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Prediction of Ecological Pressure on Resource-Based Cities Based on an RBF Neural Network Optimized by an Improved ABC Algorithm

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ABSTRACT Resource-based cities are those where resource-based industries comprise a large proportion of all industries. Sustainable development implies that cities make full use of their own resources to support current development initiatives and take sustainability into account both during and after resource consumption. To promote investment in the sustainable development of resource-based cities and to a provide a decision system for these cities, this paper uses an ecological footprint model to evaluate and analyze the per capita ecological footprint, per capita ecological carrying capacity and per capita ecological deficit of a representative resource-based city, Yulin. The data are collected from 2001 to 2015. In addition, due to the complexity of the influencing factors for ecological carrying capacity and the variety of situations that are difficult to accurately predict, this paper proposes a new urban ecological carrying capacity prediction model, which consists of a radial basis function (RBF) neural network that is optimized by an improved artificial bee colony algorithm. The prediction results show that energy consumption is the major factor affecting the urban ecosystem; moreover, the model precision of the training results and the simulation accuracy of the test results achieved by the RBF neural network model are 97.91% and 94.16%, respectively, and in 2020, the per capita ecological footprint, biocapacity, and ecological deficit of Yulin are predicted to reach 4.892 hm^2, 3.317 hm^2, and 1.575 hm^2, respectively. Accordingly, effective proactive measures should be taken in advance to maintain or reduce the ecological pressure on this resource-dependent city. This paper strives to provide a scientific basis for local government decision-making to realize the healthy, stable, and rapid sustainable development of resource-based cities.

INDEX TERMS Resource-based city, ecological pressure prediction, RBF neural network, ABC algorithm, ecological footprint theory.

I. INTRODUCTION

As an integration of the topography, landform, soil, climate, hydrology, flora and fauna as well as the human activities in a certain region, the urban ecological environment is not only affected by human activities but also serves as the basis for human survival. Regarding resource-dependent cities, the ecological environment plays a vital role in such a special urban structure. A resource-based city is defined as a city in which the leading industries depend on the exploitation

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and processing of local natural resources, such as minerals and forests, which serve as an important strategic reserve for national energy resources and provide crucial support for the sustained and healthy development of the national economy [1]. However, the extensive development mode adopted by resource-based cities provides resources and energy security for rapid economic growth and causes environmental problems that have a serious impact on urban ecological security. Due to the superposition of internal and external factors and the interweaving of old and new contradictions, resource-oriented cities are facing severe challenges in terms of sustainable development and are faced with the arduous task of accelerating the transformation of the economic development mode [2]. The increasingly severe urban ecological environment forces people to explore sustainable urban development modes, and the ability to objectively, accurately and comprehensively evaluate and predict urban ecosystem pressures is a prerequisite for formulating a reasonable urban sustainable development strategy.

The most striking feature that distinguishes mining resource-based cities from ordinary cities is the high dependence between the cities and the mining enterprises because the leading industries rely on the exploitation and processing of local natural resources such as minerals, petroleum, forests and metals. The rise of such cities is often closely related to the development of the mining industries, and the proportion of the secondary industry in the national economic composition generally accounts for 50% to 90% [3]–[5]. Regarding sustainable development, these cities make full use of their own resources to ensure the current development, while simultaneously placing particular emphasis on sustainable development during the process of resource consumption and after resource exhaustion. Because of the large-scale and high-intensity resource exploitation that occurs in the development process and the characteristics of the leading industries, particularly of their production processes, the ecological carrying capacity of resource-based cities should not only consider the importance of the overall adaptive abilities of the ecosystem but also the importance of the individual factors for resources and the environment. Overall, China has many resource-based cities, especially coal mining cities. Coal resources have an enormous influence on the economic development of coal mining cities. However, harmful substances, such as effluent and waste as well as the residues produced during the mining, transportation and usage of coal, have led to the exhaustion and degradation of urban resources and a sharp deterioration of ecological environments, including the atmosphere and water sources [6], [7]. These cities are facing severe challenges in survival and development in terms of the resource exploitation cycle, transformation of the economic structure, and the impact of opening up and importing and exporting trade on the traditional mode of ''resource-based market'' under the original closed conditions. Promoting sustainable development in resource-based cities is not only a major strategic issue for modernizing China but is also of great significance for energy resource security, economic structural transformation, new industrialization and urbanization promotion, as well as the construction of resource-saving and environment-friendly society.

To this end, scholars inside and outside of China have conducted a large amount of research on the ecological pressures faced by resource-based cities. From the early 1930s to the mid-1970s, many scholars have carried out theoretical research and empirical analysis on the transformation of resource-based cities. Mishler (1955), Parsons (1958) and Gordon (1980) applied concepts from psychology and sociology to analyze the causes of unstable development in mining areas and the social problems that have arisen [8]–[10]. From the mid-1970s to the mid-1980s, Jonassohn, Brown and other scholars shifted from individual research to group empirical and normative research [11]–[13], with research cases that included various areas such as Lorraine, Houston, and Ruhr. The EU mainly relies on government intervention to complete the transformation of resource-based cities by closing mines, adjusting industrial structures and introducing talent. Since the 1980s, scholars such as Haerle, Berbrier, and Stephenson have shifted their research on the transformation of resource-based cities to industrial restructuring, environmental governance, urban development and planning [14]–[16]. Markey applied regional planning and development economics approaches to study the issues faced by resource-based cities, and their results showed that the resource-based cities should transform to being focused on developing urban competitive advantages rather than economic and resource comparative advantages [17]. An ecological footprint analysis is a quantitative method developed in recent years to measure the sustainable development of ecosystems, and it is also a new way to measure the pressures and impacts of human activities on ecosystems. Wackernagel and McDonald used the ecological footprint methodology to conduct an assessment study on the sustainable development of regional ecological pressures using different scales [18], [19]. Scholars such as Gao employed energy analysis theory to establish an ecological footprint model based on energy analysis to measure urban ecological pressures [20]. Karl-Heinz and Hemult applied a time series method to calculate the time series value of the ecological footprint index, which compensated for the lack of instantaneity in traditional measures of ecological pressures [21]. Shi used a nonlinear dynamics model to predict and analyze the ecologically sustainable development path of China [22]. Scholars such as Torija and Ruiz relied on a neural network using back propagation to predict urban ecological footprints [23]. From the current research literature on resource-based cities, scholars have paid more attention to industrial restructuring, urban transformation, sustainable development and the implementation of new urbanization construction [24]–[26], and there are relatively few studies on the ecological pressures faced by resource-based cities. The theoretical system of ecological pressure in resource-based cities is not well developed. Although some scholars have summarized the research results of ecological pressure, biocapacity and urban ecological vulnerability, which provide important references for future research, these studies cannot fully reflect the research status of ecological pressures in resource-based cities. At present, there is still a lack of articles summarizing the research results of ecological pressure in resource-based cities. The above literature indicates that the theoretical aspects of sustainable development in resource-based cities still have the following shortcomings:

1) The understanding of the connotation of ecological pressure in resource-based cities is not unified. Due to the different academic backgrounds and research perspectives of scholars, their understanding of the connotation of ecological pressure in resource-based cities varies considerably. In addition, the connotation varies with the fields that it is applied to.
2) A Quantitative analysis of the ecological environment in resource-based cities is rare. Different researchers focus on different aspects of ecological pressure in resource-based cities with a relatively simple research perspective, namely, qualitative research, and consequently, their studies cannot reflect the overall ecological stress in resource-based cities.
3) The accuracy of a prediction of urban ecological pressure not enough. There are few dynamic and accurate predictive models based on ecological footprints that include factors related to the urban economy, society and technology to predict urban ecological pressure

In summary, the measurement of natural resources and the quantitative evaluation of the ecological environment in resource-based cities has always been a complicated problem. Taking the ecosystem pressure in resource-based cities as the research object, this paper organizes and classifies the literature according to the influencing factors, connotation, evaluation index, evaluation method and avoidance suggestions and is based on a comprehensive analysis and collation of existing literature. This paper intends to improve the ecological footprint theory and establish a radial basis function neural network (RBFNN) based on the artificial bee colony algorithm (ABC algorithm). The model will include a city's economic, social, scientific and technological factors, to achieve an accurate mapping between urban ecological pressure and its influencing factors. In this way, this paper strives to develop a model that accurately predicts urban ecosystem pressure so that it may play an important role in guiding sustainable city development. The main contributions of the paper are as follows:

1) To consistently measure the per capita ecological footprint of Yulin, starting from 2001, by using updated data and methods and to evaluate the ecological pressure. The results show that the ecological pressure is continually increasing and that the resource shortages, environmental pollution and ecological damage resulting from the resource-dependent development model are the main factors that are constraining the ecological carrying capacity.
2) To objectively reflect the ecological carrying capacity of Yulin and to propose reasonable strategies and suggestions for its future development. The paper is based on the belief that strategies for industrial structure optimization, grain for green, energy structure optimization and improving the public's awareness of environmental protection can effectively reduce ecological pressure and can provide a reference for research on ecological carrying capacity in other areas.
3) To optimize the parameters of an RBF neural network by using the artificial bee colony algorithm and to predict the urban ecological pressure. The simulation model results show that the prediction results produced by the RBF neural network optimized by the artificial bee colony algorithm have fewer errors and thus are more precise and require less training. The developed model is highly practical and applicable and it provides a reference for similar issues.

II. OVERVIEW OF THE RESEARCH AREA AND DATA SOURCES

A. OVERVIEW OF THE RESEARCH AREA

Located in the transition zone between the Loess Plateau and the Mu Us Sandland in northern Shaanxi, Yulin has a warm temperate semiarid continental monsoon climate, with an average annual temperature of 10 °C, average annual sunshine of 2600-2900 h, and an average annual precipitation of approximately 400 mm. Known as China's ''Kuwait'', it is estimated that Yulin has 271.4 billion tons of coal reserves, 5 trillion m3 of natural gas reserves and over 600 million tons of oil reserves, out of which the proved reserves are 146 billion tons, 747.4 billion m^3, and 300 million tons, respectively. Nevertheless, the Yulin is a typical arid and semiarid agro-pastoral ecotone with a remarkable ecological fragility and evolutionary history [27]. As a key area for establishing ecological construction projects, Yulin has been the site of national ecological projects such as returning farmland to forests and grassland and the ''Three-north'' Shelter Forest Program as well as provincial and municipal ecological projects including the ''Thousands of Miles of Green Corridor''. In 2015, Yulin was recognized as an ecological construction demonstration region by 11 ministries and commissions, including the National Development and Reform Commission, aiming to create a model of livability for desert oasis and mining cities in China [28]. Due to the sparse precipitation and the uneven distribution of rainfall over time and space, the natural ecology of the city is very fragile, with frequent occurrences of natural disasters, soil erosion, serious land desertification and salinization. Due to the large-scale exploitation and processing of coal, oil and natural gas resources over a long period and the rapid development of energy and chemical industries, the deterioration of the local ecological environment has been aggravated by intense disturbances caused by human activity such as ground subsidence, groundwater drainage, and the large discharges of waste gases, wastewater and solid waste in mining areas [29]. Because of natural and human factors, the ecological environment of Yulin is very volatile and

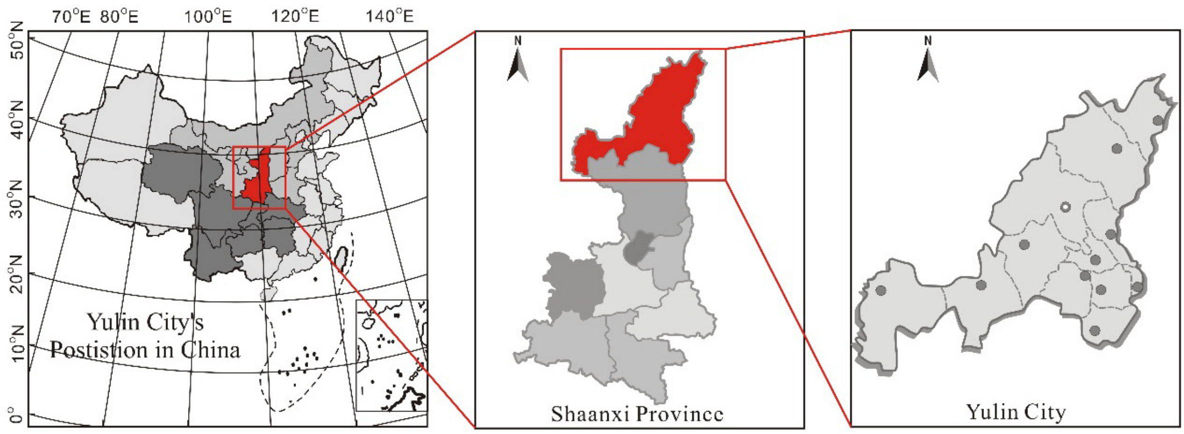

FIGURE 1. The location of the research area.

vulnerable. Accordingly, Yulin is facing severe challenges, such as the rational exploitation and utilization of resources, while protecting the ecological environment during construction. The extensive growth mode, mainly based on resource consumption, leads to prominent problems such as urban ecological destruction and geological disasters, which in turn restrict the city's future economic development [30]. In the past, the environmental pollution and ecological damage in Yulin were very serious due to the traditional development model, which restricted the sustainable development of the economy and society. Therefore, the implementation of a sustainable development strategy has become inevitable for the development of Yulin.

