Ecological Informatics 78 (2023) 102316

Contents lists available at ScienceDirect

Ecological Informatics

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

A new decision-making method for the renewal of agricultural irrigation wells: A case study of Songzhuang town, Tongzhou District, Beijing

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ARTICLE INFO

Keywords:
Agricultural pumping wells
Farmland irrigation
Refined management
Decision model
Space configuration
Regional agriculture

ABSTRACT

Pumping wells (PWs) lie at the core of agricultural irrigation infrastructure, and their spatial configuration is of great significance for the scientific management of regional agriculture and rational use of water resources. To solve the problems of unreasonable and unscientific spatial allocation of regional agricultural irrigation PWs, this paper proposes a new strategy for updating agricultural irrigation PWs based on a spatial decision model, using Songzhuang Town, Tongzhou District, Beijing as a case study. The model utilizes constraints based on local factors such as actual land use, and proposes a novel feasible solution strategy that combines random local search and abrupt jumps to increase the probability that feasible solutions will be found, addressing the performance issues of simulated annealing algorithms, influence of initial values, and parameter sensitivity. Finally, we used the proposed method to perform updated decision analysis on the spatial configuration of PWs in the study area. The results showed that most of the crops in the study area lack irrigation, and the currently available PWs cannot meet the needs for irrigation. The new PWs added based on this decision method can be more evenly distributed within the predefined optimization unit. The proposed number of PWs to be added is 166, the density of PWs is 0.04/ha, and the crop area covered by the PWs is 3350.43 ha. In contrast to the previous PW layout, the optimized PW configuration can meet the irrigation needs of residents, indicating that the new method proposed in this paper has good potential for extension and application.

1. Introduction

Food security is a critical issue that demands increasing attention in the present times (Pickson et al., 2023; Skaf et al., 2020). It is projected that the global population will reach 9.7 billion by 2050, necessitating a 60% increase in food production (De Wrachien et al., 2021; Droppers et al., 2022). Currently, approximately 40% of agricultural production worldwide has access to irrigation, accounting for approximately 20% of the total cultivated area. By contrast, rainfed agriculture accounts for 80% of the cultivated area, but contributes only 60% of the total food production (Darzi-Naftchali et al., 2020). Moreover, arable land for crop cultivation is limited, and future expansion of the cultivated area faces constraints (Bwambale et al., 2022). Under such circumstances, the growth potential for food production in already irrigated regions is modest. Conversely, dryland areas with water scarcity hold significant potential for boosting food production. Therefore, addressing the imbalance between water resources and food production, particularly through precise irrigation practices in dryland regions, has emerged as a crucial means of augmenting food production and ensuring food security. This has profound implications for the advancement of intelligent agriculture and precision farming techniques.

China's vast territory and diverse climate result in an uneven distribution of surface water resources, making groundwater a crucial source of water supply in many regions. In China, groundwater is extensively used for agricultural irrigation, residential water supply, and industrial purposes. In the agricultural sector, groundwater plays a vital role in China's food production. As one of the world's largest agricultural countries, a significant portion of China's farmland in the northern regions relies on groundwater for irrigation (McDermid et al., 2023). Groundwater helps compensate for the inadequacy of surface water

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https://doi.org/10.1016/j.ecoinf.2023.102316
Received 7 January 2023; Received in revised form 8 September 2023; Accepted 10 September 2023
Available online 27 September 2023
1574-9541/

resources to ensure the growth of crops and high agricultural yields (Y. Li et al., 2022; Zhang et al., 2022). However, excessive extraction of groundwater can lead to declining groundwater levels and depletion of groundwater resources, posing challenges to the sustainable development of agriculture (Awais et al., 2020; Mpakairi et al., 2022; Priyan, 2021; Trivedi et al., 2023). To more effectively manage groundwater resources, China has implemented various measures, including the establishment of groundwater management systems, strengthened monitoring and regulation, as well as the promotion of water-saving irrigation techniques and sustainable utilization of water resources. To efficiently utilize irrigation wells, it is necessary not only to restrict water extraction areas but also to enforce strict approval management. Well construction is an effective approach for expanding the irrigated area to address the mismatch between water and soil resources in arid regions. However, in practical construction, there is a lack of layout planning and insufficient consideration of the suitability of existing and new wells, resulting in either excessively high or low well densities (Liu and Wang, 2012; Yang et al., 2008). Given these circumstances, it is imperative to focus on and improve the layout of agricultural irrigation wells to ensure their rational distribution and efficient utilization of groundwater, further promoting sustainable agricultural production.

Agricultural PWs are fixed in space and have a spatial correlation among them. Spatial sampling theory models the layout of spatially correlated objects by essentially using intelligent algorithms (IA) to extract a subset from a limited set of sample points and optimize them according to set criteria (Jiang et al., 2009). With the development of geographic spatial sampling theory and "3S" technology (RS, GIS and GNSS), PWs can be considered as fixed points, and the PW layout optimization problem can be transformed into a layout optimization criterion with constraints that need to be satisfied from certain points.

China is characterized by spatial and temporal differences in water resources among different regions, especially in the northern regions, where a combination of PWs and canal irrigation systems is present. A significant part of agricultural research in China and other countries is focused on PW layout methods. The early methods of PW layout mainly focused on how to determine the spacing and number of PWs in an area based on hydrogeological conditions and the current status of groundwater utilization through PW tests and other means, combined with the traditional experience of PW layout (Li et al., 2007). With the continuous improvement of PW construction in irrigated areas, studies on PW layout methods mainly tended to analyze and optimize the number and layout of PWs in irrigated areas by adopting deterministic algorithms from a global perspective, such as constructing a multi-stage optimization model to minimize PW operation costs (Wang, 1998). These methods aim to establish a linear programming model with the objective of minimizing groundwater drop depth (Zhang et al., 2002), using groundwater extraction and a linear programming model with groundwater extraction as the objective function, with the groundwater level as the constraint (Zhou et al., 2007). However, because the first two methods are too empirical in their consideration of PW layout and too rigorous in their deterministic algorithms, they were gradually replaced by IAs due to recent scientific and technological developments.

