Staff Paper

Multi Agent-Based Environmental Landscape (MABEL) – An Artificial Intelligence Simulation Model: Some Early Assessments

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Multi Agent-Based Environmental Landscape (MABEL) – An Artificial Intelligence Simulation Model: Some Early Assessments†.

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Abstract

The Multi Agent-Based Environmental Landscape model (MABEL) introduces a Distributed Artificial Intelligence (DAI) systemic methodology, to simulate land use and transformation changes over time and space. Computational agents represent abstract relations among geographic, environmental, human and socio-economic variables, with respect to land transformation pattern changes. A multi-agent environment is developed providing task-nonspecific problem-solving abilities, flexibility on achieving goals and representing existing relations observed in real-world scenarios, and goal-based efficiency. Intelligent MABEL agents acquire spatial expressions and perform specific tasks demonstrating autonomy, environmental interactions, communication and cooperation, reactivity and proactivity, reasoning and learning capabilities. Their decisions maximize both task-specific marginal utility for their actions and joint, weighted marginal utility for their time-stepping. Agent behavior is achieved by personalizing a dynamic utility-based knowledge base through sequential GIS filtering, probability-distributed weighting, joint probability Bayesian correlational weighting, and goal-based distributional properties, applied to socio-economic and behavioral criteria. First-order logics, heuristics and appropriation of time-step sequences employed, provide a simulation-able environment, capable of re-generating space-time evolution of the agents.

Keywords: Agent-based modeling; heuristics; land-use/cover transformation; geo-spatial relations; human behavior.

Introduction

Our scientific ability to interpret and analyze the land use/ land cover perspectives for the future in an increasingly complex environment, often meets difficulties and barriers originating from the limitations of traditional methodologies. The need for alternative approaches and methods able to allow analysis of dynamic and complex features and relations, as well as the need for comprehensive relational schematics in land transformation observations are present, and stronger than ever. Artificial intelligence's potential role on land

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transformation systems analysis represents a useful research link. Distributed Artificial Intelligent (DAI) and Agent-Based approaches (ABM) and their contribution to research methodology increases efficiency on assessing a more real-world observational system, especially in conjunction with land use, environmental issues, and environmental economics. A 'unified' approach between living system's organizational entities in environment and land use, and socio-economic interpretations goes beyond the limitations of the traditional statistical and econometric assumptions.

Distributed artificial intelligence methodology aims on design and development of structural elements that represents abstracted relations of interactive, distributed, organizational, cooperative and collaborative systems (Brenner, *et al.* 1998, Padget 1999). Distributed systems lay its focus on problem solving (Brown and White 1990, Wagman 2002); knowledge-base acquisition (Conte and Paolucci 2001, Davis and Lenat 1982, Guida and Tasso 1994, Ringland and Duce 1988, Tecuci and Kodratoff 1995); formation and representation of strategic interactions among different agents (Bronzite 2000, Goldspink 2000, Gruber 1989); cooperation, coordination and collaboration mechanisms (Beard, *et al.* 1993, Binmore 1998, Doran 2001, Fonlupt, *et al.* 2000, Padget 1999, Schumacher 2001, Sigmund 1998, Wobcke, *et al.* 1998); organizational structure (Ascher 2001, Ber, *et al.* 1998, Goldspink 2001, Patrick, *et al.* 1999, Prietula, *et al.* 1998, Seleshi 2001). They attempt to simulate and instantiate natural, human and social systems in a series of applications, from ecosystem and natural resource management.

Computational agents, developed and designed to present these distributed characteristics are the main component that instantiates complex and dynamic behavior in a real-world simulative environment. The agents' behavior is a combination of inherited and acquired characteristics, maintained, managed, and distributed in an intelligent framework of interactions such as the 'benevolent agent assumption', the

Although distributed problem solving strategies were originally design to address a *top-down* methodology, the addition of a multi-agent environment and framework of interactions, generates an entire opposite approach, the *bottom-up* methodology. As agents interact; communicate; collaborate, defect, or conflict with each other, the combined effect of their individual and collective actions, gives birth to a complex, and highly dynamic world.

The need for economic interpretations has its source and dependence on our perceptive capabilities and behavior. In this sense, land use and relative institutional changes, reflect our historical, present and future socio-economic behavior. In a wider sense, as we perceive change in an interactive process among economic, ecological and institutional systems (Gunderson and Holling 2001), the question of how this behavior affects ecological and living systems becomes a very important one. Is there a identifiable socio-economic evolution that can be represented in land use transformation over space and time, and vice versa? If such an evolution exists, in which direction of change it moves?

MABEL is a theoretical multi-agent modeling methodology endeavor to provide a comprehensive and illustrative answer in the above questions by simulating land use changes and transformation over time and space.

An Overview of MABEL

The methodology developed throughout MABEL demonstrates a *heuristic* approach to problem-solving efficiency. MABEL utilizes a series of intelligent computational agents that use heuristics as a base for distributional, interactive, intelligent and knowledge-based characteristics (Goertzel 2002, Mohammadian 2000, Rouchier 2001, Ward 2000) in a dynamic framework of interactions. In such a framework, MABEL agents demonstrate problem-solving abilities extending beyond any traditional task-specific analyses. That is, an inherent flexibility on achieving goals in a *local minima/optima* level, and representing existing relations observed in real-world situations. Their goal-based efficiency is based in a minimum scaled perception and instantiation of problems in an individualized form.

Identifying existing scales.

Scale in conjunction with a desired representation of complex world relations, is one of the most important factors on perceiving and developing an artificial intelligent system. "If something is scale-dependent it necessarily manifests quantitative changes with a shift in scale used to observe it" (Allen and Hoekstra 1992:4). Consequently, scale defines the type and form of existing relations between autonomy; environmental and inter-agent interactions; and efficiency on pursuing and achieving goals. Although the environment within which MABEL agents interact and evolve is mainly in a geo-spatial form, the notion of scale acquires a multi-dimensional context:

(a) Geographical scale: the agents are assumed to base their interactions in a geographic; parcel-based framework (Friedman and Kandel 1999, Kirby 2001, Winter 2000). The parcel is the main scale in these terms, and thus, generating the primary array of the system.

(b) Physical scale: An agent in MABEL could be instantiated after an individual, physical person, yet, a scale-dependent definition would be of a land/parcel-based stakeholder(Dautenhahn 2000, Kennedy, *et al.* 2001, Prietula, *et al.* 1998, Sawyer 1998, Ward 2000). It could be an individual; a land-based community[3]; an agency or local government[4]; a commercial or business relation[5], or any physical, technical or artificial entity that can be assumed and considered as a stakeholder. Physical acquisition of land is not an element of generosity, yet as we will see, it plays a somewhat significant role on the agent's behavior.

(c) Social and economic scale: Agents are perceived within a social and economic framework that defines both the nature of their relationship with the environment, as well as the nature of the interaction between them. Population size and dynamics, community and social variables, economic variations and existing relations acquire a size and measurability within an agent-based approach (Dautenhahn 2000, Kluver and Schmidt 1999, Padget 1999). Thus, any featured simulation including socio-economic factors of analysis would have to be defined in a scale-dependent way.

(d) Environmental/ecosystem scale: Agents are considering, evaluating and performing their actions on different ecosystems scales such as the watershed level, or the habitat population level, and so on. Ecosystems dynamics play an important role on the health of the environment and the general welfare of various components such as the landscape, the human population, and the socio-economic welfare. Interactions and/or conflicts between human actions that alter the land use and the landscape and the ecosystem's resilience, stability and adaptation, is a contributing factor to the system's dynamics.

(e) Behavioral scale: Apart of the concrete behavioral patterns that can be observed on an individual level of perception, and affects individual agents' behavior, a set of population, and agent-type based behavioral patterns can be also observed and represented. They range in a wide variety of types such as social patterns of behavior; economic patterns of behavior; organizational patterns of behavior; policy-making patterns of behavior. Agents access, incorporate and valuate existing and observed patterns of behavior on their action-making schemes.

[3] In the sense of a community-owned land.

[4] In the sense of a public-land stakeholder.

[5] In the form of either a commercial store or a business abstraction.