B. DATA SOURCES AND PROCESSING

Various scholars study the ecological pressure on resource-based cities from different perspectives, and a particular scholar may have a different emphasis in the research, due to the various ecosystems of resource-based cities, and select different evaluation indicators. The selection of indicators should follow the principles of scientificity, qualitative and quantitative analysis, pertinence, comprehensiveness, operability and dynamicism. The common methods used for index selection and weight determination include the inverse, information quantity, data analysis, DRASTIC standard, principal component analysis, entropy, gray correlation and empirical weight methods as selection based on expert recommendation. Representative studies on the selection of ecological pressure indicators in resource-based cities include the following studies: Bo et al. used indicators from the stress status-threat perspective to analyze and evaluate the vulnerability of social systems in resource-based cities [31]; scholars such as Li employed indicators from the perspective of sensitivity-adaptability to analyze and evaluate the vulnerability of the economic system of resource-based cities [32]; and Wang et al. analyzed and evaluated the vulnerability of the human-land system from the perspective of a resource-ecology-economy-society [33]. The selection of specific indicators is shown in Figure 2.

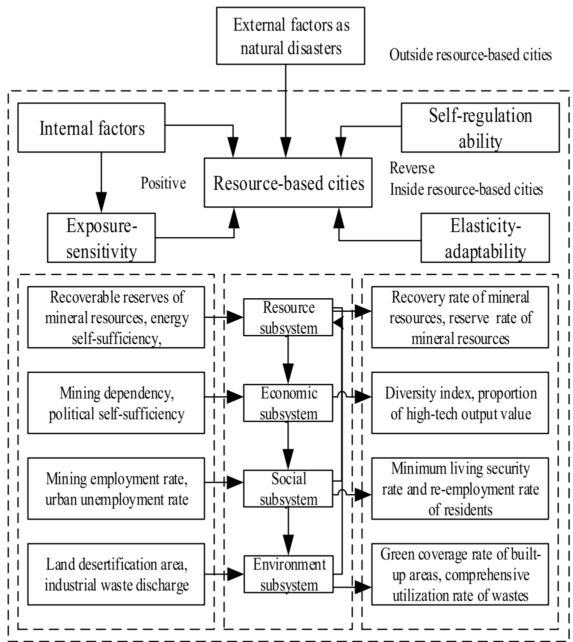

FIGURE 2. The selection of specific indicators.

In view of the fact that the ecological footprint is only a comprehensive indicator, other economic or social indicators that are related to urban sustainable development are selected as the impact factors for the ecological footprint. According to the research, this paper is based on data on Yulin from 2001 to 2015, which is mainly sourced from the Yulin Statistical Yearbook (2001-2015), Shaanxi Economic Statistical Yearbook (2001-2015), China Urban Construction Statistical Yearbook (2006-2015) and other industry data for Yulin. In addition, some data are calculated from the obtained statistical data, such as the per capita raw coal production and the scientific education expenditure as a proportion of the local general budget expenditure [34]–[36].

Meanwhile, this paper chooses 10 indicators as impact factors for urban ecological pressure, which include the GDP, annual GDP growth rate, total retail sales of consumer goods,

TABLE 1. The biological resource consumption per capita in Yulin from 2001 to 2015/kg.

Year	Grain	Veget ables	Frui ts	Veg etab le oil	Por k	Mut ton	Pou ltry	Egg s	Aqua tic prod ucts
2001	276.2	150.7	19.7	8.4	22.2	7.6	3.8	11.0	1.5
2002	278.9	147.0	32.5	8.5	23.9	7.7	4.2	12.2	1.5
2003	278.6	141.8	25.2	8.2	22.2	1.8	3.8	11.3	1.4
2004	291.3	166.6	25.2	8.9	19.6	8.6	3.5	9.6	1.2
2005	272.7	149.3	49.6	11.4	25.6	6.7	4.5	10.1	2.1
2006	269.5	140.7	53.8	11.3	22.8	2.7	4.5	9.6	1.6
2007	243.3	128.3	35.7	9.5	18.2	6.1	3.4	8.9	1.2
2008	59.9	58.9	31.3	4.3	7.9	3.8	2.7	6.0	0.9
2009	54.3	66.7	15.5	5.2	10.3	4.0	3.3	6.2	1.0
2010	87.3	76.5	25.6	7.3	12.2	5.1	4.0	7.1	1.2
2011	85.5	71.5	27.3	7.1	12.8	5.0	4.1	6.5	1.2
2012	86.7	72.3	28.9	7.0	12.5	5.2	4.4	7.0	1.3
2013	84.5	74.2	28.7	7.2	13.1	4.9	3.7	6.8	1.3
2014	83.7	76.8	27.5	7.4	13.6	4.6	3.4	7.3	1.2
2015	85.6	72.5	28.1	7.1	13.4	5.1	4.0	6.9	1.3

TABLE 2. The fossil energy consumption per capita in Yulin from 2001 to 2015.

Year	Raw coal/ 104 kg	Gasoline/ 104 kg	Diesel/ 104 kg	Liquefied petroleum gas /104 kg	Electricity/ 104(kW.h)
2001	0.779	0.004	0.007	0.001	0.077
2002	0.962	0.004	0.007	0.001	0.091
2003	1.174	0.008	0.010	0.002	0.939
2004	1.259	0.009	0.010	0.002	0.113
2005	1.866	0.010	0.011	0.002	0.195
2006	3.282	0.015	0.015	0.003	0.450
2007	3.410	0.015	0.019	0.000	0.469
2008	2.744	0.016	0.019	0.090	0.359
2009	2.885	0.016	0.019	0.030	0.384
2010	1.510	0.017	0.019	0.020	0.453
2011	1.626	0.016	0.019	0.060	0.469
2012	1.778	0.017	0.021	0.080	0.512
2013	0.972	0.018	0.020	0.020	0.513
2014	1.245	0.019	0.020	0.040	0.545
2015	2.124	0.017	0.020	0.030	0.613

total population, urbanization level, the proportion of tertiary industry in terms of GDP, total import and export volumes, contribution rate of scientific and technological discoveries, disposable income of urban residents and energy consumption. The partial least squares (PLS) and leave one out cross validation (LOOCV) methods are used in this paper to obtain the relative importance parameter values of each index relative to the ecological footprint. The impact factors with parameter values greater than 1 are selected. According to the above criteria, six indicators, GDP, energy consumption, total population, urbanization level, total retail sales of consumer goods and disposable income of urban residents, are finally selected as the impact factors for urban ecological pressure to establish the prediction model [37]. Based on the calculation method for the ecological footprint, this paper calculates and analyzes the per capita ecological footprint of Yulin. The biological consumption account is mainly composed grain, vegetables, fruits, vegetable oil, pork, mutton, milk, poultry, eggs and aquatic products. The data are shown in Table 1.

The energy consumption account is composed of fossil energy and electricity, namely, raw coal, gasoline, diesel, liquefied petroleum gas and electricity. In light of the statistics, the per capita energy consumption of Yulin from 2001 to 2015 is calculated as shown Table 2.

