Response to reviewer #1:

General comment: The article proposed an unsupervised method for identifying soybean crops within the defined croplands across China. The topic is interesting, and also important for sustainable agricultural development due to its large spatial and long-term coverage. The data is well collected and processed, and the results are properly presented. I would suggest some minor revisions as listed below.

Thank you for your positive and constructive comments, which surely encourage us to further enhance our research quality. We carefully revised our manuscript and provided a point-by-point response below. Moreover, we have positively addressed all points in the revised edition, which will be updated after responding all referees' comments.

Comment 1: L43: Not sure what are the "shortcomings of domestic supply"?

Sincerely apologize for the ambiguousness here. We have changed "shortcomings" into "shortages" throughout the manuscript.

We have further elucidated the issue of soybean supply in China in our revised manuscript. The shortages of soybean supply in China are evident in its growing dependence on imports and the decreasing share of soybean production. Specifically, the yield per unit area of soybean in China is substantially lower than that of other major crops, such as wheat, rice, and maize (Liu et al., 2021). In addition, as China shifts from domestic cultivation of soybeans to importation, a considerable amount of arable land is being repurposed for the cultivation of other, more productive crops (Cui and Shoemaker, 2018).

These points have been comprehensively addressed and supplemented with supporting literature in the revised manuscript:

"Given the rapid growth of demand and the shortages of domestic supply due to low yield and low self-sufficiency, mapping soybean planting areas across China is crucial for sustainable soybean production and management (Cui and Shoemaker, 2018; Liu et al., 2021)."

Reference:

Cui, K. and Shoemaker, S. P.: A look at food security in China, npj Sci. Food, 2, 4, https://doi.org/10.1038/s41538-018-0012-x, 2018.

Liu, Z., Ying, H., Chen, M., Bai, J., Xue, Y., Yin, Y., Batchelor, W. D., Yang, Y., Bai, Z., Du, M., Guo, Y., Zhang, Q., Cui, Z., Zhang, F., and Dou, Z.: Optimization of China's maize and soy production can ensure feed sufficiency at lower nitrogen and carbon footprints, Nat. Food, 2, 426–433, https://doi.org/10.1038/s43016-021-00300-1, 2021.

Comment 2: L46: Please add references to previous studies.

Yes, we have followed you to add references here.

"Soybean planting area in some regions of China was mapped in previous studies (You et al., 2021; Huang et al., 2022; Chen et al., 2023), but long-term soybean maps over all major producing areas in China have not been available."

Comment 3: L59-62: I would suggest revising the statements as "the previous studies made laudable efforts to craft a comprehensive national maize-soybean map for China in 2019 by combining field data and regression estimators (Li et al., 2023). Nonetheless, these studies were confined to specific regions or a single year, despite prior attempts to accurately map soybean cultivation areas."

Thank you very much for your instructive comments. Your suggestion has indeed made the statement clearer and more logically coherent. We have revised the sentence as you suggested.

Comment 4: L64-70: to me, this is not "generally" way of categorizing remote sensing classification methods. Supervised and unsupervised are the widely accepted categories. I would suggest authors revise the paragraph, link the specific classification method mentioned in L71-78 to each category, and discuss the pros and cons.

Yes, we have reorganized the previous researches and divided the commonly used remote sensing-based crop classification methods into four categories. In addition to the supervised and unsupervised classification in machine learning that you mentioned, considering that threshold segmentation based on prior knowledge and new composite index methods based on feature bands are two other methods of crop mapping, we have summarized the methods into four types. Method 5 in the original text has been incorporated into supervised classification. Additionally, we revised the corresponding section, as well as discussing the advantages and disadvantages of each method:

