Agricultural Systems 103 (2010) 117–126

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Using a role-playing game to inform the development of land-use models for the study of a complex socio-ecological system

C. Washington-Ottombre [a], B. Pijanowski [a,*], D. Campbell [b], J. Olson [c,d], J. Maitima [d], A. Musili [e,1], T. Kibaki [f,2], H. Kaburu [g,3], P. Hayombe [h], E. Owango [i,4], B. Irigia [j,5], S. Gichere [k,6], A. Mwangi [l,7]

[a] Department of Forestry and Natural Resources, Purdue University, West Lafayette, IN, USA
[b] College of Social Science, 203 Berkey Hall, Michigan State University, East Lansing, MI 48823, USA
[c] Department of Telecommunications, Michigan State University, East Lansing, MI 48823, USA
[d] International Livestock Research Institute, Nairobi, Kenya
[e] Ministry of Livestock and Fisheries Development, P.O. 34188, Nairobi, Kenya
[f] Ministry of Water Resources Management and Development, P.O. Box 49720, Nairobi, Kenya
[g] GEF Project on Management of Indigenous Vegetation, P.O. Box 350, 00618 Ruaraka, Nairobi, Kenya
[h] Physical Planning Department, Ministry of Lands and Settlement, Ardhi House RG13, Box 4025, Nairobi, Kenya
[i] Planning Department, Ministry of Agriculture, Kilimo House, Cathedral Road, P.O. Box 30028, Nairobi, Kenya
[j] Head of KWS EIA Programme, P.O. Box 40241, Nairobi, Kenya
[k] Ministry of Regional Development, P.O. Box 10280-00100 GPO, Nairobi, Kenya
[l] National Programme Manager, NEMA, Ministry of Environment, Natural Resources and Wildlife, P.O. Box 47146, Nairobi, Kenya

ARTICLE INFO

Article history:
Received 5 November 2008
Received in revised form 5 October 2009
Accepted 7 October 2009
Available online 22 December 2009

Keywords:
Land-use
Role-playing games
Geographic information systems
Multi-criteria evaluation
Machine learning tools
Comparison of models

ABSTRACT

We present an integrated methodology composed of a role-playing game on land adjudication from which we extract narrative and spatially explicit drivers of land-use decisions. We show how geographic information systems (GIS), qualitative decision-matrix analyses, a simple rule-based model using multi-criteria evaluations (MCE), and a machine learning-based land-transformation model (LTM) can be used harmoniously to study complex socio-ecological systems. We evaluate how each technique performs in the study of complex socio-ecological systems using a multi-tier framework detailing how each method analyzes the resource system, resource units, governance system, users and interactions and outcomes in the system. We show that each approach enhances our understanding of the land-use decision making process. Each method provides various information on the drivers of land-use decision, some focusing more on spatial components of socio-ecological systems (resource system and resource unit) and other having a strong emphasis on social mechanisms (governance system, users, interactions and outcomes). Furthermore, we shed light into the existence of a flow of information between the various methods enhancing our understanding of land-use drivers. We end with a discussion on methodological tradeoffs between models and the value of our more holistic approach to modeling land-use drivers and decisions.

1. Introduction

Along with climate change and invasive species, land-use change has been identified as one of the most significant environmental threats to the planet (MEA, 2005). Land-use change is the consequence of complex land-use decisions and results from multiple interactions between biophysical and socioeconomic factors (Ojima et al., 1994; Turner et al., 1990; Rindfuss et al., 2004; Foley et al., 2005; Ojima et al., 2005). Indeed, land use/cover change has been identified as an example complex socio-ecological system (GLP, 2005; Peeples et al., 2006).

Models of land-use change, which couple biophysical and socio-economic drivers, are needed to address the complex issue of land-use change and build up sustainable land-use practices and

* Corresponding author. Tel.: +1 765 496 2215; fax: +1 765 496 2242.
E-mail addresses: cottombr@purdue.edu (C. Washington-Ottombre), bpijanow@purdue.edu (B. Pijanowski), djc@msu.edu (D. Campbell), olsonjj@msu.edu (J. Olson), j.maitima@cgiar.org (J. Maitima), nileproject@wananchi.com (T. Kibaki), hkaburu@swiftkenya.com, hmkaburu@hotmail.com (H. Kaburu), rapospat@yahoo.com (P. Hayombe), tedowango@yahoo.com (E. Owango), bkaaria@kws.org, kws@kws.org (B. Irigia), gichere@treasury.go.ke (S. Gichere)..
[1] Fax: +254 20 2721005.
[2] Tel.: +254 20 2716103x42270, mobile: +0721279928.
[3] Tel.: +254 20 3760331.
[4] Tel.: +254 20 2719013x48011.
[5] Tel.: +254 20 602345/501081.
[6] Tel.: +254 20 227411.
[7] Present address: United Nations Development Programme, Dryland Development Centre, P.O. Box 30552, Nairobi, Kenya. Tel.: +254 624634.

0308-521X/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.agsy.2009.10.002

policies (Van Daalen et al., 2002; Lambin and Geist, 2006). Many models have been developed to simulate the outcomes of land-use decisions and support the analysis and understanding of land-use practices (Verburg et al., 2004). A variety of methods have been used to develop land-use models include those using statistical (Veldkamp and Fresco, 1996), machine learning (e.g. Pijanowski et al., 2002a), agent-based (Parker et al., 2003; Alexandridis and Pijanowski, 2007; Matthews et al., 2007) or simple rule-based approaches (Pontius, 2002).

Major challenges of land-use modeling include the explicit integration of biophysical and socio-economic dynamics that participate in land-use changes (Lambin and Geist, 2006). In addition, modelers willing to quantify land-use dynamics often face contexts of high uncertainty and lack of data (Rindfuss et al., 2004).

Here, we present an integrated methodology that qualifies and quantifies drivers of complex land-use decisions without using traditional data intensive methods such as remote sensing imagery or survey analysis. This paper attempts to improve the field of land-use modeling by illustrating the importance of role-playing games (RPGs) in supporting the development of models that quantify factors responsible for land-use decisions. We show how qualitative decision-matrix analyses, geographic information systems (GIS), a simple rule-based model using multi-criteria evaluation (MCE), and a machine learning-based land-transformation model (LTM) can be used harmoniously to further our understanding of land-use decision-making processes. We conclude with a discussion of what can be learned from each of these approaches and, in particular, what are the methodological tradeoffs between models and therefore the value of our more holistic approach to modeling land-use decisions.

2. Background

2.1. Modeling complex socio-ecological systems

Complex socio-ecological systems (SESs) are difficult to analyze and model because of the nature of the complexity paradigm (Janssen and Ostrom, 2006). Indeed, the paradigm of complexity emphasizes non-linear dynamics among those systems (Funtowicz and Ravetz, 1993; Vicsek, 2002) and, in particular, the importance of resilience and emergent phenomena (Walker et al., 2004; Walker and Salt, 2006). Since what really matters is the resilience of a given complex SES, researchers need to identify the core variables which would distinguish between a regime shift of a given system and a new system replacing a degraded or damaged one (Gunderson and Holling, 2001). The identification of the core variables of a complex SES is crucial to its study and modeling (Berkes and Folke, 1998). Those critical variables are composed of biophysical as well as socio-economic elements. Not taking into account those critical variables as well as the overall complexity may have devastating consequences not only on the modeling of SESs and land-use changes, but also on the management of those systems (Ostrom, 2007).

Ostrom (2007) has introduced a framework for understanding complex SESs which couples biophysical and institutional variables in order to establish better diagnostics, conduct more thorough research, and implement resilient management of complex SESs. In an innovative manner, this paper will use the multi-tier framework developed by Ostrom in order evaluate the ability of our models to analyze complex SESs (Ostrom, 2007).

