Response to reviewer #2:

Many thanks for your thoughtful and valuable comments and suggestions, which are very helpful in improving our manuscript. We have conducted substantial new experiments and analyses to ensure that the study is more comprehensive and rigorous, and our maps are more reliable. Our responses to the comments point-by-point are included below in blue. The corresponding changes in the revised manuscript are shown in purple.

General comment: The ms employed two steps method to map soybean at large scale in China for 2017-2021. While the topic and the generated dataset have great potential to benefit the agriculture community in both research and operational monitoring aspects, there are some major flaws that need to be addressed to enhance the scientific soundness of the paper and the reliability of the data. The authors listed three objectives. The new data product of soybean maps was generated and openly shared to address the third objective. However, the first two objectives have not been thoroughly investigated. Further examination is required to test the method's robustness in extracting soybean fields across different regions. Although the nationwide validation using ground samples shows generally acceptable accuracy, the variations in accuracy among regions need to be illustrated. This can be easily done as the classification was applied at the prefecture level. Additionally, the accuracy in low soybean growing regions should be specified. The proposed method appears to be ineffective in accurately extracting soybean fields and lacks effectiveness in non-soybean producing provinces. In this case, it may not be meaningful to generate soybean map at a national scale while most non-producing provinces presents unreliable results. Additionally, the validation process is questionable since the data used to determine soybean clusters was also used in the validation.

Reply: Thank you for such expert questions, which do help us to deepen our study. To respond fully the above problems, we have correspondingly revised the manuscript.

(1) We illustrated the accuracy assessment results based on statistics and samples in each sub-zone, and explained the differences among regions.

- **The variations in accuracy among sub-zones based on statistics validation:**

"The mapping accuracy in Zone I closely matched county-level statistics, showing high consistency (R^2=0.86). Zones II-IV also demonstrated reasonable agreement (R^2=0.50~0.69), despite relatively lower accuracy due to the scarcer planted areas (Fig. S5). No significant trend deviation from statistics was indicated for the mapping area in Zone I, with slight overestimates for Zone II and III, and underestimates for Zone IV (Fig. S5). These accuracy variations are acceptable, given the challenges in accurately identifying soybeans in regions in less prevalent regions. Specifically, maize is more dominant than soybeans in Zone II, while Zone III is characterized by diverse crops and complex planting patterns. Underestimation in Zone IV is possibly due to fewer clear observations in the southwest. Nevertheless, the overall accuracy across the zones is acceptable."

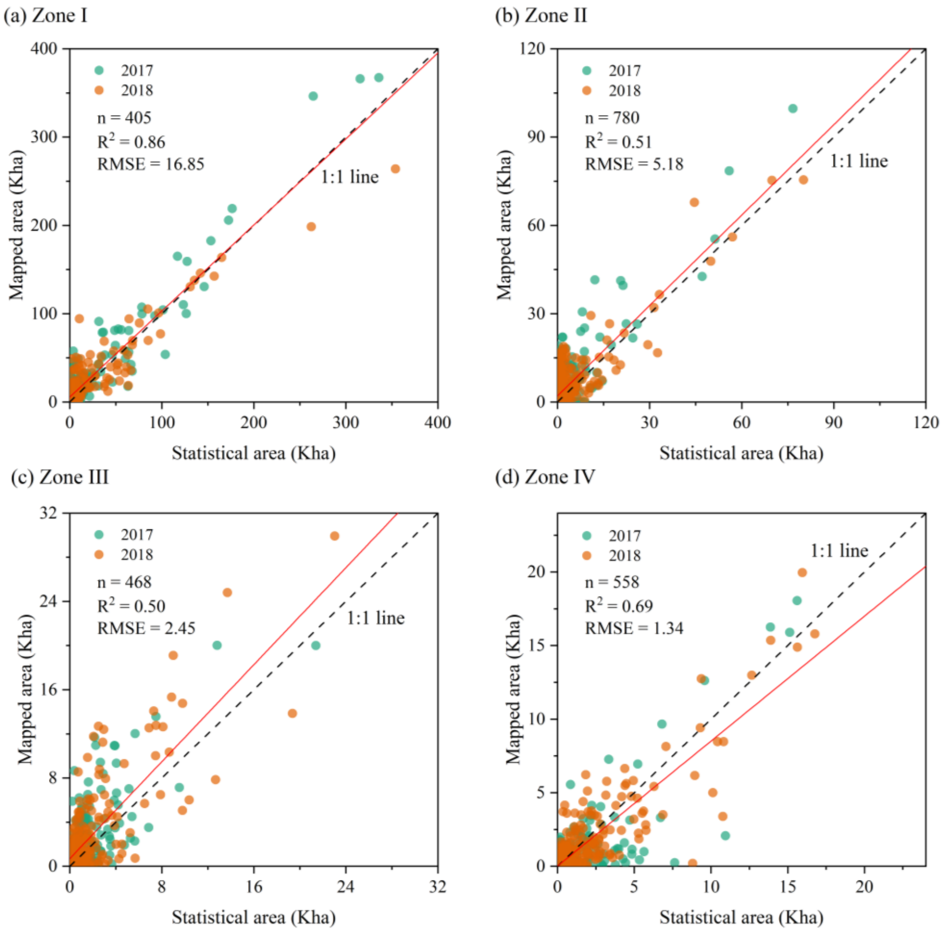

Figure S5. Comparison of soybean areas with county-level statistics in (a) Zone I, (b) Zone II, (c) Zone III, and (d) Zone IV in 2017 and 2018.

