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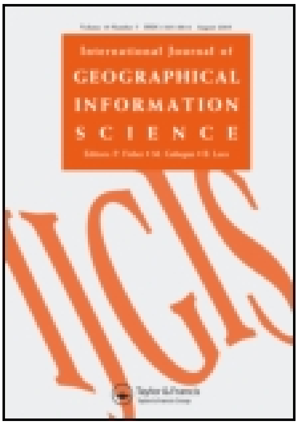

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Assimilating process context information of cellular automata into change detection for monitoring land use changes

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Assimilating process context information of cellular automata into change detection for monitoring land use changes

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This article presents a new method of assimilating process context information into change detection for monitoring land use changes. The accurate information about land use changes is important for implementing many global and regional environmental models. Two types of models have been independently developed to obtain such information, including change detection models (e.g. pixel-to-pixel comparison, post-classification comparison and object-based change analysis) and simulation models (e.g. cellular automata (CA) and agent-based modelling). These models may have limitations in capturing land use dynamics when used alone. In this study, the ensemble Kalman filter is used to obtain the best estimate of land use changes by combining remote-sensing observations with urban simulation. Urban simulation is able to provide process context information such as diffusion and coalescence of urban development. This type of complementary information is useful for improving the performance of change detection. Compared with traditional change detection models, this integrated model has the potential to improve the performance of change detection in terms of accuracies and landscape metrics. For example, the assimilating (MLC + CA) method can show improvement of the total accuracy and the kappa coefficient by 2.5–5.2% and 3.6–7.4%, respectively, in this study.

Keywords: process context; cellular automata; change detection; data assimilation; ensemble Kalman filter

1. Introduction

Studies have indicated that land use changes have profound impacts on regional and global weather and climate (Brovkin *et al*. 2004), and vice versa (Lapola *et al*. 2011). Two types of models have been proposed to obtain information about land use changes: (1) change detection models such as pixel-to-pixel comparison, post-classification comparison and object-based change analysis (Martin 1989, Walter 2004, Im 2008) and (2) simulation models such as cellular automata (CA) and agent-based models (ABMs) (Li and Yeh 2002, Parker *et al*. 2003). These two types of models are formulated based on quite different approaches. The former is to reveal land use changes according to the spectral or contextual properties of remote-sensing data. The latter is based on the mechanism of interactions and feedbacks. It attempts to describe or predict land use changes by using transition rules or behaviour rules (Li *et al.* 2011a).

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The accuracy of change detection is always a major concern for successful remote-sensing applications in a variety of disciplines (Li and Yeh 1998). The development of effective change detection methods has attracted widespread attention with rich literature (Eastman and Fulk 1993, Li and Yeh 1998). A common method for detecting land use changes is to compare two or more dates of the images that cover the same study area. The detection frequently employs two basic methods: the pixel-to-pixel comparison (without classification) and the post-classification comparison (Martin 1989). Although the pixel-to-pixel comparison is effective for detecting a pixel that has experienced changes, this method cannot know what kind of changes has taken place (Li and Yeh 1998). The post-classification comparison is to identify land use changes by carrying out two or more independent classifications. The advantage of this technique is that the land use types for each pixel are obtained from time-series images. Overlaying these classified images reveals not only the amount and location of change, but also the nature of changes (Howarth and Wickware 1981).

As one of the most appropriately and commonly used methods for change detection, the post-classification comparison is usually based on supervised classification of each remotely sensed image (Jensen 1996). Supervised classification can be carried out by using a number of methods such as the per-pixel maximum likelihood classification (MLC) (Foody 1999) and the artificial neural networks (ANNs) (Paola and Schowengerdt 1997). The former assumes that the distribution of a class sample is normal. This method adopts the Bayes' theorem for decision making. The latter attempts to simulate the vast network of neurons in the human brain for reasoning and learning. An advantage of this method is that the distribution of a class sample is not necessary to be normal during supervised classification.

Recently, object-based analysis has attracted growing attention for remote-sensing classification and change detection because of the proliferation of high-resolution satellite images (e.g. IKONOS and QuickBird). It is considered that traditional pixel-based analysis may not function well with these high-resolution satellite images (Im 2008). New algorithms for object-based analysis have been proposed to overcome this problem by using contextual information and shape properties, as well as spectral information (Walter 2004).

Change detection models may suffer from a series of errors or uncertainties. It is because these models are implemented by using only spectral or contextual information retrieved from remotely sensed imagery. The classification accuracies are affected by sensors' noises, atmospheric disturbances and limitations of classification algorithms (Yeh and Li 2006). Moreover, the mixed pixels of remote-sensing data also cause the misclassification of land use types because of the limitations of spatial resolution (Ibrahim *et al*. 2005). The errors of each independent classification can lead to inaccurate information on land use changes. Studies have indicated that these classification errors will result in the overestimation of land use changes (Fung and LeDrew 1988, Li and Yeh 1998).

The second approach for simulating land use dynamics is developed almost outside the field of remote sensing. It is well recognized that land use dynamics is a kind of non-linear geographical process (Batty and Xie 1994). These simulation models, such as CA and ABMs, have been increasingly used to simulate a variety of non-linear geographical processes since the 1980s (Batty and Xie 1994, Li and Yeh 2002, Parker *et al*. 2003, Benenson and Torrens 2004). Especially, CA have become a quite common tool for simulating urban and land use dynamics (Batty and Xie 1994, Li and Yeh 2000). CA were initially developed by Ulam in the 1940s, soon used by Von Neumann (White and Engelen 1993) and further extensively examined by Wolfram to study the logical nature of self-reproducible systems

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(Wolfram 1984, 2002). In the last three decades, a number of standard CA models or tools have been well established for urban land use simulation. They may be based on SLEUTH (Slope, Land cover, Exclusion, Urbanization, Transportation, and Hillshade) (Clarke *et al*. 1997), multi-criteria evaluation (MCE) (Wu and Webster 1998), logistic regression (Wu 2002, Li *et al*. 2008), neural networks (Li and Yeh 2002), decision trees (Li and Yeh 2004) and genetic algorithms (Li *et al*. 2008).

It is obvious that the above change detection and simulation models have their own advantages and disadvantages. Methodologies should be developed to combine these two approaches to improve the performances of change detection. It is expected that the assimilation techniques that are considered as 'the best' estimates of the current state of the system can serve this purpose (Kalman 1960). In recent years, there are increasing studies on the development of assimilation techniques by exploiting the availability of remotely sensed land surface variables (McLaughlin 2002, Andreadis and Lettenmaier 2005). For example, rapid progresses have been made in data assimilation in hydrological modelling by using available remotely sensed soil moisture data (Ni-Meister 2008). The uncertainties in environmental modelling are minimized by recursively updating model states and parameters, in which all sources of uncertainties are explicitly taken into account (Mo *et al*. 2008). Very plausible results have been achieved by applying data assimilation techniques to atmospheric, climate, hydrological and ocean modelling (Kalnay 2003).