2.2. Role-playing games and complex SESs

Researchers have turned to role-playing games (RPGs) (e.g. Barreteau et al., 2003) to capture the nature of complex SESs. Employed as a simulation tool in social sciences, RPGs can be defined as "*the performance of an imaginary or realistic situation played by people with given roles in order to analyze behavioral patterns*" (Shaftel and Shaftel, 1967).

In past research on land-use and natural resources, RPGs have mainly been used as a support for collective decision-making processes and as a learning tool for participants and researchers as well (Bousquet et al., 1999; Barreteau, 2003). Researchers among the ComMod group, for example, have parameterized agent-based models with RPGs in order to improve the knowledge as well as the integrated management of complex SESs around the world (see http://commod.fr). The ComMod group's methods focus on the use of role-playing games to foster negotiation as well as to collect additional empirical data on individual and collective management of renewable resources. They continue the negotiation process supported by the ABM which provides them with an external verification of the model (Bousquet et al., 1999).

This methodology is greatly inspiring for land-use modelers since it opens new perspectives on how to address the issues of empirical input data for models, their external validation as well as their ability to take complex dynamics into account. However, because RPGs have been mainly used for negotiation purposes (Barreteau et al., 2003; Etienne, 2003; Daré and Barreteau, 2003; Gurung et al., 2006), further work is needed to investigate how to exploit the potential of games to record information for modeling purposes (Guyot and Honiden, 2006). Here, we present a methodology designed to collect information on land-use drivers from recordings conducted during a role-playing game that can be used as inputs to traditional and more advanced models.

3. Methods

3.1. An integrated methodology

Our methodology integrates qualitative, quantitative, and spatially explicit analyses and modeling in order to study various land-use drivers and to analyze how individually and collectively each method can add to our understanding of complex SESs. We base our land-use models on a role-playing game designed to produce qualitative as well as spatially explicit outputs. Two land-use models are constructed: a neural network-based land transformation model (LTM) and a GIS-based multi-criteria evaluation (MCE) model. We calculate model goodness of fit; determine how the information flows between methods; and how each modeling approach contributes to our understanding of land-use drivers in a complex SES (Fig. 1).

3.2. The role-playing game

The RPG used here was established by Campbell and Palutikof as an educational tool to explore land adjudication issues (Campbell and Palutikof, 1978). Land adjudications are policy tools used to transition land from a situation of no formal property titles to common or individual property (cf. Kimani and Pickard, 1998; Woodhouse and Hulme, 2000; Reid et al., 2000). Eight players participated in the simulation conducted in Nairobi, Kenya in May 2004. Participants, who specialized in land-use, agriculture, or natural resources, were drawn from Kenyan governmental and academic institutions.

The exercise focused on the northern, semi-arid regions of the fictional country of Mageria. In our scenario, fictitious ethnic groups are beginning to compete for land (the Iletan Hills in particular) and water resources in the area. The participants assume the roles of members of a fictitious ethnic group of pastoralists (Tuai herders) or farmers (Sengot farmers). They are asked to prepare a

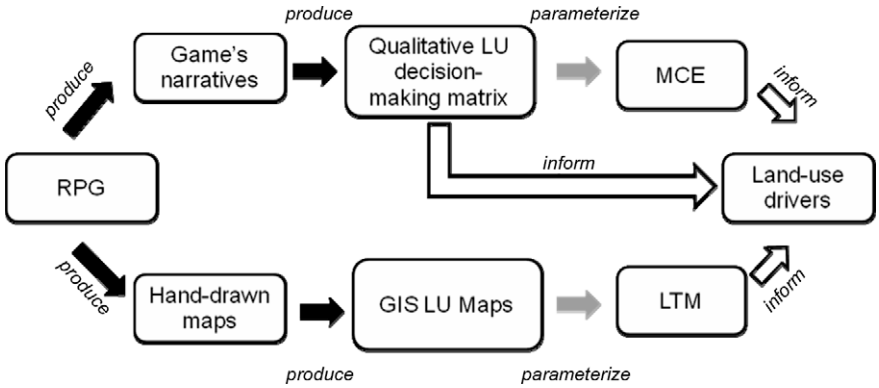

Fig. 1. An integrated and embedded qualitative and spatially explicit methodology. The RPG is used to identify land-use drivers in a qualitative manner. The MCE and the LTM then build on the outputs of the RPG (maps and narratives) to quantify the respective weight of those drivers regarding the game participants' land-use preferences and decisions.

land adjudication plan to establish formal property titles in order to resolve the conflicts of resource use. The outcome of the land-adjudication is decided by another player in the role of the District Commissioner (D.C.), a local government official.

A variety of information was used to build the RPG. One such source was a pair of household surveys conducted in 1977 and in 1996 designed to study land-use conflicts and land-use policy in the Kajiado district, Kenya (Campbell et al., 2000; Campbell et al., 2005). Numerous agricultural surveys and reports, government policy discussions and workshops with East African policy makers and researchers were used to enhance surveys. Four major local land-use change drivers were identified: alterations in both the composition and the size of the local population (Campbell et al., 2000), drastic transformations of land tenure due to processes of land-adjudication (Kimani and Pickard, 1998; Woodhouse and Hulme, 2000), and crop diversification driven by global market forces (Campbell et al., 2000; Little et al., 2001). We used the RPG and the subsequent modeling methodology to analyze land-use drivers and decision-making processes in order to deepen the understanding of the changes observed in previous research.

In this game, Sengot farmers, Tuai herders, and the D.C. proposed land-use maps for the future land adjudication and explained their motivations to one another and to the researchers. The RPG was composed of four major steps. First, we presented the participants with a fictitious landscape (base map), on which to negotiate the land adjudication, and data concerning the social and ecological conditions of the area (see http://ltm.agriculture.purdue.edu/RPG.pdf) for the complete RPG scenario and data used during the game). Then, each fictitious resource group and the D.C. (1) produced a land-adjudication map and (2) explained the drivers for their decisions. Tuai herders and Sengot farmers each sketched a map (maps 1 and 2, respectively). After presentations by the Tuai and the Sengot, the D.C. proposed a map taking into account the land-use priorities of each ethnic group and representing the final land-adjudication scheme (map 3). In total, three maps were hand-drawn by the game participants (Fig. 2). We analyzed two outputs from the RPG: (1) discussions and justifications of decisions which occurred during the game and (2) maps produced by the players.

3.2.1. Organizing narratives and discussions

The first type of output from the RPG consisted of narratives and discussions which occurred during the presentation of the proposed land-adjudication maps. Narratives and discussions were digitally recorded and used to build a qualitative-decision-making matrix representing the drivers for land-use decisions for each resource group: Tuai pastoralists, Sengot farmers, and the D.C. Those drivers were categorized according to the analytical framework of complex SESs established by Ostrom (2007). Here, the framework was used as a reference against which we evaluated the ability of our methods and models to capture the various characteristics of a complex SES. The main components of the framework are: (1) a resource system (here the grazing areas, cropping areas and water resources); (2) resource units (here livestock, crops, and wildlife); and (3) a governance system (here the interactions between the Tuai, Sengot, and the DC) (Ostrom, 2007) (Table 1).