➢ The variations in accuracy among sub-zones based on samples validation:

"The overall accuracy for each sub-zone in 2019 varied from 83.58% to 90.67% (Table S1). Specifically, Zone I demonstrated the highest producer's accuracy for soybean at 88.31%, aligning with its high consistency with statistics. Zone III achieved the highest overall accuracy at 90.67%, attributed to its superior user's accuracy for soybean, indicating fewer misclassifications, and effective differentiation from non-soybean crops (Table S1). The producer's accuracy in Zone IV was relatively lower at 63.89%, possibly due to the limited samples, high heterogeneity, and fewer clear observations (Table S1)."

Table S1. Confusion matrix of the soybean maps in each sub-zone in 2019.

	Reference	Map		Producer's	User's	F1	Overall
		Soybean	Non-Soybean	Accuracy	Accuracy	Score	Accuracy
I	Soybean	922	122	88.31%	81.09%	0.85	87.12%
	Non-Soybean	215	1358	86.33%	91.76%	0.89	
II	Soybean	233	74	75.90%	86.30%	0.81	83.58%
	Non-Soybean	37	332	89.97%	81.77%	0.86	
III	Soybean	101	26	79.53%	98.06%	0.88	90.67%
	Non-Soybean	2	171	98.84%	86.80%	0.92	
IV	Soybean	23	13	63.89%	92.00%	0.75	87.18%
	Non-Soybean	2	79	97.53%	85.87%	0.91	

(2) We further discussed the mapping accuracy in the areas planted sparely. Although the verification accuracy there are not as good as those in main producing areas, its accuracy is still acceptable. The effectiveness in key regions indicates the potential application of our method, and the mapping nationwide provides insights for differentiated policy formulation across regions. Therefore, it is meaningful to map soybean area on a national scale (see Reply for Comment 8 for more details). We have explained the accuracy differences in lower soybean producing areas (see (1) above), and added the reasons into the discussion section for the higher uncertainty there and possible solutions in the future (see Reply for Comment 9).
(3) We updated the validation results in the manuscript (see Reply for Comment 7). All points are divided according to the ratio of 3:7, which are used to determine the standard curves of each sub-zone and verify the mapping accuracy to ensure scientific and independent verification.

Specific comments:
Comment 1: Line 29, Cropland Data Layer or Crop Data Layer? The existing maps are described as crop type maps not cropland maps.
Reply: Thank you pointing out the issue. The full name of CDL was not specified in the publication, and we have changed its full name to Crop Data Layer since this dataset represents crop types.

Comment 2: In second paragraph of introduction section, it is recommended to specify the research study areas for each citation when highlighting their work. For example, line 52 to 55. I thought the research generated 20-years maize-soybean maps for whole China but it is not.
Reply: Thank you for your valuable comments. We have checked all the citations in the second paragraph and have specified the studied areas that were not clearly stated in the revised manuscript:
"More recently, 20-year soybean-corn maps with 30 m resolution across the US Midwest have been generated by collecting a large number of samples and using green chlorophyll vegetation index (GCVI) time series features, which is a large-scale, high-precision soybean mapping attempt (Wang et al., 2020)."

Comment 3: Line 145-147, does National Bureau of Statistics of China provide county and prefecture level data? How to you use national and provincial data to validate at county and prefecture level information?
Reply: We accessed to statistical yearbooks through the National Bureau of Statistics and obtained yearly county- and prefecture-level soybean planting area statistics from the yearbook of each county or province. We have declared this in the revised manuscript:
"...we utilized agricultural census data obtained from the statistical yearbook of each county or province by accessing National Bureau of Statistics of China (http://www.stats.gov.cn/, last accessed: June 2023)."
Accordingly, we used finer statistics at county- and prefecture- level for validation, rather than national and provincial data.

