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Siting MSW landfills via the integration of DEMATEL-ANP and clustering algorithm in a fuzzy logic environment (Case Study: Lanzhou, China)

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Abstract: The siting of Municipal Solid Waste (MSW) landfills is a complex decision based process that involves multiple hydrogeological, morphological, environmental, climatic, and socio-economic criteria. In a fuzzy logic environment, DEMATEL and ANP methods were employed to comprehensively consider uncertainty, fuzziness of data and the subjective scoring and stability of results to enhance the spatial decision-making process. Primarily, 21 criteria were identified in five groups through the Delphi method at 30m resolution, criteria weights were determined via the integration of DEMATEL and ANP, and seven sets of membership functions were simulated to obtain the best fuzzy logic environment. Combining GIS spatial analysis and the three clustering algorithms (DBSCAN, HDBSCAN, and OPTICS), candidate sites that satisfied the landfill conditions were identified, and the spatial distribution characteristics and reachability were analyzed. These sites were subsequently ranked utilizing the MOORA, WASPAS, COPRAS, and TOPSIS methods to verify the reliability of the results by conducting sensitivity analysis. This paper focuses on a flexible and novel framework for the selection of MSW landfill sites for Lanzhou, which is a semi-arid valley basin city in China. In contrast to common techniques, this model not only made the best recommendation scientifically and efficiently but could also provide accurate assessment data for decision makers in landfill construction and high-quality urban development.

Keywords:

DEMATEL-ANP

fuzzy logic

clustering

municipal solid waste

landfill

site selection

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Consent to participate All authors have read this manuscript and would like to have it considered exclusively for publication in **ENVIRONMENTAL SCIENCE AND POLLUTION RESEARCH.**

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1. Introduction

Rapid urbanization and population growth have posed serious challenges to the sustainable development of cities, which have also led to environmental pollution and a dramatic increase in the generation of waste (Soltani et al., 2015). MSW is a critical issue with the potential to have severe negative impacts on the environment and public health (Khan et al., 2018). The disposal of immense volumes of Municipal Solid Waste (MSW) has become a matter of great concern for urban planners and environmental managers on a global scale. Over the last decade, global MSW generation has increased from 0.68 billion tonnes per year (0.64 kg of MSW per person per day) to 1.3 billion tonnes per year (1.2 kg per person per day), which is likely to reach 2.2 billion tonnes per year by 2025 (The World Bank, 2012).

Although China has experimented with waste classification and harmless treatment policies in Shanghai and other developed cities since 2018, landfilling remains the most essential and efficacious means for disposing of most MSW for the majority of economically underdeveloped areas (Zhang et al., 2019). It was revealed that improper landfills can have long lasting damaging impacts and cause potential harm to the surrounding ambient soil, groundwater, and atmosphere (Krcmar et al., 2018). Thus, the selection of suitable sites for landfilling is considered a complex task in Municipal Solid Waste Management (MSWM) (Chabuk et al., 2016). Lanzhou is a typical semi-arid valley basin city, where water resources are scarce, environmental pollution is serious, and the contrasts between anthropogenic activities and the land is extremely poignant (Li et al., 2020). Issues such as urban environment and land have become key issues to be urgently resolved during the construction of Lanzhou. Unlike humid coastal regions, the study area is characterized by a complex terrain and a significant fragile ecological environment. Therefore, it is critical to select suitable landfill sites based on regional characteristics.

Siting MSW landfills often requires the engagement of multiple stakeholders encompassing government, municipalities, industries, experts, and the general public, where numerous criteria must be considered. Assuming no political or administrative boundaries as inputs, Karimi et al. (2020) proposed a data-driven GIS-based method that considers spatial, environmental, and economic constraints using study regions derived from nighttime light data. Based on the Analytic Hierarchy Process(AHP) and GIS technology Sener et al. (2010) combined social, environmental, and technical parameters to identify two candidate landfill sites for Konya, Turkey. Eskandari et al. (2012) conducted a similar study in Marvdasht, Iran, which drew on multi-criterion analysis and the GIS method and considering environmental, economic, and social factors. However, the aforementioned methods share a common weakness: Lack of support of relevant national standards, a low consideration for regional characteristics, and " NIMBY effects", which fail to form a perfect criterion system that is applicable to semi-arid regions. The criterion system is determined through the consideration of various factors such as environmental impacts (e.g., global warming, resource depletion, ecosystem damage), regional characteristics (e.g., waste generation rate, and social factors), associated economic costs and benefits, and resident acceptance.

Numerous Multi-Criteria Decision Analysis (MCDA) methods have been developed to support decision-making in MSWM, including AHP (Asefi et al.; Kamdar et al., 2019), Analytic Network Process (ANP) (Bahrani et al., 2016), Fuzzy logic (Chamchali and Ghazifard, 2019), Ordered Weighted Average (OWA (Gbanie et al., 2013), Weighted Linear Combination (Gorsevski et al., 2012), Fuzzy AHP(FAHP) (Hanine et al., 2016), and Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) (Beskese et al., 2015). As AHP is user-friendly, it transforms complex decision systems into simple hierarchies and paired systems, whereas GIS is a computer-based decision support system with the capacity to manage, analyze and display geospatial reference data (Khan et al., 2018). Therefore GIS-AHP has been proven to be a powerful tool for the evaluation of potential landfill sites (Mahmood et al., 2017). Gorsevski et al. (2012) who proposed a decision-making strategy regulated by AHP, OWA, and GIS, took into account environmental and economic criteria for waste disposal in various regions in Macedonia. Demesouka et al. (2013) evaluated the suitability of potential MSW landfill sites in northeast Greece by applying GIS combined with AHP and compromise programming methods. Spigolon et al. (2018) used an AHP approach in a GIS environment for the siting of sanitary landfills and the optimization of the transportation of municipal solid waste in São Paulo, Brazil. Kamdar et al. (2019) in attempting to identify a suitable MSW site in Songkhla, Thailand, analyzed the data they collected from online portals and governmental organizations, and then organized them by morphological, environmental, and socioeconomic factors through a synthetic AHP-GIS model.

However, AHP has several drawbacks including the fact that it is necessary to consider the correlations between multiple criteria, and the establishment of a large number of paired matrices to calculate weights may cause confusion. Further, the considerable reliance on expert opinion leads to strong uncertainty and subjectivity in the data and results (Hossaini et al., 2015). Consequently, it is essential to select an effective strategy to integrate the system framework in a flexible and novel way to create an optimal decision-making plan. An effective integrated model based on Decision-Making Trial And Evaluation Laboratory (DEMATEL) and ANP was employed in environmental research and other fields (Feyz et al., 2019). ANP views the mutual dependencies and feedback relationship between decision elements (criteria, sub-criteria and optimal alternatives) as network structures, and effectively determines the relative importance of evaluation criteria through the construction of a super matrix (Rezaeisabzevar et al., 2020) . There is no need to compare the evaluation criteria in pairs, and the weight depends on the mutual effects between different criteria, which can reduce the subjective impact of expert scoring to a certain extent. Moreover, there is some research that focused on integrated MCDA-GIS methods under the fuzzy environment. Isalou et al. (2013) studied the siting MSW landfills in Qom, Iran, using a linear membership function and ANP in fuzzy logic. The results revealed that the use of fuzzy, rather than Boolean theory, fully reflected the logical relationships between criterion attributes. However, various evaluation criteria have different attributes, and there are uncertainties, and a mature fuzzy environment has not yet been developed (Rahimi et al., 2020). Thus, as the literature suggests, the siting of MSW landfills requires further improvements in uncertainty, the fuzziness of data, methods and the stability of results to facilitate the evaluation process (Hariz et al., 2017).

This study proposed to integrate DEMATEL-ANP and GIS technology in the fuzzy logic environment to resolve the landfill site selection problem, while ensuring the certainty, fuzziness, and reliability of the optimal decision. Furthermore, previous studies have focused only on the process and results of the site selection, while neglecting the analysis of results. The density-based clustering algorithm can convert the suitability partition results into point elements for clustering, obtain candidate sites and analyze their spatial distribution characteristics and reachability (Eghtesadifard et al., 2020). The criteria are categorized as positive and negative, and the sites are the ranked according to the COmplex PRoportional ASsessment (COPRAS), the Weighted Aggregated Sum Product Assessment (WASPAS), the Multi-Objective Optimization method by Ratio Analysis (MOORA), and TOPSIS methods. These four methods have a high consistency with each other to and compensate for their probable shortcomings (Salabun et al., 2020). To the best of our knowledge, no study has been undertaken on the landfill site selection problem utilizing this flexible and novel comprehensive framework.

The overall objective of this study was not only to identify the most suitable site for MSW landfill by employing a decision support framework based on MCDM, but also to promote MSWM and sustainable urban development in response to regional characteristics, environmental management, and land-use planning of the study area. Specific objectives included: (a) Proposing a new flexible, practical, and comprehensive model to identify suitable landfills that minimize the negative impacts of MSW on the environment. (b) Working through the China National Standard (CNS) for site selection and construction, multiple stakeholders, literature reading, regional characteristics and the " NIMBY effect ", identifying the criteria applicable to the site selection of semi-arid river valley basin-type urban landfills via a comprehensive consideration of hydrogeological, morphological, environmental, climatic, and socioeconomic constraints. (c) In the fuzzy logic environment, the development of a network structure based on the mutual dependence between criteria rather than a pairwise comparison matrix, employing the clustering algorithm to determine a MSW landfill site that conformed to the CNS of environmental management and land use planning. Verifying the stability of the optimal decision plan according to ranking and sensitivity analysis.

This study is categorized into five main sections. In Section 1 the research background, research significance, goals, and scientific problems to be solved are introduced. In Section 2 the overview of the study area is described and the data sources are given. In Section 3 the proposed methodology including Delphi, DEMATEL-FANP, GIS, clustering algorithm, MOORA, WASPAS, COPRAS, and TOPSIS are described. Section 4 presents and discusses the results achieved by this study. Finally, Section 5 provides the concluding remarks and suggestions for further research.

2. Study area and data sources

2.1. Study area

Lanzhou (Fig.1) (103°40′E, 36°03′N) is located in the central part of Gansu Province, China. It is one of the typical river valley basin-type cities in semi-arid areas (Zhao et al., 2020). The terrain of the study area is high in the southwest and low in the northeast, with an average altitude of 1520m. The Yellow River flows from southwest to northeast across the entire territory and traverses the mountains, forming a beaded valley with alternate canyons and basins, which runs ~35 km from east to west and 2~8 km from north to south (Juang et al., 2019). The landforms are complex and diverse, with a staggered distribution of mountains, plateaus, plains, and river valleys. Due to the uplift of the Qinghai-Tibet Plateau since the new century, a temperate continental climate has been formed, with an average annual temperature of about 10.3℃ and precipitation of about 327mm (He et al., 2019).

As of July 2020, the city has jurisdiction over five districts and three counties, with the approximate area of $1.31\times10^4 km^2$ and population of over 4.13×10^6 people. According to statistics from the Gansu Environmental Statistics Bulletin (GESB, 2009), 7.30×10^5 tons of domestic waste are generated annually in the four suburban districts of Lanzhou city, with 3.30×10^5 tons (45.7%) from Chengguan, 1.26×10^5 tons (17.3%) from Qilihe, 1.43×10^5 tons (19.6%) from Xigu, and 1.27×10^5 tons (17.4%) from Anning, which is increasing by from 5% to 8% per year. The annual output of domestic waste is ~1.05×10^6 tons, which generates 3,000 tons in the urban area every day; however, only 2100 tons can be landfilled, with a disposal rate of 70%. The remaining waste is spread across the surrounding areas of the city, which seriously restricts the development of Lanzhou. Fig. 2 illustrates the framework proposed in this study.

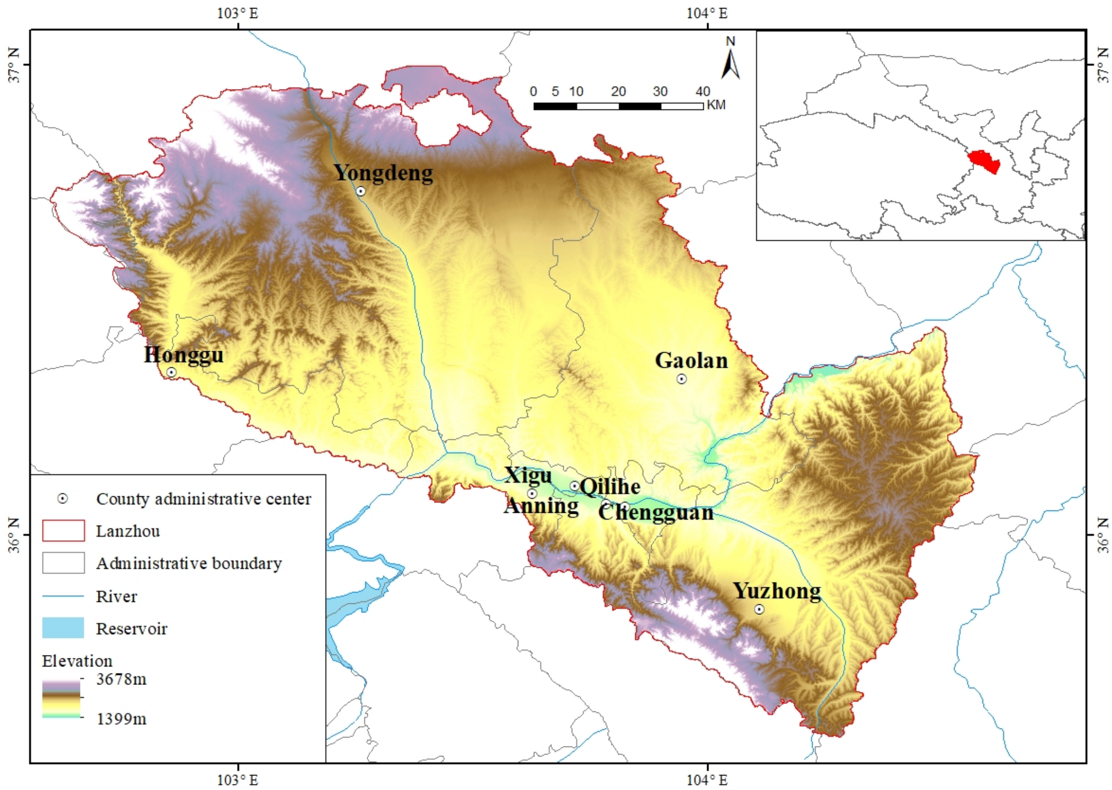

Fig. 1. Elevation of the study region. Lanzhou includes five districts (Honggu, Xigu, Anning, Qilihe, and Chengguan), and three counties (Yongdeng, Gaolan, and Yuzhong). Elevation data is from the USGS - SRTM dataset, which provides elevation data at a 30m resolution. The elevation of the study area ranged from 1399 to 3678 m.

