

Sustainable Brownfields Land Use Change Modeling Using GIS-based Weights-of-Evidence Approach

Saleh Abdullahi · Biswajeet Pradhan

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Abstract Rapid and unorganized urban growth brings about urban sprawl, which leads to the increase in the number of abandoned lands and brownfields within the cities. Revitalization and redevelopment of these areas is one of the key factors of compact urban development to achieve urban sustainability. However, not much research work has been done on the redevelopment of brownfield on the base of compact urban development paradigm in the recent literature. Most researches on this field have mainly considered a single brownfield site for redevelopment on the bases of local neighborhood demand and characteristics. The current paper proposes a brownfields land use change modeling process according to a compact city paradigm in a larger scale perspectives rather than local aspects. The proposed model is a statistical-based weights-of-evidence (WoE) approach in the GIS environment. The growth of three main land use types in Kajang city, Malaysia was predicted using several compact development parameters and other urban and physical site characteristics. Maps that have been created with this process were validated by actual growth maps of these land use types using an area under curve (AUC) technique. The AUC of residential, commercial and industrial land use were gained as 77.4, 78, and 67 %, respectively. Finally, these maps were aggregated with an existing brownfields map in order to project future land use types according to planning strategies, as well as compact development characteristics. Results indicate that according to potential and suitability of the site and neighborhood properties, each brownfield can serve the community as single or mixture of several land use types. It is concluded that the combination of land use change modeling techniques and compact urban development theory in GIS environment can provide a strong tool for brownfields redevelopment planning and strategies.

S. Abdullahi · B. Pradhan (✉)

Department of Civil Engineering, Geospatial Information Science Research Center (GISRC), Faculty of Engineering, University Putra Malaysia, 43400 UPM, Serdang, Selangor, Malaysia
e-mail: biswajeet24@gmail.com

B. Pradhan
e-mail: biswajeet@lycos.com

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Background

Brownfields are abandoned or underused properties that should be redeveloped or reused because of the real or suspected presence of hazardous substances, pollutants, or containment (Collins 2002; Oliver et al. 2005). Redevelopment of existing brownfields is one of the important objectives to enhance the sustainable urban development theory (De Sousa 2008; Nijkamp et al. 2002) and reduce urban sprawl (Nuisl and Schroeter-Schlaack 2009). However, a brownfield redevelopment needs a comprehensive effort to resolve and negotiate among several stakeholders with different interests (Bardos 2003; Gross 2010). These complexities have caused many brownfields remain undeveloped, especially in developing countries. According to the literature, there is a variety of approaches for various aspects of brownfield redevelopment such as risk assessment (Carlson et al. 2008), policy analysis (Linkov et al. 2006), optimization of remediation (Bürger et al. 2007), remediation cost assessment (Kaufman et al. 2005), general success factors for brownfield redevelopment (Lange and McNeil 2004), infrastructure redevelopment (Attoh-Okine and Gibbons 2001), urban planning, and site prioritization under budget constraints (Alvarez-Guerra et al. 2009), etc. (Schädler et al. 2011). Hence, strong approaches are required to integrate these aspects and manage complexities of information and results (Agostini et al. 2007; Bardos et al. 2000).

Land use change modeling is important for various urban planning and management issues. It is a suitable approach to deal with redevelopment and revitalization of existing brownfields. Modeling of land use changes not only improve and select various land development scenarios, but also to evaluate the impact of development alternatives. For example, proper analysis and prediction of urban growth may prevent many social and environmental problems caused by the urban sprawl (Hayek et al. 2011), suburbanization process (Helbich and Leitner 2009) and unorganized land developments. The main environmental problems that can be prevented are encroachment on valuable agricultural, forest, and natural areas. In addition, land use change modeling can help local planning authorities to provide better community facilities and services to sustain developments (Hathout 2002). In fact, most of the urban development scenarios are an act to achieve urban sustainability. Compact development, transit oriented development, and smart city are good examples of development scenarios that are based on sustainable development principles (Livingstone and Rogers 2003). One of the environmental perspectives of compact urban development is to emphasize on containment of rural developments and revitalization of central areas (Jenks et al. 1996; Lin and Yang 2006). The rationale behind this concept is to try redeveloping existing brownfields inside the cities instead of growing built up areas through rural environments. Cho et al. (2011) attempted to solve this problem by evaluating the hypothesis that land value tax contained rural area development and encouraged compact and development closer to and within built up areas. Rall and Haase (2011) assessed the brownfield revitalization program of the City of Leipzig in the context of urban sustainability. The assessment was performed through a triangular integrated evaluation method combined with site surveys and interviews, as well as expert knowledge. However, these

assessments and analyses can be improved significantly by modeling the land use changes in order to predict and propose a proper land use types for each brownfield site. Sebastian Schädler et al. (2012) described and proposed a framework which integrates a GIS-based identification of areas to be remediated, an estimation of associated clean-up costs, and an assessment of the planned future land use's contribution to sustainable urban development. In another research, Sebastian Schädler et al. (2013) proposed a scheme to transfer the evaluation of site-specific sets of sustainability indicators into automated quantitative and spatially explicit assessments, which can be integrated into multidisciplinary spatial optimization algorithms. On the other hand, the main aim of their study was to gain a site-specific understanding of sustainable land use planning, and of the potential advantages that mixed land use development may have over uniform use with only one single land use type for a brownfield site. However, the current paper attempts to deal with brownfield redevelopment based on compact development paradigms through land use change modeling to achieve urban sustainability.

