Zoning Land for Agricultural Protection by the Integration of Remote Sensing, GIS, and Cellular Automata

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Abstract
Zoning strategic agricultural land for protection has become important in reducing agricultural land loss in rapidly growing areas. In this paper, a constrained CA model based on the integration of remote sensing, GIS, and cellular automata (CA) techniques was developed to overcome the limitations of the existing methods commonly used by planners in zoning land for agricultural protection. Remote sensing data were used to calculate the normalized difference vegetation index (NDVI) which was the initial map used for the model. The factors of land suitability and geometry were embedded in the model to facilitate the rational allocation of land for agricultural protection. The CA model was implemented within a geographic information system which provided useful constraint information and modeling environment. "Grey cells" were defined in the CA model to improve modeling accuracy. The model has been tested in the Pearl River Delta, one of the fastest growing areas in China.

Introduction
There is a tendency for cities to expand into prime agricultural areas (Ferguson and Khan, 1992). In China, rapid urbanization and urban expansion have been witnessed in the last two decades (Cai and Ren, 1998). The nation has the largest population, and far below average per capita land resources, in the world. Land-use problems have been aggravated by rapid urbanization, which has led to significant loss of valuable agricultural land in recent years. The encroachment of urban land uses on agricultural land is especially severe in the Pearl River Delta, one of the fastest growing regions in China. An average of about 10 to 15 percent of agricultural land was converted into non-agricultural uses in the period 1988-1993 (Li and Yeh, 1998). Much of the land acquisition and development is driven by land speculation as evidenced by the large amount of idle land (Zhu, 1994). If the rate of land loss continues, most of the agricultural land will soon be consumed by urban development. This may cause a lot of social and environmental problems. There are urgencies to adopt some effective measures to protect agricultural land before it is exhausted.

The protection of agricultural land is important to sustainable development. Apart from supplying food and vegetables to cities, farmland protection near cities can help to promote compact development in reducing environmental costs (Ferguson and Khan, 1992). Although it is impossible to completely ban the encroachment on agricultural land, the amount of land consumption can be significantly reduced by adopting compact development patterns. Studies have shown that lavish use of land resources has led to excessive conversion of agricultural land and the proliferation of idle leveled land parcels (Yeh and Li, 1997). The preservation of a reasonable percentage of agricultural land is needed for food production and as a land reserve for the future generations.

As too much agricultural land loss took place in China during the property boom period in the early 1990s, the central government had to intervene in the process of crazy land development and speculation by implementing specific policies and ordinances. In August 1994, the State Council promulgated the *Ordinance for the Protection of Primary Agricultural Land* (State Council, 1994) to zone the best agricultural land for strict protection. According to the legislation, the land parcels that are to be protected have to be located on detailed topographical maps. The implementation of the zoning of land for agricultural protection is a top-down process that is compulsory for each level of local governments. It is hoped that agricultural land protection zoning can help to prevent urban sprawl and conserve valuable agricultural land resources. However, the effects of such types of zoning are in doubt because local government officials have carried out much of the zoning in an arbitrary manner. No scientific method has been used to carry out zoning in a rational way. Although some brief guidelines have been proposed in the legislation, they are not quantitative and are difficult to follow in practice. The ordinance lists the following descriptive guidelines for the zoning (State Council, 1994):

- to zone the best agricultural land of high yields,
- to maintain the agricultural production areas that are selected by local governments,
- to protect the agricultural land with good irrigation facilities, and
- to conserve the agricultural land which supplies basic food to cities.

These guidelines are not well bound and bear little relation to real land-use zoning. They are not operational because of the lack of quantitative criteria. They also do not consider geometric factors such as contiguity, which is important to land-use planning. There is a wide interest and need to measure and analyze geometric forms for understanding spatial patterns and processes (Li, 1996; Medda *et al.*, 1998). Compactness, which is

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an important index of geometry, can be used in land-use planning to reduce spatial inefficiency. For example, a more compact urban development can alleviate intensified land-use conflicts (Jenks *et al.*, 1996). Compactness should be an important factor in the zoning of agricultural land for protection.