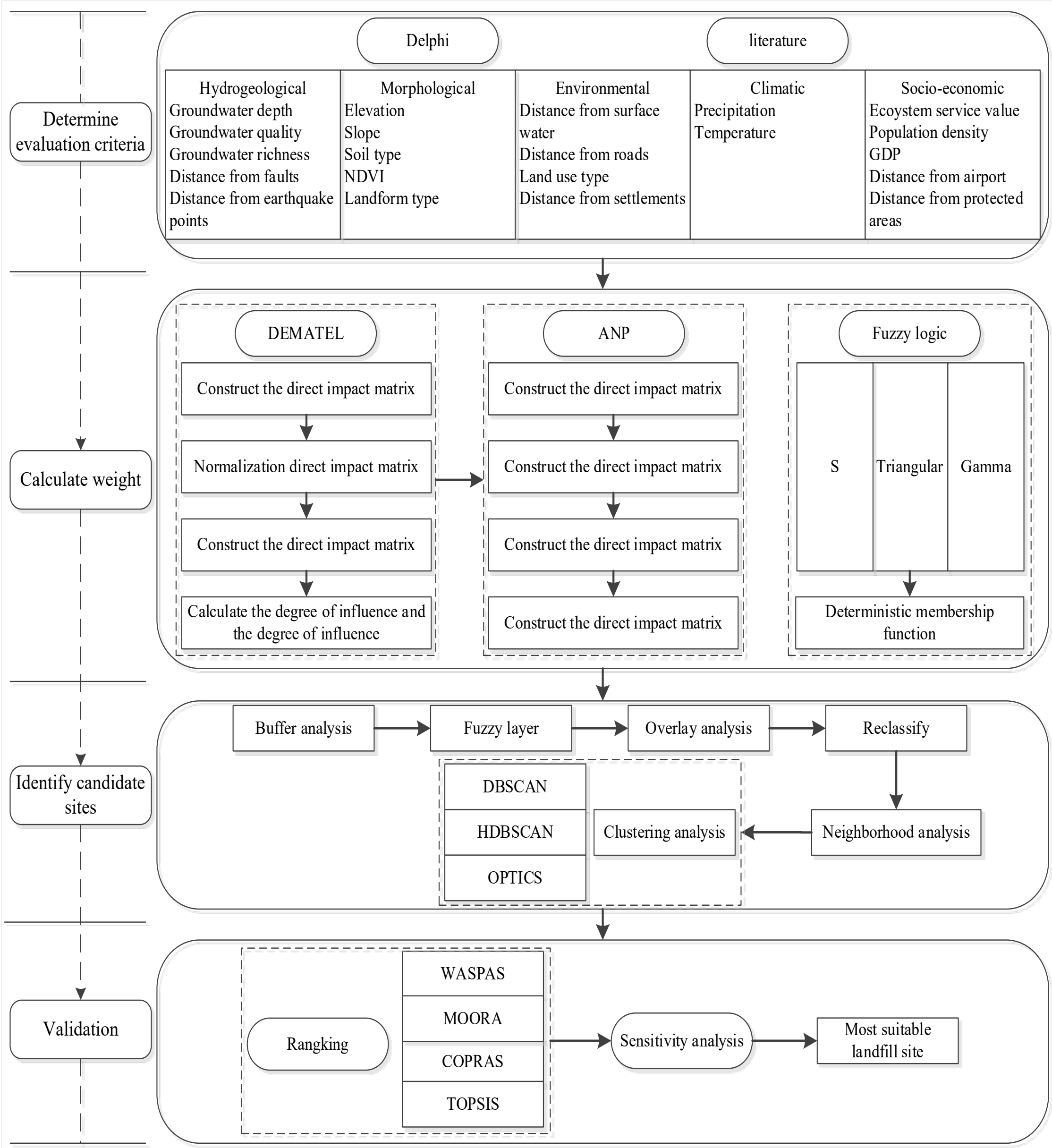

Fig. 2. Flowchart of the proposed methodology, including four main steps: determine evaluation criteria, calculate weight, identify candidate sites, and validation.

2.2. Data sources

The amount of data used in this study was large and preprocessing was time consuming. According to the data format, it was divided into vector data (point, polyline, polygon) and raster data. Vector data focused on recording the properties of criterion, while raster data focused on representing the spatial distribution of the criterion. According to the data sources, the data were obtained from the open source geographic information sharing platforms, online websites, and government agencies. The open source geographic information sharing platform included the Resource and Environmental Science and Data Center, Chinese Academy of Sciences (RESDC, 2015) and National Catalogue Service for Geographic Information (NCSGI, 2015). Online websites included the official of MODIS (MODIS, 2018), USGS Earth Explorer (USGS, 2015), and Gaode Maps (GDM, 2019). Government agencies included the Gansu Water Resources Department (GWRD, 2019), Gansu Bureau of Geology and Mineral Hydrogeology engineering Geological Exploration Institute (GBGMHEGEI, 2015), Gansu Earthquake Agency (GEA, 2015), and Portal website of Gansu Forestry and Grass Bureau (GFGB, 2015). All of the criterion data sets used in this study, as well as their formats and sources are described in Table A.1 in Appendix A.

3.Methods

3.1 Identification of evaluation criteria

The CNS have set strict standards for the evaluation criteria of landfill site selection and construction. The specific CNS for reference include: "Standard for Pollution Control on the Landfill Site of Domestic Waste" (GB16889-2008), "Technical Specifications for Sanitary Landfill of Domestic Waste" (GB50869-2013), "Standard for Pollution on the Storage and Disposal Site for General Industrial Solid Waste" (GB18599-2001), "Water Pollution Prevention Law of the People's Republic of China", "Regulations of the People's Republic of China on Nature Reserves, " Technical Regulations for Investigation of Land Use Status", and " Urban and Rural Planning Law of the People’s Republic of China". All CNS are available at the National Standard Full Text Open System (NSFTOS, 2017).

Delphi is an improved expert scoring method, which utilizes the questionnaire to continuously iterate four times anonymously to investigate the scientific evaluation of multi-domain experts on decision-making problems (Ahmed et al., 2020). The expert group consists of 30 MSW experts, including academic researchers and professors in waste, environmental, municipal management, land-use planning and geology, with an average of 12 years of practical or teaching experience in waste management. Combined with the CNS and Delphi method, 21 sub-criteria (C1, C2, C3, ..., C21) were identified and were categorized into five dimensions (B1, B2, B3, B4, and B5).

Hydrogeological aspects should be considered to avoid potential groundwater contamination in semi-arid valley basins caused by the leakage of landfill leachate, while ensuring the safety of construction and operation (Karakus et al., 2020). Morphological aspects were taken into account to reduce construction costs and increase stability during construction (Bahrani et al., 2016). Environmental aspects were taken into consideration to minimize the impacts on neighboring residents, and land/water resources (Ozkan et al., 2019). Climatic issues were reviewed to reduce potential threats and damage to the surrounding environment posed by various pollutants released from the landfill through leachate or waste gas (Lima et al., 2018). Socio-economic impacts were considered to prevent the landfill from adversely affecting surrounding ecological reserves and regional economic development (Asefi et al., 2020a). Further detailed information on the criteria selection is contained in Table B.1 in Appendix B. The interval from 0 to 1 was adopted for normalization, where the larger the value, the better the suitability (Fig. 2).

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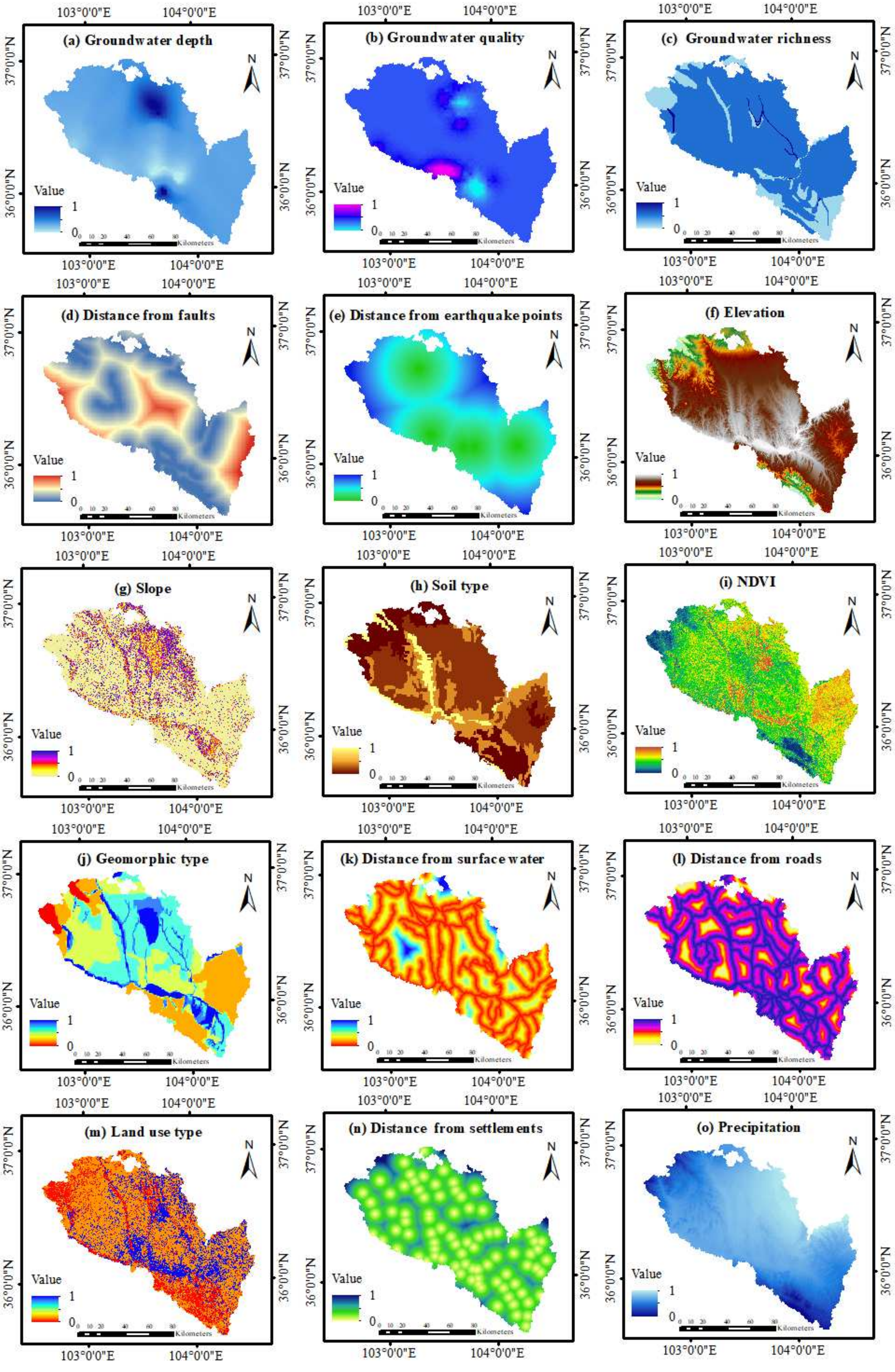


(a) Groundwater depth
(b) Groundwater quality
(c) Groundwater richness
(d) Distance from faults
(e) Distance from earthquake points
(f) Elevation
(g) Slope
(h) Soil type
(i) NDVI
(j) Geomorphic type
(k) Distance from surface water
(l) Distance from roads
(m) Land use type
(n) Distance from settlements
(o) Precipitation
Value
1
0
Kilometers
103°0'0"E
104°0'0"E
37°0'0"N
36°0'0"N
N

