URBAN PARK SUITABILITY ANALYSIS USING SPATIAL MULTI-CRITERIA FUZZY LOGIC

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การวิเคราะห์พื้นที่เหมาะสมของสวนสาธารณะชุมชนด้วยตรรกศาสตร์คลุมเครือแบบหลายเกณฑ์เชิงพื้นที่

นายอารีฟ วิจักโซโน

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรดุษฎีบัณฑิต
สาขาวิชาภูมิสารสนเทศ
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Suranaree University of Technology has approved this thesis submitted in partial fulfillment of the requirements for the Degree of Doctor of Philosophy.

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อารีฟ วิจักโซโน : การวิเคราะห์พื้นที่เหมาะสมของสวนสาธารณะชุมชนด้วยตรรกศาสตร์คลุมเครือแบบหลายเกณฑ์เชิงพื้นที่ (URBAN PARK SUITABILITY ANALYSIS USING SPATIAL MULTI-CRITERIA FUZZY LOGIC) อาจารย์ที่ปรึกษา : ผู้ช่วยศาสตราจารย์ ดร.สัญญา สราภิรมย์, 230 หน้า.

เป็นเวลาหลายปีที่ Bogor Municipality ของประเทศอินโดนีเซีย ต้องเผชิญกับการลดลงของพื้นที่กสิกรรมเพื่อแลกกับการเพิ่มมากขึ้นของพื้นที่ชุมชน ซึ่งกลายเป็นปัญหาวิกฤตเมื่อต้องการหาพื้นที่สวนสาธาณะชุมชนที่เป็นที่ต้องการมากขึ้นตลอดเวลา ส่งผลให้เกิดความยากลำบากในกระบวนการตัดสินใจ โดยเฉพาะอย่างยิ่งเมื่อต้องการคัดเลือกพื้นที่ที่มีความเหมาะสมมาก ๆ ให้เพียงพอกับความต้องการพัฒนาสวนสาธาณะชุมชนในทุกหมู่บ้าน อีกทั้งข้อมูลของเกณฑ์ต่าง ๆ เกี่ยวกับนโยบาย ความหนาแน่นของประชากร ระยะห่างต่าง ๆ ความยากง่ายของการเข้าถึง และจำนวนการเข้าเยี่ยมใช้บริการ รวมถึงความสัมพันธ์ในกลุ่มข้อมูลเหล่านี้ก่อให้เกิดความไม่แน่นอนในการวิเคราะห์ อันเนื่องมาจากคุณลักษณะแบบฟัซซีของข้อมูล เพื่อขจัดปัญหาความไม่แน่นอนเหล่านี้ วิธีการของ FISs และ DEMATELs ได้ถูกนำมาใช้สำหรับการวิเคราะห์เชิงพื้นที่เพื่อให้บรรลุวัตถุประสงค์ของการศึกษา

ความต้องการพื้นที่สาธารณะชุมชนของแต่ละหมู่บ้านที่เหมาะสมคำนวณได้จาก FISs ซึ่งเมื่อนำขนาดพื้นที่เหล่านี้ไปเทียบเคียงกับขนาดพื้นที่เหมาะต่อการพัฒนาประจำหมู่บ้านที่ได้จากแผนที่การใช้ประโยชน์ที่ดิน พบว่าผลลัพธ์ที่ได้จาก Mamdani FIS สนองต่อความต้องการของหมู่บ้านต่าง ๆ ได้ดีที่สุด จากนั้นได้จัดทำแผนที่แสดงตำแหน่งเหมาะสมสำหรับการพัฒนาเป็นสวนสาธารณะชุมชนในพื้นที่ศึกษาด้วยวิธี FISs และ DEMATELs ซึ่งเมื่อนำแผนที่เหล่านี้ไปเทียบเคียงกับพื้นที่เหมาะต่อการพัฒนาประจำหมู่บ้านที่ได้จากแผนที่การใช้ประโยชน์ที่ดินด้วยวิธีการซ้อนทับแบบ intersection ในระดับความเหมาะสมของพื้นที่ทั้งสิ้น 10 ระดับ พบว่าในระดับความเหมาะสมของพื้นที่ที่สูง ๆ วิธี Mamdani และ Sugeno-0 สามารถจัดสรรพื้นที่เหมาะต่อการพัฒนาได้มากกว่าวิธีอื่น นอกจากนี้ยังมีการนำค่า ค่าสัดส่วนของ Intersection ต่อ Union (IoU) มาใช้บ่งบอกว่าวิธีใดสามารถทำงานได้ดีกว่ากันอีกด้วย ซึ่งพบว่าวิธี DEMATELs ที่ ให้ค่า IoU ที่ดีที่สุดและจัดสรรพื้นที่เหมาะต่อการพัฒนาได้มากกว่าในเกือบทุกระดับของความเหมาะสม ในขณะที่ที่ความเหมาะสมของพื้นที่ระดับ 4-7 กลุ่มวิธี DEMATELs ให้ค่า IoU ที่ดีที่สุดและสามารถจัดสรรพื้นที่เหมาะต่อการพัฒนาได้มาก ส่วนการตอบสนองความต้องการพื้นที่สาธารณะชุมชนของทุกหมู่บ้านให้ได้ผลที่ดีขึ้นนั้น พื้นที่ที่ได้จากการ union ของทุกวิธีในแต่ละระดับความเหมาะสมของพื้นที่สามารถนำมาใช้ตอบโจทย์ได้ดีที่สุด พื้นที่ที่ได้จากการ union ของทุกวิธีตั้งแต่ระดับที่ 10 ลง

มาถึงระดับที่ 7 สามารถตอบสนองต่อความต้องการพื้นที่สำหรับพัฒนาเป็นสวนสาธารณะชุมชนได้ทุกหมู่บ้าน

ผลการศึกษาทำให้ทราบได้ว่าเกณฑ์และวิธีการต่าง ๆ ที่นำมาใช้มีประสิทธิภาพก่อให้เกิดประสิทธิผลเป็นความสำเร็จครบถ้วนทุกวัตถุประสงค์ของการศึกษา

สาขาวิชาภูมิสารสนเทศ

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ลายมือชื่ออาจารย์ที่ปรึกษา

ลายมือชื่ออาจารย์ที่ปรึกษาร่วม

ARIF WICAKSONO : URBAN PARK SUITABILITY ANALYSIS USING SPATIAL MULTI-CRITERIA FUZZY LOGIC. THESIS ADVISOR : ASST. PROF. SUNYA SARAPIROME, Ph.D. 230 PP.

PARK SUITABILITY MAPPING, FUZZY INFERENCE SYSTEMS, DEMATELS, GIS-MCDA

For years, Bogor Municipality in Indonesia has experienced shrinking agricultural lands to compensate expanding urban environment. This creates critical dilemma when searching new locations of public urban park (PUP) to meet ever increasing demand. It causes difficulty in decision making process, particularly when high agreement between optimum PUP demand and highly suitable area for development in each village is required. Plus, data of criteria on policy, population density, distances, accessibility, and number of visits including their relationships for new PUP location analysis definitely raised uncertainty in the analyses due to their fuzzy characteristics. To cope with this uncertainty, Fuzzy Inference Systems (FISs) and Decision Making Trial and Evaluation Laboratory (DEMATELs) were employed for spatial analyses to serve the study purpose.

Optimum village-based PUP demand areas in form of attributes of areal extent were estimated using FISs. Incorporating them with village-based feasible areas from Land Use Land Cover (LULC) map, the result of Mamdani FIS provides the best agreement for all villages. PUP suitable locations of the study area were then mapped by FISs and DEMATELs methods. These maps were incorporated with feasible areas from LULC by intersection in 10 suitability levels. In higher suitability levels, Mamdani and Sugeno-0 could provide more feasible PUP area than others. In addition, Intersection over Union (IoU) was used to indicate which method can perform better as well. The group of DEMATELS could provide the best IoUs and bigger feasible area for PUP development in almost all levels. To serve optimum PUP demand areas of villages more effectively, union areas or combined intersected areas of all methods in different suitability levels could provide the best solutions. The cumulatively union area from the most top down to level 7 can completely serve PUP demand areas of all villages.

Study results reveal that criteria and methods used are proper and efficient to achieve objectives of the study fruitfully.

School of Geoinformatics

Academic Year 2018

Student's Signature____________

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Co-advisor's Signature____________

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LIST OF ABBREVIATIONS

AI = Areal Interpolation

Bakosurtanal = *Badan Koordinasi Survai dan Pemetaan Nasional –Bahasa* (National Coordination Agency of Mapping and Survey)

BAPPEDA = *Badan Perencanaan Pembangunan Daerah –Bahasa Indonesia (*Agency of Planning and Development*)*

BBG = Bogor Botanical Garden

BM = Bogor Municipality

BNR = Bogor Nirwana Resident

BPS = *Biro Pusat Statistik – Bahasa Indonesia* (Central Statistics Bureau)

CERD = Cause and Effect Relationship Diagram

CoM = Center of Maximum

DBMP = *Dinas Bina Marga dan Pengairan – Bahasa Indonesia (*Irrigation and Road Development Agency)

DEMATEL = Decision Making and Trial Evaluation Laboratory

DKP = *Dinas Kebersihan dan Pertamanan – Bahasa Indonesia (*Landscape and Waste Management Agency*)*

DLLAJ = *Dinas Lalu Lintas dan Angkutan Jalan – Bahasa Indonesia (*Road Transportation and Traffic Agency*)*

FCM = Fuzzy C-means

FDEMATEL = Fuzzy Decision Making and Trial Evaluation Laboratory

LIST OF ABBREVIATIONS (Continued)

FISs	=	Fuzzy Inference Systems
GBM	=	Government of Bogor Municipality
GIS	=	Geographic Information System
GOS	=	Green Open Space
GUOS	=	Green Urban Open Space
IDW	=	Inverse Distance Weighting
IG	=	Indonesian Government
IMI	=	Indonesian Ministry of Interior
IMPW	=	Indonesian Ministry of Public Works
IoU	=	Intersection over Union
kml	=	Keyhole Markup Language
LULC	=	Land Use Land Cover
LULCC	=	Land Use Land Cover Change
MCAM	=	Multi-Criteria Aggregation Model
MCDA	=	Multi-criteria Decision Analysis
PUP	=	Public Urban Park
RT	=	*Rukun Tetangga- Bahasa Indonesia* (around 40 households neighborhood)
RW	=	*Rukun Warga- Bahasa Indonesia* (maximum 13 *RT*-level neighborhood)
SPL	=	Spatial Planning Law

LIST OF ABBREVIATIONS (Continued)

Sugeno-0	=	Sugeno FIS zero-order
Sugeno-1	=	Sugeno FIS first-order
WLC	=	Weighted Linear Combination

CHAPTER I

INTRODUCTION

1.1 Background problems of the study

In 2030, it is estimated 6 of 10 people will live in cities. Interestingly, this growth event will occur mostly in Asia, Africa, and Latin America (WHO, 2010). As the world enters 21st centuries, there is growing concern to provide more green open space for human kind (Mela, 2014). This massive urbanization rates will push city governments around the world to provide basic needs for their citizens such as foods, clean water, housing, jobs, health, education, and least but not last clean air and entertainment. Green Urban Space (GUS) as one of urban infrastructure provides service for citizens like oxygen, social place to interact and clean air (Laing, Miller, Davies, and Scott, 2006).

However, for countries which acknowledge its citizen land ownership rights such as Indonesia, it is very difficult to take over potential land to be used as public utilities. On the other hand, when it comes to commercial uses, land acquisition has increased land price speculation resulted profitable gaining for building developers and brokers and triggered massive conversion from agriculture land use to urban (Firman, 2004).

In the past, land purchasing for public infrastructures other than non-green area such as roads, schools, offices were common things, and the consideration to buy a new land to be developed as urban parks seems unthinkable. Today, as the growing demand to provide urban dwellers for adequate amount of green open space, the city governments must start to allocate sufficient budgets to purchase land to be planned and developed as green open spaces.

Bogor Municipality (BM) with an area of 11,850 hectares and population of 1,030,720 will be an interesting case for urban parks land suitability analysis, where it has world heritage Bogor Botanical Garden and large complex of green area inside Presidential Palace, yet it begins to allocate budget to purchase land for urban parks. These needs are to fulfil the obligation by the Spatial Planning Law 26 Year 2007 that every municipality and regency in Indonesia must have Green Open Space at least 30% of its area (Indonesian Government, 2007).

In the Master Plan of Bogor Municipality 2031, which was publicly announced in 2011, to increase the area of green open space proportionally, land will be purchased through land banking scheme (Government of BM, 2011). In addition, the need to acquire new land for urban parks in BM seems reasonable, since the existence of Bogor Botanical Garden (BBG) as a major green area in the center of BM is threaten by the growth of resident and commercial activities in surrounding areas in terms of water usage. Moreover, the Government of BM (GBM) tries to restrict water use for building surrounding Bogor Botanical Garden (Hotimah, Wirutomo, and Alikodra, 2015).

However, as prerequisite for land purchasing phase, land suitability analysis for urban parks selection depends on the characteristics of the area being investigated. As a result, criteria and methods has been employed in this subject become vary. Recently, there is growing concern that urban parks should be developed and accessible for poor neighborhood not only to sustain environmental quality but also to increase citizen quality of life. Therefore, accessibility to urban parks has become interesting research theme especially how to develop urban parks as close as it can to the community.

Furthermore, not only accessibility to urban parks but also distances to water body, electricity, school, etc. are closely related to distance variable. People density and policy demand are also significant criteria for Public Urban Park (PUP) location. It is not clear how to describe people perception in terms of these criteria when travelling to urban parks and how they can affect to park environment. The use of linguistic values in geographical analysis become more interesting for solution analysis, since Geographic Information System (GIS) nowadays can be integrated with various fuzzy methods. The progress in GIS which is combined with fuzzy method in Multi-Criteria Decision Analysis (MCDA), has made wider opportunity to investigate more about human perception of these criteria to urban parks.

Though recently, the search for urban park location has been done more by employing fuzzy GIS-MCDA (Givi, Karimi, Moarab, Fouroughi, and Nikzad, 2015), but in author's knowledge extent no fuzzy controller method for limiting size of or total urban park area in a village/district has been performed so far. Not to mention the parameter to decide optimum PUP area standards has not clear yet, which sparks current global debate among researchers and government agencies. In addition, current researches set up suitable index for PUP location from combining relevant criteria designed in the analysis. No one uses visit density which is the significant variable reflecting people demand in suitable location for PUP development.

To contribute to urban park suitability analysis, this study starts with estimation of optimum PUP area demand based on accessibility, policy demand, population density, and visit density using three Fuzzy Inference Systems (FISs) namely, Mamdani, Sugeno (1-order) and Sugeno (0-order). Park number of visit was estimated by combining standard service, public awareness survey, park area, and catchment population. Different from current researches, this research uses a number of visit as index for suitable park location.

Furthermore, raster based analysis of urban park suitability map by using three FISs and two Decision Making Trial and Evaluation Laboratory (DEMATELs) was presented to fulfill the second research objective. Suitable indexes of these two groups of methods are different. A number of visit as a consequent is used as suitable index of FISs while suitable index of DEMATELs is the combination of all relevant criteria selected in the analysis, as same as the index in other conventional method. Results from these two groups of method were compared and combined to take the best out of them for application.

Finally, this study describes feasibility maps as results of superimposing suitability maps with updated land use map of BM. Last but not least, feasible PUP areas resulted from every method will be compared to observe which method and suitable index is the best.

1.2 Research objectives

The major purpose of this study is to search suitable location and extent for PUP in BM, Indonesia based on three main factors namely accessibility, population density, and distant-related criteria by using Multi-Criteria Aggregation Model (MCAM) and FISs methods. In details, more specific objectives of this study can be described as follows:

1. To estimate optimum urban park area demand of villages in BM, Indonesia by using Sugeno and Mamdani FISs;
2. To develop urban park suitability mapping methods using FISs and DEMATELs;
3. To locate feasible urban park areas based on suitability maps and demands incorporating with existing land use; and
4. To compare feasible urban park areas achieved from FISs and DEMATELs.

1.3 Scope and limitations of the study

1.3.1 Scope of the study

1.3.1.1 This study is conducted in BM, Indonesia, therefore all data are within administrative boundary of BM.

1.3.1.2 Data of road network and walking-time impedance are processed by using GIS software to produce service area of urban parks, and then integrated with existing park location, classification, and population density to derive accessibility score.

1.3.1.3 Even though Green Urban Open Space (GUOS) is not exactly the same with PUP, it does not have a certain ratio between them mentioned in any plans. Therefore, both of them are assumed identical for this study.

1.3.1.4 In village-based fuzzy operation, optimum PUP demand can be estimated from optimized visit density and population in every village which has non-zero value of both antecedent and consequent variables.

1.3.1.5 Antecedent variables in village-based operation consist of accessibility score, population density, and PUP policy demand, while the consequent variable is urban park per visit.

1.3.1.6 In raster-based fuzzy operation by using MCAM, expert opinion in form of influences of criteria are input to process urban park suitability map of DEMATEL, while expert opinion in form of linguistic values are converted by using triangular fuzzy number then proceed to fuzzy DEMATEL.

1.3.1.7 In raster-based fuzzy operation by using FISs, antecedent variables consist of accessibility score, population density, and PUP policy demand, while the consequent variable is visit density which means that suitable raster cells are those with significant visit density values.

1.3.1.8 Targeted respondents for urban park satisfaction attributes are urban park managers of BM, while random survey respondents are residents in BM.

1.3.2 Limitations of the study

1.3.2.1 Since the expected result of suitability maps are displayed in raster cells, the exact size of suitable patch of cells recommends type of desired PUP. Therefore, the selection of raster cell size affects to the selected PUP location accuracy.

1.3.2.2 Urban park visitor estimation formula, which is used in this study, could explained 75% variance when applied in Victoria, Melbourne, Australia (Zanon, 1998). However, if it is applied in BM, Indonesia to estimate PUP visitor, there might be some unequal situation should be considered as limitation of the study such as lifestyle, culture, and climate.

1.3.2.3 Since there is no eligible information on previous study about the upper and lower critical value of accessibility, PUP policy demand, and population density to choose optimum visit density, therefore this study uses fuzzy c-means data clustering method as a function to classify fuzzy membership.

1.3.2.4 Another limitation of this study is the use of walking-time impedance to estimate service area of PUP and catchment area population. The consideration of using walking-time impedance is because BM does not have mass rapid urban transportation such as underground railway or inner city tramline. This considers also that in 2016, BM has been regarded as the second lowest driver satisfaction index after Cebu, the Philippines (Waze, 2016).

1.3.2.5 In this study, it is assumed in village-based fuzzy operation that optimum PUP demand derived from optimized visit density value. To obtain optimized visit density value as consequent in FISs, it will only select the villages which have non-zero value of accessibility, population density, PUP policy demand and visit density.

1.3.2.6 As the equation of PUP policy demand might be resulted in minus value, then in this study every minus value of PUP policy demand will be considered as zero. It means that there is no more PUP area required for such a village.

1.3.2.7 It is assumed that all additional PUP designated in Master Plan 2031 will be built.

1.4 Study area

1.4.1 Geographic location

BM with an area of 118.5 km^2 is located in West Java Province and about 60 km south of Indonesia's capital city, Jakarta (Figure 1.1). The population in 2014 was 1,030,720, comprises 523,479 male and 507,241 female (Biro Pusat Statistik, 2014). BM is crossed by two major rivers in West Java Province, Ciliwung and Cisadane, where water source for the two rivers come from mountainous area in the northern part of the city, which is partially belongs to Halimun and Gede-Pangrango National Parks. Inside BM, famous Bogor Botanical Gardens and Bogor Presidential Palace are located in the city center.

BM is headed by a mayor, which is elected publicly every five year. BM consists of five sub-districts, 68 villages which each village is a part of larger sub-district.

In 2015, it has comparatively dense population of 1,407,922 people in area of 118.5 km^2. The city is located on the terrain with elevation between 190-330 m at maximum. Lowest averaged daily temperature is 20^0 -34.2^0C. Monthly average rainfall is 267.9 up to 385.3 mm. In recent updating urban park database of BM, the actual urban park area is 0.25 km^2 or 0.21 %. PUP to be developed in Master Plan 2031 will be 5.37 km^2 or 4.52 % of the area. This situation creates discrepancy among actual, master plan, and minimum requirement (Wicaksono and Sarapirome, 2017).

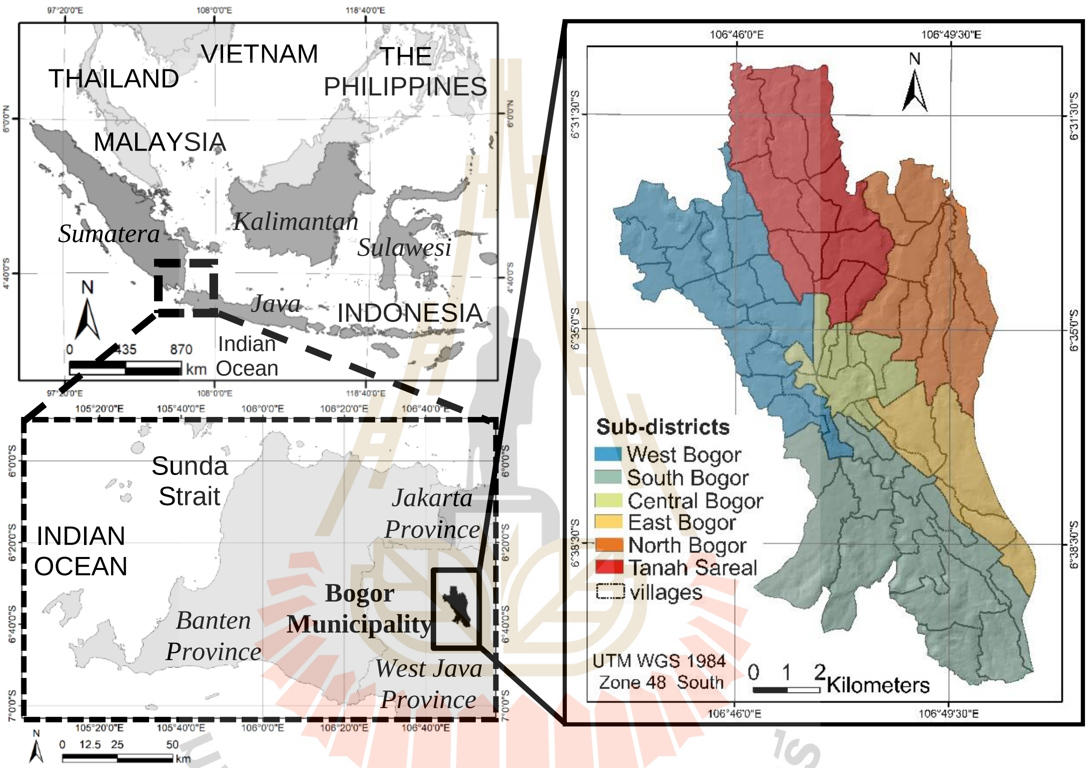


Figure 1.1 The map of study area.

1.4.2 PUP locations

PUP in BM can be classified into four classes namely, *RT-level*, *RW-level*, Village level and SD-level (Figure 1.2). There are 43 PUP in BM which will be the focus in this research (Table 1.1). Furthermore, these 43 PUP locations were listed in recent survey to acquire public satisfaction attribute value from BM residents. These locations not only were subjected for service area generation but also to estimate number of visit yearly.

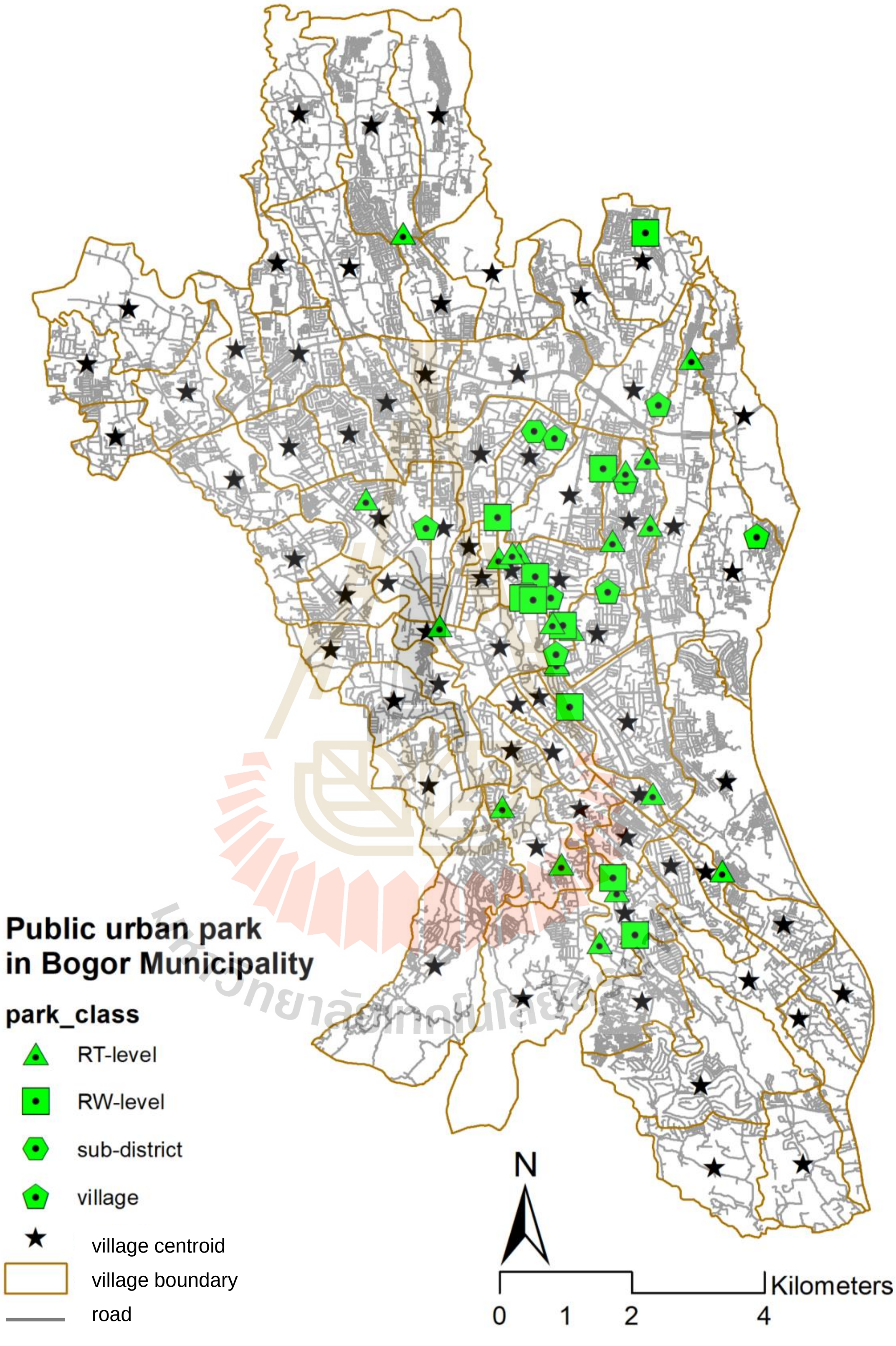


Figure 1.2 PUP locations in BM.

Table 1.1 PUP locations in BM.

No	PUP names	Villages	Area (m^2)	PUP classification
1	Heulang	Tanah Sareal	23,700	Sub-district
2	Soka	Cibuluh	20,408	Sub-district
3	Sempur	Sempur	14,470	Village
4	Ahmad Yani	Tanah Sareal	13,000	Village
5	BBG Belt	Paledang	10,954	Village
6	Palupu	Tegal Gundil	10,300	Village
7	Cimahpar	Cimahpar	9,659	Village
8	Manunggal	Menteng	9,376	Village
9	Indraprasta Soccer Field	Tegal Gundil	8,870	*RW-level*
10	Situ Anggalena	Ciparigi	5,600	*RW-level*
11	Genteng Soccer Field	Genteng	5,587	*RW-level*
12	Malabar 1	Babakan	5,518	*RW-level*
13	Cipaku	Cipaku	5,368	*RW-level*
14	Kencana	Babakan	4,796	*RW-level*
15	Ekspresi	Sempur	3,727	*RW-level*
16	Air mancur	Tanah Sareal	3,037	*RW-level*
17	Kaulinan	Sempur	2,557	*RW-level*
18	Sempur kaler	Sempur	1,920	*RT-level*
19	Tugu Talas	Babakan	1,820	*RT-level*
20	Peranginan	Sempur	1,699	*RT-level*
21	Genteng playgrounds	Genteng	1,697	*RT-level*
22	Riau	Baranangsiang	1,655	*RT-level*

Table 1.1 (Continued).

No.	PUP names	Villages	Area (m^2)	PUP classification
23	PWI	Cipaku	1,453	*RT-level*
24	BNR	Ranggamekar	1,326	*RT-level*
25	Matematika	Tegal Gundil	1,068	*RT-level*
26	Pangrango Plaza	Babakan	886	*RT-level*
27	Cidepit	Panaragan	839	*RT-level*
28	Griya Katulampa	Katulampa	690	*RT-level*
29	Corat coret	Tegal Gundil	689	*RT-level*
30	Bantarjati Permai	Bantarjati	650	*RT-level*
31	Pramuka	Tegal Gundil	603	*RT-level*
32	Malabar 2	Tegalega	601	*RT-level*
33	Sukasari III	Sukasari	460	*RT-level*
34	Rusunawa Menteng	Menteng	444	*RT-level*
35	Kebun Bibit	Sempur	408	*RT-level*
36	Tugu Kujang	Paledang	379	*RT-level*
37	Kedaton Grande	Ranggamekar	325	*RT-level*
38	Lawang Salapan	Paledang	321	*RT-level*
39	Indraprasta playgrounds	Bantarjati	272	*RT-level*
40	Legok Muncang	Cipaku	210	*RT-level*
41	Bogor Baru	Tegalega	206	*RT-level*
42	Mekarwangi	Mekarwangi	202	*RT-level*
43	Tanah Baru	Tanah Baru	153	*RT-level*

1.5 Benefits of the study

1.5.1 Optimum additional PUP area demand based on policy, accessibility and population.

1.5.2 New location of PUP based on accessibility, population and distance to geographic features.

1.5.3 FISs integration into geospatial modeling.

1.5.4 Estimated PUP visitor.

CHAPTER II

LITERATURE REVIEWS

This chapter will focus mainly on concepts and theories of PUP particularly based on how to search and define new location and minimum requirement area. Therefore, previous research will be described in detail about FIS, accessibility, population density, policy demand and park visitor estimation.

2.1 Green Urban Open Space

Recently, some countries apply more detail city master plan, i.e. Delhi 2021 Master Plan in India, which can locate future public green space of 125 m^2 in every 20 tot lot housing scale (Gupta, Roy, Luthra, Maithani, and Mahavir, 2016). However, according to Indonesia Government Regulation (IGR) Number 8 Year 2013, city master plan map scale must not be less than 1 : 25,000 (Indonesian Government, 2013). This requirement limits urban planner to explore more GUOS classification functions as social interaction which located in lower urban hierarchy. Instead of focusing to GUOS function as social interaction such as PUP or children playground, city master plan and regulation in Indonesia quickly decide 20% of urban area to be designated as public GUOS including cemetery and railway’s shoulder, which often not convenient places for people to interact.

Therefore, this study will use GUOS policy in city level master plan to be used as fuzzy controller, but for more detail raster cells fuzzy analysis it will employ PUP classification to justify the involvement of population density, distance, and accessibility score.

Green Open Space (GOS) is a clustered or belt area which its use more openly where vegetation grows naturally or planted. Public GOS is managed by municipality or regency government to be used by public. Private GOS is belonged to certain institution or people whose its use for limited such as plantation or yard of a house or building planted by vegetation (Indonesian Minister of Interior, 2007). GUOS is part of urban open space which is filled by plants and vegetation to support the benefits of ecology, social, culture, economics, and aesthetics. GUOS planning is the process of planning, using, and management. Public GUOS is GUOS which its procurement and maintenance become the responsibility of Municipality or Regency Government such as PUP. Private GUOS is GUOS which its procurement and maintenance become the responsibility of private sector and controlled by municipality or regency government.

2.1.1 PUP Classification

From literature review, different definitions about green open space and PUPs are found, so it is decided to classify PUP in BM, Indonesia based on the regulations of the Republic of Indonesia (Table 2.1).

Table 2.1 Criteria of PUP (IMPW, 2008).

Type	**Population Served**	**Distance**	**Minimum Area required (m^2)**
Small neighborhood park)*RT*-level) (40 households)	250	300 m from houses	250
Large neighborhood park (*RW*-level) (200 –520 households)	2,500	Less than 500 m from houses	2,500

Table 2.1 (Continued).

Type	Population Served	Distance	Minimum Area required (m^2)
Village's park	30,000	Within sub-district boundary	9,000
Sub -district park	120,000	Within district boundary	24,000
City park	480,000	Within city limit	144,000

2.1.1.1 PUP

PUP is open space with aesthetic and social function as recreation and educative facility in the urban level (Figure 2.1). PUP is a garden which is aimed to serve a city or part of it. This park serves minimum of 480,000 population or minimum standard of 0.3 square meters per person, or minimum area of 144,000 square meters. This park can be a green field equipped with sport and recreation facilities with minimum 80-90% green area (Table 2.2). All of inside facilities should be publicly used for free. All chosen vegetation can be evergreen trees, woody, or shrubs which are planted grouped or dispersed functioning as microclimate controller and physical barrier activities (IMPW, 2008).

Table 2.2 Required facilities in a PUP (IMPW, 2008).

Green Area	Facilities	Vegetation
70-80 %	1. Open Field 2. Basket Ball Field (14 x 26 m) 3. Volley Ball Field (15 x 24 m)	1. 150 trees (small and large)

Table 2.2 (Continued).

Green Area	Facilities	Vegetation
	4. Jogging Track width 7 m, 400 m length 5. Public Toilet 6. Amphitheatre 7. Children playground 8. Retention pool to control run-off 9. Chairs	2. shrubs 3. ground covers

Figure 2.1 Example illustration of PUP (IMPW, 2008).

2.1.1.2 *RT*-level park

According to Indonesian Minister of Public Works Regulation Number 5 Year 2008, to support social activity for 40 households, small neighborhood park should have seats, children playground, and community gardening (Figure 2.2).

2.1.1.3 *RW*-level park

The facilities in this park are available to support community sport activities like volley ball and basketball. It also provides area for social interaction facilities such as bench and lawn. In addition, children playground structures can be installed such as playhouse, climbers, and seesaw. To ignite community cohesion, benches are clustered either facing sport facilities or lawn (Figure 2.3).

Figure 2.2 Illustration of *RT*-level park (IMPW, 2008).

Figure 2.3 Illustration of *RW*-level park (IMPW, 2008).

2.1.1.4 Village park

Running track and soccer field are type of sport facilities which can be constructed in village's park. This kind of park usually provides kiosk to sell food or drink. Last but not least, village' park should be equipped with public toilettes (Figure 2.4).

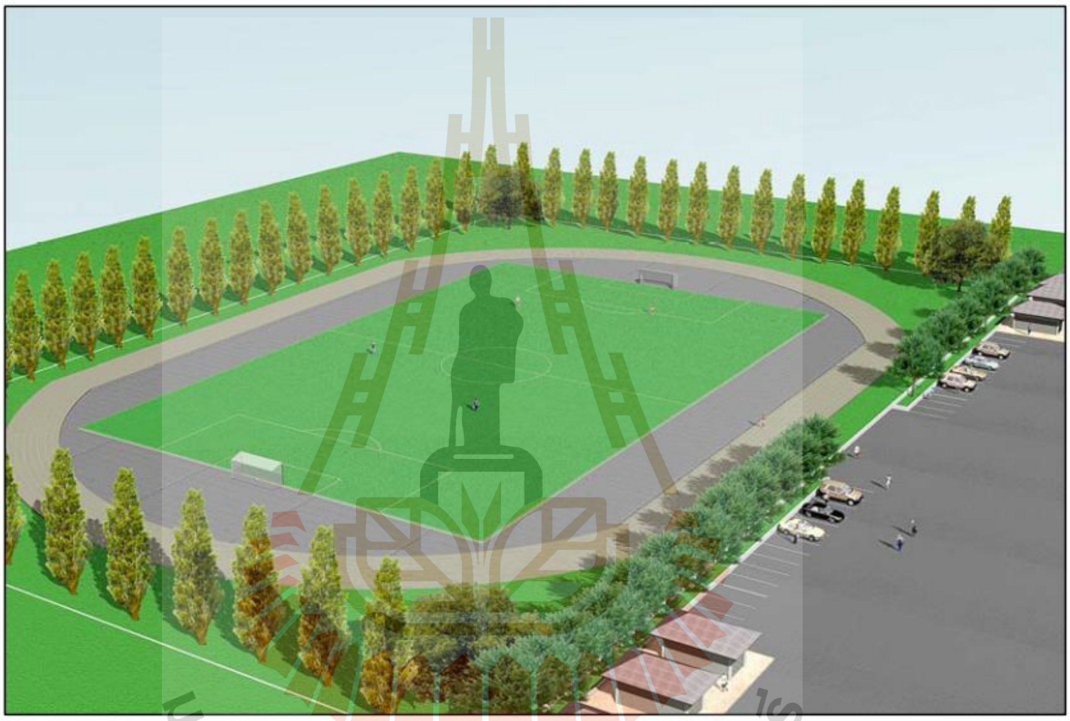


Figure 2.4 Illustration of village park (IMPW, 2008).

2.1.1.5 Sub-district park

In sub-district level, park should have more sport facilities than village' park such as volley ball, basketball, jogging track with 325 m long and 5 m width. It also provides toilette for visitor and kiosk to sell food or drink. This park is also equipped with benches and plaza (IMPW, 2008).

2.2 Fuzzy set

As mentioned in the introduction of this thesis, criteria employed in PUP suitability location analysis are ambiguity for people perception and can be solved by using fuzzy logic to generate criteria fuzzy set before input into fuzzy GIS-MCDA. Zadeh (1965) introduced fuzzy set, where objects can be classified within grades of membership function. Membership function in fuzzy set has value between zero and one (Figure 2.5). In MCDA, uncertainty can be present because of the fuzziness (imprecision) related to semantic descriptive of certain phenomena, events, or statements (Malczewski and Rinner, 2015). Membership functions to represent linguistic fuzzy can be observed in Figure 2.6.

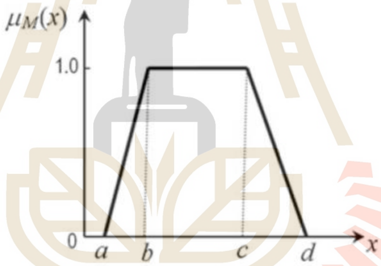


Figure 2.5 In trapezoidal, μM(*x*) represents fuzzy number, while real numbers are represented by a, b, c, and d (Malczewski and Rinner, 2015).

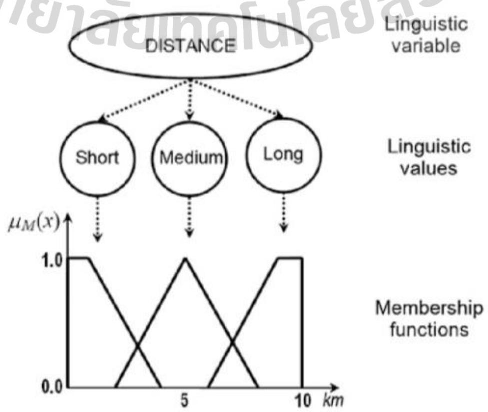


Figure 2.6 Example of fuzzy linguistic to represent distance, where 5 km is regarded as medium with fuzzy membership of 1 (Malczewski and Rinner, 2015).

Linear membership function, which is very simple membership function consists of four shapes namely increasing linear, decreasing linear, triangular and trapezoidal (Figure 2.7). It has four control points of a,b,c, and d, which define the shape of linear function and linguistic value of fuzzy membership function.

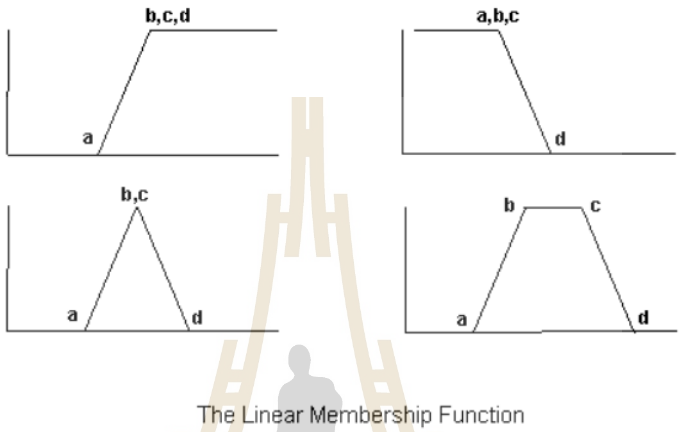


Figure 2.7 Type of linear membership function in fuzzy (Eastman, 2016).

Another type of membership function is Sigmoidal (Figure 2.8), in this type there are four major graphics of membership function. In monotonically increasing, the values of a,b,c,d are increasing when fuzzy membership increases. On monotonically decreasing sigmoidal, the values of a,b,c,d are decreasing when fuzzy membership declines.

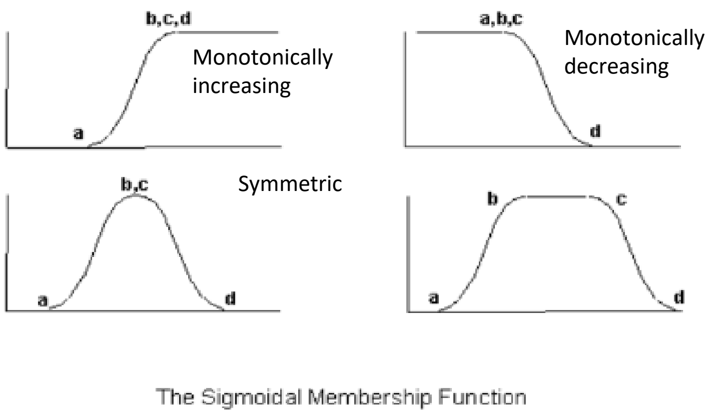


Figure 2.8 Type of sigmoidal membership function in fuzzy (Eastman, 2016).

As described in the Figure 2.9, J-shaped shows that *x* value gradually increases from 0 for increasing fuzzy membership while *x* value ends to almost infinity for decreasing fuzzy membership. The use of J-shaped is not as common as Sigmoidal, better to use Sigmoidal instead of J-Shaped (Eastman, 2016).

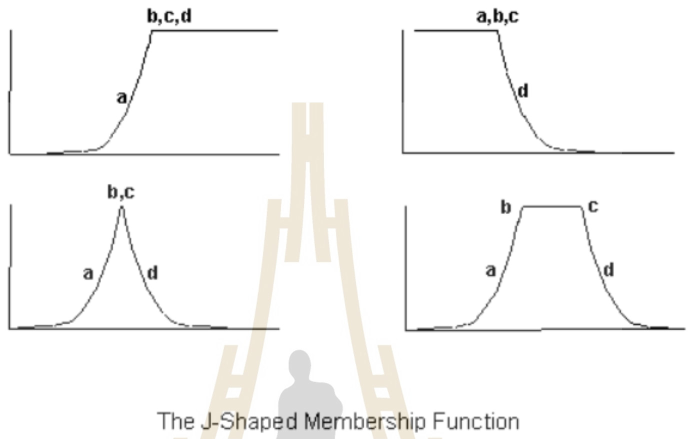


Figure 2.9 Type of J-shaped membership function in fuzzy (Eastman, 2016).

Gaussian curve membership function (Figure 2.10) is one of the curve type used to define fuzzy membership, it works by plotting value of x, standard deviation (σ), and mean (c) into equation:

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{2.1}$$

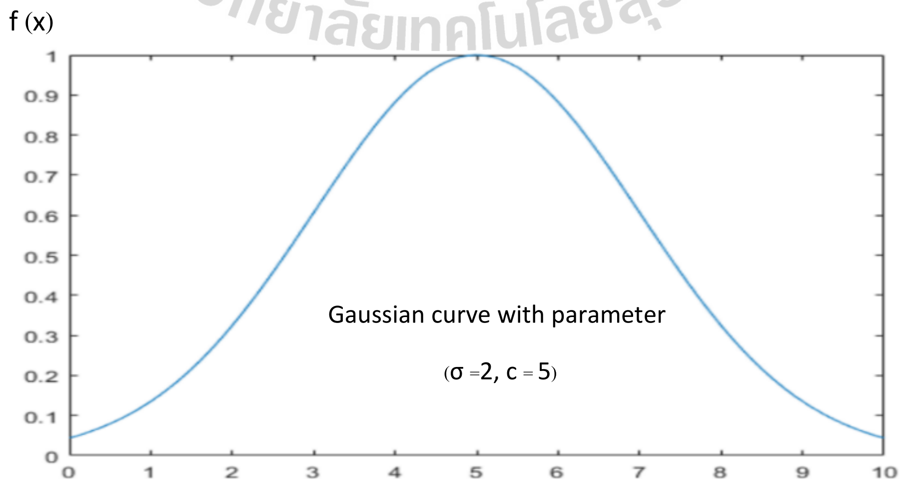


Figure 2.10 Type of gaussian membership function in fuzzy (Mathworks, 2018a).

2.3 Criteria for PUP suitability

In general, criteria employed to consider PUP suitability could involve population density, accessibility, policy demand and distant-related criteria.

2.3.1 Population density

Population density is the average number of people in a country or region per square kilometer (km^2) (Guinness and Nagle, 2016) or it can be expressed as number of people divided by the area they occupy (Hunter, 2016).

Population distribution is how people disperse on a given area, whether in small region or in the whole Earth. Regions with high population density are named densely populated, while regions with small population density used to be said sparsely populated (Guinness and Nagle, 2016).

Population density and distribution depends on the variations between physical environment and human environment. Densely populated regions usually are located where the physical environment matches with human needs if no other factors being involved. This factors determine why in desserts, rainforests, polar region, and uplands usually are associated with sparsely populated areas. Therefore, human settlements can always be associated with locations of water resources such as rivers and wells. However, in more urban environment, more densely populated areas are now associated with more employment locations where jobs and infrastructures are available (Guinness and Nagle, 2016).

In relation to land suitability analysis for green area, population forecast had been used to predict the needs of green area in El-Sadat City, Egypt (Mahmoud and El-Sayed, 2011) by using equation can be expressed as follows:

$$G_n = G_o \times (1 + M + N)^n \tag{2.2}$$

where G_n is population at the end of the period of growth being calculated, G_o is the initial population, N is natural growth rate of the population of the city, M is the influx of people from outside, n is the planning period of the year.

To display population density map in Geographic Information System, population data must be divided first with the area of region being investigated. In order to be displayed in raster data, population density based on vector data must be interpolated using spatial interpolation method. Furthermore, spatial interpolation is the procedure of forecasting the value of attributes from known locations to un-sampled, missing, or concealed positions (Yang, 2009).

One of the most common spatial interpolator used extensively in many fields is Inverse Distance Weighting (IDW), where IDW works by inverting the weight of a sample point value proportionally to its geometric distance based on predicted value resulted from specific power or exponent computation (Yang, 2009). Moreover, IDW will assume that predicted values will have influence from point values in closer distance than point values located from far away distance (Samantha, Pal, Lohar, and Pal, 2012).

2.3.2 Accessibility

In GIS, accessibility is being observed as how a location or number of locations can be accessed by population entity with distance consideration. In GIS-MCDA, weighting method can be employed to differ influence criteria among population, number of locations, and distance to PUPs accessibility (Meng and Malczewski, 2015). Accessibility can also be examined by utilizing network analysis especially with impedance travel speed to produce service area of existing green space (Gupta et al., 2016). By using modified spatial interaction model, accessibility evaluation to PUPs can also be done by heavily investigating on population and distance (Zhang, Lu, and Holt, 2011; Rosa, 2014). Meng and Maclzewski (2015) suggested that concepts of accessibility can be separated to be 3 models as displayed in Figure 2.11.

a) Covering model

In this model, the accessibility to PUPs is measured by drawing a circle from a PUP within a specified distance and from this circle, it can be calculated how many living residents are located within the circle. This circle also determining the service area of a PUP which explains how a PUP can be visited by every person with maximum distance assumption from a PUP (Hodgart, 1978). However, Meng and Malczewski (2015) argued that accessibility measurement to PUPs by using Covering Model neglected the size and type of PUPs, since size and type of PUP namely mini, neighborhood, and community should produce different size of PUP service area. By modifying covering model from Meng and Malczewski (2015) the covering distance can be calculated as follows:

$$The\ covering\ model\ = \frac{The\ total\ number\ of\ i-th\ PUP\ within\ j-th\ village}{The\ population\ of\ the\ j-th\ village} \tag{2.3}$$

The *i-th* park means a type of PUP classified based on size, distance, and served population (Table 2.1). The covering measure assumes that all people living in the same service area have the same opportunity to access PUPs located in surrounding of Dissemination Area (DA) centroid. Meng and Malczewski (2015) classified the area resulted from circle radius being drawn from PUPs as DA. In this study, Dissemination Area DA is smallest geographic population unit used for census by authorized statistics agency.

b) Travel cost model

The purpose of Travel Cost Model is to minimize the cost should be paid by park visitor in travelling from origin (house) to destination (PUP). The idea is to average the distance value between origin and destination. In addition, Meng and Malczewski (2015) predicted that the lower average distance from DA centroids to PUPs the higher accessibility to PUPs, vice versa. Travel cost for every village can be estimated by this equation:

$$Travel\ cost\ model = \frac{Population\ of\ the\ j-th\ village \times the\ total\ distance\ from\ j-th\ village\ to\ all\ i-th\ PUPs}{The\ total\ number\ of\ i-th\ PUP\ within\ j-th\ village} \tag{2.4}$$

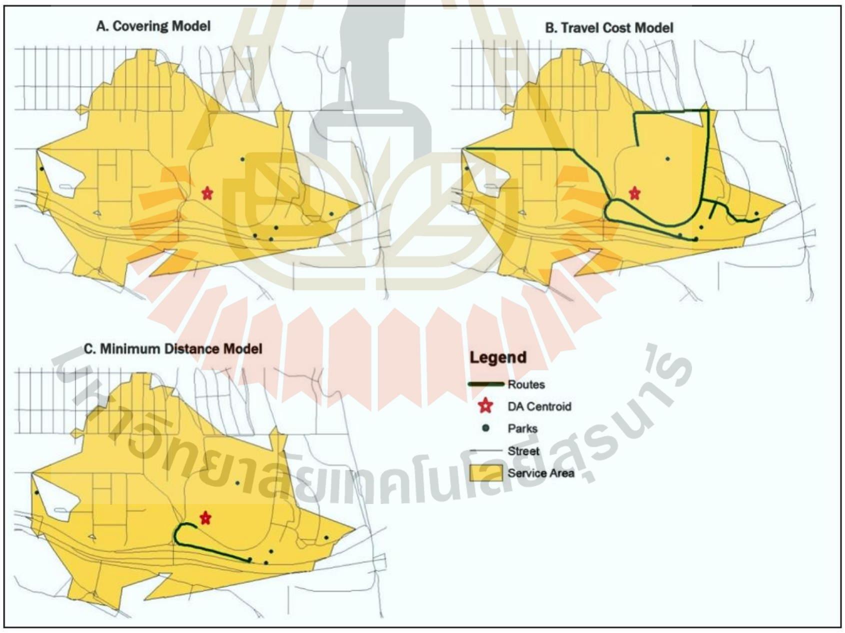


Figure 2.11 Concepts of accessibility (Meng and Maclzewski, 2015).

c) Minimum distance model

The purpose of accessibility to PUPs quantification based on closest distance from DA centroids to PUPs, is to consider the typical behavior of residents living near PUPs whom tend to use closest PUPs for daily leisure activities. Therefore, minimum distance can be computed using equation:

$$\text{The minimum distance} = \text{Population in } j-th \text{ village } \times \text{closest distance from } j-th \text{ village to } i-th \text{ PUP} \quad (2.5)$$

d) Accessibility scoring

As it was proposed by Meng and Malczewski (2015) when they applied accessibility score in Calgary, Canada, it had two advantages than other method of accessibility to PUPs namely: (i) this score considered population access to PUPs and (ii) the number of PUPs located within the specified distance from population centers. To compute accessibility score they used Equation (2.6):

$$S_j = \sum_{k=1}^{h} w_k \, p_{jk} \quad (2.6)$$

where:

W_k = weight associated with the k-th attribute ($\sum w = 1$; $k = 1,2,...,h$);

P_{jk} = normalized attribute value ($0 < P < 1$; $\sum p = 1$; j = 1,2, ..,n).

In addition, the value of each criteria needs to be normalized using Equation (2.7):

$$p_{jk} = \frac{xjkx}{\sum_{j=1}^{n} \quad jk} \quad (2.7)$$

where x_{jk} is the attribute value of the k-th attribute for j-th DAs.

In order to estimate weight in each criteria being assigned, this study uses entropy formula in Equation (2.8):

$$e_k = -\frac{\sum_{j=1}^{n} p_{jk} \ln\left(p_{jk)}\right)}{\ln(n)} \quad (2.8)$$

and then W_k (weight) can be calculated using d_k which was derived from e_k values, $d_k = 1 - e_k$ in Equation (2.9):

$$d_k = 1 - e_k \tag{2.9}$$

where d_k is degree of diversity of the k-th attribute for j-th village. As for W_k computation can be observed in Equation (2.10);

$$w_k = \frac{d_k}{\sum_{k=1}^{h} d_k} \tag{2.10}$$

where W_k is weight of the k-th attribute for j-th village.

2.3.3 PUP Policy demand

Recently, there are many terms to describe the disparity between required number and area of PUPs such as in City Master Plan, and the real existing locations. One of the terms of disparity is "Percentage of Deficit", which was suggested by Gupta et al. (2016) to measure the sufficiency needs of Urban Green Space in Delhi City, India by calculating the required number and area of parks between Master Plan of Delhi (MPD) 2021 and actual locations. When the number and area of parks in actual locations were less than in required of Master Plan of Delhi (MPD) 2021, then the situation was stated as "deficit". On the other hand, when the number and area of parks in actual locations were more than in required of Master Plan of Delhi (MPD) 2021, then the situation was stated as "sufficient". Overall, the disparity between areas with "deficit" parks and "sufficient" parks can be displayed as "Percentage of Deficit".

Legally speaking, Republic of Indonesia's SPL 26 Year 2007 definitely stated that 30% of municipality or regency area must have been designated as green open space. Specifically, Republic of Indonesia's Ministry of Interior (IMI) Regulation

1 Year 2007 defined the percentage of PUP is 20% of municipality or regency area (IMI, 2007). Unfortunately, though this legal acts are binding to every municipality and regency governments in Indonesia, due to the lack of sufficient funds this regulations seem hardly to implement in the near future. Therefore, in recent land-use of 2014, actual PUP in BM can only achieve 1,734.83 hectares from 2,436.93 hectares to be developed in Master Plan 2031. It means there is 28.81 % deficit of PUP between Master Plan 2031 and the actual locations. The illustration of PUP sufficiency needs can be seen in the Figure 2.12.

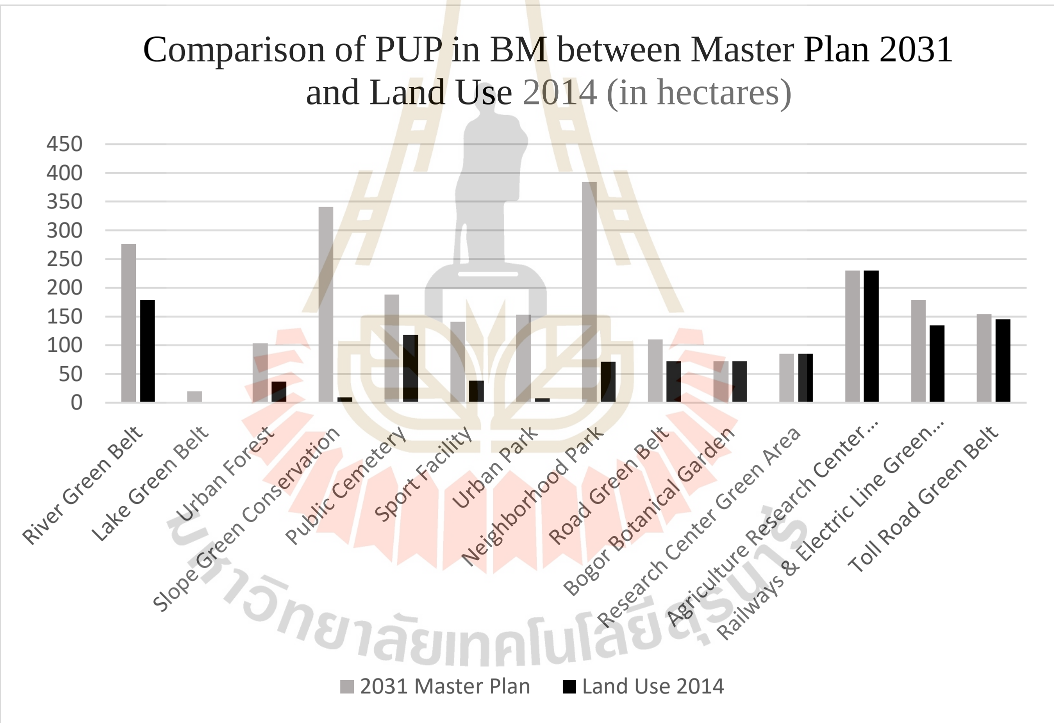


Figure 2.12 Comparison of PUP in BM between Master Plan 2031 and Land Use 2014 (GBM, 2015).