3.2.2. Creating digital maps

The second output of the RPG consisted of paper maps generated by the participants. These paper maps were scanned and imported into ArcGIS 9.1 (ESRI 2005) as images. Point, line and polygon features were digitized using the ArcGIS 9.1 Editor tool. Natural (e.g. lakes) and socioeconomic (e.g. towns) features were stored as separate layers. Land uses were digitized as polygons and labeled according to a level 2 classification so that generalized agriculture was given level 1 and subclasses (e.g. irrigated) as the second (Anderson, 1976). The level 1 classes digitized were: crops, pasture, and protected areas. The land-use maps were then rasterized into maps with 555 rows and 398 columns (for a total of 220,890 cells) for analysis and modeling. Maps contained integer values of land use codes.

3.3. Selecting drivers based on the RPG

We selected six spatial land-use drivers based on the critical spatial and socio-economic characteristics identified by the game participants (see Table 1). We selected the following drivers: distance to medium elevation, distance to high elevation, distance to rivers, distance to lakes, distance to roads, and distance to cities. Indeed, during the game, the players emphasized the importance of elevation, both for crops (to access arable land) and for pastures (for grazing during the dry season). We used distance to the contour lines of the digitized map as the midpoint of elevation classes and created two drivers for elevation: distance to medium elevation (i.e. distance to the 1000 m contour line) and distance to high elevation (i.e. distance to the 2000 m contour line). Roads, cities, and proximity to these features, appeared to constitute essential socio-economic drivers for both farmers and pastoralists in order to travel and sell their products, which is why we selected distance to roads and cities as additional drivers. Finally, lakes and rivers seemed to be highly conflicted areas desired by pastoralists and farmers but also by the D.C. to implement a protected area. Distances to lakes and rivers comprised the final set of spatial drivers.

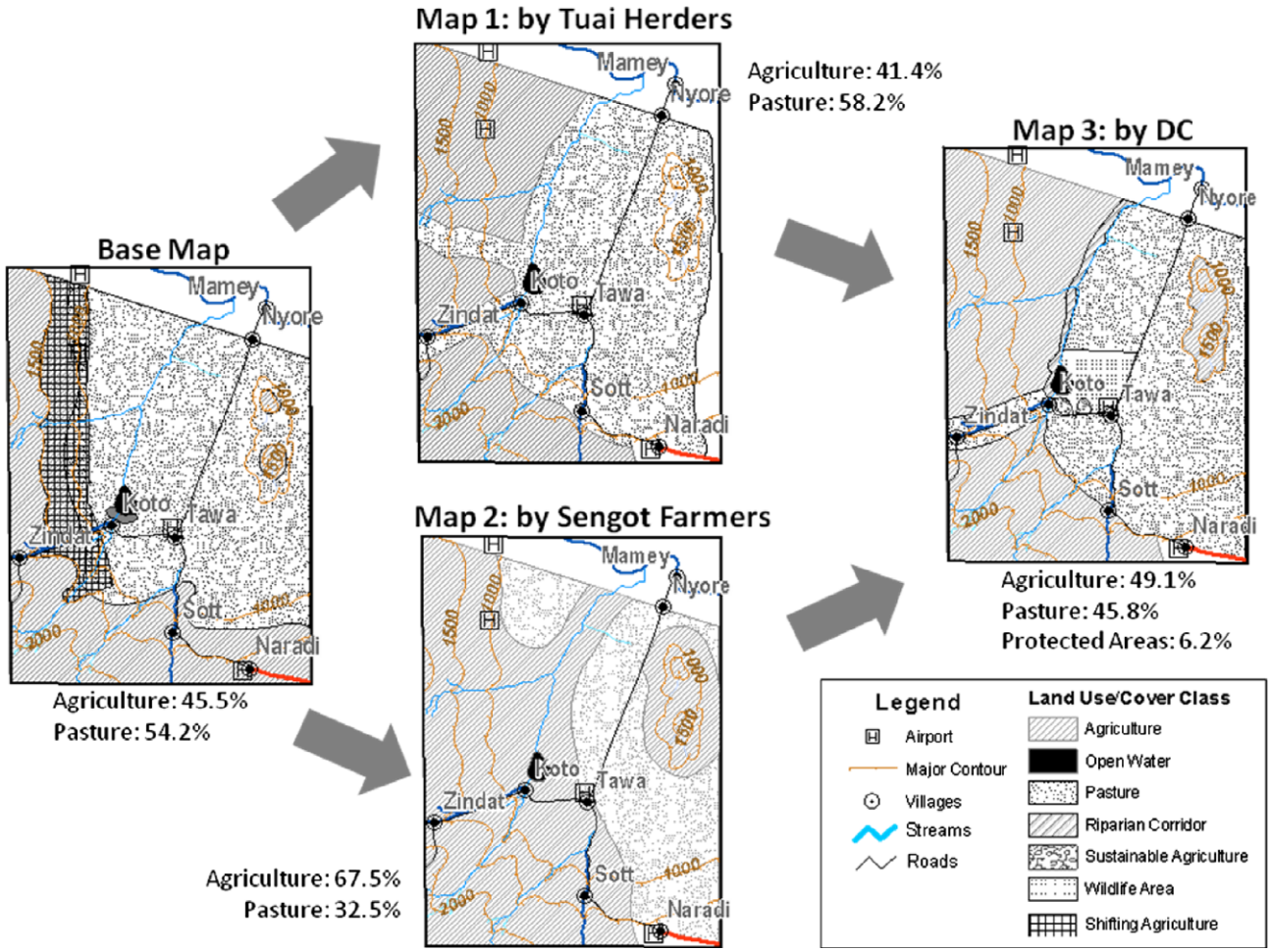

Fig. 2. Maps produced during the game by the participants.

3.4. Developing the land transformation model

We used the LTM to measure the relative spatial importance of each of the six spatial drivers for each map produced by the game participants. The LTM uses artificial neural networks to numerically relate, through non-linear algorithms, spatial maps of drivers and maps of land use (see http://ltm.agriculture.purdue.edu/ltm_tutorial/ for an online tutorial and access to LTM codes) (Pijanowski et al., 2002a; Pijanowski et al., 2005; Pijanowski et al., 2006).

The LTM was parameterized using the methodology developed by Pijanowski et al. (2006). Briefly, we used a raster map composed of "0s" (absence of a land use) and "1s" (presence of a land use) to "train" the neural network to quantify relationships between maps representing the six drivers of land-use decisions and maps containing the location of individual land uses. The LTM then uses weights from the neural network (called "testing") to produce output that contains a raster map of probabilities of the occurrence of the land use being modeled. We conducted a cross-validation of the LTM by training and testing it on different cells. We trained on one every other cell and tested on the others. We constructed five different LTMs to study the drivers for pasture on map 1, crops on map 2, pasture on map 3, crops on map 3, and protected areas on map 3.

We tested the performance of the five LTMs using the Area under the Receiver Operator Curve (AROC) metric. Briefly, AROC measures the performance of models judged against a random null model (Pontius and Schneider, 2001; Pijanowski et al., 2006). AROC values range from 0.5 to 1.0: 0.5–0.6 represent values for models that did not perform better than a random model; 0.6–0.7 are fair performing models; 0.7–0.8 are considered good models; 0.8–0.9 are very good models; and 0.9–1.0 reflect excellent models.

In order to generate weights associated to the six drivers of land-use decision, we used Pijanowski et al.'s (2002b) method. This approach involves running each of the five LTM models with the number of inputs reduced by one. In other words, for each of the five LTM models, we successively dropped the following drivers: distance to rivers, distance to the lake, distance to medium elevation, distance to high elevation, distance to cities, and distance to roads. Each LTM has hence been run with five drivers instead of six; the five drivers being different for each model. We then performed AROC tests to estimate the goodness of fit of LTM models with a driver removed.

