Landscape Fragility Assessment Based on Anthropogenic Impact in Parangtritis Coastal Dune, Yogyakarta, Indonesia

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Abstract

Landscape degradation can be investigated by ecological risk assessment, which consists of landscape disturbance and fragility assessment. The fragility index is generally based on how likely it is for a class in a landscape to change, determined by expert judgment, and ordered as an integer. This study aims to identify land cover/land use in the Parangtritis coastal dune and classify it into anthropogenic impact classes, then assess the fragility index of each class. The method in this study is visual interpretation of small-format aerial photography in 2011 and 2020, followed by field survey. The process of determining landscape fragility is carried out using a literature review and analytic hierarchy process (AHP). The study results show that there are 9 classes of anthropogenic impacts. The landscape fragility index from the largest are *natural* (1.000), *agrogenic* (0.686), *industrogenic* (0.472), *tourism-sports* (0.319), *water management* (0.215), *tree agrogenic* (0.145), *traffic* (0.098), *info-telecommunication* (0.068), and *urbanogenic* (0.048). *Natural* and *agrogenic* have the largest index because the changes from 2011 to 2020 show more extensive reductions, while *urbanogenic* has the lowest index because it tends to be permanent as a built-up area. The consistency ratio of the AHP result is 0.0754, meets the standard and can be used in ecological risk assessment.

Keywords: AHP, anthropogenic impact, landscape fragility.

Introduction

Background

Landscape degradation can be investigated by ecological risk assessments (F. Zhang et al., 2018). There are two major components in ecological risk assessment, namely landscape disturbance and fragility (Jin et al., 2019). The landscape disturbance indicates ecological processes spatially such as fragmentation, isolation, and dominance (Xie et al., 2013), while the landscape fragility depends on characteristics of the local landscape which is expressed by fragility or vulnerability index. The fragility index indicates how a landscape type or class tends to be changed (Peng et al., 2015). However, some ecological risk studies used expert judgment to assess the fragility index as an integer then be normalized (Di et al., 2014; C. Li et al., 2018; Lin et al., 2019; Peng et al., 2015; Xie et al., 2013; F. Zhang et al., 2018).

Analytic hierarchy process (AHP) is a theory and tool for decision making by deriving ratio scales paired comparisons. The comparisons come from actual measurements or relative strength of preferences expressed in a fundamental scale (R. W. Saaty, 1987). Therefore, AHP comes as an alternative to in fragility index assessment (Liu et al., 2020). AHP accommodates all landscape classes to be compared in pairs. Although it will not reduce the overall subjectivity, at least it will give a consistency ratio as a note for the landscape fragility model.

One of fragile landscape is coastal area. Complex processes of the coastal area cause a fragile landscape (Di et al., 2014; Hayes & Landis, 2004; W. Zhang et al., 2020). Its geomorphological processes come from both the land and the sea as a transition zone. In a particular coastal morphology, sand dune is formed behind the shoreline. Parangtritis coastal dune has been being formed under coastal processes such as fluvial, marine, aeolian (Kaliraj et al., 2017; Sunarto, 2014), even anthropogenic impact (Kaliraj et al., 2017; Sunarto et al., 2018). It is different from desert dune because tropical climate zone drives more intervention than in arid climate zone. It has been degraded if observed from aerial photography, which decreased about 356 hectares area in the last 50 years (BLH DIY , 2017). In Catalan shoreline, Spain, the coastal dune landscape degradation ended up with decreased in size partially or lost totally (Garcia-Lozano et al., 2018).

Small-format aerial photography (SFAP) from unmanned aerial vehicle (UAV) has been widely developed, especially in monitoring of landscape degradation on a detailed scale. Its flexibility enables landscape monitoring in a relatively narrow study area (Alvarez-Vanhard et al., 2020; Wu et al., 2021). In landscape ecology study, landscape monitoring is not only observing the dominant landscape, in which this term is bare land, but also another land cover/land use at the patch level as well as class level. Therefore, land cover/land use classification in the coastal dune landscape will be more detailed, supported by fine resolution spatial data (Feng & Li, 2020).