There is a need to provide a more scientific framework to assist planners and local government officials in zoning strategic agricultural land for protection. Land-use zoning usually involves the analysis of a large variety and amount of spatial data. The integration of remote sensing and GIS can provide the tools as well as data for such purposes. There are studies in using remote sensing and GIS for obtaining optimal land-use patterns for land-use evaluation and planning (Meaille and Wald, 1990; Brookes, 1997; Yeh and Li, 1998).

This paper proposes that a constrained cellular automata (CA) model be used to carry out the zoning of land for agricultural protection. CA models can have a great potential in dealing with complex spatial data and processes (Takeyama and Cuclelis, 1997). The model can overcome some of the shortcomings of currently used manual methods and can provide a more versatile approach for land-use zoning. It can help to generate land-use zoning by quantitatively taking both land suitability and geometric factors into account.

Methods

Zoning can be used to control development in the urban fringe (Thorson, 1994). The zoning of agricultural land for protection is to correct the market failure which converts too much land to urban use. The preparation of zoning plans usually involves the analysis of a large volume of spatial data. Zoning has been recognized as a time-consuming task in a planning department when traditional methods are used (Chen *et al.*, 1994). It is therefore desirable to automate part of the zoning process by the integration of remote sensing and geographic information system (GIS) techniques. Remote sensing data can provide useful information about land-use patterns and their changes. The data can be used to generate land suitability maps for the zoning of land for agricultural protection. A GIS can provide powerful functions for data storage, retrieval, updating, and modeling. The zoning data can be conveniently handled using the geo-processing functions of a GIS.

The purpose of this study is to develop a model to carry out the zoning of land for agricultural protection. Zoning can be carried out by the integration of remote sensing and geographic information systems (GIS) because they can conveniently deal with the factors of land suitability and geometry, which are most important in deciding the location of land for agricultural protection.

First, the proposed model is implemented in a raster system in which the basic values for each cell are land suitability scores. Land suitability is a key factor in the determination of site allocation and land-use planning. The creation of land suitability maps is easy with the assistance of GIS functions, such as a weighted overlay algorithm (Brookes, 1997; Yeh and Li, 1998). Land suitability can be used to evaluate whether a piece of land is allocated appropriately and find out how it can be allocated to its alternative or optimal use. Planning decision is a complicated process which is often made on the basis of a number of objectives or criteria. There are usually two broad types of land suitability—agricultural suitability and urban development suitability—which are essential to the allocation of land for agricultural protection and urban development. Multi-criteria decision-making techniques which can be easily integrated with a GIS can be applied to resolve land-use conflicts based on a number of criteria (Eastman *et al.*, 1993; Carver, 1991).

Second, geometry is an important factor in geographical analysis and land-use planning. No matter what approach to urban analysis is taken, cities are usually visualized at some stage in terms of their geometric form (Mesev *et al.*, 1995). Geometric forms emphasize aggregated land-use patterns rather than individual locations. Idealized geometry articulated through a theoretical framework can be applied to guide urban development towards a sustainable form. An example is to formulate compact land use so that the consumption of agricultural land can be minimized in the urbanization process.

There is a need to combine land suitability and geometry in the search for compact development. The main objective of compact development is to prevent inefficient fragmented land use. Land suitability can be used to protect the best quality of agricultural land. There is a certain degree of conflict in using these two factors in the zoning of agricultural land for protection. There are problems when land suitability maps are used alone to locate regions rather than individual cells. It is difficult to achieve compact patterns because cells with high land suitability values may not be clustered into suitable regions (Brookes, 1997). Compactness should be an important factor which can be traded off against underlying cell suitability within a GIS. A simple resolution is to treat the two factors in an equally important way in the modeling process.

