OPEN ACCESS
Vol 4, No. 1, 2017, 9-18

Geoplanning
Journal of Geomatics and Planning
E-ISSN: 2355-6544
http://ejournal.undip.ac.id/index.php/geoplanning
doi: 10.14710/geoplanning.4.1.9-18

A GIS BASED EVALUATION OF LAND USE CHANGES AND ECOLOGICAL CONNECTIVITY INDEX

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Article Info:
Received: 31 August 2016
in revised form: 8 September 2016
Accepted: 29 November 2016
Available Online: 8 March 2017

Keywords:
Land use change, landscape pattern, ecological connectivity, GIS, urban planning

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Abstract: *Recently, the Makassar region is a significant land use planning and management issue, and has many impacts on the ecological function and structure landscape. With the development and infrastructure initiatives mostly around the urban centers, the urbanization and sprawl would impact the environment and the natural resources. Therefore, environmental management and careful strategic spatial planning in landscape ecological network is crucial when aiming for sustainable development. In this paper, the impacts of land use changes from 1997 to 2012 on the landscape ecological connectivity in the Makassar region were evaluated using Geographic Information System (GIS). The resulted GIS analysis clearly showed that land use changes occurring in the Makassar region have caused profound changes in landscape pattern. The spatial model had a predictive capability allowing the quantitative assessment and comparison of the impacts resulting from different land use on the ecological connectivity index. The results had an effective performance in identifying the vital ecological areas and connectivity prior to development plan in areas.*

How to cite (APA 6th Style):
Indrayani, P., et al. (2017). A GIS based evaluation of land use changes and ecological connectivity index. *Geoplanning: Journal of Geomatics and Planning, 4*(1), 9-18. doi:10.14710/geoplanning.4.1.9-18

1. INTRODUCTION

Indonesia is one of the fastest urbanizing countries in Asia. The level of population growth in urban areas approximately reaches 2.75% per year or higher than the level of national population growth (1.49% per year). In 2015, population growth in urban areas was estimated to reach 59.35% of the total population (Parasati, 2013). Assuming that population growth in urban areas approximately reaches 2.75% per year; the Indonesian population living in urban areas in 2045 will reach 82.37% of the total population. In recent years, the impact of population growth on urban sprawl in many major cities in Indonesia has become a major issue. As the fifth fastest growing city in Indonesia, the urbanization of the Makassar region has followed a model characterized by a low density of built-up area, which has revealed itself as tremendously negative for natural habits (Turner, 2005).

In many areas with increasing urban sprawl, fragmentation has turned out to be virtually inevitable (Dupras et al., 2016). Generally, high ecological connectivity and a well-designed green network are assumed to better facilitate flows of energy, materials, and species, and thus are important for environmental conservation in developing landscapes (Crooks & Sanjayan, 2006). Similarly, green infrastructure (GI) is used emphasizing on a system of natural areas as a backbone of landscape ecology (Mathey et al., 2015; Richter & Weiland, 2011). The definition of green infrastructure is strategically planned and managed networks of natural lands, working landscapes and other open spaces that conserve ecosystem values and functions also provide associated benefits to human populations (Benedict et al., 2012; Breuste et al., 2015). Therefore, based on literatures, green infrastructures in the United States and the Europe are best achieved through an integrated approach to land use management and strategic planning in ecological network.

Ecological landscape theory has provided set quantitative methods namely landscape metrics to characterize landscape pattern. However, there is a lack of quantitative methods to effectively assess ecological connectivity at regional scale. Marulli and Mallarach (2005) proposed a methodological approach used in quantitative landscape ecology, allowing to turn current theories into useful spatial analysis tools for regional land use planning. Most of the previous research in the land use changes of Makassar area (**Figure 1**) has been carried out using a remote sensing technique. Moreover, the spatial scales of the research settings deal with the metropolitan region.

Figure 1. Geographic location of the Makassar region and Tallo River area

This study aims to evaluate land use changes using a topographical map of 1:50,000 scales with Geographic Information System (GIS) grid system analysis dealing with the Makassar city scale and assess its impacts into the landscape ecological connectivity index. In order to effectively evaluate the respective goal, land use maps using a 50 m grid mesh were developed from availability of the digital topographic maps. Land use changes during the period from 1997 to 2012 were simulated based on 50 m grid mesh calculation, then a number of landscape properties were identified. Adopting the ideas and methodologies in landscape ecology, the study provided an assessment regarding the impact of land use changes on landscape ecological connectivity index. Several landscape metrics were calculated, and the evolution of the landscape ecological connectivity was assessed using GIS.

