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RESEARCH ARTICLE

Dynamical coupling of multiscale land change models

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Abstract No single model or scale can fully capture the causes of land change. For a given region, land changes may have different impacts at different places. Limits and opportunities imposed by biophysical and socio-economic conditions, such as local policies and accessibility, may induce distinct land change trajectories. These local land change trajectories may, in turn, indirectly affect other places, as local actions interact with higher-level driving forces. Such intraregional interdependencies cannot be captured by studies at a single scale, calling for multiscale and multilocality studies. This paper proposes a software organization for building computational models that support dynamical linking of multiple scales. This structure couples different types of models, such as cell-space models with agent-based models. We show how results in multiscale models can flow both in bottom-up and top-down directions, thus allowing feedback from local actors to regional scales. The proposal is general and independent of specific software, and it is effective to model intra-regional, bottom-up and top-down interactions in land change models. To show the model's potential, we develop a case study that shows how a multiscale model for the Brazilian Amazonia can include feedbacks between local to regional scales.

Keywords Land change modelling · Multiscale modelling · Amazonia · Deforestation models · Scale feedbacks · Dynamical model integration · Agent-based modelling

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Introduction

Modelling land change involves the use of representations of interplays within the land use system to explore its dynamics and possible developments (Verburg 2006). Models are also useful to project the impact of policy changes on the current land use trajectory (Pijanowskia et al. 2002). This is not a straightforward task, as land changes are the result of interplays between human actions and biophysical limits, which occur over a wide range of temporal and spatial scales. At each scale, there are different causes associated to land change, since decisions that influence land change occur at different levels of social organization: households, communities, nations, global companies, trade agreements (Lambin and Geist 2001; Lambin et al. 2001). Thus, to understand land change, and properly subside public policies regulating land use, it is necessary to consider interests and potentially conflicting actions at different levels and geographical scales (Becker 2005).

Consider, for example, the problem of estimating land change in tropical forests and supporting policy making for environmental conservation. Evidence from studies in Brazilian Amazonia points out that localized deforestation control policies, such as creating protected areas, might stimulate occupation of other areas in the medium and long run. The productive system may reorganize and induce occupation of other areas to support a growing demand for agricultural products. Such intraregional relations result from actions on different hierarchical levels. At the global scale, the national and international commodities markets (beef, grains and timber) drives demand for land change. At the local scale, people react in accordance to their specific socio-economic and biophysical contexts, creating different trajectories. Thus, single scale modelling approaches can only provide limited support to policy scenario analysis when bottom-up and top-down interactions occur. This calls for multiscale, multiapproach studies to understand land change.

There is a great variety of modelling approaches described in the literature, with different objectives, techniques, theoretical basis and modelling traditions (Briassoulis 2000; Brown et al. 2008; Lambin 1997; Lambin et al. 2001; Verburg et al. 2006, 2004). Among them, multiscale modelling has long been in the research agenda of the land change community (Veldkamp and Lambin 2001; Turner et al. 1995; Veldkamp et al. 2001). Despite important progresses, there is still a need for approaches and techniques to deal adequately with scaling issues (Verburg 2006). Understanding the interdependencies between scales will remain a primary research frontier for the land change community for the next decade. This is one of the challenges facing the Global Land Project (Moran et al. 2005).

A natural extension to land change modelling is to use the idea of hierarchical multiscale modelling. Multiscale models have been used in ecology for solving different types of problems. Wu (1999) presents a general discussion on hierarchy and scaling issues. He proposes the hierarchical patch dynamics paradigm (HPDP), a three-step approach for developing multi-scale models: (1) identifying patch hierarchies, (2) making observations and developing models of patterns and processes around focal levels, and (3) extrapolation across the domains of scale using a hierarchy of models. Wu and David (2002) further discuss how the HPDP is used to develop a model for the Phoenix urban landscape. Li et al. (2006) show how the object-oriented hierarchical patch dynamics paradigm (HPDP) can be used for modeling complex groundwater systems across multiple-scales. Thus, the hierarchical patch dynamics paradigm is a general framework, which is applicable to different types of problems. A particular type of problem associated with hierarchical patch dynamics is the question of land change, as discussed in the present paper. In the models of land change, the hierarchical spatial structure is built as set of nested grids.

Currently, hierarchical models land change incorporates mostly top-down interactions. These models calculate the quantity of change (often referred as demand for change) using tools such as non-spatial economic model or trend analysis, usually at the national or regional scales. This demand is then spatially assigned based on suitability maps built using selected controlling factors such as soil quality and nearness to roads. The rationale for this approach is the demand-driven nature of land use change, specially related to commodities. Examples of this approach are: CLUE (Veldkamp and Fresco 1996; Verburg et al. 1999), CLUE-S (Verburg et al. 2002), Dinamica (Soares-Filho et al. 2002), GEOMOD (Pontius et al. 2001) and RIKS (White and Engelen 2000; White et al. 1997). For example, the CLUE model (Veldkamp and Fresco 1996) has two spatial grids with different resolutions, representing a coarse and a fine scale. Results of changes in the coarser scale are passed on to the finer one for change allocation. Both scales use the same allocation procedure with different driving factors, and different linear regression models estimate cell suitability for change.

Some recent applications of these models involve combining different approaches at different scales.

Castella and Verburg (2007) applied two modelling approaches to the same study area in a district in Vietnam. He used an ABM (agent-based model) and a pattern-oriented statistical model (CLUE-S) to link the underlying causes of land change to their resulting spatial patterns. The CLUE-S model covered the whole district area, while the ABM model was applied to the villages within the district. But in this case, there was no direct coupling between the models. In a broader context, the EURURALIS project (Verburg et al. 2008) coupled a global economic model and an integrated assessment model to calculate changes in demand for agricultural areas at country level in Europe, and CLUE-S translated these changes at 1 km^2 resolution. In this case, interaction was top-down only.

Bottom-up relations and scaling issues have also started to be addressed by agent-based models (ABM) (Parker et al. 2002), in which communication between individuals produces global patterns from local actions. The flexibility of ABM also allows both top-down and bottom-up relations (Brown et al. 2008). The research community views ABM as a promising approach to address multiscale modelling problems (Verburg et al. 2006).

