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Brownfields Selection for Eco-Industrial Parks Using a Novel Integrated Multi-Criteria Decision-Making Approach

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Single traditional multi-criteria decision-making (STMCDM) methods are weak in evaluating consistent criteria weights for industrial site selection. As a result, unfavourable industrial locations could not attract new industries, giving rise to brownfields with high carbon emissions. To solve the constraints of STMCDM, integrated multi-criteria decision-making (IMCDM) method was developed. The interaction of the analytic network process (ANP) and the triangular fuzzy numbers of the fuzzy-analytic hierarchy process (F-AHP) were integrated to create the Network Fuzzy-hierarchy Analytic Process (NFh-AP). Tanjung Langsat Industrial Area spatial criterion data for 2009 and 2019 were collected using GIS to test for the weighting consistency of the ANP, F-AHP, and NFh-AP. The Euclidean distance, raster layer reclassification, and land use and land cover data collected from PLANMalaysia were prepared. The weights and spatial data were submitted to weighted overlay analyses by the GIS. With the 2009 dataset, the ANP, F-AHP, and NFh-AP identified all water bodies as suitable EIP sites, highlighting the constraints of the methods with sparse criteria. The 2019 data with ANP, F-AHP, and NFh-AP identified 2 %, 3 %, and 25 % as the best sites with well-defined boundaries. Due to the poor best suitable areas produced, even with dominant criteria, single approaches have inconsistencies in criterion weighting. The NFh-AP algorithm's weighting consistency is due to networking and fuzzy logic interaction, and it is presented to assist evaluate consistent criteria weights and a simple modelling approach for brownfield-EIP (BF-EIP) site selection. Using spatial criteria for BF-EIP site selection collected elsewhere, the NFh-AP consistency can be tested.

1. Introduction

The industrial location problem can be represented as a selection process of suitable sites in which the attempt is to satisfy all requirements in the best possible way. Industrial site selection was done by traditional methods and environmental impact assessment (EIA) which is based on economic and technical criteria (Luthra et al., 2020). EIA takes a longer time to assess results and is often not reliable due to manual operations and incomplete acquisition of industrial location variables (Asadabadi et al., 2019). The decision supports tools such as traditional multi-criteria decision-making (TMCDM) which include analytic hierarch process (AHP), analytic network process (ANP), Delphi, fuzzy AHP (F-AHP), and technique for order preference by similarity to ideal solution (TOPSIS) have been used to weigh the location criteria to identify optimum industrial sites, but have consistency limitations in criteria weighting one of which is when the criteria exceed three sites (Kazemi et al., 2020). In an uncertain environment, this makes it impossible for quantitative and qualitative criteria to produce suitable industrial locations. This results in brownfields, which are abandoned/underutilized industrial parks due

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to mostly unfavourable locations, a lack of industrial clusters for industrial symbiosis, and the release of greenhouse gas (GHG), which harm the environment and cause global warming.

Brownfields must be converted into eco-industrial parks (EIPs), as EIPs require favourable locations for firms to collaborate and reduce GHG emissions. The conversion necessitates a higher degree of criteria evaluation approaches, such as integrated multi-criteria decision-making (IMCDM) and GIS technology, to meet the consistent spatial criteria weighting and site modelling needs of the ideal EIP site (Nuhu et al., 2021). Reisi et al., (2018b) chose the industrial site in Isfahan, Iran, using the ANP. Salari et al., (2019) examined land capability for industrial zones in Qeshm Island, Iran, using Delphi, ANP, and GIS. F-AHP was used to select a mineral processing site near the Gilsonite Mines in Iran (Kazemi et al., 2020). The fuzzy TOPSIS was used to select a rural industrial site in Iran (Amini, 2015). All these strategies relied on a single traditional multi-criteria decision-making (STMCDM) to identify industrial locations (Nuhu et al., 2021).

