

Methodology of the Dataset Development of the Crop Planting Structure for Changji Prefecture, Xinjiang (2020–2024)

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Abstract: Crop planting structure is a vital indicator reflecting regional agricultural cultivation patterns and serves as a crucial foundation for agricultural resource monitoring, food security assessment, and refined cropland management. Changji Prefecture in Xinjiang, as an important agricultural production base in China, is characterized by diverse cropping patterns and abundant crop varieties. This dataset focuses on Changji Prefecture, Xinjiang—a typical irrigated agricultural region—and integrates time-series Sentinel-2 optical and Sentinel-1 radar data to develop a crop classification model (Multi-source Spatial-Temporal-Phenological Integration, MSTPI), from which the Changji Prefecture crop planting structure dataset (2020–2024) was derived. The data reveals the impact of the expansion of cash crops on ecological irrigation areas, in the context of water resource red-line policies, providing a benchmark for sustainable agricultural policy assessment in arid regions and supporting food security analysis in Central Asia along the Belt and Road Initiative. The dataset has a spatial resolution of 10 m and temporal resolution of 1 year, documenting the crop planting structure of Changji Prefecture, Xinjiang from 2020 to 2024. The dataset consists of 4 files with a total data volume of 245 MB (97.8 MB compressed).

Keywords: cropping structure; crop classification; MSTPI model; multi-source remote sensing features

DOI: <https://doi.org/10.3974/geodp.2026.02.09>

Dataset Availability Statement:

The dataset supporting this paper was published and is accessible through the *Digital Journal of Global Change Data Repository* at: <https://doi.org/10.3974/geodb.2025.10.01.V1>.

1 Introduction

Crop planting structure is a fundamental aspect of agricultural geography and sustainable development research, involving the spatial combination, layout and proportions of different crop types in a specific region^[1]. It reflects the spatial distribution and combination patterns of major crop types and their spatial distribution characteristics in a specific region or

Received: 05-11-2025; **Accepted:** 12-03-2026; **Published:** 25-04-2026

Foundation: Department of Science and Technology in Fujian (2023I0007)

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Data Citation: [1] Yu, L. X., Wang, X. Q., Zhang, H. Y., *et al.* Methodology of the dataset development of the crop planting structure for Changji Prefecture, Xinjiang (2020–2024) [J]. *Journal of Global Change Data & Discovery*, 2026, 10(2): 191–201. <https://doi.org/10.3974/geodp.2026.02.09>.

[2] Yu, L. X., Wang, X. Q., Zhang, H. Y., *et al.* A plot-level cropping structure dataset based on Sentinel images and phenology information in Changji Prefecture, Xinjiang Uygur Autonomous Region of China (2020–2024) [J/DB/OL]. *Digital Journal of Global Change Data Repository*, 2025. <https://doi.org/10.3974/geodb.2025.10.01.V1>.

agricultural unit, which not only reflects the diversity of crop types but also reveals their distribution pattern in geospatial space, and is an important basis for understanding the regional differences in agricultural activities and guiding agricultural management decisions^[2]. Existing planting structure datasets mainly focuses on the extraction of planting structure over a small area, fewer crop types or a single inter-annual period, e.g., Guo, *et al.*^[3] constructed a high-precision remote sensing classification dataset of cash crops (apple, kiwifruit, etc.) in Yangling Demonstration Area with a spatial resolution of 2 m and an overall classification accuracy of 86.17%, which provides data support for the monitoring of orchards in Guanzhong Plain and the research of related algorithms. Zhang, *et al.*^[4] used Sentinel-2 and Google Earth to construct a 10-m resolution planting structure fine mapping dataset of 8 types of crops (rice, maize, etc.) in 2020 in Ningxia's Huangyang Irrigation District. Zhao, *et al.*^[5] constructed a 10-m resolution dataset of 8 types of crops (rice, maize, etc.) in 2018–2022 in the Loess Plateau based on the Sentinel-2 image. You, *et al.*^[6] used Sentinel-2 images to generate a 10-m resolution maize, rice, and soybean planting distribution map in Northeast China from 2017 to 2019 with an overall accuracy of $\geq 81\%$, soybean planting distribution maps with an overall accuracy of 0.81–0.86, which can support regional food security monitoring.

