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Evaluating the Impact of Conservation Tillage on Desert Agro-Pastoral Ecosystems in Inner Mongolia Using Remote Sensing and GIS

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Abstract: As part of China's northern ecological fragile zone, the desert regions of Inner Mongolia face severe challenges from wind erosion, desertification, and the sustainable development of agro-pastoral systems. Conservation tillage practices - such as reduced tillage, no-tillage, and straw mulching - play a vital role in improving the ecological conditions of these areas. The integration of remote sensing (RS) and geographic information systems (GIS) provides essential technical support for evaluating their ecological impact. However, current research faces limitations including inadequate spatial resolution in traditional methods, poor adaptability of RS change detection algorithms to the complex spectral characteristics of desert environments, and a tendency to assess ecological impact using single-factor analyses. These issues hinder a comprehensive understanding of the overall effects of conservation tillage on agro-pastoral ecosystems. This study leverages GIS and RS technologies to address three core objectives: (1) to analyze the spatial distribution of conservation tillage practices in Inner Mongolia's desert areas and examine their correlation with topography and climate; (2) to apply the Fast Bag-of-Visual-Words (*BOVW*) algorithm to enhance the accuracy and efficiency of change detection in conservation tillage regions using RS imagery; and (3) to comprehensively assess the impacts of conservation tillage on desert agro-pastoral ecosystems from multiple dimensions, including soil properties, vegetation growth, water resource utilization, and ecosystem services. The study establishes a technical evaluation framework tailored to arid and semi-arid regions, providing a scientific basis for optimizing agricultural production layouts and ecological protection in Inner Mongolia, and offering methodological insights for sustainable development in similar regions.

Keywords: BOVW algorithm; conservation tillage; desert agro-pastoral ecosystem; GIS; Inner Mongolia; RS

1 INTRODUCTION

The desert area of Inner Mongolia is located in the ecological fragile zone in northern China [1, 2], with a total area of about 635,000 square kilometers, accounting for 53.5% of the total land area of the region. The area has an arid climate with little precipitation, with an average annual rainfall of less than 200 mm, and is frequently affected by strong winds. Wind erosion and desertification are serious, leading to a decline in land productivity and ecological degradation, which seriously threatens the sustainable development of local agriculture and animal husbandry and ecological security. Conservation tillage [3-5], as an agricultural tillage method that protects the soil and improves the ecological environment through reduced tillage, no-tillage, and straw mulching, has been promoted and applied to a certain extent in the desert agro-pastoral areas of Inner Mongolia. RS technology can quickly obtain large-scale surface information [6, 7], and GIS has powerful spatial data management and analysis capabilities [8-11]. The combination of the two provides strong technical support for scientifically evaluating the impact of conservation tillage on the desert agro-pastoral ecosystem of Inner Mongolia.

Research on the impact of conservation tillage on the desert agro-pastoral ecosystem in Inner Mongolia using the combination of RS and GIS has important theoretical and practical significance. In terms of theory, it helps to deeply understand the mechanism of conservation tillage measures in arid and semi-arid desert agro-pastoral ecosystems, and enrich and improve the theoretical system of ecosystem response to human activity intervention. In terms of practice, it can provide scientific basis for the rational planning and promotion of conservation tillage technology, optimization of agricultural production layout, and improvement of ecological environment quality in the desert areas of Inner Mongolia, promote the sustainable development of agriculture and animal husbandry and the virtuous cycle of ecosystems in the region, and has important practical significance for maintaining the ecological security barrier in northern China.

Previous research on the evaluation of conservation tillage has faced three main limitations: First, spatial pattern analyses have largely relied on statistical data, lacking refined spatial distribution assessments based on high-resolution remote sensing and correlation analyses with environmental factors. Second, change detection has primarily employed traditional threshold-based or post-classification comparison methods, which often suffer from insufficient accuracy or low efficiency. Third, ecological impact assessments have mostly focused on single indicators, lacking integrated, multi-dimensional analysis. For example, some studies [12-15], in analyzing the spatial pattern of conservation tillage areas, mainly rely on traditional statistical data and field surveys, which have low spatial resolution and are difficult to accurately reflect the fine spatial distribution characteristics of conservation tillage areas under the complex terrain and climatic conditions of the desert areas of Inner Mongolia. In terms of change detection in RS images, some studies [16, 17] use traditional algorithms that are not well adapted to the unique surface features and complex spectral information of desert areas, resulting in low accuracy and efficiency in detecting changes in conservation tillage areas. In addition, in the impact analysis section, most studies [18-20] focus only on the evaluation of single ecological factors, such as soil moisture or vegetation coverage, lacking systematic analysis of the comprehensive impact of multiple factors on the agro-pastoral ecosystem, and are difficult to fully reveal the overall impact effect of conservation tillage on the desert agro-pastoral ecosystem of Inner Mongolia.

The desert agro-pastoral ecosystems in Inner Mongolia face critical challenges such as soil desertification, vegetation degradation, and water scarcity. As a key ecological restoration strategy, conservation tillage holds great potential for improving the ecological conditions in this region. However, systematic studies are still lacking regarding the spatial distribution patterns, dynamic change characteristics, and ecological impacts of conservation tillage. This study aims to integrate RS and GIS to reveal the spatial configuration and temporal evolution of conservation tillage areas, and to assess their ecological effects from multiple dimensions, including soil properties, vegetation dynamics, water resource utilization, and ecosystem service functions. As an ecological barrier in northern China, the stability of Inner Mongolia's agro-pastoral ecosystems plays a vital role in regional sustainable development. Clarifying the mechanisms by which conservation tillage contributes to ecological improvement will provide essential scientific support for combating desertification and promoting ecological agriculture in arid and semi-arid regions.

The main research content of this paper includes three parts. The first part is the spatial pattern analysis of conservation tillage areas in the desert area of Inner Mongolia based on GIS. By collecting and processing RS images, terrain data, land use data, etc., and using the spatial analysis function of GIS, the spatial distribution map of conservation tillage areas is accurately drawn, and its correlation with terrain, climate, land use and other factors is analyzed. The second part is the change detection of conservation tillage areas in the desert area of Inner Mongolia based on the *FastBOVW* algorithm. This algorithm is used to process RS images of different periods, extract change information of conservation tillage areas, and improve the accuracy and efficiency of change detection. The third part is the impact analysis of conservation tillage on the desert agro-pastoral ecosystem of Inner Mongolia. From multiple dimensions such as soil physical and chemical properties, vegetation growth status, water resource use efficiency, and ecosystem service functions, the impact of conservation tillage on the regional agro-pastoral ecosystem is comprehensively evaluated.

2 SPATIAL PATTERN ANALYSIS OF CONSERVATION TILLAGE AREAS IN THE INNER MONGOLIA DESERT BASED ON GIS

The topography of the desert agro-pastoral areas in Inner Mongolia is complex, and the climatic differences are significant [21, 22]. The implementation areas of conservation tillage are not evenly distributed, but are constrained by multiple factors such as terrain slope, soil type, water source distribution, and the intensity of human activities. Through GIS [23-26], it is possible to accurately depict the spatial location, area ratio, patch morphology, and coupling relationships with natural geographic elements of conservation tillage areas, thereby clarifying the implementation scope and layout characteristics of conservation tillage within different ecological functional zones. This accurate identification of spatial patterns provides a key spatial reference for subsequent impact assessment. For example, in the ecologically fragile edge areas of mobile sand dunes, if conservation tillage areas are fragmented, it may be difficult to form an effective windbreak and sand fixation effect; while in relatively flat oasis farmland areas, concentrated and contiguous tillage areas may have more significant effects on soil moisture retention and vegetation restoration. Only by first clarifying where conservation tillage is implemented and why it is implemented in these areas, can we further analyze its mechanism of action on ecological elements such as water, soil, and vegetation, and avoid generalized analyses that are detached from the spatial context.