Comment 4: Line 215-217, how high the uncertainty resulting from the cloud cover or miss values during the proposed period?
Reply: Yes, it is really interesting to quantify how much of the uncretainty from the cloud cover or miss values during the proposed period (from 15 days before the podding date to 15 days after the full-seed date). We summarized the clear observations during the proposed period in each year (Figure 1) and found that few areas in Zones I-III and less than 10% of the areas in Zone IV had 0

or 1 clear observation in each year (except for 2017). Majority of areas have more than 1 clear observation during the proposed period, so the maximum EVI can be detected. Moreover, we tried to minimize the uncertainty by reconstructing the time series, and we took an example for details:

We selected the area with cloud cover during the proposed period in 2018 (Figure 2a). The Sentinel-2 median composite image showed that some parts of the land was bare soil, with the corresponding ground sample points marked as wheat (different from the growing period of soybean). We extracted the non-fallow areas (Figure 2b), seasonal crop areas (Figure 2c), and the difference of the two layers representing non-seasonal crop areas (Figure 2d). The removed plots correspond precisely to the wheat samples and the bare soil areas in Figure 2a. The extraction results show that even with substantial cloud cover during the proposed period, areas covered by clouds are not removed as non-seasonal crops because time series reconstruction minimize the impacts of cloud cover as much as possible. We have clarified this in section 2.3.2 "(1) Potential area identification" of the revised manuscript and discussed the uncertainty in section 4.

"The impact of cloud-covered pixels appearing in the proposed period is minimized since we have reconstructed the original EVI time series."

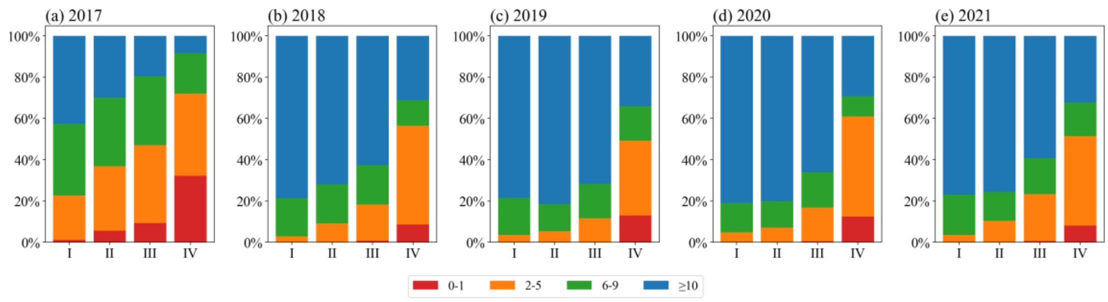

Figure 1. The times of clear observations in proposed period by sub-zone in (a) 2017, (b) 2018, (c) 2019, (d) 2020, and (e) 2021.

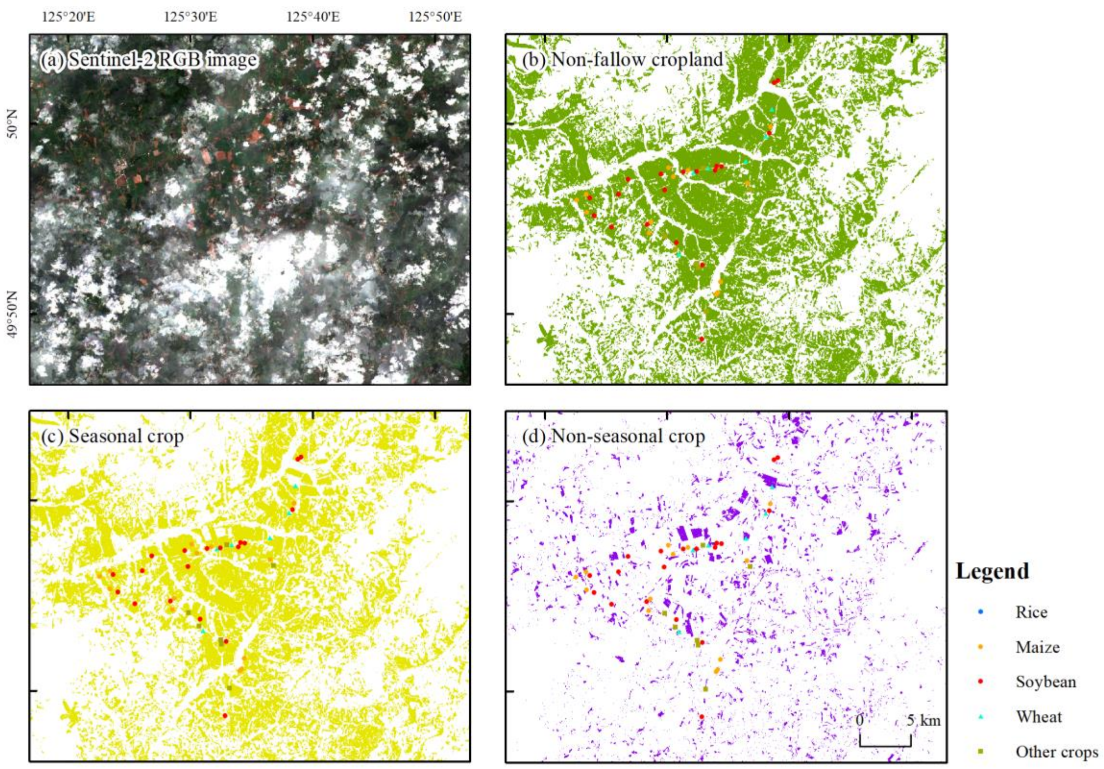

Figure 2. Case of seasonal crop identification. (a) RGB composite image comprise red (Band 4), green (Band 3), and blue (Band 2) bands from Sentinel-2 median composite images during the proposed period; (b) areas of fallow land removed on the cropland layer; (c) areas of non-seasonal crop land removed on the areas corresponding to (b); (d) non-seasonal crop mask.

