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CROSS-IMPACT ANALYSIS OF FACTORS INFLUENCING URBAN LAND PRICE: CASE OF CHIANG MAI CITY

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ABSTRACT

This study identifies factors affecting urban land price and analyzes interrelationship and probability of these factors. Chiang Mai city was used as a practical case in this study. The EDFR and CIA techniques were applied to achieve these objectives. Ten experts from public and private sectors with more than ten years' experience in land price evaluation and real estate development in Chiang Mai city were invited to be an expert panel. The results of this study revealed ten factors affecting land price in Chiang Mai city, and the most important factors are housing demand, accessibility, and distance to the city center. Three events of each influencing factor; optimistic, pessimistic, and most probable, with its occurrence and conditional probability, were determined. The Monte-Carlo technique was applied to random future situations. Thirteen scenarios occurred as a result of the scenario simulation. The change in probability of each event was a result of an interaction of its influencing factors. The event with many interrelated factors had more changing in its probability; for example, urban land price. From this study, the identified factors affecting urban land prices of the Chiang Mai city can be used as variables in land price determination to support decision-making in the urban planning and urban infrastructure project development.

Disciplinary: Civil Engineering, Urban Real Estate Business and Management, Urban City Planning.

1 INTRODUCTION

Urban land price is considered as the main index of urban land market information, which is an important reflection of the allocation of land resources in the city and the macroeconomic

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environment (Zhenyu, Meichen, Yuelong, & Jizhou, 2011). Moreover, it plays a crucial role in guiding the allocation of land for urban planning and development, especially in big cities of rapidly developing countries where frequent changes in infrastructure and population (Hu, Yang, Li, Zhang, & Xu, 2016). Furthermore, urban land price is considered as an important factor in infrastructure project development because it influences the compensation for land expropriation. Therefore, the study of land price trends and its influencing factors are important for support decision making in urban planning and infrastructure project development (Hu et al., 2016; Sampathkumar, Santhi, & Vanjinathan, 2015).

The price of land in Thailand is generally classified as an appraisal price and market price. The appraisal prices are appraised by the Treasury Department of Thailand. At present, the market prices in Chiang Mai city are generally higher than the appraisal prices, as shown in Figure 1.

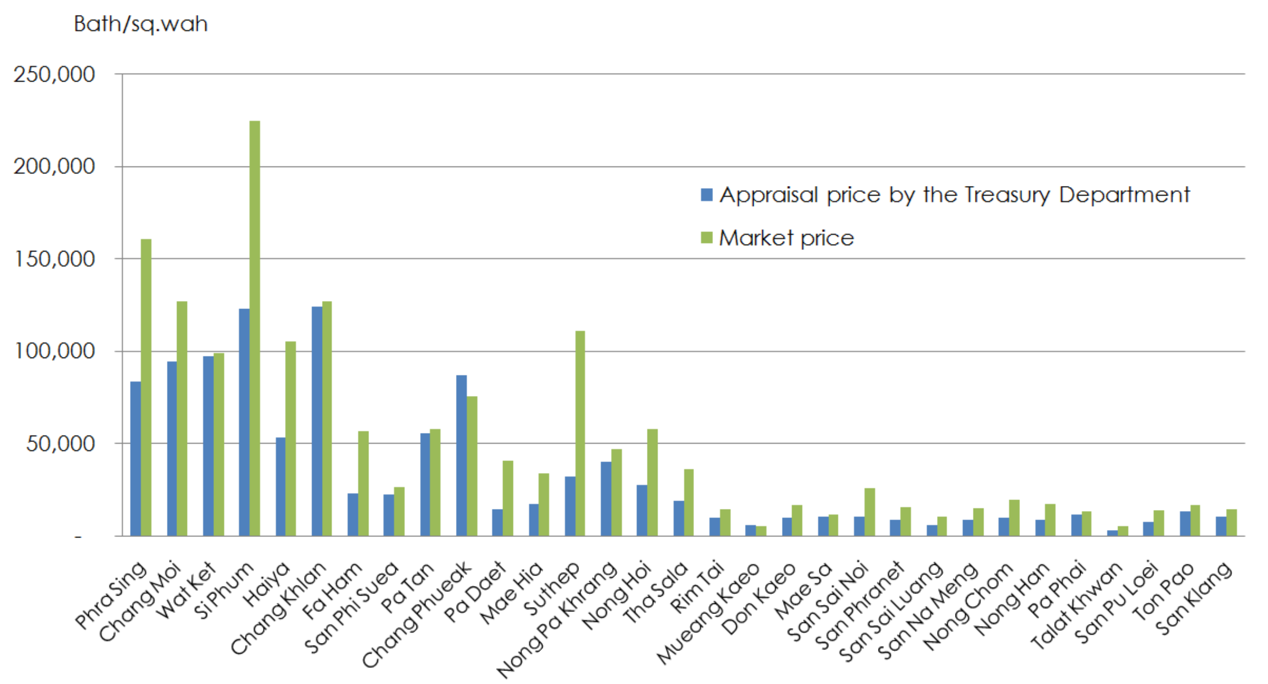

Figure 1: The 2019 land price of Chiang Mai city - the comparison of the appraisal price by the Treasury Department of Thailand and the market price (1 sq. wah = 4 m^2).

