Received: 10 April 2022 | Revised: 9 May 2023 | Accepted: 6 July 2023

DOI: 10.1002/ldr.4850

RESEARCH ARTICLE

WILEY

Land use evaluation considering soil properties and agricultural infrastructure in black soil region

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Funding information
National Natural Science Foundation of China, Grant/Award Number: 42171250; Project Supported by State Key Laboratory of Earth Surface Processes and Resource Ecology, Grant/Award Number: 2022-ZD-04; the Strategic Priority Research Program of the Chinese Academy of Sciences, Grant/Award Number: XDA23100303

Abstract

Systematic assessment of arable land use is a fundamental prerequisite to explore its sustainable development path. Agricultural infrastructure integrated with the tillage conditions and soil properties was used to evaluate the state of regional arable land use and its potential for sustainable productivity. We propose a combined weighting method integrating Delphi and entropy weights to consider both decision objectives and indicator attributes. The proposed approach takes into account both expertise and data feature, making the evaluating results more rational and applicable. The impacts of large-scale land use change and regional urban distribution on soil properties and agricultural infrastructure were also explored to develop more rational and differentiated conservation strategies. Our evaluation showed that 44% and 48% of the soil properties of arable land in Heilongjiang Province, China, are in the excellent or good grades, respectively, meaning that no or only minor remediation measures are needed to achieve optimum conditions. Agricultural infrastructure deserves more attention from the management than soil properties, as only 16% and 24% of area have the same excellent and good grades. The results of the evaluation with a combination of subjective and objective weights are closer to a normal distribution curve than if only expert weights are used, which confirms our hypothesis that the new weighting method is more reasonable. The newly proposed weighted design method and index provide a better understanding of the sustainable productivity of agricultural areas and have a promising application in large-scale black soil areas worldwide. The future rough growth strategy for resources will result in degradation and posed risks to regional ecological conservation. At the provincial level (up to 130 km), agricultural infrastructure declines and then rises as fields move away from cities, with the inflection point at 55 km. State-owned farms are mainly responsible for this inflection point, which shift the agents of arable land from small farmers to large capital, with remote arable land receiving more investment. The impact mechanisms of urbanization should be deeper explored to address the challenges for arable land conservation.

KEYWORDS

agricultural infrastructure evaluation, conservation practices, farmland development, land use systems, urbanization consequences

1 | INTRODUCTION

Food security is an important strategic issue for sustainable land and human development. This poses a daunting challenge for policy-makers around the world, especially in developing countries, to increase crop yields while improving the land's productive capacity (Ren et al., 2022; Ye, Ren, Song, et al., 2022). China uses 7% of the world's arable land to feed 22% of its population, making an important contribution to the achievement of the UN Millennium Development Goals (Deng et al., 2015; United Nations, 2005). However, the long-term intensive use of arable land has also led to a decline in its quality, resulting in a severe deterioration: decline in soil organic matter and nutrients (Yan et al., 2012), thinning of the cultivated soil horizon (Pang et al., 2009), wind and water erosion, degradation of soil structure (Wu et al., 2021), acidification (Raza et al., 2020), and soil compaction (Nawaz et al., 2013). All these are serious constraints on the sustainable use of arable land productivity (Lal, 2001; Mganga et al., 2018; Yang et al., 2015).

The main factors affecting the productivity of arable land can be categorized as agroclimatic resources, soil properties, and agricultural infrastructure, of which the latter two can be considered as arable land tillage conditions (ALTC) (Liu et al., 2020; Tan et al., 2020; Ye et al., 2019). Agroclimatic resources are often indicated as potential crop yields under specific local hydrothermal conditions and simulated by crop models and are often used to reflect the impact of climate change on farming systems (Du et al., 2016; Guo, 2015; Wen, Kong, et al., 2019; Wen, Zhang, et al., 2019). ALTC can be considered as a combination of soil properties that affect crop growth and agricultural infrastructure that can be enhanced by additional facilities and capital inputs (e.g., improving irrigation and drainage conditions, rural road construction) (Liu et al., 2020; Zhang et al., 2002). For agricultural infrastructure, irrigation facilities contribute to reducing the cost of agricultural factors by reducing the quality, and increasing the efficiency of inputs and rural roads play an important role in reducing transaction costs and increasing the potential value of agricultural products (Adamopoulos, 2011).

The uncertainty in evaluating ALTC is greater than that in assessing agro-climatic resources due to the lack of knowledge on interactions between indicators and suitable multi-indicator integration methods (Yun et al., 2008). The commonly used multi-indicator weighted average method has limitations in the selection and quantification, the design of weights, and the result evaluation (Bünemann et al., 2018; Obade & Lal, 2016). Therefore, ALTC evaluation is essential to diagnose the shortcomings of arable land use and develop sustainable management policies. Soil quality is defined as the ability of the soil to support various soil functions (Karlen et al., 2001). It mainly focuses on the ability of the soil to support agricultural output and much research has been conducted on it. A close relationship exists between soil quality and ALTC. Soil quality is typically defined as "the ability of soil to function within an ecosystem and land use to maintain biological productivity, sustain environmental quality, and promote plant and animal health" (Doran & Zeiss, 2000). The general evaluation of soil quality is to construct a system of evaluation indicators based on an analysis of the characteristics and interrelationships of the indicators and then apply a weighted average method to calculate the soil quality index (SQI). The total dataset (TDS) and minimum dataset (MDS) are the commonly used methods for constructing indicator systems (Ghaemi et al., 2014, Gholoubi et al., 2018; Kuzyakov et al., 2020; Rojas et al., 2016). For a specific region, due to variability, use and management, high cost of data acquisition, and covariance among factors, it is not possible to obtain data for all indicators. Thus, selecting a dataset that maximizes the representation of all candidate parameters (i.e., MDS) becomes the optimal strategy (Samaei et al., 2022; Shukla et al., 2006; Zhang et al., 2022). The TDS-MDS is based on aggregating as many soil quality indicators as possible to form a TDS and filtering the MDS as one evaluation indicator system through statistical methods. Principal component analysis (PCA) and correlation analysis are widely used for indicator screening, based on the principle that indicators with higher information loadings in the principal components are more representative and less redundant for the expression of soil quality (Gholoubi et al., 2018; Imaz et al., 2010; Juhos et al., 2019).

In terms of indicator selection for land use evaluation, most studies have focused on natural factors (e.g., climate, soil, and water), especially those that affect crop growth. For example, FAO (1993) developed the "Sustainable Land Use Management Framework" to evaluate land sustainability in terms of production, stability, feasibility, affordability, and conservation. Since 2001, the Cornell soil health team has determined 13 indicators (5 physical, 4 biological, and 4 chemical) to assess soil health comprehensively, taking into account the ease of data acquisition and acceptability to farmers (Sheng, 2014). Obade and Lal (2016) applied reduced regression (RR), principal component regression (PCR), partial least squares regression (PLSR), and other methods to analyze the interaction characteristics of 10 soil physical and chemical attributes and suggested that soil organic carbon, soil bulk density, carbon to nitrogen ratio, and electrical conductivity were the most important variables (Gholoubi et al., 2018; Gholoubi et al., 2019; Obade & Lal, 2016) affecting soil quality. However, these studies focus more on the "Ability of soils to support crop growth and agro-environmental protection." Also, the lack of details about the overall nature of farmland ecosystems, especially the evaluation of infrastructure construction and transformation carried out on arable land (Yun, 2015), may constrain the improvement of agricultural productivity and exacerbate ecological deterioration in less economically developed areas (Sun et al., 2019; Wen, Kong, et al., 2019; Wen, Zhang, et al., 2019).

Another difficulty in land use evaluation is the design of weights. The expert scoring method (Delphi method) is a classical method that applies expertise and regional characteristics to the design of weights (e.g., The 15-level system of agricultural land quality to assess the suitability or productivity of land was proposed by the Ministry of Land and Resources of China), but the stability of its results is weak because it is highly influenced by expert expertise and subjective attitudes (Hossain & Das, 2010; Marinoni, 2004). Objective weighting methods (e.g., entropy method, CRITIC, and factor analysis) do not rely on subjective judgment and have a strong theoretical basis; thus, the shortcomings of subjective methods can be addressed (Wang & Lee, 2009). However, these data-driven methods have difficulty drawing on existing expertise in soil science, agronomy, and geography, which leads to the calculated results being inconsistent with common experience. How to effectively combine the advantages of the two weights and make the land evaluation results more suitable for the practice and application of land management is another objective that this paper seeks to achieve.