Comment 5: Line 255-257 not clearly stated. Any quantitative information to determine whether crops are major ones or minor ones? It is problematic when statistical area of some crops in double cropping pattern, for example double rice.

Reply: Sorry for the ambiguity**.** We collected the statistical area for seasonal crops (including rice, maize, soybean, cotton, peanuts, sesame, sweet potato, and sorghum) in each prefecture in 2018. We defined "major crops" as those species cumulatively representing 95% of the whole seasonal cropping area, with an additional category for "other crops" to determine the number of clusters *k*. We have added the definition in section 2.3.2 "(3) Unsupervised learning":

"The classifier was trained individually in each prefecture based on the number of clusters *k* input. The cluster number *k* is defined as the number of "major crops" that constituting 95% of the total area of seasonal crops (including rice, maize, soybean, cotton, peanuts, sesame, sweet potato, and sorghum) according to prefecture-level statistics, plus one for "other crops"."

Double cropping pattern was mainly distributed in zone II and III, where soybean and other seasonal crops are planted in turn with winter crops (Yan et al., 2019). In particular, double-cropping rice is mainly planted in region III (Pan et al., 2021a). We collected statistical planting area of single-cropping rice and double-cropping late rice, treating them as two categories because of the different growing seasons.

Reference:

Pan, B., Zheng, Y., Shen, R., Ye, T., Zhao, W., Dong, J., Ma, H., and Yuan, W.: High Resolution Distribution Dataset of Double-Season Paddy Rice in China, Remote Sens., 13, 4609, https://doi.org/10.3390/rs13224609, 2021.

Yan, H., Liu, F., Qin, Y., Niu, Z., Doughty, R., and Xiao, X.: Tracking the spatio-temporal change of cropping intensity in China during 2000–2015, Environ. Res. Lett., 14, 035008, https://doi.org/10.1088/1748-9326/aaf9c7, 2019.

Comment 6: Ground samples were only collected from 2017 to 2019 in five provinces. How do you determine the whether the clusters are closest to the soybean samples in other 9 provinces and 2020-2021 when DTW is applied? Even during 2017 to 2019, you don't have soybean samples collected during the ground survey.

Reply: The analysis showed the standard curves of soybean is very similar in a certain area during our studied years (Figure 3). Therefore, we determined the standard curves in each sub-zone, which can be applied into other years or the similar cropping systems. In provinces without ground samples, we manually select the reference points based on GLAD soybean-maize map (Figure S1). The criterions selected are: (1) located in large plots; (2) false color composite image (R: NIR, G: SWIR2, B: SWIR1) at the peak of growing season (Song et al., 2017; You and Dong, 2020); (3) phenological characteristics similar to local observations. The seasonal change of soybean for each zone does not vary from year to year based on our analysis (Figure 3), thus the characteristic curves in 2019 were taken as uniform standard.

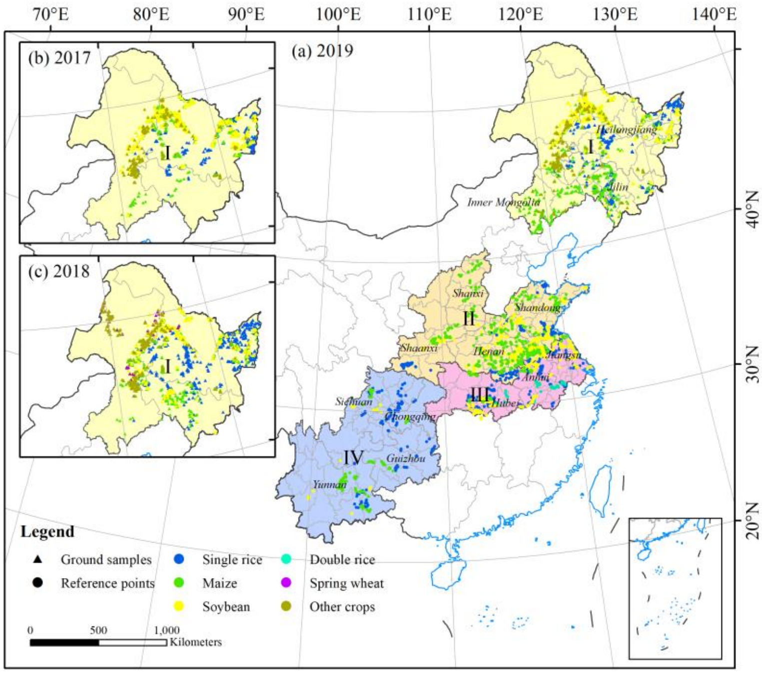

Figure S1. Spatial distribution of ground samples and reference points.

