Ensemble Belief Rule-Based Model for Ecological Security of Land Resource Evaluation

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Abstract—**Ecological security of land resource (ESLR) evaluation is a significant part in ecological environment protection and sustainable development. In order to consider the multiple influencing factors comprehensively, obtain a traceable and interpretable evaluation result, an evaluation process of ESLR based on the Ensemble Belief Rule-Based model is proposed in this paper. The Ensemble-BRB model is a combination of several weak BRB models, each of which evaluates the ESLR from part of the influencing factors. Weighted averaging is introduced as the combination method to integrate the evaluation results of different weak BRB models. An ESLR evaluation case in Hunan Province, China is investigated to validate the feasibility and efficiency of the proposed method. The evaluation results can support the decision makers to develop targeted protection measures of land ecological.**

I. Introduction

Ecological Security of Land Resource (ESLR) refers to a health state in which land ecosystem can maintain the integrity of its structure and function within a time-space, and provide stable, balanced, and abundant conditions for ensuring the sustainable development of human society, economy, and agriculture [1] [2]. A high level of the ESLR can maintain the long-term coordinated development of land nature, society, and economic complexes. With the development of social economy in recent years, the destruction of the land ecosystems has gradually intensified. The contradiction between human and land ecosystems has become increasingly prominent. As an important part of ecological civilization construction, ESLR is not only related to the sustainable development of land ecosystems, but also closely related to the indispensable food production in human's lives.

The analysis and evaluation of the ESLR have attracted extensive attentions in academia for its significance, which have become one of the central topics in ecological security management. For example, Deng et al. applied the Delphi method to establish an evaluation system of ELSR [3]. Though this method is easy to be implemented, its subjectivity is too strong. Zhang et al. introduced the P-S-R framework to construct the evaluation model of ELSR based on three aspects including ecological stress, ecological status, and ecological environment [4]. The evaluation results of this method are objective, but the factors considered are not comprehensive enough. With the deepening of research, the dominated evaluation method of ELSR has changed gradually from qualitative methods to quantitative methods. The support vector machine (SVM) [5], analytic hierarchy process (AHP) [6] and other medthods have been widely used in the ELSR evaluation.

The analysis and evaluation of the ESLR have the following three characteristics: (I) ESLR involves many influencing factors, such as forest coverage rate, agricultural acreage and so on; (II) the acquisition of some influencing factors is complicated, which may introduce uncertainty into the measurement data; (III) the evaluation model of ESLR should be traceable and interpretable, ensuring that the decision makers specify land ecosystem protection policies based on the evaluation results of ESLR. The existing ESLR evaluation models usually only contain parts of the influencing factors, but the uncertainty of data is ignored in the modeling and evaluation stage. The evaluation models using knowledge-based methods such as Delphi method are traceable, but the evaluation results are subjective. The evaluation models using data-driven methods such as neural network are more objective, but they are untraceable, uninterpretable, and prone to over-fitting.

In view of the characteristics and the shortcomings in the analysis and evaluation of the ESLR described above, the belief rule-based (BRB) model [7] is introduced. The BRB model is an analysis methods for complex systems with uncertainty based on the rule-based systems and D-S evidence theory. Belief degrees are added into the traditional "IF-THEN" rules, named belief rules [8], to describe the uncertain information. The evidential reasoning (ER) algorithm is used to aggregate the activated belief rules. Since introduced, the BRB model has been used in many fields such as complex system modeling [9] and medical diagnoses [8].

However, due to the ESLR involves many influencing factors, the traditional BRB model faces the challenge of the combinatorial explosion problem. On this basis, the Ensemble-BRB model based on the bootstrap aggregating (bagging) [10] is introduced to dealing with the analysis and evaluation of the ESLR in this paper. The Ensemble-BRB model is a combination of several weak BRB models. The m ($m < M$) attributes are randomly selected from all M influencing factors in each weak BRB model, and m is directly determined by the modelers. These weak BRBs obtain the evaluation results from different attributes respectively and their ensemble is regarded as the final evaluation results for ESLR.