Heilongjiang Province, located in northeastern China, boasts extensive black soil arable land and is recognized as a crucial agricultural region in the country. In recent years, the province has faced both challenges and opportunities for agricultural sustainability. For instance, the implementation of resource-intensive growth strategies has posed risks to resource degradation and ecological conservation. Consequently, conducting a systematic assessment and research in this region can offer valuable insights for formulating appropriate conservation strategies and establishing a path towards sustainable development. We incorporated the conditions of the soil and human use of arable land into an evaluation system. Considering that it is difficult to evaluate complex arable land systems with a single weighting method, we propose a combination of subjective and objective weights, merging subjective expertise and objective calculations to minimize the loss of information in the evaluation process. As large-scale land use change and regional urbanization can strongly impact tillage conditions, their effects are also analyzed through quantitative methods. The specific objectives of this paper include (a) to assess soil properties, agricultural infrastructure, and ALTC on the example of Heilongjiang Province, China; (b) to explore the distribution characteristics of soil properties and agricultural infrastructure using spatial autocorrelation methods; (c) to explore the impact of large-scale land use changes on regional soil properties and agricultural infrastructure from 2000 to 2010; and (d) to analyze the coupling relationships between regional urbanization, soil properties, and agricultural infrastructure. The weighted evaluation of tillage conditions and spatial characterization methods are valuable to explore the potential for arable land improvement and to develop differentiated sustainable protection policies.

2 | MATERIALS AND METHODS

2.1 | Study area

Heilongjiang Province is in northeastern China, between latitude 43°26′ ~ 53°33′ N and longitude 121°11′ ~ 135°05′ E, and has the largest arable land area accounting for approximately 1/9 of the country (Figure 1). Heilongjiang Province has excellent natural conditions for agricultural production and is in one of the three major black soil (Mollisols or Chernozems) belts in the world. It has typical black soil arable land, accounting for 56.1% of the total typical black soil area of the country. Heilongjiang Province mainly produces rice, corn, and soybeans and is a representative of intensive, large-scale agriculture in China, with the highest grain guarantee rate and commodity rate in the country. Heilongjiang Province has abundant water resources. In recent years, there has been a growing emphasis on rain-fed agriculture as a means of stabilizing grain production. However, it is imperative to simultaneously foster the expansion of irrigated agriculture to enhance both the quantity and quality of grain output. This concerted effort will lead to a notable surge in the irrigation rate of arable land. And the irrigated area of farmland in the province reached 7.27 million km^2, and the irrigation rate reached 49.6% in 2015 (Wan et al., 2021).

Arable land in Heilongjiang Province can be divided into four major regions: the Sanjiang Plain, the Songnen Plain, the mountainous and hilly areas, and the periurban areas. The Sanjiang Plain is one of the areas with a superior natural endowment of arable land resources (e.g., flat topography and mild and humid climate) and has a good match of water and soil resources, with state-owned farms widely distributed and a high degree of arable land intensification. Compared with the Sanjiang Plain, the Songnen Plain has a longer history of reclamation and complex forms of agricultural production. Therefore, the region has a more serious history of outstanding human-land conflicts and land degradation. Mountainous and hilly areas, including the Great and Lesser Xinganling Mountains and the Changbai Mountains in the southeast, have poor natural agricultural endowments and widespread fragmentation of arable land, which is not conducive to agricultural production. Periurban areas are close to consumer markets and have a higher degree of intensification (Du & Liu, 2013).

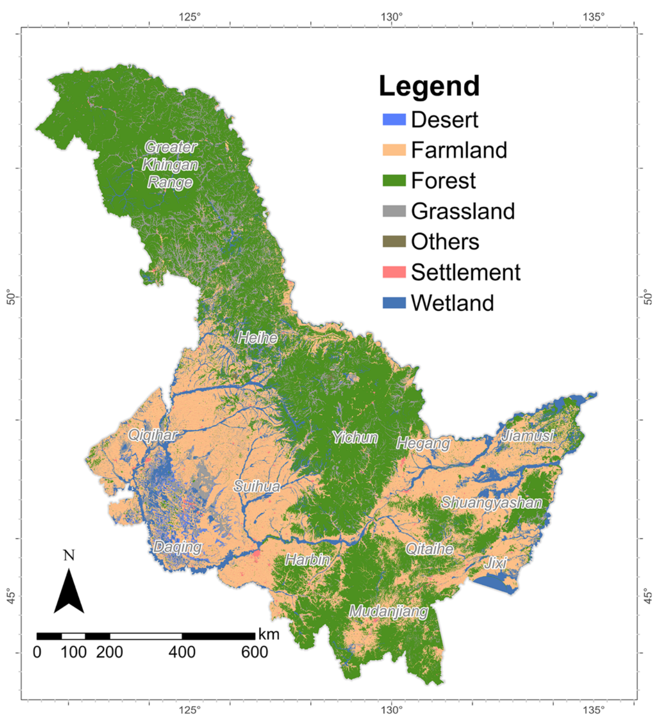

FIGURE 1 Spatial distribution of land use (2010) in Heilongjiang Province, China. [Colour figure can be viewed at wileyonlinelibrary.com]

2.2 | Data source

Among the soil properties (Table S1), the field surface slope data were obtained from the DEM of the Geospatial Data Cloud (http://www.gscloud.cn/). The other data are obtained from the results of the soil testing by county, soil journal, geochemical survey information, and arable land grading information from the agricultural, natural resources, and geological departments, respectively. Among the agricultural infrastructure, the Irrigation Guarantee Rate data are obtained from the transcript of the interview survey from the water resources department. Other data come from the arable land grading and land use survey database from the natural resources departments.

2.3 | Weighting design methods

2.3.1 | Expert weights

The Delphi method was first established by American scholars in the 20th century. It has become one of the most representative subjective methods in the field of forecasting and evaluation research (Greiner et al., 2017).

1. Expert selection. Nearly 30 experts in various fields such as land management, soil science, geography, government department personnel, and front-line arable land surveyors were selected, and the concept of weights was detailed according to the evaluation indexes listed in Table S1.
2. Tabulation and scoring. The weight ranges of all energy saving and emission reduction assessment indicators were given to each expert questionnaire, which was checked and filled in repeatedly according to steps 3–9 until there was no change.
3. Each expert member scored each indicator weight to get the weight score of each evaluation indicator.
4. All the experts compared the indicators item by item, and if there was anything wrong, the experts marked and scored the corresponding indicators again until they are satisfied.
5. Experts add up the scoring values of each evaluation indicator to arrive at the total number of all indicators.
6. Each expert member removes the scored value of each indicator with the total number obtained in step 5 to obtain the weight of each evaluation indicator.
7. Pool all the scored tables to obtain the average weight of each evaluation indicator.
8. List the average of each evaluation indicator and compare the average of each group with the weights obtained from 7.
9. After 8 comparison, if the experts want to change the previous scoring, they must repeat 3–8. If there is no objection, the process ends. The group average weights are the final weights of each evaluation index.

The expert weights are denoted as ω_j', representing the relative importance of the indicators given by expert experience in the overall evaluation.

$$\omega_j' = \frac{1}{m}\sum_{i=1}^{m} b_i, \tag{1}$$

where m is the number of experts who participate in the expert assignment, b_i is the weight value of the ith expert on the indicator, and the larger the value of ω_j', the more important the indicator.