"Mapping crops by remote sensing can be categorized into four methods : 1) supervision classification based on a large number of field samples or high quality training labels (Song et al., 2017; You et al., 2021; Shangguan et al., 2022; Li et al., 2023); 2) developing some composite indexes based on the feature bands and determining the binary classification using appropriate threshold value (Huang et al., 2022; Chen et al., 2023; Zhou et al., 2023); 3) threshold segmentation based on prior knowledge such as phenology or spectra (Zhong et al., 2016); 4) combining unsupervised classification with post-classification (Wang et al., 2019; You et al., 2023). Supervision classification methods relied on ground samples heavily, while the 2nd and 3rd methods are both based on reliable and accurate thresholds. However, mapping soybean by these methods was mainly applied in small areas, very few covering over a larger region. Because of sufficient field samples, supervision classification can achieve maps with a higher accuracy, which is relatively mature method used widely. However, collecting sufficient field samples is extremely time, money, and labor costly, and unsuitable for long-term years and over larger areas (Luo et al., 2022). Furthermore, the threshold-based methods (the 2nd and 3rd) have been applied into large areas, however, determining the thresholds will inevitably bring significant uncertainty, especially for the areas with high heterogeneity in climate, environment, and planting patterns. Thus, reproducibility of these methods is low, further hindering their application across diverse geographic areas. As for mapping soybean, it is still a big challenge due to their similar growth characteristics with many other summer crops (Wang et al., 2020; Di Tommaso et al., 2021). The thresholds that work well in some areas did not perform well in other areas (Graesser and Ramankutty, 2017; Guo et al., 2018). These limitations restrict accurate soybean maps available, especially over large regions in China."

Reference:

Chen, H., Li, H., Liu, Z., Zhang, C., Zhang, S., and Atkinson, P. M.: A novel Greenness and Water Content Composite Index (GWCCI) for soybean mapping from single remotely sensed multispectral images, Remote Sens. Environ., 295, 113679, https://doi.org/10.1016/j.rse.2023.113679, 2023.

Di Tommaso, S., Wang, S., and Lobell, D. B.: Combining GEDI and Sentinel-2 for wall-to-wall mapping of tall and short crops, Environ. Res. Lett., 16, 125002, https://doi.org/10.1088/1748-9326/ac358c, 2021.

Graesser, J. and Ramankutty, N.: Detection of cropland field parcels from Landsat imagery, Remote Sens. Environ., 201, 165–180, https://doi.org/10.1016/j.rse.2017.08.027, 2017.

Guo, W., Ren, J., Liu, X., Chen, Z., Wu, S., and Pan, H.: Winter wheat mapping with globally optimized threshold under total

quantity constraint of statistical data, Journal of Remote Sensing, 22, 1023–1041, https://doi.org/10.11834/jrs.20187468, 2018.
Huang, Y., Qiu, B., Chen, C., Zhu, X., Wu, W., Jiang, F., Lin, D., and Peng, Y.: Automated soybean mapping based on canopy water content and chlorophyll content using Sentinel-2 images, Int. J. Appl. Earth Obs., 109, 102801, https://doi.org/10.1016/j.jag.2022.102801, 2022.
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.
Luo, Y., Zhang, Z., Zhang, L., Han, J., Cao, J., and Zhang, J.: Developing High-Resolution Crop Maps for Major Crops in the European Union Based on Transductive Transfer Learning and Limited Ground Data, Remote Sens., 14, 1809, https://doi.org/10.3390/rs14081809, 2022.
Shangguan, Y., Li, X., Lin, Y., Deng, J., and Yu, L.: Mapping spatial-temporal nationwide soybean planting area in Argentina using Google Earth Engine, Int. J. Remote Sens., 43, 1724–1748, https://doi.org/10.1080/01431161.2022.2049913, 2022.
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.
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.
Wang, S., Di Tommaso, S., Deines, J. M., and Lobell, D. B.: Mapping twenty years of corn and soybean across the US Midwest using the Landsat archive, Sci. Data, 7, 307, https://doi.org/10.1038/s41597-020-00646-4, 2020.
You, N., Dong, J., Huang, J., Du, G., Zhang, G., He, Y., Yang, T., Di, Y., and Xiao, X.: The 10-m crop type maps in Northeast China during 2017–2019, Sci. Data, 8, 41, https://doi.org/10.1038/s41597-021-00827-9, 2021.
You, N., Dong, J., Li, J., Huang, J., and Jin, Z.: Rapid early-season maize mapping without crop labels, Remote Sens. Environ., 290, 113496, https://doi.org/10.1016/j.rse.2023.113496, 2023.
Zhong, L., Hu, L., Yu, L., Gong, P., and Biging, G. S.: Automated mapping of soybean and corn using phenology, ISPRS J. Photogramm. Remote Sens., 119, 151–164, https://doi.org/10.1016/j.isprsjprs.2016.05.014, 2016.
Zhou, W., Wei, H., Chen, Y., Zhang, X., Hu, J., Cai, Z., Yang, J., Hu, Q., Xiong, H., Yin, G., and Xu, B.: Monitoring intra-annual and interannual variability in spatial distribution of plastic-mulched citrus in cloudy and rainy areas using multisource remote sensing data, European Journal of Agronomy, 151, 126981, https://doi.org/10.1016/j.eja.2023.126981, 2023.

