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A Spatially Explicit Optimization Model for Agricultural Straw-Based Power Plant Site Selection: A Case Study in Hubei Province, China

Xiang Zhao [1], Xiaoya Ma [1,2,*], Kun Wang [1,3], Yuqing Long [1,4], Dongjie Zhang [1] and Zhanchun Xiao [1,5,*]

1 School of Resource and Environmental Science, Wuhan University, Wuhan 430079, China; zhaoxiang@whu.edu.cn (X.Z.); wang_k@zju.edu.cn (K.W.); yqlong2015@pku.edu.cn (Y.L.); zhang_dj@whu.edu.cn (D.Z.)
2 Department of Geography and Earth Sciences, University of North Carolina at Charlotte, 9201 University Boulevard, Charlotte, NC 28223, USA
3 Department of Land Management, Zhejiang University, Hangzhou 310058, China
4 College of Urban and Environmental Sciences, Peking University, Beijing 100871, China
5 Journal of Natural Science of Wuhan University, Wuhan 430072, China
* Correspondence: xma9@uncc.edu (X.M.); xiaozhanchun@whu.edu.cn (Z.X.)

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Abstract: Using agricultural straw to generate electricity is an effective approach for relieving the pressure of procuring a reliable energy supply and reducing environmental pollution. Because the locations of the power plants have a significant impact on the supply of raw materials and the cost of transportation, it is important to choose reasonable locations for power plants. To solve the problem of straw-based power plant site selection (SPPSS), in this paper, a spatially explicit optimization model is proposed. Compared to the existing research, the present study makes the following major contributions: (1) The agricultural land quality evaluation dataset, combined with the cropping system and theoretical yield information, is used as the basic data to estimate agricultural straw yields, thereby increasing the accuracy of the straw yield and spatial distribution estimates. (2) Geographic information system (GIS) techniques are employed to improve an artificial immune system (AIS), which is an effective and flexible approach for solving optimization problems. The Chinese province of Hubei is selected as the experimental area to evaluate the effectiveness of the proposed model. The experimental results demonstrate that of the 34.89 million tons of agricultural straw produced in Hubei Province each year, 17.45 million tons can be used for electricity generation. The optimization schemes generated by the proposed model are feasible. Our results are expected to provide an important decision-making basis for straw-based power plant (SPP) development planning in Hubei Province.

Keywords: straw-based power plants; spatially explicit optimization model; location

1. Introduction

Over the past 30 years, with the increase in rural income and improvement in rural infrastructure, straw, the traditional fuel choice in rural regions in China, has gradually been replaced by fossil fuels, such as coal and natural gas. Moreover, because of the deficiency in technologies and facilities for processing and using straw, the amount of straw discarded in fields and openly burned has been gradually rising each year, resulting in a tremendous waste of resources and a serious problem for air quality and health [1,2]. With the development and maturation of straw-based electricity generation technology, the use of agricultural straw to generate electricity has become one of the main directions of the application of straw in China [3]. Using agricultural straw to generate electricity effectively reduces environmental stress and pollution, considerably improves the energy structure in rural regions, increases rural incomes, and promotes rural economic and social development. According to the relevant investigations and studies in China, compared to coal power, producing 1 kWh of electricity from straw would reduce CO_2 by 669 g, SO_2 by 7.77 g, NO_x by 6.78 g, and ash emitted into the atmosphere by 13.34 g [4]. It has also been found that a power plant consuming 200,000 tons of straw per year could create 1000 jobs [5].

In China, of the 450 million tons of straw (mainly agricultural straw) that could be converted into energy, only 30 million tons had been used to generate energy by the end of 2015 due to policy- and technology-related issues [6]. To increase straw-use efficiency and address the environmental pollution problem resulting from the open burning of straw, the Chinese government promulgated the 13th Five-Year Plan of Biomass Energy Development in October 2015, in which it was proposed that 40 billion CNY would be invested in the construction of new straw-based power plants (SPPs) in the next five years. According to this plan, SPPs operating in China will consume 11,600 tons of raw straw and replace 26.6 million tons of fossil fuels each year by 2020.

Unlike fossil fuels, such as coal and petroleum, straw yields are closely related to the spatial distribution of agricultural lands and the cropping structure. Selecting a reasonable site for an SPP can help effectively reduce the cost of transporting raw straw and can also ensure a continuous, sufficient supply of raw materials to maintain the stable operation of the power plant. The majority of biomass-based power plants currently operating in China are running at a loss due to the lack of a continuous, sufficient, and stable supply of raw materials resulting from unreasonable construction sites [7]. To obtain sufficient raw materials for electricity generation, some power plants have had to collect raw materials within a radius as large as 200 km [8]. Moreover, power plants are overly densely constructed in some areas, resulting in cut-throat competition for purchasing straw among the power plants, which, in turn, results in an increase in the operating cost of the power plants. Consequently, unreasonable construction sites have become one of the main reasons why many SPPs are running at a loss. To increase the operating revenue of SPPs and straw-use efficiency, there is an urgent need to optimize the geographical locations of SPPs and to increase the reasonableness of the spatial distribution of SPPs with regard to planning their regional development.

The SPP site selection (SPPSS) problem is often defined as a constrained *p*-median problem [9,10], i.e., an optimization problem with the radius within which raw straw is collected (R_{SC}), the straw yield, the terrain condition, and the transport condition as the constraints and economic revenue maximization as the optimization objective. With the rapid development of straw-based electricity generation technology, relevant researchers have already conducted extensive research on and exploration into modeling and solving the SPPSS optimization problem. Based on the method and technique used, existing models can be classified into non-spatially explicit models [11–17] and spatially explicit models. [9,10,18–29]. Spatially explicit models can be used to model complex spatial objects and relationships and have thus been extensively used to solve *p*-median problems (e.g., SPPSS).

To obtain feasible spatially explicit optimization schemes, there are two technical issues to be solved: (1) accurately estimating the spatial distribution and yield of straw and (2) selecting a suitable optimization method to model and solve the SPPSS problem in a spatially explicit manner.

The spatial distribution of straw is in complete agreement with that of agricultural lands. However, straw yields are closely related to crop types and the production capacity (quality) of agricultural lands. The existing models estimate the spatial distribution and yield of straw and can be divided into three categories according to the data they use: statistical data-based models, land-use data-based models, and remote sensing data-based models. Statistical data-based models estimate the straw yield in each administrative unit based on the statistical data and grain-to-straw ratio coefficient [11,14,20,23–25,27,30,31]. Clearly, the administrative units used in statistical data-based models are too coarse for SPPSS decision-making. Land-use data-based models estimate the spatial distribution and yield of straw mainly based on land-use data and average crop yield data in combination with the grain-to-straw ratio coefficient [9,16,19,21,26,32]. However, land-use data-based models do not consider the differences in production capability between different lands. Consequently, even if the land use and cropping system of two parcels are exactly the same, there may be an enormous difference between the crop yields of the two parcels. Remote sensing data-based models typically estimate the spatial distribution and yield of straw based on remote sensing technologies and net primary productivity models [18,33]. Compared to land-use data-based models, remote sensing data-based models can accurately obtain not only the spatial distribution of land use information but also information on land productivity. However, it is difficult to identify crop information from remote sensing images.