Land use Change Modeling

According to the literature, following four core principles are the bases of all land use change simulation models; historical evidence based, suitability bases, neighborhood bases, and actor interaction bases (Verburg et al. 2004a). The logic behind historical evidence based is that, "past is the key for future". Therefore, background information can be helpful in predicting future land use change as demonstrated by Kuijpers-Linde et al. (2007). Suitability bases may consist of several factors in a land parcel in order to evaluate for an allocation of specific purpose (Abdullahi et al. 2013). Therefore, the underlying premise is to achieve maximum profit and minimize liability. Neighborhood bases deal with neighborhood interaction cells that affect the transition of one land use to another (Li et al. 2008). Actor interaction bases assume that land use change is the result of an interaction of several actors or agents. The agents can be one or a group of factors. This core principle is a promising research tool for land use change modeling (Jjumba and Dragičević 2012; Matthews et al. 2007).

There are a few main concepts of land use changes such as Markov Chains, Economic-based concept, Agent-Based Systems, Statistical Analysis, Cellular Automata, and Artificial Neural Networks. The Markov Chain concept is based on a continuation of historical trend of development. This concept calculates a probability matrix of changes of one land use type to another. The main disadvantage of this model is the lack of spatial bases of results therefore additional assumptions are required for allocation (Al-sharif and Pradhan 2014; Verburg et al. 2004a). The Economic-based concept is also an important reason for land use changes and is mainly based on the suitability of a land, although the core principle of continuation of historical development can also be included. In general, economic-based is not exactly a concept, however, cannot be left out of the list of concepts of land use change (van Schroyenstein Lantman et al. 2011). More recent applications of economic based have been reported by Nelson and Hellerstein (1997) and Walker (2004) which all use as the based theory to explain tropical deforestation. An Agent-Based Systems of land use change modeling which is based on the core principle of actor interaction, consists of

two main components: a map of a study area and a model with agents that represent human decision-making (Parker et al. 2003). An agent is a representation of actors important in the process with their own preferences (Grimm et al. 2006). These preferences can be defined by expert knowledge, by using questionnaires, or by using artificial neural networks technique (van Schrojenstein Lantman et al. 2011). Various kinds of statistical computation can be derived from land use maps. For example, logistic regression, frequency ratio, and weights-of-evidence techniques can be used to analyze the probability of occurrence of a dependent variable on each class of independent variables (Verburg et al. 2004a). The coefficients of each variable can be calculated from historical land use changes. Furthermore, they can be projected for future land use changes. Other statistical modeling approaches such as logit modeling in the planning and policy environment are also so common; like Land Use Scanner (Hilferink and Rietveld 1999), which has been used in producing sustainability outlooks for the Netherlands (Kuijpers-Linde et al. 2007). The Cellular Automata (CA) is the most well-known techniques in modeling of land use changes (White and Engelen 1993). The main logic behind CA modeling for land use changes is the current state of each cell and its interaction with neighborhood cells. Therefore, this model is based on core principles of historical trend and neighborhood interaction. However, CA does not necessarily consider the relationship and interaction among the related parameters. Thus, usually, the CA is integrated with other techniques such as Markov Chain (Al-sharif and Pradhan 2014), Fuzzy Theory (Al-Ahmadi et al. 2009a6b), etc. to increase the strength of the modelling. The use of Artificial Neural Networks (ANN) has increased significantly due to advances in computing performance and flexibility of software (Skapura 1996). The pattern recognition capability (Pijanowski et al. 2002), that makes a relationship between past and future land use and suitability maps (Verburg et al. 2004b), are important parameters that can emphasize the strength of ANN models in land use change modeling. The first to apply ANNs to a computer simulation model was Pijanowski et al. (2002). The model trains itself on a dataset and the corresponding land-use maps of different years enabling it to recognize and reproduce the pattern of land-use categories (Mas et al. 2004; Pijanowski et al. 2005). Appropriate knowledge about the land use change modeling based on their concepts allows modelers to select the most appropriate model for area of investigation.