A Layered Perception of Agents

MABEL agents' are assigned "generic" properties prior to the commencement of the simulation. That is, the establishment of data acquisition links and patterns, required to provide the necessary framework of featured agents' actions and patterns of behavior. Agents' source their instantiation in groups of discrete data sets in the form of interconnected databases – a dynamic and evolving knowledge-base. This idiomorphic disposition – the agents 'DNA' – inaugurates temperamental behavior to a fundamental element of their decision-making and action-designing process.

A layered procedural framework is designed to provide preliminary instantiation of agents prior the commencement of the simulation. The framework equips MABEL agents with the adequate access tools to the dynamic knowledge base, and an interacting determinant of their environment in a set of state variables. The procedure is structured in a series of identifiable steps and layers, and a dual – horizontal / vertical – framework of data acquisition (a graphical illustration of the process is provided in the following Figure 1):

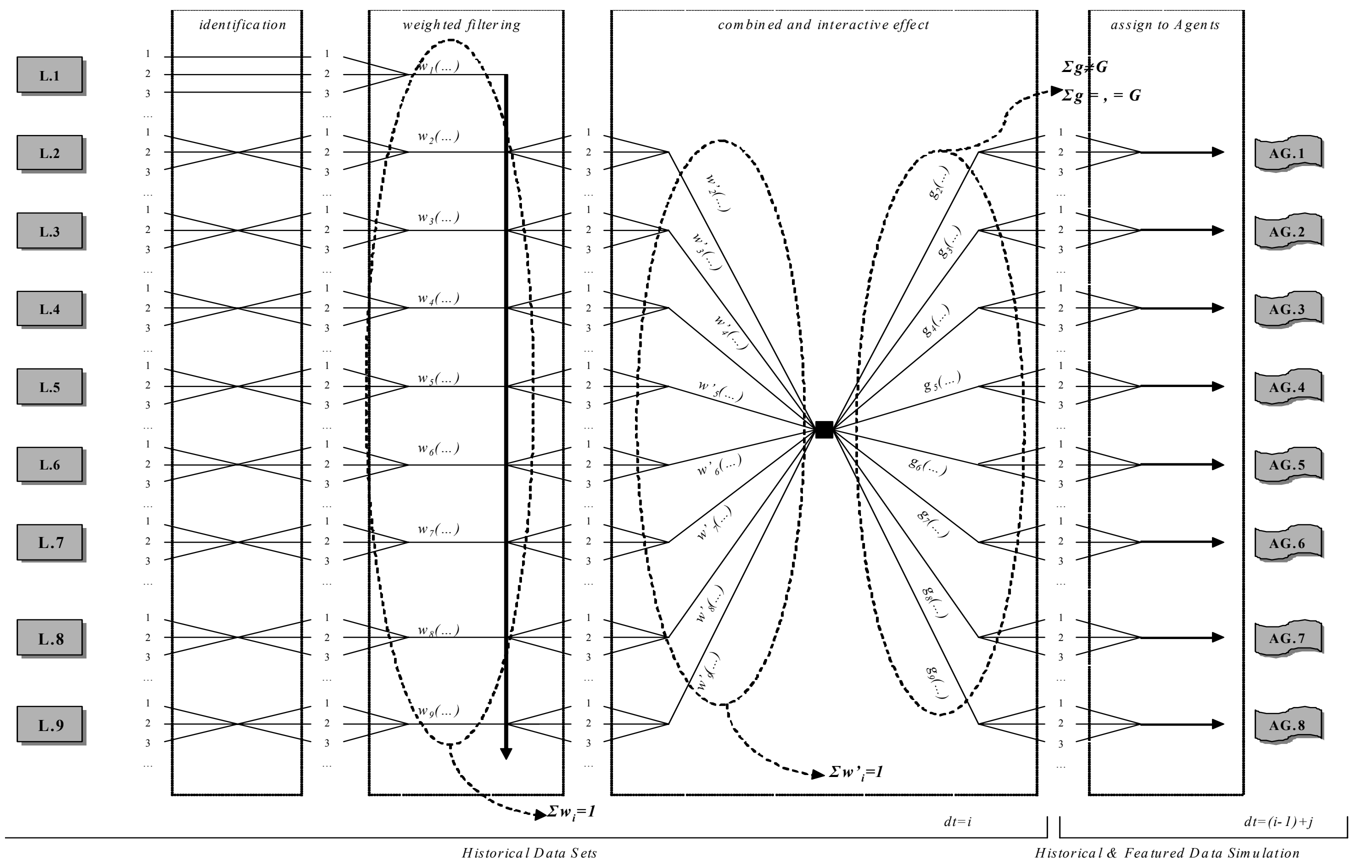


Figure 1: Layered Data Input Acquisition in MABEL

- Horizontal Framework: Identifiable Steps:

  a. *Observational filtering*: An assessment of the observations made on the research area and populations, provides an initial set of indicators for determining the extent and nature of interactions in use. Careful observation of data and GIS image layers (as shown for example in Figure 4), indicate the direction of exploring potential and featured interactions for the system. Often parcel-by-parcel comparisons are adequate to establish correlative links and behavioral attitudes over time and space. In the example provided for this purpose, potential correlations were indicated for observations regarding fragmentation, income distribution of the stakeholders, trends of land use and transformation changes, sources of conflict and policy framework for land use, demographic characteristics and so on. In a later stage, these observations can be confirmed and correlated with existing statistical trends and other sources of information. This primary filtering provides a rather qualitative approach to the changes and potential transformations in land use.

b. *Statistical filtering*: Available data collected in order to enhance a further understanding and exploration of the descriptive dynamics of the system. U.S. Census time series, data from primary and secondary information sources, collected survey and qualitative data[6], represent some of the main sources of information used for the filtering. Furthermore, the information of this step, provides a sound basis of initiating the development of a dynamic knowledge base of the agents state-space. Observational findings and notations, were cross-examined and correlated using the statistical information, and analyzed deeper and extensively for identification of additional linkages and inter-connections. Table 1 and Figure 2 bellow, provides a sample illustration of the existing data analysis.

Table 1: Long Lake Township – 1990 Housing Occupancy Characteristics.

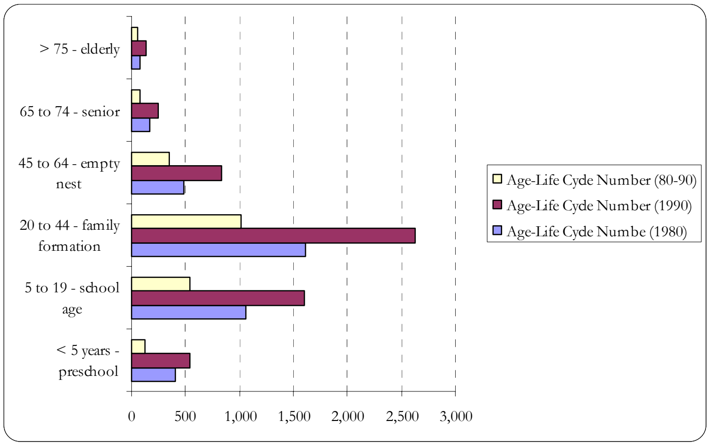
Category	*Long Lake Township*			*Grand Traverse County*		
	Number	*Percent*		*Number*	*Percent*	
		Total Units	*Occupied Units*		*Total Units*	*Occupied Units*
Occupied Housing	2,029.00	77.41	100.00	23,965.00	83.39	100.00
Owner-Occupied	1,683.00	64.21	82.95	17,922.00	62.36	74.78
Renter-Occupied	346.00	13.20	17.05	6,043.00	21.03	25.22
Vacant Units	592.00	22.59	100.00	4,775.00	16.61	100.00
Vacant for Sale	29.00	1.11	4.90	272.00	0.95	5.70
Vacant for Rent	55.00	2.10	9.29	321.00	1.12	6.72
Vacant not Available	14.00	0.53	2.36	210.00	0.73	4.40
Vacant Occasional	441.00	16.83	74.49	3,296.00	11.47	69.03
Migrant/Others	53.00	2.02	8.95	676.00	2.35	14.16
Total Housing Units	2,621.00	100.00		28,740.00	100.00	

Data compiled by Wade-Trim
Primary Source: 1990 US Census, General Housing Characteristics, Michigan; Tables 49 and 67
Secondary Source: Long Lake Township Master Plan (2000).

