

Article

Soybean Mapping Using Landsat Imagery and Deep Learning: A Case Study in Northeast China

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Abstract

Understanding soybean cultivation in Northeast China is essential for informing policies related to national food security. However, long-term, high-resolution soybean maps are still lacking, largely due to persistent cloud cover, limited availability of high-quality field labels, and the difficulty of capturing crop phenological dynamics using traditional remote sensing methods. To address this gap, this study aims to develop a robust framework for generating decade-long soybean distribution maps by integrating medium-resolution Landsat imagery with advanced deep learning techniques. We mapped the soybean distribution across Northeast China from 2013 to 2022 by constructing a bi-monthly NDVI-based composite and applying a deep learning model that combines the Transformer architecture with fully connected neural networks. The model was trained using a large set of field-surveyed samples collected between 2017 and 2019. Validation results demonstrate strong classification performance, with a user accuracy of 89.77% and a producer accuracy of 88.59%, sufficient for reliable spatiotemporal analysis. When compared with prefecture-level statistical yearbook data, the predicted annual soybean areas show a high degree of agreement ($R^2 = 0.9226$). Overall, this study not only fills an important gap in long-term soybean mapping for Northeast China, but also provides a replicable methodological framework for large-scale, time-series crop mapping. The approach has strong potential for broader application in agricultural monitoring and food security assessment.

Keywords: Landsat; soybean mapping; Northeast China; deep learning



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1. Introduction

Soybeans, as one of the most important food crops, are not only a major source of high-quality plant-based protein, but also a key raw material for the production of soybean oil and soybean meal [1–4]. Soybean meal, as a high-protein feed, is widely used in animal husbandry, particularly in the production of pork, beef, and poultry [5]. With global population growth and shifts in dietary patterns, the demand for plant-based protein and animal feed continues to rise, making soybeans an irreplaceable component in the global agricultural and food system [6,7]. In addition, soybeans are also used in the production of biodiesel, playing a crucial role in supporting the renewable energy sector [8]. China, as the fourth-largest soybean producer and the largest soybean importer in the world, plays a vital role in ensuring both food and energy security [9]. Nevertheless, due to rapid urbanization and industrialization, rising global temperatures, and the implementation of

the Soybean Revitalization Plan, significant changes have occurred in soybean production in Northeast China [10]. Therefore, mapping soybean distribution in Northeast China is of great significance for safeguarding national food and energy security.

Northeast China—primarily comprising Heilongjiang, Jilin, and Liaoning provinces—is the country’s main soybean-producing region, contributing the majority of the national soybean output [11,12]. Between 2013 and 2022, soybean cultivation in this region underwent significant spatiotemporal changes. During this period, the Chinese government introduced a series of agricultural policies aimed at optimizing the agricultural structure, enhancing food security, and improving agricultural productivity [13,14]. For example, the implementation of the soybean target price subsidy policy in 2014 [15] and the launch of the “crop rotation and fallow system pilot” in 2016 had far-reaching impacts on soybean cultivation in Northeast China. Meanwhile, during the China–U.S. trade tensions—especially after 2018—China imposed tariffs on U.S. soybeans, leading to domestic soybean price fluctuations and reduced imports [16]. This further stimulated the expansion of soybean planting areas in Northeast China. However, market uncertainty and price volatility also posed risks and challenges for farmers [10]. Moreover, the increasing frequency of extreme weather events caused by climate change, such as floods and droughts, has had a non-negligible impact on soybean production [17].

In recent decades, remote sensing imagery has played a crucial role in crop identification and monitoring [18–20]. Many researchers have utilized remote sensing data to conduct crop mapping at both national and regional scales [21–25]. Traditionally, most soybean maps have been generated through crop classification using MODIS satellite data with a coarse spatial resolution of 500 m to 1 km. While daily MODIS data can provide continuous crop phenological information at high temporal resolution, its coarse spatial resolution is insufficient to accurately capture the distribution of crops in China, which is dominated by small-scale farmland. To address this challenge, a reasonable solution is to use high-spatial-resolution satellites such as Sentinel and Landsat to generate crop maps [26–28]. Although Landsat imagery has a lower spatial resolution than Sentinel imagery, Landsat offers more than 50 years of long-term Earth observations, making it an indispensable foundation for long-term, large-scale land use analysis.

In earlier studies, scholars typically relied on single-date or multi-temporal imagery as the primary data source for crop remote sensing classification [29–31]. By acquiring one or more images during the key growth stages of crops, they could conduct classification tasks. However, such approaches often involved high computational complexity, while the extracted crop feature information remained relatively limited, leading to lower classification accuracy [32]. In recent years, time-series remote sensing data have increasingly gained attention in crop identification research because of their ability to accurately capture crop growth and development processes [33–35]. Several studies have demonstrated that leveraging time-series data can significantly enhance both the accuracy and stability of crop classification [36,37]. Meanwhile, machine learning algorithms, with their powerful self-learning capabilities and strong generalization performance, have shown remarkable effectiveness and robustness in crop classification tasks, becoming the most widely used methodological approach [36,38,39]. Nevertheless, accurately distinguishing typical crop types such as soybean and maize in remote sensing imagery remains a substantial challenge [27].

To address the above challenges, this study proposes a simple yet effective approach that integrates remote sensing time-series image synthesis with deep learning. Although recent studies have highlighted the advantages of time-series remote sensing data in capturing crop phenological trajectories, major theoretical and empirical gaps remain. Theoretically, existing methods still struggle to fully characterize asynchronous pheno-

