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Research article

Conflict resolution in the zoning of eco-protected areas in fast-growing regions based on game theory

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ABSTRACT

Zoning eco-protected areas is important for ecological conservation and environmental management. Rapid and continuous urban expansion, however, may exert negative effects on the performance of practical zoning designs. Various methods have been developed for protected area zoning, but most of them failed to consider the conflicts between urban development (for the benefit of land developers) and ecological protection (local government). Some real-world zoning schemes even have to be modified occasionally after the lengthy negotiations between the government and land developers. Therefore, our study has presented a game theory-based method to deal with this problem. Future urban expansion in the study area will be predicted by a logistic regression cellular automaton, while eco-protected areas will be delimitated using multi-objective optimization algorithm. Then, two types of conflicts between them can be resolved based on game theory, a theory of decision-making. We established a two-person dynamic game for each conflict zone. The ecological compensation mechanism was taken into account by simulating the negotiation processes between the government and land developers. A final zoning scheme can be obtained when the two sides reach agreements. The proposed method is applied to the eco-protected area zoning in Guangzhou, a fast-growing city in China. The experiments indicate that the conflicts between eco-protection and urban development will inevitably arise when using only traditional zoning methods. Based on game theory, our method can effectively resolve those conflicts, and can provide a relatively reasonable zoning scheme. This method is expected to support policy-making in environmental management and urban planning.

1. Introduction

The unprecedented urban expansion in developing countries has triggered a series of environmental and ecological issues, such as arable land loss (Yeh and Li, 1999), water pollution (Zhu et al., 2002), and soil degradation (Chen, 2007). Zoning eco-protected areas is crucial for sustainable development, ecological health, environmental management (He et al., 2005; Verdiell et al., 2005; Sabatini et al., 2007; Geneletti and van Duren, 2008), and has therefore attracted great attention worldwide. The term "eco-protected area" is also known as "eco-designated line of control" in China (Li et al., 2013a), a fast-growing country during the past three decades. Most notably, Shenzhen Government took the lead in promulgating ordinance and zoning scheme for eco-protection in 2005 (The People's Government of Shenzhen Municipality (2005)). Specifically, the regions of higher ecological suitability should be marked out as eco-protected areas in order to protect limited ecological resources, support sustainable urban development, and prevent immoderate urban expansion. Later, the municipal governments of Dongguan and Wuhan issued their own schemes in 2009 and 2012 respectively.

Unfortunately, numerous reports have revealed that the land developers in some Chinese cities appealed to modify the zoning schemes because their rights and interests were being severely constrained by the protection (e.g., Liu, 2010; Huang, 2011). Local governments had to give in after lengthy negotiations with these land developers. For example, Shenzhen Government respectively issued two modified schemes in 2011 and 2013, and promised to execute ecological compensation plan as early as possible. In fact, human-environment conflict is a long-standing phenomenon throughout the world (Lewis, 1996; DeFries et al., 2004; Colyvan

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et al., 2011). Many studies have indicated that rapid urban expansion could exert negative impacts on the performance of protected areas (DeFries et al., 2007; Hansen and DeFries, 2007; McDonald et al., 2007; McDonald et al., 2008). Urban land use will change both spatially and quantitatively every year in fast-growing regions. Although urban development should be prohibited within the eco-protected areas, many land developers may still secretly break the rules due to huge economic benefits. Illegal development easily occurs in the regions with higher development suitability (Li et al., 2013a). Those zoning schemes are unable to serve the purpose of ecological protection. Therefore, from the perspective of the land developers, the great influences from continuous urban expansion should be taken into account by policy-makers during the zoning procedures.

To date, a number of techniques have been applied to land use zoning, such as linear and integer programming (Chuvieco, 1993; Hof and Joyce, 1993), intelligent algorithms (Bos, 1993; Verdiell et al., 2005; Watts et al., 2009), and multicriteria analysis (Geneletti, 2007), but most of them failed to tackle the aforementioned problem. Recently, Li et al. (2011) proposed a method to delimitate protected areas by coupling cellular automata (CA) with ant colony optimization. Undoubtedly, CA model is a successful tool for simulating and predicting urban expansion (Wu, 2002; Li et al., 2013b), and therefore shows great potential for assisting in land use zoning. In their method, however, future urban expansion predicted by CA was only considered as a negative factor for ecological suitability analysis. The conflicts between the government and land developers, as well as the ecological compensation mechanism are still neglected. These contents can be well integrated under the framework of game theory.

Game theory is a theory of decision-making that can mathematically analyze and simulate the conflicts between rational decision-makers (Myerson, 1991). It has been successfully applied in various disciplines, such as economics, politics, and biology (Osborne and Rubinstein, 1994; Basar and Olsder, 1995). Recently, game theory has also been used to deal with land use issues. For example, Liu et al. (2015) coupled game theory and genetic algorithm to solve land use spatial optimization problems; Samsura et al. (2010) presented a game theory approach to the analysis of land and property development processes; Hui and Bao (2013) established a game theory-based framework for analyzing the conflicts in land acquisitions in China. Nevertheless, the conflicts between ecological protection and urban development still remain unresolved in such a quantitative manner. Besides, the spatio-temporal dynamics of urban expansion are rarely considered in land use games. Therefore, our study aims to address these problems based on a combined use of CA and game theory. Guangzhou, a rapidly urbanizing metropolis suffering from severe ecological issues in China, is selected as the study area.

2. Methodology

The main contribution of this study is the application of game theory to protected area zoning. First, eco-protected areas will be preliminarily delimitated in a traditional way. Then, we will predict future urban expansion by using cellular automata (CA). Finally, the conflicts between urban development and ecological protection will be resolved under the framework of game theory. More details about the procedures are provided in the following subsections, and the pseudo-codes are given in Table S1 (in supplementary material).

2.1. *Zoning eco-protected areas using multi-objective optimization algorithm*

The zoning task should maximize both: (1) the average ecological suitability of the selected cells, and (2) the compactness of the protected areas (Li et al., 2011; Liu et al., 2012). Therefore, the utility (U) of the protected areas can be formulated as follows:

$$U = w_{\mathrm{E}} \cdot S_{\mathrm{E}} + w_{\mathrm{C}} \cdot C \tag{1}$$

where S_{E} denotes the average ecological suitability, C denotes the compactness metric of a protected scenario, w_{E} and w_{C} are the weights for S_{E} and C respectively ($w_{\mathrm{E}} + w_{\mathrm{C}} = 1$).