As an important agricultural production base in China, Changji Hui Autonomous Prefecture (hereinafter referred to as “Changji Prefecture”) in Xinjiang has a diverse agricultural cropping structure with a wide variety of crops, and most of them are planted in a large-scale and continuous manner, making the region suitable for plot-level crop classification. To accurately extract the plot-scale crop information in this region, it is necessary to fully synthesize the spatial, temporal, and climatic characteristics of remote sensing images. Among them, crop phenology characteristics can be captured by time series remote sensing data, which helps to distinguish different crop types. Multi-source remote sensing data fusion technology shows unique advantages in this process, for example, SAR remote sensing has the ability of all-weather observation, which can effectively overcome the limitations of optical remote sensing under cloudy and foggy conditions and provide stable and continuous observation data^[7,8]. In addition, the Time-Weighted Dynamic Time Warping (TWDTW) algorithm has been widely used and achieved good results in the identification of temporal features in the crop phenology cycle^[9,10]. In terms of spatial feature extraction, SegFormer, a semantic segmentation model based on the Transformer structure, has been preliminarily applied to the remote sensing crop classification task, which shows a large potential for application^[11,12].

Therefore, this paper utilizes multi-source medium-resolution time-series optical remote sensing and SAR remote sensing data, integrates the advantages of spatial, temporal and crop phenology features, constructs a plot-scale oriented multi-temporal and spatial phenology feature fusion crop classification model, and extracts the crop planting structure dataset for the period of 2020–2024, with a spatial resolution of 10 m, using Changji Prefecture of Xinjiang as the study area. The time span is 5 years, aiming to provide scientific basis and decision support for precision agriculture practice and sustainable development of regional agriculture.

2 Metadata of the Dataset

The metadata of A plot-level cropping structure dataset based on Sentinel images and phenology information in Changji Prefecture, Xinjiang Uygur Autonomous Region of China (2020–2024)^[13] is summarized in Table 1. It includes the dataset full name, short name, authors, year of the dataset, temporal resolution, spatial resolution, data format, data size, data files, data publisher, and data sharing policy, etc.

Table 1 Metadata summary of A plot-level cropping structure dataset based on Sentinel images and phenology information in Changji Prefecture, Xinjiang Uygur Autonomous Region of China (2020–2024)

Items	Description
Dataset full name	A plot-level cropping structure dataset based on Sentinel images and phenology information in Changji Prefecture, Xinjiang Uygur Autonomous Region of China (2020–2024)
Dataset short name	PLOTS_CRSP_XJ2020_24
Authors	Yu, L. X., The Academy of Digital China (Fujian), Fuzhou University, 245527021@fzu.edu.cn Wang, X. Q., The Academy of Digital China (Fujian), Fuzhou University, wangxq@fzu.edu.cn Zhang, H. Y., The Academy of Digital China (Fujian), Fuzhou University, 892169168@qq.com Liu, H. W., The Academy of Digital China (Fujian), Fuzhou University, 235527039@fzu.edu.cn
Geographical region	Changji Hui Autonomous Prefecture, Xinjiang Uygur Autonomous Region, China
Year	2020–2024
Temporal resolution	Year
Spatial resolution	10 m
Data format	.tif, .txt
Data size	97.8 MB (after compression)
Data files	Plot-level cropping structure dataset in Changji Prefecture (2020–2024)
Foundation	Department of Science and Technology in Fujian (202310007)
Data publisher	Global Change Research Data Publishing & Repository, http://www.geodoi.ac.cn
Address	No. 11A, Datun Road, Chaoyang District, Beijing 100101, China
Data sharing policy	(1) <i>Data</i> are openly available and can be free downloaded via the Internet; (2) End users are encouraged to use <i>Data</i> subject to citation; (3) Users, who are by definition also value-added service providers, are welcome to redistribute <i>Data</i> subject to written permission from the GCdataPR Editorial Office and the issuance of a <i>Data</i> redistribution license; and (4) If <i>Data</i> are used to compile new datasets, the “ten percent principal” should be followed such that <i>Data</i> records utilized should not surpass 10% of the new dataset contents, while sources should be clearly noted in suitable places in the new dataset ^[14]
Communication and searchable system	DOI, CSTR, Crossref, DCI, CSDC, CNKI, SciEngine, WDS, GEOSS, PubScholar, CKRSC

3 Methods

This dataset is based on Sentinel-2 time-series optical imagery and Sentinel-1 SAR data from 2020–2024 provided by Google Earth Engine (GEE)¹. By integrating the advantages of spatial, temporal, and crop phenological information with a parcel-scale multi-spatial-temporal-phenological feature fusion crop classification model (MSTPI), crop classification and planting structure extraction were conducted for Changji Prefecture, Xinjiang. Subsequently, field survey data collected by the research team in Changji Prefecture, Xinjiang in July 2024 were utilized for accuracy validation of the 2024 results.

