Analysis of Distribution Characteristics of China' s Agricultural Population Grid Based on Land Use (Postprint)

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Abstract

High-precision research on the spatial distribution of agricultural population constitutes fundamental work for constructing a modern agricultural industry system and holds important decision-making value for cultivating new-quality productive forces in agriculture. Based on county-level data from the Seventh National Population Census of China and the China Land Use Remote Sensing Monitoring Dataset (1 km resolution), this study explores a gridding method for agricultural population and achieves visual representation of China's agricultural population density at a 1 km grid scale, with validation indicators showing good accuracy of the data results. The results demonstrate that: (1) China' s agricultural population exhibits significant differentiation characteristics along the Hu Huanyong Line, with the average grid density in the southeastern half (30.57 people · km^{-2}) being 15.9 times that of the northwestern half (1.92 people · km^{-2}). (2) Agricultural population distribution increases gradiently with the descent of the three topographic steps, with densities of 0.98 people · km^{-2}, 11.27 people · km^{-2}, and 30.76 people · km^{-2}, respectively. (3) Topography and climate in various agricultural zones exert substantial influence on agricultural population distribution, with dense populations in warm and humid low-altitude agricultural areas and relatively sparse populations in cold and arid plateau and hilly agricultural regions. The study recommends implementing differentiated strategies for advancing digital agriculture, focusing on strengthening digital transformation of agriculture in densely populated agricultural areas such as the Huang-Huai Plain region, promoting the integration of characteristic agriculture and tourism in ecologically fragile zones, and accelerating the cultivation of new-type professional farmers.

Full Text

Preamble

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Analysis of Grid Distribution Characteristics of Agricultural Population in China Based on Land Use Data

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Abstract: High-precision spatial distribution research on agricultural population constitutes foundational work for constructing modern agricultural industry systems and holds significant decision-making value for fostering new-quality productive forces in agriculture. Based on county-level data from the Seventh National Population Census and the China Land Use Remote Sensing Monitoring Dataset (CNLUCC2020), this study explores a gridding method for agricultural population and achieves a visual representation of China’ s agricultural population density at the grid scale. Validation metrics demonstrate that the results exhibit good accuracy. The findings reveal: (1) Agricultural population distribution along the Hu Huanyong Line shows significant differentiation, with the southeastern half (density mean: 30.57 persons $\cdot$ km^{-2}) being 15.9 times that of the northwestern half (1.92 persons $\cdot$ km^{-2}). (2) Agricultural population distribution increases gradiently with descending terrain, with densities of 0.98 persons $\cdot$ km^{-2}, 11.27 persons $\cdot$ km^{-2}, and 30.76 persons $\cdot$ km^{-2} across the three topographic steps, respectively. (3) Terrain and climate in each agricultural region substantially influence agricultural population distribution, with warm, humid low-altitude agricultural zones showing dense populations and cold-arid high-altitude plateau and hilly agricultural zones exhibiting relatively sparse populations. The study recommends implementing differentiated digital agriculture promotion strategies, prioritizing agricultural digital transformation in densely populated regions such as the Huang-Huai Plain, promoting integrated agritourism development in ecologically fragile areas, and accelerating the cultivation of new-type professional farmers.

Keywords: agricultural population; land use type; gridding method; Hu Huanyong Line; three-tiered terrain ladder; accuracy verification

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Introduction

Prior to reform and opening up, China’ s agricultural population accounted for over 80% of the total population, making its spatial pattern determinative of overall population distribution. In pioneering works such as “Population Density and Agricultural Regions in Anhui Province” and “Agricultural Production and Population Distribution in Changshu," Hu Huanyong integrated population distribution with factors including cultivated land, agricultural output, terrain, and rainfall, establishing that population distribution largely depended on regional agricultural productivity. With industrialization and urbanization, massive rural surplus labor transferred to non-agricultural sectors, reshaping China' s population distribution. The continuous outflow of rural youth and working-age populations has led to an aging agricultural labor force, increasingly constraining high-quality agricultural development. High-precision agricultural population spatial distribution research is fundamental to building modern agricultural industry systems. Through the lens of agricultural population spatial differentiation, we can deeply understand the human resource spatial patterns of rural revitalization and agricultural modernization. This understanding is crucial for formulating tailored rural revitalization plans, cultivating high-quality professional farmers, and optimizing agricultural resource allocation. Such research can inform differentiated agricultural support policies, promote high-quality agricultural development, and enhance China' s comprehensive agricultural competitiveness.

