The Use of Particle Swarm Optimization for a Vector Cellular Automata Model of Land Use Change

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Abstract

Cellular automata (CA) is an important area of research in GIScience, with recent research developing vector-based models in addition to the traditional raster data formats. One active area of research is the calibration of transition rules, particularly when applied to vector CA. Here we evaluate a particle swarm optimization (PSO) process to calibrate a vector CA model of land use change for a sub-region of Ipswich in Queensland, Australia, for the period 1999-2016. We compare the results with those for a raster CA of the same dataset. The spatial indices of the vector PSO-CA model exceed that of the raster model, with spatial accuracies being 82.45% and 76.47%, respectively. In addition, the vector PSO-CA model achieved a higher kappa coefficient. Vector-based PSO-CA model can be used for the exploration of urbanization process and provide a better understanding of land use change.

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1 Introduction

Cellular automata (CA) are widely used models of dispersal processes, with example applications including disease spread [6], forest fire spread [8], land use change [2, 15], traffic flow simulation [1], planning support systems [12]. Of these topics, the integration of CA and land use change analysis is of considerable significance given issues of globalization and the expansion of the human population. There are already several case studies applying the method to metropolitan areas, for example in Australia [17], Canada [21], China [23], Europe [5] and the USA [13].

The definition of transition rules, which determine the state conversion of geographical features during simulation, is a core component of CA modelling [16]. A variety of artificial intelligence and evolutionary algorithms have been used to calibrate land use transformation

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rules in an efficient and objective way, including artificial neural networks (ANN), ant colony optimization (ACO), bee colony optimization (BCO), cuckoo search (CS), decision tree (DT), genetic algorithm (GA), multi-agent system (MAS), particle swarm optimization (PSO), and support vector machines (SVM). It is generally accepted that such methods offer a capacity to minimize the disagreement between the simulations and reference maps, resulting in a set of optimized transition rules and thus improving their accuracy for urban modelling [10]. Nonetheless, most of the above-mentioned methodologies have been validated with raster CA models. There are very few analyses of the integration of evolutionary algorithms and intelligent optimization with vector CA models.

Here we report on the implementation of CA models calibrated using PSO, implemented as both vector and raster formats. The parameters and simulation processes are compared between the two formats using a case study in Queensland, Australia. The analyses were implemented using a prototype system developed using ArcEngine 10.3 and C#.

2 Particle swarm optimization (PSO)

Particle swarm optimization is a widely used intelligent optimization method in artificial intelligence algorithms, an important research area in GIScience. This method explores the optimal solution of problems with regard to a given measure of quality. The method was first proposed by Kennedy and Eberhart [7], and then developed by Shi and Eberhart [19] to enhance the efficient search for a globally optimal solution with inertia weights. The basic unit in the PSO method is the ‘particle’, which refers to one of the potential solutions in the model, and can be described as:

$$particle = (v_n, P_n) \tag{1}$$

where n is the dimensionality of the target problem, v_n and P_n are the velocity and position of a particle at a specific time point. Specifically, v_n can be described as the combination of n velocities (in n dimensions) at time t:

$$v_n = (v_1, v_2, \ldots, v_n, t) \tag{2}$$

and similarly, P_n can be represented by n positions in a n-dimensional space at time t:

$$P_n = (P_1, P_2, \ldots, P_n, t) \tag{3}$$

Furthermore, the velocity and position of each particle will be updated according to individual and global best positions:

$$\begin{cases} v(t+1) = w * v(t) + c1 * rand * (P_{ib} - P(t)) + c2 * rand * (P_{gb} - P(t)) \\ P(t+1) = P(t) + v(t+1) \end{cases} \tag{4}$$

where w is the weight of velocity at time t, $c1$ and $c2$ are two constant weights which are set in advance, and rand is a randomly generated number in the interval [0, 1]. P_{ib} is the best individual position of particle i, and P_{gb} is the best global position of particle swarm, namely the best one of all best individual positions. In addition, $v(t+1)$ is the velocity of a particle at time $t+1$, $P(t)$ and $P(t+1)$ are the positions of particle at time t and t+1, separately.

3 Case study

3.1 Study area

The study area for this research comprises two districts (Collingwood Park and Redbank Plains) of Ipswich city, with an area of 2,571 ha. Ipswich City is the second oldest local

Table 1 Driving factors of land use change in the study area.