3.1 Study Area

The study area is Changji Prefecture located in northern Xinjiang Uygur Autonomous Region, China. It is situated between the northern piedmont of the Tianshan Mountains and the southeastern margin of the Junggar Basin, with geographical coordinates ranging from 43°20'N to 45°00'N and 85°17'E to 91°32'E. The prefecture is divided into eastern and western sections by Urumqi City. The terrain is characterized by higher elevations in the south and lower elevations in the north, with a temperate continental arid climate.

Cropland is primarily distributed in the alluvial plain areas within the region, where

¹ Google Earth Engine. <https://earthengine.google.com/>.

agricultural production is dominated by irrigated agriculture. Major crops include cotton, wheat, maize, tomato, beet, pepper, edible seed watermelon, and seed gourd. The typical phenological information for these crops is presented in Table 2, providing phenological parameters for subsequent time-series remote sensing classification.

Table 2 Phenological stages and key temporal windows for major crops

Crop	Phenological information
Cotton	Sown in April; buds in June; flowers in July; bolls open August–October; growth ends late October
Wheat	Winter wheat: sown in September–October; regreens in March after overwintering; heads in May; matures in June–July
Maize	Spring wheat: sown in March–April; heads in May–June; matures in July–August
Tomato	Sown in April; enters jointing stage in June; tassels in late July; matures in early September
Beet	Seedlings raised in greenhouses in March; transplanted in late April to early May; fruit formation begins in June; matures gradually in August
Edible seed watermelon	Sown in April; enters vigorous growth in June; root enlargement and sugar accumulation in mid-September; matures in late October
Chili pepper	Sown from late April to early May; flowers in mid-June; matures from mid-August to early September
Seed gourd	Seeded in March; transplanted in April–May; fruiting begins in July; harvested from August to October depending on variety and cultivation conditions
	Sown in April; rapid growth in June; leaves yellow by late July; matures and harvested in September

3.2 Algorithm

The classification model employed in this dataset is a two-branch crop classification model (MSTPI), consisting of a TWDTW branch and a SegFormer branch, which integrates the classification results through a rule-driven plot-level weighted fusion module to achieve high-precision plot-level crop identification for extracting cropping structures. Figure 1 shows the MSTPI model framework.

(1) TWDTW branch

The DTW algorithm^[15] is a method used to measure the similarity of 2 time series by allowing nonlinear distortions on the time axis to find the optimal matching paths, and to achieve sequence alignment even if there are differences in time scales. TWDTW is an algorithm improved by the DTW algorithm, based on which the temporal weighting mechanism is introduced, which further enhances the reasonableness of the matching and the classification accuracy.

(2) SegFormer branch

SegFormer is a lightweight semantic segmentation architecture designed under the Transformer architecture, which adopts a hierarchical encoder + MLP decoder design without positional coding, and takes into account multi-scale feature extraction and efficient reasoning, and realizes high-precision segmentation in multiple scenarios. It is capable of strong context modeling and multi-scale feature fusion in remote sensing image processing, and can accurately capture spatial texture and structural features in remote sensing images.

(3) Rule-driven plot-level weighted fusion

The rule-driven plot-level weighted fusion integrates multi-source remote sensing crop classification results, with plots serving as the basic unit; then rules are formulated based on the image confidence, plot features and neighborhood consistency to compute the image-plot-level weights; finally, multi-source labels are fused with weights within the plots to output a high-precision crop structure map of the plots, which is significantly better than that of the image-level method.

