Journal of Cleaner Production 368 (2022) 133141

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Integrated modelling approach for an eco-industrial park site selection

Steven Kuba Nuhu [a,b,d], Zainuddin Abdul Manan [a,b,*], Sharifah Rafidah Wan Alwi [a,b], Mohd Nadzri Md Reba [c]

[a] Process Systems Engineering Centre (PROSPECT), Research Institute for Sustainable Environment, Universiti Teknologi Malaysia, 81310, Johor Bahru, Malaysia
[b] School of Chemical and Energy Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, 81310, Johor Bahru, Malaysia
[c] Geoscience and Digital Earth Centre (INSTeG), Research Institute for Sustainability and Environment, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor, Malaysia
[d] Department of Minerals and Petroleum Resources Engineering, Plateau State Polytechnic, Barkin-Ladi, Nigeria

ARTICLE INFO

Handling Editor: Prof. Jiri Jaromir Klemeš

Keywords:
Integrated modelling approach
Eco-industrial park site selection
Single decision-making tools inconsistency
Brownfield industrial park
Greenhouse gas emissions
Cleaner production sustainability

ABSTRACT

Inconsistencies of the single multi-criteria decision making (SMCD) methods in criteria weight assessment make them unreliable and have led to the wrong siting of industrial parks, which are often abandoned as brownfields that emit GHG. Eco-industrial parks (EIPs) are replacing brownfields but require robust decision-making tools to weigh and rank suitable locations for industry clusters' synergies. Integrated multi-criteria decision making (IMCDM) to address the weaknesses and strengthen the advantages of SMCDM methods, and a model to overlay criteria weights and spatial data easily and accurately were developed. The spatial criteria data for 2009 and 2019 from Tanjung Langsat Industrial Area were collected and prepared by GIS to test the SMCDM and IMCMD consistency weighting and the model resilience. The SMCDM (AHP, ANP and F-AHP) and the IMCDM weights with the 2009 criteria data identified the entire water bodies around the brownfield as suitable sites, making them inconsistent. The 2019 data with the SMCDM weights identified tiny sites as best, also making them inconsistent. The integrated hierarchy network fuzzy analytic process (HN-FAP) and the hierarchy network analytic process (HNAP) with the 2019 criteria data identified part of the water bodies as suitable making it inconsistent. The hierarchy fuzzy analytic process (H-FAP) and the network fuzzy hierarchy analytic process (NFh-AP) identified larger suitable sites without overlaps making them consistent algorithms. The H-FAP and NFh-AP procedures eliminate the weaknesses and consolidate the strengths, giving optimally consistent criteria weights. The two algorithms' consistency and the model efficiency can use different criteria weights and spatial data inputs from elsewhere for 4IR-driven EIP modelling to help brownfield-EIP stakeholders. Future research would address the reverse ranking of MCDM methods when alternatives are added or removed.

1. Introduction

Although industrialization is the greatest and most important economic and technological progress in human history. It is not without its drawbacks; unsuitable site selection is one that led to industrial abandonment and/or underutilisation. Traditional industries started during the pre-industrial period, which were carried out on a small scale and in small workshops located in cities (Moreau et al., 2017). Spills, waste, and noise pollution were prominent (Sarmiento and Vargas-Berrones, 2018), therefore, the industries were placed in an area – Industrial Park (IP), outside the city (Beers et al., 2019). IPs were examined using the Environmental Impact Assessment (EIA), which is a common practice of evaluating and identifying the potential effects of the project sites (Kolhoff et al., 2018). The EIA is reported to be inaccurate in assessment due to dependents, independents, manual operations (Singh et al., 2018), and incomplete acquisition of variables associated with industrial locations (Luthra et al., 2020). This led to unsuitable IP locations and hence the emergence of brownfield industrial parks (BIP).

BIPs are partially inhabited, abandoned or underutilised IPs found all over the world (Rahmat et al., 2017). BIPs occurred due to insufficient land for industries expansion, poor transportation infrastructure (Bansal et al., 2017), no industry clusters, no established power source, lack of utility and amenities, waste and wastewater management challenges, material and energy inefficiencies, and linear production process (Das and Gupta, 2021). As a result, greenhouse gases (GHG) are generated

* Corresponding author. Process Systems Engineering Centre (PROSPECT), Research Institute for Sustainable Environment, Universiti Teknologi Malaysia, 81310, Johor Bahru, Malaysia.
E-mail address: dr.zain@utm.my (Z.A. Manan).

https://doi.org/10.1016/j.jclepro.2022.133141
Received 1 February 2022; Received in revised form 11 July 2022; Accepted 12 July 2022
Available online 15 July 2022

Abbreviations

AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
CI	Consistency Index
CR	Consistency Ratio
DSS	Decision Support System
EIA	Environmental Impact Assessment
EIP	Eco-Industrial Park
ETM	Enhanced Thematic Mapper
F-AHP	Fuzzy-Analytic Hierarchy Process
GHG	Greenhouse Gas
GIS	Geographic Information System
GNU	GNU's Not Unix
H-FAP	HNAP Hierarchy Fuzzy Analytic Process Hierarchy Network Analytic Process
HN-FAP	Hierarchy Network Fuzzy Analytic Process
l, m, u	Lower, Medium, Upper
LULC	Land Use Land Cover
MCDM	Multi-criteria Decision-making
NFh-AP	Network Fuzzy Analytic Hierarchy Process
NVec	New Vector
OLI	Operational Land Imager
OPVec	Overall Priority Vector
PVec	Priority Vector
RI	Random Index
SRTM	Shuttle Radar Topography Mission
TFNs	Triangular Fuzzy Numbers
TLIA	Tanjung Langsat Industrial Area
TOPSIS	Technique for Order Preference by Similarity to the Ideal Solution
WOA	Weighted Overlay Analysis

that pollute the environment, risk human health, destroy flora and fauna, trigger global warming and contribute to climate change (Avtar et al., 2019). Since BIP emit carbon dioxide, methane, and nitrous oxides, which contribute to 28% of global GHG emissions (IPCC, 2019), there is the need to convert the brownfields into Eco-Industrial Parks (EIPs) for industrial symbiosis (UNIDO, WBG and GIZ, 2021). The anthropogenic carbon emissions from industrial zones and fossil fuel combustion release GHG into the atmosphere which agitates the air, and the air becomes heated on absorbing it causing climate change and global warming. The Keeling curve is used to find out the level of carbon in the air in parts per million by volume (ppmv) (Keeling, 1960). The carbon footprint in an industrial area can also be measured using the carbon application (Apps) calculator and carbon calculator which is easy and fast. Many measurements are conducted each year at Mauna Loa, Hawaii, to calculate the ppmv of carbon in the atmosphere (Showstack, 2013). When the Industrial Revolution began, the atmospheric carbon level was at 270 ppmv (Keeling, 1960), and it rose to an average of 310 ppmv between 1958 and 2013 (Showstack, 2013). By 2025, the level was projected to be around 418.81 ppmv (Showstack, 2013). The mission of EIP is to bring together industries in a strategic location for a circular economy (UNIDO, WBG and GIZ, 2021), which is a new model that strives to systematically emulate natural symbiotic concepts of reducing, reusing, and recycling resources for cleaner manufacturing. With the launch of the EIP concept, water bodies, available land, developed infrastructure, existing industries, proximity to urban settlement, and favourable climatic conditions amongst others are examined and required for its location (Shine et al., 2020).

The industrial site criteria weighting and ranking have a significant impact on the selection of suitable locations (Dos-Santos et al., 2019), hence strong multi-criteria decision-making (MCDM) and geospatial technologies are required. It is estimated that around 80% of the data used for EIP site selection decision-making is spatial and the non-spatial is 20% (Das and Gupta, 2021). As a result, the EIP site selection becomes an intricate spatial multi-criteria study. The multi-criteria spatial complexity demands the use of decision support systems (DSS) (Neves et al., 2020) such as geographic information systems (GIS) and integrated multi-criteria decision-making (IMCDM) technologies. GIS is "a modern software used to obtain spatial criteria, processes, assesses, stores, and overlays the spatial data positioned on the earth for site suitability selection of a specific project" (Asadabadi et al., 2019). The data is used to analyze, model, simulate (Yuen, 2012) and imagine location, human environments, and societies on the planet (Avtar et al., 2019). Multi-criteria decision-making (MCDM) is a technique for evaluating and ranking criteria weights for site suitability decisions (Monsef and Smith, 2019).

The wrong choice of locations occurs mostly due to the use of single traditional (Valenzuela-Venegas et al., 2020) or weak assessment procedures (Luthra et al., 2020) that struggle with spatial and consistent decision-making abilities. The concept of criteria/attribute interdependence has not been addressed by single MCDM methods such as AHP (Saaty, 1977), F-AHP (Buckley, 1985), WLC (Malczewski, 1996), SAW (Fishburn, 1968), TOPSIS (Hwang and Yoon, 1981), Best-Worst method (Rezaei, 2016), and DEMATEL (Gabus and Fontela, 1973), which becomes the weakness of SMCDM techniques and can lead to inconsistencies between criteria weighting and ranking (Penadés-Plà et al., 2016). Many researchers have reported that single multi-criteria decision-making (SMCDM) techniques used for site criteria weight assessment have some strengths (Chang et al., 2015) but are outweighed by the consistency problems (Donni et al., 2017), which resulted in the incorrect industrial site suitability selections (Valenzuela-Venegas et al., 2020). For example, the analytic hierarchy process (AHP) is good for making decisions with independent criteria (Saaty, 1977), but has been significantly criticised for its disadvantage in uncertainty evaluation about the criteria level of preference (Paul, 2015). AHP is often combined with other MADM tools because many do not have internal procedures to determine criteria weights. The Technique for order preference by similarity to the ideal solution (TOPSIS) has been criticised for not considering Euclidean distance and link criteria (Buckley, 1985). Fuzzy-analytical hierarchy process (F-AHP) has also been criticised by Liu and Ma (2021) for not linking criteria, but considers the uncertainty of factors. Fuzzy is the complexity of variables or criteria in an uncertain environment in which the prioritization and selection of alternatives or projects are discerned by decision-making (Zadeh, 1975). Analytic network process (ANP) interlinks criteria (Saaty, 1977), and it does not eliminate uncertainty in the selection of criteria (Tavana et al., 2017). Approximations by the weighted linear combination (WLC) have been found to not always have precise and realistic values in Euclidean distances (Moses et al., 2018). The simple additive weighting (SAW) only finds the weighted sum of each criterion, but cannot verify weight stability (MacCrimon, 1968).

2. Literature review

Inconsistencies among SMCDM methods in the assessment of criteria weights for site suitability selection can be grouped into three. First, there is the tendency to exceed the consistency threshold of 10% when more than three criteria are used (Chang and Lin, 2015). Secondly, the SMCDM methods do not manage decision problems when there may be uncertainty about the criteria level of preference (Tavana et al., 2017). Finally, the idea of criteria or attributes independence (no union) except ANP becomes a weakness and leads to inconsistencies between decision and ranking criteria (Penadés-Plà et al., 2016). The use of SMCDM techniques has recorded inconsistencies in criteria weighting (Seyedmohammadi et al., 2018), leading to wrong choices of industrial sites and suboptimal decisions in the selection of industrial parks. For example, Yousefi et al. (2016) used AHP and investigated criteria weights for EIP site selection in Birjand city, Iran, where an indistinct suitable site was obtained. When WLC was used, results showed a wide criteria weights which may produce an unreliable industrial site. Ahmadipari et al. (2018) used Delphi and FAHP to select an industrial site in Markazi province, Iran, the Delphi results were dismissed due to a wide range of extents in weight values, and the FAHP weight values were relatively fair. Naghdi et al. (2017) used TOPSIS, SAW, and WLC to examine the industrial site's quantitative suitability and proximity to faults, groundwater, communities, protected areas, and power transmission lines in East Azerbaijan province, Iran. The outcomes of the three methods were inconsistent due to the number of criteria involved. It has also been noted that many studies that used SMCDM methods did not apply sensitivity analysis (SA) to evaluate the stability of the technique.

In an attempt to solve the inconsistency of the SMCDM methods, Saaty (1977) introduced the eigenvalue in AHP to avoid the consistency ratio exceeding 10%, which examined the weight distribution consistency of various criteria to have close values to the threshold. Chang et al. (2015) later criticised this suggestion and recommended that to rectify this shortcoming is to solve the AHP inconsistency with the concept of multi-attribute utility theory (MAUT). Paul (2015) argued that MAUT methods cannot be used to select criteria in the criteria hierarchy. MAUT is a bottom-up or alternative/attribute focused approach instead of a criterion-propelled method (Kubler et al., 2016). According to Barzilai & Golany (1994), the inconsistency problem in SMCDM is caused by the additive aggregation rule, and no normalisation can prevent it except the weighted-geometric-mean (Chang, 1996). According to Buede & Maxwell (1995), employing the geometric mean does not reduce inconsistency; rather, normalising the ratio scale may solve it. Farkas et al. (2004) introduced linear algebra by establishing intervals on a 3×3 matrix and proposed a graphical tool that, according to them, boosted the level of certainty in the outcomes but cannot accommodate huge criteria. Rodríguez et al. (2013) used the technique and reported it to be inaccurate. Belton & Gear (1983) noticed the criteria rank reversal (RR) problem in SMCDM after presenting a new similar alternative. To remove the RR, a normalisation method known as reference-AHP (r-AHP) was devised (Belton and Gear, 1983). Following that, Schenkerman (1994) said that r-AHP may only be utilised for normalisation to maximum and minimum entry, as well as linking pins to avoid RR when the criteria are quantitative. Saaty (1987) discovered the RR's resolution by modifying or expanding the set of alternatives. RR in the SMCDM is produced by changes in normalised attribute values in the SAW method (Chen and Chen, 2007), whereas changes in cross-efficiency cause it in the data envelopment analysis (DEA) method (Chen et al., 2017). The vector normalisation approach causes it in TOPSIS (Kong, 2011). García-Cascales & Lamata (2012) presented two hypothetical solutions and stated that they are insufficient to solve the RR problem. According to Ceballos et al. (2016), the weight assessment inconsistency does not only occur in AHP, TOPSIS, SAW, ANP, F-AHP, and WLC, it exists in all SMCDM methods. It also occurs in multi-objective optimization ratio analysis (MOORA) (Pramanik, 2016), and Viekriterijumsko Kompromisno Rangiranje (VIKOR), (Opricovic, 1998). There are suggestions that the multiplicative geometric ratio technique (Chumaidiyah et al., 2020) or integrating the single methods (Fang and Partovi, 2021) may resolve the inconsistencies.

Integrating the single traditional methods is worth trying which may overcome the inconsistencies to eliminate the limitations and enhance their strengths. Traditional SMCDM approaches from different groupings of scoring, distance-based, pairwise comparison, outranking, utility, and uncertainty (fuzzy) assessment methods (Chumaidiyah et al., 2020) have specific assessment goals which when combined may effectively and objectively provide consistent criteria and attribute eigenvectors for industrial site suitability selection (Ahmed et al., 2020).

Brownfield industrial parks do not attract foreign direct investment (FDI) to drive industrial dynamics because of the absence of developmental space that would encourage industry clustering and carbon emission control (Torabi-Kaveh et al., 2016). Industrial site selection is a strategic problem-solving process and the first step in the development of a successful EIP (Taye et al., 2019). The conversion of brownfield industrial parks into EIP will eventually drive EIP growth as the call for industrial symbiosis to control carbon emissions has intensified (Kucukvar et al., 2018). In Vietnam, for example, UNIDO has revolutionised four brownfield industrial zones (IZ) into EIPs (Yap et al., 2019). Research and development of IMCDM methods to produce robust algorithms for the evaluation of consistent criterion weights and ranking for the selection of suitable EIP locations are required to avoid the neglect or underutilisation of industrial parks.