2.3.2 | Entropy weights

The entropy weighting method is an objective method that determines the weights of indicators and has strong operability. It can effectively reflect the information implied by the data and enhance the variability and discrimination of the indicators to avoid the uncertainties caused by too little variation in the selected indicators. It, therefore, serves the purpose of providing a comprehensive view of all types of information (Cheng, 2010). The entropy weighting method is calculated as in Equations (2)–(4).

$$y_{ij} = x_{ij} / \sum_{i=1}^{n} x_{ij}, \tag{2}$$

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n}\left(y_{ij}\ln y_{ij}\right), \tag{3}$$

$$\omega_j'' = \frac{1-e_j}{n-\sum_{j=1}^{n} e_j}, \tag{4}$$

where x_{ij} is the standardized value of the jth indicator of the ith plot, n is the number of evaluation plots, y_{ij} denotes the frequency of occurrence of x_{ij}, and e_j denotes the information entropy of the jth indicator, from which the entropy weight of the jth indicator can be calculated.

2.3.3 | Combined weights based on the Delphi and entropy method

The central presumption of the combined weights is that combining qualitative and quantitative methodologies gives an increased complete comprehension of the study issue than either approach alone. The Delphi method, based on expertise, is an expression of the importance of indicators in influencing the mechanism of the objects, while the entropy expression, based on data characteristics, is a description of the heterogeneity of the data. To combine the advantages of both, the following method is proposed, as shown in Equation (5):

$$\omega_j = \alpha\omega_j' + (1-\alpha)\omega_j'', \tag{5}$$

where ω_j indicates the comprehensive weight of the jth indicator and α is the weight correction coefficient. A larger α indicates a greater influence on subjective weights. α is used to characterize the correction magnitude of the objectively calculated data variability on the subjective perception of the indicators. In the determination of the weight combination coefficient, the credibility of the subjective and objective weights in specific practice should be considered on one hand; on the other hand, the relative importance of the subjective and objective weights in the weight combination should be considered. The weight combination coefficient can generally be in the range of 0.6–0.8, and if the subjective weights are more credible, α can be increased appropriately. Considering that the current evaluation of agricultural land in China still needs to draw on a lot of existing expertise, α is adjusted upwards and will be set to 0.7. ω_j' is the expert weight of the ith indicator. The entropy weight of the ith indicator is indicated by ω_j'' (refer to Table S2 for the scoring rules for the indicators).

The corrected combination weights are compared with the uncorrected expert weights and the histogram of the two calculations is used to see the distribution of the data. If the distribution is closer to a normal distribution (i.e., a bell-shaped curve), then the corrected weights are shown to have less error than the reality.

2.4 | Index of arable land conditions

2.4.1 | Index of soil properties and improved conditions of arable land

$$Q_i = \left(\sum_{j=1}^{n} \omega_{ij} \cdot S_{ij}\right) / \sum \omega_{ij}. \tag{6}$$

The weights are weighted and summed in raster cells, and the indices are normalized to 100. Q_i denotes the soil trait or improved conditions index. ω_{ij} denotes the combined weight of the ith indicator under the i (soil properties or improved conditions) dimension; S_{ij} denotes the score of the jth indicator under each indicator. n denotes the number of indicators under the ith dimension.

2.4.2 | Index of ALTC

$$Q = \sum \beta_{sj} Q_s + \sum \beta_{tj} Q_t, \tag{7}$$

where Q represents the ALTC index, where Q_s represents the index of soil properties and Q_t represents the index of improved conditions. β_{sj} and β_{tj} represent the weights of soil traits and agricultural infrastructure indicators, respectively.

The tillage condition index was calculated with modified expert weights. The index [0.8, 1], [0.6, 0.8), [0.4, 0.6), [0.2, 0.4), (0, 0.2) is divided into Excellent, Good, Medium, Lower, and Poor, respectively. Excellent indicates that the soil properties and agricultural infrastructure are optimal and no improvements are needed. Good and Medium indicate that the soil properties and agricultural infrastructure need to be slightly improved. Lower and Poor refer to arable land that cannot meet the regional production needs and major land remediation measures or fallowing should be carried out.

2.5 | Spatial autocorrelation analysis

The basic strategy of arable land construction in China is to form basic farmland with concentrated contiguous areas, matching facilities, and strong disaster resistance, which is compatible with modern agricultural production and operation methods through rural land reclamation (Tang et al., 2019). Identification of the scale, quality, and spatial distribution characteristics of regional arable land cultivation conditions is a prerequisite for further land remediation, differentiated utilization, and protection measures. Spatial autocorrelation analysis is an analytical method to describe the aggregation and dispersion states of spatial units, which usually consists of global spatial autocorrelation and local spatial autocorrelation (Zhao et al., 2020). Global spatial autocorrelation (Moran's I) was first proposed in the 1950s by the statistician Moran. According to the first law of geography, similar things are spatially related. Moran's I can calculate the average similarity and dependence of spatial units. Local spatial autocorrelation (Anselin Local Moran's I, LISA) explores local characteristic differences in spatial distribution, which was proposed by Anselin in the 1950s to identify whether a unit forms clusters or significant outliers in space. The calculation for Moran's I and LISA is shown in Appendix A.7.

2.6 | Land use change impact model

To explore the effects of land use conversion on ALTC, 5-year interval land use cover data (2000–2010) of Heilongjiang Province are used to develop a model of the effects of land use conversion on soil properties and agricultural infrastructure (Xu et al., 2017). The distribution of soil properties and agricultural infrastructure in 2000, 2005, and 2010 was obtained from the land use change data and the evaluation index of 2.4. The field that has been converted from other land use to agriculture gets its soil properties and agricultural infrastructure index by proximity interpolation. In contrast, fields that have been converted to other land use are considered to have an index of 0. The impact of land use change on cropland resources was analyzed by comparing the increase and decrease of soil properties and agricultural infrastructure index for every 5 years. The model treats 1 ha of arable land with a score of 100 as a standard plot. Raster cells converted from other land types to arable land are extracted and then spatially overlaid with data on the soil properties, agricultural infrastructure, and ALTC to calculate the total change.

$$A_i = \sum_{j=1}^{n} C_{ij}, \tag{8}$$

where A_i denotes the total soil properties and agricultural infrastructure index in county unit i. C_{ij} denotes the comparative score of the *j*th plot under county unit *i*, and *n* denotes the number of plots in county unit *i*.

2.7 | Pearson correlation analysis

To further explain the spatial distribution characteristics of ALTC, we analyzed the correlation between the minimum distance of the arable land from the city (MDALC) and their soil properties and agricultural infrastructure using data on the spatial distribution of cities in Heilongjiang Province in 2018 (Gong et al., 2019). All the minimum distances of arable land from the city were counted at the provincial level. Considering that the county-level administrative districts are the main body of arable land management, Pearson correlation analyses are performed at the county level. The calculation of the Pearson correlation is shown in Appendix A.8.

3 | RESULTS

3.1 | Weight differences assessed by two methods

The specific differences in weighting evaluation methods are reflected by the indicator results. Expert empirical knowledge considers the Field surface Slope and Parts of the Terrain as the fundamental indicators affecting ALTC (Table S6). The field surface slope is an important parameter affecting the tillage conditions. If the slope of the field is too steep, then it is more difficult to irrigate and the soil can be easily eroded (Zheng et al., 2011). Parts of the terrain dominate surface runoff and influence the redistribution of surface water and heat, as well as impact the physical, chemical, and biological soil properties (Ju et al., 2018). The smaller the information entropy, the greater the dispersion of the indicator and the greater its impact on the overall evaluation (Wang et al., 2020). The irrigation guarantee rate (0.23) and shelterbelt net grade (0.20) are the factors most indicative of data dispersion, which indicate that there are large differences in the level of agricultural infrastructure development.

In terms of weight differences, the field surface slope, irrigation guarantee rate, and shelterbelt net grade have large differences between the two sets of weights, with weight differences above 0.10. The field surface slope shows strong importance in terms of expert empirical knowledge but reflects poor data heterogeneity. Although the field surface slope has an important influence on the water and nutrient retention of the soil, the flat topography of most arable areas in Heilongjiang Province makes it difficult to reflect regional differences. The opposite is true for the irrigation guarantee rate and shelterbelt net grade, which reflects the limitations of expert empirical knowledge in capturing the regional variability of the indicators (Ye et al., 2014, 2016).

