MODELING LAND USE CHANGE WITH LINKED CELLULAR AUTOMATA AND SOCIO-ECONOMIC MODELS: A Tool for Exploring the Impact of Climate Change on the Island of St. Lucia

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INTRODUCTION

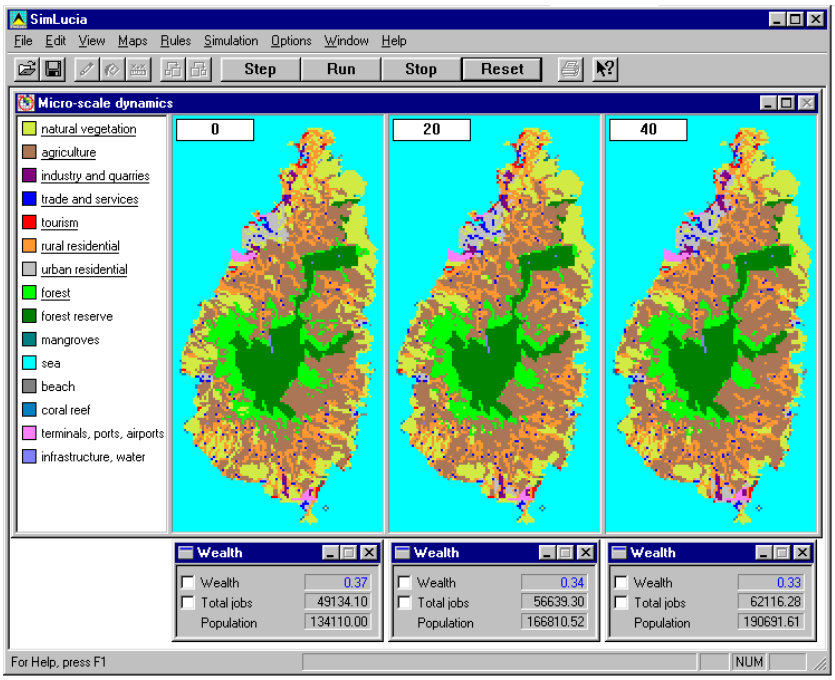
Geographical systems are in many respects the most complex phenomena that we confront, because they constitute the nexus of physical, ecological, and human systems. To be usefully understood, they must be treated as an integrated whole—but also in their parts, and in detail, since many of the most important interactions among their components take place locally. The problem of understanding the possible impacts of climate change immediately poses the question of how to deal with this complexity, because impacts are experienced at all scales from global to local, and the causal chains through which they propagate are both multifarious and characterized by numerous feedback loops.

In this chapter we describe a modeling approach that is designed to capture the essentials of the problem by integrating, in a fully dynamic way, models of natural and human systems operating at several spatial scales. The model was developed for the United Nations Environment Program Caribbean Regional Cooperating Unit (UNEP CAR/RCU) (Engelen *et al*., 1998) with the aim of providing a tool which officials in the region can use to explore possible environmental, social, and economic consequences of hypothesized climate changes. The model is thus generic in the sense that it can accommodate a variety of hypotheses regarding climate change, international economic conditions, and demographic trends, and it can be applied to any small or moderately sized region. The island of St. Lucia was chosen by UNEP as the test application.

