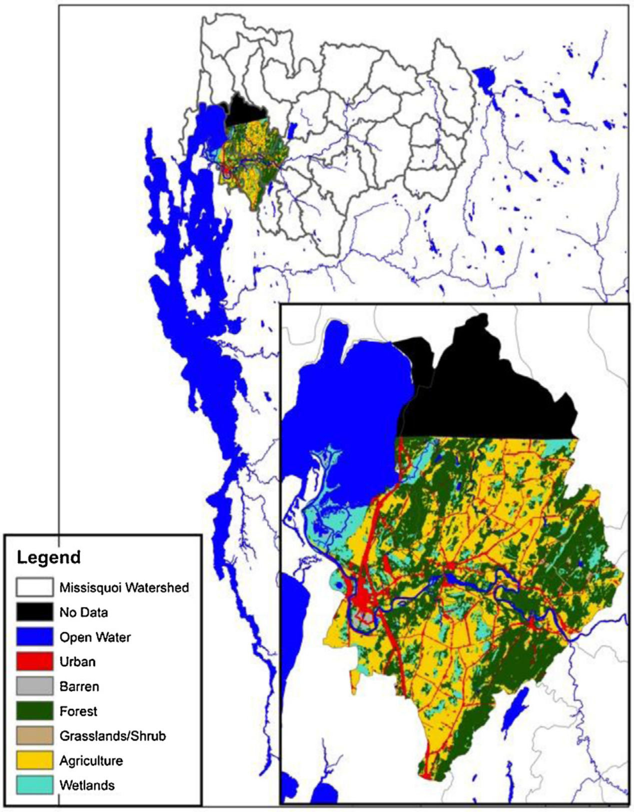

Fig. 2. The western Missisquoi Watershed (colored area) versus the entire Missisquoi Watershed. The colored area displays the observed land use pattern of the NLCD 1992 eight-class classification system.

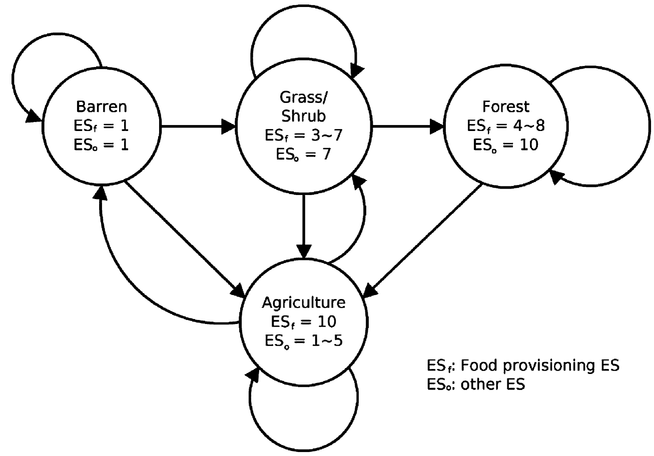

Fig. 3. Food provisioning and other ES values of a land cell given its land use.

NLCD 1992, which is the NLCD 1992/2001 Retrofit, is fed to the ILUTABM to initialize the land use patterns in 1992. The ILUTABM uses the color scheme shown in Fig. 2 to display the land use patterns. The land cells outside of the study area or lacking land use classification information are displayed in black. The NLCD records show that one of the eight land use types, permanent ice/snow, has never been observed in the western Missisquoi Watershed. More detail regarding the land cover classification legends of this retrofit dataset is available at http://www.mrlc.gov/nlcdrlc_leg.php Since the ownership of a land cell is the linkage between a land cell agent and a human agent, the ownership formulation is explained in the section describing human agents.

Incorporating the concept of ecosystem services (ES) to LULCC models provides a systematic and holistic assessment for trade-offs, interdependencies and/or conflicts between environment and human well-being (Egoh et al., 2007; Haines-Young, 2009). Consequently implications can be drawn to advance technologies and policy designs in achieving sustainability and resilience (Brandt et al., 2014). Studies relating to valuations of ES and estimations of factors impacting ES are abundant. Some of these studies can be found in recent reviews by Gómez-Baggethun et al. (2010) and de Groot et al. (2010). While both documented the development of theories and practices of incorporating ES into markets and then indicated future challenges, in particular, the latter study specifically addressed aspects relating to landscape planning. Some of these studies also found that biodiversity positively correlates with level of ES and attempt to assess effects of LULCC on biodiversity and/or ecosystem functioning either in temperate forest zones (Brandt et al., 2014; Compton and Boone, 2000; Hou et al., 2014; Poeplau et al., 2011; Ross and Wemple, 2011) or across the globe (Haines-Young, 2009). Here we adopt the concept of ES defined by Millennium Ecosystem Assessment (2005) to postulate that farmers gain from two dichotomized ES: food provisioning (ES_f) versus all other ecosystem services (ES_o). We then further assume that LULCC differentially impacts food provisioning (ES_f) and other ES (ES_o) due to the competition observed between food provision versus non-food provision and regulating services (Hanson et al., 2008; Hou et al., 2014; Schneiders et al., 2012). This kind of competition may arise from the trend of modern agricultural practices that tend to provide fewer agricultural commodity with higher returns (Hanson et al., 2008). Schneiders et al. (2012) showed a negative correlation between land use intensity and regulating ES such as flood protection, groundwater recharge, soil erosion/nutrient regulation, pollination, biological regulation, but found a positive correlation between intensification of land use (e.g., transition from forest or grasslands to agricultural lands) and certain food provisions (crops and livestock). Many other studies (Bowker et al., 2010; Clerici et al., 2014; Compton and Boone, 2000; Edmondson et al., 2014; Evrard et al., 2010; Fontana et al., 2014; Guo and Gifford, 2002; Paz-Kagan et al., 2014; Plieninger et al., 2012; Poeplau and Don, 2013; Poeplau et al., 2011; Powers et al., 2011; Recanatesi et al., 2013; Wasige et al., 2014; Wu et al., 2012) that focus on assessing the impacts of LULCC on selected few ES generally agree that increased land use intensity correlates with decreased regulating (e.g., soil erosion/nutrient regulation) and/or provisioning (e.g., non-food and/or primary productivity) ES. Generally, these studies found that an increase in these regulating and provisioning ES correlates with a land cover transition from an agricultural intensified land to a more naturally vegetated habitat with higher level of multiple ecosystem functions and biodiversity.

With this assumption, we develop a simple ES valuation system (as shown in Fig. 3) that reflects a farmer's perceived ES_f (food provisioning) and ES_o (aggregate of all other ES) for four different land uses. Instead of quantifying different types of ES with monetary values by elaborated valuation techniques requiring empirical data of various variables (e.g., studies by de Groot et al., 2010; Kareiva et al., 2011), which could be implemented in the future extensions of the ILUTABM platform, we use a normalized 1∼10 scale valuation system to assign a standardized value to ES_f and ES_o. Fig. 3 shows how values of the food provisioning (ES_f) and that of other ES (ES_o) are assigned given different land uses. These values are determined based on interviews with experts and the references aforementioned. This ES valuation system (Fig. 3) reflects that ES_o decreases when the land use is changed from a more bio-diverse land use to a less bio-diverse one and vice versa; while ES_f peaks at agricultural lands and then decreases followed by forested, grass/shrub

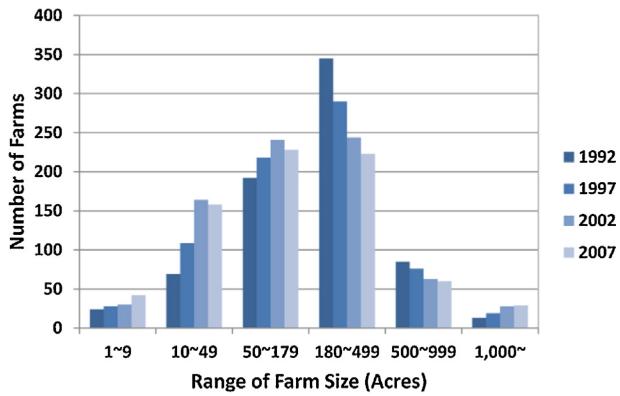

Fig. 4. Histogram showing the distribution of farm size in the Franklin County, Vermont.

and barren lands. Finally we assume that a farmer's overall perceived expected utility for managing k land cells in year t can be summed by a weighted function

$$U_t = \alpha \Sigma_k ES_{f,k,t} + b\Sigma_k ES_{o,k,t} \tag{1}$$

where a + b = 1. Because empirical data are unavailable as to how a famer evaluates ES_f, ES_o, a and b, the uncertainties arising from this ES valuation system are explored through a combination of Monte Carlo experiments (details are given in Section 2.6) in which different values of ES_f and ES_o are assigned depending on whether a farmer practices woodland and grassland pasture, applies chemical fertilizer or both. Goodness-of-fit is also assessed to evaluate the model performance under different ES valuation schemes.