The aim of the research is to develop an integrated multi-criteria decision-making (IMCDM) algorithm and an MCDM-GIS model that can assess consistent criteria weights for the selection of brownfields to convert to EIP. To accomplish this, the SMCDM methods (AHP, ANP, and F-AHP) were used to assess and established criteria weight importance. The outcomes were integrated using a proposed procedure providing the IMCDM algorithm, which also was used to assess the criteria weighting, sensitivity analysis and standard deviations of the algorithm. To test the consistency of the IMCDM and the efficiency of the MCDM-GIS, a ten-year interval spatial criterion from a brownfield industrial site was collected, screened by the Boolean logic and the GIS prepared the Euclidean distance and reclassified raster layers. PLANMalaysia provided the spatial criteria of the land use land cover (LULC) layers. The weighted overlay analyses were performed in the model where EIP site suitability layers were generated and analysed.

The choice of AHP, ANP, and F-AHP traditional methods in this study are the individual's hierarchical, networking, and triangular fuzzy numbers (TFNs), also the pairwise comparison and fuzzy groups to which they belong. The AHP is a hierarchical approach that connects criteria from one level down the structure to the attributes or alternatives (Saaty, 1977). ANP employs an interdependent/dependent network to generate interactions of criteria between the same criterion, and/or other criteria in a different loop, as well as criteria between attributes (Saaty, 1977). To facilitate uncertainty defuzzification, the F-AHP uses linguistic variables as TFNs with lower (l), middle (m), and upper (u) weight values (Zadeh, 1975) incorporating wider weight values assigned to the criteria. These techniques with different specific goals when integrated may provide a mixed algorithm for the assessment of consistent criteria weights for the selection of a suitable EIP location.

3. Method

3.1. Apparatus

The tools employed in this study are Microsoft (MS) Excel for AHP and F-AHP criteria weights evaluation, and the Octave GNU 6.1 for ANP criteria weights assessments. The EarthExplorer free software, Kompsat–3 imager, ArcMap (GIS) 10.4 software and its extensions – Boolean logic, weighted overlay analysis (WOA), raster map calculator, and ModelBuilder were used.

3.2. Site, data collection and preparation

The macro location for the collection of the brownfield spatial criteria was Johor Bahru, Johor, Malaysia. The microsite was the Tanjung Langsat Industrial Area (TLIA), the specific community of interest where the brownfield is located with potential suitable factors for EIP.

The download of the spatial criteria layer of roads, existing industries, water bodies and residential areas of 2009 and 2019 of the Tanjung Langsat Industrial Area used the GIS and prepared shapefiles (.

Table 1
Random index number of criteria.

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.58

shp). The Shuttle Radar Topography Mission (SRTM) and Operational Land Imager (OLI) Landsat downloaded the slope and the land surface temperature layers in tagged image files (.tif) formats. The Landsat-7 Enhanced Thematic Mapper (ETM) and Kompsat-3 Imager obtained the spatial data layer of 2009 and 2019 for the land use land cover through PLANMalaysia. The Boolean logic screened and selected the criteria (factors), where 1is acceptable and 0 is not acceptable, and the former gave the criteria for the assessment of the suitability of TLIA for EIP site selection. The Euclidean distance layers of roads, existing industries, water bodies, and residential areas were prepared. The GIS reclassified the six criteria, including slope and land surface temperature raster layers, where close or farther but preferred factors obtained 5 and allocated 1 to farther or close but undesired. The output cell used 30 m for the criteria raster layers.

3.3. The analytic hierarchy process criteria weights assessment

The AHP hierarchical structure was constructed into a goal, criteria, and alternatives levels. A pairwise comparison matrix was built based on the factors in the order of the 6-by-6 matrix. The diagonal elements in the matrix were kept at 1, while the triangular matrix above the diagonal was used as the decision triangle. The factors in the comparison matrix were pairwise and allocated weights according to the Saaty (1977) 1 to 9-point scale based on their significance. The lower triangular matrix was reciprocally filled up and the criteria weights were assessed. The total of each column was evaluated and the weight value in each column cell was normalised by dividing each of the values in the column cell by its column sum using Eq. (1). Equations (1)–(4) were adopted from Saaty (1977). The sum of all the outcomes in each column was equal to 1. The Priority vector (Pvec) was evaluated by taking the averages of the normalised elements in each row of the matrix and standardizing in which its sum was equal to 1.

$$w_i = \frac{1}{n}\sum_{j=i}^{n}\frac{aij}{\sum_i^p a_{ij}} \tag{1}$$

where $a_i = 1$; if $a_{ij} = n$; then $a_{ji} = 1/n$; $i, j = 1, 2, 3, \ldots \ldots \ldots, n$.

n = the number of items being compared or the order of the matrix.

The consistency ratio (CR) calculated the stability of the weight distribution (the possibility that the result is the measure of randomised and illogical choice processes) which has two steps: the Eigenvalue (λ_{max}) and the consistency index (CI). To calculate for λ_{max}, a new vector (Nvec) was obtained by multiplying the corresponding rows of the pairwise comparison matrix by the Pvec down the column. Eq. (2) calculated the sum of the ratio of all the elements of the weighted matrices Nvec to the corresponding Pvec factors $\left(\frac{\text{Nvec}}{\text{Pvec}}\right)$.

$$\lambda_{max}\left(\frac{1}{p}\right)\sum_{i=1}^{p}\left[\frac{\sum_{j=1}^{p}a_{ij}w_j}{w_i}\right] \tag{2}$$

where $\lambda_{\max}$ = the principal or maximum Eigenvalue of the matrix.

Eq. (3) calculated the CI:

$$CI = \frac{\lambda\max - n}{n-1} \tag{3}$$

where n = *6, the matrix size.*

Eq. (4) evaluated *the* CR:

$$CR = \frac{CI}{RI} \tag{4}$$

where CR is the consistency ratio.

RI is the random index, shown in Table 1 adopted from Saaty (1977) that corresponds to the number of criteria in consideration.

A CR of greater than 10% is not acceptable, which means the evaluation needs review. Similarly, a comparison matrix of the alternative was created for every criterion and pairwisely assigned weights and evaluated. The multiplication of the Pvecs of the goal, the criteria, and the alternatives for each criterion obtained the overall Pvec (OPvec).

3.3.1. Sensitivity analysis

The sensitivity analysis (SA) was performed using Eq. (5) on all the OPvec weights altering them by ±2%, ±3%, and ±5%, which evaluated the level of change in the weights in the event of a computation error. If the level of change varied greater than ±0.85%, the technique is considered unstable; thus, the assigned weights must be readjusted and reassessed at the pairwise matrix.

$$W_x = (\pm y\% \times W_1) + W_1 \tag{5}$$

where W_x = new weight, y% = percent chosen, and. W_1 = assessed weight

3.4. The analytic network process criteria weights assessment

The OPvec weights of the goal, criteria and the attributes for each criterion derived from the AHP pairwise comparison matrix procedure were used for ANP weight analysis. The arrangement of the OPvecs in the matrix columns formed the supermatrix, a two-dimensional matrix of elements by elements. The factors in the supermatrix (or non-weighted supermatrix) included all Pvecs for the node, which is the parent node in the cluster and may not be stochastic (numbers adding to 1 or 100%). The transformation of the unweighted supermatrix from the matrix of cluster priorities into a column stochastic matrix {>> *S* = *[ ]*} evaluated inside a GNU Octave 6.1 software. The upload of the outcome into a null matrix {*S* = *[ ] (0 x 0)*} and RUN produced the weighted supermatrix. The weighted supermatrix was raised to the 10th power ($Lim = W^{k = 10}; k \rightarrow \infty$) (where W = weights) and obtained the limit supermatrix. The values remained constant to the limit of the sum of all the powers of the matrix, showing a steady state because of the identical numerals in the columns.

The limit supermatrix provided the relative weights of importance for every element in the model. All the network's final priorities were standardised [that is, normalising each block (cluster) of the limit supermatrix with the associated values of the elements calculated]. This step determined the weight values of the criteria by prioritising the structure of the entire system. The final priority weights, which accounted for component (element) interactions, were extracted from the limiting matrix, and the SA was conducted.

3.5. Fuzzy-analytic hierarchy process criteria weights evaluation

The fuzzy and AHP processes used the same structure for the criteria and attributes. Unlike the AHP, the F-AHP criterion pairwise comparison matrix has three columns, the triangular fuzzy numbers (TFNs) for the weight values. The TFN is a ratio of interval values that describes ambiguous comparative judgement with the lower value (*l*), middle value (*m*), and upper value (*u*), and has the advantage of identifying the possibility of various values within this interval. Using the TFNs of l, m, and u values, the columns in the right-hand triangle were assigned weights. The weight value of 1,1,1 in the diagonal shows the same

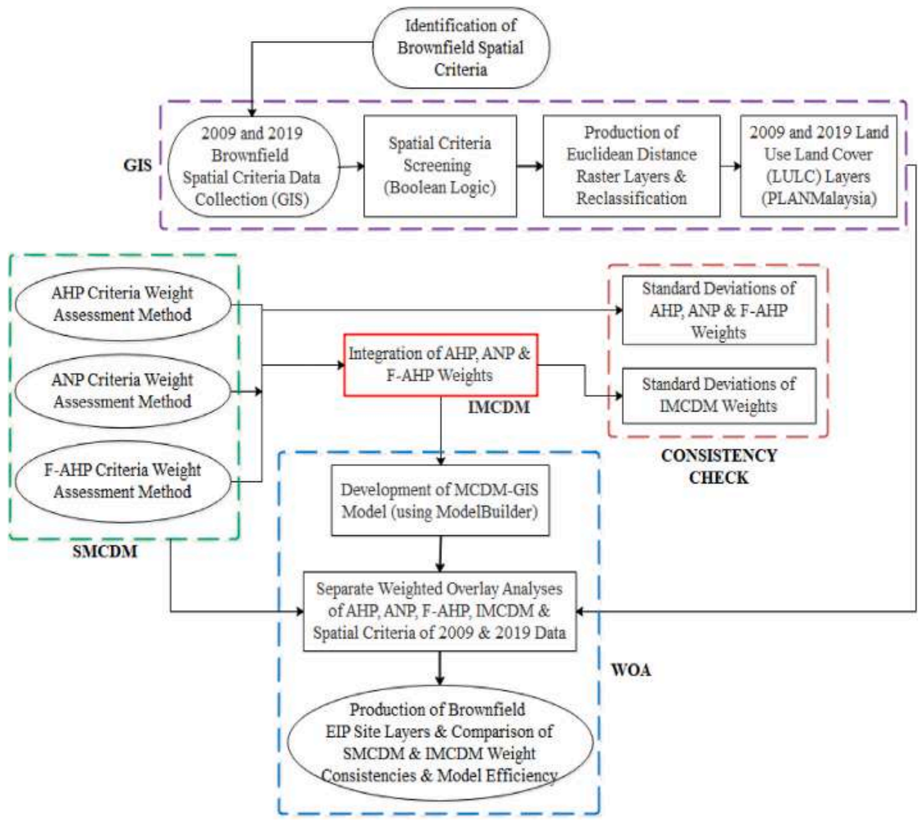

Fig. 1. GIS-MCDM flowsheet.

elements weighed against each other, while the reciprocal of the corresponding column weight in reverse order u, m, l was filled in the lower triangle.

The calculation of the geometric mean used Eq. (6) by taking the product of the l, m, u values separately from each criterion in a row and raising the outcome to the inverse power of the number of criteria. The sum of the geometric ratios was arranged in the *l, m, u*, and their columns' total calculated. In ascending order, the outcomes of the reciprocals of the total were arranged. Equations (6)–(9) were adopted from Zadeh (1975).

$$\widetilde{r}_1 = \left(\widetilde{\alpha}_{i1} \otimes \widetilde{\alpha}_{i2} \otimes \widetilde{\alpha}_{i3} \ldots \otimes \widetilde{\alpha}_{in}\right)^{\frac{1}{n}} \tag{6}$$

where $\widetilde{\alpha}_{i1}$ = first fuzzy dimension number; $\widetilde{\alpha}_{i2}$ = second fuzzy dimension number; $\widetilde{\alpha}_{in} = n^{th}$ = fuzzy dimension number; $\widetilde{r}_1$ = geometric mean.

The fuzzy relative weight was evaluated using Eq. (7) where each geometric mean in the l, m, u was multiplied by the corresponding reciprocal of the sum provided in ascending order.

$$\widetilde{w}_1 = \widetilde{r}_1 \otimes (\widetilde{r}_1 \otimes \widetilde{r}_2 \otimes \widetilde{r}_3 \ldots \otimes \widetilde{r}_n)^{-1} \tag{7}$$

where: $\widetilde{r}_1$ = first geometric mean, $\widetilde{r}_2$ = second geometric mean, $\widetilde{r}_n = n^{th}$ geometric mean, $\widetilde{w}_1$ = fuzzy weight.

The fuzzy relative weights were defuzzified using the centroid rule in Eq. (8), and the sum of the defuzzification was a unit value.

$$M_i = \frac{l_i + m_i + u_i}{3}, \; i = 1, \; \ldots\ldots.., \; n \tag{8}$$

where: M_i = crisp value, l = lower value, m = medium value, and u = upper value.

The normalisation was performed using Eq. (9) when the sum of the defuzzified values was greater than 1.

$$N_i = \frac{M_i}{\sum_{j=1}^{n} M_j}, \; j = 1, \; \ldots\ldots, \; n \tag{9}$$

where. $\sum_{i=1}^{n} N_1 = 1, \; i = 1, \; \ldots\ldots\ldots, \; n$

In a like manner, the alternatives were also assessed for each criterion, the overall criteria weights of importance were computed, and the SA was evaluated.

3.6. Integration of single multi-criteria decision-making methods

Due to the consistency constraints of single traditional criteria assessment approaches, this study designed an IMCDM algorithms procedure which is presently required for the consistent spatial criteria weighting and ranking for brownfields transformation to EIPs. Eq. (10) shows the process by which the overall priority vectors (OPvecs) of the methods can be assessed and integrated. Eq. (11) shows the normalisation of the IMCDM techniques when the OPvecs were not stochastic.

$$ItgOPvec_{(1,2,3\ldots.n)} = OPvec_{(1)} + OPvec_{(2)} + OPvec_{(3)} + \ldots + OPvec_{(n)} \tag{10}$$

where *ItgOPvec* = Integrated overall priority vector; 1,2,3…n = SMCDM methods.

$OPvec_{(1)}$; $OPvec_{(2)}$; $OPvec_{(3)}$; $OPvec_{(n)}$ = 1st method; 2nd method; 3rd method; nth method.

$$normItgOPvec_{(1,2,3\ldots.n)} = \frac{ItgOPvec_{(1,2,3\ldots.n)}}{\sum\left[ItgOPvec_{(1,2,3\ldots.n)}\right]} \tag{11}$$

where $normItgOPvec_{(1,2,3\ldots.n)}$ = normalised integrated overall priority vectors.

To measure the consistencies of SMCDM and IMCDM methods criteria weights of importance, the standard deviation (SD) as shown in Eq. (12) was employed where the distances or spread of criteria weight values from the overall averages of a set of criteria were calculated.

$$SD = \sqrt{\frac{(x - \bar{x})^2}{n - 1}} \tag{12}$$

where SD = standard deviation; x = each value of the weights; $\overline{X}$ = the weights average; n = size of the criteria.

3.7. Multi-criteria decision-making–geographic information system model building

A ModelBuilder application in the ArcMap 10.4 software accomplished the development of the multi-criteria decision-making – Geographic information system (MCDM–GIS) model. The geoprocessing tools – input, processing, and output were dragged from the catalogue pane and emerged circular, rectangular, and circular. The input tools collected and accommodated the criteria layers where they were dispatched for processing. A drop-down box was created in the input for variable model parameters denoted by "P" to allow acceptance of additional data layers or values for the model to process. If a change in the parameter is required, the tool parameter can be double-clicked and change the parameter. The Euclidean distances layers were added to the processing tools, and the outputs were connected to the next processing tools and added reclassified raster layers. An "extent" tool was created and connected to the first processing tools, which are the geographic boundaries for displaying GIS information, such as features or rasters that a tool would process. The connection of the reclassified raster layers to the weighted overlay analysis (WOA) tool, where the weights percent importance from the SMCMD and IMCDM approaches, and 2009 and 2019 spatial criteria data were separately added. A raster calculator connected to the output where the LULC layer was added/overlaid, run, processed, and generated the EIP suitability layer.