3.2 | Spatial pattern of ALTC

The evaluation results and data distribution of soil properties, agricultural infrastructure, and tillage conditions in Heilongjiang Province are visualized (Figure 2). The soil properties (88 ± 5) of the arable land are mainly excellent (index ∈[80, 100]) and good (index ∈[60, 80]), with both accounting for 92% of the total area (Figure 2a). The variation of soil properties in the province is small. In terms of spatial distribution, arable land with excellent soil properties is mainly located in the northern and eastern parts of the Songnen Plain and the northern part of the Sanjiang Plain. Land with good soil properties is widely distributed throughout the province. The agricultural infrastructure (84 ± 10) of arable land in Heilongjiang Province varies considerably (Figure 2b). In terms of spatial distribution, land with excellent and good arable technology is mainly distributed in the majority of the Sanjiang Plain and the Songnen Plain. The medium, low, and poor land is mainly distributed in the mountainous hilly areas in the north and southeast.

The ALTC (86 ± 5) in Heilongjiang Province is at a high level and is mainly classified as "excellent" and "good" (Figure 2c). Excellent and good grades are mainly found in the 46° N–49° N region, including most of the Songnen and Sanjiang plains. Medium- and low-arable land is mainly concentrated in the northwestern and southeastern mountainous hilly areas and the areas around large and medium-sized cities (e.g., Harbin and Mudanjiang) due to improved constraints. To visualize the difference between the combined weights and the uncorrected expert weights, the results of the two calculations were compared (Figure 2d). Compared with the expert weights, the proportion of "excellent" decreased significantly (61%–29%), while the proportion of "good" increased (38%–62%) and the proportion of "medium" and "low" increased slightly.

3.3 | Spatial autocorrelation of county-level tillage conditions

The results of global spatial autocorrelation indicate significant positive global spatial correlations (Moran's I > 0, $Z > 3$, $p \le 0.01$) of soil properties, agricultural infrastructure, and ALTC (Figure 3). To explore the local clustering and outliers of tillage conditions, local spatial autocorrelation analysis is conducted for each county. The types of positive correlation of soil properties on arable land in Heilongjiang Province show a "group" pattern of clustering, with High-High type dominating (Figure 3a), which indicates that areas with excellent soil properties have isotropic characteristics spatially and can be considered as a more desirable region for cropland. The flat topography of the Sanjiang Plain and the Songnen Plain has a high portion of arable land with good soil properties. The soil types in these areas are mainly Chernozems with high organic matter content (>10%) and a thicker layer of cultivation (Ap > 60 cm), resulting in better production conditions than in the mountainous and hilly areas. A "bipolar" pattern of agricultural infrastructure is found in Heilongjiang (Figure 3b). The HH clusters of agricultural infrastructure are mainly found in the Sanjiang Plain and the Songnen Plain on the east and west sides, with high levels of clustering around state-owned farms of developed agricultural conditions (Du & Liu, 2013). The HH (High-High, representing higher ALTC regions are surrounded by areas that also have similar

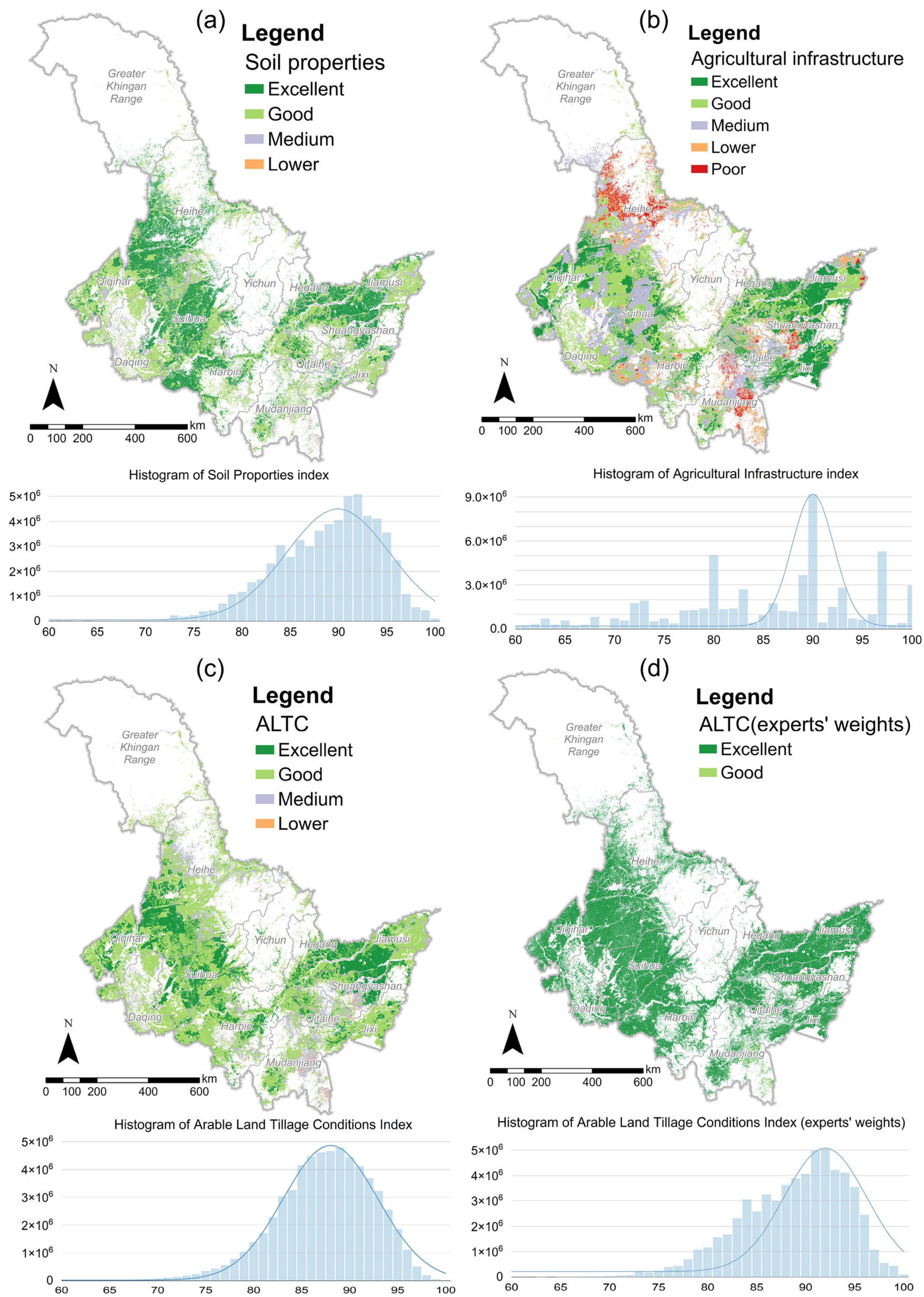

FIGURE 2 Spatial distribution and histograms of tillage conditions in Heilongjiang Province. (a) Soil properties (88 ± 5.4), (b) agricultural infrastructure (84 ± 11), (c) tillage conditions (87 ± 5.1), and (d) tillage conditions in experts' weights (91 ± 4.3). The indexs [90,100], [80,90), [70,80), [60,70), and [0,60) are classified as excellent, good, medium, low and poor, respectively. [Colour figure can be viewed at wileyonlinelibrary.com]