To address the consistency concerns of STMCDM techniques such as the inability to manage decision problems when there is uncertainty about the criteria level of preference, criteria/attributes independence become a weakness of most SMCDM methods. An IMCDM method that may resolve the assessment of criteria weight inconsistency in choosing brownfield spatial criteria for EIP site is proposed. To realise this, the STMCDM procedures were integrated and used in evaluating criteria and alternative weights. To demonstrate the weight evaluation consistencies of the STMCDM and IMCDM approaches, ANP and F-AHP and NFh-AP were applied in a case study. The spatial criteria for 2009 and 2019 from the Tanjung Langsat Industrial Area were collected and screened by the GIS. The STMCDM and IMCDM criteria weights, the Euclidean distance and reclassified raster layers were overlaid in the GIS. Several BF-EIP site suitability layers were generated and compared for accurate site selection.

2. Methodology

2.1 The Analytic Network Process

Step (i): The AHP criterion weights were computed using Microsoft Office Excel 2010. The ANP steps were performed using the AHP weights in the MATLAB software [8.7.0.347-R2009a], and the unweighted supermatrix was generated.

Step (ii): By multiplying the unweighted supermatrix (criteria) by the weights of each cluster (goal), a weighted supermatrix was created. The weighted supermatrix was increased to a limiting power of 15 (see Eq(1)) until the weights converged and remained stable, resulting in the limit supermatrix.

$$\mathrm{Lim} = W^{k} \tag{1}$$

where W is criteria weights, k is the power that the weight can be raised (k can be to infinity)

Step (iii): The final weights were standardised for them to be stochastic.

2.2 The Fuzzy Analytic Hierarchy Process

Step (i): The pairwise comparison matrix was constructed using the TFN, lower (l), middle (m), and upper (u) values, with m being the most promising. In the lower triangle, the reciprocal of the corresponding column weight was filled in reverse order (u, m, l).

Step (ii): The geometric ratio was calculated by taking the product of the l1, l2, ..., ln; m1, m2, ..., mn; and u1, u2, ..., un values from each criterion in each row. As demonstrated in Eq(2), the outcome was raised to the inverse power of the number of criteria.

$$\tilde{r}_1 = (\tilde{\alpha}_{i1} \times \tilde{\alpha}_{i2} \times \tilde{\alpha}_{i3} \ldots \times \tilde{\alpha}_{in})^{\frac{1}{n}} \tag{2}$$

where α̃_i1 is 1st fuzzy number; α̃_i2 is 2nd fuzzy number; α̃_in is nth fuzzy number; r̃ _1 is geometric ratio.

Step (iii): The geometric ratios in the l, m, and u were summed, and the totals were reversed and reorganised in increasing order.

Step (iv): The fuzzy relative weight was calculated using Eq(3), which was the multiplication of each geometric ratio by the corresponding reciprocal.

$$\tilde{w}_1 = \tilde{r}_1 \times (\tilde{r}_1 \times \tilde{r}_2 \times \tilde{r}_3 \ldots \tilde{r}_n)^{-1} \tag{3}$$

where: r̃ _1 is 1st geometric ratio, r̃ _2 is 2nd geometric ratio, r̃ _n is nth geometric ratio, w̃ _1 is fuzzy weight.

Step (v): Using the centroid rule in Eq(4), the fuzzy relative weights were defuzzified to crisp values.

$$y_i = \frac{l_i + m_i + u_i}{3}, \mathrm{i} = 1, \ldots \ldots .., \mathrm{n} \tag{4}$$

where: y_i = crisp value.

Step (vi): The sum of the crisp values was higher than one, and Eq(5) was applied to normalise the data.

$$x = \frac{y_i}{\sum_{j=1}^{n} y_j}, \mathrm{i} = 1, \ldots \ldots, \mathrm{n} \tag{5}$$

where $\sum_{j=1}^{n} y_j$ is 1, j is 1, … … …, n

Similarly, the alternative weights for each criterion were assessed, and the overall criteria weights were evaluated.