3.5. Developing a GIS-based MCE model

We translated the qualitative decision-making matrix into spatially explicit quantitative land-use drivers using multi-criteria evaluation (MCE). This step was essential for comparing the results of the LTM models with the qualitative content of the decision-making matrix. We established MCE models for each group of participants. Using the MCE, we translated the discussions and negotiations which occurred during the game into quantitative variables. Those quantitative variables weighed the importance of the six spatial drivers that we used for the LTM for the land-use decisions of each group of participants (Tuai, Sengot, and D.C.).

Table 1
Game's quotes forming a qualitative land-use decision-making matrix for each group of RPG players (using multi-tier framework proposed by Ostrom (2007).

	Tuai pastoralists	Sengot farmers	District commissioner
Resource system	"We have to have access to water and dry season grazing"	"All fertile land should be used for farming, crop production"	"We need to protect natural resource: wildlife and surface water in particular"
Resource units	"Our goal is to maximize production from livestock"	"We need arable land to produce subsistence and cash crops"	"Lake Ann and river banks are also important to wildlife"
Governance system, users, interactions and outcomes	"We are the rightful owners of all land". "We want a tenure system that provides for group territory, not under individual title deeds". "Corridors along rivers should be frequent, and shared with the Sengot so that they can have access to water, but they should not be allowed to farm along rivers". "The boundary between lands of Sengot and Tuai should be established on the west side of the river, leaving a corridor to the western hills to provide access to the hills during times of drought"	"The population of Sengot is increasing rapidly". "Tuai are lazy". "Land should be adjudicated individual titles". "Policy should facilitate production of horticultural crops grown around the lake and along rivers". "Sengot farming in the Iletan Hills should be allowed to remain there The land around Lake Ann and land of Medium Potential should be adjudicated to the Sengot for farming. The Tuai should be allocated the remaining areas, those that do not have potential for crop agriculture"	"I as District Commissioner have the prerogative to settle the issue but as our government is moving towards a more participatory process I want to be sure that I reflect upon the input from each group.""The health of the Tuai is declining due to the expansion of agriculture.""So, how do we resolve the differences?"

MCE is commonly used to translate qualitative decision criteria into quantitative variables (Voogd, 1983; Carver, 1991). In the context of natural resources and land use management, MCE models are often coupled with geographic information systems to express, in a spatial context, the decision criteria of various stakeholders (Malczewski, 1999). We adapted this methodology to the output produced during the RPG and translated the decision-making matrix into weights using a pairwise comparison method (Saaty, 1977). For a given land-use, we compared the relative weight of a pair of drivers based on the elements outlined by the participants during the game. We constructed five MCE models each focusing on the land-use of interest for each group of participants. Hence, we built one MCE for quantifying the drivers for land-use decisions for the location of pasture for the Tuai, one for agriculture for the Sengot, and one for each of the three land-uses on the map produced by the D.C. We developed pairwise comparisons between the various spatial drivers and created a ratio matrix (Saaty, 1977). The MCE models resulted in weights attributed to each driver.

These weights were then used to simulate map 1, map 2, and map 3. Translating weights of a heuristic model into spatial features is a complex process; we followed the procedures of Malczewski (1999) to develop MCE weights using a GIS. First, we normalized our spatial driver so that the sum of the weights equals 1.0. In order to strengthen our models, we directly used the drivers when they constituted a desirable feature for a given group of participants but an inverse of drivers when they were not desirable. For instance, in map 1, we used the driver distance to rivers but the inverse of the driver distance to high elevation to simulate pasture. We then multiplied each driver or inverse driver by the MCE weights produced in the previous step in order to obtain probability maps for a given land-use. We used the raster calculator in ArcGIS to normalize our maps and to remove cells that were not candidates for simulation (e.g. cells located in the lake). Finally, we performed an AROC test for each map produced by the MCE.

4. Results

4.1. Game participant's perceptions of the SES

We analyzed the discourse and negotiations that occurred during the game by applying the three variables of Ostrom's framework to the interpretation of the SES by each game participant (Ostrom, 2007). The resource system of the Tuai is organized around the production of livestock, the Sengot concentrate on crops, and the D.C. on those two resources as well as wildlife. The Tuai want to establish corridors to guarantee access to dry season grazing land for their livestock, and the Sengot wish to use all arable land and standardize the size of crop fields, whereas the D.C. insists on the creation of riparian buffers. The view of the three participant groups concerning the governance system is conflicting since the Tuai are against a new land adjudication law, the Sengot argue for individual titles, and the D.C. seeks a solution to this conflict.

Concerning perceptions of the users, the Tuai view themselves as the only rightful owners of this land whereas the Sengot argue that the Tuai are not as efficient with resource use and that the land should go to them [the Sengot] because they represent the largest and most rapidly growing population of the area. The D.C. agrees with the Tuai and argues that the Sengot are threatening the health of the Tuai by polluting the water with fertilizers. Various outcomes and interactions result from these viewpoints. The Tuai want to establish clear boundaries between crops and pasture, corridors, and guaranteed access to permanent water. The Sengot want to continue their expansion onto all arable land in the area. The D.C. attempted to resolve the differences between the two resource groups but also to establish a new protected area to conserve the wildlife around the lake. Hence, the qualitative-decision-making matrix provides us with valuable information on socio-economic, institutional, as well as spatial drivers for land-use decisions (Table 1).

4.2. Performance of the LTM and the MCE

Using AROC, we found that the LTM performs extremely well (Table 2). All LTM models produced very good to excellent AROC scores above 0.8. The AROC test for pasture in map 1 is 0.94. The score for agriculture in map 2 is 0.98. Regarding map 3, the scores of the AROC tests are 0.93 for pasture, 0.93 for agriculture, and 0.87 for protected areas. MCE models did not have such excellent performance as the LTM models but still performed satisfactorily. AROC of the MCE for pasture in map 1 is 0.72. It is 0.76 for

Table 2
Summary of AROC values for MCE and LTM models.

Models	AROC values	
	MCE	LTM
Pasture for map 1	0.72	0.94
Agriculture for map 2	0.76	0.98
Pasture for map 3	0.71	0.93
Agriculture for map 3	0.78	0.93
Protected area for map 3	0.77	0.87

agriculture in map 2, 0.71 for pasture in map 3, 0.78 for agriculture in map3, and 0.77 for protected areas in map 3 (Table 2).

4.3. Modeling the drivers of land-use decisions

4.3.1. Multi-criteria evaluation models

Normalized driver weights for the MCE model varied across models. 'Distance to rivers' and 'distance to lake' appeared to highly influence land-use decisions of the Tuai in map 1 (Table 3) (MCE score of 0.326 and 0.320). Surface water is highly valuable for cattle, in particular during the dry season. The scores of medium and high elevation (MCE score of 0.140 for each) demonstrate the interest in grazing corridors on the mountain slopes during the dry season. Distance to cities and distance to roads (MCE scores of 0.038 and 0.035, respectively) were not significant in the Tuai's discourse for the location of pasture.

Distance to rivers and distance to the lake were significant to the discourse justifying land-use decisions of the Sengot in map 2 (Table 3). Indeed, the high score of the driver distance to rivers (MCE score of 0.416) and distance to lake (MCE score of 0.235) probably reflects the economic interest emphasized during the game in developing more irrigated agriculture with a higher cash value. Even if distance to high and medium elevation appears to be particularly important on the map designed by the Sengot, the analysis of their discourse through the MCE does not make them appear as particularly significant (MCE scores of 0.136 for each driver).