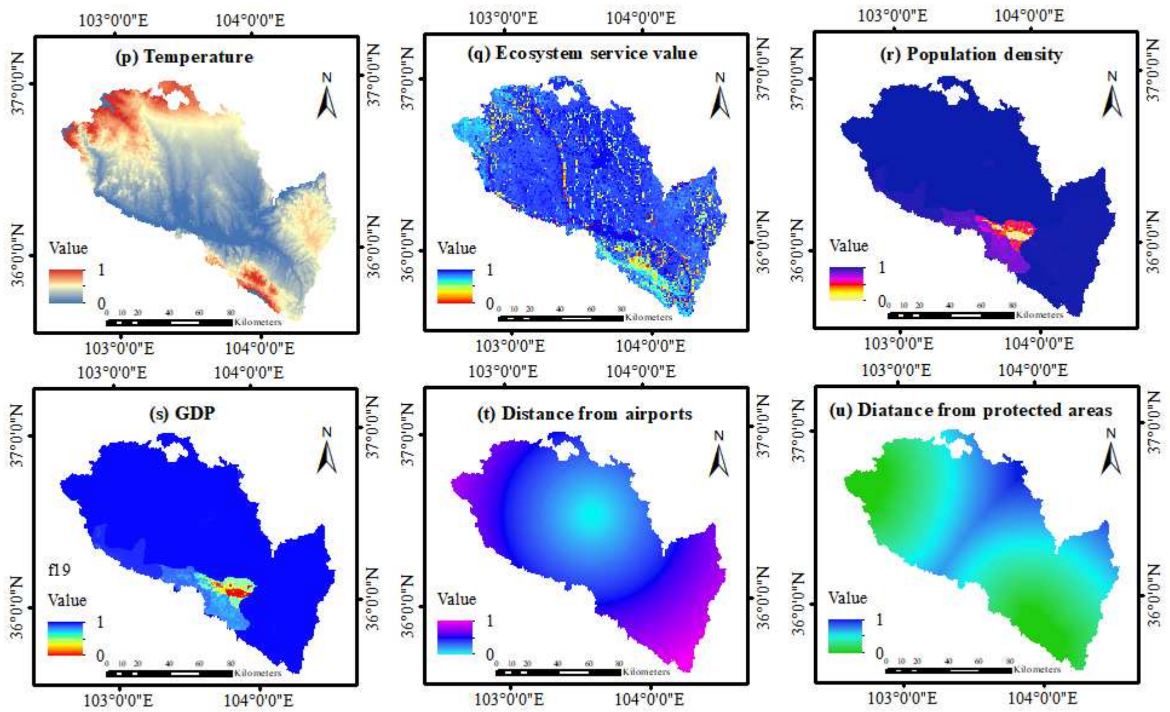


Fig. 3. Criteria included (a) groundwater depth, (b) groundwater quality, (c) groundwater richness, (d) distance from faults, (e) distance from earthquake points, (f) elevation, (g) slope, (h) soil type, (i) NDVI, (g) landform type, (k) distance from surface water, (l) distance from roads, (m) land use type, (n) distance from settlements, (o) precipitation, (p) temperature, (q) ecosystem service value, (r) population density, (s) GDP, (t) distance from airports, (u) distance from protected areas.

3.2 DEMATEL-FANP

This study aimed to integrate the DEMATEL-ANP method to establish a network structure to clarify the interdependent relationship between criteria and determine their relative weights. DEMATEL employs weighted directed figures and matrices to analyze causal relationships between criteria in complex systems, reflecting the overall impact of different criteria (Liu et al., 2020). It has the following advantages: (1) Distinguishing the attributes of criteria (positive and negative). (2) The prominence of the criteria can be determined. (3) The relationship between criteria can be quantified (direct and indirect influences). (4) A large number of samples are not required (Chang et al., 2011). It was reported that ANP was introduced to modify the AHP process, which finds the best possible solution for complex decision-making issues in the model of an ordered network structure (Afzali et al., 2014). Considering the mechanisms of dependency and feedback between the criteria makes the decision-making model closer to the actual situation. To reduce the uncertainty of data and expert ratings, ANP can utilize the causal relationship determined by DEMATEL to calculate weights (Motlagh and Sayadi, 2015).

3.2.1. Construction of direct influence matrix

According to the expert opinion obtained by Delphi method, a numerical scale of 0-4 is adopted to indicate the degree of direct influence between criteria. Where, "no influence" is 0, "low influence" is 1, "medium influence" is 2, "high influence" is 3, and "very high influence" is 4. A pairwise comparison judgment matrix is constructed respectively. Experts $(E = 1, 2, \cdots, E)$ judged the criteria in order to derive a square matrix A^E is expressed in Eq. 1. Subsequently, Eq. 1 indicates the average direct impact matrix, according to the equation, calculating the average value of the numerical scale for each matrix.

$$A^E = \begin{bmatrix} a_{11}^E & a_{12}^E & \cdots & a_{1n}^E \\ a_{21}^E & a_{22}^E & \cdots & a_{2n}^E \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1}^E & a_{n2}^E & \cdots & a_{nn}^E \end{bmatrix} \qquad \overline{A} = \begin{bmatrix} \overline{a}_{11} & \overline{a}_{12} & \cdots & \overline{a}_{1n} \\ \overline{a}_{21} & \overline{a}_{22} & \cdots & \overline{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \overline{a}_{n1} & \overline{a}_{n2} & \cdots & \overline{a}_{nn} \end{bmatrix} \tag{1}$$

3.2.2. Normalization directly influences the matrix

To unify the numerical scale into a comparable range, Eqs. 2, 3 are employed to obtain the normalized direct relation matrix, whose value is between 0 and 1.

$$Z = \min\left[\frac{1}{\max_i\left(\sum_{j=1}^{n}|a_{ij}|\right)}, \frac{1}{\max_j\left(\sum_{i=1}^{n}|a_{ij}|\right)}\right] \tag{2}$$

$$A_\alpha = Z\overline{A} \tag{3}$$

3.2.3. Deriving the comprehensive influence matrix

The comprehensive influence matrix represents the superposition of direct and indirect influences between criteria. T^B (criterion) (Eq. 5) and T^C (sub-criterion) (Eq. 6) are calculated using Eq. 4, where I is the identity matrix.

$$T^{C} = \left[t_{ij}^{C}\right]_{n\times n} = A_{\alpha}\left(I - A_{\alpha}\right)^{-1} \tag{4}$$

$$T^{B} = \begin{bmatrix} t_{11}^{B} & t_{12}^{B} & \cdots & t_{1m}^{B} \\ t_{21}^{B} & t_{22}^{B} & \cdots & t_{2m}^{B} \\ \vdots & \vdots & \ddots & \vdots \\ t_{m1}^{B} & t_{m2}^{B} & \cdots & t_{mm}^{B} \end{bmatrix} \tag{5}$$

$$T^{C} = \begin{array}{cc} & \\ & \\ B_1 & C_{11} \\ B_2 & C_{21} \\ \vdots & \vdots \\ B_m & C_{m1} \end{array} \begin{array}{c} \begin{array}{cccc} B_1 & B_2 & \cdots & B_m \\ C_{11}\cdots C_{1n_1} & C_{21}\cdots C_{2n_2} & \cdots & C_{m1}\cdots C_{mn_m} \end{array} \\ \begin{bmatrix} T_{11}^{C} & T_{12}^{C} & \cdots & T_{1m}^{C} \\ T_{21}^{C} & T_{22}^{C} & \cdots & T_{2m}^{C} \\ \vdots & \vdots & \ddots & \cdots \\ T_{m1}^{C} & T_{m2}^{C} & \cdots & T_{mm}^{C} \end{bmatrix} \end{array} \tag{6}$$

3.2.4 Computing influence and being influence of the matrix

Based on the comprehensive influence matrix, the row vectors are summed to obtain the influence of the criterion i on other criteria (influence). The column vectors are summed to obtain the influence of the other criteria on the criterion i (being influence). Further, the values of R^{B} and C^{B} denote the influence and being influence of the criteria, whereas the values of R^{C} and C^{C} denote the influence and being influence of the sub-criteria (Eqs. 7, 8).

$$R^{B} = \left[r_i\right]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}^{B}\right]_{n\times 1} \qquad C^{B} = \left[c_j\right]_{1\times n} = \left[\sum_{i=1}^{n} t_{ij}^{B}\right]_{1\times n} \tag{7}$$

$$R^{C} = \left[r_i\right]_{n\times 1} = \left[\sum_{j=1}^{n} t_{ij}^{C}\right]_{n\times 1} \qquad C^{C} = \left[c_j\right]_{1\times n} = \left[\sum_{i=1}^{n} t_{ij}^{C}\right]_{1\times n} \tag{8}$$

3.2.5. Establishing the network structure

ANP establishes the network structure with assistance from the comprehensive influence matrix and constructs the super matrix to allocate the weight for the criteria. To distinguish the difference between the criteria, Eq. 9 is employed to calculate the centrality M and causation N. The network structure is based on coordinate values (M, N) to express the interdependence and feedback influences between criteria, and its comprehensive threshold is set as the average value of the matrix and medium numerical scale.

$$M_i = R_i + C_i \qquad N_i = R_i - C_i \tag{9}$$

3.2.6. Normalization of comprehensive influence matrix

Based on the comprehensive influence matrix, the criterion normalized comprehensive influence matrix $T_\alpha^B = \left[t_{i\alpha_{ij}}^B \right]_{m\times m}$ (Eq. 10, 11) was calculated by the row vector of criterion i divided by the sum of the row vector of its corresponding row. The sum of the numerical scales for each row vector is 1: $\sum_{j=1}^{m} t_{\alpha_{ij}}^B = 1$. Similarly, the normalized comprehensive influence matrix of the sub-criterion is obtained by the same method (Eq. 12).

$$T^B = \begin{bmatrix} t_{11}^B & t_{12}^B & \cdots & t_{1m}^B \\ t_{21}^B & t_{22}^B & \cdots & t_{2m}^B \\ \vdots & \vdots & \ddots & \vdots \\ t_{m1}^B & t_{m2}^B & \cdots & t_{mm}^B \end{bmatrix} \rightarrow \begin{matrix} b_1 = \sum_{j=1}^{m} t_{1j}^B \\ b_2 = \sum_{j=1}^{m} t_{2j}^B \\ \vdots \\ b_m = \sum_{j=1}^{m} t_{mj}^B \end{matrix} \tag{10}$$

$$T_\alpha^B = \begin{bmatrix} \frac{t_{11}^B}{b_1} & \frac{t_{12}^B}{b_1} & \cdots & \frac{t_{1m}^B}{b_1} \\ \frac{t_{21}^B}{b_2} & \frac{t_{22}^B}{b_2} & \cdots & \frac{t_{2m}^B}{b_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{t_{m1}^B}{b_m} & \frac{t_{m2}^B}{b_m} & \cdots & \frac{t_{mm}^B}{b_m} \end{bmatrix} = \begin{bmatrix} t_{\alpha_{11}}^B & t_{\alpha_{12}}^B & \cdots & t_{\alpha_{1m}}^B \\ t_{\alpha_{21}}^B & t_{\alpha_{22}}^B & \cdots & t_{\alpha_{2m}}^B \\ \vdots & \vdots & \ddots & \vdots \\ t_{\alpha_{m1}}^B & t_{\alpha_{m2}}^B & \cdots & t_{\alpha_{mm}}^B \end{bmatrix} \tag{11}$$

$$T_\alpha^C = \begin{array}{cc} & \begin{array}{cccc} B_1 & B_2 & \cdots & B_m \\ C_{11}\cdots C_{1n_1} & C_{21}\cdots C_{2n_2} & \cdots & C_{m1}\cdots C_{mn_m} \end{array} \\ \begin{array}{cc} B_1 & \begin{matrix} C_{11} \\ \vdots \\ C_{1n_1} \end{matrix} \\ B_2 & \begin{matrix} C_{21} \\ \vdots \\ C_{2n_1} \end{matrix} \\ \vdots & \vdots \\ B_m & \begin{matrix} C_{m1} \\ \vdots \\ C_{mn_1} \end{matrix} \end{array} & \begin{bmatrix} T_{\alpha_{11}}^C & T_{\alpha_{12}}^C & \cdots & T_{\alpha_{1m}}^C \\ T_{\alpha_{21}}^C & T_{\alpha_{22}}^C & \cdots & T_{\alpha_{2m}}^C \\ \vdots & \vdots & \ddots & \vdots \\ T_{\alpha_{m1}}^C & T_{\alpha_{m2}}^C & \cdots & T_{\alpha_{mm}}^C \end{bmatrix} \end{array} \tag{12}$$

3.2.7. Construct and solve the limit super matrix

The weighted super matrix W_C (Eq. 13) is expressed by multiplying the normalized comprehensive influence matrix of the criterion of transpose and the sub-criterion of transpose. The weighted super matrix is limit until it converges to calculate the final weight vector (Eq. 14).

$$W_C = (T_\alpha^B)^T \times \left(T_\alpha^C\right)^T = \begin{bmatrix} t_{\alpha_{11}}^B \times t_{\alpha_{11}}^C & t_{\alpha_{21}}^B \times t_{\alpha_{21}}^C & \cdots & t_{\alpha_{m1}}^B \times t_{\alpha_{m1}}^C \\ t_{\alpha_{12}}^B \times t_{\alpha_{12}}^C & t_{\alpha_{22}}^B \times t_{\alpha_{22}}^C & \cdots & t_{\alpha_{m2}}^B \times t_{\alpha_{m2}}^C \\ \vdots & \vdots & \ddots & \vdots \\ t_{\alpha_{1m}}^B \times t_{\alpha_{1m}}^C & t_{\alpha_{2m}}^B \times t_{\alpha_{2m}}^C & \cdots & t_{\alpha_{mm}}^B \times t_{\alpha_{mm}}^C \end{bmatrix} \quad (13)$$

$$\lim_{k\to\infty} (Wc)^k \quad (14)$$

Table 1

M(R+C), N(R-C) and weights for criterion and sub-criterion.

