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Review

Converting conventional ecological datasets in dynamic and dynamic spatially explicit simulations: Current advances and future applications of the Stochastic Dynamic Methodology (StDM)

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ABSTRACT

The Stochastic Dynamic Methodology (StDM) is a mechanistic framework for simulating ecological processes, based on statistical parameter estimation methods. This methodology is a sequential modelling process primarily developed to predict impacts of anthropogenic activities in the ecological status of ecosystems. Over the last years, this approach was increasingly tested and advances as well as limitations have clearly emerged from the different ecological contexts, scales and target organisms, guilds and/or communities studied. We review the performance of the StDM applications, by system types and upgraded innovation. Most published papers with StDM models were dedicated to assess anthropogenic pressures in the scope of the ecological integrity problematic by using the state variables as ecological indicators. We discuss the StDM concepts, requirements, ecological relevance, universality and the current spatial integration with Geographic Information Systems (GIS) and other types of modelling approaches. Additionally, we describe a simple demonstrative application in order to illustrate the framework methodological steps, supporting the theoretic concepts previously presented with a study case background.

Contents

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1. Introduction

1.1. Background

Scientific models contain the fundamental features that are of interest for solving a problem and biologists improved ecological studies by creating quantitative models that simultaneously attempt to capture the structure and the composition of ecosystems (Santos and Cabral, 2004). Since whole-ecosystem properties are far too complex to be comprehensively measured and quantified, most quantitative models focus on a small subset of processes occurring in an ecological system (Gurney and Nisbet, 1998; Santos and Cabral, 2011).

Ecologists classify the most usual quantitative models in mathematical/statistical models (black-box models) and ecological driven models (system dynamics, agent based, discrete-event and others) (Aumann, 2007; Chen et al., 2011; Guisan and Zimmermann, 2000; Jørgensen, 2008). The black-box models, although used for simplifying ecological processes modelling protocol, are considered unable to describe, in a comprehensible way, the structural changes when the ecosystem conditions are substantially changing (Jørgensen, 2008; Ouyang et al., 2007; Perry and Millington, 2008). On the other hand, the strength of ecological driven models lies in its ability to take into account the individual/systemic and evolving nature of inter-related activities, showing the interactions between principal drivers (Chen et al., 2011; Mendonza and Prabhu, 2005). Although ecological models are usually data-intensive and frequently over-parameterized, many scientists consider these models useful in a wide variety of applications related to ecosystems functioning (e.g. Tyre et al., 2007; Jørgensen, 2008). Towards achieving the goal of being used by more and more scientists, Rizzo et al. (2006) have correctly observed that most ecological models need to be packaged at the level of a user who is not necessarily a programmer. Furthermore, modellers or users of these models should address the issue of the applicability of the models in data-poor conditions, especially when multitudes of field parameters, which are necessary for empiric model calibration, are not available (McInstosh, 2003).

Actually, in a reductionist analytical perspective, the parameter estimation is often the weakest point in modelling (Van Nes and Scheffer, 2005). Determining the appropriate values of the parameters entering in the model is one of the most critical and challenging parts of model building. Because of the uncertainty about the true value of a parameter, for most model techniques is important to analyze how the solution would change if the value assigned changes, namely using sensitivity analysis (Santos, 2009). If not, the data obtained to develop the estimates is often rather crude or nonexistent and the models may represent only quick rules of thumb (Moolenaar et al., 2007).

1.2. The methodology

The Stochastic Dynamic Methodology (StDM) is a mechanistic framework for understanding ecological processes based on statistical parameter estimation methods (e.g. Santos and Cabral, 2004, 2011). This methodology combines both modelling paradigms (black-box and ecological driven) within the same application. We based this recent research on the premise that general statistical patterns of ecological phenomena are emergent indicia of complex ecological processes (Cabral et al., 2008). In this way, the main objective of applying the StDM methodology is to minimize problems in model creation such as parameterization, model complexity and variables choice (Santos et al., 2011).

The StDM incorporates a number of particularities when compared to the usual ecological modelling approaches. The first and probably the most important of all differences is the calculation

a $$Y = b + a_1 x_1 + a_2 x_2 - a_3 x_3 - a_4 x_4 \; [+ \ldots + a_n x_n]$$

b

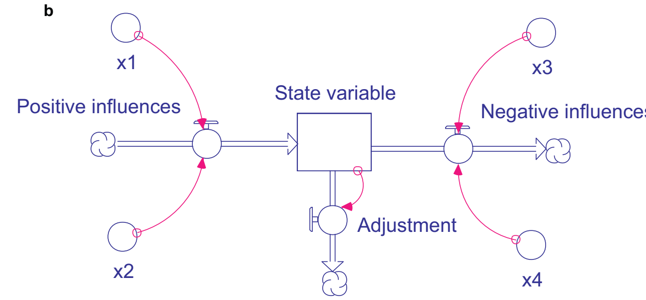

Fig. 1. (a) The StDM basic unit: the rectangle represents a state variable; parameters or constants are small circles; sinks and sources are cloudlike symbols, flows are thick arrows, and all the relations between state variables and other variables are fine arrows. (b) An example of a conventional multiple regression equation, containing the statistics used to estimate the ecological parameters, is also showed. n is the number of independent variables (X), a is the Y intercept, and $b_1, b_2, b_3, \ldots, b_n$ are the partial regression coefficients or ecological parameters.

of the parameters whose values result from statistical estimation. Therefore, the sensitivity analysis routine, considered crucial in standard modelling (Moolenaar et al., 2007; Schizas and Stamou, 2007), is not an imperative for the StDM parameter estimation and model testing (Santos, 2009). However, data consisting of n explanatory variables does not automatically imply that all variables have a significant effect on the magnitude of the response variable. Therefore, this approach uses a statistical model analysis (e.g. multivariate regression) to extract functional relations among variables. Generically, the response variables correspond to the ecological consequences or state variables under study. The explanatory variables are the principal environmental factors or drivers considered in the scope of a specific problematic.