Comment 5: L121: Please justify the impact of using TOA reflectance, rather than surface reflectance, on classification results.

During using Sentinel-2 imagery in our study, we encountered difficult with the L2A product on the GEE platform in terms of temporal coverage in China. Taking the Northeast as an example, the L2A data was only available after December 2018, whereas the L1C product offered complete coverage from 2017 onwards. Consequently, for crop mapping prior to 2019, L2A was not a viable option. To be consistency, we opted for the L1C product for mapping soybean.

Furthermore, to ensure the reliability of L1C product for classification, we analyzed spectral and vegetation indices time series from field samples in Daqing, Heilongjiang Province, for both L1C and L2A products in 2019 (Figures 1-2). The difference between two spectral profiles is minimal. More importantly, the L1C-based spectral and vegetation indices also demonstrated effective separability between soybeans and other crops. Thus, to preserve the temporal integrity without compromising classification accuracy, we chose Sentinel's L1C (TOA), rather than L2A (SR).

In section 2.2.1 of the revised manuscript, we have added an explanation for our choose for L1C instead of L2A.

"... last access: September 2023). Because of the longer temporal coverage of Sentinel-2 Level-1C TOA reflectance data, and the nearly identical spectral profile time series extracted from both products demonstrating that TOA images can equally full fill crop classification requirements, we opt for using L1C products instead of L2A (You and Dong, 2020; Han et al., 2021; Luo et al., 2022)."

Reference:

Han, J., Zhang, Z., Luo, Y., Cao, J., Zhang, L., Zhang, J., and Li, Z.: The RapeseedMap10 database: annual maps of rapeseed at a spatial resolution of 10 m based on multi-source data, Earth Syst. Sci. Data, 13, 2857–2874, https://doi.org/10.5194/essd-13-2857-2021, 2021.

Luo, Y., Zhang, Z., Zhang, L., Han, J., Cao, J., and Zhang, J.: Developing High-Resolution Crop Maps for Major Crops in the European Union Based on Transductive Transfer Learning and Limited Ground Data, Remote Sens., 14, 1809, https://doi.org/10.3390/rs14081809, 2022.

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.