Considering the current state of research, the goal of this paper is to present a method to build multiscale land change models, which makes it possible to included feedback in both top-down and bottom-up directions. We consider the case when single-scale models, using different modelling approaches, are built independently and then coupled dynamically. Such single-scale models may use an ABM or any other modelling technique. Allowing independent development of models at different scales is a convenient assumption, since many useful single-scale models exist, each using a spatial and temporal scale most convenient for its purposes.

The challenge for coupling independent models is to support a bidirectional flow of information from one model to the other. To address this challenge, this paper presents a method for dynamical coupling of land change models at different spatial and temporal scales, introducing the ideas of Spatial and Analytical Model Couplers. To show the flexibility of our approach, we present a hierarchical two-scale example for the Brazilian Amazon, which includes top-down and bottom-up feedbacks. We analyse alternative patterns of deforestation in a given site under different regional scenarios and then to test bottom-up feedback mechanisms from local decisions to regional distribution of deforestation rates.

The paper is organized as follows. We first present our method for dynamical coupling of multiscale models, highlighting the software organization. Then, we show the case study in the Brazilian Amazonia, built using the TerraME modelling environment (Carneiro 2006). We then present results of the multiscale model application in Amazonia before giving our conclusions.

Dynamically coupled multiscale, multiapproach models

This section describes the proposed software structure to build multiscale and multiapproach computational models. Similar to Gibson et al. (2000), this paper uses the term *scale* in a broader sense than its traditional cartographic meaning, which is associated to spatial measurements. For us, a scale has *spatial*, *temporal*, and *analytical* dimensions. The spatial property of scale considers the geographical area under study and the spatial resolution used for data sampling. The temporal dimension of scale considers the time period considered in the analysis and the frequency when changes are recorded. The analytical dimension of scale refers to the rules (for example, agent behaviour) and to the indirect techniques (for example, statistical methods) that represent change.

Software organization

The proposed software organization allows researchers to develop independent scale-specific models, and then combine them at run time. We expect individual models to have different temporal and spatial scales (resolution and extent) and use varied modelling techniques. When coupled, a model may be influenced by the results of the upper or lower scale at each time step. In hierarchical models such as the one shown in Fig. 1, the top-down linkages provide context information from higher levels; the bottom-up linkages provide feedbacks to the upper hierarchical model.

Our proposal allows links between as many scales as necessary. Multi-agent models can be combined to other approaches, such as cellular automata and statistical models, and the software organization

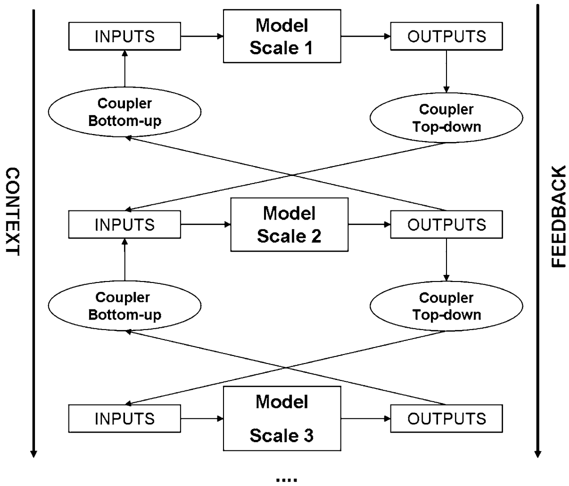

Fig. 1 Schematic representation of the multi-scale coupling mechanism

allows bidirectional feedbacks in multiscale models. By allowing mixings of different models, the proposed model organization differs from existing multiscale land change models, such as CLUE (Veldkamp and Fresco 1996), which has two spatially explicit scales that use the same allocation procedure.

Our approach to build multiscale models uses a two-step approach. First, the researcher designs a separate model for each scale, and divides each model into *Spatial, Temporal* and *Analytical* submodels. The second step introduces the idea of *Model Couplers* to define links between scales. Three types of couplers are necessary: (a) *Spatial Couplers*, which define the spatial relations between scales (for example, father-son cell links); (b) *Analytical Couplers*, which define the top-down and bottom-up flow of information between models. These couplers represent the multiscale dependencies and feedbacks; and (c) *Temporal Couplers,* which sets up the combined temporal execution of the models. The rest of this section details this software organization.

Modular design

Decades of experience in software engineering suggest the hardest parts of software production are achieving a clear *architectural design* (Brooks 1982) and setting up a feasible strategy for *modular development* (Parnas 1972). Good design and modular organization are also important for land change models, since they allow easier maintenance and reuse. Thus, to be able to handle multiple scales in a flexible way, a land change model should be organized into distinct submodels, independent of one another (Carneiro 2006). The *spatial submodel* describes the different extents and resolutions of the spatial scales used in the model. Each spatial scale can define its own proximity relations and its local properties or constraints. The *temporal submodel* describes the time period and the frequency of execution of rules and inference methods. The *analytical submodel* includes rules that describe the behaviour of agents. Alternatively, the *analytical submodel* uses pattern-oriented, empirical procedures to simulate change.

At first, it may seem difficult to design land change models that are modular. However, a modular organization brings about large gains, since it simplifies creating complex models with multiple approaches. The TerraME software used in this paper (see "Implementation using TerraME" below) is one example of a modelling environment that provides the modularity needed for flexible multiscale integration.

Model couplers: spatial couplers

A *Spatial Coupler* makes spatial relations explicit, linking geographic objects in different scales. At each spatial scale, the geographic objects may be represented differently. Examples of such representations include: (a) area regions whose boundaries are polygons; (b) cellular automata organized as sets of cells, whose boundaries are the edges of each cell; (c) point locations in two-dimensional space.