The Kalman filter was initially used as an exact optimal solution of data assimilation for a linear system (Kalman 1960). For non-linear systems, the extended Kalman filter (EKF) was developed to calculate the derivatives of linearized equations (Jacobian matrix), which propagate the error covariance to approximate the non-linearities of the prediction models. However, sometimes there are difficulties in deriving the non-linear land surface models using the EKF. The ensemble Kalman filter (EnKF) was proposed as an alternative to the EKF for non-linear problems (Evensen 1994). This method uses a Monte Carlo approach to produce an ensemble of model trajectories (Ni-Meister 2008).

Our work differs from traditional change detection methods by assimilating process models with remote-sensing data. Studies have shown that CA can be coupled with other models for obtaining better modelling results (Li *et al*. 2011b). In this study, we further propose to tackle the problem of overestimating changes by integrating these two types of approaches. It is expected that the performance of change detection can be improved by using process context information as well as contextual information and shape properties that have already been used in other studies. Change detection models and simulation models have been used independently so far. The following sections will discuss the methodology of assimilating process context information into change detection by using the EnKF for fast-growing regions.

2. Methodology

The proposed model involves a series of techniques such as change detection, urban simulation and data assimilation. First, maximum likelihood classification (MLC) and artificial neural network classification (ANNC) are carried out to obtain land use classes for each time period to provide input to post-classification comparison. Then CA are used to simulate land use dynamics for obtaining the process context information of an urban system. Such information can reveal the properties of non-linearity and fractal dimensions of land use changes. Finally, the EnKF is adopted to assimilate the process context information from urban simulation into change detection. Figure 1 is the flowchart of the proposed methodology that is elaborated in the following sections.

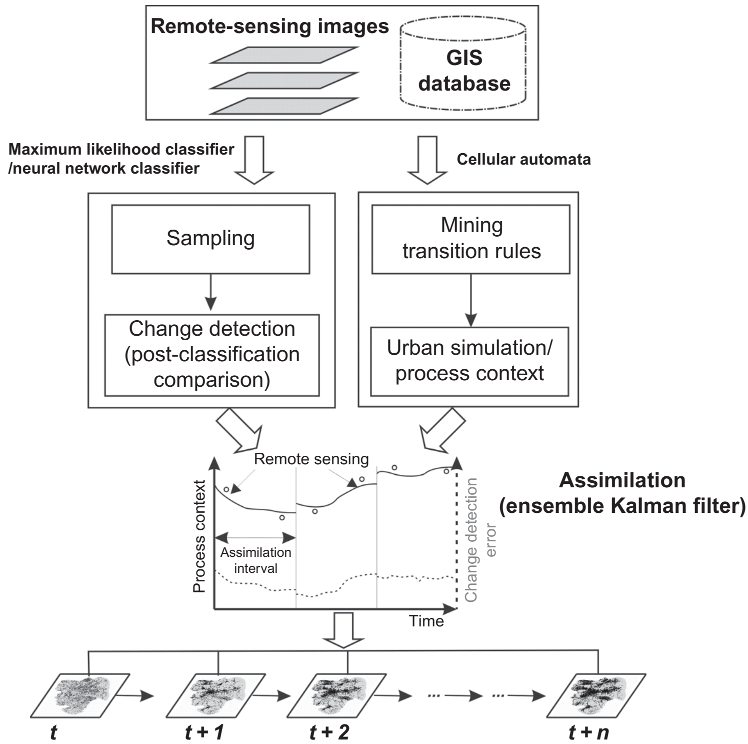

Figure 1. Flowchart of assimilating the process context information into change detection models.

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2.1. MLC and ANNC

The change detection is accomplished according to the post-classification comparison method. There are generally two major methods for classification: pixel-based approaches (Martin 1989) and object-based approaches (Hay and Castilla 2008). In our study, the classification is carried out by using a pixel-based approach as an example. This is because the process model (cellular automaton) is usually implemented based on cells or pixels (Li *et al.* 2011a). The use of a pixel-based approach can allow the implementation of assimilation more easily, although an object-based approach could be developed. Another reason is that the detection of land use changes in this study is only based on Landsat satellite images instead of high-resolution images such as Quickbird. A pixel-based approach should be much simpler to implement than an object-based approach under this situation.

The first step in using the pixel-based approach is to classify each temporal image by using two common methods: MLC and artificial neural network classification (ANNC). MLC is the most common method for the supervised classification of remote-sensing data (Li and Yeh 1998). This method assumes that assigning a pixel to a class or category can be decided by using strict conditional probabilities (Richards and Jia 1999). These probabilities are usually estimated according to the well-known Bayes' theorem if sufficient training data are available for each class (Freund 1992).

ANNs have been widely used for solving classification problems (Paola and Schowengerdt 1997). We also construct a neural network to classify land use types on each temporal image. The classification needs to train the network by determining the

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adaptive weights that address the strengths of network interconnection between associated neurons. These weights are obtained according to the back-propagation method that iteratively minimizes an error function over the network (calculated) outputs and the desired outputs by using a training data set (Foody 1999). Once the optimized weights have been obtained from the training data set, the network can yield the classification results in the output layer. For example, the neurons in the output layer can calculate the membership (probability) value of a land use type for a particular pixel.

2.2. Process context information derived from CA

CA can provide complementary information about land use dynamics, which can be used to improve change detection. CA have been successfully applied to the simulation of many complex natural systems such as the fluctuation of animal population (Couclelis 1988), settlement changes (Deadman *et al*. 1993), evolution of cities (Batty and Xie 1994), wildfire diffusion (Clarke *et al*. 1994), land use conversion (White *et al*. 1997, Li and Yeh 2002), vegetation dynamics (Balzter *et al*. 1998, Favier and Dubois 2004) and ecological changes (Wang and Zhang 2001). Studies have shown that CA can provide useful information about the emergent and non-linear behaviour (e.g. fractal dimensions) of urban systems (Batty and Xie 1994, White *et al*. 1997). These models can capture the complexity of urban patterns and processes according to local interactions.

Transition rules are used to address local interactions in urban and land use simulations. These rules can be in the form of conversion probabilities. For example, the probability for urban development is a function of the various distances to town centres and roads and the existing amount (e.g. development densities) of urban land use in the neighbourhood (Wu and Webster 1998). Actually, CA have a very similar form like many non-linear process models that are used for data assimilation. A general form of CA can be given as follows (Batty and Xie 1994, Li and Yeh 2000):

$$S_{t+1} = f(S_t, \Omega) + \varepsilon_t \tag{1}$$

where S_t is a set of possible discrete states (e.g. land use classes) at time t; S_{t+1} are the converted states at time $t+1$; Ω is the neighbourhood of all cells providing input values to the transition function f, which determines the state conversion from time t to $t+1$; and ε_t is a stochastic factor representing model errors.