By considering aforementioned methods about disparity between PUP areas in the policy and actual locations, and to integrate current situation of deficiency of PUP in BM. Therefore, in this study new method will be introduced to measure inequality of PUP between planning and real condition, which is called "policy demand". This method can be expressed as Equation (2.11):

$$\text{PUP policy demand} = \text{Minimum requirement by the law} \times \text{village area} - (\text{additional PUPs designated in master plan} + \text{actual PUPs}) \quad (2.11)$$

To apply Equation (2.11), it should be ensured first that the position of designated PUPs in master plan not overlapped with actual PUPs.

2.3.4 Distance to school

For environmental sustainability, selecting the vicinity of public green fields like protected green parks, public field and gardens for educational land use suitability and vice versa can increase students' physical and mental activity thus decrease tiredness and boredom (Javadian, Shamskooski, and Moomeni, 2011).

Variable of distance to education facility had been used before by Givi et al. (2015), to choose site for parks in urban environment which was located in Region 7, Tehran Municipality, Iran. In that case, authors explained that educational centers had functioned as favorable centers suitable for park selection.

Figure 2.13 Students from primary school use PUP in North Bogor sub-district for sport science exam.

In BM, many of the public green fields have been used extensively for sport acitivities by students located in nearby schools. This phenomena occur because most of the elementary schools in BM do not have athletics tracks for running practices. When the school has to train and test their students for running activities, they must visit nearby PUP (see Figure 2.13).

2.3.5 Distance to water body

As PUP has capability to retain storm water and preserve groundwater, therefore in this study it will consider this ecological function as suitable membership function. Not to mention that in PUPs, visitors like to try walk as close as it can to the water feature. Degree of suitability for distance to water refers to Uy and Nakagoshi (2008), within range less than 300 m will be suitable for PUPs while between 300 m and 600 m is moderate (Table 2.3).

Table 2.3 Various degree of suitability for distance to water body in previous studies.

Objective	**Degree of suitability**				**Source**
	High	**Moderate**	**Low**	**lower**	
Land Suitable Analysis for green space in Hanoi	<0.300 km	>0.300 km and <0.6 km	>0.6 km	-	Uy and Nakagoshi (2008)
Land suitability for forest park location	0-300 m	300-600 m	600-1200 m	>1200 m	Karami, Maleknia, and Piran, (2014)
Suitability analysis for greenway	Within <0.5 km	>0.5 km and < 1.5 km	> 1.5 km	none	Miller, Collins, Steiner, and Cook (1998)

2.3.6 Distance to electric power line

Related to the effect of electromagnetic fields to human health, there are current debates among people whom agree and disagree. Some people still think since current evidence of Extremely Low Frequency (ELF) to human health is weak therefore no necessary action are needed, on the other hand some people think that even small risk is enough for worry so that precaution steps are agreed (Tourab and Babouri, 2016). However, IMPW through regulation number 5 year 2008 has set up minimum distance from electric power line which is not allowed for development (see Table 2.4).

Table 2.4 Distance requirement from electric power line.

Development type	**High voltage line**		**Extra high voltage line**	**Medium voltage line**	**Low voltage line**
	66 kV	**150 kV**	**500 kV**		
Concrete building	20 m	20 m	20 m	2.5 m	1.5 m
Fence	3 m	20 m	3 m	2,5 m	1.5 m
Open field	6.5 m	20 m	15 m	2.5 m	1.5 m
Trees	3.5 m	20 m	8.5 m	2.5 m	1.5 m
Sport field	2.5 m	20 m	14 m	20 m	20 m

2.3.7 Number of visit estimation

As known, number of visit is strongly related to village characteristics. Therefore, the visit density can be used to control PUP area per head of any village. This criterion can work as a consequence of FISs to obtain optimized PUP demand of village. The following equation is proposed to calculate PUP visit density of a village:

$$PUP\ visit\ density = number\ of\ visits \div park\ area \qquad (2.12)$$

Since the GBM never perform PUP visitor survey, so data of PUP visitor is not available. However, there is a method to predict the PUP visitor which was proposed by Zanon (1998) as shown in the following equation:

$$\textit{Number of visits} = 27 \times \textit{Standard Service}^{1.04} \times \textit{Catchment Population}^{0.19} \times \textit{Area}^{0.11} \times \textit{Public Awareness}^{0.47} \tag{2.13}$$

where:

- Standard service is accumulated score for every PUP resulted from interview with park manager about park satisfaction attributes (PSA);
- Catchment population is number of population located 15 minutes' walk from every park using travel cost model;
- Area is accessible size of an PUP measured in hectare;
- Public awareness is percentage of "yes" answers when a respondent asked if he/she knows about the park in the list of PUPs.

This model provides high accuracy with 75% of variance when assessing its predictive power (Zanon, 1998). Unlike economics of countries from different regions of the world or from country to country, their structures can be chiefly different, while characteristics of park attributes are quite similar almost everywhere as evident in the Table 2.5. Zanon (1996) used 29 PUPs as samples which included many types of parks with different characteristics of various attributes and cases of visit number so that the relationship of the equation can be represented and applied to a variety of parks even parks in the study area. In this model, standard service variable is measured based on PSA (Table 2.5) proposed by Zanon (1996). Furthermore, there were original 17 questions used by Zanon (1996), however in this study it was reduced until 14 questions to match with study area condition. List of original questions which were removed namely, adequate car parking, BBQ facilities, and picnic facilities. With different lifestyles of people in the study area, they prefer to visit park in a closer distance, no barbeque is active and no picnic facility is required. So PUP visitors will not carry mat for laying or dine activity as most picnicker does.

Table 2.5 Park satisfaction attributes (modified after Zanon, 1996).

No.	Park Satisfaction Attributes	Maximum Scores
1.	Safe Access to Park Facility	7.2
	- Walking paths that provide safe access to park facilities	
2.	Adequate number of toilette facilities	8.4
	-Sufficient number of toilettes in suitable locations	
3.	Clean toilletes	10.2
	-Toilet facilities are cleaned and maintained	
4.	Tracks, Trails, and Paths	8
	-Adequate number of clearly defined tracks and trails for you to explore or use the park	
5.	Suitable surface for tracks, trails, and paths	6.7
6.	Children’s playground /play areas	7.6
	-Adequate provision of constructed play-grounds and natural areas suitable for unstructured play	
7.	Adequate litter control measures	7.9
	-Information on park litter policy or sufficient number of rubbish pins for park users	
8.	Signposting and directions	5.9
	-Adequate signs/directions for specific points of interests, trails, picnic areas, exits. etc	
9.	Shelter	10
	-sufficient shelter to provide relief from sun, wind, and rain when required	
10.	Length of grass	5.6
	- Grass not too long or too short	
11.	General maintenance standards	7.4

Table 2.5 (Continued).

No.	Park Satisfaction Attributes	Maximum Scores
	Park is well maintained, things workings as they should and everything neat and tidy	
12.	Ranger present or available	4.7
	Ranger(s) on duty during official opening times to assist visitors, handle enquiries, and monitor behavior of park users	
13.	Information about the park	5.2
	-sufficient information available either via brochures, displays, signs or other means	
14.	Suitable opening and closing times	5.2
	-Adequate to meet your needs	

In addition, to provide bench mark for each minimum-maximum scores should be filled by PUP manager, each question in PSA will be given four photographs to represent linguistic value of poor, medium, good, and best. The selection of photograph of each question will be suggested by experienced landscape architect. The best class of each attribute corresponds to maximum score in Table 2.5. The scores of classes according to photos are apparently proportional to these suggested maximum scores and can be between the classes.

Catchment population variable is the number of population located within walking time of 15 minutes from selected PUP (Zanon, 1996). While area variable is computed from accessible area location within PUP using GIS. Interestingly, the data for public awareness variable came from a number of random survey and each person was questioned whether they knew the name of PUP. The output for this random survey was percentage of public awareness for each PUP (Zanon, 1996).

2.3.8 Fuzzy membership function development and agglomeration for distance criteria

In order to process antecedent variable to become consequent variable, FISs work by using rules which can be developed if antecedent-consequent variables are classified into fuzzy membership function. This means that crisp values of each antecedent-consequent variable should be changed into linguistic classes. Additionally, the processes to create fuzzy membership function, classify, and develop rules are the basic components of Fuzzy Inference System Modelling (Mathworks, 2018b).

In researches, researchers convert crisp values into linguistic fuzzy membership classes by referring actual data resulted from experiment, historical records, or previously done research. Therefore, the distance criteria which will be employed as one of antecedences come from previous research and government regulation. Fuzzy membership function of distant-related criteria should be developed based on their different characteristics. This will be related to the farther the better or the shorter the better.

This study will apply mainly two models of fuzzy membership functions namely increasing sigmoidal and decreasing sigmoidal. Increasing sigmoidal function will determine fuzzy membership of distance to electric transmission line while decreasing sigmoidal function will be applied to distance to education facility and water bodies.

The purpose to apply increasing sigmoidal membership function is that the larger distance from object means the greater fuzzy membership, while in decreasing sigmoidal the larger distance from object means the less membership. To define the midpoint in decreasing sigmoidal, it uses the following equation (Givi et al, 2015; Gbanie, Tengbe, Momoh, Medo, and Kabba, 2013):

$$\mu(x) = cos^2\alpha, \text{ when x < point c, } \mu(x) = 1$$

where

$$\alpha = \frac{x - point\ c}{point\ d - point\ c} * \frac{pi}{2} \tag{2.14}$$

The result from above equations will be used to determine the value of fuzzy membership function for every x value by using following equation;

$$\mu(x) = \frac{1}{1 + \left(\frac{x}{f2}\right)^{f1}} \tag{2.15}$$

where $f1$ is spread and $f2$ is midpoint (ESRI, 2018a).

The illustration of how Equation (2.14) in decreasing sigmoidal works can be seen in Figure 2.14, whereas if the spread is getting bigger the fuzzy membership will increase. On the other hand, if spread value is lower and then fuzzy membership value will decline.

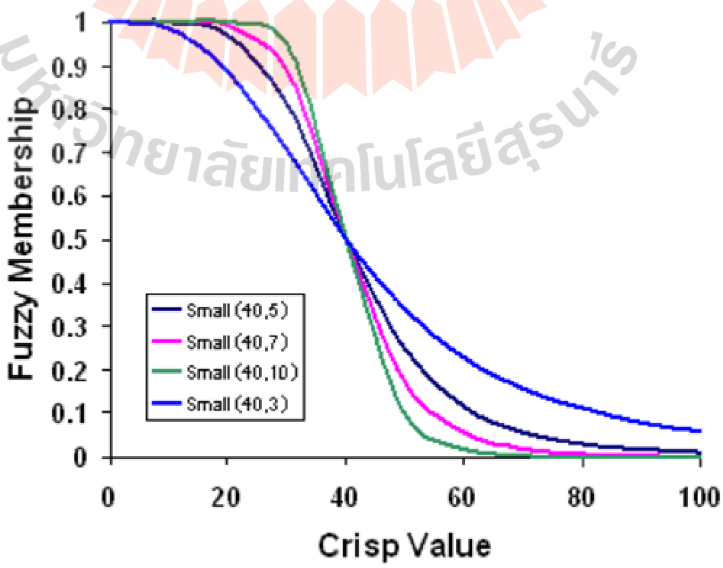


Figure 2.14 Example of decreasing sigmoidal membership function (midpoint, spread). (ESRI, 2018a).

For fuzzy membership function in increasing sigmoidal, this study uses following equation (Givi et al., 2015; Gbanie et al., 2013):

$$\mu(x) = cos^2\alpha, \text{ when x > point b, } \mu(x) = 1$$

where

$$\alpha = 1 - \left(\frac{x - point\ a}{point\ b - point\ a} * \frac{pi}{2}\right) \tag{2.16}$$

The result from above equations will be used to determine the value of fuzzy membership function for every x value by using following equation;

$$\mu(x) = \frac{1}{1+\left(\frac{x}{f2}\right)^{-f1}} \tag{2.17}$$

where $f1$ is spread and $f2$ is midpoint (ESRI, 2018a).

As for application of Equation (2.17) in increasing sigmoidal can be observed from Figure 2.15.

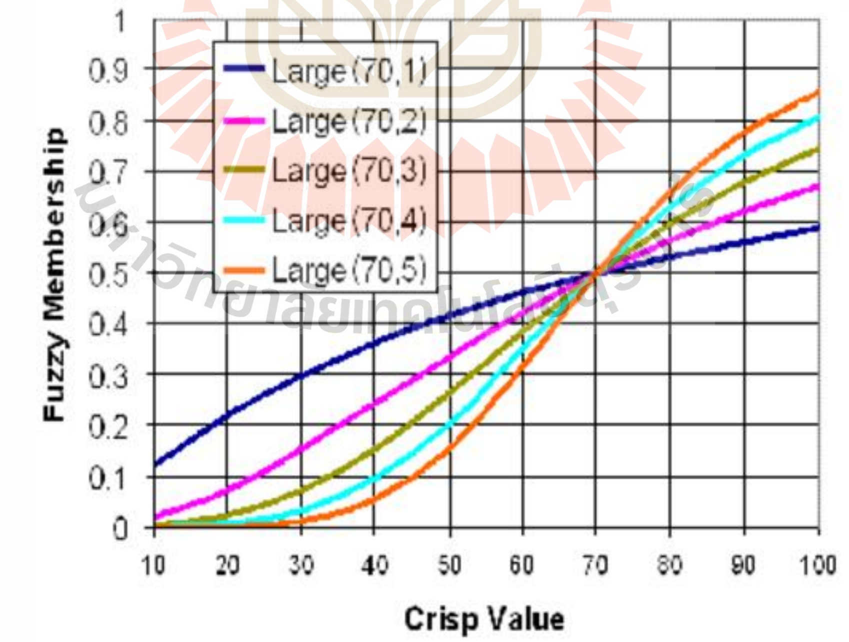


Figure 2.15 Example of increasing sigmoidal membership function (midpoint, spread) (ESRI, 2018b).

In FIS modelling, the more antecedent and consequent variables being inputted the more fuzzy rules need to be developed which will create too complicate judgement. Therefore, it is better to group the criteria with the same characteristics such as distant-related criteria to be a single criterion. To agglomerate fuzzy set of raster-based criteria, overlay tools such as fuzzy AND, fuzzy OR, fuzzy PRODUCT, fuzzy SUM, and fuzzy GAMMA are provided in GIS environment, e.g. ArcMap^{TM}. Each approach contributes a different aspect of each cell's membership to the multiple input criteria.

If fuzzy AND is applied, more preference will be directed to monotonically decreasing criteria. Vice versa more preference will be directed to monotonically increasing criteria when fuzzy OR is applied. Fuzzy membership values are reduced and the difference among them are enhanced when fuzzy PRODUCT is applied. Fuzzy SUM provides bigger fuzzy membership values but less discrimination.

2.4 Fuzzy inference systems for PUP suitability estimation

There will be two expected results of this study, the first is optimized PUP demand which will be based on village polygon. The second output is suitable locations of PUP. FISs are efficient methods to achieve these results.

FIS tries to bridge the lack of transformation from real number to linguistic value. Widely speaking, there are two Fuzzy Inference Systems (FISs) commonly recognized today in MATLAB environment, Mamdani and Sugeno. Mamdani FIS has been used in many field such as landslide susceptibility mapping (Vahidnia, Alesheikh, Alimohammadi, and Hosseinali, 2010). Mamdani FIS is widely accepted, and suites more with human input and more intuitive than Sugeno FIS. On the other hand, Sugeno

FIS more computationally efficient, works well with linear techniques and optimization, not to mention it suites well with mathematical analysis (Mathworks, 2018c).

2.4.1 Sugeno FIS

In Sugeno FIS, the mathematical equation uses ad function to inference:

$$IF\ (X_1\ IS\ A_{1i} \bullet X_2\ IS\ A_{2i} \bullet \ldots \bullet X_m\ IS\ A_{mi})\ THEN\ Y_i = g_i\ (X1, X2, \ldots . X_m) \tag{2.18}$$

AND and OR functions denoted by ● symbol, where in Sugeno model there are two models, order 0-model and order 1-model. Order 0-form is $Y_i = g_i\ (X1, X2, \ldots . X_m) = k$ *(constant), on the other hand Order 1-form is* $Y_i = a_{0i} + a_{1i} X_1 + a_{2i} X_2 + _{\ldots} + a_m X_m$, result can be varied linearly (Priyono and Surendro, 2013).

To defuzzify the result from Sugeno method, it uses:

$$Z_0 = \frac{\sum_{i=1}^{n} \mu(x)\mathrm{i}.Z\mathrm{i}}{\sum_{i=1}^{n} \mu(x)\mathrm{i}} \tag{2.19}$$

where Z_0 is crisp value, $\mu(x)_i$ is membership value in *i-th* linguistics class, Z_i is crisp value in *i-th* linguistic class.

2.4.2 Mamdani FIS

Mamdani FIS was proposed by Ebrahim Mamdani, when he attempted to control a steam engine and boiler by using linguistic control sets derived from human operator experience (Mamdani and Assilian, 1975). In Mamdani, antecedent and consequent variables are integrated by using set of rules that can be employed by min or max. The simple expression of antecedent and consequent relationship (Kolisko, 2015) can be seen as follows:

$$R_k : \text{if } X_n \text{ is } A_{nk} \text{ then } Y \text{ is } B_k, \quad k = 1, 2, \ldots, K \tag{2.20}$$

where R_k = the rule number, A_{nk} and B_k = the fuzzy sets, X_n = n-th antecedent variable, Y = the consequent variable.

To get crisp values in Mamdani FIS, consequent variables can be defuzzified by several methods. In this study, to produce Mamdani raster cells, it will use formula of Centre of Maximum (CoM) (Kolisko, 2015) which can be seen as follows:

$$y_{D_{j'}}^{CoM} = \frac{\sum_{j=1}^{k} y_j.\mu_{D_{j'}}(y_j)}{\sum_{j=1}^{k} \mu_{D_{j'}}(y_j)} \tag{2.21}$$

where

$y_{D'_j}^{CoM}$ = Defuzzified y value using Centre of maximum;

$\mu_{D'_j}$ = membership function of the conclusion of the j-th rule;

y_j = Value of y in j-th rule.

2.4.3 Fuzzy C- Means (FCM)

Currently, there are various techniques to propagate fuzzy membership function namely ANFIS, grid partition, subtractive clustering, and FCM. Limitedly ANFIS, grid partition, and subtractive clustering can only generate Sugeno FIS membership in MATLAB environment, while FCM can produce both Mamdani and Sugeno FIS membership. Therefore, this study will use FCM technique due to the dual fuzzy membership types which can be generated from.

FCM is a technique to classify sets of data into smaller groups of data based on its cluster center (centroids) means. FCM is also a clustering method that allows each data point to belong to multiple clusters with varying degrees of membership. For initial step, FCM algorithm create random cluster center in each membership grade which might incorrect. FCM algorithm then try to iteratively move the position of each cluster centre to right position in each cluster (Mathworks, 2018d).

FCM is based on the minimization of the following objective function (Bezdek, 1981):

$$J_m = \sum_{i=1}^{D} \sum_{j=1}^{N} \mu_{ij}^{m} \left\| x_i - c_j \right\|^2 \quad (2.22)$$

where

- D is the number of data points.
- N is the number of clusters.
- m is fuzzy partition matrix exponent for controlling the degree of fuzzy overlap, with $m > 1$. Fuzzy overlap refers to how fuzzy the boundaries between clusters are, that is the number of data points that have significant membership in more than one cluster.
- x_i is the i-th data point.
- c_j is the center of the j-th cluster.
- μ_{ij} is the degree of membership of x_i in the j-th cluster. For a given data point, x_i, the sum of the membership values for all clusters is one.

FCM performs the following steps during clustering:

1. Randomly initialize the cluster membership values, μ_{ij}.
2. Calculate the cluster centers:

$$C_j = \frac{\sum_{i=1}^{D} \mu_{ij}^{m} x_i}{\sum_{i=1}^{D} \mu_{ij}^{m}} \quad (2.23)$$

3. Update μ_{ij} according to the following:

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{N} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}} \quad (2.24)$$

4. Calculate the objective function, J_m.
5. Repeat steps 2–4 until J_m improves by less than a specified minimum threshold or until after a specified maximum number of iterations.

Clusters or fuzzy classes obtained from the process are used to estimate agglomerated fuzzy memberships based on rules developed. Then they are defuzzified to be the expected output depending on different inputs.

2.5 Fuzzy MCAM

2.5.1 DEMATEL

DEMATEL is a method to investigate the relationship between set of criteria (Arabsheibani, Sadat, and Abedini, 2015). Based on matrix modelling, all expert opinion in each criterion can be integrated together and then normalized. The uniqueness of this method is that it can be described in digraphs, so that user can explore further the influence and relationship of one criterion to another (Figure 2.16).

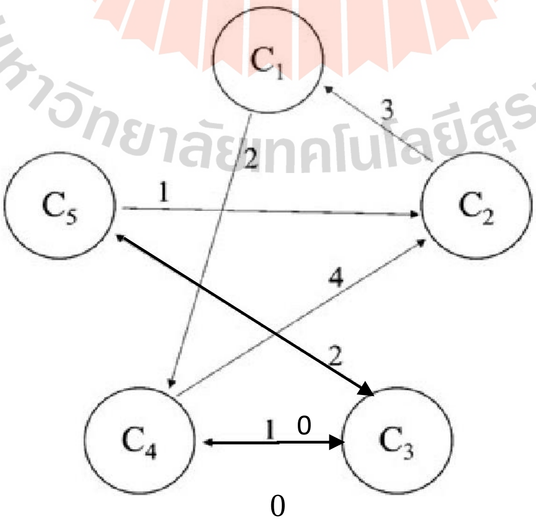


Figure 2.16 Causal interrelationship between each criteria defined from expert preference (Modified after Arabsheibani et al., 2015).

From Figure 2.16, expert opinions show that criterion C3 has influence to output more than criterion C4 in the scale of 1. The scale of influence is divided into 1 (low), 2 (medium), 3 (high), and 4 (very high). The arrow direction from C3 to C4 also confirms that C3 compared to the C4 has more influence than the threshold value calculated from the matrix.

The application of GIS-Fuzzy DEMATEL had been used by Gigovic, Pamucar, Lukic, and Markovic (2016) in "Dunaski Kljuc" region, Serbia which was aimed primarily to identify and evaluate the suitability of location for ecotourism using GIS-MCDA.

a) Creating matrix resulted from expert preferences

Each expert can give preference on each criterion based on questionnaires (Gigovic et al., 2016), and then average matrix being calculated based on equation:

$$\left[X_{ij}\right](nxn)=\frac{1}{N}\sum_{k=1}^{N}\left[E_{ij}^{k}\right](nxn) \tag{2.25}$$

where N is total number of experts, i is matrix in i-th rows, j is matrix in j-th column, and n is matrix n x n.

b) Normalizing the value of expert preference

Secondly, after it has the averaged expert preference matrix and then it needs to be normalized by using Equation (2.26) (Arabsheibani et al., 2015):

$$Y = k \,.\, X$$

where

$$k = min\left[\frac{1}{\underset{1<i<n}{max}\sum_{i=1j}^{n} x_{ij},\ \underset{1<j<n}{min}\sum_{i=1}^{n} x_{ij}}\right] \tag{2.26}$$

where

$i, j = 1,2,\ldots..,n$;

x_{ij} = preference value in the matrix, *i-th* row and *j-th* column;

Y = Normalized value in the matrix $n \times n$;

X = Average preference value from every expert.

c) Computing the relation matrix

To compute relation matrix, it needs Identity Matrix which defines as square matrix $n \times n$, consists of one values on its diagonals and zeros values on elsewhere inside the matrix. Relation matrix equation can be expressed as follows:

$$T = Y(\mathrm{I}-Y)^{-1} \tag{2.27}$$

where T = Total Influence Matrix, I = Identity Matrix $n \times n$, *and* Y = normalized value in the matrix $n \times n$ (Arabsheibani et al., 2015).

d) Computing the prominence and relation from matrix

After it has the relation matrix which contains values in rows and columns, the next step is to calculate R and D values by using equation:

$$[\tilde{\mathrm{R}}_\mathrm{i}]_{(\mathrm{nxn})} = \sum_{\mathrm{j}=1}^{\mathrm{n}} \tilde{\mathrm{t}}_{\mathrm{ij}} \tag{2.28}$$

$$[\tilde{\mathrm{D}}_\mathrm{i}]_{(\mathrm{nxn})} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \tilde{\mathrm{t}}_{\mathrm{ij}} \tag{2.29}$$

where $\tilde{R}$ is summation of *j-th* column in matrix $\tilde{T}$ and $\tilde{D}$ is summation of *i-th* row in matrix $\tilde{T}$ for FDEMATEL (Pamucar and Cirovic, 2015), while in DEMATEL *r* is summation of *i-th* row and *c* is summation of *j-th* column (Sumrit and Anuntavoranich, 2013).

To get meaning, it needs to calculate Prominence value (D+R) and Relation value (D-R). After summation and subtraction of R and D values, it can be determined which one is the most important and less important criterion. The most important criterion can be determined from criterion which has the biggest Prominence (*D*+*R*) value, while the less important criterion can be seen from its smallest Prominence (*D*+*R*) value. In case of Relation (*D*-*R*) value, the positive value determines that the criterion has net causal factor which influence other criterion which has less or negative value. On the other hand, criterion which has negative Relation (*D*-*R*) value indicates that this criterion being influenced by other criterion.

e) Creating threshold

In DEMATELs, to assess the relationship between causal factor and net influence, it will need a threshold value (Sumrit and Anuntavoranich, 2013) which is derived from Equation (2.30):

$$\sum_{i=1}^{n} \frac{t_{ij}}{N} \tag{2.30}$$

where t_{ij} is value in each component in translation matrix, *N* is total number of components in translation matrix.

The function of threshold value is to choose which criteria should be drawn in Causal and Effect Relationship Digraphs (CERD). If the value in translation matrix is bigger than the threshold value, then the relationship between criteria can be drawn into CERD. In the CERD, the arrows direction from one criterion to another criterion depends on Relation (*D*-*R*) value. The arrows will point to criterion which has negative Relation (*D*-*R*) value, however in case of most important criterion, the arrows will point to lesser important criterion despite its positive Relation (*D*-*R*) value.

f) Criteria weighting

To obtain criterion weight from DEMATEL, Gigovic et al. (2016) used equation that can be expressed as follows:

$$\widetilde{W_i} = \sqrt{\left(\widetilde{D}_i + \tilde{R}_i\right)^2 + \left(\widetilde{D}_i - \tilde{R}_i\right)^2} \tag{2.31}$$

where

$\widetilde{w}_i$ = weight of criterion in *i-th* row;

$\widetilde{D}_i$ = Summation values in *i-th* row;

$\widetilde{R}_i$ = Summation values in *j-th column*.

After that, each weight of criterion will be normalized using equation;

$$\widetilde{w_i} = \widetilde{W}_i / \sum_{i=1}^{n} \widetilde{W}_i \tag{2.32}$$

where $\widetilde{w}_i$ is weight of *i-th* criterion and $\widetilde{W}_i$= weight of criterion in *i-th* row (Gigovic et al., 2016).

To sum up, the strengths of DEMATEL are:

(1) Due to the matrix system being used in DEMATEL, it does not limit the number of experts and criteria being involved;

(2) Expert opinion as human intuition in the form of linguistic values can be incorporated in DEMATEL especially using Fuzzy Logic;

(3) Users can assess the influence from one criterion to other criteria by employing threshold value or α.

2.5.2 Fuzzy DEMATEL (FDEMATEL)

The capability of DEMATEL to be integrated with fuzzy logic and later to produce suitability maps had been practically applied in industrial park location (Arabsheibani et al., 2015) and ecotourism location (Gigovic et al., 2016). Basically, FDEMATEL integrates expert preferences which are expressed in fuzzy into translation matrix and later be defuzzified to produce set of weights.

a) Converting fuzzy expert preferences

In FDEMATEL, expert preferences to analyze relationship among criteria can be expressed in linguistic values namely No influence (NO), Very Low influence (VL), Low influence (L), High influence (H), Very High influence (VH). To be fit in the DEMATEL matrix, these linguistic values need to be transform into real numbers, which can be performed by applying certain triangular fuzzy numbers such as Lin and Wu (2004) triangular fuzzy (Arabsheibani et al., 2015) or Likert Scale (Gigovic et al., 2016). Table 2.6 shows specific triangular fuzzy number.

Table 2.6 Triangular fuzzy numbers (Arabsheibani et al., 2015).

Linguistic Terms	Triangular Fuzzy Numbers
NO	0, 0, 0.25
VL	0, 0.25, 0.5
L	0.25, 0.5, 0.75
H	0.5, 0.75, 1.0
VH	0.75, 1.0, 1.0

b) Normalizing the value of preferences

After converted from fuzzy expert preferences, the matrix of expert preferences then be averaged with Equation (2.33) (Gigovic et al., 2016):

$$\tilde{z}_{ij} = \left(z_{ij}^{(l)}, z_{ij}^{(m)}, z_{ij}^{(r)}\right) = \begin{Bmatrix} z_{ij}^{(l)} = \min\left(z_{ij}^{e}\right) \\ z_{ij}^{(m)} = \sqrt[k]{\prod_{i=1}^{k} z_{ij}^{e}} \\ z_{ij}^{(r)} = \max\left(z_{ij}^{e}\right) \end{Bmatrix} \tag{2.33}$$

where e is the opinion of expert e, while k is k-th criterion.

After averaged, the fuzzy matrix of expert preferences (Arabsheibani et al., 2015) will be displayed as;

$$\tilde{Z} = \begin{bmatrix} 0 & \tilde{z}_{12} & \cdots & \tilde{z}_{1n} \\ \tilde{z}_{21} & 0 & \cdots & \tilde{z}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{z}_{n1} & \tilde{z}_{n2} & \cdots & 0 \end{bmatrix}$$

The averaged fuzzy matrix then be normalized by dividing averaged fuzzy expert preferences matrix with $\boldsymbol{r}$ (Pamučar and Ćirović, 2015), while $\boldsymbol{r}$ can be expressed as follows:

$$\tilde{R} = \max\left(\sum_{j=1}^{n} \tilde{z}_{ij}\right) = \left(r^{(l)}, r^{(m)}, r^{(r)}\right) \tag{2.34}$$

The result of normalization of fuzzy expert preferences matrix (Arabsheibani et al., 2015) will be like this:

$$\tilde{X} = \begin{bmatrix} 0 & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & 0 & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \cdots & 0 \end{bmatrix}$$

where

$$\widetilde{x_{ij}} = \frac{\widetilde{z_{ij}}}{R} = \left(\frac{l_{ij}}{r}, \frac{m_{ij}}{r}, \frac{r_{ij}}{r}\right) \tag{2.35}$$

l_{ij} = left position of transformed fuzzy expert preferences by using triangular fuzzy numbers;

m_{ij} = middle position of transformed fuzzy expert preferences by using triangular fuzzy numbers;

r_{ij} = right position of transformed fuzzy expert preferences by using triangular fuzzy numbers.

c) Computing the relation matrix

The next step after being normalized, fuzzy expert preferences matrix needs to be converted into translation matrix. The purpose of translation matrix is for later computation of Prominence (*D*+*R*) and Effect (*D*-*R*) values. The result of translation matrix (Arabsheibani et al., 2015) will be like this:

$$\tilde{T} = \begin{bmatrix} \tilde{t}_{11} & \tilde{t}_{12} & \cdots & \tilde{t}_{1n} \\ \tilde{t}_{21} & \tilde{t}_{22} & \cdots & \tilde{t}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{t}_{n1} & \tilde{t}_{n2} & \cdots & \tilde{t}_{nn} \end{bmatrix} \tag{2.36}$$

$$\tilde{t}_{ij=(l''_{ij},m''_{ij,}r''_{ij})}$$

$$i, j = 1,2, \dots, n$$

$$[l''_{ij}] = X_l x(I - X_l)^{-1}$$

$$[m''_{ij}] = X_m x(I - X_m)^{-1}$$

$$[r''_{ij}] = X_r x(I - X_r)^{-1}$$

where

X_l = normalized value of left position inside the t_{ij} value;

X_m = normalized value of middle position inside the t_{ij} value;

X_r = normalized value of right position inside the t_{ij} value;

I = Identity matrix of matrix *n x n*;

X_l^{-1} = inverse matrix of normalized value of left position inside the t_{ij} value;

X_m^{-1} = inverse matrix of normalized value of middle position inside the t_{ij} value;

X_r^{-1} = inverse matrix of normalized value of right position inside the t_{ij} value.

d) Obtaining $\tilde{R}$ and $\tilde{D}$ fuzzy values

To produce $\tilde{D}$ fuzzy values by summing the *i-th* row of $\tilde{t}_{ij}$ inside translation matrix, and to obtain $\tilde{R}$ fuzzy values by summing the *j-th* column of $\tilde{t}_{ij}$ inside translation matrix. The detail equation of how to obtain $\tilde{R}$ and $\tilde{D}$ fuzzy values has been shown in Equation (2.28) and Equation (2.29).

e) Defuzzifying $\tilde{D} - \tilde{R}$ and $\tilde{D} + \tilde{R}$ values

To obtain Prominence (D+R) from fuzzy $\tilde{D} + \tilde{R}$ values and also Relation (D-R) from fuzzy $\tilde{D} - \tilde{R}$ (Arabsheibani et al., 2015), it needs to be defuzzified by using Equation (2.37):

$$(\tilde{D} \pm \tilde{R})^{def} = \frac{(\tilde{D}\pm\tilde{R})_l^{fuzzy} + 4(\tilde{D}\pm\tilde{R})_m^{fuzzy} + (\tilde{D}\pm\tilde{R})_r^{fuzzy}}{6} \tag{2.37}$$

where

$(\tilde{D} \pm \tilde{R})_l^{fuzzy}$ = $\tilde{D} \pm \tilde{R}$ values from left position of $\tilde{R}$ and $\tilde{D}$ in translation matrix;

$(\tilde{D} \pm \tilde{R})_m^{fuzzy}$ = $\tilde{D} \pm \tilde{R}$ values from middle position of $\tilde{R}$ and $\tilde{D}$ in translation matrix;

$(\tilde{D} \pm \tilde{R})_r^{fuzzy}$ = $\tilde{D} \pm \tilde{R}$ values from right position of $\tilde{R}$ and $\tilde{D}$ in translation matrix.

f) Criteria weighting

To derive criteria weights from FDEMATEL, it uses the same method as in DEMATEL. The detail equations of how to obtain normalized criteria weights have been shown in Equation (2.31) and Equation (2.32).

2.6 Comparison of PUP suitability methods

Based on related concepts and theories about spatial FISs and DEMATELs, it can be concluded that all methods have the ability to produce PUP suitability maps. However, main advantages of FDEMATEL are able to investigate the relationship of all criteria being assigned, and also select most/less important criteria. On the other hand, spatial FIS can be employed to produce certain values from the input, and users are able to decide rules which effect the output variables. Details of capabilities in each methods can be seen in Table 2.7.

Table 2.7 Comparison of generation procedures of suitability maps among DEMATEL, FDEMATEL, Sugeno FIS, and Mamdani FIS.

Procedures for suitability maps	DEMATEL	FDEMATEL	Sugeno FIS	Mamdani FIS
Expert preferences requirement	Yes	Yes	No	No
Criteria aggregation using linguistic values	No	No	Yes	Yes
Obvious criteria influence expression	Yes	Yes	No	No
Investigate relationship between criteria	Yes	Yes	No	No
Decide rules to effect the output	No	No	Yes	Yes
Can produce land suitability maps	Yes	Yes	Yes	Yes
Required actual cases	No	No	Yes	Yes
Variety of defuzzification methods	No	Yes	Yes	Yes
Can produce certain output value of variable	Yes	Yes	Yes	Yes

2.7 Previous studies

FDEMATEL has been performed to identify and evaluate suitable location for ecotourism in Dunaski Kljuc region of Serbia where it was crossed by famous Danube River (Gigovic et al., 2016). Another objective of this study was to explore the advantage of GIS-FDEMATEL method in locating suitability zone for ecotourism. Moreover, this study used 16 criteria which were clustered into 4 main groups namely: topography, natural, environmental and socio-economic. Furthermore, the most important process was to convert linguistic values of experts' opinion about each criterion by using fuzzified Likert Scale and later FDEMATEL to produce weights of criteria. In addition, four categorical maps of ecotourism suitability were successfully generated consisted of: high, moderate, marginal and not suitable. Interestingly, for sensitivity analysis this study used five different scenarios to detect significant changes percentage in each suitability class. If more weight given to topography group of criteria, the percentage of suitable areas for ecotourism falls under 80%. On the other hand, if more weight given to natural group of criteria, smallest percentage of unsuitable location for ecotourism when compared to any scenarios.

Another application of FDEMATEL in conjunction with Analytical Network Procedure (ANP) has been performed to search for suitable location of industrial estate in Iran (Arabsheibani et al., 2015). Interestingly, the normalized matrix of experts' opinion from FDEMATEL can be multiplied with unweighted ANP supermatrix to generate weighted supermatrix. This process was used to give weights for land cost (C1), distance to nearest fault (C2), percentage of land slope (C3), distance to nearest main road(C4), distance to nearest railway (C5), distance to nearest power transition (C6), distance to nearest water supply (C7), distance to nearest city center (C8), distance to nearest protected area center (C9), distance to nearest health care center (C10), and distance to nearest available industrial area (C11). The final product was the combination of each weight produced raster maps with five classes of suitability for industrial estate namely; very high, high, medium, low, and very low.

Related to accessibility to PUP, it can be approached by using three different models namely: covering model, travel cost model and minimum distance model (Meng and Malczewski, 2015). In each model population data in every Dissemination Area (DA) was integrated with distance and can be classified further based on three PUP classes with different sizes which consisted of Mini Park, Neighborhood Park and Community Park. In this study, accessibility scores from three models then be integrated by using Weighted Linear Combination (WLC), but firstly have to be computed with entropy technique.

The use of Sugeno framework in this study has been inspired by a research study in Yogyakarta, Indonesia which was aimed to determine whether village and infrastructure condition in neighboring village can predict economic opportunity in village level (Wismadi, Brussel, Zuidgeest, Sotomo, Nugroho, and Maarseveen, 2012). In each rule generated by specific combination of recorded actual case, dependent variable of economic opportunity was computed by using multiple regression with series of independent variables, namely: infrastructure, transport, electricity, telecom, water and demographic. For every rule different maps of classified fuzzy membership were combined by using fuzzy "AND" and then be normalized. Three different maps for villages in Yogyakarta with different economic opportunity classes were resulted namely: low, medium and high.

A research which was purposed to apply suitability location for tourism in South Moravia Region by comparing results of three defuzzification methods (Kolisko, 2015), has been a foundation technique for the Mamdani FIS weight evaluation in this study. Specifically, there were seven inputs to generate map of bike's difficulty namely: distance to protected areas, distance to water bodies, distance to monuments and historical sites, forest accessibility, motorcycle road, bike trails and hiking trails. For these criteria, fuzzy membership function was applied and then all of them were combined by using fuzzy "MIN" function. In each consequent from each rule, a midpoint value was computed to gather the relationship with its weight. After relationship between midpoint and weight for each rule was determined, then three defuzzification methods consisted of Center of Maximum (CoM), Center of Sums (CoS), and Larsen were applied. Based on these results, three different maps of bike difficulty can be generated.

2.8 Synthesis of the study approach

To contribution to the field of study, some criteria and methods were adopted from available researches. Some of them were selected and designed specifically for this research and they are different or never existed in other current researches before.

1) Criteria selection in general was adopted from available current researches.

2) Additional PUP policy demand as one of the antecedents of FISs was created. A number of visit was also created as a consequent of FISs and as suitable index of FISs' raster-based analysis.

3) As no mentioned in any available current researches, optimum demand estimation using FISs was performed first in this research. The demands can be used as

a bench mark for capability analysis in village-based demand level when incorporating with feasible PUP area.

4) Fuzzy membership functions such as decreasing and increasing linier and sigmoidal were selected to transform fuzzy criteria data to be fuzzy membership values before input into the analyses. The functions were selected to be consistent with criteria characteristics influencing to PUP suitable index.

5) Population density as one of criteria required for both village-based and raster-based analyses were estimated using Areal Interpolation (AI). This allowed selective polygon attribute interpolation for more reasonable input and accuracy.

6) In raster-based analysis, both FISs and DEMATELs with different conceptual methods were used to perform PUP suitability analysis. The results were compared when incorporating with feasible area from Land Use Land Cover (LULC).

7) To be more practical in implementation for decision makers, feasible area for PUP development was extracted from the incorporation of feasible LULC and PUP suitable area.

8) The compatibility analysis was performed to determine the degree of incorporation between village-based optimum demand and raster-based PUP feasible area in both attribute and spatial location. The performance could tell which method provide the best compatibility and how the combination of results from methods can serve the demand as a whole.

CHAPTER III

RESEARCH METHODOLOGY

The spectrum of this study focuses on the technique to integrate result from questionnaires and interviews into linguistics fuzzy numbers and geospatial modeling to determine optimum PUP area and location in BM. The overview framework of the study is presented in Figure 3.1. In detail, this chapter describes the procedures to acquire data that come from urban policy planning and regulation and how to convert the data into GIS environment with clean topology to avoid error data processing.

Moreover, detail equations to generate optimum PUP area demand based on estimated PUP visitor is explained. Furthermore, this chapter includes framework to generate suitable raster cells indicate optimum location of PUPs both in Mamdani and Sugeno FIS.

3.1 Data gathering and preparation

3.1.1 Policy and planning data

3.1.1.1 BM master plan

BM Master Plan 2011-2031 was publicly announced in 2011 and legalized as BM Regulation Number 8 Year 2011. According to this regulation, BM Master Plan is land use plan of a city based on national and provincial master plan.

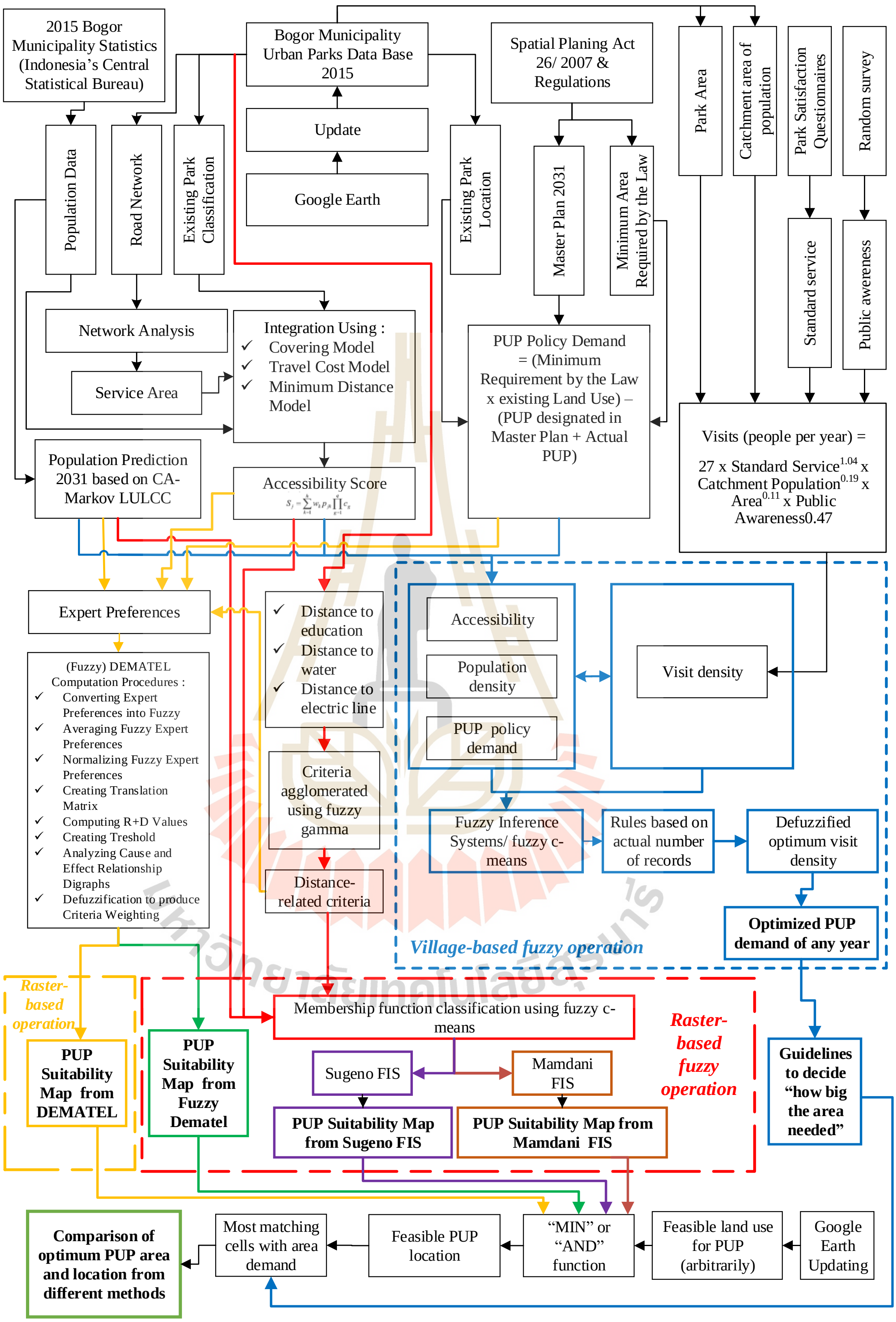


Figure 3.1 Research framework.

BM Master Plan 2011-2031 consists of: (a) objectives, (b) policy, (c) urban planning strategies, (d) urban space structure master plan, (e) urban space pattern master plan, (f) urban strategic space, (g) urban land use guidelines, and (h) criteria to control urban land use.

In terms of map, main products of BM Regulation Number 8 Year 2011 can be observed in Table 3.1.

Table 3.1 BM Master Plan Maps used for information extraction.

Map name	Scale	Digital format	Extracted data for this study	Method of information extraction
BM space structure master plan;	1:50,000	Vector	City center hierarchy to determine PUP hierarchy levels	GIS selection and query
BM space pattern master plan	1:50,000	Vector	Location of designated PUP in 2031	GIS selection and query
BM strategic regions master plan;	1:50,000	pdf	Location priority to develop PUP	digitization
BM transportation system master plan	1:50,000	pdf	Road network	digitization

Data source: *BAPPEDA.*

3.1.1.2 PUP policy and regulation compilation

As mentioned before, the umbrella for all PUP planning and policy in Indonesia is the SPL Number 26 Year 2007 which specifically defines planned PUP to be 20 percent of municipality administrative area. This then will be implemented in every municipality and regency master plan, which in this study has been transformed into BM Regulation Number 8 Year 2011.

Since the goal is to achieve PUP area by 2031 and in BM policy depends on the newly elected mayor based on his/her vision during election campaign, therefore every mayor make its own development policy. This policy is then legalized as guidelines regulation for five years duration, in this case BM Regulation Number 6 Year 2014 (see Table 3.2). All of this regulation can be accessed publicly through the BM website.

Table 3.2 PUP policy and regulation compilation.

Regulation	Regulatory Agencies	Extracted data for this study	Data source
SPL Number 26 Year 2007	Republic of Indonesia	Minimum requirement of PUP	http//:www.pu.go.id/site/view/76
IMI Regulation Number 1 Year 2007	IMI	PUP classification	http//:www.kemendagri.go.id/produk-hukum
IMPW Regulation Number 5 Year 2008	IMPW	PUP technical criteria	http//:www.pu.go.id/site/view/76
BM Master Plan (Regulation Number 8 Year 2011)	BM	Location of designated PUP in 2031	http//:siskum.kotabogor.go.id
BM Medium Range Planning Regulation Number 6 Year 2014	BM	Vision, Mission, Goal and Strategy of Bogor development 2015 - 2019	http//:siskum.kotabogor.go.id .

3.1.2 Spatial data preparation

Population data source is from the Indonesian Bureau of Statistics which provides yearly population density per village in BM. However, since the basic data of land use and existing park location comes from updating project of PUP database in 2015, therefore the year of population data will be from 2015.

Road network data of BM has already been available in 2015 BM PUP GIS database with collaboration of BM Traffic and Public Works Agency.

GIS database of existing park location is available as a result from 2015 BM PUP database project. It had been derived from satellite image of 2014 with digitization method and verified in the field by consultant from *DKP* and later be classified as GUOS (GBM, 2015).

Table 3.3 Data type and source.

Data	Data Source	Data format	Year
Population data	1. *BPS* 2. BM *BPS*	Excell	2015
Road network	1. BM *DLLAJ* 2. BM *DBMP*	GIS-vector	2015
Existing Park location	1. 2015 BM PUP GIS database	GIS-vector	2015

3.1.2.1 GIS data topology

In this study, topology check is needed to ensure that every GIS data being prepared contain no errors such as gaps between polygons or overlapping features. Topology is the arrangement for how point, line, and polygon features share geometry (ESRI, 2018c), e.g. setting up rules for adjacent village polygons so that there is no gap between villages. If the village polygons contain errors like gaps, the population data inside the polygons will create bias after raster format conversion.

There are several rules in this study which will be applied in various type of GIS data topology (Table 3.4).

Table 3.4 Various topology set of rules for different kind datasets (ESRI, 2018c).

Datasets	Criteria	Topology's rules
Polyline	Road	• Must not intersect • Must not overlapped • Must not self-intersect • Must not self-overlapped • Must not intersect or touch interior
Polygon	Village administrative	✓ Must not overlapped ✓ Must not have gaps ✓ Must not have dangles ✓ Must not intersect
Node	Existing park location as centroids Village administrative centroids	○ Contains one point ○ Must be disjoint ○ Must be covered by boundary of

3.1.2.2 Vector- to raster-based GIS data conversion

To convert spatial data from vector to be raster datasets such as accessibility and policy demand, attributes in each polygon need to be filled in form of cell database, which will lead to creation of a centroid in every polygon and eventually interpolating them using IDW. The following flowchart (Figure 3.2) displays steps of the conversion.

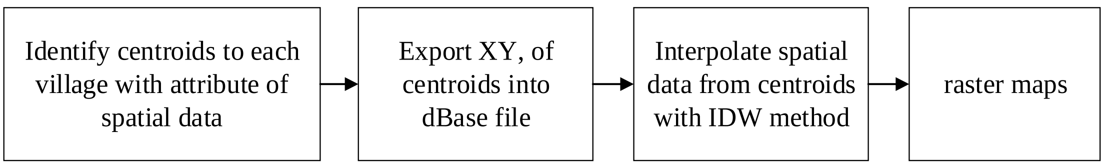


Figure 3.2 Flowchart to interpolate population density by using IDW.

In addition, to correct an error on total accessibility score and policy demand in a village resulted from interpolation, this formula was used:

$$X_{original} = a.\ X_{estimated} \tag{3.1}$$

where $X_{original}$ is the total number of accessibility/policy demand in a village, while $X_{estimated}$ is total accessibility/policy demand resulted from interpolation. The coefficient “a” of any villages is used to multiply raster layer of a corresponding village to achieve the same total accessibility/policy demand with the original.

3.2 Criteria data and map generation

3.2.1 Population density distribution

The purpose of employing population density prediction in this study is to input it into fuzzy inference systems so that the value can be classified based on its fuzzy linguistic terminology or sets. Population density prediction is very important since rules in FISs for village-based fuzzy operation will be tuned to propagate consequent variable. This assumes that population density prediction in 2031 has close relationship with PUP area per visit in village-based fuzzy operation. However, to match with the idea of Master Plan 2031, it is important to predict population density based on conditions corresponding to LULC in 2031.

Methods of predicting population density based on LULC has been performed in various researches, Gallego and Peedell (2001) compared six methods of population density prediction based on CORINE land cover. This research came out with the conclusion that results of population density estimation using land cover coefficients can be improved by simplifying land cover nomenclature. Meanwhile, Eicher and Brewer (2001) inputted socio-economic data into LULC in 159 counties of

Virginia, West Virginia, Maryland, Pennsylvania, District of Columbia using areal interpolation method for the prediction. Eicher and Brewer (2001) used 3 LULC classes namely urban, agricultural/woodland, and forested land involving in the process. Water body was not considered as inhabitant land cover class. Therefore, the method of areal interpolation of ArcGIS was used to distribute population from 68 villages into predicted LULC classes that people living in and resulted from CA-Markov model. Water class was considered as unpopulated.

3.2.1.1 LULC modelling using CA-Markov

This operation aimed to predict BM LULC in 2031 using CA-Markov method. A set of LULC data of 1992, 2005, and 2018, the same time span, were input into the process.

LULC data of 1992 was extracted from Landsat TM 5 using ISODATA clustering method, based from 1990 LULC data which was produced by Indonesian Survey and Mapping Coordination Agency (*Bakosurtanal-bahasa*).

Before classification process, radiometric correction was carried out for images using pre-processing menu in ENVI specifically designed for Landsat TM 5 calibration. At first, 10 clustered were generated using ISODATA function, ArcGIS. Furthermore, smoothing process was performed in post-image classification to reduce noise. As required, 10 original classes were grouped into 4 namely, urban, agricultural land, green area (PUP, forest, and botanical garden), and water body for population density prediction.

For validation, random 50 points of each class, following good rule of thumbs suggested by Congalton (1991), were selected from classified Landsat TM 5 image. for operating error matrix. Over all accuracy and KHAT statistics were estimated from the matrixes to validated classification results of 1992 and 2018.

In this study, the objective of CA-Markov method is to predict the 2031 LULC based on 2018 LULC (Figure 3.3). Firstly, initial cells of earlier raster image from 1992 LULC were paired with cells from 2005 LULC whereas both images have time span of 13 years. For every LULC class, the change from 1992 and 2005 image was computed to generate conditional LULC change (LULCC) probability from 0 to 1 where 0 indicates no change and 1 shows completely change (Takada et al., 2010). This score is used to give value for every cell within 2005 LULC based on assessment using Markovian change matrix. When applying this value for every LULC class, 4 suitable raster images were produced for urban, agricultural land, water body and green area. However, Markovian conditional change score was adjusted based on previous studies in CA-Markov that urban always expands and very few chances to convert into other classes (Rimal, Zhang, Keshtkar, Wang and Lin, 2017; Aunphoklang, 2018). Based on this change matrix, CA was run to simulate LULC in 2018 with 3x3 contiguity filter using TerrSet Geospatial Monitoring and Modelling System from Clark University Labs (Eastman, 2016).

All pixels in predicted 2018 LULC then paired with latest image of Google Earth 2018 to see the agreement by using overall accuracy and KHAT. Hence, if the agreement coefficients from overall accuracy and KHAT are satisfied then the CA would be reliable to simulate 2031 LULC using 2018 LULC and Markovian conditional change matrix from previous operation. In addition, 4 suitability raster images from 1992-2005 would change to 4 suitability raster images of 2018 LULC based on Markovian change matrix. The method of changing suitability map based on validated latest LULC and transition change matrix has been performed previously by Aburas, Ho, Ramli, and Ash'aari (2017) in Seremban, Malaysia by validating first the 2000-2010 predicted LULC from CA-Markov and then changed suitability map based on LULC 2010 to predict 2020 and 2030 LULC.