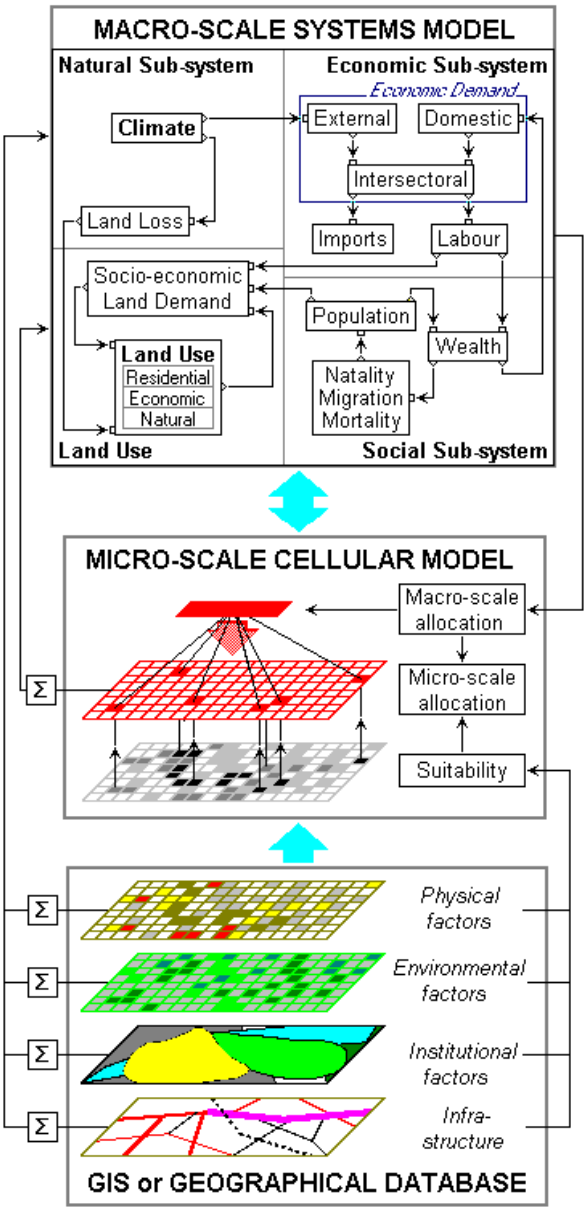
INTEGRATED MULTI-SCALE MODELING

Possible climate change in the Caribbean may be expected to have an important impact on the physical, environmental, social and economic systems of the region (Maul, 1993). Socio-economic systems in the region are already stressed, and climate change may be expected to exacerbate the situation. In St. Lucia, a volcanic island with a rugged landscape, activities are concentrated in the coastal zone. This results in competition for space and conflicts of interest, and causes stress on both terrestrial and marine ecosystems. If changes in climate should occur, or if other non-local events, such as recent changes in the world trade regime, should affect the island, the effects on St. Lucia will not be evenly felt. Some economic or demographic sectors will be affected much more dramatically than others and some parts of the island may experience a positive impact, while others will be negatively affected, or perhaps not affected at all. Climate change in the Northern Hemisphere, for example, could reduce demand for tourism on the island, with effects that would be felt throughout the economy; economic difficulties would in turn affect population growth through, for example, changes in migration. These economic and demographic changes would then have impacts on land use (Figure 1). If worsening economic conditions were not offset by increased out-

migration, then in some areas forests or other ecologically valuable land covers could be converted to agriculture, with, in turn, an additional negative impact on tourism.



To capture the response of a complex and integrated system such as this to a forcing factor like climate change requires that all important components be modeled, as well as the links between the components. Hence the model described here integrates a several sub-models operating at two spatial scales (Figure 2).



At the macro-scale, essentially the scale of the entire island, several components are specified. First, a module for developing climate change scenarios is augmented with a tool for specifying hypotheses concerning relationships between changes in climate parameters and changes in certain economic variables such as demand for tourism and agricultural output. This is linked through the economic variables to an intersectoral (Input-Output) model of the economy, which is in turn linked to a demographic model. These three models, both separately and jointly, implicitly entail changes in land use—the climate module through changes in sea level, the economic model through changes in output (which require land to be realised), and the demographic model through changes in land required for housing. But they say nothing about where the land use changes will occur, or indeed whether the changes are even possible given constraints on the amount and quality of land available.

It is at the micro-scale that the locational aspects are modeled. This is done by means of a cellular automata based model of land use dynamics which makes use not only of land use data, but also of other relevant spatial data such as soil type, slope, precipitation, and transportation infrastructure. This model is driven by the demands for land that are generated by the macro-scale model, so it is able to show the spatial manifestation of the economic and demographic impacts of climate change. Furthermore, some micro-scale spatial data is returned to the economic and demographic models where it modifies parameter values, thus enabling those macro-models to reflect the particular local conditions that affect productive activities.

This general approach, in which diverse models of human and natural systems are linked through a cellular land use model, has been implemented not just in St. Lucia, but in several other problem contexts as well. One, for example, focuses on the interrelated dynamics of metropolitan expansion, agricultural land use change, and regional hydrology in Southwest Sulawesi, Indonesia (Uljee *et al*., 1999). Another models the spatial dynamics of the Dutch population and economy down to the level of land use changes and their attendant ecological impacts; it was developed as a tool for use in the development of national land use policies (White and Engelen, 1999).

The integration of models covering several problem domains is essential to this approach. Yet other than the applications just mentioned, the area of integrated modeling offers surprisingly few examples in which models of natural and human systems are connected dynamically. Among the few are Bockstoel *et al.* (1995) and Rotmans *et al.* (1994). More common are approaches in which models are chained, without the possibility of dynamic feedback, for example models in which climate change drives changes in agriculture, but the latter have no effect on climate (e.g. Parry and Carter, 1989; Parry *et al.* 1996; Strzepek and Smith, 1995). One reason that integrated modeling is so uncommon may be that many of the relevant domain models are non-spatial, while human and natural systems tend to interact in a place specific context. Thus integration is facilitated when models are made spatial, or given a spatial interface. In this respect cellular automata constitute the heart of integrated modeling: they are dynamic, spatial, and multivariate, and thus provide an ideal interface for linking models of different phenomena.

CELLULAR AUTOMATA BASED MODELLING OF LAND USE DYNAMICS

Introduction to cellular automata

Tobler (1979) first proposed using cellular automata (CA) as a tool for modeling spatial dynamics. Couclelis (1985, 1988, 1997) explored the implications of the idea in an important series of theoretical papers. The approach has since been implemented by others in variety of applications (e.g. Batty and Xie, 1994; Benenson, 1998; Ceccini and Viola, 1990; Clark *et al*., 1997; Papini and Rabino, 1997; Phipps, 1989; Portugali and Benenson, 1995; White and Engelen, 1993, 1999; White, Engelen and Uljee, 1997; Xie, 1996). And the approach has been linked to GIS (Wagner, 1997; White and Engelen, 1994; Wu, 1998).