Current research on agricultural population distribution remains limited. Existing studies primarily employ methods including agricultural population density maps, population distribution structure analysis, population centroids and spatial inequality indices, fractal indices, and population data gridding to explore distribution characteristics. These studies reveal that China' s agricultural population distribution exhibits spatial positive autocorrelation and fractal characteristics with significant spatial imbalance. Agricultural population distribution is closely related to natural geographic conditions, directly influenced by topography and landforms, concentrating in areas with favorable natural conditions. With industrialization and urbanization, agricultural population density has rapidly declined, aggregating in cities through occupational transformation and spatial migration. While existing research provides an important foundation, several improvements are needed. First, previous studies often use "rural population" or "rural registered population" to represent agricultural population. However, "agricultural population" is an economic concept, whereas "rural population" is a geographic concept. In the information and industrial society, many rural populations have become part-time farmers or entered non-agricultural sectors, while some urban populations have acquired "new farmer" identities. Therefore, distinguishing between "rural population"and "agricultural population" is essential for research rigor. Second, existing research primarily analyzes administrative scales such as provincial, district/county, or township levels. While revealing basic distribution characteristics, these approaches cannot capture intra-administrative heterogeneity and suffer from statistical bias due to vastly different administrative areas—the "modifiable areal unit problem" (MAUP) in geographic research. Finally, existing population gridded datasets mainly target total population (e.g., WorldPop, GPW, LandScan), with limited research on specialized populations like agricultural population. High-precision simulation of thematic population data requires methodological and technical improvements.

This study utilizes agricultural population data from China' s Seventh Population Census and 2020 land use data to develop an agricultural population gridding method with good accuracy and verifiable results. We generated 1 km and 10 km agricultural population gridded datasets, with the 1 km dataset clearly displaying detailed distribution information. Compared with existing agricultural population distribution research, this dataset offers higher spatial information expression and resolution, accurately capturing China's agricultural population distribution patterns while effectively avoiding scale mixing issues caused by varying administrative unit sizes. This approach mitigates statistical bias from MAUP and expands methodological and empirical contributions to thematic population gridding research, providing scientific decision-making support for optimizing agricultural resource allocation and promoting high-quality agricultural development and comprehensive rural revitalization.

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1 Study Area Overview

China features complex and diverse topography, with terrain descending eastward across three steps. The Altun, Qilian, and Hengduan Mountains in the west form the boundary between the first and second steps, while the Greater Khingan, Taihang, Wu, and Xuefeng Mountains in the east form the boundary between the second and third steps. Average elevation decreases progressively from west to east across the three steps (Fig. 1). Temperature gradually decreases from south to north, forming five temperature zones (tropical, subtropical, warm temperate, temperate, cold temperate, and the Qinghai-Tibet Plateau vertical zone). Precipitation decreases from southeast to northwest, creating four humidity zones (humid, semi-humid, arid, and semi-arid). Modern agricultural zoning (first-level zoning) reflects regional heterogeneity in agricultural cultivation conditions under the influence of natural geography and socioeconomic factors. Due to data limitations, this study focuses only on Chinese administrative regions (excluding Hong Kong, Macao, and Taiwan).

