

Article

# Phenology-Adaptive Maize Mapping Using an Enhanced Red-Edge NDVI from Sentinel-2 Across Representative Global Agroecosystems

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## Highlights

### What are the main findings?

- An Enhanced Red-edge NDVI (ENDVIre), calculated from Sentinel-2 red-edge bands around 865 nm and 740 nm, improved the separability of maize from soybean during the silking-to-grain-filling stage and supported a phenology-adaptive decision-tree mapping strategy.
- Across six representative regions in the United States, Brazil, China, Kenya, and Ukraine, the proposed low-sample method achieved a mean overall accuracy of 93.27%, an F1-score of 93.14%, and a Kappa coefficient of 0.8652.

### What are the implications of the main findings?

- The framework provides an interpretable and practically transferable option for maize mapping in regions where large, spatially balanced training samples are unavailable, enabling consistent application of phenology-aligned rules across representative agroecosystems under limited-sample conditions.
- Temporal and spatial transfer experiments show that phenology-aligned thresholds can be extended across years and agroecological zones, although performance remains sensitive to key-period optical image availability and smallholder mixed-cropping landscapes.

## Abstract

Accurate maize distribution information is critical for crop-area statistics, food-security assessment, and agricultural monitoring, but large-scale maize-mapping remains difficult in regions with limited reference samples, heterogeneous crop calendars, and frequent optical data gaps. This study proposes a phenology-adaptive maize mapping framework based on Sentinel-2 time-series imagery and an Enhanced Red-edge NDVI (ENDVIre). ENDVIre was constructed from the Sentinel-2 red-edge 4 and red-edge 2 bands to enhance the spectral response of maize during the silking-to-grain-filling stage, when maize develops a dense canopy and high chlorophyll content but is often confused with soybean. The framework first reconstructed the NDVI time series using an upper-envelope-constrained Whittaker smoother to identify key phenological stages, including sowing–emergence, vigorous growth, and maturity–harvest. NDVI, ENDVIre, and LSWI were then integrated into an interpretable decision-tree model with phenology-aligned time windows to distinguish maize from soybean, rice, wheat, and other non-maize backgrounds. The method was



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evaluated in six representative maize-growing regions across the United States, Brazil, China, Kenya, and Ukraine, covering different crop calendars, field sizes, and agricultural systems. The mean overall accuracy, F1-score, and Kappa coefficient across the six regions reached 93.27%, 93.14%, and 0.8652, respectively. Cross-year experiments in a winter-wheat–summer-maize rotation region from 2020 to 2024 achieved overall accuracies of 89.80–96.80%, while spatial-transfer experiments in six independent regions achieved overall accuracies of 87.40–95.40%. A comparison with existing high-resolution maize products in the Huang-Huai-Hai Plain further showed that the proposed method better balanced omission and commission errors. These results indicate that ENDVIre-based phenology rules provide an interpretable and transferable solution for maize mapping under limited-sample conditions, although persistent cloud contamination and fragmented smallholder landscapes remain important challenges.

**Keywords:** Sentinel-2; red-edge vegetation index; ENDVIre; crop phenology; decision tree; spatial transferability; low-sample crop classification

## 1. Introduction

Maize is one of the most widely cultivated cereal crops and plays a strategic role in global food, feed, and bioenergy systems. Increasing food demand, climate variability, cropland degradation, and disruptions to agricultural trade have amplified the need for accurate crop-specific information at regional to continental scales [1–7]. Spatially explicit maize maps provide a basis for crop-area estimation, yield forecasting, irrigation and fertilizer management, agricultural policy assessment, and food-security early warning. However, crop maps used in operational monitoring must be both accurate and transferable, especially when they are applied beyond regions with dense field-survey systems.

Satellite remote sensing has become a primary data source for crop mapping because it provides repeated observations over large areas with consistent acquisition geometry and radiometry [8–11]. The availability of Landsat, Sentinel-1, and Sentinel-2 imagery, together with cloud platforms such as Google Earth Engine (GEE), has enabled high-resolution crop mapping over countries and continents [12–15]. Existing products such as the United States Cropland Data Layer, Canadian annual crop inventories, European crop maps, and national crop datasets in China have greatly advanced crop monitoring [16–24]. Nevertheless, many of these products depend on extensive reference samples, administrative reporting systems, or region-specific models, which are difficult to reproduce in sample-scarce regions.

Maize mapping is particularly challenging in complex agricultural landscapes. In temperate mechanized regions, maize is often confused with soybean because both crops show similar greening and senescence trajectories. In Asian rotation systems, summer maize may overlap with winter wheat residues, soybean, rice, peanut, or mixed strips. In Brazil, second-season maize follows soybean and develops under cloudy and rainy conditions. In parts of Africa, smallholder maize fields are fragmented, intercropped, and embedded within heterogeneous tea, coffee, sugarcane, and grassland backgrounds. These conditions weaken models trained in one location and highlight the importance of phenology-aware, interpretable, and data-efficient approaches [25–29].

Phenology-based methods provide an effective way to reduce the dependence on large labeled datasets. By linking remote-sensing time-series features with crop calendars, rule-based models can be transferred across years or regions using stage-specific rather than date-specific thresholds [25–34]. Previous studies have used dynamic time warping, phenology indices, early-season temporal patterns, or crop-specific indicators to map

rice, wheat, maize, soybean, and rotation systems [25–34]. Data-driven machine-learning and deep-learning methods have also improved crop classification across scenarios, but they often require representative labels and domain adaptation [35–40]. However, the performance of traditional vegetation indices can decline when maize and soybean reach high biomass, because NDVI tends to saturate and because canopy greenness alone does not fully capture structural differences during vigorous growth.