Within the current framework of statistical analyses, a calculation of primary weights deriving from existing data, were made, adjusted to their probability distribution among existing land uses as illustrated in the example of Figure 3. Although the initial statistical assessment represents a deterministic framework of data acquisition, the process gradually transforms it into a dynamic and evolving process with the addition of the next sequential steps.

[6] Especially data designed and collected to enhance understanding of inter-relational interactions, such as behavioral decision-making, environmental and ecosystem health data specific for the under research area, indented and anticipated future expectations and policies, and so on.

Figure 2: Long Lake Township – Comparative Life Cycle Distribution (1980-1990)



Sources: (a) 1980 US Census, General Population Characteristics, Michigan; Table 39a; 1990 US Census. General Population Characteristics, Michigan, Table 68. (b) Long Lake Township Master Plan, 2000.

Figure 3: Primary Socio-economic Statistical Filtering from Information Sources (example)

TYPE OF SOCIOECONOMIC CRITERIA	LAND USE							Total	Partial Weights
	Urban	*Agriculture*	*Forest*	*Open Water*	*Wetlands*	*Riparian*	*Other*		
01- Population Changes	0.60000	-0.06250	0.46260	-0.00630	0.00000	0.01250	-0.00630	1.00000	1.00000
02- Age-life	0.93333	-0.10000	0.11667	0.05000	-0.08333	-0.05000	0.13333	1.00000	1.00000
<5	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.05850
5-19	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.25020
20-44	0.80000	-0.30000	0.35000	0.15000	-0.25000	-0.15000	0.40000	1.00000	0.46940
45-64	0.80000	-0.30000	0.35000	0.15000	-0.25000	-0.15000	0.40000	1.00000	0.16110
65-74	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.03480
>75	1.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000	0.02600

c. *Systemic filtering*: The primary assignment of weights by correlating socio-economic criteria to land use categories, assigns also systemic features to the data acquisition. Classes and sub-classes of correlative elements represented by land use types, are forming a set of variables, the combined effect of which, contributes to the observed systemic behavior over time and space. Although not currently used in the development stage of the experimental form of MABEL, a provision can be made to include further systemic analysis such as a neural network training and output of the land use GIS layers prior to their inclusion to the initial data base.

d. *Sequential filtering*: A goal-based approach is formed through spatial recognition and assignment of criteria for the correlation between types of land uses. The likelihood of change in the land use type for a specific location was calculated from observations on land use changes in the previous thirty years (1970-1990). The parcelized structure of the experimental area, analyzed for three sequential GIS layers for 1970, 1980, and 1990 – shown in Figure 5 -, revealed a parcel-by-parcel change pattern and behavior, and provided indicators of behavioral patterns and expectations of the landowners and users. The data were recorded, and correlated into a unique table (example on Table 2). Another, important reason for the sequential process is that the existence of the sequence of steps ensures the existence of *environmental*[7] *history*, which, in turn implies the utilization of sequential decision problem-solving process (Russell and Norvig 1994).

Table 2: Sequential filtering: Assignment of weighted averaged criteria for land-use interactions. (example)

	Weighter Averaged Criteria												
	111	112	120	130	155	210	220	230	240	310	320	330	340
111	-0.012616667	0.536395313	0.0025875	0.002525	0	0.018584375	-0.0007	0.002159375	0	-0.015354167	-0.003226042	-0.035607292	-0.006315625
112	-0.0094625	0.71519375	0.0025875	0.002525	0	0.024779167	-0.000933333	0.003239063	0	-0.02303125	-0.006452084	-0.053410937	-0.008420833
120	-0.0094625	0.536395313	0.00345	0.002525	0	0.024779167	-0.000933333	0.003239063	0	-0.015354167	-0.003226042	-0.035607292	-0.008420833
130	-0.0094625	0.536395313	0.0025875	0.003366667	0	0.018584375	-0.0007	0.002159375	0	-0.015354167	-0.003226042	-0.035607292	-0.006315625
155	0	-0.357596875	-0.001725	-0.001683334	0	0.012389584	-0.000466667	0.001079688	0	0.015354167	0	0	-0.004210417
210	0.0094625	-0.71519375	-0.00345	-0.002525	0	-0.024779167	0.000233333	-0.001079688	0	-0.015354167	-0.003226042	-0.035607292	0.002105208
220	0.0094625	-0.71519375	-0.00345	-0.002525	0	-0.006194792	0.000933333	-0.001079688	0	-0.015354167	-0.003226042	-0.035607292	0.002105208
230	0.006308334	-0.536395313	-0.0025875	-0.001683334	0	-0.006194792	0.000233333	-0.00431875	0	-0.007677083	-0.003226042	-0.035607292	0.002105208
240	0.0094625	-0.71519375	-0.00345	-0.002525	0	-0.006194792	0.000233333	-0.001079688	0	-0.015354167	-0.003226042	-0.017803646	0.002105208
310	0.006308334	-0.536395313	-0.001725	-0.001683334	0	0.012389584	-0.000466667	0.001079688	0	0.030708333	-0.003226042	-0.017803646	-0.004210417
320	0.003154167	-0.357596875	-0.0008625	-0.000841667	0	0.006194792	-0.000233333	0.001079688	0	-0.007677083	0.012904167	0	-0.002105208
330	0.006308334	-0.536395313	-0.001725	-0.001683334	0	0.012389584	-0.000466667	0.002159375	0	-0.007677083	0	0.071214583	-0.002105208
340	0.0094625	-0.71519375	-0.00345	-0.002525	0	-0.006194792	0.000233333	-0.001079688	0	-0.015354167	-0.003226042	-0.017803646	0.008420833
350	0	0	0	0	0	0	0	0	0	0	0	0	0
380	0.006308334	-0.71519375	-0.00345	-0.002525	0	0.006194792	-0.000233333	0.001079688	0	0.015354167	-0.006452084	-0.035607292	-0.002105208

e. *Logical and agent architectural development*: The use of *heuristics* in designing and developing MABEL agent's behavior, endows them with the ability to interact, communicate and solving complex problems. Interactive behavior, flexibility on operating in dynamic environments, inherent structural ability, social behavior-base, reasoning and knowledge-acquisition, are some of the components required for a distributed multi-agent planning (Nwana and Azarmi 1997). Intelligent behavior is a product of successful combination of *fuzzy* elements of logic, such as robustness, adaptiveness, autonomy, and communication (Zadeh and Kacprzyk 1992). The use of *first order logic (FOL)* and inference rules, ensures the semantics of the data acquisition, and builds the foundation for *domains of sets* (Russell and Norvig 1994) in the Knowledge-Base.

f. *Simulation*: MABEL agents are agriculturalists, pastoralists, developers, high- or low-density residents, and policy makers. They make decisions by maximizing both their task-specific marginal utility for their actions, and their joint, weighted marginal utility for their time-stepping. They pursue specific, yet diverse goals under the Rationality assumption by reconstructing a complex, yet comprehensive environment. Agent's behavior is achieved by personalizing a dynamic utility-based Knowledge Base (Guida and Tasso 1994, Maybury 1997, Schmoldt and Rauscher 1996, Tecuci and Kodratoff 1995) throughout sequential GIS filtering (Gimblett 2002, Petkovic, *et al.* 1996), probability-distributed weighting (Drummond, *et al.* 1990, Jumarie 2000, Peck, *et al.* 1995), joint probability correlational weighting of a Bayesian form (Dal Forno and Merlone 2002, Hanson, *et al.* 1991, Islam 1999, Jamal and Sunder 2001, Kulkarni, *et al.* 1991, Smithson 2000), and goal-based distributional properties of socio-economic and behavioral criteria (Shenk and Franklin 2001, Shubic and Vriend 1999, VerDuin 1994). Agent simulations are performed and organized on a geo-spatial expressional form via a grid- and parcel-based statistical transformation. The basic database is a grid-based spatial analyzed GIS frame of the area. In the researched experimental area, the GIS data filtered and categorized by parcel-units, reflect fifteen main land-use pattern categories, represented by unique codes on the database raw data. A new

[7] Environment in this proposition, is the agents' state-space.