When making decisions on selecting sites for SPPs in a region, the constraints on SPPSS imposed by the regional geographical environment and the spatial relationships between SPPs must be considered. Furthermore, whether SPPs can collect sufficient straw within the expected R_{SC} is the most important spatial constraint on SPPSS. Additionally, most existing models can be divided into four categories according to the optimization methods that they use: multi-criteria evaluation models [10,18,19], location-allocation models [9,20–26], clustering models [27]; and mathematical programming models [28]. Multi-criteria evaluation models often obtain schemes by using basic spatial analysis techniques (e.g., overlay analysis and buffer analysis) based on subjective experiences. They are not suitable for seeking global optimal results for optimization problems. On the one hand, location-allocation models, clustering models, and mathematical programming models are not sufficiently flexible to address the complex spatial optimization objectives and spatial constraints. On the other hand, due to their flexible structure and powerful global optimization capabilities, meta-heuristic algorithms, such as genetic algorithms, have been widely used in solving *p*-median problems [34–37], providing an effective solution to SPPSS.

To address the limitations of the existing research, in this paper, a spatially explicit optimal decision-making model for SPPSS is proposed. Compared to the existing research, the present study focuses on the following: (1) Agricultural land quality evaluation data; the theoretical yields of the main crops planted on each parcel, are used to estimate straw yields, thereby increasing accuracy in estimating the spatial distribution and yield of straw; (2) Geographic information system (GIS) techniques are employed to improve an artificial immune system (AIS) in such areas as antibody encoding, mutation, and affinity evaluation. The exceptional optimization ability of the improved AIS helps improve the reasonableness of the SPPSS scheme. The effectiveness of the proposed model is evaluated based on a case study of SPP development planning in the Chinese province of Hubei, in which SPPSS optimization for Hubei Province based on the model designed in the present study is investigated. Our results are expected to provide an important decision-making basis for planning the spatial distribution of SPP sites.

2. Modeling Framework and Methodology

Because of the heterogeneity in the spatial distribution of raw resources, estimations of straw yields based on the spatial distribution of straw resources are prerequisites for modeling the SPPSS problem. Moreover, there are several steps involved in transporting straw from fields to SPPs, including harvesting, preprocessing, shipping, and storing. How raw straw is collected also affects the amount of raw straw available for electricity generation in SPPs and the operating cost of SPPs. Furthermore, the optimization algorithm determines the accuracy and reasonableness of the optimization schemes. Thus, how to estimate the spatial distribution and yield of straw, design the raw straw collection model, and model and solve the SPPSS problem in a spatially explicit manner constitute several key technical problems facing research in SPPSS models. Based on the aforementioned analysis, a framework is designed for the proposed model (Figure 1).

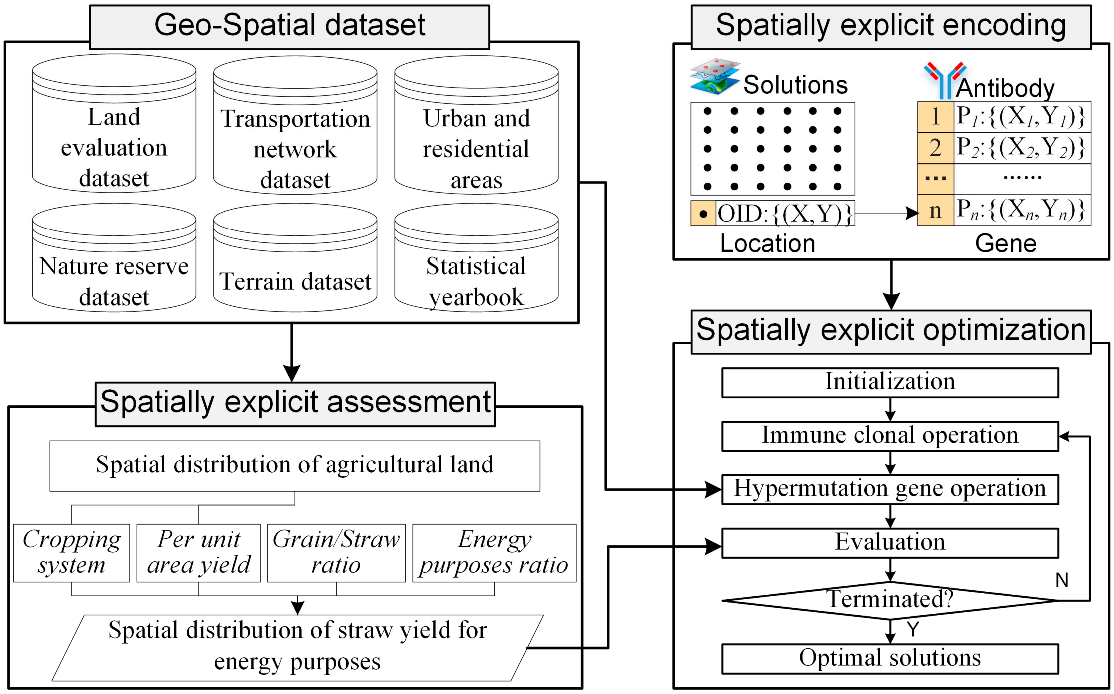


Figure 1. The framework of the spatially explicit Straw-Based Power Plant Site Selection model.

2.1. Spatially Explicit Assessment of Agricultural Straw Availability for Power Generation

Agricultural straw is a by-product of agricultural production. The spatial distribution of agricultural straw is in complete agreement with that of agricultural lands. Therefore, information regarding the spatial distribution of straw can be obtained from land-use data. Compared to remote sensing images, land-use data obtained from land-use surveys more accurately reflect the spatial distribution of agricultural lands. Moreover, straw yields are affected collectively by the agricultural land quality and crop types. The existing research demonstrates that estimates of the spatial distribution and straw yield based on land-use data and land evaluation data are more accurate and reliable than those obtained using other methods [38,39]. Additionally, to better protect agricultural lands, the Chinese government has performed agriculture land quality gradation (ALQG) on a national scale since 2000. The goal of this work is to evaluate the quality of each cultivated land and the theoretical yields of the main crops planted in each cultivated land based on comprehensive natural, social, and economic factors (e.g., soil, climate, and cropping systems). Thus, the ALQG dataset provides ideal basic data for estimating the spatial distribution and yield of straw. Based on the agricultural land evaluation dataset, a straw yield estimation equation (see Equation (1)) is designed for the proposed model:

$$Y_i = A_i \times \sum_{j=1}^{O} p_j \times G_j, \tag{1}$$

where Y_i represents the straw yield of parcel i, A_i represents the area of parcel i, p_j represents the theoretical yield of crop j in parcel i, G_j represents the grain-to-straw ratio coefficient of crop j and O represents the type of crop cultivated in the current land. All the values of the variables in Equation (1) are stored in the land evaluation results database. These values can be easily obtained by using GIS technology, and the calculation of straw yield can be implemented in most of the GIS Software, such as ArcGIS. The grain-to-straw ratio coefficient used in the model is extracted from previously published results [40–42]. Table 1 lists the grain-to-straw ratio coefficient of each main crop used in the present study based on the actual situation in the study area.

Table 1. The straw/production ratios for different crops.