IAs are generally based on stochastic search strategies, using objective functions and constraints that are generally not bound to a fixed form. Currently, IAs are widely used in agricultural fields such as agrometeorology (Shiri et al., 2014), crop yield prediction (Ali et al., 2018), crop pest and disease monitoring (Yang et al., 2021), field weed identification (Xu et al., 2018), etc. In addition, IAs can be used to optimize agricultural irrigation systems. Among IAs, the simulated annealing algorithm (SAA) is distinguished by asymptotic convergence and has been theoretically proven to be a global optimization algorithm that converges to the global optimal solution with high probability. Moreover, its efficiency and effectiveness have been demonstrated in many problems, such as finding the optimal route (Oudani, 2021; Zhai and Feng, 2022), finding the optimal location (Yu et al., 2021), determining model parameter weights (Davari et al., 2021), and determining the optimal layout (Huang et al., 2020). However, the SAA is prone to specific problems when dealing with the layout of regional irrigation PWs. Firstly, the initial value has a large impact on the results of local perturbations when the number of iterations is small, resulting in the tendency to enter a dead loop when the local perturbations cannot satisfy the conditions, as well as a slow cooling rate at the later stage. Based on this, we propose a backward simulated annealing algorithm (BSAA), which can effectively utilize constraints as well as combine local search steps with temperature, random local search capability and abrupt jump capability to ensure that feasible solutions are always found. Thus, the improved algorithm can be used for updating the optimized layout of agricultural irrigation PWs.

Given the prevailing circumstances in the realm of climate change and the advent of smart agriculture, the scarcity of water resources and the heavy reliance on surface irrigation pose significant challenges in arid regions. In response, this study proposes a decision strategy for the updating of agricultural irrigation PWs by providing a rational layout. In contrast to the traditional approach, our method can solve the multi-objective problem and reflect the actual local agricultural irrigation situation. The main innovations of this study include: 1) A new method for planning and managing the spatial layout of agricultural irrigation wells. 2) The quantitative evaluation and spatial update decision analysis of regional irrigation wells are realized. 3) The global optimal solution for the spatial pattern of irrigation wells was found to constitute a well spacing of no less than 332 m. 4) The method has good potential for application and promotion in regional agricultural water management. Our research findings provide strong support for achieving precision management, improving smart irrigation systems, and increasing farm productivity.

2. Materials and methods

2.1. Study area

This study was carried out in Songzhuang town in the north of Tongzhou district, Beijing, China (Fig. 1), at a longitude of 116°35′23"- 116°46′53 "E and latitude of 39°54′05"- 40°01′50 "N. The town is spread over an area of 115.2km^2, with 47 administrative villages. The terrain of the study area is flat, with a continental monsoon climate. The average annual temperature is 12.5–13.7 °C, the average temperature in July is 25–26 °C, and the average temperature in January is $-4 \sim -5$ °C. The average annual precipitation is 626 mm, and is characterized by seasonal as well as annual variation, with an uneven distribution of precipitation during the year. The area receives more than 80% of the annual precipitation from June to August, while only 2% of total precipitation occurs during winter (December to February).

There were 46 PWs in our study area, one of which was not intact. As shown in Appendix a, the agricultural PWs were distributed in clusters and roughly divided into two major blocks. After several years of operation, the agricultural PWs encountered problems such as sand infiltration, deformation of pipes, and low water output. According to the survey, the number of damaged PWs was 4, 10 PWs were abandoned, and 13 PWs were renewed according to the corresponding conditions in the vicinity of the original PW location (Appendix b).

2.2. Data sources

The new agricultural irrigation PW update decision method proposed in this study is an optimal decision scheme for agricultural irrigation PWs that was established through the integrated analysis of multiple source data sets. The data used in this paper is mainly derived from the following sources:

(1) Acquisition of field PW information. In January 2019, the spatial distribution, current use status (intact, damaged, or abandoned), and other attributes (PW depth, static and dynamic water level,