The flowchart of the entire methodology is depicted in Fig. 1, which begins with the identification of brownfield industrial site spatial criteria. To evaluate the criteria weights (priority vectors), the single methods of AHP, ANP, and F-AHP were adopted, which were then integrated utilising defined equations that produced the IMCDM, and the priority vectors were evaluated. The distances between the priority vectors in the SMCDM and IMCDM and the average of the criteria sets were calculated using the standard deviation. The model was developed using ModelBuilder. The final stage was to verify the consistency and efficiency of the SMCDM and IMCDM algorithms' criteria weights, where spatial criteria data for a ten-year interval were collected, screened, produced Euclidean distance, and reclassified raster layers. In addition, the LULC layers were obtained. Weighted overlay analyses (WOA) of the SMCDM and IMCDM weights with the spatial criteria data in the model were performed, and the BF-EIP site suitability layers were generated and compared.

4. Significance of criteria and alternatives for eco-industrial park site selection

The criteria and attributes for BF-EIP suitable site selection techniques are based on the principles of industrial symbiosis, resource management and efficiency (Okada and Siddharthan, 2007), cost-effectiveness, and sharing of infrastructure and utilities to cut costs (Ajibade et al., 2019) and industrialization sustainability (Pichs-Madruga et al., 2019). All of which are aimed at reducing pollution and increasing productivity. Six spatial criteria for brownfield-EIP site suitability selection are evaluated through the SMCDM, IMCDM and GIS processes. The BF-EIP proximity to the available residential areas, existing industries, slope, roads, land surface temperature, and water bodies strongly support achieving suitable EIP site selection. The environmental, economic, social, political, and technical attributes strengthen the criteria to achieve the goal.

4.1. The residential area

Residential areas accommodate important facilities such as banks, telecommunications, electricity, schools, hotels, recreational areas, public utilities, hospitals, worship centres, and labour. Azizi et al. (2014) emphasised that the proximity of the residential area to the EIP site is one of the important criteria requirements. Banks and other financial organisations close to EIP provide sufficient capital flow for transactions and obtain a supply of investment funds (Barzehkar et al., 2019). Research institutions near the EIP site inspire product research, development, and cost reduction (Rahmat et al. (2017). It also encourages efficiency and sustainability in industrial activities. Close residential areas to EIP sites readily and adequately supply both skilled and unskilled labour force. The skilled, unskilled, attitude and the educational level of the workers near the EIP site determine the labour cost (Noorollahi et al., 2016) and innovations (Babalola, 2018) in the EIP operations.

4.2. Existing industries

The existence of industries near the BFIP is critical for the exchange of a variety of resources, including materials, energy, treated wastewater, by-products, services, and training. The presence of industrial clusters near a potential EIP site connects several separate industry clusters to promote factory symbiosis and the expansion of industrial operations (Susur et al., 2019). It also resolves resource management and pollution problems and produces solutions to abate carbon emissions (Gao et al., 2019).

4.3. Slopes

The existence of highly concentrated and steeply gradient slopes characterised by hills and undulations close to the EIP site heavily adds to the cost of building and road construction for transportation. The EIP site terrain requires to be flat or the concentration and gradient of slopes to be between 1 and 12% (Reisi et al., 2018).

4.4. Roads network

Accessible and adequate road networks for transportation near the BF-EIP site are critical. Both major and internal roads enable vehicles and goods transportation to and from nearby locations and within the industry (Yang et al., 2008). This significantly reduces transportation costs which boosts the economic aspect of the industries. Muhsin et al. (2018) emphasised the need of having numerous transportation systems such as railways and airports close to the BF-EIP to have the lowest transportation costs and optimal conditions.

4.5. Land surface temperature

The land surface temperature is a crucial parameter for determining where an EIP should be located (Rizzo et al., 2015). EIP sites under favourable climatic conditions plan for solar, wind, and hydropower renewable energy (RE) generation to reduce the BF-EIP's energy production from fossil fuels, control environmental pollution and for industrial sustainability (Rizzo et al., 2015). BF-EIP sites, according to Stojcic et al. (2019), should be in locations with temperatures ranging from 20 °C to 30 °C, considerable annual rainfall ranging from 1778 mm to 3302 mm, and wind speeds reaching from 12 km/h to 14 km/h to generate cheap renewable power.

4.6. Water bodies

The presence of water bodies such as oceans, rivers, and streams close to the BF-EIP site link countries for easy transportation with bulk raw materials and finished goods (Valenzuela-Venegas et al., 2020). A

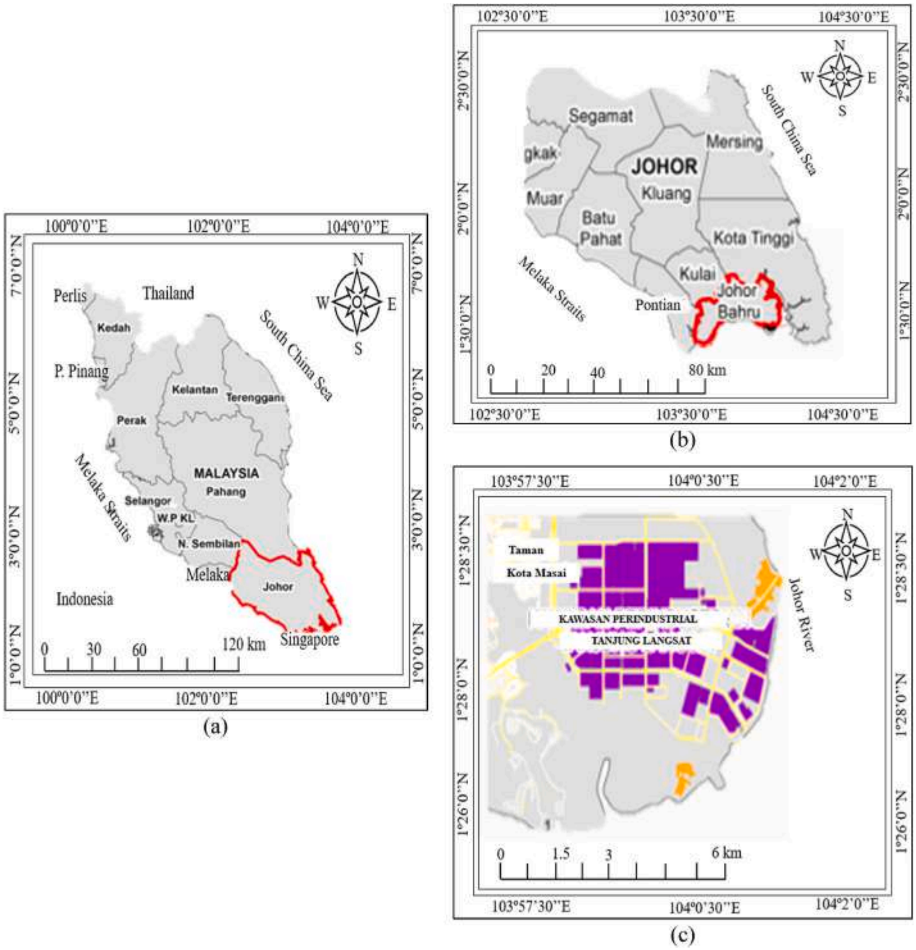

Fig. 2. (a) Extended macro location (Johor, Malaysia), (b) Narrow macro location (Johor Bahru, Johor), (c) micro location (Tanjung Langsat industrial area in Johor Bahru).

water body is also required by the utility organisations that treat the water required for domestic use, industrial cleaning and machinery cooling (Jangid et al., 2016).

4.7. The attributes

The proximity of raw materials and supply stability, as well as product competitiveness, are economic attributes considerations for selecting a suitable EIP site. According to Akther et al. (2019), the EIP's continual supply of raw materials is heavily reliant on a readily available variety of transportation systems. The proximity of residential areas to the EIP site provides adequate labour, which is a significant social and economic benefit. A technical aspect of the selection of an ideal EIP location is the topography of the land for the industrial site (Erdogan et al., 2019). Industrial synergy, wastewater treatment and recycling, zero waste compliance, and RE generation all contribute to environmental protection for industrial sustainability (Fang and Partovi, 2021). Any country or region that is politically unpredictable, regardless of whether it has good sites for EIP, has a detrimental impact on the prospect of industrial development. According to Ghobadi and Ahmadipari (2018), for EIP to flourish, the host country of a viable EIP site must be politically stable.

4.8. The land use land cover

The LULC around the EIP site usually depicts restricted areas, vacant land, and other uses. Industrial expansion is hampered by restricted areas near the BFIP. According to Kamali et al. (2017), given potential development expectations, the distance between BF-EIP and any restricted areas such as mining camps, archaeological sites, and faults should be considerable. This will keep BF-EIP sites far from ground vibrations and sinking (Erdogan et al., 2019). The low cost and the abundance of land create opportunities for potential industrial expansion. The availability and affordability of land, as well as its use, are important factors to consider when selecting an EIP site (Maurice, 2015).

5. Results and discussion

5.1. Study area

The macro location (Malaysia–Johor–Johor Bahru) of the study area is shown in Fig. 2(a) and (b), while Fig. 2(c) shows the micro-location, Tanjung Langsat Industrial Area (TLIA). It is around 8 km from the Pasir Gudang Industrial Area (Kanniah et al., 2015). The climate is tropical, with recorded average monthly temperatures of 27.10 °C in June and 25.8 °C in January, and a yearly average rainfall of 2689 mm (Kanniah et al., 2015). Agriculture/forestry/fishery, palm oil-related, petrochemical, chemicals, oil and gas, steel fabrication, marine-related, rocks and minerals, construction, and services are popular in the area (Zailan et al., 2020).

5.2. Euclidean distance raster, reclassified raster and land use land cover layers

The output of the Euclidean distance raster layers of the spatial

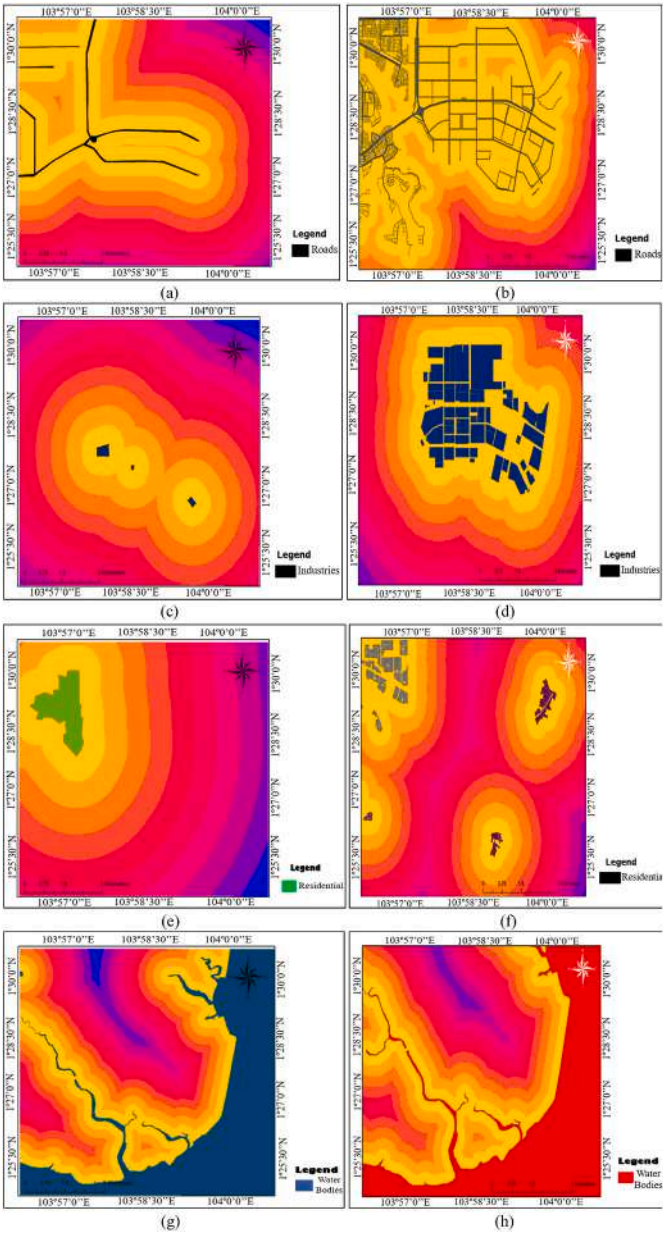

Fig. 3. Euclidean Distance Raster Layers of (a) Roads in 2009, (b) Roads in 2019, (c) Existing Industries in 2009, (d) Existing Industries in 2019, (e) Residential Area in 2009, (f) Residential Areas in 2019, (g) Water bodies in 2009, (h)Water bodies in 2019.

criteria for the study area was prepared in two parts in the span of a 10-year interval, 2009 and 2019 as shown in Fig. 3(a)–3(h). Fig. 3(a) shows a few roads in TLIA in 2009 connecting the small industries and the few residential areas. Fig. 3(b) presents the roads network in 2019 to have increased due to an increase in industries and residential areas. Fig. 3(c) shows the layer of a few existing industries in 2009 as against the expanded industries in 2019 shown in Fig. 3(d). The residential area in 2009 as shown in Fig. 3(e) is only in one place of the residential area, but in 2019, three more residential areas increased as shown in Fig. 3(f). The water bodies are shown in Fig. 3(g) and (h) having no differences within the 10 years interval, which makes them a reliable source of water for the EIP site.

The Euclidean distance assessed the assigned distances to the pixels of each criterion and used a simple differential calculation from every cell in the raster to the closest project suitable site. The 2009 and 2019 data assigned the same distances to each criterion for the EIP Euclidean

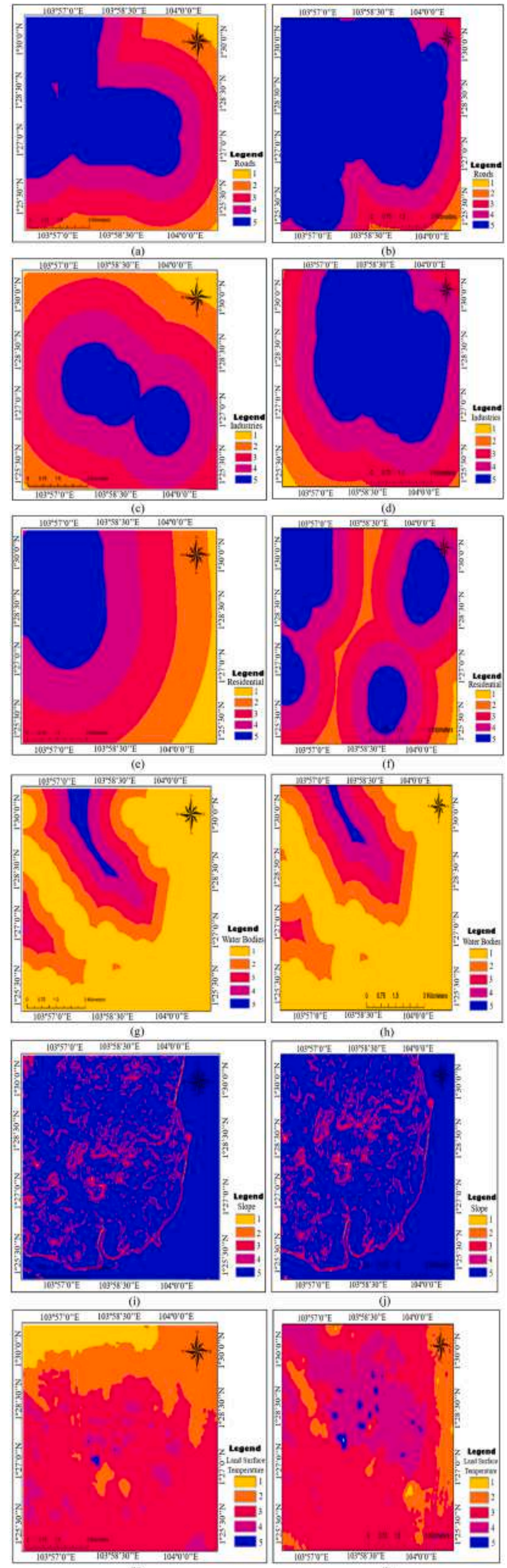

Fig. 4. Reclassified Raster Layers of (a) Roads in 2009, (b) Roads in 2019, (c) Existing Industries in 2009, (d) Existing Industries in 2019, (e) Residential Area in 2009, (f) Residential Areas in 2019, (g) Water bodies in 2009, (h)Water bodies in 2019, (i) Slope in 2009, (j) Slope in 2019, (k) Land Surface Temperature in 2009, (l) Land Surface Temperature in 2019.