Land use change modeling requires availability of rich spatial data, spatial analysis tools, and displaying capability to illustrate the output maps. Geographic information system (GIS) and remote sensing are the most useful tools to support modeling (Tehrany et al. 2013). GIS can provide a proper environment to store, manage, analyze, manipulate, and display spatial data associated with the models. In addition, GIS can aid modelers to define and create spatial variables for the models (Openshaw and Clarke 1996), predict land use changes based on several independent spatial variables (Mertens and Lambin 2000), and evaluate predicted changes in a spatial pattern. However, some capability of GIS is also questioned regarding the extent and type of GIS used in the planning practice (Olafsson and Skov-Petersen 2014). Hence, updated knowledge regarding the performance and limitation of GIS, as well as integration with other models, will improve the strength of the analysis. There are numerous studies on land use change modeling using integration of GIS technology (Li and Yeh 2002; Pijanowski et al. 2002; Verburg et al. 2004a; Wu 1998). For instance, Thomas (2002) stated that to assess land use modeling performance with respect to the redevelopment

of brownfields, accessibility of information such as land capability, environmental concerns, public preferences, etc. for both governmental agencies and decision makers are required. He discussed a GIS-based decision support system to provide access to geospatial data in various scales for better understanding of the brownfields redevelopment issue.

Although several applications of global parametric models have been used in land use change modeling (Tayyebi et al. 2014), very few urban related studies have considered city compactness as an objective of the land use change modeling process to achieve urban sustainability. The lack of this application specifically for brownfields redevelopment planning is the motivation to investigate the potential and capability of this integration modeling for existing brownfields of Kajang City, Malaysia. In addition, the current study is an attempt to analyze the urban land use changes and spatial patterns of the study area in a quantitative manner. This will benefit Malaysian case studies as these effects are usually explained without quantitative perspectives in the country (Nourqolipour et al. 2014). Therefore the main objective is to integrate the land use change modeling concept with the brownfield redevelopment plan on the bases of city compactness paradigms. Specifically, the present paper illustrates how statistical-based weights-of-evidence (WoE) approach within GIS aids in the understanding of the process of land use changes. WoE was used to measure the extent and direction of various land use growth based on temporal datasets for the year 2008 and 2012. In addition, the model was utilized to apply and evaluate the driving forces responsible for the change of land use types in a compact pattern. One benefit of using the model is the ability to extract and utilize the most effective factors from all the selected factors before evaluating the probability of land use growth. By integrating the process with brownfield redevelopment strategy, one of the environmental objectives of compact development can be fulfilled. Hence, this study initially predicts land use changes of Kajang City using the probability of growth of each land use according to compact development evidences. Consequently, the extent and direction of each land use types were projected. After validating the process, the created probability maps and the master plan of the study region was used to assess the existing brownfields land use types. It should be mentioned that, due to utilization of the standard and common urban related parameters as well as statistical based methodology, this process can be easily replicated in other international cities for brownfields redevelopment strategies.

Study Area

The proposed modeling was used to predicting the multiple land use changes for Kajang City, Malaysia (3° 00' 19" N, 101° 46' 42" E). The study area is located 21 km from Kuala Lumpur, the capital city of Malaysia (Fig. 1). According to the 2010 census data, the city has population of 246,618, with an estimated population growth of 9 % per annum. The study area covers approximately 60 km². The west parts of the city are mainly covered by agriculture and forest lands. Recent urban sprawl developments have mushroomed Kajang City because of its proximity to three main cities of Malaysia. Although there are many abandoned and brownfields in the city, most of these new developments have been constructed at the outskirts of the agricultural and forest lands. For this reason, the present research attempts to assess the brownfields

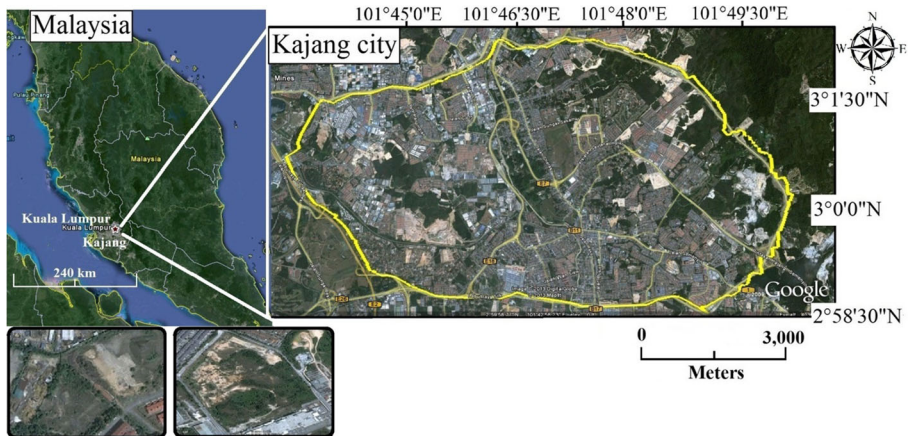


Fig. 1 The map of Malaysia, Kajang city and two examples of brownfield sites

land use changes according to the city compactness paradigm to make Kajang City more environmentally sustainable.