2. DATA AND METHODS

2.1. Land use planning of the Makassar region

Makassar is the largest city in Eastern Indonesia and the capital of the province of South Sulawesi (**Figure 1**). In 2016, the population counts about 1.7 million, with an average density of 8000 inhabitants per square kilometer. Makassar covers total area of nearly 177 km^2 which is divided into 14 districts. The Mamminasata Metropolitan Area (covering the city of Makassar and the regencies of Gowa, Maros, Takalar) has a population of approximately 2.5 million which is expected to grow to 2.9 million in 2020. Recently, the government of Makassar city proposes to create Tallo River area where the city can strategically manage urban development in the currently undeveloped land. Moreover, the large area on downstream of Tallo River is near the city center. It has been endorsed in the Makassar City's Spatial Plan (2012) identifying the Tallo River as a special development area. Therefore, an evaluation of the impact of land use changes on the ecological landscape pattern of Tallo River area is indispensable to ensure that the strategic land use planning can be optimized to protect the environment.

2.2. Land use maps in 1997 and 2012

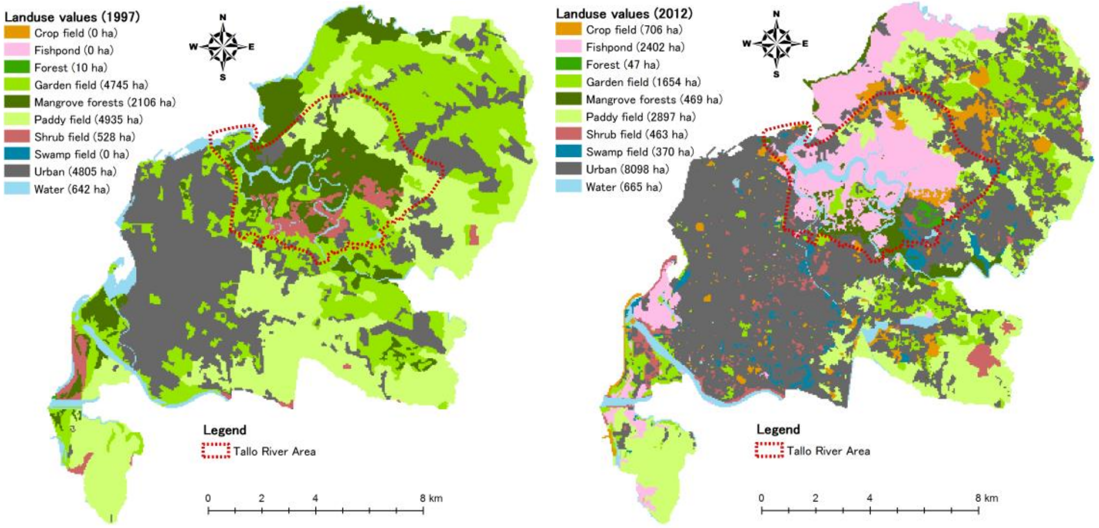
In this research, the land use maps in 1997 and 2012 were developed from the availability of digital topographic maps of 1:50,000 scales provided by the Regional Development Planning Agency of Makassar shown in **Figure 2** (Indrayani et al., 2016). Land use division was determined based on land use boundary line of the topographic maps. The land use divisions for 1997 and 2012 were reclassified into 10 categories.

2.3. Land use changes between 1997 and 2012

In GIS process, the land use polygons from the topographic maps were intersected with 50 m grid mesh from grid division analysis. The grid-mesh has orientation of the world grid system. Intersected land use polygons were calculated to obtain the maximum area in each grid feature. Land use value for each grid was dissolved based on maximum area analysis in GIS. The 50 m grid mesh based scale for land cover values can be obtained (Zhou et al., 2014); accordingly the spatial matrix analysis of GIS for land use changes can be done. By utilizing the developed land use maps, an analysis of land use changes based on 0.25 hectares area size was performed. Land uses for the period of 1997-2012 have shown important changes, urban surface has grown up from 4,805 to 8,098 hectares which represents almost twice the urban expansion of 15 years period. In the land use map of 1997, the existence of crop field, fishpond, and swamp field has not been clearly visible. It is revealed that urban, paddy field, garden field, and mangrove forest occupied 27%, 27.8 %, 26.7%, and 11.9% of the Makassar region, respectively. In the Eastern part of Makassar, the land area was bordered by the sea in which some of the sea areas were assumed as future reclaimed land.