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2 Data and Methods

2.1 Data Sources

This study employs five main datasets: agricultural population data, administrative boundary data, land use remote sensing monitoring data, three-tiered terrain ladder data, and national modern agricultural zoning data. Agricultural population data were extracted from the "Population by Industry" (long-form) in the 2020 *Seventh National Population Census Data by County*, which sampled 1,035,787 agricultural workers nationwide. Based on the 1.35% sampling rate, we reasonably estimated agricultural population size at the district/county level. China' s 2020 administrative boundary vector data were obtained from the Ministry of Natural Resources Standard Map Service System (http://bzdt.ch.mnr.gov.cn). The China Land Use Remote Sensing Monitoring Dataset (CNLUCC2020) was sourced from the Resource and Environmental Science Data Registration and Publication System. This dataset uses national-scale 1:100,000 land use data, including cropland, forest, grassland, water bodies, urban/rural, industrial/mining, residential land, and unused land. Cropland is further divided into paddy fields and dryland; urban/rural, industrial/mining, and residential land is subdivided into urban land, rural settlements, and other construction land. National modern agricultural zoning (first-level) data were obtained from the research team of *Agricultural Regional Differentiation and Modern Agricultural Zoning Scheme in China*. Three-tiered terrain ladder data were compiled based on existing research.

2.2 Research Methods

Population gridding methods typically use census data or statistical data as a foundation, combined with land use, nighttime light imagery, points of interest (POI), location data, residential attributes, or other social sensing data. Techniques include kernel density estimation, random forest models, and similarity matching models to allocate population data to grid units, thereby mitigating MAUP while enhancing spatial detail. Following existing research, this study converts agricultural population data from administrative units to grid units based on land use types. The gridding process involves four steps: suitable grid selection, land use weight determination, grid density calculation, and grid data visualization.

2.2.1 Suitable Grid Selection Appropriate grid scale enhances spatial representation. Overly large grids reduce spatial expressiveness, while overly small grids fail to improve spatial relationship representation and cause data redundancy. Existing studies select various scales (10 km, 1 km, 500 m, 100 m) depending on research area and purpose. Following Mi et al., we calculated suitable grid size based on minimum administrative area to avoid both excessively large grids that subsume small administrative units and excessively small grids that reduce spatial expressiveness. The formula for suitable grid side length is:

$$g = \sqrt{S_{\min}}$$

where g is the suitable grid side length and $S_{\min}$ is the minimum administrative area. Calculations show $S_{\min} \approx 10\ \text{km}^2$, so g should be less than 1.78 km. To enhance horizontal comparability with existing research, we selected 1 km as the primary grid scale and 10 km for comparative validation. Using the Create Fishnet tool, we generated grids, clipped them by national boundaries, and calculated each grid' s area a_n (where subscript n is the grid ID).

2.2.2 Land Use Weight Determination Determining land use weights is critical for agricultural population gridding. Research indicates rural settlements include living areas of agricultural and pastoral farms, as well as all villages, tents in pastoral areas, and isolated houses in sparsely populated regions —these constitute the basic spaces for agricultural production and living. Paddy fields and dryland are concentrated agricultural production areas; agricultural activity on urban land, other construction land, forest, and grassland is relatively low; agricultural population on water bodies and unused land is sparse but not zero. Using stepwise regression to model county-level agricultural population size against land use types, we found rural settlements have the strongest positive explanatory power, followed by paddy fields, dryland, forest, urban land, and water bodies. Other construction land, grassland, and unused land showed no statistically significant explanatory power. Based on literature review and regression results, we assigned weights using the expert scoring method (Table 1). Weights of 0.9, 0.8, and 0.7 produced similar results. Through simulation comparison, weights of 0.9 provided the most satisfactory fit, reflecting the main spatial characteristics of agricultural population residence and work, and were thus selected as the optimal weighting scheme.

2.2.3 Density Calculation Formula Overlaying land use data, county administrative data, and 1 km grid data yields minimum polygons with unique administrative (i), land use (j), and grid (n) attributes. Calculating minimum polygon area a_m (where subscript m is the polygon ID) and summarizing yields county i' s area of land use type j (a_{ij}). The agricultural population density D_{ij} for county i and land use type j is:

$$D_{ij} = \frac{p_i \times f_j}{a_{ij} \times \sum_j f_j}$$

where p_i is the agricultural population of county i from census data; f_j is the weight of land use type j; $a_{ij} \times f_j$ is the weighted area; and $p_i / \sum_j a_{ij} \times f_j$ is the baseline density when agricultural population is uniformly distributed across weighted area.