In Moreira et al. (2008), we describe spatial relations among geographic objects at different scales and consider hierarchical relations and action-at-a-distance' relations. Hierarchical relations handle nested objects, such the relation between states and municipalities. Action-at-a-distance relations handle interactions which are network-dependent, such as when a modeller uses the global wood market chain to define the relation of deforested areas in Amazonia to wood market consumers in Europe and USA. In this paper, we focus on hierarchical multiscale models. In such models, the links represent father-children (for downscaling) and children-father relations (for upscaling). We propose three specific *Spatial Coupler* strategies to deal with hierarchical relations, when geographic objects at both scales use

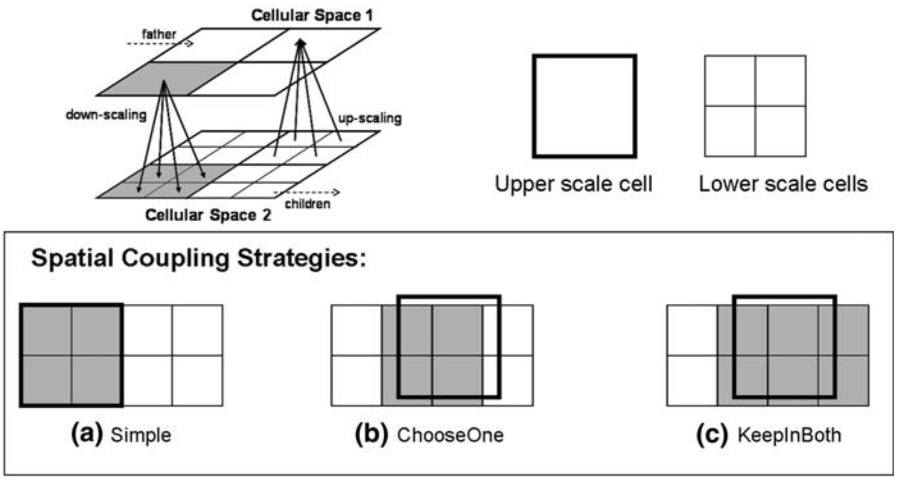

Fig. 2 Schematic representation of strategies for spatial coupling in the case of regular cells: **a** Simple; **b** ChooseOne; **c** KeepInBoth

an area representation (polygons or regular cells), as shown in Fig. 2:

(a) *Simple*: when hierarchical spatial resolutions match, and a simple "within" spatial operator can define the parenthood links between scales.

(b) *ChooseOne*: when hierarchical spatial resolutions do not match, this strategy chooses the upper scale land unit with larger percentage of intersection as the father.

(c) *KeepInBoth*: when the hierarchical spatial resolutions do not match, this strategy keeps all intersected upper land units as fathers. The percentage of each intersection is stored as an attribute of the link.

Action-at-distance relations use other coupling strategies. In Moreira et al. (2008), we show how to represent the spatial relation between two geographic objects at different scales linked though a network (a farm in Amazonia to a consumer centre in Europe). "Implementation using TerraME" describes how we carried out these hierarchical coupling strategies in the TerraME modelling environment, and how they are parameterized.

Model couplers: analytical couplers

An *Analytical Coupler* sets up the flow of information between scales. In hierarchical multiscale models, it defines how the output of a model (at a certain time step) serves as the input to another. The modeller may use top-down analytical couplers, bottom-up analytical couplers, or a strategy with both top-down and bottom-up couplers. The content of each of these couplers depends on the models being coupled, and on the multiscale application goal. Analytical couplers use spatial couplers to assess geographic object-to-object relations, in cases where the flow of information occurs between specific objects at different scales (for example, father to son). In the example below, the top-down analytical coupler is a function that sums the deforested area at the coarser scale using cells that have children at the local scale. The coupler then sends the result to the finer scale model as the demand for change. The local model uses this demand as a non-mandatory input for an agent-based model.

Model couplers: temporal couplers

A Temporal Coupler is a scheduler that controls execution of different models. Consider a model that samples forest clearing and land abandonment on a monthly basis. Suppose we couple it to hydrological model at a finer temporal resolution (weekly) and to a climate change model at a coarser temporal scale (yearly). Each model needs a different execution scheduler, defined in its temporal submodel. This scheduler coordinates execution of each *Analytical Submodel* and related *Analytical Couplers*. This *Temporal Coupler* (scheduler) defines when the results from one model are sent to another. For the nested forest clearing and hydrological model mentioned above, the Temporal Coupler would ensure the hydrological model (which has a finer temporal resolution) sends its results to the forest-clearing model at the right moment.

Illustrative example: Amazônia and São Felix do Xingu

Overview

To clarify our proposal, we built a case study for modelling deforestation in the Brazilian Amazon, using two scales. At the regional scale, we have a deforestation model, covering all Brazilian Amazonia at 25 × 25 km^2 resolution. At a local scale, we have a deforestation model in São Felix do Xingu, Pará State, a hot spot of deforestation in Central Amazonia (Becker 2005; Escada et al. 2005). The local model covers an area of roughly 50,000 km^2, using 1 × 1 km^2 cells. Figure 3 shows both study areas. The two models at different scales provide complementary information about the human occupation in the region.

At the macro scale (Amazonia) we used a statistical allocation procedure based on regression models, adapted from the CLUE model (Veldkamp and Fresco 1996) by Aguiar (2006). The statistical analysis uses a database combining remote sensing and census based information. As independent variables, we took 40 environmental, demographical, agrarian structure, technological, and market connectivity indicators. The dependent variables are the land-use patterns (pasture, temporary and permanent crops, non-used agricultural land). We projected the percentage of deforestation in each cell from 1997 until 2025 under