More detailed transition rules are required to implement CA. In this study, the CA model is based on logistic regression, although there are a number of other methods such as neural networks (Li and Yeh 2002), decision trees (Li and Yeh 2004) and genetic algorithms (Li *et al*. 2008). The logistic-CA should be one of the most popular CA models because of its calibration capability (Wu 2002, Li *et al*. 2008, 2011). This CA model is based on the estimation of the conversion probability from the non-urban land use type to the urban land use type:

$$p_{ij}^t = \frac{\exp(z_{ij}^t)}{1+\exp(z_{ij}^t)} = \frac{1}{1+\exp(-z_{ij}^t)} \tag{2}$$

where p_{ij}^t is the conversion probability at time t for cell ij; $z_{ij}^t = a_0 + a_1 x_1 + a_2 x_2 + \ldots + a_m x_m + \ldots + a_M x_M$, where a_0 is the constant; x_m is a spatial (physical) variable

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representing a driving force for urban development; and a_m is the parameter (weight) of an associated variable.

Equation (2) only addresses the global interactions that are in the form of various spatial variables. Actually, local (neighbourhood) interactions are the core of CA, which are used to simulate complex non-linear systems. Urban development should also be subject to the local interactions as well as the global interactions. Moreover, sometimes geographical constraints (e.g. topography, protected ecological land and planning schemes) can be included to address environmental and ecological conditions that restrict land development. By incorporating all these factors, the development probability is further revised as follows (Li *et al.* 2008, 2011):

$$p_{ij}^t = (1 + (-\ln\gamma)^\alpha)\frac{1}{1+\exp\left(-z_{ij}^t\right)} \times f\left(\Omega_{ij}^t\right) \times \mathrm{con}\left(s_{ij}^t\right) \tag{3}$$

where γ is a stochastic factor ranging from 0 to 1; α is a parameter to control the stochastic degree; $f(\Omega_{ij}^t)$ is the development intensity in the neighbourhood of Ω_{ij}; and $\mathrm{con}(s_{ij}^t)$ is the combined constraint score ranging from 0 to 1.

At each iteration of simulation, p_{ij}^t is compared with a threshold value to determine whether a non-urbanized cell can be converted into an urbanized cell:

$$S_{ij}^{t+1} = \begin{cases} \text{Converted}, & p_{ij}^t \geq T \\ \text{Non-converted}, & p_{ij}^t < T \end{cases} \tag{4}$$

where T is a threshold value.

The threshold T is determined in such way that the total number of converted cells will be equal to the actual one that can be estimated from the actual land demand or remote-sensing observed data (Li and Yeh 2004). This CA model is implemented by using a free GeoSOS package(available at http://www.geosimulation.cn/) (Li *et al.* 2011a). This model will be used to simulate the non-linear urban dynamics of the study area by providing the process context information for change detection. This type of information derived from urban simulation should be able to capture some distinct processes of urban development and land use changes such as evolution of fractal dimension, urban diffusion and coalescence. Section 2.3 will discuss the methodology of combining these different types of information by using the EnKF.

2.3. EnKF for assimilating process context information into change detection

In this study, the assimilation is to blend the observational measurements from remote sensing and the modelling results from CA. This is implemented by using the EnKF, which can provide the best estimate of the system states according to the model predictions and observations (Reichle 2008). The Kalman filter has been widely used for solving a variety of data fusion problems (Kalman 1960, Ni-Meister 2008). By using this Kalman filter, the uncertain states (the probabilities for land use classes) obtained from CA (X_t), given a set of observed states ($Y_{1:t}$) detected from remote sensing, can be presented by the conditional probability density function $p(X_t|Y_{1:t})$. Merging the model estimates with the observations is carried out by using this ensemble Kalman method.

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First, the model estimates could be obtained from one of these geographical process models such as climate models, hydrological models, CA and ABMs. In our study, a cellular automaton is used as the process model, which can be defined as the evolution of the states (e.g. the probability for a land use class) from time $t-1$ to time t (Ni-Meister 2008):

$$X_t = f(X_{t-1}, \mu_{t-1}) + \varepsilon_t \tag{5}$$

where X_t is a model state vector at time t; f is a non-linear function (transition rules) describing the evolution of the states from time $t-1$ to time t; μ_{t-1} is a vector of model inputs; and ε_t is the model error vector.

The simulated states (probabilities) are assumed to be related to the observed ones according to the following equation:

$$Y_t = h(X_t) + \upsilon_t \tag{6}$$

where Y_t is the observed probability; h is a non-linear transformation function; and υ_t is the observational error.

Many methods have been developed to improve the model estimates with observations. The simplistic method is to replace the model estimate with the newly arrived observation. However, this method is problematic because the observation itself is not error-free. Some optimization methods have been developed to produce better assimilation effects. The basic concept of data assimilation can be easily explained by considering a scalar model variable X with uncertainty (or error variance) σ_X^2 and a corresponding scalar observation Y with uncertainty σ_Y^2. The objective function J can be defined to measure the misfit between the true state T and the model estimate X and the observation Y (Reichle 2008):

$$J = \frac{(T_t - X_t)^2}{\sigma_X^2} + \frac{(T_t - Y_t)^2}{\sigma_Y^2} \tag{7}$$

The optimization is to find the least squares estimate $\bar{T}$ of the true state T based on the available information. The minimization can be obtained by solving $\mathrm{d}J/\mathrm{d}X = 0$. This yields the following equation (Reichle 2008):

$$\begin{aligned} \overline{T}_t &= \left(\sigma_X^2 + \sigma_Y^2\right)^{-1}\left(\sigma_Y^2 X + \sigma_X^2 Y\right) \\ &= (1-K)X + KY \end{aligned} \tag{8}$$

where the *Kalman gain* $K = \sigma_X^2 / \left(\sigma_Y^2 X + \sigma_X^2 Y\right)$ $(0 \le K \le 1)$.