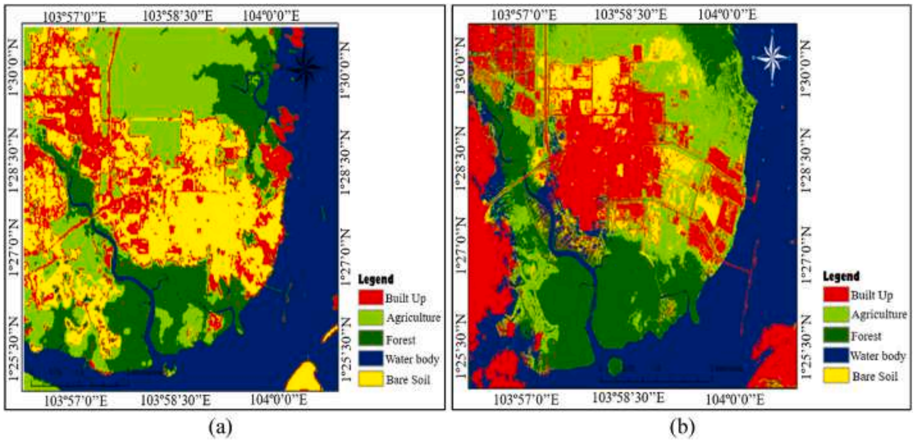

Fig. 5. Land use land cover of Tanjung Langsat industrial area (a) 2009, (b) 2019.

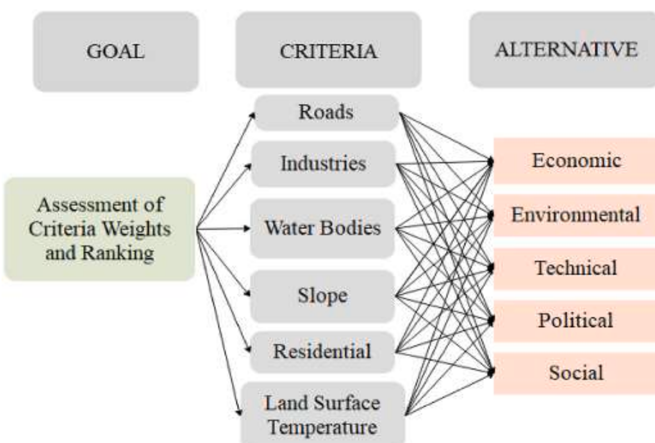

Fig. 6. Structure of AHP and F-AHP.

distance layer analyses. A distance of 5 km was assigned to the roads network to the EIP site. Deswal and Laura (2018) suggested the distance between major roads and an industrial park to be between 5 km and 8 km, and Muhsin et al. (2018) suggested between 5 km and 10 km. Industries allocated 1.5 km to shield them from the negative effects of non-food industries. Their existence close to the EIP site plays a great role in cluster symbiosis (Khan et al., 2018), which is one of the main concepts of EIP. Water bodies as one of the key infrastructures for EIP site selection assigned 3 km from the EIP site to avoid unpredictable tidal waves, typhoons, or floods. Reisi et al., (2018) proposed the distance of water bodies from an industrial area to be 1.6 km, which was too close. Residential area(s) were allocated 8 km and should be in the non-suitable EIP site to prevent any escaping toxic effects from industries. However, Valenzuela-Venegas et al. (2020) reported it to be 5 km and could not point out the location(s) to be sited.

Reclassification reassigns a range of values to a raster to produce a uniform new output scale for ease of suitability analysis (Messaoudi et al., 2019). The reclassification divided each criterion into 1–5 making the closest or farthest but preferred criterion getting 5 and, if not preferred whether close or far, got 1. The maps used a resolution of 300dpi during the reclassification. The output of the criteria reclassified raster layers of 2009 and 2019 data for roads, existing industries, residential areas, and water bodies are presented in Fig. 4(a) – 4(h). Fig. 4(i) – 4(l) show the reclassified layers of the slope and land surface temperature. The slope in Fig. 4(j) did not change over ten years. The concentration/gradient of 10% was assigned to the slope layer. Fang and Partovi (2021) stated that the best slope concentration/gradient should be between 0 and 12% to reduce construction costs and speed up infrastructure development. The land surface temperature in Fig. 4(l) increased from the initial 27 °C–30 °C, however, a temperature of 29 °C was set for the land surface. Sedrati et al. (2019) emphasised that higher solar irradiance above 30 °C over-heats surfaces of solar panels hampering solar power production. Shine et al. (2020) remarked that areas with high surface temperatures between 30 °C and 35 °C can cause wind instability, resulting in wild winds such as a hurricane. According to Chang et al. (2015), if land surface temperature steadily increases within an industrial area, it may be due to the emissions coming from the factories. Or the climate change caused by global warming through the burning of fossil fuels and carbon emissions from industrial processes and/or other activities. Fataei et al. (2015) reported that the moderate the annual land temperature of between 25 °C and 30 °C of a potential EIP site the better supply of irradiation to solar panels, the more rainfall, and the stable the winds.

Fig. 5(a) and (b) show the LULC of TLIA in 2009 and 2019 indicating water bodies, forests, agriculture, built-up areas, and bare soil. In Fig. 5 (a), the built-up is dispersed across the central area towards the north-eastern part. The agricultural area surrounds the built-up area, covering a broad field within the entire region. The northwest, south and alongside the major river moving up north are spotted with forest. The water bodies include the sea and the main river, while the empty land is prevalent between the built-up and agricultural areas and extends southward across the sea. This shows the availability of ample space for industrial expansion. Fig. 5(b) shows the reduction in forest area in the northeastern part and expansion in the south and laterally upward on the main river compared to 2009. The northeast along the coastline, the central, western, and northwestern parts of the TLIA are clustered with a built-up area (not dispersed as in 2009). The built-up area extended to the southern part of the sea, where there was an empty land in 2009. The agrarian area still held a huge fraction around the TLIA in 2019, while the empty land shrank to the buildings and other improvements.

5.3. Analytic hierarchy process

Fig. 6 illustrates the structure of the AHP and F-AHP approaches, where the goal is to design an MCDM algorithm for EIP site selection. The AHP criteria were assessed by a group of experts' opinions using choices labelled as equally (1), moderately (3), strongly (5), very strongly (7), or extremely strongly (9) as provided by Saaty (1977). After developing the hierarchy structure for BF-EIP site suitability selection, the decision experts pairwisely analysed the criteria based on the goal. The alternatives were also evaluated based on the criteria, and their relative importance at the preceding levels.

In the experts' opinions, the criteria are important to EIP site selection, as the weights are very close to each other. For instance, roads are

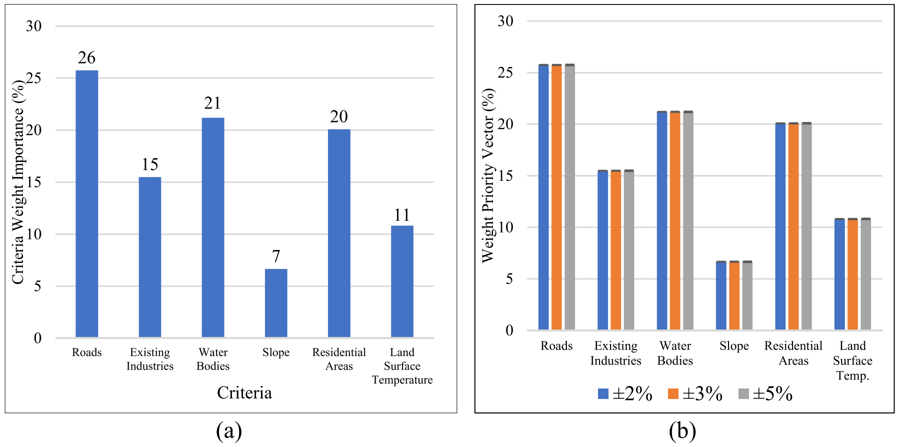

Fig. 7. (a) overall AHP criteria weight of importance, (b) AHP sensitivity analysis error bar.

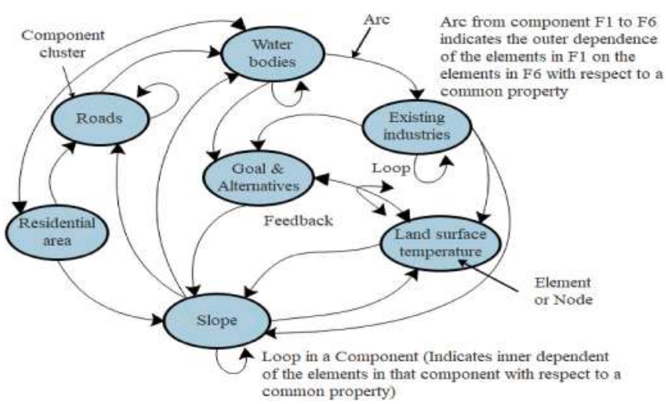

Fig. 8. Network structure of ANP

moderately more important than existing industries, slope, and land surface temperature, and are equally important as water bodies and residential areas. Water bodies are equally important as roads, existing industries, and residential areas, and are also moderately more important than slope and land surface temperature. The CR = 0.0517 shows a good distribution of the assigned weights at the pairwise comparison matrix.

Similarly, the CR of alternatives based on roads, existing industries, water bodies, slope, residential areas, and land surface temperature are 0.0982, 0.0668, 0.0830, 0.0833, 0.0404, and 0.0779. Fig. 7(a) presents the participants' overall priority vector (OPvec) pairwise comparison opinions of the weight of importance based on the goal, criteria, and attributes. The criteria weight importance of the roads has the highest ranking of 25.75%, water bodies followed with 21.20%, residential (20.09%), existing industries (15.49%), land surface temperature (10.81%) and the slope (6.66%). The alternative weights of economic, environmental, social, technical, and political aspects generated 28.54%, 22.10%, 20.90%, 19.76%, and 8.70%. As stated by Zailan et al. (2020), roads, water bodies, residential and existing industries are important to a brownfield for conversion into EIP, and the achievement of eco-industrial symbiosis centres on several attributes assessed to support the criteria to achieve the EIP aim.

The SA uses the OPvecs results to measure the stability of the MCDM method should an error occur during the evaluation. Fig. 7(b) shows the error bar generated from the SA results. If a ±2% criteria OPvecs error is calculated, roads will have a change by ±0.52%, water bodies will change by ±0.42%, and land temperature will alter by ±0.22%. If the error is ±3%, the existing industry and the slope will change by ±0.46% and ±0.20%. The SA at ±5% shifts the weight of roads by ±1.29%, which with this alone cannot affect the EIP site suitability. Any error between ±2% and ±5% is insignificant, as shown by the error bars. Rikalovic et al., (2018), provided that insignificant changes in weights assessment by MCDM tools are inevitable but should not be more than ±0.85%. The study used the assessed OPvecs for the EIP site suitability analysis. Criteria weight SA is important since it shows the extent of changes indicating the stability of the method (Li et al., 2020). Sellitto et al. (2021) applied the error interval and measured the error percentage in the AHP criteria weight assessment.

5.4. Analytic network process

Fig. 8 depicts the structure of the ANP, in which the network spreads out in all directions and the criteria (element) clusters are not arranged

Table 2
Unweighted supermatrix.

	Goal	Roads	Existing Industries	Water Bodies	Residential	Slope	Land Surface Temp.	Economic	Environ-mental	Technical	Political	Social
Goal	0	0	0	0	0	0	0	0	0	0	0	0
Roads	0.2575	0	0	0	0	0	0	0	0	0	0	0
Existing Industries	0.1549	0	0	0	0	0	0	0	0	0	0	0
Waterbodies	0.2120	0	0	0	0	0	0	0	0	0	0	0
Slope	0.0666	0	0	0	0	0	0	0	0	0	0	0
Residential	0.2009	0	0	0	0	0	0	0	0	0	0	0
Temperature	0.1081	0	0	0	0	0	0	0	0	0	0	0
Economic	0	0.2427	0.2900	0.3390	0.2831	0.2239	0.3180	1	0	0	0	0
Environmental	0	0.1923	0.2900	0.2240	0.1835	0.1170	0.3180	0	1	0	0	0
Technical	0	0.2865	0.1521	0.1524	0.2199	0.1580	0.1223	0	0	1	0	0
Political	0	0.0794	0.1157	0.0809	0.0669	0.1412	0.0803	0	0	0	1	0
Social	0	0.1992	0.1521	0.2037	0.2466	0.3599	0.1614	0	0	0	0	1

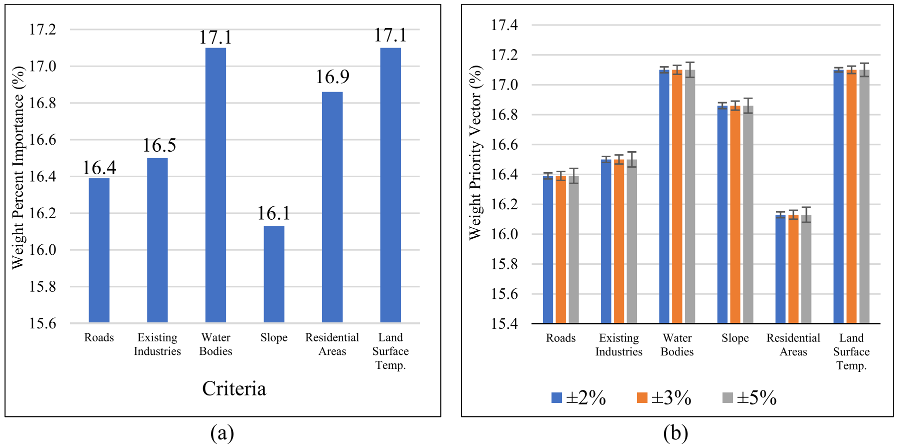

Fig. 9. (a) ANP overall normalised weight, (b) ANP sensitivity analysis error bar.

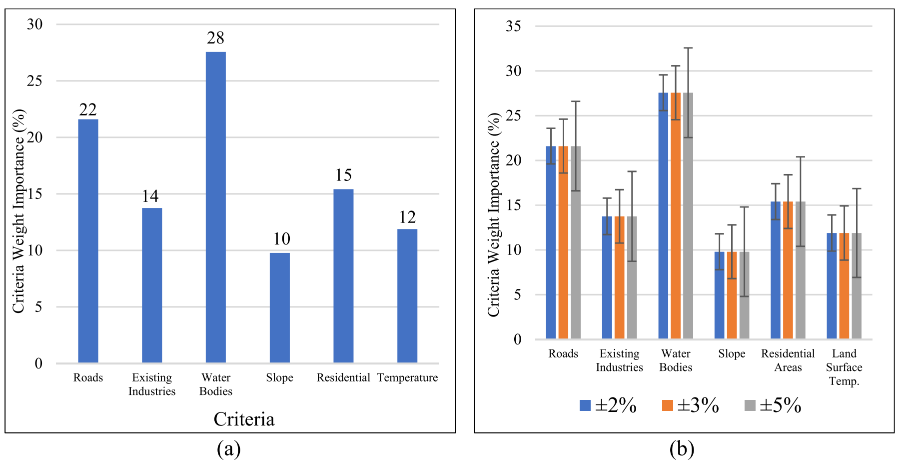

Fig. 10. (a) F-AHP criteria weight importance; (b) F-AHP sensitivity analysis error bar.