The basic unit of a StDM model (Fig. 1a) is a state variable based on the relationships detected in the regression analysis, described by difference equations. Therefore, StDM models base the inflows of these state variables on positive constants and all positive coefficients of the statistical model (Fig. 1a and b). On the other hand, all the negative constants and negative partial regression coefficients influences are associated to an outflow (Fig. 1a and b). Although the output for each state variable is composed of a given value per unit of time, the respective state variable might have a cumulative behaviour, in response to changes in the environmental conditions. Therefore, to avoid this, StDM models incorporate an additional outflow associated to the state variable. This adjustment empties the state variables in each time step, by a "flushing cistern" mechanism, before a new step with new environmental influences would begin (Fig. 1a).

Nevertheless, since the previous statistical test output is static, one of the central requirements of StDM is that the data set used in the statistical tests includes relevant gradients of changes (Santos and Cabral, 2004). Such a procedure allows more realism, as the respective parameters are being considered with regard to their embedding in time and space (Cabral et al., 2008; Santos and Cabral, 2004). This is of particular importance when it comes to the comprehension of the response. Therefore, in a holistic perspective, the partial regression coefficients represent the global influence of the environmental variables selected that are of significant importance on several complex ecological processes. Yet, the latter are not included explicitly in the model, but taken into consideration within the "data-space" of the environmental gradients monitored in changed ecosystems.

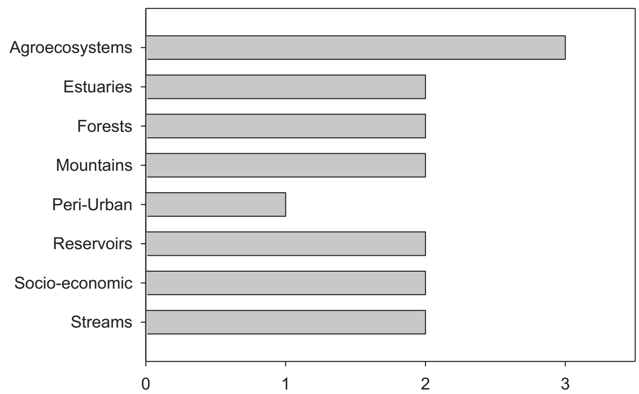

Fig. 2. Histogram of the specific type of systems where some ecological problematics were modelled using the Stochastic Dynamic Methodology (StDM), based on the sixteen published manuscripts.

2. A review of StDM models

2.1. General results

We selected all know manuscripts (published) that have used the StDM protocol to analyze several aspects of ecological relevance. The type of ecological system was rather variable (Fig. 2), although dominated by semi-natural ecosystems. The StDM has been successfully applied, tested and validated in several types of systems such as: agro-ecosystems (e.g. Santos and Cabral, 2004), mountain running waters and reservoirs (e.g. Cabecinha et al., 2004, 2009a), estuaries (e.g. Silva-Santos et al., 2006), wildlife conservation (e.g. Bastos et al., 2012; Silva et al., 2010), bird survey testing (Santos et al., 2009), fire effects in forest ecosystems (Silva-Santos et al., 2010), wind farm impacts in mountain ecosystems (Santos et al., 2010), peri-urban patch ecosystems (Santos and Cabral, 2011) and exotic plants invasion (Santos et al., 2011). Most ecologists developed StDM models for terrestrial ecosystems, although several others tested the application for aquatic and aquatic/terrestrial interface systems such as watersheds and estuaries. Concerning the taxonomic group, bird species have the highest proportion among the models reviewed (followed by invertebrates – Fig. 3), due to the relevance of this group as ecological indicator for ecosystem integrity assessments and community studies (Santos and Cabral, 2004).

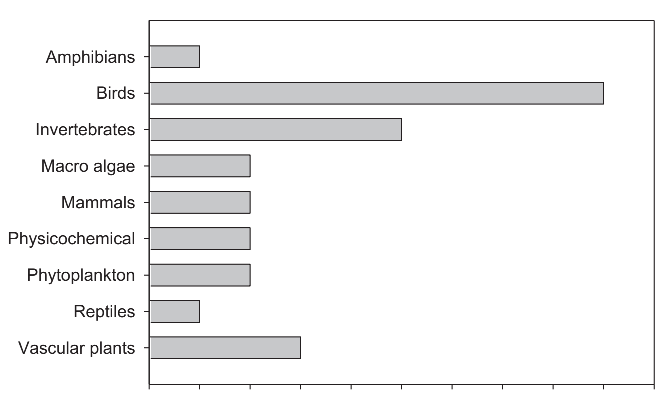

Fig. 3. Histogram of the abiotic and species/groups modelled using the Stochastic Dynamic Methodology (StDM), based on the sixteen published manuscripts. Some of the manuscripts embrace more then one item.