Criterion	M(R+C)	N(R-C)	Sub-criterion	M(R+C)	N(R-C)	Weight
Hydrogeological B_1	1.85113269	-0.81553398	Groundwater depth C_1	6.10592753	0.37294637	0.0710
			Groundwater quality C_2	3.44870236	0.68060181	0.0416
			Groundwater richness C_3	5.57912930	0.48638054	0.0642
			Distance from faults C_4	4.92364358	0.52814645	0.0582
			Distance from earthquake points C_5	3.38080534	0.38108087	0.0398
Morphological B_2	1.75674218	-0.13214671	Elevation C_6	4.55369593	0.32910353	0.0530
			Slope C_7	5.47245800	0.11232891	0.0616
			Soil type C_8	4.25869870	0.17304975	0.0432
			NDVI C_9	4.59700315	-0.90900132	0.0380
			Landform type C_{10}	4.39911408	-0.73593001	0.0380

Environmental B_3	2.59492988	0.70604099	Distance from surface water C_{11}	6.59228284	0.16569081	0.0758
			Distance from roads C_{12}	4.69565700	0.07977861	0.0523
			Land use type C_{13}	5.04036583	-0.19966298	0.0531
			Distance from settlements C_{14}	5.88668717	-0.48682537	0.0586
Climatic B_4	1.15102481	0.0399137	Precipitation C_{15}	2.09399972	0.46721654	0.0214
			Temperature C_{16}	1.29549829	0.08657056	0.0142
Socio-economic B_5	1.31283711	0.2017260	Ecosystem service value C_{17}	5.67030678	0.38012955	0.0641
			Population density C_{18}	4.31250111	-0.64084310	0.0382
			GDP C_{19}	3.74464030	-0.68676010	0.0325
			Distance from airports C_{20}	2.90147204	-0.69625477	0.0234
			Distance from protected areas C_{21}	5.50491968	0.11225335	0.0579

3.2.8 Fuzzy logic

The mapping and analysis of criteria attributes based on fuzzy logic, S-shape, Triangular shape, and Gamma shape are commonly employed fuzzy membership functions to determine fuzzy information in fuzzy logic (Table 2) (Barakat et al., 2017). The effects of the seven applied scenarios were investigated, aiming to obtain the most suitable scenario to improve the accuracy of the results and optimize the uncertainty of the evaluation criteria.

Scenario 1: All criteria employ the nonlinear fuzzy membership function (S-shape) to calculate the fuzzy membership.

Scenario 2: All criteria employ the linear fuzzy membership function (Triangular shape) to calculate the fuzzy membership.

Scenario 3: All criteria employ the linear fuzzy membership function (Gamma shape) to calculate the fuzzy membership.

Scenario 4: Criteria employ S and Triangular shapes to calculate the fuzzy membership.

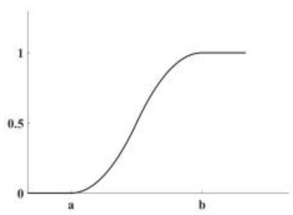
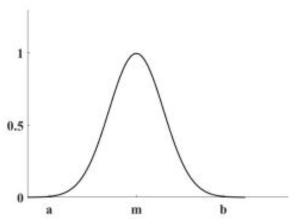
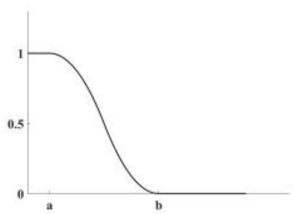
Scenario 5: Criteria employ S and Gamma shapes to calculate the fuzzy membership.

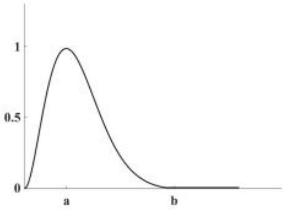
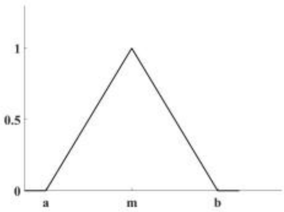
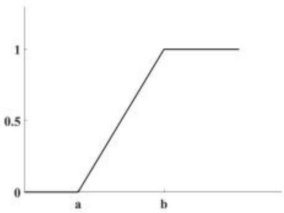
Scenario 6: Criteria employ Triangular and Gamma shapes to calculate the fuzzy membership.

Scenario 7: Criteria employ S, Triangular, and Gamma shapes to calculate the fuzzy membership.

Table 2

Fuzzy membership function.

Fuzzy Membership Function		Figure	Formula
S-shape	S-shape (increasing)		$\mu_i = \begin{cases} 0 & x_i \le a \\ 2(\frac{x_i - a}{b - a})^2 & a < x_i < b \\ 1 & x_i \ge b \end{cases}$
	S-shape (general)		$\mu_i = \begin{cases} 0 & x_i \le a \\ 2(\frac{x_i - a}{m - a})^2 & a < x_i \le m \\ 2(\frac{x_i - b}{b - m})^2 & m < x_i < b \\ 0 & x_i \ge b \end{cases}$
	S-shape (decreasing)		$\mu_i = \begin{cases} 1 & x_i \le a \\ 2(\frac{x_i - b}{b - a})^2 & a < x_i < b \\ 0 & x_i \ge b \end{cases}$

	S-shape (individual)		$\mu_i=\begin{cases}2(\frac{x_i-a}{a})^2 & x_i\le a\\ 2(\frac{x_i-b}{b-a})^2 & a<x_i<b\\ 0 & x_i\ge b\end{cases}$
Triangular shape	Triangular shape (general)		$\mu_i=\begin{cases}0 & x_i\le a\\ \frac{x_i-a}{m-a} & a<x_i\le m\\ \frac{b-x_i}{b-m} & m<x_i<b\\ 0 & x_i\ge b\end{cases}$
Gamma shape	Gamma shape (increasing)		$\mu_i=\begin{cases}0 & x_i\le a\\ \frac{b-x_i}{b-a} & a<x_i<b\\ 1 & x_i\ge b\end{cases}$

3.3.GIS modeling

3.3.1 Spatial analysis

On the basis of the unified projection coordinate system, all data are converted to raster format and resampled for 30 m. Modeling is carried out with the help of spatial analysis tools in ArcGIS software to obtain reasonable results of landfill site selection. Buffer zones are established for faults, earthquake points, surface water, settlements, roads, protected areas, and airports in accordance with the CNS for waste landfill sites, and the regional characteristics of the valley basins in the semi-arid area of Lanzhou. The weights and fuzzy layers calculated by DEMATEL-FANP are integrated, and the weighted overlay of layers and smooth the neighborhood are implemented to obtain the landfill site selection results.

3.3.2. Cluster analysis

Compared with the K-Means method, the density-based clustering analysis does not require prior knowledge of the number of clusters to be formed, the shape of the clusters is not limited, and noise points can be identified.

I. Density-Based Spatial Clustering of Applications with Noise (DBSCAN)

The input parameters are the neighborhood radius (ε) and the minimum number of entities (MinPts). The data set is divide into core, boundary and noise points. A random point is selected from the data set as the seed for traversal. When the density of any two points is reachable or direct, it is classified into the same cluster, and the number of entities in the same cluster must be greater than MinPts; when it is less, they are classified as noise points (Gui et al., 2020).

II. Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN)

The input parameter is MinPts, ε changes with the point density change, automatic clustering can be implemented without parameter adjustment. On the basis of DBSCAN and in combination with the hierarchical clustering algorithm, the concept of "Mutual Reachability Distance" was introduced (Hu et al., 2020).

$$MRD_{k(A,B)} = \max\{Core_k(A), Core_k(B), d(A,B)\} \tag{15}$$

Where, A, B are two core points; $Core_k(A)$ is the distance between A and the K-th adjacent point; $Core_k(B)$ is the distance between B and the K-th adjacent point; $d(A,B)$ is the Euclidean distance between A and B.

III. Ordering Points to Identify the Clustering Structure (OPTICS)

The input parameters were ε, MinPts, and sensitivity. The value of clustering sensitivity is 0-100. The higher the sensitivity, the smaller the clustering interval is. And introduced the "accessible distance" (Breunig et al., 2000).

$$RD_{(P,Q)} = \max\{Core(P), d(P,Q)\} \tag{16}$$

Where, P, Q are the two core points, the core distance of P, and the Euclidean distance between P and Q.

3.4. Ranking solution

3.4.1 WASPAS

Step 1 Construct a decision matrix $X=[x_{ij}]$, where x_{ij} is the response of alternative item i to criterion j.

Step 2 Normalize the decision matrix based on the maximum and minimum method (Eq. 17) (Salabun et al., 2020).

$$r_{ij}^{+}=\frac{x_{ij}}{\max_i(x_{ij})} \text{ for positive criteria } r_{ij}^{-}=\frac{\min_i(x_{ij})}{x_{ij}} \text{ for negative criteria} \tag{17}$$

Step 3 Weight normalized decision matrix (Eq. 18), w is the weight of criterion j.

Step 4 Calculate the relative importance of alternatives by utilizing weighted sum model (WSM) and weighted product model (WPM) (Zavadskas et al., 2012), where m is the number of alternatives.

$$S_{WSM}=\sum_{j}^{n} w_j r_{ij} \qquad S_{WPM}=\prod_{j=1}^{n}(r_{ij})^{w_j} \tag{18}$$

Step 5 Calculate the scores of each alternative according to Eq. 19, and arrange them in descending order.

$$Q_i=\lambda S_{WSM}+(1-\lambda)S_{WPM} \quad \lambda\in[0,1] \tag{19}$$

3.4.2 MOORA

Step 1 Construct a decision matrix $X=[x_{ij}]$, where x_{ij} is the response of alternative item i to criterion j.

Step 2 Normalize the decision matrix based on the vector method (Eq. 20), where m is the number of alternatives.

$$r_{ij}=\frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}} \tag{20}$$

Step 3 Weight normalized decision matrix (Eq. 21), w is the weight of criterion j.

$$V_{ij} = w_j r_{ij} \tag{21}$$

Step 4 Calculate the relative importance of alternatives by utilizing the ratio of the system (Eq. 22) (Brauers and Zavadskas, 2006), where n is the number of criteria.

$$S_i^+ = \sum_{j=1}^{g} V_{ij} \text{ for positive criteria} \quad S_i^- = \sum_{j=g+1}^{n} V_{ij} \text{ for negative criteria} \tag{22}$$

Step 5 Calculate the scores of each alternative according to Eq. 23, and arrange them in descending order.

$$Q_i = \sum_{j=1}^{g} V_{ij} - \sum_{j=g+1}^{n} V_{ij} \tag{23}$$

3.4.3 COPRAS

Step 1 Construct a decision matrix $X = [x_{ij}]$, where x_{ij} is the response of alternative item i to criterion j.

Step 2 Normalize the decision matrix based on the summation method (Eq. 24), where m is the number of alternatives.

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{24}$$

Step 3 Weight normalized decision matrix (Eq. 25), w is the weight of criterion j.

$$V_{ij} = w_j r_{ij} \tag{25}$$

Step 4 Calculate the relative importance of alternatives by utilizing the complex scale evaluation index (Eq. 26) (Pamucar et al., 2018), where n is the number of criteria.

$$S_i^+ = \sum_{j=1}^{g} V_{ij} \text{ for positive criteria} \quad S_i^- = \sum_{j=g+1}^{n} V_{ij} \text{ for negative criteria} \tag{26}$$

Step 5 Calculate the scores of each alternative according to Eq. 27, and arrange them in descending order. The higher the score, the higher the priority.

$$Q_i = S_i^+ + \frac{\sum_{i=1}^{m} S_i^-}{S_i^- \sum_{i=1}^{m} \frac{1}{S_i^-}} \qquad U_i = \frac{Q_i}{Q_{\max}} \times 100 \tag{27}$$

3.4.4 TOPSIS

Step 1 Construct a decision matrix $X = [x_{ij}]$, where x_{ij} is the response of alternative item i to criterion j.