In this study, a model based on cellular automata (CA) techniques is developed within a geographic information system to deal with the land suitability and compact development. Cellular automata have been used by researchers in a variety of disciplines to investigate questions concerning the origin and evolution of structures (White and Engelen, 1993). CA have the feasibility and plausibility in exploring possible urban forms and development (Batty and Xie, 1994a; Batty and Xie, 1997; White *et al.*, 1997; Wu and Webster, 1998). These models are capable of generating complicated global structures from some simple local rules. The simulation can provide useful aids for testing ideas and insights about the evolution of geographical phenomenon. The integration of cellular automata with geographic information systems (GIS) is mutually beneficial—the enrichment of modeling functions of a GIS and the satisfaction of data realism requirements of CA (Couclelis, 1997). Space no longer needs to be uniform because the spatial difference equations can be easily developed in the context of a GIS (Batty and Xie, 1994b). CA can be directly programmed within a GIS which can provide a number of advantages for CA simulation, such as seamless retrieval of data and the provision of a convenient display and programming environment.

A constrained CA model with constraints from real world data is used to formulate a rational zoning plan for agricultural land protection. Constraints which are mainly defined by land suitability are used to run the model. Land suitability and constraint scores can be easily obtained from a GIS database using their overlay functions.

Standard cellular automata are neighborhood-based. The transition potential of a central cell is determined by the states in its neighborhood. A standard cellular automaton can be defined as

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

where $f()$ is the neighborhood (transition) function that defines the change of the state from time t to $t + 1$, S is a set of all possible states of the cellular automaton, and N is a neighborhood of all cells providing input values for the function $f()$.

Cellular automata can be used to assign land to be zoned for agricultural protection. Although CA models are based on some kinds of temporal dynamics, time t does not necessarily refer to actual time. It can be a step or loop in the iterations of the computer program. At each iteration of the model, the probability P for a cell $\{x, y\}$ to be zoned for agricultural protection is devised based on the standard cellular automaton: i.e.,

$$P^t\{x,y\} = f(S^t\{x,y\}, N). \quad (2)$$

A stochastic disturbance term can be added to represent unknown errors during zoning. This can allow the generated patterns to be more close to reality. The error term is (White and Engelen, 1993)

$$\mathrm{RA} = 1 + (-\ln r)^\alpha. \quad (3)$$

Equation 2 can be revised as

$$P'^t\{x,y\} = (1 + (-\ln r)^\alpha) \times f(S^t\{x,y\}, N) \quad (4)$$

where r is a uniform random variable within the range {0,1}, and α is a parameter to control the size of the stochastic perturbation.

The stochastic term has a highly skewed distribution because very large values only occur infrequently. Most of the probabilities are close to their deterministic values (White and Engelen, 1993). It has been pointed out that many geographical phenomena have some kinds of fractal properties. The use of stochastic disturbance can permit CA to emulate and capture the key features of fractal structure in a relatively realistic way.

The neighborhood function $f()$ in Equation 4 is to count the total number of selected cells in the neighborhood. The increase in selected cells in the neighborhood will increase the probability for a central cell to be selected for agricultural protection. In standard cellular automata, there is only a binary value for the conversion of a cell: 1 for the successfully selected (converted) and 0 for the non-selected. The binary value cannot reflect the gradual change of state which is exhibited in many geographical phenomena. An improved method is to use "grey cells" to quantify the continuous change of states.

"Grey cells" are used to allow the partial selection of each cell during each iterative loop of the search. The search is an accumulative process. Each candidate cell may have an intermediate value between 0 and 1. A cell will not be completely selected for agricultural protection zoning unless it has the value of 1. A "grey" value is heuristically defined with regard to the states and constraints in the neighborhood. The influences from the states and constraints are important to generate compact or idealized patterns in the modeling of zoning. At each step of the iterations, the increase in the "grey" value $\Delta G^t\{x,y\}$ is thus proportional to the probability plus a total constraint value. It is

$$\begin{aligned}\Delta G^t\{x,y\} &= P'^t\{x,y\} \times \mathrm{CONS}^t\{x,y\} \quad (5)\\ &= (1 + (-\ln r)^\alpha) \times f(S^t\{x,y\}, N) \times \mathrm{CONS}^t\{x,y\}\end{aligned}$$

where $G\{x,y\}$ is the "grey" value for cell $\{x,y\}$, and CONS is the total constraint score.