Regarding the final land-adjudication map (map 3), it seemed that the D.C. particularly emphasized the importance of rivers (MCE score of 0.282) for pasture. Distance to medium elevation (MCE score of 0.194), and distance to high elevation (MCE score of 0.176) were also significant. Distance to roads, cities (MCE score of 0.121, respectively) as well as distance of the lake (MCE score of 0.059) seemed to matter less in the discourse of justification for the location of pasture decision. Interestingly, the weights assigned in the MCE by the D.C. occur in the same order of significance as those produced by the Tuai (Table 3).

When justifying the location of crops, the D.C. insisted on the importance of distance to the lake (MCE score of 0.255) to develop irrigated agriculture, but also of distance to high and medium elevation (MCE scores of 0.222, respectively) where the land is arable. Distance to rivers was, to a lesser degree, also important (MCE score of 0.183). In contrast, distance to cities (MCE score of 0.084) and distance to roads (MCE score of 0.033) did not seem to guide the D.C.'s decisions in the location of agriculture. Again, the weights assigned by the D.C. to the spatial drivers follow the same order as those assigned by the Sengot (Table 3).

Finally, concerning the protected areas of map 3, the D.C. argues that the protected area should be around the lake (MCE score of 0.483) and the rivers (MCE score of 0.245) where the biodiversity is most abundant. Other spatial drivers such as distance to cities (MCE score of 0.114), distance to roads (MCE score of 0.094), distance to medium elevation (0.033), and distance to high elevation

Table 3
Weights and ranking assigned to land-use drivers by the MCE and LTM models.

Drivers	Weight and ranking of drivers					
	MCE	MCE	LTM	LTM	LTM	LTM
	Variable	Variable	Normalized	Normalized	Non-normalized	Non-normalized
	Weight	Rank	Variable weight	Variable rank	AROC values	AROC ranks
Map 1 (pasture for Tuai)						
Distance to rivers	0.326	1	0.168	2	0.911	2
Distance to the lake	0.320	2	0.167	3	0.905	3
Distance to high elevation	0.140	3	0.163	6	0.884	6
Distance to mid elevation	0.140	3	0.169	1	0.917	1
Distance to cities	0.038	5	0.167	3	0.905	3
Distance to roads	0.035	6	0.167	3	0.904	3
Map 2 (crops for Senegot)						
Distance to rivers	0.416	1	0.185	2	0.981	2
Distance to the lake	0.235	2	0.186	1	0.982	1
Distance to high elevation	0.136	3	0.171	5	0.903	5
Distance to mid elevation	0.136	4	0.183	3	0.968	3
Distance to cities	0.039	5	0.183	3	0.967	3
Distance to roads	0.039	6	0.093	6	0.494	6
Map 3 (pasture by D.C.)						
Distance to rivers	0.282	1	0.172	1	0.939	1
Distance to the lake	0.059	6	0.170	2	0.930	2
Distance to high elevation	0.176	3	0.170	2	0.928	2
Distance to mid elevation	0.194	2	0.164	5	0.898	5
Distance to cities	0.176	3	0.170	2	0.931	2
Distance to roads	0.121	5	0.160	6	0.849	5
Map 3 (crops by D.C.)						
Distance to rivers	0.183	4	0.172	1	0.970	1
Distance to the lake	0.255	1	0.163	4	0.923	4
Distance to high elevation	0.222	2	0.161	6	0.908	6
Distance to mid elevation	0.222	2	0.169	3	0.956	3
Distance to cities	0.084	5	0.172	1	0.972	1
Distance to roads	0.033	6	0.163	4	0.920	4
Map 3 (protected areas, D.C.)						
Distance to rivers	0.245	2	0.180	2	0.895	2
Distance to the lake	0.483	1	0.180	2	0.894	2
Distance to high elevation	0.030	5	0.100	6	0.500	6
Distance to mid elevation	0.033	6	0.174	4	0.867	4
Distance to cities	0.114	3	0.174	4	0.864	4
Distance to roads	0.094	4	0.193	1	0.960	1

(MCE score of 0.030) seemed to only affect the decisions of the D.C. in a secondary manner (Table 3).

4.3.2. Neural network models

We used the "drop-one-out" methodology of Pijanowski et al. (2002b) to evaluate the importance of the six spatial drivers for the location of a given land-use predicted by the LTM. This methodology resulted in various AROC values attributed to each model run with five drivers instead of six (Table 3, column 3). We inferred the weight of each driver from the performance of the model (AROC values) run without this driver. In a word, if the model performs worse when a driver is removed, we infer that the weight of this driver is significant and explains land-use patterns. On the contrary, if the model performs better without a given driver, we infer from this result that this given driver does not explain land-use drivers. We therefore assimilated the AROC values assigned to each model to the weight of each driver and refer to this value as "weight". The relative weight of the drivers resulting from this methodology differed from the MCE where weights are directly interpretable. A priori, the "drop-one-out" methodology did not allow us to specify the direction of the predictor on the model since the LTM is a binary model which does not differentiate if a given driver increases or decreases the probability of a given land use (Pijanowski et al., 2002b). We interpreted the results of the drop-one-out methodology as follows: (1) if the removal of a driver decreases the performance of the model, then this driver highly influenced the location of a given land use; (2) the qualitative decision-making matrix helped us analyze if a given driver would attract or repel a given land-use; and (3) if the removal of a driver increases the goodness of fit of the model, we concluded that this driver did not influence the location of a given land-use.

We first looked at map 1 and the influence of the spatial drivers for the location of pasture (Table 3). With the six drivers, the overall performance of the model evaluated by the AROC test was 0.94 (Table 2). When we removed any driver, the performance of the model decreased which means that every driver had an important role in the LTM. The driver which appeared to be the most important was high elevation since removing it from the LTM decreased the AROC test to 0.88. Based on the discussions as well as the maps which occurred during the game, we can assume that the proximity to the high elevation contour line did not attract pastures since these are mainly located in the valley. Therefore, the driver distance to high elevation probably "repels" pasture. The relative importance of the remaining drivers in deceasing order is: distance to roads and distance to cities (weight = 0.90, respectively, attract pasture), distance to lake (weight = 0.9048, attract pasture), distance to river (weight = 0.911, attract pasture), and distance to medium elevation (weight = 0.917, repel pasture).

For agriculture of map 2, distance to roads (Table 3) had a highly significant impact on the goodness of fit of the model. The performance of the six driver model was 0.98 at the AROC test (Table 2). When we removed the driver distance to roads, the performance of the model dropped to 0.497, not different from a random model (Table 3). This result was surprising. However, as the Sengot farmers emphasized during the game, roads are crucial to the transport of crops for access to local markets. We can therefore assume that the influence of the spatial driver distance to roads on decisions related to agriculture is positive. The driver distance to high elevation also positively influenced the location of crops (weight = 0.903). The removal of any of the remaining drivers moderately affected the goodness of fit of the LTM which demonstrates the limited impact of distance to cities (weight = 0.967), distance to medium elevation (weight = 0.968), distance to rivers (weight = 0.981), and distance to the lake (weight = 0.982) on the location of crops.

The spatial driver "distance to roads" was particularly important for the location of pasture in map 3 produced by the D.C. Before the removal of any spatial drivers, the goodness of fit of the LTM was 0.93 (Table 2). Without the driver distance to roads, the goodness of fit was 0.849 (Table 3). This is probably due to the fact that the D.C. located the dry season grazing corridors on a road which drove the LTM to overweight this driver. Distance to medium elevation also constituted an important driver for pastures in map 3. The absence of pasture in the middle of the Iletan hills probably influenced the weight of this driver (weight = 0.898). The rest of the spatial drivers, namely distance to high elevation (weight = 0.928), distance to the lake (weight = 0.9301), and distance to rivers (weight = 0.939), did not highly influence the model. However, the model performed better without the driver distance to cities (weight = 0.967).