The red-edge bands of Sentinel-2 provide an opportunity to improve crop separability. Red-edge reflectance is sensitive to chlorophyll concentration, leaf area index, canopy architecture, and internal scattering, and has been widely used for crop discrimination, biomass estimation, and vegetation-status monitoring [27,32–34]. Maize, as a C4 crop with high leaf area and a relatively tall and dense canopy during silking and grain filling, can exhibit stronger red-edge and near-infrared contrast than soybean and other crops. This study therefore constructs an Enhanced Red-edge NDVI (ENDVIre) from Sentinel-2 B8A and B6 to enhance maize responses during its vigorous stage.

Compared with NDVI, which mainly contrasts red absorption and near-infrared reflectance and may saturate under dense crop canopies, ENDVIre emphasizes the contrast between Sentinel-2 red-edge 4 (RE4, B8A, approximately 865 nm) and red-edge 2 (RE2, B6, approximately 740 nm). This RE4–RE2 formulation is intended to capture both pigment absorption around the red-edge position and canopy structural scattering near the near-infrared plateau, thereby strengthening maize–soybean separability during the silking-to-grain-filling period.

The objective of this study is to develop and evaluate an ENDVIre-based phenology-adaptive maize-mapping method that can be applied under limited-sample conditions. Specifically, we aim to: (1) construct ENDVIre and analyze its separability for maize and major confusing crops; (2) automatically identify key maize phenological stages from smoothed NDVI time series; (3) integrate NDVI, ENDVIre, and LSWI into an expert decision-tree model using dynamic time windows; and (4) assess temporal generalization, spatial transferability, and product-level advantages in representative maize-growing regions across North America, South America, Asia, Africa, and Europe. The study focuses on methodological transferability in typical regions rather than claiming to produce a single global maize product.

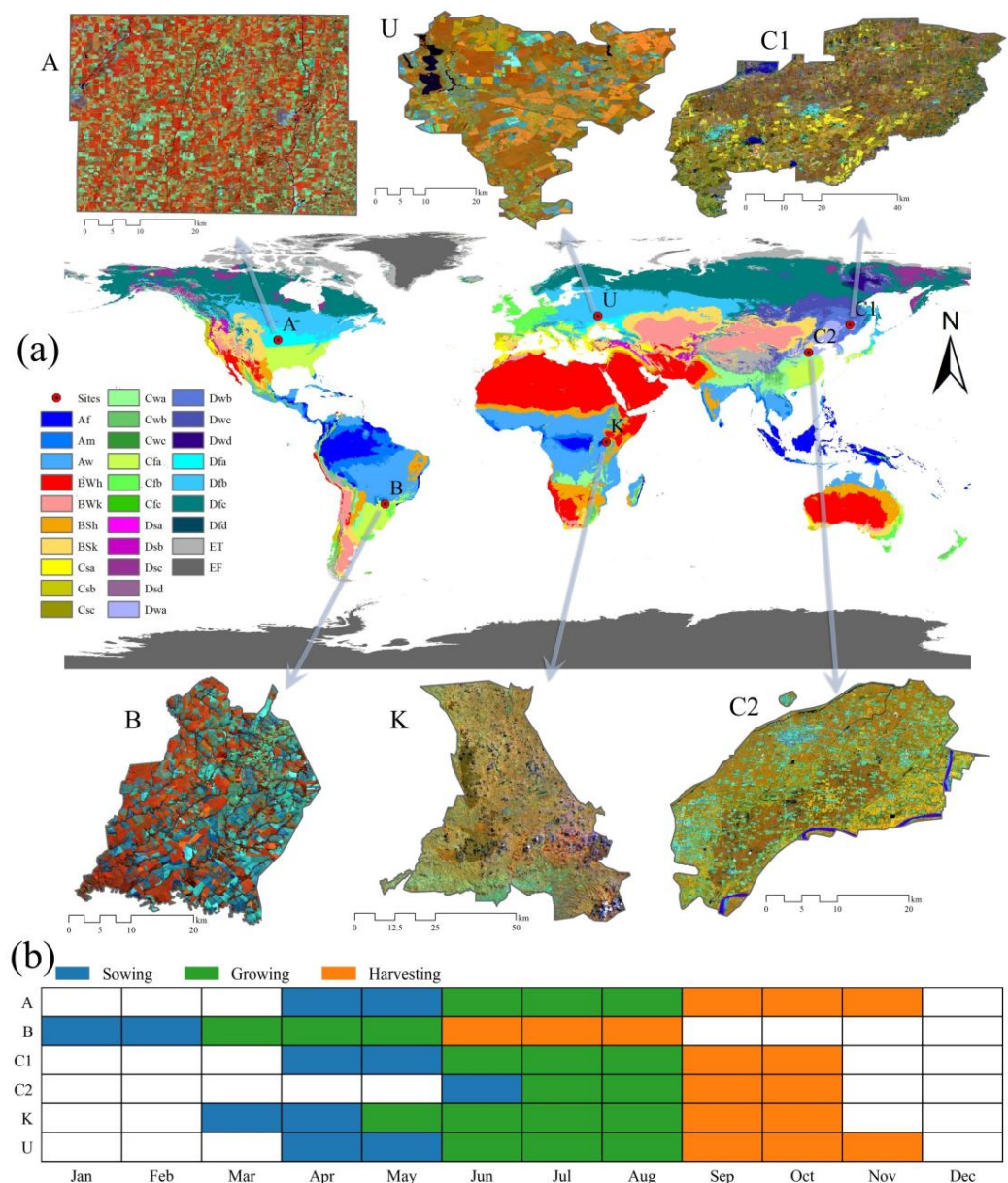
## 2. Materials

### 2.1. Study Areas

Six representative maize-growing regions were selected to cover major climate zones, cropping systems, field sizes, and confusing crop backgrounds (Figure 1 and Table 1). The regions include Page County in Iowa, USA (A); Mambore in Parana, Brazil (B); Youyi County in Heilongjiang Province, China (C1); Fan County in Henan Province, China (C2); Nandi County in western Kenya (K); and Yahotyn Raion in Kyiv Oblast, Ukraine (U). Together, these regions represent spring maize in the U.S. Corn Belt, second-season maize in Brazil, spring maize in Northeast China, winter-wheat–summer-maize rotation in the Huang-Huai-Hai Plain, long-rains maize in a tropical highland smallholder system, and mechanized spring maize in the Ukrainian forest steppe.