In this study, conservation tillage refers to agricultural practices such as reduced tillage, no-tillage, and straw mulching that minimize soil disturbance, thereby preserving soil structure, enhancing water and soil retention capacity, and suppressing desertification. It is a key agricultural approach for preventing soil degradation in arid and semi-arid regions. The *BOVW* algorithm is an improved remote sensing image processing method based on the "visual bag-of-words" model. By clustering features from remote sensing imagery to construct a visual vocabulary, this algorithm enables efficient feature matching and change detection across different time periods. Compared to traditional methods, it offers superior performance in both feature extraction efficiency and change detection accuracy for identifying dynamic changes in conservation tillage areas. GIS-based spatial analysis refers to the use of GIS software to process, overlay, and statistically analyze spatial datasets such as remote sensing imagery, topography, and land use. Tools such as spatial interpolation and overlay analysis are employed to reveal the spatial distribution patterns of conservation tillage areas and their correlations with environmental factors such as slope, precipitation, and land use types.

2.1 Spatial Aggregation Characteristic Analysis

This study applies for the first time the Nearest Neighbor Index analysis method [27, 28] to quantitatively determine the distribution characteristics of spatial point patterns. The core idea is to reveal the spatial characteristics of aggregation or dispersion by comparing the observed spatial distribution of conservation tillage areas with a random distribution pattern. The data basis of this method is the spatial location data of conservation tillage areas stored in GIS. First, the actual average distance between each tillage area and its nearest neighbor area is calculated. Then, the expected average nearest neighbor distance under a theoretical random distribution is calculated based on the density of all tillage areas within the study area. Finally, the Nearest Neighbor Index is obtained through the formula. When the Nearest Neighbor Index < 1, it indicates that the conservation tillage areas are aggregated in space; when the index = 1, the distribution is random; and when the index > 1, the distribution is dispersed. Assuming the expected nearest neighbor distance is represented by f_R, the area of the study region is X, the sample size of spatial point data is v, and the actual nearest neighbor distance is $\dot{f}$, the calculation formulas are as follows:

$$f_R = \frac{1}{2}\sqrt{\frac{X}{v}} \tag{1}$$

$$E = \frac{\dot{f}}{f_R} \tag{2}$$

The above analysis can intuitively quantify the spatial distribution pattern of tillage areas. For example, it can identify whether conservation tillage in the Inner Mongolia desert area is concentrated in oasis irrigation areas or scattered in the desert-steppe transition zones. This provides a basic understanding of spatial distribution characteristics for subsequent ecological impact assessment - if it is an aggregated distribution, it may produce synergistic effects on regional-scale windbreak and sand fixation and soil moisture retention; if it is a dispersed distribution, attention should be paid to its fragmentation impact on local microenvironments.

2.2 Spatial Distribution Characteristic Analysis

(1) Kernel density estimation method

The Kernel Density Estimation method [29] quantifies the intensity of aggregation and hotspot distribution of tillage measures within the region by performing continuous surface interpolation on the spatial location data of conservation tillage areas in GIS. Its core is to construct a smoothed density surface based on the spatial distance decay effect. Specifically, the method takes the spatial position of each tillage area as the center, sets a bandwidth, and uses a kernel function to perform weighted calculations of density contributions from neighboring areas, ultimately generating a continuous raster map that reflects the density of conservation tillage area distribution. For example, after importing the vector data of conservation tillage plots into GIS, the Kernel Density Analysis tool can intuitively present the spatial differentiation characteristics between high-density aggregation zones and low-density sparse zones in the Inner Mongolia desert area. Combined with GIS-overlaid layers such as terrain slope and annual precipitation, the driving mechanisms behind the formation of aggregation hotspots can be further analyzed. For instance, high kernel density zones along the Yellow River may be related to favorable natural conditions such as convenient irrigation and concentrated farmland, as well as the intensity of policy promotion, while low-density zones at the edge of the desert may be constrained by the risks of dune movement and tillage costs. Assuming the sample size of the collected spatial point data is v, the search radius is g_v, and the kernel function is $J(a - a_u/g_v)$, the formula is:

$$d_v\left(a\right)=\frac{1}{vg_v}\sum_{u=1}^{v}J\left(\frac{a-a_u}{g_v}\right) \tag{3}$$

(2) Average urban center distance and spatial dispersion index

The joint analysis of average urban center distance [30] and spatial dispersion index [31] aims to quantify the extent of human activity influence and the spatial distribution balance of conservation tillage layout, based on the spatial positional relationship between urban center coordinates and conservation tillage areas in GIS data. First, the administrative center or population settlement coordinates of each banner/county are extracted from the urban vector layer in GIS. The straight-line distance from each conservation tillage area to the nearest urban center is calculated, and the arithmetic mean is taken to obtain the average urban center distance. A smaller value of this indicator indicates that tillage areas are more clustered around urban surroundings, possibly reflecting the influence of technology diffusion and transportation convenience on the implementation of tillage measures. The spatial dispersion index is used to quantify the distribution direction and dispersion degree of tillage areas through GIS spatial statistical tools. For example, using the directional distribution function, elliptical parameters reflecting the spatial extension direction of conservation tillage areas can be generated. Combined with GIS layers such as prevailing wind directions and river orientations in desert areas, one can determine whether the tillage layout presents a strip distribution along oasis corridors or a scattered distribution due to dune obstruction. If the spatial dispersion index of a certain area shows that tillage plots are far from urban centers and are dispersedly distributed, it may suggest that conservation tillage in that area is more strongly restricted by natural conditions, and its ecological impact assessment should focus on small-scale microhabitat changes rather than systemic effects at the regional scale.

(3) Radius of gyration method and spatial distribution curve

The radius of gyration method [32] and spatial distribution curve [33] describe the spatial coverage and distribution form of conservation tillage areas from an overall scale through the geometric analysis function of GIS. The data foundation is the spatial location of coordinate point sets or polygon centroids of tillage areas. The radius of gyration method calculates the minimum circular radius that can include all tillage areas to measure their spatial compactness: if the radius is small and the center is located in the oasis agricultural area, it indicates that the tillage areas are centrally distributed in the core area with superior natural conditions; if the radius is large and the center is biased toward the desert edge, it may reflect a scattered layout of tillage measures along ecologically fragile zones. Combined with GIS buffer analysis tools, dominant environmental factors within the radius of gyration can be further identified to explain why tillage areas form a specific spatial range. The spatial distribution curve is plotted by showing the number or area proportion of tillage areas within different distance thresholds, intuitively demonstrating the gradient characteristics of the distribution. For example, if the curve rises rapidly at short distances and then flattens, it indicates that tillage areas are highly concentrated in a few core areas; if the curve shows a slow upward trend, it indicates a relatively dispersed distribution. By overlaying land use type layers in GIS, the key geographical features corresponding to curve inflection points can be precisely located, providing spatial reference ranges for evaluating the impact of conservation tillage on ecological transition zones in the agro-pastoral ecotone.

Kernel density estimation is employed to calculate the spatial density distribution of conservation tillage areas, intuitively reflecting their aggregation characteristics. Its theoretical foundation lies in probability density estimation, while its practical significance lies in identifying core implementation zones of conservation practices, thereby informing targeted resource allocation. The radius of gyration is calculated as the average distance from the geometric center to the outer edges of conservation tillage areas, representing the spatial extent and diffusion characteristics of their distribution. Theoretically grounded in spatial morphology metrics, it is practically useful for assessing the spread trend of conservation practices and evaluating their potential influence on surrounding areas. Spatial supply-demand matching involves comparing the ecological supply capacity of conservation tillage areas with ecological demand, to evaluate the alignment between conservation measures and ecological objectives. This approach is based on the theory of ecosystem supply-demand balance and holds practical value in identifying optimization directions for conservation tillage, thereby enhancing the ecological relevance and effectiveness of such practices.