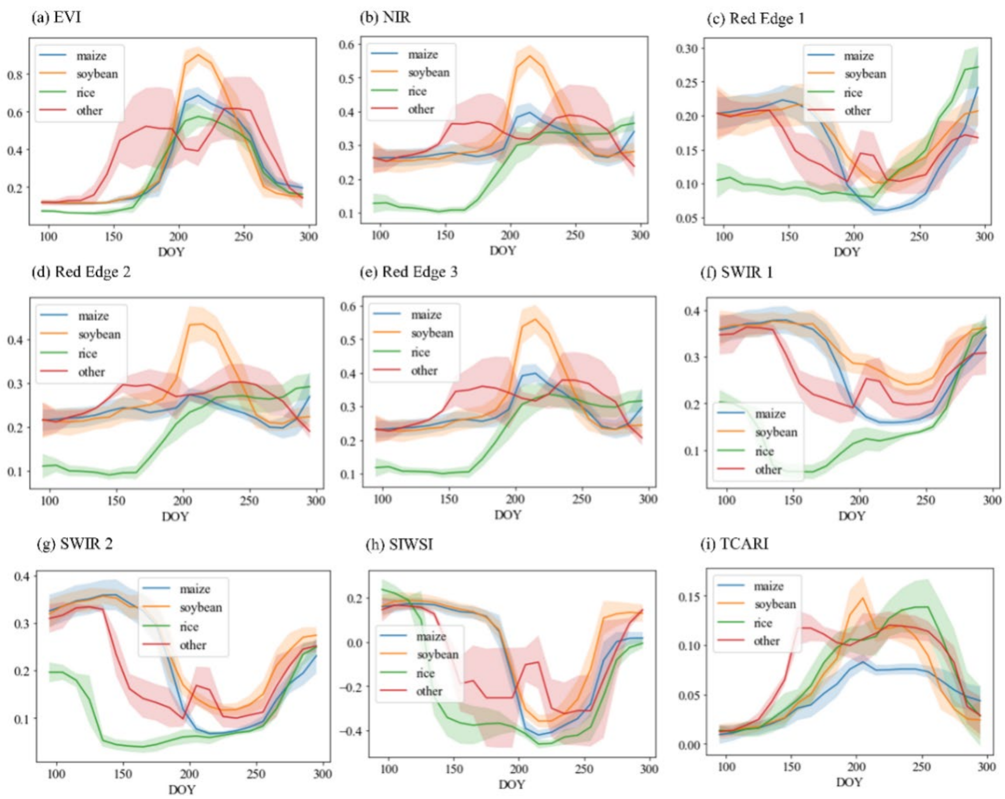

Figure 1. Temporal profiles of L2A products for major crops in Daqing, Heilongjiang based on ground samples.

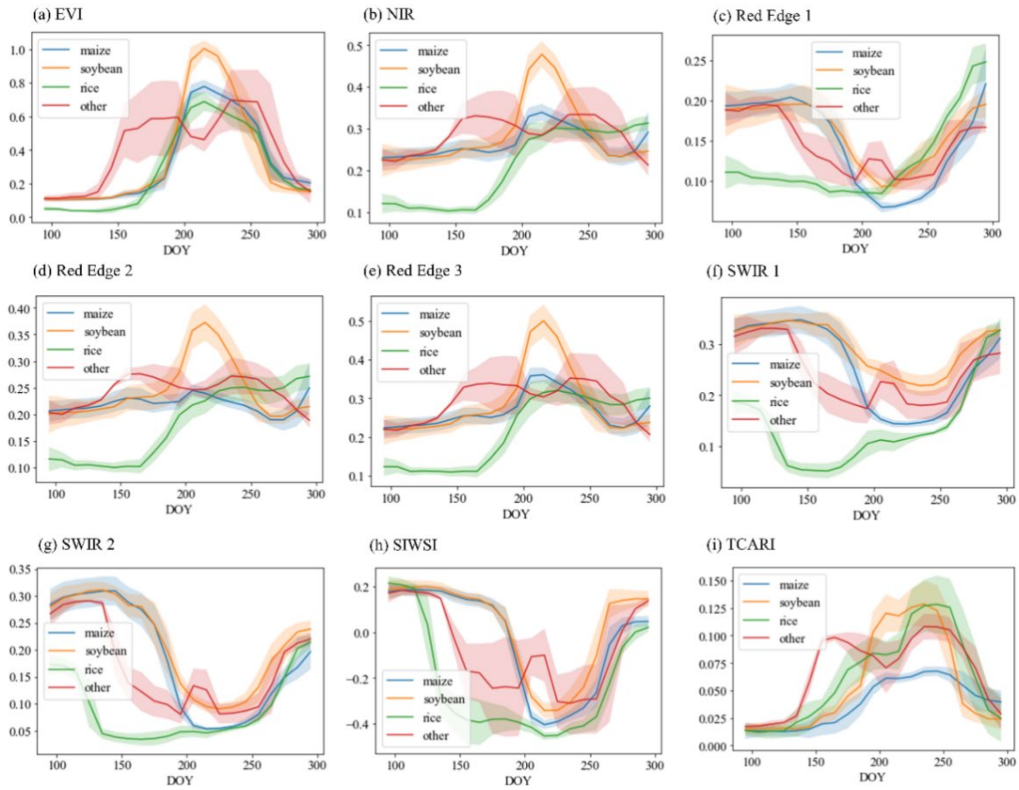

Figure 2. Temporal profiles of L1C products for major crops in Daqing, Heilongjiang based on ground samples.