It should be noted that the data for cultivated land, forestland and grassland are derived from the *Yulin Statistical Yearbook* from 2001 to 2015. The construction land and water area data from 2015 to 2020 are collected from the Yulin Bureau of Land Resources. The 2005 data are from ''Land Use Status in 2005'' in the *Yulin General Plan for Land Utilization 2006-2020*. Since there is no source for the data on the construction land and water area from 2006 to 2008, the mean value method is adopted to estimate the relevant data, considering that the short-term land data may not change very much. It is calculated by subtracting the 2005 data from that of 2015, then dividing it by 4 to obtain the annual average area change, which is then added to the base 2005 data to obtain the estimated values for 2006-2008 [38].

III. RESEARCH METHODS

A. DATA ECOLOGICAL FOOTPRINT THEORY

The ecological footprint is a method that has been widely used. This concept was first proposed by the Canadian economist Willian Rees in 1992 [39], and later the relevant calculation model was put forward and promoted by his student, Wackernagel [40]. It is a new theory and method to quantitatively measure the sustainable development status of regions where human society continuously depends on the environment. Due to its relatively complete and scientific theoretical basis, concise system of indicators and universal approach, the ecological footprint has been quickly adopted as a new theoretical method for the quantitative analysis of regional sustainable development issues. Human beings must obtain resources from nature to survive. Land is required to supply these resources, or to absorb the waste produced by humans. The ecological footprint refers to the area of ecologically productive land necessary for the sustainable survival of a population, under certain technical conditions, while maintaining a consumption level of a certain substance. Biocapacity reflects the supply capacity of an area's resources and corresponds to the ecological footprint concept. When the ecological footprint is less than the biocapacity, an ecological surplus is produced, indicating that the ecological environment is sustainable. In contrast, ecological deficits will appear when the ecological footprint is greater than the biocapacity, indicating that the ecological environment is not sustainable. Obviously, the higher the surplus is, the better the ecological environment is, while the higher the deficit is, the worse the ecological environment is [41]–[43]. The concepts of an ecological footprint and biocapacity can be applied to the ecological assessment of a country or a region within a country. Ecological footprints are needed for the six major types of ecologically productive land, including cultivated land, forestland, grassland, water areas, construction land and fossil energy land. However, due to differences in resource endowments and production capacities, the different types of ecologically productive land have different productivities for different outputs Therefore, it is not feasible to

TABLE 3. Equivalent factors of different types of land.

Land type	Cultivat ed land	Forest land	Gras sland	Water area	Construc tion land	Fossil energy land
Equilibriu m factor	2.52	1.28	0.43	0.35	2.52	1.28
Yield factor	1.32	2.55	1.93	1.00	1.32	1.14

Data source: The data are calculated by the author based on the National Ecological Footprint Account of the World Wildlife Fund (WWF).

summarize or compare them directly. Accordingly, the concept of an equivalence factor is introduced in the quantitative measurement of the resources required by humans on an ongoing basis. Wackernagel et al. adopted the relative production capacity of land to adjust the weight of each type land. This weight is called the equivalence factor. The "equilibrium factor" and the "yield factor" are derived from the Working Guidebook to the National Footprint Accounts published by the Global Footprint Network in 2018. The equivalence factors of the six types of land are shown in Table 3.

1) CALCULATION OF ECOLOGICAL FOOTPRINT

To establish the ecological footprint, all of the resources consumed and the waste produced by the subject population (individual, city, country, community) are converted into a comparable ecologically productive area, including land and water resources. The calculation formula is as follows:

$$EF = N \cdot ef = N \sum_{i=1}^{n} (r_i c_i / p_i) \tag{1}$$

where EF is the total ecological footprint, N is the total population, *ef* is the per capita ecological footprint, i is the type of the consumption item, n is the total number of consumption items, r_i is the equilibrium factor of land type i, c_i is the net consumption of the land produced resources of type i, and p_i represents the global average ecological productivity of land produced resources of type i.

2) CALCULATION OF BIOCAPACITY

Biocapacity refers to the total area of all the different types of ecologically productive land that is available in a region to provide the resources required for human activities. A measure of biocapacity is used to reflect the internal supply capacity of a region. The calculation formula is as follows:

$$EF = N \cdot ec = N \sum_{j=1}^{6} (a_j r_j y_j) \tag{2}$$

where EC is the total biocapacity, ec stands for the per capita biocapacity, j refers to one of the six ecological land types (cultivated land, pasture land, forestland, construction land, water area and fossil fuel land), a_j is the per capita land area of land type j, y_j indicates the yield factor of land type j, and r_j represents the equilibrium factor of land type j.

TABLE 4. The grade of ecological tension index.

Grade	1	2	3	4	5	6
Ecological pressure index	<0.50	0.51~ 0.80	0.81~1. 00	1.01~1 .50	1.51~2 .00	>2.00
Representa tional state	Very safe	Safe	Slightly unsafe	Unsafe	Highly unsafe	Extremel y unsafe

3) CALCULATION OF ECOLOGICAL DEFICIT/SURPLUS

An ecological deficit will arise if the ecological footprint is greater than the biocapacity, indicating that the development model of the region is relatively unsustainable. However, an ecological surplus will appear if the ecological footprint is less than the biocapacity, indicating that the consumption pattern of the region is relatively sustainable. The calculation formula is as follows:

$$ED/ER = EF - EC \tag{3}$$

where ED is the ecological deficit and ER is the ecological surplus.

4) ECOLOGICAL PRESSURE INDEX MODEL

The ecological pressure is the ratio of the per capita ecological footprint to the biocapacity of the renewable resources in a certain country or region. The index reflects the degree of pressure on the regional ecological environment. The model is as follows:

$$\mathrm{ETI} = \mathrm{ef}'/\mathrm{ec}. \tag{4}$$

where, ETI is the ecological pressure index and ef' is the per capita ecological footprint of the renewable resources in the region.

In accordance with the relevant data in the WWF2018 dataset, the ecological security evaluation indicators and classification standards are established and shown in Table 4.

B. THE RBF NEURAL NETWORK MODEL

1) PRINCIPLE OF RBF NEURAL NETWORK

The radial basis function (RBF) neural network is a three-layer network with a single hidden layer which was proposed by Moondy and Darken in the late 1980s [44]. The first layer is the input layer, which is composed of signal source nodes. The second layer is the hidden layer, and the transformation function for the hidden layer units is a locally distributed nonnegative nonlinear function with radial symmetry at the center point. The number of units in the hidden layer is determined by the needs of the problem being modeled. The third layer is the output layer, and the output of the network is produced by a linear weighting of the hidden unit outputs. It is a novel and effective feedforward neural network based on the localization of human brain neurons to external reactions. For an RBF network, the transformation from the input control to the hidden layer space is nonlinear, whereas the transformation from the hidden layer space to the output layer space is linear, thus realizing the transformation from nonlinear to linear and achieving a good predictive

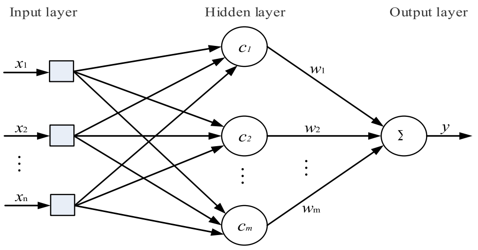

FIGURE 3. The structure of a radial basis function neural network.

ability [45]. The typical structure of an RBF neural network is shown in Figure 3.