Crop	Straw/Production Ratio
Wheat	1.16
Rice	0.96
Corn	1.75
Cotton	3.44
Rape	2.04
Wheat	1.16

In China, straw is mainly used as an industrial raw material, fodder, and fertilizer, and to generate energy. A study has shown that the amount of straw that can be used to generate energy accounts for approximately 50% of the total amount of straw [43]. Therefore, the amount of straw produced in any arbitrary parcel i (E_i) can be calculated using Equation (2):

$$E_i = 0.5 \times Y_i, \tag{2}$$

Accurate information regarding the spatial distribution and yield of agricultural straw can be obtained based on the agricultural land quality evaluation dataset in combination with the grain-to-straw ratio coefficient and the proportion of straw available for energy purposes, thereby providing important basic data for SPPSS.

2.2. *Straw Collection Model Design*

The process of supplying straw from a field to an SPP involves several steps, including harvesting, drying, weighing, crushing, baling, carrying, stacking, and storing. Based on the results of the existing research on straw collection models [8,42], a straw collection model that maximizes economic revenue is designed for the study area (Figure 2).

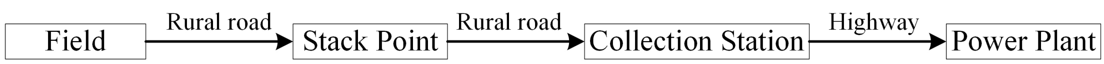


Figure 2. Workflow of straw transportation.

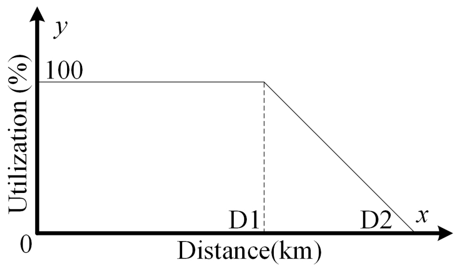
As shown in Figure 2, the straw harvesting, processing, and transport processes are as follows: (1) A stack point (SP) is set up in each residential area or settlement. Straw obtained after crop harvesting is subjected to simple preprocessing treatments (e.g., drying). Afterward, the straw available for energy generation is transported on rural roads to the nearest SP; (2) Collection stations (CSs) are set up in towns that have good transport facilities and are densely populated. The straw purchased at each SP continues to be transported on rural roads to the nearest CS; (3) The straw purchased by each CS is transported on highways to the nearest SPP. Because SPPs purchase straw directly from CSs, the present study considers only the modeling of the spatial relationships between CSs and SPPs, not the modeling of the spatial relationships between fields and SPs or the spatial relationships between SPs and CSs.

The cost of transporting straw increases with increasing transport distance. When distance is far enough, the use of straw for power generation will no longer be competitive to other uses. On the other hand, the transportation cost may become affordable to SPPs. Consequently, under the precondition that the demand for raw materials is satisfied, an SPP always prefers to purchase straw from the nearest CS. The willingness of an SPP to purchase straw from a CS gradually decreases with increasing SPP-CS distance. Therefore, the present study uses a gradual covering model [44–46] as the SPP straw collection model (see Equation (3)).

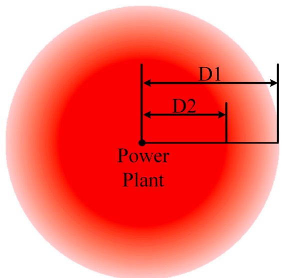
$$C_{ij} = \begin{cases} 0, \quad ClosestStationID \neq i \\ E_j,\ d_{ij} < D1 \cap ClosestStationID = i \\ E_j \times \frac{D2 - d_{ij}}{D2 - D1},\ D1 < d_{ij} < D2 \cap ClosestStationID = i \\ 0,\ d_{ij} > D2 \cap ClosestStationID = i \end{cases}, \tag{3}$$

where C_{ij} represents the amount of straw that SPP i can purchase from CS j, E_j represents the amount of straw stored in CS j, d_{ij} represents the path distance between SPP i and CS j, which can be calculated using the path analysis function of GIS software, ClosestStationID represents the identification (ID) of the SPP nearest to CS j, and $D1$ and $D2$ represent the thresholds of R_{SC}. Based on the existing published data [8,47,48], the values of $D1$ and $D2$ are set to 30 km and 50 km, respectively. Figure 3 shows the principle of the model. The basic assumptions of the model are as follows:

- Each CS supplies straw to only the SPP nearest to it;
- When the distance between a certain CS and the SPP nearest to it is less than a certain distance threshold ($D1$), all the straw collected at this CS will be supplied to the SPP nearest to it;
- When the distance between a certain CS and the SPP nearest to it is greater than a certain distance threshold ($D2$), the straw collected at the CS will not be supplied to any SPP;
- When the distance between a certain CS and the SPP nearest to it is greater than $D1$ but less than $D2$, the amount of straw that the CS can supply to the SPP nearest to it decreases linearly with increasing distance between them.



(**a**)



(**b**)

Figure 3. Straw collection model of a straw-based power plant (SPP); (**a**) gradual straw collection function of the model; (**b**) schematic diagram of the straw collection model.

As shown in Figure 3, when there is no competition from other SPPs, an SPP will purchase straw from the CSs within a certain radius. In Figure 3b, the darker an area is, the higher is the efficiency in using the straw collected at the CSs within the area.

2.3. Definition and Description of SPPSS Problems

Let $S = \{s_1, s_2, \ldots s_m\}$ be the set of CSs within the area. The amount of straw stored in a CS varies with the area that it serves. In addition, let $L = \{l_1, l_2, \ldots l_n\}$ be the set of candidate SPP sites. The SPPSS problem can be defined as follows: under the precondition that the basic demand of SPPs for raw straw is met, N number of sites are selected from set L as SPP sites that allow the SPPs to have the maximal total economic revenue. The economic revenue of an SPP is affected by various factors, such as the purchase price of the raw materials, labor cost, operating cost, and electricity price [8,48]. Because the SPPSS problem is a geospatial optimization problem, the present study considers only the factors affecting the cost and decision-making variables that are closely related to the geographical location. Of the factors affecting the economic revenue generated by running an SPP, the amount of straw that can be purchased by the SPP and the transport cost are related to the geospatial location when the thresholds of R_{SC} ($D1$ and $D2$) are given. It is assumed that the labor and operating costs of SPPs, the capital invested in the construction of SPPs, and the electricity price are basically consistent in the area and remain stable within a certain period of time. These factors are not considered as decision-making variables.

Based on the aforementioned assumptions, the SPPSS problem is defined by using the aspects of the optimization objective and constraints.

2.3.1. Optimization Objective

Let there be M number of CSs and N number of SPPs planned for construction in the area. The optimization objective function is defined by Equation (4).

$$max\ f(x) = \sum_{i=1}^{N} (TP_i - TC_i - TS_i) \quad (4)$$

where $f(x)$ represents the economic revenue function, N represents the number of SPPs, TP_i represents the total electricity sales of SPP i, TC_i represents the cost of transporting raw straw for SPP I, and TS_i represents the purchase price of raw straw for SPP i. Each cost unaffected by the spatial location is viewed as a constant and is not considered in the optimization objective function. TP_i is defined by Equation (5):

$$TP_i = PR_{Electricity} \times R \times \sum_{j=1}^{n} C_{ij} \quad (5)$$

where C_{ij} represents the amount of straw that can be purchased by SPP i from CS j, n represents the total number of CSs that supply straw to SPP i, $PR_{Electricity}$ represents the electricity price and is a constant (unit: CNY/kWh), and R represents the amount of electricity generated per kg of straw and is constant (based on the existing published data [5,8,48], the value of R is set to 1000 kWh/ton, i.e., one ton of straw can, on average, generate 1000 kWh of electricity).