Driving factors	Definition	
	Raster PSO-CA	**Vector PSO-CA**
disCom	Distance to commercial service	
disPub	Distance to public service	
disHw	Distance to highways	
disSr	Distance to secondary roads	
neigh	5×5 Moore Neighbour	Parcels intersecting a 60 m buffer zone around the 1999 residential cells
popDen	The changed density of population within a parcel over the past decade	
area	not applicable	Area of parcel

government area in the Brisbane-South East Queensland (SEQ), one of the fastest growing metropolitan region in Australia [22, 14]. The current population of approximately 200,000 in Ipswich is projected to double by 2031 [11].

In general, there are 17 land use classes in the study area. During 1999-2016, the main land use transformation was from 'grazing native vegetation' and 'residual native cover' to 'residential area'. The area of grazing native vegetation decreased by 233.95 ha over this period, representing 76.03% of all changed land use. Residual native cover is the category with the second largest reduction, at 66.3 ha, or 21.55% of the entire decreased category. There is also a 200-ha increase of residential area during the same period, which is 64.76% of all increased land use types.

3.2 Driving factors

The general objective of this study is to model the set of non-residential cells (in 1999) which were transformed in 2016, thus for the purposes of analysis, 'grazing native vegetation' and 'residual native cover' were reclassified as 'non-residential'. Between 1999 and 2016, 188.47 ha of non-residential land was transformed to 'residential', while 809.77 ha of non-residential land remained unchanged. These 'non-residential' and 'residential' land parcels are defined as the vector cells of our CA model. The raster data sets were derived by converting the land use map into 30 m grid cells, which is consistent with the Landsat Thematic Mapper data commonly used to derived such maps.

The position values of a single PSO particle correspond to one possible combination of weights. Therefore, the number of dimensions is equal to the number of driving factors of land use change in the study area (Table 1). There are six common driving factors to both the raster and vector CA models, and vector CA having an additional driving factor to represent parcel area.

3.3 Simulations

On the basis of previous work by Feng et al. [10] and experimentation, the values of w, c1, c2 were set as 1, 1.2 and 1.2, which represent the contributions of the current velocity and best position of a particle, as well as the best position of particle swarm. 50% of the transformed and non-transformed non-residential cells were randomly selected and normalized as the sample of PSO training. Derived weights for the two models are given in Table 2.

The transfer probability P_{tran}, of non-residential cells is calculated as:

$$P_{tran} = \frac{1}{1 + exp((-1) * \sum_{n}^{1}(w_i * x_i))} \quad (5)$$

Table 2 Weights of vector and raster PSO-CA models.

Driving factors		disCom	disPub	disHw	disSr	neigh	popDen	area
Weight values	Raster PSO-CA	0.023	-2.181	0.270	-0.970	2.500	-0.320	na
	Vector PSO-CA	0.025	0.312	0.390	0.080	0.650	0.880	0.800