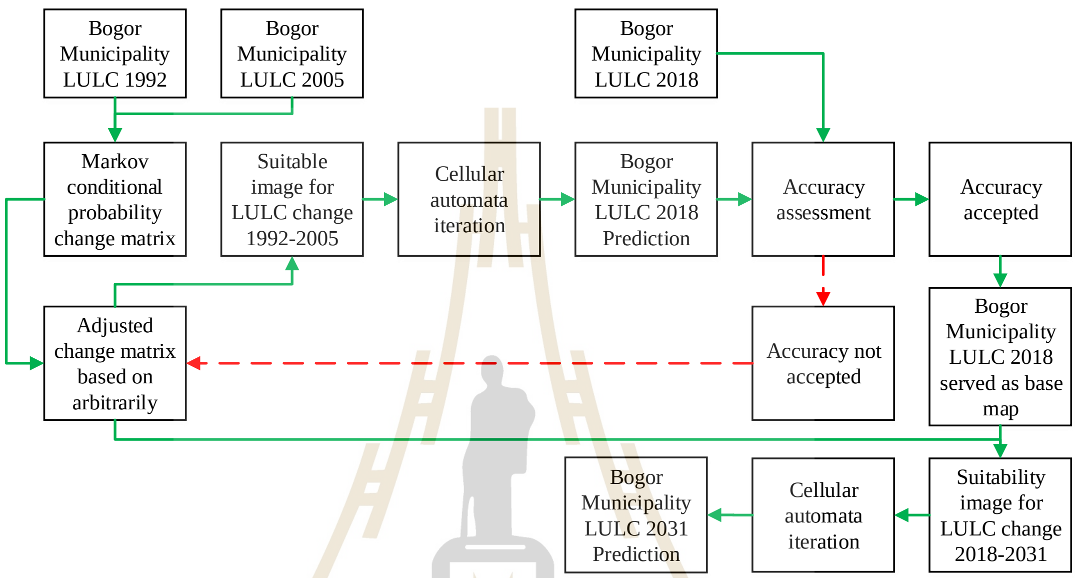


Figure 3.3 Framework for predicted 2031 LULC.

3.2.1.2 Areal interpolation

Areal interpolation refers widely to technique which allocates datasets from one or more geographic units also known as source zones where datasets being aggregated into another incompatible and overlaid target zones using spatial algorithms (Reibel and Agrawal, 2007). In this method, aggregated datasets from source polygons will be interpolated into a new surface density raster map by using kriging method (Krivoruchko, Gribov and Krause, 2011). Generated raster map then will be re-aggregated into target polygons equipped with RMSEE (Root Mean Square Standardized Error) values for every chosen aggregation method (ESRI, 2018d). It is a unique method when compared to IDW because in IDW a centroid is placed within a polygon to interpolate polygon value to become raster data while in areal interpolation a centroid is replaced by lattice spacing and from the centres of many lattice spacing within one polygon dataset is being interpolated to become raster.

Firstly, predicted population of 2031 in vector datasets of villages in BM were input-into areal interpolation of ArcGIS and since number of villages were larger than 30 it is assumed that population data were normally distributed so that Gaussian data type was chosen. After lattice spacing was set, then it simulated the valid model for kriging interpolation based on RMSEE between semi-variogram of original dataset (measured) and resulted dataset after interpolation (predicted). The RMSEE can be expressed in the following equation:

$$\sqrt{\frac{\sum_{i=1}^{n}\left[\left(\hat{Z}(s_i)-z(s_i)\right)/\hat{\delta}(s_i)\right]^2}{n}} \tag{3.2}$$

where $\hat{Z}(s_i)$=measured values, $z(s_i)$=predicted values, $\hat{\delta}(s_i)$=standard deviation, n=number of datasets. If RMSSE approaches 1, it means standard errors of the prediction are valid. When RMSSE is greater than 1 then the variability of the prediction is underestimated and while variability is overestimated RMSSE is less than 1 (ESRI, 2018d). In this study, type of interpolation method will be chosen if simulated interpolation shows RMSSE approaches 1.

In the final step, 2031 predicted population in form of density surface was re-aggregated into predicted 2031 LULC based on CA-Markov by selecting only three classes, namely urban, agricultural land, and green area while water according to Eicher and Brewer (2001) is unpopulated LULC class.

For validation and comparison, IDW was also performed to predict BM population density in 2015 and 2031. Values from IDW were compared with AI in 2 parameters, namely RMSSE and total population error.

Another parameter to indicate whether an interpolation method is good or not is to see if the total population errors from all villages resulted from an interpolation method is not so big or at least smaller than other method. This errors can be quantified by modifying equation from Gallego and Peedell (2001):

$$\text{Total Population Errors} = X_{oy}\text{-}X_{my} \tag{3.3}$$

where X_{oy} is the total population of all villages after interpolation, X_{my} is the total population of all villages from census or prediction. The better method of interpolation could be the method having smaller errors.

3.2.2 Accessibility

To generate accessibility map, this study will perform service area menu in ArcGIS software by incorporating 15 minutes of walking time impedance from PUP location in BM.

3.2.3 PUP policy demand

PUP policy demand in this study will only be acted as antecedent variable in FISs to produce PUP area per head as consequent variable. It means PUP policy demand is only involved in village-based fuzzy operation but not raster-based fuzzy operation. PUP policy demand plays important role as fuzzy controller in determining how big the PUP area is required in PUP suitability raster map.

However, there is possibility that the result of PUP policy demand computation by using Equation (2.11) will show minus value. Therefore, it is assumed that if the result of Equation (2.11) is minus then it will be considered as zero. This assumption based on consideration that minus result indicates that the village no longer needs more PUP, on the other hand positive result of Equation (2.11) indicates the demand of PUP on policy side.

3.2.4 Distant-related criteria

Firstly, it needs to set the spatial resolution which will be used in this study since spatial resolution will define the outcome of the suitability map of PUP. It also determines the distance required for buffer function in every distance criteria. In this study, the spatial resolution is set to be 10 m x 10 m for a chance to fit to the smallest type of park.

Secondly, all of these three criteria namely, distance to education, distance to water, and distance to electric power line are input into ArcMap software to produce Euclidean distance based on Table 2.3 and Table 2.4. This data will be prepared based on 10 x 10 meter spatial resolution.

3.2.5 Visit density estimation

As described in Equation (2.13), there are four main components in PUP visitor estimation namely (a) standard service, (b) catchment population, (c) park area, and (d) public awareness. While method to have catchment area population has already explained in content of service area sub-chapter, and the questionnaire of park satisfaction attribute has been displayed in Table 2.5, and this questionnaire will be performed by using social media.

3.3 Optimum PUP area demand estimation (village-based fuzzy analysis)

3.3.1 Sugeno FIS

For Sugeno FIS, three antecedent variables and one consequent variable will be classified first by using fuzzy c-means each into three classes namely high, medium, and low. Then every class of each antecedent and consequent will be paired by using rules which will be developed by observed significant PUP per visit value in every village. Three antecedent variables which will be input are accessibility, population density, and PUP policy demand while consequent variable is visit density (Figure 3.1). The output from Sugeno FIS is optimized visit density, then the optimized PUP demand of each village can be expressed as Equation (3.4):

$$\textit{Optimized PUP demand} = \textit{estimated number of visit in a village} \div \textit{optimized visit density} \tag{3.4}$$

3.3.2 Mamdani FIS

In Mamdani FIS, the classified membership function for every antecedent and consequent variables are the same with Sugeno FIS, the only difference is the way it produces consequence. While Sugeno FIS uses either 0-order or 1-order linear equation for its consequent, the Mamdani FIS uses linguistic value for its consequent variable. As a result, rule development in Mamdani will also be deployed its linguistic value both in antecedent and consequent variables.

Similar to Sugeno FIS, the optimized visit density will function for optimized PUP policy demand which in turn will control the area needed in raster-based fuzzy operation. Equation (3.4) will be used to obtain optimized PUP area demand.

3.4 Suitability map generation (raster-based fuzzy analysis)

3.4.1 Sugeno FIS

For this type of analysis, the antecedent consist of three variables namely accessibility, population density, and distant-related criteria. All of these three criteria are then input into Sugeno FISs with certain developed rules to produce consequent variable, visit density.

Firstly, all antecedent-consequent data are classified by using FCM technique, which grouped the data into low, medium, and high. Next step is to develop rules based on combination of antecedent-consequent variables, which can reach maximum of 3^4=81 rule combinations.

To reduce number of rules being applied, this study will limit percentage of actual number or data records by analysing reasonable relationship of input data. In addition, rule development table can be developed to illustrate relationship between rules (Table 3.5).

Table 3.5 Rule development in FIS and number of records/cells.

Rule	Antecedent variables			Ranking of actual case based on threshold of number of records
	Accessibility	Population density	Distance	
Rule 1	$A_{1..}A_n$	$B_{1..}B_n$	$C_{1..}C_n$	1st rank
k*th*-Rule	$A_{1..}A_n$	$B_{1..}B_n$	$C_{1..}C_n$	i*th* - rank

Remarks: A = linguistic value of accessibility, B = linguistic value of population density, C =linguistic value of distance

After it is identified which rules should be included in the analysis, all classified variables then integrated by using fuzzy overlay functions of ArcMap with

"AND" operation. The purpose of this operation is to produce weight of every rule being applied (Wismadi, et al., 2012). Each resulted raster-cells map from "AND" operation then normalized by using Equation (3.5):

$$\widetilde{\omega_k} = \frac{\omega_k}{\sum_{i=1}^{n} \omega_i} \tag{3.5}$$

where

$\widetilde{\omega_k}$ = normalized weight for every rules;

ω_k = weight of k-th rule;

$\sum_{i=1}^{n} \omega_i$ = summed weight of all rules.

Interestingly, in 1-order form, each rule in Sugeno FIS can produce new linear output by applying multiple regression only in the area which designated rule is applied. In this case, for every raster cells occupied by specific rule it will compute multiple regression by using equation:

$$Y = ß_0 + ß_1X_1 + ß_2X_2 + \ldots\ldots\ldots + ß_nX_n + \varepsilon \tag{3.6}$$

where

Y = dependent variable;

$ß_s$ = regression coefficients;

X_s = explanatory variable;

ε = random error/residuals.

Dependent variable is visit density estimation of PUP in every village (visit/km^2), while explanatory variables are (1) accessibility score, (2) population density (persons/km^2), and (3) distant-related criteria (km).

In this case, an actual case number of records for multiple regression is selected inside the area which a rule is applied. For example, if the rule indicates that the area has low access, low distance and low population density, it means only selected cells of the area will be extracted. To perform this action, it can apply raster calculator where area applied by the rule is scored 1 and non-applied is scored 0 and multiply with designated antecedent map.

Finally, all maps which are generated from all rules can be defuzzified to produce single PUP suitable map by using Equation (3.7):

$$O = \sum_{k=1}^{n} \widetilde{\omega_k}\ Z_k \qquad (3.7)$$

where

$\widetilde{\omega}_k$ = normalized weight factor for every rules;

Z_k = visit density value cells assigned for k-th rule.

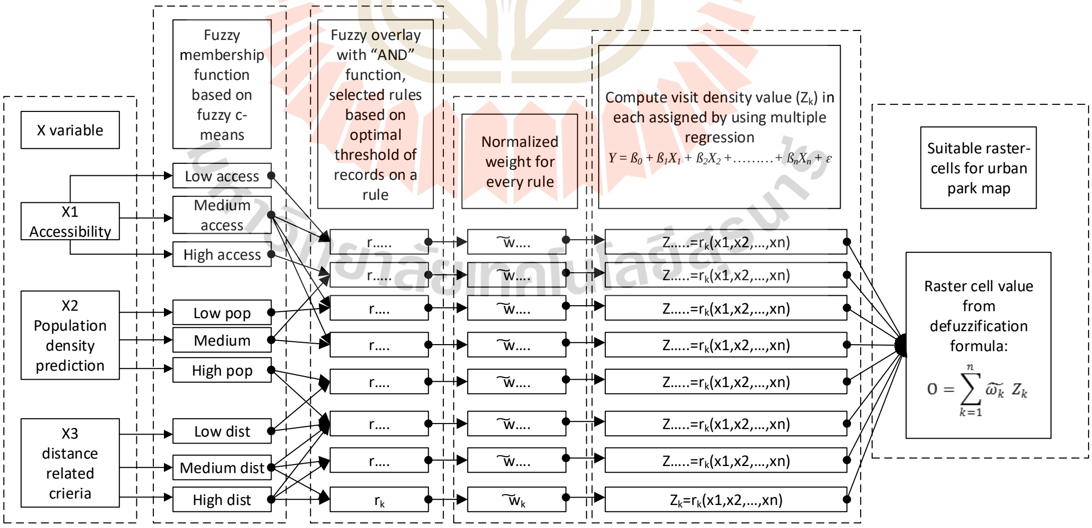


Figure 3.4 Technical flowchart to generate suitable PUP locations based on Sugeno FIS (Wismadi et al., 2012).

In detail, Figure 3.4 shows a technical process to get the value of each raster cells as a result of Sugeno FIS, which is modified from a research in Yogyakarta Indonesia aimed to generate map set of village classified based on its fuzzy value (Wismadi et al., 2012).

3.4.2 Mamdani FIS

Similarly to Sugeno FIS, all of the cells of antecedent-consequent variables are input into Mamdani FIS with distinct rules developed from actual cases. The difference is, while in Sugeno FIS deploys linear equation in its output which can be chosen whether 0-order or 1-order, Mamdani FIS's deploys rules which synchronize between antecedent and consequent by using linguistic value.

At first, all raster cells from accessibility, population density, distance suitability, and visit density are input into Mamdani FIS using fuzzy c-means data grouping method (Figure 3.5).

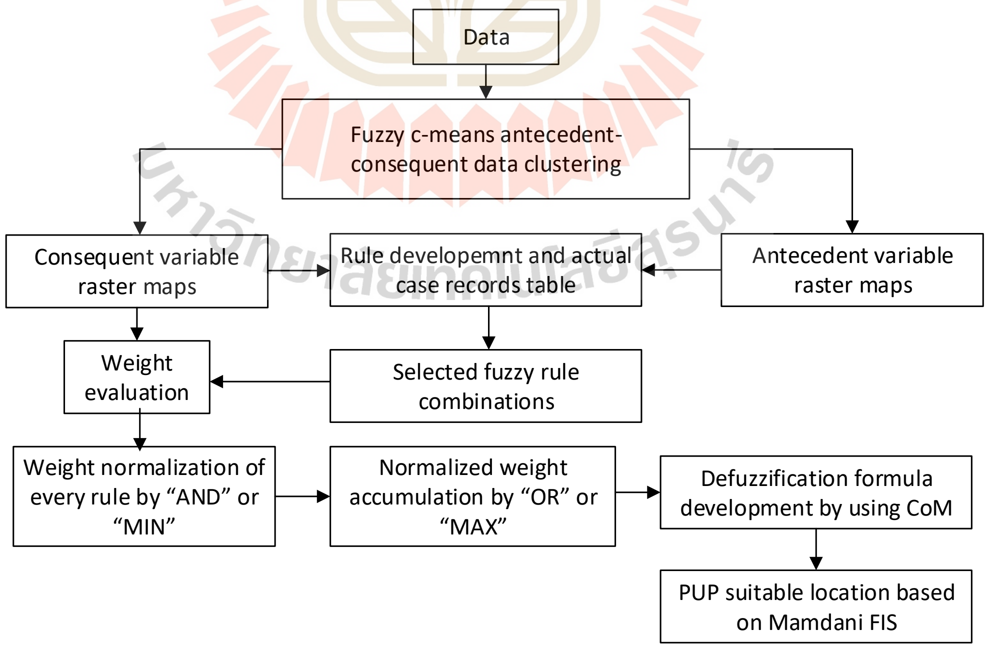


Figure 3.5 Technical flowchart to generate suitable PUP locations based on Mamdani FIS.

Secondly, fuzzy rules are concluded and developed from actual case observation basis. Weight of each fuzzy rule can be determined by "AND" or "MIN" operation and then normalized weights are accumulated by "OR" or "MAX" and then defuzzified using CoM as described in Equation (2.21).

To generate raster cells representing suitable PUP location based on Mamdani FIS, this study will employ fuzzy membership, cell statistics, and raster calculators in ArcMap menus and functions.

3.4.3 DEMATEL

The most important step in DEMATEL is how to get the expert opinions to be used in matrix propagation. In this case, ten experts will be asked to fill questionnaires and the experts' backgrounds come from four different careers which are government officers, academics, and professional landscape architects. All of experts will be chosen of whom with high concern of PUP development and planning. The minimum number of experts is referred to Gigovic et al. (2016), when they performed ecotourism evaluation in Serbia by using GIS-FDEMATEL.

As shown in Figure 3.6, an expert must fill the direct influence between factors both in left and right side. For example, if an expert fill score 4 of accessibility in the left side, it means accessibility has very high influence to population density. And if an expert fill score 1 in right side of population density, it means population density has low influence to accessibility.

QUESTIONNAIRE

Please fill X to mark the degree of influence of both factors located in left and right side which indicates: (0) no influence, (1) low influence, (2) medium influence, (3) high influence, and(4) very high influence.

Accessibility									Population density
0	1	2	3	4	4	3	2	1	0

Accessibility									GUOS policy demand
0	1	2	3	4	4	3	2	1	0

Accessibility									GUOS per head
0	1	2	3	4	4	3	2	1	0

Accessibility									PUP visit density
0	1	2	3	4	4	3	2	1	0

Accessibility									Distance to water body
0	1	2	3	4	4	3	2	1	0

Accessibility									Distance to education
0	1	2	3	4	4	3	2	1	0

Accessibility									Distance to electric power line
0	1	2	3	4	4	3	2	1	0

Figure 3.6 Example of questionnaire for expert to obtain integer score to measure direct relationship of accessibility factors to others, vice versa.

3.4.4 Fuzzy DEMATEL

Almost similar with DEMATEL, to obtain expert opinions in fuzzy DEMATEL it will only need to change its preference from crisp value to linguistic value. This study will use the triangular fuzzy number to represent linguistic value filled by group of experts (Figure 3.7). In addition, based on Figure 3.7, if an expert chooses NO it means his/her choice is translated to fuzzy number of (0,0,0.25), while VH answer is translated to (0.75,1,1). This triangular fuzzy number has been used by Arabsheibani et al. (2015) to select industrial park in Iran.

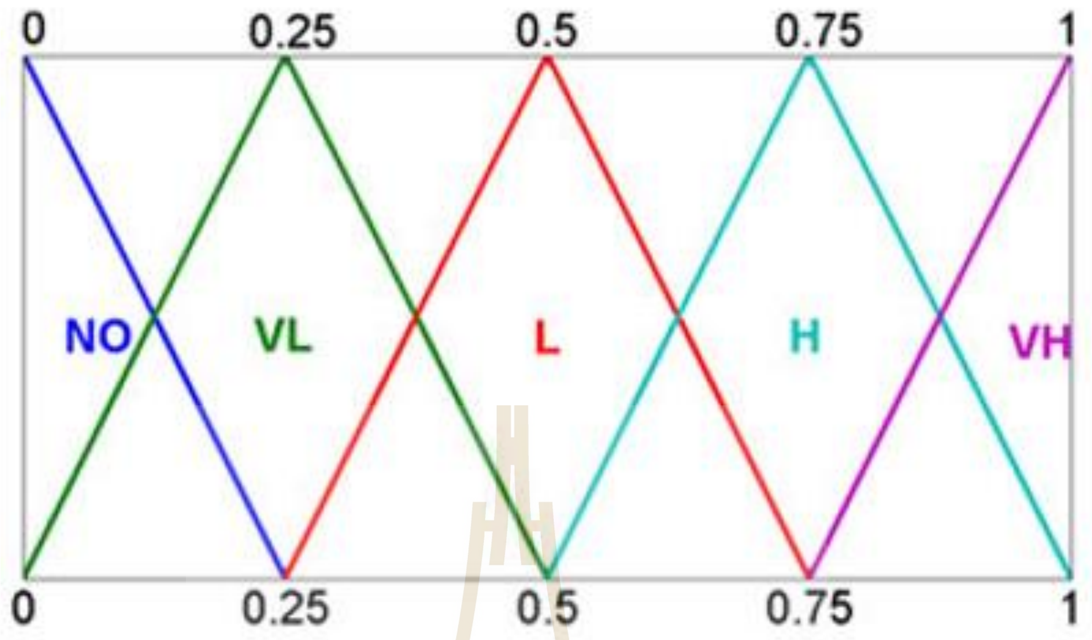


Figure 3.7 Triangular fuzzy number to transform linguistic expert opinion (Li and Wu, 2004).

3.5 Suitable PUP area and location

3.5.1 Suitability classification

The result of suitable raster cells from FISs and DEMATELS will be classified using equal interval method.

3.5.2 Feasible PUP maps generation

Suitable maps resulting from FISs and DEMATELs analysis are considered how feasible they can be developed to be PUP. Overlay and compatibility examination on existing land use data and information will be performed to find the feasible developing area. High scoring is for cell on top of existing land use class possible to develop and for cell having high compatibility to the neighbour land use.

3.6 Comparison of feasible PUP maps

The comparison of feasible maps from analyses can be performed in aspects of meeting optimized PUP demand and visit density using attribute and spatial analyses. Not only will the bigger demand from either Sugeno or Mamdani result be selected as a comparison criterion, but also the percentage of coverage from all villages.

CHAPTER IV

RESULTS AND DISCUSSIONS

This chapter reports results from this research following by discussion of every step. In summary, results from this research consist of (1) input criteria, (2) optimum PUP area based on Sugeno and Mamdani FISs, (3) PUP suitability map from FISs and DEMATELs, (4) PUP feasibility maps from FISs and DEMATELs, and finally (5) comparison among feasibility maps.

4.1 Input criteria

4.1.1 Population density prediction based on CA-Markov LULCC and Areal Interpolation

To seek for suitable park area for villages of BM in year 2031, predicted population density of the year was required. It was estimated from LULC of the year predicted using CA-Markov approach. Then, population of every polygon of land-use type people can live in was estimated and used for areal interpolation (AI) to obtain distribution of population density.

BM LULC 1992 resulted from classification through Landsat 5 TM images is shown in Figure 4.1. Accuracy assessment by comparing 50 pixels of each class between classified 1992 LULC and 1990 BM LULC as reference map showed overall accuracy 81% (Table 4.1) while KHAT coefficient reached 0.74.

Table 4.1 Accuracy assessment of classified LULC in 1992.

Classified BM LULC Landsat TM 5 (1992)**	Reference map of BM LULC (1990)* (number of points)					
	Urban	Agricultural land	Green area	Water body	User's Accuracy	Commission Error
Urban	45	5	0	0	90.00%	10.00%
Agricultural land	5	45	0	0	90.00%	10.00%
Green area	4	14	31	1	62.00%	38.00%
Water body	6	2	1	41	82.00%	18.00%
Producer's Accuracy	75.00%	68.18%	96.88 %	97.62 %	-	-
Omission Error	25.00%	31.82%	3.12%	2.38%	-	-

* Bakosurtanal, 1990.

** downloaded from https://earthexplorer.usgs.gov.

Based on this accuracy assessment, it was acceptable to be input in the further step of 2018 LULC prediction using CA-Markov. Functioned as second date image to get Markovian probability change matrix 1992-2005, BM LULC 2005 come from GBM resulted from updating project of BM LULC 1995-2005.

In addition, it can be observed that urban class in BM is getting bigger in 2018 while water body and agricultural land are decreasing. Surprisingly, green areas are increasing 1.5 km^2 in 2018 when compared to 2005 (Table 4.2). Green area can increase because of several policies such as the development of new cemeteries, golf courses and PUPs. Massive development of Chinese cemeteries in southern Bogor are pushed by Chinese philosophy (*Hongsui*) that a cemetery location should face a mountain (*Hong*) and a river (*Sui*). These two basic requirements are fulfilled by

Gunung Gadung cemeteries in southern BM where it faces Mount Salak and Cisadane River (Ningrum, 2017).

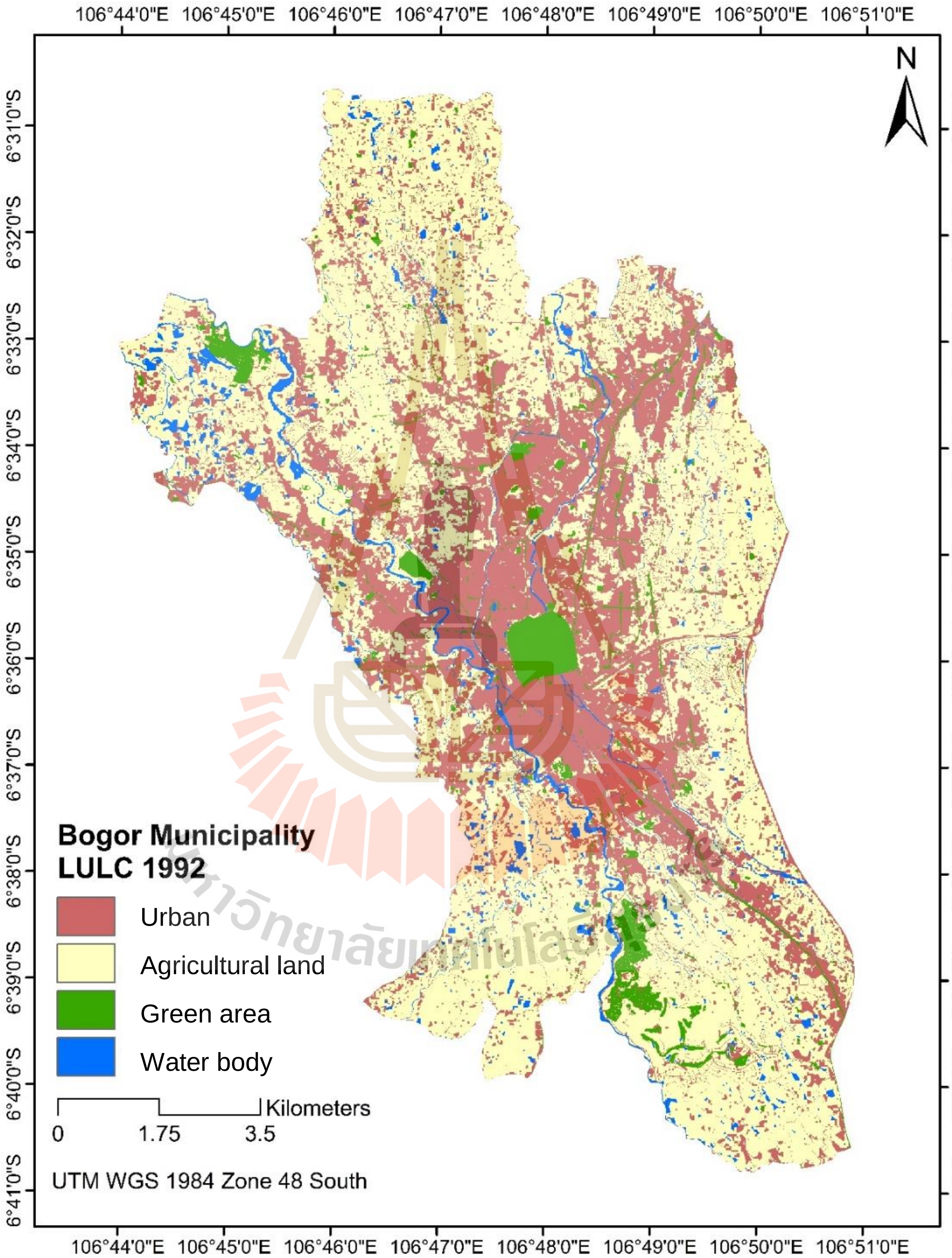


Figure 4.1 BM LULC 1992 processed from Landsat TM 5 image.

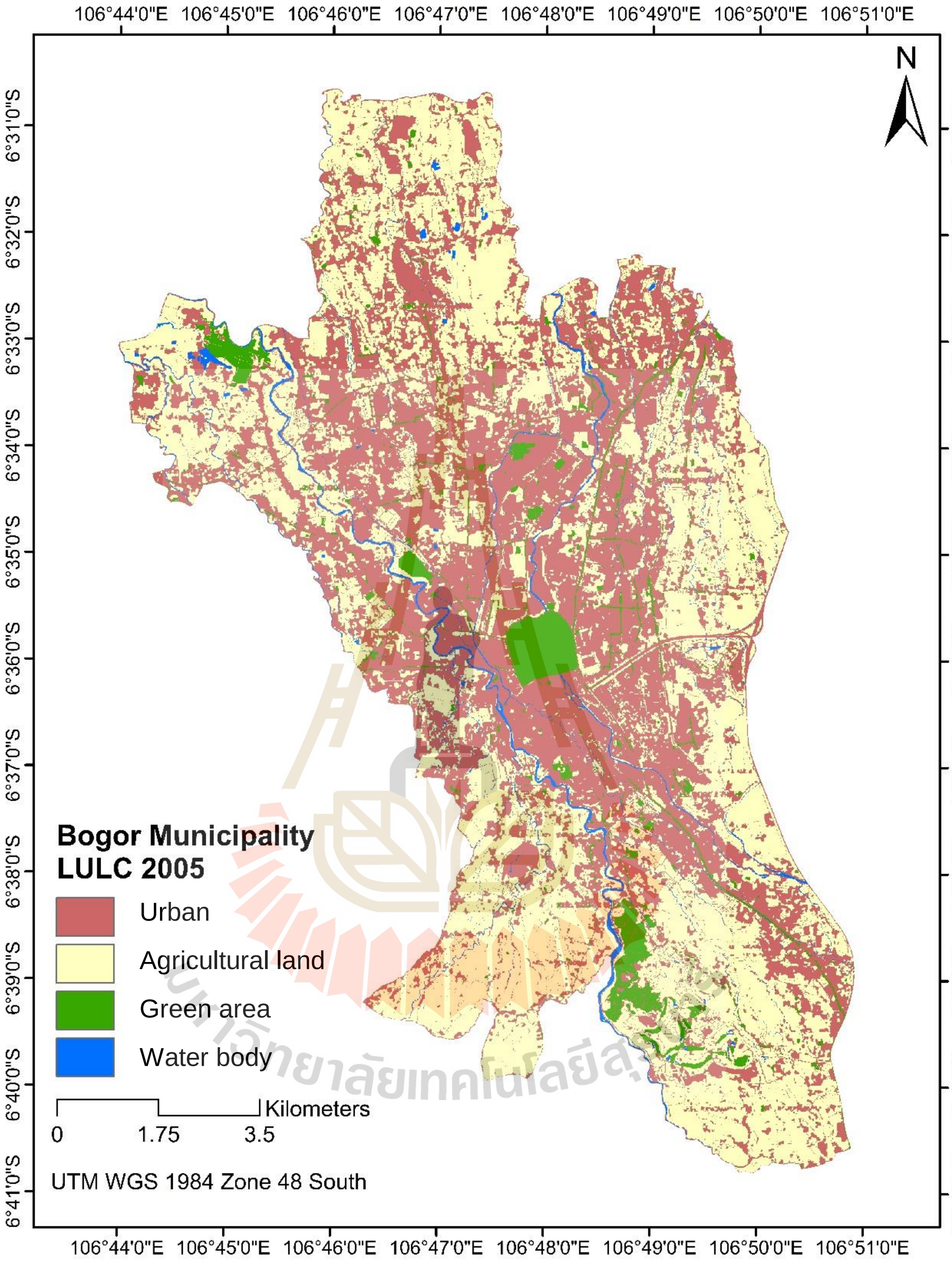


Figure 4.2 BM LULC 2005 (source: GBM, 2005).

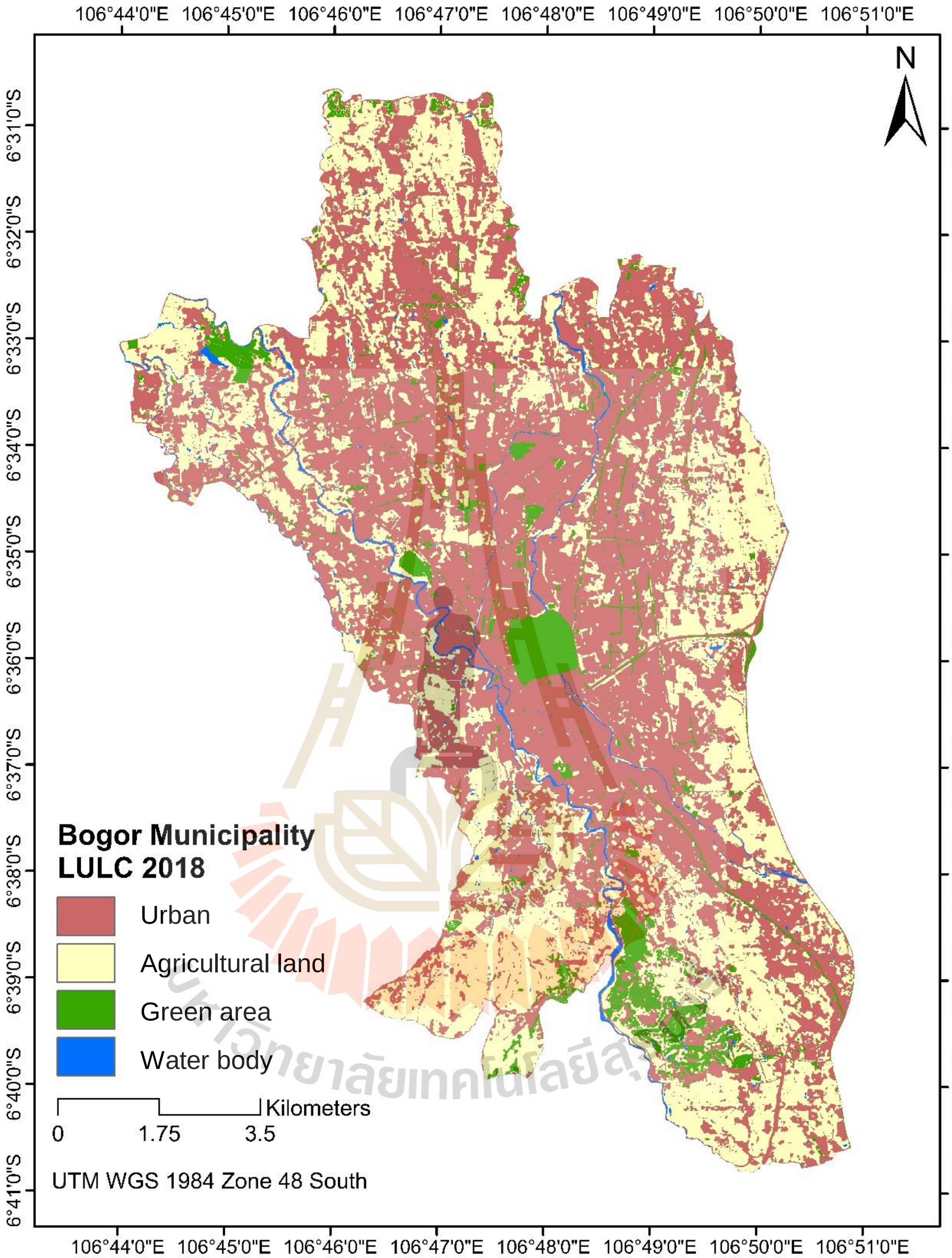


Figure 4.3 BM LULC 2018 (source: GBM (2015) updated with Google Earth image 2018).

Table 4.2 Area of each BM LULC class in every year.

BM LULC classes	Area (km^2)		
	1992	2005	2018
Urban	39.93	51.71	64.18
Agricultural land	67.56	57.93	44.41
Green area	5.16	5.13	6.63
Water body	4.30	2.18	1.73
Total	116.95	116.95	116.95

The result of BM LULC prediction in 2018 based on 1992 and 2005 LULC can be observed in Figure 4.4. Markovian conditional change probability matrix 1992-2005 can be seen in Table 4.3, where only agricultural land class has tendency to change for all classes.

Table 4.3 Markovian conditional probability change matrix 1992-2005.

Given (1992)	Probability change to (2005)			
	Urban	Agricultural land	Green area	Water body
Urban	1.0000	0.0000	0.0000	0.0000
Agricultural land	0.3027	0.6877	0.0031	0.0065
Green area	0.0000	0.0000	1.0000	0.0000
Water body	0.0000	0.0000	0.0000	1.0000

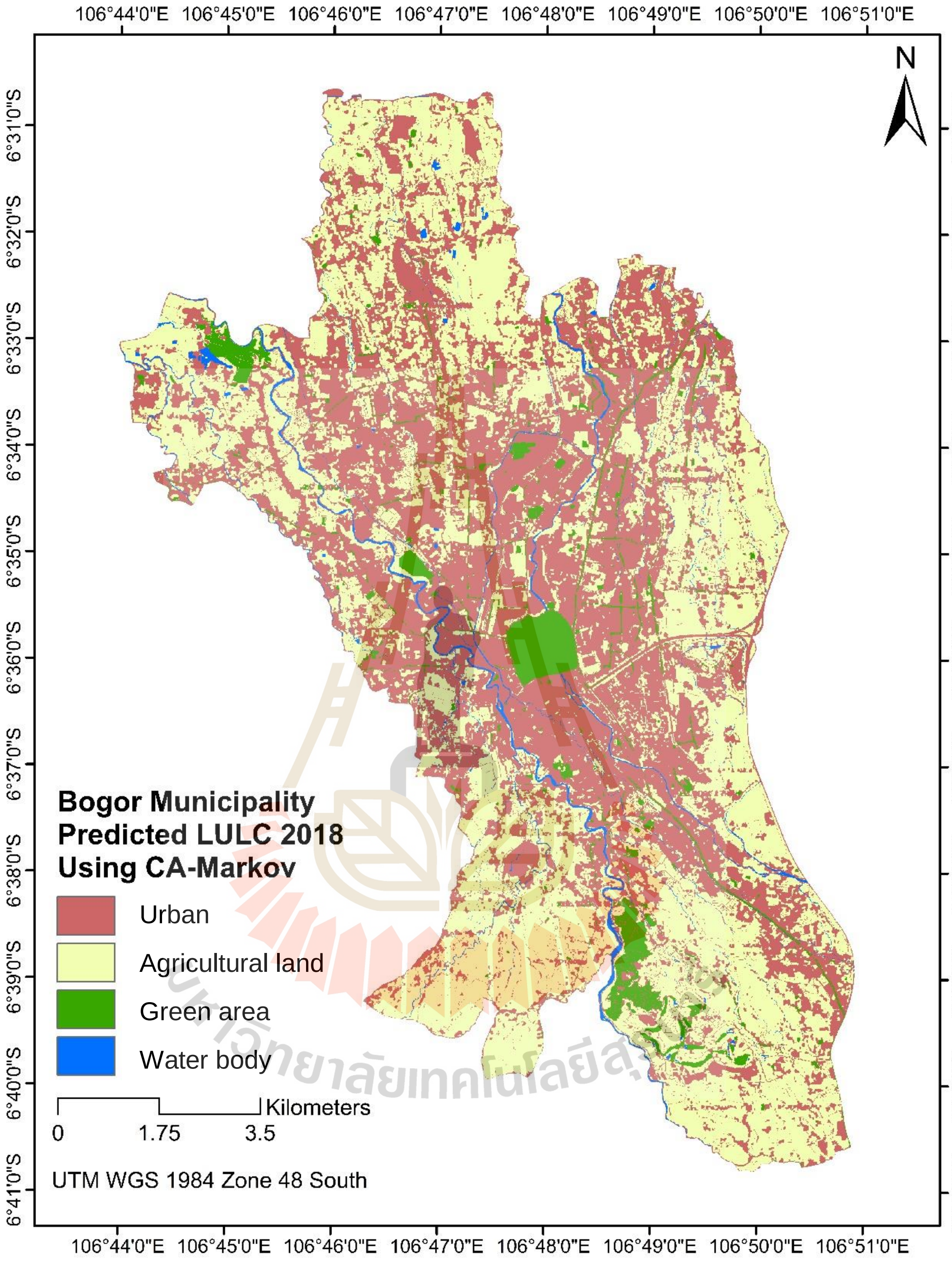


Figure 4.4 BM Predicted LULC 2018 using CA-Markov.

The accuracy assessment of BM LULC 2018 prediction based on CA-Markov when compared with actual BM LULC 2018 using wall to wall method resulted in 85.48% overall accuracy and 0.74 of KHAT coefficient (Table 4.4).

Table 4.4 Confusion matrix of predicted LULC 2018 and actual LULC 2018.

Predicted BM LULC 2018 using CA-MArkov	Ground reference of BM LULC 2018 (number of cells)				
	Urban	Agricultural land	Green area	Water body	Total
Urban	2039394	14800	12489	3323	2070006
Agricultural land	518534	1718982	72195	5691	2315402
Green area	17	24868	180419	28	205332
Water body	9729	17535	30	60003	87297
Total	2567674	1776185	265133	69045	4678037

It is acknowledged that Markovian LULC change matrix (Table 4.3) provided acceptable result and can be applied to creating raster suitability images for BM LULC prediction of 2031. Results of suitability images for 2031 LULC prediction can be observed in Figure 4.5. In 2031, it is predicted that urban class will dominate BM LULC 69.88% with areas of 81.73 km^2 while agricultural land comes as the second of around 22.81% or 26.68 km^2 (Figure 4.6). It also predicted that green area will have areas of 6.81 km^2 or 5.82% and water body class will have 1.73 km^2 or 1.48% from the total BM LULC. Green area will increase in 2031 around 0.13 km^2 or 1.93% more than 2018 areas.

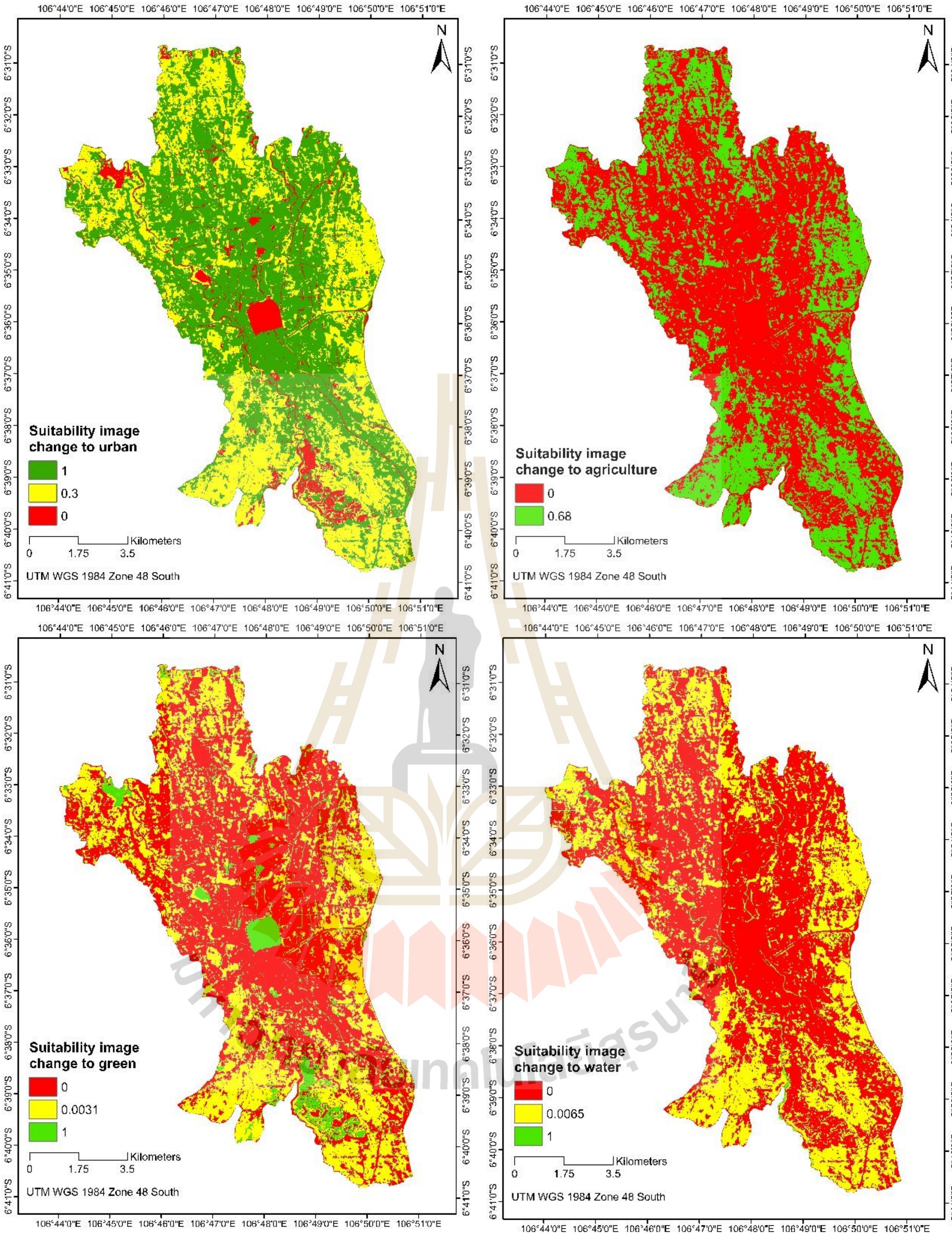


Figure 4.5 CA-Markov suitability images of changing classes for LULC 2031.

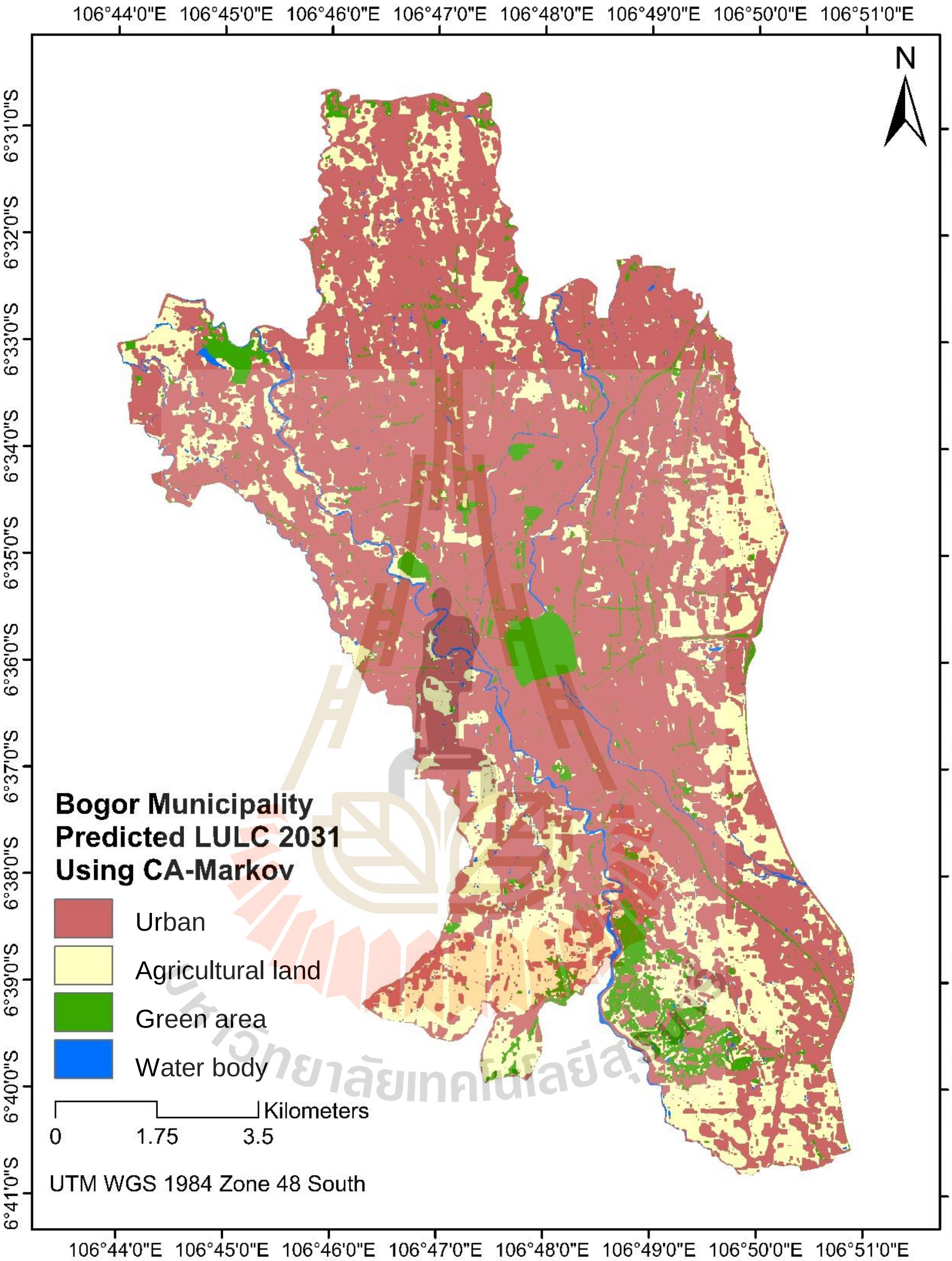


Figure 4.6 Predicted BM LULC 2031 using CA-Markov.

To proof that Areal Interpolation (AI) is the good-practical method for population distribution, the result of its operation on every village of BM based on 2015 LULC was compared to original 2015 population data of BM official census. Kriging was not considered to use in this case because samples were far less than 100 that can make semi-variogram of the process unstable (Burrough and McDonnel, 1998).

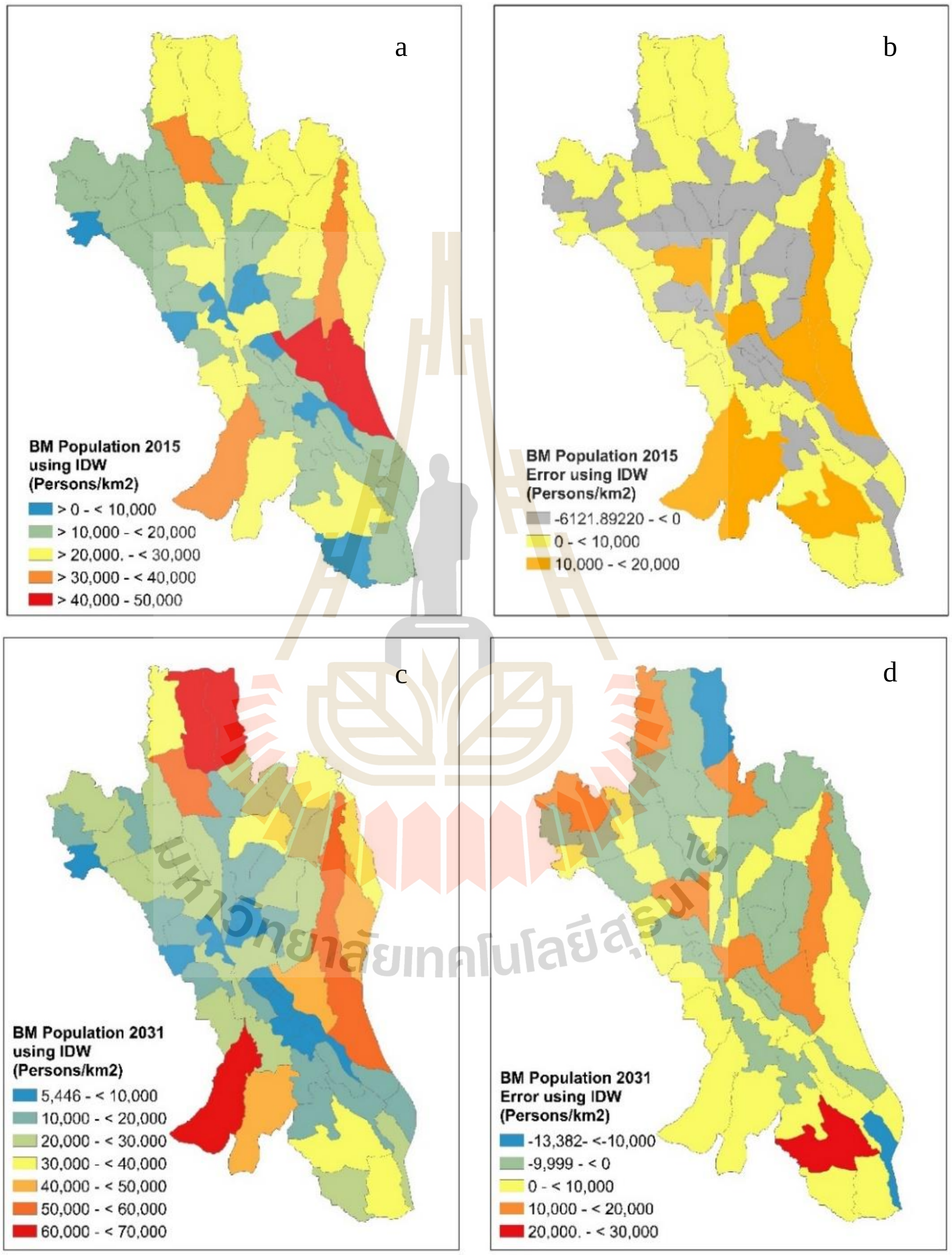


Figure 4.7 Predicted population based on IDW: (a) 2015 (b) error in 2015, (c) 2031, (d) error in 2031.

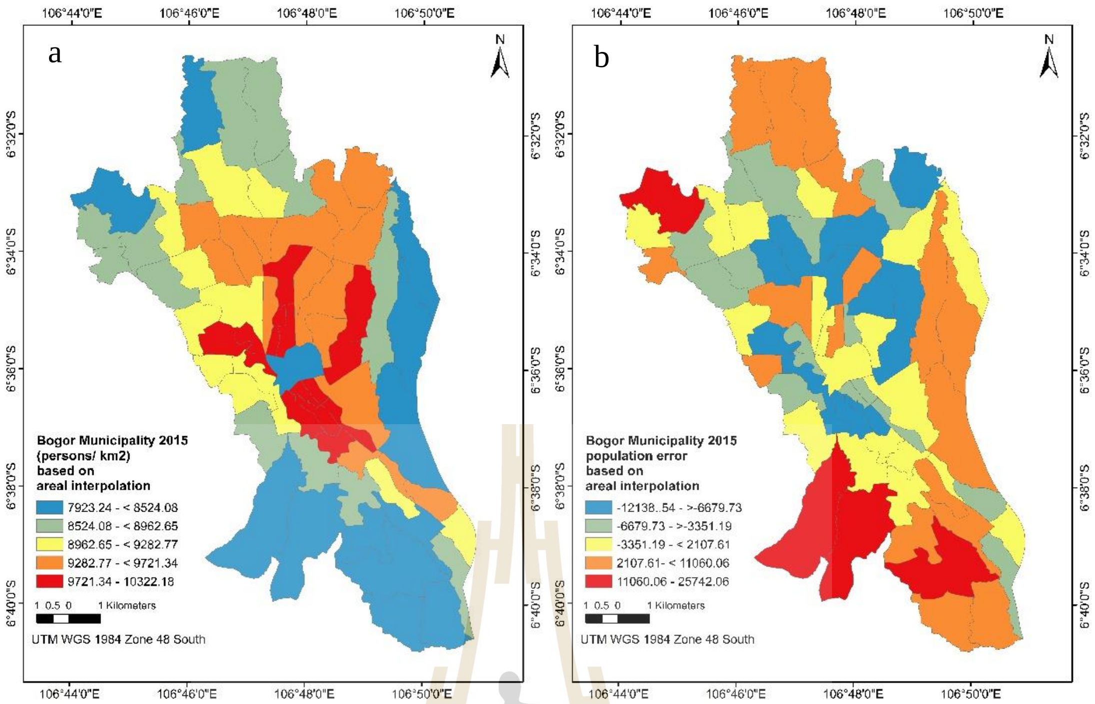


Figure 4.8 Population density based on AI in 2015: (a) population density in every village (b) error in every village.

Working with 2015 data, errors of 41 villages using IDW were above zero (Figure 4.7b) while of only 25 villages when using AI (Figure 4.8b). From this point of view, it seems that interpolation using IDW for this case was overestimated.

Considering RMSSE of AI results both in 2015 and 2031, it indicates that AI generated smaller error than IDW did. According to ESRI (2018d), RMSSE is better when approaches to 1. Due to having acceptable RMSSE and total errors values (see Table 4.5), AI method was selected to perform population distribution of BM in 2031 (Figure 4.9).

Table 4.5 RMSSE and total errors of population interpolation methods.

Method of interpolation	RMSSE	X_{oy} - X_{my}
AI with 2015 population census data	**1.002**	**31,795**

Table 4.5 (Continued).

IDW with 2015 population census data	1.098	188,611
AI with 2031 population prediction	**1.004**	**-62,231**
IDW with 2031 population prediction	1.019	83,018

Moreover, when compared to previous study that the proportion among LULC classes with inhabitant probability was 70:20:10 for urban, agricultural land, and forested (Eicher and Brewer, 2001), the interpolated population using AI both in 2015 and 2031 were almost similar (Table 4.6).

Table 4.6 Population in BM LULC classes using AI.

BM LULC classes	Population interpolation using AI 2015 (persons)	Population interpolation using AI 2031 (persons)	Proportion weight of population based on LULC (Eicher and Brewer, 2001)
Urban	622,943 (61%)	1,044,266 (71%)	70
Agricultural land	215,389 (21%)	341,958 (23%)	20
Green area	178,519 (18%)	84,253 (6%)	10 (forested)
Total	**1,016,851 (100%)**	**1,470,477 (100%)**	**100**

Visually, villages with low population density in 2031 indicated by blue color in Figure 4.9 are located within the same location with dominantly of green area class in Figure 4.6.