Cellular automata can be thought of as very simple dynamic spatial systems in which the state of each cell in an array depends on the previous state of the cells within a neighborhood of the cell, according to a set of state transition rules. Because the system is discrete and iterative, and involves interactions only within local regions rather than between all pairs of cells, a CA is very efficient computationally. It is thus possible to work with grids containing hundreds of thousands of cells. The very fine spatial resolution that can be attained is an important advantage when modeling land use dynamics, especially for planning and policy applications, since spatial detail represents the actual local features that people experience, and that planners must deal with.

A conventional cellular automaton consists of

1) a *Euclidean space* divided up into an array of identical cells;

2) a cell *neighborhood* of a defined size and shape;
3) a set of discrete *cell states;*
4) a set of *transition rules,* which determine the state of a cell as a function of the states of cells in the neighborhood;
5) and *discrete time steps*, with all cell states updated simultaneously.

However, these defining characteristics can be interpreted broadly, or relaxed in response to the requirements of a particular modeling problem, so many types of CA are possible.

Cellular automata offer a number of advantages. As already mentioned, they are computationally efficient and so, unlike traditional regional models, permit extreme spatial detail. They are thus able to reproduce the actual complexity, frequently fractal in nature, of real spatial distributions. Furthermore, because of the high resolution and raster nature, they are compatible with GIS databases, and can be linked with them in a relatively straightforward way. At the other end of the spatial scale, CA can be linked through their transition rules to other, macro-scale models that constrain or drive the CA dynamics. This facilitates comprehensive modeling of integrated environmental-human systems. Finally, CA are defined and calibrated in a single operation, since calibration amounts to finding the optimal transition rules. This means that CA are typically implemented much more quickly and easily than traditional spatial models. These advantages are illustrated in the CA model of land use dynamics in St. Lucia.

A Cellular Automata Model for St. Lucia

In the CA land use model of St. Lucia, land uses and land covers are represented by cell states, so the CA dynamics models the year-by-year changes in land use and land cover. For each cell on the map, the cell neighborhood is examined, and on the basis of the land uses and covers within the neighborhood, a set of values, or *potentials,* is calculated, one value for each possible land use that could occupy the cell. These values represent the desirability of the cell for each of the possible land uses, given the composition of the neighborhood. They thus capture local attraction and repulsion effects. In addition, the inherent suitability of the cell itself for each activity is determined; these suitabilities represent such characteristics as elevation, slope of the land, and soil type. Also, the accessibility of the cell to the transport network is calculated, and weighted according to each of the potential land uses, since for some activities accessibility is more important than for others. Finally, considering these three factors, the cell is changed to the land use for which is most desirable—but only if there is a demand for that land use, and these demands are generated outside the CA. The St. Lucia CA is specified as follows:

The Cell Space

The island of St. Lucia and the surrounding coastal waters are covered by 22 506 cells arranged in a matrix of 186 rows by 121 columns. The resolution (cell size) is 250 m., which accords well with available land use/land cover data, but does not permit a very good representation of the terrain.

Unlike traditional CA, the cell space is not assumed to be homogeneous. In order to represent the real variations in land quality, legal and administrative constraints on land use, and variations in the accessibility of land, the CA is run on a cell space in which each cell has an intrinsic suitability for each possible land use (Figure 3, upper right). The suitability of a cell for a particular land use is a measure of the capacity of the cell to support that activity. In the St Lucia model, suitabilities are calculated as a linear combination of a series of physical, environmental, and institutional factors such as topography, soil quality, rainfall, sensitivity to erosion, planning regulations, and other legal restrictions on land use; they are normalized so that all values fall within a range of zero (completely unsuitable) to one. Suitability values are treated as constants, and thus are not altered dynamically during execution of the land use model; values may change, however, as a result of user intervention or sea level changes, as

explained below. The suitability calculations are performed outside the model, in a GIS – *Idrisi* in this case.

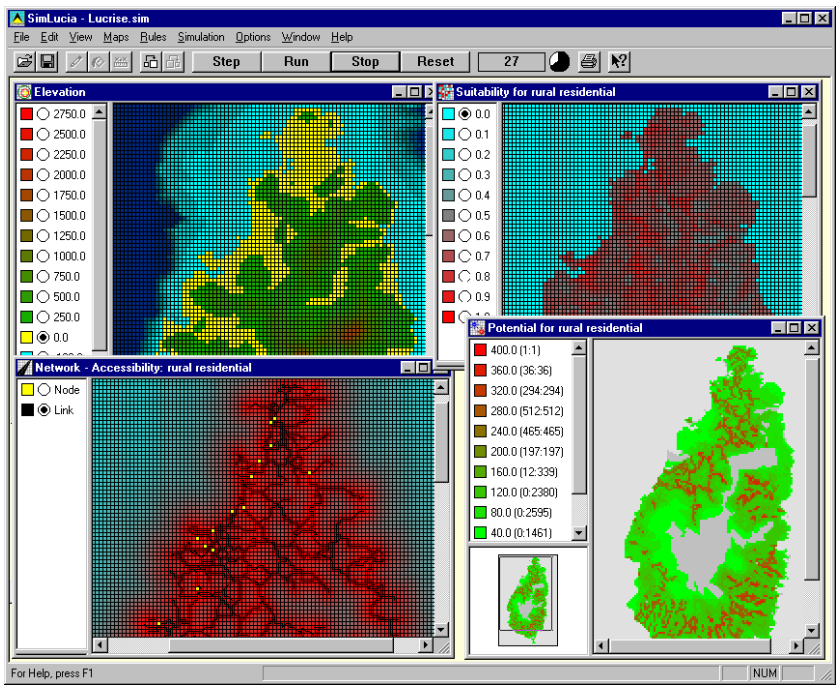


Fig. 3

Another cell space inhomogeneity is related to the accessibility of a cell to the rest of the region. The accessibility value of a cell for a particular function is a measure of the importance of proximity to the road network for that function (Figure 3, lower left). The accessibility factor of a cell for land use *z* is calculated as:

$$A_z = \frac{1}{\left(1 + \frac{D}{a_z}\right)} \tag{1}$$

where D is the Euclidean distance from the cell to the nearest cell on the road network and a_z is a parameter expressing the importance of access to a road for activity z; it is calibrated separately for each activity. The equation returns accessibility values that are in the range (0-1).

The Neighborhood

The cell neighborhood is a circular region eight cells in radius, containing 196 cells falling into 30 discrete distance bands (1, √2, 2, √5,...). This relatively large neighborhood, with a radius of two kilometers, probably comes close to encompassing the locally perceived neighborhood to which locational agents respond.

The Cell States

Fifteen land use and land cover categories are used, each represented by a cell state. These are divided into two categories: *functions*, or active states, for which CA transition rules are defined and which thus have a dynamic, and *features*, which are cell states are fixed. While features states cannot be changed by the transition rules, they may appear as arguments in those rules, and thus affect the dynamics of the function states. Furthermore, they may be changed by other rules outside the CA proper, or by user intervention.

The land use/land cover states are as follows:

Functions:	Features:
1) natural vegetation (mainly bush)	9) forest reserve
2) forest (mainly secondary forest)	10) mangroves
3) agriculture	11) sea
4) industry and quarries	12) beach
5) trade and services	13) coral reef
6) tourism	14) terminals, ports, airports, etc.
7) rural residential	15) infrastructure, water, electricity
8) urban residential	

The Transition Rules

Unlike traditional cellular automata, the transition rules are grouped into three classes which establish the priority with which they are executed. This is necessary because the CA proper cannot handle all the types of state transitions which must be included in the St. Lucia model, reflecting the fact that the model is designed to provide functionality required by the end users, rather than simply to explore the use of CA.

Rules of priority one represent user interventions. They are used to introduce hypothetical planning decisions during the execution of the model, so that the user may run what-if experiments. They include interventions such as imposing a land use on a specific cell (e.g. an airport extension); converting a water-covered area to land (e.g. a land fill project) by editing elevations in the digital elevation map; or adding a transportation link to change the relative accessibility of certain areas. These rules apply only to user designated cells, and, in the case of land use changes, apply *as rules* only for the time step in which they are made; after that, the system either accepts or rejects them on the basis of its endogenous dynamics. A rule of priority one overrides all other possible changes made by rules of priority two or three.

Rules of priority two implement land use/land cover changes caused directly by changes in sea level. With a rising sea level, cells that fall below certain threshold elevations must be converted, for example, from forest to mangrove, or from beach to sea. With a falling sea level, emerging land must be assigned a land cover; this is done on the basis of user-defined suitabilities. The following set exemplifies these rules:

$$\begin{aligned} &if\,(h<0)\,then\,Z_{sea} \\ &if\,(0\le h<0.5)\,then\left[if\left(\sum_{N8}Z_{mangrove}>\sum_{N8}Z_{beach}\right)then\,Z_{mangrove}\,else\,Z_{beach}\right] \\ &if\,(h\ge 0.5)\,then\left[if\,(S_{forest}>S_{natural})\,then\,Z_{forest}\,else\,Z_{natural}\right] \end{aligned} \qquad (2)$$

where h is the elevation, Z is the land use/land cover, N8 is the eight-cell radius neighborhood, and S is the suitability for the indicated land use.

Rules of priority three apply to the Function states listed above. They constitute the heart of the CA land use model. Except for "Natural" and "Forest", which are residual or "no-use" states, these are the land uses that correspond to state variables in the Macro-scale model. For rules of priority three it is first necessary to calculate for each cell a vector of transition potentials, one for each activity. The transition potential is an expression of the 'strength' with which a cell is likely to change state to the state for which the transition potential is calculated. Transition potentials are calculated as weighted sums:

$$P_z = f(S_z).f(A_z).\sum_d \sum_i \left(w_{z,y,d} \times I_{d,i}\right) + \varepsilon_z \qquad (3)$$

where P_z = potential for transition to state z,

$f(S_z)$ = function ($0 \le f(S_z) \le 1$) expressing the suitability of the cell for activity z,

$f(A_z)$ = function ($0 \le f(A_z) \le 1$) expressing the relative accessibility of the cell for activity z,

$$f(S_z) = S_z;\ \text{if} \sum_d \sum_i \left(w_{z,y,d} \times I_{d,i}\right) > 0 \qquad (4)$$

$$f(S_z) = (1 - S_z);\ \text{if} \sum_d \sum_i \left(w_{z,y,d} \times I_{d,i}\right) < 0 \qquad (5)$$

where $w_{z,y,d}$ = the weighting parameter applied to cells with state y in distance zone d ($0 \le d \le 30$),

i = the index of cells within a given distance zone d

$I_{d,i}$ = the Dirac delta function: $I_{d,i}$ = 1 if the state of cell i in distance zone d is y; otherwise $I_{d,i} = 0$