The remainder of this paper is organized as follows. The traditional BRB model and bagging framework are briefly introduced in Section II. In Section III, the modeling and evaluation process of the ESLR based on the Ensemble-BRB

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model is described. Section IV presents an ESLR evaluation case in Hunan Province, China to verify the feasibility and effectiveness. This paper is concluded in Section V.

II. PRELIMINARY

A. Basic of BRB Model

The BRB model is consisted with a set of belief rules, and a typical belief rule can be described as Eq. (1) [7]:

$$\begin{aligned} &R_k : IF\ (x_1\ is\ A_1^k) \wedge (x_2\ is\ A_2^k) \wedge \cdots \quad s\ A_M^k), \\ &THEN\ \{(D_1, \beta_{1,k}), \cdots \quad {}_{N,k})\}, \\ &with\ rule\ weight\ \theta_k\ and\ attribute\ weight\ \delta_1, \delta_2, \cdots \end{aligned} \tag{1}$$

In the k-th rule, $x_m(m = 1,2,\cdots$ represents the m-th attribute and $A_m^k(k = 1,2,\cdots$ represents the reference value of the m-th attribute in the k-th rule. In the ESLR evaluation, the attributes are equal to influencing factors. The n-th rank of consequents is denoted as $D_n(n = 1,2,\cdots$ with belief degree $\beta_{n,k}$ in the k-th rule.

The input of the BRB model can be recorded as follows:

$$(x_1, \varepsilon_1) \wedge (x_2, \varepsilon_2) \wedge \cdots \quad \varepsilon_M) \tag{2}$$

where x_m is the input of the m-th attribute, and ε_m denotes the belief of x_m.

The degree of activation for the k-th rule ω_k can be calculated as follows [7]:

$$\omega_k = \frac{\theta_k \prod_{i=1}^{T_k} (\alpha_{i,j}^k)^{\bar{\delta}_i}}{\sum_{l=1}^{K} \left[\theta_l \prod_{i=1}^{T_l} (\alpha_{i,j}^l)^{\bar{\delta}_i} \right]} \quad and \quad \bar{\delta}_i = \frac{\delta_i}{\max_{j=1,2,\cdots} \{\delta_j\}}, \tag{3}$$

where $\alpha_{i,j}^k(i = 1,2,\cdots$ is the belief degree to which the input for the i-th attribute belongs to its j-th referential value $A_{i,j}^k$ in the k-th rule, named individual matching degree, which can be calculated using Eq. (4). And $\bar{\delta}_i$ represents the normalized attribute weight. If $\omega_k \neq 0$, the k-th rule is activated.

$$\alpha_{i,j}^k = \frac{\varphi(x_i, A_{i,j}^k)\varepsilon_i}{\sum_{l=1}^{T_k} \varphi(x_i, A_{i,j}^k)}, \quad \varphi(x_i, A_{i,j}^k) = \begin{cases} \dfrac{A_{i,l+1}^k - x_i}{A_{i,l+1}^k - A_{i,l}^k} & j = l(A_{i,l}^k \le x_i \le A_{i,l+1}^k) \\ \dfrac{x_i - A_{i,l}^k}{A_{i,l+1}^k - A_{i,l}^k} & j = l+1(A_{i,l}^k \le x_i \le A_{i,l+1}^k). \\ 0 & else \end{cases} \tag{4}$$

The ER algorithm is used to aggregate the activated belief rules using Eq. (5) [7]:

$$\begin{aligned} \beta_n &= \frac{\mu\left[\prod_{k=1}^{K}(\omega_k\beta_{n,k} + 1 - \omega_k\sum_{n=1}^{N}\beta_{n,k} - \prod_{k=1}^{K}(1 - \omega_k\sum_{n=1}^{N}\beta_{n,k})\right]}{1 - \mu\left[\prod_{k=1}^{K}(1 - \omega_k)\right]}, \\ \mu &= \left[\sum_{n=1}^{N}\prod_{k=1}^{K}(\omega_k\beta_{n,k} + 1 - \omega_k\sum_{n=1}^{N}\beta_{n,k}) - (N-1)\prod_{k=1}^{K}(1 - \omega_k\sum_{n=1}^{N}\beta_{n,k})\right]^{-1}. \end{aligned} \tag{5}$$

The output for the object to be evaluated is described as Eq. (6) [11]:

$$S(x^*) = \{(D_n, \beta_n), n = \cdots \tag{6}$$

Eq. (6) gives a distribution of belief degree for conclusions, and the evaluation result of object x^* can be obtained by Eq. (7) [11]:

$$u(S(x^*)) = \sum_{n=1}^{N} u(D_n)\beta_n, \tag{7}$$

where $u(D_n)$ denotes the utility values of conclusion D_n.