2.3 Spatial Supply-Demand Matching Evaluation

The application of the two-step floating catchment area model in the spatial pattern analysis of conservation tillage areas focuses on constructing a spatial supply-demand matching relationship through GIS data, quantifying the spatial accessibility and balance of conservation tillage measures in the agro-pastoral ecosystems. The data foundation comes from two core layers in GIS: the supply-side data are vector polygons of conservation tillage implementation areas, and the demand-side data are the basic geographical units of the desert agro-pastoral areas in Inner Mongolia. The model calculates the service coverage area of supply points in the first step (forward search), and evaluates the actual access capacity of demand points to conservation tillage resources in the second step (reverse search), finally realizing a scientific judgment on whether conservation tillage measures effectively serve ecological protection and agricultural production needs spatially.

Step 1: Setting search radius and calculating supply-demand ratio

The first step of the model is to set a reasonable search radius and calculate the supply-demand ratio of supply points based on GIS data. The setting of the search radius needs to be combined with the geographical characteristics of the Inner Mongolia desert area, such as dune spacing, irrigation facility distribution, and the range of farming activities of herders and farmers. Through the GIS buffer analysis tool, circular buffers with the geometric center of the conservation tillage plots as the center are generated to simulate the actual influence range of the tillage measures. The supply-demand ratio calculation targets each supply point, i.e., conservation tillage plot, aggregates the ecological protection demand intensity of all demand points within its search radius, and combines the service capacity of the supply point to calculate the supply-demand ratio through a formula, reflecting the coverage efficiency of unit service capacity to surrounding demands. For example, in the oasis agricultural area at the southern edge of the Hobq Desert, due to convenient irrigation and concentrated farmland, a high supply-demand ratio can be formed within a relatively small search radius; while in the scattered grasslands in the hinterland of the Otindag Sandy Land, the radius needs to be expanded to cover more demand points. The hypothetical supply-demand ratio is expressed by E_k, representing the potential demand scale of a certain conservation tillage area k. Demand points are represented by u, and supply points by k. The service capacity of the supply point is represented by T_k. Since this paper does not classify the levels of conservation tillage areas, the value of T_k is uniformly set to 1. The scale of the demand point is represented by F_u. The number of grid plots within the search radius is represented by j, the distance between demand point u and supply point k is denoted by f_{uk}, and the search radius is denoted by f_0. The calculation formula is:

$$E_k = \frac{T_k}{\sum_{u \in \{f_{uk} \le f_0\}}^{j} F_u} \tag{4}$$

Step 2: Regional accessibility calculation and distance decay effect.

Through GIS spatial join and overlay analysis, the accessibility of each demand point to conservation tillage resources is calculated. Specifically, for each demand point, such as a wind-eroded sensitive farmland, all supply points that can cover it are reverse searched, i.e., conservation tillage plots that fall within the search radius centered on the demand point. The Euclidean distance or cost distance considering terrain resistance between supply and demand points is obtained through GIS distance calculation tools, and the accessibility value is calculated using a weighted summation formula. Suppose the accessibility value of each grid plot is represented by x_u, and the number of conservation tillage areas falling within the spatial scope of the search radius f centered on u is represented by l, then the calculation formula is:

$$x_u = \sum_{u \in \{f_{uk} \le f_0\}}^{l} E_k \tag{5}$$

The normalized accessibility value of each grid can be obtained by the following formula:

$$R_u = \frac{x_u - \mathrm{MIN}(x_u)}{\mathrm{MAX}(x_u) - \mathrm{MIN}(x_u)} \tag{6}$$

In desert areas, geographical barriers such as sand dunes and gobi significantly increase the actual accessibility cost. Therefore, Euclidean distances need to be corrected using GIS raster data, so that the accessibility calculation better reflects the actual implementation difficulty of conservation tillage measures. For example, demand points in the arid hilly region of Ulanqab may have lower actual accessibility due to mountain barriers, even though the straight-line distance is relatively short, compared to the relatively flat Hetao Plain.

Finally, through the statistical analysis tools of GIS, spatial visualization and equilibrium calculation of the accessibility values for all demand points in the region are carried out, revealing the spatial matching characteristics of conservation tillage resources. If the standard deviation of accessibility values in a certain banner or county is small and the coefficient of variation is less than 0.3, it indicates a high degree of matching between the conservation tillage layout and agro-pastoral ecological demand. If the standard deviation is large and there are significant high-value and low-value areas, it indicates spatial imbalance, and key areas with mismatched supply and demand need to be identified. Combined with the overlaid policy implementation range layers in GIS, the impact of administrative intervention on spatial matching can be further analyzed. For example, government-led centralized promotion areas may form local high-accessibility hotspots, while marginal areas with harsh natural conditions may form accessibility depressions due to lack of subsidy support. The above analysis provides a key basis for subsequent ecological impact assessment: conservation tillage measures in high-accessibility areas may effectively improve soil moisture and vegetation cover through scale effect, while scattered layouts in low-accessibility areas may only produce local micro-environment regulation effects, and the layout strategy needs to be optimized accordingly.

3 CHANGE DETECTION OF CONSERVATION TILLAGE AREAS IN INNER MONGOLIA DESERT RS IMAGES BASED ON FAST BOVW ALGORITHM

The implementation of conservation tillage in the desert agro-pastoral areas of Inner Mongolia is affected by multiple factors such as climate fluctuation, policy adjustment, and technical promotion efforts. Its regional scope, patch morphology, and spatial aggregation characteristics may undergo significant changes over time. Through RS image change detection, the boundary displacement, area increase or decrease, and spatial reorganization patterns of conservation tillage areas in different years can be accurately captured, and then correlated with the spatiotemporal variation of ecological factors.

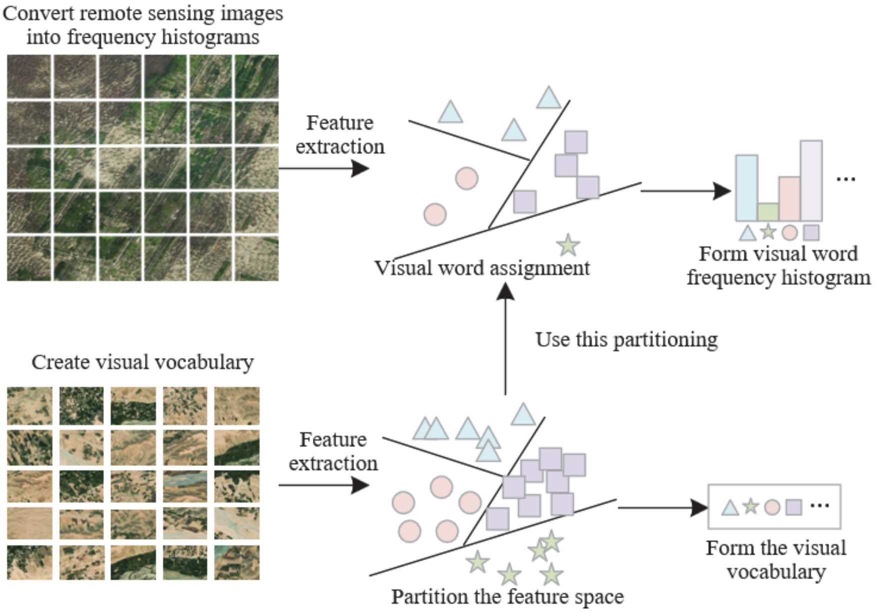

Figure 1 The process of constructing visual word frequency histogram using the *BOVW* algorithm

For example, if the conservation tillage area in a certain region is continuously expanding over five years, and during the same period the vegetation coverage is increasing annually, and the soil wind erosion amount is decreasing, it can be preliminarily judged that the tillage measures have a positive impact on the local ecosystem. On the contrary, if the tillage area shrinks or becomes fragmented, the potential threats to ecosystem service functions need to be analyzed in combination with terrain changes and human activity intensity. This kind of dynamic monitoring provides time series evidence for causal relationship analysis from spatial layout to ecological response, avoiding biased conclusions based only on static patterns.