ε_z = a stochastic disturbance term, with $\varepsilon_z = 1 + [-\ln(rand)]^a$

Thus, cells within the neighborhood are weighted differently depending on their state y and also depending on their distance d from the center cell for which the neighborhood is defined (Figure 4). Since different parameters can be specified for different distance zones, it is possible to build in weighting functions that have distance decay properties similar to those of traditional spatial interaction equations. The deterministic transition potentials are subjected to the stochastic perturbation, ε_z, to account for individual preferences and unknown factors in location decisions.

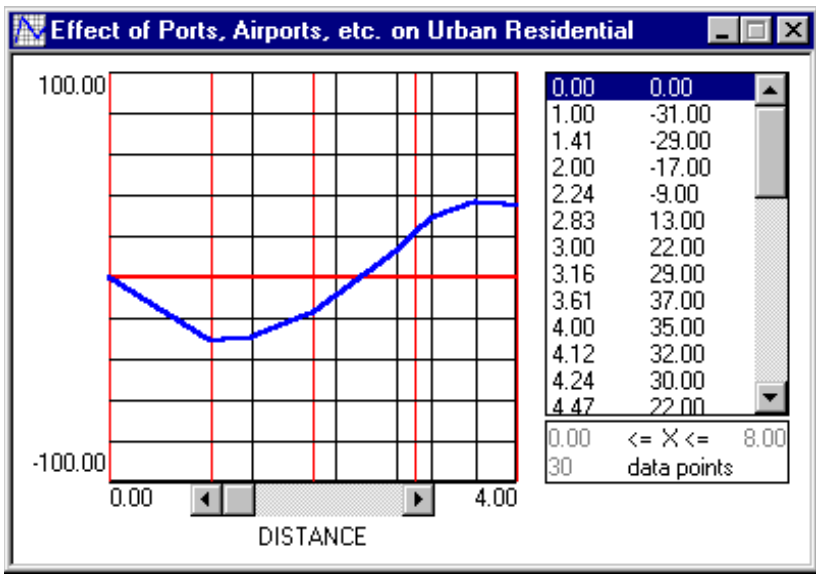


Fig. 4

Values of the weighting parameters $w_{z,y,d}$ represent the total weight accorded to the cells of a particular land use within a distance ring. Negative values express push or repulsion effects, while positive numbers express pull or attraction effects. The weighting coefficients are relative numbers; in other words, what is important is the size of the weights given to various land uses at various distances within the neighborhood, relative to each other, for calculation of the potential for transition to a particular land use, and also the sizes of these weights relative to those used in the calculation of transition potentials for other land uses.

The transition potentials calculated for each cell, one for each functional land use, represent the propensities of the cell to convert to each of these states (Figure 3, lower right). The transition rule is then to convert each cell to the state for which it has the highest potential—subject, however, to the constraint that the number of cells in each state be equal to the demand for cells established by the Macro-scale model. More specifically, to select the T_z cells to receive the function *z* at each iteration, the potentials calculated for all cells for transition to all states are ranked from highest to lowest. Starting with the highest value from this list, the T_z cells with highest potentials for transition to each state *z* are identified and the transitions are executed. Hence, a cell will change to the state for which its potential is highest, unless it is not among the T_z highest potentials, in which case it might change to a state *z'* for which its potential ranks second, and so forth. All the cells for which potentials are not among the T_z highest for any of the *z* states will remain in or return to either the *natural* or *forest* state, depending on the suitabilities.

DRIVING THE CELLULAR AUTOMATON: LINKED MACRO-SCALE MODELS

The Natural Sub-System: Specifying Hypotheses

The natural sub-system of the macro-scale model ensemble consists of a set of linked relations expressing the change through time of temperature and sea level, and the effects of these changes on precipitation, storm frequency and, secondarily, external demands for services and products from St. Lucia. This component is not a true model, but rather a set of linked hypotheses which the user is free to change.

In particular, it is assumed that exogenous changes in mean annual temperature affect precipitation and storm frequency, and that these three variables in turn drive changes in sectoral output of the economy:

$$P_t = f_P(T_t) \quad \text{and} \quad F_t = f_F(T_t), \quad \text{with} \quad T_t = f_T(t) \tag{6}$$

$$E_{i,t} = e_{i,t}\left[1 + f(T_t) + f(P_t) + f(F_t)\right] \tag{7}$$

where t = time
T_i = temperature change
P_i = precipitation change
F_i = storm frequency change
$E_{i.t}$ = vector of sectoral external demands;
$e_{i.t}$ = vector of projected sectoral external demand, *ceteris paribus*