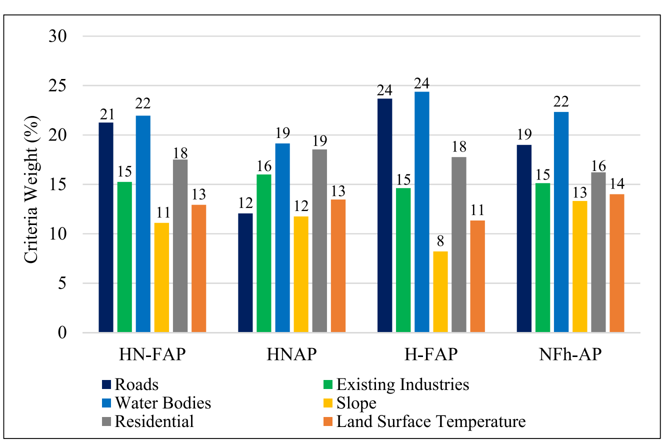

Fig. 11. The integrated algorithms criteria weight importance.

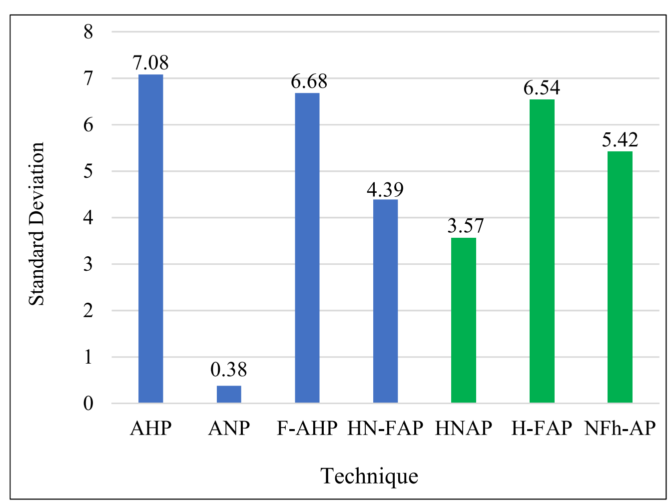

Fig. 12. Single and integrated algorithms criteria weights standard deviations.

in any specific sequence. The arrows between the nodes show the interaction of criteria, attributes and goal, whose orientation shows the direction of the influence between two or more nodes. Loops denote inner dependencies amongst nodes (criteria) of the same cluster. There were dependencies between the roads, water bodies, and residential, as well as between the land surface temperature, slope, and existing industries. There were also internal dependencies within slope and existing industries, and feedback of all criteria to the alternatives and goal.

Table 2 shows the unweighted supermatrix filled with the AHP overall eigenvectors and assessed by the GNU Octave 6.1 software, where all the criteria of the unweighted supermatrix are multiplied by

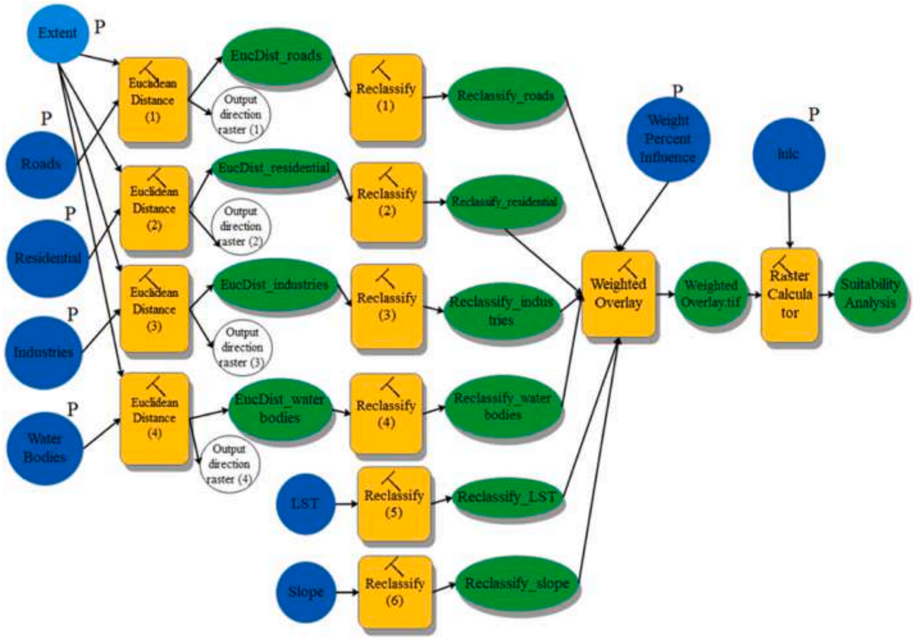

Fig. 13. MCDM-GIS model for EIP site selection suitability.

the corresponding cluster weights. According to Hassaan et al. (2020), each criterion yields the global eigenvector (priority vector) of the ANP. The impact of the criterion is shown on the left-hand side of the matrix and a criterion at the top of the matrix is based on the study area site selection control criterion. The unweighted supermatrix comprised all the network clusters and nodes and represented its interrelationship, which was based on the flow of effect from one criterion to another, or from a cluster to itself in the loop, as shown in Fig. 8. The column for a node covered the priorities of all the nodes pairwisely compared and influenced it to the control criterion of brownfield EIP site selection. The corresponding priority vector of a criterion recorded zero because it did not have input. If there was a relationship, the entry would have a value, showing that there was an external dependency.

The content of Table 2 was uploaded into a null matrix in the GNU Octave 6.1 Software, run and the weighted supermatrix was obtained. The weighted supermatrix was raised to the power $10 = k$, again run and yielded the limit supermatrix which had the same values as the weighted supermatrix because of the interaction of elements, nodes and loops that finally took place. Although any exponential could be chosen until it produced the same values as in the weighted supermatrix. The limit supermatrix signified all criteria connected in the ANP network structure. The priority vectors were obtained, and the total was required to be stochastic, which in this case it was not. Each criteria weight column sum was normalised, and the result is presented in Fig. 9(a). The ANP normalised criteria eigenvectors have water bodies and land surface temperature at 17.1% each indicating the most important criteria. Residential has 16.9% followed by existing industries (16.5%), roads (16.4%), and slope (16.1%).

Fig. 9(b) shows the error bars from the SA, which ±2% shows roads with ±0.33, industries had ±0.23%, water bodies measured ±0.34%, the slope got ±0.34%, and land temperature weighed ±0.25%. For ±3%, roads changed by ±0.49%, industries by ±0.50%, water bodies by ±0.51%, slope indicated ±0.51%, residential areas stood at ±0.48%, and land surface temperature measured ±0.42%. Roads, industries, residential areas, and land surface temperature were altered by ±0.82%, 0 ±0 .83%, ±0.81%, and ±0.76% when ±5% was assumed as the error. The SA, as reiterated by Rikalovic et al., (2018) shows that ANP error between ±2% and ±5% in criteria weight importance assessment is insignificant. The sensitivity analysis (SA) is an important step that measures the extent of changes (Nguyen et al., 2016) if there is a weight evaluation error (Kamdar et al., 2019). The attributes assessed were economic at 35.95%, social at 22.65%, environmental at 21.45%, technical at 15.77% and political at 4.18%.

5.5. Fuzzy-analytic hierarchy process

The Fuzzy Analytic Hierarchy Process (F-AHP) uses fuzzy theory to basic AHP, which was introduced firstly by Buckley (1985). The linguistic variables, which are represented by triangular integers, are used in F-AHP to execute evaluations of both criteria and alternatives. The triangular membership functions (TFNs) lower, medium, and upper (l, m, u) quantities use the nine-level scale in the pairwise comparison matrix. To incorporate the uncertainty, participants in this study employed the numerical triangular fuzzy numbers (TFNs) $\widetilde{1} - \widetilde{9}$, reflecting it to the subjective pairwise comparisons of BF-EIP site suitability choices. The TFN lower (l), middle (m), and upper (u) values set the weight of a criterion to include a broader boundary as compared to AHP, which has a single value. Its significance is to detect the likelihood of several values within this interval. For example, if 2, 3, and 4 represent the l, m, u weights, the geometric ratio solves the problem if any weights from 2.01, 2.02, 2.03, 2.04, …, 4.0 is preferred rather than only the median, which is usually required in AHP.

The experts' judgements show the roads are between moderately-less-important and moderately-more-important than the existing industries and water bodies. The existing industries are equally important as water bodies and moderately–strongly important than the slope. Water bodies are measured very strongly as more important than residential, and moderately important to land surface temperature. The land surface area was evaluated as less important to existing industries and residential areas, but moderately strong and more important than roads and slopes. The residential is moderately more important than the land surface temperature. The slopes are strongly more important than the residential areas.

The geometric mean values of the assigned criteria weights, the fuzzy relative weights, the defuzzification and the normalisation were assessed, as well as the weights importance of the attributes for each criterion and the overall priority vector. Fig. 10(a) shows the weight of water bodies at 27.56% as the most important criteria, followed by roads (21.60%), residential areas (15.42%), existing industries (13.75%), land

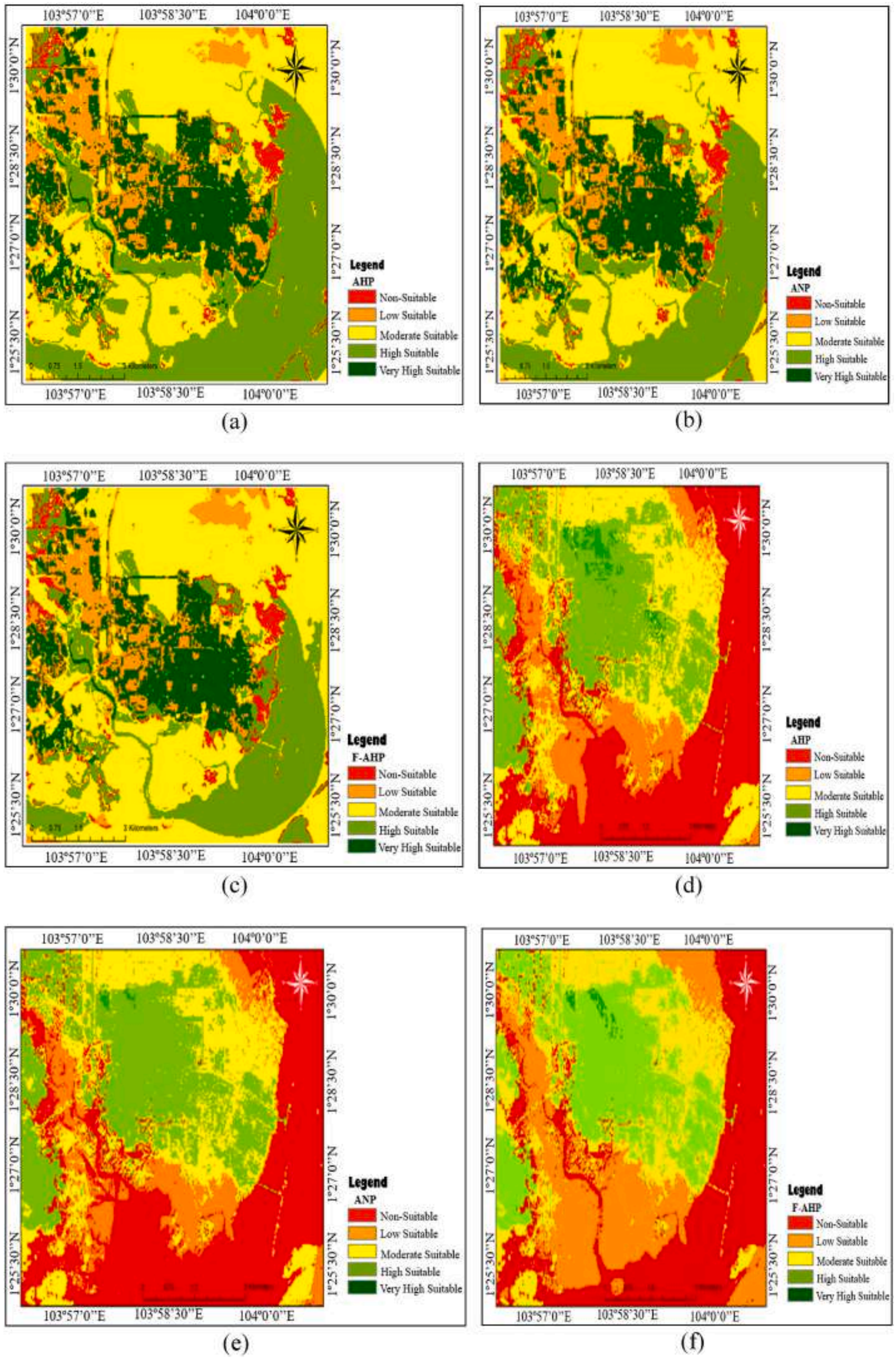

Fig. 14. TLIA Suitable EIP Site Selection using (a) AHP with 2009 Data, (b) ANP with 2009 Data, (c) F-AHP with 2009 Data, (d) AHP with 2019 Data, (e) ANP with 2019 Data, (f) F-AHP with 2019 Data.

surface temperature (11.89%), and slope (9.78%). The alternatives of economic, environmental, social, technical, and political aspects weighed 27%, 23%, 20%, 17%, and 13%.

The error bars in Fig. 10(b) show the extent of change evaluated using $\pm 2\%$, $\pm 3\%$, and $\pm 5\%$ assumed errors in the weight assessment. The error percentages for roads ($\pm 1.08\%$) and water bodies ($\pm 1.38\%$) are higher than the acceptable $\pm 0.85\%$ if an error of $\pm 5\%$ occurs. This shows that the error goes with the magnitude of the criterion weight.

5.6. The integrated multi-criteria decision-making algorithms

The MCDM integration is a novel approach to developing a reliable algorithm to address the inconsistent criteria weight evaluation problems of SMCDM. The overall criteria weights given by the AHP, ANP and F-AHP approaches were alternately integrated using Eq. (10) which provided the IMCDM methods of hierarchy network-fuzzy analytic process (HN-FAP); hierarchy network analytic process (HNAP); hierarchy-fuzzy analytic process (H-FAP), and network-fuzzy analytic process (NFh-AP). The criteria weights integration was not stochastic; therefore, Eq. (11) achieved the normalisation.

Fig. 11 shows the integrated weights of criteria assessed by each algorithm. There are fluctuations in criteria weights comparing the SMCDM methods and IMCDM methods. For example, H-FAP assessed roads at 23.68% are lower than the weight produced by AHP (26%), and

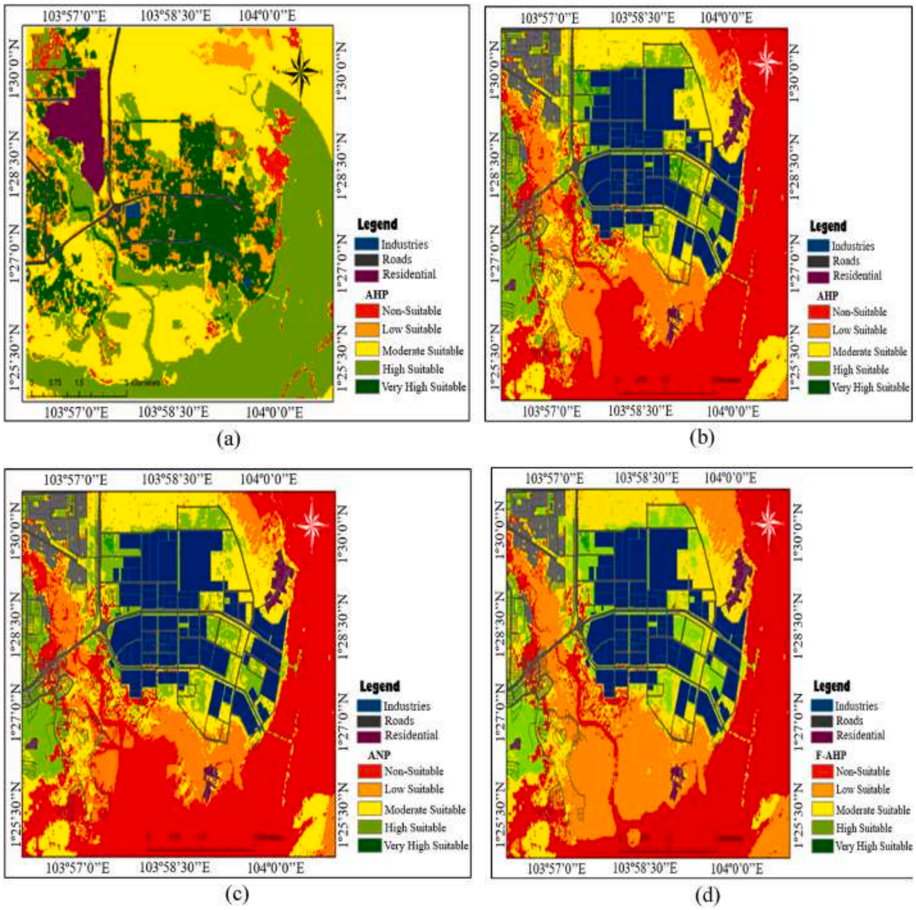

Fig. 15. Superimposed criteria layers (a) AHP with 2009 data, (b) AHP with 2019 data; (c) ANP with 2019 data, and (d) F-AHP with 2019 data.

water bodies at 24.38% are above by AHP (21%). The weights for roads (16.4%) and water bodies (17.1%) by ANP fall short of the H-NAP method, while F-AHP measured water bodies 28% above the H-NAP. The instability of the methods as measured by the sensitivity analyses between ±2% and ±5% increases from AHP, ANP and F-AHP as shown by the error bars in Figs. 7(b), 9(b) and 10(b), while for all the IMCDM methods is highly stable.