Comment 6: L123: Depending on the platform/sensor used, red edge bands are also typical "traditional bands" in vegetation-related studies.

Thank you for pointing out the issue. Indeed, the red-edge bands have been deployed on various sensors and have become primary application bands. We have removed the expressions that could cause ambiguity in the revised manuscript:

"~~In addition to the traditional bands (i.e., the visible and near infrared bands), t~~The red-edge bands and shortwave infrared bands equipped with sentinel-2 play a great role in enhancing the accuracy of crop classification."

Comment 7: L135: Please specify what is the "gaps"? If it is related to crop growth, how the "average" procedure was conducted?

Specifically, 'gaps' means the missing phenological observations in a certain year at some agricultural meteorological stations we collected. For the missing values, we inserted averages of the observations from the nearest years before and after the missing year. For example, if the flowering date in 2017 was missing, we inserted the average of flowering dates in 2016 and 2018 at that station as a substitute. We have rewritten and clarified this issue in section 2.2.2 of the revised manuscript:

"In cases of missing observation for a specific year, we inserted the average of two closest observations before and after the year. For instance, if there was missing data of flowering date in 2017, we filled it with the average of flowering records in 2016 and 2018 at the same station."

Comment 8: L189: it seems the purpose of this paragraph is to provide an overview of the method. The details regarding the "soybean mapping" can be merged with the sections below.

Thank you for the constructive suggestion. We have streamlined the description of soybean mapping methodology in this paragraph, and merged the details with the following sections as you suggested. Such revision really enhances the clarity and conciseness of the methodology section.

Comment 9: L198-L200: I recon this is also the step that deals with the data gaps due to cloud? Please add more details regarding the method incorporated (e.g. moving window size etc?) if possible.

Yes, the time series reconstruction is carried out to simultaneously fill data gaps caused by cloud removal and smooth some anomalies. In order to obtain 10-day composite time series, as well as considering the revisit cycle of Sentinel-2 and computational efficiency, we set the half-window size to 10 days. We have added the details in the revised manuscript:

"To fill the data gaps caused by cloud removal and smooth anomalies, Sentinel-2 time series was reconstructed by moving median composite method, resulting in a 10-day interval composite time series. We set the half-window size for the moving median methods to 10 days considering the 5-day revisit cycle of Sentinel-2 and computational efficiency."

Comment 10: L203: no-cropland --> non-cropland

Thank you for pointing out this mistake, we have corrected it throughout the manuscript.

Comment 11: L204: you might need to define the "starting and ending dates of the growing season" first.

Following your suggestions, we have defined the sowing dates recorded at the nearest AMS as the starting dates of growing season, and the harvesting dates as ending dates. This has been clarified in section 2.3.2 "(1) Potential area identification" in our revised manuscript:

"To minimize the impact from non-croplands, we firstly determine the potential cropping areas by masking GLAD cropland layer over study area. Sentinel-2 images within growing season were extracted by taking the sowing date and harvesting date recorded at the nearest agricultural meteorological station (AMS) as the starting and ending dates of the growing season, respectively."

Comment 12: L206: Please provide the full name for EVI first. And, revise the sentence slightly, "… we masked out the pixels with maximum EVI less than 0.4 during the growing seasons". Please also justify how the threshold (0.4) for fallow land was determined.

Thank you for your suggestion. We have followed you to provide the full name of EVI in the revised manuscript. We identified the pixels with maximum EVI values < 0.4 as fallow land because the maximum EVI values for crops are all > 0.4 (except for a few outliers) (Figure 3) based on all ground samples in 2019 (Figure 3). Thus, using 0.4 as a threshold allows us to strictly remove fallow land (Li et al., 2014). We have provided additional explanations for the threshold choice in the revised manuscript:

"Based on the cropland extracted, we filtered the pixels exhibiting an Enhanced Vegetation Index (EVI) maximum value during the growing season greater than 0.4 to remove fallow land, because ground samples and previous studies showed that nearly all crops had maximum EVI values above 0.4. (Li et al., 2014)."

Reference:

Li, L., Friedl, M. A., Xin, Q., Gray, J., Pan, Y., and Frolking, S.: Mapping Crop Cycles in China Using MODIS-EVI Time Series, Remote Sens., 6, 2473–2493, https://doi.org/10.3390/rs6032473, 2014.