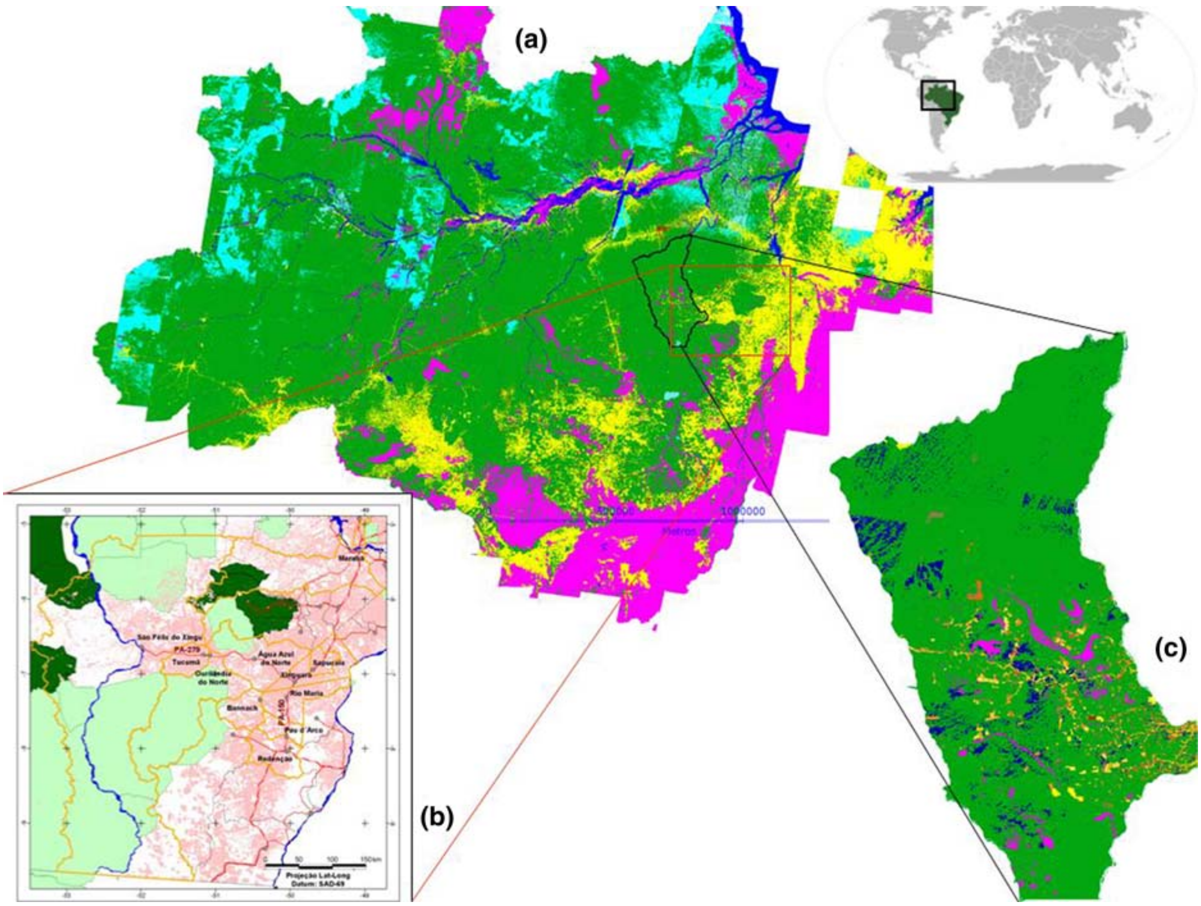

Fig. 3 Study area: **a** Macro model: Brazilian Amazonia; **b** PA 279 area, which is the connection to the local study area (Iriri/Terra do Meio), including the municipalities of São Felix do Xingu, Tucumã, Ourilândia and the southeast of Pará State; **c** Local model: Iriri/Terra do Meio (source: INPE 2008)

different scenarios of market pressure for land and conservation policies. Starting from 1997, the model captured new deforestation frontiers according to 2003/2004 deforestation maps (INPE 2008), including São Felix do Xingu. For details of model parameterization and validation, see Aguiar (2006) and Aguiar et al. (2007). In the multiscale model we build in this paper to explain our method, this macro scale model represents the agricultural frontier expansion over the whole Amazonia. It answers questions such as: *Given a certain pressure for expansion of agricultural land, which areas in the Amazonia would be occupied first?*

At the local scale, we built an agent-based deforestation model for a hot spot of deforestation in São Felix do Xingu, with two sets of agents: small and large farmers. Small settlers favour closeness to roads and urban centres. Large farmers prefer large pieces of inexpensive land, not necessarily close to roads. Each actor has its set of controlling factors and decision rules. These factors include nearness to roads, land availability and cost, and law enforcement. Currently, a Brazilian law (known as the *Forest Code*) dictates that 80% of forest inside private properties must be preserved. However, landowners largely disrespect this law. To account for this practice, the model scenarios consider cases where the law is enforced and not enforced. The quantity of change in the area is an exogenous variable. However, it may not be allocated fully, depending on the behaviour of local agents. Thus, this model answers questions such as: *Given a certain pressure for expansion of agricultural land in São Felix do Xingu, how local deforestation patterns would evolve under different scenarios?*

The case studies show our method in practice. First, we illustrate the usefulness of coupling the models using a pure top-down interaction. We combined two macro scenarios (high and low demand for new land) to a local scenario of no law enforcement. This provides alternative contexts of pressure for new agricultural land to a local scenario of no law enforcement. In a second step we illustrate a complete loop of top-down and bottom-up interactions. We compare two local scenarios (without/with law enforcement) to one macro scenario (high pressure for new land). The local model interacts with the regional model modifying the regional distribution of deforestation results according to alternative local actions to enforce the law. In the next time step, the macro models, on its turn, sends a modified pressure to the local model.

Scale interactions

This section describes how we coupled the two models, creating feedback loops. The top-down relation provides context to the local model. The regional model captures the process in which cattle ranchers decided to migrate to the São Felix area due to its biophysical, accessibility and market conditions. It signals an expected demand for new land (forest conversion to pasture) at the local scale. Local policy decisions, expressed at the local scale, may prevent all expected change from occurring. *Bottom-up feedback mechanisms* send this information back to the larger scale and thus change the macro scale model.

To build a multiscale model from the individual parts, we specify the Spatial, Analytical and Temporal coupler. For the top-down *Spatial Coupler*, we used the *KeepInBoth* strategy to set up the father-son relations, as the cellular spaces were not coincident. For the top-down *Analytical Coupler,* we defined a function which sums up the allocated area for all agricultural uses in the $25 \times 25\ \text{km}^2$ area that matches to the $1 \times 1\ \text{km}^2$ cells of the local scale. This value is the demand for change at the local scale at simulation time *t*. As bottom-up *Analytical Couplers* we defined two functions:

(a) *At time t, update land use of each* $25 \times 25\ \text{km}^2$ *cell*. This updates the result of the macro model at time t, making the percentage of agricultural land use at the regional scale compatible with the results of the local scale. A difference in total allocated area at the macro scale may arise, if local policy decisions prevent all the expected change (sent by the top-down coupler) from occurring. In this case, we change the macro demand value defined for next year, adding this difference.