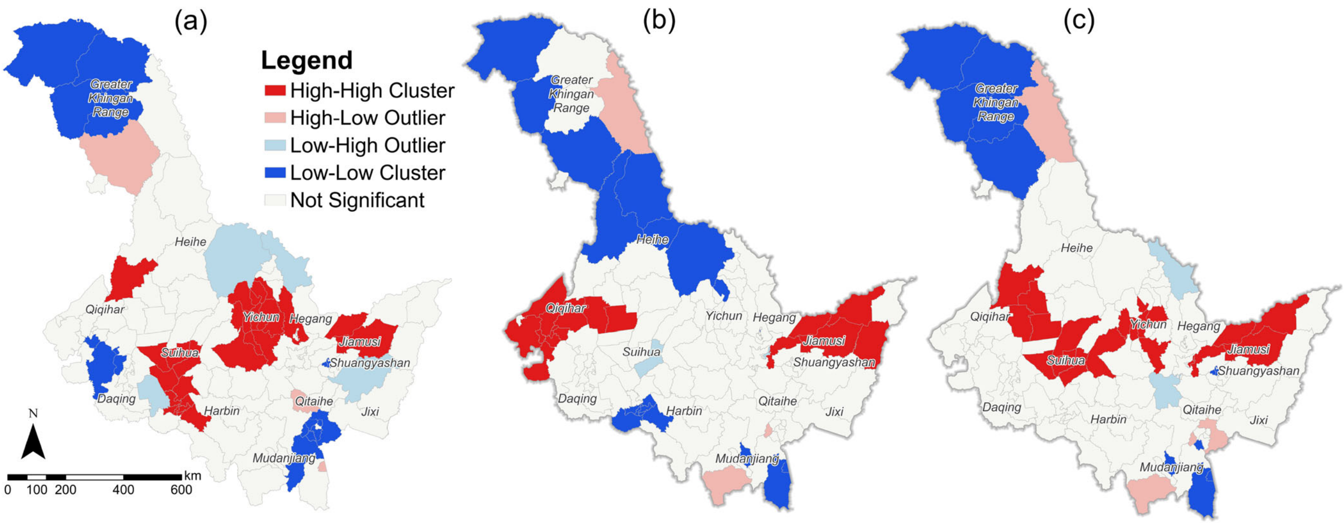

FIGURE 3 Anselin Local Moran's I of (a) soil properties, (b) agricultural infrastructure, and (c) arable land tillage condition in Heilongjiang Province at the 95% confidence level. Soil properties: Moran's $I = 0.456$, $Z = 8.52$, $p \leq 0.01$. Agricultural infrastructure: Moran's $I = 0.396$, $Z = 8.52$, $p \leq 0.01$; ALTC: Moran's $I = 0.396$, $Z = 6.36$, $p \leq 0.01$. [Colour figure can be viewed at wileyonlinelibrary.com]

spatial properties) clusters of ALTC are clustered along the latitude in a "strip" pattern, with high levels of arable land mainly distributed in counties between 46° and 49° N (Figure 3c), mainly in plain areas but also in some mountainous places with better natural conditions. The Low-Low clusters are in the hilly counties on the north and south sides.

3.4 | Impact of land use change on soil properties and agricultural infrastructure

The impact of large-scale land use change on soil properties and agricultural infrastructure in Heilongjiang Province from 2000 to 2010 was assessed with the average and total soil properties and agricultural infrastructure index being used. From 2000 to 2005, soil properties and agricultural infrastructure improved in most counties and districts, with the total index increasing counties primarily in the Sanjiang Plain and mountainous hilly areas (Figure 4a,c). The initial period of land reclamation (2000–2005) in the province, focused on the development of unused land suitable for agriculture. Because the Songnen Plain has a large undulating topography and many erosion ditches, and many difficulties to construct water storage, a large work is needed for land improvement. As a result, the improved soil properties of the newly remediated land did not "offset" the loss of arable land (Zhou et al., 2014). On the Sanjiang Plain, there are many state-owned farms with relatively simple land tenure relationships and a large amount of potentially available arable land. The overall available soil resources of the area are effectively improved as more unused land suitable for agriculture is developed. The situation changed from 2005 to 2010, as urbanization accelerated (Figure 4b,d), and high-quality arable land was taken up around the cities. The exploitable reserve resources decreased, and soils were widely degraded in the province, except in the southern mountainous and hilly counties, where some of the improved counties were concentrated. Many of the degraded counties are concentrated in the Songnen Plain, the Sanjiang Plain, and the northern Great Xinganling region (Liu et al., 2009).

To further explore the changes in resource stocks, total soil properties and agricultural infrastructure index were both calculated. The total soil properties and agricultural infrastructure index in Heilongjiang Province increased from 2000 to 2010, mainly due to the expansion of arable land area (Figure 5a,c). In the first 5 years, the total soil properties and agricultural infrastructure of arable land increased rapidly with the reclamation of a large area of farmable unutilized land (e.g., marshland and unused grassland). The main growth poles of arable land are in the Sanjiang and Songnen plains. During this period, with high-quality arable land resources concentrated in the farmable plain areas, the spatial configuration of the ALTC was constantly optimized. Between 2005 and 2010 (Figure 5b,d), the total growth rate of the area of the Songnen Plain soils lowered as the reserve arable land resources decreased, and the increase in arable land was mainly located in the Sanjiang Plain. It is alarming to note that although the total area of arable land in the Songnen Plain has increased, the soil properties and agricultural infrastructure in most counties are declining.

3.5 | Correlation between ALTC and MDALC

Soil properties and agricultural infrastructure index were curve-fitted to MDALC to explore the overall correlation. The correlation between agricultural infrastructure and MDALC at the provincial level (Figure 6) indicates a strong correlation ($R^2 > 0.6$) with the spatial distribution of urban areas having a more significant impact. Within 130 km, the soil properties of arable land do not show significant fluctuations with increasing MDALC. Consequently, the soil properties of arable land are

