Reviewer #1:

This study presents a novel data-driven framework for annual mapping of cropping patterns and produces maps of China's complex cropping systems. Overall, the study is carefully conducted and adds useful insights to the existing literature. However, several aspects of the manuscript require minor revision to improve the overall quality and interpretability. Detailed suggestions are listed below.

There is a mistake in Line 483. Based on Fig. 12, the most important embedding band for wheat is A21 rather than A22. The RGB composites using band A22 in Fig. 10 and Fig. 11 should also be replaced with A21.
Response: Thank you for your careful check. We have corrected the mistake in Line 483. The most important embedding band for wheat has been revised from A22 to A21 according to Fig 12. Accordingly, the RGB composites in Fig 10 and Fig 11 have also been updated by replacing band A22 with A21.

The proposed mapping framework uses satellite embeddings as input features for supervised classification. Given that satellite embeddings are a relatively recent and emerging data product that has not yet been widely adopted in remote sensing applications, The Discussion could be strengthened by a more detailed discussion of satellite embeddings in the context of remote sensing applications and related recent literature (In Lines 489-491).
Response: Thank you for your suggestion. We agree that a more comprehensive discussion of satellite embeddings in the context of remote sensing applications would strengthen the manuscript. In the revised Discussion (Lines 489–491), we have expanded this part by incorporating recent studies and providing a more structured perspective.

Specifically, we discuss how satellite embeddings have recently emerged from general land-cover and feature representation tasks and are gradually being extended to agricultural applications. Recent studies in land-cover mapping show that satellite embeddings outperform traditional spectral indices, improving overall accuracy by ~5% and Kappa by ~3% (Khan and Ahmad, 2025; Mantey et al., 2025). These improvements are attributed to their ability to capture high-level semantic information and integrate multi-sensor signals, thereby enhancing the discrimination of complex land-cover types and improving mapping stability.

Building on these advances, satellite embeddings have also shown strong performance in cropland mapping, with contributions more than twice those of traditional remote sensing features (Cai et al., 2026). Their non-linear response patterns suggest that embeddings encode richer and more complex information, although this may reduce their direct interpretability.

From a biophysical perspective, recent studies indicate that satellite embeddings preserve key vegetation-related information, including pigment, structural, and phenological signals, enabling accurate modeling of crop traits (e.g., R^2 up to ~0.9) while maintaining efficient representation (Alam and Simic Milas, 2025). Notably, despite being provided at annual temporal resolution, embeddings can still capture growing-season signals, suggesting their ability to retain phenological information relevant to crop dynamics.

At a more application-oriented level, AEF-based models generally achieve strong performance across a range of agricultural tasks and are competitive with purpose-built remote sensing models in applications including yield prediction ($R^2 \approx 0.7-0.8$ for major crops), as well as tillage and cover crop mapping (Ma et al., 2025).

However, several limitations have also been identified. In particular, AEF-based models may exhibit reduced spatial transferability due to region-specific feature representations, as well as limited interpretability arising from the lack of explicit physical meaning in embedding dimensions. In addition, their annual temporal resolution constrains sensitivity to within-season dynamics.

Nevertheless, these limitations do not undermine their effectiveness for large-scale crop mapping, where satellite embeddings provide a compact, information-rich, and scalable representation, as demonstrated in this study.

Reference:

Alam, M. M. T. and Simic Milas, A.: Dimensionality optimized machine learning retrieval of canopy chlorophyll, nitrogen, and phosphorus from google satellite embeddings, Smart Agricultural Technology, 12, 101601, https://doi.org/10.1016/j.atech.2025.101601, 2025.

Cai, Y., Li, B., Liu, X., Jiang, X., Zhu, Y., Luo, S., Qin, Y., Xie, S., Ye, J., Shen, H., Guo, Z., Liu, X., and Zeng, Z.: Annual 10-m high-resolution cropland maps for Southeast Asia since 2019 using AlphaEarth embeddings, Earth Syst. Sci. Data Discuss., 2026, 1-30, 10.5194/essd-2026-78, 2026.

Khan, H. and Ahmad, A.: Evaluating AlphaEarth Foundation Embeddings for Pixel- and Object-Based Land Cover Classification in Google Earth Engine, 10.20944/preprints202511.2172.v1, 2025.

Ma, Y., Shen, Y., Swatantran, A., and Lobell, D. B. J. a. p. a.: Harvesting AlphaEarth: Benchmarking the Geospatial Foundation Model for Agricultural Downstream Tasks, 2025.