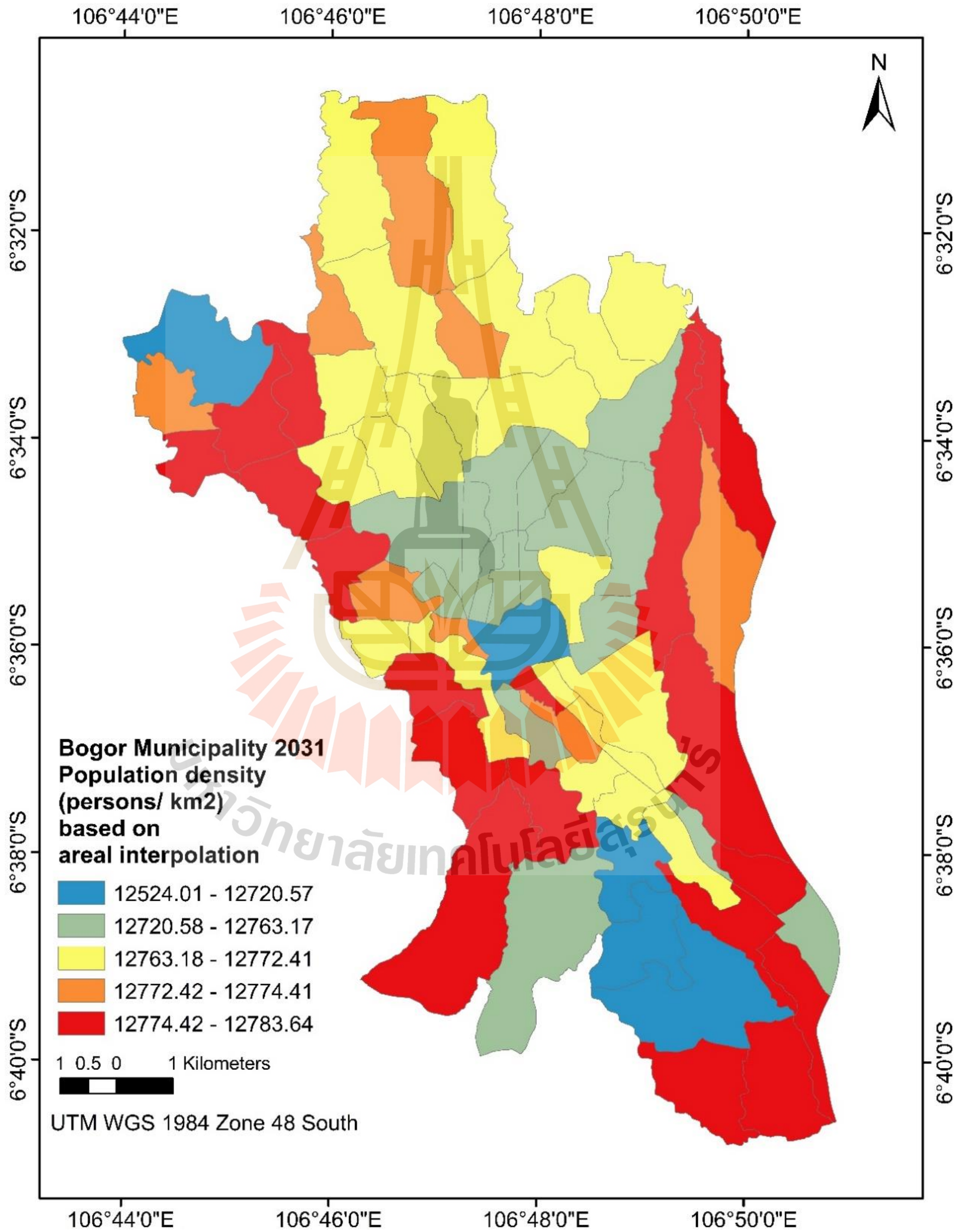


Figure 4.9 BM population density 2031 using areal interpolation.

4.1.2 Accessibility

As mentioned before in Chapter II, this study integrates three different models of travel to estimate accessibility using network analysis and population data (Meng and Malczewski, 2015). Firstly, population in each village within BM was computed according to Equation (2.2) to find *N* coefficient which represented natural increase growth from population 2014 to population 2015, and *M* represented number of people coming in from outside BM in 2015. Result from population projection in 2031 then input into GIS database for each village by creating new "Add Field" function. Population projection of BM in 2031 can be seen in Figure 4.10.

Surprisingly, most villages in the BM city center have decreasing population in 2031 while population will grow around suburbs area (Figure 4.10). In aspect of PUP demand, this phenomenon can convince GBM to plan new PUP in suburbs villages now facing fast population growth.

To compute accessibility score in each village, population, number of PUPs, and walking travel time are required to integrate into three distance models. Equations (2.3-2.5) were used to generate accessibility score in each village which having PUPs. Moreover, travel cost distance of every PUP located within one village was also summed using "closest facility" function.

In order to calculate minimum distance model in each village, ArcGIS function of "closest facility" was applied to locating the closest PUP to every village's centroid. In detail, location of a PUP at each level having minimum distance(s) to village centroid(s) can be seen in Figure 4.11. Visually, there is no single village has complete list of PUPs from *RT*-level up to sub-district level. Two villages have three level PUPs namely, Tanah Sareal and Sempur which can be predicted that both will have higher accessibility scores (Figure 4.12).

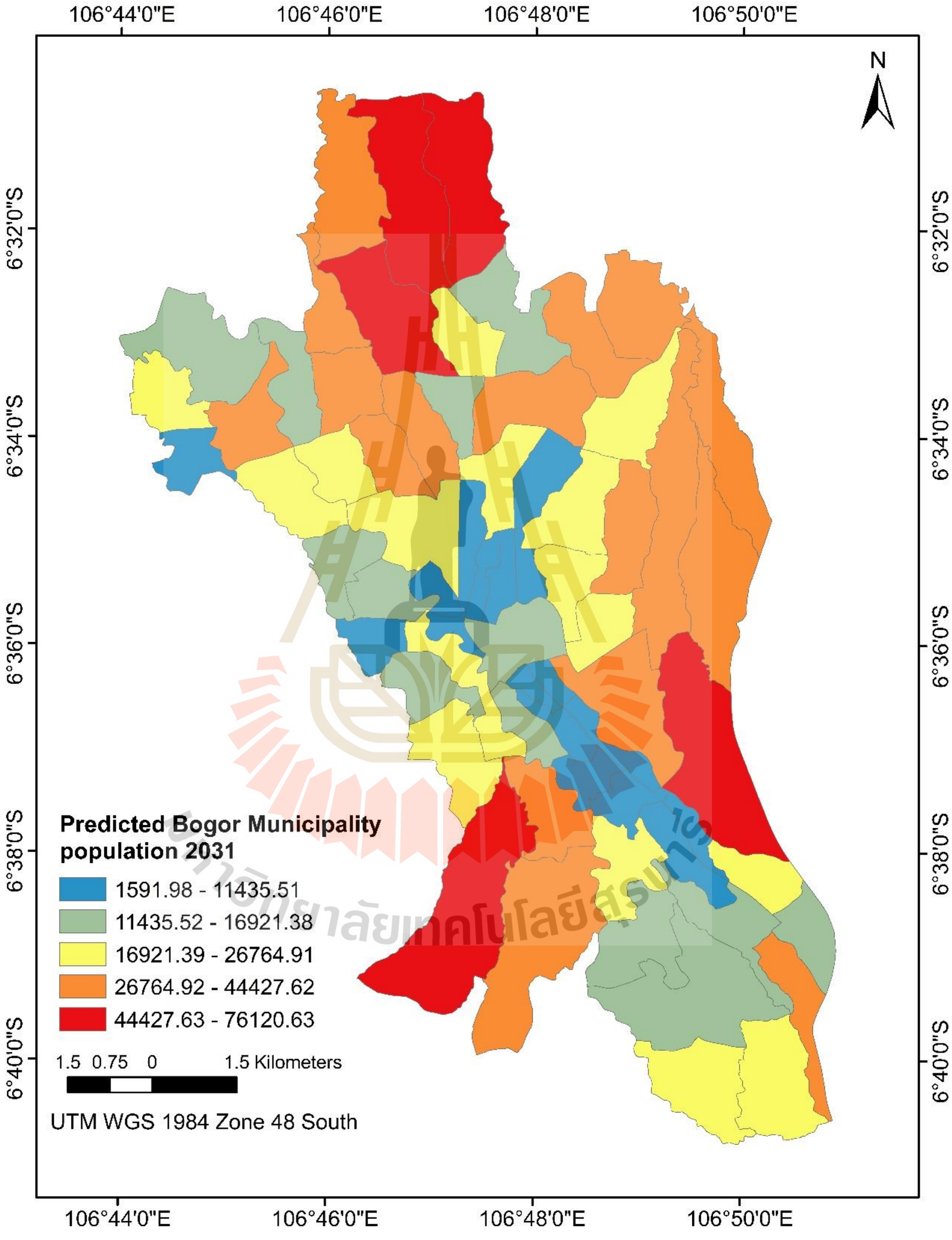


Figure 4.10 BM estimated population distribution in 2031.

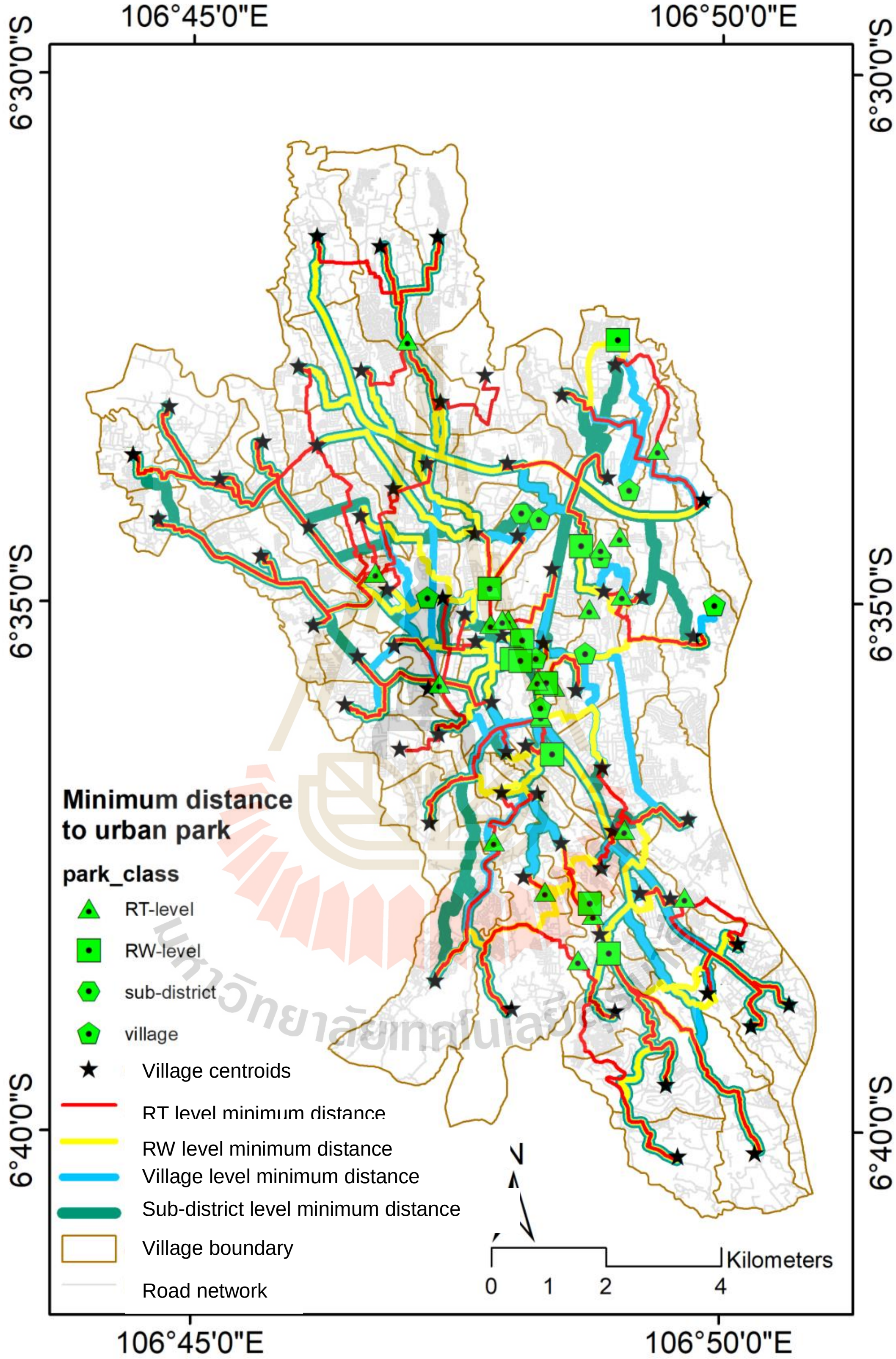


Figure 4.11. Minimum distance from various level of PUPs to village centroids.

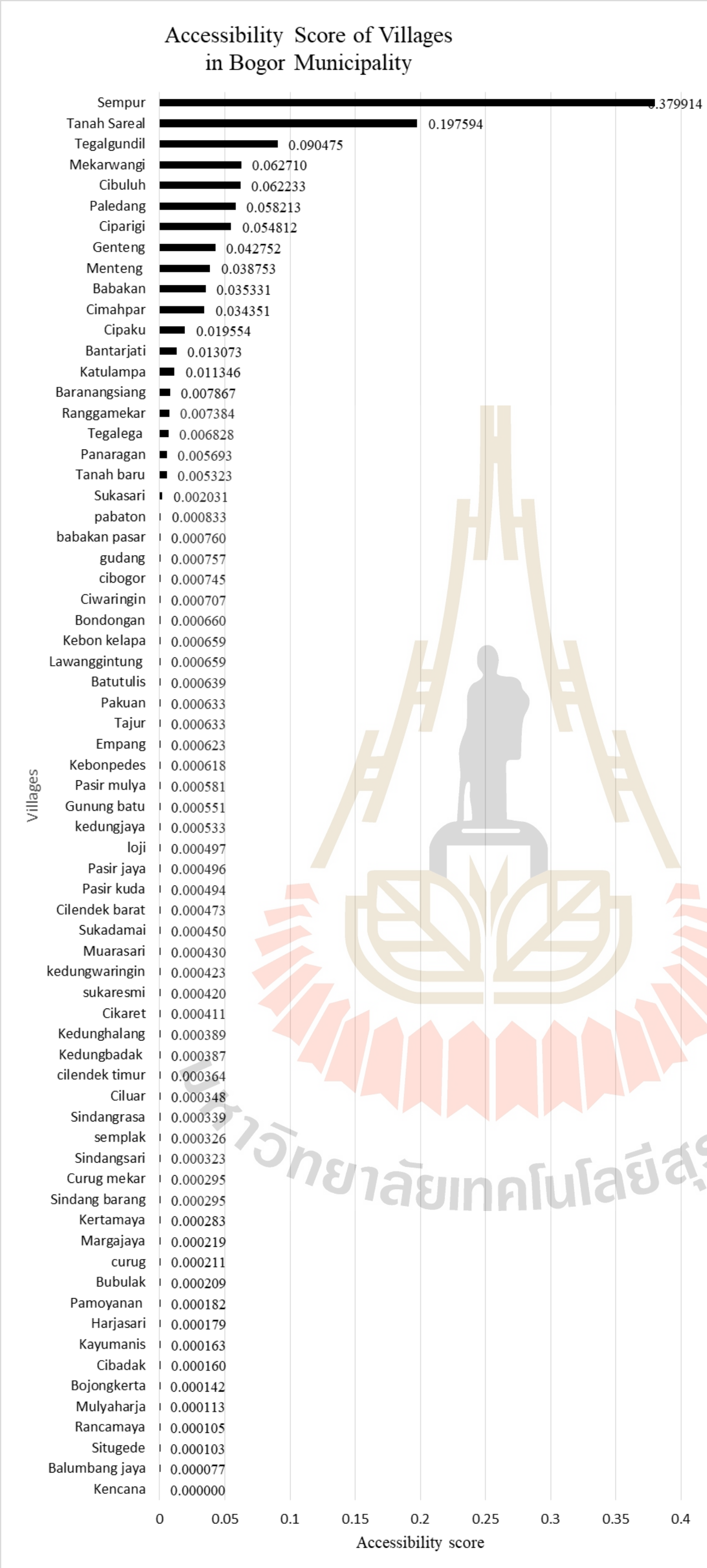


Figure 4.12. Accessibility score for every village.

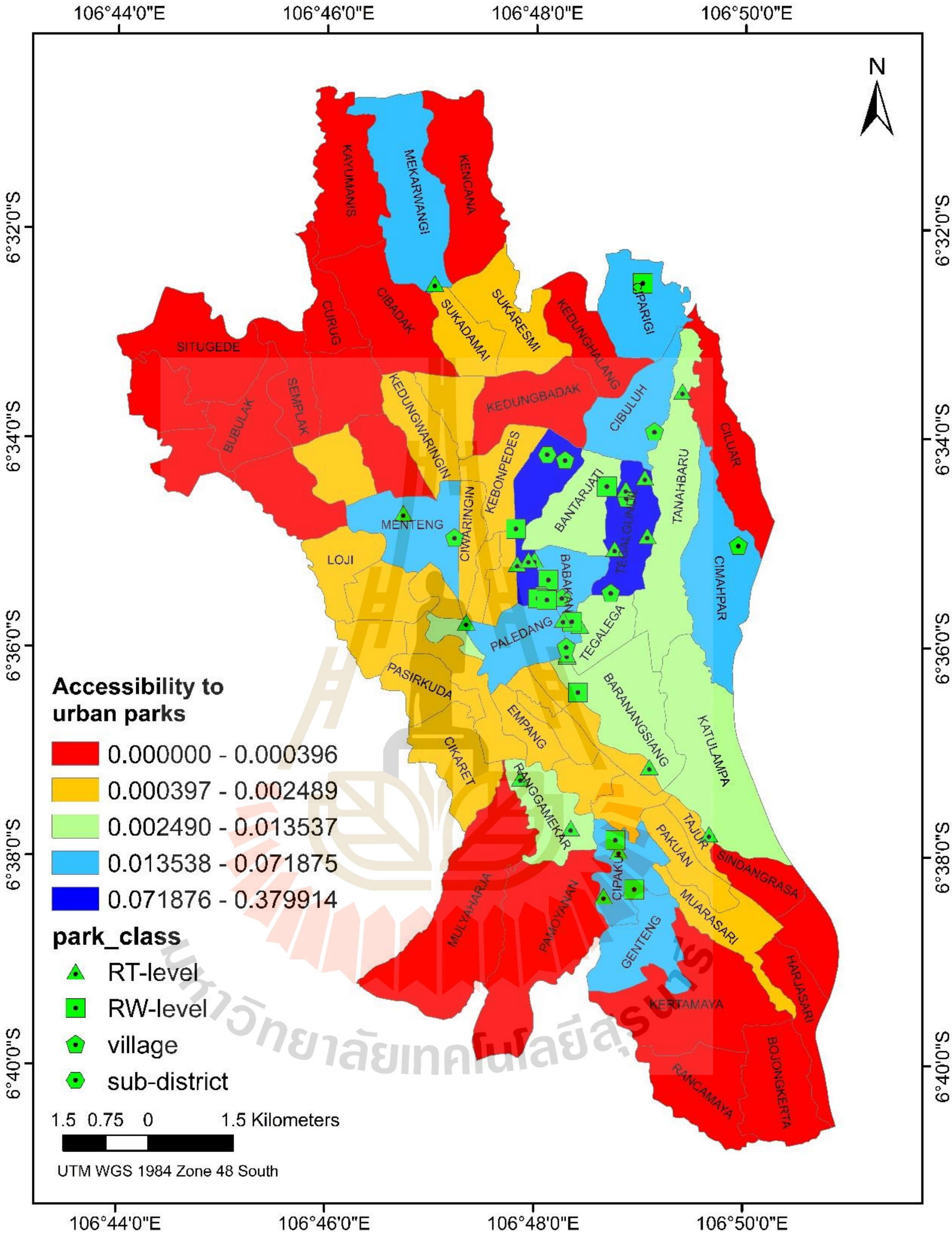


Figure 4.13. Accessibility to PUP of each village.

From Figure 4.13, villages having very high accessibility (highlighted with light and dark blue) will have at least one PUP. This proves that accessibility concept suggested by Meng and Malczewski (2015) can be applied for BM study area.

In addition, this study also improves accessibility concept where adjacent PUP might be visited by people living in surrounding villages (Figure 4.11) when in Meng and Malczewsky (2015) PUPs access can only be measured within DA.

Furthermore, this result means that villages with low accessibility need PUP development to reduce the travel cost of their citizens when visiting nearest PUPs in other villages. In Figure 4.13, villages with very low accessibility (in red) not only lack of PUP but also are influenced by higher predicted population in the future.

Interestingly, this accessibility concept explains that not only villages are evaluated based on their sufficient number of PUP but also the hierarchical level of PUP and distance to reach them. For instance, though Ranggamekar village has 2 RT-level PUP (Figure 4.13) but it has lower access score than Mekarwangi which has only one RT-level PUP. Since Ranggamekar has more travel cost to reach higher PUP level in downtown than Mekarwangi.

4.1.3 PUP policy demand

In this study, PUP policy demand was calculated by using Equation (2.11) (Wicaksono and Sarapirome, 2017) with the assumption that all designated and existing PUPs are not overlapped each other. To achieve this goal, ArcGIS function of overlay and attribute selection query were performed to make sure no single polygon overlap. Current PUP policy demand shows that villages with less demand are concentrated around city centre while the higher demand ones spread across BM suburbs (Figure 4.14).

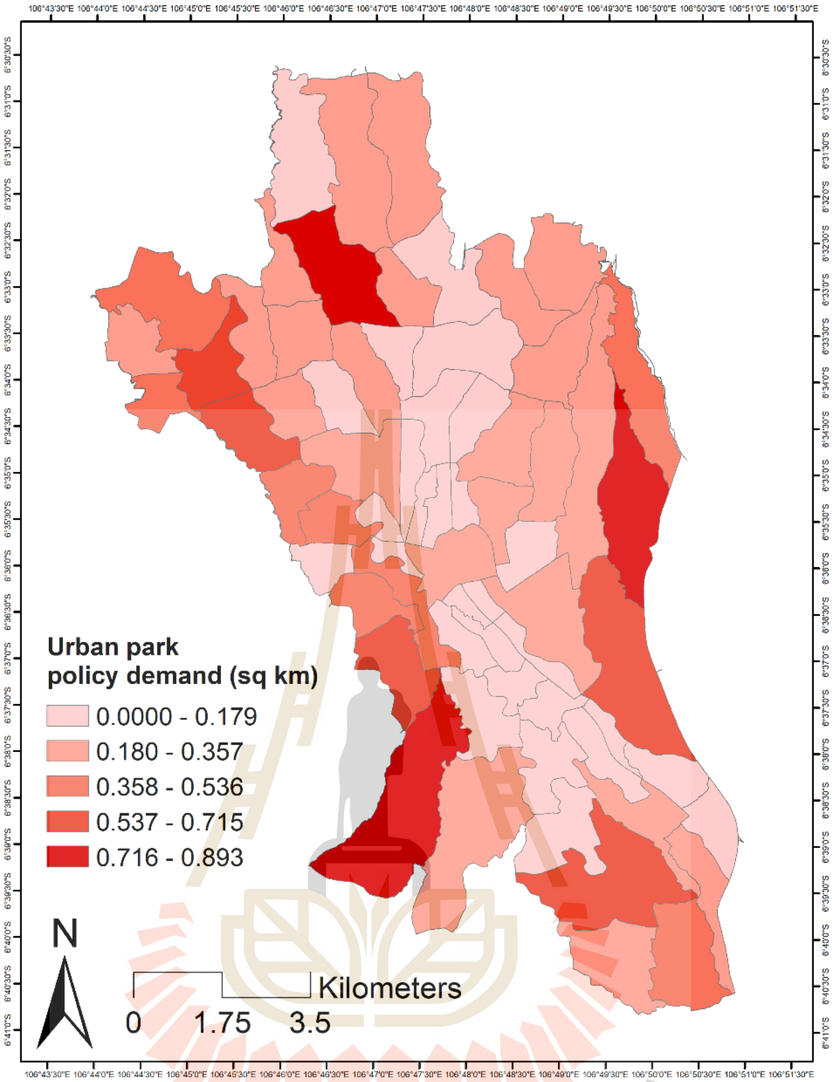


Figure 4.14. PUP policy demand in BM.

4.1.4 PUP visit density

4.1.4.1 Standard service

As an element in Equation (2.13) to estimate standard service value per a PUP, 14 questions were modified and equipped with relevant photos for PUP manager. There were 57 relevant photos which were the best photos obtained from IMPW and presented during initial phase conference of Green City Project 2013. These photos regarded as the best implementation by IMPW were collected from all of PUPs in Indonesia. The photos were then classified to support 14 questions of park satisfaction attributes modified from Zanon (1998). Classified photos were distributed to the highly experienced landscape architect to get score for every photo (Appendix A). For final process, three PUP managers collaborated together to give scores for 43 PUPs based on the guidance of those photos.

To compute PUP standard service, online questionnaires were distributed with background check to ensure that respondents are living in BM. 140 respondents answered those questionnaires and it was decided to remove 3 answers since the respondents acknowledged they lived outside BM. Questionnaires distribution was begun on 11 May 2017 and ended on 27 September 2017 with multi stage random sampling methods. Targeted respondents included the BM bike to work (B2W) members, BM teachers and government employees, Pakuan University planning students and alumni, Bogor Agricultural University students and alumni, University of Indonesia geography students and random citizens.

Result of standard service computation (Figure 4.15) indicates that Heulang Park is the top since it has most complete facilities compared to others, while Sukasari III has the lowest rank because this park receives less attention and maintenance from BM government. In 2009, local neighborhood had submitted a proposal to revitalize this PUP with early talk that locals would try to find donor for self-financing.

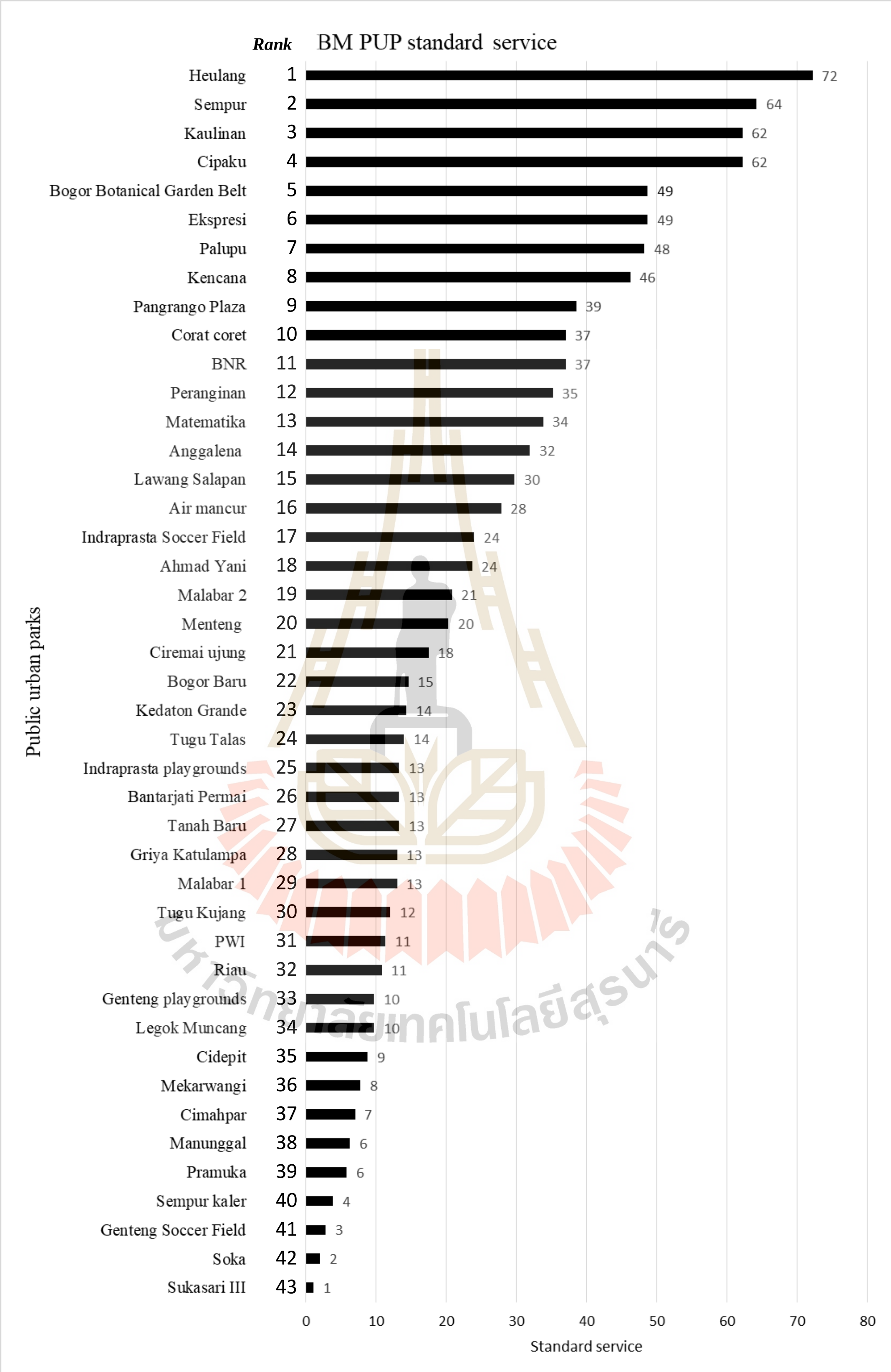


Figure 4.15. Standard service of PUPs.

4.1.4.2 Public Awareness

Minimum sample size for this study based on the Equation (4.1) adopted from prevalence of medical studies (Arya, Antonisamy and Kumar, 2012):

$$n = \frac{(z^2)P(1-P)}{d^2} \tag{4.1}$$

where *n*=number of minimum sample size, *z*=z statistics score for the level of confidence, *P*= expected prevalence, and *d*=allowable error. For *z* and *d* values, it can refer to a research aimed to investigate relationship between perceptions from public green space visitor and spatial indicator from remote sensing data, by collecting questionnaires from visitors in town of Szeged, Hungary (Kotchenz and Blaschke, 2017). In that research, used confidence level was at 95% while allowable error was 10% and distributed questionnaires were considered enough at 100 respondents.

Furthermore, expected prevalence of this study is 0.75 which obtained from previous research performed in Melbourne, Australia to estimate PUP visitor where model used could only explain 75% of variance (Zanon, 1998). Therefore, minimum requirement of sample size used in this study is 72 respondents, though it was successful to obtain 137.

It can be observed that 40.15% of the respondents are civil servants followed by employees in the second rank with 17.52% and the smallest proportions are freelance and entrepreneur, each with 0.73% of the sample population (Figure 4.16). In addition, male respondents slightly dominated the proportion of the population sample with 53.28% followed by female with 46.72% (Figure 4.17). Meanwhile, the highest proportion of respondents were at 39 years old (Figure 4.18).

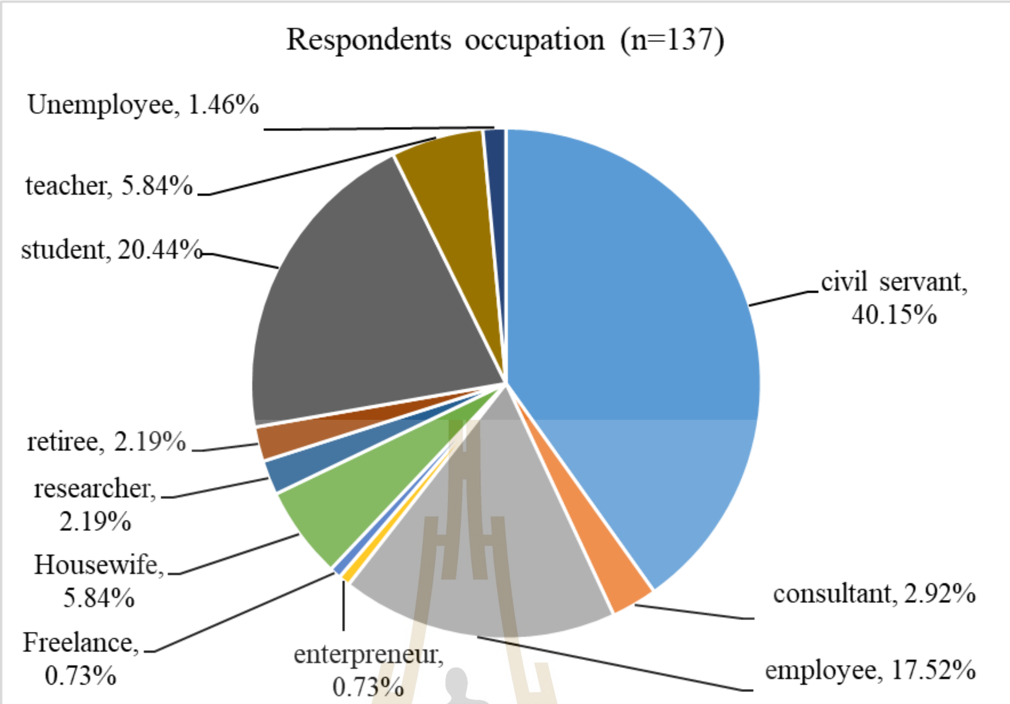


Figure 4.16. Respondents' occupation for public awareness survey.

Interestingly, more than half of the respondents have bachelor degree and very less came from elementary and junior high school. Top three respondents' professions came from civil servant, employee and student.

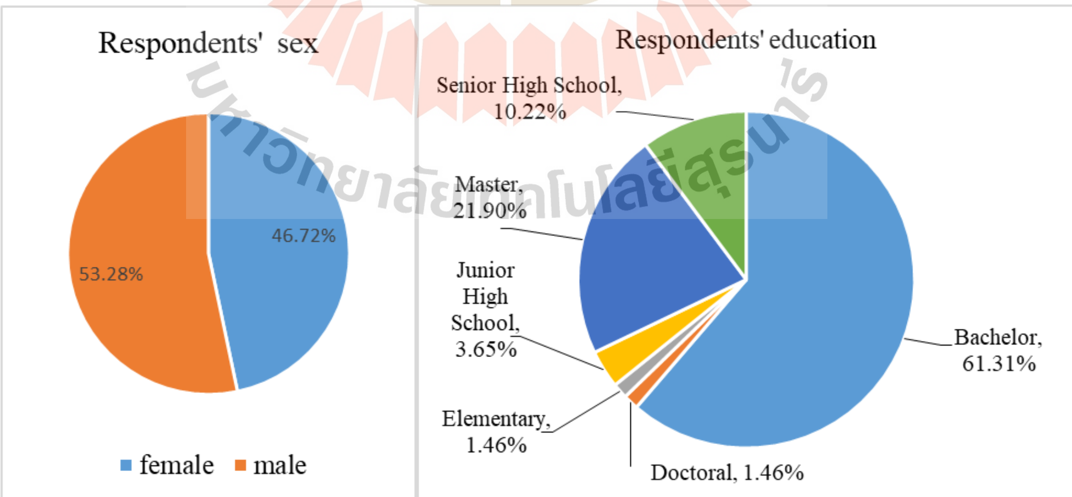


Figure 4.17. Respondents' sex and education.

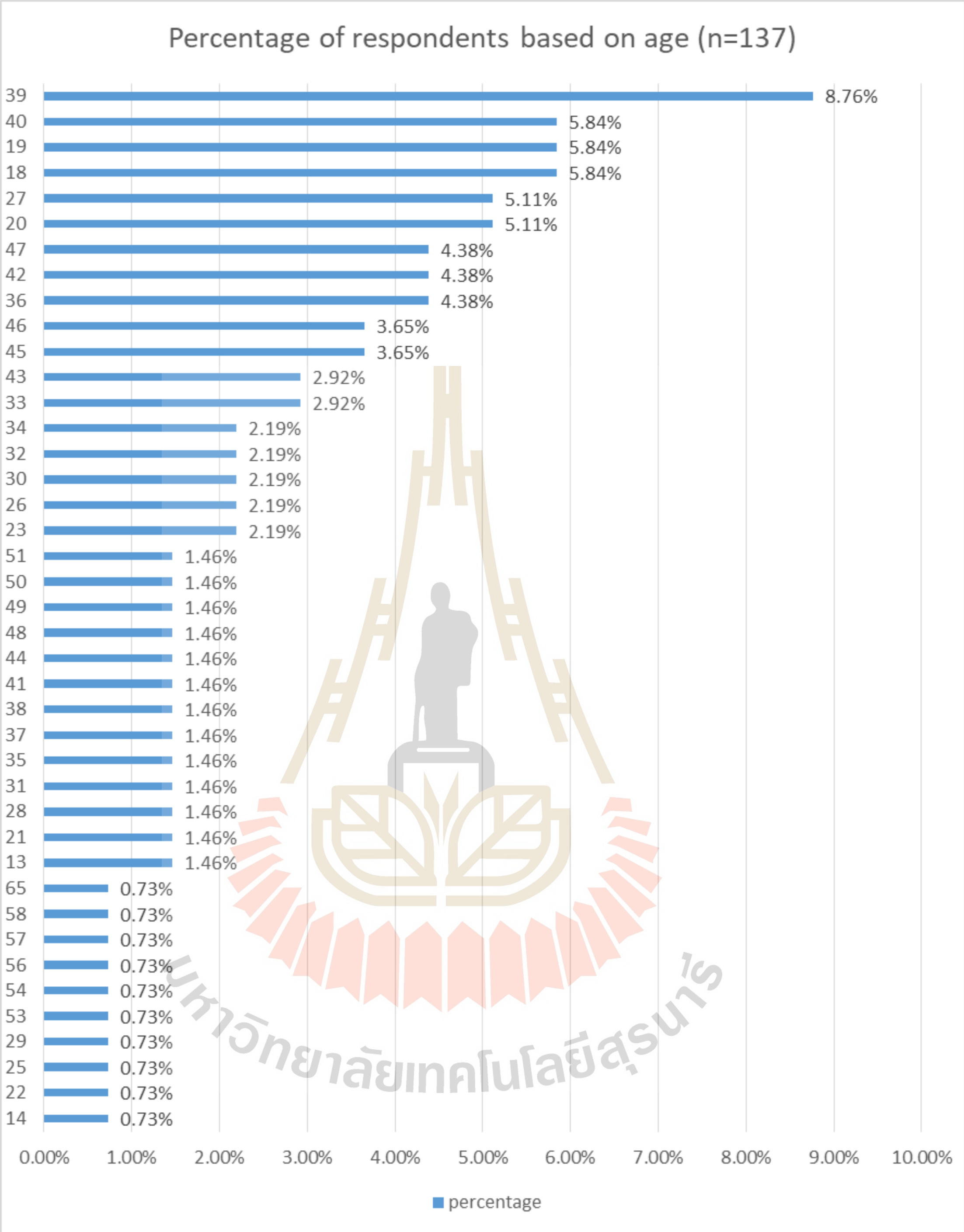


Figure 4.18. Respondents' age.

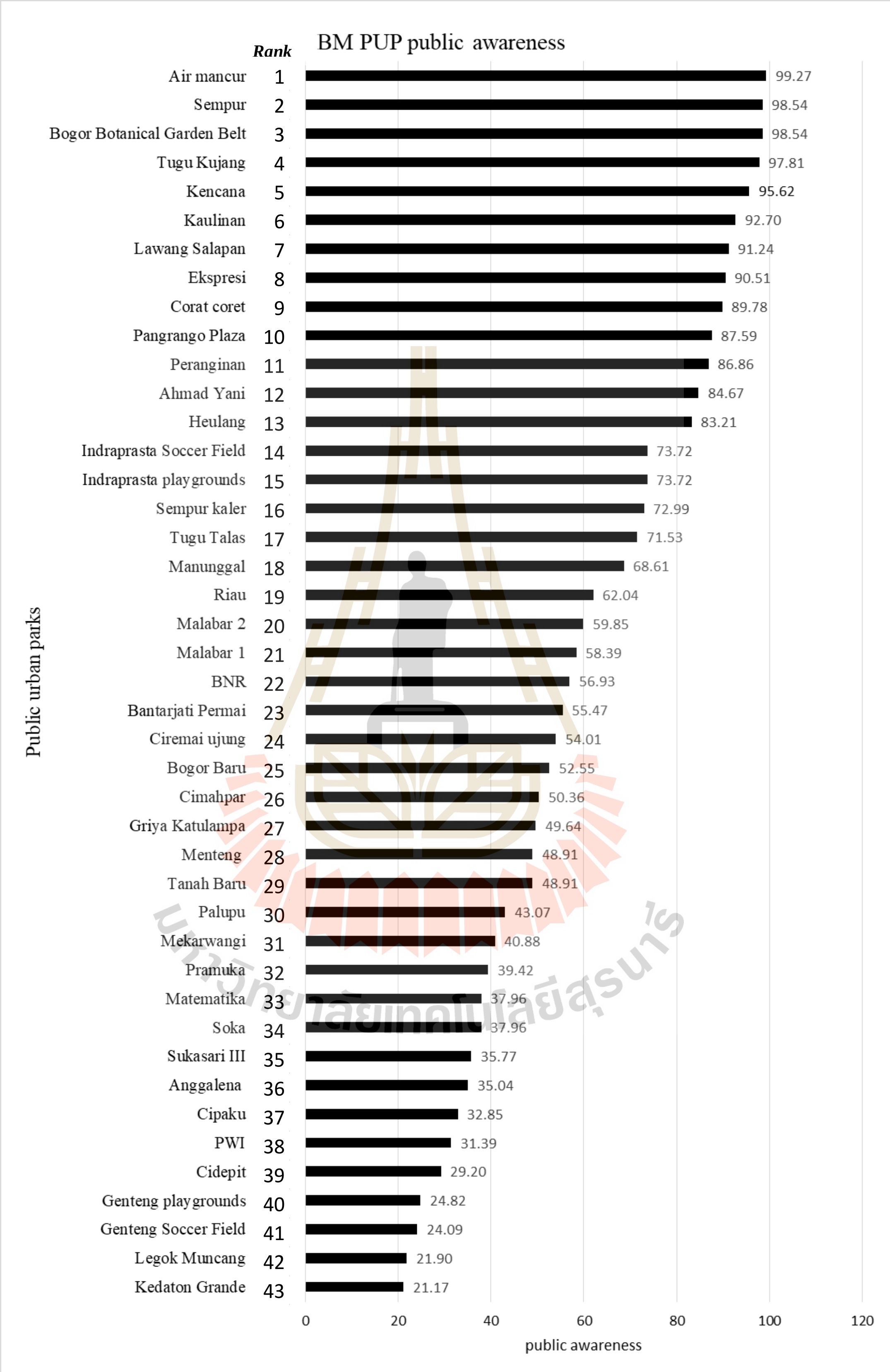


Figure 4.19. Public awareness value.

Considering public awareness, Air Mancur Park has been chosen as mostly known PUP in BM while Kedaton Grande as the most unpopular (Figure 4.19). Air Mancur is strategically situated in the city core of BM surrounded by famous culinary restaurants. No wonder that this park is crowded with people especially during Saturday's night due to its potential location. On the opposite, Kedaton Grande PUP is located in quite poor neighborhood in southern Bogor and not often visited though it was built by the city government.

4.1.4.3 Catchment population

In order to generate catchment population value for each PUP, this study uses population density map which later superimposed with service area. Firstly, service area for 43 PUPs were created using 15 minutes walking travel time and each service area was separated from each other as a single polygon (Figure 4.20).

To obtain appropriate population density map, all 68 village polygons which have population projection in 2031 were then interpolated using AI. Final product of population density map is in 10 m x 10 m (Figure 4.21). Catchment population of parks as the result of superimposed between 43 village service area and population density can be observed in Figure 4.22. The result shows that Cidepit PUP has the highest catchment population while Ekspresi PUP has the lowest. This result can be explained by the reality that Cidepit is located near slum area of Panaragan Village while Ekspresi is surrounded by parks and low-density neighborhood within city center.

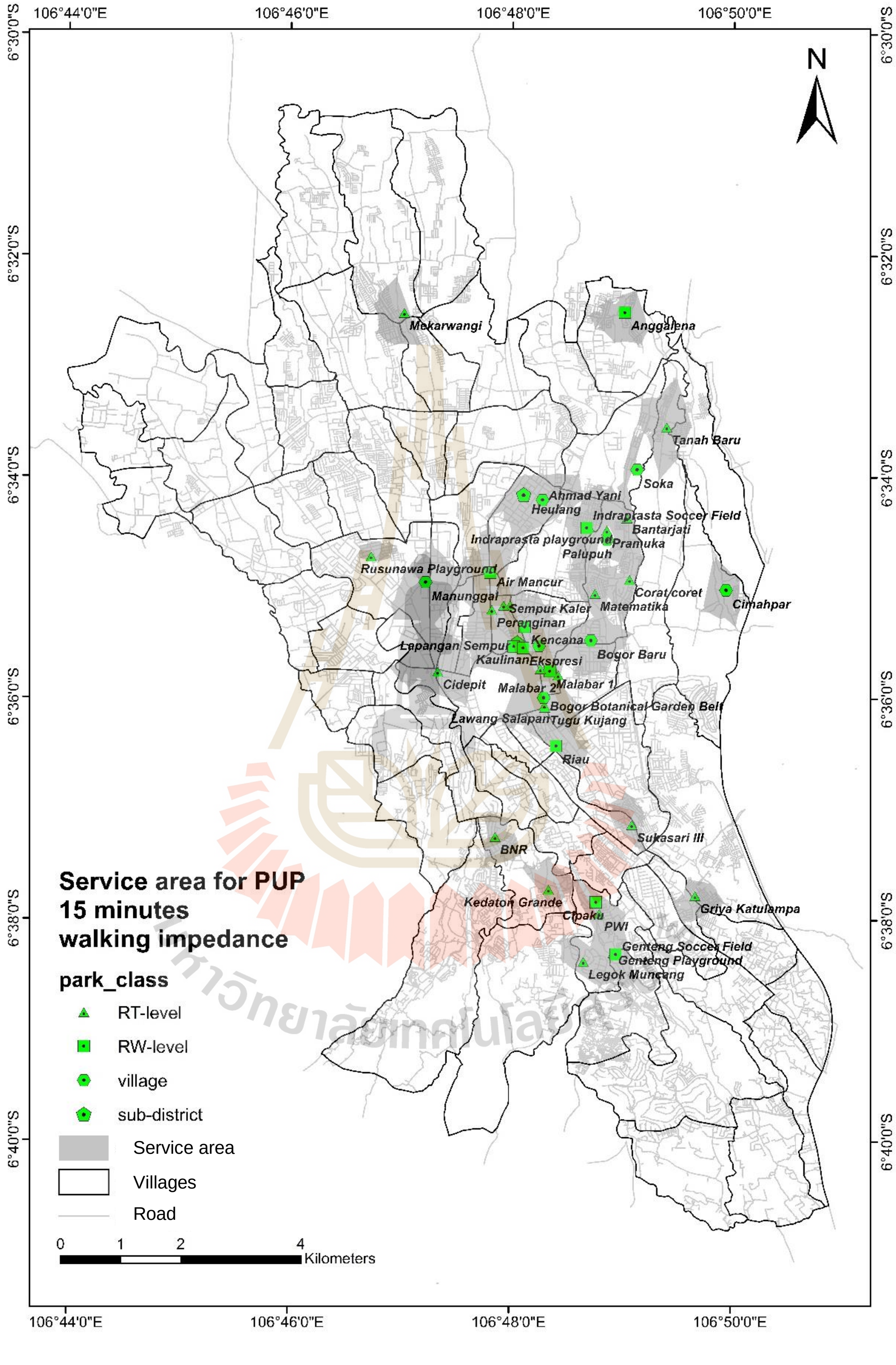


Figure 4.20 Service areas of PUPs in BM.

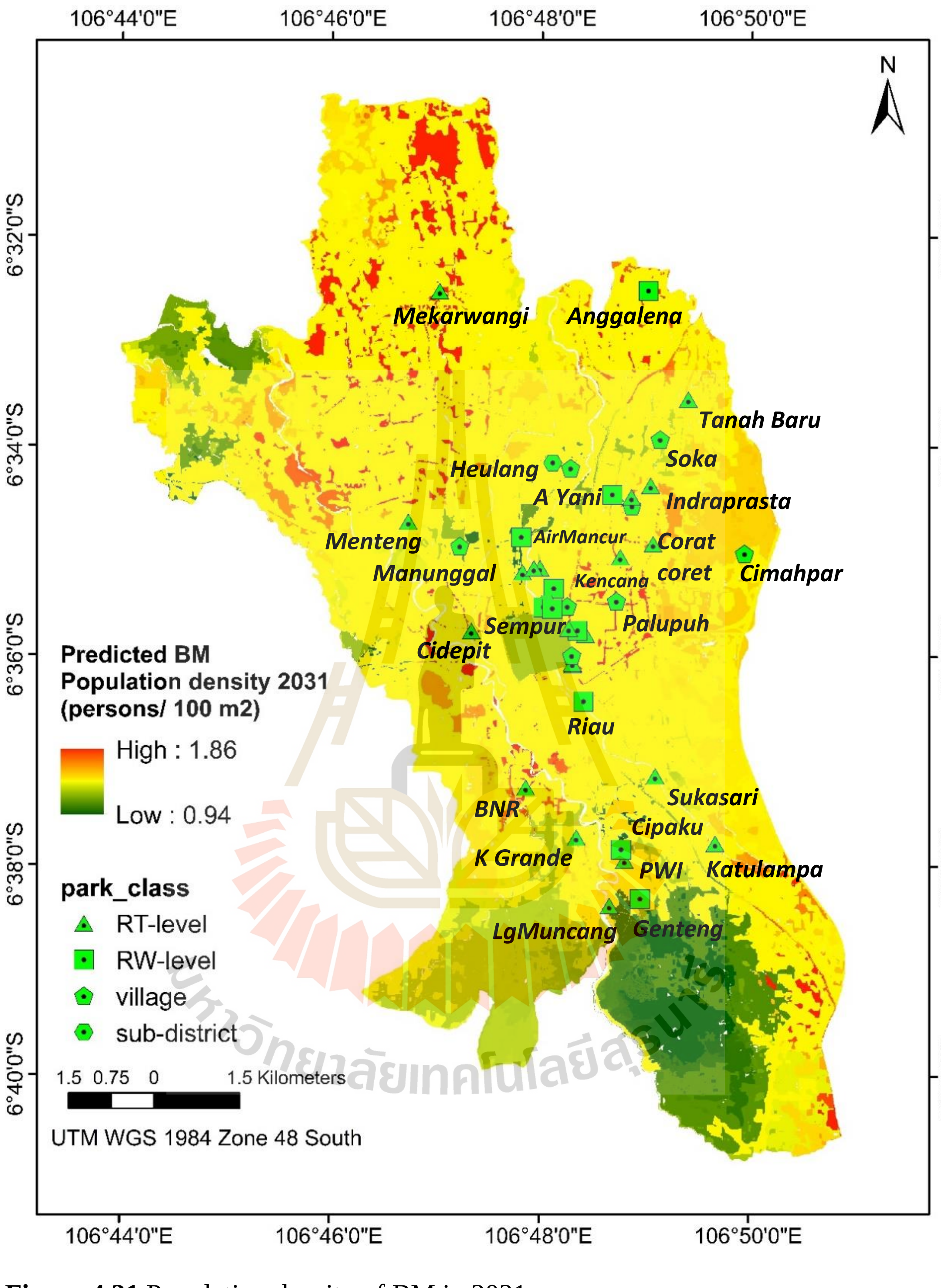


Figure 4.21 Population density of BM in 2031.

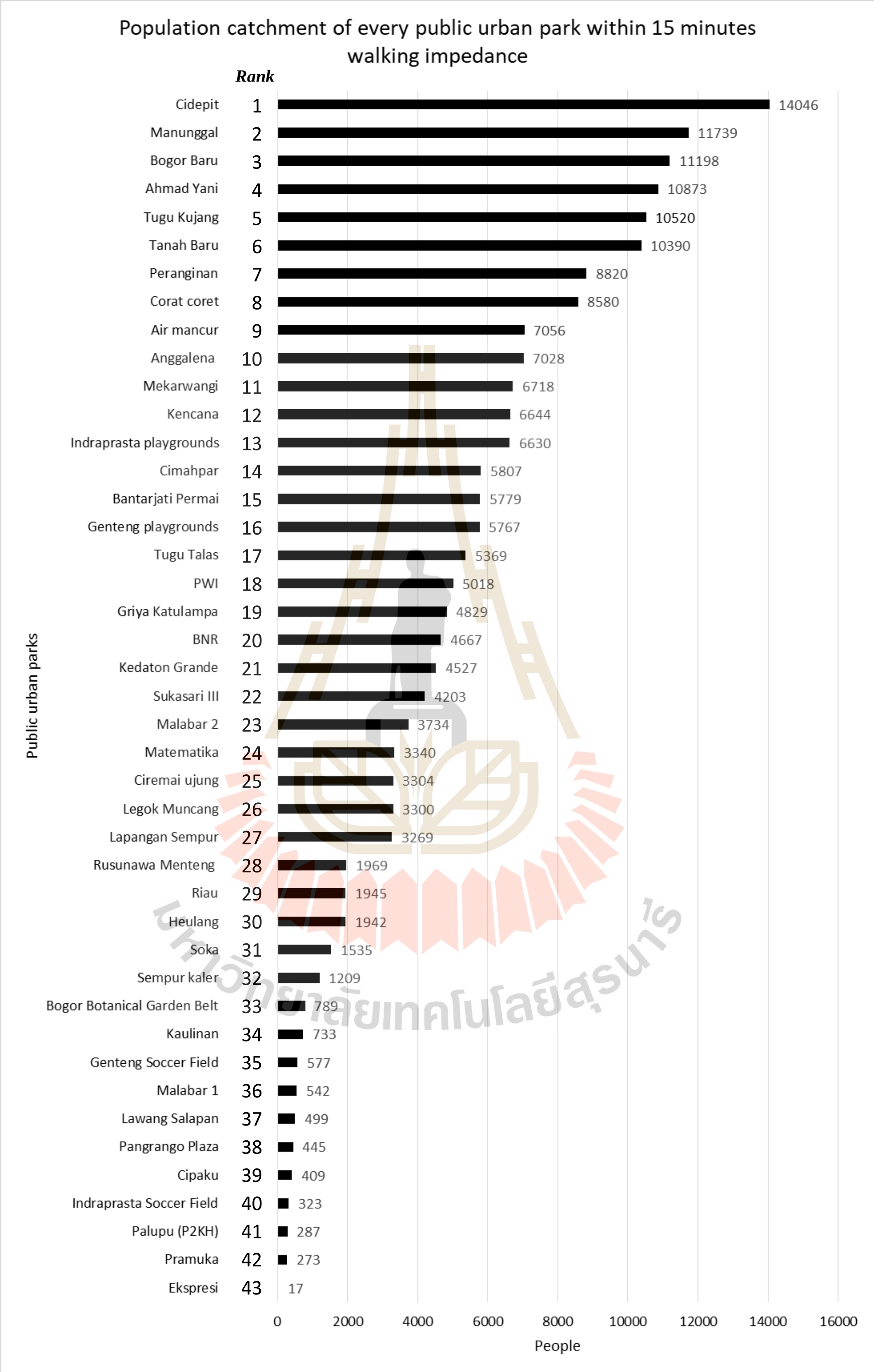


Figure 4.22 Catchment population of every PUP in BM.

4.1.4.4 Number of visit estimation

Based on Equation (2.13), number of visits can be estimated from standard service, public awareness, catchment population, and accessible area of 43 PUPs (Figure 4.23). Results are displayed in Figure 4.24, where Sempur Park ranked first while Sukasari was the least visited.

Surprisingly, BNR location has significant number of visits and was ranked as the tenth from the list. This PUP is located in neighborhood where inhabitants are considered having middle to high income level, but the park is visited frequently by children from adjacent neighborhood with low income level household.

However, this result shows concern of PUP with much lower estimated number of visits especially how the government should increase the facilities in those locations to attract more visits. For instance, Kedaton Grande and Legok Muncang parks were not so familiar with people's mind which indicated by very low public awareness ranked 43 and 42 (Figure 4.23(d)) but those two PUP's have not so bad standard service ranked 23 and 34 (Figure 4.23(a)). Otherwise, people who are living in dense areas have no choice than to visit nearby PUP regardless of low standard service such as Manunggal Field rank 38 in Figure 4.23(a) but successfully memorized by people indicated by public awareness rank of 18 in Figure 4.23 (d).

To confirm this result, it was searched in internet by typing "visitor PUP Bogor City" (*pengunjung taman kota bogor- Bahasa*). One of the results was a description of twelve PUPs in Bogor Municipality inside lovelybogor.com website (Ardyanto, 2018). Seven PUPs mentioned on that website is in the top ten list of estimated number of visit while 3 PUP's outside the top ten and 2 more are private

PUPs. That article uses 3 criteria to evaluate if a PUP is famous. Those are: (1) available bench for seat, (2) well maintained green open space, and (3) parks ornaments.

