Systemic change increases forecast uncertainty of land use change models

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Introduction

Cellular Automaton (CA) models of land use change are grounded on the conceptual distinction between 1) the quantity of change per land use type, and 2) the spatial allocation of this change (Verburg et al., 2002) (Figure 1). The quantity of change is dictated by the scenario storyline, and the spatial allocation of change is defined by the model structure. The model structure consists of a set of driving factors of location (suitability factors) that serve as proxies for the socio-economic and environmental processes in the land use system, like topography, accessibility, and potential revenues. Although there are some exceptions, the selection, relative importance and parameterization of these suitability factors, i.e. the model structure, is in current applications usually kept constant in time. A crucial assumption implicit in this method is that the relationship between land use change and its explanatory processes is **stationary** (Manson, 2007).

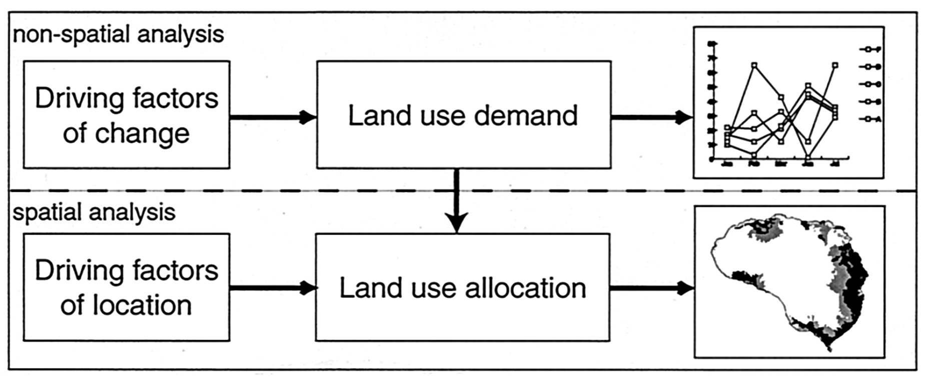


Figure 1: Conceptual model of a land use change Cellular Automaton (CA), taken from (Verburg et al., 2002). The non-spatial analysis is covered in the scenario storyline and the spatial analysis is the model structure, of which the stationarity is studied here.

This assumption ignores potential **systemic changes** in these relationships resulting from societal changes including technological, political or economic developments. A systemic change is a fundamental change in system structure. Because the notion of 'fundamental' is subjective, we recognize systemic change in the context of models by: "a system state change that cannot be simulated using a constant model structure".

Aim

Our aim is to answer the following questions: 1) Is the assumption of a land use change CA with a constant model structure, as generally used in the land use change community, an adequate representation of the land use system, or do observations of past land use over time indicate systemic changes?, 2) If systemic changes seem to occur, can these be related to known societal changes?, 3) How does the inclusion of systemic changes in the CA affect model projection uncertainty?

Case study

The evaluation of systemic changes and assessment of the consequences for projection uncertainty are performed on a case study of the expansion of **sugar cane** fields in the São Paulo state in Brazil, using an adapted form of the PCRaster Land Use Change model (PLUC) (Verstegen et al., 2012).

Four suitability factors are used as driving factors of the location of sugar cane expansion. Sugar cane in the neighbourhood (1) is expected to be important because larger plantations require less investment costs per hectare as equipment and infrastructure can be shared. The distance to the sugar cane mill (2) determines the transportation costs of sugar cane to the processing unit. Potential yield (3), an indicator linking agro-climate conditions to crop requirements, is important for the potential revenues per hectare. Slope (4) defines the potential for sugar cane harvest mechanization. The relative importance of the drivers of locations is determined by the weights of the four suitability factors: w_1, w_2, w_3, and w_4 (Figure 2).

