Sources of uncertainty in a Cellular Automata for vegetation change

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1.0 INTRODUCTION

When farmland is abandoned – stock and human disturbance removed – pasture is rapidly taken over by woody vegetation. This has ecological implications; for example the amount and spatial relationship of shrub and tree patches affect the makeup of the bird community, as different resources available in patches support different bird species. As tree dispersal depends on the presence of a seed source nearby and other local conditions, and can be measured in discrete annual time steps, a Cellular Automata (CA) is a natural fit for modelling this phenomenon.

In the context of GIS, a CA consists of a raster where each cell can be in one of a finite number of states at each time step. Cell states change simultaneously at each time step according to a set of rules, depending on the current state of the cell and its neighbours. Simple local rules can give rise to larger, dynamic, global structures (O'Sullivan and Unwin 2002).

As computing and GIS capabilities have grown, CA models have developed from experimental mathematics (Gardner, 1970) to a recognition of their application in natural sciences and geography (Wolfram, 1984; Couclelis, 1985) to useful models in human and environmental geography. Examples include urban growth and land use change (Batty & Xie, 2005), fire spread (Yassemi *et al.,* 2008), invasive plant species propogation (Dragićević, 2010), plant competition (Matsinos and Troumbis, 2002) and vegetation dynamics (Balzter *et al*., 1998).

2.0 MODEL DEFINITION AND RULES

2.1. Study area

The study area covers approximately 114,800ha between Rushworth and Heathcote in central Victoria, Australia. The vegetation occurring on abandoned farmland in this region is mainly composed of eucalypt tree species and the perennial shrub *Cassinia arcuata* (drooping cassinia). Patches are either tree or shrub dominated, and to a lesser extent pasture dominated.

2.2. Model definition

Our model is a stochastic CA, with a relaxed definition of neighbourhood. The starting raster for the model is made up of 10m cells with a value of tree, shrub or pasture, classified from aerial photography. For trees, the age is also estimated, as this determines when it matures enough to become a seed source. In addition rainfall probability values are estimated for each year of the model run. This value reflects the probability that a seed will establish, given the rainfall patterns in any given year. The model proceeds in annual time steps following the rules outlined below.

2.3. Model rules

The following assumptions apply to our model:

1. Multiple seed sources will not alter the probability of a tree establishing
2. A tree remains a tree and continues growing (i.e. cannot die and revert to pasture or shrub)
3. Shrub can change to tree (can be out-competed) or remain shrub, but cannot revert to pasture
4. Pasture can change to tree if there is a seed source (tree at least 20 years old) within 20m
5. Shrub can change to tree if there is a seed source (tree at least 30 years old) within 20m (shrub delays tree establishment)

The model rules are shown in Table 1.

Table 1. Model rules at each time step

Current state	**Conditions**	**Next time step**	**Probability**
Tree	N/A	Tree	1
Pasture	Any tree >20 years within 10m	Tree	*A* * rainfall probability
Pasture	Any tree > 20 years within 20m	Tree	*B* * rainfall probability
Pasture		Shrub	current shrub density within 100m radius * *C* * rainfall probability
Shrub	Any tree > 30 years within 10m	Tree	*A* * rainfall probability
Shrub	Any tree > 30 years within 20m	Tree	*B* * rainfall probability

A, *B* and *C* are constants (see Results)

If none of the above rules apply, then the cell state remains unchanged.

3.0 SOURCES OF UNCERTAINTY

Model uncertainty can be expected to increase with complexity. According to Childress *et al.* (1996), the main part of the art of ecological modelling is compromising among modelling objectives, ecological realism and computational tractability, in order to control complexity.

Sources of uncertainty include:

- *Cell size and structure*: In GIS, cells are generally regular squares, leaving the choice of cell size as a source of uncertainty. Cell size is a trade off between unambiguous classification and computational cost. The cell size should also reflect neighbourhood processes. The model could be run at various spatial resolutions, however this can add a huge computational burden.

- *Cell occupancy*: Uncertainty is introduced both through the problem of mixed cells (a cell may contain multiple vegetation types), and uncertainty in classification (a young tree may be misclassified as shrub or pasture). The incorporation of fuzzy sets can handle input data uncertainties (Dragićević, 2010).

- *Neighbourhood size and shape*: In traditional two-dimensional CA, the neighbourhood is usually defined as the four or eight cells immediately adjacent to the cell in question. Many model applications relax this rule however. This decision needs to be driven by ecological knowledge, and is closely linked to cell size.