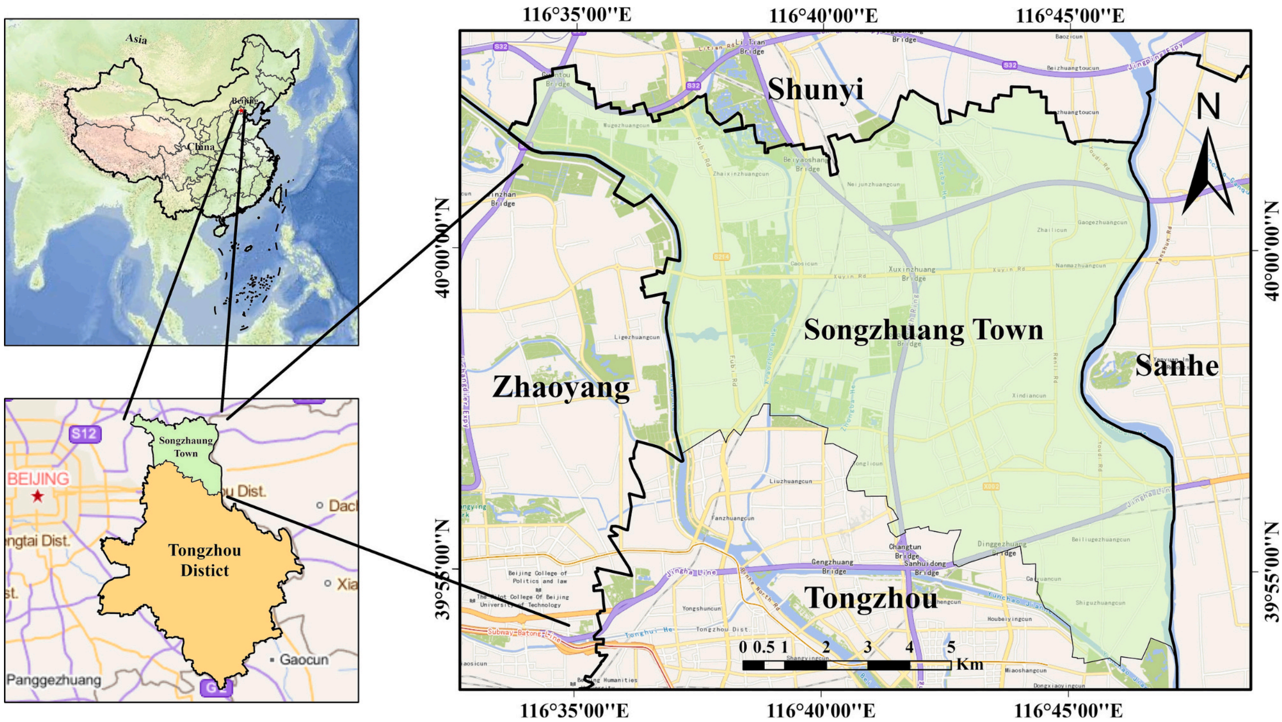

Fig. 1. Study area.

water output, types of current and planned planting, planned irrigation methods, the extent of PW irrigation, damage, whether to renew, location of renewed PWs, reasons for PW renewal, whether there is a PW house, description of the PW house, damage to PW house). The field collection photos of the study area are shown in Fig. 2.

(2) Based on local meteorological data (July 2019–July 2021) downloaded from China Meteorological Network and Beijing Municipal Water Bureau: precipitation, number of days of rainfall, depth of groundwater level (http://www.cma.gov.cn/, http://swj.beijing.gov.cn/).

(3) Land use data for 2020 based on Esri 2020 Land Cover Downloader, downloaded at 10 m resolution, which was obtained by (Karra et al., 2021) using ESA Sentinel-2 imagery for deep learning (https://www.arcgis.com/home/item.htmlid=d3da5dd386d140cf93fc9ecbf8da5e31).

(4) National urban road dataset for 2020 based on Gaode Map download.

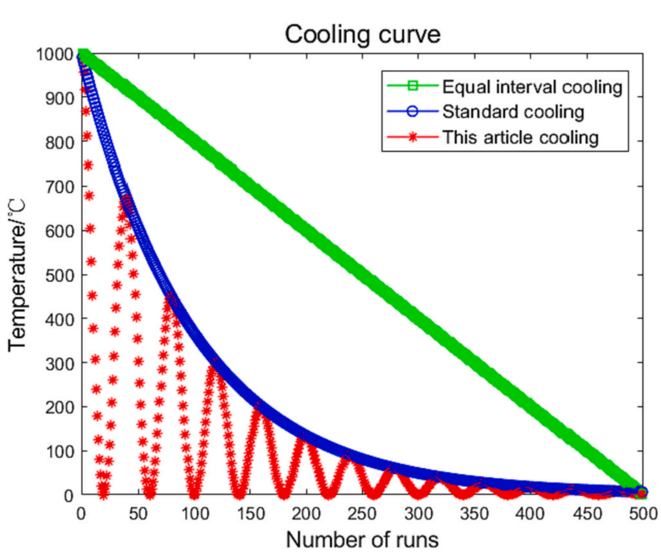

Fig. 2. Comparison diagram of temperature attenuation coefficients.

To obtain accurate point coordinates of the PWs, the relevant data such as the location of the PWs were matched with the corresponding meteorological data to realize data pre-processing and prepare for later data analysis.

For various data, the projection coordinates were transformed into CGCS 2000 3° GK Zone 39, and the geographic coordinates were transformed into GCS China Geodetic Coordinate System 2000.

2.3. Basic database construction

The decision framework structure relies on the underlying database, and the decision analysis based on it is meaningless if the underlying data is incomplete or inaccurate. In this study, we used actual PW research data and ESA Sentinel-2 satellite images for deep learning as the basis. Accordingly, the research data includes the location of the PWs, PW depth, dynamic and static water levels, water output, and irrigation range. The optimization units were divided based on road traffic data, crop area size, and meteorological data, to reasonably analyze and determine the location of new PWs.

2.4. Spatial decision model

Temperature is one of the key parameters of the algorithm used in this study, mainly including the initial temperature setting, temperature drop strategy and stopping temperature. The cooling function is used to control the temperature drop. The temperature reflects the searchability of the algorithm, so that the algorithm performs a wide-area search when the temperature is high, and a local area search when the temperature is low. A faster temperature drop will cause the algorithm to move directly from a wide-area search to a local area search, which will make it impossible to verify the solution for the current state and thus find the globally optimal solution. When the temperature drops too slowly, the algorithm's local search capability is weak and many feasible solutions will be missed. To address the problem of local search radius, we propose a backward simulated annealing algorithm (BSAA) that improves the cooling function of the SA algorithm. The BSAA is able to combine local search steps with temperature, stochastic local search capability and sudden jump-hop capability to improve the ability to search for feasible solutions and ensure that feasible solutions are always found. In addition, equal-interval cooling and standard cooling were used as two common temperature cooling methods.

$$T = T_0 - \Delta T \tag{1}$$

where T is the current temperature in the current cycle, T_0 is the initially set temperature, ΔT is the temperature drop in each cycle.

$$T = a \times T_0 \tag{2}$$

where T is the current temperature in the current cycle, a is the temperature attenuation coefficient, a is the temperature decay coefficient, and the size of a determines the rate of temperature drop. T_0 is the initial set temperature.