logical variations caused by cloud contamination, irregular image acquisition intervals, and heterogeneous farming practices. Empirically, most previous works have focused on short time spans and limited spatial extents or relied on high-quality seasonal composites that are difficult to generalize across years and regions. Furthermore, few studies have systematically evaluated how advanced deep learning architectures—particularly Transformer-based models—perform in large-scale, long-term mapping of soybean cultivation under smallholder-dominated agricultural landscapes. This study fills these gaps by developing a unified framework that combines bi-monthly Landsat NDVI maximization, time-series reconstruction, and a Transformer-based classification model. Unlike traditional unsupervised or non-temporal classification approaches, our method explicitly models multi-temporal spectral dynamics, allowing the Transformer to learn long-range temporal dependencies and phenological differences between crops. Our main contributions are as follows: (1) We collected 59,789 ground-truth samples from extensive field surveys conducted between 2017 and 2019, providing a large and reliable training dataset. (2) We developed a time-series image synthesis method tailored for large-scale soybean mapping to mitigate vegetation’s spatiotemporal variability and the effects of cloud contamination. (3) We proposed a Transformer-based deep learning method and conducted comparative experiments with classical machine learning and deep learning approaches to evaluate its superiority. (4) We applied the trained model to generate high-precision soybean distribution maps for Northeast China from 2013 to 2022, producing the first decade-long Landsat-based soybean time-series map for the region. The predicted soybean planting areas showed strong agreement with prefecture-level statistical yearbook data ($R^2 = 0.9226$), demonstrating the model’s robustness and transferability across years and heterogeneous landscapes. This confirms that the proposed framework can effectively map soybean distribution even in smallholder-dominated agricultural systems and provides a valuable reference for agricultural monitoring and food security assessment.

2. Materials

2.1. Study Area

The study area is located in Northeast China, encompassing Heilongjiang Province, Jilin Province, Liaoning Province, and four prefecture-level cities in eastern Inner Mongolia. This region spans approximately from 39° N to 54° N latitude and from 115° E to 135° E longitude, encompassing a diverse range of geographical and climatic conditions. China’s agricultural natural regions are defined by temperature and humidity levels, and Northeast China comprises four such zones, as shown in Figure 1. Due to differences in water and temperature conditions, these zones vary in heat availability, growing seasons, and crop types (Table 1).

Table 1. Agricultural regions and their climatic and crop characteristics.

Agricultural Zone	Climate Characteristics	Cropping System	Main Crops	Agricultural Features	Representative Areas
Cold Temperate Humid Zone	Accumulated temperature < 2000 °C; annual rainfall > 500 mm	Annual cropping	Spring wheat, potato, soybean, etc.	Short growing season, dominated by cool-season crops, characterized by grain–legume rotations and potato planting.	Northern Daxing’anling

Table 1. Cont.

Agricultural Zone	Climate Characteristics	Cropping System	Main Crops	Agricultural Features	Representative Areas
Temperate Humid Zone	Accumulated temperature 2500–3200 °C; annual rainfall > 700 mm	Annual cropping	Rice, soybean, maize, etc.	Favorable heat–moisture match; intensive rice cultivation, especially in Sanjiang Plain.	Sanjiang Plain
Temperate Sub-Humid Zone	Accumulated temperature 2000–3000 °C; annual rainfall 400–700 mm	Annual cropping	Maize, soybean, spring wheat, sugar beet, etc.	Typical black soil farming zone, fertile soils, dominated by grain–legume cropping, with widespread crop rotation systems.	Songnen Plain, Liaohe Plain
Warm Temperate Humid Zone	Accumulated temperature 3200–4000 °C; annual rainfall > 700 mm	Annual to biennial cropping	Maize, rice, vegetables, fruits, etc.	Diverse crop varieties, high farmland utilization, intensive agriculture in warm-humid coastal areas.	Liaodong Peninsula, southern coastal regions
Warm Temperate Sub-Humid Zone	Accumulated temperature 3200–4000 °C; annual rainfall 400–800 mm	Annual to biennial cropping	Maize, peanut, rice, vegetables, etc.	Transition zone between Northeast and North China, high cropping intensity and crop diversity.	Southern Liaoning coastal zone
Arid Temperate Semi-Arid Zone	Accumulated temperature 2000–3000 °C; annual rainfall 300–500 mm	Annual cropping	Maize, millet, soybean, etc.	Unstable precipitation, mainly rainfed farming; suitable for dryland rotation systems and drought-resistant crops.	Western Liaoning, Northwestern Heilongjiang
Arid Temperate Arid Zone	Accumulated temperature 1700–3500 °C; annual rainfall < 200 mm	Annual cropping	Spring wheat, maize, sunflower, etc.	Plateau animal husbandry, oasis irrigated agriculture; drought-resistant farming dominates.	Northeastern Inner Mongolia
Agricultural Zone	Climate Characteristics	Cropping System	Main Crops	Agricultural Features	Representative Areas
Cold Temperate Humid Zone	Accumulated temperature < 2000 °C; annual rainfall > 500 mm	Annual cropping	Spring wheat, potato, soybean, etc.	Short growing season, dominated by cool-season crops, characterized by grain–legume rotations and potato planting.	Northern Daxing'anling