With respect to the zoning of eco-protected areas in China, S_{E} has two ecological meanings: (1) the regions that are rich in ecological resources should be protected, and (2) the regions that are unsuitable for urban development should not be developed. Some municipal governments have consequently promulgated ordinances and requirements for eco-protected area zoning. In general, vegetated areas, aquatic areas, natural habitat, vulnerable areas, and other regions of higher ecological suitability should be marked out for conservation. Therefore, in accordance with related studies (Li et al., 2011; Liu et al., 2012), S_{E} can be estimated by a number of spatial variables, all of which are introduced as follows:

(1) Normalized difference vegetation index (NDVI)

The vegetated area should be protected because it plays a key role in various aspects, such as air purification, and soil conservation (Tucker, 1979). Many vegetation indices have been developed to monitor vegetation conditions and biomass. NDVI is a widely used one that can be directly obtained from Moderate Resolution Imaging Spectroradiometer (MODIS) products. To minimize the influence of aerosols, water vapors, and clouds, a series of multi-temporal images within a 1-year period will be processed to a new $\mathrm{NDVI}_{\max}$ image through the maximum value composite procedure (Holben, 1986).

(2) Normalized difference water index (NDWI)

The aquatic natural area should also be taken into consideration since it is crucial for water supply, climate regulation and so on. NDWI can effectively separate water bodies from other land cover types. This index can be calculated using the equation given by (McFeeters, 1996):

$$\mathrm{NDWI} = \frac{\rho_{857} - \rho_{1241}}{\rho_{857} + \rho_{1241}} \tag{2}$$

where ρ_{857} denotes the reflectance value in the band at 857 nm, and ρ_{1241} denotes the reflectance value in the band at 1241 nm.

(3) Habitat heterogeneity ($\mathrm{H_h}$)

Habitat heterogeneity is a good metric for representing the spatial distribution pattern of the heterogeneous environmental conditions of a region (Svoray et al., 2005; Liu et al., 2012). Previous studies have shown that eco-diversity will increase with habitat heterogeneity on a landscape scale (Freemark and Merriam, 1986; Benton et al., 2003). The habitat of land units consists of three parts: wetness index, slope orientation, and soil attributes (Svoray et al., 2005). The wetness index was calculated as follows:

$$\text{Wetness index} = \ln\left(\frac{\text{Asi}}{\tan\beta}\right) \quad (3)$$

where Asi denotes the specific catchment area, which can be obtained by using the ArcGIS flow accumulation function, and β denotes the slope angle of the surface.

Besides, the slope orientation was generated by using the ArcGIS spatial analyst tools, and the soil attribute map was obtained according to field surveys (Liu et al., 2012). Lastly, habitat heterogeneity (H_h) can be calculated based on the Shannon-Weaver Index (Svoray et al., 2005):

$$H_h = -\sum_i P_i(\ln P_i) \quad (4)$$

where P_i is the proportion of an individual habitat i in relation to all habitats.

(4) Slope

Topography is another important factor for environmental management (Withers and Lord, 2002). The regions with steeper slopes should be included in the protected areas. Slope can be calculated directly from digital elevation data.

(5) Soil type (S_t)

Soil protection is also an urgent task because rapid urbanization in China poses great challenges to soil resources and food security (Chen, 2007). Different soil types are treated differently. For example, paddy soils, which are suitable for rice cultivation, should be preferentially protected (Wong et al., 2002).

The selection of the above variables is based on domain knowledge and data availability. However, the feasibility of our method remains unchanged if other data are involved. We then used the multi-criteria evaluation method (Eastman et al., 1998) to estimate the ecological suitability based on the variables. All of them will be normalized into the range [0, 1] for consistency. A suitability map can be generated by a weighted linear combination method as follows (Li et al., 2011; Liu et al., 2012):

$$S_E = w_1 \cdot \text{NDVI} + w_2 \cdot \text{NDWI} + w_3 \cdot H_h + w_4 \cdot \text{Slope} + w_5 \cdot S_t \quad (5)$$

where w_m ($m = 1, 2, \ldots, 5$) is the weight for each variable, and $\sum_m w_m = 1$.

In addition, the compactness metric in Eq. (1), which is designed to avoid the fragmentation of the protected areas, can be measured as follows (Li et al., 2011):

$$C = \frac{4\sqrt{A}}{P} \quad (6)$$

where A and P are the area and perimeter of a protected scenario, respectively.

Finally, genetic algorithm (GA) can be used to search for the optimal pattern for the eco-protected areas. In this study, each candidate solution (i.e., a zoning scheme) is encoded as a grid-based chromosome (Cao et al., 2012; Liu et al., 2014). That is to say, the whole study area can be represented by a randomly initialized binary two-dimensional matrix (1 for protected cells, and 0 for non-protected cells). The best chromosome can be obtained through iterative runs of selection, crossover, and mutation operations (Holland, 1975; Goldberg, 1989). At each iteration, the chromosomes will be selected as parents to procreate offspring. The probability of being selected increases with the chromosome's fitness value (utility). Elitism strategy was employed to ensure the best solution will survive to the next generation. Besides, we adopted the patch-based crossover and mutation strategies proposed by Cao et al. (2011) for obtaining compact solutions. Crossover operation randomly chooses several 3 × 3 windows, and the cells within each window from two chromosomes will interchange. Similarly, several 3 × 3 windows are randomly chosen in mutation operation, and the cell values within each window in one chromosome will become identical guided by the window's neighborhood. If the total number of protected cells falls outside a reasonable range (±5%) of the area constraint, the values for some randomly chosen cells will be reversed to satisfy the constraint. More detailed techniques can be found in the work of Cao et al. (2011). It is also feasible if other multi-objective optimization algorithms are used for zoning.

Although eco-protected areas can be effectively created through this method, it cannot deal with the conflicts between continuous urban expansion and ecological protection. Other traditional zoning methods are also unable to solve this problem because multiple objectives are involved. We argue that it is more reasonable to take into account both preexisting and potential urban developments. The details of our proposed method are discussed in the following subsections.