TC_i in Equation (4) is defined by Equation (6):

$$TC_i = PR_{Trans} \times \sum_{j=1}^{n} C_{ij} \times d_{ij} \quad (6)$$

where d_{ij} represents the transport distance between SPP i and CS j (unit: km), and PR_{Trans} represents the unit transport cost (based on the existing published data [47] in combination with the information of the actual situation in the study area obtained through a survey, the value of PR_{Trans} is set to 2.5 CNY/ton·km).

TS_i in Equation (4) is defined by Equation (7):

$$TS_i = (PR_{Straw} + PR_{Pretreat}) \times \sum_{j=1}^{n} C_{ij} \quad (7)$$

where PR_{Straw} represents the unit price at which CSs purchase straw from farmers and SPs and $PR_{Pretreat}$ represents the unit cost of the straw preprocessing treatments unrelated to the spatial distance (e.g., stacking, storing, loss prevention, loading, unloading, and the operation cost), excluding the transport cost (based on the existing published data [8,47,48] in combination with the information of the actual situation of the study area obtained from a survey, the values of PR_{Straw} and $PR_{Pretreat}$ are set to 250 and 140 CNY/ton, respectively).

2.3.2. Constraints

SPPSS is often limited by a series of geospatial constraints. Table 2 lists the constraints on SPPSS, which are designed based on published data [12,26,49] in combination with the actual situation of the study area, with the aim of facilitating the transport of raw materials and reducing the impact of SPPs on human living and production activities.

Table 2. The constraints of spatial distance for the site selection for straw-based power plants (SPPs).

ID	Constraints	Value
1	Distance to natural protected areas	$\geq$3000 m
2	Distance to airport	$\geq$2000 m
3	Distance to urban area	$\geq$3000 m
4	Distance to rural settlements	$\geq$1000 m
5	Distance to wetland	$\geq$1500 m
6	Distance to highway	$\leq$1000 m
7	Slope	$\leq 15^{\circ}$
8	Available straw in supply area	$\geq$18 tons [48]

The geospatial data involved in the aforementioned constraints can be obtained using GIS spatial analysis methods.

2.4. Design of the Spatially Explicit Optimization Algorithm

Intelligence algorithms, represented by genetic algorithms, AISs, and ant colony optimization algorithms, are considered ideal methods for solving complex optimization algorithms and are thus extensively used to solve various types of optimization problems. Of the aforementioned algorithms, AISs are a type of artificial intelligence method designed through the simulation of various types of immune mechanisms in natural immune systems [50]. Owing to their exceptional optimization ability and flexible algorithm structure, AISs have been successfully used in various fields [51]. In the field of geospatial optimization, AISs combined with GIS techniques have also been effectively used to solve path optimization [52], land-use allocation [53–55] and *p*-median [52] problems. Hence, the present study uses an AIS algorithm as the optimization algorithm for the SPPSS problem. As shown in Figure 1, an AIS algorithm has the following main steps:

1. Algorithm initialization. Based on the antibody-encoding strategy, an initial antibody population containing a certain number of antibodies is randomly generated.
2. Cloning. Based on the magnitudes of their affinities, the antibodies in the population are replicated. The higher the affinity of an antibody is, the more times the antibody is replicated.
3. Hypermutation. Based on a certain mutation probability, the gene values of the cloned antibodies are altered to generate new antibodies.
4. Affinity evaluation. The affinities of the new antibodies generated by mutation are calculated using an affinity evaluation function. The higher the affinity of an antibody is, the better the quality of the schemes corresponding to the antibody.

Details on AIS algorithms can be found elsewhere [50]. Classical AISs are mainly used to model and solve non-spatial problems. Thus, before using an AIS algorithm to model and solve spatial problems (the SPPSS problem, in the case of the present study) in an explicitly spatial manner, modifications to the algorithm using GIS techniques must be made in such areas as antibody encoding, mutation, and affinity evaluation to enable the algorithm to meet the problem-solving requirements.

2.4.1. Antibody Encoding

Encoding is the process in which an AIS algorithm models an actual problem. An optimization scheme converts an actual problem based on a certain encoding strategy into virtual artificial antibodies in a computer environment. Therefore, using GIS techniques to modify the antibody-encoding method is a precondition for optimizing the SPPSS problem in a spatially explicit manner. As shown in Figure 1, the key techniques of the spatially explicit antibody-encoding scheme used in the present study are as follows:

5. Determination of candidate sites. To meet the requirements of antibody encoding, candidate sites spaced at the same interval (e.g., 1 km × 1 km) are established in the study area to discretize the continuous geographical space.
6. CS and candidate site data model. Based on the object-oriented approach, GIS techniques are used to model, store, and process the CSs and candidate sites. As shown in Figure 1, the x- and y-coordinates indicate the spatial locations of the candidate sites, and each site has a unique ID number. To meet the requirements of antibody affinity evaluation, the amount of straw that can be collected by each CS is stored in the form of attribute information.
7. Antibody model. As shown in Figure 1, each antibody in the AIS corresponds to an optimization scheme for the actual problem. Each gene of an antibody stores a candidate site object. Each gene must have a unique value. The gene length corresponds to the number of SPPs (N) in the optimization scheme.
8. The terrain, transport network, and natural reserves data required for antibody affinity evaluation are stored and managed using a geodatabase model [56].

2.4.2. Antibody Mutation Algorithm

The basic principle of antibody mutation is that a new optimization scheme is generated by altering the gene status and value. Antibody mutation is closely related to the antibody-encoding scheme and is a main method by which an AIS algorithm generates new optimization schemes. Figure 4 shows the antibody mutation algorithm designed in the present study.

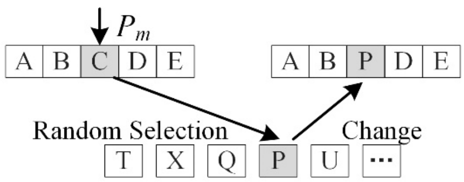


Figure 4. Antibody mutation algorithm.

As shown in Figure 4, the antibody mutation algorithm has the following steps:

1. Antibody genes are traversed. For any arbitrary gene g, a random number, Pg, is generated. If Pg < Pm, then gene g is mutated.
2. For a gene (g) that requires a mutation, a candidate site is randomly selected. If the selected site is not in the current antibody gene set, then the current site in gene g is replaced; otherwise, a new candidate site is selected until the selected candidate site is no longer in the current antibody gene set.