The algorithm used in this study sets the temperature decay coefficient as dynamic to speed up the late temperature drop, and the improved cooling function allows the algorithm to jump out of a local optimal solution to accelerate convergence. The cooling function used in this study is:

$$\mathrm{T1} = a \times T_0 \tag{3}$$

$$\mathrm{T} = T1 \times \left(1 + sin\left((L+10)^{*}pi/20\right)\right) \tag{4}$$

where $T1$ is the current temperature in the current cycle, a is the temperature attenuation coefficient, and T_0 is the initial set temperature.

where T is the corrected temperature in the current cycle, $T1$ is the current temperature in the current cycle, and L is the number of iterations.

The initial conditions for the three cooling functions tested in this study are shown in Table 1, and the temperature decay curves are shown in Fig. 2. Equal-interval cooling can be performed at a uniform rate, and the step length of its search for feasible solutions decreases uniformly with the temperature, so that the local perturbation ability is weak. Standard cooling still cannot reach the low-temperature state in several iterations, and the number of iterations required to reach the low-temperature state is too high. In this study, the cooling curve undergoes a tempering and warming process during the entire annealing period, and its algorithm can jump out of the local optimum when perturbed so that it has a better chance to find the globally optimal solution.

The objective function used in this study was the distance from any new PWs in the study area to the new PWs closest to it or the currently available PWs (see formula 5). For the PW layout optimization problem, the feasible solution is not always found when the current solution is locally perturbed due to constraints such as optimization unit and PW spacing. Accordingly, the search step becomes small when the temperature is low. Therefore, when no feasible solution is found after a certain number of iterations, the algorithm randomly generates an initial solution, performs a reassignment, and restarts the search for a feasible solution.

$$minF(L) = \sum_{i=1}^{n} \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} \Big/ n \tag{5}$$

where (x_i, y_i) are the coordinates of the new PWs in the optimization unit, (x_0, y_0) are the coordinates of the PWs in the study area, N is the number of PWs in the current area (including the new PWs), F (L) is the distance between the current PW point and its nearest new PW point or the currently available PWs.

The main steps of this algorithm are as follows:

1) Setting the initial temperature T, whose value is 1000; the cooling coefficient a, whose value is 0.99; the number of iterations L.
2) Randomly selecting a sample S_0 that satisfies the conditions and calculating the objective function $\varphi(S_0)$. After a certain local random perturbation, a new sample S_1 satisfying the conditions is generated and if the points in the current region still do not satisfy the conditions, when the number of iterations L reaches 5000, alternative points satisfying the current conditions are found again in the whole optimization region, the objective function $\varphi(S_1)$ is calculated, and the new sample is accepted or rejected according to the Metropolis criterion.:

$$P_c(S_0 - S_1) = \begin{cases} 1, & \varphi(S_0) \geq \varphi(S_1) \\ e^{\frac{\varphi(S_0)-\varphi(S_1)}{t}}, & \varphi(S_0)\langle\varphi(S_1) \end{cases} \tag{6}$$

where $P_c(S_0 - S_1)$ is the probability of replacing S_1 to S_0, generating a random number Rand between 0– 1, if $P_c(S_0 - S_1)\rangle Rand$, S_0 is replaced with S_1, otherwise S_0 is discarded.

3) Performing the cooling process: $T1 = a \times T_0$, $T = T1 \times \left(1 + sin\left((L+10)^{*}pi/20.\right)\right)$
4) Repeating the first 3 steps and the algorithm terminates when $T1 > T_{min}$, where the value of T_{min} is 1. Then, the final sample S_0 is generated as the output.

3. Results

3.1. Evaluation of the current situation of agricultural irrigation PWs

This study quantitatively evaluated the environment of agricultural irrigation PWs in the study area based on actual research data on PWs and land cover data from ESA Sentinel-2 satellite images for deep learning. There were 47 administrative villages in the study area, and PWs were available in 12. The crop area of the administrative villages with PWs ranged from 14.59 to 345.97 ha, with a total of 989.96 ha (Table 2). A total of 46 PWs were available in the district, and the average density of PWs was 0.05 ha^{-1}, with 8 administrative villages having an above-average density of PWs. The density of PWs in the administrative villages ranged from 0.02 to 0.09, with the highest value recorded in Zhaili village and the lowest value in Fuhao village. The irrigation range of PWs in the study area was between 2.67 and 56.00 ha, with a total of 275.07 ha. The average irrigation rate of PWs in the study area was 27.79%, and was higher than average in six administrative villages. The irrigation rate of PWs in the study area ranged from 11.81 to 85.50%, with the highest value in Yingezhuang village and the lowest value in Gangzi village.

The study area covered a total of 115.2 km^2, among which 45.06 km^2 was the main agricultural area. There were 46 PWs as of 2019. The

Table 1
Initialization parameters of the temperature decay function.

Cooling method	Cooling function	Initialization parameters
Equal interval cooling	$T = T_0 - \Delta T$	T_0=1000 ; ΔT=20
Standard cooling	$T = a \times T_0$	T_0=1000 ; a=0.99
This study	$T1 = a \times T_0$ $\mathrm{T}=T1 \times \left(1 + sin\left((L+10)^{*}pi/20\right)\right)$	T_0=500 ; a=0.99

Table 2
PW density and PW irrigation rate of available PWs in the study area.