During the past several years, there have been numerous studies analyzing land prices and influencing factors. Kilpatrick (2000) showed the usefulness of a time-series regression model that used economic data to provide more accurate forecasts of the central business district (CBD) land prices in rapidly moving land price markets. Sampathkumar et al. (2015) modeled and forecasted land prices in Chennai metropolitan area, India, by using multiple regression and neural network techniques. Even though both models were well fit to the trend of land price, the neural network model shown better accuracy. Hu et al. (2016) revealed the study of spatially non-stationary relationships between urban residential land price and impact factors in Wuhan city, China, by using geographically weighted regression analysis. Kheir and Portnov (2016) presented the use of time trend analysis and multivariate regressions to study economics, demographic, and environmental factors affecting urban land prices in the Arab sector in Israel.

Since the price of land depends on several factors (Kheir & Portnov, 2016), then the most crucial thing in analyzing land prices is to identify these influencing factors. Many factors affect the level of land price and its changing trend, and these factors may occasionally fluctuate according to social and economic development and people's demand (Song et al., 2011). Wang et al. (2009) employed statistical methods; for example, T-test and Pearson correlation, to explore the driving forces of residential land prices in Beijing. This study indicated that the primary factor influencing residential land price was the distance to the central area, followed by the plot ratio and accessibility. Besides, urban subways and cultural and sports infrastructure had a significant value-added function to residential around. Song et al. (2011) studied the influences and interactions of factors affecting land prices in China by using hierarchical linear models. Both urban construction land area and real estate investment are the most important factors which have a significant influence on land price growth rate. Still, farmland protection policies have a significant effect on controlling the level of land price and its growth rate.

At present, most research on factors affecting urban land price mainly focuses on the identification and importance determination of factors influencing urban land price. In contrast, the interactions between influencing factors with the occurrence probabilities and conditional probabilities of events of each influencing factor are not determined. For these reasons, the cross-impact analysis (CIA) method was employed to analyze these influencing factors and their events in this study.

The CIA method is a well-known technique specifically designed to predict future events by analyzing the interactions among variables (Han & Diekmann, 2001b). It was originally developed by Theodore Gordon and Olaf Helmer in 1966, as a result of a simple question: can forecasting be based on perceptions about how future events may interact? (Gordon, 1994; Han & Diekmann, 2001b). It appeared as a methodological tool for dealing with the complexity and could be described as a high-level system modeling approach (Panula-Ontto et al., 2018). The initial experiments with the CIA method of forecasting were published in 1968 (Gordon & Hayward, 1968).

The CIA is a set of related methodologies that enable to analyze events; for example, the occurrence probabilities of events and the conditional probability of one event given another (Blanning & Reinig, 1999; Moutinho & Witt, 1994; Schuler, Thompson, Vertinsky, & Ziv, 1991; Thorleuchter & Van den Poel, 2014). It has been combined approaches to increase its functionality and improve its outcome (Bañuls & Turoff, 2011). The CIA can be used for creating a model from a set of significant events (Bañuls & Turoff, 2011). There are different ways of calculating the CIA (Friðgeirsson & Steindórsdóttir, 2018). The critical step in the CIA method is to define the events by interviewing key experts in the field being studied (Gordon, 1994). Since this step can be crucial to the success of the study, the Ethnographic Delphi Futures Research (EDFR) was applied to collect data.

The EDFR is a synthesis of Ethnographic Future Research (EFR) (Textor, 1979) and the Delphi technique. It was first introduced by Poolpatarachewin (1980). The EDFR was designed to combine the strengths of both procedures while minimizing their methodological weakness. Its advantage is a certainty that the participants will be intensely involved in generating the issues to be considered for group response. For this reason, the scope and focus of the issues under consideration cannot be significantly narrowed or distorted by the biases of the researcher (Passig, 1998).

Chiang Mai city is the economic, investment, and transport center of northern Thailand. Nowadays, Chiang Mai city has rapid expansion and increasingly faces problems common to large cities; for example, unplanned and sprawling development, and traffic congestion (Chiang Mai Municipality, 2014). The uncontrollable land developments and urban sprawl affect the transport network of the city. The public transportation system unable to support the needs of people; therefore, ninety percent of the Chiang Mai population uses a private vehicle as to the first mode of transportation (ExCITE, 2017). These days, the government has an effort to reduce traffic congestion and improve urban transportation by using the road network expansion policy.

For this reason, Chiang Mai city has many road network expansion projects in the present and more in the near future. These projects need land expropriation. As a result, many households will be affected by land expropriation, while the government has not yet clarified the appropriate compensation for land expropriation.

The objectives of this study are (1) to identify factors affecting urban land price and (2) to analyze interrelationship and probability of these factors. The future research techniques; EDFR and CIA, were applied to achieve these objectives. Chiang Mai city was used as a practical case in this study. The results of this study can be used as important data in land price-determining for support decision making in urban planning and infrastructure project development.