2.2. Predicting future urban expansion by using CA

In this study, we chose the commonly used logistic regression cellular automaton (Logistic-CA) to simulate and predict urban expansion (Wu, 2002). It is also acceptable if other CA models are adopted. In Logistic-CA, the development potential of each non-urbanized cell is calculated using a logistic function (Li et al., 2013b):

$$p_{ij}(S = Developed) = \frac{\exp(z_{ij})}{1+\exp(z_{ij})} = \frac{1}{1+\exp(-z_{ij})} \quad (7)$$

where p_{ij} is the development potential of cell ij, S denotes the state (developed or not), and z_{ij} is calculated according to a series of proximity variables (i.e., distances from a cell to the nearest transportation networks or urban centers) related to urban dynamics:

$$z_{ij} = b_0 + \sum_k b_k x_{k,ij} \quad (8)$$

where b_0 is a constant, x_k is the kth proximity variable (normalized into the range [0, 1]), and b_k is the parameter for x_k.

Furthermore, the impacts of stochastic perturbation, neighborhood function, and geographical constraints, should be included in Eq. (7). The new equation is given as follows:

$$p_{ij}^t = (1 + (-\ln\gamma)^\alpha) \cdot \frac{1}{1+\exp(-z_{ij})} \cdot \Omega_{ij}^t \cdot con_{ij} \quad (9)$$

where p_{ij}^t is the development probability of cell ij at time t, γ is a stochastic number ranging from 0 to 1, α is used to control the stochastic degree, Ω_{ij}^t is the development density in a 3 × 3 Moore neighborhood of cell ij at time t, and con_{ij} is a constraint score for cell ij within the range [0, 1]. Specifically, if a cell falls within the areas that are intrinsically impossible for urban development (e.g., large rivers, reservoirs), then its score is set to zero. Otherwise, the score is one. The higher the value of p_{ij}^t, the higher the development probability for cell ij.

Then, a threshold is used to determine whether each non-urbanized cell should be developed to an urbanized cell during the iterations. This procedure can be represented by the following equation:

$$S_{ij}^{t+1} = \begin{cases} Developed, & p_{ij}^{t} \geq p_{threshold} \\ NonDeveloped, & p_{ij}^{t} < p_{threshold} \end{cases} \tag{10}$$

where S_{ij}^{t+1} denotes the state of cell ij at time $(t+1)$, and $p_{threshold}$ is a threshold determined by the total number of urbanized cells derived from the last land use dataset.

After calibrating the CA model through logistic regression, we still need to estimate future demand for urban development in order to predict urban expansion. Many studies have demonstrated that urban land area has a strong relationship with population (López et al., 2001; He et al., 2008). Therefore, we can build a regression model to estimate future urban land area based on population data obtained from the bureau of statistics.

Finally, future urban expansion can be predicted by the above calibrated CA model constrained by the land demand. The zoning result achieved in Section 2.1 will be overlaid with current land use map and the prediction result respectively. The overlaps are defined as two types of "conflicts", which should be resolved by the next step of our approach. In the next subsection, game theory is introduced to tackle this conflicting issue.

2.3. Resolving conflicts under the framework of game theory

Game theory, a theory of decision-making, can provide a framework for conflict resolution between ecological protection and urban expansion. It can simulate the interactions among different stakeholders who have conflicting interests. Any individual's benefit depends on the others' behaviors. Game theory will find an equilibrium (solution) when all of them reach an agreement (Myerson, 1991). Generally, game theory consists of three basic elements: player, strategy, and payoff, all of which are introduced below. More detailed information about game theory can be seen in the works of Osborne and Rubinstein (1994), and Basar and Olsder (1995).

2.3.1. Player

The decision-makers serve as "players" in a game. Only two players, namely the municipal government (G) and land developers (LD), are involved in our study. This game can be deemed as a two-person dynamic game with perfect information. The term "dynamic" means that the players take actions in turn, while "perfect" indicates that each player exactly knows the actions made by other players in a previous stage.

2.3.2. Strategy and payoff

The actions took by the players are called "strategy". A basic assumption lies behind a game is that all the players are rational. That is to say, they will always adopt the best strategies that can maximize their own payoffs (e.g., economic benefit). The game in this study has two types: (1) one for conflict resolution between eco-protected areas and preexisting urban development, and (2) one for conflict resolution between eco-protected areas and potential urban development. A conflict zone, the basic unit of one single game, consists of several adjacent cells with the same type of conflict (Liu et al., 2015). Fig. S1 (in supplementary material) presents an example of these conflict zones and the corresponding neighborhoods.

For type (1), the government takes action first. It can choose to expropriate land from land developers or give up. If the government does not give up, it must compensate for the expropriation, and then land developers should make a decision by comparing the compensation with the potential economic benefit for urban development. If the land developers reject the compensation, the government should decide whether to increase the compensation or give up. They play the game back and forth for several rounds until they come to an agreement. The corresponding negotiation process is displayed in Fig. 1a. In this figure, E_L denotes the economic benefit for a conflict zone, C_G^r denotes the compensation provided by the government in the rth round, and R_G^r denotes the government's net revenue in the rth round.

The value of ecosystem services is often ignored in policy-making because the potential economic benefit for urban development is much higher in terms of monetary value per unit area (Costanza et al., 1997). This is particularly true in some large cities such as Guangzhou, whose GDP is over nine hundred billion RMB in 2009. However, ecosystem services are much more critical to human welfare. Therefore, an adjustment coefficient was employed to pay more attention to eco-protection. The government, who holds a dominant position in real-world, has the discretion to decide whether each conflict zone should be protected or not. Then, the above three variables can be represented as follows (Hui and Bao, 2013; Liu et al., 2015):

$$E_L = A \cdot B_U \cdot (S_U + N_U/N) \tag{11}$$

where A is the area of a conflict zone, B_U is the basic economic benefit per unit area, S_U is the average urban development suitability for the zone, N is the area of the neighborhood, and N_U is the area of urbanized cells within the neighborhood. S_U can be estimated by a series of proximity variables (the same as those used in Eq. (8)):

$$S_U = \sum_k b_k x_k \tag{12}$$

where x_k is the kth proximity variable, and b_k is the weight for x_k $(\sum_k b_k = 1)$.