(b) *At time* $t + 1$*, update suitability of each* $25 \times 25\ \text{km}^2$ *cell*. Changes the suitability of the $25 \times 25\ \text{km}^2$ cells based on the previous results at the local scale. If local actions prevent full allocation of the projected demand, the upper scale cells will decrease the original suitability estimate.

In this example, the *Temporal Coupler* is sequential, as both temporal scales are the same. Both models run from 1997 to 2025, in a yearly basis. At each time step, we first run the macro scale analytical submodel (Amazonia), followed by the top-down *Analytical Coupler* (*pressure for new land*). Afterwards, we run the local analytical submodel (São Felix) and then the bottom-up *Analytical Couplers*.

Implementation using TerraME

We used the TerraME software (Carneiro 2006) to test our proposal and build case studies. This software matches our needs for modular multiscale model development, providing a high-level modelling language and direct access to a geographic database, and supporting the broader definition of *scale* proposed by Gibson et al. (2000) and adopted by the authors. TerraME provides the *Environment* data type, which encapsulates the analytical, spatial and temporal dimensions of a scale, which are modelled separately. *Environments* can be nested, creating a multiscale model from individual parts. To build our proposed software organization in TerraME, we use the *Environment* data type as a container for each model. The software also provides a scheduler that controls the flow of execution for each *Environment*, which matches our idea of a *Temporal Coupler*. We used TerraME functions to build our *Analytical Couplers*.

We added the *Spatial Coupler* data type to TerraME, as an extension to the basic Neighbourhood functions provided by the software, which use a Generalized Proximity Matrix (GPM) (Aguiar et al. 2003). A GPM is generic way of expressing spatial relations between geographic objects such as cells and agents. The original implementation of the GPM captured absolute and relative space neighbourhood relations among objects of the same type at the same scale. The *Spatial Coupler* is an extended GPM that links objects of different geometries (points, lines, cells, polygons) at different scales. Moreira et al (2008) details how to parameterize Spatial Couplers.

We now describe the steps to create a multiscale model using TerraME. First, the single-scale models are developed in modular way describing their spatial, temporal and analytical dimensions. Then, we enclose each model in a *Model Environment*. For each pair of *Model Environments* to be coupled, at least one *Analytical Coupler* function (top-down or bottom-up) has to be implemented, and a specific *Coupling Environment* created to encapsulate them. Then, we choose the suitable *Spatial Coupler*. We create an *Integration Environment* nesting the two *Model Environments,* the necessary *Coupling Environments* (bottom-up and top-down) and the *Spatial Coupler*. Figure 4 shows the TerraME approach conceptually and in our case study.

Case study results and discussion

Top-down influences: comparison of local model results under two alternative macro scenarios

In this section we show how local patterns of occupation evolve under two alternative macro scenarios related to the overall distribution of

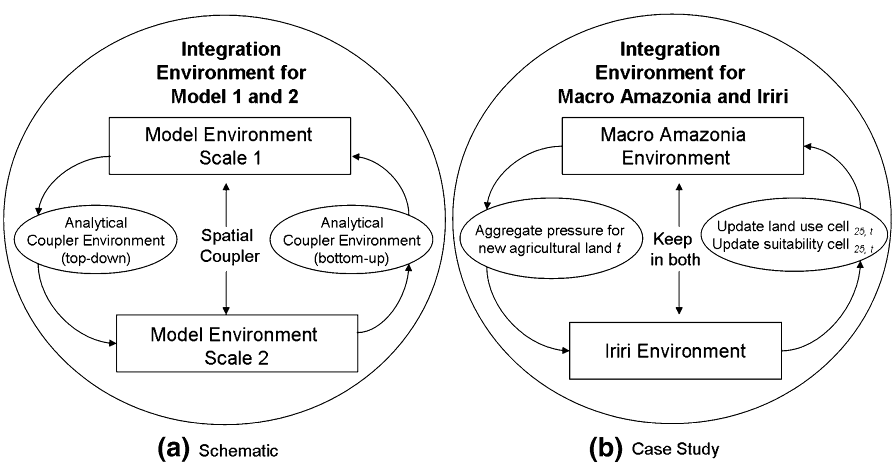

Fig. 4 Implementation approach in TerraME: **a** schematic representation; **b** case study

deforestation over the whole Amazon. The macro model uses the quantity of change (deforestation demand) for the whole region from 1997 to 2025 as an exogenous variable. Macro Scenario A (*high deforestation pressure*) assumes that deforestation rates after 2008 will be similar to the average of last decade (around 19,400 km^2/year). Macro Scenario B (low deforestation pressure) represents a constant decrease of rates until they reach a low rate of 1,000 km^2/year, assuming combined market and policy mechanisms will work to achieve a low residual rate. The projected percentage of deforested areas in Amazonia would rise from the current 17% (in 2007) to 27% (in 2025) in the Macro Scenario A, and to 20% (in 2025) in Macro Scenario B.

At the local scale, we used a scenario with no law enforcement. Figure 5a, b show the spatial patterns of deforestation projected for 2025 for both macro scenarios. Figure 5c, d show the real deforestation patterns in the São Félix region (INPE 2008) and the simulated one in 2005, using 1997 as the starting date. The simulated pattern matches the real deforestation. The projected deforestation for 2025 at the local scale for both macro scenarios is shown in Fig. 5e, f.