In addition, the exogenous hypothesized change in sea level causes changes in beach area, and this, together with the climate variables, is assumed to affect the demand for tourism, since beach area in St. Lucia is limited while tourism is heavily beach oriented:

$$E_{tourism,t} = e_{tourism,t} \times \frac{1-\beta \times \exp(-\alpha \times N_{beach,t})}{1-\beta \times \exp(-\alpha \times N_{beach,t=0})} \times [1 + f(T_t) + f(P_t) + f(F_t)] \quad (8)$$

where $L_t = f_L(t)$ = sea level change
$N_{beach,t}$ = number of beach cells
α = resilience of tourism industry to changing beach area
β = relative importance of beach tourism in total tourism industry

The relationships described by eqs. 6-8 are obviously strong simplifications of the actual phenomena. In principle, they could be replaced by more elaborate climate models, but realistic climate models are notoriously complex; and while models of the response of agricultural productivity to climate changes are available, for other economic sectors no such models exist. Since the purpose of the St. Lucia model is to provide a tool for exploring the impacts of climate change, rather than to model climate change itself, it seems reasonable to treat these forcing relationships as user-modifiable hypotheses. Nevertheless, the specific default relationships used in the model reflect discussions with members of the UNEP/IOC Task Team on the Implications of Climatic Change in the Wider Caribbean Region.

The Demographic Model

The demographic model calculates the population in St. Lucia at yearly intervals on the basis of estimated births, deaths, and net migration. It is extremely simple in that it is not disaggregated by sex or age cohort; but on the other hand, it does include features that allow it to capture the effects changing economic conditions. Birth, death, and net migration rates are each assumed to be characterized by a secular structural trend; these trends can be defined by the user. In addition, in the case of the mortality and migration rates, the structural component is supplemented by an economic component. While the structural component represents the long term, underlying change in the rate, the economic component captures changes in the structural rate due to changes in economic trends. The economic component is particularly important in the case of migration, since the volume of migration responds quickly to changes in relative economic conditions. Initial values of birth, death, and migration rates are taken from statistics published by the Government of St. Lucia; structural trends in the mortality and migration rates are estimated from time series data in the same sources (Government of St. Lucia, 1992a, 1992b, 1993).

$$bb_t = f_b(t) \quad (9)$$

$$dd_t = 0.5 r_2 f_d(t)[1 + \exp(-r_3(u_t - u_{t=0}))] \quad (10)$$

$$mm_t = r_4 + \frac{[1 - r_5 \exp(u_t - u_{t=0})]}{[1 - r_5]} - 1 \quad (11)$$

$$\Delta p_t = p_t(bb_t - dd_t - mm_t) \quad (12)$$

$$p_{t+1} = p_t + \Delta p_t \quad (13)$$

where p_t = population
bb_t = birth rate
dd_t = mortality rate

mm_t = migration rate
u_t = employment participation index, calculated as the sum of sectoral production data (generated by the economic model), divided by the population.
$f_b(t)$ = structural reproduction rate
$f_d(t)$ = structural mortality rate
r_2 = structural death rate
r_3 = variable mortality rate
r_4 = structural migration rate
r_5 = variable migration rate

The Economic Model: An input-output approach

The economy of St. Lucia is modeled by means of a highly aggregated input-output (I-O) model (Figure 5) which is coupled to the demographic sub-model which describes the economy of the island as a set of linear equations. This approach has the advantage of ensuring that the output of the economic model is internally consistent. In addition, it captures the interdependencies between economic sectors and thus well represents the multiplier effects by which changes in one sector propagate through the entire economy. On the other hand, the method is based on an assumption of constant technical coefficients, so that changes in the underlying structure of the economy, due, for example, to technological innovations, import substitution, or factor substitutions in response to changes in relative prices are not represented. This is not a serious problem for short run situations, but becomes much more of a concern when the modeling period runs to several decades. Ideally, in the context of the present model, the technical coefficients would evolve in response to changes in productivity generated by the cellular model. For example, if agricultural activity is forced onto less suitable land, the output per unit of labor, as represented by a technical coefficient in the I-O model, should decline.

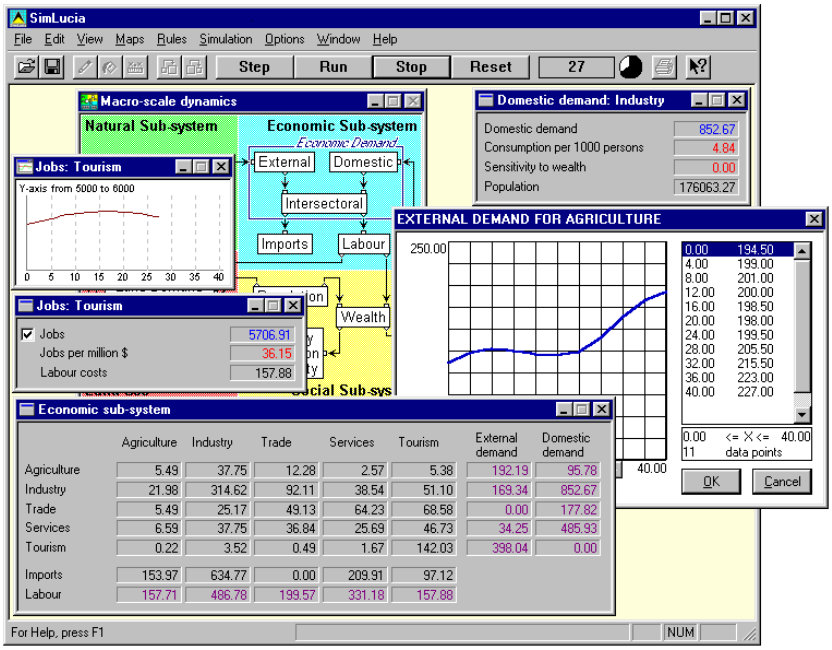


Fig. 5

The I-O model is used in a quasi-dynamic manner, since at each iteration the final demand sectors change exogenously: the domestic demand changes in response to population growth or decline, and exports change in response to both secular trends and the climate