The compensation provided by the government in the rth round (C_G^r) can be calculated by the following equation:

$$C_G^r = A \cdot \left(K_G + \frac{p \cdot K_G \cdot (1 - q^{r-1})}{1 - q} \right) \tag{13}$$

where K_G is the initial compensation per unit area provided by the government, r is the number of negotiation rounds, and p, q are the parameters for controlling the compensation increment ($0 < p$, $q < 1$).

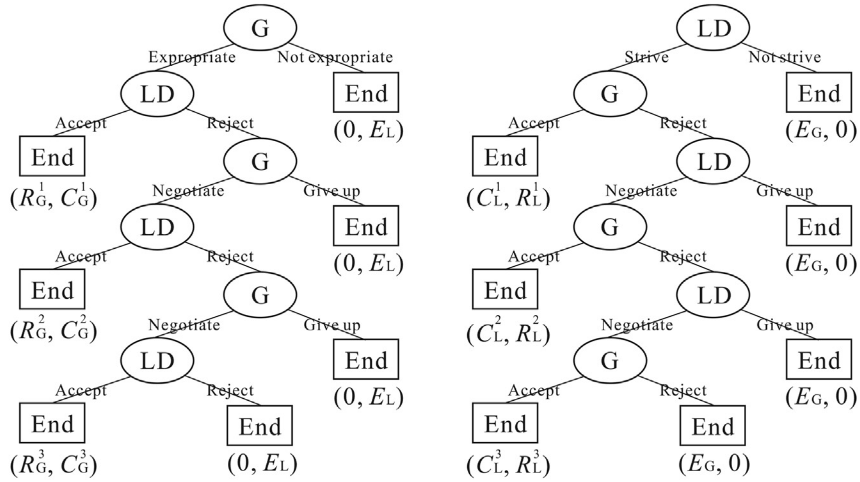
The government's net revenue in the rth round (R_G^r) can be formulated as follows:

$$R_G^r = A \cdot B_E \cdot T \cdot (S_E + N_E/N) \cdot (1 - e) - C_G^r \tag{14}$$

where B_E is the basic ecological benefit per unit area, which can be represented by the mean value of ecosystem services, T is an adjustment coefficient, S_E is the average ecological suitability for the conflict zone, which can be estimated through Eq. (5), N_E is the area of protected cells within the neighborhood, and e is the cost for turning preexisting urban development into protected area.

Type (2) is virtual but similar to type (1) except that the land developers make the first move. They can choose to strive or give up. If the land developers strive, they must compensate for their damages to the environment, and the government should make a decision by comparing the compensation with the potential ecological benefit for the conflict zones. If the government rejects the compensation, the land developers should determine whether

所有括号里面的左边和右边分别代表政府和开发商的纯收益。
如果征地成功，政府的收益是土地的生态效益减去征地补偿金，而开发商的收益是补偿金；如果不成功，政府收益为0，开发商收益为土地开发的经济效益。



(a) Type (1) (b) Type (2)

Fig. 1. The negotiation processes between municipal government (G) and land developers (LD). Note: Characters in parentheses denote the payoffs for G and LD respectively.

to increase the compensation or quit. Similarly, they play the game back and forth until a compromise is reached. Fig. 1b illustrates the corresponding negotiation process. Let E_G denote the potential ecological benefit for a conflict zone, C_L^r denote the compensation provided by the land developers in the rth round, and R_L^r denote the land developers' net revenue in the rth round. These three variables can be formulated as follows (Hui and Bao, 2013; Liu et al., 2015):

$$E_G = A \cdot B_E \cdot T \cdot (S_E + N_E/N) \tag{15}$$

where B_E is calculated differently from the one in Eq. (14):

$$B_E = \frac{\sum_{i=1}^{n} A_i \cdot VC_i}{A} \tag{16}$$

where A_i is the area of ecosystem type i within a conflict zone, and VC_i is the value coefficient of type i estimated by Xie et al. (2003).

The compensation provided by the land developers in the rth round (C_L^r) can be represented by the following equation:

$$C_L^r = A \cdot \left(K_L + \frac{p \cdot K_L \cdot (1 - q^{r-1})}{1 - q} \right) \tag{17}$$

where K_L is the initial compensation per unit area provided by the land developers.

The land developers' net revenue in the rth round (R_L^r) can be calculated as follows:

$$R_L^r = A \cdot B_U \cdot (S_U + N_U/N) - C_L^r \tag{18}$$

We assume that neither of the two players gives up at first. For type (1), the government will quit when R_G^r becomes negative, while the land developers will accept the expropriation when C_G^r is greater than E_L. Similarly, for type (2), the land developers will give up when R_L^r is negative, whereas the government will accept the compensation when C_L^r exceeds E_G. Besides, we need to determine the largest number of rounds (r_{max}) since the games cannot be played endlessly (Liu et al., 2015).

3. Model implementation and results

3.1. Study area and data

The proposed method was tested in Guangzhou, a metropolis situated in southern China. It consists of twelve administrative districts with an area of approximately 7434 km^2. This region has witnessed rapid urbanization since the adoption of reform and opening-up policy. Despite the substantial economic growth, the continuous urban expansion has resulted in serious ecological and environmental problems. As a consequence, eco-protected area zoning has become an urgent agenda for conservation in this fast-growing region (Li et al., 2011).

In this study, ecological suitability analysis necessitates a number of spatial variables. Although some higher spatial resolution products (e.g., Landsat images) have been commonly used as the basic input, it remains a little difficult to acquire high quality data in humid sub-tropical regions such as Guangzhou, due to the relatively long revisit time (Leckie, 1990). Therefore, MODIS images were adopted given the higher temporal resolution. We obtained the 500 m MODIS surface reflectance (MOD09A1) and NDVI (MOD13A1) products in 2009 from the National Aeronautics and Space Administration (http://reverb.echo.nasa.gov/reverb/). The former was used to calculate NDWI according to Eq. (2), while the latter was processed to a new $NDVI_{max}$ image through the maximum value composite procedure (Holben, 1986; Lin et al., 2014). Other variables were provided by Guangdong Institute of Eco-environmental and Soil Sciences. All of them were resampled to a spatial resolution of 500 m for consistency (Fig. S2). In addition, several proximity variables and land use data in 2005, 2009 were used to calibrate the CA model (Fig. S3). More detailed descriptions of the spatial data used here are provided in Table S2. In this study, all the computational tasks were fulfilled in the MATLAB Platform after converting the data into ASCII format.