Data and Methodology

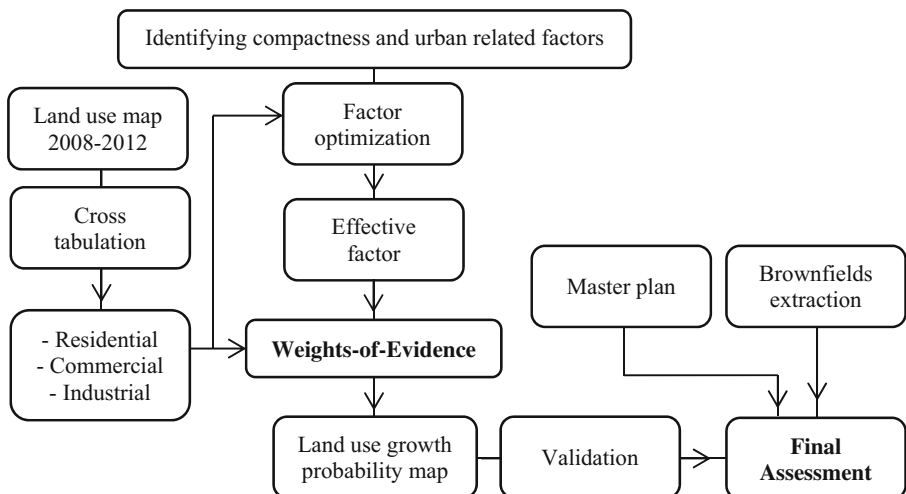
In the first stage, a contextualized definition of the compact urban development and its indicators was needed. Generally, in a large scale study area, urban compactness is measured based on the cellular bases and the concentration of the built up cells in a specific area as in the study conducted by Li and Yeh (2004) which assesses the urban compactness using entropy and compactness index methods. Due to availability of several urban detail layers, the current study performed a compactness assessment in more accurate and detail bases. There are three main city compactness indicators: urban density, land use diversity, and urban intensity (Abdullahi et al. 2014; Burton 2002). Each of these indicators is divided into several parameters according to the availability of data and the objective of the research. In addition to city compactness indicators, other related urban parameters that are important for land use changes and some physical properties of the sites were included in the analysis, as shown in Table 1. The overall methodology flowchart of the process is shown in Fig. 2.

Most of the data, such as the land use map of year 2008 and 2012, the road network, the soil map, etc., were collected from the local planning authority of Kajang City. Other layers were also extracted or created from existing layers. It was essential to select the most important parameters among others, which have a significant effect on the land use conversion for the specific study area. Therefore, an optimization process was applied to select the most effective parameters. This process was performed by the frequency ratio (FR) approach, which is the initial step of running the weights-of-evidence technique (Pourghasemi et al. 2013a; Pradhan et al. 2010). FR had the ability to examine the existence and changes (the increase or decrease) of land use types with respect to each class of all parameters. In this manner, the effectiveness of each parameter could be assessed by investigating the trend of land use changes based on their classes. This process also assessed the spatial dependency of the factors. The

Table 1 Land use change modeling parameters

No.	Parameters	Categories
1	Population density	City compactness
2	Built up density	City compactness
3	Residential density	City compactness
4	Land use diversity	City compactness
5	Proximity to public transportation facilities	Site specific/City compactness
6	Proximity to recreation facilities	Site specific/City compactness
7	Proximity to community facilities	Site specific/City compactness
8	Proximity to infrastructure	Site specific/City compactness
9	Proximity to road networks	Site specific/City compactness
F	Proximity to same land use types	Site specific
il	Distance from agricultural fields	Site specific
es	Soil and geology properties	Physical properties
(Distance from flood zones	Physical properties

classification of the parameters was defined according to their types. For instance, a proximity analysis was performed for the distance-based parameters. Then these distances were divided into classes, which include their spatial extent. Every cell are in a distance class: “near” to, “middle”, and “far” from land uses or points of interest. For ordinal parameters, such as the land use diversity and urban population, “high”, “moderate”, and “low” mixed or density were applied respectively. In the case of nominal parameters such as soil types or geology types, each type was used as one class. The entire base layer of all factors was converted into a grid cell to assess the growth of each land use type in their classes. For instance, the proximity to industrial land use causes a reduction in existence of residential land use cells. In contrast, in areas near to recreational facilities, more number of residential cells can be observed.

**Fig. 2** Methodology flowchart of the process

However, various geological types do not have any significant effect on existence or absence of residential cells. Hence, the proximity to industrial and recreational facilities selected as important parameters. Moreover, geological characteristic assumed as not an effective factor, hence were removed from the process.

As previously mentioned, historical evidence bases are one of the core principles of land use change modeling. In order to investigate the trend of the land use changes during a 4 years period, a cross-tabulation analysis of land use maps was performed between the years 2008 and 2012. A cross-tabulation enabled the observation of the significant growth of the main land use types. This process is a mathematical matrix, which gives unbiased information concerning the entire area of interest, to derive unbiased summary statistics (Pontius and Millones 2011). For this case study, the matrix gave unbiased information concerning the relationship between the land use maps of 2008 and 2012. It showed that only three main land use types (residential, commercial and industrial) were growing and changing significantly than others. New-build gentrification literature also proved that the land use change process is mainly from pre-industrial or brownfields to residential, commercial or institutional uses (Davidson and Lees 2005; Sabri et al. 2012). Furthermore, the growth of these three land use types resulted in the reduction of agricultural fields. Hence, it is decided to focus on residential, commercial, and industrial land use types, to evaluate and project their growth through other land use types.