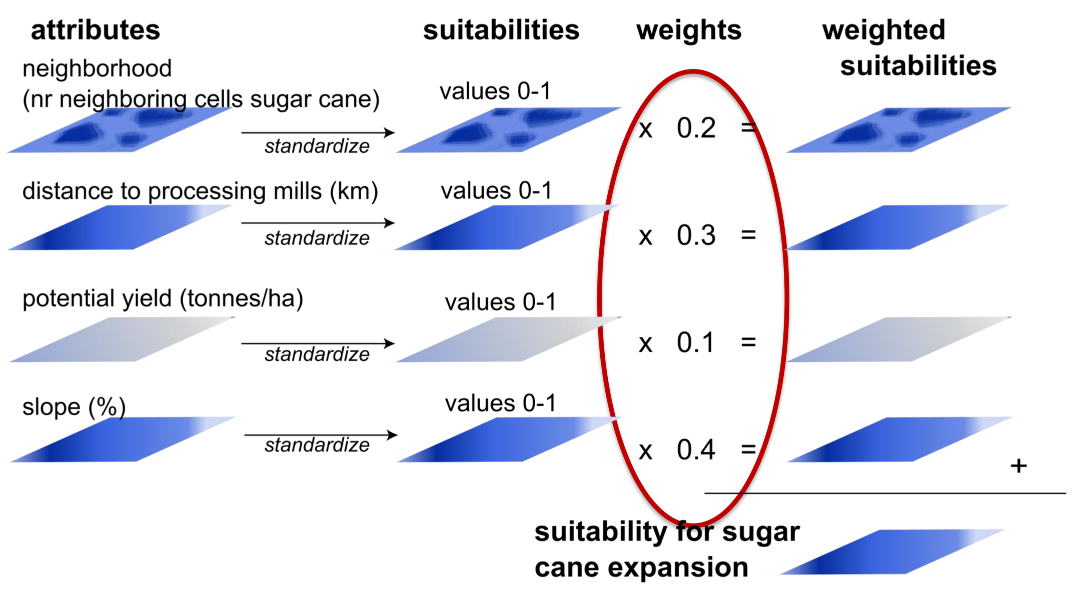


Figure 2: Method to calculate the suitability map. The weights, indicated by a red ring, are the variables for which stationarity is tested.