3.3 Synergistic Mechanism of Crop Classification Based on MSTPI Model

The technical route for generating the 2020–2024 crop planting structure dataset of Xinjiang Changji Prefecture using the MSTPI model is shown in Figure 2. Firstly, Sentinel-2 true-color

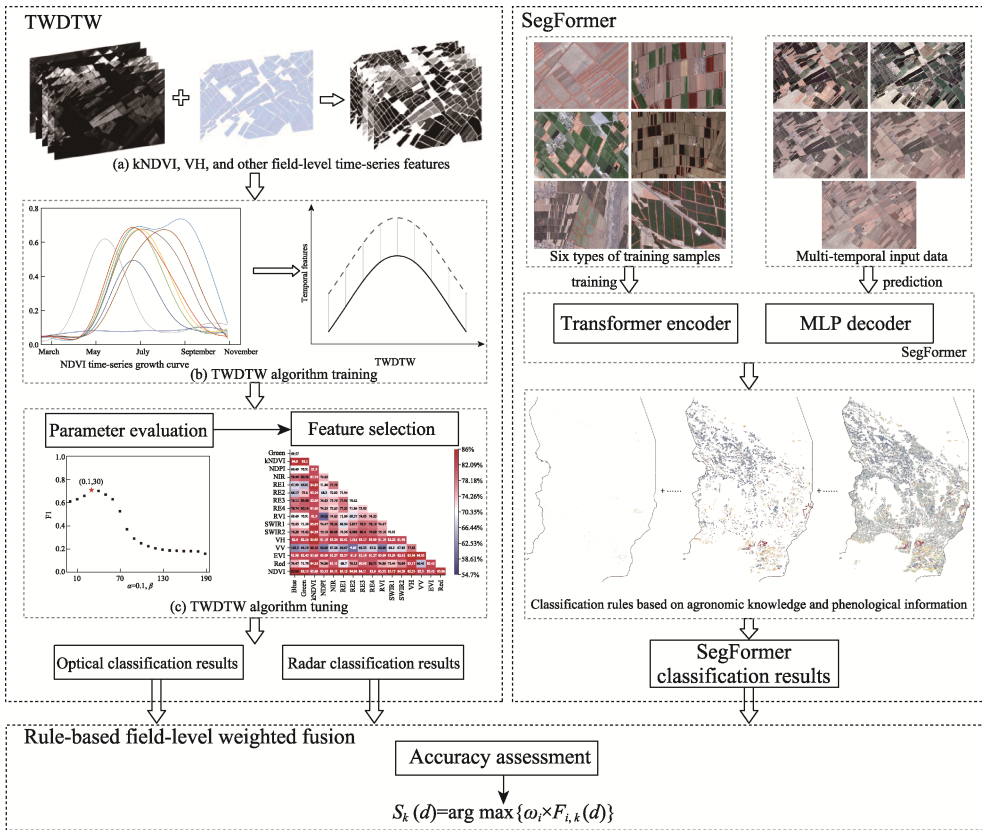


Figure 1 Schematic framework of the MSTPI model

images were used to automatically extract farmland plot boundaries in the CLCFormer model to form a plot-level spatial unit base. Then the Sentinel-2 multi-temporal image is combined with crop phenology features to construct a multi-temporal phenology knowledge classification framework, label the samples, and use the SegFormer model to generate preliminary crop classification results. The optical and radar remote sensing data are then integrated to construct an optical-radar temporal feature database, and the TWDTW algorithm is applied to optimize the temporal weight parameters to find the optimal feature combination with kNDVI and VH. Then the multi-temporal RGB imagery, radar time series and optical time series are fused to generate classification results by SegFormer and TWDTW dual branching, respectively, and finally crop classification mapping is completed based on the rule-driven weighted fusion method at the plot level to complete the extraction of planting structure for crop classification of consecutive years from 2020 to 2024.

(1) Farmland plot information extraction

Long, et al.^[16] proposed the cross-learning network CLCFormer, which effectively integrates the advantages of Convolutional Neural Network (CNN) and Transformer to realize the effective fusion of spatial detail features of the image with the long-range contextual features. This dataset utilizes the model to extract parcel data and carry out classification with parcel-scale mean features. The parcel samples are manually labeled based on Sentinel-2 true-color images, combined with data enhancement and the introduction of samples from Denmark, the Netherlands, and Korla, Xinjiang, to improve the model generalization ability. The extraction process adopts a county-by-county strategy, using the previous corrected samples to continuously optimize the extraction accuracy.

The preliminary extraction results are post-processed by morphological processing, image quality optimization (denoising and hole filling), boundary smoothing of the Douglas-Peoke

algorithm and manual refinement, etc., and ultimately obtain complete and clear-bordered farmland parcel data within the scope of Changji Prefecture.