2 MATERIALS AND METHODS

2.1 OVERVIEW OF THE STUDY AREA: CHIANG MAI CITY – CHIANG MAI COMPREHENSIVE PLAN AREA

Chiang Mai province is the second-largest province by land area (20,107 square kilometers) and the fifth-largest province by population (approximately 1.7 million people) of Thailand. It is located in the northern part of the country, approximately 685 kilometers from Bangkok. It is situated on the Mae Ping River basin and surrounded by high mountain ranges.

Figure 2: The Doi Suthep-Pui National Park on the west edge of the CMCP area.

Chiang Mai city in this study is referred to as the Chiang Mai Comprehensive Plan (CMCP) area, which locates in the center of Chiang Mai province. The CMCP area has been determined by the Town Planning Act, B.E.2518 of Thailand, in 2012. It covers an area of 429 square kilometers and covers 49 sub-districts in 7 districts, i.e., Muang, Mae Rim, San Sai, Doi Saket, San Kamphaeng, Saraphi, and Hang Dong. The Muang district is the center of the CMCP area. The west edge of the city is adjacent to the mountain (the Doi Suthep-Pui national park), as shown in Figure 2. Accordingly, the urban area has expanded to the north, south, and east direction of the city during the last twenty years from the year 1990 to 2010, as shown in Figures 3 and 4.

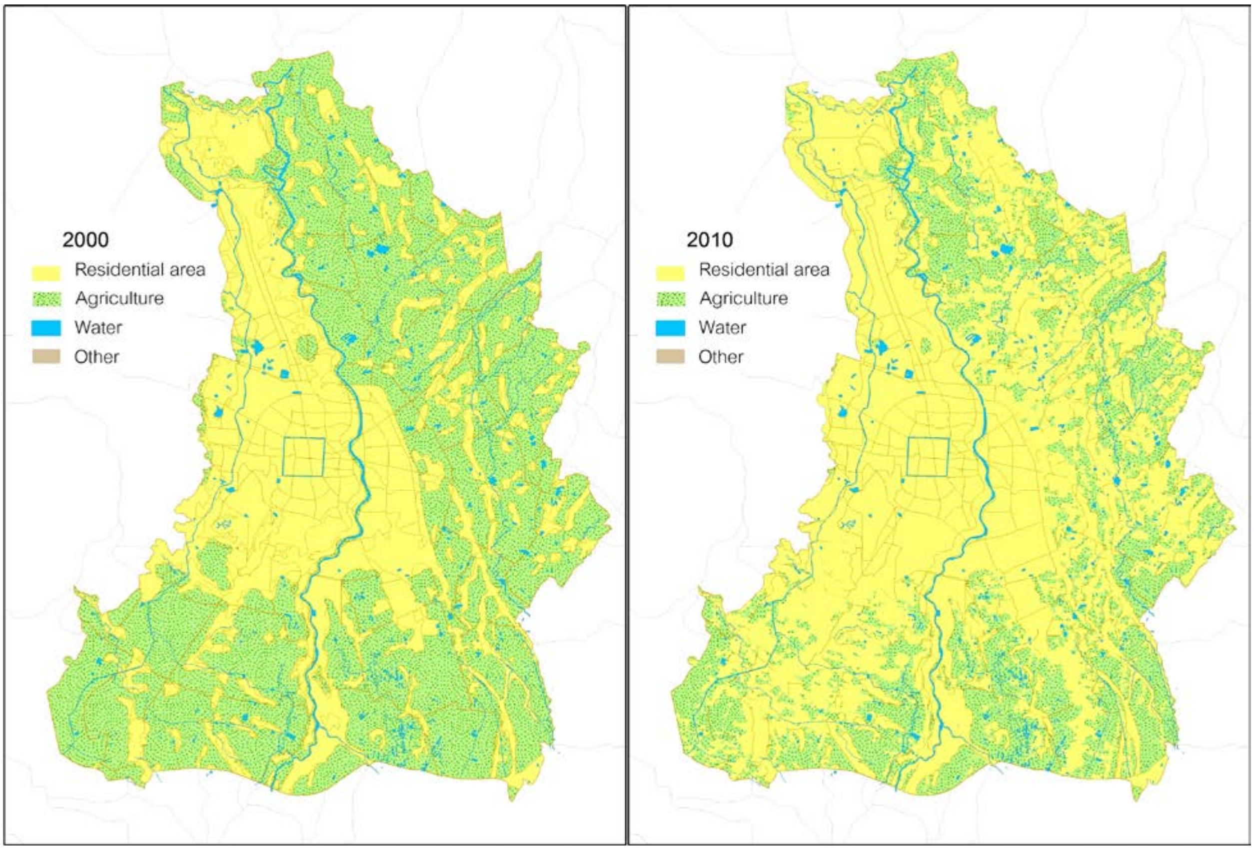

Figure 3: A comparison of land uses of the Chiang Mai Comprehensive Plan (CMCP) area between 2000 and 2010.

Figure 1, the market prices of land in Chiang Mai city in the year 2019 are generally higher than the appraisal prices by the Treasury Department of Thailand. Also, the prices of land areas in Muang district are higher than the other districts. The highest appraisal price of land is in the Chang Khlan sub-district. But the highest market price of land is in the Si Phum sub-district and Phra Sing sub-district, respectively; besides, there are higher than the market price of land in Chang Khlan sub-district. The Si Phum and Phra Sing sub-district are located in the city center of Chiang Mai city. The city center is located in Muang district, and it is characterized by the ancient rectangular wall and surrounded by the moat. It is known as the old town neighborhood, which is full of historical and cultural sites. On the other hand, the Chang Khlan sub-district is located outside the old town; it is known as the commercial area of Chiang Mai city.