2.4. Human agents

According to Census of Agriculture in 1992, approximately 47% of the lands within the Franklin County in Vermont are managed by agricultural landowners. The western Missisquoi Watershed is located within Franklin County and accounts for one fifth of the county's area, thus it is reasonable to assume that the landowner population within the watershed primarily consists of agricultural landowners. The ILUTABM is programmed so that the human agents update their expected utilities by accounting for the ES provided by the lands. The human agents are assumed to be risk neutral. The financial states, a surrogate for the expected utilities, of the human agents over time are considered to follow a dynamic process. A human agent at a given year has the following attributes: property size, land cell ownership, financial state, probability that the financial state changes, and ES changes due to land use transitions. The property boundaries of the human agents reflect the typical farm size observed within the western Missisquoi Watershed. The distribution of farm size for the Franklin County is fairly normal (Fig. 4), therefore, using the averaged farm size to represent the size of a typical farm is appropriate. According to the Census of Agriculture from years 1992 to 2007, the averaged farm size within the Franklin County ranges from 0.98×10^6 m^2 (243 acres) to 1.10×10^6 m^2 (280 acres). This allows us to assume that each farmer owns a rectangular farm of 30 land cells by 40 land cells, which is approximately 1.08×10^6 m^2 (267 acres). The property sizes and the landownerships are assumed to remain static over time, which is one of the limitations of this version of the ILUTABM. However the size heterogeneity will be implemented in a future version.

A farmer's financial state in a given year can be described as any of the three discrete independent states: financially feeling good (p), moderate stress (1 – p – q) or major stress (q). The number of the farms reporting net gains and net losses documented by the Census of Agriculture in years 1992, 1997, 2002 and 2007 are used to estimate the means and variances of the probabilities that a farmer is in p, 1 – p – q or q. Here by assigning $f_{\text{gain,good}}$% of the farms reporting net gains to the "financially feel good" group, $f_{\text{loss,sress}}$% of those reporting net losses to the "financially major stress," and the remainder to "financially moderate stress" for each Vermont county in each of the four years, the means and standard deviations of p, 1 – p – q and q can be estimated. Ideally the farmers' attributes for the study area should be estimated using farm- or zip-level data for Franklin County Vermont since the study area is located within the county. However because the Census of Agriculture only provides county level data, we use the data for all 14 Vermont counties to estimate the means (μ) and standard deviations (σ) of p, 1 – p – q and q. We then employ a Monte Carlo experiment design in which these means and standard deviations are plugged into a stochastic process for generating p, 1 – p – q and q to capture the uncertainties. Here we assume that the underlying distributions for p and q are symmetric triangular distributions. A triangular distribution is designated because the shape of distributions for p and q are unknown and therefore we assume that p and q arise from normal distributions. However, p and q range between zero and one but a normal distribution has infinite lower and upper bounds. Instead a triangular distribution enabling closed-form solutions is used to approximate a normal distribution (Scherer et al., 2003). Many studies have employed a triangular distribution with Monte Carlo simulations to investigate uncertainties and risks (Cox, 2012; Gibbons et al., 2006; Joo and Casella, 2001; Stern, 1993; Uddameri and Venkataraman, 2013). The symmetric triangular distributed random variate p given a uniform random variate u is:

$$\begin{cases} p = \mu_p + \left(\sqrt{2u} - 1\right) d_p & \text{for} \quad 0 < u < 0.5 \\ p = \mu_p + \left(1 - \sqrt{2(1-u)}\right) d_p & \text{for} \quad 0.5 \le u < 1 \end{cases} \tag{2}$$

where μ_p represents the mean of p and d_p represents the distance from the mean μ_p. A process similar to equation (2) but with a check preventing p + q > 1 is used to generate q:

$$\begin{cases} q = \mu_q + (\sqrt{2u} - 1)d_q & \text{for } 0 < u < 0.5 \quad \text{and} \quad p + q \le 1 \\ q = \mu_q + (1 - \sqrt{2(1-u)})d_q & \text{for } 0.5 \le u < 1 \quad \text{and} \quad p + q \le 1 \\ q = 1 - p \quad \text{for} \quad p + q > 1 \end{cases} \tag{3}$$

where μ_q represents the mean of q and d_q represents the distance from the mean μ_q. The distance from mean, denoted by d, of p and q are defined as

$$\begin{cases} \text{maximum} = \mu + d \\ \text{minimum} = \mu - d \end{cases} \tag{4}$$

where maximum and minimum represent the upper and lower bounds for a symmetric triangular variate. By plugging equation (4) into equation (5), d can be estimated by using the standard deviation σ of a symmetric triangular variate.

$$\sigma = \sqrt{\frac{(\text{maximum} - \text{minimum})^2}{24}} = \sqrt{\frac{d^2}{6}} \tag{5}$$

The farmers' overall expected utilities in year t, i.e., U_t in equation (1), represented by the financial states, are affected by the total ES obtained from all of their land holdings. The ILUTABM compares a farmer's overall expected utility at year t (U_t) to that of the previous year (U_{t-1}) and then determines that the states of the farmer' financial state will change if the expected utilities at these two time periods are different and with a probability of η, which is a random variate representing the unobserved influences on the chance of financial changes. Fig. 5 shows the state

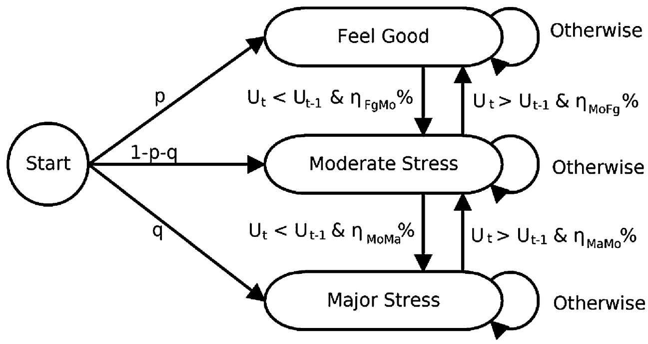

Fig. 5. The dynamics of the farmers' financial conditions over time. η_{FgMo}%, η_{MoFg}%, η_{MoMa}% and η_{MaMo}% are probabilities that a farmer's financial conditions change from one state to another in year t.

chart of a farmer's financial state within year t given the comparison between the farmer's expected utilities at years t and t-1 and the unobserved influences affecting transitions of the farmer's financial states: η_{FgMo}, η_{MoFg}, η_{MoMa} and η_{MaMo}. For example, a farmer financially feeling good in year t finds the change in expected utility in year t is less than that of year $t-1$, then there is a probability of η_{FgMo} that this farmer expects that he or she will fall into financially moderate stress category in year $t+1$. The ILUTABM draws η_{FgMo}, η_{MoFg}, η_{MoMa} and η_{MaMo} from a symmetric triangular distribution with $(\mu_\eta, d_\eta) = (0.5, 0.5)$. The ES_o setting in the ES valuation system (Fig. 3) provides a negative feedback loop to agricultural land expansion, whereas the ES_f provides a positive feedback loop to agricultural land expansion. When a farmer converts more lands into agricultural lands, the overall ES_o diminishes that implies a decrease in soil fertility and ecosystem functions. Introduction of agro-ecological practices can be potentially used to mitigate the effect size of this negative feedback loop (e.g., Dawoe et al., 2014).