Administrative village	Crop Area (ha)	Number of PWs	PW Density (ha $^{-1}$)	Scope of PW Irrigation (ha)	Irrigation Ratio (%)
Dinggezhuang	14.59	1	0.07	2.67	18.28%
Renzhuang	19.67	1	0.05	3.33	16.95%
Caiyuan	32	3	0.09	6.00	18.75%
Gangzi	52.49	2	0.04	6.20	11.81%
Gaoxinzhuang	34.2	2	0.06	13.33	38.99%
Guanxinzhuang	42.55	4	0.09	17.33	40.74%
Xiaodenggezhuang	28.87	2	0.07	18.00	62.35%
Dadengezhuang	35.67	4	0.11	21.33	59.81%
Fuhao	236.04	4	0.02	29.53	12.51%
Zhaili	345.97	12	0.03	48.00	13.87%
Xinggezhuang	62.38	4	0.06	53.33	85.50%
Baimiao	85.53	7	0.08	56.00	65.47%
Total	989.96	46	0.05	275.07	27.79%

estimated density of PWs in the study area in 2019 was approximately 0.01 ha $^{-1}$, and the average density of PWs in administrative villages with PW distribution was 0.05 ha $^{-1}$. The PW density calculated in this study is based on the crop area only, rather than the whole area. This value is larger than what would be calculated using traditional methods, but it is also more accurate. After comparing the PW density of the study area with the average PW density of the whole country or the five provinces of the North China Plain, it is easy to conclude that the PW density of the study area is the lowest.

3.2. *Coverage of agricultural irrigation PWs for different land use types*

Karra and Kontgis used ESA sentinel-2 images to divide the land type coverage data obtained by in-depth learning into 10 categories, including water, trees, grass, flooded vegetation, crops, scrub, built area, bare ground, snow, and clouds. There were eight land use types in the study area, including water, trees, grass, flowing vegetation, crops, scrub, built area, and bare ground, respectively accounting for 489.84 ha, 226.47 ha, 77.23 ha, 1.72 ha, 4506.02 ha, 607.38 ha, 5523.46 ha, and 0.62 ha. The study area is mainly dominated by 10,029.48 ha of crops and buildings, accounting for 87.73% of the total.

In general, when the density of PWs in an area is high, there is a greater incentive for farmers to compete with each other for water when using groundwater for irrigation (Gong et al., 2019). Therefore, choosing the right PW density is an essential part of PW layout optimization for the sustainability of groundwater-based irrigation. The main consideration in selecting different radii is the possible radius of the impact of the PWs. For this purpose, we set the radius of the PW buffer zone to 50 m, 100 m, 150 m, 200 m, 250 m, and 300 m, thus comparing the area of land use types within the buffer zone per 50 m unit and calculating the actual PW irrigation range, as shown in Table 3.

As can be seen in Table 3, the crop area increases and then decreases between 1 and 300 m within the PW buffer zone. To maximize the crop area covered by the PW distribution, the concept of marginal effect was introduced in a recent study (Cao et al., 2021). In the study area, for every 1 m increase in the radius of the PW buffer zone, the crop area that can be covered within this 1 m range was calculated, so that the relative efficiency of PW utilization can be maximized when the crop area per unit margin is maximized.

The multi-loop buffer analysis tool in ArcGIS was used to calculate the crop area within the PW buffer in 1 m units. It was found that the crop area per unit covered by the buffer zone reached the maximum when the radius of the PW buffer was 166 m, and its value was approximately 1.66 ha (Fig. 3). Therefore, the crop area per unit covered by the PWs reached the maximum when the PW spacing was 332 m. Using this configuration, the PW efficiency was relatively high and the PW density was appropriate.

3.3. *Decision analysis for the renewal of agricultural irrigation PWs*

To better meet the irrigation needs of local farmers that rely on regional agricultural PWs and maintain the sustainable use of groundwater resources, an effective decision analysis of the future spatial distribution of agricultural irrigation PWs was conducted based on the decision model developed in this study, after which a targeted and feasible renewal plan was developed.

The crop area of the administrative villages with PWs in the study area was 989.96 ha, and there were 46 PWs with an average irrigated area of 21.52 ha per unit. Using this irrigation range as the standard, we calculated the need for 120 new PWs in the future. According to Fig. 4, when the buffer radius of the PWs is 166 m, the crop area per unit covered by the buffer zone reaches the maximum, so the optimal spacing between PWs is 332 m. According to ArcGIS, the crop area in the study area was calculated to be 4092.40 ha after subtracting the crop area covered by the PWs with a radius of 332 m. This was done to better meet the local irrigation level based on the current situation. The optimized area was 2579.41 ha, and was divided into blocks based on administrative boundaries, road traffic, and other data. The blocks were numbered from top to bottom and left to right, finally forming 51 optimization units.

The original PW data were exported to text coordinate form in ArcGIS, and the PW optimization units were exported in .SHP format. In MATLAB, the PW optimization unit, the number of new PWs, and the spacing between PWs were set as constraints, and the different stages of PW layout optimization were obtained using the proposed algorithm (Fig. 4).

The optimized distance of the initial layout in Fig. 5 was 337.09 m. As the number of iterations of the proposed algorithm increased, the optimization degree also increased and the target optimization distance decreased. After several rounds of optimization, the optimized distance of the intermediate layout was 322.39 m. When the final convergence state was reached, the optimized distance was 294.17 m.

The data of the final layout points of the PWs generated by the algorithm developed in this study were imported into ArcGIS (Fig. 5), and the PWs were more evenly distributed within the optimization unit we set. The number of new PWs in the study area was 166, and the density of PWs was 0.04/ha. The crop area covered by this range was 3350.43 ha, accounting for 74% of the crop area in the whole study area. Crucially, the optimization results met the irrigation demand of local

Table 3
Land use types in different buffer zones of available PWs in the study area.