3.2. Implementation and results

3.2.1. Zoning eco-protected areas by using GA

First, ecological and urban development suitability analyses were carried out by using the above variables. The weights for each variable should be defined based on domain knowledge and expert experiences. Multi-criteria evaluation method was adopted in this study (Eastman et al., 1998). Table 1 lists the weights for calculating ecological and urban development suitability. Both of them passed the consistency check. The final suitability values were normalized into the range [0, 1].

Subsequently, GA was employed to search for the optimal pattern of the eco-protected areas. Several parameters needed for running this algorithm were determined according to previous studies (Table 2) (Cao et al., 2012; Liu et al., 2015). In addition, the weights for ecological suitability and compactness metric (Equation (1)) were both set as 0.5. The area for the eco-protection is approximately 4460 km^2 in light of the city master plan of Guangzhou. It also stipulates that some fundamental water bodies (e.g., the Pearl River), mountains (e.g., the Baiyun Mountain), and farmlands must be strictly protected. Therefore, they were marked out in advance as a basic framework, which will remain unchanged during the optimization process. Fig. 2 displays the optimal result. Its average ecological suitability and compactness are 0.5425 and 0.1875, respectively.

3.2.2. Simulating and predicting urban expansion by Logistic-CA model

The widely used Logistic-CA model was employed in the simulation and prediction of urban dynamics in Guangzhou. We randomly selected 20% of samples from land use data to calibrate this CA model. The corresponding parameters (Equation (8)) are listed in Table 3. Then, the urban expansion from 2005 to 2009 can be simulated by the calibrated CA (Fig. 3a–b). The cell-by-cell simulation accuracy is up to 93.6%, which indicates that this model is reliable enough for prediction.

Subsequently, we obtained historical population data from Statistics Bureau of Guangzhou Municipality. A linear regression model was first constructed to predict future population in Guangzhou. The result shown in Fig. S4 indicates that the population correlates well with time (years), with an r^2 of 0.9990. As suggested by López et al. (2001), another linear regression model, rather than exponential model, was built to quantify the relationship between urban land area and population (Fig. S5). Since the validity period for land use planning in China is generally fifteen to twenty years, we estimated the demand for urban development in 2024 based on the regression model (r^2 is up to 0.9783).

Lastly, we predicted the future urban expansion (from 2009 to 2024) for Guangzhou based on the transition rule (i.e., the parameters in Table 3) under the area constraint. The prediction result is displayed in Fig. 3c.

3.2.3. Resolving the conflicts between ecological protection and urban expansion

A total of 99 conflict zones of type (1) and 105 of type (2) (see Section 2.3.2 for the definitions) were generated by an overlay analysis. The spatial distribution of these zones is shown in Fig. 4. Most of them are located in suburban regions. For type (1), the detailed land use type can be identified with the support of high-resolution remote sensing images. It is found that almost all the type (1) conflicts are low-rise industrial areas (see the enlarged view in Fig. 4 for example). Here, we employed another commonly-used zoning method, density slicing, for comparison. Specifically, the cells with higher suitability values were incorporated into the protected areas (Li et al., 2011). Similarly, many conflict zones inevitably arose (Fig. S6). This result also indicates the necessity for conflict resolution.

Therefore, two game models were constructed to simulate two types of negotiation processes between the government and land developers. The parameter B_U is represented by the ratio of gross domestic product to urban land area, while B_E is the mean value of natural ecosystems (Xie et al., 2003). The value for B_U can be determined accordingly if detailed data for each conflict zone are available. In addition, T is equal to "B_U/B_E", and K_L is equivalent to K_G for simplicity. Other parameters were defined in accordance with related studies (Liu et al., 2015). The detailed settings are listed in Table 4.

After running the game models, the conflict resolution and final zoning scheme are presented in Figs. 4 and 5, respectively. For comparison, we calculated the average ecological suitability and

Table 1
Weights for calculating ecological and urban development suitability.

Ecological suitability	NDVI	NDWI	H_h	Slope	S_t
	0.296	0.237	0.191	0.123	0.153
Urban development suitability	$D_{MainCenter}$	$D_{DistrictCenters}$	$D_{LTownCenters}$	$D_{STownCenters}$	
	0.109	0.137	0.153	0.184	
	$D_{Railways}$	$D_{Subways}$	$D_{Expressways}$	D_{Roads}	
	0.192	0.029	0.171	0.025	

Table 2
Parameters for running GA.

Population size	Number of generations	Crossover rate	Mutation rate
100	10,000	0.90	0.90

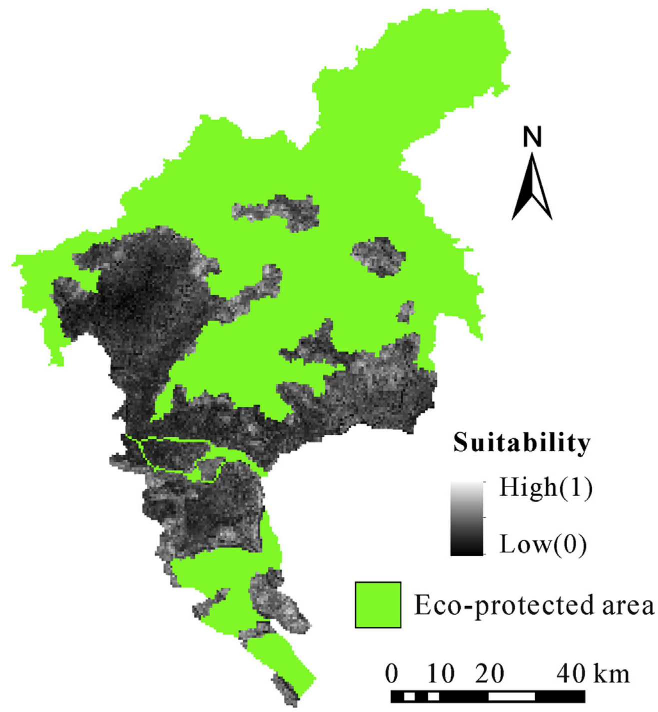


Fig. 2. Zoning of eco-protected areas using GA.