3. Methodological developments, current advances and future outcomes

3.1. Deterministic versus stochastic simulations

The first models developed under a StDM approach used deterministic pathways (Cabral et al., 2008) to calculate "the most probable scenario" (Table 1). Nevertheless, models should also simulate the trends of each selected state variable facing more "realistic scenarios" (Bolliger et al., 2005). StDM models base these "realistic scenarios" on stochastic principles, which take into consideration the random behaviour of the environmental variables with influence on the response variables selected. Usually, to achieve this objective, the limit values for the stochastic environmental variables were determined in accordance with their real ranges. Both types of objectives may be complementary in the same StDM model by selecting the model-running mode – switching between deterministic or stochastic calculations. Thus, many recent StDM models were prepared to work with table functions for deterministic purposes and to produce stochastic simulations, testing the model performances in different random conditions (Table 1).

3.2. Self-maintenance

We classify all conventional dynamic state variables, coupled with (and within) an StDM approach, as with self-maintenance properties, i.e., mediated by rates and conditions to simulate autonomous phenomena such as post-fire ecological successions, plant invasion processes, patch dynamics and land use changes (Table 1). It is easy to achieve this connection because the platforms for the development of StDM models are system dynamics software, enabling more sophisticated, quantitative simulation capable of more robust and reliable outcomes. Considering that system-based modelling is a method of thinking about problems using reproductions organized around real world concepts, system-based software enables the organization of collections of discrete objects that incorporate both data structure and system behaviour (Elshorbay and Ormsbee, 2006). Data are organized into discrete, recognizable entities called objects that may be concrete (number of individuals of a species) or conceptual (policy decisions). For academic research and project management, understanding the benefits and limitations of systems based software could improve the accuracy of results and broaden the user audience (Rizzo et al., 2006).

3.3. Complexity

As with any ecological modelling procedure, the complexity of a StDM model is determined by the problem, the choice of the key-components in the studied ecosystem and the available data (Cabral et al., 2008). Moreover, it is useful to keep in mind the objectives of the final simulations when the modeller selects the complexity and the structure of the model. The complexity of a StDM model increases up to a certain level when the dependent variables are selected as representative of a "trophic chain" (Table 1). In this case, each living key-component should interact with other living components (e.g., competition and predation interactions) and non-living features of their shared habitat.

Usually and from a bottom up perspective, the first component (the environmental scenario) interacts with the other components (biological response). These connections give realism to the trophic interactions considered by incorporating into the model a typical "cascade effect" observed in the dynamics of many systems (Cabral et al., 2008). A case study for illustrating this aspect was a StDM application for predicting changes in Iberian wolf population due to the new highways construction, increasing road traffic density and