Land use type	0–50 m	50 m ~ 100 m	100 m ~ 150 m	150 m ~ 200 m	200 m ~ 250 m	250 m ~ 300 m
Water	0	0.16	0.98	1.55	2.84	3.24
Trees	0	0.21	0.02	0.17	1.6	2.18
Grass	0.28	0.66	0.4	0.46	0.44	0.18
Crops	18.32	53.03	73.27	79.46	71.63	71.16
Scrub	2.66	4.78	4.92	7.58	7.41	8.85
Built Area	12.96	34.07	51.74	66.19	84.98	97.27
Bare ground	34.22	92.91	131.32	155.41	168.89	182.89
Total	0	0.16	0.98	1.55	2.84	3.24

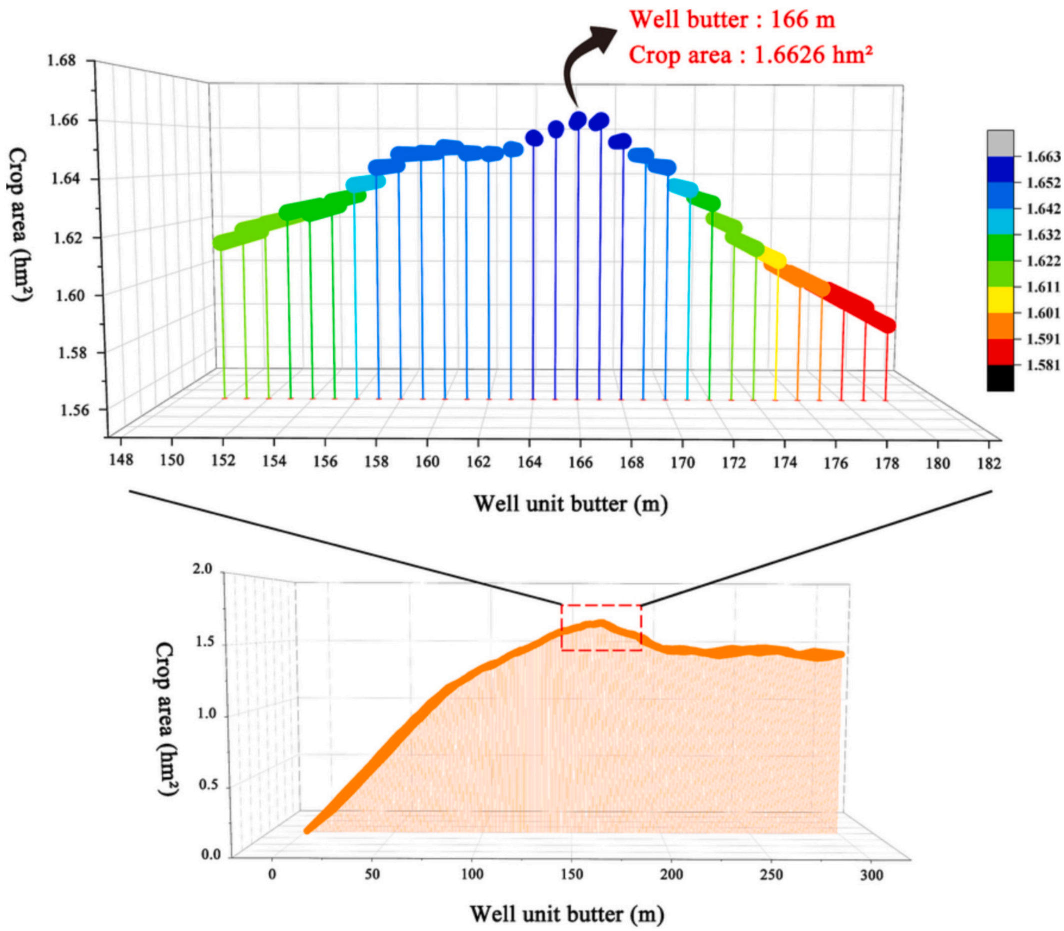

Fig. 3. Area of crops in different buffer zones of available PWs in the study area.

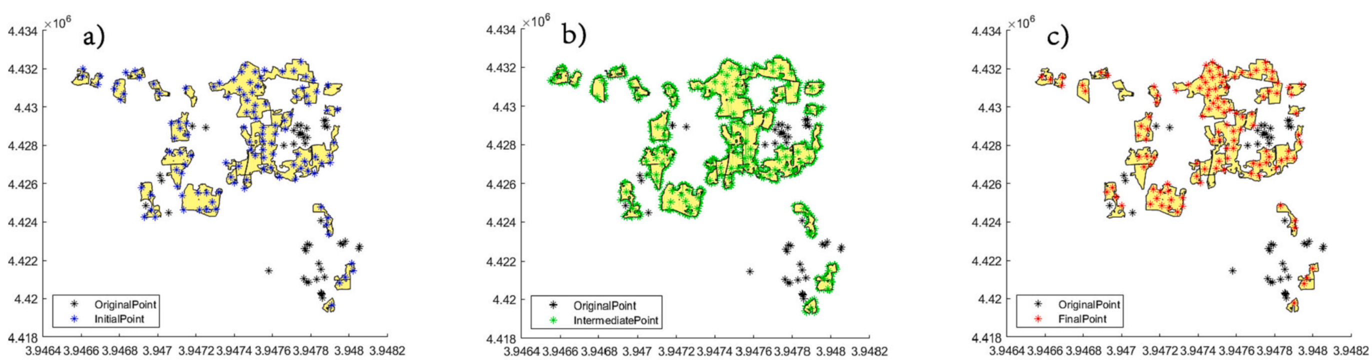

Fig. 4. Distribution of the initial layout (a), intermediate layout (b), and final layout (c) of new PWs in the study area. OriginalPoint is the original point of the PWs, InitalPoint is the initial layout point of the PWs, IntermediatePoint is the intermediate layout formed after a certain degree of optimization, and FinalPoint is the final layout formed after the PWs were optimized.

residents, which indicates that the layout optimization method used in this study is practical.