"Distance to high elevation" positively affected the decision regarding agriculture in map 3 which corroborates the Sengots' expressed need of more arable land at higher altitude. With the six spatial drivers, the performance of the LTM was 0.93 (Table 2) but dropped to 0.90 (Table 3) without the driver "distance to high elevation". Distance to roads (weight = 0.92) and distance to the lake (weight = 0.923) did not greatly affect the performance of the model. In contrast, the removal of distance to medium elevation (weight = 0.956), distance to rivers (weight = 0.9701), and distance to cities (weight = 0.972) improved the overall performance of the model. We can interpret those results by assuming that those drivers were not fundamental in the location of crops in map 3.

Finally, concerning the spatial drivers for protected areas in map 3, distance to high elevation seemed to highly repel them. Indeed, with all six drivers, the overall performance of the model was 0.87 (Table 2) but dropped to 0.5 (Table 3) without distance to high elevation. This can be explained by the fact that protected areas were located in the valley at a high distance from the contour line of high elevation. The removal of the drivers distance to medium elevation (weight = 0.867) and distance to cities (weight = 0.864) and even distance to the lake (weight = 0.864) did not significantly affect the performance of the model. The removal of the drivers distance to rivers (weight = 0.895), and distance to roads (weight = 0.960) improved the performance of the LTM.

5. Discussion

5.1. The added-value of our integrated methodology to analyze land-use drivers and decisions

5.1.1. The complementary nature of the models

The goodness of fit of our ten models ranged from good to excellent. Indeed, AROC tests for the LTMs ranged from 0.87 to 0.98. The excellent performance of the LTMs can be explained by the adequate selection of the spatial drivers as well as by the relative simplicity of the landscape we simulated. The AROC tests of the MCEs ranged from 0.71 to 0.78, which are considered good. We explain the mediocre performance of the MCEs by the relative disconnection between the land-use justifications expressed by the players during the game and the spatial features designed by the participants on maps. The discovery of this disconnection exemplifies the value of using multiple methods to model land-use decisions.

The analysis of the effect of each driver on the models demonstrates the differences between the MCEs and the LTMs as well as the value of coupling these models. Indeed, the weights and the ranking of the driver strength of the MCEs and the LTMs were not identical. From this observation it could be inferred that the conclusions of our models diverge and that at least one type of model must be unfit. On the contrary, the variations among the

rankings and the weights of the drivers of the MCEs and the LTMs confirm the inherent differences between our models and suggest the value of coupling them. By essence, MCEs are heuristic models representing the decision-making process of participants applied here to a spatial context. In contrast, LTMs are machine learning tools which establish numerical relationships between spatial features. The analysis of each spatial driver emphasized the differences between the heuristic nature of the MCE and the spatial one of the LTM.

We argue that far from confusing our understanding of land-use drivers, coupling a heuristic model such as the MCE and a machine learning model such as the LTM can highly enhance our analysis of land-use drivers. Indeed, information on land-use drivers produced by the MCE complement elements outlined by the LTM. For instance, in map 1, the MCE told us that distance to river and distance to the lake were crucial drivers in the decision-making process of the Tuai for the location of pasture. In addition, we learned from the LTM that the Tuai had an aversion for high elevation. We can learn from the combination of the MCE and the LTM that not all rivers or lakes matter in the decision-making process of the Tuai; only those located at lower elevations. The MCE for map 2 placed a heavy weight on distance to rivers since the Sengot had emphasized the importance of rivers to develop high cash value irrigated agriculture. In contrast, the LTM emphasized the traditional interest of arable land in areas of higher elevation. Both pieces of information complement each other, and we can observe here a change in land-use drivers from traditional drivers to more recent ones driven by irrigated agriculture.

In map 3, the D.C. outlined the importance of rivers for pasture, in rainy as well as in dry seasons, which reflected itself in the MCE by the heavy weight attributed to the driver distance to rivers. We can learn from the LTM that not only distance to rivers matters but also distance to roads which might reflect the wish of the D.C. to develop more market-oriented pastoralism. For agriculture, the MCE outlined the weight of distance to the lake, medium elevation and high elevation. In addition, we learned from the LTM that both distance to rivers and distance to cities were not pertinent land-use drivers since their removal improves the performance of the model. Finally, the MCE confirmed the importance of the lake in the location of the protected area. We learned from the LTM that the driver distance from high elevation had a fundamental role in the model since the protected areas were located in the valley. In addition, we also discover that the driver distance to roads did not matter in the location of protected areas since its removal improved the general performance of the model.

5.1.2. Use of the decision-making matrix

We thus argue that MCEs and LTMs complement each other. However, aside from the RPG's role in providing data for the construction of MCEs and LTMs, these models also profit from the support of the discussions which occurred during the RPG which were translated into the decision-making matrix. Those discussions were important to the analysis as well as the validation of the MCEs and the LTMs. First, the decision-making matrix provided an additional meaning to the figures from the MCEs and the LTMs. It helped for instance to distinguish between traditional and new land-use drivers in order to explain differences between the MCE and the LTM for map 2. Second, the decision-making matrix provided elements of validation for the interpretation of results of LTM.

5.1.3. Information flows between methods and models

The unique understanding that results from this integrated methodology sheds light on the flow of information between the decision-making matrix, the MCEs, and the LTMs. More precisely, two kinds of flows of information occur in this research: (1) information from the models about various kinds of land-use drivers, and (2) information circulating between models to improve our understanding of land-use drivers (Fig. 3).

First, each model concentrates on various kinds of land-use drivers. The decision-making matrix is particularly effective at elucidating drivers related to the interactions between the game participants which of course impact land use. For instance, it is clear in the game that the DC favors the Tuai and allocates them a large part of the landscape despite the fact that the population of the Sengot is growing. The MCEs render explicit the discourse of land-use choices whereas the LTMs elucidate drivers related to spatial features.

Second, the information flowing between the models enhance our general understanding of land-use drivers. The MCE concentrates heuristic elements from the decision-making matrix and allows us to compare the qualitative data recorded during the RPG with a quantitative and spatially explicit model such as the LTM. The decision-making matrix provides essential elements of validation for the LTM. Finally, the comparisons of the MCEs and the LTMs help draw contrasts between subjective land-use drivers expressed in narratives and spatial ones sketched on a map. Hence, there is a twofold information flow between the decision-making matrix, the MCEs, and the LTMs that result in the analysis of complex land-use drivers and decision-making processes.

5.2. Methodological tradeoffs

The analysis of our results shows that each model has various abilities. More precisely, each model and method exhibit a significant tradeoff between its capacity to analyze complex SESs and its goodness of fit when compared with the initial maps produced by the game participants (Fig. 4). The qualitative decision-making matrix gives us a high level of understanding of the complex SES but does not directly produce quantitative results that we could use to validate our findings. The MCEs demonstrate mediocre performances regarding both the understanding of the SES and the goodness of fits of the map they produced. In contrast, the LTMs produce maps with very satisfactorily goodness of fits when compared to the original maps but provide an understanding of the SES limited to the spatial dynamics. We therefore observe tradeoffs within and between models/methods which strengthened our argument in favor of the use of multiple models in an holistic manner in order to analyze and model complex SESs.