Table 3
Parameters of the Logistic-CA model.

Constant	$D_{MainCenter}$	$D_{DistrictCenters}$	$D_{LTownCenters}$	$D_{STownCenters}$
2.533	−2.979	−2.814	−2.757	−0.416
$D_{Railways}$	$D_{Subways}$	$D_{Expressways}$	D_{Roads}	
−2.296	1.542	−1.584	−4.910	

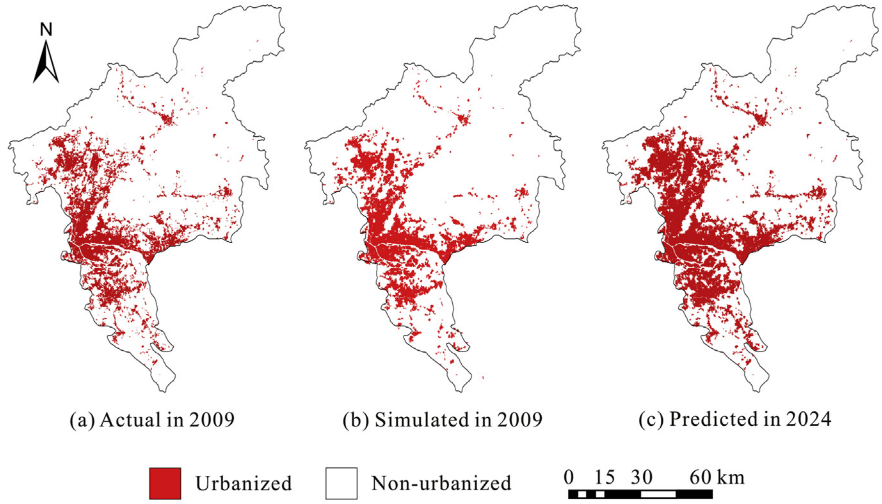


Fig. 3. Simulation and prediction of urban growth in Guangzhou: (a) actual in 2009, (b) simulated in 2009, and (c) predicted in 2024.

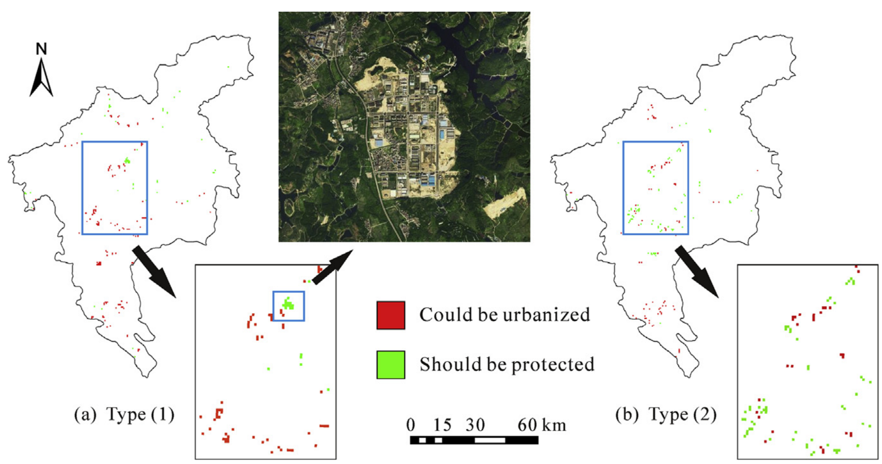


Fig. 4. Spatial distribution of the conflict zones: (a) type 1 zone, and (b) type 2 zone.

Table 4
Parameters of the game models.

p	q	e	r_{max}	B_U (RMB·m^{-2}·a^{-1})	B_E (RMB·m^{-2}·a^{-1})	T	K_L (RMB·m^{-2}·a^{-1})	K_G (RMB·m^{-2}·a^{-1})
0.4	0.6	0.2	10	989	1.2	824.2	593	593

compactness metric of the scheme. While the compactness inevitably decreased from 0.1875 to 0.1611, the average ecological suitability increased from 0.5425 to 0.5469. We further focused on the conflict zones. If they are either all included in or excluded from the eco-protected areas without distinction, the corresponding average benefits for the government ("B_E (S_E+N_E/N)" in Equation (15)) or land developers ("B_U (S_U+N_U/N)" in Equation (11)) are shown in Table 5. It is found that both of them increased by about 10% after the conflict resolution. The results demonstrate that our proposed method can reasonably decide whether each conflict zone should be protected or not.

With respect to the prospects of the eco-protected areas, the development of the northwestern and southern parts of Guangzhou will be constrained if the original zoning scheme (Fig. 2) is adopted, while our scheme can alleviate this problem to some extent. Overall, the proposed method is effective and valuable for protected area zoning, particularly in fast-growing regions. Nevertheless, several aspects could still be improved in future studies. We only made a rough estimation of the ecological and economic benefits due to a lack of detailed data. We will try to define the parameters of the game models according to the government's attitude toward ecological protection. For example, if the government gives a higher priority to eco-protection, T could be set higher. Instead, a lower value for T is applied when the government pays little attention to it. In addition, more advanced CA models may be employed to better predict urban expansion. It may also be better if more spatial variables are involved in the ecological suitability analysis. Besides, higher spatial resolution data (e.g., Landsat images) could be adopted when dealing with cloudless or smaller regions.