- *Transition rules*: These rules must also be founded in ecological theory. They can be refined empirically, but it is difficult to define the uncertainty related to transition rules.

- *Probabilities in stochastic rules*: In a stochastic model, probabilities that a rule will apply are estimated. These probabilities can reflect uncertainty in the ecological process (how likely it is that a seed will establish?) and will result in a different model outcome each time it is run.

- *Time step*: CA require a discrete time step where all cells update simultaneously. The choice of time step again should reflect ecological processes.

- *Future conditions*: When the model is used for future predictions or scenario modelling, there will be many unknowns introduced. Many of these can be handled by constraining scenarios.

- *Unmodelled variables*: All models must decide which variables to include and which to exclude. Some of the uncertainties introduced here (e.g. by ignoring soil type) can be partially addressed with the probabilities in stochastic rules.

- *Unknown factors*: There will be factors influencing the outcome of the model that simply are not known. This uncertainty could be randomly incorporated into the model.

The model outputs aim to at least acknowledge these uncertainties, while incorporating techniques for handling them, including fuzzy sets, stochasticity, sensitivity modelling and multiple model runs to estimate confidence intervals.

4.0 RESULTS

The model was tested on a small number of paddocks comprising just over 2,000ha within the study area (10km south-west of Murchison). The cell size (10m), the time step (1 year) and the transition rules were not varied. At this stage limited sensitivity analysis has been run varying the probabilities for establishment of trees and shrubs.

Calibration was carried out by varying the values for A, B and C (see Table 1) and minimising RMSE for the resulting proportions of tree, shrub and pasture in three locations within the study site (circles with 250m radius) (see Figure 1). The model parameters are set with $A = 0.1$, $B = 0.02$ and $C = 0.35$.

Figure 1 shows predicted vegetation change from 1970 to 2070 for one run of the model. In locations with few trees, shrubs quickly spread, with trees eventually dominating. Pasture only remains in paddocks that are not abandoned. Figure 2 shows the proportions of vegetation in the three locations shown in Figure 1 from 1970 to 2070. In all three locations, pasture rapidly declines as shrubs and trees increase. Proportions vary, but masks 1 and 3 show typical patterns of shrubs initially increasing and then starting to decrease, while trees continue to increase and eventually dominate. In mask 2 shrubs rapidly dominate because of the low starting proportion of trees. Although the proportions appear to stabilise, this reflects the 30-year delay for new trees to establish and mature enough to take over shrubs.