Step 2 Normalize the decision matrix based on the minimum-maximum method (Eq. 28), where m is the number of alternatives.

$$r_{ij}^{+} = \frac{x_{ij} - \min_j (x_{ij})}{\max_j (x_{ij}) - \min_j (x_{ij})} \text{ for positive criteria}$$

$$r_{ij}^{-} = \frac{\max_j (x_{ij}) - x_{ij}}{\max_j (x_{ij}) - \min_j (x_{ij})} \text{ for negative criteria} \tag{28}$$

Step 3 Weight normalized decision matrix (Eq. 29), w is the weight of criterion j.

$$V_{ij} = w_j r_{ij} \qquad V_j^+ = \{\max_j (V_{ij})\} \qquad V_j^- = \{\min_j (V_{ij})\} \tag{29}$$

Step 4 Calculate the relative importance of alternatives by utilizing the distance index (Eq. 30) (Rashid et al., 2014), where n is the number of criteria.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (V_{ij} - V_j^+)^2} \qquad S_i^- = \sqrt{\sum_{j=1}^{n} (V_{ij} - V_j^-)^2} \tag{30}$$

Step 5 Calculate the scores of each alternative according to Eq. 31, and arrange them in descending order

$$Q_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{31}$$

4. Results and discussion

4.1 Determining the weight

The comprehensive influence matrix of the criterion and sub-criterion (Tables B.2, B.3 in Appendix B) are derived by calculating the mean value of the direct and the normalized direct impact matrices. Ultimately, a statistical analysis was performed on the criteria (Table 1). It can be seen from the table that in the criteria, the environmental criterion shows the highest M value (2.5949) and the highest N value (0.7060). The climatic criterion M value (1.1510) is the lowest, and the hydrogeological criterion N value (-0.8155) is the lowest. In the sub-criteria, soil type, landform type, land use type, distance from settlements, population density, GDP, and distance from airports are the being affected criteria, while the others are affected criteria. The M value (6.5923) of distance from surface water was the highest, and the N value (0.6806) of groundwater quality was the highest. The M value (1.2955) of temperature was the lowest, and the N value (-0.9090) of NDVI was the lowest. Furthermore, the weight of temperature (0.0142) and precipitation (0.0214) was lowest, due to the dry climate, low annual precipitation, and lower leachate pollution generated by landfills in the semi-arid region of Northwest China, which is significantly different from that in humid regions. The weights of land use type (0.0531) and ecological service value (0.0641) were relatively high, which was due to the scarcity of land in river valleys and basins. In particular, urban expansion leads to the development and utilization of farmland, forestland, water, and other ecological land that is close to central urban areas. Lanzhou is one of the cities with the most serious geological disasters in China. It is located in the Qilian Mountain earthquake belt, where the abundance of historical landslides, debris flows, and earthquakes should not be underestimated. Considering the geological structure and development of the study area, the weights of faults and earthquake points are 0.0582 and 0.0398, respectively. Water areas, settlements, and protected areas are constraints that are strictly stipulated by the CNS; thus, the relative weight value is also high.

4.2 Identifying the landfill site

The suitability map is generated through overlaying the fuzzy normalized layer of all criteria and assigning weights for each criterion. Subsequently, the results are divided into five categories: "most suitable, more suitable, suitable, less suitable, and unsuitable". Its area and proportions were "6288 km^2 (0.48), 3275 km^2 (0.25), 2358 km^2 (0.18), 917 km^2 (0.07), and 262 km^2 (0.02)", respectively. Simultaneously, non-constructible areas are eliminated according to the CNS, including mainly rivers, protected areas, central urban areas, airports, and so on.

It was found that there were slight differences by comparing the application results of the six scenarios of fuzzy logic with the initial scenario. The most suitable area ratios of scenarios 1-7 were 0.05, 0.06, 0.06, 0.04, 0.04, 0.05, and 0.02, respectively. In addition, Spearman's correlation coefficient values of scenario 1 and the others were compared, which confirmed the similarities between them. Scenarios 2 and 3 had the highest degree of variation in area ratio, which is why they reduced the correlation coefficient (0.94). The coefficient scores of scenarios 4 and 7 were 1, where the results graphically highlighted that the expression of the criterion fuzziness was not limited to linear functions. The reliability of the results could be improved by establishing corresponding membership functions according to different criterion attributes to indicate the logical relations and fuzziness.

The "most suitable" category in the results of scenario 7 was selected, and 140103 data points were extracted for density-based cluster analysis to intuitively display the spatial distribution characteristics and reachability of candidate sites (Figs. C.1, C.2, Appendix C). The DBSCAN method has the fastest calculation speed, where following many experiments and comparisons, it selects the ε of 1600 m and the MinPts of 1000 for cluster analysis, and obtains 15 clusters, and 1 is the noise point. Overall, the U-3 candidate sites located ~1700 m southeast of Liangjiawan in the Xigu District had the smallest density and area, and were closest to the Yellow River among all candidate sites; thus, they were classified as noise points. As a method to merge as many entities as possible, HDBSCAN is data-driven and can directly reflect the aggregation of the data itself. 1000 MinPts were taken to obtain 15 clusters, and 1 was the noise point. As can be seen from the results, a small part of the U-3 candidate sites located ~1700 m southeast of Liangjiawan in the Xigu District were divided into noise points, while the rest were grouped together with S-11, and the value of probability 1 was the highest in the membership probability distribution presented. OPTICS overcomes the shortcoming that low-density clusters within a neighborhood radius contains high-density clusters. Meanwhile, it is not completely data-driven and has obvious advantages for the analysis of spatial distribution characteristics. The ε was set to 1600 m, MinPts to 1000, and cluster sensitivity to 10, after which a total of 13 classes of clusters were obtained, and the 1 was the noise point, including U-1, U-2, and U-3. Lower vertical coordinates in the Reachability Chart translate to lower reach distances. The blue area in Fig. D2 indicates a higher clustering density and better suitability due to the lowest ordinate. The corresponding candidate site (S-6) is located on the east side of Ruijiawan, Lanzhou. Eleven candidate sites were identified by integrating the three clustering algorithms (Fig. 4). It can be seen that the sites are primarily distributed across Yongdeng, Gaolan, and Yuzhong Counties, with a lower distribution in central urban areas and smaller areas. The major reasons are that counties contain more unused land, are close to central urban areas, and transportation is convenient. Conversely, in central urban areas there are mass settlements, land is limited, and water resources are scarce.

The daily MSW capacities of the candidate sites were calculated according to the "Construction Standard of MSW Landfill Disposal Engineering Project" (Tables D.1, D.2, Appendix D). There were four candidate landfills (S-3, S-5, S-7, and S-8) in Yongdeng, three candidate sites (S-4, S-5, and S-6) in Gaolan, and one candidate site (S-2) in Yuzhong, each of which could accommodate more than 1200 tons/day of MSW. One of the most suitable candidate landfill sites in Honggu (S-9) had a capacity of 500 to1200 tons/day of MSW. The candidate sites in Xigu and Anning were S-10 and S-11, both of which could accommodate 200 to 500 tons/day of MSW. Qilihe and Chengguan had no optimal sites. A comparison of the population densities in the study area, the official forecast of garbage growth, and the capacity of the candidate sites indicated that the landfill capacity would not reach saturation for at least a decade.

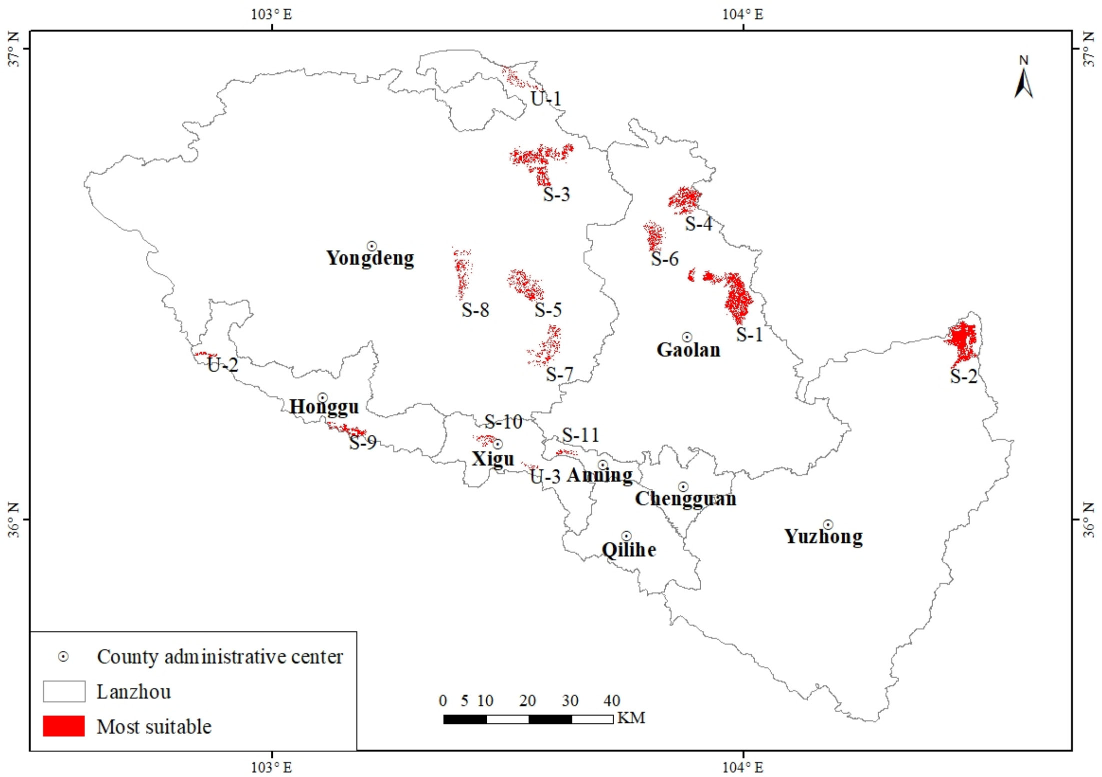


Fig. 4. Site selection of MSW landfills in Lanzhou. The red areas were the most suitable landfill sites, with a total of 11 candidate sites selected.

4.3. Validation

The 11 candidate sites identified by cluster analysis were satisfactory from the perspective of hydrogeological, morphological, environmental, climatic, and socio-economic factors, as they were all based on criteria analysis. However, to ensure that the candidate sites conformed to the CNS and the urban planning measures of the study area, it was necessary to evaluate them relatively. We conducted field visits and selected four methods: WASPAS, MOORA, COPRAS, and TOPSIS to determine the final ranking of the candidate sites by according to expert opinions and regional characteristics. As can be seen from Table 3, the ranking results of WASPAS and COPRAS were the same, as were MOORA and TOPSIS, whereas the four methods were slightly different for S-5, S-7, S-8, and S-10. The correlation coefficient of WASPAS-COPRAS and MOORA-TOPSIS was 1, and for WASPAS-MOORA, WASPAS-TOPSIS, COPRAS-MOORA, and COPRAS-TOPSIS was 0.94. As such, it was confirmed that there was a high degree of consistency between the ranking results of the candidate sites, with S-1 being the most suitable.

In this study, sensitivity analysis charts were established for 13 scenarios with different weights to reflect the influences of changes in criterion weights on the final results and ranking stability (Fig. E.2 in Appendix E). Spearman's correlation coefficient was employed to analyze four ranking methods in the scenario simulation with different weights (Table E.1 in Appendix E). As can be seen from the Figure, the ranking of scenarios 4, 6, and 7 changed among the four ranking methods, which was due to their low correlation coefficients between and the original weighting scenario 1. The ranking order of the other 10 scenarios remained unchanged, which indicated the stability of the site selection results and the reliability of the method. Furthermore, the criteria for ranking the first, second, and third sites were all decisive and evenly distributed. Their relative importance was balanced, although the scores of candidate sites varied under different scenarios.

Table 3

Ranking of candidate sites through WASPAS, MOORA, COPRAS, and TOPSIS.

		S-1	S-2	S-3	S-4	S-5	S-6	S-7	S-8	S-9	S-10	S-11
WASPAS	Q_i	0.802	0.795	0.528	0.755	0.602	0.670	0.594	0.569	0.735	0.553	0.486
	Rank	1	2	10	3	6	5	7	9	4	8	11
MOORA	Q_i	0.256	0.243	0.099	0.217	0.133	0.152	0.131	0.118	0.189	0.117	0.058
	Rank	1	2	10	3	7	5	6	8	4	9	11
COPRAS	Q_i	0.219	0.203	0.111	0.185	0.139	0.151	0.138	0.121	0.170	0.126	0.102
	Rank	1	2	10	3	6	5	7	9	4	8	11
TOPSIS	Q_i	0.426	0.432	0.240	0.408	0.289	0.321	0.299	0.266	0.373	0.265	0.213
	Rank	1	2	10	3	7	5	6	8	4	9	11

5. Conclusion

This study identified and assessed the most suitable landfill sites in Lanzhou and conducted a field investigation to avoid the "NIMBY effect". In doing so, the 11 selected candidate sites would not affect the health of the population, rivers, protected areas, etc., which will enhance the acceptance of the government and be of benefit to society for at least ten years. For this study, we initially established a standard evaluation system of semi-arid valley basin municipal waste landfill site selection. This was an integrated flexible and novel comprehensive framework for reducing the subjectivity and uncertainty of weight, and the fuzzy logic relation of different criteria was explored. The DEMATEL-ANP method proved to be more preferable to ANP as it could deal with all types of dependencies systematically. The simple ANP method directly constructed the network relations between the input criteria according to a scale of from 1-9, which had the subjective disadvantage of AHP. This integration framework allowed for complex issues to be explored and fed back to decision makers. Hybrid fuzzy logic is preferable to a simple method, as it can better express the fuzziness and uncertainty of criterion, to obtain more accurate results. The three density-based clustering algorithms (DBSCAN, HDBSCAN, and OPTICS) were utilized to identify 11 candidate sites for landfills, analyze their spatial distribution characteristics and reachability, and calculate the relative MSW capacities according to the area. The high consistency of the four sorting methods of MOORA, WASPAS, COPRAS, and TOPSIS fulfilled a comprehensive ranking of candidate sites. Sensitivity analysis enabled scenario simulation with different weights set by multiple criteria, which can effectively guide planners to consider the uncertainty of weights in the decision-making evaluation process to obtain more satisfactory solutions.