changes as described in eqs. 7 and 8. The equations must therefore be solved at each iteration. In turn, the output of the I-O model affects the demography (eqs. 10 and 11), and through changes in the amount of land required to accommodate changes in sectoral production, it affects also the land use dynamics of the cellular model. The actual I-O table for 1990 was estimated from economic data published by the Government of St. Lucia (Government of St. Lucia, 1992a, 1992b, 1993). It consists of five industry sectors and two final demand sectors. The industry sectors—agriculture, industry, trade, services, and tourism—correspond, after combining trade and services into a single category, to the four economic functions in the cellular model. The final demand sectors—domestic final demand and exports—are exogenous, and drive the I-O model. Domestic final demand is a function of population and the employment participation rate, while exports are given by a user defined temporal trend. The model is as follows:

$$\Delta Y_{i,t} = \Delta Dom_{i,t} + \Delta E_{i,t} \tag{14}$$

$$Y_{i,t} = Y_{i,t-1} + \Delta Y_{i,t} \tag{15}$$

$$\Delta S_{i,t} = \sum_j A_{i,j} \Delta S_{j,t-1} + \Delta Y_{i,t} \tag{16}$$

$$S_{i,t} = S_{i,t-1} + \Delta S_{i,t} \tag{17}$$

$$\Delta M_{i,t} = I_i \times \Delta S_{i,t} \tag{18}$$

$$M_{i,t} = M_{i,t-1} + \Delta M_{i,t} \tag{19}$$

$$\Delta X_{i,t} = \frac{\Delta S_{i,t}}{B_i} \tag{20}$$

$$X_{i,t} = X_{i,t-1} + \Delta X_{i,t} \tag{21}$$

where
$S_{i,t}$ = vector of total sectoral outputs
$Y_{i,t}$ = vector of final demands
$X_{i,t}$ = vector of sectoral employment
$M_{i,t}$ = vector of sectoral imports
$Dom_{i,t}$ = vector of sectoral domestic demands
$E_{i,t}$ = $f_e(t)$ = vector of sectoral external demands
$A_{i,j}$ = matrix of technical coefficients for endogenous sectors
I_i = vector of import coefficients
B_i = vector of employment coefficients

The employment coefficients B_i representing output per employee, were calculated from 1990 sectoral output and employment data. Further,

$$E_{i,t} = f_e(t) \tag{22}$$

and

$$\Delta Y_{i,t} = \Delta p_t c_i \exp\left(n_i \left(u_t - u_{t=0}\right)\right) + \Delta E_{i,t} \tag{23}$$

where
u_t = employment participation index
p_t = total population
c_i = vector of sectoral domestic demand coefficients
n_i = vector of influences of employment index on domestic consumption

Equation 23 expresses changes in domestic demand for the economic sectors in terms of the change in population and the consumption *per capita* of the sectoral product. Consumption *per capita* in turn depends on the relative employment level, reflecting the fact that people

spend differing proportions of their budget on each type of good as their economic status changes.

Land productivity Calculations: The Link to the Cellular Model

Changes in economic activity and population entail changes in the amount of land required to carry out the activity or to house the people. Thus changes in sectoral output and population must be translated into demands for land, using current land productivity or density levels. The new demands for land are then passed to the cellular model, which then allocates the required land (Figure 6).