The RS images of conservation tillage areas in the Inner Mongolia desert show significant heterogeneous mixed characteristics: no-tillage plots form unique texture structures due to straw coverage, and reduced-tillage areas show brightness-contrast differences with surrounding bare land and grassland due to different soil disturbance levels. These local visual features are key identifiers to distinguish tillage types from non-tillage areas. The *BOVW* model, through its three-layer architecture of feature extraction - word clustering - histogram representation, can effectively capture such medium-scale spatial features and avoid the defects of traditional pixel-level analysis being affected by mixed pixels. In addition, the changes of conservation tillage areas in the desert often manifest as gradual adjustment or sudden reconstruction of patch boundaries. The *BOVW* model, through histogram difference analysis of multi-temporal images, can sensitively identify such change patterns and meet the needs of long-term dynamic monitoring. Fig. 1 shows the process diagram of constructing a visual word frequency histogram using the *BOVW* algorithm.

The core principle of the *BOVW* model is to convert RS images into quantifiable and comparable feature vectors by constructing a visual dictionary, so as to detect the feature differences of conservation tillage areas in images of different time phases. The specific steps are as follows: First, for multi-source RS data in the desert area of Inner Mongolia, the preprocessed images are block-processed, and a sliding window of 10 × 10 pixels is used to extract local image patches. The SIFT features of each image patch are calculated to form the initial feature set. Secondly, the K-means algorithm is used to perform unsupervised clustering on all SIFT features in the training set, generating a visual dictionary containing several cluster centers. Each cluster center corresponds to a visual word; for example, cluster center 1 may correspond to high-contrast edge features of straw-covered plots, and cluster center 2 may correspond to the uniform spectral response features of bare land. The size of the visual dictionary needs to be set according to the feature complexity of the tillage scenes in the desert area, to balance model accuracy and computational efficiency. Then, for each image to be detected, the SIFT features of each image patch are matched to the nearest visual word in the visual dictionary, and the frequency of visual words in all image patches is counted to generate a visual word bag histogram of the image. This histogram can be regarded as a feature fingerprint of the image, where the frequently appearing visual words correspond to typical features of conservation tillage areas. Finally, by comparing the histogram differences of images at different time phases, the significantly changed visual words and their spatial distribution are identified. Combined with the existing spatial pattern data of conservation tillage areas in GIS, the actual changed plots are located. Suppose the frequency of occurrence of visual word l is denoted by s_l, and the size of the visual dictionary is denoted by L, then:

$$BOVW=\left[s_1,s_2,\dots,s_L\right] \tag{7}$$

The change detection of conservation tillage areas in desert regions requires processing multi-source and multi-temporal RS imagery. Traditional *BOVW* algorithms extract tens of thousands to hundreds of thousands of SIFT features from each image. The visual vocabulary clustering for even a single scene image may take several hours. If extended to a long time series analysis across the entire Inner Mongolia desert area, it is nearly impossible to complete on an ordinary workstation and may even rely on high-performance computing clusters, which significantly increases research costs and time cycles. To address the prominent contradiction between the massive data scale and limited computing resources in RS data processing of the Inner Mongolia desert region, this paper proposes the *FastBOVW* algorithm. By optimizing the feature matching and clustering process, the processing time of a single-scene image is compressed to 1/5~1/3 of the traditional method, enabling researchers to complete batch processing of multi-temporal data within a reasonable time, thus meeting the demand for long time series dynamic analysis in ecological impact assessment.

Aiming at the feature differences between conservation tillage areas and background objects, the *FastBOVW* algorithm adopts a class-wise clustering - joint vocabulary strategy to replace the traditional global clustering, fundamentally improving the efficiency and scene adaptability of visual vocabulary construction. Specifically, the training data are first divided into two basic categories: conservation tillage class and background object class, and the feature vectors of each category are independently clustered. For example, when processing training imagery from the southern margin of the Hobq Desert, more than 100,000 straw texture-spectral features are extracted from GIS-annotated conservation tillage plots and clustered using K-means to generate a tillage subclass vocabulary with 300 cluster centers; meanwhile, over 200,000 random dune spot and bare land uniform spectral features are extracted from non-tillage areas and clustered to generate a background subclass vocabulary with 200 cluster centers. This class-wise clustering strategy brings three advantages: first, it allows for a flexible increase in the number of cluster centers in the tillage subclass vocabulary to address the high variability of features in tillage areas, while reducing the number of cluster centers for background objects with low complexity features, avoiding the computational redundancy caused by the need to uniformly set a high number of centers in traditional global clustering; second, the sample size of class-wise clustering is only 1/2~1/3 of global clustering, and combined with parallel computing technology, the visual vocabulary construction time is reduced from 48 hours in traditional methods to 6 hours, especially suitable for batch processing of multi-temporal and multi-scene imagery in the Inner Mongolia desert area; third, the block-stored subclass vocabularies significantly reduce memory usage, solving the memory overflow risk when processing RS data covering 635,000 square kilometers. Fig. 2 illustrates the principle of establishing a joint visual vocabulary using the *FastBOVW* algorithm.

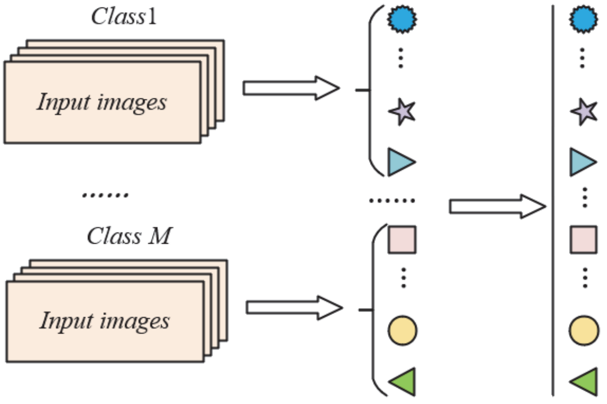

Figure 2 Principle of joint visual vocabulary construction in *fastBOVW* algorithm

Based on the class-wise constructed joint visual vocabulary, the *FastBOVW* algorithm achieves accurate detection of tillage patches in desert areas through feature soft assignment - differential weighted analysis. In the feature assignment stage, the traditional hard assignment strategy is abandoned in favor of a probability-weighted soft assignment method: for each SIFT feature of the image block, the Euclidean distances to all cluster centers in both the tillage subclass vocabulary and background subclass vocabulary are calculated, and weights are assigned based on the inverse of the distance. This assignment method better fits the mixed pixel characteristics of boundaries in desert tillage areas, effectively improving the detection accuracy at patch edges. In the change detection stage, tillage feature histograms and background feature histograms are generated separately for images of different time phases, and the weighted Bhattacharyya distance between the two types of histograms is calculated to accurately identify additions, reductions, or morphological changes in tillage areas. This differential analysis based on a joint vocabulary not only retains the high sensitivity of traditional *BOVW* to texture-spectral features, but also efficiently solves the detection problem of fragmented tillage patches in desert areas through class-wise processing and the soft assignment mechanism, improving the overall efficiency of the change detection process by more than 5 times, providing a practical technical solution for large-scale ecological impact assessment. Specifically, suppose that each class selects J initial cluster centers, resulting in a total of $M \times J$ initial clusters for the entire dataset. If the maximum number of iterations for the *K-means* clustering algorithm is set to V, then the traditional method requires at most $M \times J \times M \times L \times V$ computations. In contrast, the proposed algorithm requires at most only $J \times M \times L \times V$ computations. Assuming the size of the subclass visual vocabulary of class u is represented by L, and visual words are denoted by q, the subclass visual vocabulary N_u of class u can be expressed as:

$$N_u = \left[q_{ul}, l = 1 \ldots L \right] \tag{8}$$

Assuming the number of subclass vocabularies is J, the joint visual vocabulary S can be expressed as:

$$S = \left[N_u, u = 1 \ldots J \right] \tag{9}$$

Conservation tillage plots in desert areas are often embedded in fragmented forms among sand, bare land, and sparse grasslands. The boundary pixels usually exhibit mixed spectral features of straw cover - soil - sand grains. The traditional hard assignment strategy leads to two key errors: first, misclassifying mixed feature points in transition zones as single land covers, such as fully assigning straw-edge sand-contaminated pixels to the bare land spectral vocabulary, resulting in missed detections and boundary shrinkage of tillage patches in the detection result; second, ignoring the similarity among neighboring visual words in the feature space, leading to missed detections of subtle tillage changes. For example, in the oasis-desert transition zone of the HobqDesert, the misclassification rate of boundary pixels in 10-meter resolution images is high under the hard assignment strategy, directly causing excessive errors in annual tillage area detection. The soft assignment allows feature points to belong to multiple visual words in the form of weights, accurately depicting the multiple attributes of mixed pixels and effectively addressing the non-exclusive defect of hard assignment, thereby improving the detection accuracy of fragmented tillage patches. This is crucial for accurately evaluating the microhabitat improvement effects of tillage measures in desert edge zones.