The standard deviation (SD) values in Fig. 12 show the consistency of the IMCDM (HN-FAP, HNAP, H-FAP, and NFh-AP) and SMCDM (AHP, ANP, and F-AHP) approaches. The SD compares the dispersion of the value of a criterion given by the technique to the average of the values of the set of criteria to determine the consistency of a technique in weight evaluation. In other words, if the SD value is larger, the criteria value deviates greatly from the average of the set, making the approach unreliable; otherwise, it is consistent and dependable. In the ranking of spatial criteria and decision-making methods, SD values of less than 5.0 and more than 6.5 reflect measurements of criteria values that are too close and far from the average of the set of criteria (Pacheco and Krohling, 2018). As a result of this issue, criteria become more competitive and tougher to rate, posing consistency issues. Fig. 12 indicates that the SD of AHP and F-AHP are 7.08 and 6.68 higher than the acceptable limit of 5–6.5, whereas ANP (0.38) is significantly lower, indicating that consistency issues exist. The SD of HN-FAP and HNAP is below the consistency index because both contain AHP and ANP, which are from the same MCDM scoring group. The SD values of the H-FAP (6.54) and NFh-AP (5.42) methods are within the reliability index, which improved against the SMCDM methods due to the hierarchy-fuzzy and network-fuzzy methods from different MCDM groups, which have neutralised the weaknesses of each and enhanced their advantages.

5.7. The MCDM-GIS model

Fig. 13 shows the MCDM–GIS model built for the criteria weight and spatial data layers overlay analysis. The input tools initially appeared grey, indicating no data, but by adding data, they changed into blue colour. The processing and output tools also changed into yellow and green, ready to process and give results. The “P” indicates a dialogue box for a parameter to be added by a third party to process a larger dataset. The criteria raster layers and the criteria weights were overlaid, RUN, and the EIP suitable sites layers were generated. Only the model parameters added to the map became the model outputs, and each output tool formed a shadow indicating a successful run.

5.8. EIP site layers produced by single criteria weights in weighted overlay analysis

The EIP site suitability was grouped into 5 namely: very-highly-suitable, highly-suitable, moderately-suitable, low-suitable and unsuitable sites. As shown in Fig. 14(a) and (b) and 14(c), the TLIA 2009 spatial data with AHP, ANP, and F-AHP weights display the same site suitability of 17% shown in dark green for very-highly-suitable, 21% for highly-suitable in light green, 42% moderately-suitable in yellow, 15% in pink as low-suitable, and 5% non-suitable sites noticeable in red. The three SMCDM techniques identified the whole of water bodies as a suitable EIP. Identifying the entire water bodies by AHP, ANP, and F-AHP weights with 2009 spatial criteria data shows that either the methods have inconsistency in criteria weighting and difficulty in detecting sparse criteria or the model has a deficiency. Fang & Partovi (2021) reported that water bodies can only be closed to the EIP site which is important for easy and cheap transportation of bulk raw and

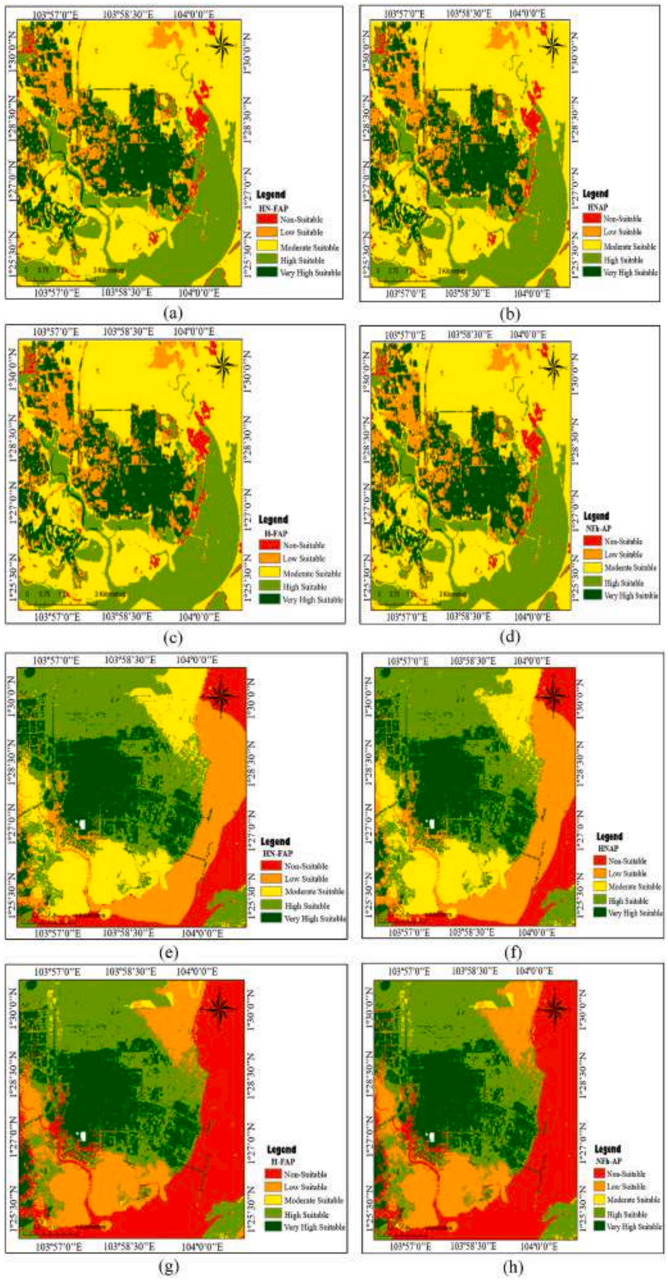

Fig. 16. Selection of Suitable EIP Sites Using Integrated MCDM Weights of (a) HN-FAP and 2009 Data, (b) HNAP and 2009 Data, (c) H-FAP and 2009 Data, (d) NFh-AP and 2009, (e) HN-FAP and 2019 data (f) HNAP and 2019 Data, (g) H-FAP and 2019 Data, (h) NFh-AP and 2019 Data.

finished products.

The spatial criteria data of 2019, a ten-year interval, was used to test the efficiency of the model while maintaining the same criteria weights of importance for the three methods. Fig. 14(d) generated by the AHP method shows 5% as the very-highly suitable site, 24% as highly-suitable, 26% as moderately-suitable, 16% as low-suitable, and 29% as non-suitable. Fig. 14(e) shows ANP with 2%, 24%, 26%, 15%, and 33% for the very-highly-suitable, highly-suitable, moderately-suitable, low-suitable, and non-suitable sites. F-AHP in Fig. 14(f) ranked the very-highly-suitable, highly-suitable, moderately-suitable, low-suitable, and non-suitable EIP site as 3%, 23%, 26%, 20%, and 28%. The AHP identified a little larger very-highly-suitable sites compared to ANP and F-AHP. The SMCDM methods responded to concentrated spatial criteria, generating well-defined EIP suitability maps. However, the weaknesses are the tiny areas (in thick green) identified as very-highly-suitable EIP sites found in the northern part. SMCDM approaches are weak with concentrated criteria for computing spatial criteria weights for industrial site selection. Nevertheless, Danesh et al. (2017) reported that they are useful for comparing non-spatial quantities.

5.9. Criteria layers superimposed on EIP suitability maps produced by SMCDM

Fig. 15 shows the superimposed roads, residential area, and industry spatial criteria on the EIP site suitability layers. Fig. 15(a) is a representation of the layers in which the weights assessed by SMCDM methods weights overlaid with 2009 spatial data. The roads and industries aligned with the very-highly-suitable sites, while the residential consumed part of the very-highly-suitable site in the north-eastern part. Fig. 15(b), (c), and 15(d) generated using 2019 criteria data with AHP, ANP, and F-AHP methods show very-highly-suitable locations outside the existing industries. This is a drawback of the SMCDM methods. Asadabadi et al. (2019) emphasised the importance of geospatial technologies in the investigation and selection of industrial sites, as they help in determining site suitability.

5.10. Suitable EIP site layers produced by integrated criteria weights in weighted overlay analysis

The criteria weight consistencies were further tested, where the IMCDM weights were run into the model with the 2009 and 2019 spatial criteria data, while the MCDM-GIS model was also further tested for efficiency. As shown in Fig. 16(a) and (b), 16(c) and 16(d), the HN-FAP, HNAP, H-FAP, and NFh-AP with the 2009 data generated the same sizes of EIP sites identified at 17% as very-highly-suitable, 21% highly-suitable, 42% moderately-suitable, 15% low-suitable, and 5% non-suitable sites. These methods also scored the entire water bodies as suitable sites, suggesting the scarcity of the criteria compelled the algorithm to pick on water bodies. When the same IMCDM criteria weights were overlaid with 2019 spatial criteria data, large and varied sizes of the suitable EIP sites layers were generated. Fig. 16(e) and (f) show HN-FAP and HNAP ranked 24%, 33%, 21%, 12% and 10% each as very-highly-suitable, highly-suitable, moderately-suitable, low-suitable, and non-suitable EIP sites. These tools also measured about 12% of parts of the water bodies as low-suitable EIP sites, showing a slight weakness of the techniques. Water bodies can only be closed to the potential EIP site, which this study assigned 3 km to the Euclidean distance layers. The inside of an ocean cannot be used to build an industry even if the suitable sites get exhausted. According to Reisi et al., (2018), water bodies near the EIP location are one of the most important factors for establishing an industrial park.

The H-FAP and NFh-AP in Fig. 16(g) and (h) identified equal sites of very-highly-suitable, highly-suitable, moderately-suitable, low-suitable, and non-suitable sites of 24%, 33%, 4%, 18%, and 21%. These techniques distinctly identified the five categories of suitability without overlapping and marked the water bodies to be non-suitable but must only be close to the EIP sites. These integrated tools have used and consolidated the hierarchical, networking, and fuzzy reasoning to overcome the weaknesses and improved the strengths of the tools which assessed consistent criteria weights. As Pourahmad et al. (2015) suggested, the integrated MCDM tools eliminated the disadvantage and improved the advantages of another. The overlay of the reliable MCDM algorithm weights with spatial criteria in the GIS makes a powerful approach for the selection of the best EIP site (Pourahmad et al., 2015).

5.11. Criteria layers superimposed on EIP suitability maps produced by IMCDM

Fig. 17(a) and (b) show the existing industries exactly in the very-highly-suitable sites. Residential area engulfed part of the highly-

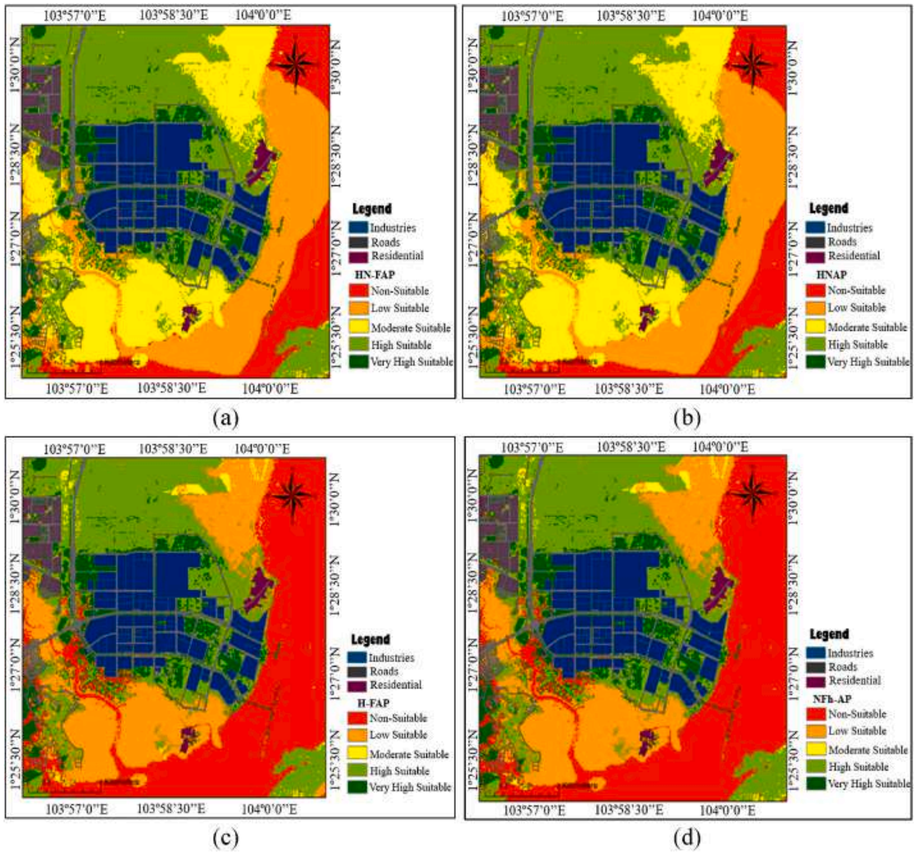

Fig. 17. Superimposed criteria layers of (a) HN-FAP with 2019 data, (b) HNAP with 2019 data, (c) H-FAP with 2019 data, (d) NFh-AP with 2019 data.

suitable areas in the eastern part, which of course could have been built in the moderately-suitable site of the north-east in Fig. 17(a) and (b), and in the low-suitable site of north-east in Fig. 17(c) and (d). The precise location of existing industries in the very-highly-suitable sites in Fig. 17(c) and (d) further demonstrated the H-FAP and NFh-AP weighting consistencies and the model efficiency. Ahmed et al. (2020) informed that suitable EIP sites increase for industry expansion when features such as residential areas are established in the low or non-suitable sites.

SMCDM methods with scanty or concentrated spatial criteria have been indicated to be unreliable for brownfield and greenfield investigation for EIP sites. Since AHP and ANP belong to the same paired comparison group, it is difficult to provide a consistent MCMDM algorithm when combined. Integrating hierarchical, geometric ratios and networking which formed paired comparison and uncertainty, produced weights optimally away from the average of the set of the criteria as shown by the SD. This resulted in the consistent integrated H-FAP and NFh-AP algorithms that expressed the strengths in eliminating the restrictions and produced consistent weights. The H-FAP and NFh-AP demonstrated to be the best integrated algorithms along with concentrated spatial criteria for the investigation of brownfield industrial parks for EIP development. This is because of the distinct separation of all the five suitable sites which showed the water bodies as unsuitable but should be closed to the suitable site. The model in its part is efficient since it defined different categories of suitable sites as expected under various weights and spatial criteria conditions. In comparison to Yousefi et al. (2016), who used AHP and WLC independently and obtained wide criteria weights with unreliable industrial sites, these algorithms and the model performed well in providing better and more specified BF-EIP suitable sites. When Ahmadipari et al. (2018) employed Delphi and FAHP to choose an industrial site, the conclusions were rejected due to a large spectrum of variances in weights. When TOPSIS, SAW, and WLC was applied to analyze the suitability of the industrial site and its proximity to restricted areas, the outcomes of Naghdi et al. (2017) reported inconsistencies due to the high number of criteria involved. The IMCDM approaches solved the limitations and strengthened the advantages of the associated tools (Nuhu et al., 2021). H-FAP and NFh-AP algorithms eliminated the uncertainties of criteria having near weights, few number of criteria and permitted interdependence which produced consistent weights for decision-making.