For the proposed land use change modeling, Bayesian theorem was applied, with an update of prior probabilities through the weights-of-evidence (WoE) approach (Bonham-Carter 1994; Pradhan et al. 2010). Dempster–Shafer theory of evidence developed by Dempster (1967) and then by Shafer (1976) is a spatial integration model with mathematical representations (Althuwaynee et al. 2012; Carranza 2009).

The selected parameters from the optimization process were utilized as evidence in order to evaluate the probability of growth for each main land use type. The WoE allowed the ability to assess and combine evidences according to variation of the land use changes. The advantage of this theory is its flexibility to compute uncertainty and to combine evidences from different sources of data (Thiam 2005; Tien Bui et al. 2012). The model created an opportunity to analyze land use changes according to the city compactness paradigm. In general, WoE evaluates the degree to which evidences support the hypothesis, in this case the land use change occurrence, and the degree to which those evidences do not refute the hypothesis (Dempster 1967; Shafer 1976). The WoE has been widely applied in the literature in a variety of applications such as geological mapping (Chen et al. 2013; Nampak et al. 2014), and natural disaster management (Althuwaynee et al. 2012; Pourghasemi et al. 2013a, b; Tien Bui et al. 2012; Mohammady et al. 2012; Pradhan et al. 2014; Tehrany et al. 2014). However, a few studies have utilized this approach in urban applications such as land use dynamic modeling by Maria de Almeida et al. (2003) and mixed land use development probability mapping by Abdullahi et al. (2015). As an example, the WoE of residential land use growth with respect to the proximity to the road is shown in Table 2. The value of C was calculated by subtracting W^+ (natural logarithm of occurrence) and W^- (natural logarithm of non-occurrence). This value represents the spatial association of each land use pixel and each class of evidence. A positive value represents a higher number of specific land use pixels occurring in this class. In contrast, a negative value represents a lesser number of land use pixels occurring in this class. $S_2(W^+)$ and $S_2(W^-)$ are

Table 2 Weights-of-evidence for residential land use growth based on “proximity to road” evidence

Factor	Class	Frequency Ratio	W+	W-	C	S2(W+)	S2(W-)	S(C)	C/S(C)
Proximity to residential	Near	1.08	0.08	-0.04	0.12	0.000007	0.000004	0.00	38.23
	Middle	1.04	0.04	-0.02	0.07	0.000007	0.000004	0.00	20.49
	Far	0.87	-0.14	0.06	-0.20	0.000007	0.000004	0.00	-59.78

variances of W^+ and W^- , respectively, and $S(C)$ is the standard deviation of the contrast. Finally, $C/S(C)$ is the standardized value of C which represents the significance of the spatial association and measures the relative certainty of the posterior probability (Bonham-Carter 1994). Further detailed description of the mathematical formulation is available in Maria de Almeida et al. (2003), Pradhan et al. (2010) and Regmi et al. (2010). The probability value of the land use growth for every cell of the study area is calculated by considering the prior probability of occurrence and non-occurrence of land use types in each class of evidence. The majority of the evidences are distance-based or accessibility. Hence assessing the weights across the different distance ranges is possible. The other two evidences were the main city compactness characteristics and characterized in ordinal bases. The transitional probability was computed according to the proportion of the observed transition in each predefined class of evidences.

The output of this process is the three land use growth probability maps which show the probability of each land use growth according to the selected evidences separately. Each map was later classified into three classes: areas with very high, moderate, and low probability of growth of a specified land use type. Finally, all three maps as first scenario which was equal priority scenario were aggregated with the same weights. The first scenario was to illustrate the overall view of the study area regarding the growth of each single land use types, as well as mixture of them. The other scenarios were defined according to the master plan of the study area, where each land use growth map had different priority values. Hence, the site potential and suitability, the local demands of the neighborhood, and the local planning and development policy can assist to assign a proper priority to each land use type.

The next step was to extract the existing brownfields of Kajang City. For this process, the site indicators and criteria as listed in study conducted by Thomas (2002) were tested. All open spaces such as the buffer zone around rivers and highways, recreational play grounds, and natural landscapes were excluded from the analysis. As shown in Fig. 3, most of the small brownfield sites are located in the center, south, and southeast. They are near dense residential and commercial areas or compact regions. In contrast, brownfields with larger area are located in the east, west, and central west near to industrial and agricultural fields or less compact regions.

