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A spatial allocation procedure to model land-use/land-cover changes: Accounting for occurrence and spread processes

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ABSTRACT

Land-use/land-cover (LULC) change models integrate the effects of anthropogenic drivers of landscape change. Spatially explicit LULC change models help at understanding the landscape mosaic that emerges from the interplay between local-scale decisions as well as regional and national policies. These models produce valuable spatially explicit scenarios of LULC change that underpin biodiversity impact and ecosystem services assessments. Most raster-based LULC change models adopt the demand-allocation approach to simulate land transitions (i.e. the transformation of one land-cover type to another for a given spatial unit). In a demand-allocation framework the expert fixes the demand (or quantity of change) and the LULC change model uses a spatial procedure to allocate the change (i.e. to select the cells to be transformed to the target land-cover type). Here, we propose a spatial allocation procedure that builds on the assumption that land transitions occur in two phases: change occurrence and change spreading (or contagion). The allocation procedure uses a sorted queue of cells waiting to undergone change. Three parameters (rate of change occurrence, rate of change spreading and acceleration of change-contagion) control the order of cells order in the queue, and ultimately determine the emergence and extent of patches-of-change. We performed a sensitivity analysis where we show that the relation between both rates (i.e. change occurrence and change spreading) allows patches-of-change expand before other patches arise or vice versa. We provide a simple protocol to implement the allocation procedure as the core of a spatial explicit LULC change model, and we applied this protocol in the development of a new model, called MEDLUC, that intends to replicate the most relevant transitions observed in Mediterranean landscapes: urbanisation, rural abandonment and agriculture conversion. For Catalonia, a region in NE Spain, MEDLUC reproduces the empirical patches-of-change distributions from a 16-year period at two spatial resolutions (1 km^2 and 1 ha). Overall, our allocation procedure performs better than a null model for urbanisation and rural abandonment at both resolutions, while it does worse when modelling agriculture conversion.

1. Introduction

Land-use/land-cover (LULC) spatial distribution emerges from the dynamic interplay between human and natural complex systems. Models of LULC change have become helpful tools to test hypotheses about anthropogenic and environmental drivers of change, to investigate feedback dynamics, as well as to anticipate possible future landscape changes (Brown et al., 2013). Two broad classes of LULC change models have independently emerged within social and natural sciences (Geoghegan et al., 1998). Based on household surveys, agent-based models developed mostly within social sciences simulate the decision-making processes that result from the interactions among individuals and the environment (Parker et al., 2003). In many applications, agent-based models are used to explore land systems from a theoretical perspective (Janssen and Ostrom, 2006; Matthews et al., 2007)

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and are restricted to relatively small areas (Valbuena et al., 2010). Because agent-based models seldom incorporate explicitly the spatial dimension of the system, they have been mainly used to understand the processes rather than to project scenario outcomes, but see Gibon et al. (2010). On the other hand, based on remote sensing imagery, interpreted orthophotos, or historic cartography, LULC studies in natural sciences first focused on recognizing land-cover spatial patterns and then on spatially characterizing land transitions and the processes underlying them. This knowledge was later used to develop spatially explicit LULC change models based on the empirical relations between observed drivers of LULC and resulting various landscape configurations (Veldkamp and Lambin, 2001). These modelling frameworks can integrate climatic, biophysical, or socio-economic factors of change operating from local to global scales to relate causes and consequences of LULC changes (Lambin et al., 2001).

Spatially explicit LULC change models applied in a variety of research contexts have been used to anticipate and predict the effects of multiple land transitions on regional climate, greenhouse gas emissions, biodiversity, and socio-economic welfare at a range of different spatio-temporal scales (Nelson et al., 2009; Rounsevell et al., 2006a; Schulp et al., 2008). Since LULC maps are essential for local and regional assessments of ecosystem service provisioning, the importance of LULC modelling has strongly increased in recent years (Metzger et al., 2006).In the future, models of this kind may become fundamental tools to accurately inform policy makers and land managers committed to sustainable development, biodiversity conservation, and/or climate warming mitigation (Renwick et al., 2013; Rounsevell and Reay, 2009). To be used for this purpose, LULC modelling tools need to be able to translate socio-economic trends or future land policies into spatially explicit LULC change projections that are easily interpretable and suitable to integrate in multidisciplinary assessments (Turner et al., 2007). However, this is not always the case, especially if the assumptions underlying land transitions are not made explicit or if the algorithms employed to spatialize scenario storylines are too complex and/or ambiguous. Thus, what often determines reliance on a spatially explicit LULC change model in a decision-making context is the model's transparency and flexibility, as well as the availability of standard procedures to validate the model and quantify the uncertainty on results (Sohl and Claggett, 2013).