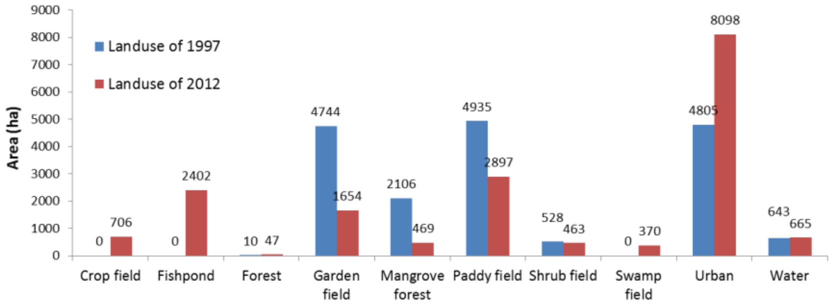
In 2012, urban has increased to 45.6 % of the Makassar region, in contrast that of paddy field, garden field, and mangrove forest has decreased to 16.3%, 9.3%, and 2.6%, respectively. The increasing phenomenon of urban area from 1997 to 2012 have caused the land cover of fishpond (13.5%) and swamp field (2.1%) existed in 2012. Moreover, a large area of fishpond was developed due to the conversion of mangrove forest for local peoples to practice fishery In recent years, the impact of regular flooding could be potentially increased in the Tallo River basin as a natural drainage catchment area, supported the local peoples to create the fishpond as a livelihood. In addition, the occurrence of swamp field and fishpond counted as 15.6% from the Makassar region, has transformed the pattern of mangrove forest, shrubs field in the vicinity of Tallo River area. **Figure 3** shows the comparison of the area (hectares) of land use change values in the Makassar region from 1997 to 2012.

Figure 2. Development of land use maps of the Makassar region



(1997) (2012)

Figure 3. Comparison of land use change values from 1997 to 2012



3. RESULTS AND DISCUSSION

3.1. Identification of Ecological Functional Areas

The decision about the ecological functional areas that needs to be connected is essential for assessing the ecological connectivity (Girvetz et al., 2008; Li et al., 2013). Using the land use maps, a topological analysis of the land cover categories was performed (**Table 1**). Based on a review of existing literatures, depending on each land cover, simple ecological functional areas are defined by a minimum surface (S_r = 50 hectares) (Bender, Contreras, & Fahrig, 1998). The areas that could not be considered as simple ecological functional areas can be grouped into forest, agricultural or agroforest mosaics (Forman, 1995). The GIS spatial analysis obtained six types of ecological functional areas, as shown in **Table 2**. Forest is considered as a relative small spectrum size (less than 50 hectares), thus it is not included in the ecological functional areas. All remaining areas were considered fragmented areas. Results of the ecological functional areas in the Makassar region are shown in **Figure 4**.

As expected, the ecologically functional areas C'_r (55.42%) of the total area in 2012 was lower than the ecologically functional areas C'_r (87.79%) in 1997. The largest ecologically functional areas in 1997 were paddy field covering 98.0% of the total area, followed by garden field and mangrove forest covering 86.9% and 77.1%, respectively. In 2012, paddy field, garden field and mangrove forest decreased into 79.5%, 38.2% and 50.7% of the total area, respectively. In particular, small swamp field, which hold the vertebrate biodiversity (13.7% of the total area) were the important habitat type, and therefore the most vulnerable. To deal with the landscape ecological connectivity analysis, the following sections described the Barrier Effect Index (BEI) and the Ecological Connectivity Index (ECI).