2.3 Integrated Multi-Criteria Decision-Making methods

The IMCDM algorithms developed for assessing consistent spatial criteria weights for brownfield transition to EIPs are in Eq(6) and Eq(7).

$$\mathrm{ItgOPVec}_{(n)} = \mathrm{OPVec}_{(1)} + \mathrm{OPVec}_{(2)} + \cdots + \mathrm{OPVec}_{(\mathrm{n})} \tag{6}$$

where $\mathrm{ItgOPvec}$ is the Integrated overall priority vector; n is the STMCDM method; $\mathrm{OPVec}_{(1)}$; $\mathrm{OPVec}_{(2)}$; $\mathrm{OPVec}_{(n)}$ is 1st technique; 2nd technique; nth technique

$$\mathrm{NItgOPVec}_{(1,2,3\ldots.n)} = \frac{\mathrm{ItgOPVec}_{(n)}}{\sum[\mathrm{ItgOPVec}_{(1,2,3\ldots.n)}]} \tag{7}$$

where $\mathrm{NItgOPVec}_{(1,2,3\ldots.n)}$ is normalised integrated overall priority vectors.

To assess the stability of the techniques, the sensitivity analysis (SA) employing ±2 %, ±3 %, and ±5 % of the ANP, F-AHP, and IMCDM weights were performed using Eq(8).

$$\mathrm{NItgOPVec}_{(1,2,3\ldots.n)} = \frac{\mathrm{ItgOPVec}_{(n)}}{\sum[\mathrm{ItgOPVec}_{(1,2,3\ldots.n)}]} \tag{8}$$

where $\mathrm{W_p}$ is new weight; z % is any per cent chosen, and $\mathrm{W_1}$ is assessed weight

3. Study area and spatial criteria collection

Tanjung Langsat Industrial Area (TLIA) is in Johor Bahru, Johor state, Malaysia. The United States Geological Survey (USGS) was used and ESRI Inc's ArcMap 10.5 software (Kanniah et al., 2015) to collect shapefile and tagged picture files of the geographic criteria of 2009 and 2019 at a scale of 1:250,000. At less than 10 % cloud cover, the spatial criteria of roads, land surface temperature, residential areas, slope, water bodies and existing industries were collected and analyzed for the EIP site suitability. PLANMalaysia supplied the land use land cover (LULC) layers. The Digital Elevation Model was used to digitize the criteria. The Euclidean distance rasters and reclassifications were prepared using the Spatial Analyst Add-on.

Figure 1 shows the methodology's flowchart; the acquisition and preparation of data, assessment of criteria weights, overlay of MCDM weights and spatial criteria, and the EIP site suitability layers generation.

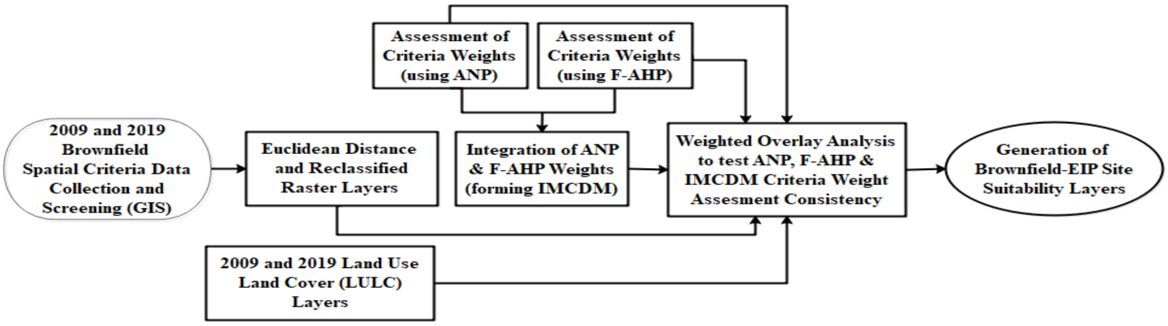

Figure 1: Methodology process flow

4. Results and discussion

The ANP criteria overall priority vector (OPVec) in Figure 2a shows the water bodies having 17.1 % the highest weight of importance followed by land surface temperature with 17.01 %. Four criteria weights are measured very closely and may be difficult for this method to discern and rank the criterion appropriately. One of the inconsistencies of STMCDM is the difficulty to ascertain competing criteria due to near weights importance (Asadabadi et al., 2019). The economics attribute weighs 35.95 %, the highest amongst social, environmental, technical, and political aspects. In the SA, the ±2 % and ±3 % by the ANP and F-AHP slightly changed the overall criteria weights indicated by the error bars in Figures 2a and 2b, but below the limit of ±0.85 % as proposed by Rikalovic et al. (2018b). The changes with ±5 % is more pronounced in Figure 2b for all the criteria. This indicates the weight evaluation inconsistency by ANP and F-AHP techniques. The F-AHP TFN approach was proposed to solve the limitations of AHP, yet it has its drawbacks (Hafeznia et al., 2017).