Results and Discussion

In the first step to understand the current trend of land use change of the study area, a cross tabulation process was run between the land use map of year 2008 and 2012. This process revealed that residential land use attempts to capture almost all types of

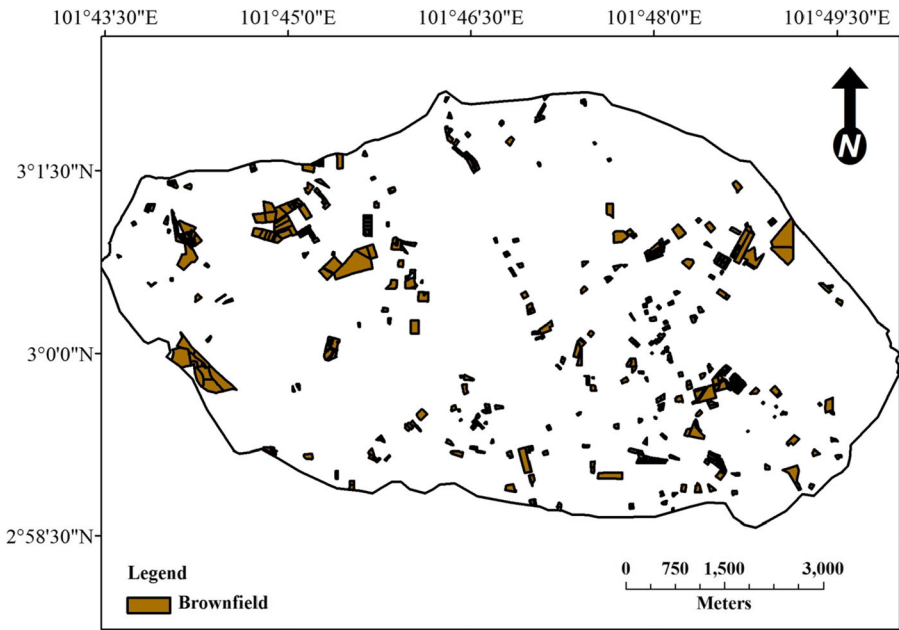


Fig. 3 Brownfields of Kajang city

activities. However, this growth is more noticeable through open spaces and agricultural fields. In fact, the growth in main land use types through brownfields and abandoned land is desirable. However, loss of 345 ha of agricultural fields in 4 years only from residential land use development is an unsustainable problem that should be avoided. Unfortunately, loss of agricultural fields can be seen from the growth of commercial and industrial land use as well. By running a cross tabulation process, the total growth and total loss of each land use types were computed. Residential, commercial, and industrial land use had growth values of 367, 72, and 75 ha, respectively, during 4 years period. Moreover, in overall Kajang City has lost more than 348 ha area of its agricultural fields in same period.

After evaluation of the land use growth with respect to all selected parameters, it was noticed that some of them do not have influence on these growths. Therefore, by running the optimization process, the most effective factors as shown in Table 3 were extracted. Residential and industrial land use types apparently are more similar in factor effectiveness rather than commercial land use. However, it should be noted that most the factors have an inverse relationship with these two land use types: the proximity to community and recreational facilities, the population density, and the land use diversity. In contrast, commercial and residential land uses have a direct relationship in case of the most factors.

The probability value of land use growth ($C/S(C)$ value) for every cell of study area was calculated considering the prior probability of occurrence and non-occurrence of land use types in each class of evidences. A summarized weights-of-evidence calculation for each land use growth is given in Table 4.

A majority of evidences were based on distance or accessibility and it was possible to examine the probability of growth of land use types across the different distance

Table 3 Most effective parameters for land change modeling

Important factors	Land use type
Proximity to residential	Residential, commercial, industrial
Proximity to commercial	Residential, commercial, industrial
Proximity to industrial	Residential, commercial, industrial
Proximity to roads	Residential, commercial, industrial
Proximity to public transportation	Residential, commercial, industrial
Proximity to community facilities	Residential, industrial
Proximity to recreational facilities	Residential, Industrial
Proximity to infrastructure	Residential, industrial
Proximity to agricultural fields	Residential, commercial, industrial
Population density	Residential, commercial, industrial
Land use diversity	Residential, commercial, industrial

classes. On Table 4 and as shown in Fig. 4, the probability of growth for each land use types is higher in close proximity to the same land use types. In contrast, the residential and industrial land uses tend to keep distances from each other. In general, proximity to recreational and community facilities offer advantages for the housing environment. In this specific case study, the proximity caused positive probability values for residential and negative values for industrial land use growth. This confirms the inverse relationship of the residential and industrial land uses theory.

Accessibility to main roads and public transportation facilities is another important characteristic of site suitability. Having proper accessibility is a positive factor for most of new developments. However in Kajang City, most of the industrial land uses are located near agricultural fields or rural areas, which not much urban development is observed. This issue can be seen from the proximity to agricultural fields as well. Consequently, in the case of industrial land use, negative values are for classes near to main roads and public transportation facilities.

Population and land use diversity evaluation were in the range of high and low population and single to mixed land use, respectively. These two compactness-based evidences revealed straightforward effects on the land use growth. Higher population and higher land use diversity resulted positive values of $C/S(C)$ for residential and commercial land uses. In contrast, the area in single land use and lower population density has a higher probability for industrial land use growth.