Fig. 6 shows all possible land use decision making processes of a farmer given the financial state of the farm and his or her perceived ES_f and ES_o within a given year. When facing major financial stress during a given year, farmers decrease agricultural activities due to lack of financial support. Here we assume that a financially major-stressful farmer lacks the resources to get loans for increasing inputs to the land to attain more food production. This results into some of the agricultural lands being abandoned. Among these abandoned agricultural lands, the previous crop lands are either left as barren lands, and the previous hay lands are most likely to transition into grass/shrub lands. Thus the ILUTABM is implemented so that $x_{AgBaSum}$ represents the simulated transition probability of these abandoned agricultural lands transitioning into barren lands and $x_{AgGrSum}$ represents the simulated transition probability from agriculture to grass/shrub. The barren lands, if left undisturbed for three consequent years, will naturally progress into grass/shrub lands with a probability of $x_{BaGrSum}$. The grass/shrub lands, if left undisturbed for two consequent years, will then transition into forest lands with a probability of $x_{GrFoSum}$. When facing moderate financial stress, the farmers are assumed to keep their current farming practices in a given year, hence, the agricultural lands will not change during that year, but the barren, grass/shrub and forest lands will undergo natural vegetation progression. However a financially feel-good farmer's decisions on whether to expand agricultural lands depend on the comparison of ES_f with ES_o. The assumption supporting Fig. 6 is that when a well-off farmer perceived that food provisioning $(ES_f) >$ other ES (ES_o), then (s)he is most likely to expand the agricultural land. However if his/her perceived food provisioning $(ES_f) <$ other ES (ES_o), then (s)he is most likely to let some of his/her agricultural lands go fallow and ready for turning into grass/shrub lands. Lastly if the farmer perceives that food provisioning $(ES_f) =$ other ES (ES_o), then (s)he is most likely to keep his/her current farming practices. In Fig. 6, $x_{AgBaSum}$, $x_{AgGrSum}$, x_{FoAg}, x_{BaAg} and x_{GrAg} represent the simulated probabilities that a land cell is chosen to undergo the land use transitions from agriculture to barren, from agriculture to grass/shrub, from forest to agriculture, from barren to agriculture, and from grass/shrub to agriculture, respectively. These land use transition probabilities also arise from a stochastic process, and the estimation of these probabilities is explained in Section 2.5.

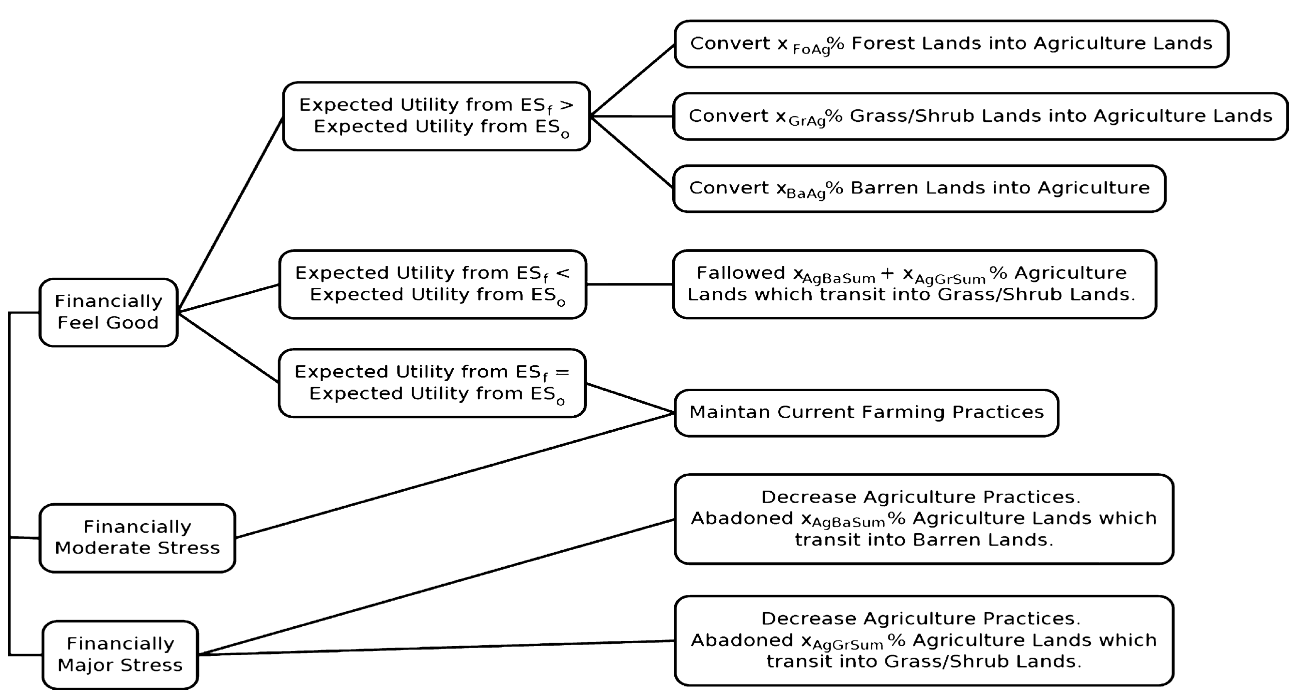

Fig. 6. Farmers' land use decision making processes with respect to their financial conditions.

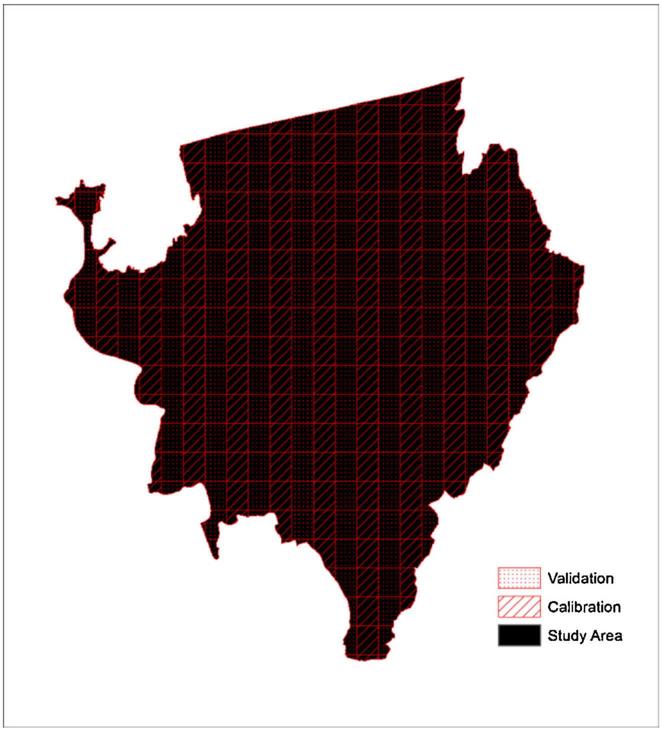

Fig. 7. The land cells used for calibration versus those for calibration in the entire study area.