(2) Multi-temporal primary classification and sample construction

Using agricultural knowledge and crop phenology information, 5 Sentinel-2 images from June to October 2022 were selected to construct 6 typical color training sample sets, which are: class A (gray and white), class B (yellow and brown), class C (dark green), class D (green), class E (light green), and class F (red). The classification weights corresponding to each color category are obtained by training 6 sets of SegFormer sub-models. The time-series sample set of 396 plots (8 crop categories + bare ground) was constructed with Hutubi County as a typical district in 2022, and the growth curve extract weather characteristics were fitted by the GAM (Generalized Additive Model). Finally, cross validation was performed with the results of field survey in 2024. samples from other regions in 2020–2023 were obtained through stratified sampling.

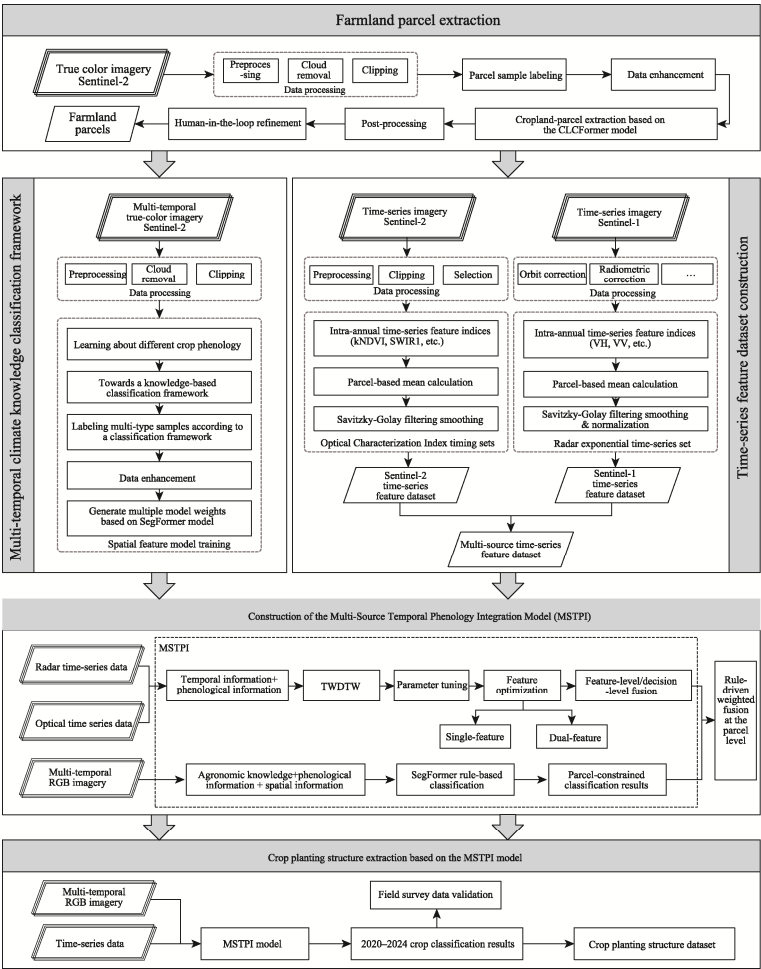


Figure 2 Flowchart of the dataset development

(3) Dual-branch synergistic classification and rule-driven weighted fusion at the plot level

Crop classification was performed in the SegFormer branch and the TWDWT branch using the constructed samples described above.

In the SegFormer branch a classification scheme is developed based on the typical climatic characteristics of different crops by using the 6 categories of color training samples

divided earlier, specifying the required time phases and corresponding weight settings. Subsequently, for a specific crop, the images of the corresponding month are selected according to the scheme, and the weights of the specified categories are applied to perform binary classification, so as to obtain multi-temporal crop-background binary classification results, and the classification accuracy is further improved by screening the stable features through the superposition of multi-temporal phases.

In the TWDTW branch, the 2 feature combinations of VH and kNDVI are selected as the classification features, and the similarity between the plots and the standard growth curves is calculated by using the TWDTW algorithm based on the temporal feature dataset constructed above to realize crop classification.

Finally, the results of the above 2 branches are subjected to rule-driven plot-level weighted fusion based on the specific process of calculating the F1 scores of the outputs of SegFormer and TWDTW on each crop category in terms of plots, and then assigning weights for fusion on this basis.