The other side of AHP is its impossibility in comparing many pairs (Ozdemir, 2005), including many attributes such as land cover/land use. The detailed subclass of land cover/land use could not be processed in AHP. Therefore, land cover/land use classification should be standardized to simplify the pairs in AHP. One way of simplification in classifying land cover/land use is reclassifying them into intervention types (Adzima et al., 2020), which is called anthropogenic impact (Szabó, 2010). The objectives of this study are to (1) identify land cover/land use in the Parangtritis coastal dune, (2) classify land cover/land use of the Parangtritis coastal dune into anthropogenic impact, and (3) assess the fragility index of each landscape class in the Parangtritis coastal dune.

Methodology

This study was conducted in the Parangtritis coastal dune, Yogyakarta, which covers 412.8 hectares area (**Figure 6**). It is a unique coastal dune in tropical zone because of the barchan presence (Sunarto, 2014), besides the common form of parabolic. One of the factors in dune formation is climate. Parangtritis has D climate (moderate) based on Schmidt-Ferguson classification (Putri, 2008). The average wind speed is 5.3-9.2 ms^{-1} (Department of Public Works, Housing and Energy 2014), besides monsoon wind presence regionally (Aldrian and Susanto, 2003).

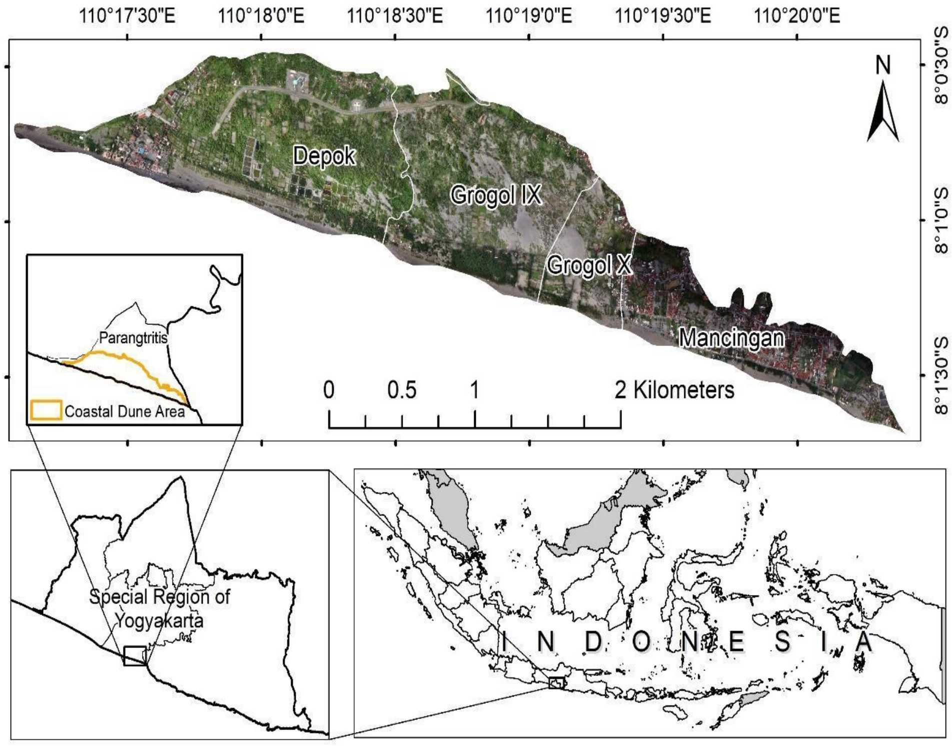


Figure 6. Study area

There are 4 administrative hamlets in the coastal dune, namely Depok, Grogol IX, Grogol X, and Mancingan. Each hamlet population in 2020 is 622, 429, 502, and 1.571, respectively. The population does their economic activity by adapting to the local environment, as well as doing an intervention. Some types of intervention enable landscape ecology change.

This study used SFAP covering Parangtritis coastal dune temporally as the main spatial data. SFAP in 30 cm and 10 cm resolution of 2011 and 2020 respectively were used to interpret land cover/land use visually using geographic information system (GIS). The SFAPs were integrated with hillshade generated by digital surface model (DSM). With the scale of 1:2,000, it requires a minimum legible area of 158.76 m^2 (Rossiter, 2000). A field survey was also conducted to validate the land cover/land use map and classification. The anthropogenic impact was also observed during the field survey, considering types of intervention by Szabó (2010).