Page County is a typical county of the U.S. Corn Belt with a humid continental climate, large mechanized fields, and maize–soybean rotation. Maize is generally planted from April to May, grows vigorously from June to August, and is harvested between September and November. Mambore is a subtropical Brazilian municipality where maize is commonly planted as a second-season crop after soybean; sowing normally occurs from late January to early March, vigorous growth from April to May, and harvest in July. Youyi County is located in the Sanjiang Plain of Northeast China and is dominated by single-season

maize, soybean, and rice. Fan County lies in the lower Yellow River alluvial plain, where summer maize is usually planted after winter wheat and where rice and soybean also occur locally. Nandi County is a tropical highland, rainfed agricultural region, with maize planted during the long-rains season and often mixed with tea, coffee, sugarcane, and other crops. Yahotyn Raion is a black-soil agricultural region in Ukraine, with spring maize, wheat, sunflower, and sugar beet. Although Region B contains maize and soybean as the dominant mapped crops, its double-season system is not a simple single-date separation problem: second-season maize is commonly planted after soybean and may overlap with soybean residues, late soybean, and cloudy rainy-season observations. Therefore, relying only on NDVI at a fixed calendar date may be insufficient, whereas phenology-aligned ENDVIre provides additional evidence during the vigorous growth stage.



**Figure 1.** Locations (a) and crop calendars (b) of the six representative study regions. The regions cover the United States (A), Brazil (B), China (C1 and C2), Kenya (K), and Ukraine (U), and include different climate zones, cropping systems, and maize phenological schedules. The colored climate symbols in panel (a) denote the Köppen climate classification zones in which the selected study regions are located [41].

**Table 1.** Study region characteristics and reference data.

| Region | Country/Area           | Typical Crops                          | Cropping System                    | Area (km <sup>2</sup> ) | Reference Data                 |
|--------|------------------------|----------------------------------------|------------------------------------|-------------------------|--------------------------------|
| A      | Page County, USA       | Maize, soybean                         | Single-season crop rotation        | 1387                    | USDA Cropland Data Layer (CDL) |
| B      | Mambore, Brazil        | Maize, soybean                         | Double-season system               | 788                     | MapBiomass                     |
| C1     | Youyi County, China    | Maize, soybean, rice                   | Single-season system               | 1684.24                 | Field survey; China Crop Map   |
| C2     | Fan County, China      | Maize, soybean, rice, wheat            | Winter-wheat–summer maize-rotation | 617                     | Field survey; China Crop Map   |
| K      | Nandi County, Kenya    | Maize, soybean, tea, coffee, sugarcane | Rainfed smallholder system         | 2884.5                  | Nandi crop-type dataset        |
| U      | Yahotyn Raion, Ukraine | Maize, soybean, wheat, sunflower       | Single-season system               | 793.25                  | KPI-Ukraine crop maps          |

## 2.2. Satellite Data

Sentinel-2 multispectral imagery was used as the core data source because it provides visible, near-infrared, shortwave-infrared, and red-edge bands at 10–20 m resolution. The red-edge bands are essential for constructing ENDVI<sub>re</sub>, while visible, NIR, and SWIR bands were used to compute NDVI and LSWI. Image preprocessing included filtering by study area and period, cloud and cloud-shadow masking, scaling of reflectance values, and temporal compositing within phenology-related windows. For each region, the selected image windows were aligned with the local maize calendar rather than fixed to a single global date, allowing the model to adapt to spring maize, summer maize, second-season maize, and tropical long-rains maize.

All Sentinel-2 images were preprocessed in Google Earth Engine, including cloud and cloud-shadow masking, temporal filtering, and compositing according to the phenological windows of each study region. The resulting NDVI, LSWI, RENDVI, and ENDVI<sub>re</sub> time-series features provided the core input for the phenology-adaptive maize-mapping rules described below.

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \quad (1)$$

$$LSWI = \frac{\rho_{NIR} - \rho_{SWIR1}}{\rho_{NIR} + \rho_{SWIR1}} \quad (2)$$

$$RENDVI = \frac{\rho_{NIR} - \rho_{Re2}}{\rho_{NIR} + \rho_{Re2}} \quad (3)$$

$$ENDVI_{re} = \frac{\rho_{Re4} - \rho_{Re2}}{\rho_{Re4} + \rho_{Re2}} \quad (4)$$