2.4.3. Antibody Affinity Evaluation

In an AIS, the higher the affinity of an antibody is, the higher is the quality of the optimization scheme corresponding to the antibody. Based on this principle, an antibody affinity evaluation function is designed (see Equation (8)).

$$Affinity_i = \frac{f(x)_i}{v+1}, \tag{8}$$

where $Affinity_i$ represents the affinity of antibody i, $f(x)_i$ represents the value of the optimization objective of the optimization scheme corresponding to antibody i, and v represents the number of sites in the antibody that violate the constraints listed in Table 2.

3. Case Study

3.1. Description of the Study Area

Situated in the middle reaches of the Yangtze River and to the north of Dongting Lake in central China, Hubei Province, with an area of 185,900 km^2 (Figure 5), has abundant water resources due to the presence of numerous rivers and lakes, in addition to ample sunlight and heat resources, providing excellent natural conditions for agricultural production. Consequently, Hubei Province is one of the most important major agricultural provinces in China. The main crops produced in Hubei Province include rice (Rc), wheat (W), corn (Cn), rape (Rp), and cotton (Ct). Table 3 lists the main cropping system in each area. The statistical data of 2015 [57] show that in 2015, Hubei Province had a cultivated area of 44,660 km^2 for grain crops (including rice and corn), a total grain yield of 27.03 million tons, a cultivated area of 12,320 km^2 for rape, a rapeseed yield of 2.55 million tons, a cultivated area of 2647 km^2 for cotton, and a cotton yield of 298,000 tons. A preliminary estimation shows that over 30 million tons of straw are produced from agricultural production in Hubei Province.

Table 3. Dominant cropping systems in Hubei Province (abbreviations shown above).

Districts	Cropping Systems
E Zhou (EZ)	Rp-Rc-Rc; W-Rc; W-Ct
En Shi (ES)	Rc-Rc; W-Rc; W-Cn
Huang Gang (HG)	Rp-Rc-Rc; W-Rc; W-Ct; W-Cn
Huang Shi (HS)	Rp-Rc-Rc; W-Rc; W-Ct
Jing Men (JM)	Rp-Rc-Rc; W-Rc; W-Ct
Jing Zhou (JZ)	Rp-Rc-Rc; W-Rc; W-Ct
Qian Jiang (QJ)	Rp-Rc-Rc; W-Rc; W-Ct
Tian Men (TM)	Rp-Rc-Rc; W-Rc; W-Ct
Xian Tao (XT)	Rp-Rc-Rc; W-Rc; W-Ct
Shen Nong Jia (SNJ)	W-Rc; W-Cn; Rp-Cn
Shi Yan (SY)	W-Rc; W-Cn; Rp-Cn
Sui Zhou (SZ)	Rp-Rc; W-Rc; W-Ct
Wu Han (WH)	Rp-Rc-Rc; W-Rc; W-Ct
Xian Ning (XN)	Rp-Rc-Rc; W-Rc; W-Ct
Xiang Yang (XY)	W-Rc; W-Cn; W-Ct; Rp-Rc
Xiao Gan (XG)	Rp-Rc-Rc; W-Rc; W-Ct
Yi Chang (YC)	W-Rc; W-Cn; Rp-Cn

To improve eco-environmental protection and increase rural incomes, the provincial government of Hubei Province proposed in 2015 to increase straw-use efficiency by strengthening technological research and development, increasing investment, and establishing a complete straw collection, storage, and transport system. Moreover, to promote the development of the straw-based electricity generation industry, the provincial government of Hubei Province also implemented an electricity price subsidy policy, which subsidies the straw-based electricity price to 0.831 CNY/kWh from 0.75 CNY/kWh. It is anticipated that the next five to ten years will see relatively significant transformation and development in the straw-based electricity generation industry in Hubei Province. Therefore, how to reasonably plan the geospatial locations of SPPs to reduce the cost of straw-based electricity generation and to increase the economic revenue of SPPs has already become a challenge facing the straw-based electricity generation industry in Hubei Province that must urgently be addressed. Under this circumstance, the present study conducts a case study with Hubei Province as the study area to investigate SPPSS optimization.

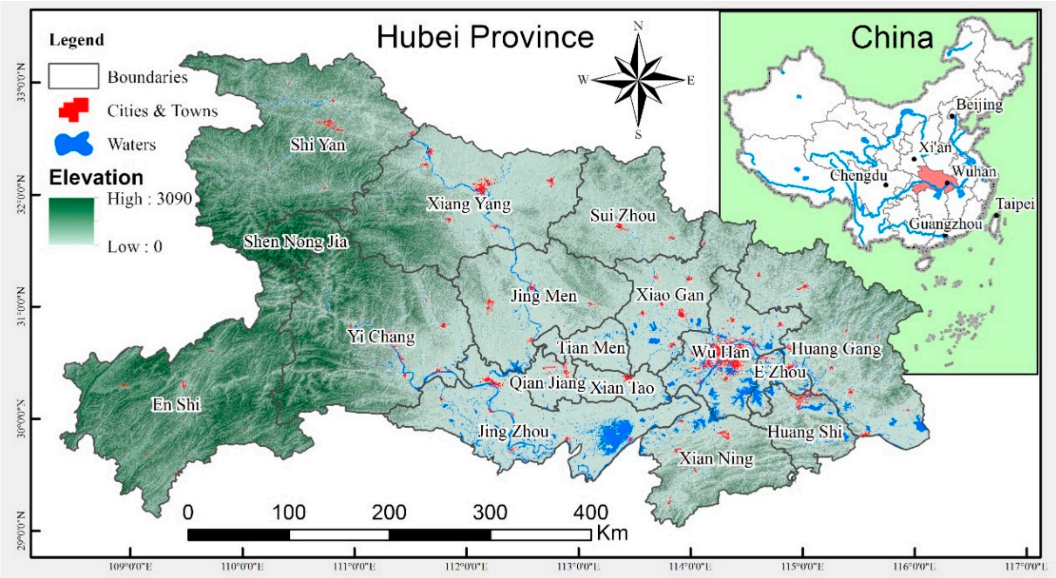


Figure 5. Location map of the study area, Hubei Province, China.

3.2. Data Acquisition and Preprocessing

According to the requirements of SPPSS optimization modeling, the ALQG dataset, wetland distribution data, natural reserves data, and data on highway networks in urban and rural residential areas were acquired from the Department of Land Resources Management of Hubei Province; statistical yearbook data were acquired from the Hubei Provincial Bureau of Statistics; airport distribution data were obtained using Baidu Maps (http://map.baidu.com); and the 30 m-resolution digital elevation model (DEM) data products for Hubei Province were acquired from the online data services of the GeoSpatial Data Cloud (http://www.gscloud.cn). Each type of data was preprocessed as follows:

1. Estimating the amount of straw available for electricity generation. The spatial distribution and yield of straw available for electricity generation in Hubei Province were estimated based on the ALQG dataset as well as the straw yield estimation model described in Section 2.1 and its parameters (Figure 7). To visualize the data processing process and its results, the estimation results were transformed from vector polygons to raster data consistent with the spatial resolution of the DEM. As shown in Figure 7, agricultural straw is mainly distributed in the plain regions in eastern and central Hubei Province, where river networks and lakes are densely distributed. Through analysis based on the estimation results, the entirety of Hubei Province has an annual straw yield of approximately 34.89 million tons, of which 17.45 million tons can be used for electricity generation.
2. Estimating the amount of straw collected by the CSs. Because townships are the lowest-level administrative unit in China, township-level governments are often based in residential areas with a relatively large population and good transport facilities. It is assumed that one CS is set up in each residential area where a township-level government is located. On this basis, the spatial distribution of CSs in the study area was obtained. Because it is difficult to obtain rural road data, the amount of straw that each CS can collect was estimated based on the shortest Euclidean distance. The area within which each CS collects straw was defined using a Voronoi diagram. On this basis, the amount of straw that each CS can collect was calculated using the rasterized straw estimation data and the ArcGIS Desktop spatial statistics tool. Figure 6 shows the spatial distribution of CSs within Hubei Province as well as the area within which each CS collects straw and the amount of straw that each CS can collect.