2.5. Probabilities of landuse transitions

Three snap shots of the observed land use data are available for the model calibration and validation: NLCD 1992, 2001 and 2006. For the purpose of exploring the capability of the ILUTABM for projecting future land use patterns, we should have calibrated the ILUTABM by using NLCD 1992 and 2001; and then validated the model by comparing the simulated land use of 2006 to that of NLCD 2006. However, NLCD show that the time period of 1992 ~ 2001 is too short to manifest all possible land use transitions. For examples, transitions of barren to forest and grass/shrub to forest are not observed in 1992 ~ 2001 but they can be observed in 1992 ~ 2006. Thus, we calibrate the model with NLCD 1992 and 2006 by only including the land cells in the farms labeled with odd identity numbers; and then validate the model by comparing the simulated and observed land use in 2006 by only accounting the land cells in the farms labeled by even identity numbers (Fig. 7). The farms are labeled in such a way that an odd identity numbered farm is adjacent to an even identity numbered farm horizontally. This design of odd and even splitting, assuring that the farms used for validation are adjacent to those used for calibration, largely controls for spatial covariations of land use and biophysical properties such as soil, slope, elevation, vegetation, temperature and precipitation. The ILUTABM is calibrated through parameterization of the observed annual land use transition probabilities, which represent the percentage of land cells transitioning from one land use class to another in a year. The observed land use transition probabilities from 1992 to 2006 are estimates across 14-year intervals by accounting only odd numbered farms. These transition probabilities observed across N years, $\zeta_{\iota,\kappa,\mathrm{N}}$, are estimated by:

$$\zeta_{\iota,\kappa,\mathrm{N}} = \frac{\Omega_{\iota,\kappa,\mathrm{N}}}{\Sigma_{\kappa=1}^{7}\Omega_{\iota,\kappa,\mathrm{N}}} \tag{6}$$

where $\Omega_{\iota,\kappa,N}$ represents the number of land cells that are in land use ι in year t and are in land use κ in year t + N. A simple Markov Chain data mining method is used to estimate the observed annual land use transition probabilities $\zeta_{\iota,\kappa,1}$ based on the transition probabilities observed across N years $\zeta_{\iota,\kappa,\mathrm{N}}$:

$$\begin{cases} \zeta_{\iota,\kappa,1} = \dfrac{\zeta_{\iota,\kappa,\mathrm{N}}}{\mathrm{N}} & \text{for } \iota \neq \kappa \\ \zeta_{\iota,\kappa,\mathrm{N}} = 1 - \Sigma_{\text{for all } \iota \neq \kappa}\, \zeta_{\iota,\kappa,1} & \text{for } \iota = \kappa \end{cases} \tag{7}$$

where ι and κ are the "from" and "to" land use types of the land use transition. Here, for the purpose of calibrating the ILUTABM, we estimate $\zeta_{\iota,\kappa,1}$ based on $\zeta_{\iota,\kappa,14}$, which were observed during 1992 ~ 2006 in the agricultural parcels labeled by odd identity numbers (Fig. 7) where land use transitions occur among four land use types: forest, agriculture, barren and grass/shrub. Not all of the 16 transitions are accounted for by the ILUTABM. The only land use transition probabilities that have been simulated by the ILUTABM are x_{AgBaSum}, x_{AgGrSum}, x_{FoAg}, x_{BaAg}, x_{GrAg}, x_{BaGrSum} and x_{GrFoSum}, which represents the simulated annual transition probabilities. These are estimated by using the annual observed land use transition probabilities $\zeta_{\iota,\kappa,1}$. The estimates of x_{AgGrSum}, x_{FoAg}, x_{BaAg}, x_{GrAg}, x_{BaGrSum} and x_{GrFoSum} are documented in Table 1. In reality, $\zeta_{\iota,\kappa,1}$ where ι is agriculture (ι = 6) and κ is grass/shrub (κ = 5) or forest (κ = 4) are unlikely to occur in one year. These transitions occur only if (1) abandoned agricultural lands were transitioned into barren lands, which were left undisturbed and then turned into grass/shrub lands, (2) abandoned agricultural lands were transitioned into barren lands, which were left undisturbed and then turn into forest lands, or (3) abandoned agricultural lands were transitioned into grass/shrub lands, which left undisturbed and then turn into forest lands. Therefore, the observed annual transition probability of agriculture to grass/shrub ($\zeta_{6,5,1}$) and that of agriculture to forest ($\zeta_{6,4,1}$) can be considered as parts of the simulated probability of agriculture to barren (x_{AgBaSum}) given the agriculture lands are crop lands or that of agriculture to grass/shrub (x_{AgGrSum}) given the agriculture lands are pasturelands. According to the Census of Agriculture 2002, the land use within farm lands in Vermont are 45.6% cropland and 7.2% pastureland and rangeland, an estimate of the percentage of abandoned agricultural lands that are to be transitioned into barren land is 45.6%/(45.6% + 7.2%) = 86.4% and that are to be turned into grass/shrub lands 13.6%. Thus, the simulated annual transition probability of agriculture to barren lands:

$$x_{\mathrm{AgBaSum}} = 0.864(\zeta_{6,3,1} + \zeta_{6,5,1} + \zeta_{6,4,1}) \tag{8}$$

where $\zeta_{6,3,1}$, $\zeta_{6,5,1}$ and $\zeta_{6,4,1}$ represent the observed annual land use transitions probabilities: from agriculture to barren, grass/shrub and forest, respectively. Similarly the simulated annual transition probability of agriculture to grass/shrub lands:

$$x_{\mathrm{AgGrSum}} = 0.136(\zeta_{6,3,1} + \zeta_{6,5,1} + \zeta_{6,4,1}). \tag{9}$$

Subsequently, based on natural vegetation progression, $\zeta_{6,5,1}$ and $\zeta_{6,4,1}$ can be considered as parts of the simulated transition probability of barren to grass/shrub (x_{BaGrSum}) and that of grass/shrub to forest (x_{GrFoSum}) when the abandoned agriculture lands are undisturbed for a specific time period to complete the transitions from agriculture to barren to grass/shrub and then to forest. Given this, $\zeta_{6,5,1}$ and $\zeta_{6,4,1}$ can be added to the simulated annual transition probabilities of barren to grass/shrub (x_{BaGrSum}) and of grass/shrub to forest (x_{GrFoSum}). In addition, because the transition of barren to forest lands is most likely to be the transition of barren to grass/shrub and then to forest, the observed annual transition probability of barren to forest ($\zeta_{3,4,1}$) can be added to the simulated probability x_{BaGrSum}. Thus

$$x_{\mathrm{BaGrSum}} = \zeta_{3,5,1} + \zeta_{3,4,1} + 0.864(\zeta_{6,5,1} + \zeta_{6,4,1}) \tag{10}$$

where $\zeta_{3,5,1}$ and $\zeta_{3,4,1}$ represent the observed annual transition probabilities from barren to grass/shrub and from barren to

Table 1
Probabilities of land use transitions (LUTs) derived from the NLCD 1992 and 2006 by including parcels labeled with odd identity numbers.

Land use transitions from ι to κ		Annual Probabilities of Land use transitions	
ι	κ	Expressions	Estimates (1992 ∼ 2006, parcels with odd identity numbers)
Agriculture	Barren	$x_{AgBaSum}$	0.00140
	Grass/Shrub	$x_{AgGrSum}$	0.00022
Barren	Agriculture	x_{BaAg}	0.00013
	Grass/Shrub	$x_{BaGrSum}$	0.00322
Grass/Shrub	Agriculture	x_{GrAg}	0.00010
	Forest	$x_{GrFoSum}$	0.00575
Forest	Agriculture	x_{FoAg}	0.00037

forest, respectively. Then the simulated annual transition probability from grass/shrub to forest is estimated by:

$$x_{GrFoSum} = \zeta_{3,5,1} + \zeta_{3,4,1} + \zeta_{6,5,1} + \zeta_{6,4,1}. \tag{11}$$

The land use transitions from forest to agriculture (with the simulated probability = x_{FoAg}), from barren to agriculture (x_{BaAg}) and from grass/shrub to agriculture (x_{GrAg}) can occur within one year, therefore, these simulated annual probabilities are equal to their corresponding observed annual land use transition probabilities:

$$\begin{cases} x_{FoAg} = \zeta_{4,6,1} \\ x_{BaAg} = \zeta_{3,6,1} \\ x_{GrAg} = \zeta_{5,6,1} \end{cases} \tag{12}$$

where $\zeta_{4,6,1}$, $\zeta_{3,6,1}$ and $\zeta_{5,6,1}$ represent the observed annual land use transitions probabilities: from forest, barren and grass/shrub to agriculture, respectively.