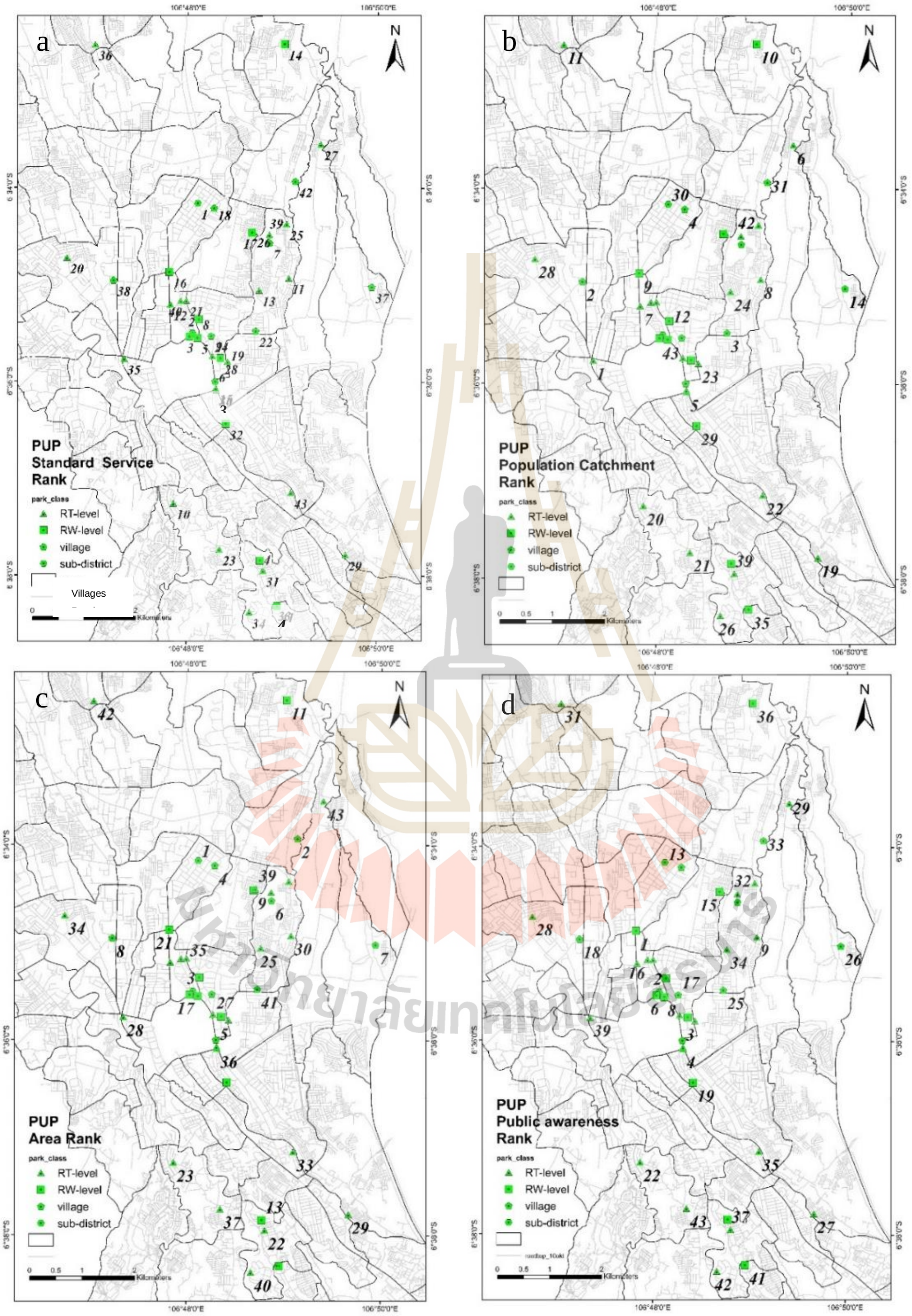


Figure 4.23 Maps of variables, with ranking number for number of visit estimation: (a) standard service, (b) catchment population, (c) area, (d) public awareness.

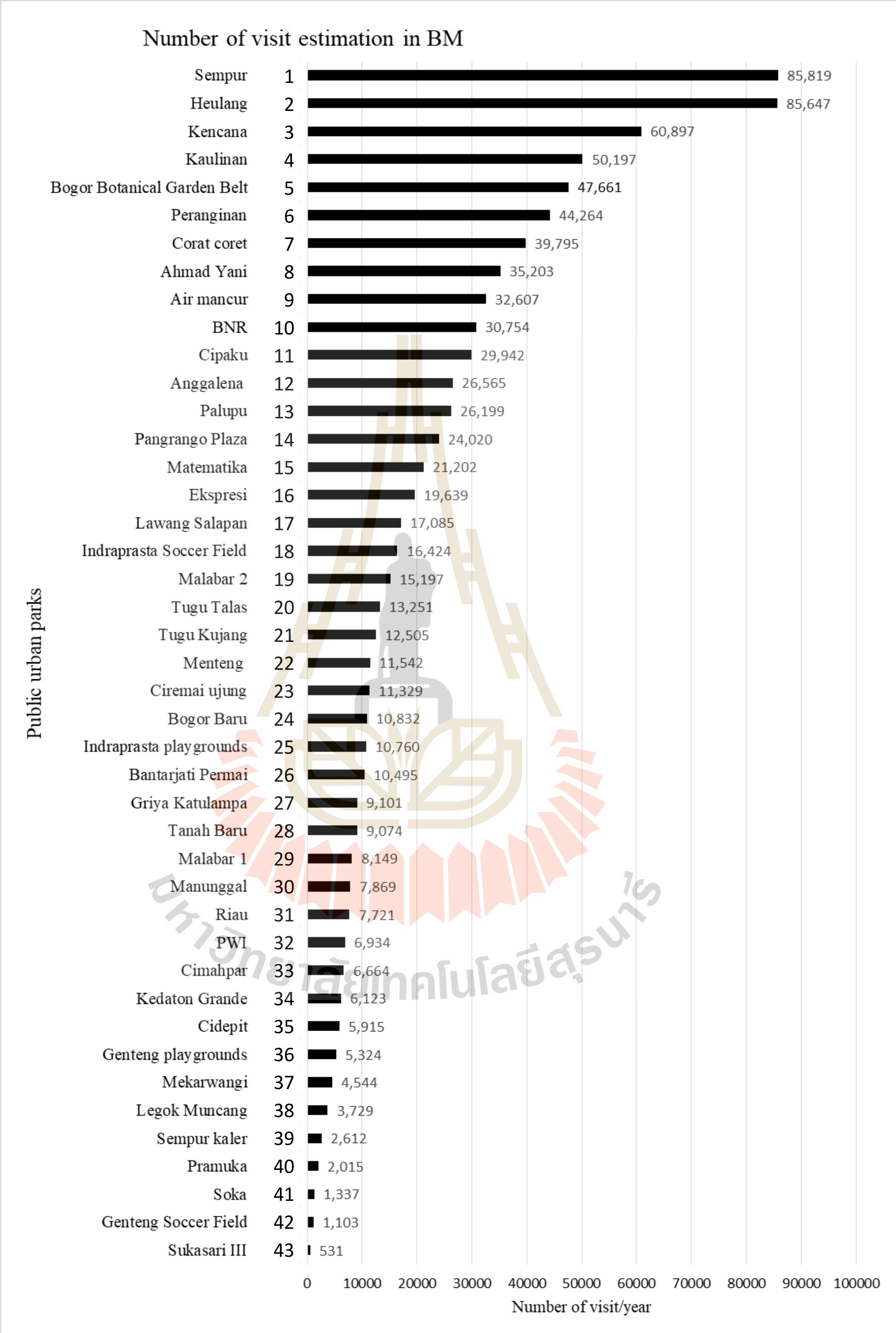


Figure 4.24 Number of visit estimation in BM.

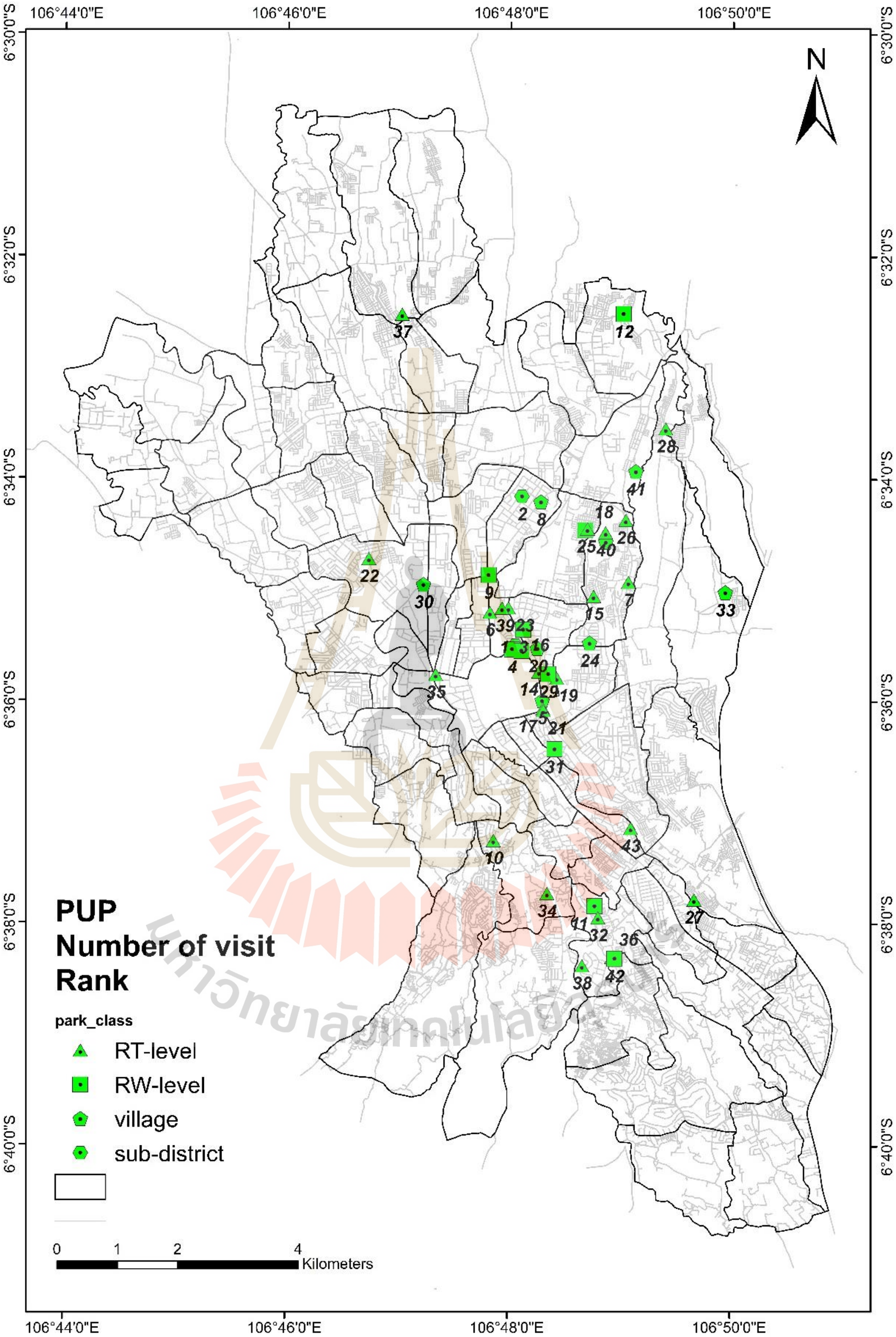


Figure 4.25 PUP number of visit rank.

4.1.4.5 Visit density

Related to visit density value for every village which functions as a consequent in both Sugeno and Mamdani FIS, the estimated number of visit needs to be converted into visit density per village. This purpose is achieved by dividing estimated number of visits with PUP area.

The village with high visit density does not reflect that it has large area of PUP, for example, Tanah Baru village has only one PUP with size around 150 m^2 but having a potential number of visits up to 22,857 per year. On the other hand, Sukasari village has visit density of 3.09 people/m^2 on a single PUP having area up to 459.6 m^2 and estimated number of visit only 1,471 per year (Figure 4.26). Actually, the uncertainty outcome of visit density is a strong reason why this study uses non-linear system like Sugeno and Madani FIS to provide optimum visit density.

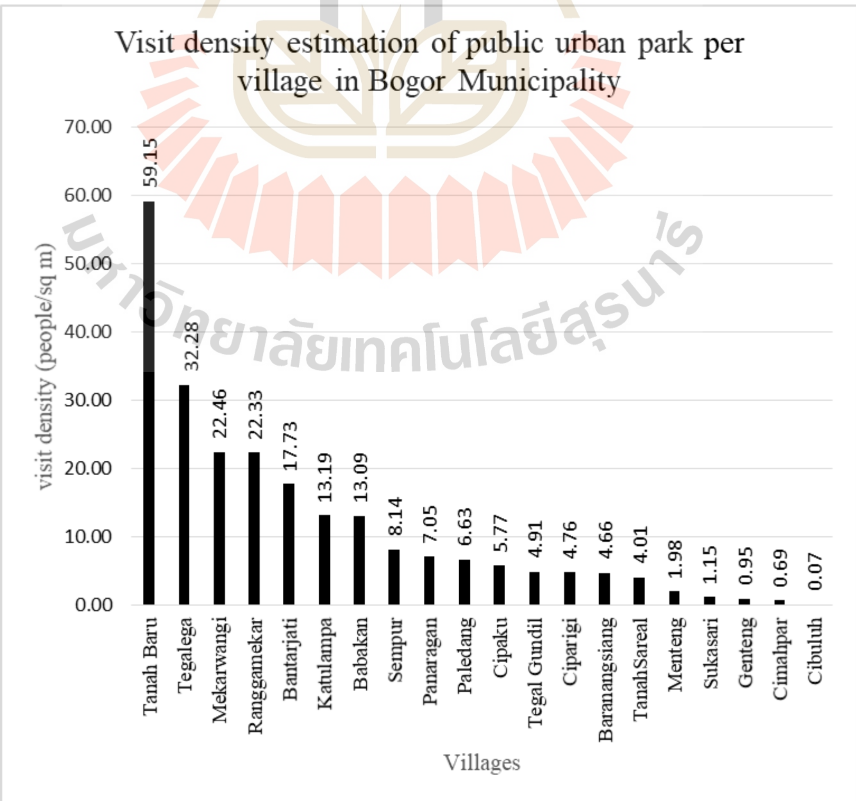


Figure 4.26 Visit density estimation per village in BM.

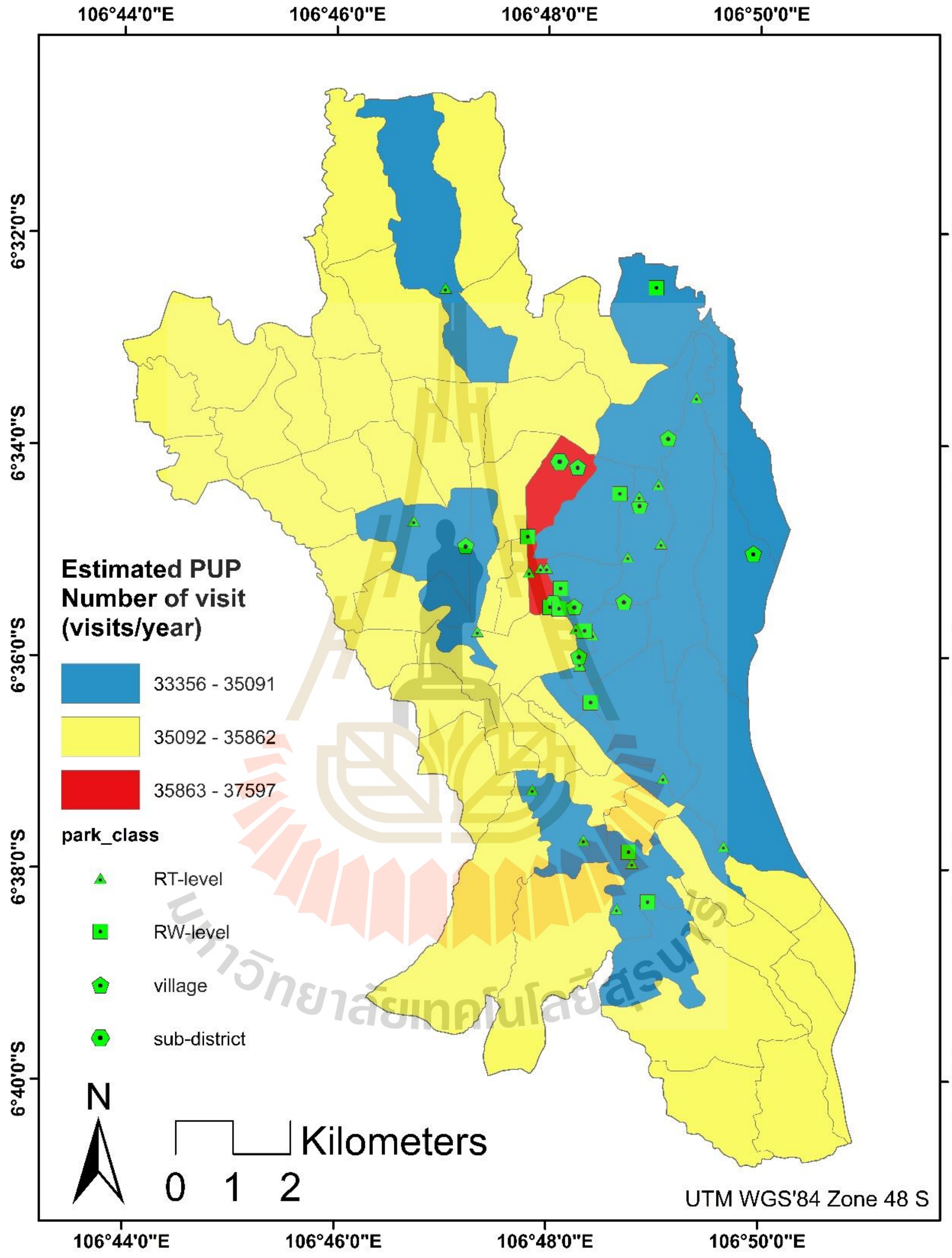


Figure 4.27. Interpolated number of visits of PUPs in villages.

In order to predict number of visit of PUPs in 68 villages, estimated number of visit from 43 PUPs were interpolated using AI method. Model fitting of semi-variogram with circular model at 95 confidence level was chosen because it provided the best RMSSE of 1.002. When RMSSE approaches 1, standard errors are valid (ESRI, 2018e) or it can be concluded that errors from predicted when compared with actual almost similar with its standard deviation after divided by number of datapoints. The estimated number of visits from 43 PUPs are shown in Figure 4.27.

The result of interpolated number of visit showed that two villages have high visits (displayed in red in Figure 4.27) while low visits are in villages with blue colors. Interestingly, two villages with higher visits are those having top accessibility score, namely Sempur and Tanah Sareal (Figure 4.12). This confirms the concept of strong relationship between PUP accessibility, estimated from park hierarchy and population (Meng and Malczewski, 2015), and park visits (Zanon, 1998). In other words, when a village has high accessibility score due to having complete park hierarchy, it will increase number of visits.

4.2 Village-based PUP optimum area demand using Mamdani

Firstly, all of antecedents and consequent were necessary to be normalized before input into FISs. This step of normalization has been performed previously in various studies such as daily cellphone usage from grid cells (Demissie et al., 2015). Furthermore, FCM used in this study has been applied successfully to cluster NDVI and NDWI of Landsat 8 to generate three classes namely, water, vegetation, and non-vegetation (Taufik et al., 2017). In addition, Z-score data normalization (Abdi, 2010) was selected to apply in this study since it is more successful when compared to other data normalization methods like total summation and vector norm to one. Both methods were performed with 17 villages and resulted in number of visits with negative values in Sugeno FIS, while no such a case occurred when using Z-score data normalization.

This study uses fuzzy partition matrix *m*=2 for FCM data clustering according to the recommendation of Gueorguieva, Valova, and Georgiev (2017). When *m* value approaches to 1, the membership degree becomes more crisp value (Gueorguieva et al., 2017). Another important component to consider is minimum improvement objective to measure distance among data points to its cluster centers. By default, Mathworks (2018d) suggests 1.10^{-5} as minimum improvement objective, but after simulations applying this threshold, it makes membership curves become overlapped. To avoid this, this study applies 1.10^{-3} to give chance for data points to be clustered moderately.

Final fuzzy membership curves show not much overlapping and almost similar to fuzzy membership function shown in Wismadi et al. (2008) (Figure 4.28).

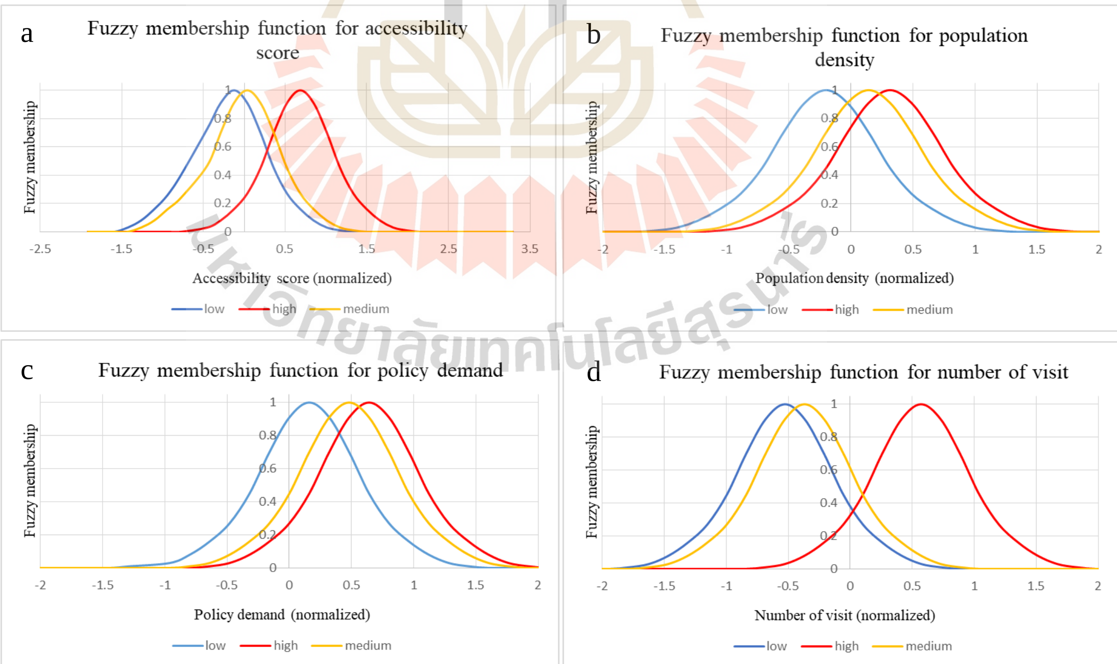


Figure 4.28. Membership functions of antecedents and consequent using Mamdani FCM; (a) accessibility, (b) population density, (c) policy demand, (d) visit density.

As a result, when input into Mamdani FCM within Matlab environment, aggregated rules were automatically developed and eventually resulted in defuzzified consequent using CoM method (Equation 2.21). Three rules were produced by Mamdani FCM as shown in Table 4.7.

Table 4.7. Aggregated rules developed using Mamdani FIS with FCM.

Rule	**Antecedents**			**Consequent**
	Accessibility	**PUP policy demand**	**Population density**	**Visit density**
1	Low	Low	High	High
2	Medium	High	Low	Medium
3	High	Medium	Medium	Low

As a consequent of the process, optimum PUP visit density of each village was obtained. It was then processed using Equation (3.4) to obtain optimum PUP area demand. The demands of villages from Mamdani FIS are displayed in Figure 4.29.

Obviously observable in Figure 4.29, high optimum PUP demand appears in Tegalgundil village (highlighted in orange color) which has PUPs of two levels. This occurred because optimum PUP area demand was also influenced by policy. Even though a village has adequate PUP and high accessibility score but if lacks of future PUP development in master plan, the minimum requirement by law can make its demand increased. This makes proposed policy demand works similarly when Gupta et al. (2012) includes not only public park hierarchy but also Delhi master plan to assess the sufficiency of urban green space. Hence, this study proves that not only accessibility and population density but also policy demand plays important role to estimate PUP area demand.

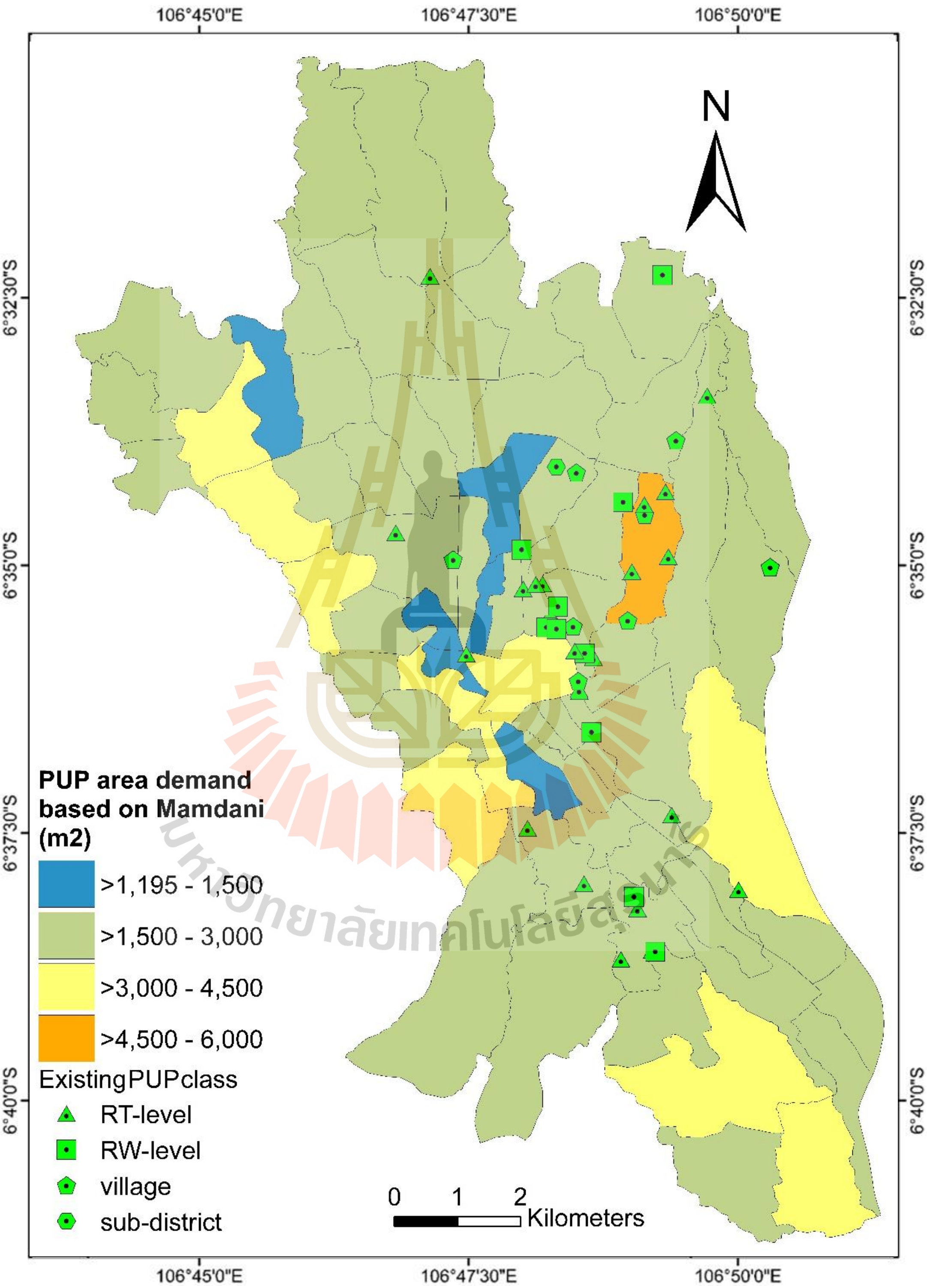


Figure 4.29. Optimum PUP area demand based on Mamdani FIS.

More information from Figure 4.29, 58 villages or 85.3% have low area demand between 1,190 and less than 3000 m^2 (presented in blue and brown colors), while the rests, 11.7%, need more park area ranging 3000-4500 m^2. As minimum standard for the smallest PUP of RT-level (250 m^2), it can alternatively develop 6 PUPs for the demand of 1500 m^2 within one village.

4.3 Village-based PUP optimum area demand using Sugeno-1

Inputs for Sugeno FIS were the same as for Mamdani FIS. The membership functions for antecedents and consequent from FCM (Figure 4.28) were applied and the aggregation rules for Sugeno FIS were developed and are shown in Table 4.8. According to the concept of Sugeno-1, visit density as a consequent was presented in linear relationship of the antecedents.

Table 4.8. Rule development using Sugeno FIS with FCM.

<table>
<tr><th rowspan="2">Rule</th><th colspan="3">Antecedents</th><th>Consequents</th></tr>
<tr><th>Accessibility</th><th>PUP policy demand</th><th>Population density</th><th>Visit density</th></tr>
<tr><td>1</td><td>Low</td><td>Low</td><td>High</td><td rowspan="3">-0.35*access + 0.09*popdens - 0.12*policy + 196.10^{-16}</td></tr>
<tr><td>2</td><td>Medium</td><td>High</td><td>Low</td></tr>
<tr><td>3</td><td>High</td><td>Medium</td><td>Medium</td></tr>
</table>

Resulted optimum PUP area demand for every village based on Sugeno-1 can be seen in Figure 4.30. Only one village (highlighted in red) has optimum PUP demand beyond 6,000 m^2 while only one village with the lowest demand (blue color) requires less than 1,500 m^2. Interestingly, one village with the demand of 4,500-6,000 m^2

(orange color) appears the same in results from both FISs. Generally, from Sugeno-1, 86.7% of villages is dominated by villages with 1,500-3,000 m^2 demand.

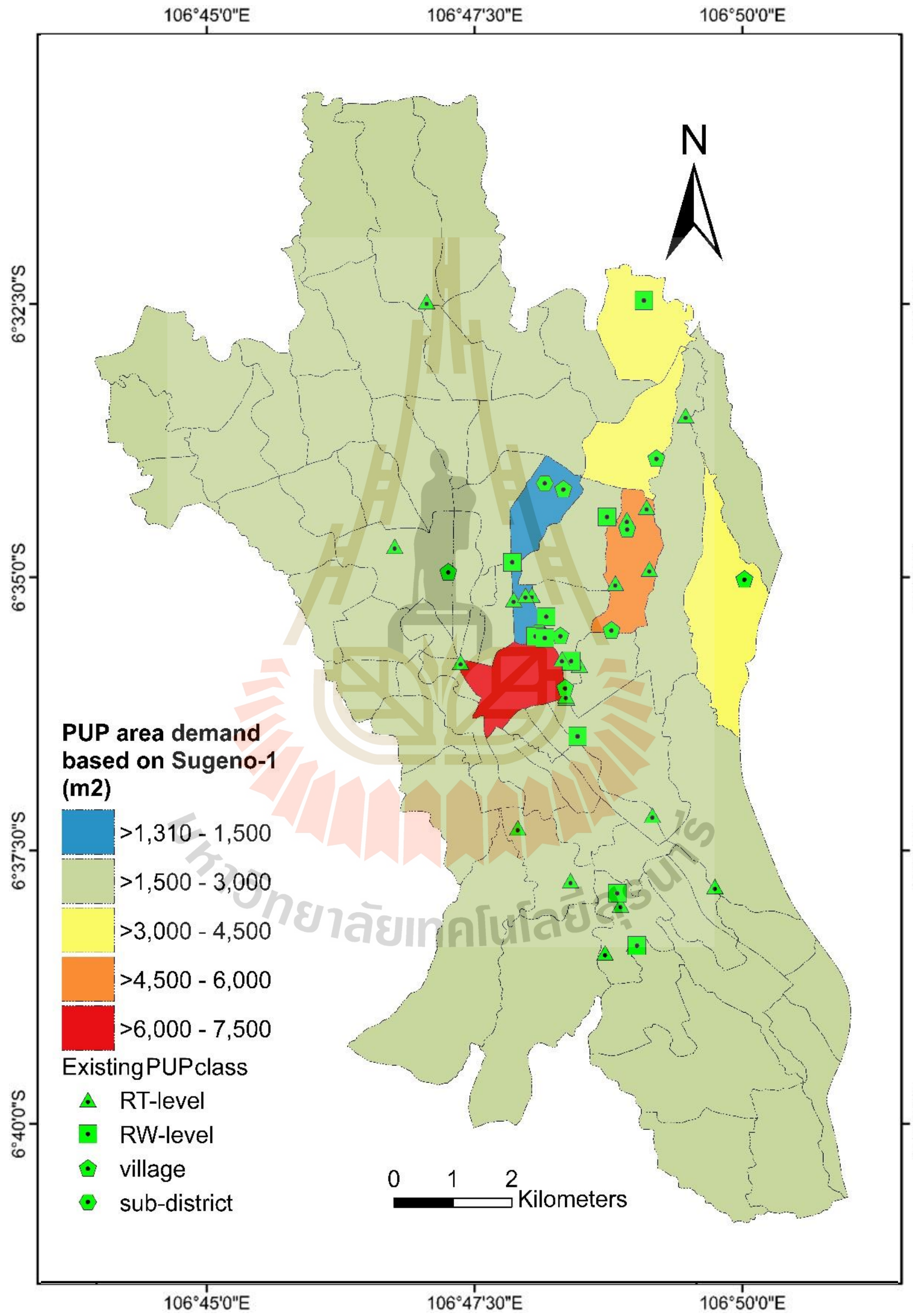


Figure 4.30. Optimum PUP area demand using Sugeno-1.

The linear regression relationship among these variables - defuzzied visit density as the dependent and accessibility, population density, and policy demand as the independents - was investigated. The correlation coefficient (*R*) is 0.832 when correlated with defuzzied visit density from Mamdani FIS, while it is 0.753 for visit density from Sugeno FIS. *R* from both Mamdani and Sugeno are between 0.7 and 0.9. This indicates that accessibility, population density, and policy demand are highly correlated with number of visit (Calkins, 2005).

4.4 Village-based PUP optimum area demand using Sugeno-0

Generally, Sugeno-0 is the same with Sugeno-1 when performs fuzzy membership function using FCM. The difference is in Sugeno-0 the defuzzified visit density comes from constant value.

In this study, the constant value of visit density for every village was 12.7 visits/m^2/year which resulted from defuzzification of Sugeno-0. When transformed into polygons, the optimum PUP area demands were not so different as they fall into the narrow range between 2626-2690 m^2 (Figure 4.31). Needless to say, Sugeno-0 offered almost the same PUP area demand for every village while Mamdani and Sugeno-1 did not. In details, optimum PUP area for 68 villages from three FISs can be seen in Appendix B.

The PUP demand areas from these methods are village-based attributes. Therefore, the incorporation of these demand areas and village-based feasible PUP areas is still required to identify the most optimum demand.

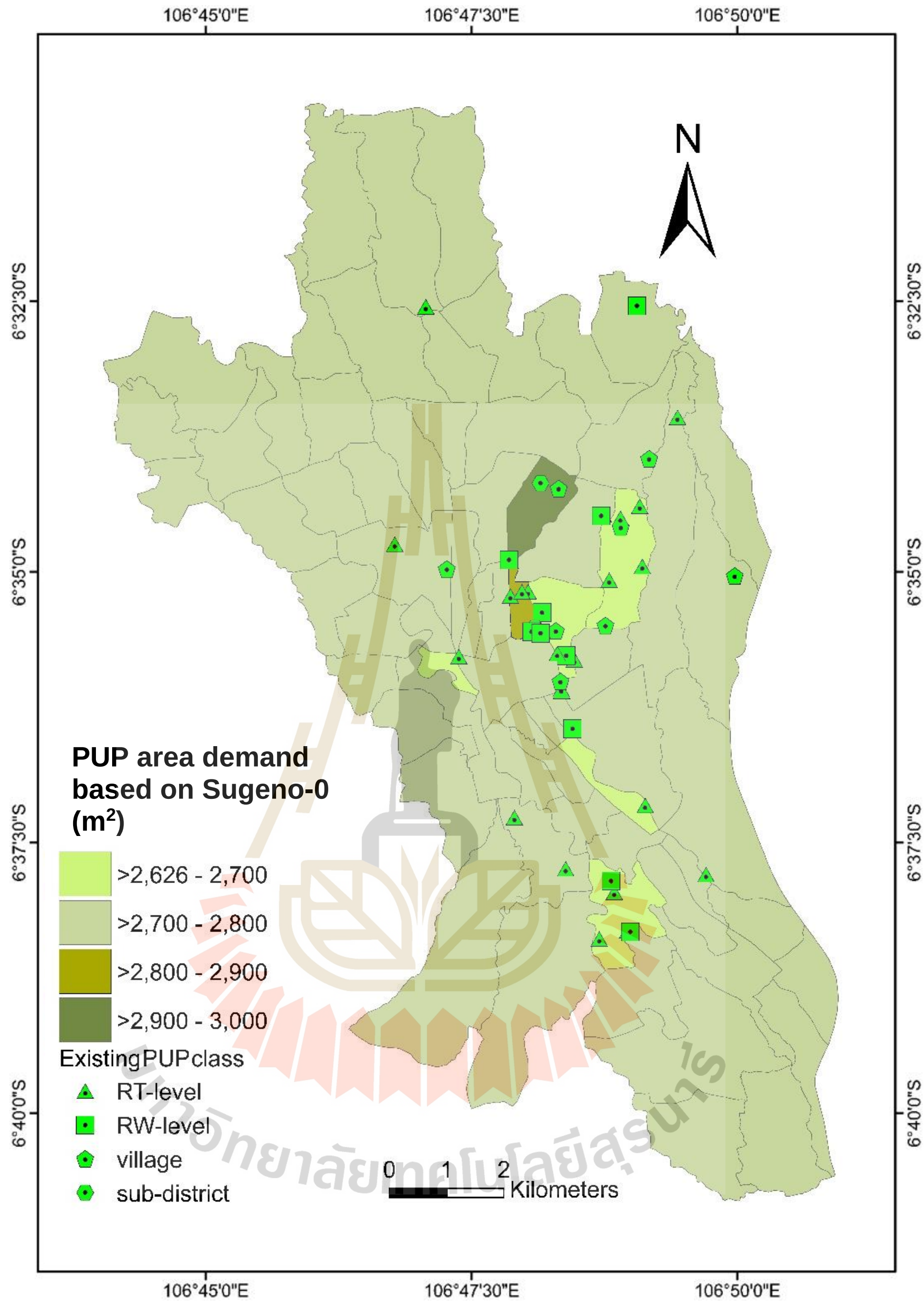


Figure. 4.31 Optimum PUP area demand using Sugeno-0.

4.5 Agreement of village-based PUP demand areas

The availability of area for PUP development in each village was obtained by selecting the area of feasible land use classes from Google Earth image of 2018. Unlike the urban and water body classes that seems infeasible for PUP development, agricultural land class was feasibly chosen for this study to meet the class having the least obstacle for future development. In addition, river, lake, and urban classes were considered infeasible while paddy field was moderately feasible (Uy and Nakagoshi, 2008). Figure 4.32 shows that most of available area are in villages located far away from the city center. M2

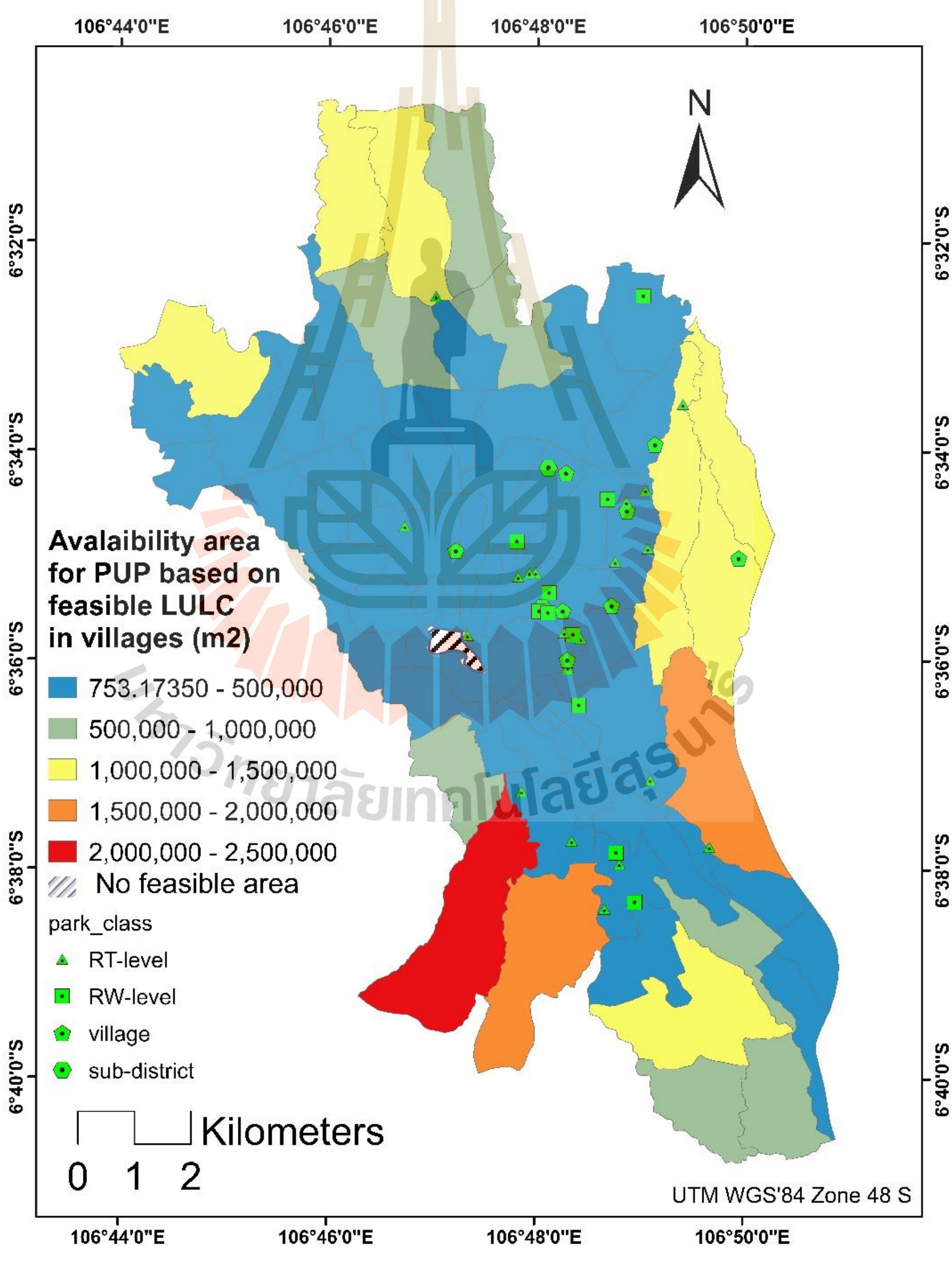


Figure. 4.32 Available area for optimum PUP development based on feasible LULC.

Considering only attribute as areal extent of demand area (without suitability level), to assess which method is most suitable to provide optimum PUP area, the agreement between demand area and area of feasible land use classes was performed using equation:

$$agreement = \frac{number\ of\ villages\ having\ optimum\ park\ area \leq feasible\ LU\ area}{total\ villages} \text{ x } 100\% \quad (4.2)$$

It revealed that the result from Mamdani FIS provided the best 97.1% agreement, while Sugeno-1 and Sugeno-0 had the same agreement of 94.12%. Total feasible area provided by Sugeno-0, Sugeno-1, and Mamdani were 0.19, 0.15, and 0.13 km^2, respectively (Figure 4.33).

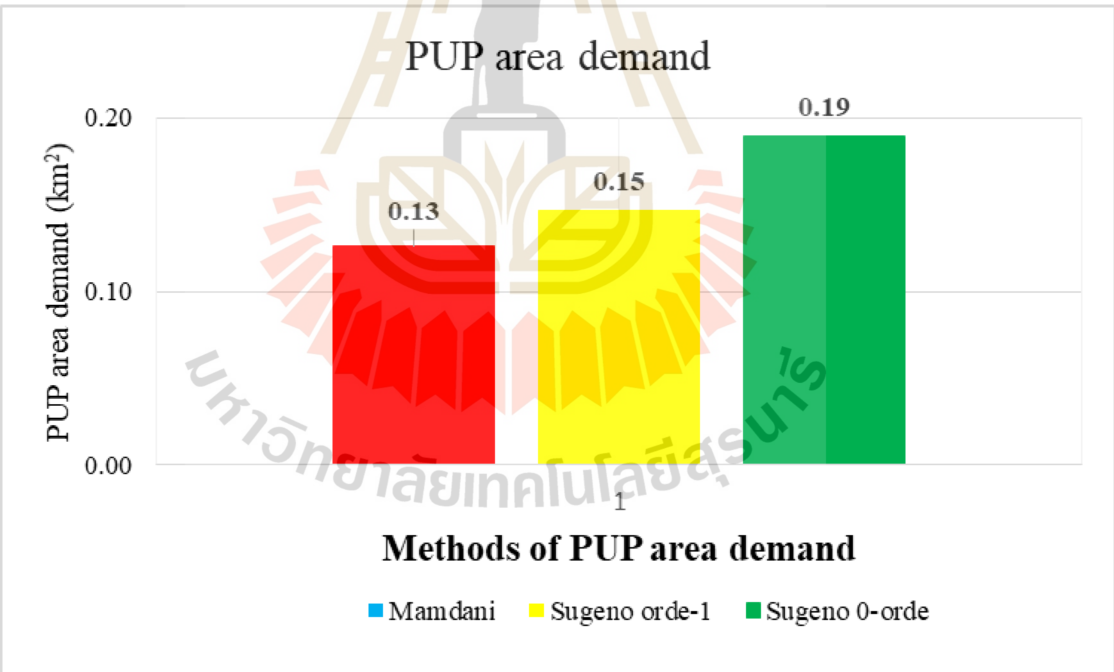


Figure 4.33 Total PUP demand area based on different FISs.

The prominent feature of this analysis is that though Mamdani generates smallest total area for PUP demand but it provided the highest agreement due to having better distribution to villages.

4.6 Raster-based criteria data for PUP suitability mapping

4.6.1 Population density

Based on predicted 2031 LULC prediction using CA-Markov, the population density of polygons of LULC that people living in were estimated from village population by AI. The layer of estimated population density was then converted to be a raster layer with 10 m x 10 m spatial resolution and is displayed in Figure 4.21. This raster map was used to estimate catchment population from 43 PUPs and to extract population density information from each PUP to input into FISs.

4.6.2 Accessibility

At first, all of PUPs were classified based on its size and then using network analysis of 15 minutes walking impedance and population to generate their service areas. Each component score of each PUP based on minimum distance, covering, and travel cost were computed using Equations (2.3-2.5). All of scores based on these models then integrated using entropy within Equations (2.6-2.10) so that every PUP has its accessibility score. Accessibility score was then be divided by area of each village to represent distinctive score per administrative area. Then they were interpolated to be raster layer of 10 m x 10 m spatial resolution.

In order to reduce the disparity between original and estimated accessibility map, Equation (3.1) was employed to generate ‘a’ coefficient and multiply the later with estimated raster cells so that the value in each new raster cells match with the original polygon value. The corrected accessibility raster maps was then classified using geometrical interval to fit with the distribution of data frequencies and is displayed as a raster map in Figure 4.34.

Visually, higher accessibility score follows the spatial distribution of existing PUPs (Figure 4.34). This result confirms previous study by Meng and Malczewski (2015) that accessibility of PUP depends of distance, population and hierarchical classification of PUPs. With shorter distance, higher population, and higher in the hierarchy, a park is more likely to have the higher accessibility.

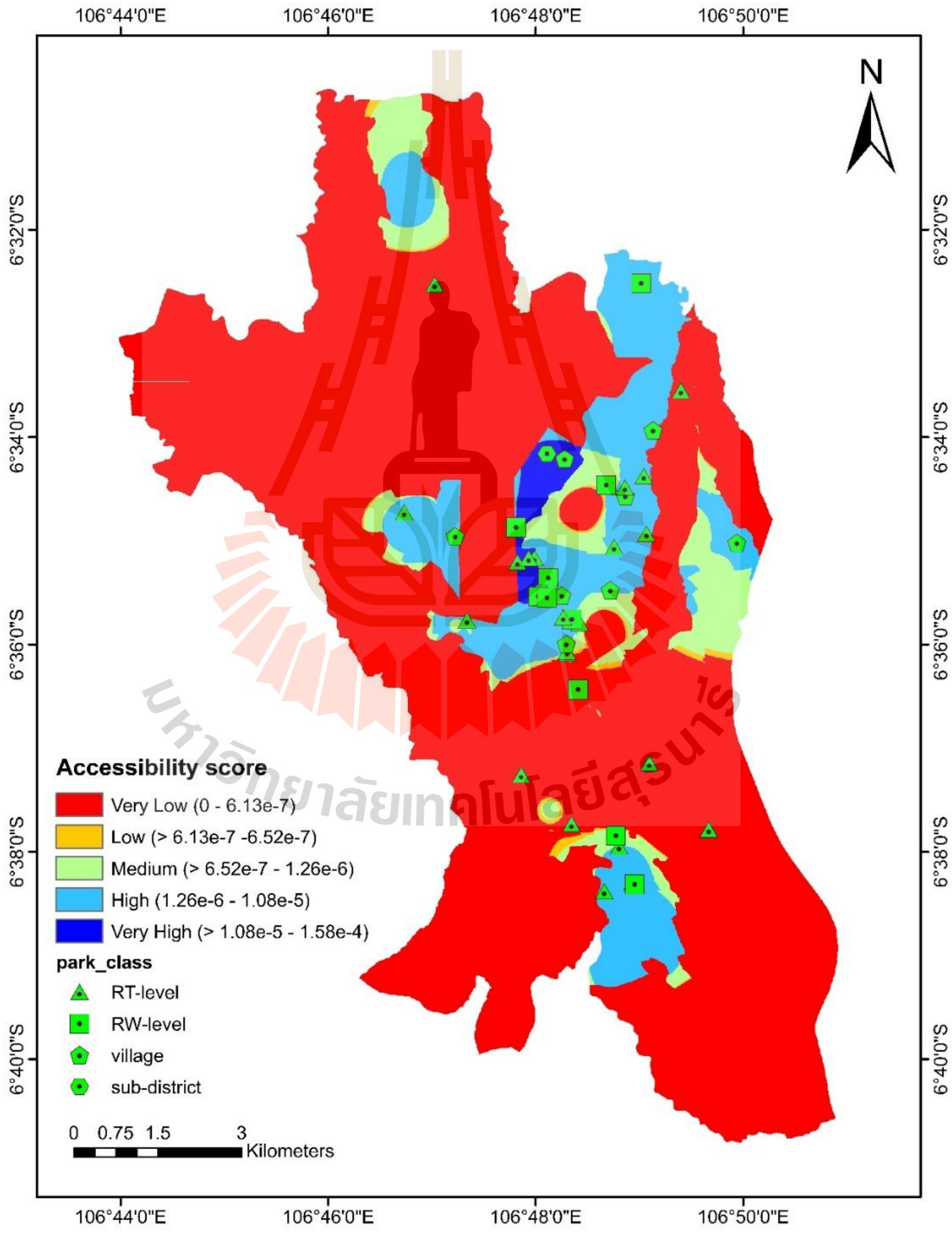


Figure 4.34. Accessibility raster map of Bogor Municipality.

4.6.3 PUP policy demand

Nowadays, as being implemented by the central government of Indonesia that every municipality in Indonesia must have at least 20% of its area as public green open space. This study applied this regulation as a foundation to observe whether villages in BM can meet this demand and how the current status of this policy is when compared to the master plan 2031 and existing green open space.

In addition, as BM has not legalized PUP planning at the scale of 1:5,000 or at the scale of sub-district level so this study will employed the green open space condition and planning at the scale of municipality to assess if a village has meet this demand. On the other hand, some of villages in USA especially in Ada County, Idaho have the policy to develop minimum 5% of its village administrative area as PUP (Ada County Planning and Development Board, 2007). Equation (2.11) is used to quantify the PUP policy demand of each village (Wicaksono and Sarapirome, 2017).

As indicated by the spatial distribution of PUP policy demand (Figure 4.35), most of the villages have the BM has the higher PUP area demand are located in the western part of BM. Furthermore, for the PUP development both master plan or existing, the western part of BM contains only parks on traffic islands while most residential parks have not been transferred to government for public use yet.

Most of villages with low urban policy demand are concentrated in city center and the south. While In city center villages tend to have existing large size public parks on the other hand while in southern part where public and private cemeteries dominate the landscape might give advantage for villages to have lower demand.

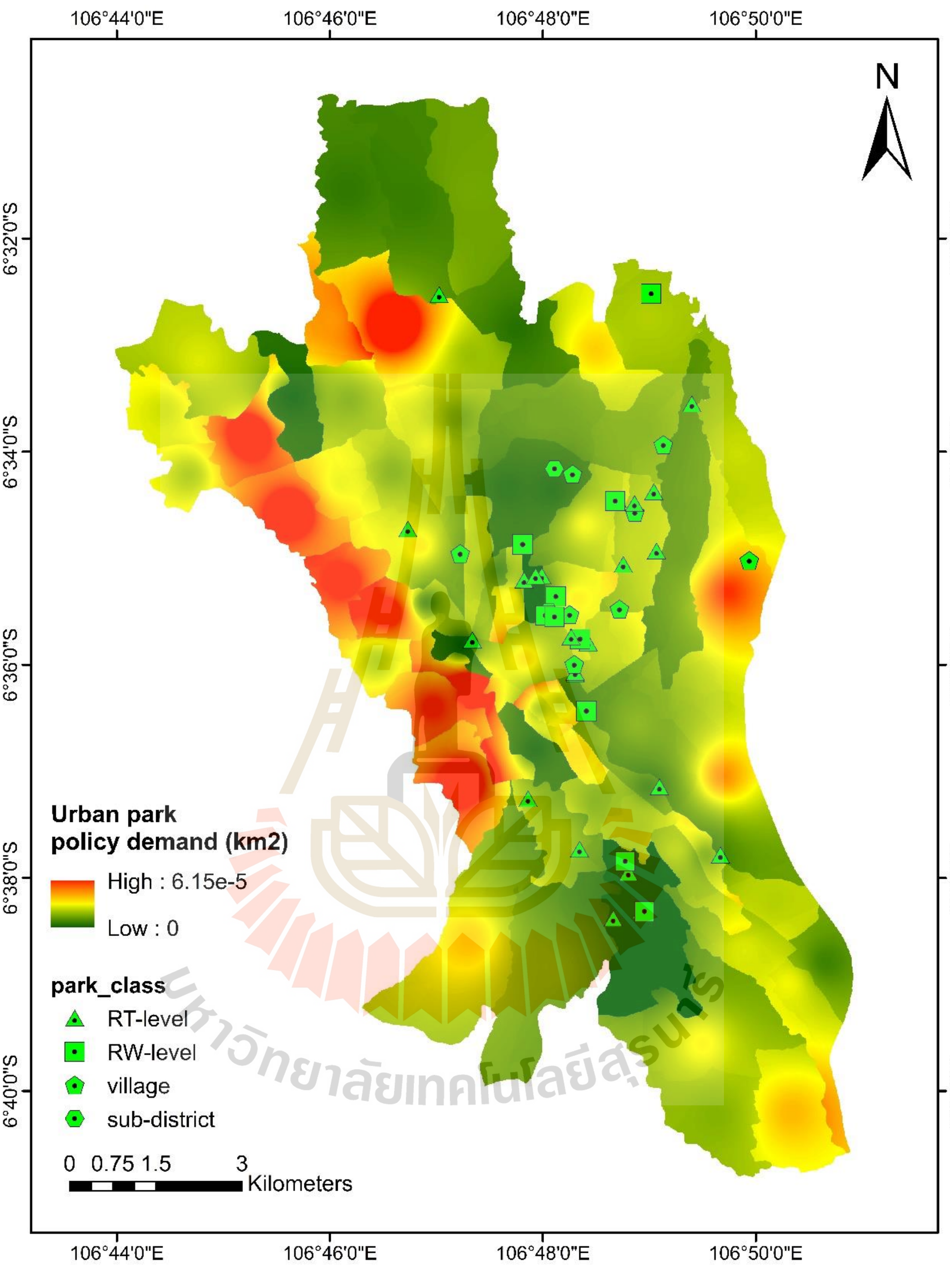


Figure 4.35 PUP policy demand.