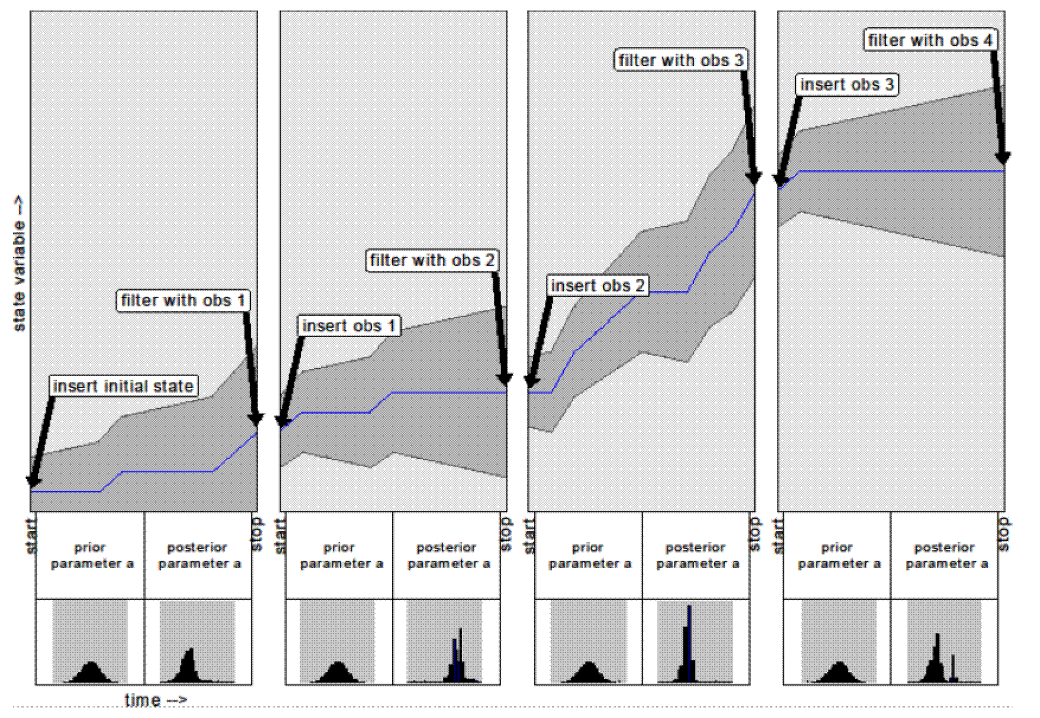


Figure 3: Schematic representation of the particle filter method. 'Obs 1' means observations at filter moment 1, the blue line indicates the median system state, grey areas represent the confidence interval. Histograms underneath the plots illustrate the effect of the filter moments on a general parameter *a*.

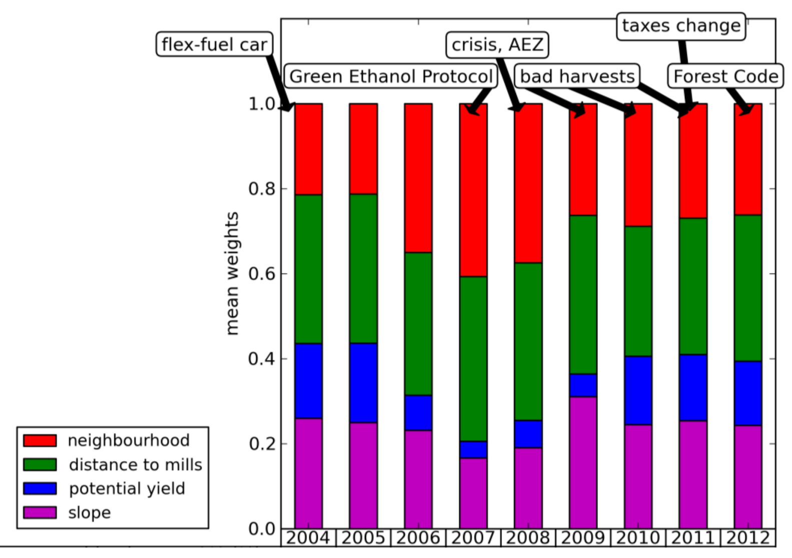
Methods

A time series of observations of real land use (Rudorff et al., 2010) is assimilated into the land use change CA using a Bayesian data assimilation technique, the **particle filter** (as shown in Verstegen et al., accepted) (Figure 3). The particle filter is used to update the prior knowledge about model structure, i.e. relative importance of the drivers of location of land use change (w_1, w_2, w_3, w_4), for each year from 2004 to 2012. In this way the optimal model structure is determined for each of these years. We use the non-parametric Wald-Wolfowitz test, also called **Runs test** (Wald and Wolfowitz, 1940) to test whether or not the obtained time series of model structures is stationary. We apply a level of significance of 10%. If the null hypothesis is rejected (p-value > 0.1) the variable cannot be considered stationary, so a systemic change is present.

Results

The mean weight of distance to sugar cane mills, w_2, seems stationary (Figure 4). This is confirmed by the Runs test, using a 10% significance level (table on right hand side of Figure 4). The mean weights of the other factors clearly change over time. In the period 2006 to 2008, the weight of sugar cane in the neighbourhood, w_1, is higher than in other years, and the weights of slope, w_4, and potential yield, w_3, are lower. This **non-stationarity**, indicating **systemic change**, is confirmed for all three factors by the Runs test (Figure 4). The start of the systemic change, 2006, is a year with no identified societal changes (Figure 4). The 'recovery' period of the system, 2009 to 2010, coincides with years of bad harvests.