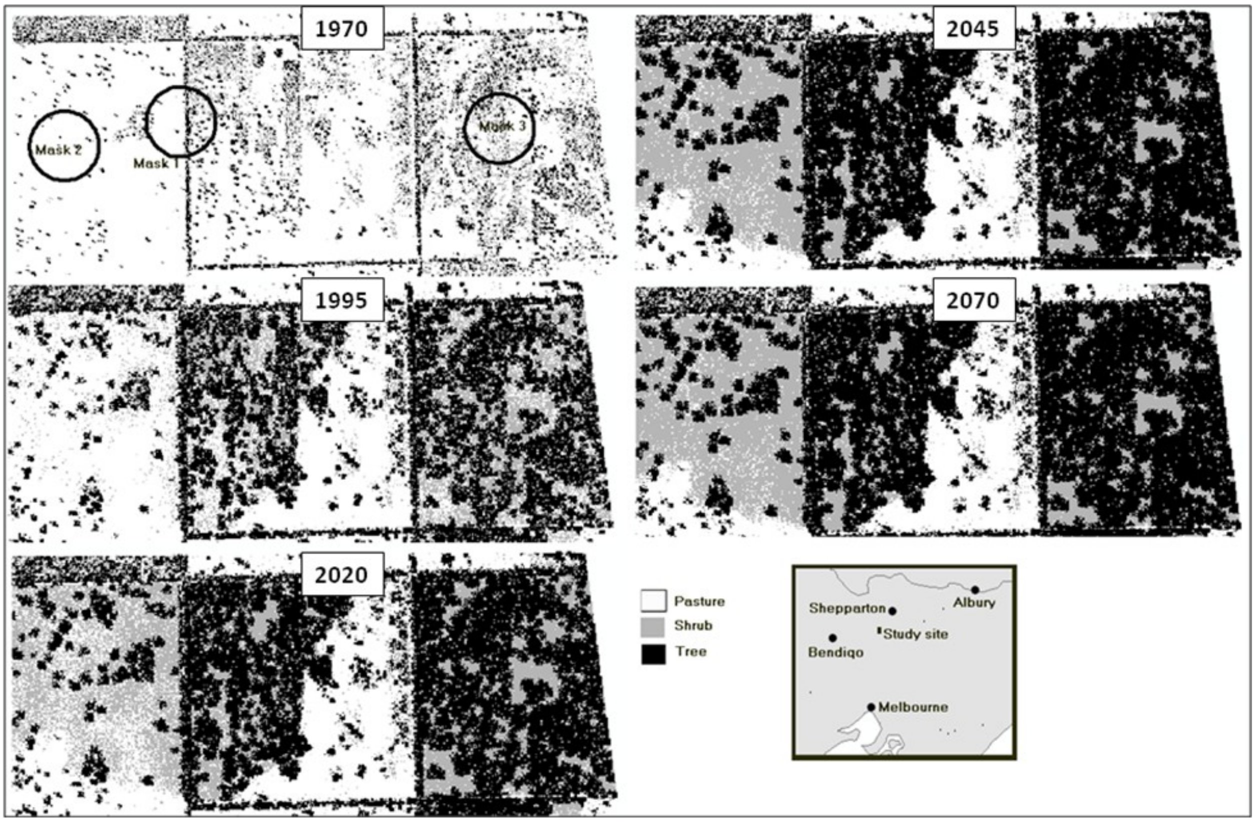

Figure 1: Predicted vegetation cover 1970 – 2070.

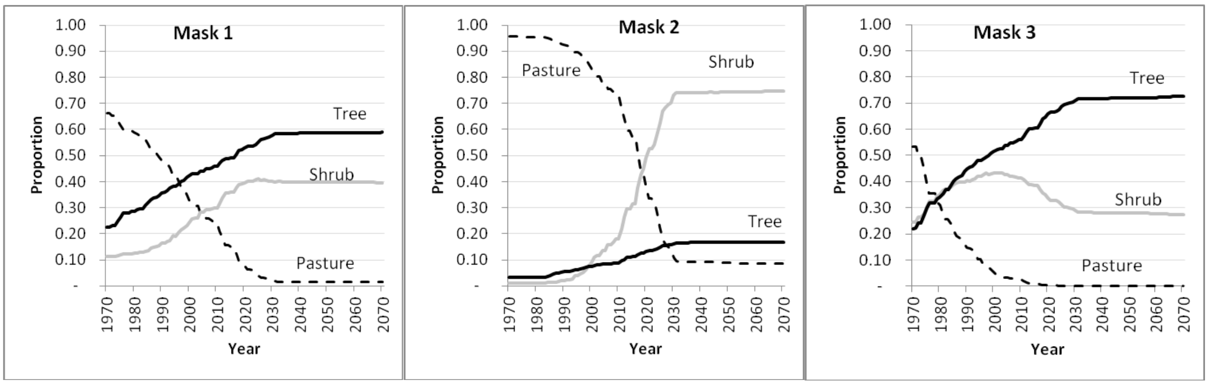

Figure 2: Change in proportion of pasture, shrubs and trees from 1970 to 2070

5.0 DISCUSSION

CA are difficult to calibrate, and sensitivity modelling is a useful tool for estimating parameters. In modelling future scenarios, probabilities and confidence intervals allow a range of vegetation proportions to be predicted rather than exact values in each location. The model estimates the relative proportions of these vegetation types under future rainfall and abandonment scenarios (not included here for brevity).

Including uncertainty explicitly in the modelling is important for explaining and understanding the model outcomes and for future decision making. Regrowth has the potential to provide important habitat for species and reconnect a fragmented agricultural landscape. By incorporating uncertainty, management options for different outcomes can be fine tuned to maximise the benefits.

6.0 CONCLUSION AND FUTURE WORK

This research is still at the initial stages; however the results show that it is possible to realistically model vegetation change using CA. The next steps are sensitivity analysis on neighbourhood size and shape, rainfall probabilities and introducing fuzzy sets for cell states.

For the 2,000ha testing raster, aerial photographs are available for 1970, 1982, 1989, 1999 and 2007. This allows for robust calibration and validation. The ultimate aim is then to model future scenarios under different rainfall and human disturbance conditions, and assess the resulting landscapes for the biodiversity benefit to the woodland bird community.

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