4.6.4 Distant-related criteria fuzzy membership

In this study, three distant-related criteria namely, distance to school, water body, and electric power line will be were inputted as antecedent in both Sugeno and Mamdani FIS. In order to shorten the rule development of FIS, decision has been made to combine all of distant-related criteria using ArcGIS fuzzy overlay function. Decreasing sigmoidal function was applied for distance to school and water body, while increasing sigmoidal function was applied to distance to electric power line. As for the midpoint values to each distant-related criterion, Equation (2.14) was applied to distance to school and water body while Equation (2.16) to distance to electric power line (Table 4.9).

Table 4.9. Fuzzy membership function for distant-related criteria.

Criteria	**A point**	**B point**	**Mid-point**	**Source**
Distance to school	100 m	1000 m	550 m	Givi et al, 2015
Distance to water body	300 m	600 m	450 m	Uy and Nakagoshi, 2008
Criteria	**C point**	**D point**	**Mid-point**	**Source**
Distance to electric power line	20 m	40 m	30 m	Indonesian Ministry of Public Works, 2008

Using various methods of integration as results shown in Figure 4.36, fuzzy AND has been herein chosen as fuzzy overlay function to integrate all of three distant-related criteria since it selectively chose the most clearly relationship among criteria for less suitable location (ESRI, 2018e). If any 2 criteria are highly suitable for PUP while 1 criterion is less suitable, fuzzy AND decides final output as less suitable (Figure 4.37). This means fuzzy AND selects more carefully and provides safest opinion to counter doubt of final cell output. Result explanations from different methods were presented in Figure 4.36.

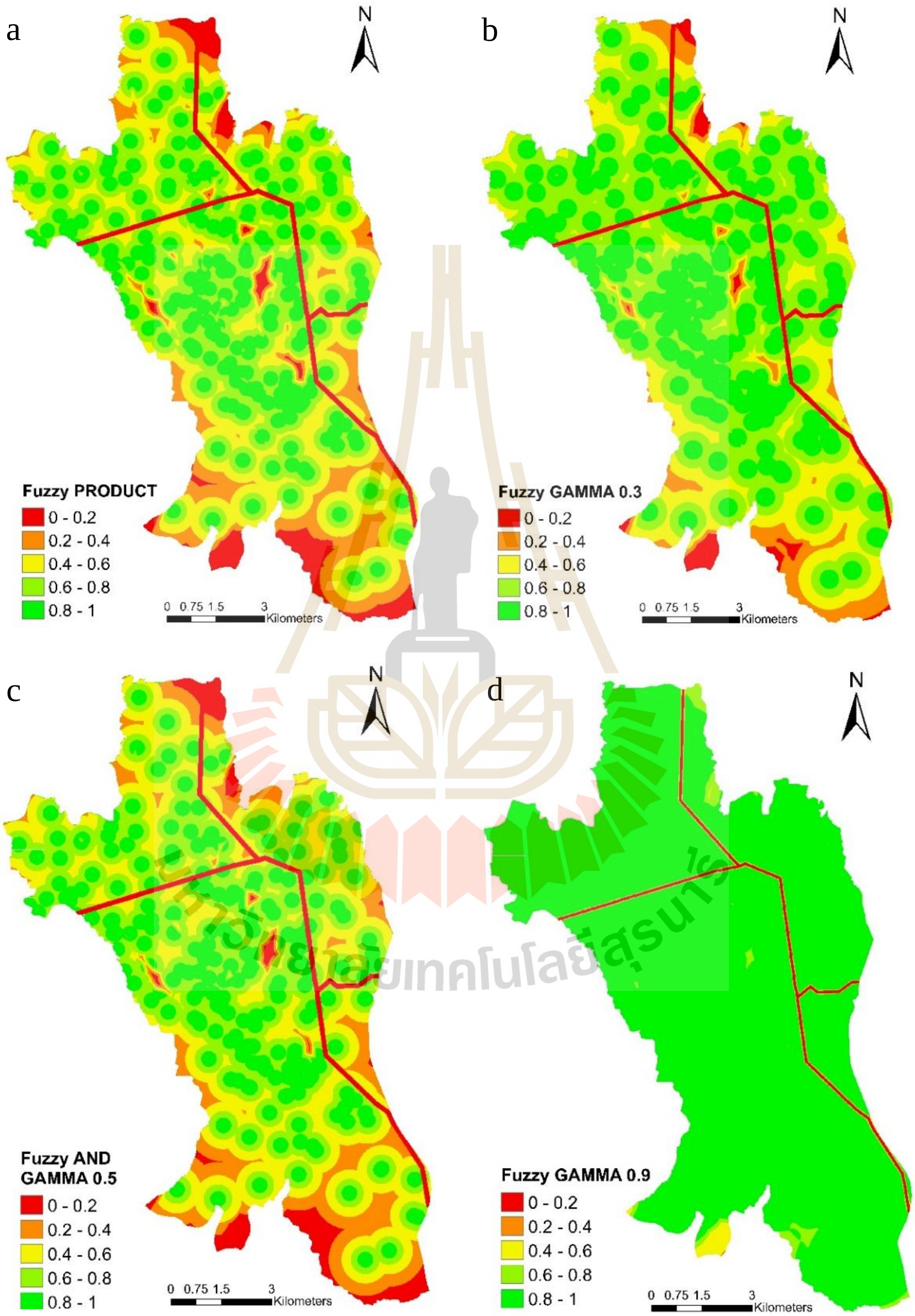


Figure 4.36. Fuzzy overlay models for raster-based suitability mapping: (a) Fuzzy PRODUCT, (b) Fuzzy GAMMA 0.3, (c) Fuzzy AND, (d) fuzzy GAMMA 0.9.

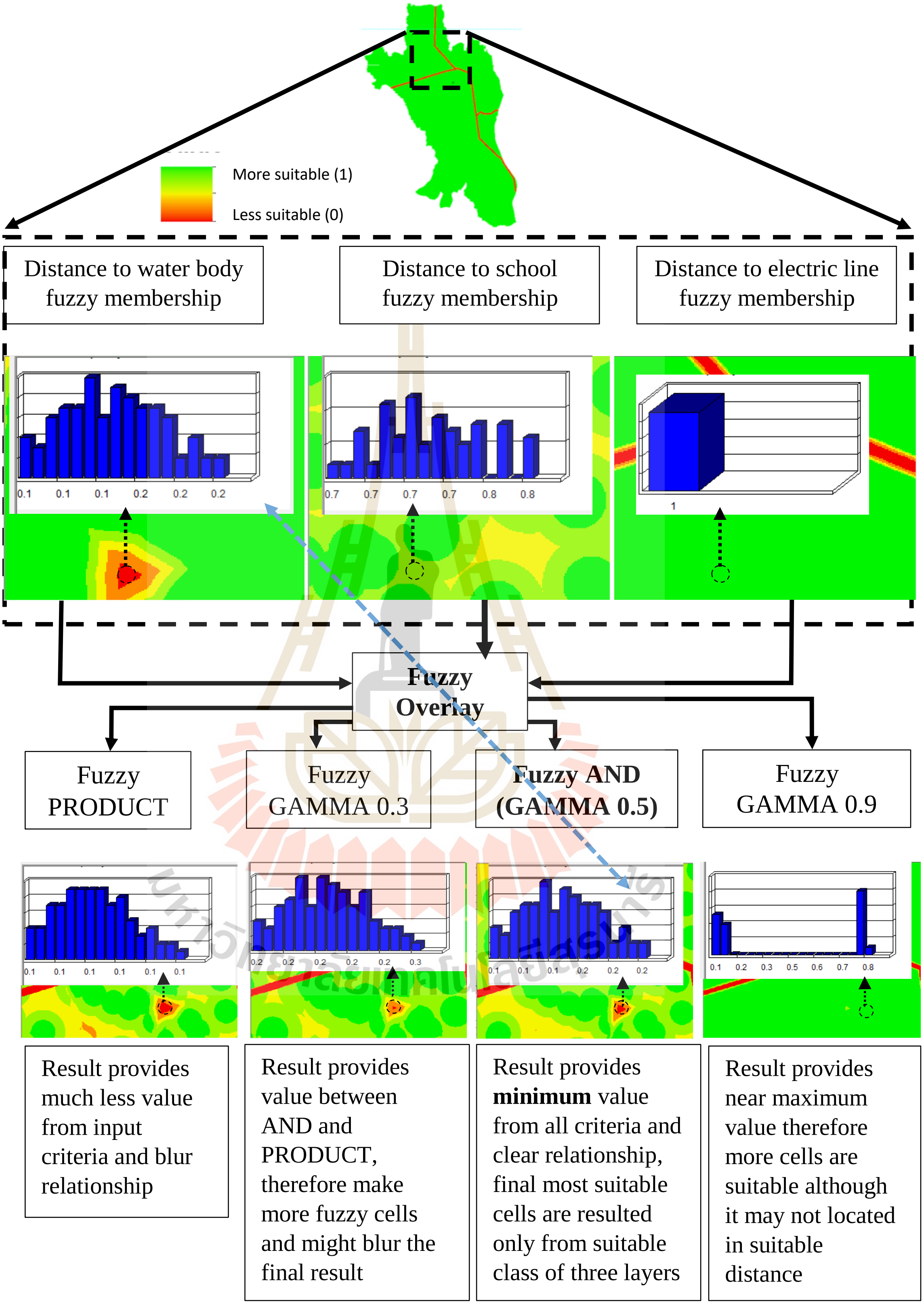


Figure 4.37 Results of fuzzy overlay from various methods.

Look at the combination result, it is shown that the result from fuzzy AND can provide **minimum** value from all criteria and clear relationship. Final most suitable cells are resulted only from suitable class of three layers. Other methods provide either not clear relationship or over favorable cells.

In addition, Gamma 0.3 (Givi et al., 2015) method generated values between AND and PRODUCT, where resulted cells are moderate in case of 2 high suitable cells and 1 low cell which will be dangerous especially for unfavorable locations such as electric power line that should be forbidden for PUP. Fuzzy PRODUCT produces cells in which values are lower than input therefore undermining suitable cells located within distance of favorable locations. Moreover, Fuzzy AND also recommended by ESRI (2018f) when doing analysis with 0.5 or greater value represented higher possibility for suitable location.

4.7 PUP suitability map based on Mamdani FIS with FCM

4.7.1 Fuzzy membership and rule development

Automatically, Mamdani FIS with FCM will decide the applied developed rules to generate defuzzified values of consequent altogether with agglomerate fuzzy memberships of antecedents and consequents and then defuzzifid using CoM. Firstly, all PUP polygons with visit density data were converted to raster cells with 10 m x 10 m resolution. This step is meant to achieve direct relationship of antecedent-consequent within raster cells with condition of non-zero value input. Secondly, converted raster cells of visit density values were masked to raster maps of population density, accessibility, and distant-related criteria by using “extract value to table” in ArcGIS environment. Furthermore, selected cells were aggregated into same files of MS Excel and normalized using *Z*-score method.

Careful identification of zero values in MS Excel could detect and ignore cells which were located within PUP policy demand and water body class of LULC and this step reduced the number of cells being input to Matlab system. Finally, 1585 cells of each antecedent-consequent were successfully input to Mamdani FIS with FCM to gain fuzzy membership function and rules for defuzzification.

As required to input involved criteria into Mamdani FIS, at first all antecedent-consequent variables were classified using FCM. In addition, Mamdani FCM was run using m=2.6 for degree of partition matrix and J_m=1.10^{-5} while maximum iteration was set at 10,000. This follows suggestion by Ozkan and Turksen (2007) that for upper bound of fuzziness approximately 2.6 for practices in FCM system development.

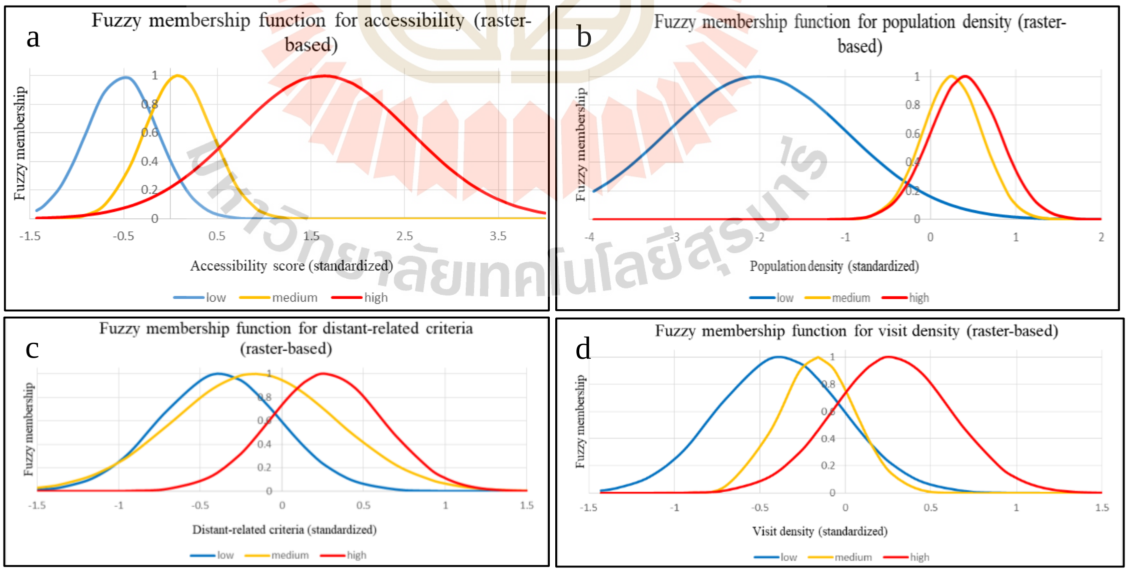


Figure 4.38 Fuzzy membership function based on Mamdani FIS with FCM for raster-based: (a) accessibility, (b) population density, (c) distant-related, (d) visit density.

Generated fuzzy membership from FCM for Mamdani FIS satisfactory grouped data points into three clusters centers (Figure 4.38), where their curves similarly follow the previous study (Wismadi et al., 2012). As an advantage from FCM system, Mamdani FIS automatically generates rule development and configuration for defuzzification application (Table 4.10 and Figure 4.39) which were used to identify raster cells with suitable PUP locations.

Table 4.10. Rules development for Mamdani FIS with FCM.

Rule	Antecedents			Consequents
	Accessibility	**Population density**	**Distant related criteria**	**Visit density**
1	Low	Medium	Low	Low
2	Medium	Low	Medium	Medium
3	High	High	High	High

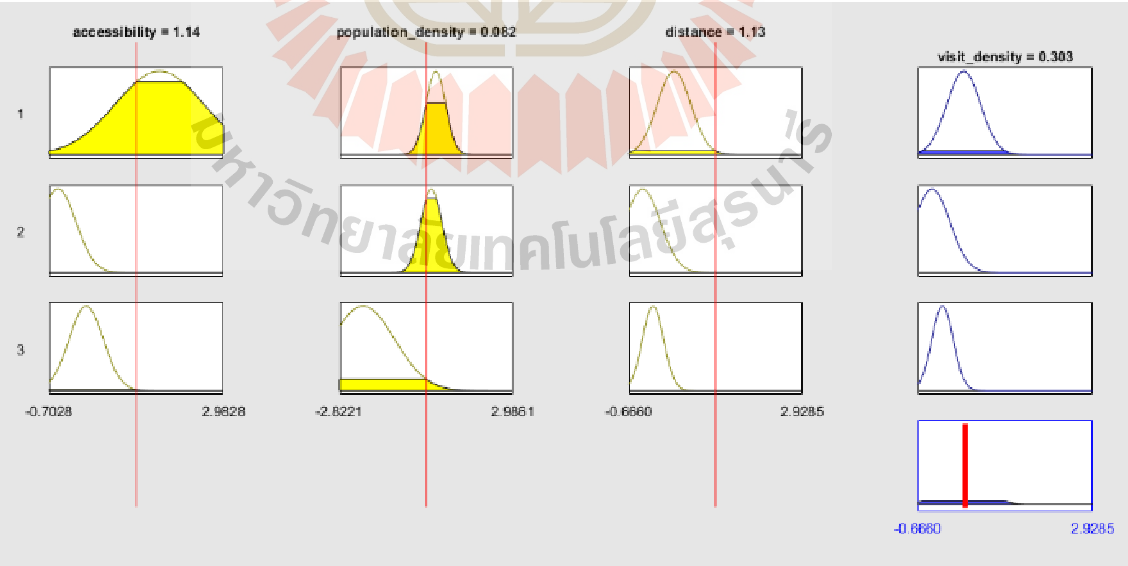


Figure 4.39 Rule configuration resulted from Mamdani FIS with FCM.

Interestingly, rule development based on Mamdani FIS with FCM relates high visit density with high antecedents. This indicates that high visit density raster cells concurrent with high antecedent classes. It means when raster cells are located within locations having high population density, access, and near suitable distance then predicted that number of visit will be high.

To validate the data clustering resulted from FCM, this study uses Partition Entropy (v_{PE}^{FCM}) (Pal and Bezdek (1995):

$$v_{PE}^{FCM} = -\frac{1}{n}\sum_{i=1}^{n} u_{ci}\, log_a u_{ci} \tag{4.3}$$

where u_{ci}=membership for i-th datapoints in c cluster, a=base for log, n=total datapoints. When m approaches 1 then v_{PE}^{FCM} resulted value nearly 0 (Pal and Bezdek, 1995).

Table 4.11 Partition entropy for criteria clustering validation

Clusters	$u_{ci} * log_a u_{ci}$, a=2			
	Accessibility (n=100)	Population density (n=100)	Distant-related (n=100)	Visit density (n=100)
Low	-2.45	-5.59	-4.05	-3.64
Medium	-4.13	-2.9	-3.64	-2.98
High	-10.33	-5.4	-4.69	-6.11
$\sum_{i=1}^{n} u_{ci}\, log_a u_{ci}$	-16.91	-13.89	-12.38	-12.73
v_{PE}^{FCM}	**0.17**	**0.056**	**0.04**	**0.13**

Hence**,** 400 data points were randomly selected from standardized 1585 cells representing 100 data points for each cluster. Furthermore, these data points were computed to generate membership degree (u_{ci}) for each criteria's cluster using

Gaussian membership function (Equation (2.1)). It can be observed that all criteria have v_{PE}^{FCM} values approaches 0 (Table 4.11). It confirms previous study (Pal and Bezdek, 1995) that when m approaches 1 and c=3, v_{PE}^{FCM} value near 0.

4.7.2 Rule evaluation to gain COM defuzzification formula

Interestingly, to gain crisp output from Mamdani FIS each of weight generated from each rule must be evaluated to acquire defuzzification formula. This procedure was suggested by Kolisko (2015) when bike trail difficulty path in South Moravia was defuzzified from fuzzy rules which integrated slope and road condition fuzzy membership. Therefore, in rule 1 which integrates low accessibility, medium population density and low distance suitability classes, weight will be assessed using low class of consequent membership from FCM (Figure 4.39).

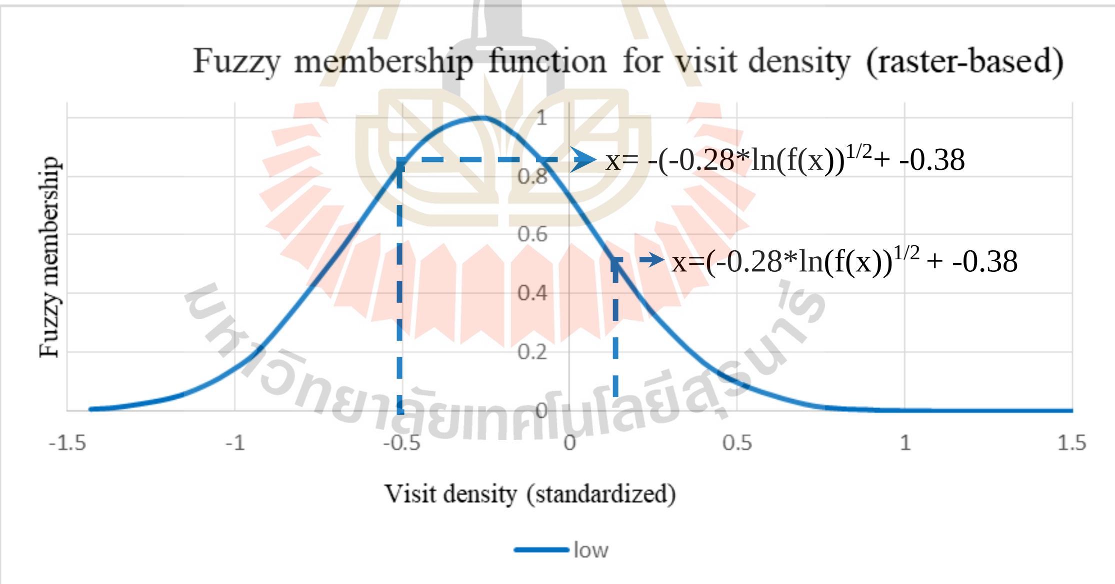


Figure 4.40 f(x) and x relationship for rule 1 Mamdani.

Because resulted low visit density fuzzy membership (FM) curve is expressed in gaussian function which can be written as f(x,σ,c)= e $^{-(x-c)^2/2\sigma^2}$ (Mathworks, 2018a), and from data processing using FCM σ=0.37 and c=-0.38. Hence, relationship between f(x) and x can be expressed as x= (-ln (f(x).2σ^2))$^{1/2}$ + c or x=(-0.28*ln(f(x))$^{1/2}$ + -0.38 for right side, while for left side x=-(-0.28*ln(f(x))$^{1/2}$ + -0.38 (Figure 4.40).

Moreover, rule 2 integrates medium accessibility, low population density and low distance suitability classes, where weight from medium class of consequent membership from FCM will be assessed (Figure 4.41).

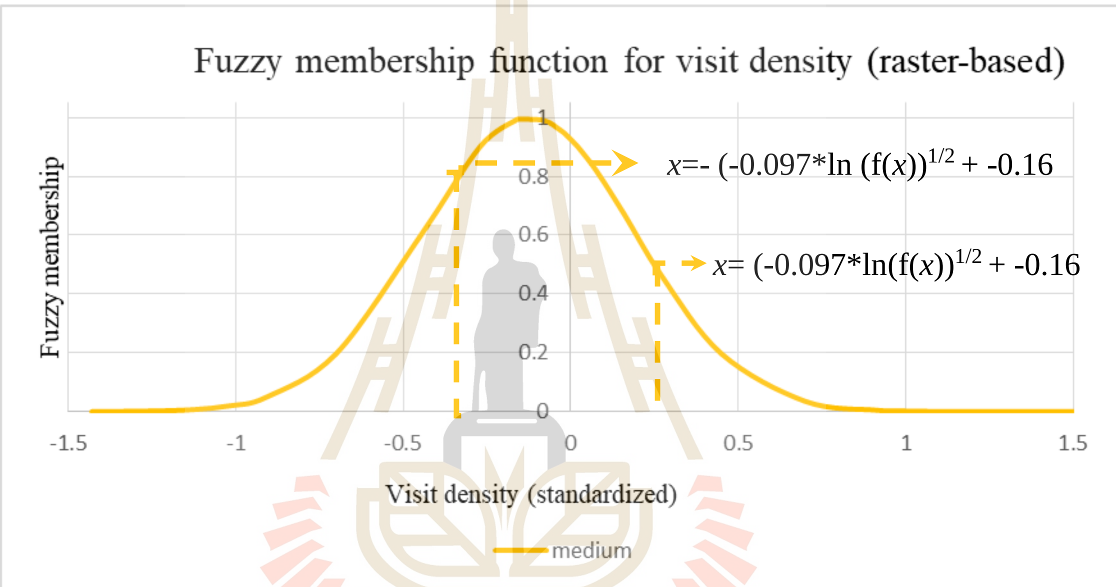


Figure 4.41 f(x) and x relationship for rule 2 Mamdani.

For rule 2, based on FCM data processing to generate medium class of visit density where σ=0.22 and c=-0.16. Therefore, the relationship of x and f(x) can be written as x=- (-0.097*ln (f(x))$^{1/2}$ + -0.16 for left side and x=(-0.097*ln(f(x))$^{1/2}$ + -0.16 for right side of the curve (Figure 4.41). Furthermore, FCM data processing for rule 3 of high visit density MF curve shows that σ=0.35 and c=0.27. Hence, x and f(x) relationship which can be expressed as x=(-0.25*ln(f(x))$^{1/2}$ + 0.27 for right side of the curve, while for the left side of the curve is x=- (-0.25*ln(f(x))$^{1/2}$ + 0.27 (Figure 4.42).

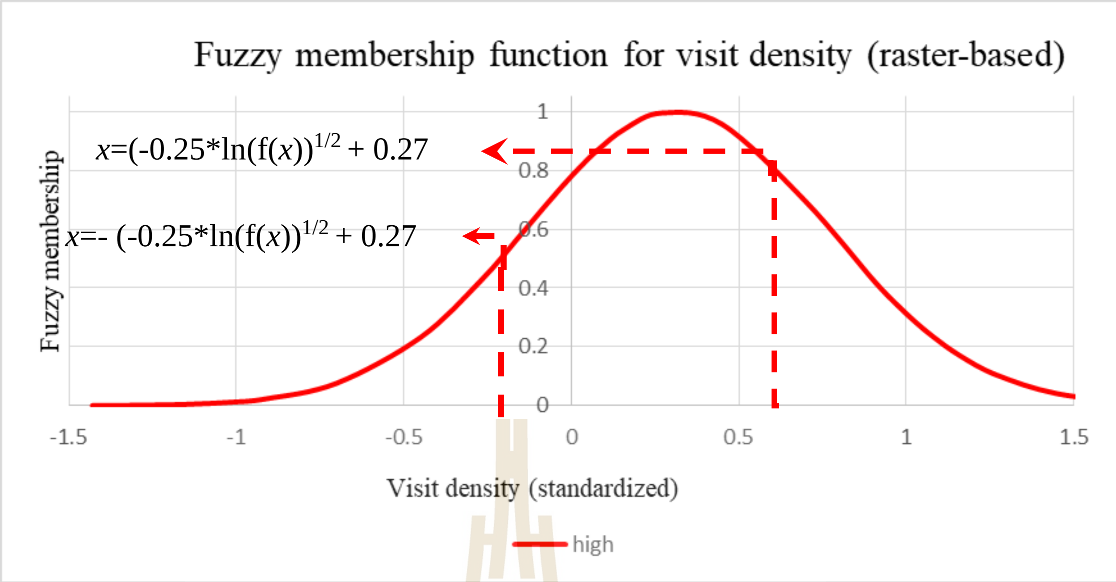


Figure 4.42 f(x) and x relationship for rule 3 Mamdani.

As suggested by Kolisko (2015) x and f(x) relationship represents relationship between weight of rule and y value (Equation 2.21) therefore for final defuzzification formula x is replaced with w. Finally, based on previously rules evaluation total defuzzification formula for Mamdani FIS using CoM can be expressed in Equation (4.4):

$$\frac{\frac{-0.38+-0.38}{2}w1+\frac{-0.16+-0.16}{2}w2+\frac{0.27+0.27}{2}w3}{w1+w2+w3}= \tag{4.4}$$

$$\frac{-0.76*w1+\ -0.32*w2+0.54*w3}{w1+w2+w3}$$

where w_1=weight gained from rule 1, w_2=weight gained from rule 2 and w_3=weight resulted from rule 3 of Mamdani FIS.

Finally, 9 raster maps of corresponding classes resulted from Gaussian MF were input into three FIS rules configuration based on Table 4.10 and Figure 4.39. As prerequisite before converted into MF, cells from 9 maps were standardized using Z formula. After being standardized, these 9 raster maps were converted into MF using Gaussian function (as displayed in Figure 4.43). Green colors indicate high value of suitability for each classification while red colors highlight low value. Based on 3 rules, there are three combinations of fuzzy memberships resulted from Mamdani FIS displayed in Figure 4.44(a-c).

4.7.3 Suitability map of PUP based on Mamdani FIS

For the final product, 3 raster maps were generated based on 3 FIS rules especially using AND function in ArcGIS fuzzy overlay menu to produced three different weights (Figure 4.44). These 3 raster maps are represented 3 weights in Equation (4.3). It can be observed from raster maps of 3 rules that few suitable cells indicated by green colors and visually were dominated by less suitable cells with red color. It could imply that Mamdani FIS generated more selective suitable cells for PUP based on fuzzy rules. These raster maps were then defuzzified to be a single raster map. In the final step, defuzzified raster map then converted again based on Z to recover original visit density value functioned as suitable map for PUP (Figure 4.45).

In addition, cells with higher visit density are considered as most suitable map for PUP. In this map, equal interval of 200 visits/100 m^2 is used to classify suitability index for PUP where very high ranges between >800 visits/100 m^2 and high suitability ranges between >600-800 visits/100 m^2 and so on decreasing finally to very low suitability.

Surprisingly, resulted PUP locations from Mamdani are scattered all over BM, not only concentrated in some parts of the city (Figure 4.45). This occurs because weights from 3 different rules are quite balance among accessibility, population density and distant-related as resulted from CoM defuzzification.

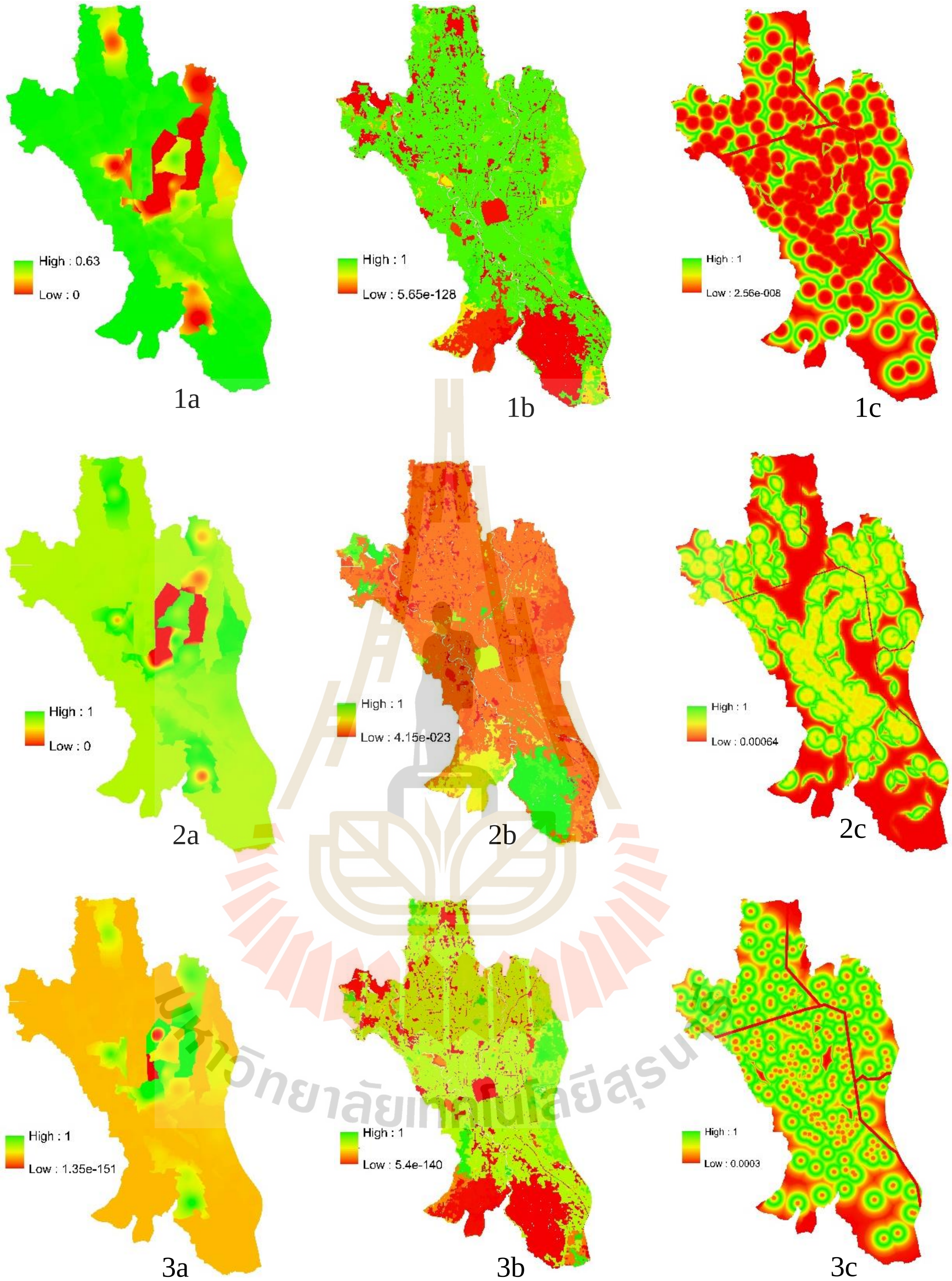


Figure 4.43 Criteria input for rule 1 Mamdani and Sugeno: (1a) low accessibility, (1b) medium population density, (1c) low distant-related, rule 2: (2a) medium accessibility, (2b) low population density, (2c) medium distant-related, rule 3: (3a) high accessibility, (3b) high population density, (3c) high distant-related.

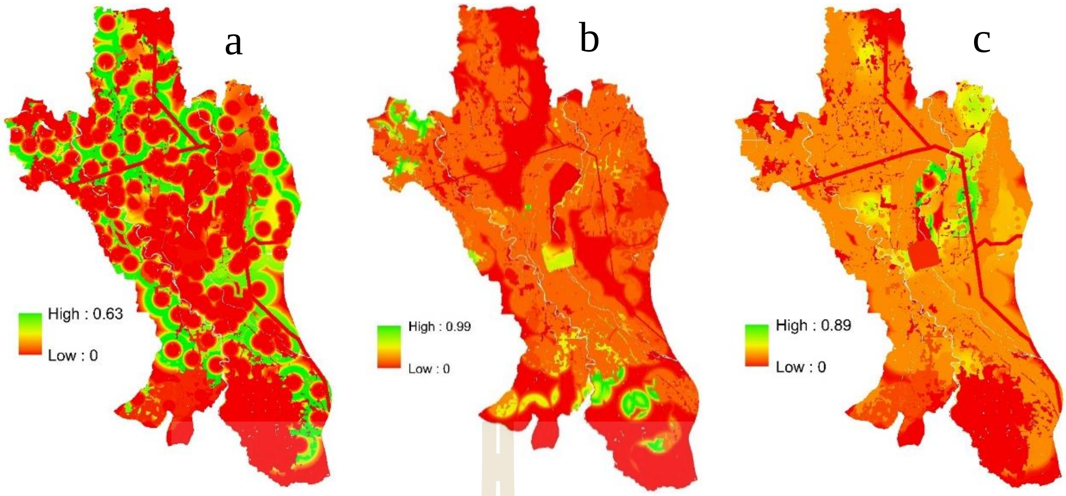


Figure 4.44 Mamdani and Sugeno FIS: (a) rule 1, (b) rule 2, (c) rule 3.

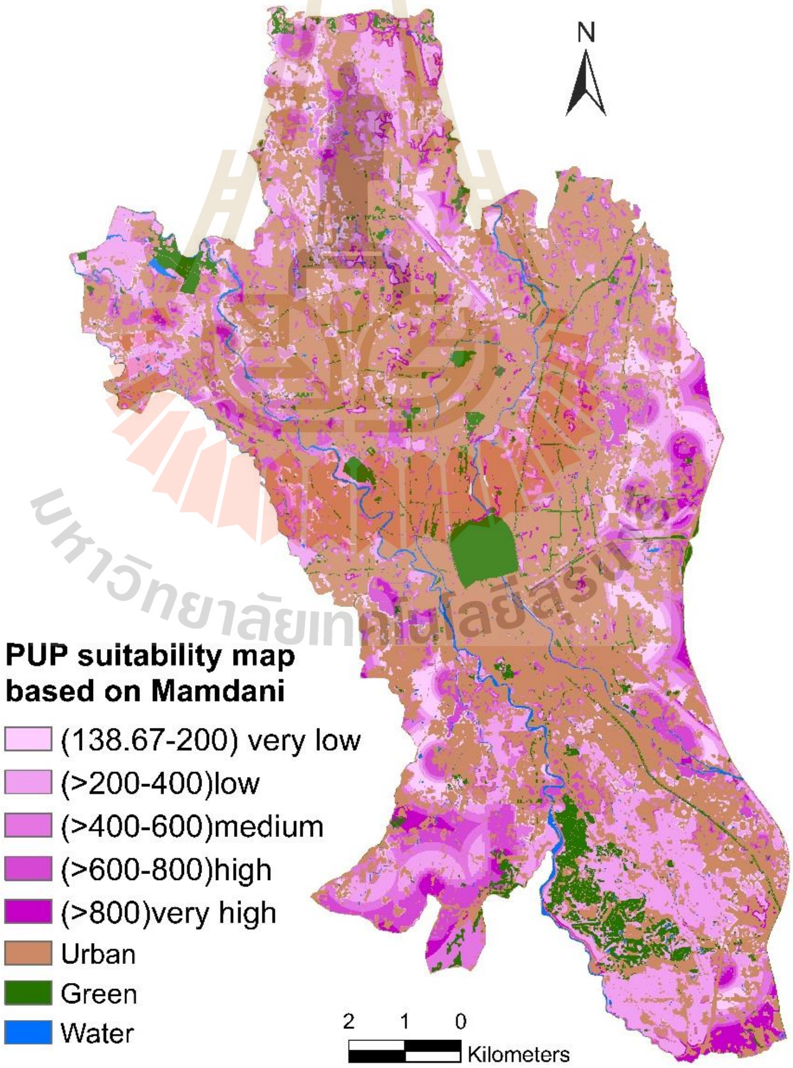


Figure 4.45 PUP suitability map using Mamdani.

4.8 PUP suitability map based on Sugeno FIS with FCM

4.8.1 Fuzzy membership and rule development

Processing 1585 rows from 3 antecedents and 1 consequent into Sugeno FIS with FCM data clustering generates the same FM as Mamdani FIS (Figure 4.38), thus based on these FMs 9 raster maps were created representing fuzzy membership with 3 clusters in each criterion namely low, medium and high (Figure 4.43(a-c)).

The same parameters with Mamdani were used to generate fuzzy rules and memberships in Sugeno 1-order FIS, m=2.6 (Ozkan and Turksen, 2007) with J_m=1.10^{-5} by default in Matlab environment while maximum iteration was set at 10,000. The difference between Mamdani and Sugeno is that in Sugeno visit density consequent is represented by linear regression equation (Table 4.12).

Table 4.12. Rules development for Sugeno FIS with FCM.

Rule	Antecedents			Consequents
	Accessibility	Population density	Distant related criteria	Visit density
1	Low	Medium	Low	0.19**access* + 0.063**popdens* + 0.069**distance* – 0.095
2	Medium	Low	Medium	
3	High	High	High	

4.8.2 Suitability map of PUP based on Sugeno-1

To generate defuzzified visit density based on Sugeno rules, 3 raster maps resulted from 3 Sugeno rules will be multiplied with linear equation in Table 4.12 as required in Figure 3.7. Therefore, 3 raster maps from Sugeno rules were normalized first before multiplied with raster map from linear equation (Figure 4.46 (a-c)).

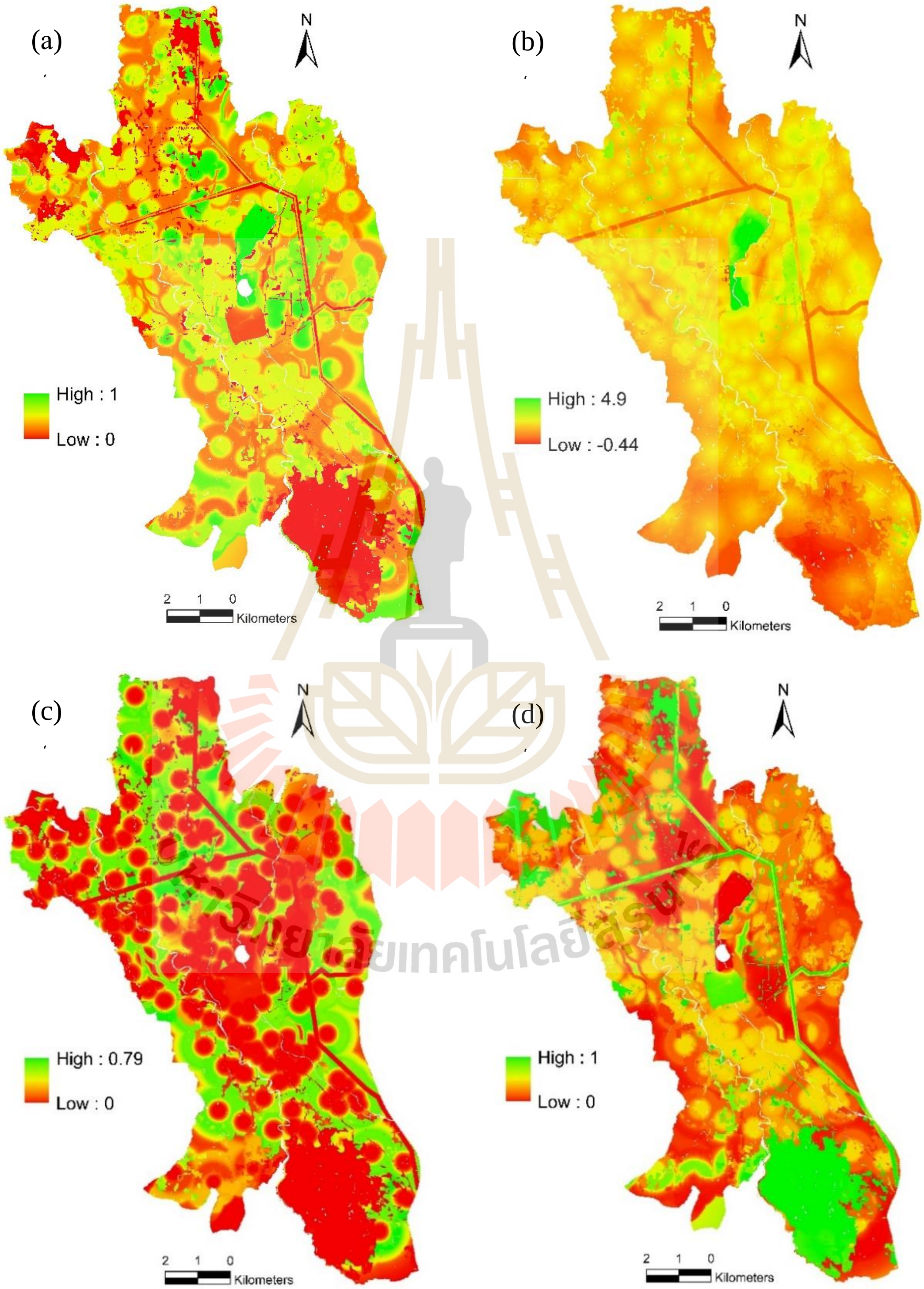


Figure 4.46 Sugeno FIS: (a) normalized rule 1 (w1), (b) normalized rule 2 (w2), (c) normalized rule 3 (w3), (d) visit density based on Sugeno linear (Z).

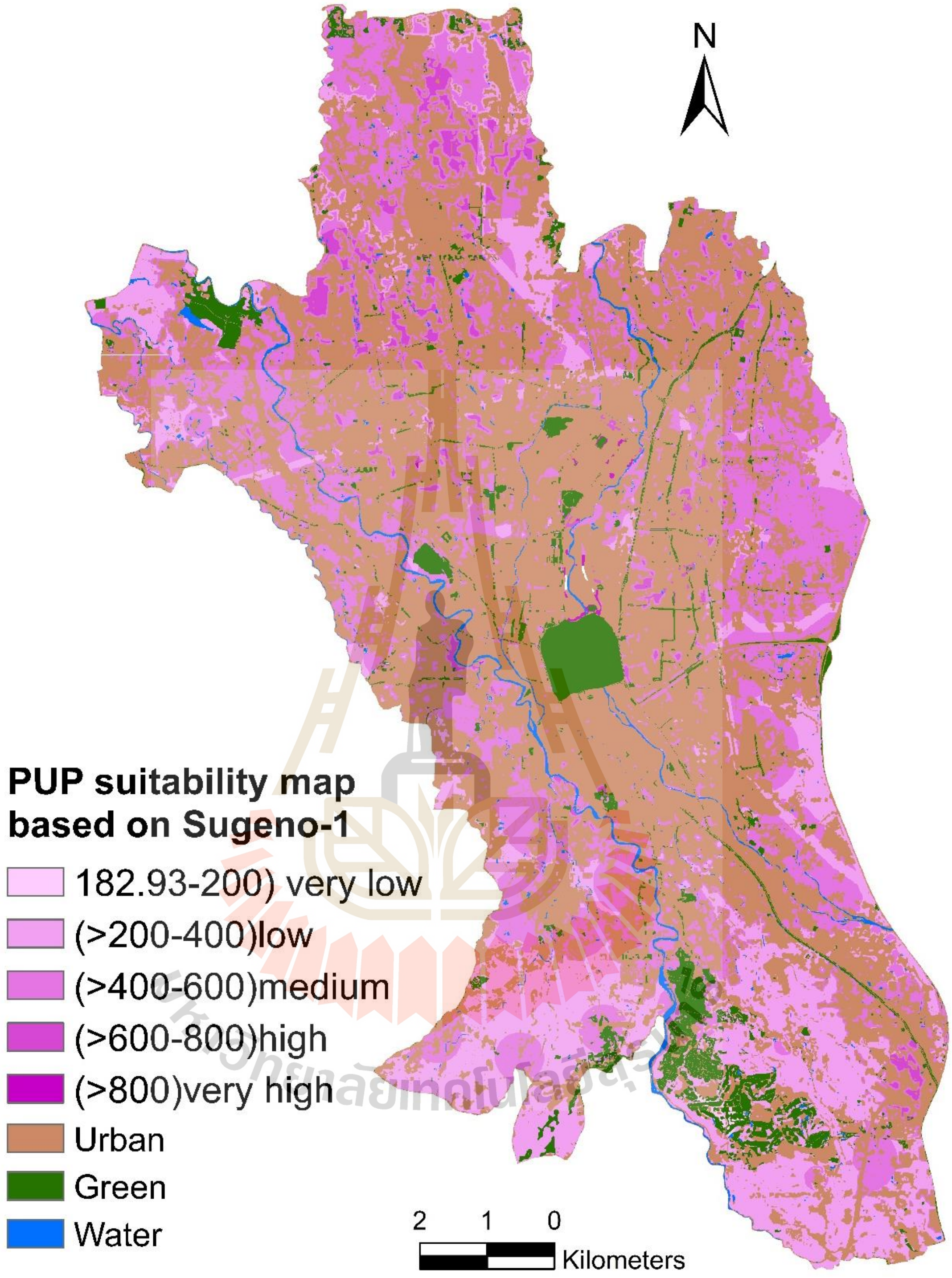


Figure 4.47 PUP suitability map based on Sugeno-1.

By using AND function in ArcGIS, according to its rule 3 raster maps were integrated to form weight (w_i). These maps functioned as weights which were multiplied with visit density raster map resulted from linear regression (Figure 4.46 (d)). When compared**,** Mamdani's consequent actually only need linguistic value based on human intuition (Kolisko (2015), while Sugeno needs more computation steps to generate normalized rule and visit density rater map from linear regression (Figure 4.47).

Noticeably, resulted highly suitable PUP locations from Sugeno-1 are concentrated in the northern part of BM while only a few in the southeastern part. This result can fulfil increasing population in the northern area especially in 2031 where predicted growth in northern villages are among the highest growth (Figure 4.47).

4.8.3 Suitability map of PUP based on Sugeno-0

By using constant value resulted from linear regression functioned as consequent in Sugeno FIS, weights from 3 rules were multiplied with this constant value. Resulted raster cells from this operation were then de-standardized again using the previously visit density average (μ=517.99) and standard deviation (σ=767.98) which were used to standardize 1583 rows of 3 antecedents and 1 consequent. The final suitability map of PUP resulted from Sugeno-0 was then classified into three classes namely, low (>400-600 visits/100m^2), medium (>600-800 visits/100m^2) and high (>800 visits/100 m^2) (Figure 4.48).

Tangibly, the suitability map from Sugeno-0 provides more distributed PUP requirement in BM (Figure 4.48) when compared with the result of Mamdani while Sugeno-1 has PUP heavily concentrated in northern BM (Figure 4.47). In terms of computation using ArcGIS, Sugeno-0 also offers more simple steps than Sugeno-1 and Mamdani because it needs only to multiply each weight with constant value and not necessarily to produce visit density raster image resulted from the whole regression linear.

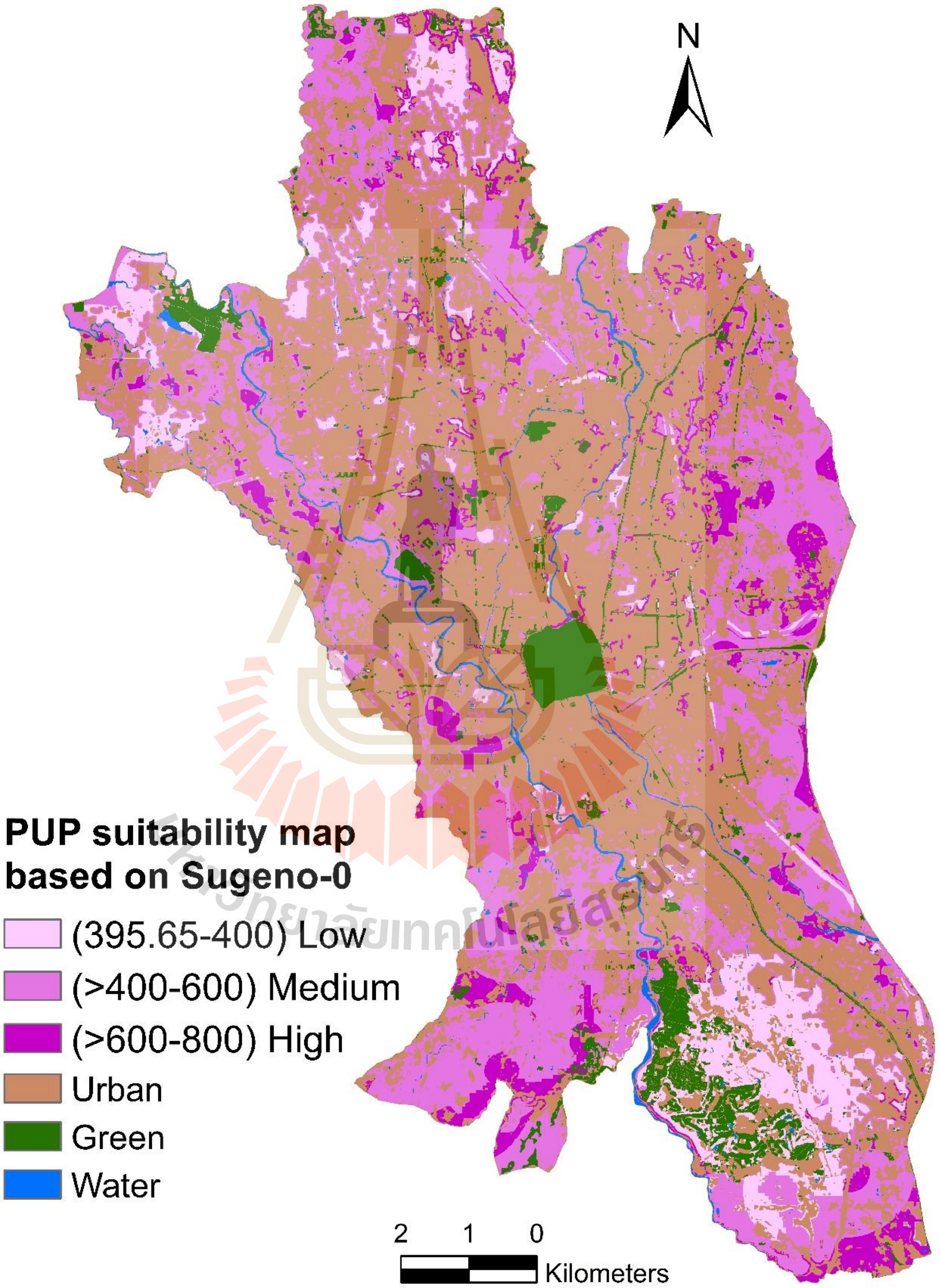


Figure 4.48 PUP suitability map based on Sugeno-0.

4.9 PUP suitability map based on DEMATEL

4.9.1 Input criteria

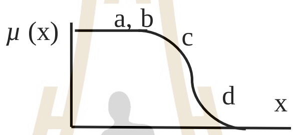
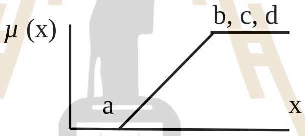
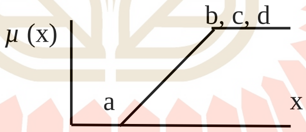
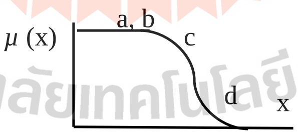
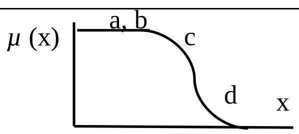
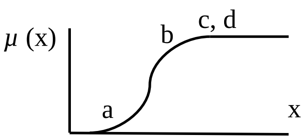
For this purpose, all spatial criteria in form of raster cells with 10 m x 10 m spatial resolution were needed to be normalized so that they can be integrated using WLC with weights come from DEMATEL. Previously, spatial criteria normalization within FDEMATEL using fuzzy membership from 0 to 1 where 0 represents least suitable and 1 is the most suitable (Gigovic et al., 2016). Hence, this study applied diversified fuzzy membership functions to normalization because collected data were from multi-representation factors, namely socio-economic (population density), planning policy (PUP policy demand), physical (accessibility, distances to favorable and unfavorable locations).

In normalizing population density raster map, fuzzy membership function was increasing linear function (Givi et al., 2015) where the raster cell with higher population density was considered the most suitable PUP location. Decreasing sigmoidal was chosen to normalize accessibility since accessibility score comes from entropy method (Meng and Malczewsky, 2015) where mostly used natural logarithmic (*ln*) function to integrate population and number of parks from 68 villages in BM. Raster cell with lower access more suitable for PUP development because higher access means more existing PUP in the village, and this study concerns to develop more PUP in villages with rare access.

Increasing linear was chosen to normalize policy demand raster cell because demand comes from linear regression (Equation 2.11) where PUP location will suit in cell with more demand so that new location can fulfil PUP deficiency in every village.

In addition, as the shorter distance to water body and school is more favorable location for PUP, it will be normalized using decreasing sigmoidal (Givi et al., 2015). Increasing sigmoidal was used to normalize distance to electric power line as the shorter is more unfavorable (Table 4.13).

Table 4.13. Fuzzy membership function for input spatial criteria in DEMATELS

Spatial criteria	**Fuzzy membership function**	**Fuzzy shape function** (Givi et al., 2015; Gigovic et al., 2016)	**Control points**			
			a	**b**	**c**	**d**
Accessibility	Decreasing sigmoidal		0	0	1.6 x 10^{-13}	1.6 x 10^{-4}
Population density (p/100m^2)	Increasing linear		0.94	1.86	-	-
PUP policy demand (km^2)	Increasing linear		0	6.15 x 10^{-5}	-	-
Distance to water body (m)	Decreasing sigmoidal		-	-	300	600
Distance to school (m)	Decreasing sigmoidal		-	-	100	1000
Distance to electric power line (m)	Increasing sigmoidal		20	40	-	-

Those fuzzy membership functions were performed to normalize spatial criteria and the results are shown in Figure 4.49. Green color is used for more suitable cells for PUP development while red color indicates less suitable cells.