B. Ensemble Framework

The core idea of ensemble is to integrate multiple weak learners based on certain combination methods to obtain the final results. In the evaluation problem, the weak learners give the evaluation result of the object only from partial influencing factors, so the accuracy of them are relatively low. Integrating multiple weak learners is equivalent to integrating the evaluation results from multiple perspectives, which can effectively improve the reliability of the evaluation results. Weighted average is a commonly used combination method for evaluating problems. Assuming that the normalized weight of i-th weak learner is $\bar{w}_i$, the final result of the ensemble learner can be calculated using Eq. (8) [12]:

$$U = \sum_{i=1}^{I} \bar{w}_i u_i, \quad \bar{w}_i = \frac{w_i}{\sum_{i=1}^{I} w_i}, \tag{8}$$

where u_i denotes the evaluation result of the i-th weak learner, and U denotes the final result after combination.

III. APPLICABILITY OF ENSEMBLE-BRB MODEL IN ESLR EVALUATION

In this section, the main ideas of the Ensemble-BRB model are illustrated in Section III.A, and the modeling steps of the Ensemble-BRB model for ESLR evaluation are given in Section III.B.

A. Main Idea

The Ensemble-BRB model is an applicability of the BRB model under the ensemble framework. The BRB models are defined as the weak learners in the Ensemble-BRB model, where each of them contains parts of antecedent attributes. The framework of the Ensemble-BRB model is demonstrated in Fig. 1.

Supposing that there are four influential factors in the evaluation problem, which are regarded as the antecedent attributes. For constructing a traditional BRB model based on these attributes directly, its k-th rule can be defined as follows:

$$\begin{aligned} &R_k : IF\ (a_1\ is\ A_1^k) \wedge (a_2\ is\ A_2^k) \wedge (a_3\ is\ A_3^k) \wedge (a_4\ is\ A_4^k), \\ &THEN\ \{(D_1, \beta_{1,k}), \cdots \quad {}_{N,k})\}, \\ &with\ rule\ weight\ \theta_k\ and\ attribute\ weight\ \delta_1, \delta_2, \cdots \end{aligned}$$

The increase of antecedent attributes will increase the size of BRB. In order to avoid the combinatorial explosion problem, we constructed six weak BRBs, each of which contains only two antecedent attributes. The k-th rule in the first weak BRB is defined as follows:

$$R_k^1: IF\ (a_1\ is\ A_1^k)\wedge(a_2\ is\ A_2^k), THEN\ \{(D_1^1,\beta_{1,k}^1),\cdots \qquad {}^{1}_{N,k})\},$$
$$with\ rule\ weight\ \theta_k^1\ and\ attribute\ weight\ \delta_1^1,\delta_2^1,\cdots$$

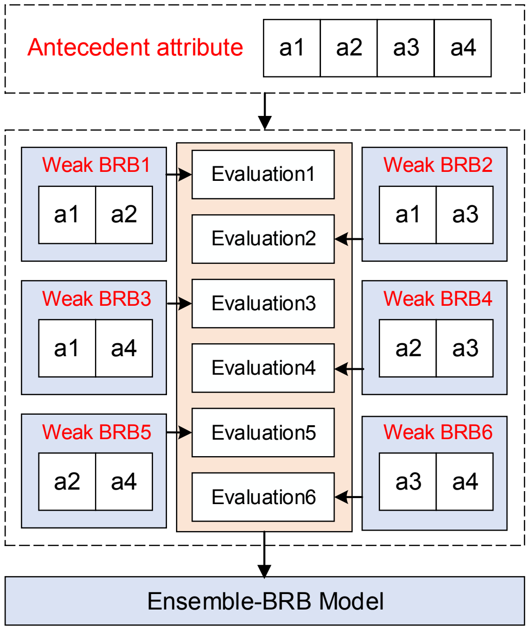

Figure 1. Framework of the Ensemble-BRB model

The traditional BRB model contains $\prod_{i=1}^{4} J_i$ rules, and the first weak BRB model contains $J_1 \times J_2$ rules, where J_i denotes the number of the reference values in the i-th attribute. Supposing that $J_i = 10 \quad (i = 1,2,3,4)$, the traditional BRB model contains 10,000 rules. The weak BRB model only contains 100 rules, which is one percent of the rules' number in the traditional BRB model. With the increase of antecedent attributes, the weakening effect of the weak BRB model will be more significant.