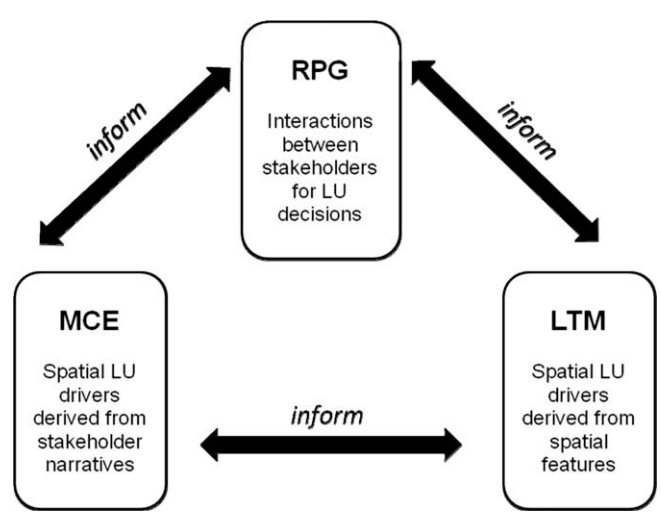

Fig. 3. Information on land-use drivers provided by each method as well as information flows between models for the analysis of land-use drivers and decisions.

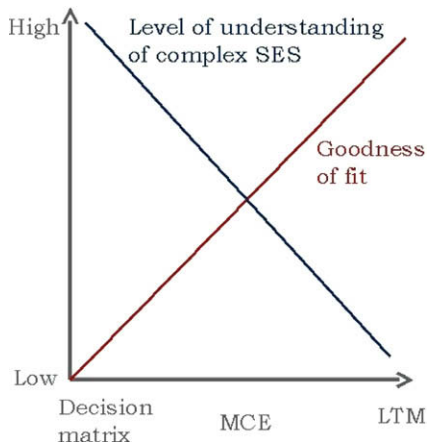

Fig. 4. Methodological tradeoffs between models.

Indeed, the various type of information, the flow of information, as well as the methodological tradeoffs between out models/methods allowed us to study more in depth a complex socio-ecological system using Ostrom's framework. First, the decision-making matrix provided information on the three categories of the multi-tier framework. In particular, the decision-making matrix explored in detail the governance system in place or desired by the resource users as well as the interactions between resource users and the outcomes resulting from the resolution of conflicts over natural resources. Second, the LTM informed us about the resource system as well as the resource units. The five LTMs correlated land use with a set of spatial drivers enlightening the spatial complexity of the resource systems. Then, by using the dropping-one-out methodology, we were able to analyze the role of each land-use driver as a resource unit on a given landscape. Finally, the MCE gave us a meaningful insight into the question of how given spatial drivers were considered in the resource users' decision-making process. Hence, by using multiple models in a holistic manner, we were able to analyze the various complex aspects of a complex SES.

Examining both the results of the MCEs and the LTMs we had confirmation of the crucial aspect of elevation either as an attractive or repulsive driver of land-use location and decisions for all land-uses (pasture, crops, and protected areas). We also discovered that not all rivers in our landscape where valued equally by the resource users. During the game, the participants did not differentiate between one river and another but the analysis of the results of the LTMs and the MCEs demonstrated that mainly the river located at the bottom of the valley mattered in land-use decisions because of its strategic position close to roads, cities, and as a separation between agriculture and pastoralism. Finally, we also observed an adaptation phenomenon from rain-fed agriculture to irrigated agriculture and the appearance of surface water as a new critical variable for farmers.

6. Conclusion

This integrated methodology built from a RPG allowed us to improve our general knowledge of land-use drivers and land-use change dynamics. Coupling a RPG with a traditional multi-criteria evaluation model and a machine learning based tool provided us with new insights that were not apparent if we had used a single model or approach. Indeed, we have shown that (1) different approaches provide us with different perspectives related to complex SESs; (2) a flow of information circulates between the methods improving the overall performance of our methodology; and that (3) tradeoffs exist between methods that relate to level of understanding of complex SESs and a high goodness of fit.

To further enhance the performance of this integrated methodology, other methods could be added to studying land-use decisions. For example, we also have coupled surveys, group interviews, interviews of key informants with remote sensing and GIS analysis in the framework of the Land-Use Change Impact and Dynamics Project (Maitima and Olson, 2001; Smucker et al., 2007). Complex land-use change dynamics emerged from this methodology including the importance of biophysical, political and socio-economic drivers operating at various spatial scales from local to global (Campbell et al., 2000; Campbell et al., 2005; Reid et al., 2000).

The use of a role-playing game in the present integrated methodology deepened our understanding of land-use dynamics acquired in previous research. In the past, Campbell has used the game presented here with students enrolled in universities in East Africa. This is the first game that involved high-level natural resource professionals. The level of complexity of the conversations and the information from the debriefing were very sophisticated leading us to believe that our RPG simulations incorporated more realistic, subtle or nuanced factors that might explain land-use patterns in semi-arid areas. In addition to past research, this present work, due to the integration of a role-playing game with several modeling approaches allowed us to observe in a more realistic setting the complex land-dynamics influencing a land-adjudication process. We therefore argue for the integration of RPGs along with other methods in quantitative studies to analyze complex land-use dynamics.

Acknowledgements

We would like to thank the following individuals for GIS and LTM support: Brian Napoletano, Kat Lillie, Deepak Ray and Amélie Davis. Alex Pijanowski and Garrett Washington provided comments on earlier drafts of the paper. This research has been funded by the National Science Foundation Biocomplexity of Coupled Human and Natural Systems Program (BCS-0308420), a Department of Education Graduate Area of National Needs (GAANN) grant, National Science Foundation III-XT Grant (IIS-0705836) and the Department of Forestry and Natural Resources, Purdue University. Human subjects' research was approved by the Purdue IRB (#051003196) and MSU IRB (#X02-917).

References

Alexandridis, K., Pijanowski, B., 2007. Assessing multi-agent parcelization performance in the MABEL simulation model using Monte Carlo replication experiments. Environment and Planning B: Planning and Design 34, 223–244.

Anderson, J.R., 1976. A Land Use and Land Cover Classification System for Use with Remote Sensor Data. United States Government Printing Office, Washington. 28pp.

Barreteau, O., 2003. The joint use of role-playing games and models regarding negotiation processes: characterization of associations. Journal of Artificial Societies and Social Simulations 6. <http://jasss.soc.surrey.ac.uk/6/2/3.html>.

Barreteau, O., Le Page, C., D'Aquino, P., 2003. Role-playing games, models and negotiation processes. Journal of Artificial Societies and Social Simulation 6 (2).

Berkes, F., Folke, C. (Eds.), 1998. Linking Social and Ecological Systems: Management Practices and Social Mechanisms for Building Resilience. Cambridge University Press, Cambridge, UK.

Bousquet, F., Barreteau, O., Le Page, C., Mullon, C., Weber, J., 1999. An environmental modeling approach the use of multi-agents simulations. In: Blasco, F., Weill, A. (Eds.), Advances in Environmental and Ecological Modeling. Elsevier, Paris (pp. 113–122).

Campbell, D.J., Palutikof, J.P., 1978. Allocation of land resources in semi-arid areas: a simulation based on the East African experience. Discussion Paper, 262, Institute for Development Studies, University of Nairobi.

Campbell, D.J., Gichohi, H., Mwangi, A., Chege, L., 2000. Land use conflict in S.E. Kajiado district, Kenya. Land Use Policy 17 (4), 337–348.

Campbell, D.J., Lusch, D., Smucker, T., Wangui, E., 2005. Multiple methods in the study of driving forces of land use and land cover change: a case study of SE Kajiado District, Kenya. Human Ecology 33, 763–794.