2.2 RESEARCH METHODOLOGY

The research methodology (Figure 5) involves identifying factors affecting urban land price. The influencing factors are gathered from literature and expert interview. These influencing factors are screened using five-point Likert's scale for scoring and using statistical techniques to analyze data. The CIA method and the EDFR technique were used to determine interrelation, interaction, occurrence probability, and the conditional probability of influencing factors.

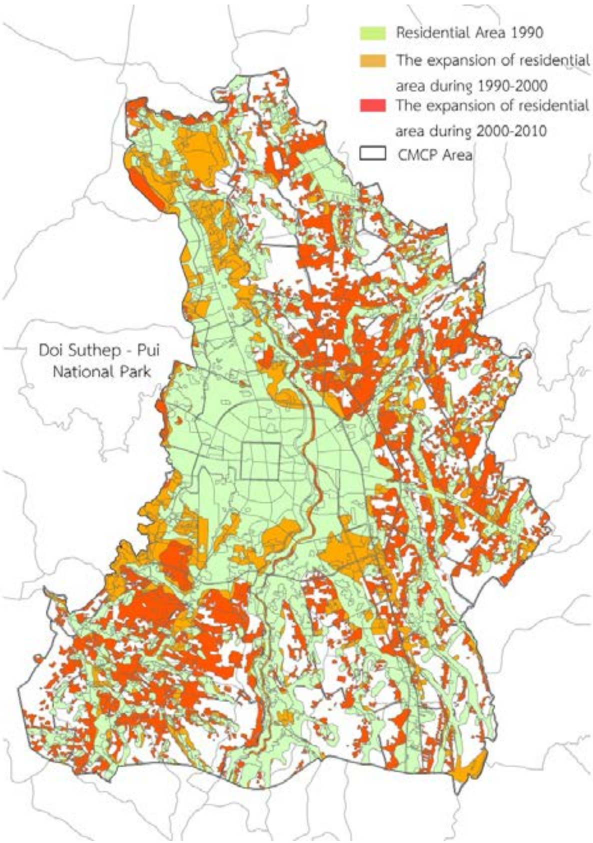

Figure 4: The expansion of the residential area in the Chiang Mai Comprehensive Plan (CMCP) area in 1990, 2000, and 2010.

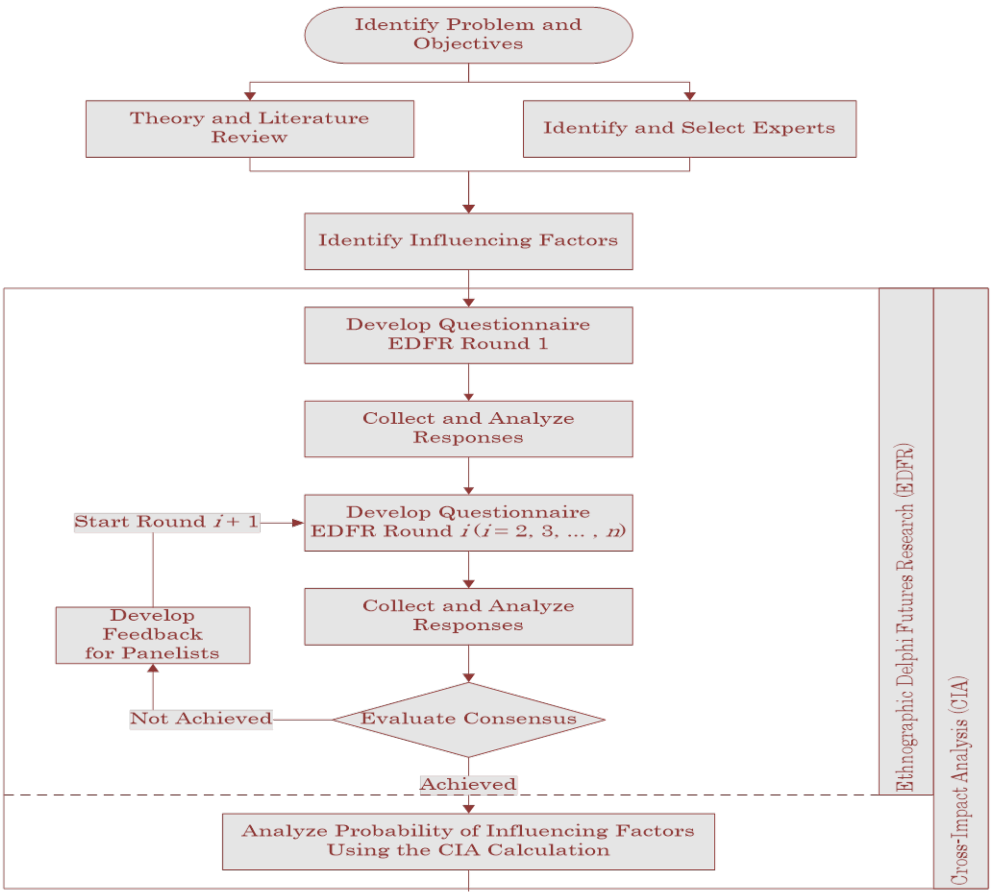

Figure 5: Research Methodology.