3. Preprocessing candidate sites. Based on the antibody-encoding scheme designed in Section 2.4.2, a set of candidate sites spaced at 1 km ×1 km intervals in the study area was generated. To decrease the optimization space, candidate sites that failed to satisfy distance constraints 1–7 listed in Table 2 were eliminated through GIS spatial overlay analysis and buffer analysis. Thus, a set of candidate sites containing 77,285 candidate sites was obtained.

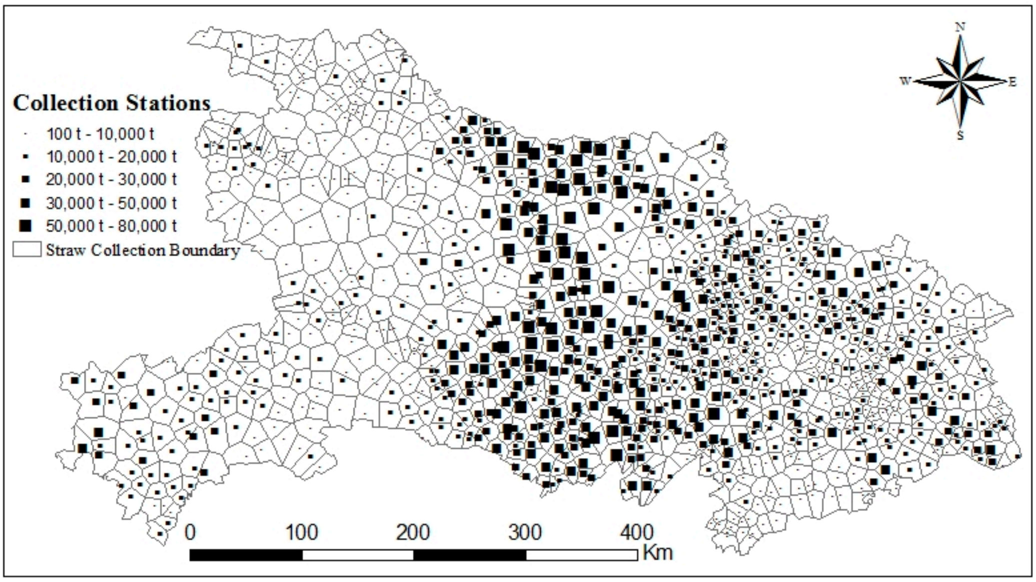


Figure 6. Distribution of the straw collection stations (CSs) in Hubei Province.

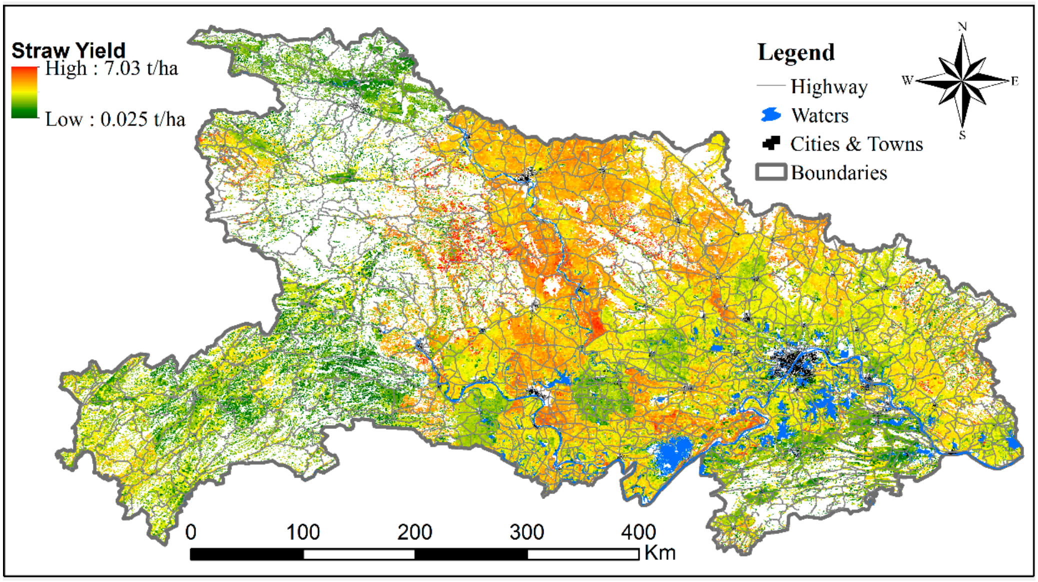


Figure 7. Straw available for electricity generation in Hubei Province.

4. Results and Discussions

The optimization model was implemented using a geospatial optimization tool developed by Zhao et al. [52] as well as the C # language and ArcObjects Software Development Kit for Net Framework [52]. *N* affects the capital invested in the construction of SPPs and significantly affects the cost of transporting straw. Under ideal circumstances, *N* is inversely proportional to the cost of transporting straw. It is assumed that each SPP collects straw within a radius of 30 km, and 65 SPPs are required to completely cover the study area under ideal circumstances. Because it is difficult to reasonably determine N in advance, N was set to 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, and 65 for experimentation. Moreover, the straw-based electricity price also affects the economic revenue generated by running SPPs. Therefore, the present study performed experimentation and analysis based on two scenarios, namely, a scenario in which an electricity subsidy policy was implemented (hereinafter referred to as the subsidy scenario) and a scenario in which there was no electricity subsidy policy (hereinafter referred to as the non-subsidy scenario). The electricity price was 0.75 CNY/kWh without the subsidy and 0.831 CNY/kWh with the subsidy. A total of 26 experiments were performed using the experimental software. Table 4 and Figure 8 show the experimental results.

Table 4. Straw-based power plant site selection (SPPSS) optimization results and economic revenue data under various scenarios.