Since each weak BRB constructs belief rules only from partial attributes, reducing the reliability of the evaluation results. The ensemble framework is introduced into the Ensemble-BRB model to combine the evaluation results of each weak BRB and obtain the final evaluation result further. The combination method has been illustrated in Section II.B with Eq. (8).

B. Modeling Steps

In the analysis and evaluation of ESLR using the Ensemble-BRB model, the influential factors of ESLR are regarded as antecedent attributes, and the evaluation results are denoted as the conclusion in the belief rules. The modeling steps of the Ensemble-BRB model in the ESLR evaluation are given in Fig. 2.

Step 1. Select influential factors. Select influential factors of ESLR based on expert experience and actual conditions, and regard them as antecedent attributes.

Step 2. Weak BRB construction. The antecedent attributes of each weak BRB are determined by experts in relevant fields according to the actual situation, and give the belief rules further.

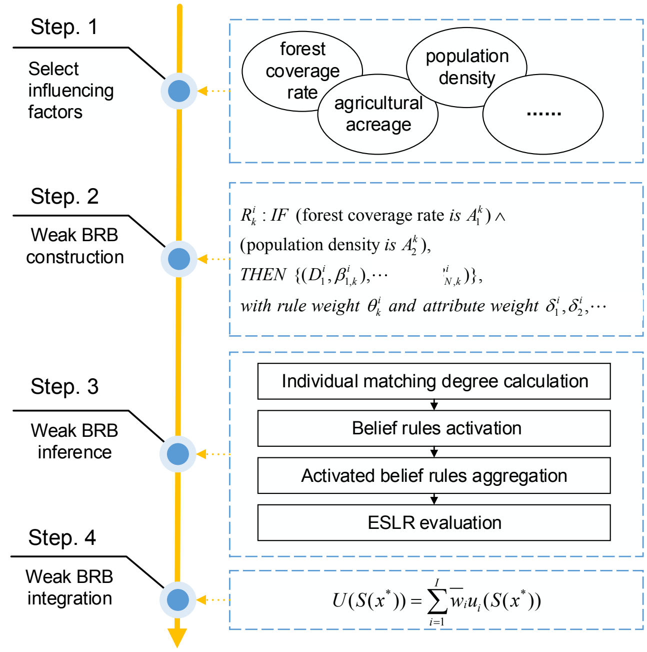

Figure 2. Modeling steps of Ensemble-BRB model in ESLR evaluation

Step 3. Weak BRB inference. Using Eq. (3) ~Eq. (7) to calculate the evaluation results from each weak BRB.

Step 3.1. Calculate individual matching degree using Eq. (4);

Step 3.2. Activate belief rules using Eq. (3);

Step 3.3. Aggregate activated belief rules using Eq. (5);

Step 3.4. Evaluate ESLR using Eq. (7).

Step 4. Weak BRB integration. Using Eq. (8) to combine the evaluation results from each weak BRB and get the final ESLR evaluation result for the object to be evaluated.

IV. CASE STUDY

In this section, an analysis and evaluation case of ESLR in Hunan Province, China is studied to illustrate the feasibility of Ensemble-BRB model in ESLR evaluation.

A. Overview of Hunan Province in ESLR

Hunan Province is located in the middle reaches of the Yangtze River, and its landforms are mainly mountainous and hilly. Besides, Hunan Province is densely populated. Because of many factors, the land resources are facing the problems of decreasing cultivated land area, prominent land pollution, serious soil erosion, and other serious problems. What is worse, the ecological security situation is increasingly grim. Thus, assessing the ecological security situation of Hunan Province and understanding its ecological security are of great significance for the maintenance of regional ecological security in the province.