Table 1. Land cover categories

Code	Land Cover
B_1	Urban
B_2	Water
B_3	Fishpond
C_1	Forest
C_2	Mangrove forest
C_3	Swamp field
C_4	Paddy field
C_5	Garden field
C_6	Shrub field
N_1	Crop field

Table 2. Results of topological analysis showing the ecological functional areas

Code	Land cover	Total area (ha)		S_r (ha)	1997		2012	
		1997	2012		ha	%	ha	%
C'_1	Forest	8.58	44.52	50	0	0	0	0
C'_2	Mangrove forest	2,088.57	471.69	50	1,610.20	77.10	239.13	50.70
C'_3	Swamp field	0	382.74	50	0	0.0	52.40	13.70
C'_4	Paddy field	4,805.79	2,795.54	50	4,711.80	98.0	2,222.43	79.50
C'_5	Garden field	4,705.47	1,663.63	50	4,088.34	86.9 0	634.93	38.20
C'_6	Shrub field	520.2	476.58	50	237.47	45.60	84.73	17.80
	Total	**12,128.61**	**5,834.70**		**10,647.81**		**3,233.62**	

3.2. Calculation of the Barrier Effect Index (BEI)

Urban development often hinders the movement of ecological processes. Barriers include all artificial land uses that create obstacles to the flow of energy, information, or matter across the matrix, or in other words, the landscape resistance. To reflect the barrier effects in measuring ecological connectivity, a group of artificial attributes were designated with different weights on each attribute depending on the relative influence on the entire landscape. The maximum level of weight was given to the built-up areas comprised of high and medium-density residential development because for the most time the built-up areas are impermeable to movement of many species (Fahrig, 2003). Since this study does not consider water body related species, water bodies such as rivers, lake and fishpond were counted as medium-level barriers. The ecological connectivity model is primarily based on the least-cost analysis considering the ecological functional areas and an impedance surface which incorporates the barrier effect and the potential affinity matrix. To calculate the effects of artificial barriers on ecological and landscape connectivity, a barrier effect index (BEI) was defined (Marulli & Mallarach, 2005) as follows:

$$\mathrm{BEI} = Y_i/Y_{max} \quad [1]$$

where,

Y_i: the value of the barrier effect in a pixel,
Y_{max}: the maximum value of the barrier effect calculated on a given area.

The BEI was based on the weight that each barrier type (**Table 3**), the affected land use class, and the distance from the barrier, according to the assigned potential impact matrix and logarithmic relationship with distance. Thus, it reflects an impedance surface, where a_i corresponds to the maximum significantly affected distance for each type of barrier, and A_i corresponds to the potential impact value for each type (**Table 4**). Based on Marulli and Mallarach (2005), it was assumed that the effect of a single barrier from a given point is logarithmic and decreasing as distance increases, according to the following expression:

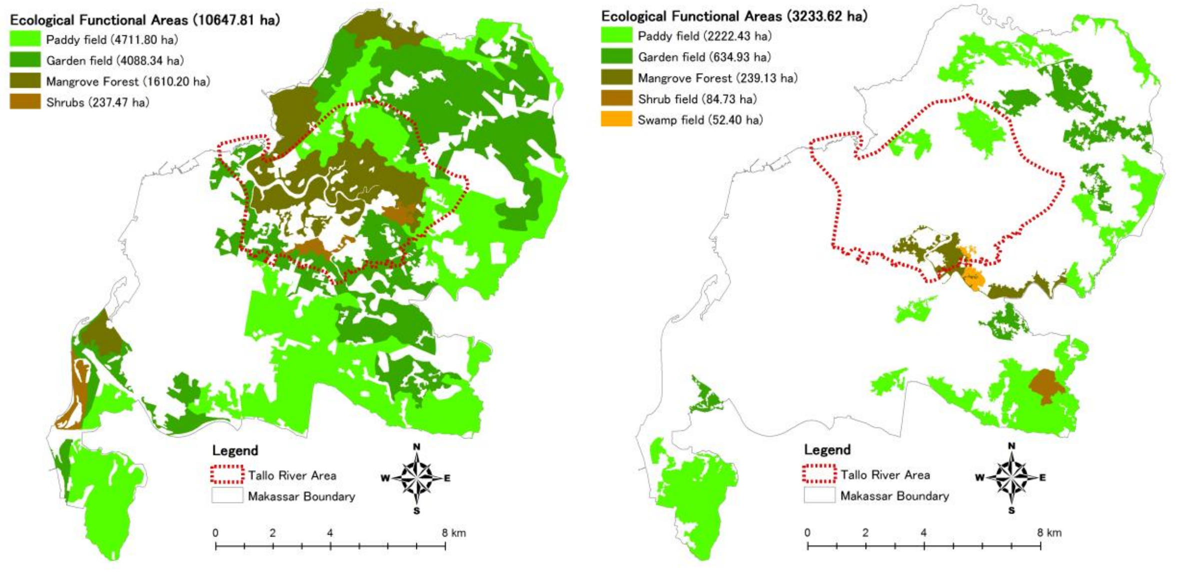
$$Y_s = b_s - k_{s1}.\ln(k_{s2}(b_s - d'_s) + 1) \quad [2]$$