The results show that change in the macro scenarios is not homogenous over Amazonia, as socio-economic and biophysical conditions vary. Some areas are more suitable for agricultural expansion than others. Connectivity to markets has a strong

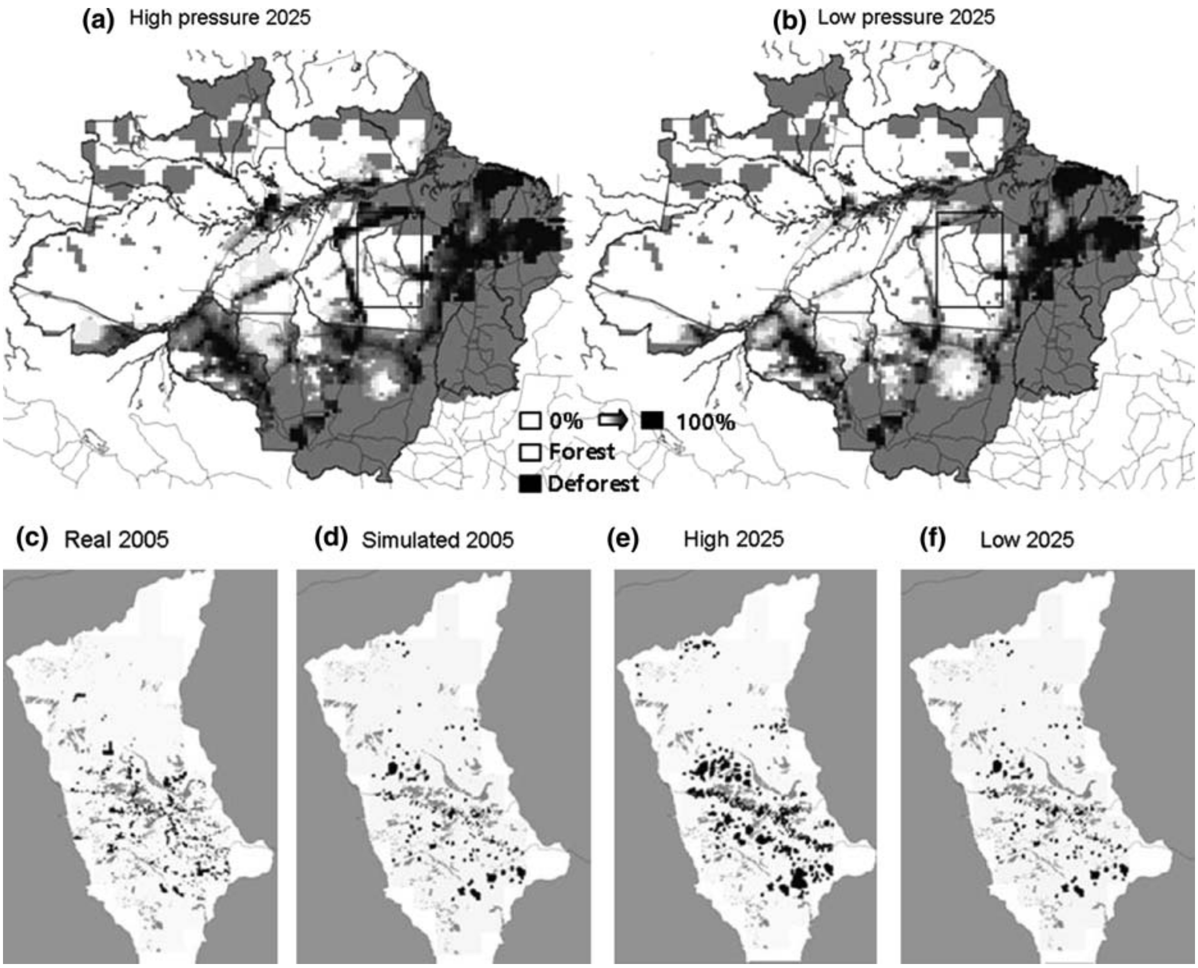

Fig. 5 Case study simulation results of top-down interaction: **a** Percentage of deforestation in each cell projected to 2025 in Macro Scenario A; **b** Percentage of deforestation in each cell projected to 2025 in Macro Scenario B; **c** Deforestation pattern in the Iriri region in 2005; **d** Simulated pattern in 2005; **e** Simulated pattern in 2025 nested in Macro Scenario A; **f** Simulated pattern in 2025 nested in Macro Scenario B

influence on the spatial patterns, as shown in Aguiar (2006). If we compare the increase in deforested areas in the whole Amazonia and in a hot spot of deforestation such as São Felix, relative increases are different. For the whole Amazonia from 2007 to 2025, the model projects an increase of 55% in the deforested area in Macro Scenario A and of 15% in Macro Scenario B. The change in São Felix is higher for the same period, even in a low-pressure demand scenario. In Macro Scenario A, the projected deforested area São Felix would increase by 263% and by 143% in Macro Scenario B.

This shows that pressure for change at different sites in a large region such as Amazonia depends not only on local conditions, but also on processes that act at higher hierarchical levels. The higher pressure for change in São Felix compared to other places reflects its higher suitability for cattle expansion when compared to other areas in Amazonia, due to climatic, soils and market conditions. Other areas may be more suitable for mechanized agriculture with plain relief and easier access to export facilities. This shows the potential of multiscale models to reveal local and regional land change processes, taking in account limits and opportunities associated to diverse biophysical and socioeconomic contexts.

Combining top-down and bottom-up influences: comparison of macro Amazonian results with feedback from the two alternative local scenarios

In this section we show the effects of combining top-down and bottom-up linkages. We used Macro Scenario A which assumes a growth of deforestation rates after 2008 to the levels of the last decade. Two spatial projections for deforestation in 2025 for the regional scale are shown in Fig. 6, given alternative scenarios at the local scale. Local Scenario A assumes no law enforcement in obedience to the *Forest Code*. The whole area could be deforested given enough pressure. Local Scenario B assumes law enforcement in obedience to the Forest Code. Only 20% of farm areas will be deforested, independent of the external pressure for land.

As the São Felix region is one of the hot spots of deforestation in Amazonia, the effect of having local law enforcement in the area is felt regionally at the macro scale model, due to the feedback mechanisms. Deforestation resulting from the simulation depends on the local scenario conditions and the agents' behavioural rules. When the finer scale model rejects the demand projected by the macro model, the bottom-up feedback corrects the projected areas at the macro scale and changes the suitability of the upper scale cells. The macro scale model assumes the demand for deforestation is an exogenous variable, dependent on external market forces. Demand increase and decrease are proxies of market constraints, representing higher or lower pressure for forest conversion. When the finer scale model rejects the demand projected for a given area, the difference will be redistributed as pressure to other locations. This simulates the intraregional "leakages" using the Kyoto protocol terminology. This shows an effect not previously considered in other modelling exercises in the Amazon (Soares-Filho et al. 2006; Laurance et al. 2001). The productive system may reorganize when certain policies impose localized constraints (Aguiar 2006). Thus, models incorporating top-down and bottom-up interactions project effects not easily detectable by single scale models.