4. Conclusions and policy implications

Various methods have been developed to facilitate the zoning of

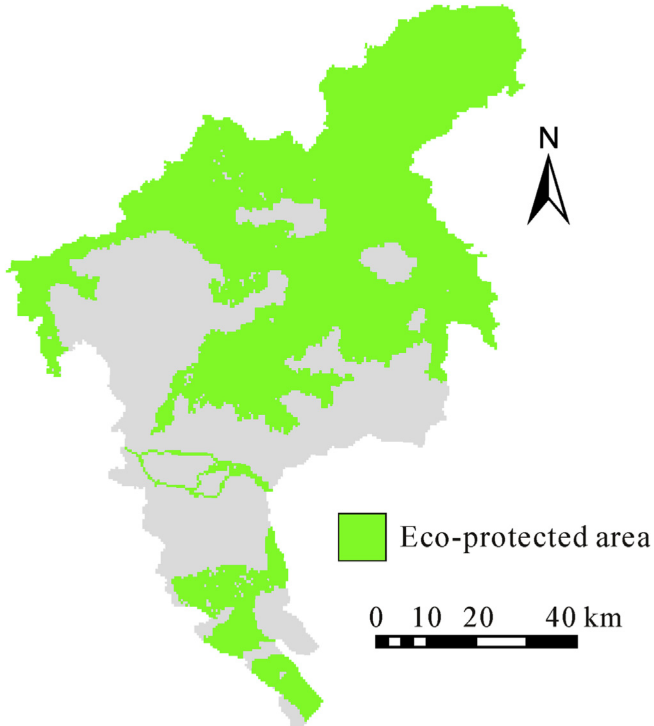


Fig. 5. Final zoning result after conflict resolution.

Table 5
Comparison of average ecological and economic benefits before and after conflict resolution.

	Type (1) conflict		Type (2) conflict	
	Before	After	Before	After
Ecological benefit (RMB·m^{-2}·a^{-1})	1.47	1.63	1.29	2.08
Economic benefit (RMB·m^{-2}·a^{-1})	1127.46	1240.01	1171.18	1267.90

protected areas, but most of them failed to resolve the conflicts between ecological protection and rapid urban expansion in a quantitative manner. In China, several municipal governments promulgated ordinances and zoning schemes for eco-protection without considering the negative impacts from potential urban development. The authorized protected areas even overlapped with preexisting urban development. Such schemes have to be remedied occasionally due to the negligence, and therefore defeated their own purpose.

To alleviate this problem, our study has presented a convenient method for conflict resolution between ecological protection and urban expansion. First, eco-protected area zoning was performed in a traditional way. Second, we predicted future urban expansion using a well-known Logistic-CA model. Finally, two types of conflicts between them were resolved under the framework of game theory. In fact, the stakeholders lie behind the conflicts are local government and land developers. While the government shows concern for ecological and environmental issues, the land developers only care about their economic benefits. Game theory can well simulate the negotiation processes between them.

The proposed method was applied to the eco-protected area zoning in Guangzhou, a large rapidly urbanizing city. The final zoning result is more reasonable than the original one because the trade-off between urban development and ecological protection can be well balanced by the game models. The average ecological and economic benefits can increase by about 10% after conflict resolution. Our method is expected to support policy-making in environmental management and urban planning. The government could still make some modifications according to local conditions. But once the decision is made, urban development must be strictly prohibited within the protected areas. The government should also execute reasonable ecological compensation plans based on the negotiation results, and pay enough attention to those conflict zones since they are prone to be illegally developed.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2015.11.036.

References

Basar, T., Olsder, G.J., 1995. Dynamic Noncooperative Game Theory. Society for Industrial and Applied Mathematics, Philadelphia.
Benton, T.G., Vickery, J.A., Wilson, J.D., 2003. Farmland biodiversity: is habitat heterogeneity the key? Trends Ecol. Evol. 18, 182–188.
Bos, J., 1993. Zoning in forest management: a quadratic assignment problem solved by simulated annealing. J. Environ. Manag. 37, 127–145.
Cao, K., Batty, M., Huang, B., Liu, Y., Yu, L., Chen, J., 2011. Spatial multi-objective land use optimization: extensions to the non-dominated sorting genetic algorithm-II. Int. J. Geogr. Inf. Sci. 25, 1949–1969.
Cao, K., Huang, B., Wang, S., Lin, H., 2012. Sustainable land use optimization using boundary-based fast genetic algorithm. Comput. Environ. Urban Syst. 36, 257–269.
Chen, J., 2007. Rapid urbanization in China: a real challenge to soil protection and food security. Catena 69, 1–15.
Chuvieco, E., 1993. Integration of linear programming and GIS for land-use modelling. Int. J. Geogr. Inf. Sci. 7, 71–83.
Colyvan, M., Justus, J., Regan, H.M., 2011. The conservation game. Biol. Conserv. 144, 1246–1253.
Costanza, R., d'Arge, R., Groot, R.D., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O'Neill, R.V., Paruelo, J., 1997. The value of the world's ecosystem services and natural capital. Nature 387, 253–260.
DeFries, R., Foley, J., Asner, G., 2004. Land-use choices: balancing human needs and ecosystem function. Front. Ecol. Environ. 2, 249–257.
DeFries, R., Hansen, A., Turner, B., Reid, R., Liu, J., 2007. Land use change around protected areas: management to balance human needs and ecological function. Ecol. Appl. 17, 1031–1038.
Eastman, J.R., Jiang, H., Toledano, J., 1998. Multi-criteria and Multi-objective Decision Making for Land Allocation Using GIS, Multicriteria Analysis for Land-use Management. Kluwer Academic Publishers, Dordrecht, pp. 227–251.
Freemark, K.E., Merriam, H., 1986. Importance of area and habitat heterogeneity to bird assemblages in temperate forest fragments. Biol. Conserv. 36, 115–141.
Geneletti, D., 2007. An approach based on spatial multicriteria analysis to map the nature conservation value of agricultural land. J. Environ. Manag. 83, 228–235.
Geneletti, D., van Duren, I., 2008. Protected area zoning for conservation and use: a combination of spatial multicriteria and multiobjective evaluation. Landsc. Urban Plan. 85, 97–110.
Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimizing, and Machine Learning. Addison-Wesley, Boston, MA.
Hansen, A., DeFries, R., 2007. Ecological mechanisms linking protected areas to surrounding lands. Ecol. Appl. 17, 974–988.
He, C., Okada, N., Zhang, Q., Shi, P., Li, J., 2008. Modelling dynamic urban expansion processes incorporating a potential model with cellular automata. Landsc. Urban Plan. 86, 79–91.
He, C., Zhang, Q., Li, Y., Li, X., Shi, P., 2005. Zoning grassland protection area using remote sensing and cellular automata modeling-a case study in Xilingol steppe grassland in northern China. J. Arid. Environ. 63, 814–826.
Hof, J.G., Joyce, L.A., 1993. A mixed integer linear programming approach for spatially optimizing wildlife and timber in managed forest ecosystems. For. Sci. 39, 816–834.
Holben, B.N., 1986. Characteristics of maximum-value composite images from temporal AVHRR data. Int. J. Remote Sens. 7, 1417–1434.
Holland, J.H., 1975. Adaptation in Natural and Artificial Systems: an Introductory