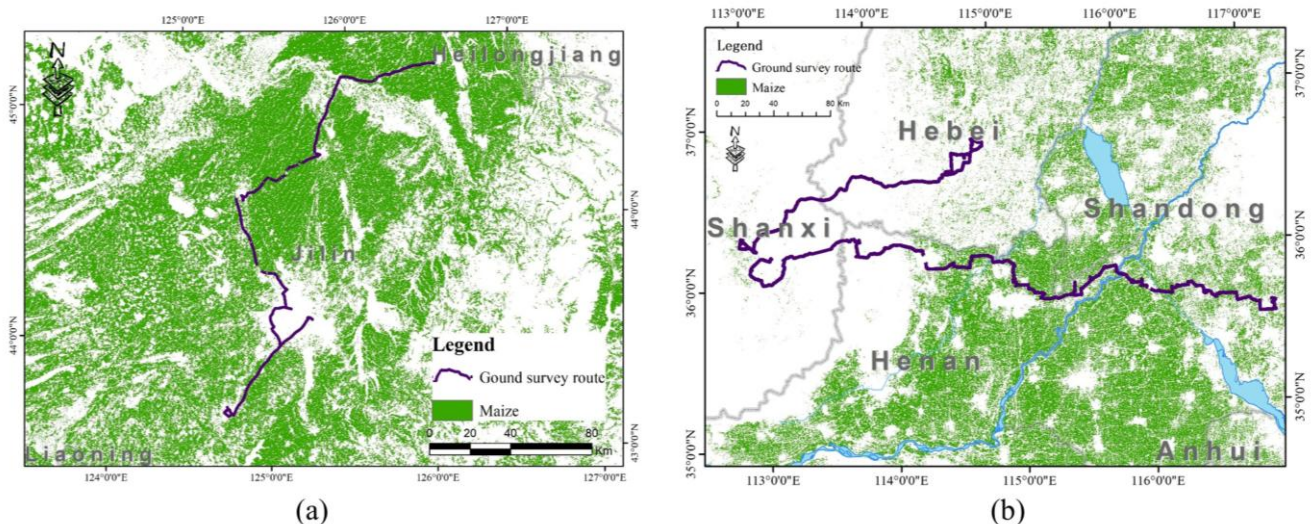
where  $\rho_{NIR}$ ,  $\rho_{Red}$ ,  $\rho_{SWIR1}$ ,  $\rho_{Re2}$ , and  $\rho_{Re4}$  denote the surface reflectance values of the near-infrared, red, shortwave-infrared 1, red-edge 2, and red-edge 4 bands, respectively. In Sentinel-2 imagery, these bands correspond to B8, B4, B11, B6, and B8A, with central wavelengths of approximately 842, 665, 1610, 740, and 865 nm, respectively.

## 2.3. Ground Survey and Auxiliary Data

Because a unified benchmark sample repository for major maize-growing regions worldwide is still unavailable, the reference information used in this study was constructed by combining field-survey samples with publicly available high-quality crop products. This

design was intended to support reliable accuracy assessment and interpretable phenological analysis under limited-sample conditions.

For the Chinese study regions, field surveys were conducted in Northeast China and North China in August 2024. A total of 4172 ground samples were collected along survey routes covering both maize and non-maize farmland backgrounds, including Youyi County in Northeast China and the winter-wheat–summer-maize rotation area in the Huang-Huai-Hai Plain (Figure 2). These field records served as the primary reference source for the Chinese study areas. In addition, the 10 m maize and soybean product released by the University of Maryland was used as auxiliary information because of its high reported accuracy and direct availability on the Google Earth Engine platform [25].



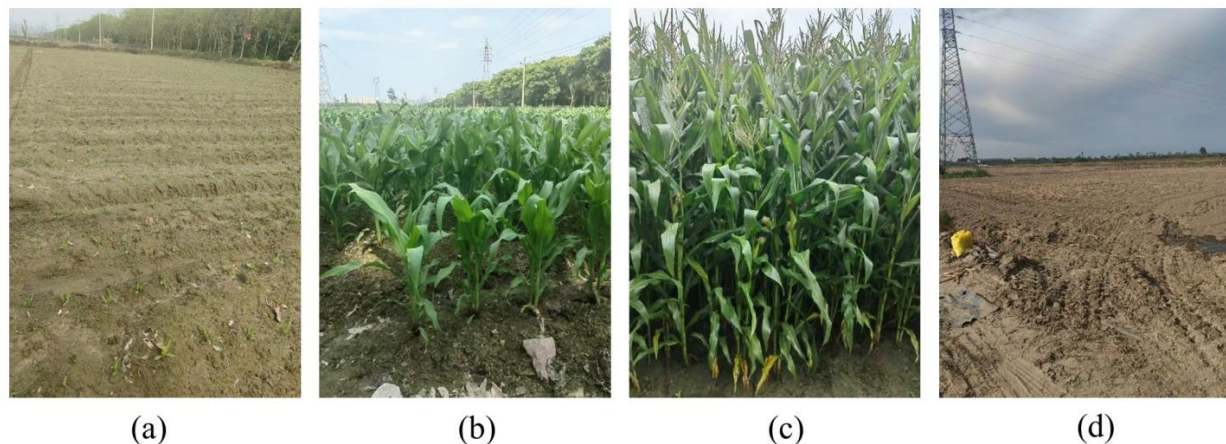
**Figure 2.** Field survey routes in Northeast China and the Huang-Huai-Hai Plain: (a) Northeast China; (b) Huang-Huai-Hai Plain.

For other countries and regions, publicly available crop products were used as reference data. In the United States, the USDA Cropland Data Layer (CDL) was adopted because it is widely used in crop-mapping studies and provides reliable annual crop-type information [16]. In Brazil, MapBiomass land-cover data and related crop-mapping studies were used as baseline references [42–45]. Because soybean is extensively planted in Brazil and maize is commonly cultivated as a second-season crop after soybean, first-season soybean masks were combined with second-season imagery and visual interpretation to identify maize samples. In Kenya, the Nandi County crop-type dataset and an in-season Sentinel-2 crop-mapping study were used to support the analysis of smallholder farming landscapes [46,47]. In Ukraine, the KPI-Ukraine Maps dataset and related crop-mapping products were adopted as reference sources for crop distribution analysis [48].