Knowledge Base (KB) is created by transforming the original grid-based database into a parcel-based spatial KB through a procedural transformation[8].

g. *Iterations/repeatability*: MABEL modeling development, allows multiple iterations and repeatability of results as an agent-based artificial intelligent architecture (Axelrod 1997, Kennedy, *et al.* 2001, Rouchier 2001, Russell and Norvig 1994). Iterations enhance model validation of results, and minimize error propagation in evolving and interactive ways. Furthermore, repeatability of simulation allows for trial-and-error approaches to modeling, and featured decision-making assumptions for the agents and their behavior.

h. *Output, data layouts and formatting*: The simulation outputs and data layouts are fully compatible with GIS software application, permitting further analysis and testing of results. The outcome of the simulation can be formatted or deconstructed to its original-formatted databases – with the new entries reflecting the simulated outcomes -. The particular design of the simulation process, may allow graphic representation of periodic state-space captures of the system's dynamics. Agents are not required to actually achieve any of the pre-determined goals, but they are flexible enough to address the different interactions with their environment and other agents by pursuing their individualized goal-sets.

i. *Sensitivity – scenario analysis and testing methods*: Simulated results can be subject to various testing and validating techniques. Testing the confidence range of the simulation (comparative study of simulated vs. historical database); performing a Turing test for the validity of results; spectral analysis; and other statistical tools and hypothesis-testing techniques, are examples of tests that can be employed.

[8] Additional information on the procedural transformation of the KB are provided in following paragraphs.

Figure 4: Land Use transformation over a 30-year period in GIS layers (1970-1990)

- Vertical Framework: Identifiable Layers:

  a. *Land use types (L.1)*: An assessment of the observations made on the research area and populations, provides an initial set of observations for determining the extent and nature of interactions in use. Classification and subsumption[9] plays a very important role on the simulation. Agents' are assigned and acquire their state-spaces, and their goal-based utility functions based in the land use types classification.

  b. *Demographics & population dynamics (L.2)*: A series of variables such as total and diverse population distribution, age, income, demographic characteristics, follow distributional spatial patterns, as discussed in the previous section, and can be represented and transformed into a geospatial form.

  c. *Topology (L.3)*: Elements such as roads, infrastructure, sites of selected features, are following a spatial distribution, and a correlation with land use changes and other socioeconomic, demographic and behavioral characteristics can be established. In the experimental area used for the architectural development of MABEL model, a significant correlation was found between land use changes and expansion to low-density residential development areas and the existence of roads and highways. In

[9] *Subsumption* – the process of querying if an existing category is a subset of another by definition (Brenner 1999, Brooks 1986, Russell and Norvig 1994)

addition, elevation, soil and geological characteristics, as well as landscape aesthetics (such as wetlands, existence of lakes, and so on), can contribute to an extend to land use changes.

d. *Behavior, attitudes, actions, human precipitation (L.*4): Patterns of behavior and action, trends, logic, interactive reasoning are some of the elements of change perceived to be assigned to MABEL agents. Agents demonstrate adaptive and resilient characteristics, and their intelligent problem-solving capability is challenged by the existence of uncertainty and risk domains. A set of tools can be employed to assist the simulation: Bayesian logic, rules and inference; utility-based functionality; dynamic belief networks – Markov chains (Russell and Norvig 1994).

e. *Policy, legal & public framework (L.*5): Local, state and federal laws and legislations, planning and zoning ordinances, organizational entities and groups, citizen and community involvement, sustainability and integrated approaches are taken into account in the formation of the MABEL agent's Knowledge-Base. The basic reason is that often, the existence of this dynamic framework, not only affects land-use and changes over time, but also can pose serious restrictions and conditions to the simulation, or generating dangerous computational 'loops' on the iterative process that cannot be easily overweighed. A layered sequential decision-making process ensures and enhances the policy framework among agents in a communicational level.

f. *Expectations & adaptation (L.*6): Expected and projected behavior, actions and expected actions for the future, logical predictions and projections, adaptive expectations, are taken into account and contribute to the simulated environment. Bayesian techniques and the dynamic Knowledge-Base that the agents valuate, as well as the expected utility-based functionality of MABEL, ensures the inclusion of layered variables of this nature.

g. *Climate control & vulnerability (L.7*): Climatic data (Forsyth 2000, Ministry of the Environment - Sweden 2001, Olmos 2001, White and Ahmad 2001, Zwiers 2002), correlations with human population (Githeko and Ndegwa 2001, Kondratyev 1988, Kovats, *et al.* 2000, Parker 1995, Peterson and Johnson 1995, Smit, *et al.* 2000, Tarr 1998), potential interactions and effect to other variables and controls, and their systemic and modeling functionality (Githeko and Ndegwa 2001, Ollinger 1995, Pinto and Harrison 2000, Reilly and Schimmelpfennig 2000, Thornton 2002, UCAR 2002), are some of the issues involved and considered in the design and development of MABEL, although not taken into account in the current stage of MABEL development[10].

h. *Natural resources, wildlife, habitats & ecology, ecosystems & resilience (L.*8): biodiversity, vegetation and land cover, surficial data analysis, habitat and ecosystem health indicators, and similar considerations can be also taken into account on developing MABEL dynamic knowledge-based acquisition (Allen and Hoekstra 1992, Ascher 2001, Carpenter, *et al.* 1999, Goerner 1993, Goodchild 1994, Gunderson and Holling 2001, Hartvigsen, *et al.* 1998, Holling 2001, Holling and Gunderson 2001, Holling, *et al.* 2001, Levin 1998; 2000, Millington, *et al.* 2001, Parker, *et al.* 2001b, Pickett and Cadenasso 2002, Pritchard, *et al.* 2000, Scheffer, *et al.* 2001, Schultz, *et al.* 2000, Wessman 1992). In conjunction with the previous variables and layers, the integration of ecosystem-based variables (Gimblett, *et al.* 2002) with the other observational and experimental variables of the model, reveals complex systemic properties that MABEL agents valuate in assessing their Knowledge-Base.

[10] Consideration and design was given in MABEL with respect to climate change, vulnerability and adaptation issues. In the current development stage of the primary experimental testing, a choice was made to maintain the simplicity of assumed interactions, in order to enhance the ability of testing internal systemic features and functionality of MABEL. Recently, an on-going effort begun for incorporating MABEL-based simulation analysis to climate change research.

i. *Social, socioeconomic, community-based & cultural effects (L.9)*: Beliefs, norms, actions, patterns of