Figure 2c shows water bodies have the highest importance of 22.33 %, while for the attributes, economics takes the lead with 31 % importance. The higher the physical weight, the more important the criteria for EIP site selection. The error bars of ±2 %, ±3 % and ±5 % SA of the criteria weights of the NFh-AP algorithm for all the criteria shown to be below the allowable limit demonstrating a negligible weight change. The integrated NFh-AP can be applied to help in selecting a favourable EIP site.

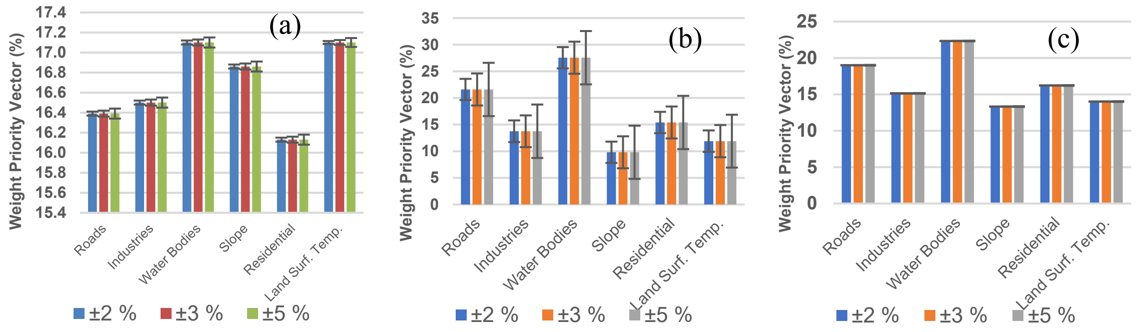

Figure 2: Priority vectors and error bars of the sensitivity analyses of (a) ANP, (b) F-AHP, (c) NFh-AP

The TLIA with a total size of about 20,000 m^2 is situated at longitude 1°28′N 104°01′E (Kanniah et al., 2015).. It has an average monthly temperature of 27 °C and an annual rainfall of 2,700 mm (Kanniah et al., 2015). TLIA aimed to cater for fishery, marine and palm oil-related, petrochemical, oil and gas, steel fabrication, rocks and minerals, construction, and services. The LULC layers of 2009 (Figure 3a) show the dispersed built-up area, forest, water bodies, land, built-up and agricultural areas. Figure 3b shows the LULC in 2019 with an increase in forest area, less bare ground, increased built-up industrial and residential areas, and no change in water bodies.

A scale of 1:250,000 was used to derive the Euclidean distance layers, which Rahmat et al. (2017) reported to be ideal. The Euclidean distance raster layers output for roads network in 2009 and 2019 were assigned the same distances of 5,000 m, industries at 1,500 m, water bodies at 3,000 m, and residential at 8,000 m. The proximity of the EIP site to the road network reduces transportation costs which boosts the economic aspect of the industrial activities. The industries close to the best EIP site facilitate a cheap exchange of waste energy and materials for symbiosis. Water bodies within a good distance prevent unforeseen pollution from residential and industrial areas. The far residential distance to the EIP site prevents any escaping toxic effects from industries. It is also an important criterion where different institutions, social amenities, and workforce are found. The class of 1 to 5 was used for the criteria reclassification where the closest or farthest preferred criteria were assigned a value of 5 and the farthest or closest undesired criteria were allocated 1. All maps were reclassified with a resolution of 300 dpi. Slopes and land surface temperature are not quantities of distance, only the reclassification was carried out. The slope was set at 10 % for this study. A good slope concentration is 0–12 % to accelerate infrastructure development and reduce environmental degradation (Wang et al., 2018) since steep gradients increase the expense of road and building construction and erosion. The land surface temperature was allocated 28.5 °C because the 2019 temperature data indicated a small increase. The annual average land surface temperature in an area should be between 25–30 °C for best results in RE generation (Wang et al., 2018). A temperature above 35 °C can cause wild winds such as a hurricane and can over-heat surfaces of materials such as solar panels making it undesirable (Wang et al., 2018).