Number of SPPs	Total Benefit (Million CNY)		Total Transportation Cost (Million CNY)	Total Straw Yield (Million tons)	Marginal Revenue (Million CNY)	
	Without Subsidy	With Subsidy			Without Subsidy	With Subsidy
5	956	1215.	211	3.24	-	-
10	1700	2160	370	5.75	148.78	188.91
15	2243	2851	493	7.60	108.63	138.21
20	2783	3535	601	9.40	107.97	136.78
25	3292	4178	694	11.08	101.93	128.71
30	3608	4574	739	12.08	63.18	79.22
35	3905	4947	782	13.02	59.39	74.48
40	4115	5208	802	13.66	42.04	52.26
45	4286	5420	818	14.18	34.16	42.46
50	4428	5592	809	14.55	28.41	34.37
55	4526	5711	810	14.82	19.46	23.83
60	4589	5781	772	14.90	12.75	13.89
65	4608	5801	761	14.92	3.73	4.09

Based on Table 4, the total economic revenue of SPPs within the study area and the amount of straw available for electricity generation gradually increased with increasing N. The implementation of the electricity price subsidy resulted in a significant increase in the economic revenue of SPPs. Although increasing N can help increase the straw-use efficiency and the economic revenue generated by generating electricity from straw, an increase in N also means an increase in the capital invested in the construction of SPPs. To determine N, the relationship between the return on investment (ROI) for an SPP and the economic revenue of the SPP was further analyzed using the economic law of diminishing marginal utility [58]. Marginal revenue (MR) was estimated using the Equation (9).

$$\mathrm{MR} = (TB_i - TB_{i-5})/5 \tag{9}$$

where TB_i represents the total economic revenue. Table 4 and Figure 8b list the MR estimation results. Based on these results, MR gradually decreased with increasing N, indicating that the increase in the economic revenue resulting from the construction of a new SPP decreases as more SPPs are constructed. For example, under the subsidy scenario, there will be an average annual increase of 188.91 million CNY in the total economic revenue resulting from the construction of each new SPP when N increases from 5 to 10. However, under the subsidy scenario, there will be an average annual increase of only 4.09 million CNY in the total economic revenue resulting from the construction of each new SPP when N increases from 60 to 65.

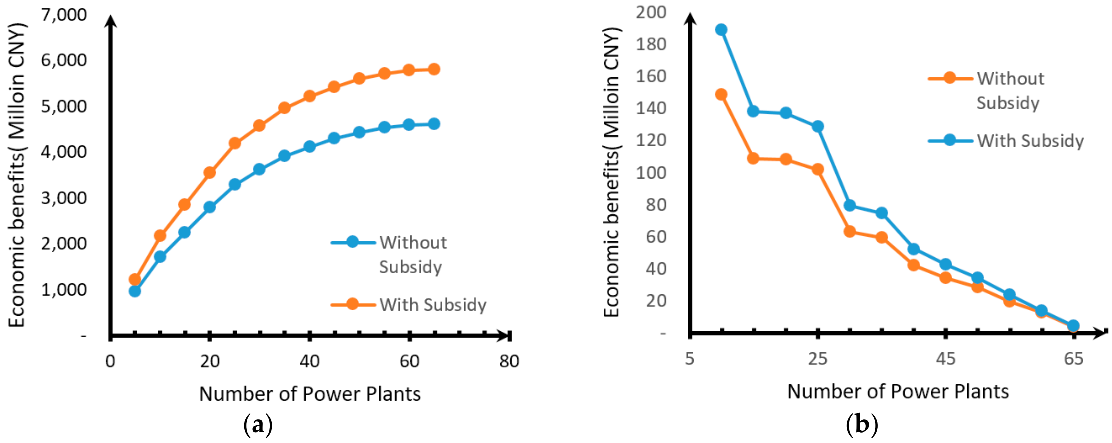
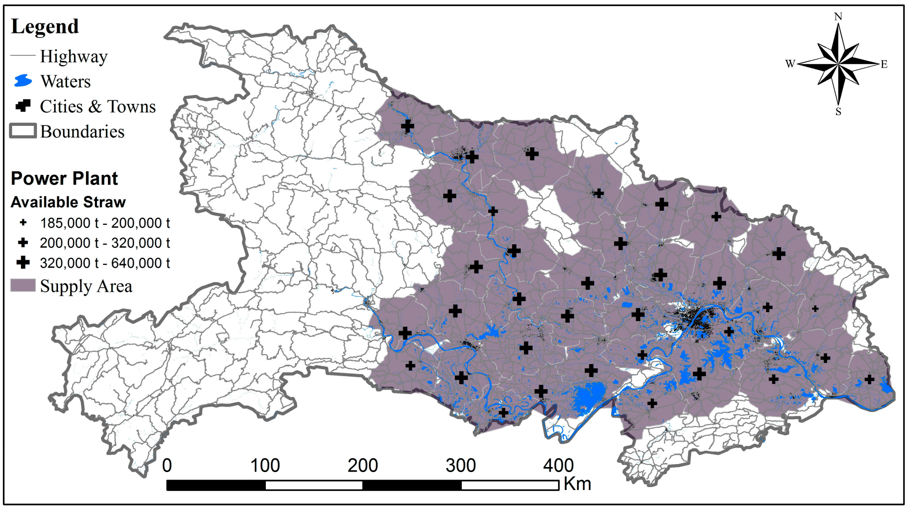


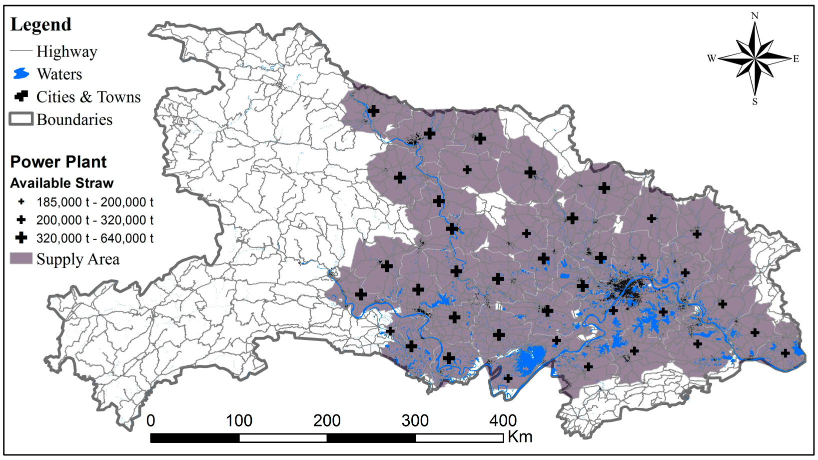
Figure 8. Relationship between *N* and the economic revenue: (**a**) relationship between *N* and the total economic revenue; (**b**) relationship between *N* and marginal revenue (MR). *N* is the number of power plant.

Based on previous studies [47,48], it is assumed that the average capital invested in the construction of one SPP amounts to 250 million CNY; the average operating cost, excluding the cost of raw straw, amounts to 9.0 million CNY; and the rate of ROI for SPPs is 10%. To ensure normal operation and profitability, each SPP should generate a total annual revenue greater than 34 million CNY. According to the economic law of diminishing marginal utility, the construction of an SPP is profitable from the perspective of economic returns only if the increased revenue resulting from the construction of the SPP exceeds the capital invested. Based on Table 4, to ensure that the straw-based electricity generation industry is profitable as a whole, *N* should not exceed 50 under the subsidy scenario and 45 under the non-subsidy scenario for the entire Hubei Province. Therefore, the optimization schemes corresponding to an *N* of 35, 40, 45, and 50 were selected as the candidate decision-making schemes for the SPPSS problem of Hubei Province (Figure 9).