The total constraint score is within the range of 0 to 1, which can be regarded as a scaling factor to readjust the probability. The total score is decided by the combination of a number of constraints that is embedded in the model. Multi-criteria evaluation (MCE) (Wu and Webster, 1998) can be applied to obtain the total constraint score from various types of constraints. It is given by

$$\mathrm{CONS}^t\{x,y\} = \left(\sum_{i=1}^{k} w_i \mathrm{cons}_i^t\{x,y\}\right) \prod_{i=k+1}^{n} \mathrm{cons}_i^t\{x,y\} \quad (6)$$

where cons_i is the ith constraint and w_i is weight for the ith constraint. $1 \le i \le k$ are non-restrictive constraints whereas $k + 1 \le i \le n$ are the restrictive constraints.

Non-restrictive constraints are the constraints that have some influences but do not have critical impacts on the modeling process. Restrictive constraints are those that have important effects on the modeling process. For simplicity, only the restrictive constraints are used in this study. Equation 6 is simplified as

$$\mathrm{CONS}^t\{x,y\} = \prod_{i=k+1}^{n} \mathrm{cons}_i^t\{x,y\} \quad (7)$$

Finally, the "grey" value for a cell in time $t + 1$ is thus expressed by an iterative formula: i.e.,

$$G^{t+1}\{x,y\} = G^t\{x,y\} + \Delta G^t\{x,y\} \quad G\{x,y\} \in (0, 1) \quad (8)$$

The "grey" value should be kept within the range of 0 to 1. $\Delta G^t\{x,y\}$ should be assigned to 0 when $G^t\{x,y\}$ is equal to or greater than 1. The cells with "grey" values equal to 1 will be finally selected to be zoned for agricultural protection.

The Implementation and Results

The proposed model was implemented and tested in a study area situated in the Pearl River Delta which is recently the fastest growing region in China. The study area includes the whole administrative area of Dongguan—a city proper and 29 towns, covering an area of 2,465 km^2. About 70 percent of the area was dedicated to agricultural activities in the 1980s. However, intensive land development and land-use conversion have been witnessed, triggered by rapid urbanization. Tremendous land-use changes and a large amount of agricultural land loss were detected by using multi-temporal satellite images (Li and Yeh, 1998). About 15.1 percent of the total agricultural land was converted to non-agricultural uses from 1990 to 1993. Diversification of land use in agricultural land was found because many paddy fields had been converted to orchards and fishponds due to agricultural restructuring driven by market mechanisms. There are lots of idle land parcels that have been converted from the most fertile agricultural land as a result of land speculation.

There is an urgent need to implement the *Ordinance for the Protection of Primary Agricultural Land* to protect the best agricultural land. The legislation is rather top-down and its implementation is compulsory to local authorities. Higher-level governments decide the amount of agricultural land for local authorities to protect. At present, this is set by applying a fixed proportion of 60 percent to the existing amounts of available agricultural land. Local authorities are required to convert the quota into exact land parcels for agricultural protection by marking them on the maps under their jurisdiction. However, the zoning maps produced may not be consistent and rational due to the lack of updated land-use information and appropriate zoning tools. Local governments also have no interest in protecting agricultural land because the protection will make it difficult for future land acquisition or development.

The proposed constrained CA model was applied to zone land for agricultural protection in a more scientific way. First, the normalized difference vegetation index (NDVI) was calculated to provide the initial state for the model. Landsat TM imagery dated 29 August 1997 was used to classify land-use types and obtain the NDVI. The image taken in the growing season of crops can reflect vegetation-growing conditions. The NDVI was obtained using the following equation (Rouse *et al.*, 1973; Tucker, 1979):

$$\mathrm{NDVI} = \frac{\mathrm{TM4} - \mathrm{TM3}}{\mathrm{TM4} + \mathrm{TM3}}. \quad (9)$$

Remote sensing techniques can provide useful information about the conditions of agricultural crops quantitatively and instantaneously. Studies have demonstrated the possibilities of applying remote sensing in agriculture, particularly with regard to its relation with crop characteristics such as plant cover and the leaf area index (Clevers, 1988). Numerous vegetation indices have been developed from remote sensing data for characterizing vegetation canopies and obtaining quantitative information on the change of land cover (Tucker, 1979; Anderson and Hanson, 1992; Lyon *et al.*, 1998). The use of a near-infrared/red ratio method for estimating biomass or leaf area index was first reported by Jordan (1969). The NDVI may be the most popularly used index. It was identified as one of the few most accurate change detection techniques (Singh, 1989; Lyon *et al.*, 1998).