Land use growth map for residential, commercial, and industrial are given in Fig. 4, respectively. The white areas are constraint areas such as transportation, flood zone, and water bodies, which have been removed from the analysis.

For the validation of land use change simulation, it is desirable to quantitatively evaluate the degree of fitness or similarity between the projected land use and the actual land use map. This similarity assessment was performed using the relative operating characteristic (ROC) based area under curve (AUC) to evaluate the probability of growth maps created by WoE approach (Chen et al. 2013; Pontius and Schneider 2001; Van Eck and Koomen 2008). To run AUC, WoE was applied on the land use map

Table 4 Summarized weights of evidence for main three land use growths

Factors	Class	C/S(C)	C/S(C)	C/S(C)
		Residential	Commercial	Industrial
Proximity to residential	Near	364	-14	-365
	Middle	-264	41	330
	Far	-156	-45	126
Proximity to roads	Near	53	167	-137
	Middle	29	-88	-40
	Far	-86	-89	172
Proximity to recreational facilities	Near	129	-	-225
	Middle	42	-	-85
	Far	-188	-	300
Population density	Low	-158	-99	251
	Moderate	112	40	-114
	High	18	60	-142
Proximity to commercial	Near	14	198	-163
	Middle	60	-131	-6
	Far	-77	-70	159
Proximity to public transportation	Near	63	117	-172
	Middle	-3	-99	-6
	Far	-62	-17	174
Proximity to infrastructure	Near	40	-	-70
	Middle	60	-	30
	Far	-105	-	37
Land use diversity	Low	-79	-120	216
	Moderate	74	73	-76
	High	2	56	-156
Proximity to industrial	Near	-206	-60	380
	Middle	108	65	-241
	Far	76	-6	-166
Proximity to community facilities	Near	72	-	-222
	Middle	88	-	-75
	Far	-174	-	287
Proximity to agricultural fields	Near	-132	-42	2
	Middle	21	6	75
	Far	100	36	-78

of 2008 in order to create the main land use (residential, commercial and industrial) probability of growth for the future. Subsequently, the similarity of these three maps was assessed by the actual residential, commercial and industrial land use of year 2012. In this manner, the process determined how well the method and parameters produced the land use growth map. The AUC of 50 % indicates random results. The AUC of residential, commercial and industrial land use were gained as 77.4, 78, and 67 %, respectively.

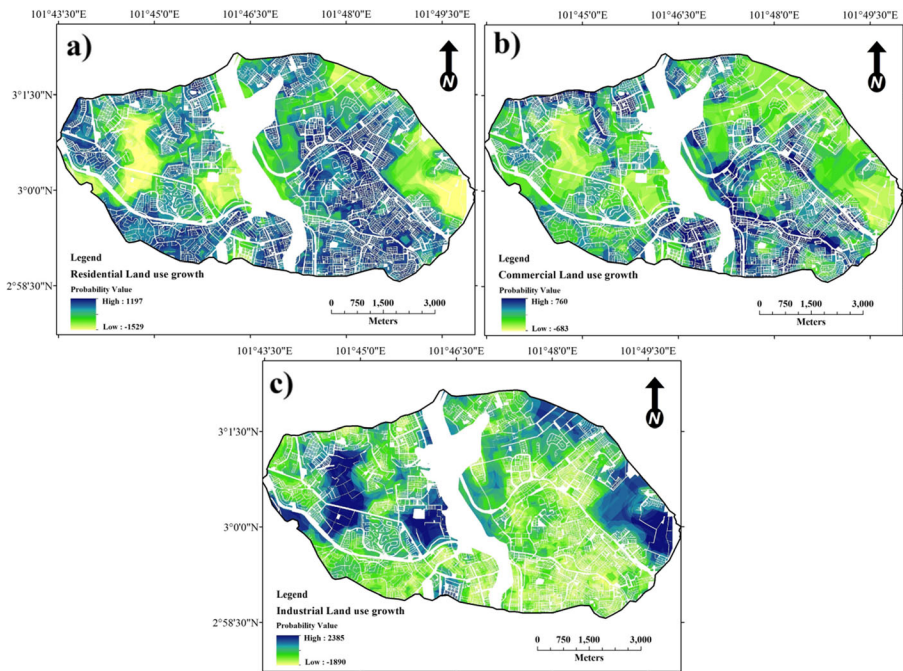


Fig. 4 a) Residential, b) commercial and c) industrial land use growth map from WoE model

respectively. Lower AUC value of industrial land use indicated that, industrial land use growth is more depend on economical perspectives rather than physical or proximity to same land use type parameters.

After the aggregation of land use growth maps as the first scenario (equal priority), with the brownfields map, from a total area of brownfields (2,908,550 m²), 400,000 m² was assigned as the single land use growth (Fig. 5 and Table 5). The rest of them were projected for mixture of two or three land use types.