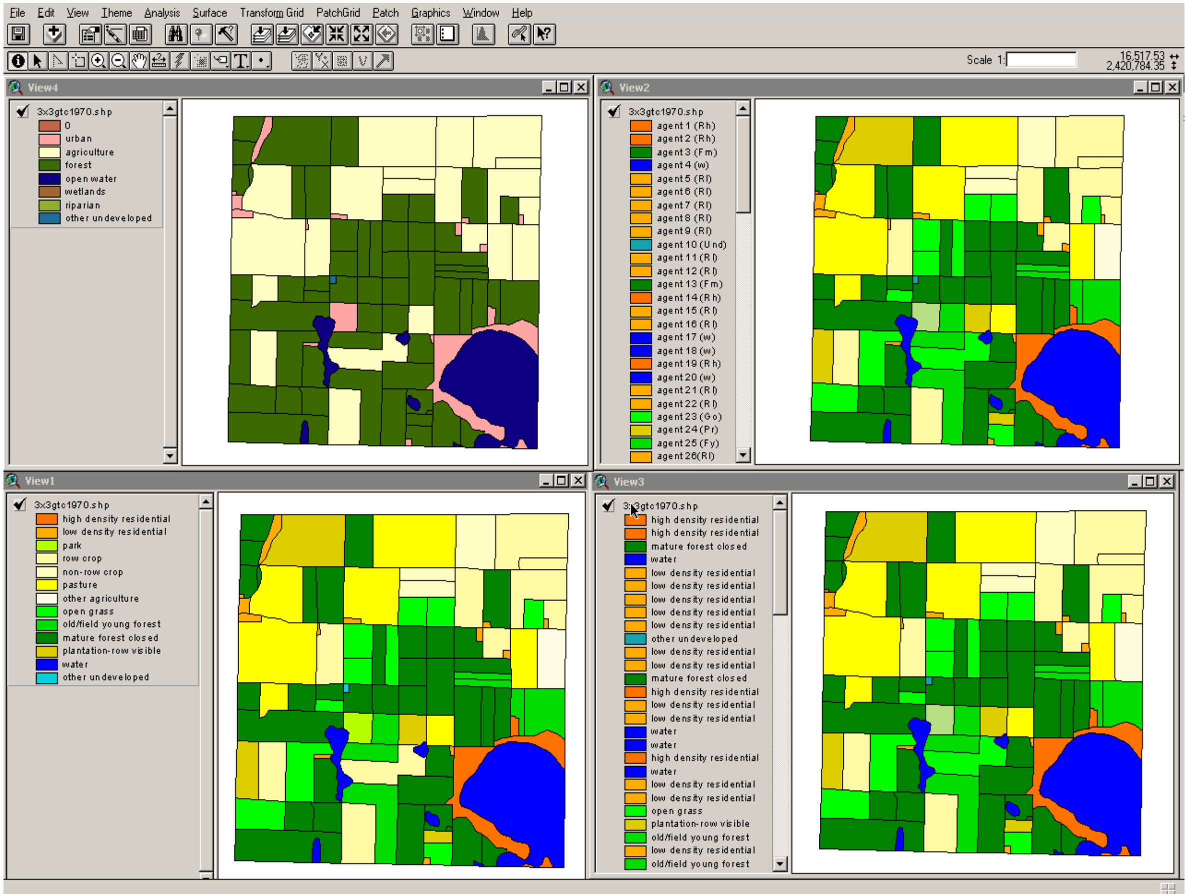


Figure 5: Example of 1970 GIS Data Layers and Agent Assignment for Long Lake Township, Grand Traverse County, Michigan: (a) Land use major classes; (b) agent assignment; (c) land use minor classes; (d) individual parcel-based agent assignment.

behavior, economic variables, and relevant variables are incorporated into MABEL in a spatial form, with respect to the horizontal framework dynamics explained in the previous section. The importance of these interactions (Agre 1997, Brock and Durlauf 2000, Carraro and Metcalf 2000, Corraliza and Berenguer 2000, Durlauf and Young 2001, Flentge, *et al.* 2001, Herrmann 1998, Kohler and Gumerman 2000, Parker, *et al.* 2001a, Plantinga and Provencher 2001, Shubic and Vriend 1999, Stocker, *et al.* 2001, Tzafestas 2000), with respect to the remaining spatial layers provides a comprehensive understanding of the dynamics of the MABEL systemic functionality.

The dual (horizontal – vertical) framework illustrated here, represents a minimal approach to the dynamics observed for a selected location of study. The initial data acquisition and the formation of a dynamic knowledge-base, follows a local minima/local optima approach to a featured Knowledge Base (KB), a hill-climbing technique (Edmonds 2000, Goertzel 2002, Kennedy, et al. 2001, Klugl 2001, Rouchier 2001, Russell and Norvig 1994). The results of this initial data acquisitions were tabulated (example in Table 3 and

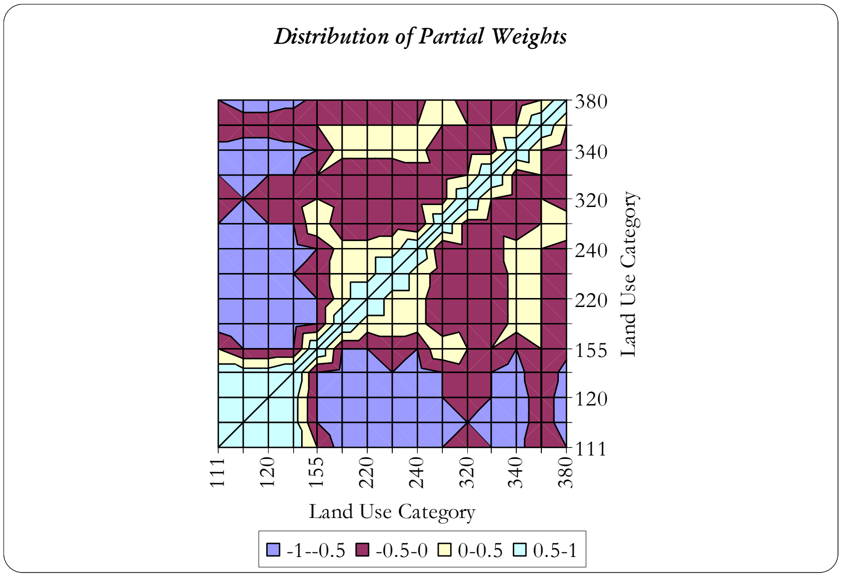
Figure 6) and formatted for initiation of the MABEL simulation.

Table 3: Formation of Partial Weights in correlative spatial form for MABEL

Partial weights

	111	112	120	130	155	210	220	230	240	310	320	330	340
111	1	0.75	0.75	0.75	0	-0.75	-0.75	-0.5	-0.75	-0.5	-0.25	-0.5	-0.75
112	0.75	1	0.75	0.75	-0.5	-1	-1	-0.75	-1	-0.75	-0.5	-0.75	-1
120	0.75	0.75	1	0.75	-0.5	-1	-1	-0.75	-1	-0.5	-0.25	-0.5	-1
130	0.75	0.75	0.75	1	-0.5	-0.75	-0.75	-0.5	-0.75	-0.5	-0.25	-0.5	-0.75
155	0	-0.5	-0.5	-0.5	1	-0.5	-0.5	-0.25	-0.5	0.5	0	0	-0.5
210	-0.75	-1	-1	-0.75	-0.5	1	0.25	0.25	0.25	-0.5	-0.25	-0.5	0.25
220	-0.75	-1	-1	-0.75	-0.5	0.25	1	0.25	0.25	-0.5	-0.25	-0.5	0.25
230	-0.5	-0.75	-0.75	-0.5	-0.25	0.25	0.25	1	0.25	-0.25	-0.25	-0.5	0.25
240	-0.75	-1	-1	-0.75	-0.5	0.25	0.25	0.25	1	-0.5	-0.25	-0.25	0.25
310	-0.5	-0.75	-0.5	-0.5	0.5	-0.5	-0.5	-0.25	-0.5	1	-0.25	-0.25	-0.5
320	-0.25	-0.5	-0.25	-0.25	0	-0.25	-0.25	-0.25	-0.25	-0.25	1	0	-0.25
330	-0.5	-0.75	-0.5	-0.5	0	-0.5	-0.5	-0.5	-0.25	-0.25	0	1	-0.25
340	-0.75	-1	-1	-0.75	-0.5	0.25	0.25	0.25	0.25	-0.5	-0.25	-0.25	1
350	0	0	0	0	0	0	0	0	0	0	0	0	0
380	-0.5	-1	-1	-0.75	-0.25	-0.25	-0.25	-0.25	-0.25	0.5	-0.5	-0.5	-0.25

Figure 6: Initial Weighted Filtering for MABEL Agents. The Agents (types, categories, classes), acquire their state-space by referring to this Knowledge-Base. The interaction is bidirectional, dynamic and evolving through time.



Data Acquisition and Dynamic Knowledge-Base in MABEL

Five abstract steps can summarize the sequence of procedures leading to the simulation (the graphical illustration of these schemes is provided in the Figure 1, in the previous section) :

a. Primary identification
b. Weighted filtering
c. Combined and interactive effect
d. Assignment to agents
e. Agent Simulation and modeling

Two basic functions are fundamental for the creation of the dynamic knowledge base: parcel identification and recognition, and socio-economic filtering, and thus, special attention is drawn here.

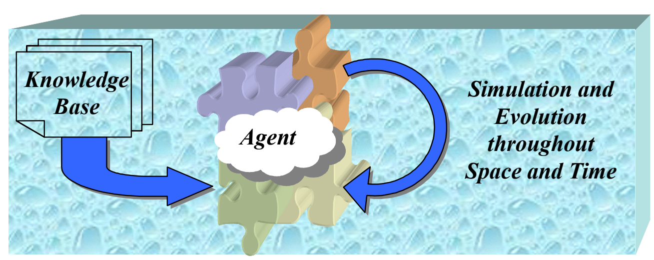


Figure 7: A graphic illustration of Agent-environment interactions

Parcel Identification & Recognition.