Carver, S.J., 1991. Integrating multi-criteria evaluation with geographical information systems. International Journal of Geographical Information Systems 5, 321–339.
Daré, W., Barreteau, O., 2003. A role-playing game in irrigated system negotiation: between play and reality. Journal of Artificial Societies and Social Simulation 6. <http://jasss.soc.surrey.ac.uk/6/3/6.html>.
Etienne, M., 2003. SYLVOPAST: a multiple target role-playing game to assess negotiation processes in sylvopastoral management planning. Journal of Artificial Societies and Social Simulation 6. <http://ideas.repec.org/a/jas/jasssj/2003-14-1.html>.
Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N., Snyder, P.K., 2005. Global consequences of land use. Science 309 (5734), 570–574.
Funtowicz, S., Ravetz, J., 1993. Science for the post-normal age. Futures 25, 739–755.
Gunderson, L., Holling, C., 2001. Panarchy; Understanding Transformations in Systems of Humans and Nature. Island Press, Washington, D.C., USA.
Gurung, T., Bousquet, F., Trébuil, G., 2006. Companion modeling, conflict resolution, and institution building: sharing irrigation water in the Lingmuteychu Watershed, Bhutan. Ecology and Society 11. <http://www.ecologyandsociety.org/vol11/iss2/art36/>.
Guyot, P., Honiden, S., 2006. Agent-based participatory simulations: merging multi-agent systems and role-playing games. Journal of Artificial Societies and Social Simulation 9. <http://jasss.soc.surrey.ac.uk/9/4/8.html>.
Janssen, M., Ostrom, E., 2006. In: Tesfatsion, L., Judd, K.L. (Eds.), Governing Social-Ecological Systems. Handbook of Computational Economics II: Agent-Based Computational Economics. Elsevier Publisher, pp. 1465–1509.
Kimani, K., Pickard, J., 1998. Recent trends and implications of groups ranch subdivision and fragmentation in Kajiado District, Kenya. The Geographical Journal 164, 202–213.
Lambin, E., Geist, H. (Eds.), 2006. Land-Use and Land-Cover Change: Local Processes and Global Impacts. Springer, Berlin, New York. 222pp.
Little, P., Cellarius, B., Coppock, D., Barrett, C., 2001. Avoiding disaster: diversification and risk management among East African Herders. Development and Change 32, 387–419.
Maitima, J., Olson, J., 2001. Guide to Field Methods for Comparative Site Analysis for the Land Use Change, Impacts and Dynamics Project. LUCID Working Paper Series Number 15. <http://www.lucideastafrica.org/publications/Maitima-Olson_LUCID_WP15.pdf>.
Malczewski, J., 1999. GIS and Multicriteria Decision Analysis. John Wiley and Sons, New York. 392pp.
Matthews, R., Gilbert, N., Roach, A., Polhill, G., Gotts, N., 2007. Agent-based land-use models: a review of applications. Landscape Ecology 22, 1447–1459.
Millennium Ecosystem Assessment Program, 2005. Ecosystem and Human Well-being: Our Human Planet. Summary for Decision Makers. Island Press, Washington DC, 109pp.
Ojima, D., Galvin, K., Turner II, B., 1994. The global impact of land-use change. BioScience 44, 300–304.
Ojima, D., Moran, E., McConnell, W., Stafford-Smith, M., Laumann, G., Morais, J., Young, B., 2005. Global Land Project. Science Plan and Implementation Strategy. IGBP Report No. 53/IHDP Report No. 19, IGDP Secretariat, Stockholm.
Ostrom, E., 2007. A diagnostic approach for going beyond panaceas. Proceedings of the National Academy of Science of America 104, 15181–15187.
Parker, D., Manson, S., Janssen, M., Hoffmann, M., Deadman, P., 2003. Multi-agent systems for the simulation of land-use and land-cover change: a review. Annals of the Association of American Geographers 93, 314–337.
Peeples, M., Barton, C., Schmich, S., 2006. Resilience lost: intersecting land use and landscape dynamics in the prehistoric southwestern United States. Ecology and Society 11. <http://www.ecologyandsociety.org/vol11/iss2/art22/>.
Pijanowski, B., Brown, D., Manik, G., Shellito, B., 2002a. Using neural nets and GIS to forecast land use changes: a land transformation model. Computers, Environment and Urban Systems 26, 553–575.
Pijanowski, B., Shellito, B., Pithadia, S., Alexandridis, K., 2002b. Forecasting and assessing the impact of urban sprawl in coastal watersheds along eastern Lake Michigan. Lakes and Reservoirs: Research and Management 7, 271–285.
Pijanowski, B., Pithadia, S., Alexandridis, K., Shellito, B., 2005. Calibrating a neural-network based urban change model for two metropolitan areas of the Upper Midwest of the United States. International Journal of Geographic Information Science 19, 197–215.
Pijanowski, B., Alexandridis, K., Mueller, D., 2006. Modeling urbanization in two diverse regions of the world. Journal of Land Use Science 1, 83–108.
Pontius, R.G., 2002. Statistical methods to partition effects of quantity and location during comparison of categorical maps at multiple resolutions. Photogrammetric Engineering and Remote Sensing 68, 1041–1049.
Pontius, R.G., Schneider, L., 2001. Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA. Agriculture Ecosystems and Environment 85, 239–248.
Reid, R., Kruska, R., Muthui, N., Taye, A., Wotton, S., Wilson, C., Woudyalew, M., 2000. Land use and land cover dynamics in response to changes in climatic, biological and socio-political forces: method development and a test case in Southwestern Ethiopia. Landscape Ecology 15, 339–355.
Rindfuss, R., Walsh, S., Turner II, B., Fox, J., Mishra, V., 2004. Developing a science of land change: challenges and methodological issues. Proceedings of the National Academy of Sciences 101, 13976–13981.
Saaty, T., 1977. A scaling method for priorities in hierarchical structures. Journal of Mathematical Psychology 5, 234–281.
Shaftel, F., Shaftel, G., 1967. Role-Playing for the Social Values: Decision-Making in the Social Studies. Prentice-Hall, NJ. 431pp.
Smucker, T., Campbell, D., Olson, J., Wangui, E., 2007. Contemporary challenges of participatory field research for land use change analyses: examples from Kenya. Field Methods 19, 384–416.
Turner, B.L., II, Clark, W.C., Kates, R.W., Richards, J.F., Mathews, J.T., Meyer, W.B. (Eds.), 1990. The Earth As Transformed by Human Action. Cambridge University Press, NY. 713p.
van Daalen, C.E., Dresen, L., Janssen, M., 2002. The roles of computer models in the environmental policy life cycle. Environmental Science and Policy 5, 221–231.
Veldkamp, A., Fresco, L., 1996. CLUE-CR: an integrated multi-scale model to simulate land use change scenarios in Costa Rica. Ecological Modelling 91, 231–248.
Verburg, P.H., Schot, P., Dijst, M., Veldkamp, A., 2004. Land use change modelling: current practice and research priorities. Geojournal 61 (4), 309–324.
Vicsek, T., 2002. The bigger picture. Nature 418, 131.
Voogd, H., 1983. Multicriteria Evaluation for Urban and Regional Planning. Pion Ltd., London. 367pp.
Walker, B., Salt, D., 2006. Resilience Thinking: Sustaining Ecosystems and People in a Changing World. Island Press, Washington DC. 174p.
Walker, B., Holling, C.S., Carpenter, S.R., Kinzig, A. 2004. Resilience, adaptability and transformability in social–ecological systems. Ecology and Society 9, 5. URL: <http://www.ecologyandsociety.org/vol9/iss2/art5/> (online).
Woodhouse, P., Hulme, D., 2000. African Enclosures? The Social Dynamics of Wetlands in Drylands. David Philip Publishers (Pty) Ltd., Cape Town.