Landscape fragility assessment was carried out by combining literature review, observation result analysis, and spatial change analysis of each intervention class. Literature review gives the order of fragility as an integer, based on expert judgment. Result observation analysis becomes the basis of correction in coastal dune landscape fragility order. The spatial change analysis of each intervention class will the basis for determining whether a landscape class is more vulnerable than another. The previous step in fragility assessment tent to be a qualitative method. To make it less subjective, semiquantitative of AHP using spatial multicriteria tool in ILWIS 3.4 has been applied in paired landscape class matrix comparison.

Determining the priority values of fragility and fragility categories using AHP is needed to quantify data of expert judgment. The following steps according to Chen et al. (2020) and Ying et al. (2007) explain the process of AHP. First, the judgment matrix was created. Suppose the matrix is Q, a set of fragility is calculated by the average comparative importance of each two fragilities (**Equation 1**).

$$Q = [q_{ij}]_{nxn} = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1n} \\ q_{21} & q_{22} & \cdots & q_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ q_{n1} & q_{n2} & \cdots & q_{nn} \end{bmatrix} \quad \textbf{(1)}$$

Where
q_{ij}: average importance of the i-th fragility to the upper tier when compared to the j-th fragility (evaluated by the experts based on fundamental scales, **Table 6**).
n: number of the fragilities
The fundamental scales of AHP are shown in **Table 6**.

Table 6. Fundamental scales of AHP

Intensity of importance	Scale	Note
Equally	1	two classes contribute equally to loss or vulnerable
moderately more	3	slightly favors one over another
strongly more	5	strongly favors one over another
very strongly more	7	dominance of the demonstrated importance in practice
extremely more	9	evidence favoring one over another of highest possible order of affirmation
intermediate value	2, 4, 6, or 8	when compromise is needed
reciprocals of above	1/2, 1/3, 1/4, 1/5, 1/6, 1/7, 1/8, or 1/9	if class i has one of the above nonzero numbers assigned to it when compared with class j, then j has the reciprocal value when compared with i
(R. W. Saaty, 1987; T. L. Saaty, 1990, adapted)		

After defining the AHP scales, eigenvector and eigenvalue of judgment matrix were calculated, see **Equation (2)** and **(3)**.

$$w_i = \frac{\sqrt[n]{\prod_{j=1}^{n} q_{ij}}}{\sum_{i=1}^{n} \sqrt[n]{\prod_{j=1}^{n} q_{ij}}} \quad \textbf{(2)}$$

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^{n} \frac{(QW)_i}{w_i} \quad \textbf{(3)}$$

where
w_i: eigenvector
Π: product of every element
λ_{max}: eigenvalue
W: corresponding eigenvector of λ_{max}
w_i: weight value for ranking
Consistency is then tested by two indicators, namely CI and CR, see **Equation (4)** and **(5)**.

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad \textbf{(4)}$$

$$CR = \frac{CI}{RI} \quad \textbf{(5)}$$

where
CI: consistency index
CR: consistency ratio
RI: random index, average of the resulting consistency index depending on the order of the matrix
If CR is less than 0.10, the matrix consistency is reasonable or accepted.
Overall, flow chart of steps in this study is summarized in **Figure 7**.

Result And Discussion

Land cover/land use as landscape subclass

The results of this study show that there are 34 types of land cover/land use in 2011, then increased in 2020 to be 37 types in 2020. The study area is dominated by bare land and sparse shrub. Bare land covers 123.17 and 81.64 hectares, while sparse shrub covers 82.10 hectares and 106.02 hectares area in 2011 and 2020, respectively. Each land cover/land use is called landscape subclass. Some subclasses are merged into an intervention class after reclassification. There are one class of natural intervention and eight classes of non-natural intervention which give impact to morphological, or processes change called anthropogenic impact.