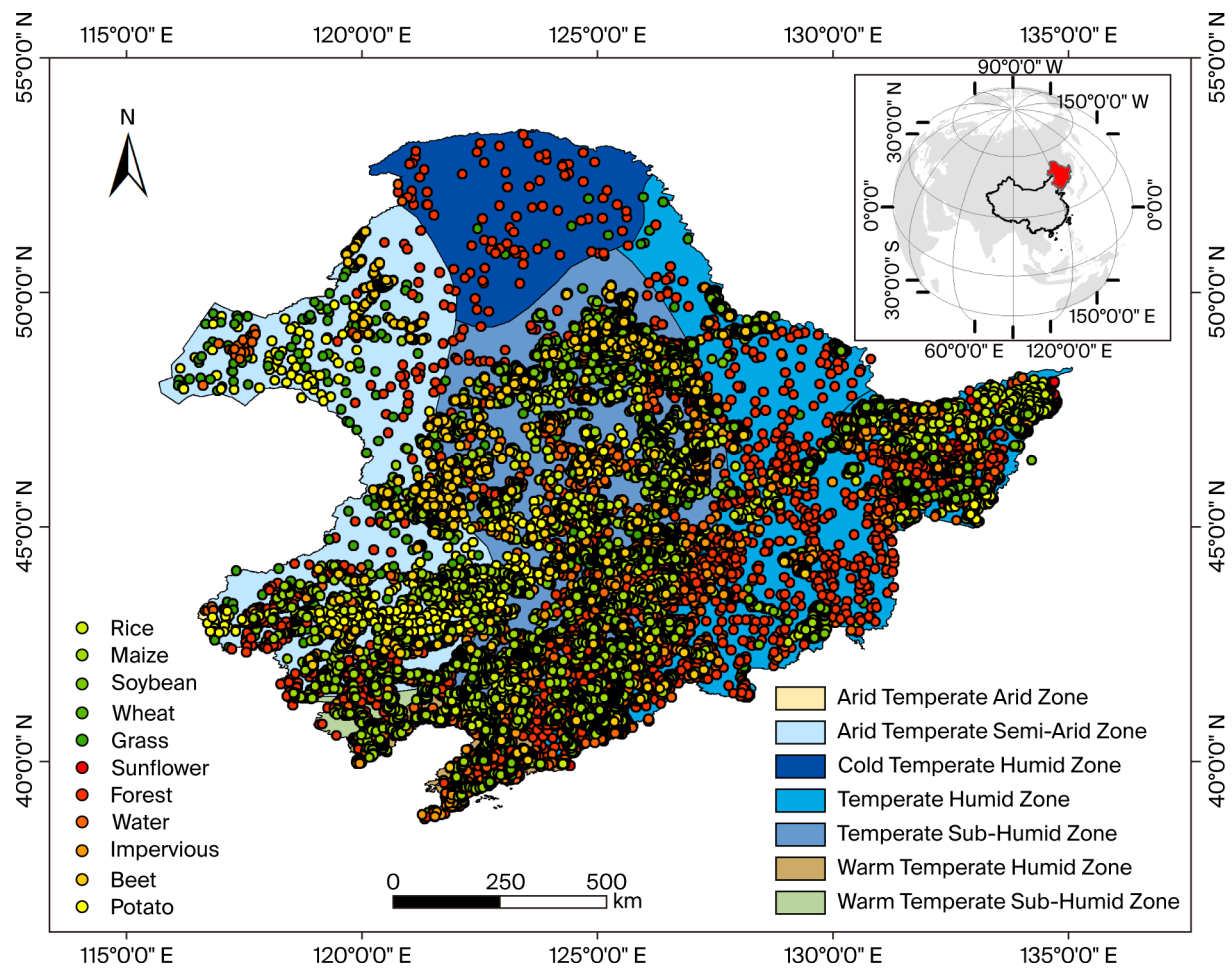


Figure 1. Location of the study area, with agricultural natural zones with crop sample collection points from field surveys highlighted.

2.2. Landsat Images

The Landsat data used in this study were obtained from the United States Geological Survey (USGS) and include imagery from Landsat 1, 2, 3, 5, 7, 8, and 9 [40,41]. We specifically employed Landsat 8 and Landsat 9 datasets for our analysis. Landsat 8 imagery from the OLI sensor covering the years 2013–2021 and Landsat 9 imagery from the OLI sensor for the year 2022 were selected. For each image, we extracted the Blue, Green, Red, NIR, SWIR1, and SWIR2 spectral bands, as well as the Normalized Difference Vegetation Index (NDVI) [42] and the image acquisition date. We used the Landsat 8 Collection 2 Tier 1 and near real-time data in DN values, which represent scaled and calibrated sensor radiance. Cloud masking was performed using the QA band. To ensure cloud-free imagery and meet the multi-temporal requirements for crop identification, we adopted a two-month compositing strategy, using data from April–May, June–July, August–September, and October–November (Figure 2). In cases where certain pixels lacked cloud-free coverage, we filled the gaps with imagery from adjacent months, ensuring a largely cloud-free time series. Ultimately, we obtained four temporal composites per year during the soybean growing season. To ensure the acquisition dates were as close as possible across years, we selected the images corresponding to the maximum NDVI value for each period—an important step for image acquisition in the Google Earth Engine (GEE) platform.

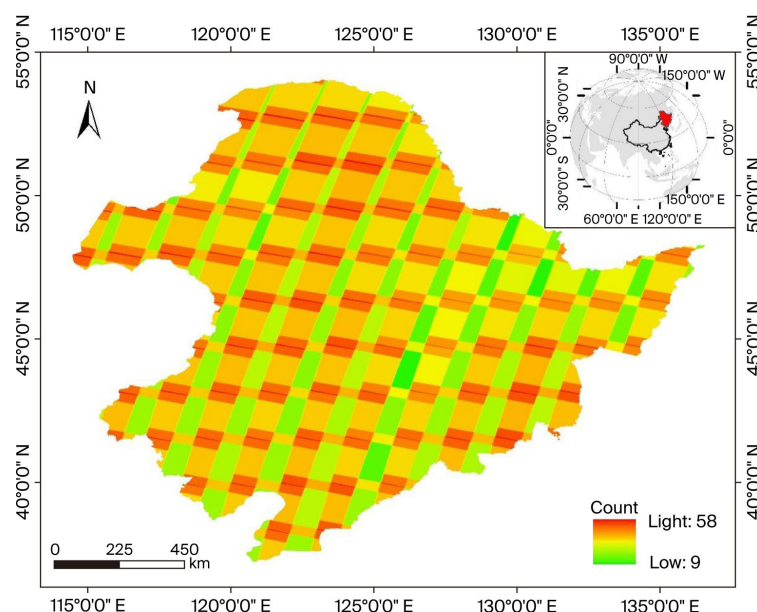


Figure 2. The number of remote sensing images identified in the period from April to November.

2.3. Sample Data

Each year, independent reference samples were collected across Northeast China, covering Heilongjiang, Jilin, Liaoning, and eastern Inner Mongolia. The dataset included samples from various crop types (Table 2)—such as soybean, rice, corn, potato, and wheat—as well as multiple non-crop categories, including forest, grassland, shrubland, and bare land. This comprehensive sampling ensured the spatial representativeness of each selected sample and the broad distribution of crop samples across the entire region. Crop samples and part of the non-crop samples were obtained through field surveys using handheld electronic devices. All collected field samples were then cross-validated and corrected using Google Earth imagery and Sentinel-2A images to eliminate potential misidentifications, particularly along roads or field boundaries. Additional non-crop samples were derived from a visual interpretation of Google Earth imagery, where the central points of homogeneous land-cover patches were selected as representative samples to minimize mixed-pixel effects. To ensure maximum representativeness, the samples covered all climatic zones within the study area, providing a balanced distribution across different environmental conditions. All samples were merged and randomly divided into training, testing, and validation sets in proportions of 70%, 15%, and 15%, respectively. By pooling all samples together rather than segmenting them by region, the model’s generalization ability was enhanced, thereby improving its temporal transferability across different years.