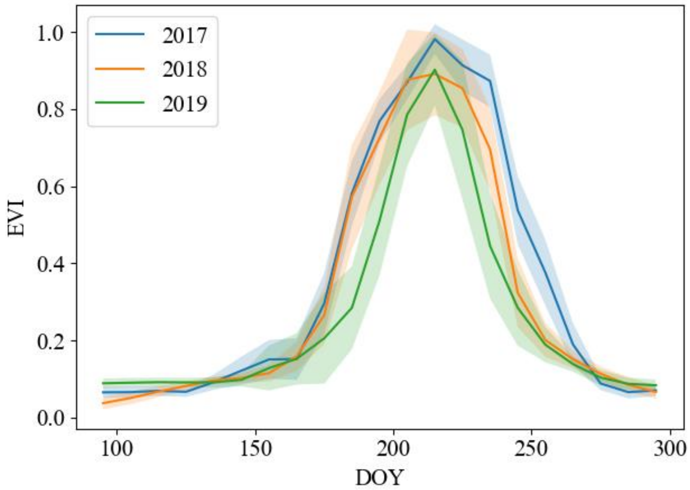

Figure 3. EVI of soybean ground samples in a same area from 2017 to 2019.

We updated the description of data sources in section 2.2.4 "Census data and ground samples" of the manuscript:

"We used both ground samples and reference points based on available datasets to determine soybean standard curves and assess the reliability of the soybean maps (Fig. S1). All points were randomly divided in a 3:7 ratio for standard curve calculation and accuracy validation, respectively. We collected ground samples from field surveys from 2017 to 2019 in Heilongjiang (HLJ), Inner Mongolia (NMG), Anhui (AH), Henan (HN), and Jilin (JL), which account for more than 70% of the country's total soybean planting area (Table 1). Crop types (soybean, maize, rice, wheat, others) and other land cover types were recorded. To ensure the impartiality of verification results, we only selected crop samples for validation. In provinces without ground samples, we manually selected reference points on large soybean plots based on GLAD (https://glad.earthengine.app/view/china-crop-map, last access: March 2024) soybean layer.

The criterions selected are: (1) located in large plots; (2) false color composite image (R: NIR, G: SWIR2, B: SWIR1) at the peak of growing season (Song et al., 2017; You and Dong, 2020); (3) phenological characteristics similar to local observations. Additionally, the reference points of maize, single-cropping rice and double-cropping rice in 2019 were selected based on GLAD maize layer, high resolution single-season rice map (https://doi.org/10.57760/sciencedb.06963, last access: March 2024), and double-season rice map (https://doi.org/10.12199/nesdc.ecodb.rs.2022.012, last access: March 2024) with the same principle to explore the spectral characteristics of crops in each sub-zone of the studied areas. The overall accuracy of all available maps in 2019 is above 85% (Pan et al., 2021; Li et al., 2023; Shen et al., 2023)."

Reference:

Pan, B., Zheng, Y., Shen, R., Ye, T., Zhao, W., Dong, J., Ma, H., and Yuan, W.: High Resolution Distribution Dataset of Double-Season Paddy Rice in China, Remote Sens., 13, 4609, https://doi.org/10.3390/rs13224609, 2021.

Li, H., Song, X.-P., Hansen, M. C., Becker-Reshef, I., Adusei, B., Pickering, J., Wang, L., Wang, L., Lin, Z., Zalles, V., Potapov, P., Stehman, S. V., and Justice, C.: Development of a 10-m resolution maize and soybean map over China: Matching satellite-based crop classification with sample-based area estimation, Remote Sens. Environ., 294, 113623, https://doi.org/10.1016/j.rse.2023.113623, 2023.

Shen, R., Pan, B., Peng, Q., Dong, J., Chen, X., Zhang, X., Ye, T., Huang, J., and Yuan, W.: High-resolution distribution maps of single-season rice in China from 2017 to 2022, Earth Syst. Sci. Data, 15, 3203–3222, https://doi.org/10.5194/essd-15-3203-2023, 2023.

Song, X.-P., Potapov, P. V., Krylov, A., King, L., Di Bella, C. M., Hudson, A., Khan, A., Adusei, B., Stehman, S. V., and Hansen, M. C.: National-scale soybean mapping and area estimation in the United States using medium resolution satellite imagery and field survey, Remote Sens. Environ., 190, 383–395, https://doi.org/10.1016/j.rse.2017.01.008, 2017.

You, N. and Dong, J.: Examining earliest identifiable timing of crops using all available Sentinel 1/2 imagery and Google Earth Engine, ISPRS J. Photogramm. Remote Sens., 161, 109–123, https://doi.org/10.1016/j.isprsjprs.2020.01.001, 2020.