Equation (8) indicates that the best estimate (or analysis) $\overline{T}_t$ is a weighted sum of the model background X and the observation Y. It is apparent that the gain will be large if the measurement error variance σ_Y^2 is small, and the resulting estimate will be very close to the observation, and vice versa. Equation (8) can be rewritten as follows:

$$\overline{T}_t = X + K(Y - X) \tag{9}$$

The above method may be too simplified to solve real-world problems. Actually, data assimilation consists of two steps: prediction (background) and updating (analysis). The prediction step is the transition of state variables from one observation time to the next according to the transition function. The updating (analysis) step involves the updation of the forecasted (propagated) states when the new observation arrives. These two steps can be represented using the following equations:

$$X_t^- = f\left(X_{t-1}^-, \mu_{t-1}\right) \tag{10}$$

$$X_t^+ = X_t^- + K_t\left[Y_t - h(X_t^-)\right] \tag{11}$$

where X_t^- is the background state at time t predicted by the model; X_t^+ is the analysis state updated by the newly arrived observation; the measured and predicted vector difference, $\left[Y_t - h(X_t^-)\right]$, is used to make a correction to the model predicted system state vector to improve the state; and K is the Kalman gain.

The calculation of derivatives of linearized equations (Jacobian matrix) is required to propagate the error covariance to approximate the non-linearities of the process models (Quaife *et al*. 2008). This can be carried out by using the so-called EKF (Reichle 2008). However, EKF has a series of limitations in terms of implementation and tuning. It is only reliable for solving the problems that are almost linear on the timescale of the updates (Ni-Meister 2008). As an alternative to the EKF for non-linear problems, the EnKF was developed to reduce the number of degrees of freedom to a manageable level (Evensen 1994).

In EnKF, a state variable (X) from a process model has n ensemble members, that is,

$$X_t^- = \left\{x_t^{1-}, x_t^{2-}, x_t^{3-} \ldots x_t^{n-}\right\} \tag{12}$$

where $x_t^{1-}, x_t^{2-}, x_t^{3-} \ldots x_t^{n-}$ are the ensembles of the forecasted model state at each time t. These ensemble members can be created by adding random noises to the parameters of a process model (Huang *et al.* 2008).

The model error covariance matrix can be calculated from these ensembles according to the following equation:

$$P_t^- = \frac{1}{N-1}\sum_{i=1}^{N}\left(X_t^- - \overline{X_t^-}\right)\left(X_t^- - \overline{X_t^-}\right)^T \tag{13}$$

where

$$\overline{X_t^-} = \frac{1}{N}\sum_{i=1}^{N} X_t^i$$

The Kalman gain in Equation (11) is given as follows (Moradkhani 2008):

$$K_t = P_t^- H^T\left(HP_t^- H^T + R\right)^{-1} = C_t^{xy}\left(C_t^{yy} + R\right)^{-1} \tag{14}$$

where H is the Jacobian of the function h and R is the sample covariance matrix of the observation ensemble $\{y_t^i\}$; $C_t^{xy} = P_t^- H^T$ and $C_t^{yy} = HP_t^- H^T = \frac{1}{N-1}\sum_{i=1}^{N}\left[H\left(X_t^-\right) - H\left(\overline{X_t^-}\right)\right]\left[H\left(X_t^-\right) - H\left(\overline{X_t^-}\right)\right]^T$.

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3. Model implementation and results

3.1. Spatial data and model parameters

The proposed model is applied to the change detection in the study area of Panyu. Panyu has a total area of 786.2 km^2, situated in the core of the Pearl River Delta, China (Figure 2). Recently, the study area witnessed fast land use changes because of economic and population growth. According to the classified satellite Thematic Mapper (TM) images, its urban area was 173.3 km^2 in 2003, but expanded to 243.6 km^2 in 2008. The annual rate of urban expansion was as high as 7% in that period. Empirical studies have shown that the urban land expands by 3% when the economy, measured by gross domestic product, grows by 10% in China (Deng *et al.* 2008). In terms of its economic growth, the rate of land consumption in Panyu is unusually higher than the normal average rate in China.

The change detection needs to use time-series satellite images for monitoring land use changes in the study area. These data include cloud-free Landsat TM images dated 30 December 1995, 9 December 1999, 17 October 2003 and 4 March 2008. The study area of Panyu was extracted from the Guangzhou Landsat TM scene (No. 122-44 in the Reference System of China Remote Sensing Ground Station). Each subscene has an area of 1295 pixels (columns) × 1123 pixels (rows), equivalent to a total area of 1308.9 km^2.

The radiometric correction and geometric correction were carried out for these multitemporal images. First, the dark object subtraction method was used to minimize the influences of different weather and light conditions on land use classification (Chavez 1988). Second, geometric corrections for these images were carried out by using ground control points. The total root mean squared error of the geometric correction was less than 0.5 pixels. These images were finally georeferenced into the Transverse Mercator system.

Figure 2. The study area of Panyu in the Pearl River Delta.

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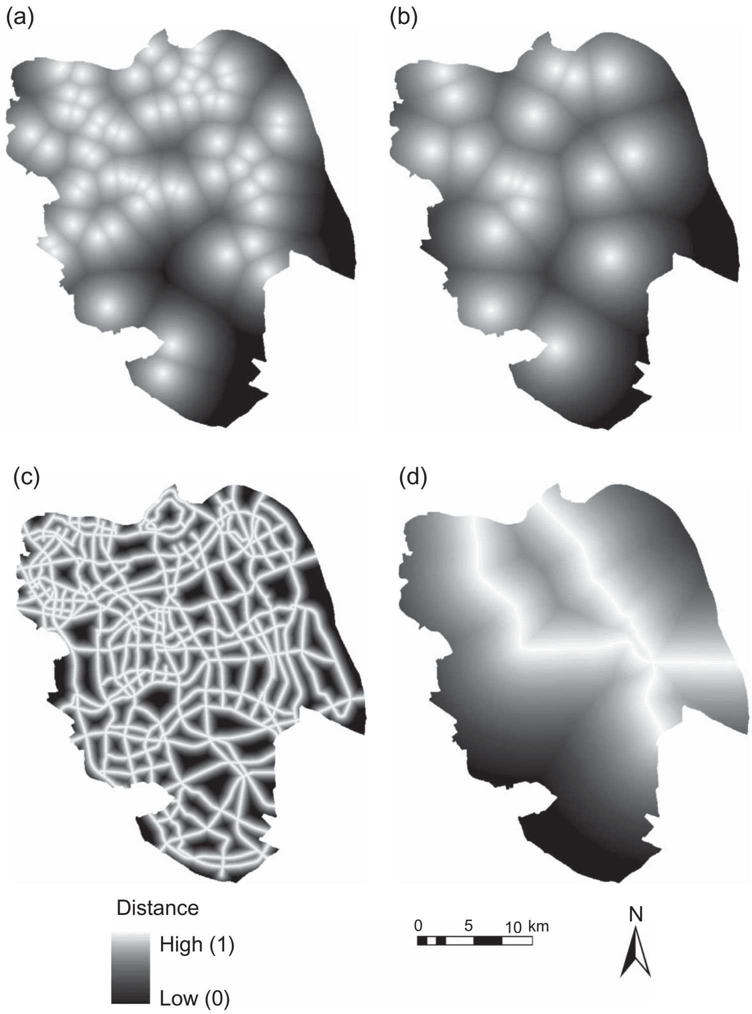

Figure 3. Various proximity variables of the cellular automaton. (a) Distance to settlement centres. (b) Distance to town centres. (c) Distance to roads. (d) Distance to underground stations.