2.6. Monte Carlo experiments for sensitivity assessments

Uncertainties of the ILUTABM arise from (1) a farmer's initial financial state arises from a stochastic process due to unavailability of the disaggregated data, i.e., populations of two groups of farmers are unknown: feel-good farmers who report net gains by the Census of Agriculture and major-stressful farmers who report net losses, (2) the valuations of ES, (3) the time lags for barren-to-grass/shrub and grass/shrub-to-forest transitions to be observed, (4) the probabilities that the state of the farmer's financial state changes are also affected by unobserved factors (i.e, η_{FgMo}, η_{MoFg}, η_{MoMa} and η_{MaMo}), and (5) a farmer randomly chooses land cells for land use transitions from their land holdings based on the estimates of the annual land use transition probabilities $\zeta_{\iota,\kappa,1}$. To understand how uncertainties from each of (1)∼(3) combined with (4) and (5) would affect the land use trajectories, Monte Carlo experiments are conducted to assess sensitivity of the ILUTABM under six different socio-economic conditions, four sets of ES assigning schemes, three sets of {a, b} for the a and b in equation (1), four different time periods needed for barren to grass/shrub transition and three different time periods needed for grass/shrub to forest transition.

The six Monte Carlo experiments under different socio-economic conditions, each with different values of $f_{gain,good}$ and $f_{loss,sress}$ assigned for 1992 (Table 2), are performed by executing the ILUTABM 20 times each with a different seed for stochastic processes. These six experiments are designed to explore the changes in land use due to different socio-economic conditions shaped by various exogenous socio-economic factors. These exogenous factors may include but are not limited to losses due to natural disasters, institutional reforms, and public policies relating to taxes and subsidies as incentives. Fig. 8 shows the farmers' financial states in 1992 that are generated from stochastic processes for all six experiments. Based on Fig. 8, we termed the first experiment Moderate Downward Wealth Redistribution (MDWR) because wealth was moderately redistributed from well-off to average (moderate stress) farmers. Comparing to the numbers of farmers in "feel good" and "major stress" categories under MDWR, the second experiment represents the condition where a moderate increase in the number of farmers feeling good ($f_{gain,good}$) was increased from 47% to 70% and a moderate decrease in the number of farmers feeling major stress ($f_{loss,stress}$) was decreased from 64% to 45%. We termed this experiment Moderately Alleviated Poverty (MAP) because, comparing to MDWR, there are more farmers feeling good and less farmers feeling major stress while the size of famers feeling moderate stress remains the same. We termed the third experiment Increase Economic Disparity (IED) because Fig. 8 shows that in 1992 the size of farmers feeling good largely increased and the size of farmers feeling major stress is slightly larger than these feeling moderate-stressful. We termed the fourth experiment Large Downward Wealth Redistribution (LDWR) because wealth was largely redistributed from well-off to average (moderate stress) farmers comparing to MDWR. We termed the fifth experiment Increase Poverty (IP) because the size of farmers feeling major stress was larger than the sizes of farmers feeling moderate stress and good. The sixth experiment was termed Largely Alleviated Poverty (LAP) because a very small size of farmers feeling major stress while a very large size of farmers feeling moderate stress comparing to all other experiments.

Because empirical data relating to farmers' perceived ES values, we construct two different ES valuation assigning schemes, i.e., No Pasture All Chemical Fertilizers (NPACF) and Some Pasture Less Chemical Fertilizer (SPLCF), to explore the model sensitivity. Description of these two schemes is provided in Table 3. Under SPLCF, a farmer's ES_f and ES_o are drawn from two discrete probability distributions. The two cutoff points, 0.5915 and 0.7056, are obtained from the Agriculture Census 1992. The value 0.5915 represents the fraction of farmers who did not purchase feed. We use this to make assumption that 59.15% of farmers do not practice grassland and woodland pasture because they need to purchase feed. The value 0.7056 represents the fraction of farmers who used chemical fertilizers. With this value, we assume that 70.56% of farmers use chemical fertilizers. In addition, three sets of coefficients {a, b} in equation (1) are set to explore the effects of different weights of ES_f versus ES_o on model sensitivity. These experiments are termed High-Food (HF), Medium-Food (MF) and Low-Food (LF) where {a, b} = {0.8, 0.2}, {0.5, 0.5}, {0.2, 0.8}, respectively.

To explore the impacts of different time periods needed for barren-to-grass/shrub and grass/shrub-to-forest transitions on land use changes, we conducted six additional Monte Carlo experiments for three different time periods for the occurrence of the barren to grass/shrub transition (three, five and seven years) and three different time periods for the occurrence of the grass/shrub to forest transitions (two, six and 10 years).

Table 2
Conditions fed to the ILUTABM for land use pattern simulations.

#	Experiments under various Socio-economic Conditions	In 1992, percent (%) of farmers reporting		Mean (Standard deviation)	
		Net gains, financially feel good, $f_{gain,good}$	Net losses, financially feel major stress, $f_{loss,stress}$	p	q
1	Moderate Downward Wealth Redistribution (MDWR)	47	64	0.23 (0.05)	0.33 (0.06)
2	Moderately Alleviated Poverty (MAP)	70	45	0.34 (0.07)	0.23 (0.04)
3	Increase Economic Disparity (IED)	95	64	0.45 (0.09)	0.33 (0.06)
4	Large Downward Wealth Redistribution (LDWR)	20	64	0.10 (0.02)	0.33 (0.06)
5	Increase Poverty (IP)	47	95	0.23 (0.05)	0.50 (0.09)
6	Largely Alleviated Poverty (LAP)	47	10	0.23 (0.05)	0.05 (0.01)

Table 3
Rationales for alternate valuations in ES.

#	Experiments under different ES Valuation Schemes	ES_f for {Barren, Grass/Shrub, Forest, Agriculture}	ES_o for {Barren, Grass/Shrub, Forest, Agriculture}	Rationales
1	No Pasture All Chemical Fertilizers (NPACF)	{1, 3, 4, 10}	{1, 7, 10, 1}	No farmers have any grass/shrub/wood land pasture; similarly, all farmers do purchase and thereby apply chemical fertilizers.
2	Some Pasture Less Chemical Fertilizer (SPLCF)	{1, 3 ~ 7, 4 ~ 8, 10} ES_f for Grass/Shrub = {3, 4, 5, 6, 7} and ES_f for Forest = {4, 5, 6, 7, 8} with a discrete probability distribution of {0.5915, 0.1021, 0.1021, 0.1021, 0.1021}	{1, 7, 10, 1~5} ES_o for Agriculture = {1, 2, 3, 4, 5} with a discrete probability distribution of {0.7056, 0.0736, 0.0736, 0.0736, 0.0736}	59.15% of farmers do not practice grass/shrub land or woodland pasture by purchasing feed and they use chemical fertilizer; other (70.56-59.15)% of farmers practice pasture but also use chemical fertilizers. the remaining farmers practice grass/shrub land or woodland and they do not use chemical fertilizer. A uniform distributed random variant is used to determine the cutoff points for ES_f and ES_o.

3. Simulation results and discussion

3.1. Validation by comparing goodness-of-fit

The ILUTABM is validated by comparing the observed and simulated land use percentages in 2006 by accounting only those cells in farms labeled by even identity numbers (Fig. 7). Here, Nash–Sutcliffe efficiency index (NSEI) is used to assess the goodness-of-fit of the ILUTABM under each experiment. NSEI is a widely used and potentially reliable statistic for assessing the goodness-of-fit of hydrologic models (McCuen et al., 2006). The values of NSEI range from $-\infty$ to 1. NSEI = 1 indicates that a model is able to reproduce observations. We use NSEI to evaluate the efficiency of the ILUTABM under each Monte Carlo experiment for reproducing the observed percentages of the four land use types ι (i.e., 3: barren, 4: forest, 5: grass/shrub, or 6: agriculture) in 2006; The Nash-Sutcliffe efficiency index for the percentages of land uses ($NSEI_{plu}$) is defined as

$$NSEI_{plu} = 1 - \frac{\Sigma_\iota \left(Plu_{t,\iota} - \widehat{Plu}_{j,t,\iota} \right)^2}{\Sigma_\iota \left(Plu_{t,\iota} - \overline{Plu}_{t,\iota} \right)^2} \quad (13)$$

where $Plu_{t,\iota}$ represents the observed percentage of the land use ι in year t; $\widehat{Plu}_{j,t,\iota}$ represents the simulated percentages of the land use type ι in year t for model run j; $\overline{Plu}_{t,\iota}$ is the mean of the observed percent land use $Plu_{t,\iota}$; j = 1, 2,. . .,20; t = 2006; and ι = 3, 4, . . ., 6. As indicated in Fig. 9 that most of the land cells in the study area