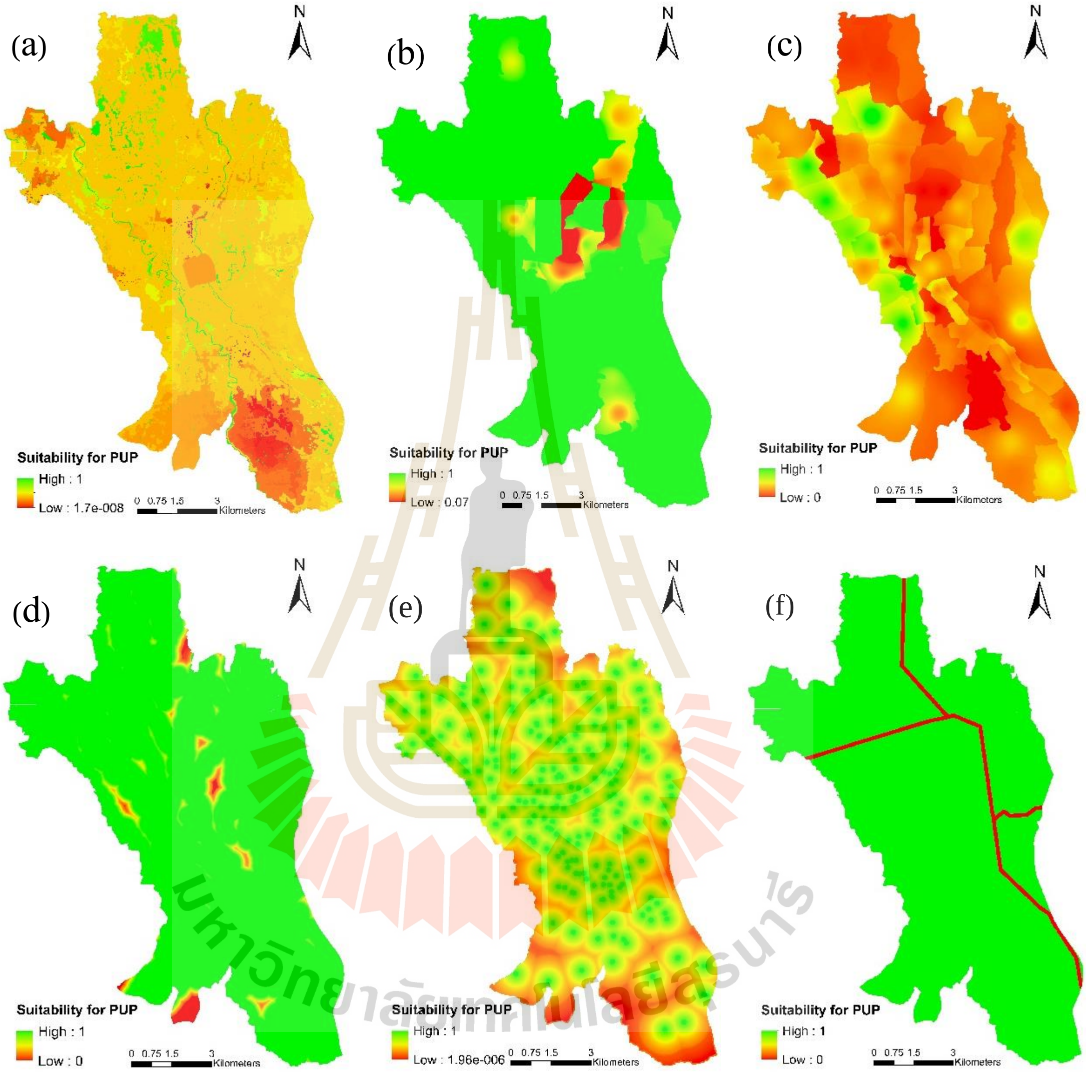


Figure 4.49 Input spatial criteria for DEMATELs**:** (a) population density, (b) accessibility, (c) PUP policy demand, (d) distance to water body, (e) distance to school, and (f) distance to electric power line.

4.9.2 Suitability mapping based on DEMATEL

At first, questionnaires were distributed to six experts from 3 main backgrounds namely, government, academics, and professional from private sector.

Academics experts are lecturers of the Department of Landscape Architecture, Bogor Agricultural University. Two government experts are from two offices, the Landscape Planning Section in Housing and Settlements Agency and the Development Agency of BM. Another group of experts is professional landscape architect. They are residents in BM and familiar with actual condition of town dynamic development and conservation. Both of them have highly experience in landscape planning projects (Wicaksono and Sarapirome, 2017).

Table 4.14 Averaged experts' opinions.

Input Criteria	Access	Population density	Policy demand	Distance to water body	Distance to school	Distance to electric power line
Accessibility	0.00	2.67	2.33	2.00	2.83	1.17
Population density	2.83	0.00	3.67	1.33	2.67	2.00
Policy demand	2.33	3.33	0.00	2.67	1.83	1.83
Distance to water body	2.00	2.67	2.67	0.00	1.33	0.83
Distance to school	2.67	2.83	2.67	0.83	0.00	2.17
Distance to electric	3.00	3.33	3.00	2.17	2.50	0.00

During questionnaires, interviews with these experts were also conducted not only to explore their opinions but also to explain about detail of this research so that experts were able to fill the questionnaires clearly. Most of the experts had very good brainstorming for the relationship of multi-spatial criteria with PUP location.

The first step in DEMATEL is to aggregate experts' opinions into a single matrix (Table 4.14) showing influence comparison between each pair of criteria. Secondly, averaged experts' opinions then normalized using *k* coefficient from Equation (2.26), selected *k* coefficient is 0.067 (Table 4.15).

Table 4.15 Normalized experts' opinions.

Input Criteria	Access	Population density	Policy demand	Distance to water body	Distance to school	Distance to electric power line
Accessibility	0.00	0.18	0.16	0.13	0.19	0.08
Population density	0.19	0.00	**0.25**	0.09	0.18	0.13
Policy demand	0.16	0.22	0.00	0.18	0.12	0.12
Distance to water	0.13	0.18	0.18	0.00	0.09	0.06
Distance to school	0.18	0.19	0.18	0.06	0.00	0.15
Distance to electric power line	0.20	0.22	0.20	0.15	0.17	0.00

In Table 4.15, the number in each row represents how big a criterion in a row can influence a criterion in opposite column. For example, 0.19 in second row and first column means that population density can influence access with proportion of 19% of the total maximum influence. On the other hand, 0.18 in first row and second column means that access can influence population density with proportion of 18% of the total maximum influence. From Table 4.15, the biggest influence is population density to policy demand in second row and third column, with proportion of 25% from the maximum.

The normalized experts' opinions then subtracted by a 6 x 6 identity matrix, then converted into an inverse matrix according to Equation (2.27). Moreover, this inverse matrix multiplied with its normalized matrix to produce a new translation matrix (Table 4.16).

Table 4.16 Translation matrix.

Input Criteria	Accessibility	Population density	Policy demand	Distance to water body	Distance to school	Distance to electric power line	*r*
Accessibility	0.5103	**0.7257***	**0.7068***	0.4893	**0.6182***	0.4221	3.4724
Population density	**0.7369***	**0.6493***	**0.8443***	0.5123	**0.6703***	0.506	3.9191
Policy demand	**0.684***	**0.7959***	0.6112	0.5576	0.5974	0.4746	3.7207
Distance to water body	0.5623	**0.6567***	**0.6537***	0.3332	0.4849	0.3615	3.0523
Distance to school	**0.6891***	**0.7609***	**0.7481***	0.4557	0.4826	0.4935	3.6299
Distance to electric power line	**0.8024***	**0.895***	**0.8746***	0.5995	**0.7154***	0.4288	4.3157
c	3.9850	4.4835	4.4387	2.9476	3.5688	2.6865	

To gain a weight for each criterion, Equation (2.31) was employed to compute the square root of powered (r+c) and (r-c) value from relation matrix (Table 4.17).

Fortunately, DEMATEL offers advantage to investigate relationship among factors which relate PUP suitability by analyzing threshold value α (Sumrit and

Anuntavoranich, 2013) generated from Equation (2.30). In this case, α is 0.6142 and values in translation matrix bigger than α coefficient are marked by * symbol which indicate that these values can be inserted into CERD.

In detail, population and policy are spatial criteria which influenced by all remaining criteria indicated by * in Table 4.16 and pointed arrows in Figure 4.50. On the other hand, distance to electric power line plays role as a driving factor and have influence to almost all other criteria. This confirms by two experts from government and professional background based on interviews, that distance regulations play role as limiting factor for PUP location suitability. Interestingly, population density is influenced by all other criteria, which indicates by having all stars in every row of its column. This occurs because all 6 experts give weights between 2.67 and 3.33 in population density column (Table 4.14).

Table 4.17 Criteria weighting.

Input Criteria	$r+c$	r-c	$(r+c)^2$	$(r$-$c)^2$	$\widetilde{W}_i$	$\widetilde{\boldsymbol{w}}_{\boldsymbol{i}}$
Accessibility	7.46	-0.51	55.61	0.26	7.47	0.17
Population density	8.40	-0.56	70.60	0.32	8.42	0.19
Policy demand	8.16	0.72	66.58	0.52	8.19	0.18
Distance to water	6.00	-0.10	36.00	0.01	6.00	0.13
Distance to school	7.20	-0.06	51.82	0.004	7.20	0.16
Distance to electric power line	7.00	1.63	49.00	2.65	7.19	0.16
Total					44.48	1

Finally, to produce PUP suitability map, all weights from DEMATEL process were inputted to ArcGIS environment using raster calculator (Figure 4.51). In addition, equal interval of 0.2 was employed to gain 3 suitable classes. Surprisingly, policy demand (C3) in CERD has the lowest position because of its negative *r*-*c* due to its *r* value smaller than its *c* value therefore it has been influenced by almost all spatial criteria.

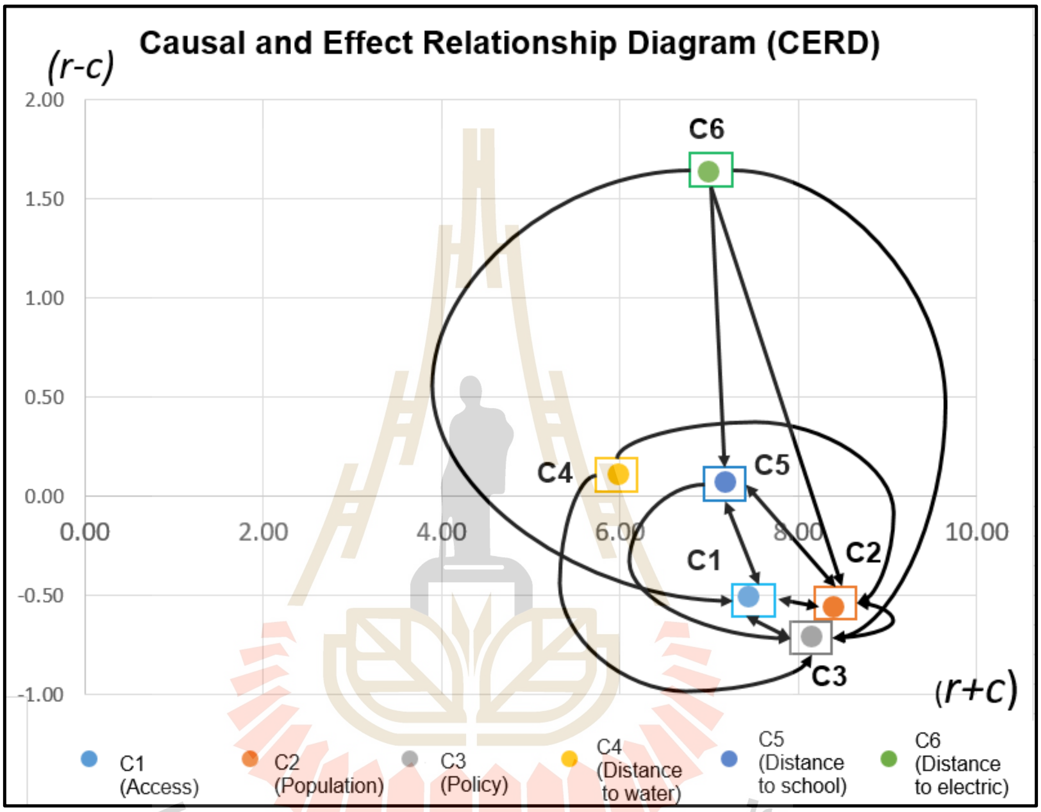
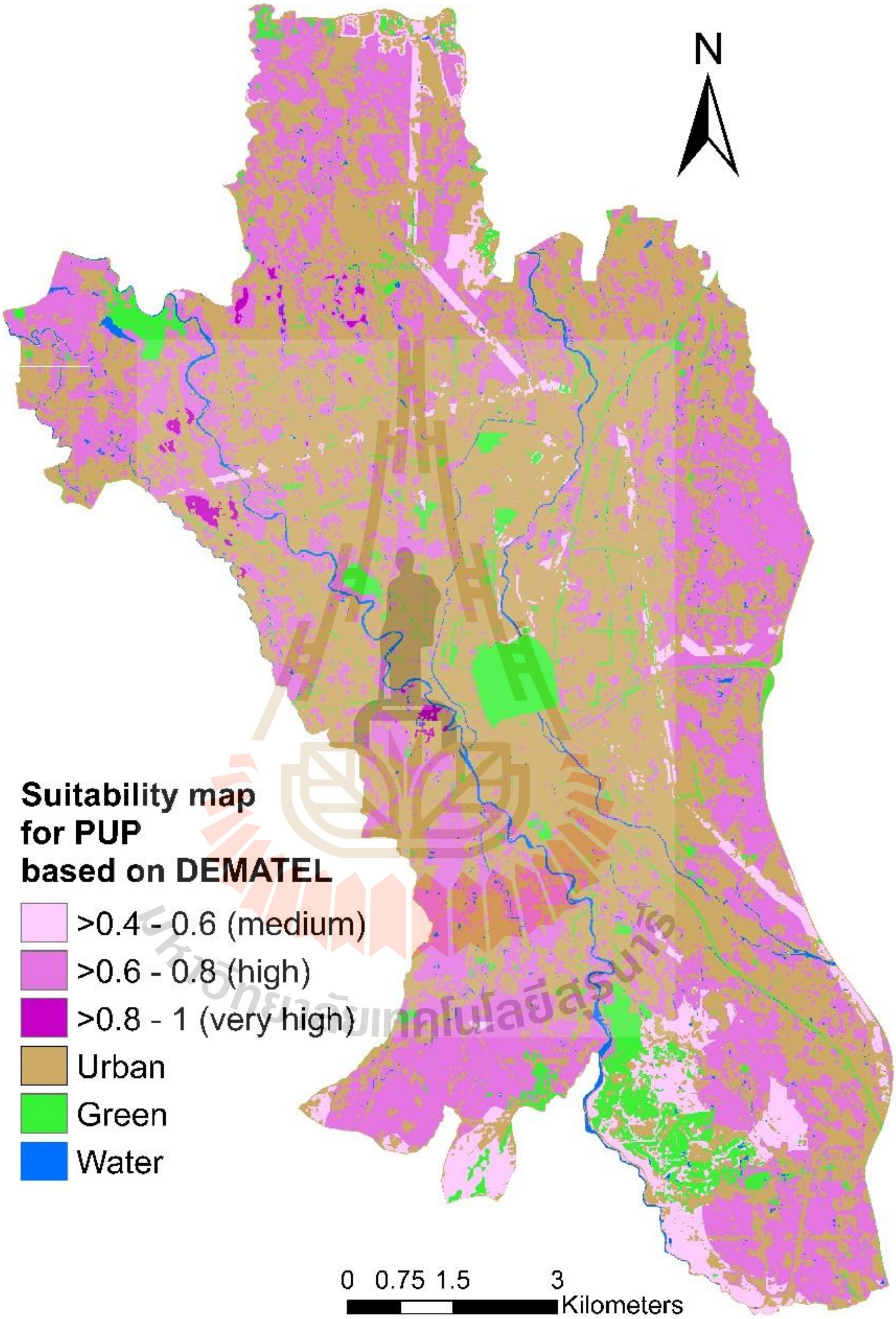


Figure 4.50. CERD for PUP suitability analysis

Table 4.18 Criteria identification using CERD.

Type of *r*+*c* and *r*-*c* values (Sumrit and Anuntavoranich, 2013)	**Spatial criteria**
(*r*-*c*) is positive or net cause, it means these criteria are cause group and directly affected other spatial criteria.	• Distance to electric • Distance to school • Distance to water body
(*r*-*c*) is negative or net receiver, it means these criteria are effect group and largely influenced by other criteria.	• Policy demand • Population density • Accessibility



4.51 PUP suitability map based on DEMATEL.

4.10 PUP suitability map based on FDEMATEL

Generally, FDEMATEL begins with experts' opinions collection regarding to the influence of each spatial criteria. In FDEMATEL, experts' opinions are stated with linguistic values instead of real numbers. These linguistic values need to be represented by triangular fuzzy numbers (Appendix C).

In this study, conversion into real number performed using method proposed by Pamucar and Cirovic (2015) where a single linguistic value is converted into three separated numbers, left, middle and right (Equation (2.33)).

In order to normalize fuzzy experts' opinions, Equation (2.35) employed to generate *k* coefficient, where in this case $k(l)$ =0.17, $k(m)$ = 0.102 and $k(r)$ = 0.05. As a result, normalized experts' opinions using *k* coefficient can be observed in Appendix D.

Based on Equation (2.36) translation matrix was generated by involving the inverse matrix of identity matrix 6 x 6 subtracted by normalized matrix. The result of this operation can be seen in Table 4.19.

All values in Table 4.19 were defuzzified using Equation (2.37) so that relationship arrow can be drawn in FDEMATEL CERD (Figure 4.52), while α shows 0.46 derived from Equation (2.30). Any values bigger than 0.46 were tagged with * symbol (Table 4.20).

Table 4.19 Translation matrix resulted from transpose operation (l,m,r).

Spatial criteria	Accessibility	Population density	PUP policy demand	Distance to water body	Distance to school	Distance to electric power line
Accessibility (C1)	(0.0664, 0.0614, 1.6931)	(0.1743, 0.0971, 2.0077)	(0.1627, 0.0964, 2.0077)	(0.0537, 0.0222, 1.7761)	(0.3907, 0.279, 1.7761)	(0, 0, 1.7857)
Population density (C2)	(0.0472, 0.0654, 1.8023)	(0.2971, 0.2173, 1.7776)	(0.7371, 0.4664, 1.9442)	(0.2432, 0.1073, 1.6849)	(0.2774, 0.2975, 1.7228)	(0, 0, 1.7336)
PUP policy demand (C3)	(0.0259, 0.0296, 1.7917)	0,0.27,4.17	0,0,4	0.5,0.23,4	0,0,4	0,0,3.77
Distance to water body (C4)	0,0,3.5	0,0.23,0.35	0,0.21,0.35	0,0,3.17	0,0.11,3.3	0,0,2.95
Distance to school (C5)	0,0.22,4.02	0.5,0.25,4.12	0.5,0.22,4.02	0.25,0,3.82	0,0,3.7	0,0,3.54
Distance to electric line (C6)	0,0.24,4.16	0,0.27,4.16	0,0.27,4.16	0,0,4	0,0.21,4	0,0,3.5

Table 4.20 Defuzzified translation matrix.

Spatial criteria	Accessibility	Population density	PUP policy demand	Distance to water body	Distance to school	Distance to electric power line
Accessibility (C1)	0.33	0.43	0.43	0.32	**0.55***	0.30
Population density (C2)	0.35	**0.49***	**0.76***	0.39	**0.53***	0.29
PUP policy demand (C3)	0.32	**0.67***	**0.49***	**0.54***	0.39	0.29
Distance to water body (C4)	0.28	**0.63***	**0.63***	0.29	0.43	0.21
Distance to school (C5)	**0.48***	**0.66***	**0.65***	0.34	0.38	0.27
Distance to electric line (C6)	**0.57***	**0.75***	**0.76***	0.40	**0.63***	0.27

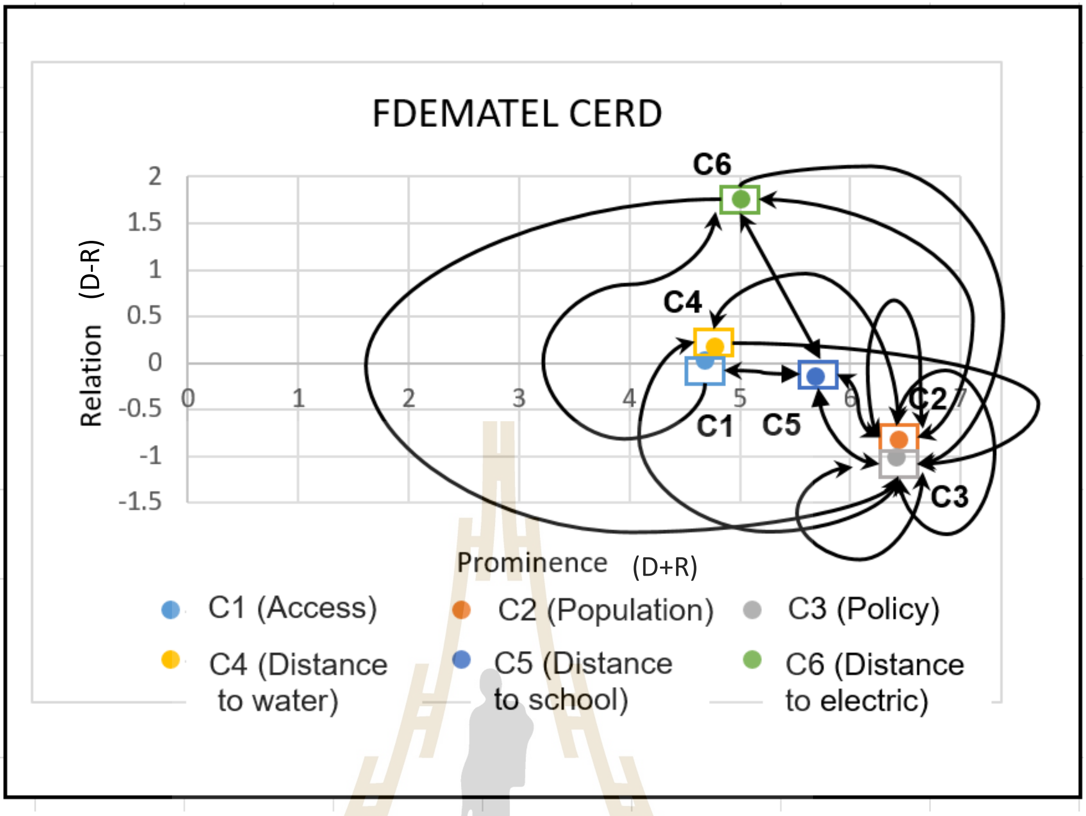


Figure 4.52 FDEMATEL CERD.

Table 4.21 Criteria identification using FDEMATEL CERD.

Type of Prominence and Relation Values (Tsai et al, 2015)	**Spatial criteria**
(Dk—Rk) is positive and (Dk ＋ Rk) is large, this means the criterion is cause or driving factor	• **Distance to electric power**
(Dk—Rk) is negative and (Dk ＋ Rk) is small: This criterion is independent and can be influenced by few criteria	• Distance to school
(Dk—Rk) is negative and (Dk ＋ Rk) is large: This criterion is core problem though it cannot be straightly improved	• Population density • Policy demand
(Dk—Rk) is positive and (Dk ＋ Rk) is small: This indicates the criterion is independent and influence a few criteria	• Accessibility • Distance to water

From Table 4.21, the relation value of distance to school decrease significantly when compared with itself in DEMATEL. Its position changes from a driving factor to be independent in FDEMATEL. On the other hand, both policy and population criteria are still core problems in FDEMATEL which receive many influences from all criteria. This can be suggested that both policy and population density occurs lately when PUP firstly exist due to water body, school and power line.

Table 4.22 Criteria weights of PUP suitability based on FDEMATEL.

Multi-spatial criteria	$D+R_{(l)}$	$D+R_{(m)}$	$D+R_{(r)}$	$D-R_{(l)}$	$D-R_{(m)}$	$D-R_{(r)}$	$D+R$	$D-R$	$\widetilde{W}_i$	$\widetilde{w}_i$
C1	1.47	1.36	21.20	0.22	-0.24	0.89	4.68	0.02	4.68	**0.14**
C2	4.02	3.23	21.71	-0.81	-0.93	-0.38	6.44	-0.82	6.50	**0.19**
C3	4.04	3.21	21.64	-1.38	-1.05	-0.45	6.42	-1.01	6.50	**0.19**
C4	2.92	1.97	17.80	0.47	0.53	-1.52	4.77	0.18	4.77	**0.14**
C5	3.23	2.86	19.44	-0.09	-0.23	0.13	5.69	-0.15	5.69	**0.17**
C6	1.59	1.92	20.76	1.59	1.92	1.33	5.00	1.77	5.31	**0.16**
Total									33.44	**1**

From Table 4.22, it can be observed that population density and policy demand have higher weights than the others. It seems all experts concern more on PUP location to serve population and regulation. Nevertheless, weights from all multi-spatial criteria seem not much different. This might be due to the characteristics of FDEMATEL that compute both row and column to measure influence from both column and row.

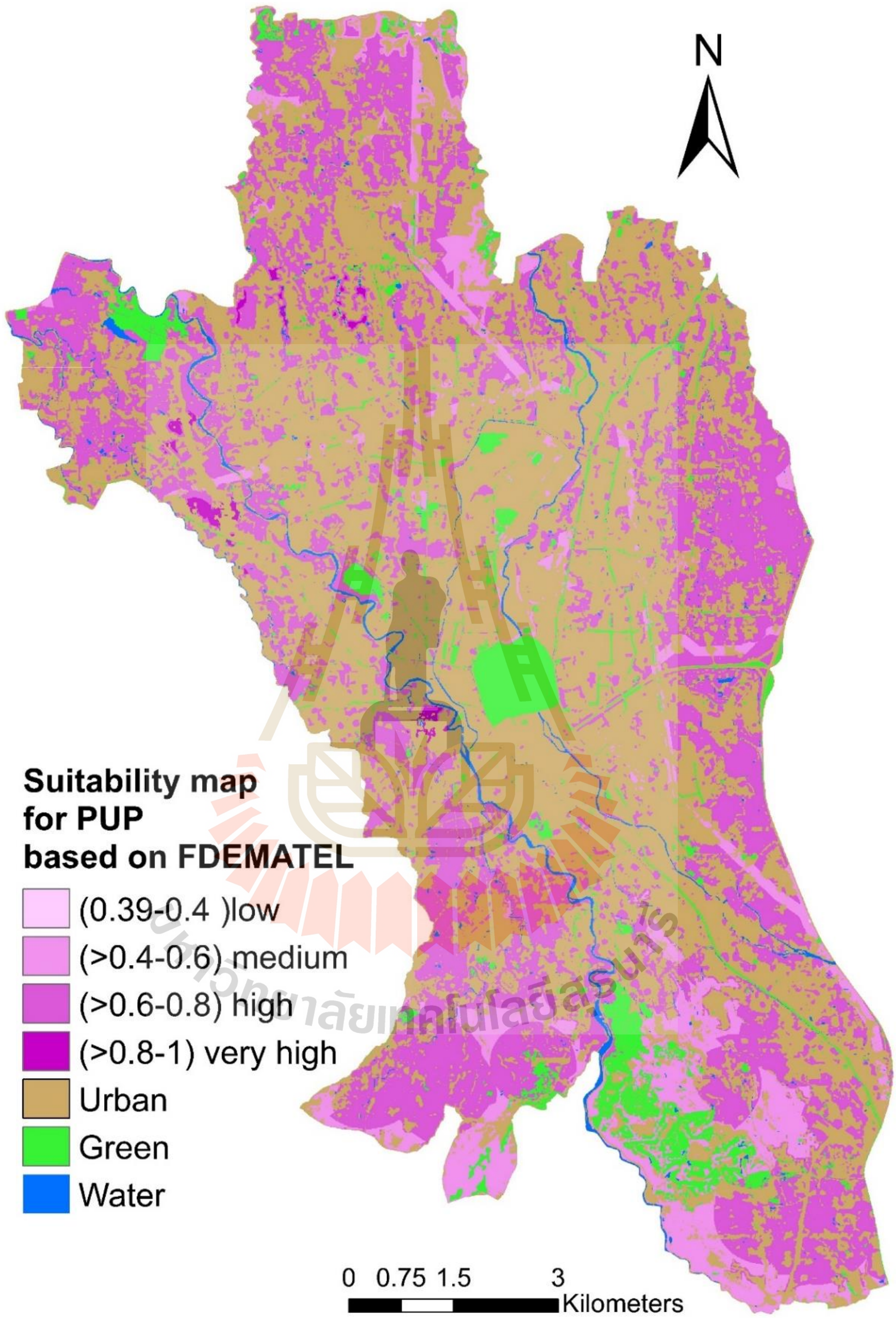


Figure 4.53 PUP suitability map based on FDEMATEL.

After all, weights resulted from FDEMATEL were multiplied with criterion map in Weighted Linear Combination (WLC) method. Tangibly, the location of suitable PUP based on both DEMATEL and FDEMATEL (Figure 4.51 and 4.53) are visually dominated with suitable cells with values between 0.6-0.8, highlighted with darkest pink.

4.11 PUP feasibility maps

4.11.1 Feasible LULC map

As pivotal to achieve third objective of this study, PUP feasibility map was analyzed from the incorporation of suitability map and LULC feasibility map of BM. Started with BM LULC map produced in 2015 by the Agency of Waste Management and Landscape, Furthermore, attribute query function in ArcGIS was performed to select the feasible area/class criteria for feasibility namely, paddy fields, crop fields, shrubs, and idle lands, to be LULC feasibility map showing possible area for PUP development.

This map was then updated uploaded to Google Earth website with conversion first to kml format. Based on Google Earth image dated 13 August 2018 new polygons were created online if the old land use classification has changed. The new online polygons then exported back to shapefile in ArcGIS. The updated polygons used as mask to eliminate 2015 land use map using ‘erase’ function in ArcGIS, while the rest of polygons serves as new updated feasibility map.

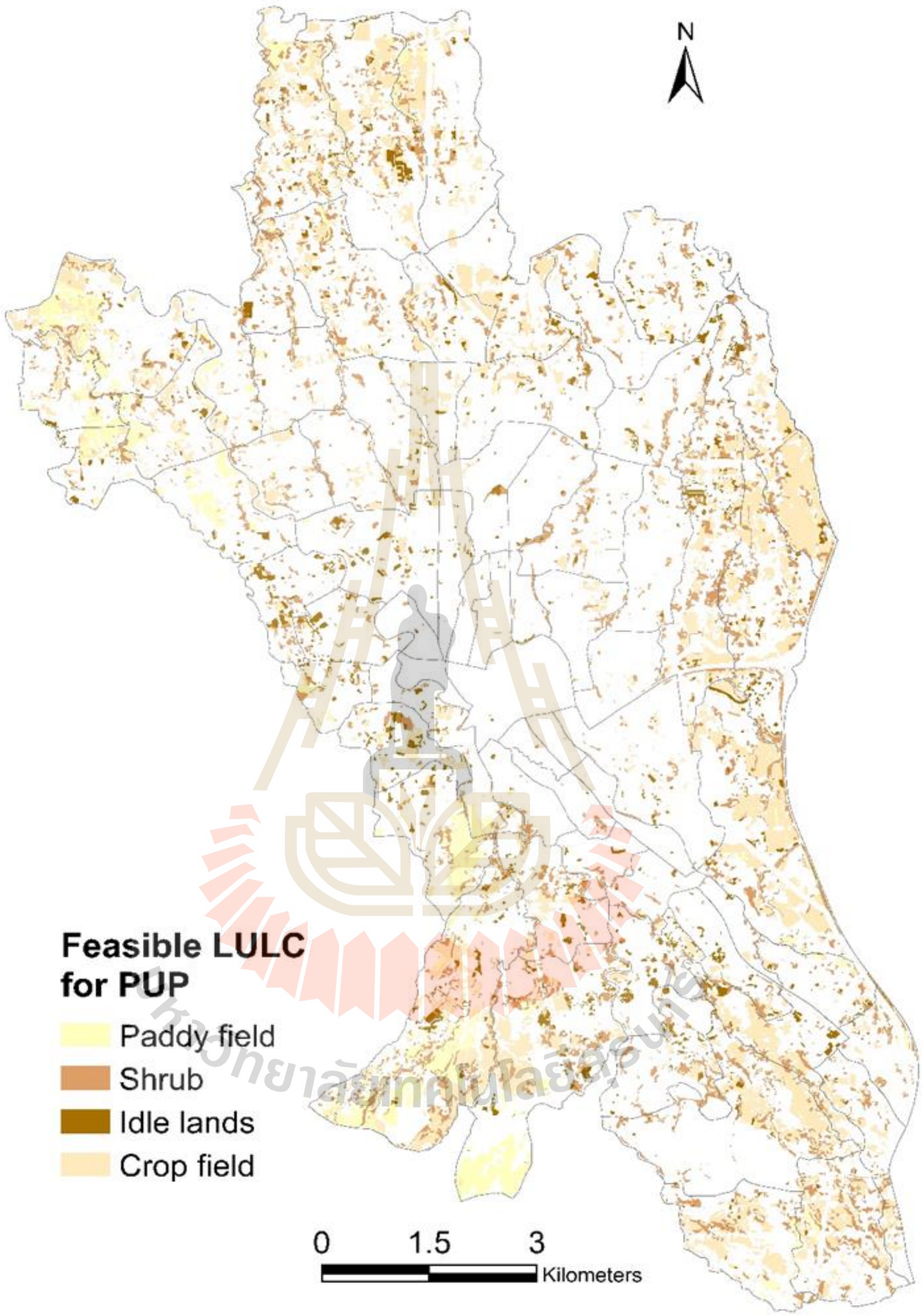


Figure 4.54. Feasible LULC for PUP development.

Moreover, The LULC feasibility map containing selective land use classes of the map was then superimposed to each of five PUP suitability maps from: a) Mamdani, b) Sugeno-1, c) Sugeno-0, d) DEMATEL, and e) FDEMATEL.

Obviously, the feasible area of the LULC feasibility map (Figure 4.54) is not available within and around the city centre. This occurs as because most area of city centre is occupied by living quarters, service, and commerce, classes which cannot be reclaimed for PUP development.

4.11.2 Optimum feasible PUP area and location

The feasible area for PUP development of the study are intersected area between suitable area from FISs and DEMATELs and feasible areas from LULC. Suitable maps from different methods have diversified ranges of suitable indexes. Suitable area can be increased or decreased when varying suitability index. To observe this variation, suitability indexes from each method were divided into 10 levels with equal interval. Then, intersect areas and their union in different levels can be displayed in Figure 4.55 and Table 4.23.

To make them comparable, the intersected and their union areas were normalized by dividing by the maximum feasible area of all methods. It means that if the intersect and union areas are close to 1, they will be close to feasible area. For example, from level 6 the normalized intersect areas from DEMATEL, FDEMATEL, Sugeno-0, Mamdani, and Sugeno-1 are about 0.38, 0.36, 0.12, 0.08, and 0. It means that the suitable areas of DEMATEL and FDEMATEL can intersect the feasible area about 38% and 36%. Or from level 2, suitable areas of Sugeno-1, Mamdani, and Sugeno-0 can intersect feasible area about 42%, 27%, and 11%. The graph provides the same information for union area.

From Figure 4.55, levels 2 and 6 having higher potential of intersected and union areas of methods were chosen to display distribution of them and feasible area as examples. Figures 4.56 and 4.57 show the distribution of intersected and feasible areas of methods. Figure 4.58 shows the distribution of union and feasible areas of each level.

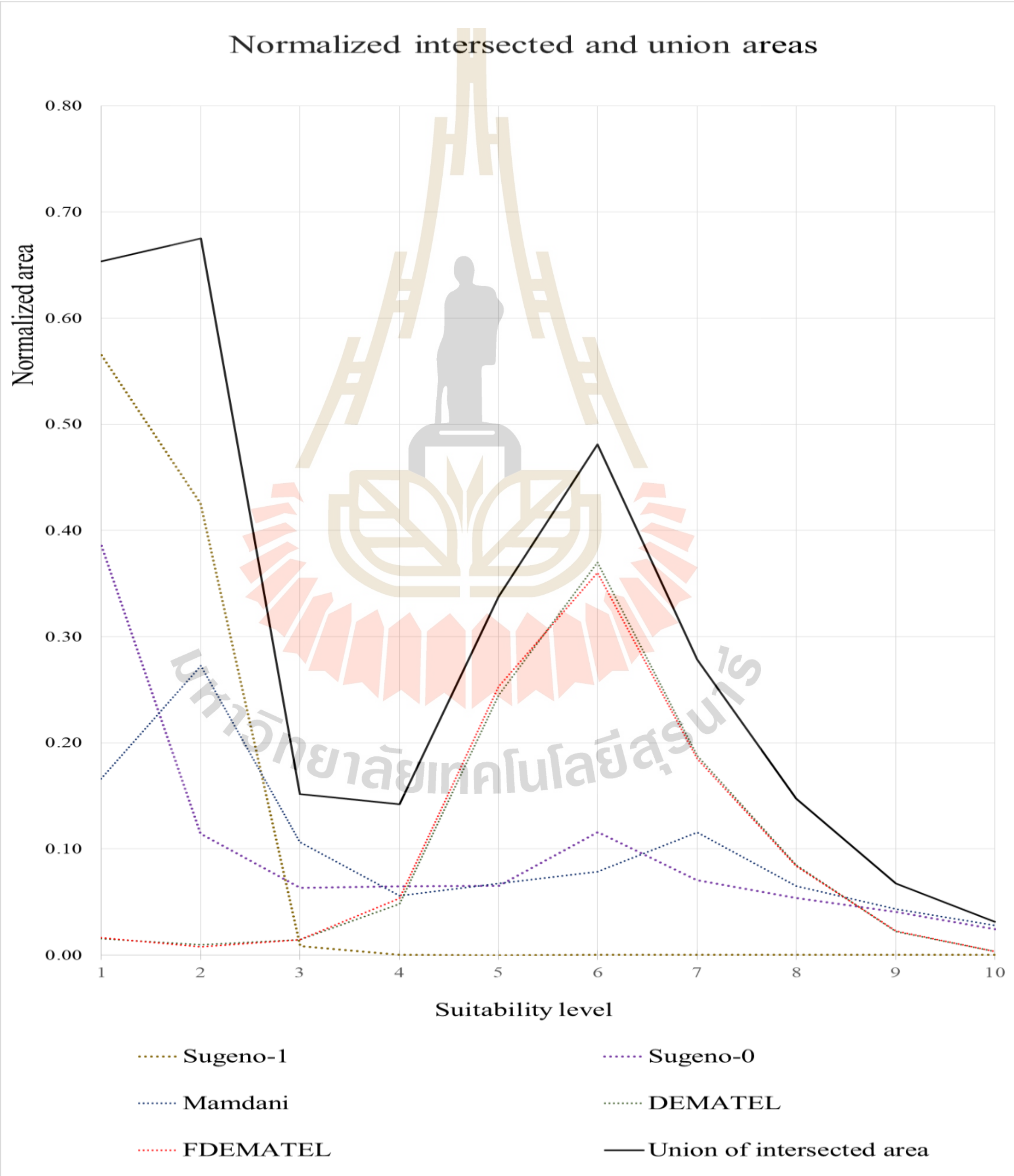


Figure 4.55 Normalized intersected and union area from methods.

Table 4.23 Suitability levels and normalized intersected areas of methods.

	Mamdani		Sugeno-1		Sugeno-0		DEMATEL		FDMATEL		
	Suitability index (visits/100m^2)	Intersect area (km^2) (norm)	Suitability index (visits/100m^2)	Intersect area (km^2) (norm)	Suitability index (visits/100m^2)	Intersect area (km^2) (norm)	Suitability index (0-1)	Intersect area (km^2) (norm)	Suitability index (0-1)	Intersect area (km^2) (norm)	Union area (km^2) (norm)
Level 1	136.87-215.96	4.3772 (0.1652)	182.93-438.36	15.1064 (0.5701)	395.65-426.98	10.1894 (0.3845)	0.409-0.456	0.4062 (0.015)	0.391-0.439	0.4467 (0.017)	17.31 (0.653)
Level 2	215.97-295.06	7.1946 (0.2715)	438.37-693.79	11.1514 (0.4209)	426.99-458.96	3.0358 (0.1146)	0.457-0.501	0.2541 (0.009)	0.440-0.486	0.2050 (0.008)	17.89 (0.675)
Level 3	295.07-374.15	2.8572 (0.1078)	693.80-949.22	0.2117 (0.0080)	458.97-490.94	1.6569 (0.0625)	0.502-0.548	0.386 (0.014)	0.487-0.534	0.3934 (0.015)	4.02 (0.151)
Level 4	374.16-453.25	1.4845 (0.0560)	949.23-1204.65	0.0054 (0.0002)	490.95-522.92	1.7294 (0.0653)	0.549-0.593	1.2713 (0.049)	0.535-0.582	1.4994 (0.057)	3.76 (0.141)
Level 5	453.26-532.34	1.7743 (0.0670)	1204.66-1460.08	0.0006 (0.00002)	522.93-554.90	1.7312 (0.0653)	0.594-0.639	6.4871 (0.245)	0.583-0.629	6.8789 (0.260)	8.94 (0.337)
Level 6	532.35-611.44	2.0745 (0.0783)	1460.09-1715.51	0.0060 (0.0002)	554.91-586.88	3.0663 (0.1157)	0.639-0.686	9.8053 (0.37)	0.630-0.677	9.5304 (0.360)	12.75 (0.481)
Level 7	611.45-690.53	3.0774 (0.1161)	1715.52-1970.94	0.0044 (0.0002)	586.89-618.86	1.8887 (0.0713)	0.687-0.731	4.9798 (0.188)	0.678-0.725	4.7754 (0.180)	7.38 (0.278)
Level 8	690.54-769.63	1.7260 (0.0651)	1970.95-2226.37	0.0038 (0.0001)	618.87-650.84	1.4289 (0.0539)	0.732-0.778	2.2443 (0.085)	0.726-0.773	2.1511 (0.081)	3.89 (0.147)
Level 9	769.64-848.72	1.1535 (.0435)	2226.38-2481.8	0.0067 (0.0003)	650.85-682.82	1.0650 (0.0402)	0.779-0.824	0.5900 (0.022)	0.774-0.820	0.5451 (0.021)	1.79 (0.068)
Level 10	848.73-927.82	0.7805 (0.0295)	2481.9-2737.23	0.0033 (0.0001)	682.83-715.44	0.7081 (0.0267)	0.825-0.870	0.0889 (0.003)	0.821-0.868	0.0848 (0.003)	0.83 (0.031)

From the Figure 4.55, if the difference between union and maximum intersected area in a level is lower, it means that the spatial duplicating areas from methods of that level are bigger. The bigger duplicating area indicates better consistency of results. The best consistency appears in the level 10 while level 2 shows the least. Other levels show fairly high consistency.

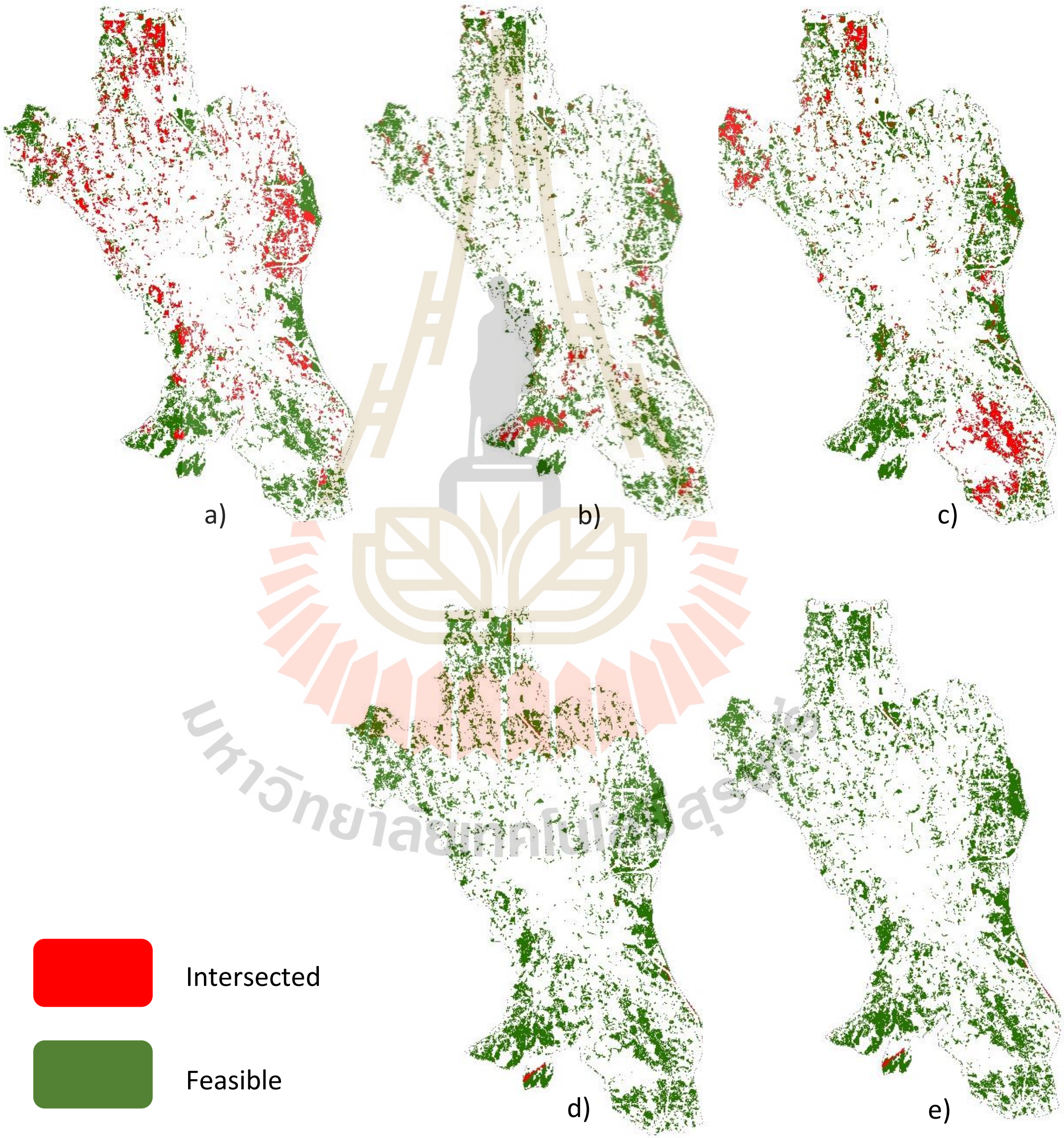


Figure 4.56 Intersected and feasible area for level 2 from methods: a) Sugeno-1, b) Sugeno-0, c) Mamdani, d) DEMATEL, e) FDEMATEL.

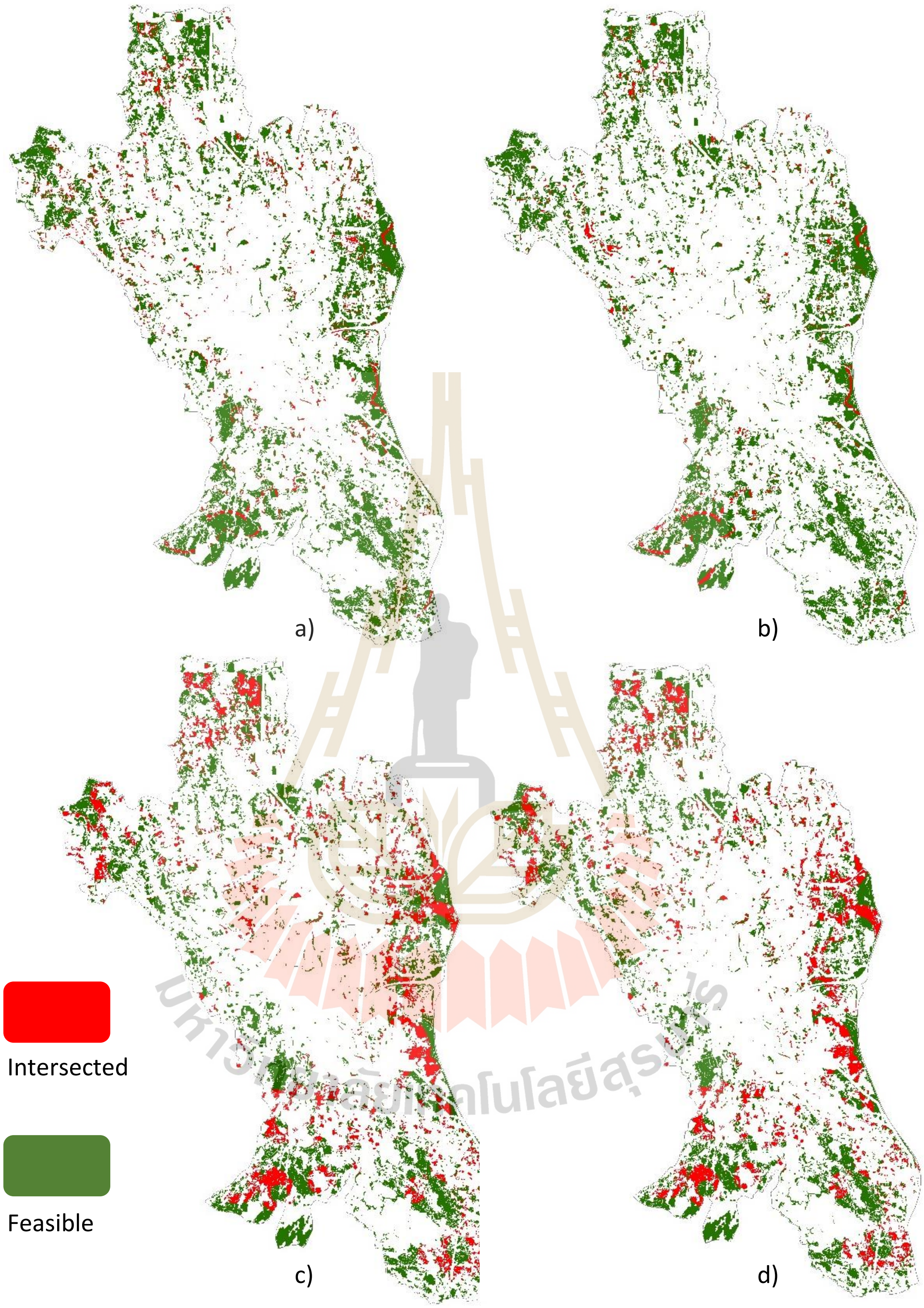


Figure 4.57 Intersected and feasible area for level 6 from methods: a) Sugeno-0, b) Mamdani, c) DEMATEL, d) FDEMATEL.

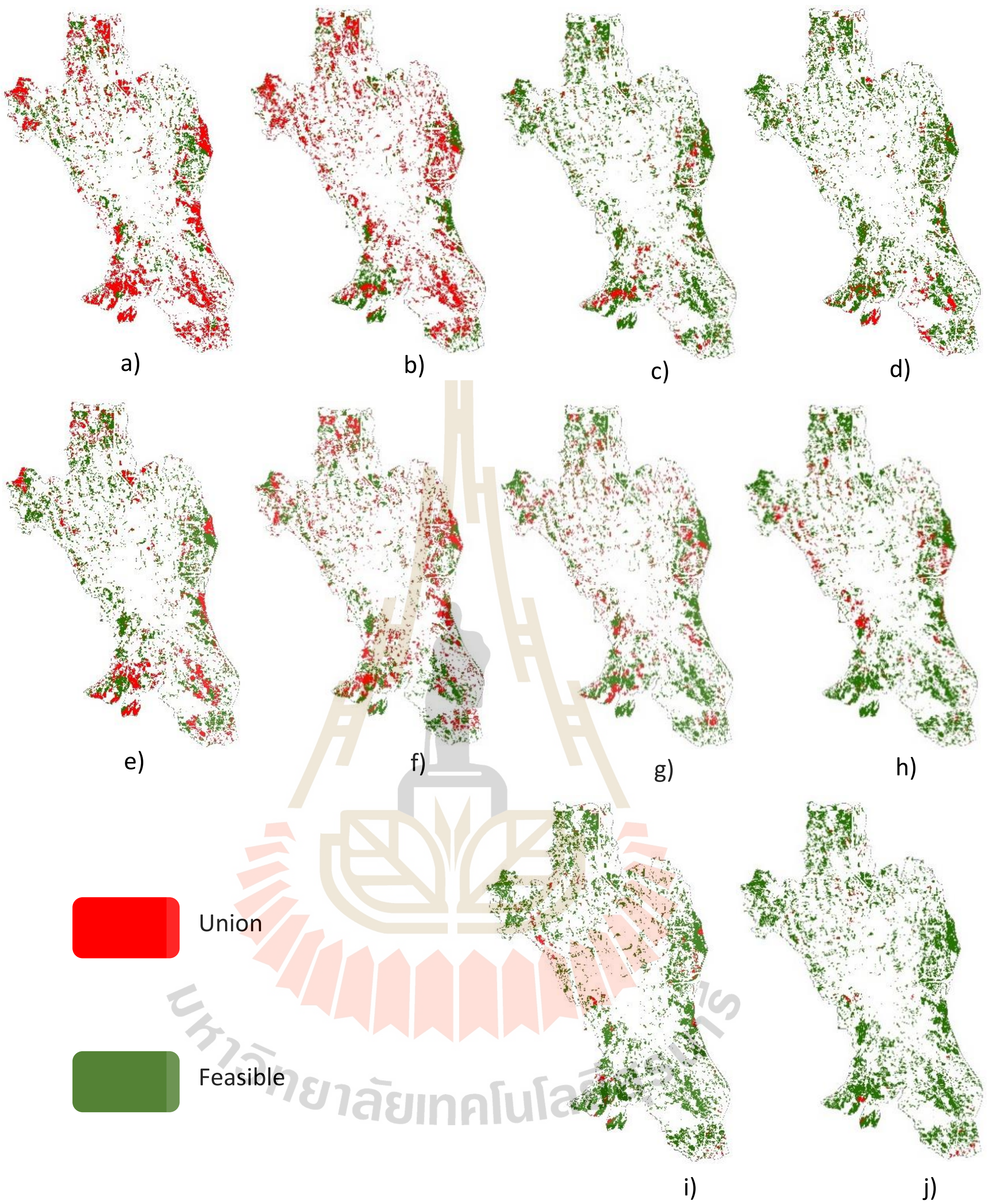


Figure 4.58 Union and feasible area for every suitability level: a) level 1, b) level 2, c) level 3, d) level 4, e) level 5, f) level 6, g) level 7, h) level 8, i) level 9, j) level 10.

4.12 Results comparison

The comparison was performed on the behavior of intersect area, suitable area and Intersection over Union (IoU) of each suitability level of all methods. IoU or also known as Jaccard Index (Jaccard, 1912) can provide more accurate comparison and be expressed with following equation:

$$IoU(A,B) = \frac{area|A \cap B|}{area|A \cup B|} \tag{4.5}$$

where A=feasible area from LULC for PUP development, B= cumulative suitable area of each suitability level (under the condition equal or more than lower bound suitability index of a certain level). If IoU of any method is closer to 1, it means that the method in that level can performs better by providing solution on areal extent and location fitting more to feasible area.

Intersected and suitability areas of each level are displayed in Figure 4.59. IoUs and cumulatively normalized suitability areas of each level of methods can be shown in Figure 4.60. Result from these figures can be compared and discussed as follows:

1) Obviously, from Figure 4.59 the behavior of intersect area can be separated to be 2 groups corresponding to groups of methods-FISs and DEMATELs. The group of FISs intersect areas appear higher in lower suitability levels 1 and 2 while intersect areas of group of DEMATELs show more in higher levels of 5-7. This indicates that group of DEMATELs can provide better solution than FISs because they can offer bigger intersect areas in higher suitability levels. However, in suitability levels 9 and 10, even though small intersect areas are provided, it is crucial to note that Mamdani and Sugeno-0 offer a bit higher intersect area than the group of DEMATELs. The

reason causing the difference can be not only different techniques but also different sets of input criteria of these 2 groups of methods.

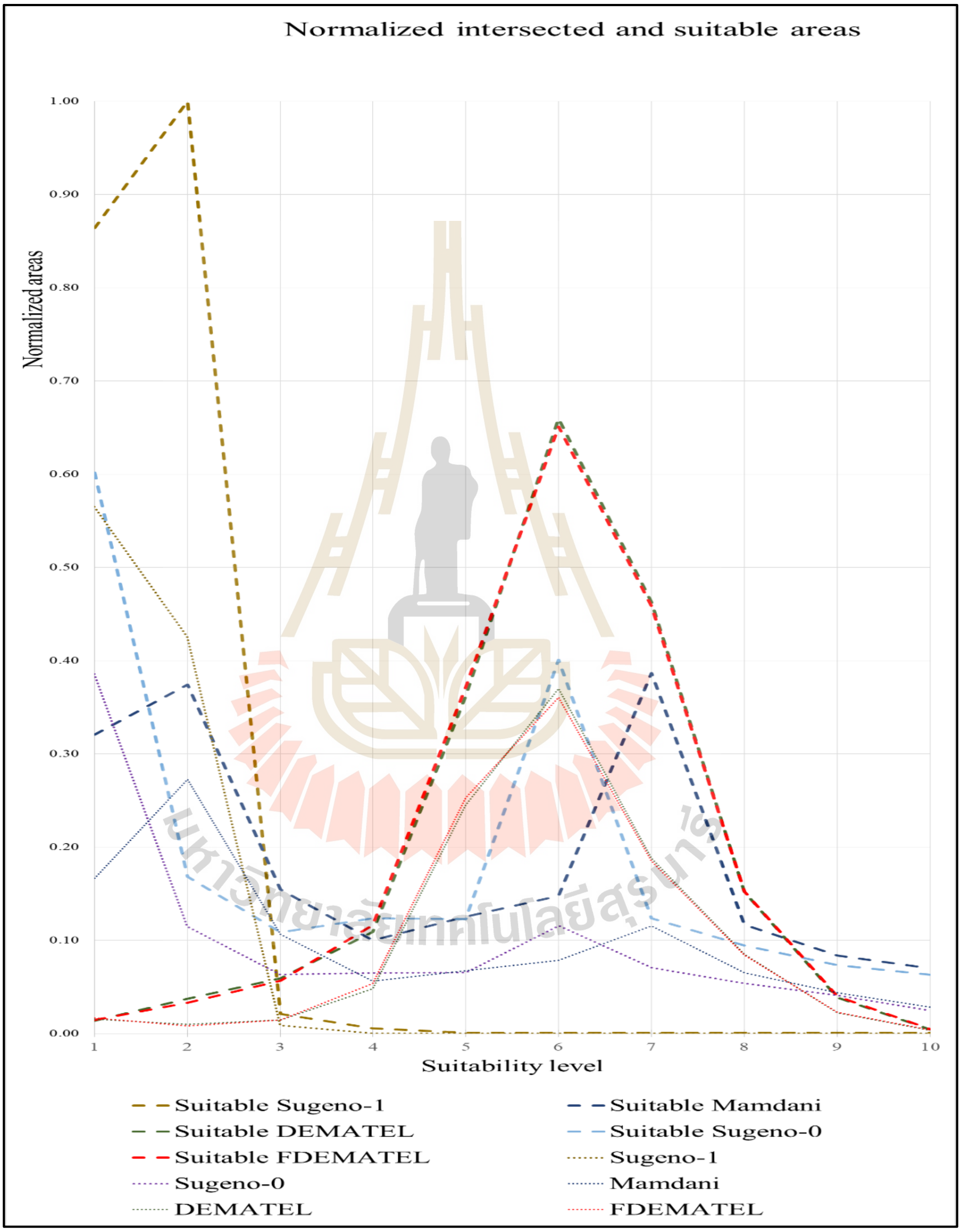


Figure 4.59 Normalized intersected and suitable areas of each suitability level in methods.