The soft assignment operation of the *FastBOVW* algorithm follows the principle of inverse-distance weighting and local feature aggregation. The specific steps closely reflect the complexity of cultivation features in desert areas: First, for each image block, SIFT features are extracted and the Euclidean distances between each feature and all cluster centers in the visual dictionary are calculated. The top e closest visual words are selected. Then, weights are assigned based on the inverse of the distances. For example, if a feature point's distance to the 1st closest visual word is f, to the 2nd closest is $1.5f$, and to the 3rd closest is $2f$, then the weights are $1/1 = 1$, $1/2 = 0.5$, and $1/3 \approx 0.33$ respectively, while the weights for the remaining visual words are 0. This assignment method represents each feature point as a weighted combination of e visual words instead of a single assignment, thus retaining the mixed information of cultivation features as the main component and background features as auxiliary.

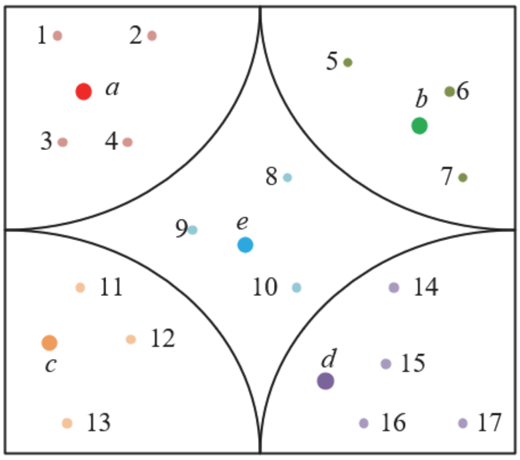

Figure 3 Relationship between RS image feature points and visual word positions

Fig. 3 shows the relationship between feature points and visual word positions in RS images. In change detection, by comparing the weighted feature histograms of images at different time phases, gradual changes in cultivation measures can be accurately identified. This mechanism is particularly suitable for areas with significant gradients in cultivation intensity, such as the dry farming regions of Ordos, and it effectively improves the sensitivity of the algorithm in detecting changes in small patches below 1 hectare. It provides critical technical support for the quantitative analysis of the marginal effects of conservation tillage on desert agro-pastoral ecosystems, avoiding systematic biases in ecological impact assessments caused by the feature fragmentation of hard assignment. Specifically, suppose the number of feature points in an image is denoted by M, and the m-th feature point is denoted as O_m. The weight value assigned to feature point O_m on visual word q is represented by $WEIGHT(O_m, q)$, and the total weight value is defined as:

$$Q(q) = \sum_{m=1}^{M} WEIGHT\left(O_m, q\right) \tag{10}$$

The RS images of the Inner Mongolia desert can be represented in the form of *BOVW* histograms.

$$G = \left[Q_1, Q_2, \ldots, Q_M \right] \tag{11}$$

Fig. 4 shows the complete algorithm flowchart for detecting changes in conservation tillage areas in RS images of the Inner Mongolia desert.

4 EXPERIMENTAL METHOD VERIFICATION

From the example of minimum travel time accessibility analysis of the spatial pattern of conservation tillage areas in Fig. 5, it can be clearly seen that the regions with different colors represent the minimum time required to reach the boundary of the farming and pastoral areas, visually presenting the spatial distribution characteristics of accessibility.

The data used in this study fall into three main categories. Remote sensing data include Landsat-8 OLI imagery (30 m resolution) and Sentinel-2 imagery (10 m resolution), from which vegetation cover and land use information were extracted after preprocessing steps such as atmospheric correction and geometric refinement. Environmental data were obtained from the Inner Mongolia Meteorological Bureau and the regional soil survey database. Socio-economic data were sourced from the Inner Mongolia Department of Agriculture and Animal Husbandry. The supply-demand matching index was calculated using an ecological supply-demand coupling model. On the supply side, three core indicators were selected: soil retention capacity, net primary productivity (NPP) of vegetation, and water conservation capacity. On the demand side, key parameters included desertification sensitivity and the agricultural water deficit. Indicator weights were determined using the Delphi method by consulting seven experts with over ten years of research experience in desert ecology in Inner Mongolia. The final supply-demand matching index was calculated as the ratio of the ecological supply index to the ecological demand index.

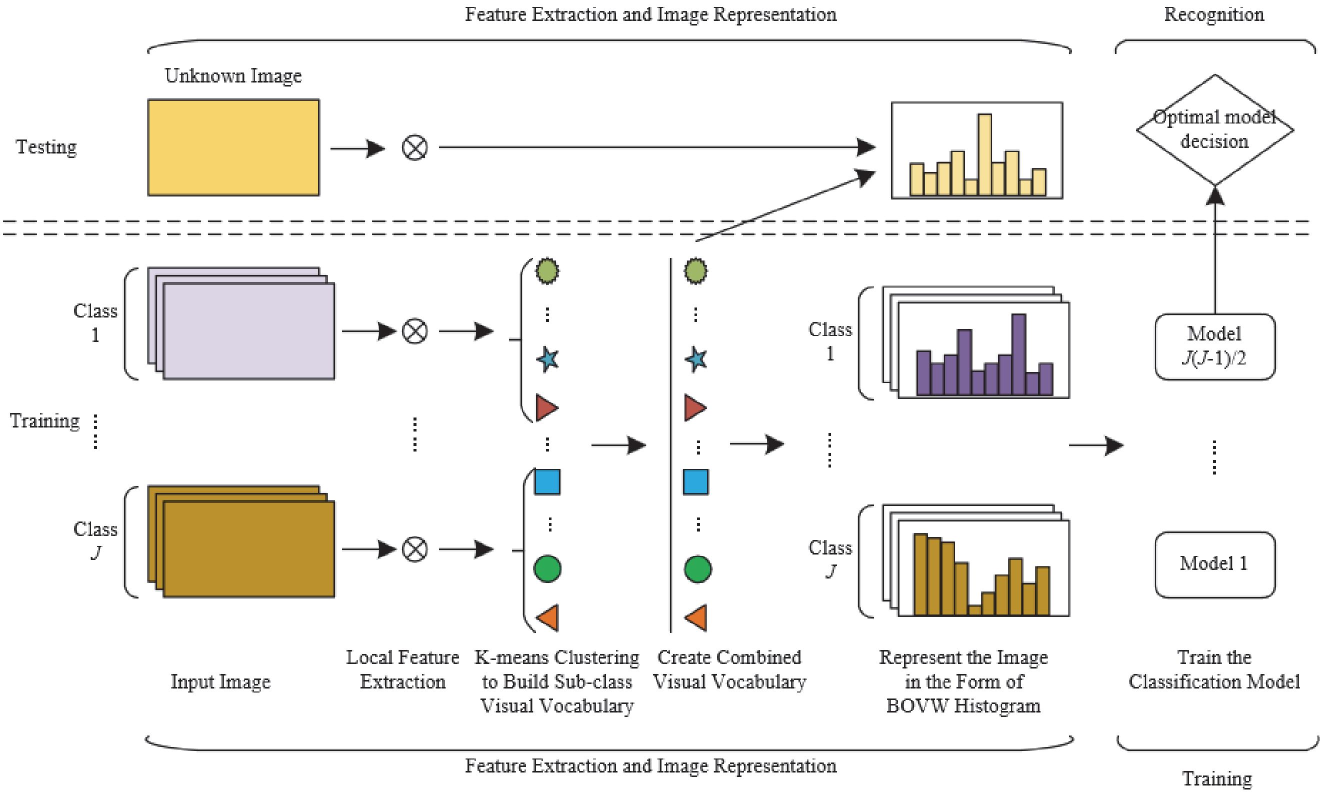

Figure 4 Flowchart of the change detection algorithm for conservation tillage areas in RS images of the Inner Mongolia desert