When the network input training sample is *xn*, the functional relationship between the inputs and outputs of the RBFNN is:

$$Y(X_n) = \sum_{i=1}^{I} \omega_i \varphi(X_n, t_i) \tag{5}$$

where $X = (x1, x2, \ldots, xn)T \in Rn$ represents the input vector, *yi*is the output value of the *i*-th output unit, *m* stands for the number of centers, *wij* indicates the weight of the *j*-th hidden neuron to the*i*-th output unit, and *bj* is the bias value. The functions mainly used for an RBF network are the Gaussian function, multiquadratic function, inverse multiquadratic function, thin plate spline function, etc. This paper uses the Gaussian function in the form of:

$$\varphi(x, t_i) = \exp(-\frac{\|x - t_i\|^2}{2\sigma_i^2}) \tag{6}$$

where $cj \in Rn(1 \leq j \leq m)$ is the center of the RBF and σ is the width parameter that regulates the sensitivity of the RBF neurons. Among them, σi is the standardization constant of the *i*-th hidden unit, which represents the width of the basis function around the center. $\|x$-*ti* indicates the norm of the vector *x-ti*. Due to the characteristics of the radial basis function, i.e., a Gaussian function, only a small part of the center value near x is activated for a given input. When the RBF neural network is used for correlation prediction, it is necessary to learn the weight between the hidden unit and the output unit as well as the center and variance of the basis function [45]. Different learning methods are selected for different research purposes.

2) THE ARTIFICIAL BEE COLONY ALGORITHM

The artificial bee colony (ABC) algorithm is a nonnumerical optimization method based on the self-organization of bees and swarm intelligence. Since the algorithm was proposed in 2001, it has attracted great attention from scholars and has been widely used in the fields of combinatorial optimization, network routing, function optimization, and robot path planning [46]. In 2005, Shmygelska successfully applied the honeybee honey-collecting principle to the numerical optimization of functions and proposed a systematic ABC algorithm [47]. The ABC algorithm simulates the honey gathering process of bees and realizes swarm intelligence through the communication, transformation and collaboration among bees with different roles. There are three roles in the artificial bee colony: a leader, follower and scout. Suppose that there are SN food sources, each food source $x_i = |x_{ij}|\,(i = 1, 2, \cdots, SN, j = 1, 2, \cdots, D)$ is represented by a D-dimensional vector, and the total number of cyclic searches of bees is set as MCN. The leader bees first conduct a neighborhood search for the corresponding food sources and the greedy principle is applied to the selection of the food sources. That is, if the new bee colony search is to realize the collective intelligent behavior of honey gathering, it must contain three basic parts, including the honey source, employed foragers (EF) and unemployed foragers (UF), and three basic behavior patterns, namely, searching for nectar sources, recruiting nectar sources, and giving up nectar sources. The working diagram of bee colony collection is shown in Figure 4.

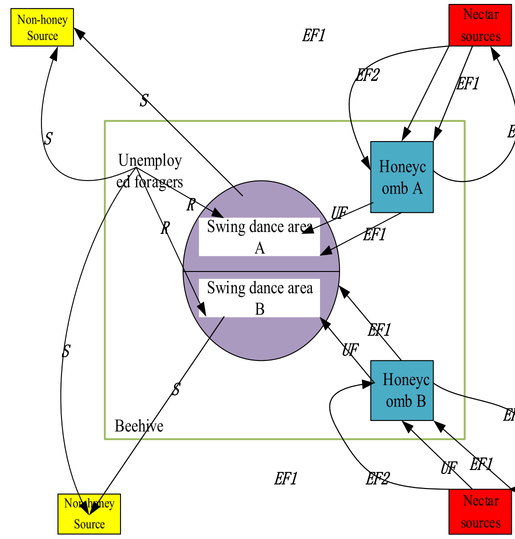

FIGURE 4. The working diagram of the bee colony collection.

When the ABC algorithm is used to solve the optimization problem, the position of the food source represents a feasible solution to the optimization problem, the profitability of the food source indicates its fitness value according to the optimization problem, the artificial bee colony search process for the maximum profit food source is equal to the process of searching for the optimal solution, and the maximum profit food source refers to the optimal solution to the optimization problem. During initialization, SN solutions are randomly generated by formula (7).

$$x_{ij} = (x_{ij})_{\min} + rand(0, 1)((x_{ij})_{\max} - (x_{ij})_{\min}) \tag{7}$$

where $(x_{ij})_{\max}$ and $(x_{ij})_{\min}$ stand for the upper limit and lower limit of x_{ij}, and *rand* means a random number between (0,1).

Leader bees and follower bees update their solutions on the basis of the formula (7)

$$v_{ij} = x_{ij} + r_{ij}(x_{ij} - x_{kj}) \tag{8}$$

where v_{ij} represents a new solution generated nearby to x_{ij}, $k \in \{1, 2, \cdots, SN\}$. k and j are randomly selected, k cannot be equal to i since k is a solution in the neighborhood of i, $r_{ij} \in [-1, 1]$ is a random number that controls the generation range of the x_{ij} neighborhood. The follower bees select the solution by observing the swing dance of the leader bees to determine the fitness value of the solution and choose whether to follow a certain leader bee according to the selection probability. The calculation formulas of the fitness value, fit_i, and selection probability, p_i, are as follows:

$$fit_i = \begin{cases} \frac{1}{1+f_i} f_i > 0 \\ 1 + |f_i| f_i \leq 0 \end{cases} \qquad P_i = \frac{fit_i}{\sum\limits_{i=1}^{SN} fit_i} \tag{9}$$

where f_i is the objective function value of the i-th solution. In the ABC algorithm, a control parameter *limit* is used to record the number of times a solution has been updated. If a solution is not improved after successive *limit* cycles, it means that the solution is trapped in a local optimum and it is abandoned. Assuming that the abandoned solution is x_i, a new solution can be randomly generated by formula (7) to replace the original solution, x_i.