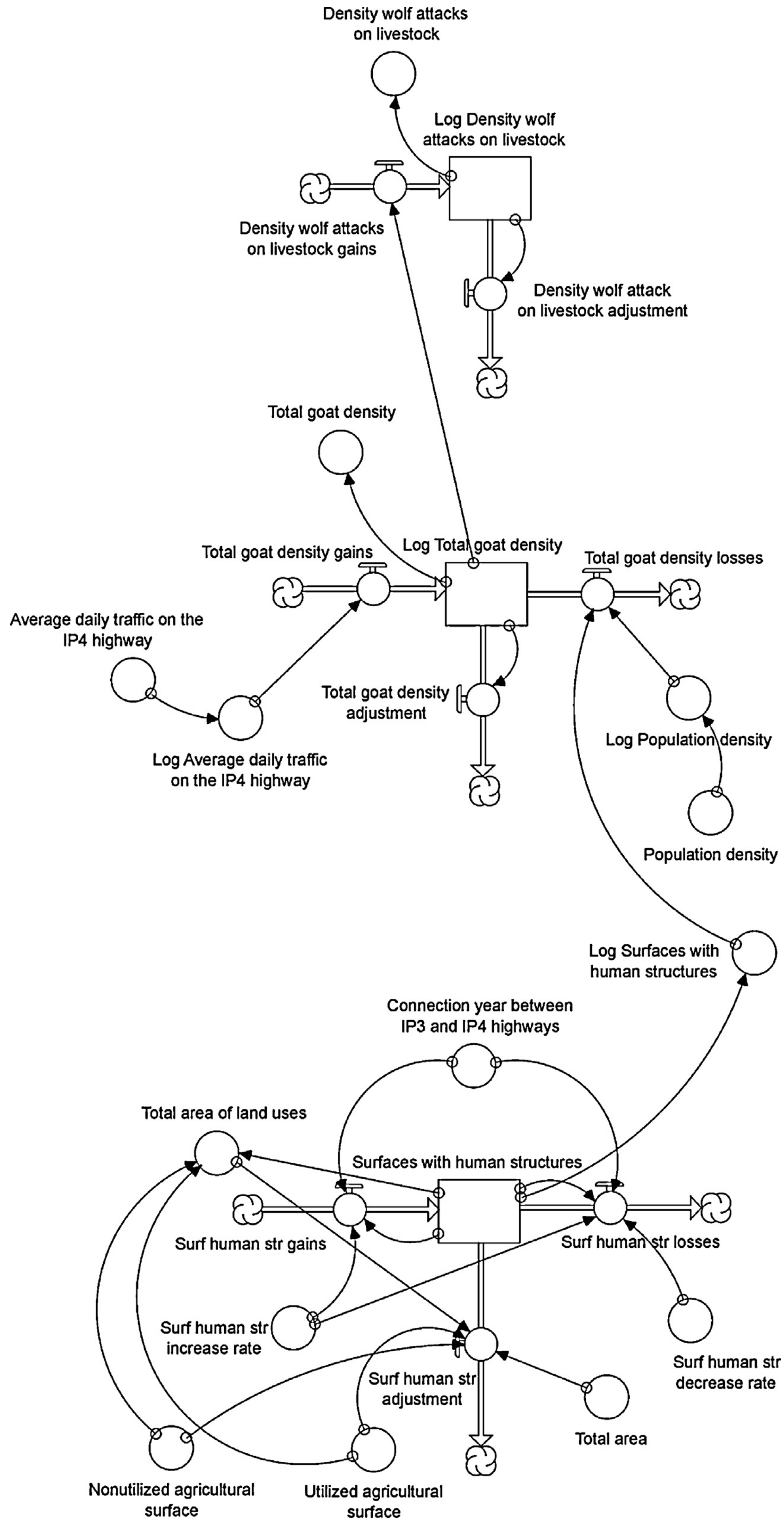

Fig. 4. Illustration of the "cascade effect" in a StDM sub-model, used to predict changes in the density of wolf attacks on livestock, considered a indicator of Iberian wolf populations, due to habitat fragmentation and livestock availability. The model is organized in three components (bottom-up): (a) socio-economic, such as percentage of area occupied by land use, population density and road net characteristics, (b) livestock abundances/density and (c) livestock fatalities caused by wolves.

Source: Adapted from Santos et al. (2007).

Table 1
Specification of the modelling attributes associated to each published StDM application.

Article	StDM modelling attributes					
	Deterministic	Stochastic	Self maintenance	Complexity	Spatially explicit	Validation
Santos and Cabral (2004)			×	×	×	
Cabecinha et al. (2004)	×					×
Silva-Santos et al. (2006)	×			×		×
Cabral et al. (2007)	×					
Santos et al. (2007)	×		×	×		
Cabecinha et al. (2007)	×	×		×		×
Silva-Santos et al. (2008)	×	×		×		×
Santos et al. (2009)	×	×				
Cabecinha et al. (2009a)	×	×	×	×		×
Cabecinha et al. (2009b)		×	×		×	
Santos et al. (2010)			×	×		×
Silva-Santos et al. (2010)		×	×			
Silva et al. (2010)	×		×			×
Santos et al. (2011)	×					×
Santos and Cabral (2011)	×	×				
Bastos et al. (2012)	×	×	×	×	×	
Diagnosis	12	8	8	8	3	8

urbanization in Trás-os-Montes e Alto Douro region (North-eastern Portugal) (for details please see Santos et al., 2007). The authors estimated ecological indicators for wolf presence and abundance indirectly from the density of attacks on livestock. They organized the variables in three components (Fig. 4). The first component included variables related with several economic, social and environmental data, such as the percentage of area occupied by the principal land uses considered, the human population density, the road net characteristics and the traffic density (Fig. 4). The second component was considered as a "hinge group" of variables related to the livestock abundance/density and the third component is composed by dependent variables, also expressed in densities and roughly associated with wolf occurrence, such as the livestock fatalities caused by wolves (Fig. 4). From a bottom up perspective, the first component (the environmental scenario) interacts with the other two components, and the second component (the availability of preys) interacts with the third component (the wolf indirect indicators).

Nevertheless, this strategy may contribute to the creation of "artefactual delays". An "artefactual delay" results from the conceptual distinction between stocks and flows. Actually, the more we add levels to a "cascade effect", the more a StDM model increases the delay and contribute to the distortion of the model's dynamics (Stella® Technical Documentation, 2005). The interval of time between calculations is expressed as *dt* and the distortion may be reduced by adjusting the *dt* as an equilibrium between speed against smoothness and numerical precision (Rizzo et al., 2006). If the *dt* defined is below the unit of time that we want to simulate the output then the "artefactual delays" are usually unimportant (Santos, 2009). In most StDM applications this potential problem was integrated as a quality because the ecological responses to environmental stresses are usually not instantaneous and the "artefactual delay" may in fact add realism to our simulations. In reality, the "artefactual delay" may indeed represent the lag of time associated to the input of a stimulus versus the response of a specific system (Santos, 2009). Anyway, in specific situations when the delay is useless and even considered a problem, we can substitute the state variable by a direct converter and in this way no time lag is required (for details please see Section 4).

3.4. The spatially explicit StDM framework

Many authors consider modelling spatial-temporal dynamics of ecosystems a fundamental and challenging task (e.g. Costanza and Voinov, 2004). System dynamics based models, such as StDM, are useful methods to understand system changes with time, however, the underneath assumption of spatial uniformity is easily violated in real systems. Indeed and as the name indicates, although StDM is efficient in handling the dynamic behaviour of system, it is not perceived to be representative of spatial variability within the system (Santos, 2009). The development and application of spatial-dynamic models intends to remediate this disadvantage. When localized processes become so significant that affect the global dynamics, spatially explicit methods are proposed, providing powerful ways to link fine-scale local interactions to coarse-scale global dynamics (Chen et al., 2011). As a result, several researchers have dedicated themselves to the development of landscape dynamics simulation models, thus contributing to a diversity of approaches, which can be found in modelling frameworks such as the Spatial Modelling Environment (SME) (Costanza and Voinov, 2004; Maxwell et al., 2004) and the DinamicaEgo (Soares-Filho et al., 2006). Although with different characteristics, both program incorporate the single cell dynamics using system-based software (such as Stella® or Vensim®) assuming the dynamic relationships between the neighbouring cells.