For subsequent research, more consideration should be given to the environmental pollution generated by selected sites. Dynamic data for landfill sites can be obtained in real time through atmospheric monitoring, soil detection, and remote imaging for standardized management. Similarly, the amount of carbon contained in landfill emissions is also a major factor that affects the environment, which warrants further study. In addition, we are currently exploring the use of various deep learning algorithms and known landfill sites that conform to the CNS for supervised or unsupervised classification. This to obtain the weight of evaluation criteria, while inviting experts to score and modify the results to eliminate uncertainties in site selection, which is crucial for site selection research. The classification of MSW is not complete, and industrial solid waste is still divided as MSW for landfill disposal in areas with a small amount of production, such as Construction and Demolition Waste (CDW), which is difficult to manage, lacks landfill space, increases costs and has other defects, which are further issues to resolve.

Appendix

Appendix A

Table A.1

Data Format and Source.

Dataset	Format	Data Source
Groundwater depth	Vector (Point)	Gansu Groundwater Report (Gansu Water Resources Department) (http://slt.gansu.gov.cn/)
Groundwater quality	Vector (Point)	Gansu Groundwater Report (Gansu Water Resources Department) (http://slt.gansu.gov.cn/)
Groundwater richness	Vector (Polygon)	" Gansu Hydrogeological Map " (Gansu Bureau of Geology and Mineral Hydrogeology engineering Geological Exploration Institute) (http://www.gssgy.com/)
Faults	Vector (Polyline)	" Gansu Hydrogeological Map " (Gansu Bureau of Geology and Mineral Hydrogeology engineering Geological Exploration Institute) (http://www.gssgy.com/)

Earthquake points	Vector (Point)	"China Historical Earthquake Catalog" (Gansu Earthquake Agency) (http://www.gsdzj.gov.cn/)
DEM	Raster	USGS Earth Explorer (https://earthexplorer.usgs.gov/)
Soil type	Raster	"The Soil Atlas of the People's Republic of China (1: 1 million)" Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences(http://www.resdc.cn/)
NDVI	Raster	MODIS (https://modis.gsfc.nasa.gov/)
Landform type	Raster	"Landscape Atlas of the People's Republic of China (1: 1 million)" Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences(http://www.resdc.cn/)
Surface water	Vector (Polyline)	National Catalogue Service for Geographic Information (https://webmap.cn/)
Roads	Vector (Polygon)	National Catalogue Service for Geographic Information (https://webmap.cn/)
Land use type	Raster	Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences(http://www.resdc.cn/)
Settlements	Vector (Point)	National Catalogue Service for Geographic Information (https://webmap.cn/)

Precipitation	Raster	Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences(http://www.resdc.cn/)
Temperature	Raster	Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences(http://www.resdc.cn/)
Ecosystem service value	Raster	Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences(http://www.resdc.cn/)
Population density	Raster	Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences(http://www.resdc.cn/)
GDP	Raster	Data Center for Resources and Environmental Sciences of the Chinese Academy of Sciences(http://www.resdc.cn/)
Airports	Vector (Point)	Crawled POI data Official website of Gold Maps (https://lbs.amap.com/)
Ecological function reserves	Vector (Polygon)	Portal website of Gansu Forestry and Grass Bureau and its administrative departments (http://lycy.gansu.gov.cn/)

Appendix B

Table B.1

Attribute, conditions to be met and type of evaluation criterion.

Criteria	Sub-criteria	Attribute	Rank	Conditions to be met	Type
Hydrogeological B_1	Groundwater depth C_1（m）	<5	1	The landfill should develop at locations with sufficient groundwater depth (Rezaeisabzevar et al., 2020)	positive
		5-20	2		
		20-50	3		
		50-70	4		
		>70	5		
	Groundwater quality C_2	I	1	The landfill should be located in areas with poor water quality (Przydatek and Kanownik, 2019)	negative
		II	2		
		III	3		
		IV	4		
		V	5		
	Groundwater richness C_3（m³/L）	>1000	1	The landfill should be located in an area with low groundwater richness (Sener et al., 2011)	positive
		600-1000	2		
		300-600	3		
		100-300	4		
		<100	5		
	Distance from faults C_4（km）	<1	1	The landfill avoided in areas with active geological structures or other underground terrain (Eskandari et al., 2012)	negative
		3-1	2		
		5-3	3		
		6-5	4		
		>6	5		

	Distance from earthquake points C_5 （km）	<5	1	The landfill should be located far away from the earthquake point to reduce the possibility of natural disasters (Eskandari et al., 2012)	negative
		15-5	2		
		25-15	3		
		30-25	4		
		>30	5		
Morphological B_2	Elevation C_6（m）	>2000	1	The landfill should not be located in high-altitude areas (Sener et al., 2010)	positive
		1750-2000	2		
		1500-1750	3		
		1250-1500	4		
		1000-1250	5		
	Slope C_7（%）	>60	1	The landfill should be located in a low slope area (Chabuk et al., 2016)	positive
		40-60	2		
		20-40	3		
		10-20	4		
		<10	5		
	Soil type C_8		1	The landfill should be located in areas with sandy soil (Soroudi et al., 2018)	negative

		Semi-aqueous soil, rock soil, calcareous soil, primordial soil, semi-leached soil	2		
		Arid soil	3		
		Alpine soil, desert soil	4		
		Saline soil	5		
	NDVI C_9	>0.8	1	The landfill should be located in an area with low vegetation coverage (Kara and Doratli, 2012)	positive
		0.5-0.8	2		
		0.3-0.5	3		
		0.2-0.3	4		
		<0.2	5		
	Landform type C_{10}	Medium and large rolling mountains	1	The landfill should be located in the plain area (Sureshkumar et al., 2017)	negative
		Small rolling mountain	2		
		hills	3		
		Terraces	4		
		Plains	5		
Environmental B_3	Distance from surface water C_{11}	<0.5	1	The landfill should not be located near ambient surface water such as ponds, lakes,	negative
		1-0.5	2		

	（km）	1.5-1	3	rivers, and streams to avoid their contamination (Uyan, 2014)	
		2-1.5	4		
		>2	5		
	Distance from roads C_{12}（km）	>3	1	In view of the high transportation costs, the landfill should not be too far away from the road network (Chabuk et al., 2016)	positive
		<0.5	2		
		2-3	3		
		0.5-1	4		
		1-2	5		
	Land use type C_{13}	Water, snow, farmland, forestland	1	The landfill should be located in unused areas such as bare land (Motlagh and Sayadi, 2015)	negative
		Wetland	2		
		Shrubland	3		
		Grassland	4		
		Bare land	5		
	Distance from settlements C_{14} (km)	<0.5	1	The landfill should not be located near residential areas (Wang et al., 2009)	negative
		1-0.5	2		
		1.5-1	3		
		2-1.5	4		
		>2	5		
Climatic B_4	Precipitation C_{15}（mm）	>300	1	The landfill should be located in arid areas (Augusto et al., 2019)	positive
		250-300	2		
		200-250	3		

		180-200	4		
		<180	5		
	Temperature C_{16} (°C)	<3 | >10	1	The landfill should be located in a mild area (Aksoy and San, 2016)	negative
		2-4	2		
		4-6	3		
		6-8	4		
		8-10	5		
Socio-economic B_5	Ecosystem service value C_{17}	>15000	1	The landfill should be as cheap as possible, and the value of ecosystem services represents the value of land use (Alavi et al., 2013)	negative
		10000-15000	2		
		5000-10000	3		
		3000-5000	4		
		<3000	5		
	Population density C_{18}	>300	1	The landfill should be located in areas with low population density (Farahbakhsh and Forghani, 2019)	positive
		200-300	2		
		150-200	3		
		100-150	4		
		<100	5		
	GDP C_{19}	>1000	1	The landfill should be located in areas with low GDP (Aracil et al., 2018)	negative
		<300	2		
		600-300	3		
		800-600	4		

	1000-800	5		
Distance from airports C_{20}（km）	<3	1	The landfill is a potential risk to aviation safety because they attract flocks of birds. Therefore, landfills should not be located near airports (Wang et al., 2009)	negative
	6-3	2		
	9-6	3		
	12-9	4		
	>12	5		
	<1	1	The landfill should be located in close proximity to natural reserves (Sener et al., 2010)	positive
	4-1	2		
	7-4	3		
	10-7	4		
	>10	5		

Table B.2

The total influence matrix of the criteria (T_C).

	B_1					B_2					B_3				B_4		B_5				
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}	C_{17}	C_{18}	C_{19}	C_{20}	C_{21}
C_1	0.1513	0.0615	0.2485	0.1242	0.0466	0.2178	0.2252	0.1058	0.2684	0.2250	0.3049	0.0975	0.1288	0.1312	0.0548	0.0183	0.2538	0.1220	0.1159	0.0884	0.2503
C_2	0.0763	0.0526	0.0649	0.0716	0.1718	0.0566	0.0950	0.1650	0.0585	0.0866	0.0779	0.0700	0.2049	0.2189	0.0161	0.0054	0.0674	0.1900	0.1808	0.0605	0.0776
C_3	0.1399	0.1587	0.1128	0.2126	0.0603	0.2078	0.2081	0.2094	0.2331	0.2064	0.2558	0.0953	0.1403	0.1488	0.0488	0.0163	0.1322	0.1266	0.0981	0.0937	0.1278
C_4	0.2230	0.0393	0.1049	0.0796	0.0522	0.1980	0.1015	0.1886	0.1209	0.1216	0.1441	0.1072	0.0933	0.2300	0.0270	0.0090	0.2230	0.1288	0.1160	0.1859	0.2321
C_5	0.0954	0.0316	0.0616	0.0482	0.0333	0.0428	0.2779	0.1556	0.0797	0.0723	0.1002	0.0970	0.0913	0.0801	0.0169	0.0056	0.1831	0.1143	0.0695	0.1541	0.0703
C_6	0.1137	0.0386	0.1090	0.0972	0.0471	0.0839	0.0935	0.1757	0.2005	0.1024	0.2349	0.0890	0.0956	0.2004	0.0337	0.0112	0.2054	0.1092	0.1061	0.0815	0.2129
C_7	0.1127	0.0655	0.0983	0.1127	0.0655	0.0983	0.1209	0.0786	0.2241	0.1011	0.2655	0.1847	0.2132	0.1257	0.0361	0.0120	0.2210	0.1960	0.0915	0.0680	0.1312
C_8	0.0872	0.0670	0.0803	0.0676	0.0666	0.0520	0.0781	0.0435	0.0817	0.1790	0.0822	0.1688	0.2124	0.1510	0.0290	0.0097	0.0581	0.2811	0.1811	0.1499	0.0899
C_9	0.0796	0.0395	0.0877	0.0688	0.0282	0.0564	0.0635	0.0502	0.0673	0.0648	0.1963	0.0757	0.0633	0.0755	0.1258	0.0419	0.1713	0.0786	0.0772	0.1547	0.1777

C_{10}	0.1823	0.0464	0.0755	0.0678	0.0501	0.0671	0.0782	0.0428	0.1795	0.0715	0.0990	0.0676	0.1581	0.1788	0.1390	0.0463	0.0776	0.0452	0.0398	0.0459	0.0733
C_{11}	0.2604	0.0797	0.3485	0.3482	0.0617	0.2576	0.2431	0.1402	0.1656	0.1306	0.2021	0.0943	0.2221	0.1592	0.0329	0.0110	0.1658	0.1135	0.0901	0.0968	0.1557
C_{12}	0.2166	0.0437	0.1955	0.0829	0.1550	0.0915	0.2370	0.0768	0.2241	0.0965	0.1407	0.0825	0.0814	0.1875	0.0356	0.0119	0.1227	0.0806	0.0576	0.0707	0.0973
C_{13}	0.1157	0.1554	0.1997	0.2155	0.1712	0.1070	0.1292	0.1056	0.0891	0.0907	0.2137	0.0728	0.0942	0.2181	0.0200	0.0067	0.1016	0.0843	0.0670	0.0743	0.0869
C_{14}	0.2466	0.0363	0.1044	0.1792	0.1611	0.1999	0.2371	0.0915	0.1441	0.1989	0.1433	0.1917	0.0958	0.1256	0.0381	0.0127	0.1430	0.0884	0.0663	0.0772	0.1186
C_{15}	0.0473	0.1251	0.0397	0.0227	0.0439	0.0223	0.0485	0.0313	0.0463	0.0636	0.0332	0.1706	0.0407	0.0587	0.0122	0.3374	0.0285	0.0344	0.0301	0.0189	0.0258
C_{16}	0.0443	0.0100	0.0301	0.0167	0.0228	0.0176	0.0350	0.0133	0.0448	0.1298	0.0266	0.1278	0.0266	0.0407	0.0194	0.0065	0.0223	0.0140	0.0108	0.0130	0.0190
C_{17}	0.2389	0.0606	0.1447	0.1036	0.0600	0.0983	0.1210	0.1754	0.1360	0.2289	0.2481	0.1879	0.1420	0.1495	0.0410	0.0137	0.1110	0.2178	0.2266	0.0796	0.2373
C_{18}	0.0691	0.1491	0.0723	0.0708	0.0664	0.0562	0.0688	0.0531	0.0629	0.0733	0.0839	0.0515	0.1870	0.2101	0.0151	0.0051	0.0633	0.0678	0.1871	0.0476	0.1753
C_{19}	0.0728	0.0336	0.0661	0.0633	0.0476	0.0517	0.0603	0.0356	0.0687	0.1645	0.0776	0.0461	0.1636	0.1850	0.0259	0.0086	0.0580	0.0470	0.0543	0.0414	0.1573
C_{20}	0.0591	0.0255	0.0413	0.0370	0.0425	0.0386	0.0603	0.0246	0.0479	0.0410	0.0409	0.1473	0.0405	0.1693	0.0099	0.0033	0.0365	0.1374	0.0346	0.0212	0.0435
C_{21}	0.1103	0.0645	0.2155	0.1075	0.0460	0.0909	0.0984	0.0805	0.2060	0.1193	0.2425	0.0827	0.1247	0.1425	0.0315	0.0105	0.1996	0.2039	0.3136	0.1752	0.1369

Table B.3

The total influence matrix of the criteria (T_B).