Comment 7: Those ground samples were used in both cluster assignments and validation. Scientifically, independent validation shall be applied.

Reply: Thank you very much for your instructive comments. Yes, the ground samples used to cluster assignment and validation should be separated. The samples were randomly divided according to the ratio of 3:7 for standard curves calculation and accuracy validation respectively. The average characteristic curves of the points drawn according to the 30% ratio are almost indistinguishable from the average curves of all points. The accuracy verification results of 70% sample points are updated as follows:

Table 2. Confusion matrix of the soybean maps during 2017-2019.

	Reference	Map Soybean	Map Non-Soybean	Producer's Accuracy	User's Accuracy	F1 Score	Overall Accuracy
2017	Soybean	679	352	65.86%	72.47%	0.69	77.08%
	Non-Soybean	258	1372	84.17%	79.58%	0.82	
2018	Soybean	799	246	76.46%	74.19%	0.75	85.16%
	Non-Soybean	278	2208	88.82%	89.98%	0.89	
2019*	Soybean	1279	235	84.48%	83.32%	0.84	86.77%
	Non-Soybean	256	1940	88.34%	89.20%	0.89	

* Including ground samples and nationwide reference points based on existing datasets.

Comment 8: According to the validation in 3.1, it seems that the mapping accuracy is much lower in counties with less soybean area at both county and prefecture level. This does not surprise me due to the combined resolution bias and the algorithm uncertainties. This raise up another question, is it meaningful to generate soybean maps at almost whole national scale?

Reply: We recognize the limitations in non-main producing areas, yet it still makes sense to conduct a nationwide soybean areas extraction based on the following reasons.

(1) The validation accuracy of each sub-zone is acceptable. By integrating ground samples with reference points from existing datasets, we have supplemented the validation results for each sub-zone in 2019 (Table S1). The OA values reached 83.58% ~ 90.67%, with only producer's accuracy of Zone IV was relatively lower at 63.89%, which may be due to the limited samples, high heterogeneity, and fewer clear observations.

(2) Errors can be caused by multiple sources. In scarcer planted areas, the misclassification or omissions show a greater impact on the results. In addition to classifier constraints, the mapping area aggregate based on pixel counts may also lead to errors due to mixed pixels and resolution limitations in scattered planting areas.

(3) The method still has great application potential in main soybean-producing areas. Our mapping results showed robust interannual high R^2 and OA, demonstrating that mapping is valid and reliable in key areas. Therefore, the method can be used in other major soybean production areas in the world and has great practical application potential.

(4) Conducting nationwide soybean mapping is beneficial, providing insights for practical use and method improvement in future. Even with uncertainties in non-main producing areas, identifying possible soybean distributions can provide references for local agricultural monitoring and policy making. In addition, understanding soybean planting patterns in different regions and further exploring the spatial differences in production are very beneficial to soybean production adjustment at the national level. The method can be further improved by collecting more detailed crop pattern information, classifying on finer scale, improving classification algorithms, and integrating more various data sources to identify soybean plots in these regions (see Reply for Comment 9 for more details).

Comment 9: The discussion needs significant improvements. The author discussed the limitations of the research while ignoring the strong points of the research. Also, the uncertainty of the classification at small-scale soybean cultivation areas shall be addressed from a more theoretical way.

Reply: Thank you for your instructive suggestion. We added "4.1 Our advantages and potential applicability" to the discussion. We highlighted the strengths of our method: its independence from extensive requirements for samples, and its capability for rapid mapping in other regions along with excellent spatial scalability. Unlike the previous products relied on extensive samples for supervised classification, our approach could be applied into other major soybean-producing areas with simple inputs.

4.1 Our advantages and potential applicability

The methodology developed for identifying soybean planting areas indicate several notable strengths that make it an attractive option for wide application. Firstly, it operates independently, without extensive ground samples required. The conventional approaches depend on quantities of observational data, with much money, time, and labor consumed. In contrast, our strategy leverages a specific, pre-existing set of samples to discern soybean characteristics, which can accurately map annual dynamics without updated requirement in annual samples. Consequently, this method significantly weakens limitations in crop classification during years without specific samples, enabling crop mapping consistently and continually.

Another key advantage of our spectra-phenology integration approach is its quick applicability over larger areas, coupled with excellent spatial scalability. The only inputs required are the phenological information of soybeans and the number of other primary crops during the same growing season in the targeted area. This allows to classify crop swiftly and efficiently without additional inputs for background knowledge or setting complex thresholds. The input of phenological information in each prefecture enhanced the zonal adaptive assessment of soybean growth status across various areas, thereby facilitating crop classification. This innovative approach ensures its applicability into other soybean-producing areas, showcasing its potential for broader implementation.

In addition, we added a reasonable explanation for the limitations from classifiers in section 4.3 and discussed possible means for future research. This error is caused by characteristics of the algorithm, such as strong dependence on the initial cluster center, spherical cluster assumption, etc. In future research, we could reduce the uncertainty by adjusting the classification scale, optimizing data preprocessing and using improved algorithms.