One of the aims of most published works with StDM models has been the final integration with Geographic Information Systems (e.g. Santos and Cabral, 2004). In Santos and Cabral (2004), within each cell the StDM works independently using the environmental variables (e.g. land-uses, actualized by time-step) and generates discrete indicator's responses. This "naïve" approach is a preliminary starting point to the current developments of the StDM (Table 1). To our knowledge, such integration of StDM and spatial analysis tools has only been recently developed and tested as a robust management and decision-support tool in the works of Cabecinha et al. (2009b) and Bastos et al. (2012) (Table 1). Bastos et al. (2012) developed a spatially explicit StDM framework with the goal of implementing conservation actions for an endangered species, using the Azores bullfinch (*Pyrrhula murina*) as a test species. The paper discusses the applicability of this integrative tool to discern and predict the spatial patterns of the Azores bullfinch abundance in its main distribution area, as a response to present and future changes in the laurel forest composition related to alternative habitat management options.

The proposed spatially explicit StDM framework is a sequential modelling process initiated by the analysis of landscape and habitat composition (Fig. 5a), which defines the convenient parameters that contextualize the physical and biotic descriptors at the study unit level. This procedure involves the use of a robust information-theoretic approach based on generalized linear models (Fig. 5b) in

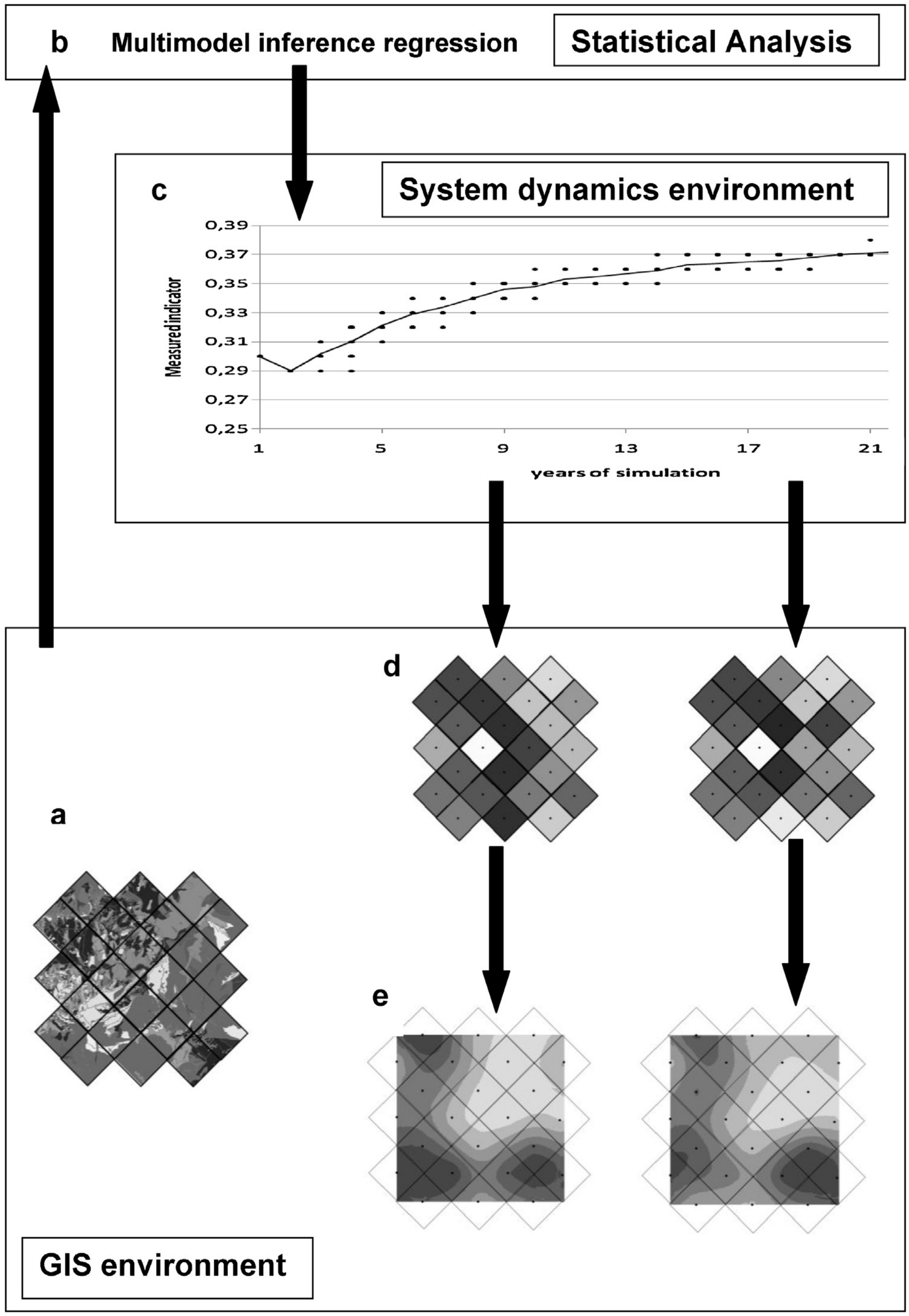

Fig. 5. Spatially Explicit StDM: (a) study area assessment; (b) statistical analysis for estimation of ecological relevant parameters; (c) model conceptualization and stochastic dynamic simulations; (d) geographic projection; (e) geostatistical interpolation of the stochastic dynamic simulations.

order to establish the interaction criteria between the construction of the dynamic model and the resulting stochastic dynamic simulations for each study unit (Fig. 5c). These simulations, when projected into a geographic space (Fig. 5d) and submitted to an appropriate geostatistical interpolation (Fig. 5e) create an integrative picture, in space and time, of the responses to the gradients of habitat changes. Since the dynamics of the response is driven by the interaction between biophysical and human dimensions, the combined use of such statistical modelling and geostatistical techniques was considered a promising approach to address complex emergent problems, from the individual habitat patch to the whole landscape context.