Vegetation indices are commonly used for monitoring vegetation biomass and forecasting crop production. Many studies indicate that vegetation indices are well correlated with various vegetation properties including green leaf area, biomass, percent green cover, productivity, and photosynthetic activity (Huete, 1988; Nalepka *et al.*, 1977; Colwell, 1974; Sellers, 1985). Therefore, NDVI calculated from the image taken in the growing season of crops is a good indicator of agricultural production suitability. High values of NDVI correspond to the top-quality agricultural land in agricultural production areas.

The NDVI image can be used as the basis for zoning land for agricultural protection. A simple way to zone the best agricultural land is to slice the NDVI image using a threshold value. The slicing threshold is decided by including a sufficient number of pixels that can satisfy the quota of agricultural protection zoning. Before density slicing, a mask based on land-cover classification is needed to sieve out the forest areas so that the NDVI can accurately reflect the quality of agricultural land.

According to the amount assigned by the provincial government, the region should reserve a total of 43,333 ha (650,000 *mu*) of agricultural land for protection. Figure 1 shows part of a zoning plan that is generated by the density slicing method. However, it can be easily observed that the density slicing method cannot generate satisfactory patterns. The major problem is that the cells with high values of NDVI may not be contiguous, and compact zones may not be formed.

The constrained CA model was used as an alternative method to zone land for agricultural protection. The model was directly developed in the raster GIS of ARC/INFO GRID. It can benefit from easy access to the GIS database for constructing constraints and executing the modeling process. The first step was to prepare land suitability maps from the GIS database, which stores the spatial data such as terrain, soil, and land-use maps of the study area. Suitability scores were scaled down to the range 0 to 1. The maximum value of 1 for agricultural suitability represents the best agricultural land. Constraint scores can be calculated from suitability maps. Higher values of agricultural suitability should have higher values of constraints. This can enable the "grey" value in Equation 5 to increase more rapidly in the places of the best agricultural land during the modeling process. The result is that a larger amount of the best agricultural land can be secured in the zoning.

A non-linear transformation of suitability was applied to produce the constraint score. The transformation is given by

$$\text{cons} = \text{SUIT}^k \tag{10}$$

where SUIT is the suitability score and k is a control parameter.

The transformation can allow a control parameter k to be added into the modeling. The advantages of using the power function are its simplicity and effectiveness in controlling the compactness of zoning and the weight to protect the best agricultural land in a balancing way. A set of transformation curves can be produced by changing the values of parameter k (Figure 2). This is especially useful when there is a need to put more weight on protecting the best quality agricultural land by choosing a higher k value. However, the increase in the weight will be compensated by the loss of compactness of generated zones.

A "seed" image was created from the NDVI as the initial condition for the constrained CA model for the zoning of land for agricultural protection. The density slicing method was applied to get the "seeds" by sieving sufficient pixels with higher NDVI values (Figure 3). The pixels of the "seeds" accounted for about 10 percent of the final zoning areas. The areas of zoning grew around the "seeds" during the CA modeling process. Compact patterns were formulated by spatial interactions using neighborhood functions of CA.