Table 2. Yearly distribution of crop type samples.

Class	2017	2018	2019	All
Soybean	4927	4795	5072	14,794
Maize	4178	4927	5561	14,666
Rice	1886	2525	2320	6731
Wheat	0	501	0	501
Sunflower	73	292	73	438
Beat	0	814	0	814
Potato	704	851	327	1882
Grass	2040	3691	1722	7453
Forest	1204	1597	4990	7791
Water	520	607	1018	2145
Impervious	655	831	1088	2574
Total	16,187	21,431	22,171	59,789

2.4. Cropland Mask

In our study, we applied a cropland mask to exclude non-agricultural pixels from the soybean mapping process. Previous studies have demonstrated that using a cropland mask can effectively reduce topological errors in crop mapping [23]. Therefore, we utilized the China Land Cover Dataset (CLCD) [43] to extract the cropland layer for each year from 2013 to 2022. After performing soybean classification, we applied this cropland layer to mask the resulting soybean maps. This procedure allowed us to remove non-cropland areas and produce more accurate representations of soybean distribution.

2.5. Agricultural Statistics

We collected municipal-level soybean census data from the Agricultural Statistics Bureau's statistical yearbooks [44] to validate the soybean planting area extracted in our study. The dataset mainly covers the years 2013–2022. In our analysis, we examined soybean statistics for 298 municipalities from 2013 to 2022.

3. Methods

As shown in Figure 3, we developed and trained an end-to-end deep learning model to extract soybean cultivation areas. The entire process consists of four main steps: image preprocessing, feature selection, sample collection, and supervised classification. Among them, image preprocessing and feature selection were performed on the GEE platform; sample collection was conducted through field surveys; and supervised classification was carried out on a local server using Python 3.9 and the PyTorch 1.13.1 framework. The trained model was then applied to identify soybean cultivation areas from satellite images spanning 2013–2022.

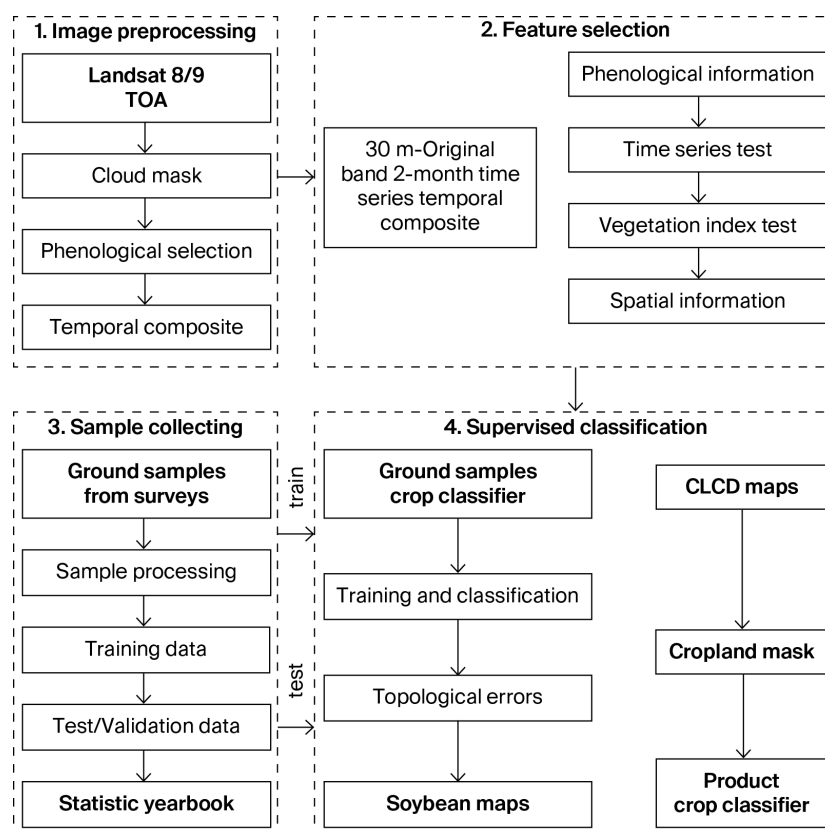


Figure 3. Workflow for Soybean Extraction.

3.1. Data Preprocessing

Image processing in this study includes both image inspection and subsequent processing, all of which were conducted on the GEE cloud platform. Building on previous research, we used the Landsat 8 top-of-atmosphere (TOA) product as the data source. The product has already undergone radiometric, topographic, and geometric corrections, which helps minimize the influence of solar elevation angle, terrain, and other factors on crop identification [45]. First, we inspected the image coverage during the crop growing season within the study area on the GEE platform. Cloud removal was applied to the images, and in line with the requirements for subsequent crop classification, we ensured that each scene contained at least a minimum number of valid pixels. In cases where large portions of an image had very few valid pixels, we reconsidered the compositing strategy. In Northeast China, the main crop growing season spans from May to October. However, studies have shown that the period after maize harvest is also a favorable time for crop identification. Therefore, we analyzed images from April to November. Using 2019 as an example, each year's dataset contained more than eight valid scenes for classification. The cloud platform was also used to visually inspect the coverage of different phenological periods. Cloud and haze pixels were removed based on the QA_PIXEL band in the Landsat data, which encodes various pixel quality flags. This resulted in a cloud-free time series, though it contained many missing values. To address this, we performed image compositing to replace missing values. We primarily adopted a two-month compositing strategy, which our experiments determined to be an optimal choice.