B. ESLR Evaluation

By consulting the literature, we obtained 10 influencing factors for the ESLR of 14 administrative units in Hunan Province [4] and see Table A1 in *Appendix* for details.

The modeling steps are given in Section III. B above. According to the characteristics of the ESLR evaluation in Hunan Province, the experts construct 15 weak BRB models. The antecedent attributes in each BRB model are given in Table A2 in *Appendix*. The conclusion part is the same in each weak BRB model, which has been set as $\{ESLR_1 = worse, ESLR_2 = medium, ESLR_3 = good\}$, with the corresponding utility values as $u(worse) = 0, u(medium) = 50, u(good) = 100$. Different weak BRB models evaluate the ESLR from different perspectives, but the antecedent attributes in different weak BRBs may be the same. The evaluation results of weak BRB models and the final results in different administrative units are shown in Table 1.

Table 1. ESLR Evaluation in Hunan Province

Administrative units	***Changsha***	***Zhuzhou***	***Xiangtan***	***Hengyang***	***Shaoyang***	***Yueyang***	***Changde***	***Zhangjiajie***	***Huaihua***	***Yiyang***	***Loudi***	***Binzhou***	***Yongzhou***	***Zizhizhou***
weak BRB1	20.80	51.36	16.44	27.84	30.90	56.20	64.72	**98.25**	92.44	44.63	19.88	86.40	63.27	96.27
weak BRB2	19.69	46.25	10.93	16.85	78.77	0.00	15.18	**97.24**	55.27	39.18	28.96	60.72	65.27	80.43
weak BRB3	10.78	40.28	0.64	30.84	26.25	**90.39**	32.22	90.01	85.75	36.09	39.16	63.72	66.52	67.47
weak BRB4	86.13	59.22	10.23	83.15	67.53	44.43	37.41	94.54	97.56	32.35	43.07	8.93	80.27	**99.94**
weak BRB5	35.52	51.21	37.42	16.75	47.09	8.40	42.64	23.35	63.15	38.75	21.35	51.26	**67.65**	33.15
weak BRB6	9.90	44.13	5.08	7.47	28.71	8.32	**73.61**	29.96	40.53	50.71	25.10	44.21	64.75	39.31
weak BRB7	26.20	49.06	5.71	32.64	32.97	**97.82**	97.42	15.06	73.84	50.56	33.00	56.54	73.52	36.09
weak BRB8	5.96	52.11	5.20	6.61	64.28	2.40	13.35	**92.04**	86.97	16.31	6.39	79.66	62.64	78.07
weak BRB9	5.05	49.15	0.71	12.82	38.14	26.57	42.78	74.51	**96.50**	22.96	8.38	84.74	74.01	82.30
weak BRB10	4.83	26.73	0.50	11.29	9.58	39.51	5.26	84.56	83.05	14.42	26.71	35.37	41.19	**91.64**
weak BRB11	29.58	77.04	12.42	45.31	27.17	94.04	88.93	**99.92**	99.67	71.45	20.71	21.45	93.74	99.84
weak BRB12	12.53	39.91	15.19	20.86	21.53	79.48	36.45	**98.46**	74.71	40.31	23.61	56.15	56.23	78.01
weak BRB13	11.27	44.85	6.45	9.87	8.41	**88.86**	88.07	29.37	73.96	41.63	10.02	53.37	66.07	46.43
weak BRB14	25.05	75.39	10.19	31.97	76.57	10.01	75.57	**99.99**	84.63	84.57	48.02	16.39	93.19	97.43
weak BRB15	14.73	41.73	12.01	15.70	37.35	6.23	7.69	**97.14**	78.86	24.53	26.05	57.83	59.11	63.31
Ensemble-BRB	21.20	49.89	9.94	24.67	39.68	43.51	48.09	74.96	**79.13**	40.56	25.36	51.78	68.50	72.65

C. Analysis

As shown in Table 1, different weak BRB models may give the evaluation results with great differences for the same administrative units. For example, Zhangjiajie get the best evaluation scores in weak BRB model 1, 2, 8, 11, 12, 14 and 15 (above 90 points), but it only got 15.06 points in the 7-th weak BRB model. The antecedent attributes in 7-th weak BRB model are area of cultivable land and soil erosion, while Zhangjiajie has a high rate of soil erosion. In other weak BRB models with soil erosion, such as 5-th and 6-th weak BRB models, Zhangjiajie's evaluation scores in ESLR are also lower. As mentioned above, since each weak BRB model contains only a part of the influencing factors, its evaluation results are one-sided. Combine the results of multiple weak BRB models is equivalent to evaluating ESLR from multiple perspectives, which ensure the reliability of the evaluation results of the Ensemble-BRB model.