The "grey" value was calculated by using the neighborhood function and constraints according to Equation 5. The neighborhood function $f()$ was used to address the influences from neighboring cells. A higher value of the function will be obtained for a central cell if it is surrounded by more selected cells. This helps to generate the compact patterns during the modeling process. The study uses a circular neighborhood

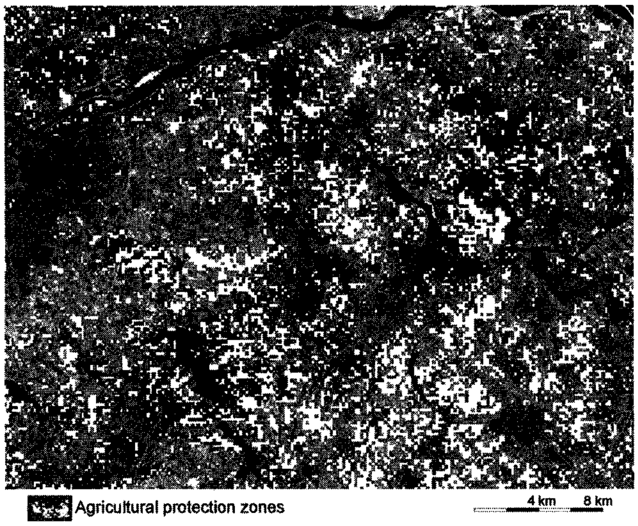

Figure 1. Allocation of agricultural protection zones using NDVI Index.

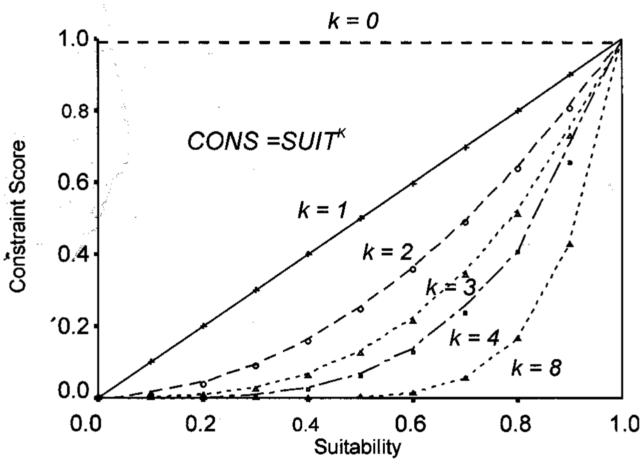

Figure 2. Constraint based on power transformation of suitability.

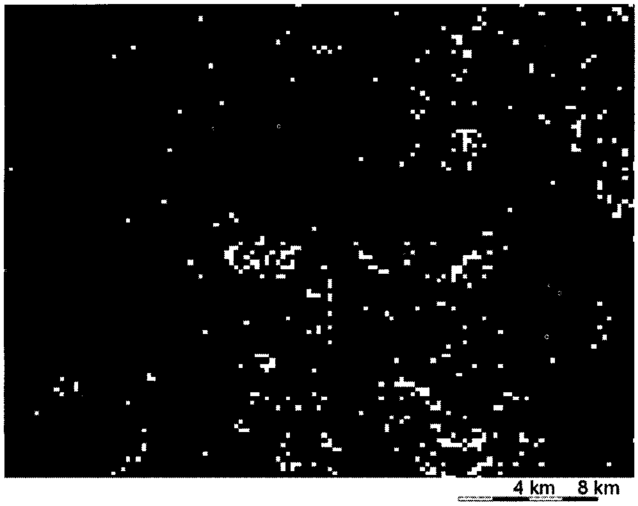

Figure 3. Initial seeds for modeling of agricultural protection zones.