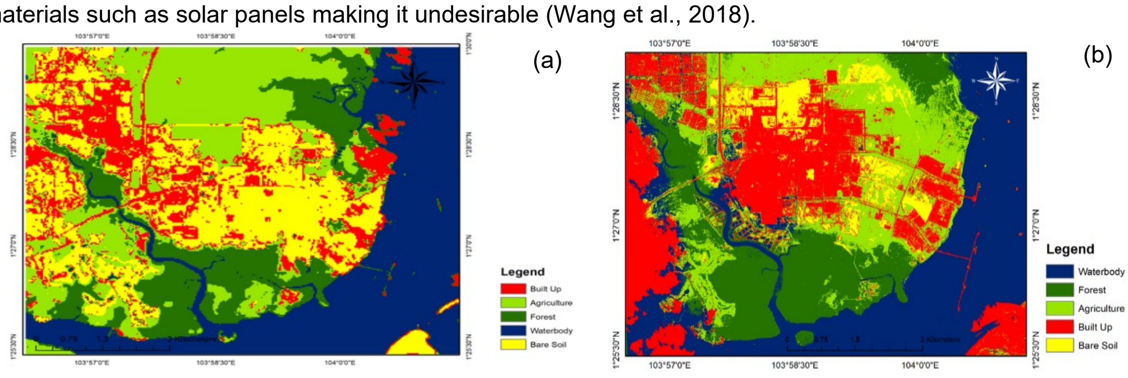

Figure 3: Land use Land Cover (a) 2009, (b) 2019

In the weighted overlay analysis (WOA), the suitability levels were categorised into five groups: very–highly–suitable, highly–suitable, moderately–suitable, low–suitable and unsuitable. From the ANP criteria weights importance and the 2009 data, the WOA in the GIS generated a suitability layer shown in Figure 4a as 17 % for the very-highly-suitable and highly-suitable site of 21 %. The F-AHP and NFh-AP algorithms using the 2009 criteria data generated a replica of map layers like the ANP. The three algorithms' weights of importance classified the water bodies as part of the highly-suitable and moderately-suitable sites which show inconsistency in the criteria weighting. Water bodies are required to be a few metres away from the EIP suitable site, not them becoming a criterion upon which EIP can be built. The ANP weights with the 2019 dataset produced a site layer represented in Figure 4b. The very-highly-suitable site measured 2 % defined by two dark green small patches at the upper end, and the highly-suitable site accounted for 24 %. The F-AHP weight with the 2019 criteria dataset is shown in Figure 4c which produced 3 % very-highly-suitable sites having two small strips shown in dark green colour in the northern region. The light green describes the highly-suitable site accounting for 23 %. The NFh-AP criteria weights with the 2019 spatial data generated 25 % and 33 % for very-highly-suitable and highly-suitable sites shown in Figure 4d. These suitable sites are conspicuously separated without overlapping. The ANP and F-AHP using concentrated criteria separated the five suitable sites without overlapping, but the drawback is its inability to indicate a substantial best suitable site even with concentrated criteria data.