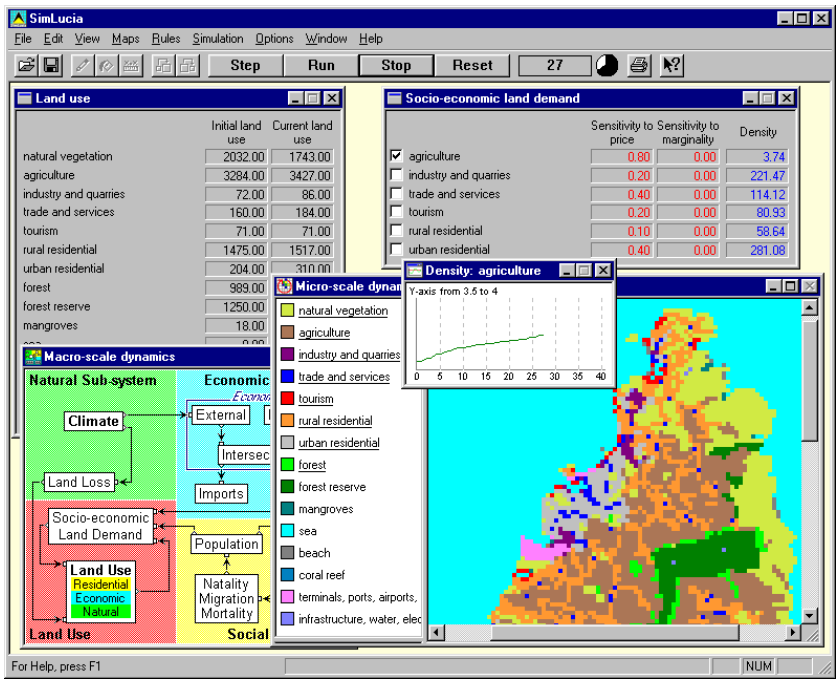


Fig. 6

Density is defined as the number of people who can live or work on one cell. It varies through time primarily as a function of the demand for land relative to its availability—i.e. the scarcity of land. Scarcity is defined in terms of the amount of land occupied by an activity as a proportion of the total amount of land available for the activity, with the latter being defined as the land already occupied by the activity together with land in the *natural* and *forest* states; both quantities are weighted by the suitability of the land. The greater the scarcity of suitable land, the higher the density, *ceteris paribus*. Density also depends directly on the mean suitability of the land occupied by the activity: the more suitable the land, the higher the density. Specifically,

$$W_{i,0} = \frac{X_{i,0}}{N_{i,0}} \tag{24}$$

$$W_{i,t} = W_{i,0} \left(\frac{SS_{i,t}}{TS_{i,t}} \frac{TS_{i,0}}{SS_{i,0}} \right)^{\sigma_i} \left(\frac{SS_{i,t}}{N_{i,t}} \frac{N_{i,0}}{SS_{i,0}} \right)^{\zeta_i} \tag{25}$$

where the subscript i includes both residential and economic activities, and

$W_{i,t}$ = density of activity i
$SS_{i,t}$ = suitabilities for activity i summed over the cells occupied by the activity
$TS_{i,t}$ = suitabilities for i summed over all natural and forest cells
$N_{i,t}$ = total cells required for activity i
$X_{i,0}$ = initial sectoral employment
σ_i = sectoral sensitivities to land pressure
ζ_i = sectoral sensitivities to land quality

Finally, the total land that is required for each activity is calculated, and these demands are then passed to the cellular model; thus the loop between macro- and micro-models is closed:
:

$$N_{i,t+1} = \frac{X_{i,t}}{W_{i,t}} \tag{26}$$

$$N_{p,t+1} = \frac{p_t}{W_{i,t}} \tag{27}$$

where p_t = total population and other symbols are as above.

In addition, while the model is running, the suitability values for all cells actually occupied by a particular land use are monitored. Changes in the total and average suitability for each land-use are passed back to the macro-level and result in further changes in the land density variables. In other words, the detailed land suitabilities and land-use patterns in the micro-level model have their effect in processes that are modeled at the Macro-level. The geography at the micro-level thus affects the global dynamics directly and continually.

DISCUSSION AND CONCLUSIONS

It might seem that linking a number of models, each with its own uncertainties and inadequacies, would result in a multiplication of errors to the point where the output of the integrated model would be useless. That does not seem to be the case. Since the models are generally complementary, each tends to limit the size of errors that the others can produce. For example, a runaway population model might try to put an impossible number of people in the region. But before that could happen, feedback from the economic model would increase the out-migration rate to limit the population. The economic model would in turn be responding to information on land availability and suitability fed to it from the CA and the GIS. Experiments with a model which operates at three spatial scales (national, regional, and cellular) show that errors in both the macro-scale economic-demographic model and the CA land use model are reduced substantially (on the order of 70% for the former) when they are linked (White and Engelen, 1999).

The integrated modeling approach described in this chapter brings together not only different models but also different modeling techniques. The macro-scale models represent the system dynamics tradition of modeling using differential or difference equations. At the micro-level, GIS capabilities are used to model the suitabilities and other spatial inhomogeneities that characterize the cell space—which is essentially the same as a GIS raster space. The CA itself might thus be considered, in a sense, to be a fully dynamic GIS. This “dynamic GIS” interpretation of the CA makes explicit the fact that the spatial patterns stored and manipulated in a GIS are typically dated: in general they represent an unstable situation that will evolve toward an equilibrium configuration. But that final state is not reached, because the macro-scale models continuously displace the equilibrium that the CA is

trying to find. Similarly, the dynamics of the CA displace the equilibrium which the macro-scale models are trying to reach. This propagation of disequilibrium exemplifies the non-linearity of the linked models.

The non-linearity (together with the stochasticity) allows the model to capture explicitly two aspects of the inherent unpredictability of the world. It also means that the system trajectories are subject to bifurcations. In other words, near critical points, small changes in parameter values or initial conditions, as well as the stochastic fluctuations, can alter the future of the system substantially. Bifurcations are the key to proper use of this type of model. They define domains in parameter space where the results are qualitatively similar regardless of the precise values of the parameters. Once the limits of the domain are passed, however, the behavior of the model, and thus the results generated, will change noticeably. So while we can never know precisely what the future will bring, the model will give a usefully reliable indication that if current conditions are like *this*, then the situation in ten years will probably be substantially like *that*. Such general indications of future conditions are potentially quite useful to planners and policy makers.

SOFTWARE

A fully functional demo version of the SIMLUCIA software, as well as a manual, can be downloaded from http://www.riks.nl .

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