	B_1	B_2	B_3	B_4	B_5
B_1	0.1100	0.3247	0.0529	0.0151	0.0151
B_2	0.3851	0.1365	0.1850	0.0529	0.0529
B_3	0.4757	0.3058	0.1893	0.3398	0.3398
B_4	0.2265	0.0901	0.1775	0.0507	0.0507
B_5	0.1359	0.0874	0.3398	0.0971	0.0971

Appendix C

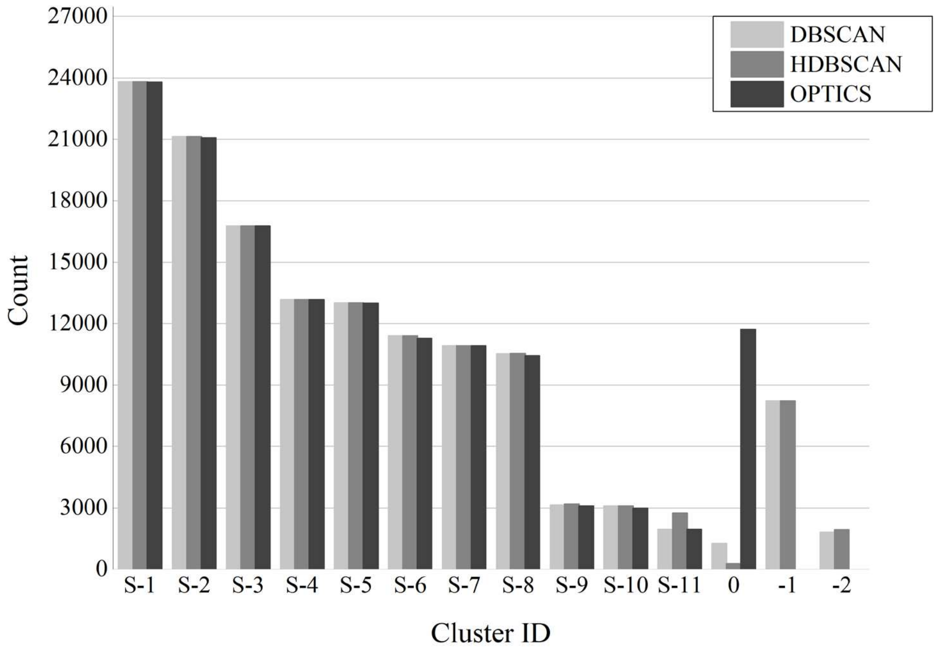


Fig. C.1. A comparison of values of the candidate sites in each cluster for the DBSCAN, HDBSCAN, and OPTICS.

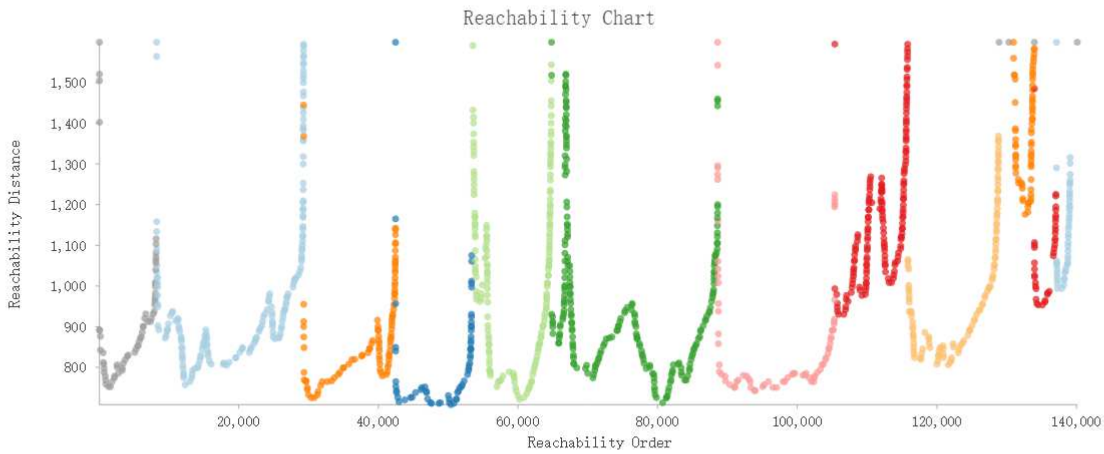


Fig. C.2. The reachability chart of OPTICS algorithm, different colors represent different clusters.

Appendix D

Table D.1

"Construction Standard of MSW Landfill Disposal Engineering Project". The landfill is divided into four levels according to the area of the landfill. The smaller the area, the higher the level, and the lower the amount of MSW to be disposed.

Landfill	I	II	III	IV
Area（Km^2)	>12	5-12	2-5	1-2
Amount of MSW（Tons/day）	>1200	500-1200	200-500	<200

Table D.2

Candidate site latitude, longitude, area, and MSW disposal capacity. S-1 and S-2 had the highest MSW disposal capacities, S-4, S-6, and S-10 had the lowest MSW disposal capacities.

Country/ District	Candidate site	Longitude	Latitude	Area （Km^2)	Amount of MSW （Tons/day）
Yongdeng	S-3	103°31′25″E	36°47′43″N	40.3	>1200
	S-5	103°33′12″E	36°30′37″N	29.9	>1200
	S-7	103°37′14″E	36°20′52″N	28.2	>1200
	S-8	103°25′47″E	36°33′12″N	27.6	>1200
Gaolan	S-1	103°58′40″E	36°29′14″N	41.4	>1200
	S-4	103°53′15″E	36°39′55″N	27.7	>1200
	S-6	103°48′19″E	36°32′35″N	15.3	>1200
Yuzhong	S-2	104°27′50″E	36°22′56″N	35.5	>1200
Honggu	S-9	103°12′11″E	36°10′58″N	9.8	500-1200
Xigu	S-10	103°27′46″E	36°11′14″N	3.7	200-500
Anning	S-11	103°37′05″E	36°8′37″N	2.6	200-500
Qilihe	-	-	-	-	-
Chengguan	-	-	-	-	-

Appendix E

Table E.1

Weighting scenarios and Spearman's correlation coefficient values of WASPAS, MOORA, COPRAS, and TOPSIS.

Scenario	Scenario description	Spearman's correlation coefficient			
		WASPAS	MOORA	COPRAS	TOPSIS
1	original weight	1	1	1	1
2	The weight of the first-ranking is substituted with the second-ranking	1	1	1	1
3	The weight of the first-ranking is substituted with the third-ranking	1	1	1	1
4	The weight of the first-ranking is substituted with the fourth-ranking	0.9428	0.8857	0.9428	0.8857
5	The weight of the second-ranking is substituted with the third-ranking	1	1	1	1
6	The weight of the second-ranking is substituted with the fourth-ranking	0.9428	0.9428	0.9428	0.9428
7	Omitting the first-ranking criterion	0.8857	0.9428	0.8857	0.9428
8	Omitting the second-ranking criterion	1	1	1	1
9	Omitting the third-ranking criterion	1	1	1	1
10	Increasing the first-ranking weight	1	1	1	1

	by 5%				
11	Decreasing the first-ranking weight by 5%	1	1	1	1
12	Increasing the second-ranking weight by 5%	1	1	1	1
13	Decreasing the second-ranking weight by 5%	1	1	1	1

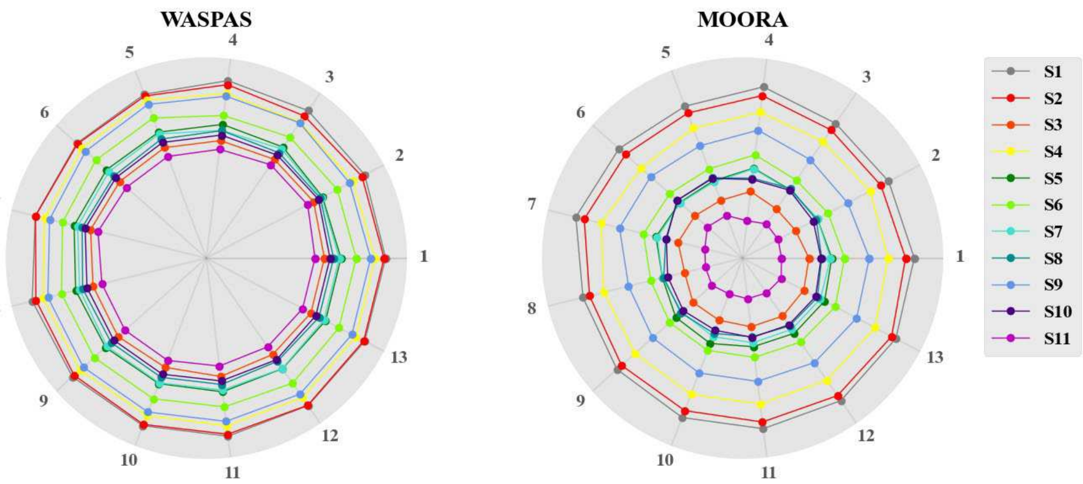


Fig. E.2. The left figure shows a comparison of the values of WASPAS for the candidate sites in each scenario. The right figure shows a comparison of the values of MOORA for the candidate sites in each scenario.

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Figures

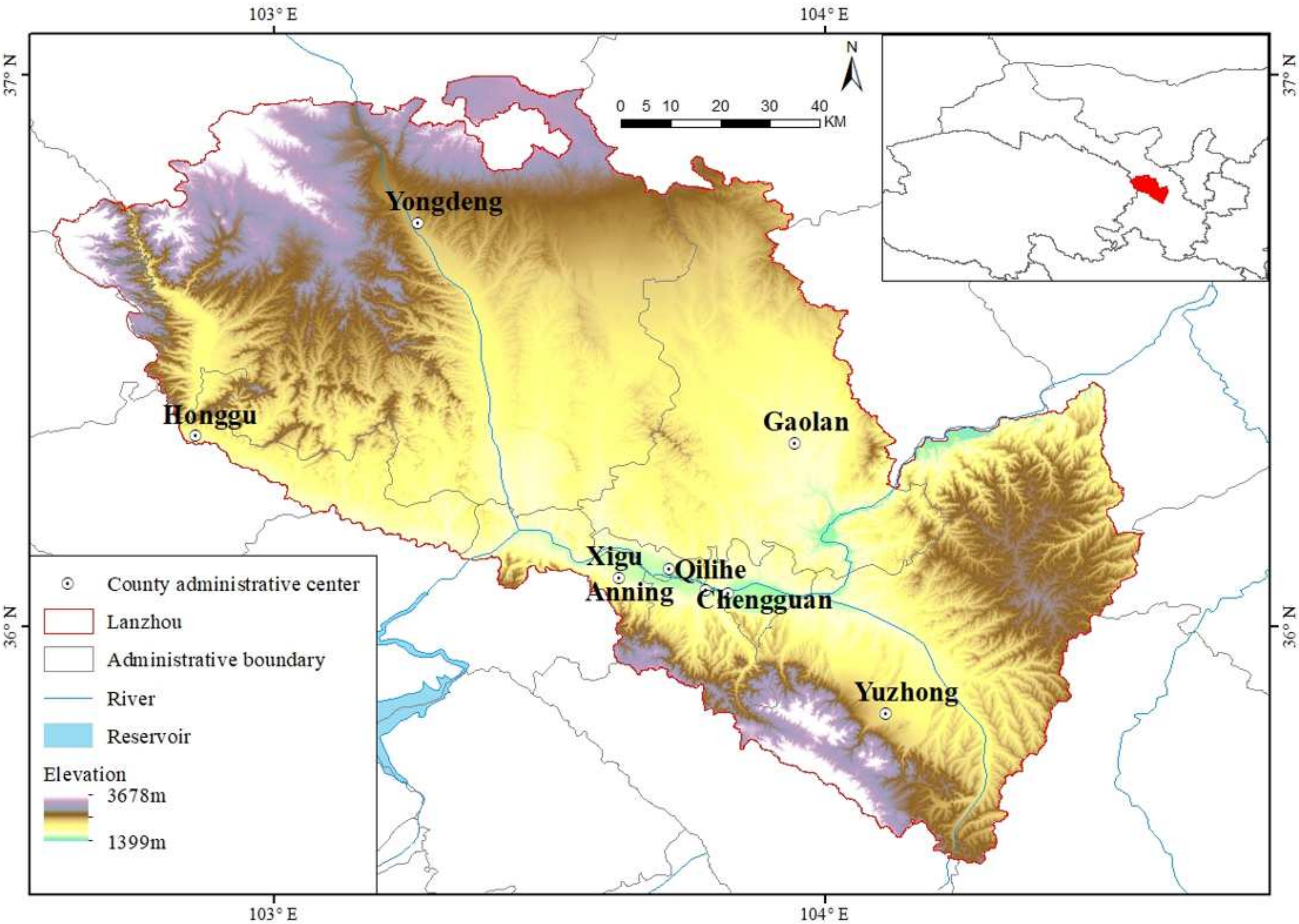

Figure 1

Elevation of the study region. Lanzhou includes five districts (Honggu, Xigu, Anning, Qilihe, and Chengguan), and three counties (Yongdeng, Gaolan, and Yuzhong). Elevation data is from the USGS - SRTM dataset, which provides elevation data at a 30m resolution. The elevation of the study area ranged from 1399 to 3678 m. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