2.3 DATA AND ANALYSIS

2.3.1 IDENTIFICATION OF FACTORS AFFECTING URBAN LAND PRICE

At first, sixteen factors affecting urban land prices were gathered by reviewing literature and consulting with a few experts. The list of these influencing factors is illustrated in Table 1.

All sixteen gathered influencing factors in Table 1 were employed to develop a five-point Likert scale questionnaire (1 is "least important," and 5 is "most important"). The questionnaires were transited to an expert panel to screening these influencing factors.

In this study, an expert panel comprised of ten experts. It consists of five experts from the public sector (two from the Department of Highways and three from the Treasury Department of Thailand) and five experts from the private sector (real estate investors). All of them have more than ten years' experience in land price evaluation and real estate development in Chiang Mai city.

Table 1: Factors affecting land price.

No.	Factor	References
1	Housing demand	Kilpatrick, 2000; Reed, 2001; Song et al., 2011
2	Accessibility	Cervero & Duncan, 2004; Cervero & Kang, 2011; Hu et al., 2016; Mirkatouli, Samadi, & Hosseini, 2018; Wang et al., 2009
3	Distance to center city	Cervero & Duncan, 2004; Hu et al., 2016; Mirkatouli et al., 2018; Wang et al., 2009
4	Economy	Kheir & Portnov, 2016; Mirkatouli et al., 2018; Sampathkumar et al., 2015; Song et al., 2011
5	Land use planning	Cervero & Duncan, 2004; Cervero & Kang, 2011; Mirkatouli et al., 2018; Song et al., 2011
6	Public policy	Cervero & Duncan, 2004; El Araby, 2003
7	Infrastructure investment	Cervero & Kang, 2011; Song et al., 2011; Wang et al., 2009
8	Political situation	El Araby, 2003
9	Population	Mirkatouli et al., 2018; Sampathkumar et al., 2015; Song et al., 2011
10	Household income	Cervero & Duncan, 2004; Mirkatouli et al., 2018; Song et al., 2011
11	Investment demand	Song et al., 2011
12	Land environment	Song et al., 2011; Wang et al., 2009
13	Interest rate	Sampathkumar et al., 2015
14	Construction cost	Sampathkumar et al., 2015
15	Tax policy	Song et al., 2011
16	Fuel price	Sampathkumar et al., 2015

Table 2: An analysis of the influencing factors.

No.	Factor	Importance score										Mean	Median	Median - Mode	IQR
		Expert No.													
		1	2	3	4	5	6	7	8	9	10				
1	Housing demand	5	5	5	4	4	5	4	5	5	5	4.7	5	0	0.75
2	Accessibility	5	5	5	4	4	4	5	4	5	4	4.5	4.5	-0.5	1
3	Distance to center city	5	4	5	5	5	4	4	4	3	5	4.4	4.5	-0.5	1
4	Economy	4	5	5	3	5	5	4	4	4	4	4.3	4	0	1
5	Land use planning	5	3	4	3	4	4	5	5	5	4	4.2	4	-1	1
6	Public policy	4	5	4	4	4	5	3	4	5	4	4.2	4	0	0.75
7	Infrastructure investment	3	5	4	4	4	4	4	4	4	5	4.1	4	0	0
8	Political situation	3	3	3	4	4	4	4	4	5	3	3.7	4	0	1
9	Population	4	1	4	4	4	4	4	3	4	4	3.6	4	0	0
10	Household income	4	3	3	3	5	3	4	3	4	4	3.6	3.5	0.5	1
11	Investment demand	4	3	4	3	3	4	3	3	4	3	3.4	3	0	1
12	Land environment	2	3	4	3	3	4	4	3	3	4	3.3	3	0	1
13	Interest rate	3	2	4	3	3	3	3	4	3	5	3.3	3	0	0.75
14	Construction cost	3	2	4	2	3	4	3	3	4	4	3.2	3	0	1
15	Tax policy	2	2	4	3	4	3	3	3	4	3	3.1	3	0	0.75
16	Fuel price	3	1	3	2	3	3	4	3	3	3	2.8	3	0	0

2.3.2 INTERRELATIONSHIP AND PROBABILITY OF INFLUENCING FACTORS

The first round EDFR questionnaire was a semi-opened end form question regarding ten appropriateness and compatibility influencing factors from Table 2. Experts were asked to define the interrelation of all influencing factors and define three events of each influencing factor based on the EFR technique; optimistic, pessimistic, and most probable (Mitchell, 2002). Also, an initial probability (occurrence probability) of each event was given simultaneously by the experts.

The interrelation of all factors affecting urban land price is shown as a causes-effect relation map in Figure 6. The initial probability of each event of all influencing factors is demonstrated in Table 3.