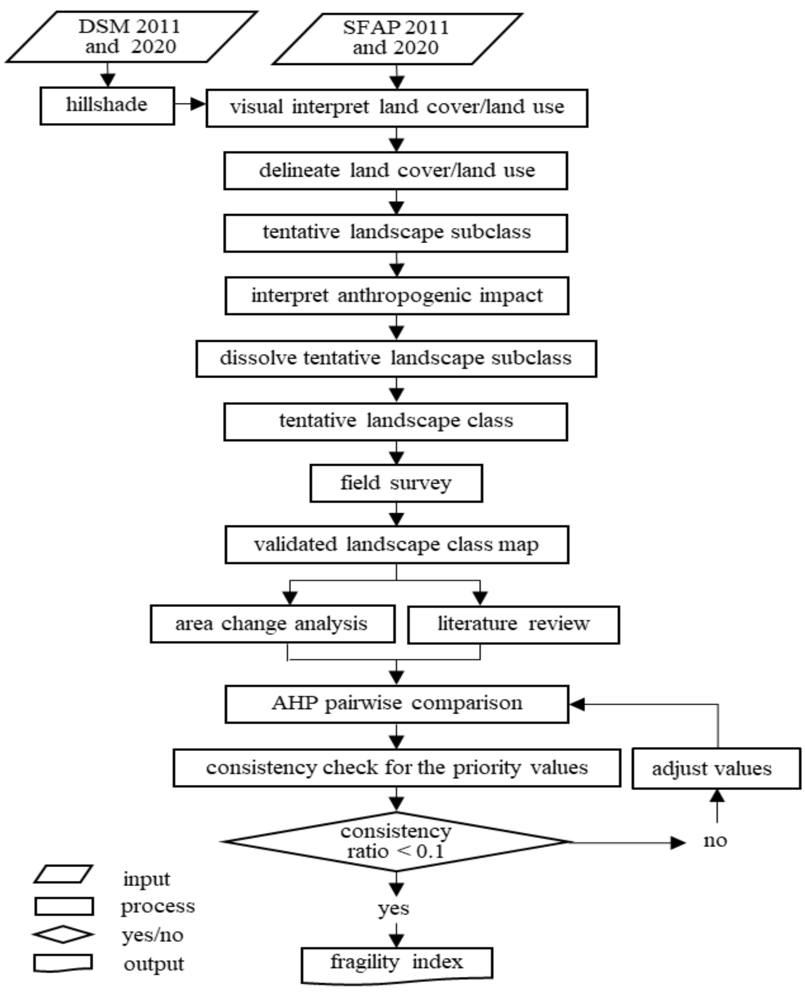


Figure 7. Flow chart of steps in the study

Anthropogenic impact as landscape class

The merged group of landscape subclasses (land cover/land use) into landscape classes (anthropogenic impact) are presented in **Table 7.** That reclassification is conducted based on anthropogenic impact either on morphology or process of landform changes. An example for each landscape class picture is presented in **Table 8**.

Natural class does not give significant change either on the coastal dune morphology or process. Bare land, grassland, sparse shrub, footpath, litter accumulation, natural river are subclasses which do not show anthropogenic impact. Bare land is one of the most representative *natural* landscape classes. Grassland, footpath, and litter accumulation do not have significant anthropogenic impact. Sparse shrub contains vegetation, but it does not disturb the transportation process of sand materials. Natural river is regarded as natural landscape because its process is still natural, namely fluvial process.

Table 7. Land cover/land use classification 2011 and 2020

Land cover/land use	Anthropogenic impact
bare land, grassland, sparse shrub, footpath, litter accumulation, natural river	*Natural*
rice field, non-irrigated cropland, fishpond, plantation, livestock farm	*agrogenic*
green path, dense shrub, casuarina forest, multiple-species forest	*tree agrogenic*
shed*, fishery**	*industrogenic*
transceiver station, monitoring station**	*info-telecommunication*
unroofed/outdoor tourist attraction, roofed/indoor tourist attraction, swimming pool, sports field, parking area, market, bus terminal	*tourism-sports*
main road**, collector road, local road, other road, runway, street setback**	*Traffic*
office building, place of worship, settlement, school	*urbanogenic*
irrigation channel, seasonal river	*water management*

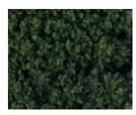
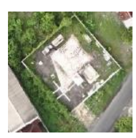
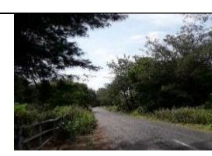
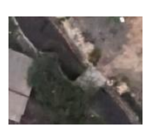
* existed only in 2011, ** existed only in 2020

Agrogenic was differentiated from *tree agrogenic* because *agrogenic* tends to give change on morphology directly, while *tree agrogenic* changes the morphology indirectly through decreasing on aeolian process intensity. *Agrogenic* changes the micromorphology through land planation such as planation of uneven land for plantation and non-irrigated cropland, also filling depression or marsh for rice field), accumulation of planting strips, and excavation for fishpond. Livestock farm has its characteristic to change micromorphology by the accumulation of haystack and slightly breaking the wind through the hedgerows.