Diversification and individualization of MABEL agent behavior is achieved through sequential filtering in GIS database form (Duke-Sylvester and Gross 2002). Although land use categorization and parcelization preexists on a GIS data form, agent data acquisition requires additional GIS analysis. Parcels belonging to the same category bare no difference on their category coding to the GIS layers and data sets. In other words, a 'low-density residential' classification of a parcel bears classification coding similar to any other 'low-density residential' parcel of land. Agents targeted to simulate individual behavior correlated to a specific parcel (i.e. an individual resident- occupant of the parcel), does not have the ability to identify their state-space and thus, achieve diverse individual behavior. In this sense, agents of the same category would had to be assumed to behave in the same way (an abstraction that significantly increases error propagation and biases through the simulation in space and time).

MABEL spatial data acquisition solves this abstraction problem, by using function-identification recognition in database records. This functional identification is performed in a parcel-by-parcel form. A unique identifier is assigned for every parcel of the spatial area of the simulation (the 'world' variable).

An example is provided below. An initial GIS database has the following form:

- Parcel no.1: 112
- Parcel no.2: 112
- Parcel no.3: 112

....

- Parcel no.i: 112

$$grid(C) = \begin{bmatrix} c(n)_{11} & c(n)_{12} & c(n)_{13} & \cdots & c(n)_{1j} \\ c(n)_{21} & c(n)_{22} & c(n)_{23} & \cdots & c(n)_{2j} \\ c(n)_{31} & c(n)_{32} & c(n)_{33} & \cdots & c(n)_{3j} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ c(n)_{i1} & c(n)_{i2} & c(n)_{i3} & \cdots & c(n)_{ij} \end{bmatrix} \qquad \textit{Eq. 1}$$

Whereas, a featured GIS Knowledge base is transformed in the following manner:

- Parcel no.1: 112.001
- Parcel no.2: 112.002
- Parcel no.3: 112.003

....

- Parcel no.i: 112.00i

$$parcel(C) = \begin{bmatrix} c(n,m)_{11} & c(n,m)_{12} & c(n,m)_{13} & \cdots & c(n,m)_{1j} \\ c(n,m)_{21} & c(n,m)_{22} & c(n,m)_{23} & \cdots & c(n,m)_{2j} \\ c(n,m)_{31} & c(n,m)_{32} & c(n,m)_{33} & \cdots & c(n,m)_{3j} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ c(n,m)_{i1} & c(n,m)_{i2} & c(n,m)_{i3} & \cdots & c(n,m)_{ij} \end{bmatrix} \qquad \textit{Eq. 2}$$

The two settings (Eq. 1 and Eq. 2), are connected via a function of the following form:

$$c(n,m) = f\big(c(n)\big) = c(n) + \frac{m}{1000} \qquad \textit{Eq. 3}$$

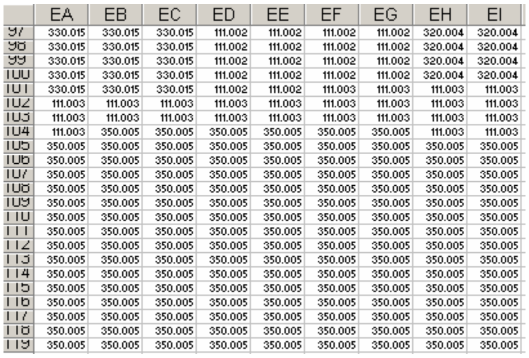
where, *c(n)*: the class code for the land use category

n: the class differentiation

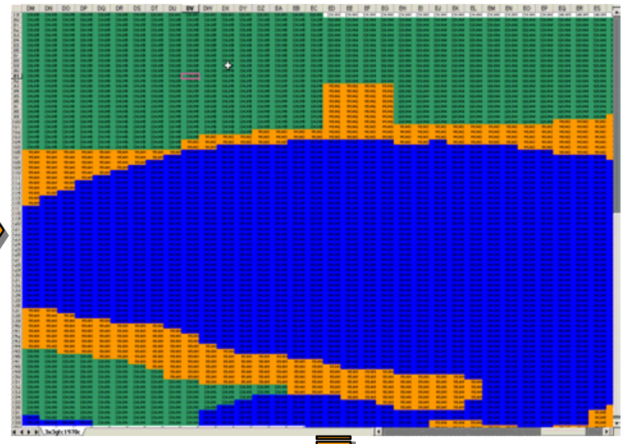
(*i*,j): the dimensions of the class element (grid) within the spatial database

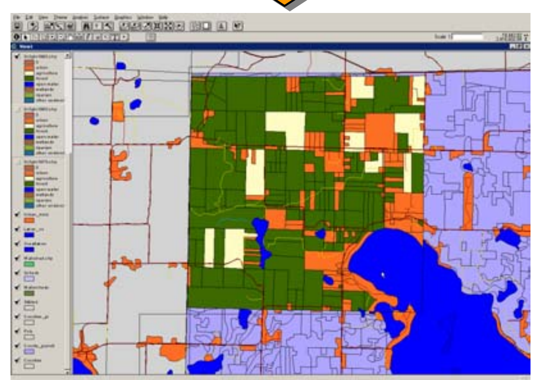
(n,m): the identifiable parcel combination, since the *m* element is unique for each parcel.

Figure 8: Interactive formation of MABEL Knowledge-Base's parcel identification



	EA	EB	EC	ED	EE	EF	EG	EH	EI
97	330.015	330.015	330.015	111.002	111.002	111.002	111.002	320.004	320.004
98	330.015	330.015	330.015	111.002	111.002	111.002	111.002	320.004	320.004
99	330.015	330.015	330.015	111.002	111.002	111.002	111.002	320.004	320.004
100	330.015	330.015	330.015	111.002	111.002	111.002	111.002	320.004	320.004
101	330.015	330.015	330.015	111.002	111.002	111.003	111.003	111.003	111.003
102	111.003	111.003	111.003	111.003	111.003	111.003	111.003	111.003	111.003
103	111.003	111.003	111.003	111.003	111.003	111.003	111.003	111.003	111.003
104	111.003	350.005	350.005	350.005	350.005	350.005	350.005	111.003	111.003
105	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
106	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
107	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
108	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
109	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
110	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
111	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
112	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
113	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
114	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
115	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
116	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
117	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
118	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005
119	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005	350.005





Socio-economic Indicators.

A second, supplementary database developed to reflect socio-economic, behavioral and subjective criteria (Conte and Paolucci 2001) considered affecting land use pattern changes over space and time (Conroy and Moore 2001). Basic assumptions are built on close relation with the area's specific statistical, demographic and behavioral data, as illustrated in the agents' layered framework in the previous parts. First-order logics, heuristics and appropriation of the time-step sequences are used to provide a simulational environment, capable of re-generating a space-time evolvement of the agents. The data are weighted and series of (a) case specific; (b) behavior/action specific; (c) outcome specific utility function estimations are being made. Via Bayesian approximations, weighted values are produced, and consequential database tables are formed. The agent's valuate these data to calculate their accumulative (overall) utility for each potential action. A goal-based rule of utility maximization for each sequential time-step directs and identifies agent's behavior for the future.

As it is shown in the early Figure 1 on the data acquisition, the model necessitates its first acquisition of data before simulating its own reality. As the figure shows, the primary data acquisition and filtering should be formed on a way that agents must be able to read, comprehend, and valuate. In this context, a sequence of features could be illustrated:

(a) *Primary identification*. Data forming the different layers of analysis, must be identified, correlated and weighted, by valuating observational filtering and assessment and statistical filtering (of the deterministic form).

(b) *Weighted filtering*. A weight could be given to any observed variable in particular, as well as an overall (weighted average) for every layer. For example, if we consider a layer *(L.n)*, that has *i* sub-variables of analysis, say $n_1, n_2, \ldots, n_i$ we can assign *i* different weights for each of the sub-variables of the *L.n* layer, $w_{n1}, w_{n2}, \ldots, w_{ni}$ respectively. Then, we can assume an overall weight for the layer *L.n*, of the form

$$w_n = f(w_{n1}, w_{n2}, \ldots, w_{ni}) \qquad \textit{Eq. 4}$$

In the simplest case the function *f* of the sub-weights, could be represent the sum of the weights, $w_n = \sum_i w_{ni}$. In this case then, a restriction of the form $\sum_i w_{ni} = 1$, could be assumed for the different weights for all the layers.