3.2. Soybean Growth Curve

The soybean growth cycle can generally be divided into three stages: the seedling stage, the vegetative growth stage, and the reproductive stage [46]. During the seedling stage (from sowing to emergence), NDVI values remain low due to limited vegetation coverage. Entering the vegetative growth stage, soybean plants grow rapidly in height, and leaf area expands quickly, leading to a significant increase in NDVI values that reflects the enhanced green vegetation cover. In the reproductive stage, soybeans enter flowering, pod-setting, and maturity phases; NDVI reaches its peak and then gradually declines as leaves turn yellow and drop off, and vegetation vigor diminishes. Overall, the NDVI curve exhibits a pattern of gradual increase, peak, gradual decline, with the peak usually occurring in the mid to late growing season. This pattern is quite similar to that of certain other crops, such as maize, particularly during the seedling and vegetative growth stages (Figure 4). However, it is worth noting that maize generally has a longer growing period, with a faster NDVI increase, higher peak, and longer duration at the peak. In contrast, soybeans often have a slightly shorter growth cycle in some regions, with a relatively flatter NDVI peak and an earlier onset of decline. These differences can be effectively used for crop classification or phenology identification based on NDVI time series.

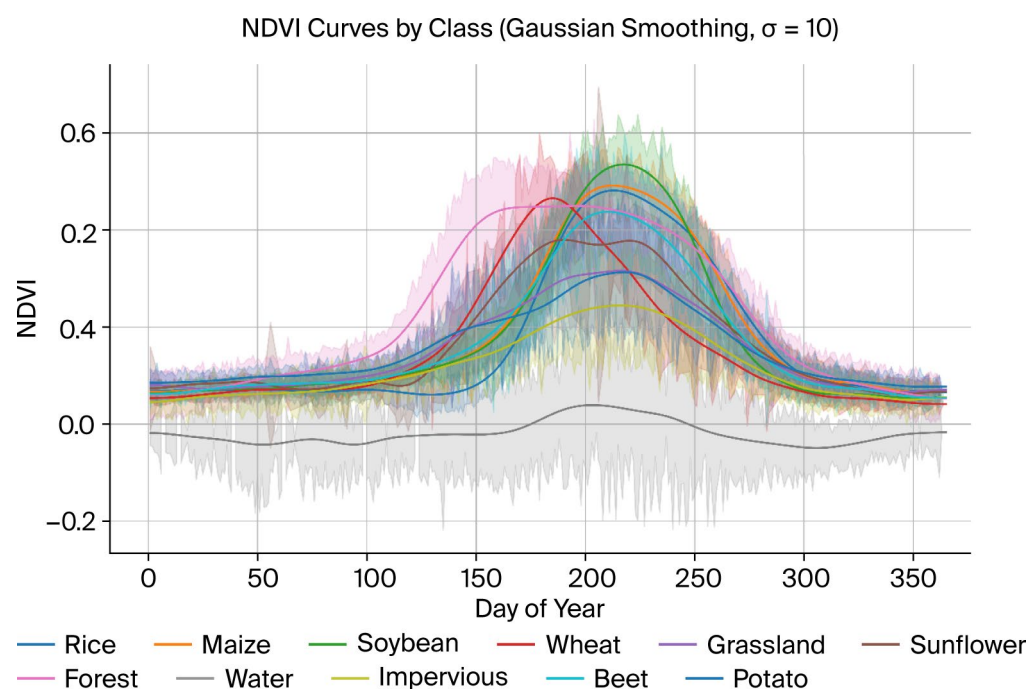


Figure 4. NDVI curves of different crops.

3.3. Feature Selection

To obtain suitable imagery, we used all Landsat 8 images covering the crop growing season in the study area from 2013 to 2022. Considering cloud cover and crop phenological information, we applied a two-month compositing strategy for crop identification, namely April–May, June–July, August–September, and October–November, each composited into a single image. Specifically, crop extraction was performed by identifying the bands from the image in which the NDVI reached its maximum value. Despite these efforts, approximately 5% of the pixels still remained cloud-contaminated, and we conducted additional experiments to assess the impact of residual clouds. In addition to the direct use of spectral bands, we also tested four widely used vegetation indices, which were derived from the spectral data of Landsat imagery. These indices include the NDVI, the Enhanced Vegetation Index (EVI), the Land Surface Water Index (LSWI) and Green Normalized Difference Vegetation Index (GNDVI), as shown in Table 3.

Table 3. Vegetation indices and their computational methods.

Index	Formulation	Reference
NDVI	$NDVI = (NIR - RED) / (NIR + RED)$	[42]
EVI	$EVI = 2.5 \times (NIR - RED) / (NIR + 6 \times RED - 7.5 \times BLUE + 1)$	[42]
LSWI	$NDWI = (GREEN - NIR) / (GREEN + NIR)$	[47]
GNDVI	$GNDVI = (NIR + Green) / (NIR - GREEN)$	[48]

On the GEE cloud platform, the default compositing approach typically relies on the maximum value, which can lead to inconsistencies across bands because the sampled time for each band may differ. To address this issue, we improved the method by using all bands from the image corresponding to the maximum NDVI value as the composite. This approach not only helps to improve classification accuracy but also enhances the model's generalization ability, feature extraction capability, and spatiotemporal transferability.

3.4. Crop Classification Model

We employed a Transformer model combined with a Multi-Layer Perceptron (MLP) for the classification of soybeans and other crops [49,50]. The Transformer architecture is based on the self-attention mechanism, which enables it to capture global dependencies between any time steps in a sequence without relying on sequential propagation. This property provides strong representational power when dealing with remote sensing time series, particularly for capturing the asynchronous phenological patterns that different crops exhibit at various stages. The Transformer has a notable advantage in modeling long-range dependencies and frequency variations, making it well-suited to flexibly extract temporal feature differences across spectral bands and growth stages. In our model design, the remote sensing image time series is first fed into a Transformer encoder, which consists of multi-head self-attention mechanisms and feedforward neural networks. This encoder extracts multi-scale, cross-temporal key features. A positional encoding mechanism is integrated into the Transformer to preserve the temporal order of the sequence and prevent information loss. The feature representations generated by the Transformer encoder are then passed to a three-layer MLP with hidden layers of 128, 128, and 64 neurons, respectively, to further learn higher-order nonlinear features. Finally, a sigmoid activation function is applied at the output layer to predict the crop category for each sample.