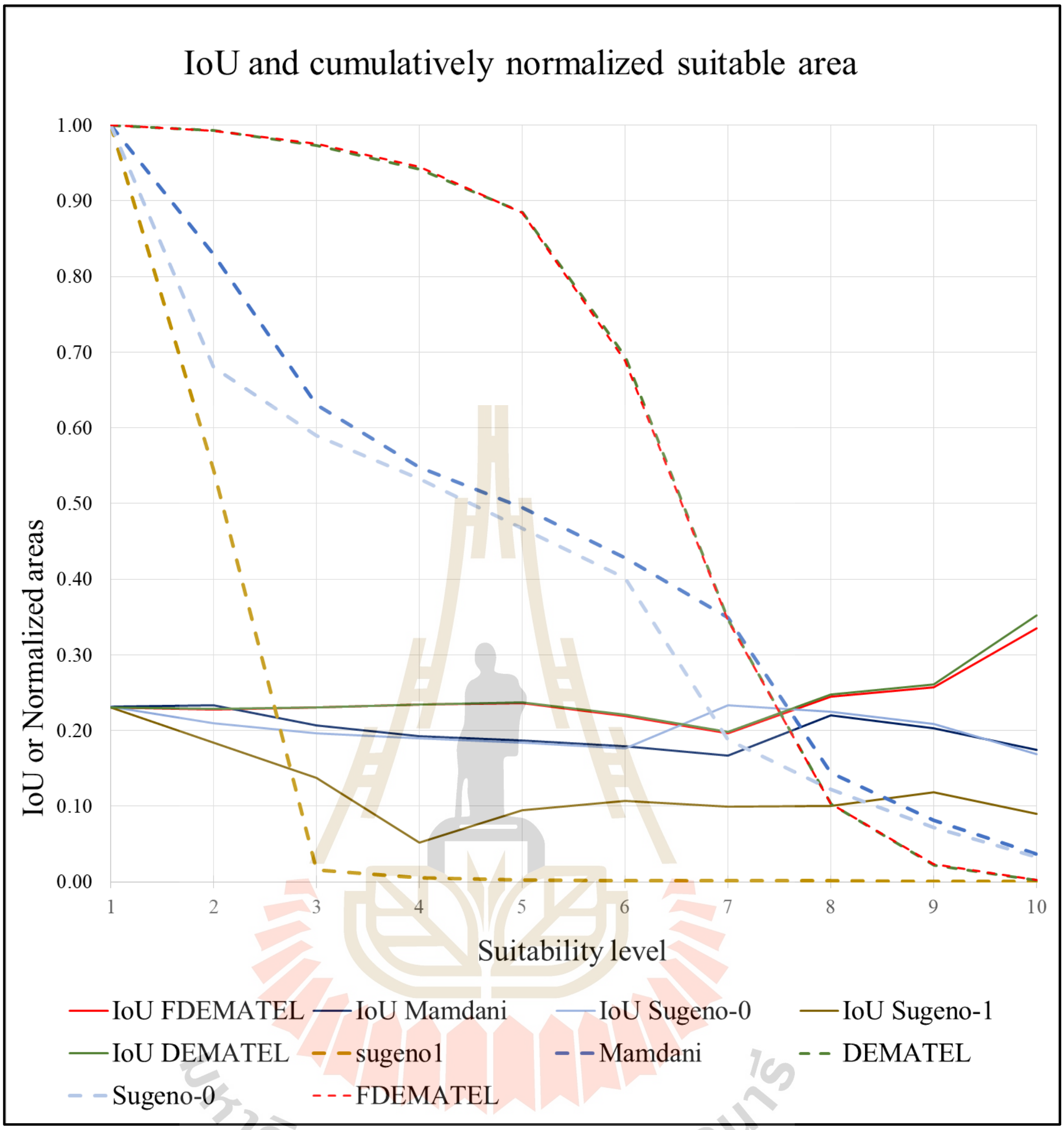


Figure 4.60 IoU and cumulatively normalized suitable area of each suitability level in methods.

It is observable that in all methods the behavior of intersect area (Figure 4.59) of each level corresponds very well with the suitable area in the same level.

2) From Figure 4.60 the behavior of IoU can be observed in 3 different groups namely DEMATELs, Mamdani and Sugeno-0, and Sugeno-1. Its behavior in general shows that from level 3-10 the group of DEMATELS express the best IoUs when

compared to others. IoUs of the group of Mamdani and Sugeno-0, as the second rank, performs better than the one of Sugeno-1 in all suitability levels. From 8-10 suitability levels, even though DEMATELs show smaller suitable area but their IoUs, 0.22-0.33, show obvious increasing trend indicating the presence of bigger percentage of matching between highly suitable area and feasible area from LULC. Unfortunately, the area extent of feasible PUP area from these levels are not big compared to lower levels. In this range of levels, IoUs of Mamdani and Sugeno-0 show increasing trend from 7-8 levels, 0.17-0.22, and then sudden drop in levels 8-10, 0.22-0.17. Remarkably, at level 7, even though Sugeno-0 provides small suitable area, its IoU shows bigger value compared to others. This means its suitable area highly fit to feasible LULC. From levels 3-7, both DEMATELs and Mamdani groups display almost flat trending, 0.23-0.20 and 0.20-0.17, respectively. Sugeno-1 provides the poorest IoUs for all levels.

IoUs do not seem to correspond with intersect or suitability areas and their cumulative.

From the comparison a group of DEMATELs performs better than others, particularly in very high suitability levels. Sugeno-1 has a poor performance for all of suitability levels.

4.13 The compatibility of PUP demand and feasible PUP areas

The information on union area of each level is very useful for application on identifying potential area for PUP development. The information provides areal extents and locations in different suitability levels that can be extracted for specific locations or villages having PUP demand. Then, the PUP demand can be managed more efficiently in terms of suitability level, areal extent, and location.

The compatibility of village-based PUP demand and the union of feasible PUP areas was carried out and displayed in Figure 4.61. Any village having enough supply of feasible PUP areas over the demand becomes compatible village. This compatibility is considered to meet both spatial and attribute demand. For example, at level 7, Mamdani demand can be served about 94% of compatible villages while Sugeno-1 and Sugeno-0 can be served about 91% and 88%, respectively. Even though numbers of compatible villages among different demands are not significant different. Mamdani demand seems to offer more compatible villages in all suitability levels, particularly more obvious in 2 and 7 levels. Therefore, it can be concluded that Mamdani demand is optimum.

Actually, the study results are a number of GIS data layers providing variety of information on PUP area demands, suitable and feasible PUP areas. These appear in diversified methods and suitability levels. Therefore, they can provide more flexibility and alternatives to policy makers for allocating feasible PUP area to meet the demand. For example, from Figure 4.61, if only about 50% of compatible villages is required the union areas of level 10 is recommended. Or, if about 94% of compatible villages (Mamdani's demand), is required, union area at level 7 is recommended. If any specific village demand is required, the searching can be started from union area of the toppest level down until the requirement is fulfilled.

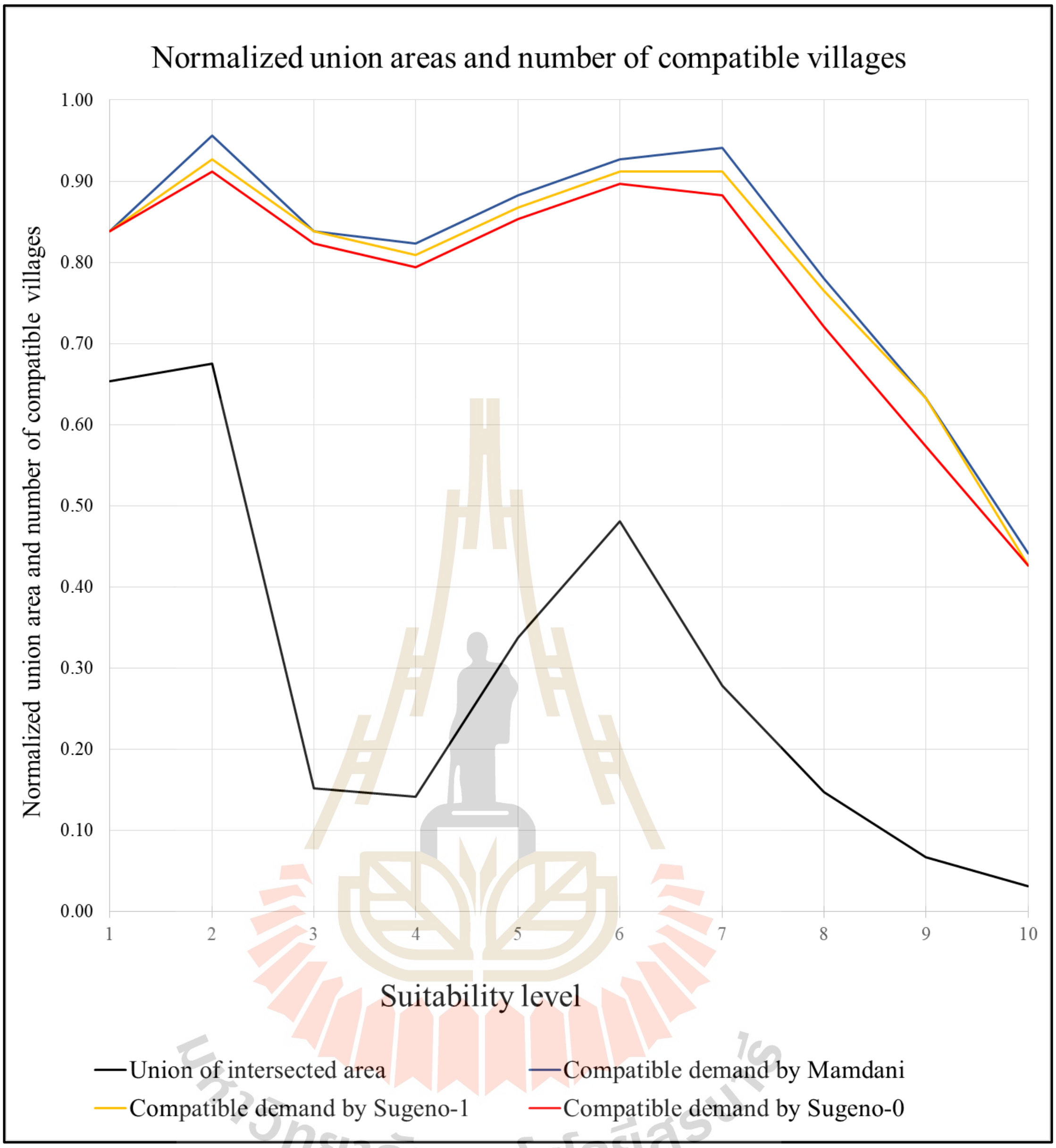


Figure 4.61 Normalized union area and compatible number of villages.

The result can also provide information on cumulatively union area of each suitability level as displayed in Figure 4.62. Observing the graph of normalized cumulatively union area, from the most top down to level 3 the cumulativeness can cover the whole feasible PUP area. Considering how cumulatively union area can completely serve village-based optimum demands of methods or provide compatibility to the whole villages, it is found that at level 7 the cumulativeness can completely serve the Mamdani and Sugeno-1 demands while down to level 5 it can completely serve Sugeno-0 demand.

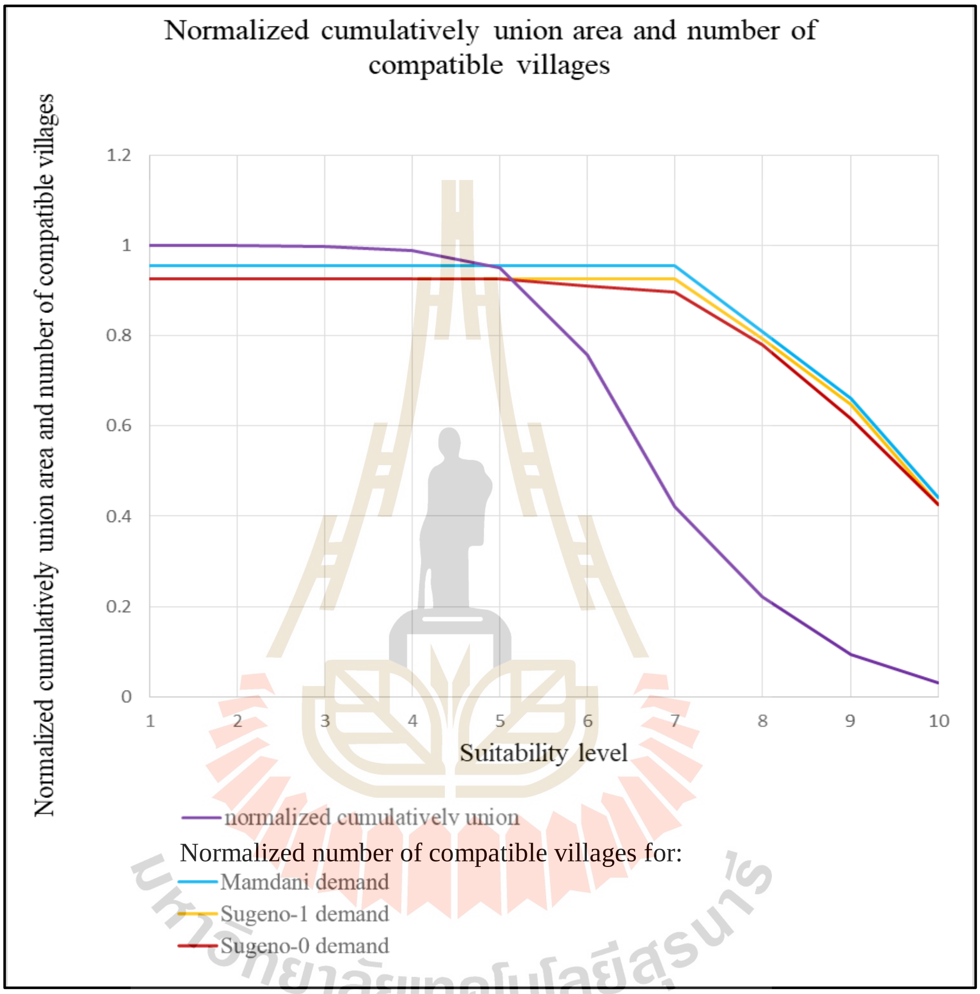


Figure 4.62 Normalized cumulative union area and number of compatible villages.

Finally, it can be concluded that suitability level 7 is the best level of solution which can provide the maximum union areas and completely serve optimum demands of all villages.

In addition, analysis of steps in 4.11-4.13 were performed using ArcGIS Model Builder and Python (Appendix E).

CHAPTER V

CONCLUSION AND RECOMMENDATION

5.1 Conclusion

As home to famous tourism destinations such as Bogor Botanical Garden and Presidential Palace, PUP development in BM has been the foci to serve growing demand of citizen to joy the city. However, since BM has grown to become more densed urban environment, it effects that not so many spaces are left for new PUP development. Therefore, GIS-MCDA-based methods are needed to give new locations of PUPs in BM by integrating various input spatial criteria with novel techniques. Hence, FISs and DEMATELs have been chosen in this research to overcome uncertainty might raise during data preparation and processing which have been described and discussed in previous chapters. The result of the study can be conclusively reported as follows:

1) For the first objective of this research, optimum PUP area demands for 68 villages in BM were derived from 3 FISs. Considering only attribute of areal extent, the agreement of the demand and feasible LULC area of every village was performed and resulted that Mamdani FIS provides the best agreement with least total demand area but the best distribution to villages.

2) Successful suitability mapping development is achieved in this study indicated by generating 3 PUP suitability maps from FISs and 2 maps from DEMATELs. Since they have different methods and techniques including input criteria,

the final raster-based maps from FISs are in form of defuzzified visit density while in DEMATELS are in suitability indexes. FISs methods require many computation steps with variety of platforms, while DEMATELs were performed mainly in GIS platform. Due to these differences, results from both groups of method have their own benefits. Therefore, application of the combined results or their union areas could have higher efficiency to providing sufficient PUP area in high suitability level for villages. This finding serves the second objective of the study.

3) Feasible PUP areas or intersected areas from 5 methods were obtained by incorporation of suitable areas in 10 levels and feasible areas from LULC. A group of DEMATELs methods provide the biggest feasible PUP area in suitability level 6 while a group of FISs show the biggest feasible PUP area in levels 1and 2. The consistency between the union and intersected areas show very high in level 10 while the least is in level 2. The bigger duplicating area of them indicates better consistency of results. These results serve the third objective of the study.

4) The comparison of results from methods is the fourth objective of the study. The comparison was performed on the behavior of intersect area and IoU of each suitability level of all methods. For intersect area, the group of FISs show more in lower suitability levels 1 and 2 while the group of DEMATELs show more in higher levels of 5-7. The group of DEMATELs can provide better solution than FISs because they can offer bigger intersect areas in higher suitability levels. Remarkably, at level 7, even though Sugeno-0 provides small suitable area, its IoU shows bigger value compared to others. This means its suitable area highly fit to feasible LULC.

5) The interesting finding from the study is that the suitability level 7 (Figure 5.1) is the best. In this single level the union area is the maximum to serve the village-

based optimum demands. Also, the cumulatively union area from the most top down to this level can completely serve PUP demand areas of all villages.

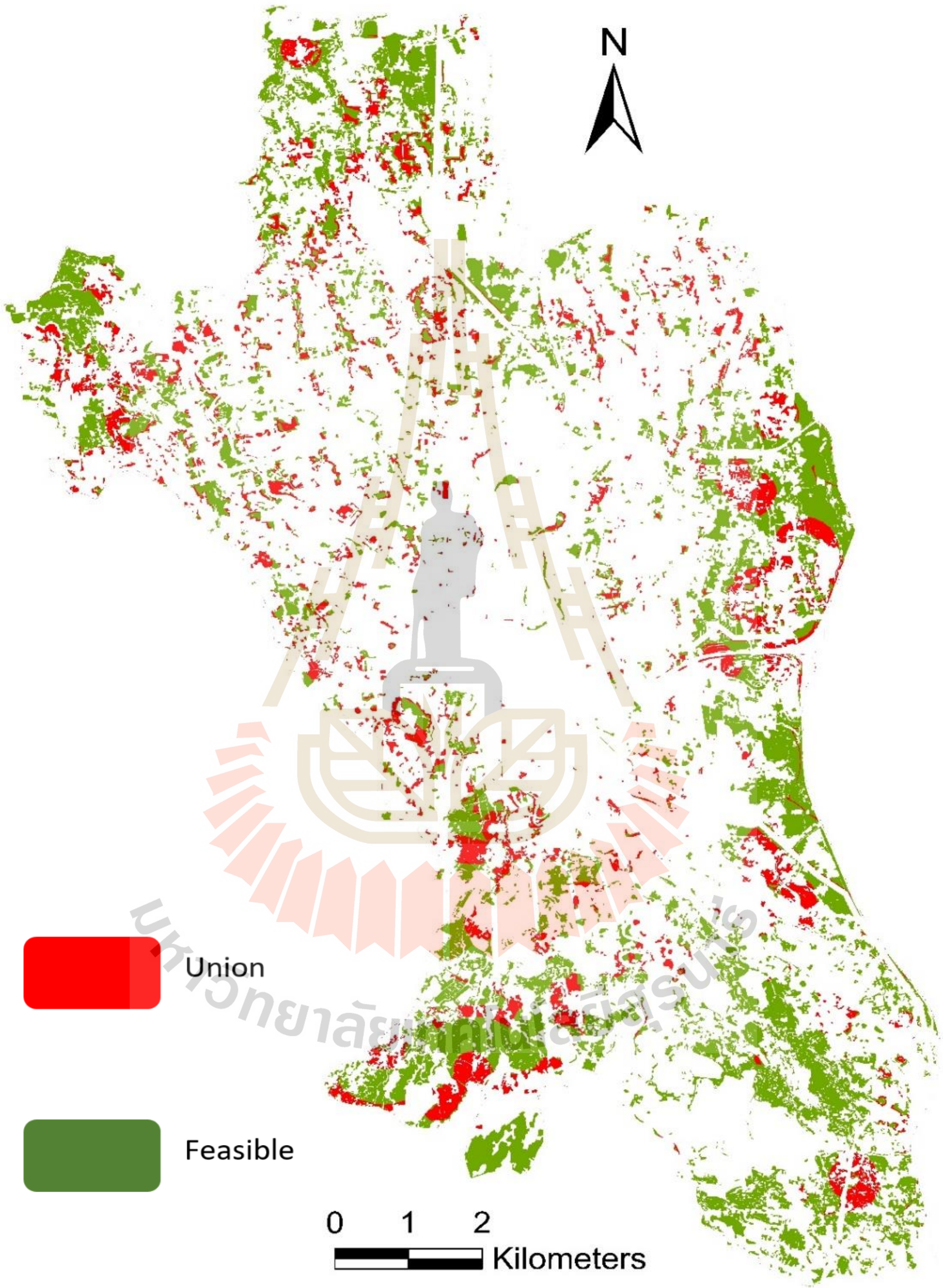


Figure 5.1 Union feasible PUP location based on suitability level 7.

6) Profitably, the study results are in form of a number of GIS data layers providing variety of information on PUP area demands, suitable and feasible PUP areas

in different level of methods. It can provide more alternatives in practice to policy makers for flexible allocation of feasible PUP area to meet the demand and constraints of villages.

5.2 Recommendations

5.2.1 Number of spatial criteria can be increased for further research whether as driving factors or as constraints for PUP area demands and suitable locations.

5.2.2 The methods and techniques used in this study can be applied to other kinds of suitability mapping. Also, different geographic characteristics of the study area should be aware because they can influence in different sets of input criteria and constraints.

5.2.3 For better accuracy of future study, the municipalities in Indonesia need to do yearly systematic survey to collect number of PUP visits and people's satisfaction. Otherwise, data on people preference in visiting PUP can be increased by collecting big data through social media.

5.2.4 The study result provides a big set of GIS data layers obtained from varying methods and techniques, sets of criteria, and suitability levels. They are certainly useful for serving dynamic solutions to variety of requirements of policy makers. Tangibly, they can be used more efficiently and interactively through the Spatial Decision Support System (SDSS). Therefore, the development of SDSS to make use of the study results is strongly recommended for future study.

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APPENDICES

APPENDIX A

PARK SATISFACTION ATTRIBUTE

QUESTIONNAIRES

WITH PHOTO SERIES

(Photo source: IMPW, 2013)

The purpose of this questionnaire is to get park satisfaction score for every PUP in BM based on available photos as attached. Score for every photo was given as a guide by a professional landscape architect with 7 years experiences. This questionnaire is addressed to existing PUP managers as target group. The obtained score of each park was used for number of visit estimation.

Questions in questionnaire were modified from Zanon (1996) to fit situation and condition in BM.

Table A1 Park satisfaction attributes (modified after Zanon, 1996).

	Park Satisfaction Attributes	**Maximum Scores**
1.	Safe Access to Park Facility	7.2
	- Walking paths that provide safe access to park facilities	
2.	Adequate number of toilette facilities	8.4
	-Sufficient number of toilettes in suitable locations	
3.	Clean toilletes	10.2
	-Toilet facilities are cleaned and maintained	
4.	Tracks, Trails, and Paths	8
	-Adequate number of clearly defined tracks and trails for you to explore or use the park	
5.	Suitable surface for tracks, trails, and paths	6.7
6.	Children’s playground /play areas	7.6
	-Adequate provision of constructed play-grounds and natural areas suitable for unstructured play	
7.	Adequate litter control measures	7.9
	-Information on park litter policy or sufficient number of rubbish pins for park users	
8.	Signposting and directions	5.9

Table A1 (Continued).

	Park Satisfaction Attributes	Maximum Scores
	-Adequate signs/directions for specific points of interests, trails, picnic areas, exits. etc	
9.	Shelter	10
	-sufficient shelter to provide relief from sun, wind, and rain when required	
10.	Length of grass	5.6
	- Grass not too long or too short	
11.	General maintenance standards	7.4
	Park is well maintained, things workings as they should and everything neat and tidy	
12.	Ranger present or available	4.7
	Ranger(s) on duty during official opening times to assist visitors, handle enquiries, and monitor behavior of park users	
13.	Information about the park	5.2
	-sufficient information available either via brochures, displays, signs or other means	
14.	Suitable opening and closing times	5.2
	-Adequate to meet your needs	

Question 1	0 to < 0.9
Question 4	0 to < 1
Question 5	0 to < 0.8

Question 1	0.9 to < 1.8
Question 4	1 to < 2
Question 5	0.8 to < 1.7

Question 1	1.8 to < 2.7
Question 4	2 to < 3
Question 5	1.7 to < 2.5

Question 1	2.7 to < 3.6
Question 4	3 to < 4
Question 5	2.5 to < 3.4

Question 1	2.7 to < 3.6
Question 4	3 to < 4
Question 5	2.5 to < 3.4

Question 1	4.5 to < 5.4
Question 4	5 to < 6
Question 5	4.2 to < 5

					
Question 1	4.5 to < 5.4	Question 1	5.4 to < 6.3	Question 1	6.3 to 7.2
Question 4	5 to < 6	Question 4	6 to < 7	Question 4	7 to 8
Question 5	4.2 to < 5	Question 5	5 to < 5.9	Question 5	5.9 to 6.7
					
Question 2	0 to < 1.7	Question 2	1.7 to < 3.4	Question 2	3.4 to < 5
Question 3	0 to < 2	Question 3	2 to 4.1	Question 3	4.1 to < 6.1

Question 2	5 to < 6.7
Question 3	6.1 to < 8.2

Question 2	6.7 to 8.4
Question 3	8.2 to 10.2

		
Question 6 — 0 to 1.3	Question 6 — 1.3 to 2.5	Question 6 — 2.5 to < 3.8
		
Question 6 — 0 to 1.3	Question 6 — 5.1 to < 6.3	Question 6 — 6.3 to 7.6

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<tr>
<td>Question 7</td><td>0 to < 1.3</td>
<td>Question 7</td><td>1.3 to < 2.6</td>
<td>Question 7</td><td>2.6 to < 3.9</td>
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<tr>
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<td>Question 7</td><td>5.2 to < 6.5</td>
<td>Question 7</td><td>6.5 to 7.9</td>
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Question 8	0 to < 0.7	Question 8	0.7 to < 1.5	Question 8	1.5 to < 2.2

Question 8	2.2 to < 2.9	Question 8	2.9 to < 3.7	Question 8	3.7 to < 4.4

Question 8 | 4.4 to < 5.1

Question 8 | 5.1 to 5.9

Question 9 | 0 to < 1.1

Question 9 | 1.7 to < 3.3

Question 9 | 3.3 to < 5

					
Question 9	5 to < 6.7	Question 9	6.7 to < 8.3	Question 9	8.3 to 10
					
Question 10	0 to < 0.94	Question 10	1.1 to < 2.2	Question 10	2.2 to < 3.4

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<tr><td>Question 10</td><td>3.4 to < 4.5</td><td>Question 10</td><td>4.5 to 5.6</td><td>Question 11</td><td>0 to < 1.8</td></tr>
<tr><td colspan="2"></td><td colspan="2"></td><td colspan="2"></td></tr>
<tr><td>Question 11</td><td>1.8 to < 3.7</td><td>Question 11</td><td>3.4 to < 4.5</td><td>Question 11</td><td>5.5 to 7.4</td></tr>
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Question 12	0 to < 0.9	Question 12	0.9 to < 1.9	Question 12	1.9 to < 2.8
					
Question 12	2.8 to < 3.8	Question 12	3.8 to 4.7	Question 13	0 to <1.3

Question 13	1.3 to <2.6

Question 13	2.6 to < 3.9

Question 13	3.9 to 5.2

APPENDIX B

VISIT DENSITY FROM FISs AND OPTIMUM PUP AREA DEMAND

Table B1 Antecedents and consequent of villages in BM.

No.	Villages name	Accessibility	Population density (persons/km^2)	PUP demand (km^2)	Visit density (visits per year/m^2)
1	Tanah Baru	0.006	12775	0.28	59.15
2	Tegalega	0.008	12752	0.17	32.28
3	Mekarwangi	0.037	12773	0.19	22.46
4	Ranggamekar	0.008	12778	0.19	22.33
5	Bantarjati	0.014	12762	0.25	17.73
6	Katulampa	0.012	12779	0.62	13.19
7	Babakan	0.037	12764	0.19	13.09
8	Panaragan	0.006	12773	0.01	7.05
9	Paledang	0.060	12524	0.26	6.63
10	Tegal Gundil	0.093	12763	0.26	4.91
11	Ciparigi	0.056	12768	0.29	4.76
12	Baranangsiang	0.008	12764	0.22	4.66
13	TanahSareal	0.202	12743	0.03	4.01
14	Menteng	0.040	12739	0.33	1.98
15	Sukasari	0.002	12768	0.05	1.15
16	Cimahpar	0.035	12773	0.78	0.69
17	Cibuluh	0.064	12761	0.21	0.07

Table B2 Optimized visit density values of villages in BM.

No.	Villages name	Visit density from Mamdani (visits per year/m^2)	PUP area demand based on Mamdani (m^2)	Visit density from Sugeno-1 (visits per year/m^2)	PUP area demand based on Sugeno-1 (m^2)	Visit density from Sugeno-0 (visits per year/m2)	PUP area demand based on Sugeno-0 (m^2)
1	Babakan	20.41	1677.61	13.99	2444.52	12.71	2694.74
2	Babakan Pasar	22.92	1518.23	19.12	1820.28	12.71	2737.59
3	Balumbang Jaya	22.25	1581.56	17.43	2017.85	12.71	2764.62
4	Bantarjati	20.90	1660.66	15.90	2182.89	12.71	2732.90
5	Baranangsiang	21.73	1601.24	16.88	2056.03	12.71	2735.98
6	Batutulis	22.59	1553.57	18.85	1857.71	12.71	2764.62
7	Bojongkerta	10.04	3511.06	14.90	2356.42	12.71	2764.62
8	Bondongan	22.37	1567.44	18.66	1877.57	12.71	2764.62
9	Bubulak	9.92	3546.53	14.54	2421.42	12.71	2764.62
10	Cibadak	13.70	2562.82	12.21	2877.92	12.71	2764.62
11	Cibogor	23.47	1494.07	18.70	1877.57	12.71	2764.62
12	Cibuluh	13.30	2588.35	10.90	3158.26	12.71	2710.63
13	Cikaret	11.26	3107.14	13.57	2581.66	12.71	2764.62
14	Cilendek barat	22.25	1581.56	17.27	2029.52	12.71	2764.62
15	Cilendek Timur	22.25	1581.56	18.25	1929.16	12.71	2764.62
16	ciluar	21.85	1601.08	16.41	2138.02	12.71	2760.91
17	cimahpar	13.63	2555.79	8.75	3995.25	12.71	2736.90
18	cipaku	22.34	1514.14	16.32	2071.50	12.71	2658.69
19	ciparigi	16.48	2116.20	11.02	3174.30	12.71	2749.39
20	ciwaringin	22.44	1554.27	18.40	1892.16	12.71	2741.39
21	curug	22.73	1546.72	16.45	2127.92	12.71	2764.62
22	curug mekar	22.25	1581.56	17.93	1961.49	12.71	2764.62
23	empang	24.13	1456.87	19.09	1838.25	12.71	2764.62
24	genteng	14.60	2374.66	12.70	2729.93	12.71	2729.93
25	gudang	22.97	1526.55	19.29	1819.20	12.71	2764.62
26	gunung batu	19.67	1782.27	16.06	2180.78	12.71	2764.62
27	harjasari	22.28	1574.47	17.24	2041.32	12.71	2764.62

Table B2 (Continued).

No.	Villages name	Visit density from Mamdani (visits per year/m^2)	PUP area demand based on Mamdani (m^2)	Visit density from Sugeno-1 (visits per year/m^2)	PUP area demand based on Sugeno-1 (m^2)	Visit density from Sugeno-0 (visits per year/m2)	PUP area demand based on Sugeno-0 (m^2)
28	katulampa	10.42	3365.69	12.88	2713.42	12.71	2756.15
29	kayumanis	22.25	1581.56	18.26	1918.61	12.71	2764.62
30	kebon kelapa	23.21	1496.27	19.03	1827.03	12.71	2733.35
31	kebon pedes	23.71	1480.95	19.23	1828.05	12.71	2763.66
32	kedung badak	22.09	1588.72	18.01	1950.59	12.71	2764.62
33	kedung halang	22.56	1553.57	16.11	2180.78	12.71	2764.62
34	kedung jaya	22.44	1567.44	18.70	1877.57	12.71	2764.62
35	kedung waringin	22.25	1581.56	17.36	2017.85	12.71	2764.62
36	kencana	22.26	1574.47	16.97	2065.33	12.71	2764.62
37	kertamaya	10.65	3312.32	13.26	2639.90	12.71	2764.62
38	lawanggintung	22.50	1560.45	18.73	1877.55	12.71	2764.58
39	Loji	11.28	3107.14	15.37	2279.91	12.71	2764.62
40	Margajaya	22.25	1581.56	18.16	1929.16	12.71	2764.62
41	Mekarwangi	20.33	1719.85	14.17	2458.66	12.71	2749.05
42	Menteng	16.21	2126.27	11.79	2919.11	12.71	2712.25
43	Muara sari	22.28	1574.47	17.65	1994.92	12.71	2764.62
44	mulyaharja	13.36	2620.20	12.61	2786.56	12.71	2764.62
45	pabaton	22.68	1551.69	17.92	1967.78	12.71	2773.48
46	pakuan	22.25	1581.56	18.29	1918.61	12.71	2764.62
47	paledang	10.70	3083.87	5.49	6435.94	12.71	2787.22
48	pamoyanan	22.67	1546.57	16.26	2153.81	12.71	2764.34
49	panaragan	25.08	1328.93	19.29	1728.30	12.71	2626.47
50	pasir jaya	11.02	3191.88	14.81	2372.34	12.71	2764.62
51	pasir kuda	14.72	2388.48	15.38	2279.91	12.71	2764.62
52	pasir mulya	22.25	1581.56	18.16	1929.16	12.71	2764.62
53	rancamaya	22.28	1574.47	17.28	2029.52	12.71	2764.62
54	ranggamekar	21.76	1585.78	17.43	1986.78	12.71	2722.05

Table B2 (Continued).

No.	Villages name	Visit density from Mamdani (visits per year/m^2)	PUP area demand based on Mamdani (m^2)	Visit density from Sugeno-1 (visits per year/m^2)	PUP area demand based on Sugeno-1 (m^2)	Visit density from Sugeno-0 (visits per year/m2)	PUP area demand based on Sugeno-0 (m^2)
55	semplak	24.18	1450.85	19.68	1782.27	12.71	2764.62
56	sempur	13.75	2640.78	27.60	1031.87	12.71	2848.72
57	sindang barang	10.87	3221.16	13.63	2581.66	12.71	2764.62
58	sindang rasa	22.25	1581.56	18.26	1918.61	12.71	2764.62
59	sindang sari	22.61	1553.57	18.70	1877.57	12.71	2764.62
60	situ gede	15.53	2265.20	14.54	2421.42	12.71	2764.62
61	sukadamai	22.25	1577.53	18.01	1945.62	12.71	2757.57
62	sukaresmi	23.14	1519.94	18.76	1867.59	12.71	2764.62
63	sukasari	22.53	1510.92	19.20	1770.61	12.71	2676.83
64	tajur	22.82	1517.25	18.82	1840.07	12.71	2723.89
65	tanah baru	22.02	1589.99	16.79	2082.13	12.71	2754.31
66	tanah sareal	13.72	2744.33	28.25	1333.24	12.71	2960.42
67	tegalega	21.84	1588.77	17.09	2025.45	12.71	2727.18
68	tegalgundil	7.03	4836.51	7.24	4702.17	12.71	2665.80

APPENDIX C

EXPERTS' OPINIONS IN FUZZY NUMBER FOR FDEMATEL PROCESS

Table C1 Experts' opinions in left fuzzy numbers.

Left fuzzy numbers	Accessibility	Population density	PUP policy demand	Distance to water body	Distance to school	Distance to electric power line
Accessibility	0	0	0	0	2	0
Population density	0	0	3	0	1	0
PUP policy demand	0	1	0	2	0	0
Distance to water body	0	2	1	0	1	0
Distance to school	1	2	1	0	0	0
Distance to electric line	1	1	1	0	1	0

Table C2 Experts' opinions in middle fuzzy numbers.

Middle fuzzy numbers	Accessibility	Population density	PUP policy demand	Distance to water body	Distance to school	Distance to electric power line
Accessibility	0.00	0.00	0.00	0.00	2.38	0.00
Population density	0.00	0.00	3.02	0.00	2.16	0.00
PUP policy demand	0.00	2.58	0.00	2.25	0.00	0.00
Distance to water body	0.00	2.21	2.12	0.00	1.22	0.00
Distance to school	2.19	2.38	2.16	0.00	0.00	0.00
Distance to electric line	2.34	2.58	2.38	0.00	2.03	0.00

Table C3. Experts' opinions in right fuzzy numbers.

Right fuzzy numbers	Accessibility	Population density	PUP policy demand	Distance to water body	Distance to school	Distance to electric power line
Accessibility	0	4	4	4	4	4
Population density	4	0	4	3	4	4
PUP policy demand	4	4	0	4	3	4
Distance to water body	3	4	4	0	2	1
Distance to school	3	4	4	2	0	4
Distance to electric line	4	4	4	4	4	0

APPENDIX D

NORMALIZED EXPERTS' OPINIONS

Table D1 Normalized Experts' opinions in left fuzzy numbers.

Left fuzzy numbers	Accessibility	Population density	PUP policy demand	Distance to water body	Distance to school	Distance to electric power line
Accessibility	0.00	0.00	0.00	0.00	0.33	0.00
Population density	0.00	0.00	0.50	0.00	0.17	0.00
PUP policy demand	0.00	0.17	0.00	0.33	0.00	0.00
Distance to water body	0.00	0.33	0.17	0.00	0.17	0.00
Distance to school	0.17	0.33	0.17	0.00	0.00	0.00
Distance to electric line	0.17	0.17	0.17	0.00	0.17	0.00

Table D2 Normalized Experts' opinions in middle fuzzy numbers.

Middle fuzzy numbers	Accessibility	Population density	PUP policy demand	Distance to water body	Distance to school	Distance to electric power line
Accessibility	0.00	0.00	0.00	0.00	0.24	0.00
Population density	0.00	0.00	0.31	0.00	0.22	0.00
PUP policy demand	0.00	0.26	0.00	0.23	0.00	0.00
Distance to water body	0.00	0.23	0.22	0.00	0.13	0.00
Distance to school	0.22	0.24	0.22	0.00	0.00	0.00
Distance to electric line	0.24	0.26	0.24	0.00	0.21	0.00

Table D3 Normalized Experts' opinions in right fuzzy numbers.

Right fuzzy numbers	Accessibility	Population density	PUP policy demand	Distance to water body	Distance to school	Distance to electric power line
Accessibility	0	0.2	0.2	0.2	0.2	0.2
Population density	0.2	0	0.2	0.15	0.2	0.2
PUP policy demand	0.2	0.2	0	0.2	0.15	0.2
Distance to water body	0.15	0.2	0.2	0	0.1	0.05
Distance to school	0.15	0.2	0.2	0.1	0	0.2
Distance to electric line	0.2	0.2	0.2	0.2	0.2	0

APPENDIX E

ARCGIS MODEL BUILDER AND PYTHON CODING

Figure E1 ArcGIS model builder to compute agreement between PUP area demand and feasible.

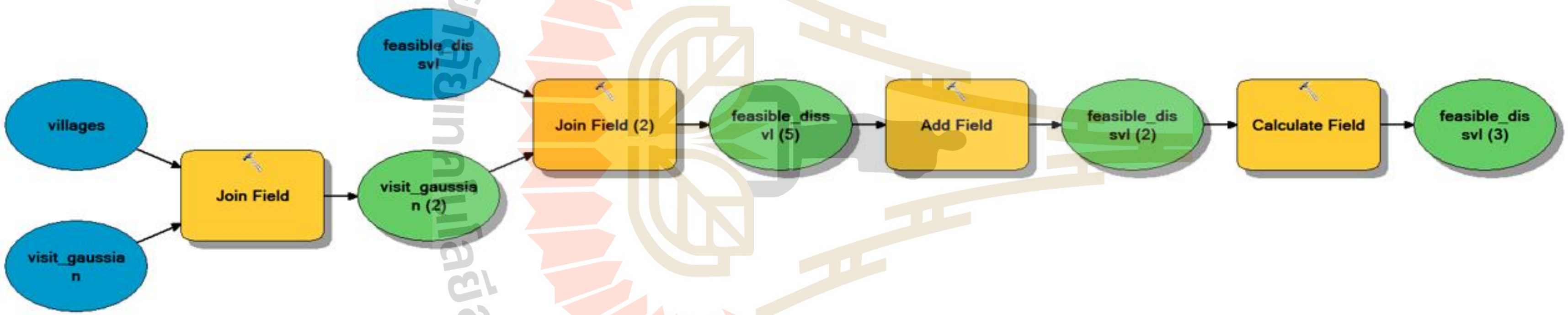


Figure E2 ArcGIS model builder to compute union feasible area in each suitability level.

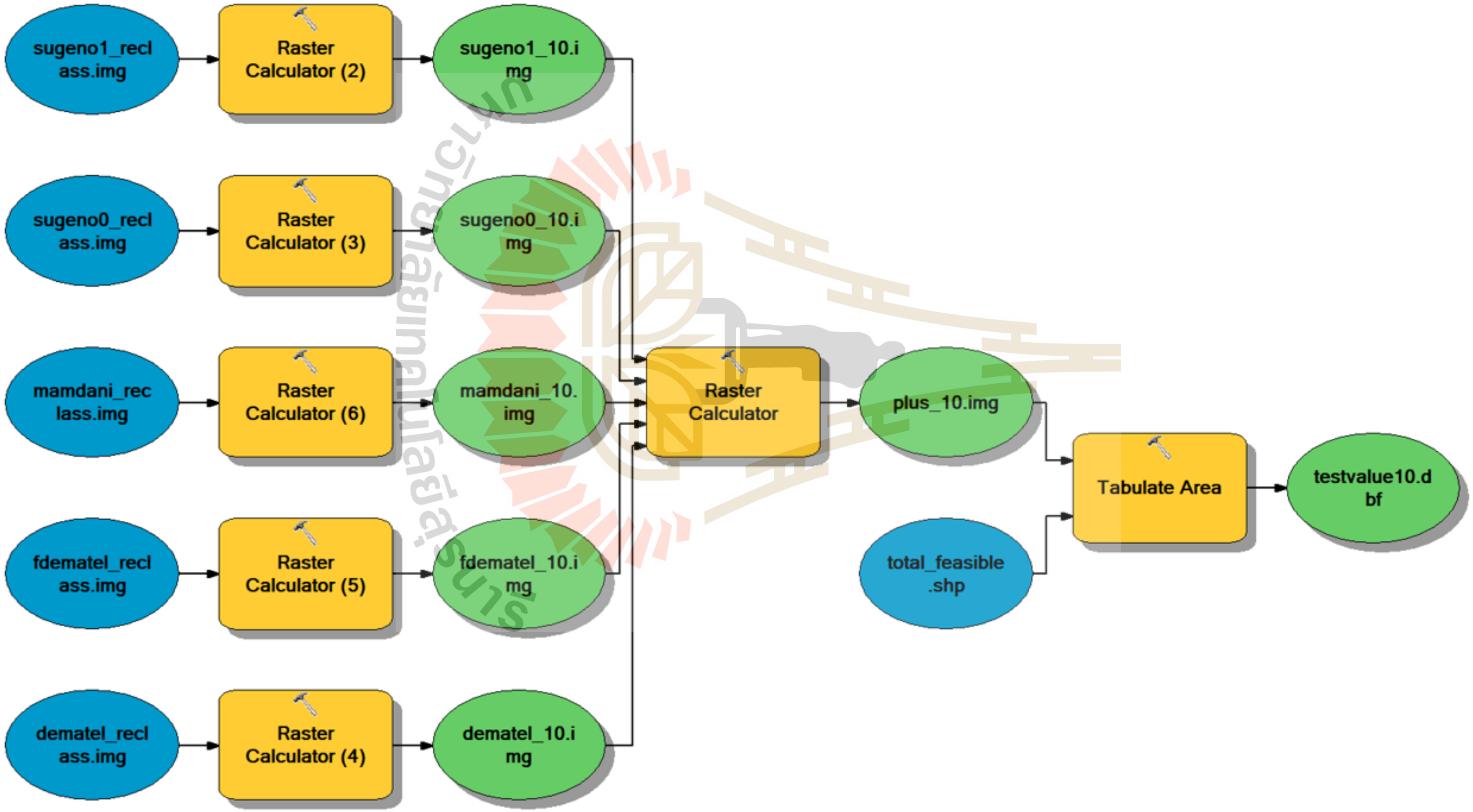
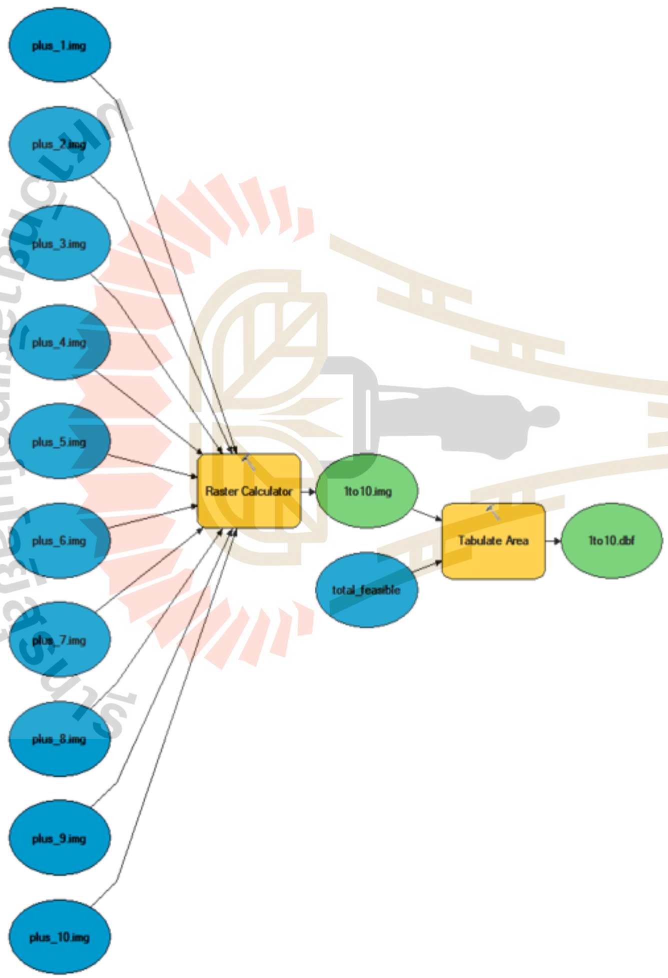


Figure E3 ArcGIS model builder to compute cumulatively union feasible area in each suitability level.



E5 Python coding to compute compatible villages from union in each level.

```
# Determine village-based PUP area surplus from union raster-based location for PUP

# Import arcpy module
import arcpy
arcpy.env.overwriteOutput=True

# Script arguments
# File location of vector file of feasible LULC for PUP development
total_feasible = "D:\\thesis\\phytonmodel\\newajan6sept\\feasible_dissvl.shp"

# File location of union raster file in specific suitability level
sugeno1_reclass_img =
"D:\\thesis\\phytonmodel\\newajan6sept\\unionfeasible\\plus_10.img"

# File location of resulted from intersect operation between feasible LULC and union
sugeno_1feasible_img = "D:\\thesis\\phytonmodel\\newajan6sept\\unionfeasible\\
sugeno_1feasible.img"

# File location of reclass operation from feasible raster
feasible_sugeno1_reclass_img =
"D:\\thesis\\phytonmodel\\newajan6sept\\feasible_sugeno1_reclass.img"

# File location of optimum PUP area demand
visit_gaussian_shp = "D:\\thesis\\visitdensity\\visit_gaussian.shp"

# File location of 68 villages vector file
villages_shp = "D:\\thesis\\villages.shp"

# File location of table to do deficiency analysis
table = "D:\\thesis\\phytonmodel\\newajan6sept\\table"
table__2_ = "D:\\thesis\\phytonmodel\\newajan6sept\\table"
table__3_ = "D:\\thesis\\phytonmodel\\newajan6sept\\table"

# File location of total area of feasible from union in each village
feasible_sgn1_v = "D:\\thesis\\phytonmodel\\newajan6sept\\feasible_sgn1_v"
table__4_ = "D:\\thesis\\phytonmodel\\newajan6sept\\table"
table__6_ = "D:\\thesis\\phytonmodel\\newajan6sept\\table"

# File location of table showing surplus/minus indicator
sugeno_assmnt = "D:\\thesis\\phytonmodel\\sugeno_assmnt"

Row_Count = "D:\\thesis\\phytonmodel\\sugeno_assmnt"

# Process: Table Select
arcpy.TableSelect_analysis(visit_gaussian_shp, table, "\"FID\" <68")
```

```
# Process: Calculate Field (3)
arcpy.CalculateField_management(table, "FID", "[Rowid] -1", "VB", "")

# Process: Extract by Mask
arcpy.gp.ExtractByMask_sa(sugeno1_reclass_img, total_feasible, sugeno_1feasible
_img)

# Process: Reclassify
arcpy.gp.Reclassify_sa(sugeno_1feasible_img, "Value", "0 NODATA;1 4 1;",
feasible_sugeno1_reclass_img, "NODATA")

# Process: Tabulate Area
arcpy.gp.TabulateArea_sa(villages_shp, "FID", feasible_sugeno1_reclass_img,
"VALUE", feasible_sgn1_v, "10")

# Process: Join Field
arcpy.JoinField_management(table__2_, "FID", feasible_sgn1_v, "FID",
"FID;VALUE_1;op_ar_mmdn;op_ar_sgn1;op_ar_sgn0")

# Process: Add Field (2)
arcpy.AddField_management(table__3_, "deficiency", "DOUBLE", "15", "5", "", "",
"NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
arcpy.CalculateField_management(table__4_, "deficiency", "[VALUE_1] -
[op_ar_sgn0]", "VB", "")

# Process: Table Select
print "fdematel raster-based with sugeno-0 village-based area demand"

arcpy.TableSelect_analysis(table__4_, sugeno_assmnt, "\"deficiency\" >0")
selectSurplusCount = arcpy.GetCount_management(sugeno_assmnt)
print "villages with surplus feasible areas",selectSurplusCount

arcpy.TableSelect_analysis(table__4_, sugeno_assmnt, "\"deficiency\" <0")
selectMinusCount = arcpy.GetCount_management(sugeno_assmnt)
print "villages with minus feasible areas",selectMinusCount

arcpy.TableSelect_analysis(table__4_, sugeno_assmnt, "\"deficiency\" =0")
selectBestfitCount = arcpy.GetCount_management(sugeno_assmnt)
print "villages with best fit feasible areas",selectBestfitCount
```

E6 Python coding to compute compatible villages from cumulative union in each level.

```
# Determine village-based PUP area surplus from cumulative union raster-based
location for PUP


# Import arcpy module
import arcpy
arcpy.env.overwriteOutput=True

# Script arguments
# File location of vector file of feasible LULC for PUP development
total_feasible = "D:\\thesis\\phytonmodel\\newajan6sept\\feasible_dissvl.shp"

# File location of cumulatively union raster file in specific suitability level
sugeno1_reclass_img = "D:\\thesis\\phytonmodel\\newajan6sept\\unionfeasible\\NEW
DEMATEL_plus_9.img"

# File location of resulted from intersect operation between feasible LULC and
cumulative union
sugeno_1feasible_img = "D:\\thesis\\phytonmodel\\newajan6sept\\unionfeasible\\
sugeno_1feasible.img"

# File location of reclass operation from feasible raster
feasible_sugeno1_reclass_img = "D:\\thesis\\phytonmodel\\newajan6sept\\feasible_
sugeno1_reclass.img"

# File location of optimum PUP area demand
visit_gaussian_shp = "D:\\thesis\\visitdensity\\visit_gaussian.shp"

# File location of 68 villages vector file
villages_shp = "D:\\thesis\\villages.shp"

# File location of table to do deficiency analysis
table = "D:\\thesis\\phytonmodel\\newajan6sept\\table"
table__2_ = "D:\\thesis\\phytonmodel\\newajan6sept\\table"
table__3_ = "D:\\thesis\\phytonmodel\\newajan6sept\\table"

# File location of total area of feasible from cumulative union in each village
feasible_sgn1_v = "D:\\thesis\\phytonmodel\\newajan6sept\\feasible_sgn1_v"
table__4_ = "D:\\thesis\\phytonmodel\\newajan6sept\\table"
table__6_ = "D:\\thesis\\phytonmodel\\newajan6sept\\table"

# File location of table showing surplus/minus indicator
sugeno_assmnt = "D:\\thesis\\phytonmodel\\sugeno_assmnt"
Row_Count = "D:\\thesis\\phytonmodel\\sugeno_assmnt"

# Process: Table Select
```

```
arcpy.TableSelect_analysis(visit_gaussian_shp, table, "\"FID\" <68")

# Process: Calculate Field (3)
arcpy.CalculateField_management(table, "FID", "[Rowid] -1", "VB", "")

# Process: Extract by Mask
arcpy.gp.ExtractByMask_sa(sugeno1_reclass_img, total_feasible, sugeno_1feasible_
img)

# Process: Reclassify
arcpy.gp.Reclassify_sa(sugeno_1feasible_img, "Value", "0 NODATA;1 10 1;",
feasible_sugeno1_reclass_img, "NODATA")

# Process: Tabulate Area
arcpy.gp.TabulateArea_sa(villages_shp, "FID", feasible_sugeno1_reclass_img,
"VALUE", feasible_sgn1_v, "10")

# Process: Join Field
arcpy.JoinField_management(table__2_, "FID", feasible_sgn1_v, "FID",
"FID;VALUE_1;op_ar_mmdn;op_ar_sgn1;op_ar_sgn0")

# Process: Add Field (2)
arcpy.AddField_management(table__3_, "deficiency", "DOUBLE", "15", "5", "", "",
"NULLABLE", "NON_REQUIRED", "")

# Process: Calculate Field
arcpy.CalculateField_management(table__4_, "deficiency", "[VALUE_1] -
[op_ar_mmdn]", "VB", "")

# Process: Table Select
print "cumulatively union raster-based with sugeno-0 village-based area demand"

arcpy.TableSelect_analysis(table__4_, sugeno_assmnt, "\"deficiency\" >0")
selectSurplusCount = arcpy.GetCount_management(sugeno_assmnt)
print "villages with surplus feasible areas",selectSurplusCount

arcpy.TableSelect_analysis(table__4_, sugeno_assmnt, "\"deficiency\" <0")
selectMinusCount = arcpy.GetCount_management(sugeno_assmnt)
print "villages with minus feasible areas",selectMinusCount

arcpy.TableSelect_analysis(table__4_, sugeno_assmnt, "\"deficiency\" =0")
selectBestfitCount = arcpy.GetCount_management(sugeno_assmnt)
print "villages with best fit feasible areas",selectBestfitCount
```

CURRICULUM VITAE

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