Tree agrogenic contains introduced vegetation which can reduce the aeolian processes. Casuarina forest were planted on purpose to break the wind (Forman, 1995; Syahbudin et al., 2012). Green paths, dense shrub, and multiple species forest also can break the wind although they were not directly planted on purpose to break the wind. The green paths are usually dominated by *Gliricidia sepium*, the dense shrub is characterized by homogeneous higher and thicker *Gliricidia sepium* in the form of hedgerows, while the multiple-species forests contain non-native vegetation with certain regular pattern, such as *Acacia mangium*, *Swietenia mahagoni*, and *Anacardium occidentale*. Both casuarina forest and multiple-species forest produce organic litters which are potential to form soil as surface materials.

Industrogenic, *info-telecommunication*, *tourism-sports*, *traffic*, *urbanogenic*, and *water management* are the other landscape class which indicate the anthropogenic impacts. *Industrogenic* exists in the form of semipermanent objects which changes the morphology slightly through planation (for shed) and excavation process followed by water filling for fisheries. *Info-telecommunication* is differentiated from *urbanogenic* because it has lower density and gives less impact on aeolian process intensity change by transceiver and monitoring stations. The *Tourism-sports* is defined based on the utilization, although the impact is like or between *urbanogenic* and *natural*. It gives impact on dune micromorphology and process through the massive human activity, especially in holidays, which can produce accumulated impacts. *Traffic* changes the micromorphology through planation for roads. *Urbanogenic* changes the morphology through excavation for foundation and planation for buildings. *Urbanogenic* also changes the aeolian process intensity by breaking the wind. *Water management* covers the smallest area after *info-telecommunication*. It gives an impact on morphology through channel excavation or riverside construction as well as discontinuing aeolian process by flowing water.

Table 8. Example of landscape class in SFAP and field view

Landscape class and the example	**SFAP view (2020)**	**Field view (2020)**
Natural (bare land)		
Agrogenic (non-irrigated cropland)		
Tree agrogenic (causarina forest)		
Industrogenic (fishery)		
Info-telecommunication (transceiver station)		
Tourism-sports (unroofed/outdoor tourist attraction)		
Traffic (local road)		
Urbanogenic (place of worship)		
Water management (seasonal river)		

The spatial distribution of landscape classes is illustrated in **Figure 8**. *Natural* has the largest area in 2011 and 2020, while *info-telecommunication* has the smallest area. The west part or supported zone is dominated by *tree agrogenic* and *natural*. The east part which is called restricted zone was dominated by *urbanogenic*, while the middle part or core zone is dominated by *natural*. The linear component which covers overall study area is *traffic*.

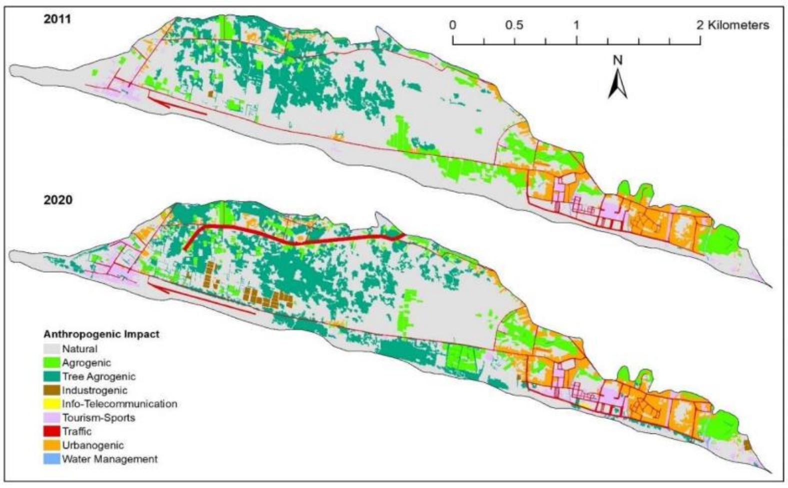


Figure 8. Spatial distribution of landscape class

Landscape classes of anthropogenic impact changed from 2011 to 2020, the summary is shown in **Table 9**. The classes which remain constant are various from 0.08 hectares up to 180.25 hectares. They are generally located at the same position in the SFAPs of 2011 and 2020. The decreased area from one class becomes another class has occurred in less class than the increased area. It indicates that landscape diversity increased during the nine years of observation, especially caused by the increased area of *tree agrogenic, industrogenic, tourism-sports, traffic, and urbanogenic*. **Table 9** is one of the aspects considered in the matrix of AHP pairwise comparisons (**Table 10**).