Locational (spatial) factors play an important role in driving land use changes (Wu and Webster 1998). In urban simulation, these factors usually include various proximities to attraction centres (Batty and Xie 1994, Wu 2002, Li *et al*. 2011a). In this study, these factors include the distances to the settlement centres ($D_{\mathrm{SettleCentre}}$), town centres ($D_{\mathrm{TownCentre}}$), roads ($D_{\mathrm{Road}}$) and underground stations ($D_{\mathrm{Groundstation}}$) (Figure 3).

The total number (size) of ensemble members may have effects on the performance of data assimilation. The model predictions are poor when the ensemble size is small (e.g. <5) (Reichle and Koster 2003). The increase in the ensemble size will improve the performance of data assimilation, but at the cost of increasing computation time. The ensemble size of 10–20 is usually acceptable because the model predictions improve very little, especially when the ensemble size is greater than 50 (Crow and Wood 2003, Reichle and Koster 2003). In this study, the ensemble size was set to 20 for the computational reason.

3.2. Obtaining model results from CA and observations from remote sensing

Training data were selected from time-series TM images (e.g. 1995, 1999, 2003 and 2008 TM images) to calibrate CA and derive the maximum likelihood classifier and the artificial neural network classifier (Li and Yeh 2004, Pal 2008, Bazi and Melgani 2010). For each temporal image, a total of 53 sites (patches) were selected to obtain the training and test data. These sites consisted of a total of 12,390 pixels. The selection of these sites was to cover broad geographical features and land classes as much as possible (Figure 4).

Among these 12,390 pixels, 10,000 pixels were used as the training samples while 2390 pixels were reserved as the test samples. Twenty ensembles for the assimilation were created by using different subsets of training samples for calibrating the CA model. For creating a subset, 2000 samples were randomly drawn from these 10,000 training data. This procedure was repeated 20 times to obtain a total of 20 training subsets. Then these subsets were used to obtain various combinations of parameters for the logistic-CA (Wu 2002). These combinations yielded 20 simulation results that were used as the ensembles $\left(X_t^-\right)$ for the assimilation.

The simulation of land use dynamics was implemented by using the logistic-CA provided by the free GeoSOS package (Li *et al.* 2011a). This package is equipped with a variety of tools that can calibrate CA after the empirical data about urban development and independent spatial variables (e.g. proximity variables) have been defined. CA are usually calibrated by using the empirical information in the early stage, and then the calibrated models can predict the future changes if the growth trend continues. The empirical information about the land use changes was obtained from the classifications of the first two TM images in 1995 and 1999. With this empirical information as the dependent, the transition rules of CA were derived through the logistic regression using a series of proximity variables as independents (Wu 2002, Li *et al.* 2008).

The calibrated CA are obtained by using different training subsets. These models were then used to simulate the urban dynamics for the study area in 1995–2008 (Figure 5). The simulation assumes that the development trajectory of the study area remains unchanged.

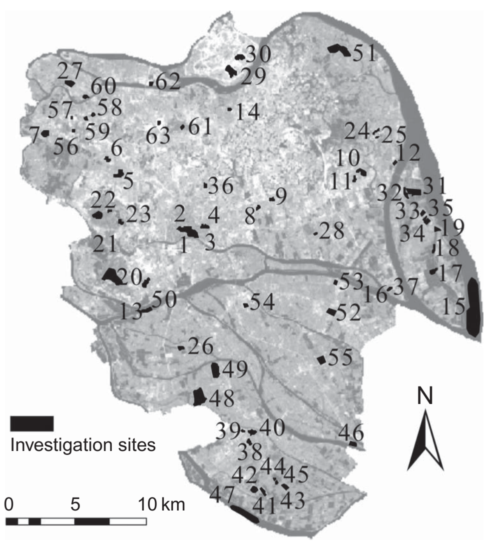

Figure 4. Investigation sites for constructing land use classifiers and calibrating cellular automata.

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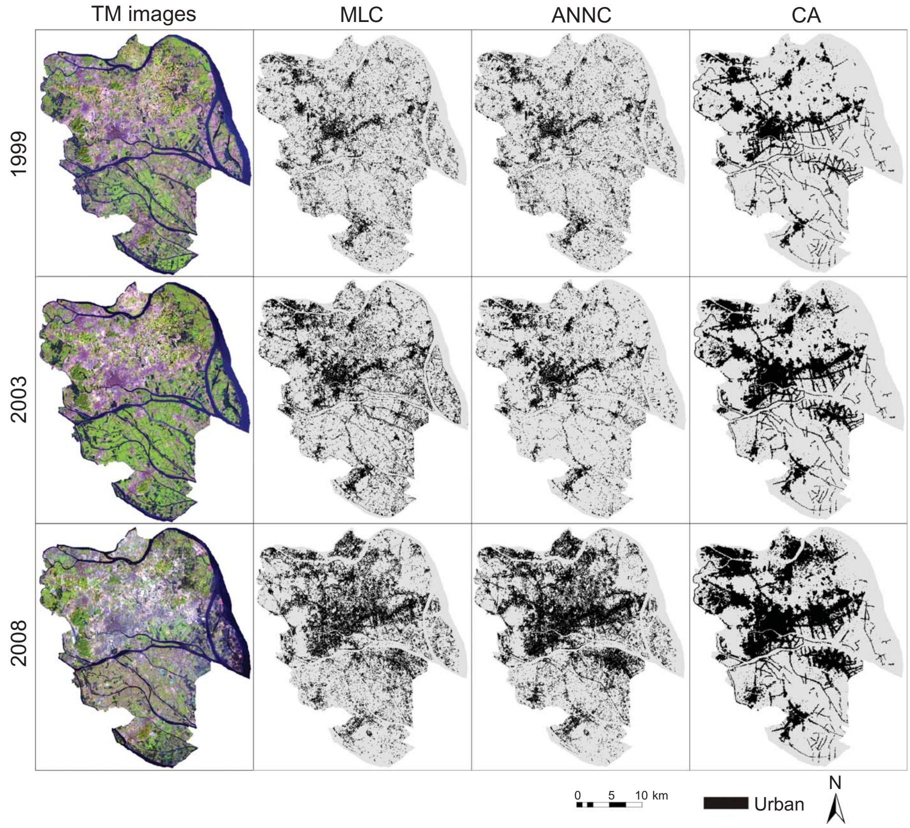

Figure 5. Obtaining urban land and non-urban land classes in the study area in 1999, 2003 and 2008, respectively, using MLC, ANNC, and cellular automata (CA).