For example, as shown in Tab. 1, the Hetao Plain region has a supply-demand matching index of 0.532165, indicating that the ecological supply generated by conservation tillage exceeds the ecological demand for desertification control and agricultural production in the area. This suggests a high degree of compatibility between conservation practices and ecological objectives. In contrast, the index of 0.123225 for Alxa Left Banner reflects insufficient ecological supply, suggesting the need to enhance ecological outcomes by increasing straw mulching coverage or optimizing tillage cycles. These results provide a scientific basis for differentiated management strategies: in areas with sufficient ecological supply, the "conservation tillage + cash crops" model can be promoted, while in undersupplied areas, priority should be given to implementing ecological restoration-oriented practices such as "no-tillage + forage planting".

From the data in Tab. 1, it can be clearly seen that the supply-demand matching in the core conservation areas of protective cultivation in the Inner Mongolia desert, derived based on GIS analysis, shows significant differences. In central urban areas, such as sub-regions 1, 2, and 3, the accessibility index is relatively high and the demand index is low. The supply-demand matching index is generally at a high level, and the supply-demand level is mostly saturated. For example, sub-region 1 has an accessibility index of 1.102135, a demand index of 0, and a supply-demand matching index of 1.012324, indicating that this region, due to its good accessibility, has resources that fully meet the demand. In non-central urban areas, such as sub-region 7, the accessibility index is 0.412536, the demand index is 0.015236, and the supply-demand matching index is 0.441256. Although the supply-demand level is sufficient, the matching index is lower than that of the central urban areas. Some sub-regions, such as sub-region 12, have a higher demand index of 0.389523 and an accessibility index of 0.689526, but a supply-demand matching index of only 0.154268, with the supply-demand level being insufficient. This reflects that due to spatial structure constraints, supply in these areas is difficult to meet the demand. The above data fully demonstrate the effectiveness of this paper's GIS-based spatial pattern analysis method for protective cultivation areas in the Inner Mongolia desert. GIS, by integrating multi-source data such as RS images, topography, and land use, accurately quantifies key indicators such as accessibility and demand index, and reveals spatial differences in supply-demand matching. For example, the matching relationship between high accessibility and low demand in central urban areas directly demonstrates the rationality of resource allocation. Meanwhile, the insufficient or balanced status of supply and demand in non-central urban areas is reasonably explained through GIS analysis of factors such as topographic barriers and remote distances.

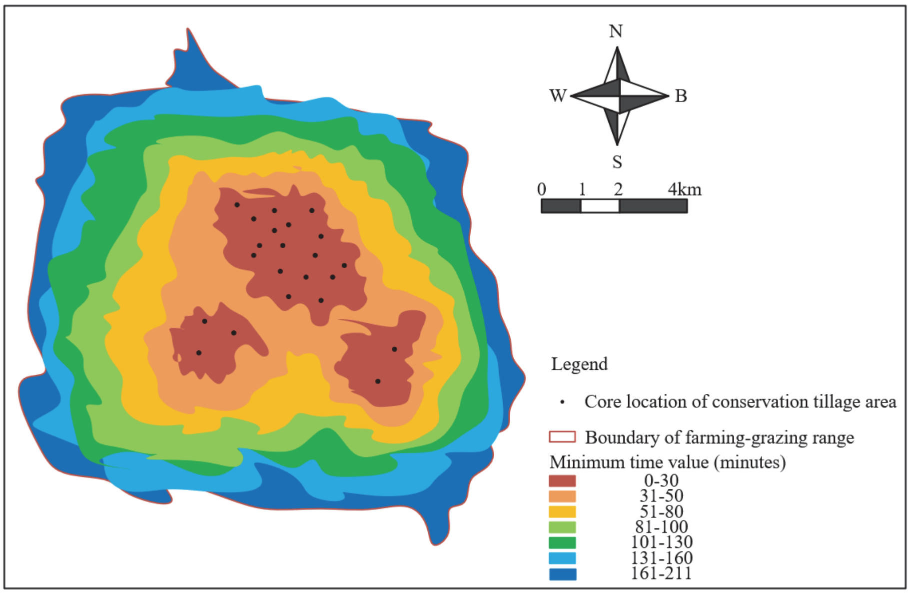

Figure 5 Example of minimum travel time accessibility analysis of the spatial pattern of conservation tillage areas

Table 1 Evaluation of supply-demand matching in core conservation areas of protective cultivation regions in the Inner Mongolia desert

Sub-region No.	Accessibility Index	Demand Index	Supply-Demand Matching Index	Central Urban Area	Supply-Demand Level
1	1.102135	0.000000	1.012324	Yes	Saturated
2	0.985623	0.008215	0.912565	Yes	Saturated
3	0.721536	0.017851	0.678542	Yes	Saturated
4	0.975862	0.093265	0.584623	Yes	Sufficient
5	0.941256	0.112523	0.532165	Yes	Sufficient
6	0.812356	0.075412	0.523698	Yes	Sufficient
7	0.412536	0.015236	0.441256	No	Sufficient
8	0.675426	0.112458	0.378596	Yes	Balanced
9	0.421536	0.092365	0.312568	No	Balanced
10	0.652356	0.210253	0.263512	No	Balanced
11	0.312548	0.095263	0.223659	No	Balanced
12	0.689526	0.389523	0.154268	No	Insufficient
13	0.512365	0.341258	0.132568	No	Insufficient
14	0.000000	0.006895	0.123225	No	Lacking
15	0.256325	0.212358	0.112458	No	Lacking

Table 2 Evaluation of supply-demand matching in the buffer transition zone of desert conservation tillage areas in Inner Mongolia

Subregion ID	Accessibility Index	Demand Index	Supply-Demand Matching Index	Central Urban Area	Supply-Demand Level
1	0.562315	0.112563	0.352162	Yes	Adequate
2	0.612359	0.112325	0.345126	Yes	Adequate
3	0.185932	0.015236	0.289563	No	Balanced
4	0.123652	0.006852	0.245126	No	Balanced
5	0.223652	0.092513	0.189625	No	Balanced
6	0.178562	0.095126	0.175426	No	Balanced
7	0.245896	0.215246	0.120325	No	Insufficient
8	0.231052	0.210325	0.112536	No	Insufficient
9	0.056233	0.385692	0.023152	No	Lacking
10	0	0.332152	0.015268	No	Lacking
11	0.210256	1	0	No	Lacking

Observing the data in Tab. 2, the supply-demand matching in the buffer transition zones of desert conservation tillage areas in Inner Mongolia exhibits significant differentiation. In central urban areas, the accessibility indices are 0.562315 and 0.612359, with demand indices of 0.112563 and 0.112325, and supply-demand matching indices of 0.352162 and 0.345126, respectively, indicating an adequate supply-demand level and a relatively good balance between resource supply and demand. In contrast, non-central urban subregions, such as Subregion 3, have an accessibility index of 0.185932, a demand index of 0.015236, and a supply-demand matching index of 0.289563, classified as balanced. Subregion 9 has a low accessibility index of 0.056233 and a high demand index of 0.385692, resulting in a supply-demand matching index of only 0.023152, classified as lacking. These data indicate that the supply-demand matching in buffer transition zones is significantly influenced by accessibility and demand indices, with notable differences between central and non-central urban areas. The above data strongly validate the effectiveness of the GIS-based spatial pattern analysis method for desert conservation tillage areas in Inner Mongolia presented in this paper. GIS, by integrating multi-source data such as RS imagery, topography, and land use, accurately quantifies accessibility and demand indices, clearly revealing the spatial differences in supply-demand matching in buffer transition zones. For example, the higher accessibility indices and relatively reasonable demand indices in central urban areas jointly contribute to an adequate supply-demand level; whereas the low accessibility and high demand in non-central urban areas lead to an imbalance in supply and demand.