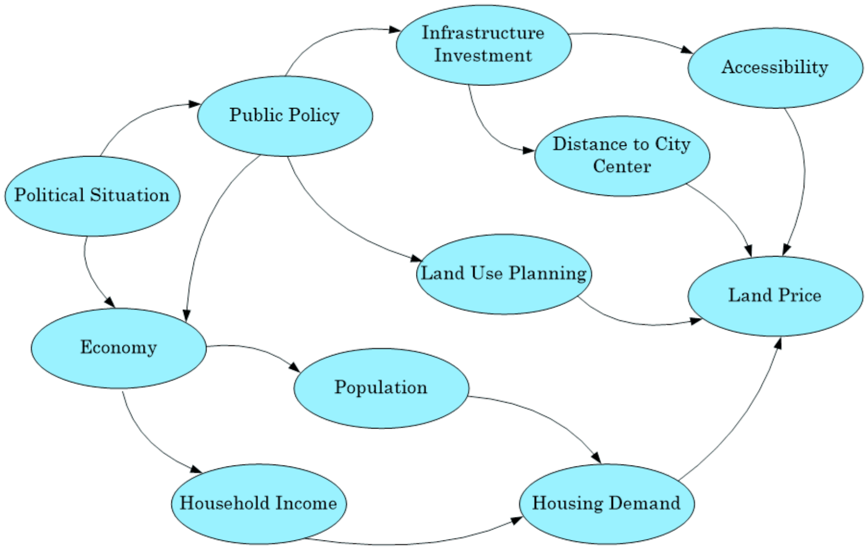

Figure 6: Causes-effect relationship map of factors affecting urban land price in Chiang Mai city.

Table 3: The initial probability of each event of influencing factors.

Variable	Variable's name	Event	Event's name	Initial probability
A	Political situation	A1	Good	0.455
		A2	Balanced	0.385
		A3	Poor	0.160
B	Economy	B1	Good	0.455
		B2	Balanced	0.325
		B3	Poor	0.220
C	Public policy	C1	Good	0.375
		C2	Fair	0.445
		C3	Poor	0.180
D	Infrastructure investment	D1	Increase	0.590
		D2	Stable	0.330
		D3	Decrease	0.080
E	Population	E1	Increase	0.620
		E2	Stable	0.250
		E3	Decrease	0.130
F	Household income	F1	Increase	0.575
		F2	Stable	0.330
		F3	Decrease	0.095
G	Accessibility	G1	Good	0.675
		G2	Fair	0.240
		G3	Poor	0.105
H	Distance to the city center	H1	Short	0.700
		H2	Medium	0.205
		H3	Long	0.095
I	Land use planning	I1	Good	0.540
		I2	Fair	0.295
		I3	Poor	0.165
J	Housing demand	J1	High	0.630
		J2	Average	0.240
		J3	Low	0.130
K	Land price	K1	Increase	0.675
		K2	Stable	0.255
		K3	Decrease	0.070

The results from the experts' responses in the EDFR first round, all events of all influencing factors were employed to construct the cross-impact relationship table in the second round EDFR questionnaire. Experts were requested to give a cross-impact index value of each interaction event in a cross-impact relation table by using the patterns (Alarcón & Ashley, 1998; Han & Diekmann, 2001a; Honton, Stacey, & Millett, 1985) in Table 4. Table 5 shows the example of an experts' response in the EDFR second round.

Table 4: Cross-impact relation patterns.

Index value	Signification
+3	Significantly increases the probability in the same direction
+2	Moderately increases the probability in the same direction
+1	Slightly increases the probability in the same direction
0	No effect on the probability
-1	Slightly increases the probability in the opposite direction
-2	Moderately increases the probability in the opposite direction
-3	Significantly increases the probability in the opposite direction

Table 5: An example of an experts' response in the EDFR second round.

Factor	Factor's name	Event	A			B			C			D			E			F			G			H			I			J			K		
			A1	A2	A3	B1	B2	B3	C1	C2	C3	D1	D2	D3	E1	E2	E3	F1	F2	F3	G1	G2	G3	H1	H2	H3	I1	I2	I3	J1	J2	J3	K1	K2	K3
A	Political situation	A1																																	
		A2																																	
		A3																																	
B	Economy	B1	1	1	-1				1	1	-1																								
		B2	1	2	-1				1	1	-1																								
		B3	-1	-2	1				1	-1	1																								
C	Public policy	C1	1	1	-1																														
		C2	1	1	-1																														
		C3	-1	-1	1																														
D	Infrastructure investment	D1							3	2	-2																								
		D2							0	2	0																								
		D3							-3	-1	2																								
E	Population	E1				3	2	-3																											
		E2				2	3	-2																											
		E3				-3	-2	3																											
F	Income	F1				3	1	-3																											
		F2				1	3	-1																											
		F3				-3	-1	3																											
G	Accessibility	G1										3	2	-3																					
		G2										2	3	-2																					
		G3										-3	-1	3																					
H	Distance to city center	H1										3	2	-3																					
		H2										0	3	0																					
		H3										-3	-2	3																					
I	Land use planning	I1							3	1	-3																								
		I2							1	3	-1																								
		I3							-3	-1	3																								
J	Housing demand	J1													3	2	-3	3	2	-3															
		J2													2	3	-2	2	3	-2															
		J3													-3	-1	3	-3	-2	3															
K	Land price	K1																			2	0	-2	2	0	-2	2	0	-2	2	0	-2			
		K2																			0	2	0	0	2	0	0	2	0	0	2	0			
		K3																			-2	0	2	-2	0	2	-2	0	2	-2	0	2			

In general, if the results (from the experts' responses in the second round of the EDFR) are not reaching the consensus, the results will be developed to the questionnaire for the panelists in the next round. This process will be repeated until the experts' responses are reaching the consensus.