4. Discussion

Agricultural irrigation wells are common facilities in the farming regions of northern China, particularly in high-standard farmland construction. Well irrigation is the most stable irrigation method, capable of maintaining stable and increased crop yields even under water scarcity conditions (Cai and Zeng, 2019; Zhuo, 2021), and as such holds significant importance for the overall agricultural development of the region. There were 46 existing agricultural irrigation wells within the study area, but most of them were farmer-built and lacked unified planning, resulting in limited well numbers with an uneven distribution. Consequently, the existing irrigation wells were unable to meet the local agricultural irrigation needs. In light of this, we conducted preliminary survey work and proposed a novel decision approach based on a spatial decision model for updating agricultural irrigation wells. Our research findings indicated that the well density in the study area was low compared to the five provinces in the North China Plain. Setting the unit buffer radius for agricultural irrigation wells at 166 m maximizes the coverage of agricultural land. After optimizing the well layout using the

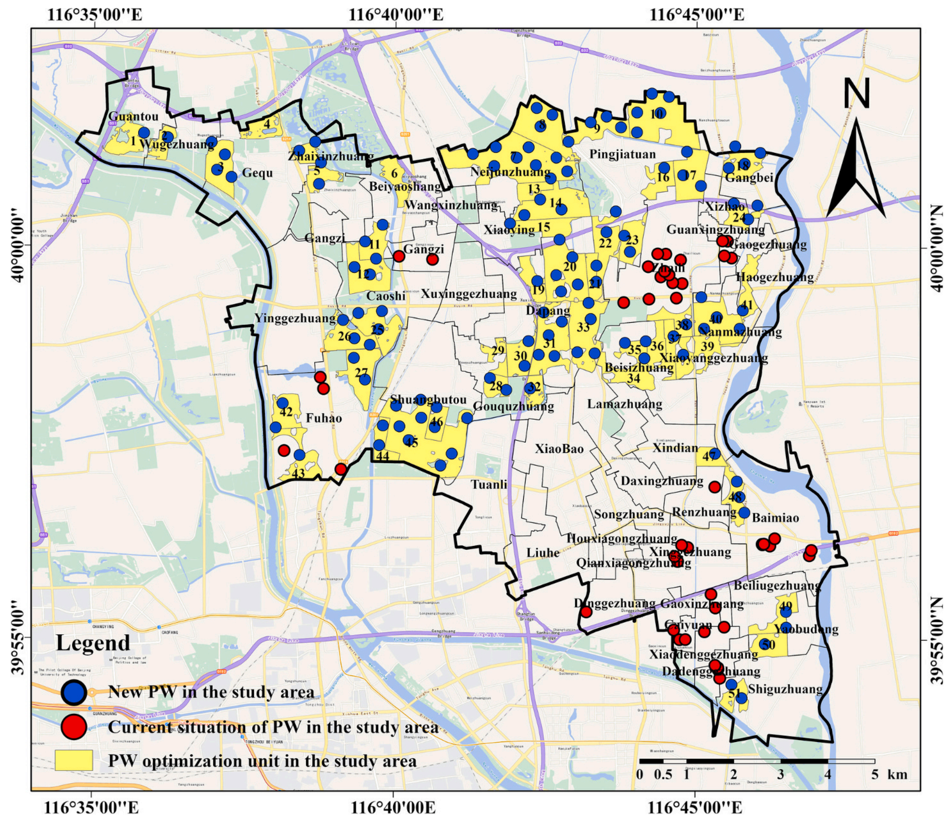

Fig. 5. Decision analysis of PW renewal in the study area.

proposed method, new wells were distributed more evenly within our designated optimization units. Specifically, the addition of 166 new wells within the study area was predicted to result in a density of 0.04 wells/ha, covering an area of 3350.43 ha. Compared to the previous scenario, there is an increase of 120 wells, leading to an expanded irrigation coverage of 3075.36 ha.

Groundwater irrigation is a complex process that requires the comprehensive consideration of multiple factors. Firstly, the sustainability of water resources is of paramount importance. As groundwater is a finite resource, water resource assessment and monitoring are necessary to ensure its sustainable utilization (Kumar et al., 2023; Pham et al., 2021). Secondly, groundwater levels and recharge conditions are crucial for the design and operation of irrigation systems. Monitoring groundwater levels (Mirzavand and Ghazavi, 2015; Zhang et al., 2015) and understanding the sources of groundwater recharge (Khan et al., 2020) help determine appropriate irrigation quantities and frequencies. Additionally, soil characteristics and crop water requirements should also be considered. Different soil types exhibit varying water-holding capacities and permeabilities, while crop water demands vary depending on crop types, growth stages, and climatic conditions. Finally, environmental impacts and water quality protection must be taken into account. Groundwater irrigation can potentially impact the surrounding environment and water quality (Gurbuz, 2019; Sutradhar and Mondal, 2021), necessitating measures to reduce pesticide and fertilizer use, prevent soil erosion, and minimize pollution by agricultural runoff. In this study, we prioritized the effective range of well irrigation and did not extensively consider groundwater factors. This choice is based on two factors. Firstly, our study area is relatively small and located in a plain with relatively stable and consistent hydrogeological conditions. Within the study area, the average groundwater depth is 8.06 m, and over the past two years, the groundwater level has remained relatively stable with a slight upward trend. Therefore, we consider the influence of groundwater factors on well irrigation to be minimal under these circumstances. Secondly, China's current agricultural production is still characterized by small-scale farming, with relatively dispersed production factors (Chen et al., 2021). This means that land cannot be consolidated for large-scale operations but exists in small scattered plots. The characteristics of this land use type have an impact on agricultural production in China. Hence, we focused on the effective range of well irrigation to meet the practical needs of agricultural production.