The spatial resolution and harmonization of reference data were also considered. Most reference sources used in this study are available at, or were harmonized to, a 10 m scale, including the Sentinel-2-based China maize/soybean products and the crop-type layers used for sample extraction. For products with coarser native resolution or different classification schemes, reference pixels were selected only from spatially homogeneous cropland patches and were cross-checked with Sentinel-2 composites, local crop calendars, and visual interpretation. Boundary pixels and mixed pixels were avoided where possible to reduce scale mismatch between reference data and Sentinel-2 features.

In addition to the reference samples used for classification and validation, an auxiliary maize observation site was established in Hangzhou, Zhejiang Province. The complete maize growth process was photographed and recorded at approximately 15-day intervals, and the corresponding NDVI trajectory was summarized from emergence to harvest

(Figure 3). This auxiliary observation was not used as an independent validation dataset. Instead, it provided visual and temporal evidence for interpreting maize phenological stages, understanding the rapid increase in vegetation indices after emergence, and explaining the spectral response of ENDVI<sub>re</sub> during the vigorous growth period.

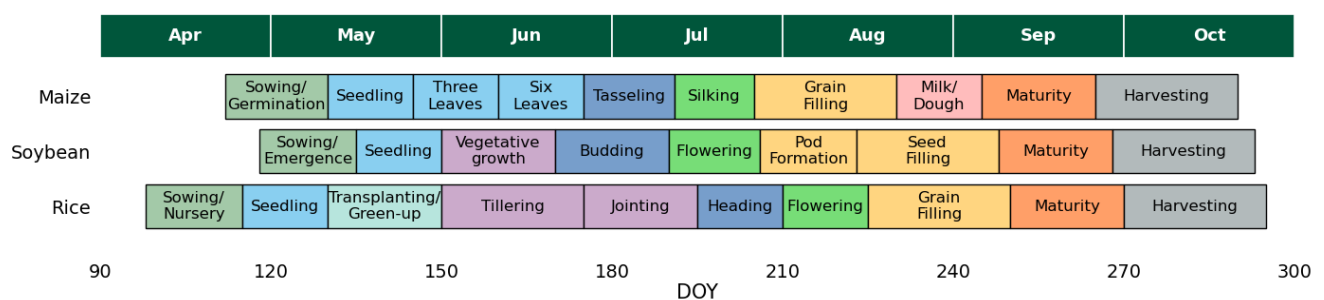


**Figure 3.** Field observations of maize growth stages. (a–d) Correspond to emergence (VE), V7–V12, the silking and grain-filling stage, and the harvest stage, respectively. These photographs provide auxiliary evidence for phenological window selection and ENDVI<sub>re</sub> interpretation.

### 3. Methods

#### 3.1. Phenological Analysis and Automatic Stage Extraction

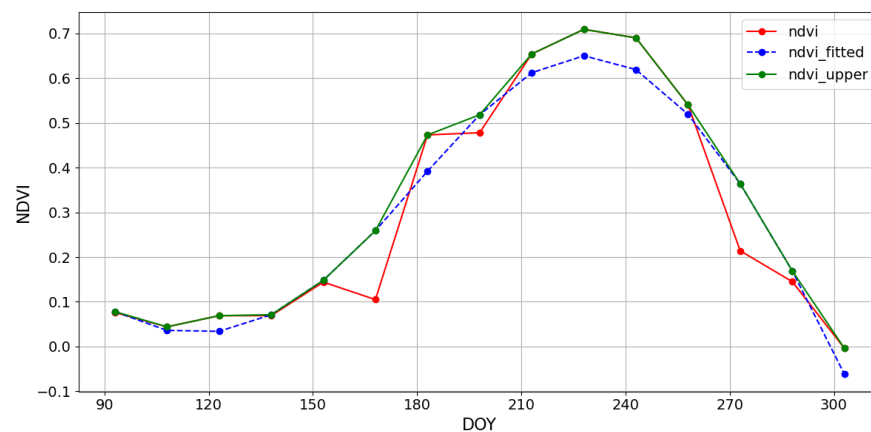
Phenological analysis links crop growth processes with remote-sensing time-series features. Maize, soybean, and rice may exhibit similar greening trajectories in some regions, but they differ in the timing and spectral characteristics of emergence, canopy closure, reproductive growth, water management, and harvest. In Youyi County, for example, maize and soybean both emerge in late spring and reach high greenness in summer, making them the main confusing crop pair. Rice, by contrast, differs from upland crops because transplanting and field flooding produce a distinct water-related signal during early growth (Figure 4).



**Figure 4.** Phenological stages of maize, soybean, and rice in the C1 region. The figure illustrates why maize–soybean confusion is prominent in single-season upland systems and why rice can be separated using water-sensitive features during transplanting.

The three phenological stages correspond to different spectral mechanisms. During sowing–emergence, low NDVI is useful for identifying newly established cropland and excluding perennial vegetation. During silking and grain filling, maize develops a tall, dense, chlorophyll-rich canopy, making red-edge indices such as ENDVI<sub>re</sub> more sensitive to maize–soybean differences than greenness alone. During maturity–harvest, decreasing NDVI helps remove late green vegetation, while water-related LSWI information helps exclude rice fields and other water-affected non-maize backgrounds.