Analysis with Applications to Biology, Control, and Artificial Intelligence. The University of Michigan Press, Ann Arbor.
Huang, W., 2011. A Game for the Modification of Eco-designated Line of Control, Nanfang Daily, Guangzhou.
Hui, E., Bao, H., 2013. The logic behind conflicts in land acquisitions in contemporary China: a framework based upon game theory. Land Use Pol. 30, 373–380.
López, E., Bocco, G., Mendoza, M., Duhau, E., 2001. Predicting land-cover and land-use change in the urban fringe: a case in Morelia city, Mexico. Landsc. Urban Plan. 55, 271–285.
Leckie, D.G., 1990. Advances in remote sensing technologies for forest surveys and management. Can. J. For. Res. 20, 464–483.
Lewis, C., 1996. Managing Conflicts in Protected Areas. The World Conservation Union.
Li, X., Lao, C., Liu, X., Chen, Y., 2011. Coupling urban cellular automata with ant colony optimization for zoning protected natural areas under a changing landscape. Int. J. Geogr. Inf. Sci. 25, 575–593.
Li, X., Lao, C., Liu, Y., Liu, X., Chen, Y., Li, S., Ai, B., He, Z., 2013a. Early warning of illegal development for protected areas by integrating cellular automata with neural networks. J. Environ. Manag. 130, 106–116.
Li, X., Lin, J., Chen, Y., Liu, X., Ai, B., 2013b. Calibrating cellular automata based on landscape metrics by using genetic algorithms. Int. J. Geogr. Inf. Sci. 27, 594–613.
Lin, J., Liu, X., Li, K., Li, X., 2014. A maximum entropy method to extract urban land by combining MODIS reflectance, MODIS NDVI, and DMSP-OLS data. Int. J. Remote Sens. 35, 6708–6727.
Liu, F., 2010. A Game for Eco-designated Line of Control in Shenzhen. China Youth Daily, Beijing.
Liu, X., Lao, C., Li, X., Liu, Y., Chen, Y., 2012. An integrated approach of remote sensing, GIS and swarm intelligence for zoning protected ecological areas. Landsc. Ecol. 27, 447–463.
Liu, Y., Tang, W., He, J., Liu, Y., Ai, T., Liu, D., 2015. A land-use spatial optimization model based on genetic optimization and game theory. Comput. Environ. Urban Syst. 49, 1–14.
Liu, Y., Yuan, M., He, J., Liu, Y., 2014. Regional land-use allocation with a spatially explicit genetic algorithm. Landsc. Ecol. Eng. 1–11.
McDonald, R.I., Kareiva, P., Forman, R.T., 2008. The implications of current and future urbanization for global protected areas and biodiversity conservation. Biol. Conserv. 141, 1695–1703.
McDonald, R.I., Yuan-Farrell, C., Fievet, C., Moeller, M., Kareiva, P., Foster, D., Gragson, T., Kinzig, A., Kuby, L., Redman, C., 2007. Estimating the effect of protected lands on the development and conservation of their surroundings. Conserv. Biol. 21, 1526–1536.
McFeeters, S., 1996. The use of the normalized difference water index (NDWI) in the delineation of open water features. Int. J. Remote Sens. 17, 1425–1432.
Myerson, R.B., 1991. Game Theory: Analysis of Conflict. Harvard University Press, Cambridge.
Osborne, M.J., Rubinstein, A., 1994. A Course in Game Theory. MIT Press, Cambridge, MA.
Sabatini, M.C., Verdiell, A., Rodríguez Iglesias, R.M., Vidal, M., 2007. A quantitative method for zoning of protected areas and its spatial ecological implications. J. Environ. Manag. 83, 198–206.
Samsura, D., van der Krabben, E., van Deemen, A., 2010. A game theory approach to the analysis of land and property development processes. Land Use Pol. 27, 564–578.
Svoray, T., Bar, P., Bannet, T., 2005. Urban land-use allocation in a mediterranean ecotone: habitat heterogeneity model incorporated in a GIS using a multi-criteria mechanism. Landsc. Urban Plan. 72, 337–351.
The People's Government of Shenzhen Municipality, 2005. Ordinance of Eco-designated Line of Control in Shenzhen last accessed 24 August 2015. http://www.szpl.gov.cn/main/csgh/zxgh/stkzx/index.htm.
Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sens. Environ. 8, 127–150.
Verdiell, A., Sabatini, M.C., Maciel, M., Rodríguez Iglesias, R., 2005. A mathematical model for zoning of protected natural areas. Int. Trans. Oper. Res. 12, 203–213.
Watts, M.E., Ball, I.R., Stewart, R.S., Klein, C.J., Wilson, K., Steinback, C., Lourival, R., Kircher, L., Possingham, H.P., 2009. Marxan with Zones: software for optimal conservation based land-and sea-use zoning. Environ. Model. Softw. 24, 1513–1521.
Withers, P.J., Lord, E.I., 2002. Agricultural nutrient inputs to rivers and groundwaters in the UK: policy, environmental management and research needs. Sci. Total Environ. 282, 9–24.
Wong, S., Li, X., Zhang, G., Qi, S., Min, Y., 2002. Heavy metals in agricultural soils of the Pearl River Delta, South China. Environ. Pollut. 119, 33–44.
Wu, F., 2002. Calibration of stochastic cellular automata: the application to rural-urban land conversions. Int. J. Geogr. Inf. Sci. 16, 795–818.
Xie, G., Lu, C., Leng, Y., Zheng, D., Li, S., 2003. Ecological assets valuation of the Tibetan Plateau. J. Nat. Resour. 18, 189–196.
Yeh, A.G.O., Li, X., 1999. Economic development and agricultural land loss in the Pearl River Delta, China. Habitat Int. 23, 373–390.
Zhu, Z., Deng, Q., Zhou, H., Ouyang, T., Kuang, Y., Huang, N., Qiao, Y., 2002. Water pollution and degradation in Pearl River Delta, South China. AMBIO 31, 226–230.