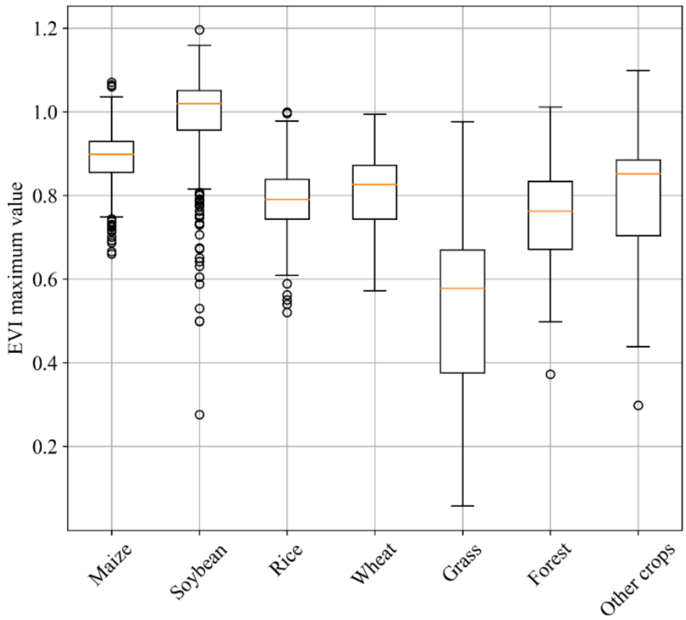

Figure 3. Box plot of the EVI maximum in 2019 based on ground samples.

Comment 13: L296- : it is good that the authors noticed the large estimation uncertainties in small-planting regions (figure 4, and figures 5). It would help to justify why this happened by looking into several regions and checking the reasons.

Also, given the great similarities of maize and soybean index profiles (Figure 3), it is important to check whether the overestimated regions belong to maize crops? Since the classifiers are trained for individual regions, the authors might consider increasing the number of clusters for sparsely planting regions if maize is mixing with soybean due to their similarities? One potential way to check is to compare the ChinaSoyArea10m with the GLAD layer, especially the overestimating regions?

Yes, we compared ChinaSoyArea10m with the GLAD layer in the Shandong region, as the consistency between GLAD and statistics is higher there. Apart from the pixels consistently recognized as soybeans by both layers, some cornfields identified by the GLAD layer are classified into soybeans by ChinaSoyArea10m.