(4) Accuracy validation

By combining the 2024 fieldwork data for accuracy evaluation, this dataset uses Overall Accuracy (OA) and F1 scores as the core indexes to comprehensively measure the model's classification effect and generalization ability in complex agricultural regions.

4 Data Results and Validation

4.1 Dataset Composition

The dataset includes crop planting structure data for Changji Prefecture, Xinjiang spanning from 2020 to 2024, including annual crop spatial distribution data with a spatial resolution of 10 m in raster format, archived as .tif and .txt files.

4.2 Data Results Analysis

The crop cultivation structure of Xinjiang Changji Prefecture in 2020–2024 was extracted, primarily the 8 types of crops with the largest cultivation area, which were cotton, wheat, maize, tomato, beet, edible seed watermelon, pepper, and seed gourd, as well as the 2 types of cultivated land, namely other cultivated land and bare land. Its crop distribution map is shown in Figure 3. The regional characteristics of crop spatial distribution in Changji Prefecture are clearly evident, with wheat and corn dominating in the east, cotton dominating in the west, and cash crops interspersed in the south-central part of the state, which is overall consistent with the planting layout of “western cotton, eastern grain, and central gourds and vegetable”^[17].

Among the various crops accounted for as shown in Figure 4, it can be seen that cotton, wheat and maize are the main crops in Changji Prefecture, of which cotton has the largest planted area, wheat and maize are the second largest, and there is not much difference between the two planted areas. The remaining five crops are planted on a smaller area. Among these five cash crops, edible seed watermelon has the largest acreage, tomato and pepper have similar acreage due to crop rotation requirements, and beet has the smallest acreage.

Table 3 shows the statistics of crop cultivation area in Xinjiang Changji Prefecture from 2020 to 2024. Among them, the overall trend of the planted area of wheat and maize is decreasing, with the area of wheat decreasing from 1,241.32 km² in 2020 to 827.36 km² in 2024; and the area of maize decreasing from 1,233.90 km² in 2020 to 713.27 km² in 2024. The area planted with cash crops such as tomato, beet, edible seed watermelon and pepper fluctuates considerably, of which tomato and edible seed watermelon declines after a significant increase in 2022; beet planting is small and fluctuates in a limited way; and the area planted with pepper reaches a high in 2021 and then declines gradually. The planted