"The lower accuracy in soybean area sparely planted could be explained by the characteristics of K-means algorithm. K-means algorithm is developed to minimize the distance between each point within a cluster and the cluster's centroid. When the sample size in a particular category substantially exceeds those of others, the algorithm might preferentially optimize the cohesion of the larger category, and would neglect the accurate clustering for smaller categories (Tan et al., 2016). The effectiveness of K-means classification is highly dependent on the selection of initial clustering centers. In scenarios of unbalanced categories, initial centers randomly selected might inadequately represent the minor categories, resulting in inaccurate results (Tan et al., 2016). Additionally, K-means assumes that each cluster is spherical; therefore, it does not perform well when clusters are non-spherical and uneven in size and density. Hence, in areas with unbalanced crop categories, the algorithm faces challenge to assign each crop to a corresponding cluster precisely (Tan et al., 2016; Wang et al., 2019).

Our regional adaptive large-area crop mapping method in future will further be improved by the follows: (1) Classification on a finer scale by specifying a more precise number of target clusters can reduce spatial heterogeneity and emphasize the relative importance of non-dominant categories, and increase classification accuracy consequently (Li and Yang, 2017). (2) Optimizing data preprocessing methods. Outliers can interrupt classification because the unsupervised methods is highly sensitive to anomalies (Raykov et al., 2016; Wang et al., 2019). Therefore, eliminating outliers can further improve the classification validity. In addition, since K-means weights all dimensions equally, minimizing the features' correlation and reducing irrelevant variables are also important means to enhance the classification effect (Hastie et al., 2009). (3) Improving algorithm performance. A variety of algorithms have been proposed to address the inherent defects of K-means (Ahmed et al., 2020), such as by optimizing the initial clustering center (e.g., K-means++), weighting classes (e.g., Weighted k-means), and non-spherical clustering assumptions (e.g., DBSCAN, Spectral Clustering) (Ester et al., 1996; Bach and Jordan, 2003; Kerdprasop et al., 2005; Arthur and Vassilvitskii, 2007). The improved algorithms will address the issues on complex and highly diverse crop classification in some degrees (Li et al., 2022;

Rivera et al., 2022). (4) Better post-processing of data. Misclassification of field ridges and image speckles is inevitable during mapping crops over large areas. With the progress of computing power, auxiliary data and image processing algorithms can further eliminate these issues (Liu et al., 2018; Li and Qu, 2019; Hamano et al., 2023). We are sure that integrating cloud computing platforms with advanced algorithms will provide substantial potential for accurate crop identification covering larger areas in future."

Reference:

Ahmed, M., Seraj, R., and Islam, S. M. S.: The k-means Algorithm: A Comprehensive Survey and Performance Evaluation, Electronics, 9, 1295, https://doi.org/10.3390/electronics9081295, 2020.

Arthur, D. and Vassilvitskii, S.: k-means++: The advantages of careful seeding, in: Soda, 1027–1035, 2007.

Bach, F. and Jordan, M.: Learning spectral clustering, in: Advances in neural information processing systems, 2003.

Ester, M., Kriegel, H.-P., Sander, J., and Xu, X.: A density-based algorithm for discovering clusters in large spatial databases with noise, in: kdd, 226–231, 1996.

Hamano, M., Shiozawa, S., Yamamoto, S., Suzuki, N., Kitaki, Y., and Watanabe, O.: Development of a method for detecting the planting and ridge areas in paddy fields using AI, GIS, and precise DEM, Precis. Agric., 24, 1862–1888, https://doi.org/10.1007/s11119-023-10021-z, 2023.

Hastie, T., Tibshirani, R., Friedman, J. H., and Friedman, J. H.: The elements of statistical learning: data mining, inference, and prediction, Springer, 2009.

Kerdprasop, K., Kerdprasop, N., and Sattayatham, P.: Weighted k-means for density-biased clustering, in: International conference on data warehousing and knowledge discovery, 488–497, https://doi.org/10.1007/11546849_48, 2005.

Li, B. and Yang, L.: Clustering accuracy analysis of building area in high spatial resolution remote sensing images based on k-means algorithm, in: 2017 2nd International Conference on Frontiers of Sensors Technologies (ICFST), 2017 2nd International Conference on Frontiers of Sensors Technologies (ICFST), 174–178, https://doi.org/10.1109/ICFST.2017.8210497, 2017.

Li, T., Johansen, K., and McCabe, M. F.: A machine learning approach for identifying and delineating agricultural fields and their multi-temporal dynamics using three decades of Landsat data, ISPRS J. Photogramm. Remote Sens., 186, 83–101, https://doi.org/10.1016/j.isprsjprs.2022.02.002, 2022.

Li, Y. and Qu, H.: LSD and Skeleton Extraction Combined with Farmland Ridge Detection, in: Advances in Intelligent, Interactive Systems and Applications, Cham, 446–453, https://doi.org/10.1007/978-3-030-02804-6_59, 2019.