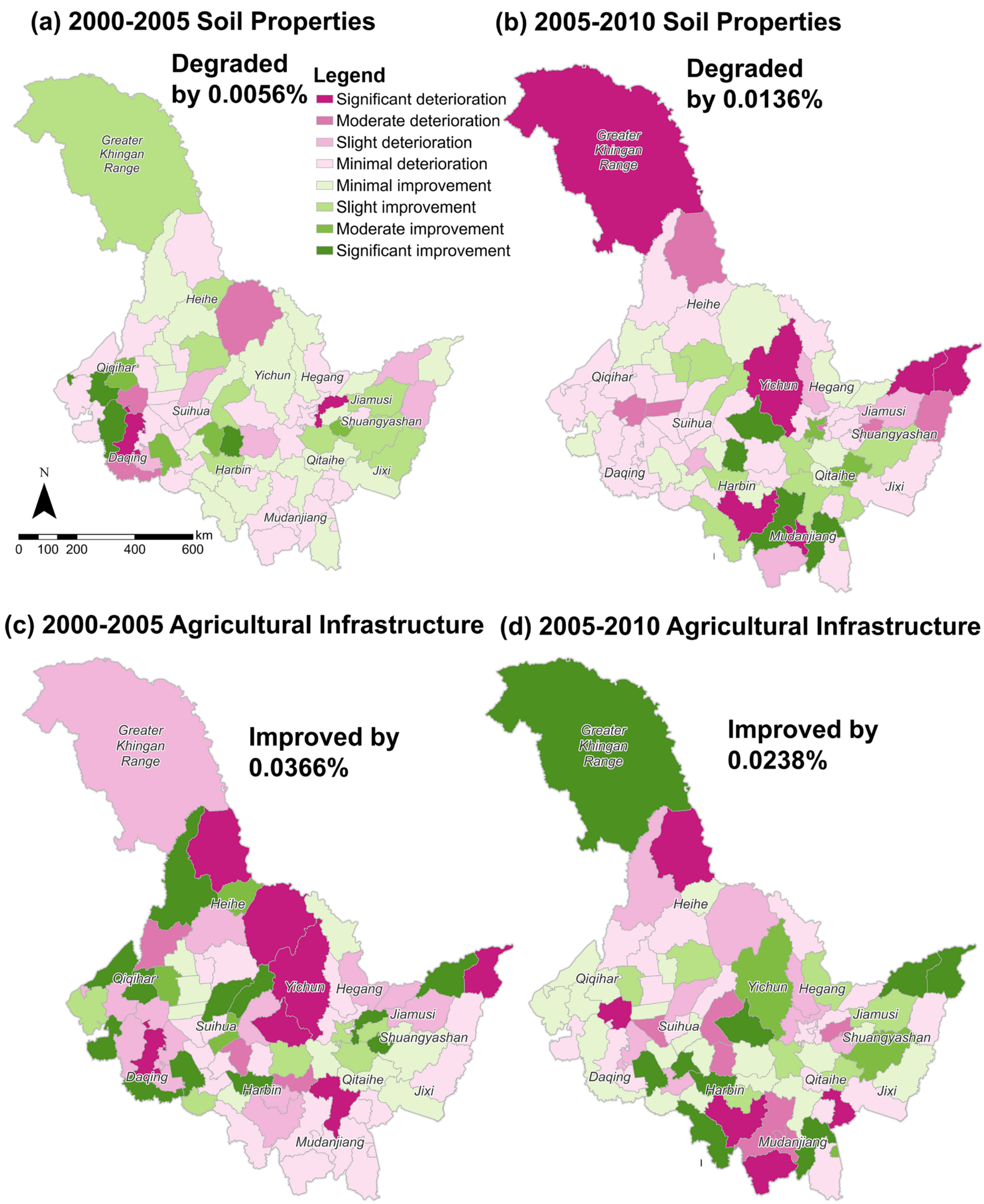

FIGURE 4 Changes in the average level of soil properties and Agricultural infrastructure of arable land in Heilongjiang Province, China (2000–2005, 2005–2010). The map reflects changes in the average soil properties and agricultural infrastructure index and is used to characterize the improvement and degradation of the average level of soil properties and agricultural infrastructure. [Colour figure can be viewed at wileyonlinelibrary.com]

evenly distributed throughout the province without the strong influence of urban infrastructure. Unlike the soil properties, the agricultural infrastructure of arable land in Heilongjiang Province shows distinct regional characteristics. In the area with a radius of 55 km, there is an initial rapid decay of the agricultural infrastructure as MDALC increases. It shows that the agricultural infrastructure is gradually weakening as it moves away from urban and consumer markets. After a short distance, the agricultural infrastructure of the arable land is again increasing with MDALC. As the distance from the city increases, the agricultural infrastructure of the arable land rises rapidly, reaching a peak at approximately 105 km, and declines rapidly thereafter to a lower level.

Spatial heterogeneity in the impact of urban distribution is explored, through the correlation between soil properties, agricultural infrastructure index, and MDALC for each county (Figure 7). For most

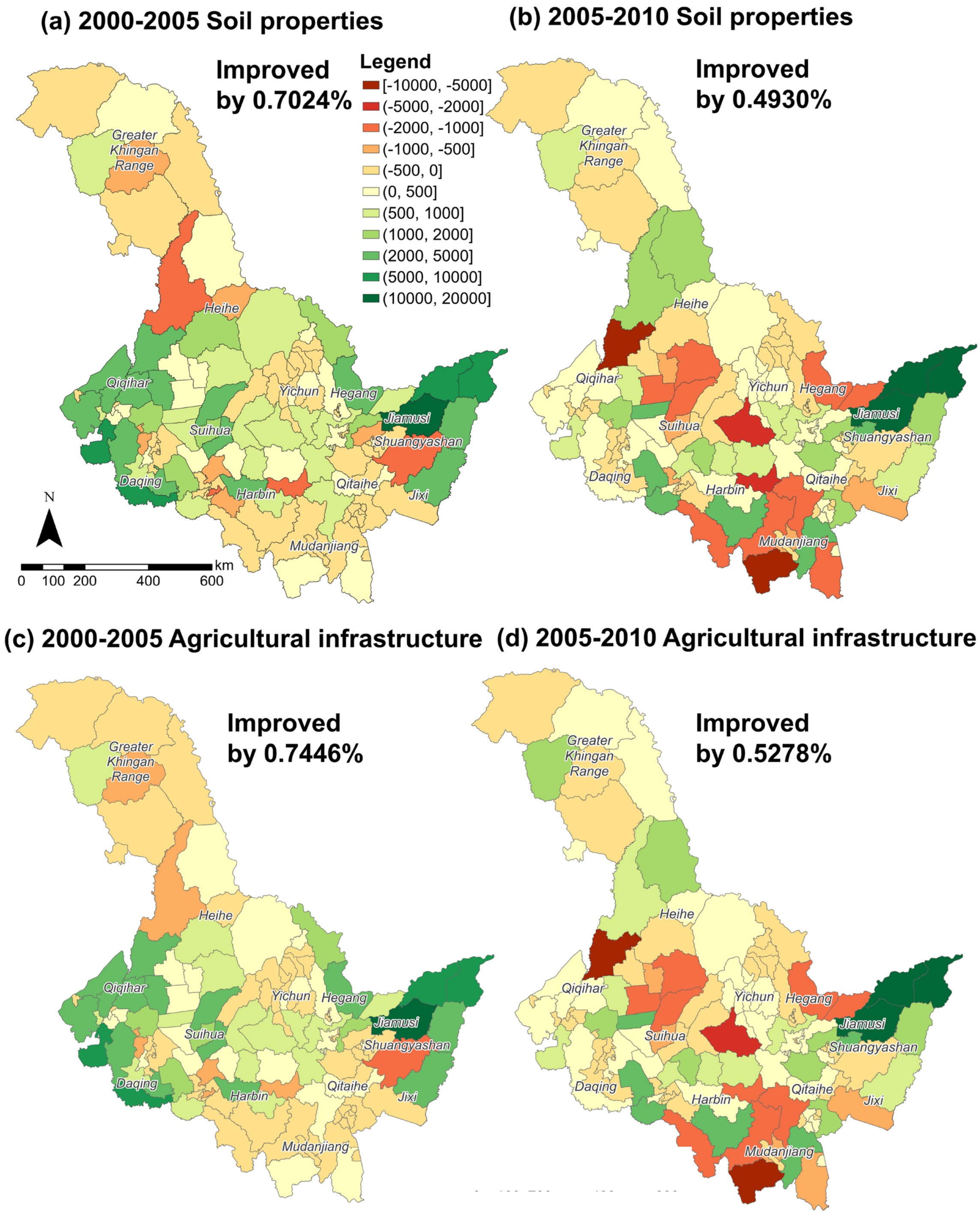

FIGURE 5 Overall changes in soil properties and agricultural infrastructure of arable land in Heilongjiang Province, China (2000–2005, 2005–2010). The map reflects changes in the total soil properties and agricultural infrastructure index, which represents the sum of index of soil properties or agricultural infrastructure for all raster cells in the county and is used to characterize the improvement and degradation of the overall level of soil properties and agricultural infrastructure. [Colour figure can be viewed at wileyonlinelibrary.com]

of the counties, soil properties were independent ($p < 0.05$) ($|r| < 0.2$; $p < 0.05$) on MDALC (Figure 7a). This is consistent with the provincial scale, where most counties have similar climatic conditions and soil types, so that distance to the nearest urban edge has only a small effect on the spatial heterogeneity of soil properties. Agricultural infrastructure shows a stronger correlation with MDALC than with soil properties, because more counties have seen an increase in the $|r|$ (Figure 7b). In terms of agricultural infrastructure, counties with weak, moderate, or strong negative correlations ($0.2 \le |r| < 0.4$; $p < 0.05$) are mainly located in mountainous or hilly areas, especially along lesser Xinganling and southern mountainous and hilly counties. In these counties, the agricultural infrastructure around cities is better than those of