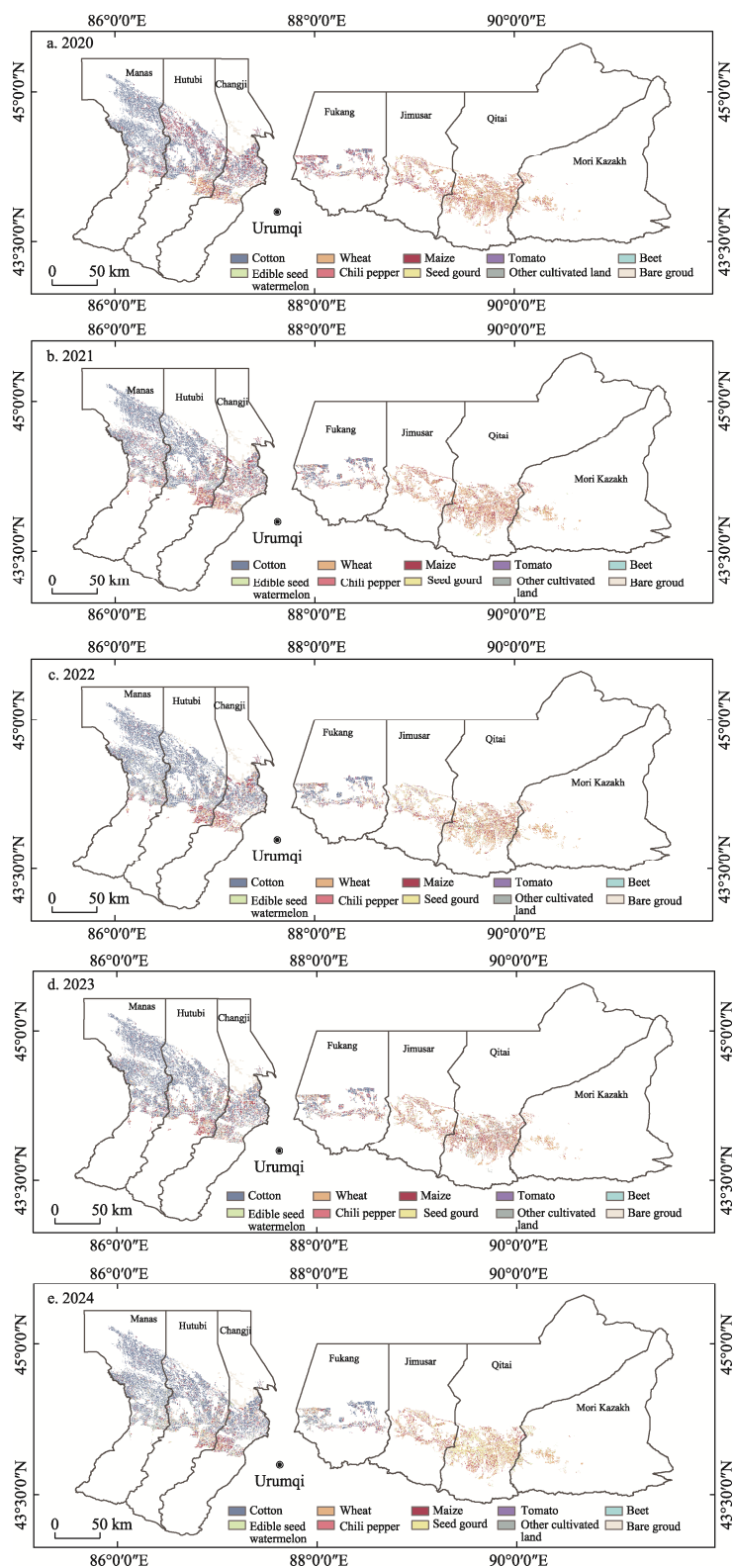


Figure 3 Distribution maps of crops in Changi Prefecture (2020–2024)

area of seed gourd increases significantly to 495.32 km² in 2024, which is significantly higher than the previous level.

4.3 Data Validation

For accuracy validation, this dataset employs field survey data collected by authors in Changji Prefecture in July 2024 (Table 4), with sample distribution conforming to the proportions of cultivated areas for each crop in the extraction results (cotton being the most abundant, followed by wheat and maize). The spatial distribution of field survey sites is shown in Figure 5. A total of 2,821 sampling points were established along predetermined routes during the field survey, covering the entire territory of Changji Prefecture. These data were primarily used to validate the reliability of the MSTPI model classification results and the 2024 crop classification outcomes. The results demonstrate that the MSTPI model achieved relatively stable classification performance across all areas of Changji Prefecture, with an average overall accuracy (OA) of 86.24% and an average F1 score of 85.10%.

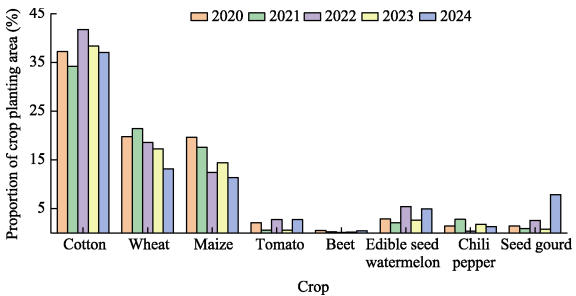


Figure 4 Statistics of the proportion of planting area for major crops in Changji Prefecture (2020–2024)

Crops	2020	2021	2022	2023	2024
Cotton	2,336.72	2,148.97	2,622.02	2,408.07	2,325.74
Wheat	1,241.32	1,346.13	1,164.78	1,083.93	827.36
Maize	1,233.90	1,103.18	781.54	907.62	713.27
Tomato	133.48	37.78	175.88	36.59	172.83
Beet	32.61	17.88	9.52	12.97	28.53
Edible seed watermelon	180.95	133.10	341.11	164.88	311.01
Chili pepper	89.93	177.22	25.85	111.82	84.26
Seed gourd	90.95	57.45	161.42	52.21	495.32

	Cotton	Wheat	Edible seed watermelon	Maize	Tomato	Seed gourd	Chili pepper	Beet	Other	Bare ground
Number	869	460	125	670	173	195	33	38	202	56

In addition, this dataset's accuracy was validated through comparison with publicly available remote sensing data products, specifically through consistency assessment using publicly released remote sensing classification products for cotton, maize, and winter wheat in the Xinjiang region.