2.2.4 Grid Data Visualization Assigning corresponding D_{ij} values to each minimum polygon based on its administrative and land use attributes, we multiplied D_{ij} by a_m to obtain agricultural population counts (p_m) for each polygon. Summarizing by grid attribute (n) yielded agricultural population counts (p_n) per grid. Dividing p_n by grid area (a_n) produced agricultural population density (D_n) per grid. Finally, we applied natural breaks classification with manual adjustment of upper/lower bounds to create agricultural population density maps, achieving spatial visualization of gridded agricultural population data.

3 Results

3.1 Agricultural Population Distribution Across the Hu Huanyong Line

Using the Hu Line as a boundary, we analyzed spatial differentiation patterns of China's agricultural population distribution (Fig. 2). Under the influence of natural factors including topography, altitude, monsoon climate, temperature, and precipitation, the southeastern half of the Hu Line possesses relatively higher agricultural productivity and population carrying capacity, resulting in higher agricultural population density. Conversely, influenced by high altitude, mountainous terrain, arid/semi-arid conditions, and alpine climate, agriculture in the northwestern half focuses on animal husbandry and specialty crops, with overall low agricultural population density concentrated in locally favorable areas such as plains, river valleys, terraces, basins, and oases. Densities are extremely sparse on the Qinghai-Tibet Plateau, in desert zones, ecological protection areas, and water source conservation zones. Overall, under multiple natural factors including temperature, precipitation, topography, and altitude, the Hu Huanyong Line serves not only as a crucial demarcation for China' s total population but also for agricultural population distribution, showing a clear "high east, low west" pattern.

Statistics for land area, per capita cultivated land, and agricultural population density across the Hu Line (Table 2) reveal that the southeastern half, with 42.65% of national territory, contains 98.14% of paddy fields and 92.22% of dryland, concentrating 77.86% of agricultural population at a density of 30.57 persons $\cdot$ km^{-2} and per capita cultivated land of 1.18 hm^2. The northwestern half, with 57.35% of territory, has only 1.86% of paddy fields and 7.78% of dryland, supporting just 22.14% of agricultural population at a density of 1.92 persons $\cdot$ km^{-2} and per capita cultivated land of 2.86 hm^2.

3.2 Agricultural Population Distribution Across the Three-Tiered Terrain Ladder

To analyze distribution characteristics across China' s three topographic steps, we created agricultural population density contour maps based on 1 km gridded data (Fig. 3). Contour mapping, introduced from geology, meteorology, and hydrology, connects areas with equal population density to concisely reflect distribution patterns. Contour density indicates population concentration changes —dense contours signify significant variation, while sparse contours indicate uniform distribution. Closed contours denote high- or low-value centers, identified by color and scale.

The three terrain steps show markedly different agricultural population distributions. The first step has very sparse, few contours, indicating low and relatively uniform density. The second step shows varying contour density, reflecting significantly increased density with substantial spatial variation. Northern areas of the second step have relatively insufficient hydrothermal conditions with sparser contours, while central-southern areas with good hydrothermal conditions show denser contours and numerous closed centers, indicating intense density variation and several high-density zones. The third step has the densest contours with clear regional differences: northern areas are cold with complex terrain and dramatic density variation; central plain regions contain several peak density zones; southern hilly areas with good hydrothermal conditions have relatively high but alternating peak-valley densities due to terrain. Overall, altitude significantly influences agricultural population distribution, with density increasing as the three-tiered terrain descends, making the terrain step boundaries important demarcations for agricultural population distribution.

Statistics across the three terrain steps (Table 3) show the first step (27.71% of territory) contains only 0.20% of paddy fields and 2.35% of dryland, supporting 1.92% of agricultural population at 0.98 persons $\cdot$ km^{-2}. The second step (43.13% of territory) has 34.47% of paddy fields and 22.55% of dryland, supporting 29.16% of agricultural population at 11.27 persons $\cdot$ km^{-2}. The third step (29.16% of territory) contains 65.33% of paddy fields and 77.25% of dryland, with favorable hydrothermal conditions supporting 63.61% of agricultural population at 30.76 persons $\cdot$ km^{-2}. Overall, agricultural population differentiation across terrain steps is primarily influenced by altitude and closely related to cultivated land proportion and agricultural conditions.