The 95% confidence interval for the projected fraction of sugar cane per block is **twice as large** with systemic change as without (Figure 5), indicating that the use of a different model structure in each year results in a higher uncertainty.



variable	p-value
w_1	0.051
w_2	0.148
w_3	0.039
w_4	0.051

Figure 4: Mean of the posterior distributions of the weights of the suitability factors. Occurrences of societal changes are indicated above the bar graph. Results of the Runs test for the weights (of neighbourhood, w_1, distance to mills, w_2, potential yield, w_3, and slope, w_4) are given in the table on the right hand side. Values that indicate non-stationarity at a significance level of 10% are coloured grey.

Discussion and Conclusion

In our case study of sugar cane expansion in Brazil, the assumption of a constant CA model structure was not an adequate representation of the land use system given a time series of observations of past land use. Clear evidence was found of non-stationarity of the system, indicating systemic change. Because no clear reason was detected for the model structure and parameter changes in the identification period (2004 to 2012), we assumed that a future model structure could be any of ones found in the past. Applying this resulted in an increase of the uncertainty in the model output by a factor of two compared to a stationary model structure.

In view of the above, we recommend land use change modellers to check, if permitted by data availability, whether or not the system was stationary in the past and if potential causes can be found for detected non-stationarity. The methodology shown here can be used for such an analysis. Non-stationarity in land use change projections is challenging to model, because it is difficult to determine when the system will change and how. We cannot expect land use change modellers to incorporate systemic changes in their models. Nonetheless, we believe that they should be more aware, and communicate more clearly, that what they try to project is at the limits, and perhaps beyond the limits, of what is still projectable, because systemic changes do occur in reality.

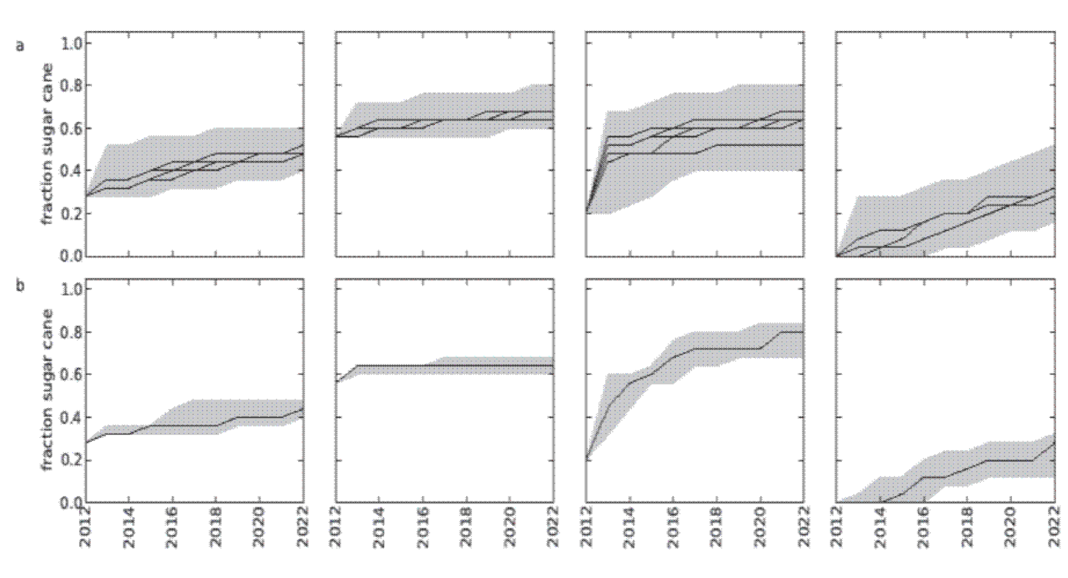


Figure 5: Projection of fraction of sugar cane in zones in the study area for. In panel a, it is assumed that any of the model structures identified in the years 2004 to 2012 can be valid in the future, so a random model structure is drawn from these years for all future years. This is done five times to show how the uncertainty resulting from the systemic change. Black lines represent the median of the block value, grey areas are 95% confidence intervals (for scenario 2 calculated over all values of the five runs together).

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