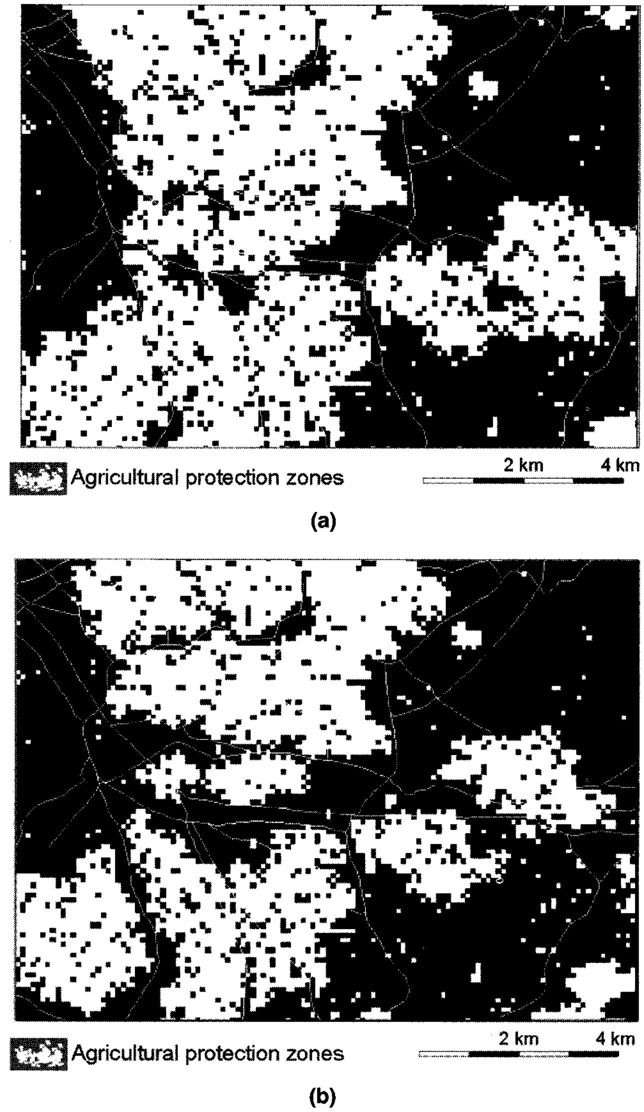

Figure 4. Influences of urban suitability on modeling. (a) Based on agricultural suitability constraint. (b) Based on agricultural and urban suitability constraints.

which has a radius of two pixels to count the number of selected cells in the neighborhood. A value of 1 will be assigned to the function $f()$ if a central cell has more than three neighboring cells selected in the previous step. A value of 0 will be assigned to the function $f()$ if it has no neighboring cells selected in the previous loop. Intermediate values will be assigned proportionally by a linear function.

Agricultural suitability is the main constraint in the model because the zoning emphasizes the protection of strategic agricultural land. However, there is a need to consider the factor of potential urban development. Urban development suitability can be used to reserve the land of high development potential values for future urban uses. For example, some sites which have good accessibility are very suitable for future urban development. It is unrealistic to zone these sites for strict agricultural protection. The constraint based on urban development suitability can be embedded in the model to solve the problem in a compromising way. Urban suitability maps can be easily obtained based on accessibility using the functions of a GIS. The effects of using multiple-constraints in the CA modeling are clearly shown in Figures 4a and 4b. Figure 4a is the modeling result with the use of agricultural suitability only. Figure 4b is the result by incorporating the additional constraint of urban development suitability in the model. The additional constraint is useful because it can avoid the inclusion of the land that has good accessibility for future urban development along transport corridors (white lines in Figure 4b).

Reasonable zoning patterns can be produced by heuristically defining and using additional constraints. More constraints can be added to the model to regulate the zoning process for better results. Constraints can be classified as local, regional, and global according to their spatial characteristics. Local constraints are created based on a small area. Land suitability can be regarded as a local constraint because it is cell-based. Social, economic, and environmental data which are aggregate or partially spatial can be used to obtain regional constraints. For example, the available land resource of a town can be regarded as a regional constraint in the model. Global constraints are usually temporal variables which are homogeneous in space but changeable in time. They simply control the system growth rate in the CA model.

In this model, local constraints were transformed from agricultural suitability and urban development suitability. The populations of the towns were used as regional constraints to reserve relatively more amounts of agricultural land to towns with larger population sizes. The global constraint was the total amount of agricultural protection land set by the provincial government for the whole region. The model stops running when the area of land zoned for agricultural protection reaches the limit set by the global constraint. Figure 5 shows the agricultural protection zones generated by the CA model using the local, regional, and global constraints. It has a much more compact pattern than that of Figure 1, which is obtained by using the NDVI density slicing method.