3.3 Agricultural Population Distribution by Agricultural Region

Based on China' s modern agricultural first-level zoning, we examined spatial differentiation characteristics (Fig. 4). Results show significant inter-regional differences and clear spatial agglomeration patterns (Table 4). The Huang-Huai Plain Region and Beijing-Tianjin-Hebei-Shandong Plain-Hill Region have the densest populations due to flat terrain and fertile soil. The Sichuan Basin Region, South China Tropical Crop Region, and Middle-Lower Yangtze Plain Region have high concentrations due to low average elevation, good hydrothermal conditions, and developed irrigation agriculture. The Southeast Coastal Hill Region has relatively dense populations with tea, fruit, and rice cultivation. The Yunnan-Guizhou Plateau Region has complex topography with alternating dense and sparse areas. The Northeast Plain Region has dense populations in the Songnen and Liaohe Plains despite low average temperatures. The Northeast Mountain-Hill Region, Inner Mongolia Plateau Region, Gansu-Xinjiang Desert Plateau Region, and Qinghai-Tibet Plateau Region have the lowest densities due to cold-arid climates and complex terrain.

Statistical analysis (Table 4) shows the Huang-Huai Plain Region (7.47% of territory) has 11.98% of paddy fields and 13.97% of dryland, concentrating 12.70% of agricultural population at the highest density of 51.86 persons $\cdot$ km^{-2}. The Beijing-Tianjin-Hebei-Shandong Plain-Hill Region (3.41% of territory) has 2.97% of dryland, supporting 0.54% of agricultural population at the second-highest density of 48.12 persons $\cdot$ km^{-2}. The Qinghai-Tibet Plateau Region (24.07% of territory) has only 0.43% of dryland, supporting just 1.97% of agricultural population at the lowest density of 2.51 persons $\cdot$ km^{-2}. Overall, agricultural population distribution across agricultural regions is closely related to cultivated land area, average elevation, topography, and hydrothermal conditions.

3.4 Validation

3.4.1 Weight Scheme Effectiveness Validation To examine how weight assignments affect accuracy, we created agricultural population density maps under different weight schemes (Fig. 5). While weight schemes 0.8, 0.7, and 0.9 show minor differences in detail, all reflect the main spatial characteristics of China' s agricultural population distribution without significant variation due to weight settings.

Following Xiao et al., we validated dataset quality by aggregating gridded data to the district/county scale and comparing with census data, calculating absolute and relative estimation errors:

$$\mathrm{AEE}_i = |\mathrm{PE}_i - P_i|$$

$$\mathrm{REE}_i = \frac{\mathrm{PE}_i - P_i}{P_i} \times 100\%$$

where AEE_i is absolute error, PE_i is estimated agricultural population, P_i is census value, and REE_i is relative error. We defined critical thresholds: $\mathrm{REE}_i \leq -10\%$ indicates severe underestimation; $(-10\%, -5\%]$ indicates underestimation; $(-5\%, 5\%]$ indicates correct estimation; $(5\%, 10\%]$ indicates overestimation; $\mathrm{REE}_i > 10\%$ indicates severe overestimation.

Spatial distribution of relative errors under different weight schemes (Fig. 6) shows that weight scheme 0.9 correctly estimates 90.16% of administrative units, with 4.80% severely underestimated/overestimated. Weight schemes 0.8 and 0.7 correctly estimate 90.55% and 89.85% of units, respectively, with 4.72% and 5.00% severely estimated. All three schemes show good consistency with census data without systematic bias.