3) THE OPTIMIZED RBF NEURAL NETWORK PREDICTION MODEL BASED ON AN IMPROVED ABC ALGORITHM

The optimized RBF neural network prediction model based on the improved ABC algorithm is divided into three parts: data normalization, bee colony clustering and RBF neural network modeling.

a: DATA NORMALIZATION

In the course of processing different types of data, different evaluation indexes often have distinct dimensions and dimensional units, which will affect the results of the data analysis. To eliminate the dimensional influence among indexes, data standardization is adopted to address the comparability among data indexes. The data normalization is processed as follows:

$$a = \frac{x_k - \frac{1}{N}\sum\limits_{k=1}^{N} x_k}{\max(X) - \min(X)} \tag{10}$$

where *max(X)* is the maximum value of the sample data, and *min(X)* is the minimum value of the sample data. After data normalization, the original data are mapped to [0,1], so that all indexes have the same order of magnitude, which is suitable for a comprehensive comparative evaluation.

b: BEE COLONY CLUSTERING

The normalized data are clustered to find the optimal clustering results. The specific steps to improve the bee colony clustering algorithm are as follows:

Algorithm 1 Algorithm Steps

1. Step 1 Randomly initialize M individuals as the initial population ($0 < M < sn/2$), and the number of clusters required. The parameters, such as population size, sn and threshold, are set.
2. Step 2 Calculate the mean entropy of the population, randomly initialize a new individual, and determine whether the new individual can be added to the existing initial population by using the size relationship between the mean entropy and the set threshold value.
3. Step 3 Repeat Step 2 until the population size is sn, i.e., generate sn solutions to establish the initial honey source positions.
4. Step 4 Leader bees search for a new honey source and calculate the fitness of the positions. If the new position is better than the original one, replace it with the new position.
5. Step 5 Follower bees select the honey source.
6. Step 6 Follower bees update the honey source and calculate its fitness value.
7. Step 7 Follower bees use the greedy selection mechanism to select the honey source position.
8. Step 8 Scout bees update each one-dimensional component of the precocious individuals and generate a new honey source to replace the one with the worst honey content.
9. Step 9 Record the current optimal honey source position and fitness value.
10. Step 10 Determine whether the termination condition is satisfied, and if so, output the optimal clustering solution set. Otherwise, return to step 4.

c: RBF NEURAL NETWORK MODELING

The center value of the bee colony clustering is taken as the center value of the hidden layer in the RBF network, and the number of bee colony clusters is taken as the number of hidden layer units. Then, the standardized constants of each hidden layer unit and the weights between each hidden layer unit and the output unit are calculated. Finally, the ecological pressure data are input into the trained RBF network, and the predicted data are processed by applying inverse normalization to obtain the true predicted value and calculate the error. The flow chart of the neural network algorithm is shown in Figure 5.

In the process of neural network training and testing, all the input data are used as training data. The network uses the data from 2001 to 2010 as the training samples for network fitting training. The aim is to obtain the correct number of hidden units to minimize the error and to determine the weights of the output layer to establish the network. Taking the data from 2011 to 2015 as the test sample, the simulation accuracy of the network and the usability of the model are tested, namely, the ecological pressure data sequence in the first n time periods, while the output of the neural network testing is the ecological pressure data sequence for the n + 1 time periods.

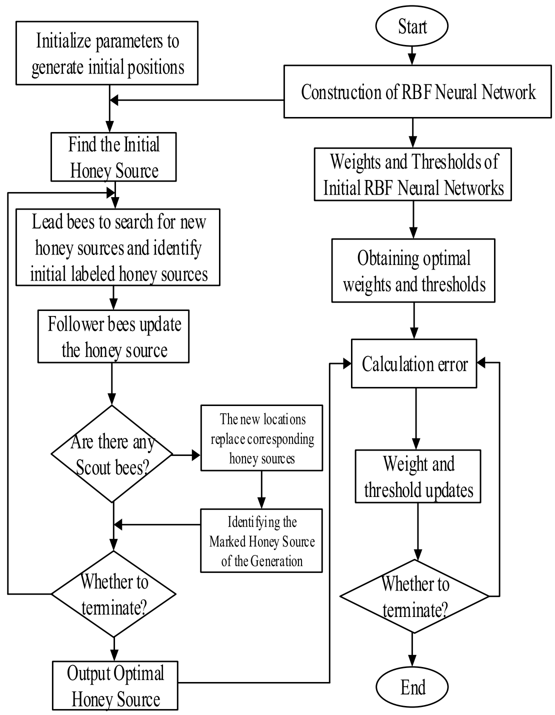

FIGURE 5. The flow chart for the neural network algorithm.

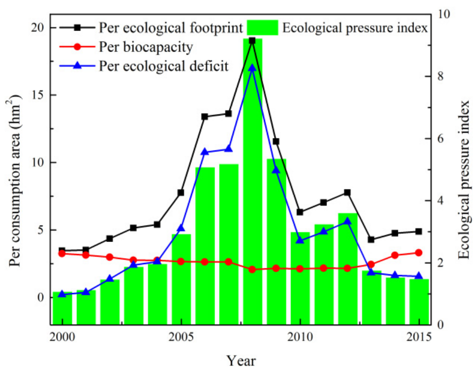

FIGURE 6. The calculations for the ecological footprint.

IV. RESULTS ANALYSIS

A. CALCULATION RESULTS OF THE ECOLOGICAL FOOTPRINT FOR YULIN CITY FROM 2001 TO 2015

According to the ecological footprint model, we obtained the results of the ecological footprint, biocapacity, ecological surplus/deficit and ecological footprint structure of Yulin from 2001 to 2015, the details are shown in Figure 6 and Figure 7.

From Figure 6, according to the calculation, the per capita ecological deficit of Yulin City in 2000-2015 shows an upward trend in the 2000-2008 period, during which, the average growth rate is 72.6%, while in the 2009-2015 period, the overall trend is downward, with an average annual decline of 9.8%. According to formula (4) and the grading criterion of the ecological pressure index, the ecological pressure index of Yulin City increased year by year from 2000 to 2008, and the ecological pressure index showed a significant downward trend from 2009 to 2015, especially in the 2012-2015 period, the ecological pressure index

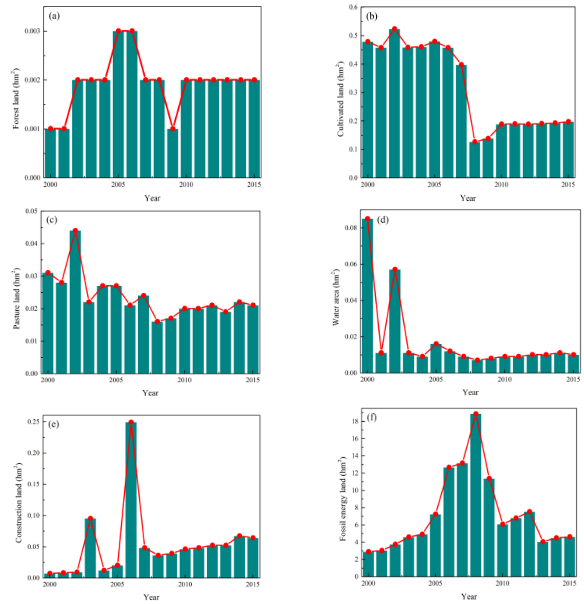

FIGURE 7. The structure of the ecological footprint.

decreased from 3.599 to 1.575 with an even larger decline. It is quite clear that the ecological deficit of Yulin increased from 4.423 hm^2 in 2001 to 6.105 hm^2 in 2015, and the per capita ecological footprint increased from 4.987 hm^2 to 6.640 hm^2. Nevertheless, the per capita biocapacity decreased from 0.564 hm^2 to 0.535 hm^2. Obviously, the per capita ecological footprint is 11 times the per capita biocapacity. Moreover, the ecological footprint and ecological deficit are on the rise, but the biocapacity has a declining trend. Thus, the urban development is in an unsustainable state.