Table 1a also shows the average accuracies of the land use simulation based on the test data.

Two types of classifiers, MLC and ANNC, were also constructed according to the traditional methods of using these training data. Then MLC and ANNC were used to classify the urban land and the non-urban land in the study area in 1995, 1999, 2003 and 2008, so that urban expansion could be revealed (Figure 5). It is straightforward to use overall accuracy to assess the performances of these classifiers by using the test samples. However, studies have shown that the kappa coefficient is a better indicator than the overall accuracy because the former can address the difference between the actual agreement and the chance agreement (Li and Yeh 1998). Table 1a provides the classification assessment of MLC and ANNC in terms of the overall accuracy and the kappa coefficient with these test data.

3.3. Assimilating process context information into change detection

The EnKF was then used to assimilate urban dynamics into change detection. Table 1a indicates that both the change detection models (e.g. MLC and ANNC) and CA models have their own classification errors. It is expected that EnKF will obtain the better estimate

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Table 1. Improvement of classification accuracies by using the assimilation method and the voting method.

Year	Overall accuracy MLC (%)	Overall accuracy ANNC (%)	Overall accuracy CA (%)	Kappa coefficient MLC	Kappa coefficient ANNC	Kappa coefficient CA
(a) Original classification accuracies of MLC, ANNC and CA						
1995	82.67	84.42		0.562	0.577	
1999	81.74	83.73	82.16	0.558	0.562	0.560
2003	79.92	82.04	79.28	0.536	0.559	0.534
2008	76.43	77.06	75.49	0.472	0.479	0.463

Year	Overall accuracy Voting MLC + CA (%)	Overall accuracy Voting ANNC + CA (%)	Overall accuracy Assim MLC + CA (%)	Overall accuracy Assim ANNC + CA (%)	Kappa coefficient Voting MLC + CA	Kappa coefficient Voting ANNC + CA	Kappa coefficient Assim MLC + CA	Kappa coefficient Assim ANNC + CA
(b) Improvement of classification accuracies								
1999	83.57	84.68	85.17	85.64	0.561	0.569	0.578	0.591
2003	81.31	82.68	84.05	85.36	0.549	0.560	0.565	0.583
2008	77.57	77.63	78.32	79.01	0.481	0.489	0.507	0.520

Note: CA, cellular automata.

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of classified land use types for these temporal satellite images and then yield the better change detection results by combining the advantages of these models.

First, the background probability for a land class, X_t^-, was simulated according to the logistic-CA. The observations for the actual probability were obtained by using MLC and ANNC. Then the EnKF was used to obtain the analysis state (the updated probability), X_t^+, which was updated by the new arrived observation based on Equation (11). Since the updated probability is the best estimate of the 'true' probability, it was used to replace the original one of MLC and ANNC during the final land use classification.

As a comparison, a voting method was also used to combine different models to improve the change detection. Each model has a weight contributed to the classification. The weight is estimated according to its classification accuracy as follows:

$$W_i = \frac{E_i}{\sum_j E_j} \tag{15}$$

where W_i is the weight for model i and E_j is the classification accuracy for model j.

The final probability based on this voting method is given as follows:

$$P = \sum_i W_i P_i \tag{16}$$

where P is the final probability and P_i is the probability estimated by model i.

There are a number of combinations in terms of different models (e.g. MLC, ANNC and CA) and different merging methods (the assimilation method and the voting method). Figure 6 shows the effects of different model combinations on improving the performance of change detection.

It is interesting to find that the accuracies of MLC, ANNC and CA unanimously decrease with time (Table 1a). The decrease in the accuracies of MLC and ANNC is rather related to the increase in the complexity of land use patterns. Figure 7 shows the evidences of the increase in the complexity of land use patterns in the selected areas of Panyu with time. This increase is caused by more diversified and fragmented use of land resources in this fast-growing region. It is reasonable that the increase in the complexity of land use will make the identification of training samples more difficult. This will probably result in the decrease in classification accuracies. However, the accuracies of CA will degrade with time because this model is built by using the earlier training data in 1995 and 1999.

The capability of capturing and predicting urban dynamics by CA can also be demonstrated by using some landscape metrics as well as the above accuracy indicators. These landscape metrics may include the fractal dimension and entropy, which can reveal the process context information related to non-linear properties of an urban system. Studies have shown that the fractal dimension is one of the inherent and important features of an urban system (Batty and Longley 1994). The fractal dimension reflects the fact that urban forms are usually irregular and complicated. As a city evolves, the fractal dimension tends to increase steadily because urban land will fill up the space. This has been proven by examining the historical growth of many cities in the world (Batty and Longley 1994). Figure 8a compares the fractal dimensions of the study area, which were obtained by using remote sensing and urban simulation, respectively. These two fractal dimensions increase with time, sharing a very similar growth trend. Therefore, urban simulation is able to capture the process context information of urban systems.

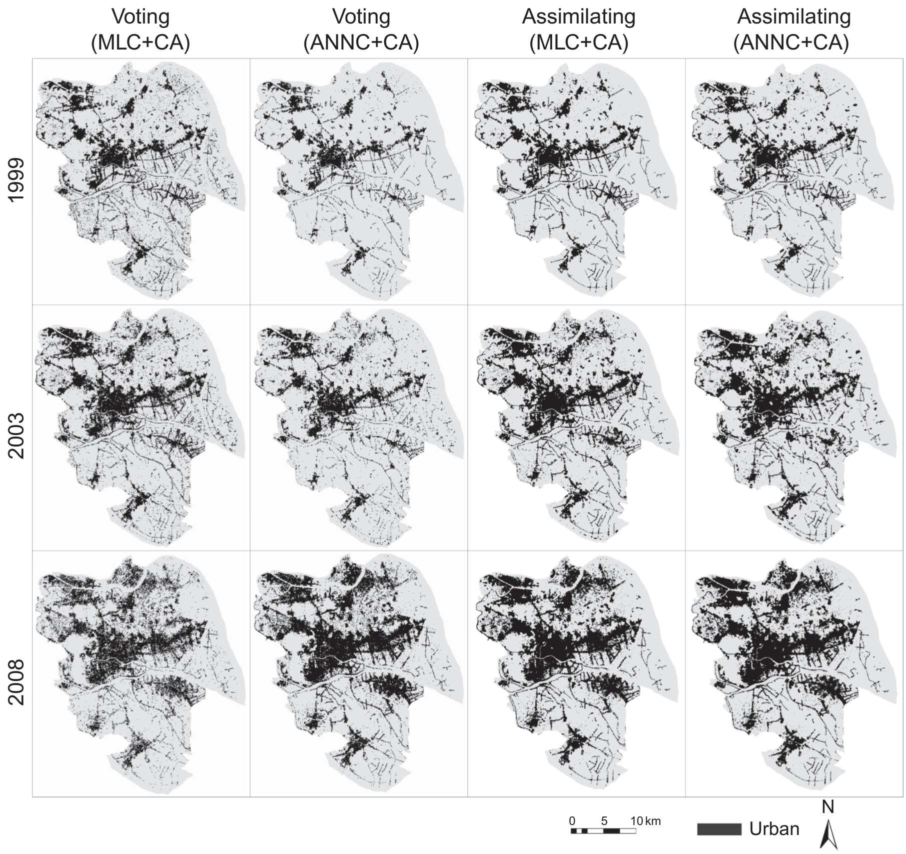

Figure 6. Effects of improving the performance of change detection by using different models (e.g. MLC, ANNC and cellular automata (CA)) and different merging methods (the assimilation method and the voting method).