To compare the classification accuracy of different machine learning and deep learning approaches for processing remote sensing time-series data, we selected four representative models: Random Forest (RF) [51], XGBoost [52], LSTM + MLP [50,53], and Transformer + MLP [49,50]. RF is a classical ensemble learning algorithm that has been widely used in remote sensing classification. It serves as a benchmark for traditional, interpretable, and stable models. XGBoost, as an advanced tree-based boosting algorithm, demonstrates excellent performance in structured tabular data such as multi-temporal vegetation indices, representing state-of-the-art ensemble methods that excel in high-dimensional feature learning. LSTM + MLP combines the Long Short-Term Memory (LSTM) network—designed to capture sequential dependencies and temporal dynamics—with a Multi-Layer Perceptron (MLP), effectively learning both temporal and nonlinear spectral relationships. This hybrid architecture represents deep learning methods that focus on modeling time-series data. Transformer + MLP, based on the self-attention mechanism, excels at capturing long-range dependencies without the limitations of recurrent structures. Its integration with an MLP further enhances nonlinear feature learning. This model represents cutting-edge deep learning architectures capable of learning highly generalizable multi-temporal and multi-spectral relationships.

3.5. Quantitative Evaluation Metrics

In this study, we evaluated the accuracy of soybean extraction results using both validation sample data and official municipal-level statistical census data on soybean planting areas. The evaluation employed a sample-based confusion matrix, from which several widely used quantitative metrics were derived, including the F1-score (F1), Overall Accuracy (OA), User's Accuracy (UA) and Producer's Accuracy (PA). The formulas are expressed as follows:

$$F1 = (2 \times UA \times PA) / (UA + PA), \quad (1)$$

$$OA = (TP + TN) / (TP + TN + FP + FN), \quad (2)$$

$$UA = TP / (TP + FP), \quad (3)$$

$$PA = TP / (TP + FN), \quad (4)$$

where

TP (True Positive) represents the number of soybean samples correctly classified as soybeans.

TN (True Negative) represents the number of non-soybean samples correctly classified as non-soybeans.

FP (False Positive) represents the number of non-soybean samples incorrectly classified as soybeans.

FN (False Negative) represents the number of soybean samples incorrectly classified as non-soybeans.

4. Results

4.1. Accuracy Assessment with Ground Samples

We evaluated the classification performance for soybean and non-soybean categories using F1, OA, UA, and PA. As shown in Table 4, the proposed maps achieved high accuracy across all years, with an overall accuracy of approximately 89%. To further assess the temporal transferability of the model, we trained the classifier using samples from 2018—selected because this year had the most complete set of crop types within the 2017–2019 sample pool—and tested it on data from 2017 and 2019. In both cases, the model maintained an accuracy of around 89%. Given the comprehensive coverage of crop types in the collected samples, these results indicate that the classifier remains stable across different years. This provides strong support for using the model trained on 2017–2019 samples to generate soybean maps for the entire 2013–2022 period.

Table 4. Evaluation of soybean classification accuracy using four models.

Model	F1	OA	UA	PA
RF	0.8810	0.8868	0.8887	0.8734
XGBoost	0.8879	0.8902	0.8971	0.8789
LSTM + MLP	0.8726	0.8797	0.8730	0.8721
Transformer + MLP	0.8918	0.8938	0.8977	0.8859

To further validate model performance, we compared four models: RF, XGBoost, LSTM + MLP, and Transformer + MLP. The detailed results are presented in Table 4. The quantitative evaluation shows that the models were ranked in terms of accuracy as Transformer + MLP > XGBoost > RF > LSTM + MLP.

Among them, the Transformer + MLP model achieved the highest accuracy, while the LSTM + MLP model had the lowest. Although LSTM can capture temporal features, it suffered from overfitting on our dataset, with an F1-score of only 87.26%.

4.2. Comparison of the Classification with Agricultural Statistics

The soybean distribution maps of Northeast China from 2013 to 2022 are presented in Figure 5. We employed a pixel-counting method to calculate the annual soybean planting area for each prefecture-level administrative unit. The estimated soybean areas showed a significant correlation with the prefecture-level statistics reported in the Statistical Yearbooks of Northeast China, with an overall R^2 reaching 0.9226 (Figure 6). However, it is noteworthy that our estimates consistently exhibited an overestimation compared with the statistical records. This highlights the limitations of soybean mapping based on land satellite images; despite the use of a large number of ground truth samples and high-performance Transformer models, some non-soybean crops are still misclassified as soybeans due to the presence of mixed pixels.