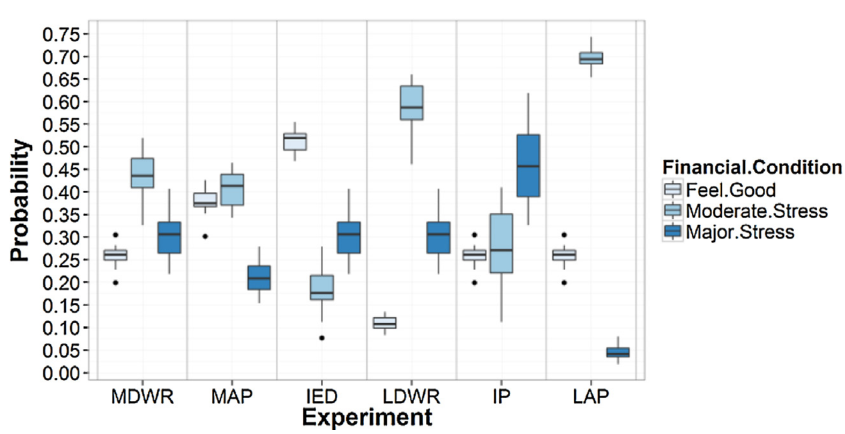

Fig. 8. Farmers' initial financial conditions in 1992 under all six socioeconomic conditions.

remain unchanged for both observed and simulated, this greatly biases the estimates of $NSEI_{plu}$ to being very close to one when both changed and unchanged land cells are included for the estimation of $NSEI_{plu}$. Thus, we exclude the land cells that are unchanged in both observed and simulated for the estimation of $NSEI_{plu}$. The best goodness-of-fit measure yielded from all Monte Carlo experiments is $NSEI_{plu} = 0.6206$. The settings of this Monte Carlo experiment is Increase Economic Disparity (IED) Some Pasture Less Chemical Fertilizer (SPLCF) High Level of Food Provisioning versus Other ES (HF) lags of {grass/shrub, forest} occurrence = {3, 10} year. The land use difference map shown in the Fig. 9 is drawn based on this experiment. Even though the $NSEI_{plu}$ (=0.6206) of this experiment indicates that the ILUTABM is able to reproduce 62% of the observed land cell transitions, Fig. 9 shows that the spatial patterns of the observational land use transitions are markedly more clustered than the simulated counterparts. This maybe because the current version of the ILUTABM does not estimate land use suitability for a land cell by accounting for neighboring land use. The second best fit experiment is the combination of IED, SPLCF and MF, which yields $NSEI_{plu} = 0.5424$. The goodness-of-fit estimates indicate that the combination of IED, SPLCF and HF best reflects the "business as usual" scenario for the study area.

Generally SPLCF (Some Pasture Less Chemical Fertilizer) yields the same or slightly better goodness-of-fit than NPACF (No Pasture All Chemical Fertilizer). The fit of the ILUTABM varies given different socio-economic conditions and different weights of food provisioning versus other ES, i.e., ratio of a to b in equation (1). We also find that the lag of barren to grass/shrub transition has little effect on the fit of the ILUTABM, while the lag of grass/shrub to forest transition can significantly influence the fit of the ILUTABM.

3.2. Impacts of exogenous socio-economic factors combined with ES weights

Results of the 18 Monte Carlo experiments, with Some Pasture Less Chemical Fertilizers (SPLCF) and the lags of {grass/shrub, forest} occurrences being {3, 10} years, are further analyzed (Figs. 10 and 11) to investigate impacts of different socio-economic conditions combining with ES weights on land use patterns. These experiments are chosen for further analyses because SPLCF combined with lags = {3, 10} years usually provide slightly better goodness-of-fit than No Pasture All Chemical Fertilizers (NPACF) combined with other lags of {grass/shrub, forest} occurrences. Furthermore, since Increase Economic Disparity (IED) can be considered as the experiment that best represents the "business as usual" scenario based on the goodness-of-fit analysis, the purpose of the analyses here is to explore the impacts of alternate socio-economic and ES weights conditions on projected land use patterns comparing to "business as usual." Fig. 10 illustrates changes in forest and agricultural lands across the entire simulation horizon for different combinations of six socio-economic with three ES weight conditions. It shows a relatively flat U shape trend for forest transition across the entire simulation horizon for all six socio-economic under Medium-Food (MF) and Low-Food (LF) conditions. These two ES weight conditions, MF and LF, produce similar forest transition trends for each socio-economic condition. However, the shapes of the forest transition trends and the turning points where forest expansion occurs are different when comparisons are made across the six socio-economic conditions. These forest transition trends may be resulting from the interplays of "economic development pathway" and "smallholder, tree-based land use intensification pathway" (Lambin and Meyfroidt, 2010; Rudel et al., 2005) under the conditions where a farmer values food provisioning ES less than (or equal to) other ES. In the Missisquoi Watershed, the economic development pathway is most likely caused by non-farm jobs that reduce farming; and large portion of land marginally suitable for agriculture is abandoned and left to forest regeneration. The smallholder, tree-based land use intensification pathway is most likely caused by abandoned pastures or fallows, smallholders' efforts on ecological and economical diversification to decrease their vulnerability to economic or environmental factors, innovation of farming systems (to maintain ES from farming and also gain ES from managing non-farm lands), restoring degraded lands to forests, and maintaining wildlife-friendly or environment-friendly farming.

Generally Fig. 11 indicates that ES weight settings have great and different influences on the populations of the three farmers' perceived financial states across time horizon, that also have great impacts on changes in land use over time. Results shown in Fig. 10 indicate that there is one condition where both forested and agricultural lands expand: Largely Alleviated Poverty (LAP) combined with the ES weights Low Food (LF). This type of land use change trend is caused by a fraction of feel-good farmers becoming moderate-stressful farmers during 1992 ~ 2001 and then gradually resuming to being feel-good in later time periods under LF (Fig. 11 LAP). This fraction of feel-good turning into moderate-stressful farmers is small enough to maintain a leveled size of agricultural lands in earlier simulation periods; and when they resume to feel-good status, the importance of the total food-provisioning ES versus that of the total other ES may be different, and hence that resulting into forest regrowth. Interestingly, High Food (HF) combined with Largely Alleviated Poverty (LAP) produces an agriculture expansion but with a decrease in forest. According to Fig. 11, this type of land use change trend may be caused by HF that tends to generate a large population of feel-good farmers combined with a small population of major-stressful farmers. The former population, being large in size, causes agriculture expansion; while the latter, being

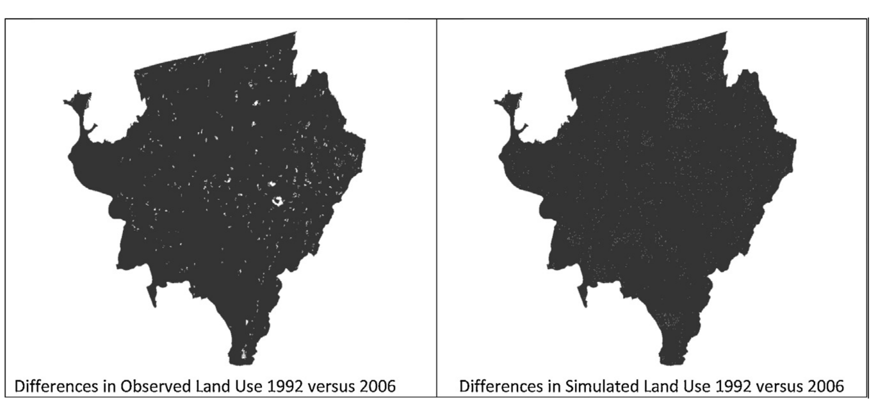

Fig. 9. Comparisons of the observed versus the simulated land use transitions among the four land use type: barren, forest, grass/shrub and agriculture, where light-colored pixels in the study area represent land use changes during 1992 ~ 2006. The settings for the simulated results are Increase Economic Disparity (IED) Some Pasture Less Chemical Fertilizer (SPLCF) High Level of Food Provisioning versus Other ES (HF) lags of {grass/shrub, forest} occurrence = {3, 10} year.