To further assess reliability, we calculated RMSE, MAE, MAPE, and correlation coefficient (r):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathrm{PE}_i - P_i)^2}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|\mathrm{PE}_i - P_i|$$

$$\mathrm{MAPE}=\frac{1}{N}\sum_{i=1}^{N}\left|\frac{\mathrm{PE}_i-P_i}{P_i}\right|\times 100\%$$

All metrics show good performance (Table 5), with r close to 1, indicating high accuracy. Weight scheme 0.9 achieves the highest precision.

3.4.2 Grid Scale Effectiveness Validation To validate grid scale effectiveness, we created agricultural population distribution maps at 1 km, 10 km, and 50 km scales (Fig. 7). All scales reflect main distribution patterns, but 1 km grids provide stronger texture and detail. As grid scale increases, spatial variability weakens and detail information is lost. The 1 km grid shows peak densities up to 51.86 persons$\cdot$km^{-2}, with mean and standard deviation decreasing as grid side length increases, demonstrating that larger grids significantly reduce spatial detail.

Spatial distribution of relative errors at different scales (Fig. 8) shows that correctly estimated administrative units ($-5\% < \mathrm{REE}_i \leq 5\%$) account for 90.55% at 1 km, 47.24% at 10 km, and 31.32% at 50 km. Severely estimated units ($\mathrm{REE}_i \leq -10\%$ or $\mathrm{REE}_i > 10\%$) account for 4.80%, 13.97%, and 73.38%, respectively, indicating significantly decreasing accuracy with increasing grid scale.

Calculating RMSE, MAE, MAPE, and r across scales (Table 6) confirms that the 1 km scale achieves the highest r and lowest errors, while 50 km scale shows significantly reduced accuracy. This demonstrates that selecting an appropriate grid scale is crucial for dataset precision.

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4 Discussion

4.1 Conclusions

This study yields three primary conclusions: (1) China' s agricultural population distribution exhibits significant spatial heterogeneity, with the Hu Huanyong Line serving as a crucial demarcation. The southeastern half has abundant paddy fields and dryland, supporting 77.86% of agricultural population, while the northwestern half has limited cultivated land and poor hydrothermal conditions, supporting only 22.14% of agricultural population. (2) Average elevation importantly influences distribution, causing agricultural population density to increase progressively across the three terrain steps. Within each step, density is affected by topography and temperature-precipitation patterns: plains and basins show higher densities, while mountains and hills are sparsely populated; warm, water-rich areas have higher densities than cold-arid regions. (3) Under natural geographic, socio-economic, and locational factors, agricultural regions show significant differentiation. High-density regions include the Huang-Huai

Plain and Beijing-Tianjin-Hebei-Shandong Plain-Hill regions; low-density regions include Northeast Mountain-Hill, Inner Mongolia Plateau, Gansu-Xinjiang Desert Plateau, and Qinghai-Tibet Plateau regions. Industrialization and urbanization have reduced agricultural population densities in major city centers.

4.2 Recommendations

Based on these findings, we propose three policy recommendations: (1) West of the Hu Line, where ecological environments are fragile with limited cultivated land and agricultural population, we recommend building water conservancy facilities where feasible, reclaiming deserts and swamps into arable land, enhancing ecological functions, and promoting integrated agritourism. East of the Hu Line, with abundant cultivated land and high agricultural population density, we recommend accelerating agricultural digitalization, developing agricultural socialized services, and supporting smallholders' integration into modern agricultural cooperation systems. (2) On the first terrain step with extremely fragile ecology and low agricultural population density, prioritize ecological protection while developing characteristic ecological agriculture and agritourism. On the second step with better agricultural resources and higher population density, accelerate soil improvement and farmland transformation, develop smart agriculture, and enhance mechanization. On the third step with the best cultivation conditions and highest population density, advance high-standard farmland construction and promote primary-secondary-tertiary industry integration. (3) Given significant differences in agricultural resource endowments across regions, we recommend differentiated and flexible agricultural policies tailored to each region. Promote agricultural digitalization adapted to local terrain and climate conditions, develop digital agricultural tools, train farmers in digital literacy, cultivate new-type professional farmers, and prioritize digital transformation in high-density regions like the Huang-Huai Plain and Beijing-Tianjin-Hebei-Shandong Plain-Hill areas.

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