Conclusions

No single model or scale can fully capture the causes of land change. This paper presents a software organization for building multiscale, multilocality land change models that include top-down and bottom-up relations. We developed a two-scale model to show how to build top-down and bottom-up feedbacks in a real world hierarchical model that covers different spatial extents. This method works when single-scale models are built independently and then coupled dynamically. One hindrance of the proposed approach is the need to adopt a modular design, where each individual model needs to distinguish its analytical, spatial and temporal dimensions. At first, it may seem difficult to design modular land change models. However, a modular organization brings about large gains, since it simplifies creating complex models with multiple approaches. Another challenge is shared by coupled models in general. We need good techniques to validate coupled models, especially when they include multiple feedbacks.

This paper is a first step towards more detailed studies on the balance between regional and local interactions. Our aim is to continue to improve such

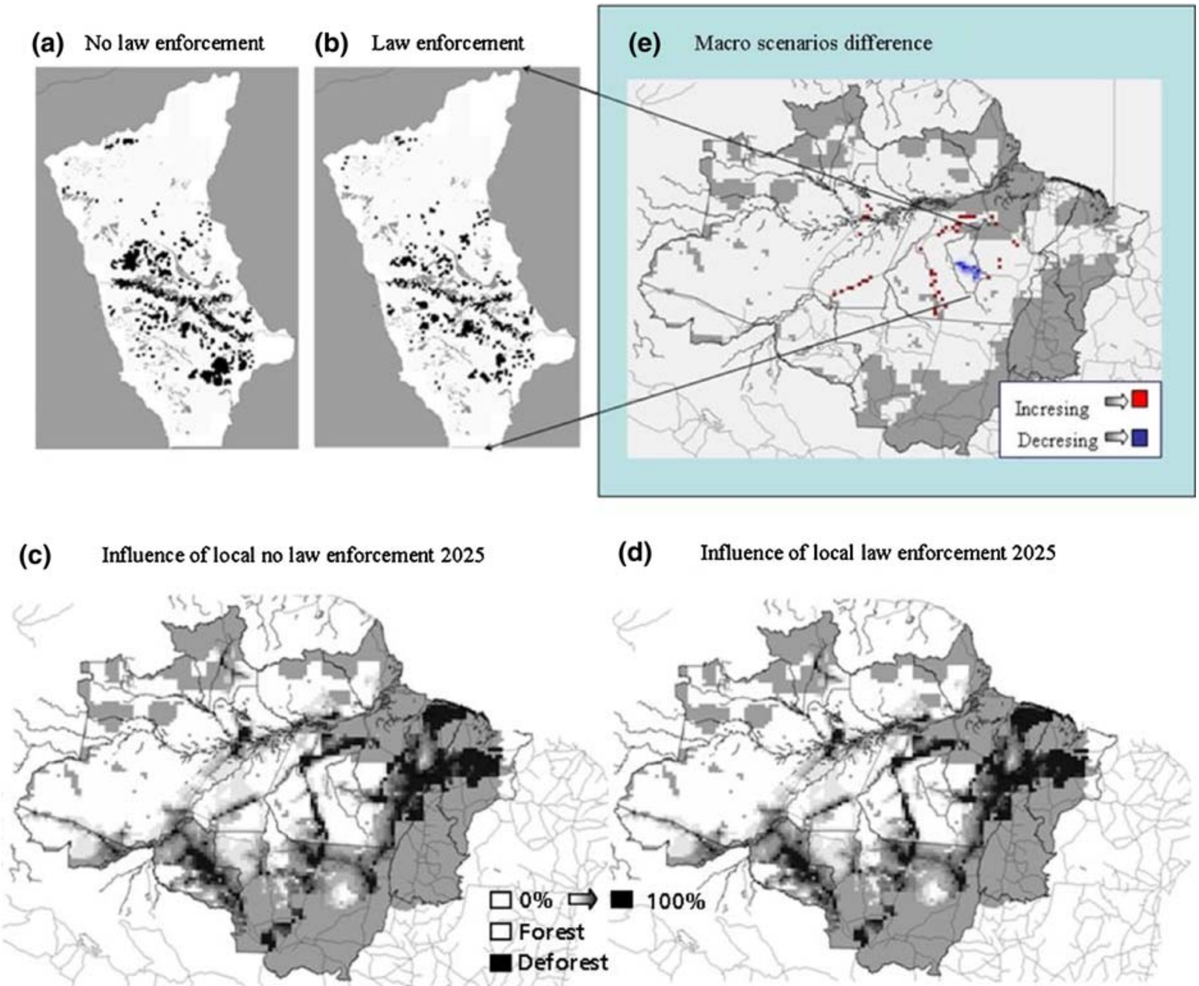

Fig. 6 Case study simulation results of *top-down* and *bottom-up* interactions: **a** Local A: projected deforestation pattern in 2025; **b** Local B: projected deforestation pattern in 2025; **c** Macro A: percentage of deforestation in each cell projected to 2025 with bottom-up feedback from Local A; **d** Macro A: percentage of deforestation in each cell projected to 2025 with bottom-up feedback from Local B; **e** Difference between (**c**) and (**d**)

models and use them to better support policy making in Amazonia. Multiscale models provide insights of broader scope and complementary perspectives. They may help us to answers to questions such as: *Which local measures could prevent the projected macro scenario of aggressive forest conversion to pasture? Are local actions enough? How would other regions—with heterogeneous socio-economic and biophysical conditions—be affected?* The software organization we propose contributes to the efforts to answer such complex questions. We consider that similar approaches could be applied to many other situations and parts of the world. We also believe this methodology is general enough also to be applied to other types of applications, and contribute to create dynamic coupled Integrated Environmental Models from local to global scales.