3.5. Validation and the performance of StDM simulations

One of the most important problems identified in the StDM approach is linked to the genesis of this method: the quality of the data-base is crucial in the model outputs imposing significant limitations to the performance of a StDM application. The database quality for a StDM application may be defined in terms of two different proprieties: (1) the amount of data, because in the regression analysis the slope is chosen so that the sum-of-squares distance between each data point and the fitted line is minimized (Sokal and Rohlf, 1995) and (2) the gradient of situations captured in the field, in face of the required scenarios to perform, given that

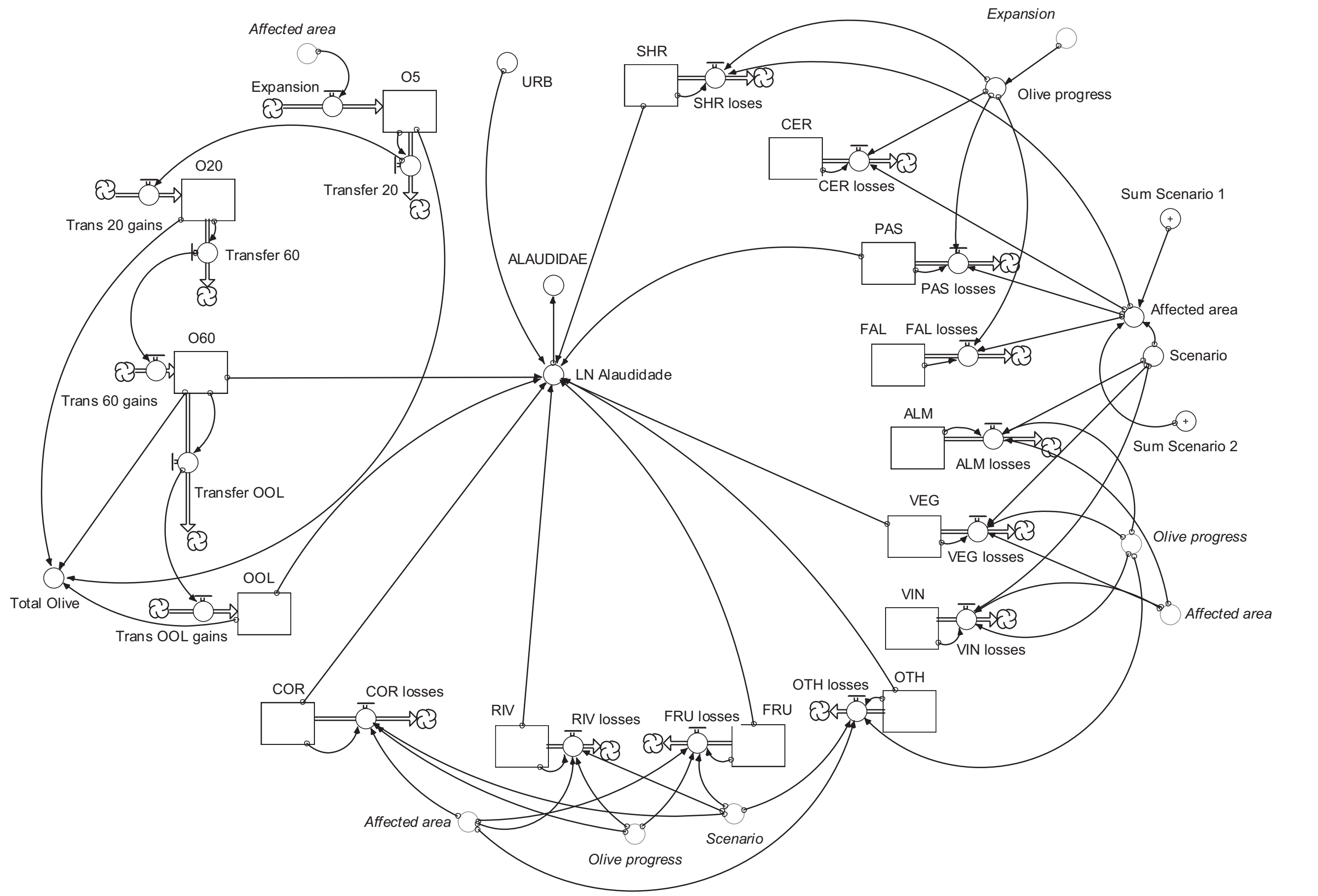

Fig. 6. Conceptual diagram of the model used to predict the impact on the species richness of Alaudidae produced by the plantation of intensive olive orchards in agroecosystems of north-eastern Portugal. Rectangles represent state variables; parameters or constants are small circles; sinks and sources are cloudlike symbols, flows are thick arrows, and all the relations between state variables and other variables are fine arrows.

in regression analysis the limits of the *Y* prediction are imposed by the extreme points of the fitted line (Waite, 2000; Steele et al., 2005). Consequently, working with a data-base that includes variable values that are broad enough to capture a wider gradient of the pertinent scenarios is an imperative (Santos et al., 2011). Nevertheless, given a certain amount of data, the addition of new state variables or parameters beyond a certain model complexity does not contribute necessarily to improve simulations. To obtain the "right" information from a StDM, the choice of the model complexity involves always a conceptualization of the system under study (Jørgensen, 2001).