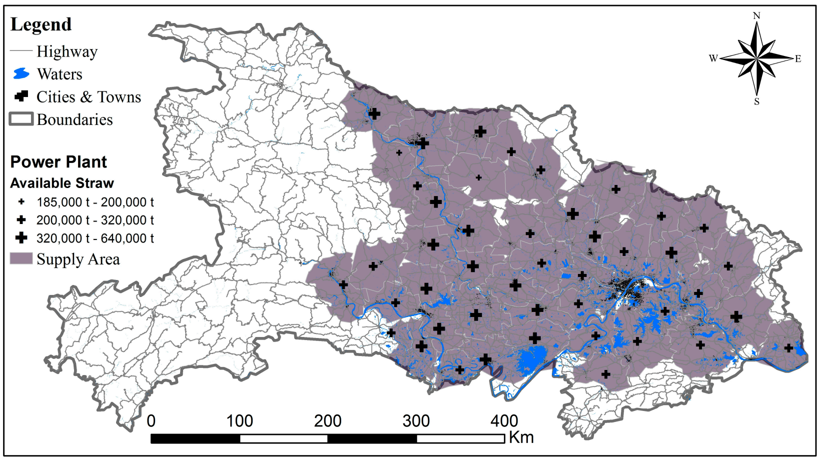


(**a**)

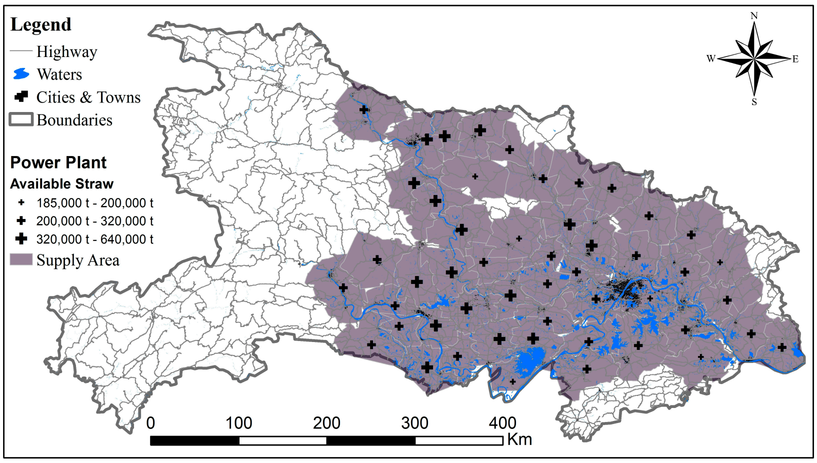
Figure 9. *Cont.*



(**b**)



(**c**)



(**d**)

Figure 9. The optimal locations of SPPs in Hubei Province, China: (**a**) N = 35; (**b**) N = 40; (**c**) N = 45; (**d**) N = 50.

Based on Figure 9, with increasing N, although the area in which straw can be collected for electricity generation increases, the scale and R_{SC} of each SPP gradually decrease. Regardless of the value of N, overall, the optimal SPP sites are distributed in eastern and central Hubei Province but not in western Hubei Province. The reason is that mountains and hills are the main terrain types in western

Hubei Province, and agricultural lands and agricultural straw in this region are distributed in an overly scattered pattern, which is unfavorable to the collection and transport of straw. To further analyze its feasibility, each candidate optimization scheme was further analyzed in terms of the amount of available straw, the average straw-SPP transport distance, and the area within which straw is collected. Table 5 lists the results.

Table 5. Statistical analysis of each candidate scheme in terms of the area of straw collection by SPPs.

Number of SPPs	Average Transport Distance of Straw (km)	Supply Area (km^2)				Available Straw (1000 tons)			
		Max	Min	Avg	Total	Max	Min	Avg	Total
35	24.0	3719	1521	2668	93,366	636	197	372	13,021
40	23.5	3572	207	2347	93,868	585	181	342	13,660
45	23.1	3326	463	2121	95,453	504	195	315	14,179
50	22.3	3177	887	2001	100,044	465	185	291	14,551

As shown in Figure 4, the average straw-SPP transport distance decreased from 24 km to 22.3 km as N increased from 35 to 50. In addition, the average straw supply area and the average amount of available straw increased as N increased from 35 to 50. Overall, each optimization scheme met the requirements for raw materials that ensure the efficient operation of SPPs based on the analysis results concerning the average straw-SPP transport distance, the average straw supply area, and the average amount of available straw. Furthermore, considering the possible uncertainties of the straw-based electricity price subsidy policy, it is recommended that N should not exceed 40 to ensure that each SPP is profitable. The scheme demonstrated in Figure 9b can be used as a reference for SPP development planning and for making decisions on SPP locations in Hubei Province.

Furthermore, the development of SPP will have a great positive impact on environmental protection and job creation in Hubei Province. As shown in Table 4, when $N = 40$, the total amount of straw that can be used for power generation in Hubei Province is approximately 13.66 million tons. According to the existing studies [4,5], it can substitute 6.83 million tons of coal power and reduce CO_2 by 9.14×10^6 tons, SO_2 by 1.06×10^5 tons, NO_X by 9.26×10^4 tons, and ash emitted into the atmosphere by 1.82×10^5 tons. Furthermore, it would create 68,300 jobs in Hubei Province.

5. Conclusions

Whether an SPP can obtain a sufficient, stable supply of raw straw depends on the reasonableness of its geospatial location. Therefore, the normal operation of SPPs is decisively affected by the reasonableness of their locations specified in SPP planning. To address the limitations of the existing research on SPPSS, the present study proposes a spatially explicit optimal decision-making model for SPPSS using GIS spatial analysis methods, with an AIS optimization algorithm as the framework. Compared to the existing models, improvements in the following areas are made when establishing a decision-making model for SPPSS: (1) Straw yields are estimated using agricultural land quality evaluation data and GIS spatial analysis methods, thereby increasing the accuracy of estimating the spatial distribution and straw yield. (2) GIS techniques are employed to improve the AIS in such areas as antibody encoding, mutation, and affinity evaluation. The exceptional optimization ability of the improved AIS helps improve the reasonableness of the SPPSS optimization scheme.

To evaluate the effectiveness of the proposed model, the SPP development planning of Hubei Province is selected as the application setting of the proposed model, and SPPSS optimization for Hubei Province is investigated through experimentation based on the collected data. The experimental results demonstrate that Hubei Province can produce 34.89 million tons of agricultural straw each year, of which 17.45 million tons can be used for electricity generation. Based on the results concerning the average straw-SPP transport distance, R_{SC}, the amount of available straw, and economic revenue, the optimization schemes generated by the proposed model are feasible. To ensure that the straw-based electricity generation industry in Hubei Province is profitable as a whole, N in the entire province should not exceed 50 when there is an electricity price subsidy policy in place and 45 when there is no electricity price subsidy policy. By comprehensively considering each uncertainty involved in the operation of SPPs, it is recommended that approximately 40 SPPs should be planned and constructed in Hubei Province to ensure maximum economic revenue. Our results are expected to provide an important decision-making basis for SPP development planning in Hubei Province. The model designed in the present study can also provide solutions for the optimal decision-making problem involved in SPPSS in other regions.

The main limitation of this study is that the capital costs were not incorporated in our model. Therefore, using dynamic capital cost analysis methods to support capital costs analysis will be one of the most immediate improvements. In addition, an improved straw collection model is essential to accurately simulate the reality straw acquisition in future studies.

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