The method proposed in this study employs the distance from any newly added irrigation well in the study area to the nearest newly constructed well or an available existing well as the objective function. It is based on the criterion of minimizing the average minimum spatial distance (Dong, 2018; Jiang et al., 2009; Wu et al., 2015; Zhang et al., 2012), which aims to achieve the most uniform feasible distribution of sampling points throughout the sampling area. Therefore, the setting of the objective function is reasonable. There are multiple ways to set the objective function. The method proposed in this study utilizes the constraints of the spacing between newly added irrigation wells, the number of new wells, and the optimization unit for new wells. The parameter for the spacing between new wells is derived from the concept of marginal land use efficiency. When the spacing between new wells reaches a certain threshold, further increasing the well spacing would result in a decrease of the irrigated area per well, leading to resource waste. In our research, we found that the spacing between new wells should not be less than 332 m. Existing methods for determining well spacing mainly include empirical methods, pumping test methods, single-well irrigation area methods, and allowable exploitation modulus methods (Liu and Wang, 2012; Zhang et al., 2016). Among them, the calculation of well spacing based on the single-well control irrigation area method and the allowable exploitation modulus method are two commonly used approaches. Both methods consider the water resource carrying capacity and are relatively simple to calculate. However, they require data on local irrigation systems and relevant hydrogeological parameters, and do not take into account the socioeconomic benefits. For example, Wu et al., 2015) determined a minimum well spacing of 275.02 m using the single-well control irrigation area method. Zhao (2022) recently used this method to calculate well spacing based on different layout configurations, resulting in a spacing of 188 m for grid-shaped well configurations and 202 m for clover-shaped well configurations. These variations in well spacing were attributed to differences in water resources between the two regions. However, our primary consideration is the fragmented nature of agricultural land. Therefore, the well spacing method proposed in this study is more in line with the actual situation of small-scale farming in China. Additionally, this spacing parameter is consistent with the findings of Yang et al. as well as Zhao et al., who observed that the typical well spacing is approximately 300 m (Yang et al., 2008; Zhao, 2022). Thus, this parameter is reasonable. Furthermore, the parameter for the irrigation range of a single well was calculated based on the actual local land use conditions and amounted to 21.52 ha. With the addition of 120 new wells, this parameter is also deemed reasonable.

The accuracy of the algorithm largely depends on the rationality of parameter values (Dymond et al., 2011; Strąk et al., 2019). In this paper, the algorithm sets the temperature decay coefficient dynamically and associates the search step size with the temperature. Compared to traditional simulated annealing algorithms, the improved cooling function developed in this study enables the algorithm to effectively escape from local optima, which enhances its ability to locally search for feasible solutions. The algorithm introduced in this paper incorporates optimization units as constraint conditions. In contrast to traditional simulated annealing algorithms, if the relevant conditions cannot be satisfied during the local perturbation process, the algorithm will enter into a deadlock. To address this, our algorithm generates a random initial solution, performs a reassignment, and restarts the search for feasible solutions. In this study, the values of the algorithm-specific parameters such as initial temperature, termination temperature, and number of iterations were strictly determined based on general convergence conditions. Accordingly, the initial temperature was set sufficiently high, the thermal equilibrium time was sufficiently long, the termination temperature was sufficiently low, and the cooling process was adequately slow, which was in agreement with the literature (Amine, 2019; Wu et al., 2015). Therefore, the parameters used in our algorithm are reasonable, resulting in good convergence and practical optimization results for well layout. The setting of algorithm-specific parameters requires a specific analysis based on the problem at hand. In this study, the determination of parameters is based on empirical methods. However, there are various other methods for parameter selection. For example, researchers can experiment with different parameter combinations to determine the optimal set (Kucukkoc et al., 2013; Myers and Hancock, 2001), employ orthogonal experimental design to identify the best algorithmic parameters (Jiao et al., 2020; Xu et al., 2022), or utilize multiple algorithms and integration strategies to determine the best parameters (Li et al., 2022).

Finally, there are also some limitations of this study that need to be addressed. Firstly, the proposed method has only been validated on a small scale, and further verification at a larger scale is necessary to meet the requirements of smart agricultural development. Secondly, the complexity of the groundwater system was not fully considered in the proposed method. To ensure the scientific and rational application of this method, future research should comprehensively consider the various factors that influence groundwater irrigation. Thirdly, the impact of damaged wells on irrigation has not been taken into account in this study. To address this, IoT sensor technology will be incorporated to integrate information on damaged wells into the smart irrigation system, enabling timely repairs.

5. Conclusions

In the context of climate change and smart agriculture, our objective was to develop an intelligent and precise system for accurate irrigation, particularly in the arid and semi-arid regions of northern China. However, due to water scarcity and heavy reliance on surface irrigation, efficient utilization becomes challenging, hampering the maximization of agricultural production. To address this issue, we have conducted a preliminary survey and proposed a novel decision approach for updating agricultural irrigation well systems based on spatial decision models. This method is based on spatial sampling theory, where the minimum distance from any newly added well to the nearest newly constructed or available existing well within the study area serves as the decision variable. It incorporates constraints such as the optimization unit for new well additions, well spacing, and the number of new wells. By leveraging GIS and MATLAB platforms, we employed geospatial analysis techniques and spatial optimization methods to achieve an optimal well layout. Our research findings reveal the following: 1) The well density in the study area was relatively low compared to the average of the five provinces in the North China Plain; 2) The spacing of agricultural irrigation wells should not be less than 332 m; 3) After applying this method, new wells were distributed relatively evenly within our designated optimization units. Specifically, the addition of 166 new wells was predicted to result in a well density of 0.04 wells/ha, covering an area of 3350.43 ha, which accounts for 74% of the total agricultural land in the study area. Our research outcomes can greatly enhance the intelligent management of precision agriculture at a large regional scale, which will have a significant impact on grain production and food security.

Funding

This work was jointly supported by the National Natural Science Foundation of China under Grant 32001249, the State Key Laboratory Foundation of China under Grant A314021402-202220 and Chinese Universities Scientific Fund under Grant 2452019223.

Declaration of Competing Interest

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

Data availability

I have shared the data at the Attach File step

Acknowledgments

The authors would like to acknowledge the Beijing Institute of Surveying and Mapping for providing the field survey data of PWs. In addition, we also express our gratitude to others who have contributed to this work.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2023.102316.

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