The expansion of predictive models is consistent with Peters's view of "more rigorously scientific, more informative and more useful ecology" (Guisan and Zimmermann, 2000). Specific papers covered some aspects of model development, with very special attention given to the evaluation, usefulness and testing (Efron, 1982; Guisan and Zimmermann, 2000; Rykiel, 1996; Scott et al., 2002; Tuckey, 1958). In general, the StDM models whose data-base was considered large enough were validated using the data-split validation method (also known as split-sample approach) coupled to standard statistical techniques, such as fitted line regression and Model II regression (Sokal and Rohlf, 1995) (Table 1). For the performance comparisons, scientists may introduce into the model fluctuations of environmental variables as table functions. Some papers used this deterministic procedure in StDM models to evaluate the trends of a given state variable or to validate the respective simulations when compared with the correspondent values from the reality (Table 1). We could even consider this validation method inaccurate: bearing in mind that models are approximations of a much more complex reality, the fundamental step in validation is pre-defining the context of application (Guisan and Zimmermann, 2000; Manel et al., 2001; Rykiel, 1996).

4. An integrative case study

A spatially explicit StDM modelling framework was developed by focusing the interactions between local passerine communities and changes in the habitat conditions of Mediterranean agroecosystems (North-eastern Portugal). The ecological integrity of the characteristic mosaic of this region, with respect to land use, can be assessed partially by the observation of passerine species richness occurrence (e.g. Bignal and McCracken, 2000; Sokos et al., 2012). For demonstration purposes, the family Alaudidae (Larks) was used as state variable in the StDM model construction to indicate the ecological changes that will result from the expected intensification of olive orchards plantations in such systems (Santos and Cabral, 2004). The data used in this study were obtained from an exhaustive snapshot survey of the bird populations during the breeding season of 2001 (see Santos and Cabral, 2004, for detailed methods). To assess environmental factors with potential influence in the Alaudidae species richness several parameters of the study area were considered within a representative 900 ha area. The selected 16 predictors (habitat classes; Appendix 1) for the Alaudidade species richness were tested for pairwise correlation using Spearman's rho correlation coefficient and only predictors with correlation lower than 0.7 (Elith et al., 2006; Wisz and Guisan, 2009) and generalized

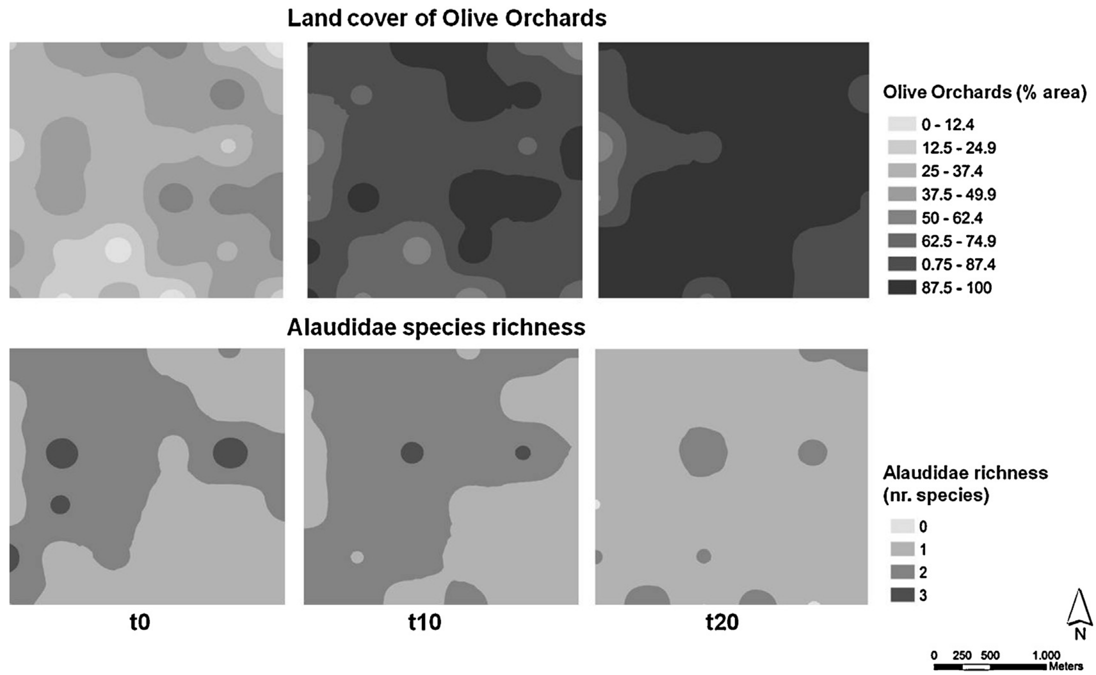

Fig. 7. Spatial-dynamic representation of the olive orchards expansion and the Alaudidae species richness associated trends, considering a continuous distribution function based on a simple interpolation and its temporal variation throughout the 20 years simulation period for $t=0$, $t=10$ and $t=20$.