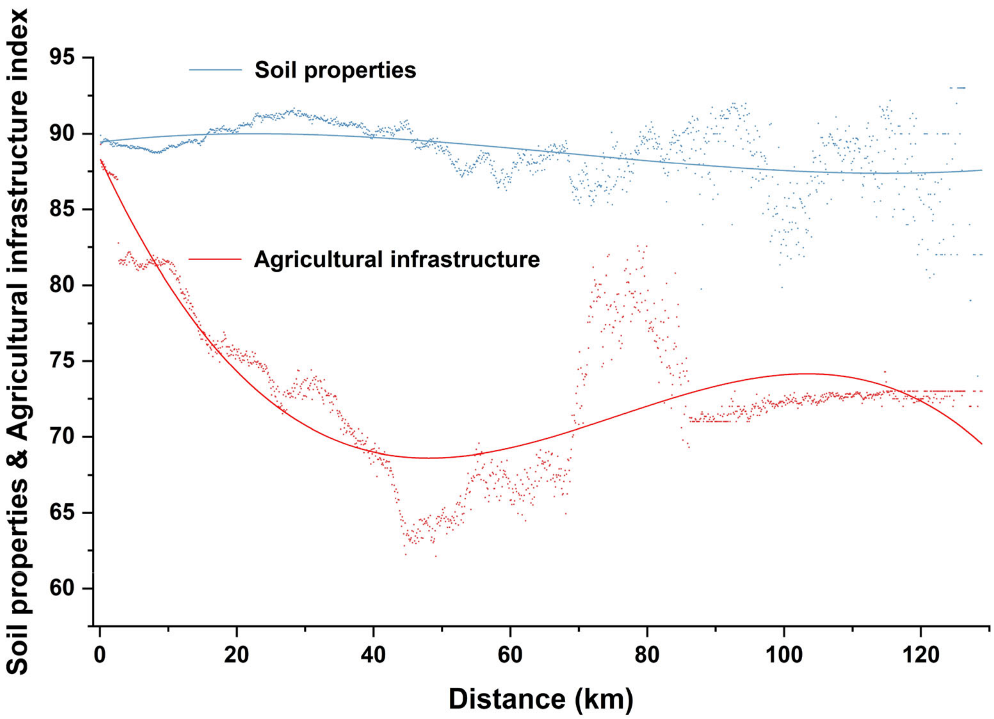

FIGURE 6 Overall variation of soil properties and agricultural infrastructure with the minimum distance of the arable land from the city in Heilongjiang Province. The R^2 for the soil properties and agricultural infrastructure fitted curves are 0.205 and 0.644, respectively. [Colour figure can be viewed at wileyonlinelibrary.com]

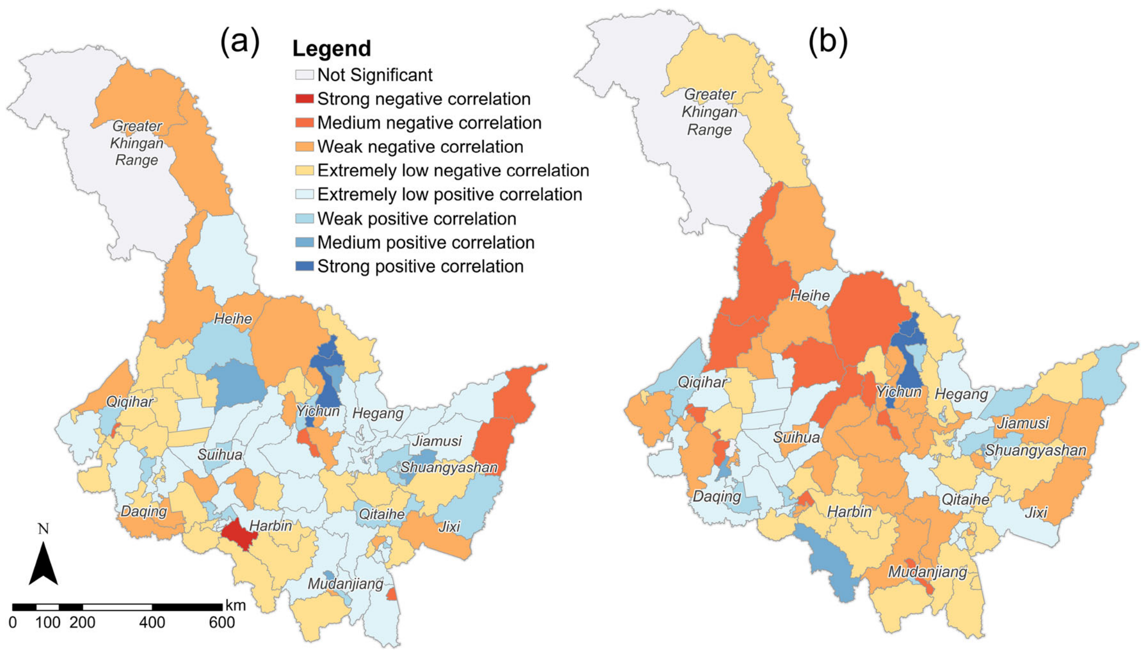

FIGURE 7 Pearson correlation indices of (a) soil properties and (b) agricultural infrastructure and minimum distance of arable land from the city for county-level units in Heilongjiang Province. Strong positive (negative) correlation (0.6 ≤ |*r*| < 1), medium positive (negative) correlation (0.4 ≤ |*r*| < 0.6), weak positive (negative) correlation (0.2 ≤ |*r*| < 0.4), and weak positive (negative) correlation (0 ≤ |*r*| < 0.2) were assigned at the 90% confidence interval. [Colour figure can be viewed at wileyonlinelibrary.com]

newly reclaimed land away. For counties around large- and medium-sized cities, especially regional metropolitan cities (e.g., Harbin and Qiqihar), the agricultural infrastructure of arable land around cities is better than arable land far from cities. In such scenarios, the key factor influencing the agricultural infrastructure of arable land is its distance from the nearest consumer market. The agricultural infrastructure of arable land closer to the urban edge is improved due to the driving force of urban economies and incentives from consumer markets, such as better irrigation and drainage facilities and less resistance to tillage paths (Jiang et al., 2013; Jiang & Zhang, 2016). In this context, the Pearson correlation is an indicator to quantify the coherent relationship between urban expansion and agricultural infrastructure of arable land.

4 | DISCUSSION

4.1 | Key issues and countermeasures for arable land conservation

An effective evaluation of ALTC can improve the country's potential to cope with natural resource risks. The results of ALTC evaluation in Heilongjiang Province show that the quality of arable land is generally good. However, due to the wide variation in topography, the ALTC depends on the region. The flat topography of the Sanjiang Plain and the Songnen Plain has a large portion of Excellent and Good arable land. These areas of arable land, which have long and warm vegetation periods and have excellent soil properties and agricultural infrastructure, should be fully and effectively protected. A reasonable crop rotation system and a scientific fertilizer application system should also be established to prevent the ALTC decline caused by improper agricultural management.

A decline in agricultural infrastructure was also observed. Some of the arable lands in the Great and Lesser Xinganling and southern Changbai Mountains are in poor conditions, with a certain degree of fragmentation and slope cultivation. It has a direct or indirect negative impact on arable land resources, such as an increase in cultivation costs and an increased risk of soil erosion (Xu et al., 2021). In addition, the lack of water conservation facilities and supporting infrastructure severely restrict and limit arable land productivity.

Agricultural practices are an important factor influencing the pattern of distribution of agricultural infrastructure. In Heilongjiang Province, most areas with state-owned farms have received large investments in agriculture and have a higher intensification (An & Xin, 2020). Urbanization impacts the agricultural infrastructure, and arable land close to cities is more likely to be improved due to economic reasons (Liu et al., 2023; Ye et al., 2020). However, periurban arable land resources are also under greater pressure from urbanization, and the resulting reduction in production stability is a problem (Wu, 2008). Soil acidification, declining surface organic matter content, and reduced soil nutrient levels due to industrialization put arable land at risk of reduced productivity (Li, 2018; Raza et al., 2020; Zhao et al., 2013). Therefore, based on the current situation of arable land and the direction of urban development, the pattern of arable land use should be optimized through the allocation of land resources and agricultural planning. At the same time, measures should avoid the negative effects of urbanization on farming conditions and the regional ecological environment to better exploit the overall effects on food production.