To model the complex social and ecological dynamics of any coupled human-environment system, many spatially explicit LULC change models have adopted the demand-allocation principle. In a demand-allocation framework, the quantity of change (i.e. the demand) is independently estimated first, followed by the spatialization of these quantities (i.e. the allocation) (Verburg et al., 2002). The two main advantages of this modular structure are: (1) model validation can be split in two independent analyses to better isolate different sources of error and uncertainty (Camacho Olmedo et al., 2015; Pontius et al., 2004), and (2) since drivers of the quantity of change may not be the same as those driving the spatial location of change, this structure allows estimating both according to the most appropriate socio-economic and environmental factors (Veldkamp and Lambin, 2001). To apply this modelling approach to study the behaviour of a socio-ecological system, a previous step is to identify and describe the set of land transitions that potentially will take place on the system. A land transition is the transformation of a land-use/land-cover type (hereafter LCT), or a set of them, to a target LCT. For example, urbanisation may be defined as the transition between bare soil and abandoned crops to housing covers, while rural abandonment may be defined as the transition between agricultural lands to semi-natural vegetation areas. In many applications, the demands are externally assessed using specialized quantitative socio-economic models (Asselen and Verburg, 2013). Therefore, the key differences between demand-allocation LULC change models arise from the approach used to dynamically allocate the quantity of change in space.

Most common spatially explicit LULC change models rely on regression-type methodologies to integrate socio-economic and biophysical factors of change. They derive either potential-transition maps that indicate the likelihood of a land transition (Pérez-Vega et al., 2012) or potential-occurrence maps that indicate the spatial suitability of land-cover types (Castella and Verburg, 2007; Verburg et al., 2002). Both types of maps are used to stochastically forecast the location of changes (i.e. the maps become the probabilistic basis to spatially-allocate the demand) (Poelmans and Van Rompaey, 2010). For example, the large family of CLUE models bases the spatial allocation on empirical multivariate logistic regressions (Castella and Verburg, 2007; Verburg et al., 2002; Verburg and Overmars, 2009). Spatial land-cover type suitability, derived from biophysical and socio-economic drivers specific of the studied region, leads the iterative spatialization of the demand while considering competition between land-cover types for the most productive locations. Artificial neutral networks allow the integration of empirical data to learn about past functional relationships and, for example, predict urbanisation (Pijanowski et al., 2002) or deforestation (Mas et al., 2004). Some disadvantages of regression-type data-based methodologies are: (1) they do not allow distinguishing between empirically-good predictors of changes from the spatio-temporal mechanisms that determine occurrence, extent, and spatial configuration of changes (Rosa et al., 2013); (2) they are constrained by data availability of all the drivers of change at the spatial resolution of the model (Sohl et al., 2007); (3) the relations are static (Poelmans and Van Rompaey, 2010); and (4) they do not focus on the explicit modelling and validation of the spatial patterns of land-cover change (Brown et al., 2002).

It has been argued that LULC change processes (chiefly urban development) are self-organising, path-dependent phenomena (Wu, 2002). On one hand, this means that although macroscopic patterns are regulated by upper-level administrative policies, they emerge from local factors, individual behaviours and the corresponding interactions (Verburg et al., 2004). On the other hand, this also implies that land changes derive from two interrelated processes: occurrence (or origination) and spreading (Clarke et al., 1997; Soares-Filho et al., 2002). A large family of models aiming to capturing these two processes have relied on a cellular automata (CA) approaches (White and Engelen, 2000). A CA operates over a n-dimensional grid, each cell is in a discrete system state (i.e. a LCT), and it updates to a new state according to the composition of the neighbourhood and specific expert-defined transition rules. Mainly applied to simulate urban growth, CA have also been useful to spatialize the dynamics in Amazonian landscapes (Soares-Filho et al., 2002). Customized cellular automata may allow for a higher control of when patches-of-changes initiate and how (or where) they expand (Liu and Phinn, 2003; Ward et al., 2000). But CA-based models operating at regional scales have been revealed to be extremely difficult to calibrate for reproducing multiple, real LULC changes (Dietzel and Clarke, 2007; Straatman et al., 2004). Therefore, there is a need of approaches capable of modelling multiple LULC changes accounting for both occurrence and spreading in a simple yet flexible way.

Here, we introduce a new spatial demand-allocation procedure for modelling LULC change dynamics. The novelty of this procedure is that it explicitly addresses the two phases inherent on land transitions: (1) land change occurrence (i.e. origination of a new patch-of-change) and (2) change spreading (or the spatial contagion of the land transition) that will generate the final spatial extent and configuration of that patch-of-change. LULC change occurrence and spreading have been identified as critical phases to explain observed patterns of land change, for example, those generated by deforestation in the Amazon (Rosa et al., 2013), or by urbanisation