variance inflation factor lower than 5 were considered (Neter et al., 1996). From the 15 surviving predictors we fitted a set of competing quasi-poisson models and chose the "best model" supported by the data (lower AIC and higher adjusted R^2; e.g. Santos et al., 2011) (Appendix 1 and Table 2). Other strategies, like multi-model inference (MMI) (Burnham and Anderson, 2002) could be used to calculate the averaging model to incorporate in the StDM (for method details please see Bastos et al., 2012). The diagram presented in Fig. 6 shows the Alaudidae species richness StDM model, influenced by the changes associated with the landscape dynamics, mediated by the holistic parameters estimated from the results of the statistical treatment and from regional data regarding land use tendencies. This model reproduces the influence of the land cover/land use dynamics on the Alaudidae species richness, at each study unit level (a point-count area of 25 ha), in a sampling grid composed by 36 study units regarding the plantation trends of intensive olive orchards (Santos and Cabral, 2004). To create the spatial dynamic projections, every study unit was characterized according to the known initial land covers/uses and the respective areas were included into the StDM model in order to recreate their dynamics and estimate the response of the local species richness of Alaudidade throughout a simulation period of 20 years. Since the dynamic projections neglect spatial relationships among individual study units, an interpolation method (e.g. Cressie, 1990; Lu and Wong, 2008; Sherman, 2011) was applied to project and integrate those populations attributes for the overall study area (regional scale), by incorporating spatial autocorrelation among richness per study unit (Zhang and Murayama, 2011; for method details see please Bastos et al., 2012). In order to illustrate the spatial dynamic variation of the olive orchards intensification and the response of the Alaudidae species richness, three time frames of the simulation period were selected: the first year ($t=0$) the 10th year ($t=10$) and the 20th year ($t=20$), from which the respective spatial projections were carried out (Fig. 7). The final framework provided some basis to analyze, through time and space, the structural drift within the Alaudidae family under the environmental scenarios that will characterize the new agroecosystems of the region. The possible local extinction of such steppe passerine species might be related with dramatically functional changes of the traditional systems and a probable loss in their ecological integrity. Therefore, a new structure of the passerine communities indicates that the future agroecosystems will diverge from the initial or actual ecological state (Sokos et al., 2012).

Table 2
Results of the "best model", based on the Akaike information criterion adjusted (AIC) = 206.69 and on the adjusted coefficient of determination (R^2adj.) = 29.45. The estimates of parameters (soil cover) for all the explanatory variables selected as relevant to estimate the Alaudidae richness: variable coefficient (coefficient), variable standard error (SE), variable t-value (t).

Variable	Coefficient	SE	t
(Intercept)	1.29	0.14	9.40
Forests area	−5.34	3.60	−1.49
Vegetables area	−4.26	1.95	−2.18
Shrublands area	−1.43	0.33	−4.32
Mature olive orchards area	−1.45	0.38	−3.87
Very old olive orchards area	−2.24	0.36	−6.14
Pastures area	−2.65	1.92	−1.38
Riverine forests area	−3.90	2.42	−1.61
Urban area	−2.43	1.09	−2.23
Fruit orchards area	−3.59	2.04	−1.76
Cork forests area	−4.23	1.11	−3.82

5. Concluding remarks and future outcomes

The StDM is still very recent, with the first results published in 2003/2004 (Cabecinha et al., 2004; Santos and Cabral, 2004). Meanwhile, ecologists applied, tested and validated StDM applications in several types of scenarios (Table 1). We consider that models produced in the form of rules, such as the machine learning approaches, are transparent and easily understood by experts (Mendonza and Prabhu, 2005; Williams and Poff, 2006). The structure of such models should be straightforwardly interpretable in order to allow a decision maker to incorporate pertinent qualitative data before the model simulations. The StDM exhibits these structural qualities but provides also simple, suitable and intuitive outputs, easily interpreted by non-experts (ranging from resource users to senior policy makers) (Bastos et al., 2012; Santos et al., 2011). Although conceptually simple, the StDM models capture the stochastic complexity of some holistic ecological trends, including relevant temporal and spatial gradients of stochastic environmental characteristics, which allowed the simulation of structural changes when habitat and environmental conditions are substantially changing. The published results seem to demonstrate the StDM reliability in capturing the dynamics of the studied ecosystems by predicting the behavioural pattern for the key components selected under very complex and variable environmental scenarios, namely when conditions relatively unaffected by human activities were changed by man-induced disturbances. Another goal when developing methodologies for assessing changes in the ecological integrity of ecosystems is the feasibility of application and extent to which the results are applicable in other contexts (Andreasen et al., 2001; Cabral et al., 2008). Since the StDM is easily applicable to data from natural, semi-natural, and artificial ecosystems affected by gradients of changes, we believe that our approach will provide the development of more global techniques in the scope of this research area.

This manuscript tried to show the StDM evolution, major trends and flaws. Since the review of the StDM models suggest that the methodology is maturing, becoming more spatially explicit and incorporating other approaches and scales, it seems that the potentialities of StDM have not, yet, been fully exploited. Nevertheless, many of these studies consider the final model an absolute entity without testing how the results change if the model is simplified or refined, or different scenarios are studied. The decision of selecting the information to be used in a StDM model seems to be connected to concepts of the researchers involved and in many models there are no objective criteria of selection (Santos, 2009). In fact, StDM is a holistic “top-down” approach, rooted in system dynamics and many reductionist details are not considered, such as individual variability and local space positional characteristics. Although this simplification enables the understanding of whole-system processes such as resilience, resistance, persistence, regulation, density dependence, is difficult to follow at other scale approaches, namely when individual properties are crucial to the collective behaviour. In fact this is one of the major advantages of “bottom-up” models, such as agent based models (ABM) (Grimm, 1999; Schmolke et al., 2010) that enable to cross-information, potentiating a better understanding of ecosystem dynamics (Rahmandad and Sterman, 2008). Therefore, we believe that the combination of both, StDM and ABM, will result in promising future outcomes, allowing a better understating of ecosystems functioning, which will make the methodology more instructive and credible to decision-makers and environmental managers (Hughes et al., 2012; Singh et al., 2012; Zhao et al., 2005).

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolmodel.2013.02.028.

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