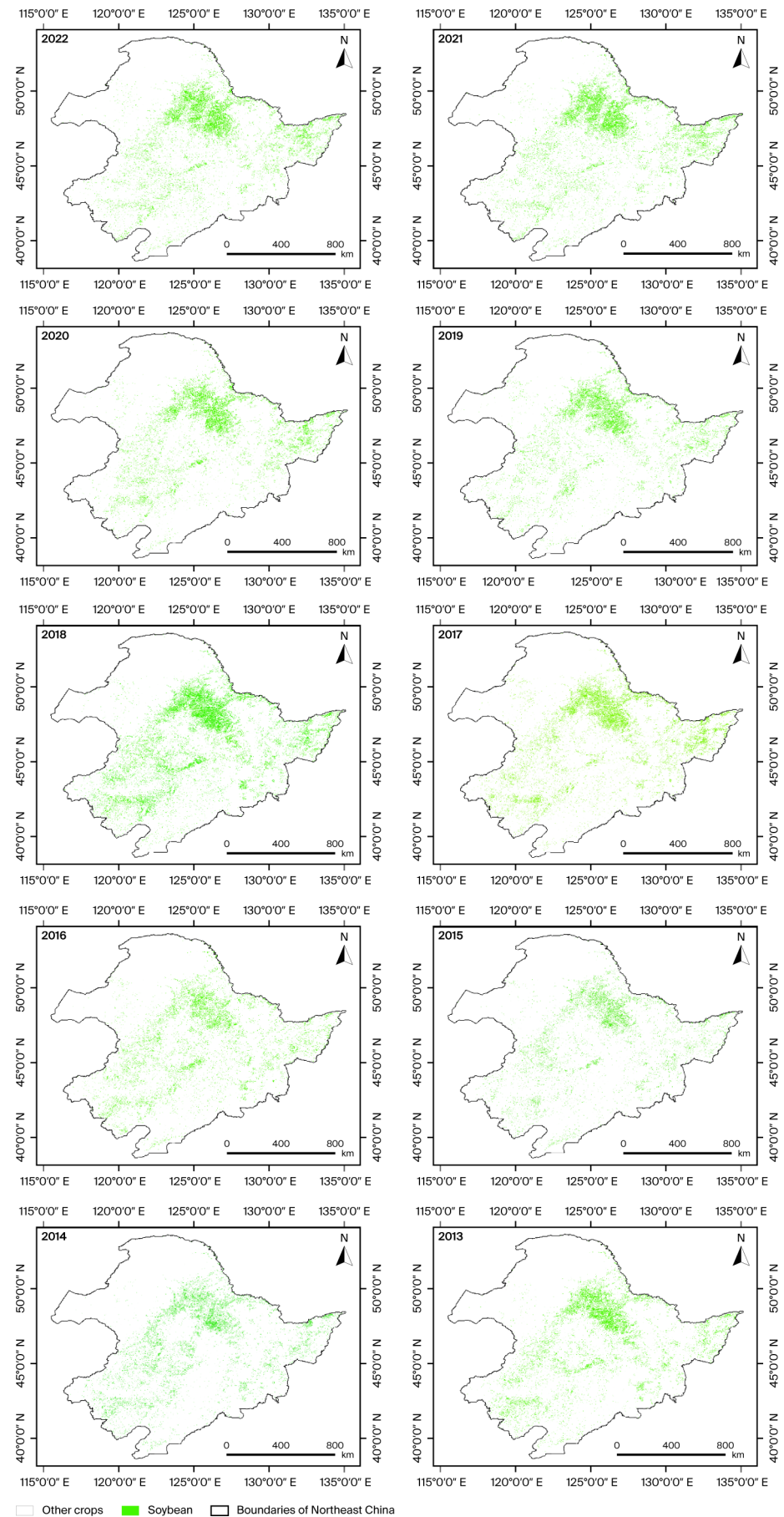


Figure 5. The soybean distribution maps for Northeast China from 2013 to 2022.

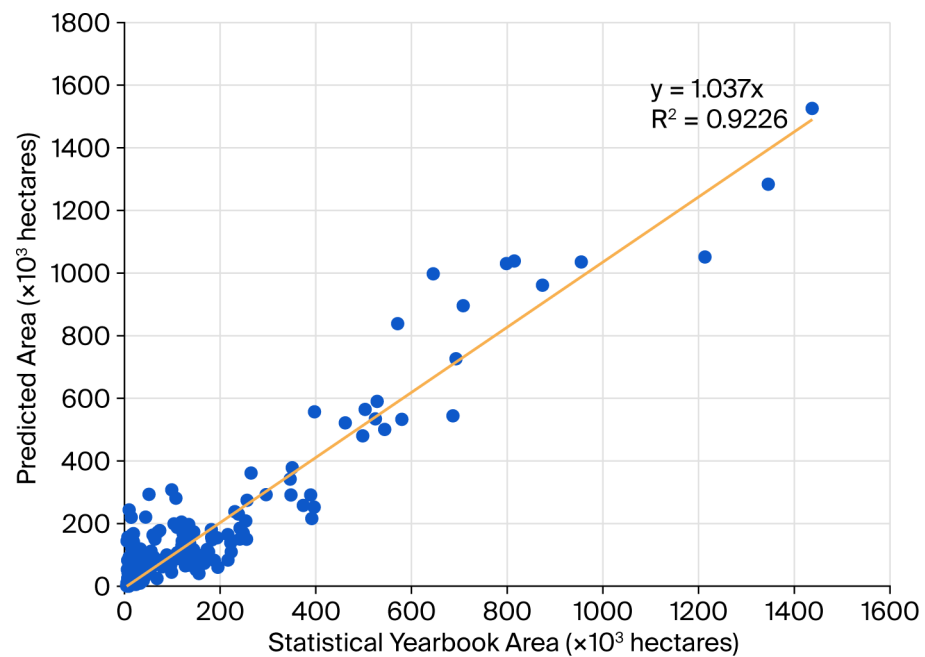


Figure 6. Comparison between predicted soybean area and statistical yearbook area (The blue points in the figure represent the values of soybean area from prefecture-level statistical yearbooks and the predicted area, while the yellow line represents the linear regression line).

5. Discussion

In this study, we systematically compared the performance of four representative models for soybean classification, namely RF, XGBoost, LSTM + MLP, and Transformer + MLP, using multi-temporal Landsat imagery. The results demonstrate that the Transformer + MLP model consistently achieved the highest overall accuracy and F1 score across all study years, outperforming both classical machine learning and other deep learning approaches. This indicates that the Transformer architecture, when combined with an MLP classifier, can effectively capture the spatiotemporal dependencies inherent in crop phenological dynamics, thereby providing a more robust framework for long-term crop mapping [54].

Our findings are consistent with recent advances in remote sensing and time-series modeling. Prior studies have demonstrated that the attention-based Transformer model excels in capturing long-range temporal dependencies and global contextual relationships, surpassing recurrent neural networks (RNNs) and LSTMs in various Earth observation tasks. Unlike traditional sequential models that rely on stepwise propagation of temporal information, the self-attention mechanism of the Transformer enables simultaneous modeling of all temporal positions, which enhances its ability to discern asynchronous phenological changes among different crops. Compared to the Transformer-based model, RF and XGBoost showed moderate performance but maintained strong robustness, aligning with previous studies reporting their effectiveness in medium-resolution crop classification [55]. These tree-based ensemble methods benefit from non-parametric decision boundaries, insensitivity to noise, and fast convergence, making them suitable for datasets with limited features or moderate temporal variability.

In contrast, LSTM + MLP exhibited some capacity for time-series modeling but performed worse than both ensemble methods and Transformer + MLP. This outcome supports prior findings that LSTMs often face overfitting and gradient vanishing issues when trained on limited or noisy remote sensing time series. While LSTM architectures are theoretically capable of capturing temporal dependencies, their sequential computation and limited memory make them less efficient for long-term satellite records spanning multiple years.