where,

b_s: the weight of each barrier type, k_{s1} and k_{s2} are constants for logarithmic decreasing function
d'_s: the adapted cost distance per barrier type.

The BEI model applies the cost distance analysis using GIS and requires two GIS layers (a source layer and a friction resistance layer) as the input of the model: one is origin surface for each barrier type and second is impedance surface from the potential impact matrix. The principal algorithm underlying the cost distance model is the least-cost method. In this way, the cost value in each cell represents the distance to the source, measured as the least effort (lowest cost) in moving over the resistance layer. The cost distance model individually calculates the barrier effect Y_s for each sub-class type. Thus, the entire barrier effect in the landscape is defined as the addition of the effects of all barrier types on a given area. BEI is relative index to give values within an ordinal scale from 1 to 10, as shown in **Table 5**. The application of the BEI shows that in 1997 at least 61.08 % of the Makassar region was under negative impact from urban area, and increased at least 83.54% in 2012 (**Figure 5**). The maps resulting from the application of the BEI confirmed the distribution of areas in 2012 slightly affected by barrier in the Tallo River area (red-dotted lines), in contrast with the pervasive impacts spreading in the eastern part of the Makassar region.

Figure 4. Distribution of the ecological functional areas in the Makassar region (Own Analysis, 2016)



(1997) (2012)

Table 3. Weighted value system for the calculation of the BEI

Code	Type	Weight (b_s)	ks_1[a]	ks_2[a]
B_1	Urban	$b_1= 100$	$k1_1=55.52$	$k2_1=0.051$
B_2	Water	$b_2= 60$	_[b]	_[b]
B_3	Fishpond	$b_3= 60$	_[b]	_[b]

[a] Constants for a logarithms decreasing function (α=0.3)

[b] For s = 2 there is not surrrounding spatial affectation; $Y_2 = B_2$

Table 4. Impact matrix for the calculation of the Barrier Effect Index (Own Analysis, 2016)

Code	Type	Classes included[a]	Affectation coefficient (a_1)[b]	Affectation value (A_1)
V_1	Neutral	N_1	a_1=1000m	A_1=0.10
V_2	Agriculture	C_4, C_5	a_2=750m	A_2=0.13
V_3	"Natural"	C_1, C_2, C_3, C_6	a_3=500m	A_3=0.20
V_4	Barrier	B_1, B_2, B_3	a_4=250m	A_4=0.40
($A_n=b_1/a_n$)				

[a] class description in previous table

[b] a_1 defines the maximum significantly affected distance by each type

Table 5. Ranking of the barrier effect in the landscape (modified from Marulli and Mallarach (2005))

Barrier Effect Index	Effect	Type of barriers
0	Non existent	Lack of anthropogenic barriers. Total permeability of matter, energy and information
1	Low impact	Small and scattered barriers, such as isolated farms
2		High ecological permeability remains
3	Medium impact	Low density residential areas
4		Medium ecological permeability remains
5	High impact	Scattered urban, commercial or industrial areas
6		Low ecological permeability
7	Very high	Synergic combination of urban areas
8		Very low ecological permeability
9	Critical impact	Synergic combination of large, high density urban areas
10		Minimum ecological permeability