4.2 | Indicators and weights for tillage conditions evaluation and decision-making

Weights are a key step in the aggregation of indicators and the assessment of the soil quality and arable land utilization systems (Chou et al., 2008). Classical weighting methods can usually be divided into two categories: (i) subjective weighting–based on decision-makers' subjective preferences; and (ii) objective weighting—based on data which are given in the decision table of the attributes for each alternative (Liu et al., 2016). In the case of subjective weighting methods, the weights of the decision-makers (DMs) are usually given in advance or the evaluation matrices are built to determine the relative importance of the factors (e.g., Delphi, AHP) (Liang et al., 2019). Subjective weighting methods require DMs to be very familiar with the decision problem and are therefore used extensively for the evaluation of fuzzy arable land systems, such as the assessment of arable land quality and agricultural land grading (e.g., carried out by the Chinese national departments, Sun et al., 2019). Their subjectivity and uncertainty are still very strong. Objective weighting methods have received more attention than subjective methods because the importance of the attributes is calculated only from the data in the decision table. As these methods are more objective and accurate, they became popular for research and practices of soil quality evaluation (Hyun et al., 2022; Nabiollahi et al., 2018; Zhang et al., 2022). To combine the advantages of both, our approach considers both attribute and DMs weights, subjective preferences, and objective weights and combines them effectively. Through the methodology of the evaluation index distribution analysis, subjective weights that are not combined with objective weights are compared with those that have been combined to test the validity. As a result, the proposed method leads to more accurate decision results than studies that use only subjective or objective methods.

Correlation analysis can help to clarify the trade-offs and synergies between ALTC indicators and streamline of practice operationalization (Ye, Song, Gao, et al., 2022). Positive correlations ($p \leq 0.05$) between most of the ALTC indicators (Table S7) have the r values were between 0 and 0.20, indicating only very weak correlations. This is in line with the independence principle of comprehensive evaluation. However, there was a strong positive correlation between the field conditions vs. farm flood control standards ($r = 0.53$, $p \leq 0.01$) and effective soil layer thickness versus soil constraint depth ($r = 0.51$, $p \leq 0.01$). The Field Condition, consisting of field surface regularity, internal height difference, and field size, is a comprehensive indicator to reflect the ease of cultivation. Farm flood control standards are indicated by the construction of water storage, the tilth project, and other engineering measures. A large amount of contiguous prime arable land is laid out here. In addition, there are fewer obstacles to carrying out farmland flood protection projects in plain areas. Thus, the standard of farmland flood protection can be improved more easily. The soil constraint layer refers to the layers below the common tillage horizon (Ap), where constraint factors (e.g., white slurry layer, gravel layer) occur, effectively characterize the soil obstacles supporting crop growth. The effective soil depth is the sum of the soil horizons and the loose parent material layer, which importantly influences soil productivity (Xie et al., 2005; Yi et al., 2015). Correlation analysis of ALTC indicators provides an effective tool for streamlining indicator evaluation practices and exploring the coupling and coordination of the influencing factors (Wang et al., 2022; Ye et al., 2018).

4.3 | Towards the path of sustainable arable land use

How to deal with the contradictions between urbanization and arable land conservation is an important issue for country development. The study in the black soil region of northeast China shows that total arable land resources in Heilongjiang Province were not at risk of decline during 2000–2010. From 2000 to 2005, the soil properties and agricultural infrastructure of the province's arable land rapidly improved, with the major growth poles located in the Sanjiang and Songnen Plains. During this period, a large area of arable land was replenished through the reclamation of a large area of unused land, effectively compensating for the loss of arable land resources due to urbanization and infrastructure constructions (Li et al., 2021). At the policy level, the increase is both a direct result of arable land protection policies such as the "balance of occupation and replenishment" and an indirect result of national agricultural support policies (Liu et al., 2015). However, the increase in total arable land in Heilongjiang Province slowed down between 2005 and 2010 with the reduction of developable reserves, and extensive soil degradation is observed in the Songnen Plain. At the provincial scale, the spatial allocation of arable land resources has been optimized. The agricultural infrastructure improvement further tends to concentrate on the two major plains, especially the Sanjiang Plain on the east side. With the adjustment of agricultural structure and the layout of construction land, arable land in mountainous and hilly areas with poor conditions is gradually being converted to forest plantations. From the local perspective, however, and against the background of the massive occupation of the high-quality arable land around cities, rural governments must reclaim a certain amount of inferior arable land as a supplement, resulting in the phenomenon of taking advantage of the best to compensate for the worst. This in turn affects the sustainable development of regional arable land use (Gao et al., 2019; Xu et al., 2015).

Correlations between tillage conditions and MDALC indicate that regional urbanization has a strong impact on agricultural infrastructure (Ye, Ren, Song, et al., 2022; Ye, Song, Kuzyakov, et al., 2022). As it moved away from urban and consumer markets, the improved conditions showed stages of decline and then increase with troughs and peaks at 55 km and 105 km, respectively. Firstly, the closer the agricultural infrastructure is to the town, the more likely it is to be improved, which reflects the driving effect of economic development on agricultural infrastructure. After 55 km, however, a turnaround occurs, as it moves further away from the city, the agricultural infrastructure starts to get better. This phenomenon has been observed in Heilongjiang due to extensive arable land for large-scale operations (such as state-owned farms, which are unique to northeastern China) located on the urban periphery (Check Figure S1 for the distribution of state-owned farms). Most of the agricultural infrastructure inputs require a large space, with a high concentration of capital, labor, and other production factors (Wu et al., 2019). The benefits of agricultural infrastructure development are generally not directly available to the individual farmer. The lower willingness of farmers to invest has led directly to an imbalance in agricultural infrastructure in Heilongjiang Province. To address this problem, on one hand, macroeconomic control should be increased to organize and coordinate the investment in agricultural infrastructure construction (d'Amour et al., 2017). On the other hand, the rate of return on capital for agricultural infrastructure should be increased to encourage the diversification of investment bodies (Li et al., 2014; Liu, 2018).

5 | CONCLUSIONS

A new integrated approach combining agricultural infrastructure and soil properties was developed and used to assess the status and potentials of regional arable land use. The newly developed weighting approach incorporating Delphi and entropy weights is proposed to account for decision-makers and indicator attributes, respectively. It was found that 44% and 48% of the soil properties of arable land in Heilongjiang Province were in the Excellent or Good grades, respectively, meaning that no or only minor remediation measures are needed. Agricultural infrastructure deserves more attention from the management department than soil properties, as only 16% and 23% of area achieve the same excellent and good levels. Combining subjective and objective weights leads to reasonable and practical evaluation for fuzzy systems, such as large-scale arable land. The effects of large-scale land use changes and regional urban distribution on soil properties and agricultural infrastructure were investigated by these new approaches. The future growth strategy for resources in Heilongjiang Province will lead to some degradation and risks to regional ecological conservation. At the provincial scale (up to 130 km), agricultural infrastructure has a stronger correlation ($R^2 = 0.64$) and volatility than soil properties ($R^2 = 0.21$), indicating that the impact of urban areas on agricultural infrastructure is complex and nonlinear. Within 55 km from the cities, the agricultural infrastructure index decrease. After 55 km, however, this trend begins to reverse, with the state-owned farms leading to a shift in the agents of arable land from smallholders to large-scale operators.

The newly proposed weighted design method and index provide a better understanding of the sustainable productivity of agricultural areas and is a promising application for large-scale black soil areas worldwide. The spatial distribution of ALTC index refers for land use planning and land reclamation planning, and at the same time, the index can be used to construct land approval and compensation methods of cultivated land to avoid encroachment of urbanization. Overall, the importance to consider both qualitative and quantitative factors when assessing arable land use status and enhancement potential is highlighted. The exploration of the complex mechanisms of impacts on agricultural infrastructure should be strengthened to meet the challenges of urbanization on the conservation of arable land.

ACKNOWLEDGMENTS

We thank the high-performance computing support from the Center for Geodata and Analysis, Faculty of Geographical Science, Beijing Normal University (https://gda.bnu.edu.cn/). YK is grateful for the support of the "RUDN University Strategic Academic Leadership Program" and the Russian Science Foundation project 19-77-30012.

FUNDING INFORMATION

This work was supported by the National Natural Science Foundation of China (grant number 42171250), the Strategic Priority Research Program of the Chinese Academy of Sciences (grant number XDA23100303), and State Key Laboratory of Earth Surface Processes and Resource Ecology (2022-ZD-04).

CONFLICT OF INTEREST STATEMENT

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 STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Ren, S., Song, C., Ye, S., Cheng, F., Akhmadov, V., & Kuzyakov, Y. (2023). Land use evaluation considering soil properties and agricultural infrastructure in black soil region. *Land Degradation & Development*, 1–16. https://doi.org/10.1002/ldr.4850