NDVI was selected as the basis for automatic phenological stage extraction. The original NDVI time series can be affected by clouds, shadows, aerosol contamination, and local outliers. Therefore, an upper-envelope-constrained Whittaker smoother was used to reconstruct the NDVI trajectory [49]. The Whittaker smoother balances fidelity to the original observations with temporal smoothness, while the upper-envelope constraint reduces the underestimation of vegetation signals caused by cloud contamination by retaining the larger value between the original observation and the smoothed estimate. This reconstruction preserves the overall crop growth trajectory and improves the robustness of phenological stage detection (Figure 5).



**Figure 5.** Example of NDVI time-series reconstruction for maize. The original NDVI, Whittaker-smoothed NDVI, and upper-envelope-constrained curve are shown, with the constrained curve used for phenological stage detection.

The date of the maximum reconstructed NDVI was defined as the vigorous growth stage. The minimum NDVI on the rising limb before the peak was regarded as the sowing–emergence stage, while the minimum NDVI on the descending limb after the peak was regarded as the maturity–harvest stage. To standardize stage extraction across regions with different crop calendars, the rising and descending limbs were normalized separately.

For the rising limb,

$$NDVI_{ascend}^{normalized} = \frac{NDVI_{ascend} - NDVI_{min}^{ascend}}{NDVI_{max} - NDVI_{min}^{ascend}} \quad (5)$$

For the descending limb,

$$NDVI_{descend}^{normalized} = \frac{NDVI_{descend} - NDVI_{min}^{descend}}{NDVI_{max} - NDVI_{min}^{descend}} \quad (6)$$

The normalized curves were then used to locate the date windows corresponding to early, vigorous, and late maize stages.

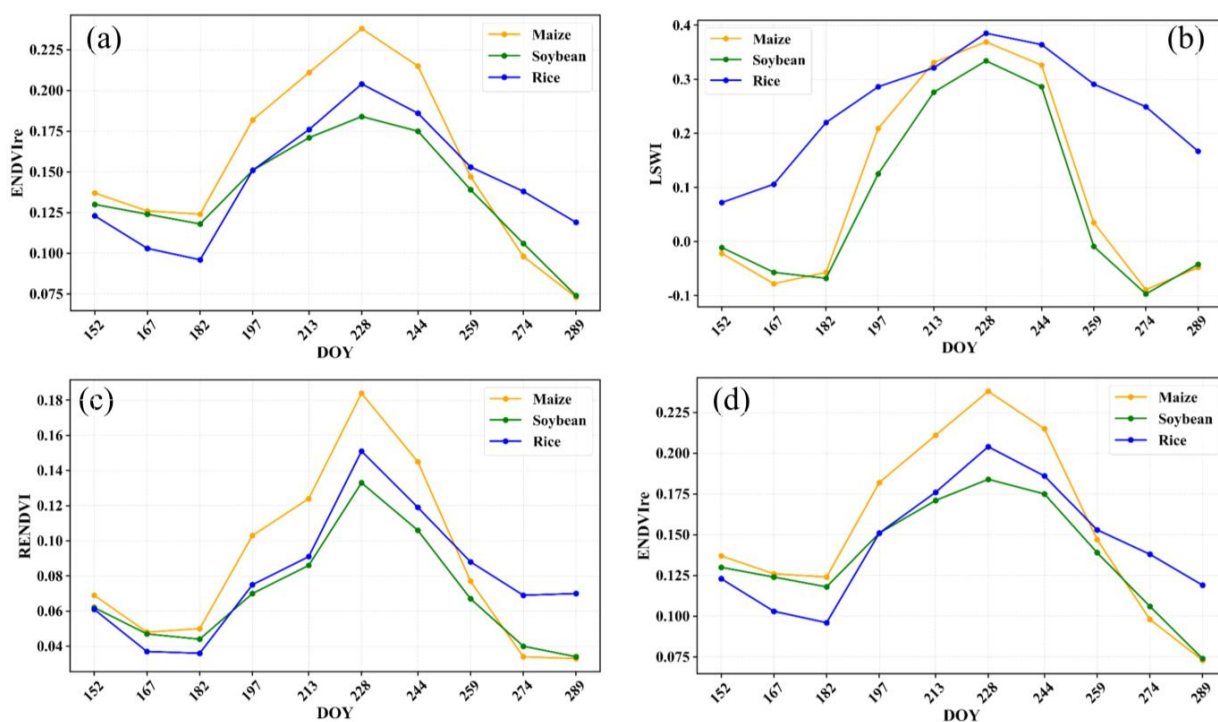
Based on the normalized NDVI time series, three main maize phenological stages were automatically determined using relative thresholds rather than fixed calendar dates. On the ascending limb, pixels or dates with  $0 \leq NDVI_{ascend}^{normalized} \leq 0.15$  were assigned to the sowing–emergence stage. The reproductive stage, corresponding approximately to silking–grain filling, was identified when  $0.90 \leq NDVI_{ascend}^{normalized} \leq 1.00$  or  $0.90 \leq NDVI_{descend}^{normalized} \leq 1.00$ . On the descending limb,  $0 \leq NDVI_{descend}^{normalized} \leq 0.25$  was used to identify the maturity–harvest stage. These normalized thresholds reduced the influence of regional differences in planting dates and crop-calendar length, allowing the subsequent ENDVI<sub>re</sub>, NDVI, and LSWI thresholds to be applied within phenologically comparable windows across the six study regions.

### 3.2. Enhanced Red-Edge NDVI (ENDVIre)

To improve the discrimination of maize from soybean and other crops during the vigorous growth stage, we constructed an Enhanced Red-edge NDVI (ENDVIre) using Sentinel-2 red-edge-related bands. In this study, RENDVI was retained as a conventional red-edge normalized-difference index for comparison, whereas ENDVIre used the RE4–RE2 formulation as the main maize-discrimination feature. The RE2 band is located in the red-edge region and is sensitive to chlorophyll concentration, while the RE4 band is close to the near-infrared plateau and responds strongly to canopy structure, leaf area index, and internal scattering. Similar to NDVI, ENDVIre uses a normalized-difference form, but the use of red-edge-related bands helps reduce saturation and enhances spectral differences among dense crop canopies.