3.3. Evaluation of the Ecological Connectivity Index (ECI)

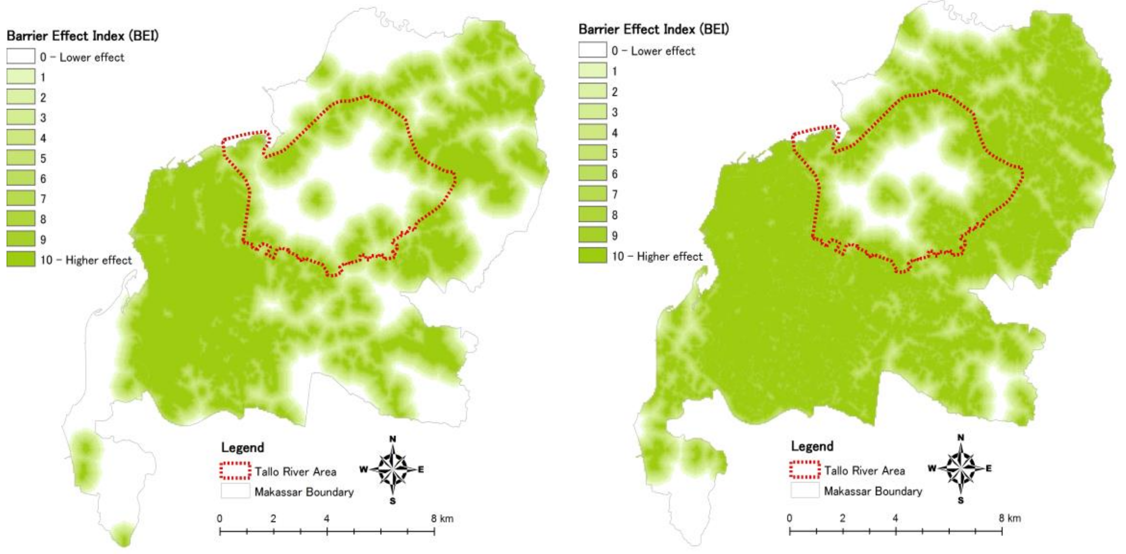
Ecological connectivity refers to the functional aspects of the actual connection between the different elements of the landscape (Pino & Marull, 2012). An ecological connectivity index (ECI) was defined based on a least-cost model that considers the different functional ecological areas and an impedance surface which incorporates the barrier effect and a potential affinity matrix for all the land use types. The model applied the cost distance analysis in GIS using two input data: one is origin surface for each type of ecological functional area and second is impedance surface resulting from the application the effect of the barriers. Finally, to transform the continuous values of the cost distance to discrete values based on a decimal scale, the ECI was calculated, according Marulli and Mallarach (2005) to the following expression:

$$ECI = 10-9.\ln(1+(x_i-x_{min}))/\ln(1+(x_{max}-x_{min}))^3 \qquad [3]$$

Where, x_i is the adapted cost distance value in a pixel, x_{max} is the maximum and x_{min} is the minimum cost distance values on a given area.

It is considered that this index reflects a kind of general ecological connectivity, since its computation includes all the ecological functional areas. Thus, it is a generic approach untied to specific indicator species. An interesting propriety of the ECI is that it has a relativistic distribution of values, always giving values between 0 and 10. This feature is useful to compare different alternatives. Ranking distribution of ECI allows the identification of areas of low absolute value as the only viable way of connecting existing ecological functional areas.

Figure 5. Maps resulting from the application of the BEI on the Makassar region (Own Analysis, 2016)



(1997) (2012)