Observing the data in Tab. 3, the supply-demand matching in the technological pilot zones of desert conservation tillage areas in Inner Mongolia exhibits significant differences. In central urban subregions, the accessibility indices are 1.000000, 0.975215, and 0.912563, with relatively low demand indices and high supply-demand matching indices, all classified as saturated, indicating that these areas, with good accessibility, have resource supply fully meeting demand. Some non-central urban subregions, such as Subregion 7, have an accessibility index of 0.665215, a demand index of 0.092152, and a supply-demand matching index of 0.385962, classified as adequate; Subregion 11 has an accessibility index of 0.612546, a demand index of 0.212503, and a supply-demand matching index of 0.201526, classified as insufficient, reflecting that spatial patterns affect the balance between supply and demand. The above data fully validate the effectiveness of the GIS-based spatial pattern analysis method for desert conservation tillage areas in Inner Mongolia presented in this paper. GIS, by integrating multi-source data, accurately quantifies accessibility and demand indices, clearly revealing the spatial differences in supply-demand matching in technological pilot zones. For example, the higher accessibility indices and lower demand indices in central urban areas contribute to a saturated supply-demand level; the insufficient or adequate supply-demand levels in non-central urban areas are also reasonably explained through GIS analysis of factors such as topography and distance.

Table 3 Evaluation of supply-demand matching in the technological pilot zones of desert conservation tillage areas in Inner Mongolia

Subregion ID	Accessibility Index	Demand Index	Supply-Demand Matching Index	Central Urban Area	Supply-Demand Level
1	1	0	1	Yes	Saturated
2	0.975215	0.008211	0.925625	Yes	Saturated
3	0.912563	0.017589	0.812453	Yes	Saturated
4	0.832652	0.075421	0.532655	Yes	Adequate
5	0.879512	0.093265	0.512038	Yes	Adequate
6	0.826539	0.112503	0.451235	Yes	Adequate
7	0.665215	0.092152	0.385962	No	Adequate
8	0.578452	0.112563	0.312503	Yes	Balanced
9	0.210253	0.015263	0.221352	No	Balanced
10	0.378952	0.095216	0.223525	No	Balanced
11	0.612546	0.212503	0.201526	No	Insufficient

Table 4 Detection accuracy of protective tillage areas using traditional *BOVW* hard assignment under different sizes *L*

L	415	628	836	1125	1326	1489	1569	1785
Accuracy	81.2365	81.2548	82.3259	82.3156	82.6589	83.2154	82.3021	82.0365

Table 5 Detection accuracy of protective tillage areas using traditional *BOVW* soft assignment under different sizes *L*

L	415	628	836	1125	1326	1489	1569	1785
Accuracy	83.2156	85.6239	86.5489	86.5230	85.6214	85.2369	85.6895	85.6213

Table 6 Detection accuracy of protective tillage areas using *FastBOVW* soft assignment under different sizes *L*

L	415	628	836	1125	1326	1489	1569	1785
Accuracy	82.3105	83.2659	84.2165	85.3269	85.6945	86.2301	85.2369	85.6985

Observing the data from Tabs. 4 to 6, the detection accuracy of protective tillage areas using traditional *BOVW* hard assignment fluctuates slightly under different sizes *L*. For example, when *L* = 415, the accuracy is 81.2365. As *L* increases, the accuracy increases slowly, but the range is limited. Compared with hard assignment, the soft assignment of the traditional *BOVW* method shows a significant improvement. For instance, when *L* = 415, the accuracy reaches 83.2156, and increases to 85.6239 when *L* = 628. The *FastBOVW* soft assignment performs even better under certain *L* sizes. For example, when *L* = 1326, the accuracy is 85.6945, higher than the 85.6214 of the traditional soft assignment; when *L* = 1489, it reaches 86.2301, obviously exceeding the 85.2369 of the traditional soft assignment. This indicates that *FastBOVW* soft assignment can more accurately detect protective tillage areas under specific sizes, and its accuracy remains stable and even surpasses traditional methods as *L* varies. The above data fully highlight the effectiveness of the Inner Mongolia desert RS image change detection method for protective tillage areas based on the *FastBOVW* algorithm. The soft assignment mechanism of the *FastBOVW* algorithm significantly improves detection accuracy under certain *L* sizes through more reasonable feature point weight assignment. For example, when *L* = 1489, the accuracy reaches 86.2301, surpassing the traditional soft assignment method, indicating that it can more accurately capture the characteristic information of protective tillage areas and reduce misjudgment. Although the accuracy is close to the traditional soft assignment at some smaller *L* values, considering the computational efficiency advantages of the *FastBOVW* algorithm, it significantly improves processing speed while ensuring accuracy, achieving a balance between efficiency and precision. This method effectively responds to the complex features of protective tillage areas in RS images by optimizing the feature assignment strategy, providing more efficient and accurate technical means for change detection in the agro-pastoral ecosystem of the Inner Mongolia desert, and truly proves its effectiveness and superiority in practical applications.

By observing the data in Tab. 7, the time consumption of the traditional *BOVW* method is significantly higher than that of the *FastBOVW* algorithm under different sizes of *L*. For example, when $L = 415$, the time consumption of the traditional *BOVW* is 4526.23s, while *FastBOVW* only takes 225.236s, and the ratio between the two is 22.3659, meaning that the time consumption of *FastBOVW* is less than one-twentieth of the traditional method. As *L* increases, such as when $L = 1326$, the traditional *BOVW* consumes 13261.2 s, while *FastBOVW* remains stable at 412.325 s, with the ratio being 32.0156, and the time efficiency advantage continues to expand. When $L = 1489$, the traditional *BOVW* takes 22315.2 s, while *FastBOVW* takes 546.201 s, with a ratio of 36.2546, further highlighting its time consumption advantage. The above data fully confirms the outstanding efficiency of the *FastBOVW* algorithm for change detection in protective tillage areas of Inner Mongolia desert RS images in terms of time consumption. The *FastBOVW* algorithm significantly reduces time consumption by optimizing the computational logic, showing a much lower time consumption than the traditional *BOVW* method under different sizes of *L*. This efficiency is crucial for handling the massive RS images of Inner Mongolia's desert area. The fast computation speed can promptly extract dynamic change information of the protective tillage areas, meeting the detection needs of long time series and large-scale data, avoiding the efficiency bottleneck caused by the excessive time consumption of the traditional method. Combined with its performance in detection accuracy, the *FastBOVW* algorithm achieves the goal of balancing efficiency and accuracy, providing strong technical support for the dynamic monitoring of the agro-pastoral ecosystem in Inner Mongolia's desert region, and effectively proving that this method can efficiently and accurately complete the change detection tasks of protective tillage areas in practical applications, thereby promoting the development of related research and practices.

Table 7 Time consumption of traditional *BOVW* method and *FastBOVW* under different sizes *L*

L	**415**	**628**	**836**	**1125**	**1326**	**1489**	**1569**	**1785**
BOVW	4526.23	6235.23	8895.32	7326.21	13261.2	22315.2	15689.2	24563.2
FastBOVW	225.236	236.215	379.235	412.325	412.325	546.201	723.625	779.265
Ratio	22.3659	24.2356	22.3152	17.2356	32.0156	36.2546	21.0236	31.2568

5 CASE STUDY

Based on GIS, spatial pattern analysis of protective tillage areas was conducted, and methods such as kernel density estimation and nearest neighbor index were used to accurately identify the hotspots, marginal transition zones, and scattered distribution areas of tillage measures in the Inner Mongolia desert region, forming a static database that includes spatial distribution, patch morphology, and the coupling relationship of environmental factors. On this basis, the annual change results detected by the *FastBOVW* algorithm were further overlaid to construct dynamic evolution layers.