Liu, H., Zhang, J., Pan, Y., Shuai, G., Zhu, X., and Zhu, S.: An Efficient Approach Based on UAV Orthographic Imagery to Map Paddy With Support of Field-Level Canopy Height From Point Cloud Data, IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., 11, 2034–2046, https://doi.org/10.1109/JSTARS.2018.2829218, 2018.

Raykov Y. P., Boukouvalas A., Baig F., and Little M. A.: What to Do When K-Means Clustering Fails: A Simple yet Principled Alternative Algorithm, PLOS ONE, 11, e0162259, https://doi.org/10.1371/journal.pone.0162259, 2016.

Rivera, A. J., Pérez-Godoy, M. D., Elizondo, D., Deka, L., and del Jesus, M. J.: Analysis of clustering methods for crop type mapping using satellite imagery, Neurocomputing, 492, 91–106, https://doi.org/10.1016/j.neucom.2022.04.002, 2022.

Tan, P.-N., Steinbach, M., and Kumar, V.: Introduction to data mining, Pearson Education India, 2016.

Wang, S., Azzari, G., and Lobell, D. B.: Crop type mapping without field-level labels: Random forest transfer and unsupervised clustering techniques, Remote Sens. Environ., 222, 303–317, https://doi.org/10.1016/j.rse.2018.12.026, 2019.

Comment 10: The ms does not consider the soybean-maize intercropping systems in part of China.

Reply: We have considered all cropping patterns related with soybean as possible. For example, we have identified the banded areas planted by soybean as shown in Figure 4. Soybean and other crops are interplanted with the narrowest strip width detectable at about 2-3 pixels, equivalent to 20-30 meters. However, if the strip widths in soybean-maize intercropping system are less than a meter (Yang et al., 2014; Du et al., 2018), the 10-meter resolution provided by Sentinel-2 imagery will fail in capturing these planting stripes due to mixed pixels problems. With the help of higher resolution remote sensing data, such as sub-meter level satellite images or local unmanned aerial vehicle (UAV) images, such dense intercropping systems will be identified more accurately. We added discussion to state the uncertainty caused by this agricultural pattern:

"The growth periods of soybean, peanut, potato, and maize are similar, dominantly indicated by a mixed planting pattern, which has contributed to the low accuracy of non-main soybean producing areas in southern China (Liu et al., 2020). Additionally, soybeans are intercropped with maize or other crops in some areas, where the strip width is less one meter (Yang et al., 2014; Du et al., 2018). This planting pattern will introduce the mixed pixels problem as well under the background of 10 m resolution crop mapping."

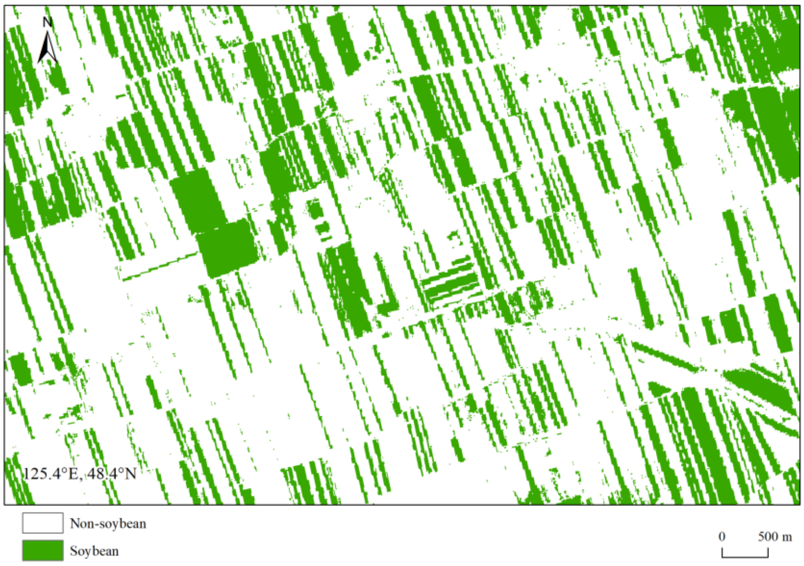

Figure 4. The case of soybean banded planting pattern in northeast China.

Reference:

Du, J., Han, T., Gai, J., Yong, T., Sun, X., Wang, X., Yang, F., Liu, J., Shu, K., Liu, W., and Yang, W.: Maize-soybean strip intercropping: Achieved a balance between high productivity and sustainability, J. Integr. Agric., 17, 747–754, https://doi.org/10.1016/S2095-3119(17)61789-1, 2018.

Yang, F., Huang, S., Gao, R., Liu, W., Yong, T., Wang, X., Wu, X., and Yang, W.: Growth of soybean seedlings in relay strip intercropping systems in relation to light quantity and red:far-red ratio, Field Crops Res., 155, 245–253, https://doi.org/10.1016/j.fcr.2013.08.011, 2014.