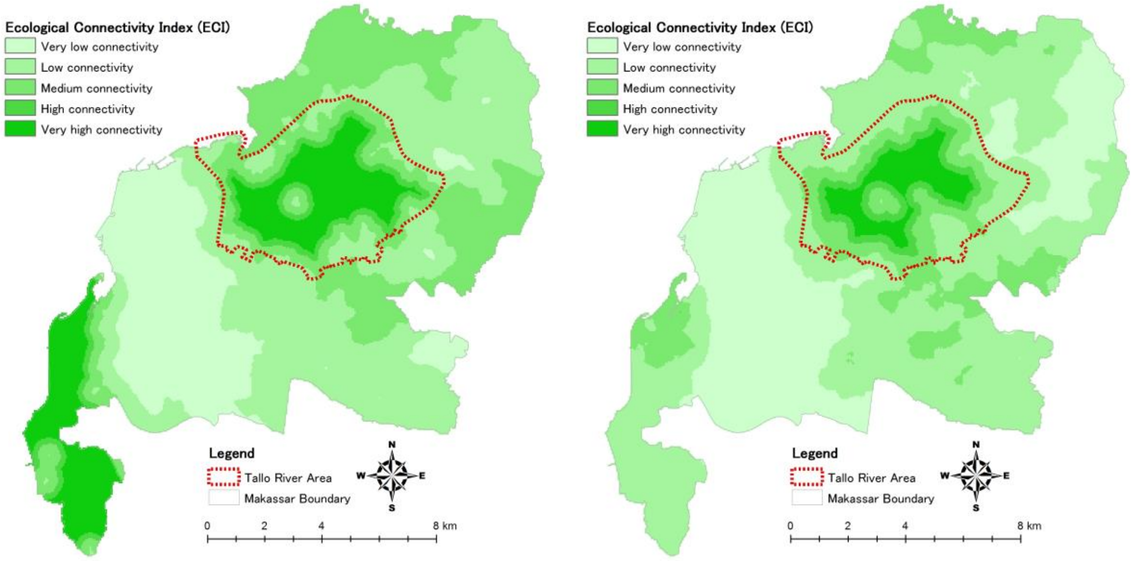
Forman (1995) described landscape connectivity as a degree of spatial connectedness among landscape elements such as patches, corridors, and matrix. Patch connectivity focuses on amount and arrangement of habitat patches, and thus effective distance between the patches becomes an important issue (Broquet et al., 2006). Corridor connectivity identifies linear features to promote dispersal through connectivity restoration (Graves et al., 2007). Matrix connectivity evaluates overall landscape mosaic, including landscape matrix to maintain maximum landscape continuity of non-built areas (Levin et al., 2007).

Various methods were developed from general landscape ecological principles to measure landscape connectivity. Although there are a wide range of proposed connectivity measures and geometric analyses from very simple to highly sophisticated (Selman, 2006), the approaches were categorized into four groups (connectivity metrics, least-cost analysis, empirical models and graph-based models). The use of least-cost analysis has been increased in recent landscape and ecological connectivity research because it calculates effective distance, a measure for distance modified with the landscape resistance (Adriaensen et al., 2003). This method can be implemented in GIS efficiently and effectively. Comparing to the previous similar study, the results of GIS analysis were able to evaluate each of the land use changes and its effects on the value of landscape connectivity index, spatially and temporally.

The GIS methodology employed in this study to assess ecological connectivity in the Makassar region revealed spatial processes, such as land use changes based on 50 m grid mesh analysis, and assess spatial differentiation of ecological connectivity index from urban expansion between 1997 and 2012. The analysis result observably showed that land use changes between 1997 and 2012 which occurred in the Makassar region have in turn caused profound changes on landscape pattern. While in 1997, the Makassar region was mainly a paddy field, garden field and mangrove forest, recently it is an urban area where urban spaces occupy most of the area. There has been a large decrease in ecological connectivity in the entire Makassar region due to the high fragmentation produced by urban sprawl (**Figure 6**).

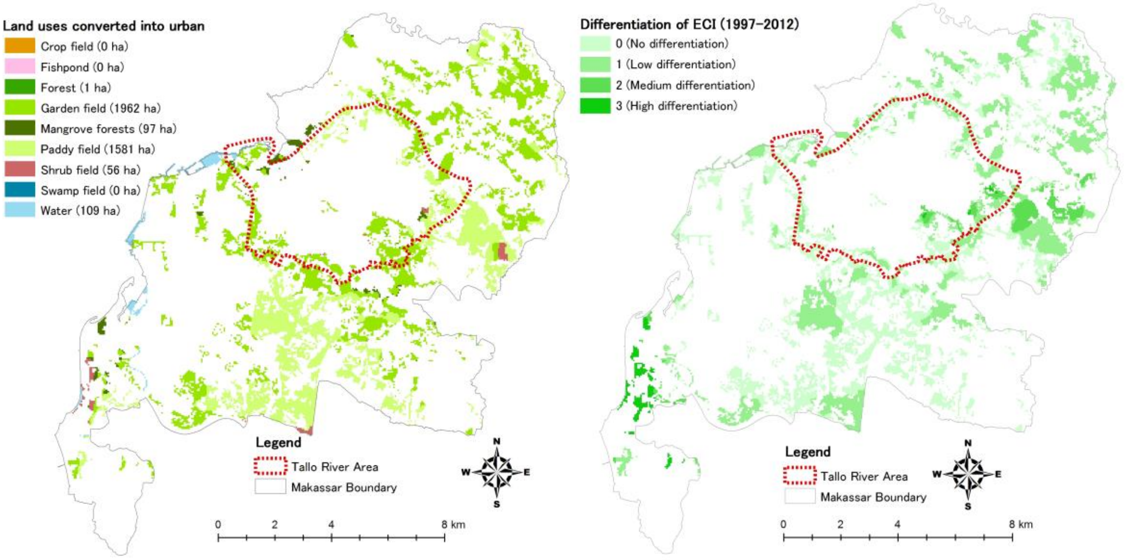
From a landscape ecological point of view, one of the main trends in the Makassar area during the last fifteen years has been the rapid fragmentation and transformation of the natural landscape, creating numbers of patches of habitat, increasingly smaller and disconnected. Conversion of each land use value into urban area such as paddy field to urban, garden field to urban, mangrove forest to urban and shrubs field to urban showed different levels of impact on the ECI (**Figure 7**). The distribution differentiation of ECI due to conversion of each land use value (1997) changed into urban (2012) using analysis of GIS showed that the shrub and mangrove forest in the vicinity of Tallo River Area has relatively high impact levels to the ECI (**Figure 8**). Therefore, a development plan is currently being considered in the Tallo River Area and if appropriately designed it could mitigate the loss of ecological connectivity.