(c) *Combined and interactive effect*. The complexity nature of the model and the feature interactions indicates that just summing up the combined interactions is not adequate to explain how real-world interactions are formed. Internal structures, communication, collaboration, conflict and various relations among variables and layers, are forming a dynamic environment and cobweb of relationships. The overall weights on the previous paragraph, could be different when such a dynamic environmental interactive frame is introduced into the analysis. Thus, the effect of this permeability is a new weighted measurement of each of the variables and layers. In accordance to the previous example, we can consider a new set of weights, , w_{n1}', w_{n2}' ,..., w_{ni}' respectively. Then, we can assume a new overall weight for the layer *L.n*, of the form

$$w_n' = f(w_{n1}', w_{n2}', \ldots, w_{ni}') \qquad \textit{Eq. 5}$$

And again, in the simplest case the function *f* of the sub-weights, could be represent the sum of the weights, $w_n' = \sum_i w_{ni}'$. In this case then, a relevant restriction of the form $\sum_i w_{ni}' = 1$, could be assumed for the different weights for all the layers. What differentiates this framework from the previous one, is that now, the different layers of analysis, must be combined and examined jointly, as in a central analysis pool, and a combined effect should be drawn.

This procedure, in addition, equips the framework with an additional tool. A set of goals for every layer could be derived also. Goal-sets in this case represent the objectives of every layer. If the weight w' of a layer characterizes the type of interactions of the complex system and the layer's contribution to the overall model, then we can define a goal-set *g* that a potential agent could assume for its development. It is of course case-sensitive (for example, an agent could be considered to have as a goal to maximize its' weight w' to the model's acquisition), but clearly defined goal sets for every variable, could help on the formation of the overall goal of the model, namely *G*.

Thus, an assignment of goals correlated to the weights w' could be considered, and a new set of goals, g_{n1}, g_{n2} ,...,g_{ni} respectively derived for each variable. Then, we can again assume a new overall goal for the layer *L.n*, of the form

$$g_n = f(g_{n1}, g_{n2}, \ldots, g_{ni}) \qquad \textit{Eq. 6}$$

But, in this case the assumption that the function f of the sub-goals, could be represent the sum of the goals, $g_n = \sum_i g_{ni}$ *could not* be drawn. Nor a relevant restriction of the form $\sum_i g_{ni} = 1$, could be assumed for the different goals for all the layers. In contrast, we can consider that $\sum_i g_{ni} \neq G$. In fact, $\sum g_n$ could be bigger, smaller or equal to *G*, at any combination of sub-goals. There are no restrictions in this sense.

(d) *Assignment to agents*. Using the set of sub-goals, a series of agents could be defined. Agents are defined on a spatial form, expressed on terms of the *L.1* pattern layer, which is in a land use type form. This procedure assists agents to maintain a certain level of spatial information sharing and interacting to each other and their environments. The internal architecture of the model does not have to address spatial information as such, but as a series of informational numerical sequence. When there is a need for external output of data for the viewer of the simulation process, then the numerical abstractions of spatial data could be transferred on its original form. MABEL agents are agriculturalists, pastoralists, developers, high- or low-density residents, and policy makers[11]. But another differentiation could be made, upon the different state that any agent could be found. State refers to a space-time-state, whereas different qualitative and quantitative characteristics in terms of information defines, and drives the agent's actions for the future.

(e) *Agent Simulation and Modeling*: the final stage is the actual simulation of the agents. Agents communicate, interact, conflict, and collaborate, to their environment and to each other. They generate a complex, dynamical system of changes that leads to the land transformation patterns throughout time. After the first, primary stimulus data acquisition (of a historical form), every agent's internal structure and defined goals, allows them to redefine their own state and re-assess their situation and their own goal-oriented structure for the future. In a sequential time step, a new generation of agents is being activated, by partly inherent the previous agent's features and partly filtering them under the new data set acquired from the renewed knowledge-based database. In other words, agents possess the internal features, mechanisms and methodology, to return back on point (d) of the sequence (*combined and interactive effect*) and redefine the structure of the data base. Distributed Artificial techniques and methodologies, as described the logical and agent architectural development part, are used.

Multi-Agent Design and Architectural Properties in MABEL

Agent Behavior and Uncertainty in MABEL

A general conceptual assumption for MABEL is that agents allows emergence of rational behavior - the rational agents assumption (Campbell and Snowden 1985, Carroll 2002, Dal Forno and Merlone 2002, Deadman, et al. 2000, Edmonds 1999, Macy and Castelfranchi 1998, McCain 1999, Paredes and Martinez 1998, Roehrl 1999). In this context, indicator of agent's space-state and perspective best next actions are their utility maximization (Kennedy, et al. 2001, Russell and Norvig 1994, Shubic and Vriend 1999). Rational agents in MABEL base their behavior and actions on their perception of maximizing their total utility. Thus, an agent could perform an action only when its marginal utility is maximized with respect to their available next actions. In other words, agents select their best next action that maximizes its utility for the future among the common-pool-available actions in their dynamic Knowledge-Base. A dynamic update of their KB after each step is performed as prescribed in the previous section (Table 2, Table 3 and

Figure *6*).

Queries and considerations dealing with uncertainty have to take into account optimal decisions (and goals), de-pending on the information available, and other agents' actions (Chavas 2000, Lowell and Jaton 1999, Mowrer and Congalton 2000, Plantinga and Provencher 2001). An assessment on uncertainty of actions is performed by introducing the use of randomness. Every agent's action includes a percentage of uncertainty, via the use of a random generator, personalized for every agent in a deviational form (Crutchfield and Feldman 2001a, Islam 1999, Pal and Skowron 1999, Peck, *et al.* 1995, Wu and Axelrod 1995). Uncertainty assessments in MABEL are closely related to theoretical issues sourced from issues such as resilience (Gallopin 2001, Holling 1973, Holling and Gunderson 2001) and adaptation (Deadman, *et al.* 2000, Frenken, *et al.* 1999, Glantz and Johnson 1999); genericity (Decker 1995, Rosen 2000) and emergence (Costopoulos 2001, Emmeche, *et al.* 1997, Hoffmeyer 1997, Kunreuther 2001, Reschke 2001, Thobaud and Locatelli 2001).

[11] In this initial, pilot-experimental form of MABEL these are the categories of agents developed. The model is designed and modeled for a wide and diverse variety of agents, yet their introduction to the simulation is assigned to a future stage of the research.

Farmer:
- maintain land
- maximize utility
  - ✓ *if* farming utility < selling utility ⇔ SELL
- maximize revenew
  - ....

Resident:
- minimize housing cost (~land)
- maximize utility
  - ✓ *Go to* > R_l
- maintain homogeneity
  - ....

Policy-Maker:
- maintain rules (~restrictions, genericity)
- minimize conflicts
- maximize average utility (from average of Σw_i)
- minimize sprawl ($min\Sigma R_l$)
  - ....

Figure 9: An example of goal-based properties.

Access Controls and Action Hierarchy

MABEL agents develop specific and individualized behavior. Examples of the behavioral elements are beliefs – every agent has a set of *beliefs*, collaborative, conflictive or indifferential, where each seeks the best available strategy for achieving its goals –, and *intentions* – agents do not have to choose optimal solutions: they choose from the available ones (the closest to their goals that maximizes their marginal utility).

By definition, agents of the spatial type developed for MABEL (such as farmer, resident, policy-maker, etc...), have different degree of access on information and decision-making (Bell, *et al.* 1988, Bouchon-Meunier, *et al.* 2000, Brock and Durlauf 2000, Brown and White 1990, Crutchfield and Feldman 2001b, Heer, *et al.* 1981, Kacprzyk and Yager 1985, Sauerbier 2002, Tomic-Koludrovic, *et al.* 2002, Verdú, *et al.* 2000). The *access-control system* in MABEL, prioritize the tasks of decision-making and acting among agents, using a *Boolean* (binary) tabulation that correlates the access on a [restricted (0) – unrestricted (1)] basis. Alternatively, for further enhancement of details[12] a correlation table of the [limited – restricted – no/access] controls could be constructed. An example of such a table is given from the MABEL experimental pilot area of study in Table 4. The tabulation assists on the design properties of the goal-based architecture. Prioritization assigns tasks on a *logical* basis using heuristics. The following **Error! Reference source not found.** (schematic representation of a set of hypothetic functions for MABEL agents), demonstrates this architecture[13]

Table 4: An Example of a Access Control Table

	F	***R_l***	***R_h***	***PM***
F	y	y	y	r
R_l	y	y	y	r
R_h	y	y	y	r
PM	y	y	y	y

y = unlimited access
n = no access
r = restricted access

F = farmer
R_l = Resident (low density)
R_h = Resident (high density)
PM = Policy-maker

Hierarchy of actions in the MABEL computational environment follows the patterns and protocols identified by the access controls and the logical and heuristic architecture. An example is provided below (). Updating of agents state-space, is very important, since communication among agents, and between agents with their KB; and agents with their environment; depends on their ability to update their current states. Acquisition without previous update would propagate biases about other agent's state, and could even lead to a complete crash of the simulation after a few generations of agents.