Single land use developments are assigned to brownfields located in an area with high probability of growth for only one land use type. For instance, as shown in Fig. 4, the central west of Kajang City is only suitable for the industrial land use type. Therefore, most of the brownfields located in these areas were automatically assigned as a single land use development for industrial purposes. However, according to Fig. 4a and b, most of the commercial land use growth are suitable for residential as well. Residential-commercial mixed land use area covered more than one third of whole city (1,107,877). This large area could be expected due to the high similarity of the C/S(C) value and the direct relationship of residential and commercial land use with respect to all evidences. These areas can be developed in vertical mixed use, which means the basement floors are for commercial use and upper floors for housing purposes. In addition, significant differences of the C/S(C) values of commercial and industrial caused only 136,000 m² area to become a mixture of these two land use types. Areas with mixture of residential-industrial are mainly located in the borders of these land use types. It should be mentioned that the industrial use which assigned for these areas are mainly light industry. The rest of the area was assigned as a mixture of all three land use types. Considering the size, potential, and suitability of these locations, these

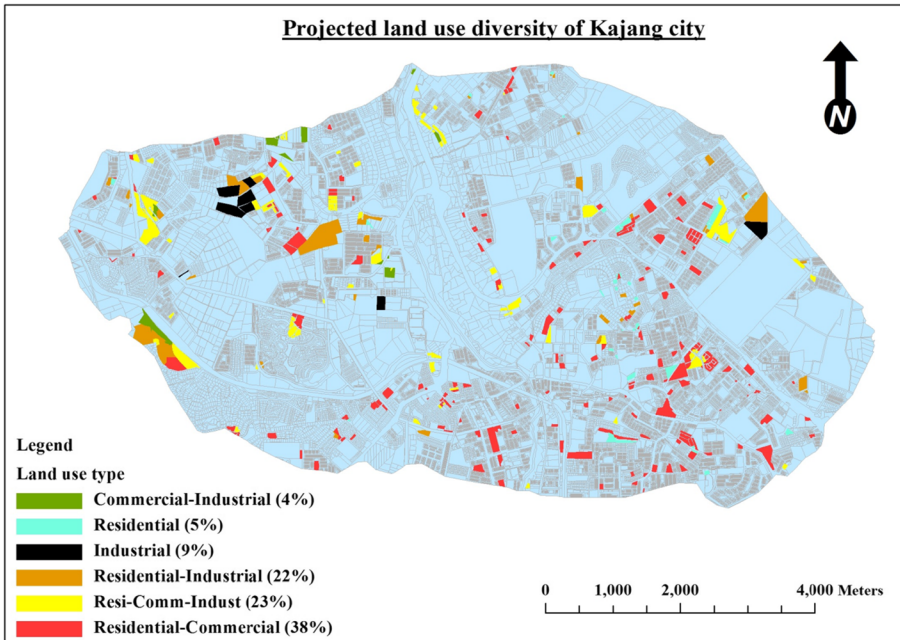


Fig. 5 Projected land use types for existing brownfields

brownfields can serve the neighborhood as mixed land use development. Further scenarios can be defined by consideration of local expert knowledge in order to give different priority values for each land use type.

Conclusion

Rapid urban growth has resulted in intensive loss of natural and valuable agricultural lands especially in fast growing regions. Therefore, the simulation or projection of the

Table 5 Projected land use types for existing brownfields

Land use diversity	Land use type	Area (m ²)
Single land use development	Residential	140,222.3
	Commercial	0
	Industrial	258,892.5
	Total	399114.8
Mixed land use development	Residential-commercial	1,107,877.2
	Residential-industrial	625,962.9
	Commercial-industrial	136,064.8
	Residential, commercial, industrial	639,531.7
	Total	2,509,436.6
Total		2,908,551.4

future urban growth and land use changes provide very beneficial information for local planners and decision makers. However, like other urban related issues, land use change modeling is often difficult to simulate due to its complexities, uncertainties, and several numbers of involved parameters and/or stakeholders. These difficulties need to be dealt with multidisciplinary geospatial techniques and other systematic procedures.

The present paper illustrates the application of GIS-based WoE for modeling the brownfields land use changes. The future land use type of each existing brownfield could be identified. This projection can be in single land use or a mixture of two or more land use types depending on brownfield properties, potential, and surrounding environment conditions. The model process was based on the trend and historical land use changes of the study area. Furthermore, the projected land use changes were based on city compactness paradigms such as urban density, urban intensity, and land use diversity in order to develop the city according to sustainable development theory. Several other urban related factors were involved in the analysis as well. However, the results show that one of the main controlling factors for these changes was based on spatial autocorrelation of land use types.

The WoE model is a statistical-based model. Hence, the parameters were evaluated statistically instead of subjective choice of weighing technique by expert knowledge, which is the main source of uncertainty. For this reason, it can be concluded that the model revealed reliable and promising results for brownfields land use change modeling. The final outputs provide valuable land use growth maps and information about the future of existing brownfields of the city. Redeveloping and revitalizing these areas according to compact development concept will make Kajang City environmentally more sustainable.

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