The Transformer architecture, by contrast, employs parallel computation and global attention mechanisms that allow for more scalable and interpretable time-series modeling.

Theoretically, this study contributes to bridging the gap between spectral feature extraction and phenological pattern recognition in remote sensing. By integrating the Transformer's temporal attention with the MLP's nonlinear feature transformation, we demonstrate a unified deep learning framework that can jointly model both temporal continuity and spatial heterogeneity. This methodological innovation expands upon previous approaches that either relied solely on spectral information or treated temporal features as static inputs. Moreover, our approach emphasizes the importance of data synthesis in mitigating cloud contamination and seasonal gaps—an aspect that has been a persistent limitation in Landsat-based agricultural studies.

Empirically, the study underscores the potential of combining deep learning with medium-resolution imagery for long-term agricultural monitoring in smallholder-dominated regions. The high correlation ($R^2 = 0.9226$) between the predicted soybean area and prefecture-level statistical data validates the reliability of our method under heterogeneous landscape and management conditions. This strong agreement supports the feasibility of using freely available Landsat archives and cloud-based processing platforms (e.g., GEE) for national-scale crop monitoring, especially in regions where field data are sparse or inconsistent. These findings align with global efforts to enhance agricultural transparency and food security assessment through open-access Earth observation data.

From a practical perspective, our results highlight distinct model strengths across different application scenarios. Transformer-based models are better suited for tasks that require the learning of complex spatiotemporal dependencies, such as multi-year crop rotation detection or phenological phase tracking. In contrast, RF and XGBoost remain valuable for rapid assessments where model interpretability, computational efficiency, and robustness to noise are prioritized. Future research could explore hybrid frameworks that integrate the interpretability of ensemble learning with the representational power of deep attention networks. Such hybrid strategies could improve both classification accuracy and model generalization across different agro-ecological zones.

Despite the promising performance of the proposed Transformer + MLP framework, several limitations should be acknowledged. First, the computational cost associated with large-scale data processing on the GEE platform is nontrivial. Although GEE provides efficient access to massive Landsat archives, running multi-temporal composites and exporting high-resolution results requires substantial cloud resources and time, which may limit scalability for near-real-time applications or global mapping initiatives. Future studies could explore more lightweight model architectures or distributed training strategies to reduce computational overhead. Second, the method relies heavily on the availability and representativeness of ground-truth samples. The accuracy of supervised models such as Transformer + MLP is constrained by the quality, spatial coverage, and temporal consistency of field data. Given the heterogeneity of agricultural landscapes in Northeast China, future work should consider semi-supervised or active learning approaches to reduce dependence on extensive field surveys while maintaining classification reliability. Third, the mapping results may be sensitive to interannual variations driven not only by biophysical factors but also by socio-economic and policy changes. For instance, government subsidies or land use regulations could influence soybean planting patterns independently of environmental drivers, introducing additional uncertainty in time-series classification. Integrating auxiliary datasets—such as agricultural census data, policy indicators, or economic statistics—could help disentangle human-induced variability from natural vegetation dynamics. Overall, while the Transformer + MLP framework demonstrates strong generalization and robustness for large-scale crop mapping, addressing these

computational, sampling, and socio-economic sensitivities will be essential for advancing its operational applicability and policy relevance in future research.

6. Conclusions

This study developed a novel method for large-scale crop mapping by integrating Landsat imagery, the GEE cloud platform, and deep learning models, and applied it to produce long-term soybean distribution maps for Northeast China. The proposed approach fully leveraged the spatiotemporal resolution of Landsat data by constructing a bi-monthly NDVI maximum composite and combining it with a Transformer + MLP architecture. Validation using extensive ground-truth samples demonstrated high classification accuracy, with F1, OA, PA, and Recall values reaching 0.8918, 0.8938, 0.8977, and 0.8859, respectively. Furthermore, the comparison with prefecture-level statistical yearbook data yielded a strong correlation ($R^2 = 0.9226$), confirming the reliability and generalizability of the proposed method.

In the field of soybean remote sensing identification, the Transformer + MLP model has shown superior performance compared with traditional unsupervised and label-free crop classification methods [56,57]. Its key advantage lies in its ability to efficiently extract and integrate multi-temporal and multi-spectral features from remote sensing imagery, thus enhancing both classification accuracy and computational efficiency. The proposed method provides a robust framework for large-scale and long-term soybean mapping, with strong potential for extension to other staple crops. It offers valuable support for agricultural monitoring, food security assessment, and the sustainable management of cropland resources.

Despite these promising results, several limitations should be acknowledged. First, soybean mapping accuracy is still affected by mixed-pixel and field-size constraints inherent to Landsat's 30 m resolution. In Northeast China's smallholder-dominated landscapes, individual fields often range from 0.1 to 0.5 ha, meaning that many boundary pixels contain mixtures of soybean, maize, and non-crop vegetation. Such mixed pixels likely contribute to a portion of the observed overestimation and classification errors, especially along field edges. Although the use of cropland masks helps mitigate this effect, a systematic quantification of mixed-pixel influence remains an open task for future work. Second, residual uncertainty arises from cloud contamination and missing observations, which can weaken the temporal signature even after applying NDVI compositing. This introduces additional noise into the classification and may slightly reduce accuracy in humid or mountainous areas. Third, although the Transformer model effectively captures temporal dependencies, its high computational cost poses challenges for large-scale or near real-time applications. Finally, this study focuses on soybean mapping in Northeast China; therefore, the model's transferability to other regions, crops, or management systems has not yet been fully evaluated. A more comprehensive uncertainty analysis and cross-regional validation would further strengthen the generalizability of the proposed framework.

Future work should focus on integrating multi-source satellite data, such as Sentinel-1/2, MODIS, and hyperspectral imagery, to improve temporal continuity and spatial precision. In addition, coupling deep learning with physical process models or data assimilation frameworks could enhance the interpretability of crop growth dynamics. Developing lightweight or hybrid models that balance accuracy, generalization, and computational efficiency will be crucial for large-scale operational deployment. Finally, extending this approach to assess crop yield, phenology, and climate resilience would provide deeper insights into agricultural sustainability and contribute to national food security strategies.

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