The IMCDM is simple to design once the SMCDM methods can be constructed and evaluated. The standard deviation helps in checking the consistency which decreases multiple trials for modelling. The evaluation and integration of the SMCDM methods can be done without the use of complex software. The advantage of the MCDM-GIS model is that it allows a third party to add additional criteria spatial layers for modelling. It also detects incorrect spatial criteria layer upload, which results in no shadow at the processing and outcome tools, indicating an unsuccessful execution. The disadvantage of both the IMCDM and the model is that the knowledge and understanding of GIS for the conversion of spatial criteria to raster layers are essential, otherwise, the analysis can be impossible.

Selecting a suitable location is the basic approach to EIP development (Pramanik, 2016), and it is a decision that has an important impact on the environment (Chumaidiyah et al., 2020), which can make EIP attain or fail its goals. The transformation of BFIP to BF-EIP is increasing general recognition due to the 2015 Paris Agreement for reduction of carbon footprint and improved cleaner production, and the UNIDO effort for industries synergies. The development and usage of the IMCDM techniques for the evaluation of consistent criteria weights and combined with the GIS to identify accurately suitable EIP sites is strongly required. Suitable EIP sites attract industry clusters whose companies seek not only to go beyond the sustainable green goals of re-using or decreasing waste, energy, and pollution management but also to make profits and take part in innovation strategies to gain viable benefits (Sellitto and Hermann, 2016).

6. Conclusion

The purpose of this study was to build a consistent IMCDM algorithm from SMCDM traditional methods which have limitations in evaluating consistent spatial criteria weights, also to design an MCDM-GIS model for easy and accurate weighted overlay analysis to select brownfields for suitable EIP sites. The AHP, ANP, and F-AHP were used to assess the spatial criteria weights and were subsequently integrated into four algorithms. The MCDM-GIS model overlaid the criteria weights with the 2009 and 2019 spatial layers of Tanjung Langsat Industrial Area (TLIA) and tested for EIP site suitability selection. All SMCDM and IMCDM criteria weights using 2009 spatial data recorded 17% for very-highly-suitable sites. Using the 2019 spatial data, AHP, ANP and F-AHP identified 5%, 2% and 3% tiny very-highly-suitable sites in the northern part. The SMCDM methods included the water bodies as suitable sites and identified tiny best suitable sites in the northern part. These show consistent criteria weight assessment limitations even by using both scarce and concentrated criteria. The weighting consistency, the criteria insufficiency, and the model efficiency were further verified using the IMCDM weights. The HN-FAP and HNAP algorithms with the 2019 spatial data identified 24% very-highly-suitable sites but included about 12% of water bodies as low-suitable sites. Water bodies themselves cannot be suitable criteria because industries cannot be built inside water. Rather, water bodies need to be close to the EIP suitable site. The H-FAP and NFh-AP scored 24% for the best suitable site using the 2019 spatial data showing a clear partition of the various suitable sites.

The integrated H-FAP and NFh-AP algorithms achieved the purpose of the integration for generating well defined and larger EIP suitable sites. The criteria weights of the two methods show nearness to the averages of the criteria sets, making them robust, but only with dense brownfield spatial criteria. The algorithms can be put to test using spatial criteria collected from any part of the globe. The MCDM-GIS model is efficient and owing to the drop-down menu (P), a third party can add new spatial criteria. The H-FAP and NFh-AP integrated algorithms and the model will assist the government, EIP investors/developers, and researchers in evaluating consistent criteria weights for the selection and conversion of brownfield to EIP sites for industry clusters symbiosis, pollution control, and industrial sustainability. The addition/withdrawal of alternatives leading to a rank reversal of MCDM could be future research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgement

The authors are grateful to the Ministry of Higher Education for providing the research grant MRUN 4.2–Online System for Industrial Energy and Emission Reductions (Grant No. R.J130000.7808.4L884) to support this research.

References

Ahmadipari, M., Hoveidi, H., Jafari, H.R., Pazoki, M., 2018. An integrated environmental management approach to industrial site selection by genetic algorithm and fuzzy analytic hierarchy process in a geographical information system. Global J. Environ. Sci. Manag. 4 (3), 339–350. https://doi.org/10.22034/GJESM.2018.03.007.

Ahmed, W., Tan, Q., Solangi, Y.A., Ali, S., 2020. Sustainable and special economic zone selection under fuzzy environment: a case of Pakistan. Symmetry 12 (2). https://doi.org/10.3390/sym12020242.

Ajibade, F.O., Olajire, O.O., Ajibade, T.F., Nwogwu, N.A., Lasisi, K.H., Alo, A.B., Owolabi, T.A., Adewumi, J.R., 2019. Combining multicriteria decision analysis with GIS for suitably siting landfills in a Nigerian state. Environ. Sustain. Indicat. 3–4, 100010 https://doi.org/10.1016/j.indic.2019.100010.

Akther, A., Ahamed, T., Noguchi, R., Genkawa, T., Takigawa, T., 2019. Site suitability analysis of biogas digester plant for municipal waste using GIS and multi-criteria analysis. Asia-Pacific J. Reg. Sci. 3 (1), 61–93. https://doi.org/10.1007/s41685-018-0084-2.

Asadabadi, M.R., Chang, E., Saberi, M., 2019. Are MCDM methods useful? A critical review of the analytic hierarchy process (AHP) and analytic network process (ANP). Cogent Eng. 6 (1), 1–11. https://doi.org/10.1080/23311916.2019.1623153.

Avtar, R., Sahu, N., Aggarwal, A.K., Chakraborty, S., Kharrazi, A., Yunus, A.P., Dou, J., Kurniawan, T.A., 2019. Remote sensing and GIS — a review. Resources 8 (3), 149. https://doi.org/10.3390/resources8030149.

Azizi, A., Malekmohammadi, B., Jafari, H.R., Nasiri, H., Parsa, V.A., 2014. Land suitability assessment for wind power plant site selection using ANP-DEMATEL in a GIS environment: a case study of Ardabil province, Iran. Environ. Monit. Assess. 186 (10), 6695–6709. https://doi.org/10.1007/s10661-014-3883-6.

Babalola, M., 2018. Application of GIS-based multi-criteria decision technique in exploration of suitable site options for anaerobic digestion of food and biodegradable waste in oita city, Japan. Environments 5 (7), 77. https://doi.org/10.3390/environments5070077.

Bansal, A., Kumar, B., Garg, R., 2017. Multi-criteria decision-making approach for the selection of software effort estimation model. Manag. Sci. Lett. 7 (6), 285–296. https://doi.org/10.5267/j.msl.2017.3.003.

Barzehkar, M., Dinan, N.M., Mazaheri, S., Tayebi, R.M., Brodie, G.I., 2019. Landfill site selection using GIS-based multi-criteria evaluation (case study: SaharKhiz Region located in Gilan Province in Iran). SN Appl. Sci. 1 (9), 1–11. https://doi.org/10.1007/s42452-019-1109-9.

Barzilai, J., Golany, B., 1994. AHP rank reversal, normalization and aggregation rules. INFOR Inf. Syst. Oper. Res. 32 (2), 57–64. https://doi.org/10.1080/03155986.1994.11732238.

Beers, D. van, Flammini, A., Meylan, F.D., Stucki, J., 2019. Lessons learned from the application of the unido eco-industrial park toolbox in Viet Nam and other countries. Sustainability 11 (17), 1–18. https://doi.org/10.3390/su11174687.

Belton, V., Gear, T., 1983. On a shortcoming of Saaty's method of analytic hierarchies. Omega 11 (3), 228–230. https://doi.org/10.1016/0305-0483(83)90047-6.

Buckley, J.J., 1985. Fuzzy hierarchical analysis. Fuzzy Set Syst. 17 (3), 233–247. https://doi.org/10.1016/0165-0114(85)90090-9.

Buede, D.M., Maxwell, D.T., 1995. Rank disagreement: a comparison of multi-criteria methodologies. J. Multi-Criteria Decis. Anal. 4 (1), 1–21. https://doi.org/10.1002/mcda.4020040102.

Ceballos, B., Lamata, M.T., Pelta, D.A., 2016. A comparative analysis of multi-criteria decision-making methods. Prog. Artif. Intell. 5 (4), 315–322. https://doi.org/10.1007/s13748-016-0093-1.

Chang, D.Y., 1996. Applications of the extent analysis method on fuzzy AHP. Eur. J. Oper. Res. 95 (3), 649–655. https://doi.org/10.1016/0377-2217(95)00300-2.

Chang, P., Lin, H., 2015. Manufacturing plant location selection in logistics network using analytic hierarchy process. J. Ind. Eng. Manag. 8 (5), 1547–1575. http://hdl.handle.net/10419/188749.

Chang, P.Y., Lin, H.Y., Fataei, E., erdi, M.A., Farhadi, H., Mohammadian, A., Rikalovic, A., Cosic, I., Labati, R.D., Piuri, V., Chang, P.Y., Lin, H.Y., Feiz, R., Rikalovic, A., Cosic, I., Labati, R.D., Piuri, V., 2015. A comprehensive method for industrial site selection: the macro-location analysis. IEEE Syst. J. 8 (5), 1547–1575. https://doi.org/10.3384/lic.diva-105942.

Chen, S.J., Chen, S.M., 2007. Fuzzy risk analysis based on the ranking of generalized trapezoidal fuzzy numbers. Appl. Intell. 26 (1), 1–11. https://doi.org/10.1007/s10489-006-0003-5.

Chen, W., Zhu, Y., Yang, M., Yuan, J., 2017. Optimal site selection of wind-solar complementary power generation project for a large-scale plug-in charging station. Sustainability 9 (11). https://doi.org/10.3390/su9111994.

Chumaidiyah, E., Dewantoro, M.D.R., Hakimah, D.A., Arffan, Z., Robbi, R.M.N., 2020. Measurement of criterion weight to determine industrial area location using AHP for economic growth. IOP Conf. Ser. Mater. Sci. Eng. 1, 1003. https://doi.org/10.1088/1757-899X/1003/1/012154.

Danesh, D., Ryan, M.J., Abbasi, A., 2017. A systematic comparison of multi-criteria decision-making methods for the improvement of project portfolio management in complex organisations. Int. J. Manag. Decis. Making 16 (3), 280–320. https://doi.org/10.1504/IJMDM.2017.085638.

Das, S., Gupta, A., 2021. Geoscience Frontiers Multi-criteria decision based geospatial mapping of flood susceptibility and temporal hydro-geomorphic changes in the Subarnarekha basin. Geosci. Front. 12 (5), 101206 https://doi.org/10.1016/j.gsf.2021.101206.

Deswal, M., Laura, J.S., 2018. GIS-based modelling using Analytic Hierarchy Process (AHP) for optimization of landfill site selection of Rohtak city, Haryana (India). J. Appl. Nat. Sci. 10 (2), 633–642. https://doi.org/10.31018/jans.v10i2.1753.

Donni, M., Siahaan, L., Surbakti, A.B., Lubis, A.H., 2017. Implementation of simple additive weighting algorithm in particular instance. Int. J. Sci. Res. Sci. Technol. 3 (6), 442–447.

Dos Santos, P.H., Neves, S.M., Sant'Anna, D.O., Oliveira, C.H. de, Carvalho, H.D., 2019. The analytic hierarchy process supporting decision making for sustainable development: an overview of applications. J. Clean. Prod. 212, 119–138. https://doi.org/10.1016/j.jclepro.2018.11.270.