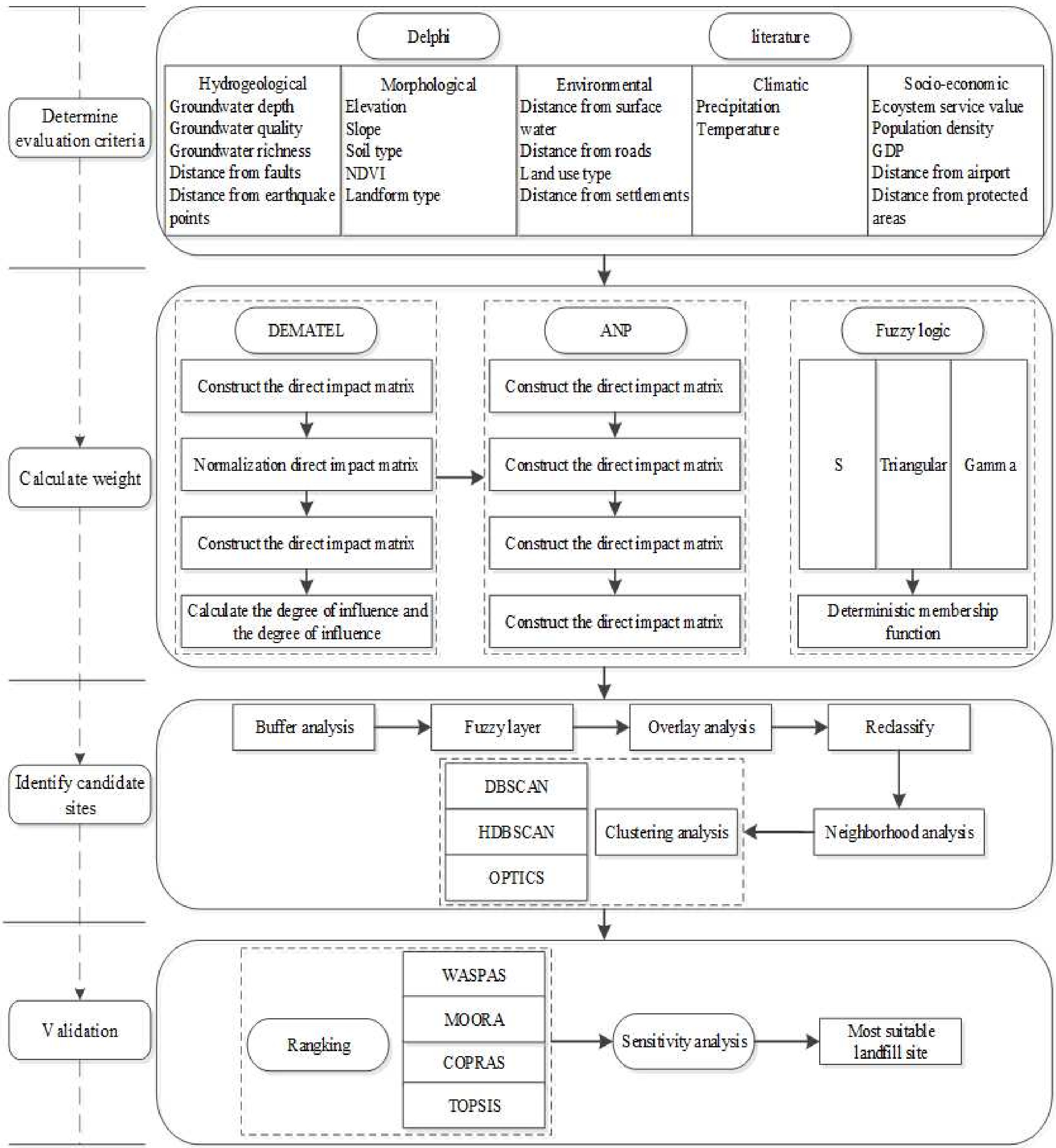

Figure 2

Flowchart of the proposed methodology, including four main steps: determine evaluation criteria, calculate weight, identify candidate sites, and validation.

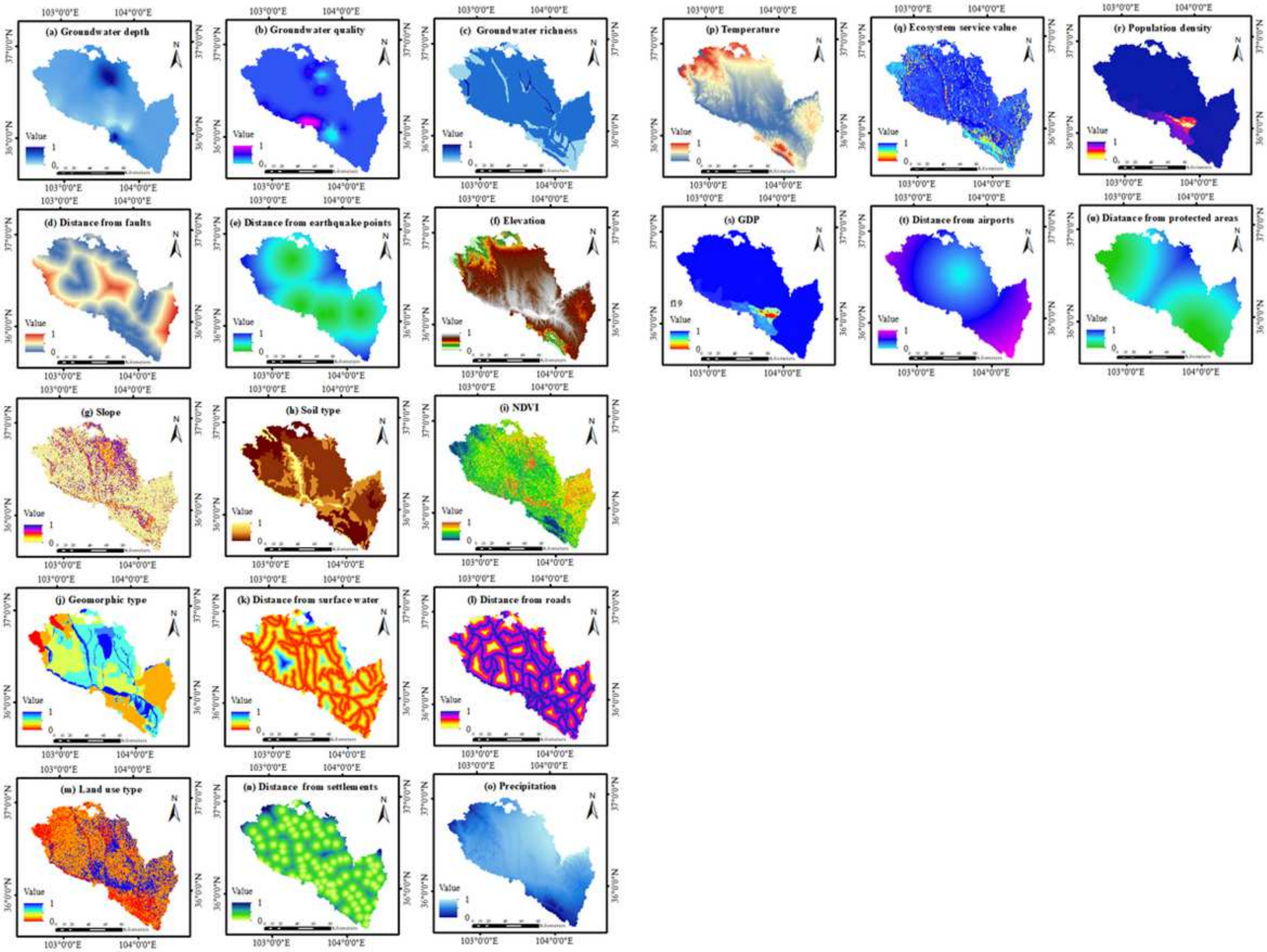

Figure 3

Criteria included (a) groundwater depth, (b) groundwater quality, (c) groundwater richness, (d) distance from faults, (e) distance from earthquake points, (f) elevation, (g) slope, (h) soil type, (i) NDVI, (g) landform type, (k) distance from surface water, (l) distance from roads, (m) land use type, (n) distance from settlements, (o) precipitation, (p) temperature, (q) ecosystem service value, (r) population density, (s) GDP, (t) distance from airports, (u) distance from protected areas. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

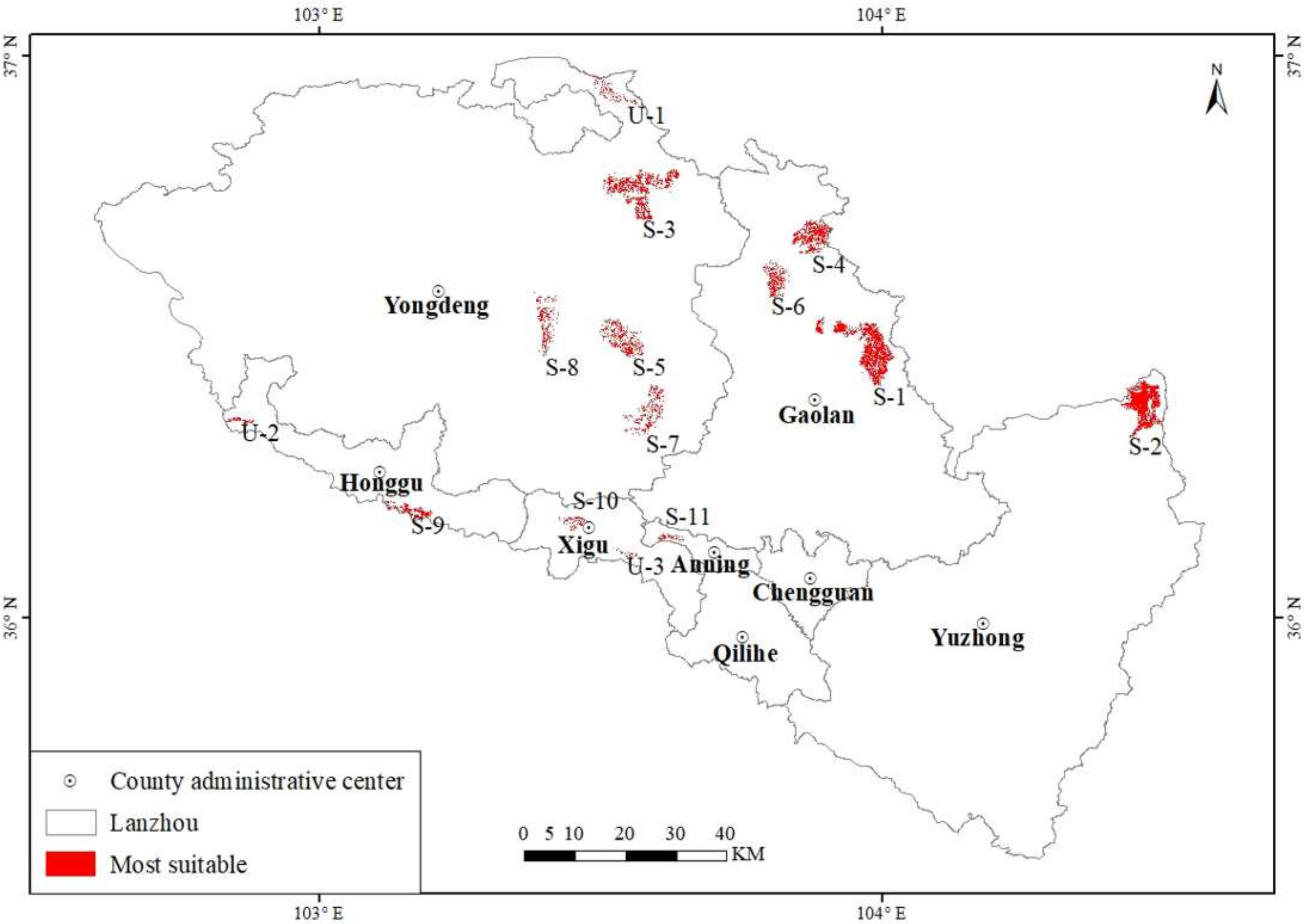

Figure 4

Site selection of MSW landfills in Lanzhou. The red areas were the most suitable landfill sites, with a total of 11 candidate sites selected. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.