The ESLR evaluation results of 14 administrative units in Hunan Province based on the Ensemble-BRB model are visually shown in Fig. 3.

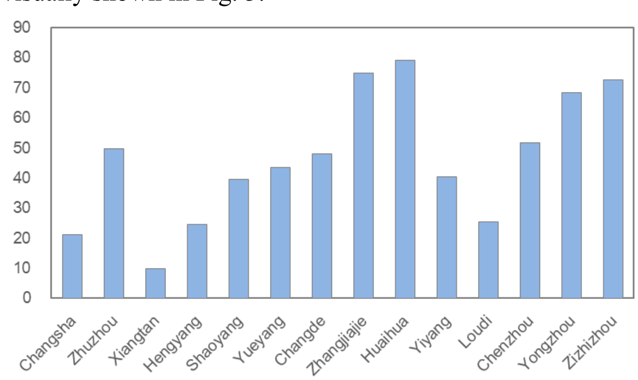

Figure 3. ESLR evaluation in Hunan Province

As shown in Fig. 3, Huaihua get the best score, while the ESLR evaluation of Zhangjiajie, Zizhizhou and Yongzhou are also at a good level. The ESLR evaluation of Xiangtan is worse than other administrative units, which is only 9.94 points. This result indicates that the ESLR of Xiangtan has been very severe. The influencing factors, such as per capita water capacity, are at a low level. It is urgent to formulate reasonable policies to protect the ecological environment. Administrative units such as Changsha, Hengyang and Loudi also with the low scores, and targeted solutions can be developed to improve their short-board weaknesses based on the evaluation results of weak BRB models.

V. CONCLUSION

This paper proposes an evaluation process of ESLR based on the Ensemble-BRB model, which can guide the decision makers to develop targeted protection measures of land ecological. Firstly, the influencing factors are determined based on the actual condition, which are regarded as the antecedent attributes in the BRB model. Secondly, the antecedent attributes and parameters in different weak BRB models are given by experts, each of which performs ESLR evaluation independently. At last, the weighted averaging strategy is used to combine the evaluation results of weak BRB models as the final evaluation result of the Ensemble-BRB model. A case in Hunan Province is studied to verify the effective of the proposed Ensemble-BRB model based ESLR estimation process in practical application.

The Ensemble-BRB model not only combines the advantages of BRB model in multiple uncertain information integration, but also solves the combinational explosion problem in the BRB modeling. The Ensemble-BRB model can comprehensively evaluate the ESLR through multiple influencing factors, and the evaluation results can be traced and explained. The Ensemble-BRB model provides a suitable solution framework for ESLR evaluation, and the evaluation results can support the decision makers to develop targeted protection measures of land ecological.