Table 9. Summary of anthropogenic impact change from 2011 to 2020

Class	**2011-2020**		
	constant (ha)	**decreased (ha)**	**increased (ha)**
Agrogenic	27.00	13.97	11.39
Tree agrogenic	32.63	24.46	58.02
Industrogenic	0.09	0.10	5.08
Info-telecommunication	0.08	0.00	0.15
Natural	180.25	84.37	31.33
Tourism-sports	10.45	0.63	6.26
Traffic	9.69	0.14	6.29
Urbanogenic	27.01	0.95	6.06
Water management	0.88	0.08	0.13

Landscape fragility assessment

Results of the AHP calculation are the normalized priority values or landscape fragility indices, as presented in **Table 11**. Normalization is conducted in AHP to show total dominance of the alternatives (T. L. Saaty, 1990). Landscape class area tendency to decrease significantly is considered in landscape fragility assessment. In the study area, natural is the most reduced area. It indicates that *natural* is the most fragile, vulnerable to loss because it is easily occupied by another landscape type (Gong et al., 2015; Liu et al., 2020; Mo et al., 2017; Peng et al., 2015; H. Shi et al., 2015; Xie et al., 2013; F. Zhang et al., 2018; W. Zhang et al., 2020). *Natural* class consists of mainly bare land, which some previous studies called unused land. It is determined moderately more up to extremely more vulnerable than another in the pairwise comparisons. Its fragility index is 1.000.

The *agrogenic* class is the most reduced area after the natural in this study, even according to Di et al. (2014), it is the most vulnerable class. It is the second most fragile landscape because the main subclasses in *agrogenic* are rice field, non-irrigated cropland, and fishpond. Those landscape subclasses do not need too much effort to occupy. Moreover, those landscape subclasses are open area and have slight surface height. However, the difference between decreased area and increased area of *agrogenic* is small enough. Plantation and livestock farm relatively need more effort to be changed because they have slightly more surface height resulted from the commodity and the cattle pen. Therefore, its fragility index is 0.686.

Table 10. Landscape class AHP pairwise comparison for fragility assessment

Class	*Agro-genic*	*Tree agro-genic*	*Industro-genic*	*Info-telecommu-nication*	*Natural*	*Tourism-sports*	*Traffic*	*Urbano-genic*	*Water manage-ment*
Agrogenic		strongly more	moderately more	very strongly more	moderately less	moderately more	strongly more	extremely more	strongly more
Tree agrogenic			strongly less	moderately more	very strongly less	strongly less	moderately more	strongly more	moderately less
Industrogenic				very strongly more	moderately less	moderately more	strongly more	very strongly more	moderately more
Info-telecommu-nication					extremely less	strongly less	moderately less	moderately more	strongly less
Natural						strongly more	very strongly more	extremely more	strongly more
Tourism-sports							strongly more	very strongly more	moderately more
Traffic								moderately more	moderately less
Urbanogenic									strongly less
Water management									

Landscape class other than natural and *agrogenic* has the fragility index in the order of the smallest as follows: *urbanogenic, info-telecommunication, traffic, tree agrogenic, water management, tourism-sports,* and *industrogenic*. *Urbanogenic* has the least fragility index (0.048) because it is the least vulnerable landscape class (Gong et al., 2015; J. Li et al., 2017; Liu et al., 2020; Mo et al., 2017; Xie et al., 2013; W. Zhang et al., 2020; X. Zhang et al., 2013). It needs very much effort to occupy, including massive and/or permanent built-up land. Other constructed land such as *info-telecommunication* and *traffic* also have low fragility (C. Li et al., 2018; Liu et al., 2020; H. Shi et al., 2015), because they tend to be difficult to change. Their fragility indices are 0.068 and 0.098, respectively. More specifically, *traffic* is more vulnerable than *info-telecommunication* because *traffic* does not have significant surface height. *Tree agrogenic* has a fragility index of 0.145. It is mainly composed of green path and forest which are man-made. Artificial green paths and forests tend to have a low vulnerability (Di et al., 2014; Peng et al., 2015; F. Zhang et al., 2018) since they are dense, have surface height. Therefore, *tree agrogenic* tends to be difficult to change. Additionally, the evidence of artificial *tree agrogenic* is the spread of introduced vegetation type, not native to the Parangtritis coastal dune ecosystem (BLH DIY, 2017; Oktavianto & Handayani, 2017; Widyantoro & Handayani, 2017). *Water management* and *tourism-sports* are a combination of built-up land and non-built-up land. They have higher probability to change than *tree agrogenic*, but lower than *industrogenic* (Liu et al., 2020). The fragility index of *water management* is 0.215, while *tourism-sports* is 0.319. *Industrogenic* is relatively easy to change since the shed and fisheries are included in semipermanent even non-permanent objects. Its fragility index is 0.472.