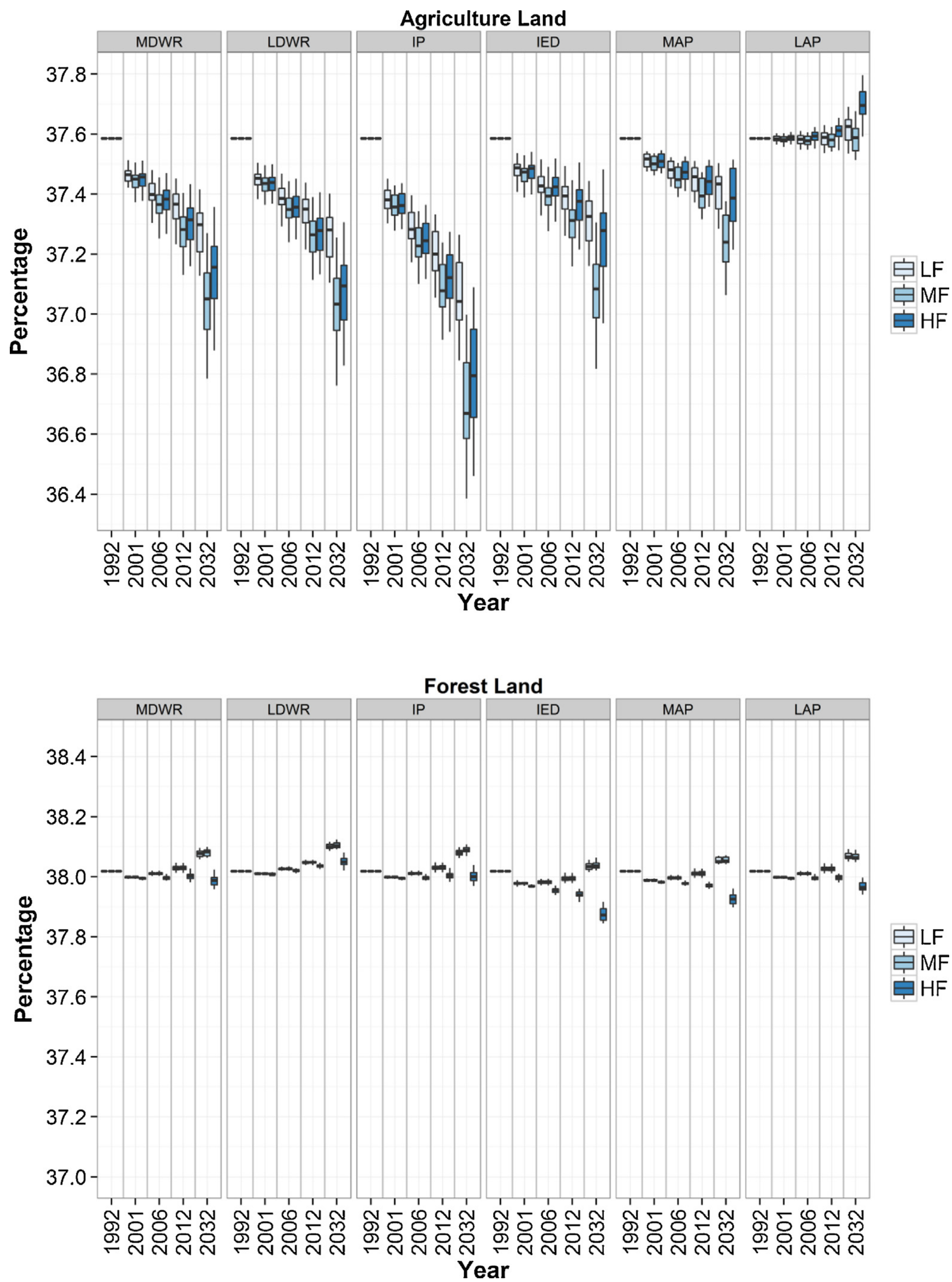

Fig. 10. Comparisons of the landowners' financial conditions under the six scenarios across simulation horizon. Please note that the horizontal time scale is not linear.

small, causes little agriculture-transitioning-to-forest. HF condition leads to a decrease in forested lands for all socio-economic conditions except for Large Downward Wealth Redistribution (LDWR). However, only one (LAP) out of six socio-economic conditions, when combined with HF, leads to agricultural expansion, while the other five leads to diminishing in agricultural lands (Fig. 10). Increase Poverty (IP) combined with High Food (HF) ES weight leads to the largest decrease in agricultural lands and a significant decrease in forested lands; while Increase Economic Disparity (IED) and HF combination leads to a significant decrease in agricultural lands and the largest decrease in forested lands (Fig. 10). As shown in (Fig. 11), the IP is gradually turning into Increase Economic Disparity (IED) under the HF setting. This IP-transitioning-to-IED phenomenon renders (1) a slowly increasing feel-good farmers that are not able to maintain the agricultural practices at the level of 1992; and (2) a slowly decreasing population of major-stressful farmers that cannot produce substantial forest regrowth. Similar socio-economic transition trends exist for the populations of feel-good and major-stressful farmers under MDWR and LDWR, when combined with MF and LF. However, under HF, MDWR leads to an irreversible decreasing trend in forested lands while LDWR leads to forest transitions.

3.3. Impacts of different time periods for occurances of forests

It is found that different time periods needed for barren to grass/shrub transition do not significantly impact on land use patterns generated by the ILUTABM. However, the land use patterns