A quantitative comparison was made between the CA method and the NDVI density slicing method based on the measurement of agricultural suitability and the compactness of zoning. The total agricultural suitability score for all the selected pixels was summed using the overlay functions of the GIS. Given the same amount of agricultural protection land, a

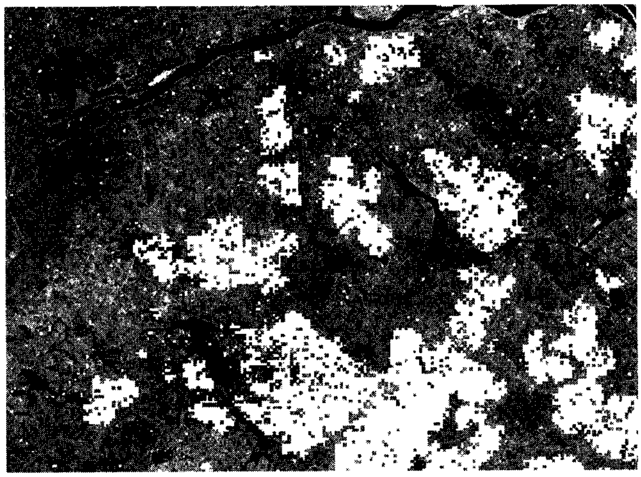

Figure 5. Agricultural protection zones with local, regional, and global constraints using Cellular Automata.

TABLE 1. COMPARISON BETWEEN THE CA METHOD AND THE NDVI DENSITY SLICING METHOD

Method	The Total Agricultural Suitability Score	Compactness Index (10^{-3})
Constrained CA Model	1,541	6.9
NDVI Density Slicing	1,526	2.5

higher value of the total agricultural suitability score means that zoning can protect a higher proportion of the best agricultural land. The compactness index was also conveniently calculated with the aid of the GIS. The compactness index is given by (Li, 1996)

$$\mathrm{CI} = \sqrt{S}/P \tag{11}$$

where S is the total area and P is the total perimeter of the zoning. Any single circle, which is in the most compact form, will always maintain the highest value (about 0.282) for the compactness index. A dispersed or fragmented pattern will have a much lower value of the CI index.

Table 1 shows that the proposed CA model has a much better performance than the NDVI density slicing method in the zoning of land for agricultural protection. Although the NDVI density slicing method chooses the cells of higher values of NDVI for the zoning, the CA model can still produce a slightly higher value of the total agricultural suitability score because it directly uses the suitability constraint. Moreover, the CA model can significantly increase spatial efficiency using the neighborhood function of CA. The value of the compactness index of the CA model is 2.65 times that of the NDVI density slicing method.

Conclusion

The primary objective of this research was to experiment with a new method for carrying out zoning by the integration of remote sensing, GIS, and cellular automata (CA) techniques, using the zoning of land for agricultural protection as an example. The constrained CA model uses "grey cells" for the measurement of the influences of neighborhood and constraints. Various kinds of constraints are embedded in the CA model to allow the zoning towards reasonable and optimal patterns. Agricultural suitability is an important constraint for protecting fertile agricultural land. However, the model also uses other supplementary constraints for more realistic zoning. As an example, urban development suitability is considered in the model to take into account the need of future urban development. These constraints are directly measured and generated from the GIS database. Non-linear transformation of the constraints can help to choose a proper weight for protecting the best agricultural land while maintaining the compactness of zoning.

The proposed method has been tested in the Pearl River Delta, a fast growing region in China. The application shows that the constrained CA model can explore various alternatives conveniently and generate much better zoning patterns. The modeling results can be used to zone land for agricultural protection for promoting sustainable land-use development in the region. Although the present study only demonstrates how this model is applied to the zoning of land for agricultural protection, it can also be applied to other applications in environmental planning and management. This can be done by substituting the agricultural protection objective with other environmental objectives using specified environmental constraints. The constrained CA model can be a good tool to assist planners and government officials in the preparation of zoning plans in a scientific and efficient way.

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