For this study, the experts' responses reached a consensus in the third round. The cross-impact index of each interaction event pair was employed to calculate the coefficient value (*CV*) and the posterior probability (posterior P_i) by using Equation (1) and (2), respectively.

$$CV = |cross - impact\ index| + 1 \qquad \text{if cross-impact index} \geq 0 \qquad (1),$$

$$= \frac{1}{|cross - impact\ index| + 1} \qquad \text{if } cross\text{-}impact\ index < 0$$

$$\text{Posterior } P_i = \frac{Initial\ P_i \times CV_{ij}}{1 - Initial\ P_i + (Initial\ P_i \times CV_{ij})} \qquad (2),$$

Monte-Carlo technique, using Oracle© Crystal Ball, was applied to generate 10,000 random numbers with every 10,000 trials, which for use in event sequence scenario simulation.

3 RESULTS AND DISCUSSION

The results of the event sequence scenario simulation for 10,000 times revealed 13 scenarios have occurred, as shown in Tables 6 and 7.

Table 6: The result of event sequence scenario simulation for ten thousand times.

Event sequence scenario No.				1	2	3	4	5	6	7	8	9	10	11	12	13	Initial prob.	Freq. of occurrence	Posterior prob.
Frequency of occurrence				4,548	224	752	158	16	148	281	656	1,571	83	694	363	506			
A	Political situation	A1	Good	1	0	0	0	0	0	0	0	0	0	0	0	0	0.46	4,548	0.45
		A2	Balanced	0	1	1	1	1	1	1	1	1	1	0	0	0	0.39	3,889	0.39
		A3	Poor	0	0	0	0	0	0	0	0	0	0	1	1	1	0.16	1,563	0.16
B	Economy	B1	Good	1	1	1	1	0	0	0	0	0	0	0	0	0	0.46	5,682	0.57
		B2	Balanced	0	0	0	0	1	1	1	1	1	1	0	0	0	0.33	2,755	0.28
		B3	Poor	0	0	0	0	0	0	0	0	0	0	1	1	1	0.22	1,563	0.16
C	Public policy	C1	Good	1	0	0	0	0	0	0	0	0	0	0	0	0	0.38	4,548	0.45
		C2	Fair	0	1	1	1	1	1	1	1	1	1	0	0	0	0.45	3,889	0.39
		C3	Poor	0	0	0	0	0	0	0	0	0	0	1	1	1	0.18	1,563	0.16
D	Infrastructure investment	D1	Increase	1	1	1	0	0	0	0	0	0	0	0	0	0	0.59	5,524	0.55
		D2	Stable	0	0	0	1	1	1	1	1	1	1	0	0	0	0.33	2,913	0.29
		D3	Decrease	0	0	0	0	0	0	0	0	0	0	1	1	1	0.08	1,563	0.16
E	Population	E1	Increase	1	1	1	1	1	0	0	0	0	0	0	0	0	0.62	5,698	0.57
		E2	Stable	0	0	0	0	0	1	1	1	1	1	0	0	0	0.25	2,739	0.27
		E3	Decrease	0	0	0	0	0	0	0	0	0	0	1	1	1	0.13	1,563	0.16
F	Income	F1	Increase	1	1	1	1	0	0	0	0	0	0	0	0	0	0.58	5,682	0.57
		F2	Stable	0	0	0	0	1	1	1	1	1	1	0	0	0	0.33	2,755	0.28
		F3	Decrease	0	0	0	0	0	0	0	0	0	0	1	1	1	0.10	1,563	0.16
G	Accessibility	G1	Good	1	1	1	1	1	1	0	0	0	0	0	0	0	0.68	5,846	0.58
		G2	Fair	0	0	0	0	0	0	1	1	1	1	0	0	0	0.24	2,591	0.26
		G3	Poor	0	0	0	0	0	0	0	0	0	0	1	1	1	0.11	1,563	0.16
H	Distance to city center	H1	Short	1	1	1	1	1	1	1	0	0	0	0	0	0	0.70	6,127	0.61
		H2	Medium	0	0	0	0	0	0	0	1	1	1	0	0	0	0.21	2,310	0.23
		H3	Long	0	0	0	0	0	0	0	0	0	0	1	1	1	0.10	1,563	0.16
I	Land use planning	I1	Good	1	1	0	0	0	0	0	0	0	0	0	0	0	0.54	4,772	0.48
		I2	Fair	0	0	1	1	1	1	1	1	1	1	0	0	0	0.30	3,665	0.37
		I3	Poor	0	0	0	0	0	0	0	0	0	0	1	1	1	0.17	1,563	0.16
J	Housing demand	J1	High	1	1	1	1	1	1	1	1	0	0	0	0	0	0.63	6,783	0.68
		J2	Average	0	0	0	0	0	0	0	0	1	1	0	0	0	0.24	1,654	0.17
		J3	Low	0	0	0	0	0	0	0	0	0	0	1	1	1	0.13	1,563	0.16
K	Land price	K1	Increase	1	1	1	1	1	1	1	1	1	0	1	0	0	0.68	9,048	0.90
		K2	Stable	0	0	0	0	0	0	0	0	0	1	0	1	0	0.26	446	0.04
		K3	Decrease	0	0	0	0	0	0	0	0	0	0	0	0	1	0.07	506	0.05