In this context, ENDVIre differs from conventional RENDVI not only in band selection but also in its crop-physiological interpretation. RENDVI mainly reflects the contrast between a red-edge band and NIR reflectance, whereas ENDVIre uses two red-edge-related bands positioned near the red-edge slope and the NIR shoulder. This design reduces reliance on the potentially saturated red–NIR contrast and better captures the high-biomass canopy structure of maize during the reproductive stage.

The rationale for ENDVIre is closely related to maize physiology and canopy structure. During silking and grain filling, maize develops a tall and dense canopy with a high leaf area and chlorophyll content. RE4 reflectance increases with canopy closure and enhanced multiple scattering, whereas RE2 remains strongly affected by pigment absorption and red-edge displacement. Soybean, by contrast, generally has a shorter canopy and a smoother structural development process. Therefore, the contrast between RE4 and RE2 is expected to be stronger for maize than for soybean during the vigorous growth stage. This pattern is also reflected in the time-series curves of NDVI, LSWI, RENDVI, and ENDVIre for maize, soybean, and rice (Figure 6).



**Figure 6.** Time-series curves of spectral indices for maize, soybean, and rice. (a) NDVI time-series curves; (b) LSWI time-series curves; (c) RENDVI time-series curves; and (d) ENDVIre time-series curves. ENDVIre exhibits enhanced maize–soybean separability during the silking-to-grain-filling period.

### 3.3. Separability Assessment Using the Jeffries–Matusita Distance

The Jeffries–Matusita (J-M) distance was used to quantify the separability of crop types for different vegetation indices and growth stages. The J-M distance ranges from 0 to 2, with larger values indicating stronger separability. Assuming approximately normal feature distributions: The J-M distance was selected because it is bounded, interpretable, and widely used to compare spectral separability among land-cover or crop classes; values approaching 2 indicate near-complete class separation, which makes the metric suitable for screening vegetation indices and phenological windows before rule construction [27].

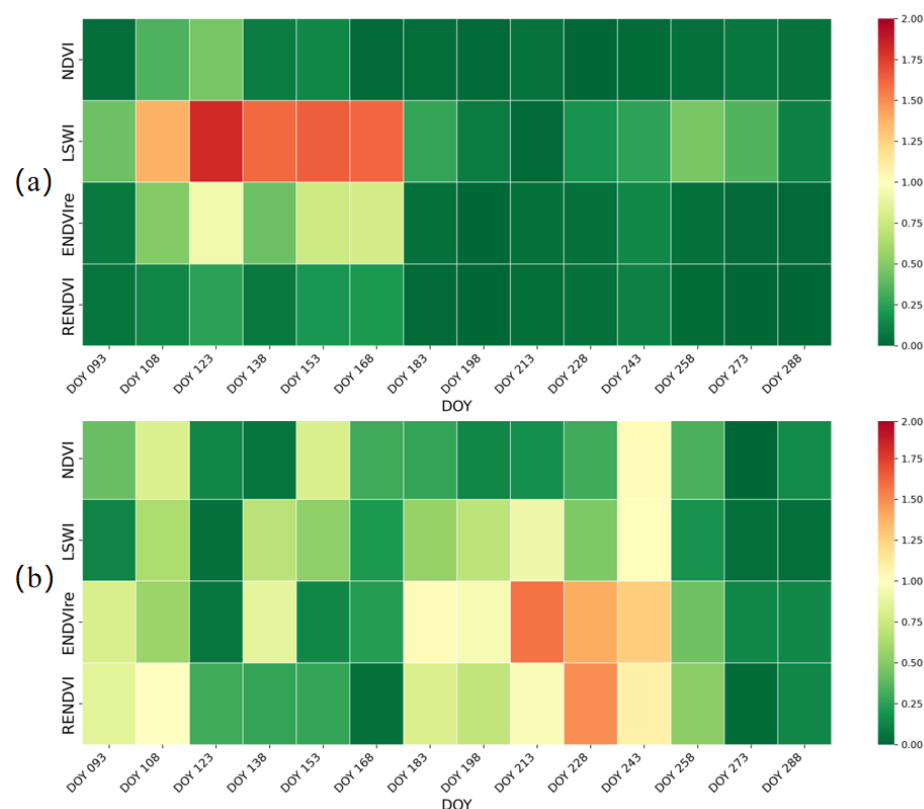
$$J_{ij} = 2 \left( 1 - e^{-B_{ij}} \right) \quad (7)$$

where B is the Bhattacharyya distance.

$$B_{ij} = \frac{1}{8} (\mu_i - \mu_j)^T \left( \frac{\Sigma_i + \Sigma_j}{2} \right)^{-1} (\mu_i - \mu_j) + \frac{1}{2} \ln \left( \frac{|\Sigma_i + \Sigma_j|}{2 \sqrt{|\Sigma_i| |\Sigma_j|}} \right) \quad (8)$$

The Bhattacharyya distance is calculated from the class means and covariance matrices of the feature distributions. Although the normality assumption is a simplification, the metric provides a useful comparative indicator for selecting indices and time windows.

The J-M heatmaps showed that ENDVIre provided high separability between maize and soybean during the silking-to-grain-filling stage, while LSWI provided strong separability between rice and upland crops during the rice transplanting or flooding period (Figure 7). These results support the subsequent rule design: ENDVIre was used as the primary feature for separating maize from soybean, while LSWI was introduced to reduce confusion between maize and rice.