Figure 6. Comparison of ECI for ecological functional areas (Own Analysis, 2016)



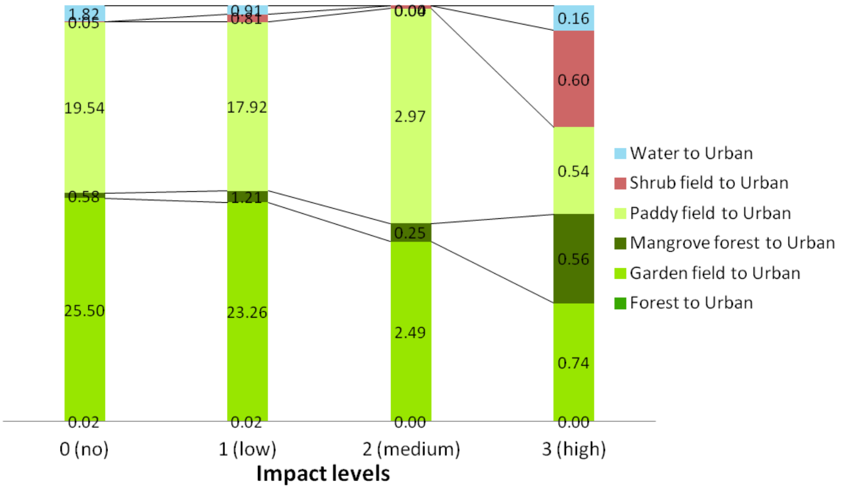
(1997) (2012)

Figure 7. (a) Land use values changed into urban; (b) Differentiation of the ECI (Own Analysis, 2016)



(a) (b)

Figure 8. Differentiation of ECI resulting from the conversion of each land use (Own Analysis, 2016)



Moreover, there is an urgent need for green infrastructure strategies that facilitate the protection and restoration of environment, especially the remaining few mangrove forest, swamp field and agricultural field in the Tallo River area. Study on the GIS based green infrastructure planning coordinated with ecological connectivity analysis is essential (Mao et al., 2012). There is an urgent need for strategies that facilitate the protection and restoration of ecologically connected landscapes (Parcerisas et al., 2012; Tscharntke et al., 2012).

4. CONCLUSION

An evaluation of land use changes and landscape connectivity index was conducted using GIS. The ecological functional areas were identified by topological analysis using the developed land use maps of 1: 50,000 scales. Landscape metrics method proposed by Marulli and Mallarach (2005) was adopted to calculate the BEI and ECI in the Makassar region. The impact of the conversion of each land use value in 1997 into the urban area in 2012 on the differentiation of the ecological connectivity index level was evaluated. It is shown that the GIS has important function to proceed each step of spatial analysis for land use changes and landscape pattern analysis model.

5. ACKNOWLEDGMENTS

This work was supported in part by Indonesian Government Scholarship Program (DIKTI), Indonesia.

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