The most likely event sequence scenario was scenario No.1, with the frequency of occurrence equal to 4,548. Table 7, the sequence of events of scenario No.1 (A1C1B1E1F1J1D1I1G1H1K1) starts from a good political situation (A1) that affects the good public policy (C1) and the good economy (B1). Other than the good political situation which affects the good economy, the good public policy is also. The good economy affects to increasing population (E1) and increasing income (F1), and these two factors affect increasing housing demand (J1). The good public policy affects to increasing infrastructure investment (D1) and the good land use planning (I1). The increase in infrastructure investment affects good accessibility (G1) and a short distance to the city center (H1). Eventually, the four events, i.e., the increasing housing demand, the good land use planning, good accessibility, and the short distance to the city center, affect the increasing land price (K1).

Table 7: The occurrence event sequence scenarios.

Scenario No.	Event sequence scenario	Frequency of occurrence	Percentage
1	A1C1B1E1F1J1D1I1G1H1K1	4,548	45.48
2	A2C2B1E1F1J1D1I1G1H1K1	224	2.24
3	A2C2B1E1F1J1D1I2G1H1K1	752	7.52
4	A2C2B1E1F1J1D2I2G1H1K1	158	1.58
5	A2C2B2E1F2J1D2I2G1H1K1	16	0.16
6	A2C2B2E2F2J1D2I2G1H1K1	148	1.48
7	A2C2B2E2F2J1D2I2G2H1K1	281	2.81
8	A2C2B2E2F2J1D2I2G2H2K1	656	6.56
9	A2C2B2E2F2J2D2I2G2H2K1	1,571	15.71
10	A2C2B2E2F2J2D2I2G2H2K2	83	0.83
11	A3C3B3E3F3J3D3I3G3H3K1	694	6.94
12	A3C3B3E3F3J3D3I3G3H3K2	363	3.63
13	A3C3B3E3F3J3D3I3G3H3K3	506	5.06
Total		10,000	100.00

The frequency of occurrence of each event was calculated to be a posterior probability by using the CIA method. Table 6, percent changes of all events can be noticed between the posterior probability and initial probability. The initial probability and the posterior probability of the political situation not changed because it was not affected by any factors. In contrast, the initial probability and the posterior probability of the other factors were different. For example, the economy was affected by the political situation and public policy; therefore, its event probabilities changed. The probability of a good economy increased while balanced and poor economy decreased.

The change in probability of each event was a result of an interaction of its influencing factors. The factor with many interrelated factors, it will have more changing in a probability; for example, urban land price. Accordingly, the calculated posterior probability is more accurate than the initial probability. The posterior probability can be used in another model to evaluate the urban land price of Chiang Mai city. Also, this urban land price can be used to support decision making for policy planners in urban planning and urban infrastructure project development.

4 CONCLUSION

This study analyzed factors influencing urban land price with the interaction between these factors and its conditional probabilities. The research techniques, EDFR and CIA were used to analyze factors influencing urban land prices. The EDFR was applied to collect important data, identify the influencing factors and events with the occurrence probability of each event by interviewing the key experts. The CIA method was used to analyze the conditional probability of one event given another. This study result revealed ten factors affecting urban land price and their interrelation. These influencing factors were (1) political situation, (2) economy, (3) public policy, (4) infrastructure investment, (5) population, (6) household income, (7) accessibility, (8) distance to city center, (9) land use planning, and (10) housing demand.

The political situation affected the economy and public policy. The public policy affected infrastructure investment, land use planning, and the economy. The economy affected the population and household income. The population and household income affected the housing demand. The infrastructure investment affected the accessibility and the distance to the city center. The accessibility, the distance to the city center, the housing demand, and the land use planning affected the land price. The Monte-Carlo technique was applied to random future scenario simulation, resulted in thirteen scenarios. The most likely event sequence scenario of the urban land price of Chiang Mai city was scenario No.1, with a frequency of occurrence equal to 4,548. This sequence of events was a good political situation, good public policy, good economy, increasing population, increasing income, high housing demand, good land use planning, increasing infrastructure investment, good accessibility, short distance to the city center, and increasing land price.

The change in probability of each event was a result of an interaction of its influencing factors. The event with many interrelated factors will have more changes in its probability; for example, urban land price. The factors affecting urban land prices of the Chiang Mai city identified in this study can be used as variables in land price determination to support decision-making in the urban planning and urban infrastructure project development.

5 AVAILABILITY OF DATA AND MATERIAL

Data can be made available by contacting the corresponding author.

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