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The indicator of entropy can also be used to measure the landscape changes related to the urban dynamics. Studies have shown that Shannon's entropy is a good statistic for measuring the spatial distribution of various geographic phenomena (Yeh and Li 2001). Figure 8b clearly shows that there is a similar trend of increase in entropy from both remote sensing and urban simulation. The indicator of compactness (area/perimeter ratio) can also well reveal the patterns and processes of land use dynamics (Li and Yeh 2000). It is interesting to see that the compactness obtained from both remote sensing and urban simulation increases with time because the space has been filled up with built-up areas (Figures 6 and 8c). Therefore, CA models can yield useful information about the process context of urban dynamics, which should be incorporated to improve change detection. It is because CA have the capability of simulating non-linear processes in an urban environment.

Table 1b compares the classification performance of different combinatorial methods. It is found that the assimilating (MLC + CA) method shows the general improvement of the total accuracy and the kappa coefficient by 2.5–5.2% and 3.6–7.4%, respectively, compared with a pure classification method (MLC). The assimilating (ANNC + CA) method also shows the improvement of the total accuracy and the kappa coefficient by 2.3–4.0% and 4.3–8.6%, respectively, compared with a pure classification method (ANNC).

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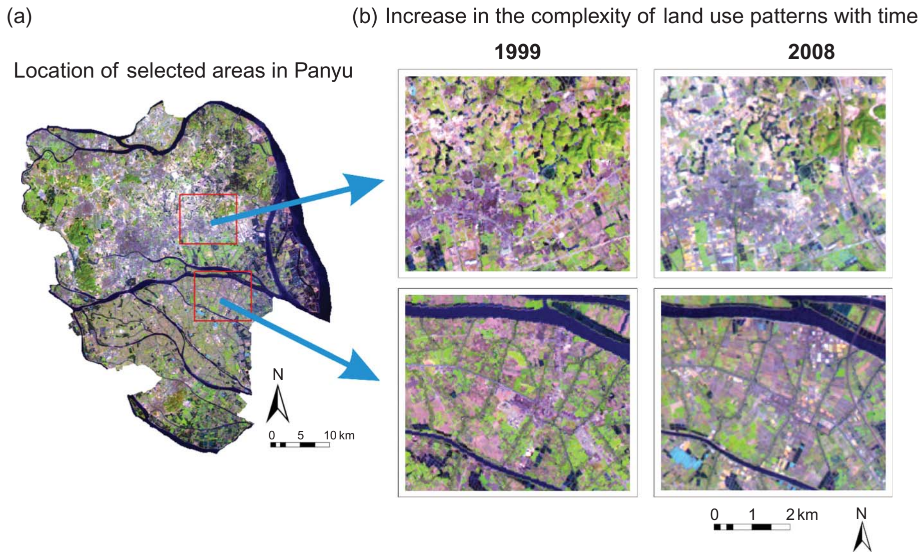

Figure 7. Increase in complexity of land use patterns with time in selected areas (b) in a selected area in Panyu (a).

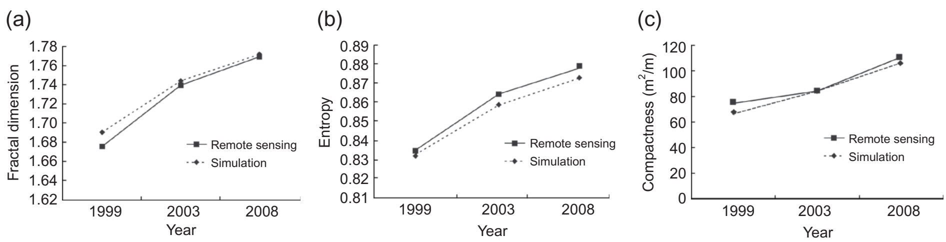

Figure 8. Increase in the values of fractal dimension (a), entropy (b) and compactness (c) with time.

The voting method (MLC + CA) shows the improvement of the total accuracy and the kappa coefficient by 1.5–2.2% and 0.5–2.4%, respectively, compared with a pure classification method (MLC). The voting method (ANNC + CA) shows the improvement of the total accuracy and the kappa coefficient by 0.7–1.1% and 0.2–2.1%, respectively, compared with a pure classification method (ANNC).

Another convenient way of identifying the effects of the proposed method is to inspect the zoomed-in original TM image and its various classified images. For example, the 'true' land use classes can be obtained by using the simple visual interpretation of the TM image in 2003 (Figure 9). It is found that classification errors are obvious in the areas within the red circles at locations A, B, C and D if conventional methods (MLC and ANNC) are used alone (Figure 9b). Location *A* is bare land, location *B* is agricultural land and locations *C* and *D* are fishponds according to the colour and tone of the TM image in 2003. All of them are non-urban land use type. However, it is found that some of these non-urban pixels are misclassified as urban pixels (black colour in Figure 9b) at these locations by using the conventional methods (MLC and ANNC) alone. It is because there are spectral confusions between these land use types. However, the assimilation method,