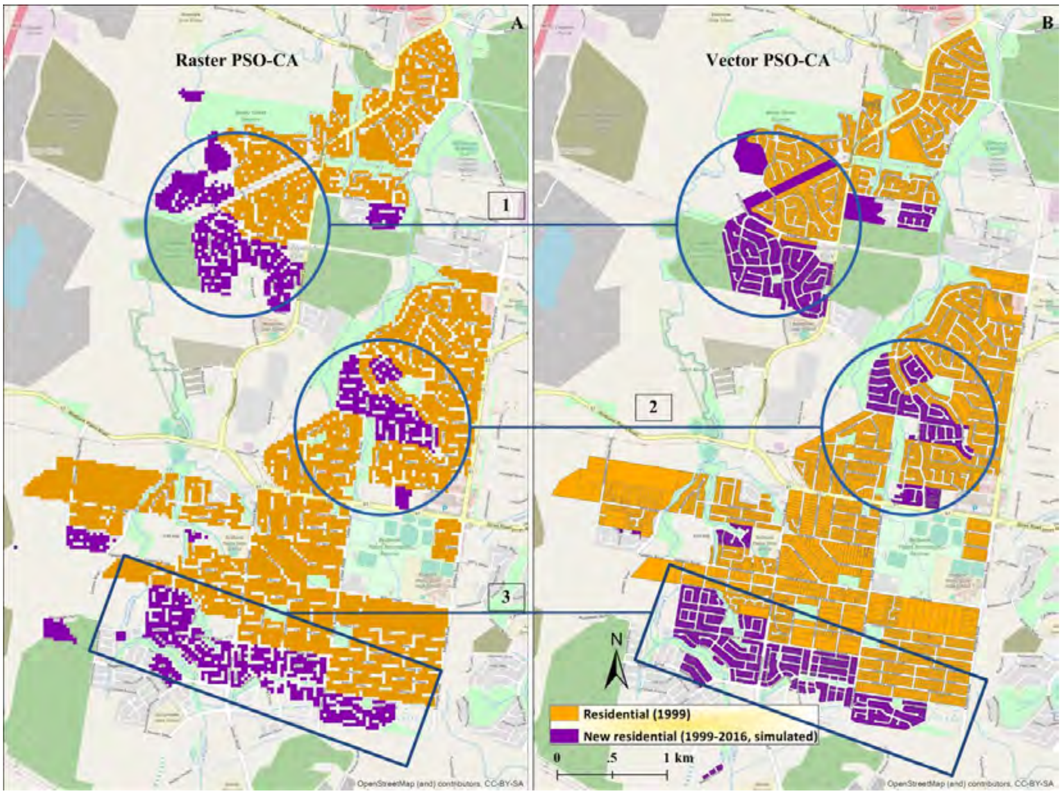

Figure 1 Simulation results of raster (A) and vector (B) PSO-CA models (Base map: OpenStreetMap).

Table 3 Spatial accuracies of PSO-CA models.

Model type	Spatial accuracy (%)	Kappa coefficient
Raster PSO-CA	76.47	0.886
Vector PSO-CA	82.45	0.916

where w_i is the weight of corresponding driving factor, x_i is the normalized value of a non-residential cell. P_{tran} is in the interval [0, 1]. A larger number of iterations, which means a shorter iteration interval, are required for completing CA-based simulations [3]. Accordingly, the number of iteration is set as 100 in this study.

The simulation results (Figure 1) show that the general distribution of simulated new residential cells is similar. Specifically, these cells are located in the north (part 1), east (part 2) and south (part 3) of the study area. These are near the 1999 residential areas, consistent with previous studies [9].

Two spatial indices, spatial accuracy and kappa coefficient, are calculated using observed and real land use for years 1999 and 2016. The value of spatial accuracy indicates the proportion of correctly predicted new residential cells, and the inter-rater agreement for cell categories is demonstrated by kappa coefficient [4]. It is clear from the results that the vector CA performs better than the raster CA (Table 3).

4 Discussion and conclusion

The weights of driving factors, which describe their contribution to the transformation of non-residential cells during the period 1999 to 2016, is the main reason for the differences between simulation results. In the raster PSO-CA, neighbouring cells have the largest positive contribution to land use transformation, which is as much as 2.5. Distances to highways and commercial service are the second and third positive driving factors, but only with values of 0.270 and 0.023, respectively. The remaining three driving factors have negative influences on land use transformation from non-residential to residential in raster PSO-CA. Apart from the inconsistency of weight values in the raster PSO-CA, all the seven driving factors of vector PSO-CA have positive influences on the same type of land use transformation, where population growth (0.880), area of cell (0.800) and neighbouring cells (0.650) ranking in the top three. The vector PSO-CA models are more reasonable considering the fact that land use transformation is usually dependent on a series of spatial variables in terms of accessibilities or proximities [15, 20].

The spatial accuracy of PSO-CA is 5.98% higher for the vector format (Table 3). In addition, the kappa coefficient for the raster PSO-CA is also 0.03 lower than the vector CA. Therefore, the vector-based PSO-CA has the capability to produce a more accurate prediction of land use change, which is consistent with previous research on vector CA [18].

In this paper, the effect of data format on PSO-CA model has been assessed by taking a sub-region of Ipswich, Southeast Queensland, Australia. Considering the weights of driving factors, spatial accuracy and kappa coefficients, vector-based PSO-CA achieves a higher accuracy of simulation, which produces a more realistic model of the expansion of residential area. Future research will have a further exploration of the uncertainties of random disturbance [10], which could lead to a different simulation result (such as another combination of driving weights).

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