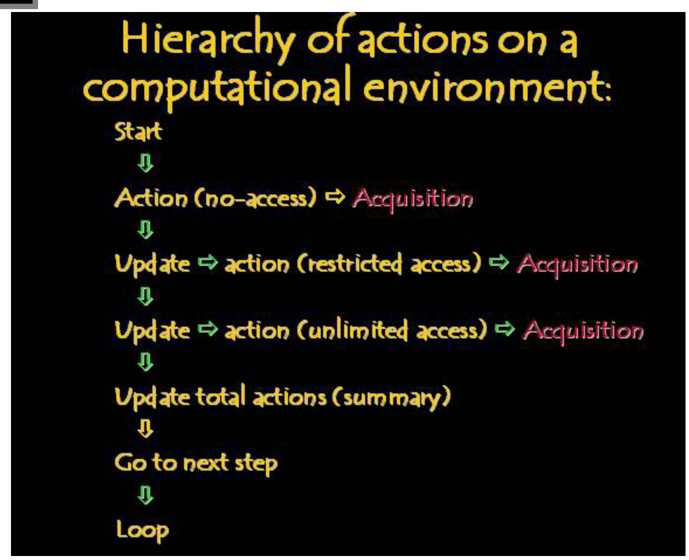
[12] Especially when the number of agents' classes is large, and/or when the quantity and complexity of observed and anticipated interactions can be anticipated to be increased.

[13] The example is written on a *pseudo code*.

```
// Template application. Copyright © 1996-2000 Swarm Development Group.▯// This library is distributed wi
 obj->increment = 1;▯▯  obj->FarmAgents = 21;
 obj->ResAgents = 19;
 obj->PolicyAgents = 64;
 obj->worldXsize = 161;
 obj->worldysize = 160;
 ▯  return obj;▯}▯▯// MODIFY: possible creation objects here.▯- createEnd ▯{▯  return [super createEnd];
[self initWorld];▯▯  return self;▯}▯▯-initWorld{
 int i, j, k, l;

 world= [Grid2d CreateBegin: [self getZone]];
 [world setSizeX: worldXSize Y: worldYSize];
 world = [world createEnd];

 FarmerList = [List create: [self getZone]];
 ResList = [List create: [self getZone]];
 PolicyList = [List create: [self getZone]];
 cellList = [List create: [self getZone]];

 [world setOverwriteWarnings: 0];

 for(i=0;i<worldYSize;i++){
        for(j=0;j<worldySize;j++){

                Cell * cell;
                id settlerSet;

                //initialize new cell
                settlerSet = [Set create: [self getZone]];
                cell = [Cell createBegin: [self getZone]];
                [cell setWorld: world]
                [cell setX: j Y: i];
                [cell setSettlerSet: (id) settlerSet];
                cell = [cell CreateEnd];
                [cellList addLast: cell];

                }
        }

        //create farmer agents
        for( i = 0; i < FarmAgents; i++){
                id aFarmer;
                int height = 0;
                int heightRange[2];
                double ranA[160], ranB[160];
                bool hrange = false;
                int a, b;
                int kind;
                bool initflag = false;
                bool flag = true;
                bool heightflag = true;
                double temp = i * 0.001; // crucial to see which agent we are adding
                int agentnum;
                int totalcells = 0;

                for(k=0; k <= 159; k++){
                        heightflag = true;
                        a = 0;
                        b = 0;
                        for(l=0; l<=160; l++){
                                if(data[k][l] >=200 && data[k][l] <= 299){
                                        int temp2 = data[k][l];
```

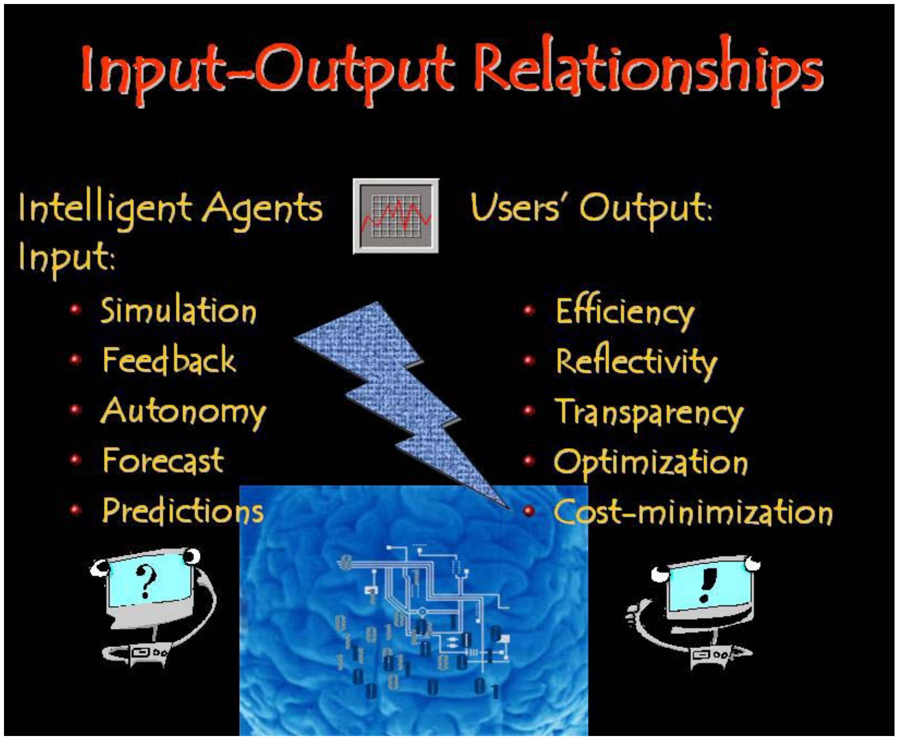
Figure 11: Example of agents code in MABEL

Figure 10: Example of the hierarchical actions in MABEL



Conclusions

An analysis of input versus output relations in MABEL is an adequate demonstration of multiple benefits that can be derived from a multi-agent modeling framework. Distributed Artificial Intelligent (DAI) and Multi Agent-Based (ABM) methodologies providing a very useful tool for observance, interpretation,



analysis and estimating land use patterns in correlation to changes in behavioral characteristics, that can be appended on a geospatial scale. Perceiving landscape as a complex, dynamic, interactive system that involves topological, geographic, environmental, climatic, social, socioeconomic, enviro-economic, and behavioral characteristic, is more consistent to the notion of accessing and observe a holistic, real-world interactive image of our environment in a global scale.

The proposed methodology for MABEL, attempts to overcome various restrictions imposed by traditional methods, and enhances in-depth analysis of qualitative aspects of adaptive changes, without affecting the efficiency of quantitative observation analysis. Especially in long-term observations, estimations and assessment of a time-depth interactions, traditional methodologies, present many weak and restrictive points, resulting to serous barriers for research.

Future research for MABEL intents to increase the complexity of observed interactions, and wider the Knowledge-Base. Ecosystem's management in relation with behavioral changes and land use transformation, propagation of health conditions, or distribution of epidemics in relation with land use, climatic vulnerability, resilience and adaptation to land-use changes and anthropogenic behavioral changes, organizational dynamics and land transformation, are some of the areas that MABEL is anticipated to be valuated. In addition, further enhancement of architectural elements in a purely theoretical level, such as entropy-information dissemination and inter-connectivity, the role of *maximum entropy* and fuzzy systems, interactive experimentation with neural networks and adaptive learning techniques, are some of the directions of future research.

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