Table 11. Normalized priority values: fragility index of landscape class

Agrogenic	Tree agrogenic	Industro-genic	Info-telecommu-nication	Natural	Tourism-sports	Traffic	Urbano-genic	Water management
0.686	0.145	0.472	0.068	1.000	0.319	0.098	0.048	0.215
							consistency ratio	0.0754

The priority values resulted by AHP need to be evaluated. The consistency ratio gives a value of 0.0754. Therefore, the inconsistency of fragility indices come from AHP priority values are accepted because less than 0.1 (Ying et al., 2007). Besides the evaluation of AHP consistency ratio, it is known that its validity is good enough because the number of classes is around 7±2 (Ozdemir, 2005). However, the pairwise comparisons were processed using ILWIS 3.4 in spatial multicriteria analysis. The landscape class fragility level was determined relatively as presented in Table 9, showing neither integer nor fractional number as in Table 6. The priority values are not complemented with the value of calculation processes such as the eigenvector, eigenvalue, and consistency index.

There is a similar pattern between ecological risk and disaster risk formula. Disaster risk is the function of hazard (H), vulnerability (V), and coping capacity (C), written as R=f(H,V,C) (BNPB, 2012; Mardiatno, 2014) or the function of hazard, exposure (E), and vulnerability, written as R=f(H,E,V) (ADB, 2017; P. Shi, 2019). The hazard is like an external component, while the vulnerability, followed by exposure or coping capacity, is like an internal component in disaster risk. Therefore, in ecological risk, landscape disturbance in line with the hazard, and so does landscape fragility with the vulnerability. Vulnerability assessment plays a role in disaster risk assessment, so the fragility assessment plays a role too in ecological risk assessment.

Fragility assessment is important as the part of an ecological risk assessment. The consistency ratio in **Table 11** denotes the nine priority values can be used as fragility indices. The ecological risk assessment is usually carried out temporally. Therefore, fragility indices will be various depending on time (Di et al., 2014). In this study, the fragility indices as shown in **Table 11** are valid both for 2011 and 2020 spatial data because the two periods are assumed and observed as one stage of land transformation process. This assumption is supported by the study of J. Li et al. (2017) that ecological risk assessment was conducted using 1990, 2000, and 2010 spatial data, yet each landscape class has the same fragility index in the three years data. Ecological risk can also be assessed at either the class level or subclass level. Although the two levels give different landscape type classification, the fragility indices at the subclass level can be the same as the class level (H. Shi et al., 2015; Xie et al., 2013). Therefore, AHP utilization in fragility assessment on a detailed scale can be continued with ecological risk assessment, both in class level of anthropogenic impact and subclass level of land cover/land use at a relatively narrow area like Parangtritis coastal dune ecosystem.

Conclusion

Landscape fragility can be assessed based on anthropogenic impact in Parangtritis coastal dune. The anthropogenic impact classification has been resulted from land cover/land use reclassification. There are 34 and 37 subclasses of land cover/land use in 2011 and 2020, respectively. Some landscape subclasses are merged into 1 natural landscape class, which has the highest fragility index (1.000), and 8 anthropogenic landscape classes with various fragility indices. The fragility indices of each anthropogenic landscape classes from the largest are: *agrogenic* (0.686), *industrogenic* (0.472), *tourism-sports* (0.319), *water management* (0.215), *tree agrogenic* (0.145), *traffic* (0.098), *info-telecommunication* (0.068), and *urbanogenic* (0.048). The highest index is caused by the changes from 2011 to 2020 showing the most reduced area, while the lowest index is caused by the characteristics of landscape, those are landscape permanence and surface height. The AHP inconsistency is acceptable, with consistency ratio of 0.0754 (< 0.1). The fragility indices resulted by AHP can be continued with ecological risk assessment on a detailed scale such as in Parangtritis coastal dune ecosystem, temporally and spatially at class level as well as subclass level.

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