Mantey, S., Attipoe, I., and Alhassan, A.: A Comparative Analysis of Satellite Imagery for Land Cover Classification: Evaluating Google Satellite Embeddings, Sentinel-2, And Landsat-8 Data with XGBoost, 2025.

In Line 221, “Multi-cropping” is used, whereas “Multi-cropped” appears in the legend of Fig. 2. Please ensure consistent terminology throughout the manuscript.

Response: Thank you for your suggestion. We apologize for the inconsistency in terminology. We have standardized the term to “Multi-cropping” throughout the manuscript, including Line 221 and the legend of Figure 2. All related occurrences have been carefully checked and revised to ensure consistency.

In the Table 1, NorthEast should be revised to Northeast. Sourthern should be Southern. In Line 184, check the punctuation in this sentence, as there appears to be an extra comma at the end. Also, check the manuscript for inconsistent capitalization within sentences. (e.g. In Line 529).

Response: Thank you for your careful review. We have corrected “NorthEast” to “Northeast” and “Sourthern” to “Southern” in Table 1. The extra comma in Line 184 has also been removed. In addition, we have carefully checked the entire manuscript and corrected inconsistent capitalization within sentences (e.g., Line 529) to ensure consistency throughout.

This study produces a national-scale annual mapping product of cropping patterns in China for 2018–2021, which is valuable given the complexity of cropping systems and the limited availability of similar products. Nevertheless, it would be helpful for the Discussion to consider the potential extension of the proposed framework to broader spatial and temporal contexts, including cross-year transferability and within-season mapping, particularly given that the satellite embeddings are provided as annual products, which may limit their flexibility for in-season applications.

Response: Thank you for this constructive comment. We agree that the potential extension of the proposed framework to broader spatial and temporal contexts is an important aspect. We clarify that the current study is based on year-specific model training using locally derived samples, and does not explicitly address cross-year or cross-region transfer.

Recent studies indicate that, while satellite embeddings achieve strong performance under within-region settings, their spatial transferability can be limited due to geographic shifts in the feature space, which may reduce generalization performance in cross-region applications, particularly for tasks such as yield prediction (Ma et al., 2025).

In addition, we note that the current generation of satellite embeddings is typically provided at annual temporal resolution, which limits their ability to capture intra-seasonal crop dynamics and constrains their applicability for in-season mapping.

Despite these limitations, the contribution of this study lies in providing a more accurate and consistent baseline mapping product of cropping patterns at the national scale. Historical crop mapping products have been widely used to support subsequent prediction and in-season mapping. For example, in the United States, the long-term and consistently updated CDL dataset has enabled the development of automated national-scale in-season crop mapping and temporal transfer frameworks (Zhang et al., 2021; Li et al., 2024; Zhang et al., 2025). Similarly, the mapping results generated in this study can serve as a valuable reference for future work on spatiotemporal transfer and in-season crop mapping.

Reference:

Li, H., Di, L., Zhang, C., Lin, L., Guo, L., Yu, E. G., and Yang, Z.: Automated In-Season Crop-Type Data Layer Mapping Without Ground Truth for the Conterminous United States Based on Multisource Satellite Imagery, IEEE Transactions on Geoscience and Remote Sensing, 62, 1-14, 10.1109/TGRS.2024.3361895, 2024.

Ma, Y., Shen, Y., Swatantran, A., and Lobell, D. B. J. a. p. a.: Harvesting AlphaEarth: Benchmarking the Geospatial Foundation Model for Agricultural Downstream Tasks, 2025.

Zhang, C., Di, L., Hao, P., Yang, Z., Lin, L., Zhao, H., and Guo, L.: Rapid in-season mapping of corn and soybeans using machine-learned trusted pixels from Cropland Data Layer, International Journal of Applied Earth Observation and Geoinformation, 102, 102374, https://doi.org/10.1016/j.jag.2021.102374, 2021.

Zhang, H. K., Shen, Y., Zhang, X., Li, J., Yang, Z., Xu, Y., Zhang, C., Di, L., and Roy, D. P.: Robust and timely within-season conterminous United States crop type mapping using Landsat Sentinel-2 time series and the transformer architecture, Remote Sensing of Environment, 329, 114950, https://doi.org/10.1016/j.rse.2025.114950, 2025.