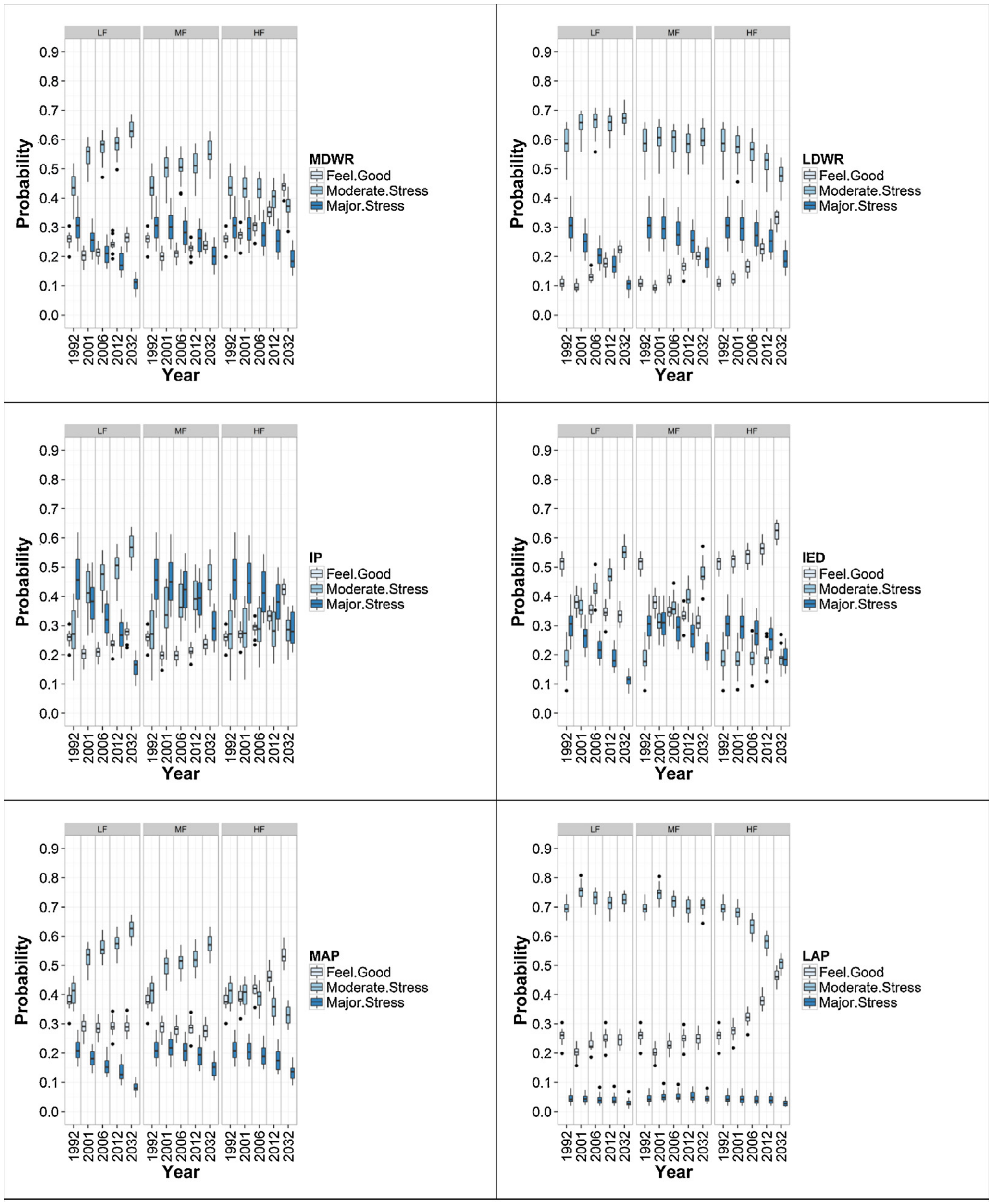

Fig. 11. Comparisons of the landowners' financial conditions under the six scenarios across simulation horizon. Please note that the horizontal time scale is not linear.

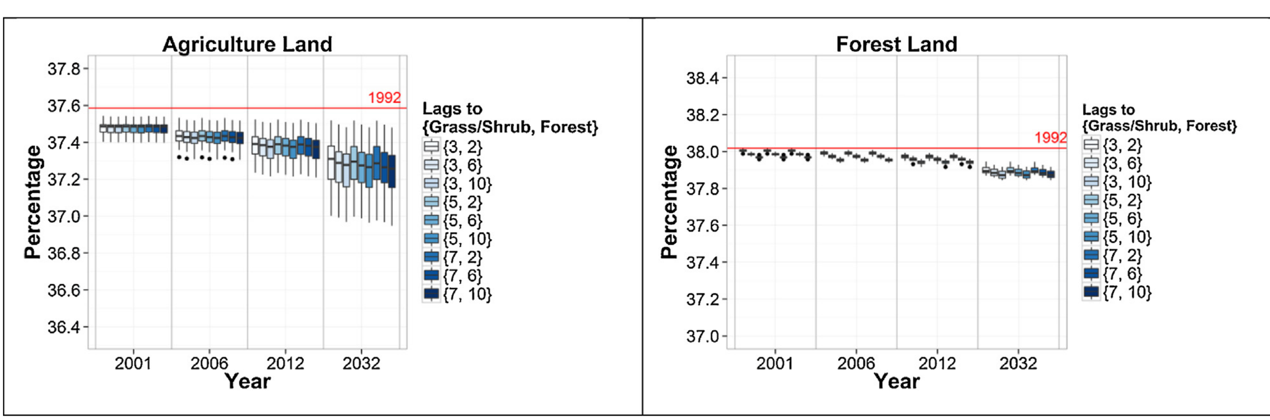

Fig. 12. Comparisons of the acreages of forest and agricultural lands for all different time periods needed for occurrences of barren to grass/shrub transitions and for grass/shrub to forest transitions. Please note that the horizontal time scale is not linear.

generated by the ILUTABM is sensitive to different time periods needed for the occurrence of grass/shrub to forest transition (Fig. 12). Results shown in Fig. 12 summarize the influences of different lags on changes in forest and agricultural lands under the combination of IED, SPLCF and HF. The longer the lag of grass/shrub to forest transition, the larger the decreases in both forested and agricultural lands are.

3.4. Assumptions, limitations and future work

Some underlying assumptions of the ILUTABM are less sound and the ILUTABM has some limitations. (1) It is unrealistic to assume that the entire study area is managed by farmers only. Other types of landowners, such as, foresters, businesses and residences should also be considered. Land use decision making processes of additional landowner categories will be accounted for in the next version of the ILUTABM. (2) The farm size of each farm remains constant across the entire study area and study period. (3) The landownership remains constant over time. The size heterogeneity will be implemented in the next version of the ILUTABM to further explore the impacts of property size dynamics over time on land use transition dynamics. (4) Only one factor, the ES value, is programed into the ILUTABM to influence the changes in the farmers' financial states. The impacts of other unobservable factors on the farmers' financial states are grossly explained by a random triangular variate. In addition, a simple ES valuation system is employed by this study. A more sophisticated ES valuation system such as these suggested by de Groot et al. (2010) and Kareiva et al. (2011) can be programmed into the future version of the ILUTABM. (5) The land use transitions only occur among agriculture, barren, grass/shrub and forest. The observed land use data (NLCD) show that the land use transitions among urban, wetlands are also important and should be considered. (6) The ILUTABM randomly selects a land cell to undergo a specific land use transition. The land cells suitable for a certain land use and the cells likely to be subject to a certain land use transition depends on several factors, such as neighboring land use, elevation, soil, zoning laws, and current and historical land use. (7) A farmer's financial state is not designed to change from feel-good to major-stress and vice versa. Although these abrupt state changes may be unlikely to be observed, they can occur with a very small probability. (8) The assumption that a financially major-stressful farmer lacks the resources to acquire loans to increase the food production is not realistic, given the plethora of subsidies offered by the USDA to sustain financially stressful farmers over time. (9) In the current version of the model, farmers do not interact with each other and a land cell agent does not influence its neighbors. Interplays among human agents and these among land cells agents can be implemented in the future version to account for effects of the agent interactions, including reflexive behaviors by human agents and adaptive ecosystem responses in the constellations of landscape agents. (10) Discrete land cell agents, as in 30 by 30 meter resolution, cannot adequately represent continuous features such as rivers, soil, and parcel boundaries. The representation of continuous features as discrete agents in the current ILUTABM could be improved over the current 30 by 30 meter resolution from widely available NLCD data, if both high resolution data (e.g., one by one meter) and computational power are made available.

4. Conclusions

Our results suggest that a simplistic modelling platform, with parsimonious factors, a farm-level heuristic-based land use decision making process and a simple ecosystem service (ES) valuation system, is able to mimic 62% of the observed land use transitions by calibrating our model to NLCD and Agriculture Census. Our results also indicate that, when farmers value less food provisioning than other ES (e.g., non-food provisioning, water and soil regulating), reforestation as suggested by forest transition theory (FTT) is observed. The goodness-of-fit analyses show that, under the conditions of the best fit experiment, i.e., Increase Economic Disparity (IED) Some Pasture Less Chemical Fertilizer (SPLCF) High Level of Food Provisioning versus Other ES (HF) lags of {grass/shrub, forest} occurrence = {3, 10} year, forest transition is not observed. However, under the conditions of the experiment producing the second best fit, i.e., combination of IED, SPLCF, MF, lags = {3, 10}, forest transition can be observed. In a rural watershed such as the western Missisquoi Watershed, reforestation may be the results of the complex interactions of "economic development pathway" and "smallholder, tree-based land use intensification pathway" that are possibly triggered by a shift of labor from farms, restoration of forest on degraded lands, ecological and economical diversification in farms and wildlife-friendly farming. However, when farmers value food provision ES more than other ES, deforestation is observed. Under this condition, farmers' incentives of reforestation and practicing ecological friendly farming are dampened by producing more food through intensified agricultural practices. Farmers' socio-economic conditions significantly affect the forest recovery rate and deforestation rate. Extent of agricultural lands over time depends on farmers' socio-economic conditions and farmers' perceived weights of food provisioning ES versus other ES. When the population of feel-good famers increases over time, the agricultural lands increase, such phenomena can be observed under two conditions: Increase Economic Disparity (IED) combined with higher weights for food provisioning than other ecosystem services (HF) and IED with MF (median weights for food provisioning ES). Implication of land use change from public policy affecting farmers' socio-economic conditions may be drawn. However, due to the simplicity of the current modelling platform, limitations of the ILUTABM must be addressed before using the simulation results for policy advice.

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