APPENDIX

Table A1. INFLUENCING FACTORS IN ADMINISTRATIVE UNITS

Administrative units	***Changsha***	***Zhuzhou***	***Xiangtan***	***Hengyang***	***Shaoyang***	***Yueyang***	***Changde***	***Zhangjiajie***	***Huaihua***	***Yiyang***	***Loudi***	***Binzhou***	***Yongzhou***	***Zizhizhou***
Population density (person/hm2)	4.92	3.29	5.57	4.59	4.84	2.49	3.29	1.63	1.75	3.64	4.88	2.33	2.52	1.68
Per capita cultivated land (mu)	0.737	0.841	0.776	0.795	0.863	0.966	1.171	1.083	0.95	0.93	0.69	0.943	0.918	1.121
Per capita water capacity (kt)	1.7	3.2	1.7	1.8	2.4	2	2.3	4.8	4.5	2.2	1.8	4.3	3.3	4.3
Forest coverage rate	48.37	55.08	42.88	42.68	74.45	24.18	35.89	64.77	63.09	42.83	41.82	59.87	59.11	58.87
Area ratio of ecological forest	5.25	9.13	3.27	5.65	14.36	3.02	7.79	31.42	8.56	13.35	8.52	13.4	16.21	22.63
Area of cultivable land (Million mu)	88	119	64	166	155	242	195	103	224	122	115	178	180	169
Soil erosion	24.44	19.17	19.63	28.75	28.06	13.78	12.38	33.72	19.59	18.94	26.2	22.36	17.37	27.91
Land barrenness rate	31.03	23.39	30.32	27.97	28.72	17.89	28.87	16.13	18.18	24.73	23.62	19.69	19.41	19
Land pollution rate	0	0.08	0	0	0.11	0	0	0	0	0.07	0.17	0.48	0	0
Chemical fertilizers (Kg/mu)	55.33	59.73	78.73	56.87	53.67	66.07	67.47	40.67	35.4	67.8	59	61.53	58	26.87

Table A2. ANTECEDENT ATTRIBUTES IN WEAK BRB MODEL

No. of weak BRB model	**Antecedent attribute**
1	Population density; Per capita cultivated land; Per capita water capacity
2	Forest coverage rate; Area ratio of ecological forest
3	Area of cultivable land; Land barrenness rate
4	Land pollution rate; Chemical fertilizers
5	Forest coverage rate; Soil erosion
6	Area ratio of ecological forest; Soil erosion
7	Area of cultivable land; Soil erosion
8	Per capita water capacity; Forest coverage rate
9	Per capita water capacity ; Area of cultivable land
10	Land barrenness rate; Chemical fertilizers
11	Population density; Land pollution rate
12	Per capita cultivated land; Land barrenness rate
13	Population density; Soil erosion
14	Area ratio of ecological forest; Land pollution rate
15	Forest coverage rate; Land barrenness rate

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REFERENCES

[1] Zhang H B, Liu L M. Main Progress and Prospects of Land Resource Ecological Security Research [J]. Progress in Geography, 2006, 25(5):77-85.

[2] Westing A H. The environmental component of comprehensive security [J]. Bulletin of Peace Proposals, 1989, 20(2): 129-134

[3] Deng C X, Xie B G. Evaluation and Construction of Land Resources Ecological Security in Hill Area: A Case Study of Wugang City of Southwest Hunan Province [J]. Research of Agricultural Modernization, 2007, 28(2):225-228.

[4] Zhang J X, Xing X D, Liu X E. Evaluation On Ecological Security Of Sustainable Utilization Of Land Resource [J]. Hunan Geology, 2002, 21(2):119-121.

[5] ZHANG Zhi-yong, LIU Xi-yu．Research on land resource eco-security assessment based on Support Vector Machines．Computer Engineering and Applications，2009，45(10)：245-248．

[6] Liu Y, Liu Y Z, Xu P. Evaluation on Ecological Security of Regional Land Resources: A Case Study of Jiaxing City, Zhejiang Province [J]. Resources Science, 2004, 26(3):69-75.

[7] Yang J B, Liu J, Wang J, et al. Belief rule-base inference methodology using the evidential reasoning Approach-RIMER [J]. IEEE Transactions on Systems Man and Cybernetics - Part A Systems and Humans, 2006, 36(2):266-285.

[8] Kong G , Xu D L , Yang J B , et al. Belief rule-based inference for predicting trauma outcome[J]. Knowledge-Based Systems, 2015:S0950705115004645.

[9] Leilei C , Zhijie Z , Yuwang C , et al. Akaike Information Criterion-based Conjunctive Belief Rule Base Learning for Complex System Modeling[J]. Knowledge-Based Systems, 2018:S0950705118303812.

[10] Cutler A, Cutler D R, Stevens J R. Random forests [J]. Machine Learning, 2011, 45(1):157-176.

[11] Yang J B. Rule and utility based evidential reasoning approach for multi-attribute decision analysis under uncertainties [J]. European Journal of Operational Research, 2001, 131(1):31-61.

[12] Zhou Z H. Ensemble Methods - Foundations and Algorithms [M]. Taylor & Francis, 2012.