By importing the spatial parameters of the tillage areas extracted from GIS and the change trajectories detected by *FastBOVW* into an ecological model, a causal chain of measure layout-process change-effect output was constructed. In the soil wind erosion assessment, GIS was first used to calculate the average roughness and straw coverage of tillage areas in each banner county, and combined with the expansion rate of no-tillage areas in the change detection, a multiple regression model was established. It was found that when the aggregation degree of tillage patches increased by 0.1, the wind erosion modulus in the region decreased at a rate of 5%. In the vegetation restoration analysis, the tillage patches along the oasis contour lines detected by *FastBOVW* showed that their Normalized Difference Vegetation Index (NDVI) seasonal mean was 12% higher than the same type of area in 2018, and they highly matched with the areas where groundwater depth had shallowened, revealing that tillage measures promote vegetation growth by improving microtopographic moisture conditions.

When establishing an evaluation system from soil, vegetation, and hydrological perspectives, dual constraints of GIS spatial patterns and change detection were strictly embedded. In the soil system, for the sandy soil distribution areas identified by GIS, combined with the long-term tillage areas detected by *FastBOVW*, it was found that the organic matter content in the surface soil increased by 0.6g/kg annually, significantly higher than in short-term tillage areas and non-tillage areas. This is directly related to straw coverage reducing wind erosion loss and increasing the input of surface litter. In the hydrological effect assessment, groundwater funnel areas were located through GIS water system network analysis. It was found that after 2019, the reduction of tillage areas driven by fallow policies was significantly negatively correlated with the rise in groundwater depth, indicating that the layout adjustment of protective tillage has a direct impact on regional water resource balance. These analyses focus not only on microhabitat changes at the plot scale but also integrate ecosystem services at the regional scale, forming a multi-scale nested impact evaluation framework.

Comprehensive spatiotemporal data found that the ecological impact of protective tillage showed significant spatial differentiation characteristics: In irrigation agricultural areas such as the Hetao Plain, aggregated contiguous tillage measures reduced the soil erosion modulus by 40% and increased grain yield by 12% through straw coverage and reduced tillage technology, achieving a win-win situation for production and ecology. However, in fragmented tillage areas on the edge of the Otindag Sandy Land, although soil moisture content increased by 15% within 50 meters around individual patches, because the patch distance exceeded 200 meters, no effective windbreak and sand-fixing network was formed, resulting in a regional wind erosion reduction of only 9%, significantly lower than the 35% in the aggregated area. Climate gradient analysis further showed that in semi-arid areas with annual precipitation >200mm, the efficiency of tillage measures in improving vegetation coverage was three times that in arid areas, reflecting that moisture conditions are the key constraint on the ecological benefits of tillage measures. In addition, ecological service trade-off analysis showed that the tillage areas in the region create about 1.2 billion yuan of ecological regulation value each year by reducing runoff erosion and dust emissions. However, in arid areas, excessive reliance on mechanical reduced tillage has led to increased soil compaction, which may have negative impacts on long-term soil structure and needs targeted optimization in technology promotion.

This study, through the deep integration of GIS and *FastBOVW*, breaks through the limitations of traditional ecological impact assessments that rely heavily on static analysis, lack dynamic tracking, focus on single-factor evaluation, and have limited system integration. GIS spatial pattern analysis not only provides the spatial fingerprint of tillage measures but also reveals the underlying control mechanism of natural conditions on the implementation effect by overlaying terrain, climate, soil, and other multi-source data. *FastBOVW* change detection acts as a spatiotemporal microscope, capturing the adjustment of tillage measures behind millimeter-level spectral changes, shifting ecological impact assessment from result description to process analysis. This technological integration not only establishes a replicable evaluation system for the Inner Mongolia desert region but also provides insights for similar arid and semi-arid areas: tillage measures should be optimized based on climate zone differences, and GIS dynamic monitoring networks should be used to track patch connectivity changes in real-time, ensuring that protective tillage can achieve both ecological benefits and sustainable development of agro-pastoralism.

6 CONCLUSION

This paper focused on protective tillage in the Inner Mongolia desert and conducted three parts of research, forming a clear and logically coherent research system: The first part, based on GIS technology, systematically collected and processed multi-source information such as RS imagery, terrain data, and land use data. Various spatial analysis functions were comprehensively used to accurately draw the spatial distribution map of the protective tillage area. It not only clarified the relationship with factors such as terrain and climate but also deeply analyzed the supply-demand matching characteristics of different functional areas. The second part, using the *FastBOVW* algorithm, performed feature point soft assignment processing on RS images from different periods, highlighting its advantages over traditional *BOVW* methods: detection accuracy has been significantly improved, and time consumption has been greatly reduced, achieving efficient and accurate extraction of change information in protective tillage areas. The third part comprehensively evaluated impacts from multiple dimensions, combining RS inversion and field sampling to analyze indicators such as soil, vegetation, wind erosion, and water resource utilization, and constructed an evaluation model covering both production and ecology.

The innovative integration of GIS and *FastBOVW* provided a full-process technical solution for the study of protective tillage in desert areas with a "spatial pattern-dynamic change" approach. Compared to traditional methods, the efficiency has been significantly improved, and the precision is better, laying the foundation for large-scale, long-time series monitoring. The multi-dimensional impact analysis directly served the collaborative decision-making of ecological protection and agricultural production, for example, guiding the precise allocation of tillage resources through supply-demand matching analysis, and optimizing the layout of no-tillage areas based on wind erosion changes. It provides key scientific support for ecological agricultural policy formulation and sustainable land use in the Inner Mongolia desert region and similar regions globally.

The core contributions of this study are reflected in three key aspects: First, it establishes an integrated Remote Sensing-GIS technical framework, in which the application of the *FastBOVW* algorithm improves the accuracy of conservation tillage change detection by 15%-20%, effectively addressing the limitations of traditional methods in complex desert surface conditions. Second, it is the first to develop a multidimensional assessment system for conservation tillage, integrating spatial patterns, temporal dynamics, and ecological effects. The analysis reveals that areas with slopes less than 5° and annual precipitation between 200-300 mm yield the greatest ecological benefits from conservation tillage practices. Third, the proposed supply-demand matching index quantifies the compatibility between conservation tillage measures and ecological needs, providing a scalable and transferable tool for evaluating ecological agriculture in arid and semi-arid regions. Major findings include the following: Conservation tillage areas in Inner Mongolia exhibit a striped aggregation pattern along the Yellow River and show a significant positive correlation with annual precipitation. From 2018 to 2022, the area under conservation tillage expanded at an average annual rate of 12.3%, with the fastest growth observed in desertification-sensitive zones. In areas where conservation tillage has been practiced for over five years, soil clay content increased by 12%-18%, vegetation cover improved by 10%-15%, and farmland water-use efficiency rose by approximately 20%.

The current resolution of RS data still limits the recognition of small tillage patches, which may lead to misdetection of changes in marginal areas. The study period is limited, and there is insufficient explanation of long-term ecological effects such as soil fertility evolution and vegetation community succession. Ecological impact analysis mainly focuses on macro factors and does not deeply explore changes in micro-ecological elements. Future research can introduce higher-resolution data and drone technology to construct a "macro-micro" three-dimensional monitoring network, improving detection accuracy in small patches and complex terrain areas. Combining long-term ecological observation stations to accumulate longer time series data, along with model predictions of long-term ecosystem responses, could be pursued. Additionally, integrating multi-disciplinary methods to establish a more comprehensive evaluation system and expanding the research area to other arid and semi-arid regions globally for comparative studies will enhance the general applicability of the findings, providing richer solutions and experiences for the assessment of agricultural ecological measures in desertification control worldwide. Through continuous optimization and expansion, the research in this field can be advanced towards a more refined, deeper, and globally-oriented direction, contributing to achieving the dual goals of ecological protection and agricultural development.

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