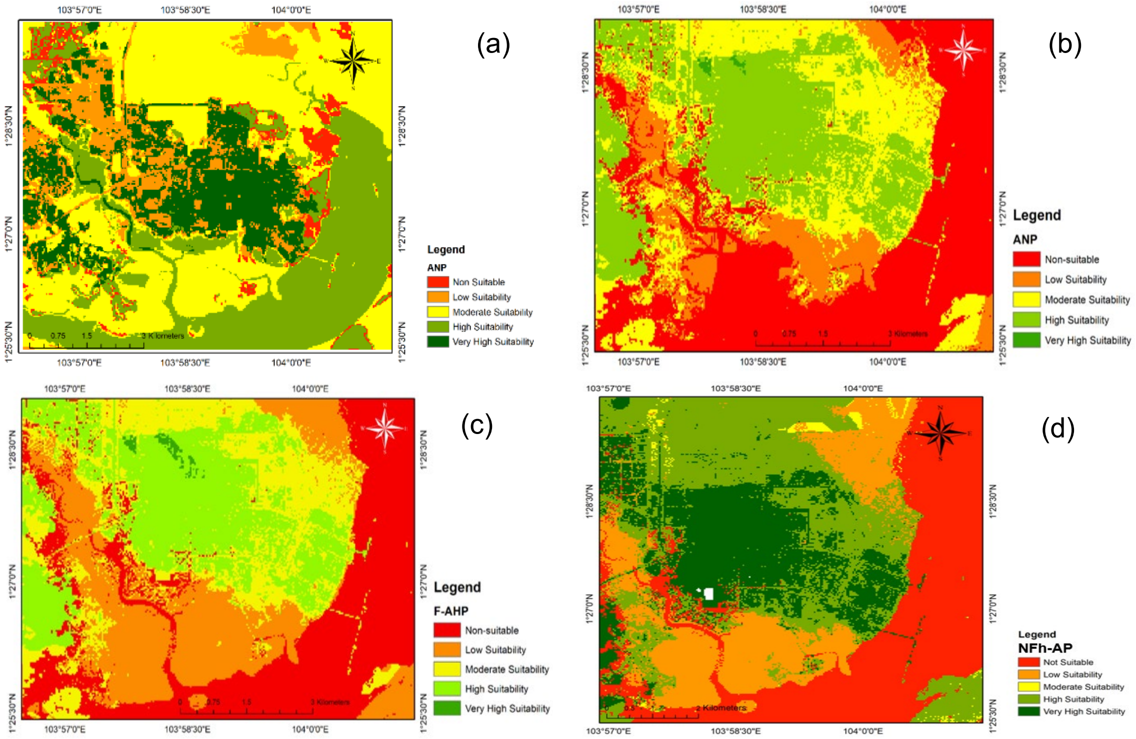

Figure 4: EIP Suitability Layer from (a) ANP Weights with 2009 Data, (b) ANP Weights with 2019 Data, (c) F-AHP Weights with 2019 Data, (d) NFh-AP Weights with 2019 Data

The IMCDM method is observed to maximise their strength potential due to the combination of the hierarchical, geometric ratio, and networking from the two groups produced. This provides a state-of-the-art technique for the assessment of consistent criteria weights for brownfield conversion to EIP sites. SMCDM methods fairly strived with concentrated criteria data because they identified tiny very-highly-suitable sites away from the existing industries' location making it insufficient in evaluating brownfield criteria for a suitable EIP site. The concentration of criteria within the brownfield is a significant factor in the NFh-AP weight evaluation consistency.

5. Conclusions

This study used the STMCDM and developed the IMCDM technique which is not available to use in assessing consistent brownfield criteria weights for EIP sites. ANP and F-AHP methods were used and SA was employed to check their stabilities. The ANP and F-AHP were integrated through formulated equations and formed the NFh-AP algorithm for assessing consistent criteria weights for overlay in the GIS for industrial site suitability modelling. The weighting consistency of the STMCDM and the IMCDM methods with 2009 and 2019 spatial criteria and LULC of the TLIA in the GISshowed ANP, F-AHP and IMCDM with equal suitable areas and entire water bodies as suitable for EIP. This shows the inconsistency of the methods. The 2019 criteria data shows ANP, and F-AHP weights with well-defined but small suitable areas of 2 % and 3 %, while NFh-AP identified a substantial best EIP site of 25 %. Large water bodies, concentrated roads network, established residential areas, sizeable existing industries, elevated temperature, and low slope gradient are necessary for brownfield-EIP site suitability. The study presents NFh-AP a novel algorithm for evaluating consistent criteria weights for the precise investigation of brownfields to EIP to promote cleaner production, circular economy, GHG reduction and industrial sustainability. The investigation of the reverse ranking of IMCDM tools when alternatives are added or removed is good future work.

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