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References

Aguiar APD (2006) Modeling land use change in the Brazilian Amazon: exploring intra-regional heterogeneity. PhD thesis in remote sensing, INPE: Sao Jose dos Campos

Aguiar A, Câmara G, Cartaxo R (2003) Modeling spatial relations by generalized proximity matrices. In: Casanova M (ed) Brazilian symposium in geoinformatics—GeoInfo 2003, Campos do Jordão, SP, Brazil

Aguiar AP, Câmara G, Escada MI (2007) Spatial statistical analysis of land-use determinants in the Brazilian Amazon: exploring intra-regional heterogeneity. Ecol Modell 209:169–188

Becker BK (2005) Geopolítica da Amazônia (Amazonian Geopolitics). Estu Avançados (J Inst Advanced Stu University Sao Paulo) 19:71–86

Briassoulis H (2000) Analysis of land use change: theoretical and modeling approaches. Regional Research Institute, West Virginia University, Morgantown

Brooks F (1982) No silver bullet: essence and accidents of software engineering. IEEE Computer 20:10–19

Brown DG, Robinson DT, An L et al (2008) Exurbia from the bottom-up: confronting empirical challenges to characterizing a complex system. Geoforum 39:805–818

Carneiro T (2006) Nested-CA: a foundation for multiscale modeling of land use and land change. PhD thesis in computer science, INPE, Sao Jose dos Campos

Castella J-C, Verburg PH (2007) Combination of process-oriented and pattern-oriented models of land-use change in a mountain area of Vietnam. Ecol Modell 202:410–420

Escada MI, Vieira IC, Kampel S et al (2005) Processos de ocupação nas novas fronteiras da Amazônia: o interflúvio do Xingu/Iriri. (Occupation process in the new frontiers of the Amazon (the Xingu/Iriri region). Estu Avançados (J Inst Advanced Stu University Sao Paulo) 19:9–24

Gibson CC, Ostrom E, Ahn TK (2000) The concept of scale and the human dimensions of global change: a survey. Ecol Econ 32:217–239

INPE (2008) Monitoramento da Floresta Amazônica Brasileira por Satélite (Monitoring the Brazilian Amazon Forest by Satellite). Available at www.obt.inpe.br/prodes. Accessed in 29 July 2008, INPE, São José dos Campos, Brazil

Lambin E (1997) Modeling and monitoring land-cover change processes in tropical regions. Prog Phys Geogr 21:375–393

Lambin EF, Geist HJ (2001) Global land-use and cover change: what have we learned so far? Glob Chang Newsl 46:27–31

Lambin EF, Turner BLI, Geist HJ et al (2001) The causes of land-use and land-cover change: moving beyond the myths. Glob Environ Change 4:261–269

Laurance W, Cochrane M, Bergen S et al (2001) The future of the Brazilian Amazon. Science 291:438–439

Li S, Liu Q, Afshari S (2006) An object-oriented hierarchical patch dynamics paradigm (HPDP) for modeling complex groundwater systems across multiple-scales. Environ Model Softw 21:744–749

Moran E, Ojima D, Buchmann N et al (2005) Global land project: science plan and implementation strategy. IGBP report no 53/IHDP report no 19. IGBP Secretariat, Stockholm

Moreira EG, Aguiar AP, Costa SS, Câmara G (2008) Spatial relations across scales in land change models. In X Brazilian symposium on geoinformations, GEOINFO 2008, Rio de Janeiro, RJ, Brasil

Parker D, Berger T, Manson S, McConnel S (2002) Agent-based models of land-use/land-cover change. Report and review of an international workshop. lucc report series no 6. lucc project, Irvine, California, USA

Parnas DL (1972) On the criteria to be used in decomposing systems into modules. Commun ACM 15:1053–1058

Pijanowskia BC, Brownb DG, Shellitoc BA, Manik GA (2002) Using neural networks and GIS to forecast land use changes: a land transformation model. Comput Environ Urban Syst 26:553–575

Pontius RG, Cornell J, Hall C (2001) Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica. Agric Ecosyst Environ 85: 191–203

Soares-Filho B, Cerqueira G, Pennachin C (2002) DINAMICA–a stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier. Ecol Modell 154:217–235

Soares-Filho B, Nepstad D, Curran L et al (2006) Modeling conservation in the Amazon basin. Nature 440:520–523

Turner B, Skole D, Sanderson S et al (1995) Land-use and land-cover change (LUCC): science/research plan, HDP report no. 7. IGBP Secretariat, Stockholm

Veldkamp A, Fresco L (1996) CLUE: a conceptual model to study the conversion of land use and its effects. Ecol Modell 85:253–270

Veldkamp A, Lambin E (2001) Predicting land-use change. Agric Ecosyst Environ 85:1–6

Veldkamp A, Verburg P, Kok K et al (2001) The need for scale sensitive approached in spatially explicit land use change modeling. Environ Model Assess 6:111–121

Verburg PH (2006) Simulating feedbacks in land use and land cover change models. Landscape Ecol 21:1171–1183

Verburg P, Veldkamp A, Fresco LO (1999) Simulation of changes in the spatial pattern of land use in China. Appl Geogr 19:211–233

Verburg PH, Soepboer W, Veldkamp A et al (2002) Modeling the spatial dynamics of regional land use: the CLUE-S model. Environ Manage 30:391–405

Verburg PH, Schot PP, Dijst MJ, Veldkamp A (2004) Land use change modelling: current practice and research priorities. GeoJournal 61:309–324

Verburg PH, Kok K, Pontius RG Jr, Veldkamp A (2006) Modeling Land-Use and Land-Cover Change. In: Lambin E, Geist H (eds) Land-use and land-cover change: local processes and global impacts. Springer, Berlin

Verburg PH, Eickhout B, Meij Hv (2008) A multi-scale, multi-model approach for analyzing the future dynamics of European land use. Ann Reg Sci 42:57–77

White R, Engelen G (2000) High-resolution integrated modelling of the spatial dynamics of urban and regional systems. Comput Environ Urban Syst 24:383–400

White R, Engelen G, Uljee I (1997) The use of constrained cellular automata for high-resolution modelling of urban land use dynamics. Environ Plann B Plann Des 24:323–343

Wu J (1999) Hierarchy and scaling: extrapolating information along a scaling ladder. Can J Remote Sens 25:367–380

Wu J, David J (2002) A spatially explicit hierarchical approach to modeling complex ecological systems: theory and applications. Ecol Modell 153:7–26