Regarding the urban ecological footprint structure, it can be seen from Figure 7 that fossil energy consumption accounts for the largest proportion, followed by cultivated land, whereas the demand for other ecologically productive land areas is very small. Fossil energy consumption increased from 2.865 hm^2 in 2000 to 18.853 hm^2 in 2008 and then gradually decreased to 4.598 hm^2 in 2015, which illustrates that the economic development of Yulin significantly relies on fossil energy consumption.

B. DYNAMIC PREDICTION OF ECOLOGICAL PRESSURE IN YULIN CITY FROM 2016 TO 2020

The developed RBF neural network prediction model is applied against the training sample set, test sample set and prediction sample set. The RBFNN prediction model is composed of output neurons, namely, the per capita ecological footprint, as well as input neurons that contain 6 indicators which affect urban ecological sustainable development, i.e., the GDP, energy consumption, total population, urbanization level, total retail sales of consumer goods and disposable income of urban residents. This network uses the data from 2001 to 2010 as training samples for network fitting and training, aiming to obtain the number of hidden units that produce the minimum error and determine the weights of

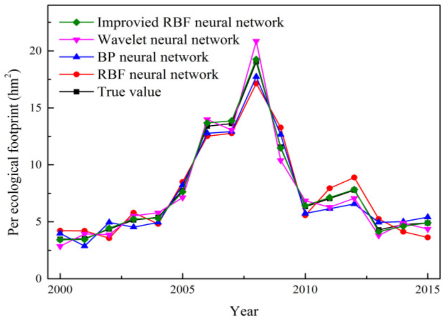

FIGURE 8. Comparison of test values and real values.

output layer to establish the network. Meanwhile, the data from 2011 to 2015 are taken as the test samples to verify the simulation accuracy of the network and the usability of the model. Furthermore, the network model is used to dynamically predict the ecological pressure on Yulin from 2016 to 2020. The algorithm is realized through programming using the MATLAB neural network toolbox platform.

1) TRAINING THE MODEL

The experimental environment of this paper is as follows: The CPU is an Intel i5 8500 3.7 GHz, the amount of memory is 8.00 GB, the operating system is Windows 7, and the software platform is the MATLAB 2012a Neural Network Toolbox. The experimental dataset is based on the ecological pressure data calculated from the biological consumption accounts of Yulin City from 2001 to 2015. The training sample set is based on the ecological pressure data from 2001 to 2010, and the test sample set is based on the data from 2011 to 2015. Using the data from 2001 to 2010, the four models, the traditional RBF neural network, traditional BP neural network, wavelet neural network and RBF neural network based on the bee colony algorithm proposed in this paper, are trained 100 times in the experiment, and then the trained neural networks are used to make predictions for the period from 2011 to 2015. The radial basis function is called the newrb function within the neural network. After repeated tests, the mean square error for the network parameters in the newrb function is set as goal = 0.1, and the expansion speed is set as speed = 0.7. The relative training error of the RBF neural network based on the improved ABC algorithm is less than 3%, which meets the error requirements and has a high prediction accuracy. After the completion of network training, the data from 2011 to 2015 are tested, and the network simulation accuracy reaches 94.16%. To further test the simulation accuracy of the network, the entire dataset from 2001 to 2015 is tested, with the results shown in Figure 8.

It is apparent from Figure 8 that the predicted values of the model are very close to the actual calculated values, which meets the requirement for predicting the future development trend of urban ecological pressure. In conclusion, the RBF neural network prediction model based on the improved ABC algorithm can predict urban ecological pressure more successfully than the traditional prediction models.

TABLE 5. Test results of the neural networks.

Error/%	Minimum absolute error	Maximum absolute error	Mean absolute error
RBF neural network	0.06	24.71	4.93
BP neural network	0.02	25.32	5.83
Wavelet neural network	0.01	26.07	5.16
Improved RBF neural network	0.001	22.54	2.21

TABLE 6. The predicted result of ecological footprint (hm^2/person).

Year	Ecological footprint	Biocapacity	Ecological deficit
2016	4.975	3.481	1.494
2017	5.173	3.646	1.527
2018	5.063	3.512	1.551
2019	5.271	2.979	2.292
2020	5.677	2.876	2.801

The comparison of the prediction error indexes of the four neural network is shown in Table 5.

BP neural networks usually uses sigmoid function, which causes the fewer layers, the less weight needed to be confirmed, so that the faster computing speed will be achieved. While the active function of RBF neural networks is radial basis function. Thus, RBF neural network is a feedforward neural network with excellent performance. RBF neural networks makes it possible that arbitrary precision can approach any nonlinear function. It has global approximation capability, which radically solves the problem of local optimum of BP network. Besides, with the compact topological structure, structure parameters can achieve separate learning and fast-speed convergence.

2) PREDICTION RESULTS

In view of the work requirements of the RBF neural network prediction model, it is necessary to adopt a time series method to arrange the six selected influencing factors for the ecological footprint from 2010 to 2015. Given that these factors have the characteristics of irregularity, chaos and nonlinearity, this study employs MATLAB to optimize the historical data length by testing different historical data lengths and using the least square error length to predict the influencing factors of ecological pressure from 2010 to 2015, which avoids designing the network parameters empirically. On this basis, this paper conducts the prediction of ecological pressure, makes use of the time series method to predict the per capita biocapacity during the specified period, and calculates the corresponding per capita ecological deficit as per formula (3). The statistical results are shown in Table 6.

C. DISCUSSION

1) ECOLOGICAL FOOTPRINT DEMAND ANALYSIS

As shown in Table 6, the per capita ecological footprint of Yulin city from 2016 to 2020 is on the rise with an average annual growth of 0.140 hm^2/person, which will reach 5.677 hm^2/person in 2020, specifically, it 1.14 times more than that of 2016, indicating that the demand for material resources from urban residents is also increasing with the improvement of living standards. From 2016 to

2020, the average per capita ecological footprint demand is 5.231 hm^2/person, which is 1.58 times more than the average ecological supply capacity, which indicates that the per capita ecological footprint demand is far greater than the existing urban ecological supply capacity. In such a heavily overloaded ecological environment, the urban ecological supply capacity cannot meet the per capita ecological demand, which will lead to importing or resource overuse to satisfy the high material demand from urban residents. This resource overuse will damage the urban ecosystem and reduce the supply capacity of the ecosystem, which is very similar to the current development situation of Yulin. In light of the high demand of the ecological footprint in Yulin City from 2016 to 2020 and the composition of the demand in the ecological footprint in Yulin City from 2001 to 2020, it is not difficult to find that fossil energy represents the biggest share of the demand in the per capita ecological footprint, accounting for 86.7% of the total demand, followed by cultivated land at 8.3%, while other ecological land demand is very small. This means that the development of Yulin mainly depends on the excessive use of existing energy resources which is causing a serious imbalance in the ecological environment. Furthermore, this type of high-energy consumption development model which depletes its own resources is the principle contradiction of urban sustainable development.