Erdogan, S.A., Šaparauskas, J., Turskis, Z., 2019. A multi-criteria decision-making model to choose the best option for sustainable construction management. Sustainability 11 (8). https://doi.org/10.3390/su11082239.
Fang, J., Partovi, F.Y., 2021. Criteria determination of analytic hierarchy process using a topic model. Expert Syst. Appl. 169, 1–13. https://doi.org/10.1016/j.eswa.2020.114306.
Farkas, A., György, A., Rózsa, P., 2004. On the spectrum of pairwise comparison matrices. Lin. Algebra Appl. 385 (1–3), 443–462. https://doi.org/10.1016/j.laa.2003.12.034.
Fataei, E., erdi, M.A., Farhadi, H., Mohammadian, A., 2015. Industrial state site selection using MCDM method and GIS in Germi, ardabil, Iran. J. Ind. Intel. Inf. 3 (4), 324–329. https://doi.org/10.12720/jiii.3.4.324-329.
Fishburn, P.C., 1968. Utility theory. Manag. Sci. 14 (5), 335–378. https://doi.org/10.1287/mnsc.14.5.335.
Gabus, A., Fontela, E., 1973. Perceptions of the World Problem-Matique: Communication Procedure, Communicating with Those Bearing Collective Responsibility. DEMATEL, vols. 11–18. Geneva Research Center, Battelle, Geneva.
Gao, Chengkang, Gao, Chengbo, Song, K., Ye, Z., Dong, J., 2019. Regional water ecosystem risk assessment based on GIS and pollutant diffusion model: a case study of Shenzhen eco-industrial park. Process Saf. Environ. Protect. 130, 182–189. https://doi.org/10.1016/j.psep.2019.08.004.
García-Cascales, M.S., Lamata, M.T., 2012. On rank reversal and TOPSIS method. Math. Comput. Model. 56 (5–6), 123–132. https://doi.org/10.1016/j.mcm.2011.12.022.
Ghobadi, M., Ahmadipari, M., 2018. Environmental planning for wind power plant site selection using a fuzzy PROMETHEE-based outranking method in. Geograph. Inf. Syst. 2 (2), 75–87. https://doi.org/10.22097/eeer.2018.148760.1041.
Hassaan, M.A., Hassan, A., Al-Dashti, H., 2020. GIS-based suitability analysis for siting solar power plants in Kuwait. Egy. J. Remo. Sens. Space Sci. 24 (3), 453–461. https://doi.org/10.1016/j.ejrs.2020.11.004.
Hwang, C.L., Yoon, K., 1981. Basic concepts and foundations: in multiple attribute decision making. Lect. Notes Econ. Math. Syst. 186, 16–57. https://doi.org/10.1007/978-3-642-48318-9_2. Springer.
IPCC, 2019. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. In: Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., et al. (Eds.), Climate Change: Mitigation of Climate Change. Cambridge.
Jangid, J., Bera, A.K., Joseph, M., Singh, V., Singh, T.P., Pradhan, B.K., Das, S., 2016. Potential zones identification for harvesting wind energy resources in the desert region of India – a multi-criteria evaluation approach using remote sensing and GIS. Renew. Sustain. Energy Rev. 65, 1–10. https://doi.org/10.1016/j.rser.2016.06.078.
Kamali, M., Alesheikh, A.A., Alavi Borazjani, S.A., Jahanshahi, A., Khodaparast, Z., Khalaj, M., 2017. Delphi-AHP and weighted index Overlay-GIS approaches for industrial site selection case study: large extractive industrial units in Iran. J. Settlements Spat. Plan. 8 (2), 99–105. https://doi.org/10.24193/JSSP.2017.2.03.
Kamdar, I., Ali, S., Bennui, A., Techato, K., Jutidamrongphan, W., 2019. Municipal solid waste landfill siting using an integrated GIS-AHP approach: a case study from Songkhla, Thailand. Resour. Conserv. Recycl. 149, 220–235. https://doi.org/10.1016/j.resconrec.2019.05.027.
Kanniah, K.D., Sheikhi, A., Cracknell, A.P., Goh, H.C., Tan, K.P., Ho, C.S., Rasli, F.N., 2015. Satellite images for monitoring mangrove cover changes in a fast growing economic region in southern peninsular Malaysia. Rem. Sens. 7 (11), 14360–14385. https://doi.org/10.3390/rs71114360.
Keeling, C.D., 1960. The concentration and isotopic abundances of carbon dioxide in the atmosphere. Tellus 12 (2), 200–203. https://doi.org/10.3402/tellusa.v12i2.9366.
Khan, M.M.U.H., Vaezi, M., Kumar, A., 2018. Optimal siting of solid waste-to-value-added facilities through a GIS-based assessment. Sci. Total Environ. 610–611, 1065–1075. https://doi.org/10.1016/j.scitotenv.2017.08.169.
Kolhoff, A.J., Driessen, P.P.J., Runhaar, H.A.C., 2018. Overcoming low EIA performance - a diagnostic tool for the deliberate development of EIA system capacities in low and middle-income countries. Environ. Impact Assess. Rev. 68, 98–108. https://doi.org/10.1016/j.eiar.2017.11.001.
Kong, F., 2011. Rank reversal and rank preservation in TOPSIS. Adv. Mater. Res. 204–210 (1), 36–41. https://doi.org/10.4028/www.scientific.net/AMR.204-210.36.
Kubler, S., Robert, J., Derigent, W., Voisin, A., Le Traon, Y., 2016. A state-of-the-art survey & testbed of Fuzzy AHP (FAHP) applications. Expert Syst. Appl. 65, 398–422. https://doi.org/10.1016/j.eswa.2016.08.064.
Kucukvar, M., Onat, N.C., Haider, M.A., 2018. Material dependence of national energy development plans: the case for Turkey and United Kingdom. J. Clean. Prod. 200, 490–500. https://doi.org/10.1016/j.jclepro.2018.07.245.
Li, C., Wu, J., Zeng, T., 2020. Global industrial park research trends: a bibliometric analysis from 1987 to 2016. Environ. Monit. Assess. 192 (1) https://doi.org/10.1007/s10661-019-7993-z.
Liu, X., Ma, Y., 2021. A method to analyze the rank reversal problem is the ELECTRE II method. Omega (United Kingdom) 102, 102317. https://doi.org/10.1016/j.omega.2020.102317.
Luthra, S., Kumar, A., Zavadskas, E.K., Mangla, S.K., Garza-Reyes, J.A., 2020. Industry 4.0 as an enabler of sustainability diffusion in the supply chain: an analysis of influential strength of drivers in an emerging economy. Int. J. Prod. Res. 58 (5), 1505–1521. https://doi.org/10.1080/00207543.2019.1660828.
MacCrimmon, K.R., 1968. Decision Marking Among Multiple–Attribute Alternatives: A Survey and Consolidated Approach, RAND Memorandum, second ed. The Rand Corporation, Santa Monica, Califonia, U.S.A, p. 72.
Malczewski, J., 1996. International Journal of Geographical Information A GIS-based approach to multiple criteria group decision-making. Int. J. Geogr. Inf. Syst. 37–41.
Maurice, J., 2015. UN set to change the world with new development goals. Lancet 386 (9999), 1121–1124. https://doi.org/10.1016/S0140-6736(15)00251-2.
Messaoudi, D., Settou, N., Negrou, B., Rahmouni, S., Settou, B., Mayou, I., 2019. Site selection methodology for the wind-powered hydrogen refuelling station based on AHP-GIS in Adrar, Algeria. Energy Proc. 162, 67–76. https://doi.org/10.1016/j.egypro.2019.04.008.
Monsef, A.H., Smith, S.E., 2019. Integrating remote sensing, geographic information system, and analytical hierarchy process for hazardous waste landfill site selection. Arabian J. Geosci. 12 (5), 155.
Moreau, V., Sahakian, M., van Griethuysen, P., Vuille, F., 2017. Coming full circle: why social and institutional dimensions matter for the circular economy. J. Ind. Ecol. 21, 497–506. https://doi.org/10.1111/jiec.12598.
Moses, A., Iwara, E., Gbadebo, N., Olubukola, O., Omin, I., et al., 2018. Geographic foci of industries: A suitability analysis. J. Geogr. Environ. Earth Sci. Int. 14 (1), 1–14. https://doi.org/10.9734/jgeesi/2018/39994.
Muhsin, N., Ahamed, T., Noguchi, R., 2018. GIS-based multi-criteria analysis modelling used to locate suitable sites for industries in suburban areas in Bangladesh to ensure the sustainability of agricultural lands. Asia-Pacific J. Reg. Sci. 2 (1), 35–64. https://doi.org/10.1007/s41685-017-0046-0.
Naghdi, F., Monavvari, S.M., Hosseini, S.M., Gharagozlu, A., 2017. Industrial zoning of east Azerbaijan province of Iran using multi-criteria evaluation modelling. J. Appl. Ecol. Environ. Res. 15 (3), 1565–1576. https://doi.org/10.15666/aeer/1503_15651576.
Neves, A., Godina, R., Azevedo, S.G., Matias, J.C.O., 2020. A comprehensive review of industrial symbiosis. J. Clean. Prod. 247, 119113 https://doi.org/10.1016/j.jclepro.2019.119113.
Nguyen, H.T., Md Dawal, S.Z., Nukman, Y., Rifai, A.P., Aoyama, H., 2016. An integrated MCDM model for conveyor equipment evaluation and selection in an FMC based on a Fuzzy AHP and Fuzzy ARAS in the presence of vagueness. PLoS One 11 (4), 1–26. https://doi.org/10.1371/journal.pone.0153222.
Noorollahi, Y., Yousefi, H., Mohammadi, M., 2016. Multi-criteria decision support system for wind farm site selection using GIS. Sustain. Energy Technol. Assessments 13, 38–50. https://doi.org/10.1016/j.seta.2015.11.007.
Nuhu, S.K., Manan, Z.A., Alwi, S.R., Reba, M.N.M., 2021. A new hybrid modelling approach for an eco-industrial park site selection. Chem. Eng. Trans. 89, 343–348. https://doi.org/10.3303/CET2189058.
Okada, A., Siddharthan, N., 2007. Industrial Clusters in India: Evidence from Automobile Clusters in Chennai and the National Capital Region. Institute of Developing Economies, pp. 1–107.
Opricovic, S., 1998. Multicriteria optimization of civil engineering systems. Facul. Civil Eng. 2 (1), 5–21. Belgrade.
Pacheco, A.G.C., Krohling, R.A., 2018. Ranking of classification algorithms in terms of mean–standard deviation using A-TOPSIS. Annal. Data Sci. 5 (1), 93–110. https://doi.org/10.1007/s40745-018-0136-5.
Paul, S.K., 2015. Supplier selection for managing supply risks in the supply chain: a fuzzy approach. Int. J. Adv. Manuf. Technol. 79 (1–4), 657–664. https://doi.org/10.1007/s00170-015-6867-y.
Penadés-Plà, V., García-Segura, T., Martí, J.V., Yepes, V., 2016. A review of multi-criteria decision-making methods applied to the sustainable bridge design. Sustainability 8 (12). https://doi.org/10.3390/su8121295.
IPCC, Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., B., I., 2019, 1454. In: Climate Change: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, p. 147. www.cambridge.org/9781107654815United Kingdom and New York, NY, USA.
Pourahmad, A., Hosseini, A., Banaitis, A., Nasiri, H., Banaitienė, N., Tzeng, G.-H., 2015. Combination of fuzzy-AHP and DEMATEL-ANP with GIS in a new hybrid MCDM model used for the selection of the best space for leisure in a blighted urban site. Technol. Econ. Dev. Econ. 21 (5), 773–796. https://doi.org/10.3846/20294913.2015.1056279.
Pramanik, M.K., 2016. Site suitability analysis for agricultural land use of Darjeeling district using AHP and GIS techniques. Model. Earth Syst. Environ. 2 (2), 1–22. https://doi.org/10.1007/s40808-016-0116-8.
Rahmat, Z.G., Niri, M.V., Alavi, N., Goudarzi, G., Babaei, A.A., Baboli, Z., Hosseinzadeh, M., 2017. Landfill site selection using GIS and AHP: a case study: behbahan, Iran. KSCE J. Civ. Eng. 21 (1), 111–118. https://doi.org/10.1007/s12205-016-0296-9.
Reisi, M., Afzali, A., Aye, L., 2018a. Applications of analytical hierarchy process (AHP) and analytical network process (ANP) for industrial site selections in Isfahan, Iran. Environ. Earth Sci. 77 (14), 1–13. https://doi.org/10.1007/s12665-018-7702-1.
Reisi, M., Afzali, A., Aye, L., 2018b. Applications of analytical hierarchy process (AHP) and analytical network process (ANP) for industrial site selections in Isfahan, Iran. Environ. Earth Sci. 77 (14), 1–13. https://doi.org/10.1007/s12665-018-7702-1.
Rezaei, J., 2016. Best-worst multi-criteria decision-making method: some properties and a linear model. Omega (United Kingdom) 64, 126–130. https://doi.org/10.1016/j.omega.2015.12.001.
Rikalovic, A., Cosic, I., Labati, R.D., Piuri, V., 2018. Intelligent decision support system for industrial site classification: a GIS-based hierarchical neuro-fuzzy approach. IEEE Syst. J. 12 (3), 2970–2981. https://doi.org/10.1109/JSYST.2017.2697043.
Rizzo, E., Pesce, M., Pizzol, L., Alexandrescu, F.M., Giubilato, E., Critto, A., Marcomini, A., Bartke, S., 2015. Brownfield regeneration in Europe: identifying stakeholder perceptions, concerns, attitudes and information needs. Land Use Pol. 48, 437–453. https://doi.org/10.1016/j.landusepol.2015.06.012.
Rodríguez, A., Ortega, F., Concepción, R., 2013. A method for the selection of customized equipment suppliers. Expert Syst. Appl. 40 (4), 1170–1176. https://doi.org/10.1016/j.eswa.2012.08.021.
Saaty, T.L., 1977. A scaling method for priorities in hierarchical structures. J. Math. Psychol. 15 (3), 234–281. https://doi.org/10.1016/0022-2496(77)90033-5.

Saaty, T.L., 1987. Concepts, theory and techniques: rank generation, preservation, and reversal in the analytic hierarchy decision process. Decis. Sci. J. 18 (2), 157–177. https://doi.org/10.1111/j.1540-5915.1987.tb01514.x.

Sarmiento, R., Vargas-Berrones, K.X., 2018. Modelling the implementation of green initiatives: an AHP-BOCR approach. Cogent Eng. 5 (1), 4–17. https://doi.org/10.1080/23311916.2018.1432120.

Schenkerman, S., 1994. Avoiding rank reversal in AHP decision-support models. Eur. J. Oper. Res. 74 (3), 407–419. https://doi.org/10.1016/0377-2217(94)90220-8.

Sedrati, M., Maanan, M., Rhinane, H., 2019. PV power plants sites selection using GIS-FAHP based approach in north-western Morocco. Int. Arch. Photogram. Rem. Sens. Spatial Inf. Sci. ISPRS Archives 42 (4/W19), 385–392. https://doi.org/10.5194/isprs-archives-XLII-4-W19-385-2019.

Sellitto, M.A., Hermann, F.F., 2016. Prioritization of green practices in GSCM: a case study with companies of the peach industry. Gestão Produção 23 (4), 871–886. https://doi.org/10.1590/0104-530X2516-15.

Sellitto, M.A., Valladares, D.R.F., Pastore, E., Alfieri, A., 2021. Comparing competitive priorities of slow fashion and fast fashion operations of large retailers in an emerging economy. Global J. Flex. Syst. Manag. 23 (1), 1–19. https://doi.org/10.1007/s40171-021-00284-8.

Seyedmohammadi, J., Sarmadian, F., Jafarzadeh, A.A., Ghorbani, M.A., Shahbazi, F., 2018. Application of SAW, TOPSIS and fuzzy TOPSIS models in cultivation priority planning for maize, rapeseed and soybean crops. Geoderma 310, 178–190. https://doi.org/10.1016/j.geoderma.2017.09.012.

Shine, T.A.L., James, J., Dolly, D.E., Mathew, M., 2020. Design concepts of green and sustainable industrial park. Int. J. Sci. Res. Eng. Trends 6 (2), 734–738.

Showstack, R., 2013. Carbon dioxide tops 400 ppm at Mauna Loa, Hawaii. Trans. Am. Geophys. Union 94 (21), 192. https://doi.org/10.1002/2013eo210004. ISSN 0096-3941.

Singh, L.K., Jha, M.K., Chowdary, V.M., 2018. Assessing the accuracy of GIS-based Multi-Criteria Decision Analysis approaches for mapping groundwater potential. Ecol. Indicat. 91, 24–37. https://doi.org/10.1016/j.ecolind.2018.03.070.

Stojcic, M., Zavadskas, E.K., Pamucar, D., Stevic, Z., Mardani, A., 2019. Application of MCDM methods in sustainability engineering : a literature review 2008 – 2018. Symmetry 11 (350), 2–24. https://doi.org/10.3390/sym11030350.

Susur, E., Martin-Carrillo, D., Chiaroni, D., Hidalgo, A., 2019. Unfolding eco-industrial parks through niche experimentation: insights from three Italian cases. J. Clean. Prod. 239, 118069 https://doi.org/10.1016/j.jclepro.2019.118069.

Tavana, M., Yazdani, M., Di Caprio, D., 2017. An application of an integrated ANP–QFD framework for sustainable supplier selection. Int. J. Logist. Res. Appl. 20 (3), 254–275. https://doi.org/10.1080/13675567.2016.1219702.

Taye, B., Gebre, S.L., Gemeda, D.O., Getahun, K., 2019. Using geospatial techniques in the selection of potential ecotourism sites in menz-Geramidir district, Ethiopia. Ghana J. Geograh. 11 (1), 201–227.

Torabi-Kaveh, M., Babazadeh, R., Mohammadi, S.D., Zaresefat, M., 2016. Landfill site selection using a combination of GIS and fuzzy AHP, a case study: iranshahr, Iran. Waste Manag. Res. 34 (5), 438–448. https://doi.org/10.1177/0734242X16633777.

UNIDO, WBG and GIZ, 2021. An International Framework for Eco-Industrial Parks. World Bank, Washington, DC, USA. Version 2.0. https://openknowledge.worldbank.org/handle/10986/35110 License: CC BY-NC 3.0 IGO.

Valenzuela-Venegas, G., Vera-Hofmann, G., Díaz-Alvarado, F.A., 2020. Design of sustainable and resilient eco-industrial parks: planning the flows integration network through multi-objective optimization. J. Clean. Prod. 243, 118610 https://doi.org/10.1016/j.jclepro.2019.118610.

Yang, C.L., Chuang, S.P., Huang, R.H., Tai, C.C., 2008. Location selection based on AHP/ANP approach. In: IEEE International Conference on Industrial Engineering and Engineering Management. IEEM, pp. 1148–1153. https://doi.org/10.1109/IEEM.2008.4738050, 2008.

Yap, J., Ho, C., Ting, C., 2019. A systematic review of the applications of multi-criteria decision-making methods in site selection problems. Built Environ. Project Asset Manag. 9 (4), 548–563. https://doi.org/10.1108/BEPAM-05-2018-0078. J., Ho, C., & Ting, C.

Yousefi, E., Esmail, Salehi, Seyed, Hamid, Zahiri, yavar, Ahmadreza, 2016. Green space suitability analysis using evolutionary algorithm and weighted linear combination (WLC) method. Space Ontol. Int. J. 5 (4), 51–60 https://doi.org/20.1001.1.23456450.2016.5.4.5.5.

Yuen, K.K.F., 2012. Membership maximization prioritization methods for fuzzy analytic hierarchy process. Fuzzy Optim. Decis. Making 11 (2), 113–133. https://doi.org/10.1007/s10700-012-9119-8.

Zadeh, L.A., 1975. The concept of a linguistic variable and its application to approximate reasoning-I. Inf. Sci. 8 (3), 199–249. https://doi.org/10.1016/0020-0255(75)90036-5.

Zailan, R., Saad, S.F., Jamaluddin, K., Wan Alwi, S.R., Shiun, L.J., Tan, Y.D., Mohamad, S.N.H., Lawal, M., Misrol, M.A., Nuhu, S.K., Reba, M.N.M., Chin, T.A., Aspan, N., 2020. Towards eco-industrial park in Malaysia: promising opportunities, challenges and regulator roles. Int. J. Psychosoc. Rehabil. 24 (1), 562–570. https://doi.org/10.37200/IJPR/V24I1/PR200162.