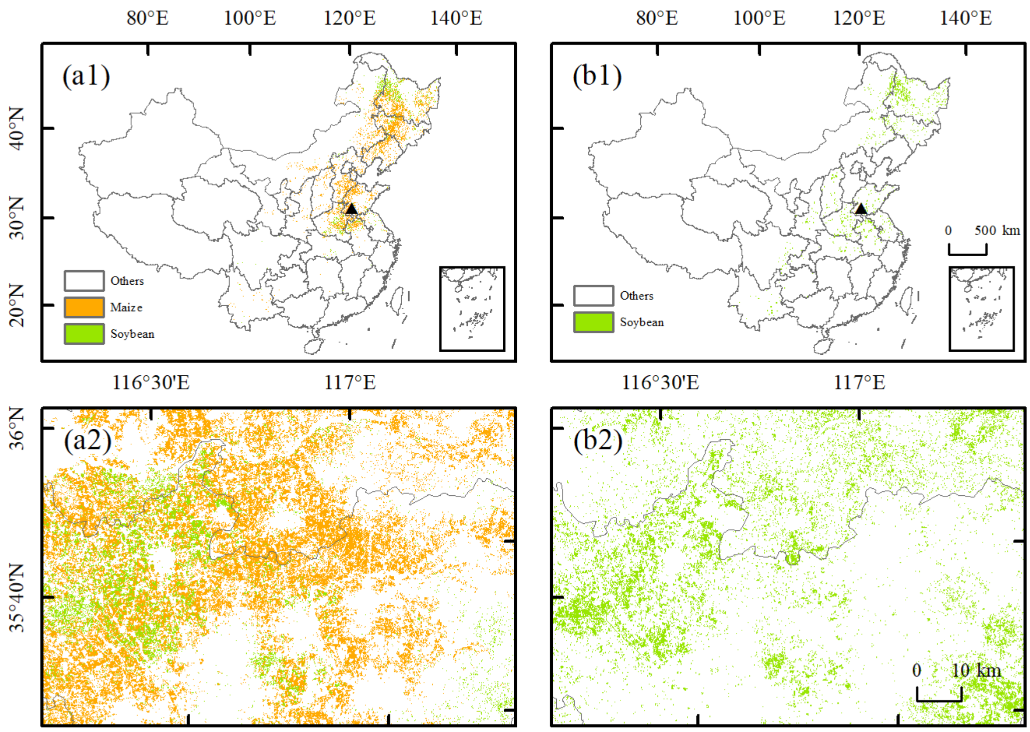

Figure 4. Visual comparison of GLAD (a1-a2) and ChinaSoyArea10m (b1-b2) in China (a1-b1) and a typical area in Shandong province (a2-b2).

In some provinces where we might overestimate soybean areas (e.g. Sichuan, Shaanxi, and Shanxi), GLAD significantly underestimated the soybean areas comparing with statistics (Figure 5). Therefore, it is very hard for us to determine which product is more accurate and reliable in such areas sparsely planted. We have discussed the uncertainties in details in the first paragraph of section 3.1.

"This uncertainty, particularly overestimation, could be caused by the low proportion of soybean cultivation. In areas where maize or other same-season crops are planted in a much larger proportion than soybeans, soybeans, as a less prevalent crop, pose a challenge for classifiers to distinctly recognize them as a separate category, resulting in clusters being identified as soybeans containing maize or other crops."

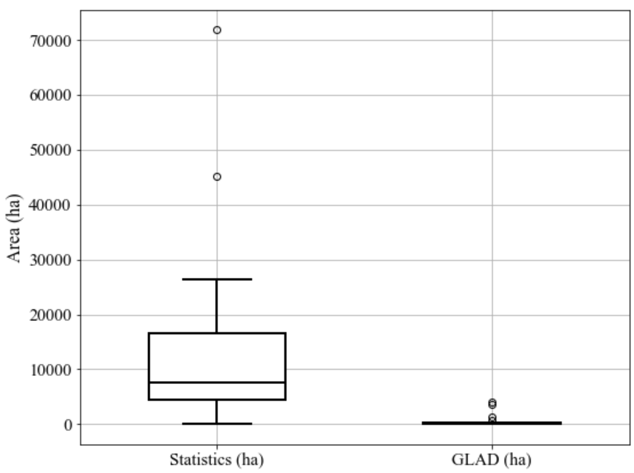

Figure 5. Box plot of soybean areas of statistics and GLAD map in Sichuan, Shaanxi, and Shanxi.

Comment 14: L315: to me, “became higher and higher” is not a scientific way to describe the trend here. Please consider “increased” or similar terms for the statement if it is a critical finding.
Thanks! We have used ‘increased’ in the manuscript.

Comment 15: L353: It is good to see the authors outline the limitations of the proposed method in regard to its sensitivity to data availability and applicability in sparsely planted regions. It would be good to have some insights into the advantages of the method compared to the mentioned GLAD and CDL products and promote its applications in some suggested circumstances.
Thank you for your suggestion. We have added a section on our advantages and potential applicability. 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 sample points 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 sample points to discern soybean characteristics. This approach can accurately map annual dynamics of soybean planting areas 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 rapid applicability over wide areas, coupled with excellent spatial scalability. The only inputs required for our mapping technique are the phenological information of soybeans and other primary crops during the same growing season in the target area. This allows to classify crop swiftly and efficiently without additional needs for background knowledge or setting complex thresholds. The input of phenological information in each prefecture ensured that the zonal adaptive soybean growth status across various regions could be taken into account in classification. Given that soybeans exhibit similar spectral characteristics during identical phenological stages from the same sub-zone in the study area, our method utilizes standard soybean sample curves from various regions to identify clusters most likely representing soybeans. This innovative approach ensures our methodology's applicability across major soybean-producing regions, showcasing its potential for broader implementation.