2) ANALYSIS OF THE ECOLOGICAL FOOTPRINT SUPPLY

The per capita biocapacity decreases at a rate of 3.47% from 3.481 hm^2/person in 2016 to 2.876 hm^2/person in 2020, whereas the average per capita ecological requirement is 5.23 hm^2/person. The ecological supply capacity is far from being enough to meet the living needs of local residents, which means that in addition to consuming their own energy resources, more energy will have to be obtained from other regions to overcome the regional ecological constraints. This situation coincides with that of Yulin as a heavy industry resource-based city. Considering the unreasonable industrial structure and that energy resources are on the verge of exhaustion, the decision makers of Yulin, in addition to improving the efficiency of energy utilization, should also focus on upgrading the resource industry and adjusting the urban industrial structure so that the city will gradually decrease its energy consumption by developing the tertiary industry sector.

3) ANALYSIS OF ECOLOGICAL DEFICIT

The ecological deficit slowly increased at a rate of 1.2% from 6.106 hm^2/person in 2016 to 6.490 hm^2/person in 2020, indicating that the urban ecological pressure is still in an unsustainable state of development. However, the average growth rate of the ecological deficit in the 2016-2020 period is 1.79%, which is lower than the average growth rate of 2.9% in the 2001-2015 period. Since the demand for natural resources in Yulin has far exceeded its biocapacity, it is difficult to maintain its rapid development by relying solely on its own resource development. However, the trend toward unsustainable urban growth has been improved with more attention paid by policymakers.

4) ANALYSIS ON UTILIZATION EFFICIENCY OF ECOLOGICAL RESOURCES

According to the predicted results, with the increase of the ecological footprint, the ecological footprint per 10,000 yuan GDP can indicate the difference in resource utilization efficiency among the different regions. The larger the ecological footprint per 10,000 yuan GDP is, the lower the technical level and the output rate of ecologically productive land are, and vice versa. While the ecological footprint increases, the ecological footprint per 10,000 yuan GDP generally shows a downward trend, of which the average growth rate is 5.11% in the 2016-2020 period, much higher than the average growth rate of the per capita ecological footprint, which is 2.82%. Therefore, along with the increasing demand for urban materials, the resource utilization efficiency is also improving. The production mode of "high investment, high energy consumption, high pollution and low benefit" in Yulin is slowly changing, and the regional economic growth mode presents a trend towards benign development. Notwithstanding, in view of the high ecological deficit in Yulin, it is necessary to accurately grasp the development trend of urban ecological pressure to formulate corrective and effective sustainable development policies and fundamentally change the current unsustainable high deficit development model.

V. CONCLUSION

Chinese society is in a transition from a traditional society to a modern society. With the acceleration of urbanization, a large number of people are flocking to cities. The problems caused by the ecological pressure on resource-based cities have become increasingly apparent in terms of resource depletion, ecological destruction, social employment and economic transformation, and seriously restrict the speed and quality of the development of resource-based cities and hinder sustainable development. Since it was proposed as a new method for measuring sustainable development capability, the ecological footprint model has been widely discussed in various studies and its advantages and disadvantages have been assessed by different scholars. Based on the traditional ecological footprint theory and the RBF neural network model based on the improved ABC algorithm, this paper makes an accurate prediction of the ecological pressure faced by Yulin, a typical mining resource-based city, from 2016 to 2020. The main conclusions are as follows:

1) It is predicted that the development of Yulin from 2016 to 2020 is in a state of unsustainable development. The per capita ecological footprint will increase from 4.975 hm2 in 2016 to 5.677 hm2 in 2020, and the per capita biocapacity will decrease from 3.481 hm2/person to 2.876 hm2/person. The demand for natural resources in the city is on the rise; however, the regional ecological supply capacity is in the decline, resulting in an increasing ecological deficit. In addition,

urban development is excessively dependent on the consumption of energy resources.

2) Compared to an ordinary RBF neural network, a BP neural network or a wavelet neural network, the RBF neural network model based on the improved ABC algorithm takes advantage of the ABC algorithm to determine the center value and the number of units in the hidden layer, which reduces the need to tediously adjust the parameters during training, significantly reduces the prediction error for urban ecological pressure and relatively improves the prediction accuracy.
3) For the RBF neural network prediction model based on the improved ABC algorithm, the fitting accuracy is up to 97.91%, and the simulation accuracy is as high as 94.16%. Considering the calculation process, it is clear that the model is particularly suitable for solving problems with complex internal mechanisms as it has a compact topology, fast convergence speed, rapid study speed and high classification ability. The model can reveal the inherent nonlinear and complex relationships between the urban socioeconomic factors and ecological pressure and thus can achieve a more accurate prediction for complex problems concerning urban ecological pressure.

However, due to the complexity of ecosystems, it is difficult for a traditional theoretical model of an ecological footprint to systematically and comprehensively reflect the status of sustainable development in a region. Therefore, it is necessary to further improve the ecological footprint theory and prediction algorithm. Based on the analysis in this paper, future studies on the prediction of urban sustainable development should focus on the following issues:

1) In terms of the calculation of the ecological footprint, with incomplete consideration of pollutants it does not include the groundwater footprint and the substitution between nonrenewable resources and renewable resources. Accordingly, it is necessary to further improve the ecological footprint index system and strengthen the study by including the effects of the groundwater and pollutant footprints and resource substitution. Since the natural ecosystem is linked by energy, energy theory could be used as a guide for solving the above problems.
2) In the research process, owing to the limitation of the data sources, the secondary processing of energy data is completed under certain assumptions, which may lead to a difference between the ecological footprint composition of the energy consumption account and the actual situation. In addition, this paper does not mention the transformative relationship between stock capital and flow capital as well as the utilization efficiency of natural capital, which will be a direction for future research.
3) In addition, studies on the evolution and early warning mechanisms can be strengthened. The purpose of the research on ecological pressure in resource-based cities is to measure and compare the degree of safety, understand the existing development problems, and take effective proactive measures to maintain or reduce the ecological pressure and provide a scientific basis for decision-making to local government to achieve healthy, stable and rapid sustainable development.
4) Because the ecological pressures of different systems in the same resource-based city are different, the influencing factors cannot be simply classified and isolated. We should fully consider the interactions of the influencing factors to comprehensively and systematically evaluate and respond to the ecological pressure on the research object and thus provide a theoretical and practical basis for the government to formulate sustainable development policies.

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