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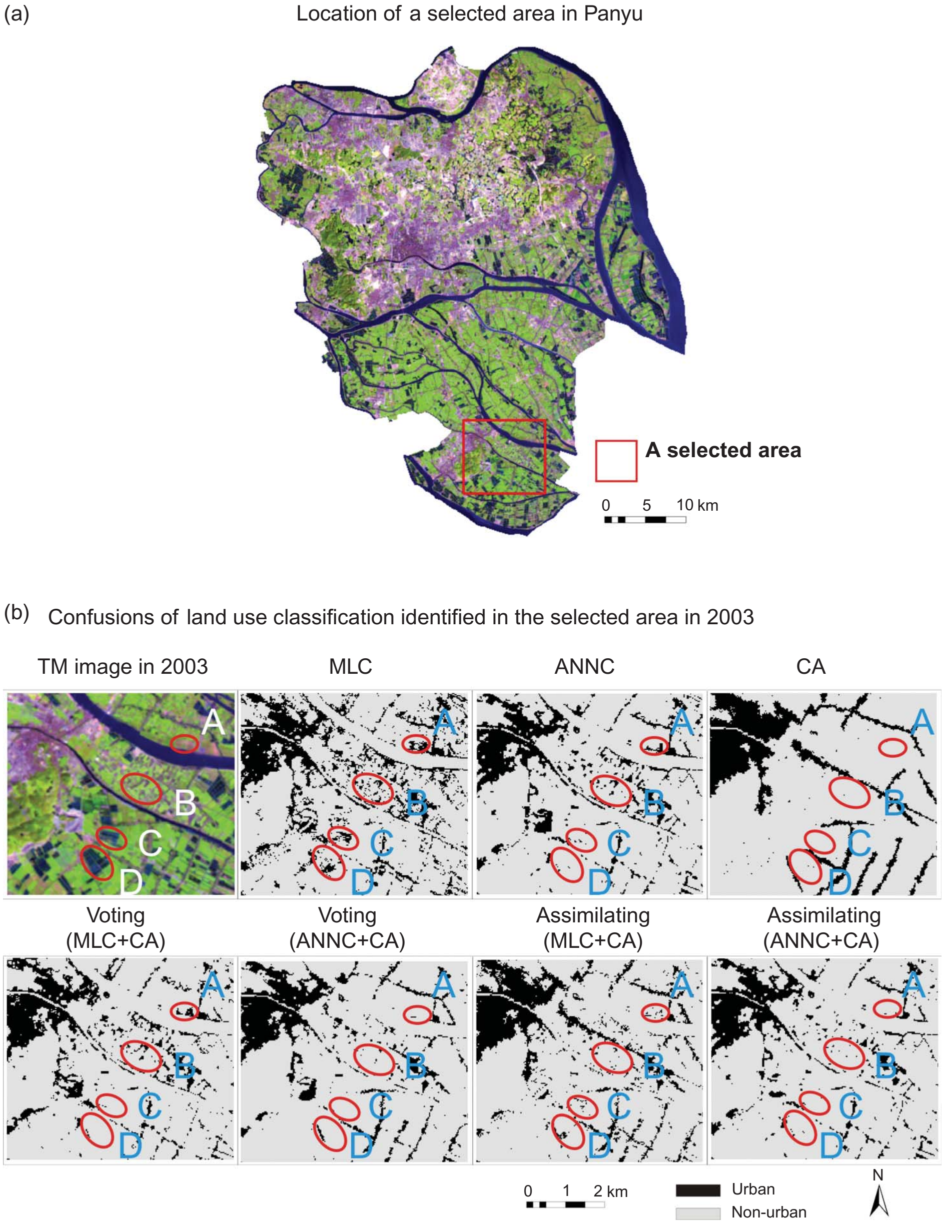

Figure 9. Confusions of land use classification by traditional methods (b) in a selected area in Panyu (a).

the assimilating (MLC + CA) and the assimilating (ANNC + CA), can reduce the number of misclassified pixels (the pixels of black colour) at these locations by incorporating the information of process context.

The above experiments have demonstrated that properly combining different models can help in improving the performance of classification. Both the assimilating model and the voting model can yield better classification accuracies than the pure classification methods (MLC and ANNC). However, the assimilating model can have a better improvement of the classification than the voting method according to the comparison. As a result, the improvement of classification can yield better results of change detection because of post-classification comparison.

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4. Conclusion

The information about land use changes is usually obtained by the overlay of classified temporal remote-sensing data. Land use classification is subject to a series of uncertainties. There is overestimation of the degree of land use changes because of classification errors (Li and Yeh 1998). Various techniques have been proposed to improve the performances of change detection. However, traditional techniques have limitations because of purely using the spectral or contextual information extracted from remote-sensing data.

In this article, we present a new method for improving the performance of change detection by using the process context information derived from urban simulation. The reduction in uncertainty through the assimilation of change detection models with CA models can lead to more accurate change detection results. This study has demonstrated that the EnKF can be effectively used to merge these different types of models. By integrating various amounts of satellite data and model predictions, this proposed method can have the potential to improve the estimates of land use changes in terms of overall accuracy and pattern/process metrics. CA can provide additional information about the process context (spatiotemporal relationships), which is useful in reducing change detection errors, because urban simulation is effective in capturing some distinct processes of urban dynamics, such as diffusion and coalescence, with each process following a regular pattern (Batty and Xie 1994).

Our experiments have indicated that the proposed assimilating model exhibits an increase in overall detection accuracy compared with the original maximum likelihood classifier (MLC) and artificial neural network classifier (ANNC). For example, the assimilating (MLC + CA) shows the general improvement of the total accuracy and the kappa coefficient by 2.5–5.2% and 3.6–7.4%, respectively, compared with the pure MLC. The assimilating (ANNC + CA) shows the improvement of the total accuracy and the kappa coefficient by 2.3–4.0% and 4.3–8.6%, respectively, compared with the pure ANNC. The voting model can also have better accuracies of change detection than these traditional methods. However, this voting model has relatively poorer effect than the assimilating model.

It is also interesting to find that the accuracies of urban simulation and change detection decrease in the study area as a result of increasing complexity of land use patterns. The landscape patterns evolve as the fractal dimension and entropy unanimously increase. The process context information is useful for enhancing the capability of change detection by providing more detailed spatiotemporal information. The analysis also indicates that this approach could derive more generic results as well as improve the overall accuracy. Although the rate of improvement is not that impressive, this approach can allow change detection to capture the overall trend in urbanization but the exact locations could be different or have a shift caused through other systematic biases. More specifically, CA can well reflect the information of fractal dimensions and shape metrics, although this may not be on a cell-by-cell basis.

This study only demonstrates the possibility of assimilating some common change detection methods (e.g. maximum likelihood classifier and artificial neural network classifier) with CA. Future studies may need to consider other models of assimilation such as

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ABMs, object-based change detection models and an integrated model with less-expensive computing. A simplified method could be developed that would allow to incorporate the process/context for change detection more conveniently. Moreover, there is also a growing trend to move from the pixel-based analysis to Geographic Object-Based Image Analysis (GEOBIA) (Hay and Castilla 2008). GEOBIA is especially useful for representing geographical entities by using high-resolution remote-sensing images such as Quickbird images (Chen and Hay 2011). Future studies may need to develop a better assimilation method under the object-based framework, since high-resolution remote-sensing images are available and more frequently used recently. This challenging work will require the change detection models, the simulation models and the assimilation models to be implemented based on an object-based approach.

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