The cotton data were derived from the 10-m resolution classification results (2020–2021) released by Kang, et al.^[18], the maize data were selected from the Xinjiang subset of Peng, et al.^[19] 30-m resolution for maize in China, and the winter wheat data were selected from Yang, et al.^[20] 10-m resolution data products. The maize and wheat data were obtained through the National Ecological Science Data Center, with the maize data spanning 2020–2023^[21] and the winter wheat data covering 2020–2024^[22]. The results showed that the consistency of cotton classification was more than 83% during 2020–2021 in all cases; the average consistency of maize classification was 75.81% during 2020–2023, with the highest value (81.17%) reached in 2022; and the consistency of winter wheat classification remained stable at 90% during 2020–2024. The consistency of winter wheat classification between 2020 and 2024 stably stays above 90%. This indicates that the accuracy of this dataset is good.

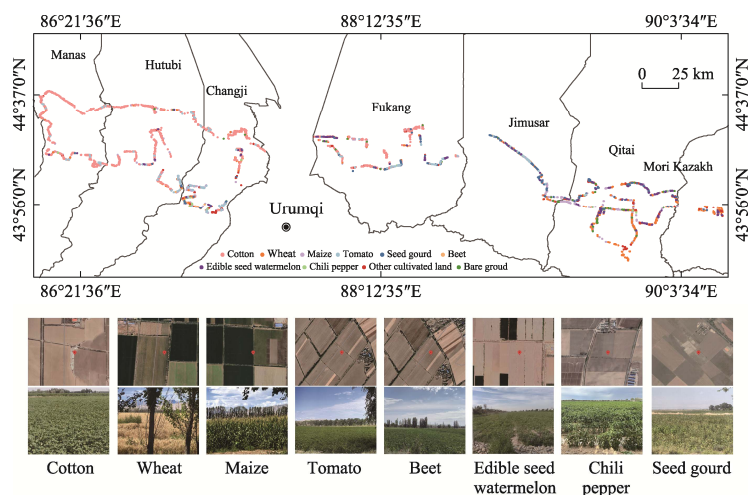


Figure 5 Distribution map of the field survey sites in Changji Prefecture (2024)

5 Discussion and Conclusion

Annual large-scale, multi-crop planting structure data play a crucial role in regional agricultural development, optimal allocation of water resources, and regulation of “non-grain” cropland use. However, planting structure data for the Xinjiang region remains limited, particularly annual large-scale multi-crop data on planting structure. Based on multi-source time-series Sentinel-1/2 remote sensing imagery and parcel-scale cropland extraction, this study proposes the MSTPI crop classification model that integrates spatial-temporal and phenological features, achieving the extraction of parcel-level crop planting structure for Changji Prefecture, Xinjiang from 2020 to 2024 and analyzing its characteristics.

The dataset features a spatial resolution of 10 m and a temporal resolution of 1 year, providing comprehensive coverage of Changji Prefecture, Xinjiang. It provides crucial support for water resource control and allocation, planting structure optimization, and desertification prevention in Changji Prefecture, Xinjiang, while also offering scientific evidence for assessing sustainable development goals and ecological conservation.

Although this dataset provides relatively comprehensive data support, several challenges were encountered during its construction: (1) Imbalanced category distribution in sample collection, with particular difficulty in obtaining samples for minor crops such as beet; (2) Constraints imposed by the 10-m spatial resolution, uncertainty exists in the delineation of fragmented parcel boundaries; (3) Temporal discontinuity issues in optical remote sensing data due to cloud cover affect the completeness of data during critical growth stages; (4) Limitations in the spatial-temporal coverage of samples make it difficult to comprehensively reflect crop phenological variations under different conditions; (5) Labeling consistency in collaborative multi-person annotation requires improvement, particularly for crops with similar phenological characteristics.

Author Contributions

Wang, X. Q. designed the algorithms of dataset. Yu, L. X., Zhang, H. Y., Liu, H. W. collected and processed the remote sensing data and field survey data. Zhang, H. Y. designed the models and algorithms. Yu, L. X. contributed to the data validation and wrote the data paper.

Conflicts of Interest

The authors declare no conflicts of interest.

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