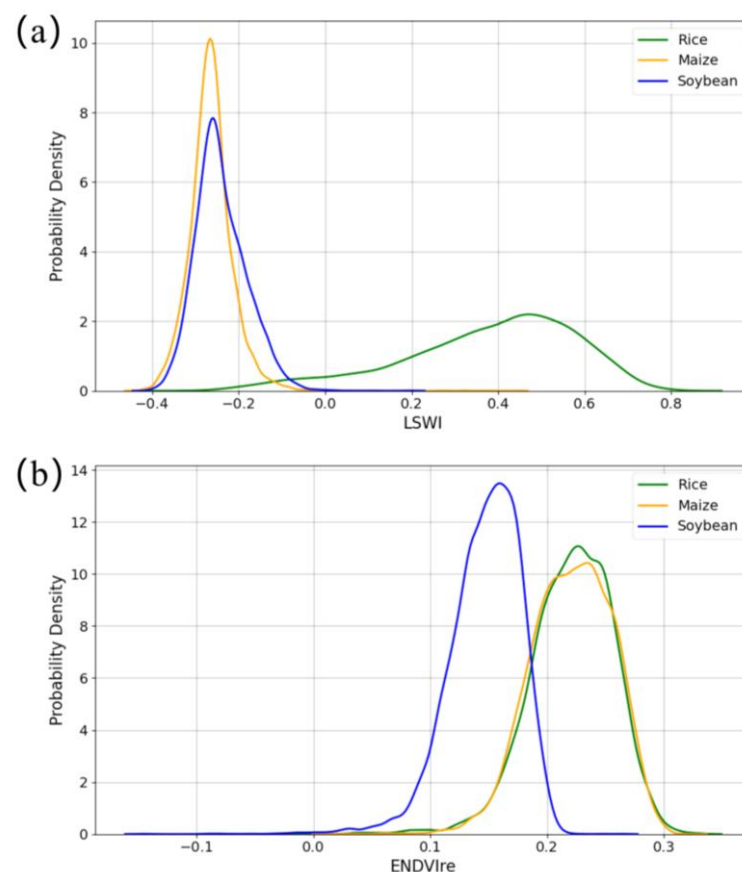


**Figure 7.** Jeffries–Matusita distance heatmaps. (a) Evaluates maize–rice separability, and (b) evaluates maize–soybean separability for different indices and stages.

### 3.4. Phenology-Adaptive Decision Rules

The decision-tree model integrates three types of phenology-aligned evidence: (1) NDVI conditions during sowing–emergence and harvest, which were used to exclude forests, water bodies, and other non-crop background classes; (2) ENDVIre conditions during the silking-to-grain-filling stage, which were used to identify the high-biomass maize canopy and reduce maize–soybean confusion; and (3) LSWI conditions during rice transplanting or other water-sensitive periods, which were used to exclude flooded rice fields. A decision-tree framework was adopted because it is interpretable, has transparent thresholds, and has been widely used for land-cover and crop classification from remote-sensing data [50,51].

The default thresholds were determined from sample probability density distributions (Figure 8) and multi-region statistics. The early-stage NDVI threshold was set to 0.35, and the late-stage NDVI threshold was set to 0. The ENDVIre threshold was set to 0.20 because the maize and soybean distributions overlapped around 0.18, and a slightly higher threshold helped reduce soybean commission errors. The LSWI threshold was set to 0 because maize and rice distributions overlapped near this value, whereas flooded rice fields generally exhibited higher LSWI values. In specific applications, the LSWI threshold in the C2 region was adjusted to  $-0.1$ , and the ENDVIre threshold in the K region was adjusted to 0.15 to account for local phenological and background differences.



**Figure 8.** Probability density distributions used for threshold selection. (a) Shows ENDVIre distributions of rice, maize, and soybean in August; (b) shows LSWI distributions in May.

The thresholds were not treated as globally optimized constants, but as interpretable baseline values derived from class probability density distributions and were cross-checked across the representative regions. The ENDVIre threshold of 0.20 was selected because maize and soybean distributions overlapped near 0.18 during the vigorous growth window,

and a slightly stricter value helped reduce soybean commission errors. The LSWI threshold of 0 was used as a conservative separator between upland crops and water-affected rice or flooded backgrounds. Local adjustment was considered only when clear phenological shifts, persistent cloud effects, or highly fragmented mixed-cropping landscapes were observed.

For a pixel  $x$ , the default maize rule can be summarized as follows:

In Equations (9)–(12),  $\theta_1$  and  $\theta_2$  denote the NDVI thresholds used for sowing–emergence and maturity–harvest background exclusion, respectively;  $\theta_3$  denotes the ENDVI<sub>re</sub> threshold used for maize candidate identification during silking-to-grain-filling; and  $\theta_4$  denotes the LSWI threshold used to remove rice or water-affected cropland. The corresponding image windows were determined from the local maize calendar and the normalized NDVI trajectory.

$$\max[NDVI_{I_{\text{sowing-seedling}}}] \leq \theta_1 \quad (9)$$

$$\min[NDVI_{I_{\text{harvest}}}] \geq \theta_2 \quad (10)$$

$$\max[ENDVI_{re_{\text{silking-grain-filling}}}] \geq \theta_3 \quad (11)$$

$$\max[LSWI_{I_{\text{transplanting}}}] \leq \theta_4 \quad (12)$$

When multiple images were available within the same phenological stage, different logical rules were applied according to the purpose of each condition. For sowing-stage NDVI, harvest-stage NDVI, and LSWI, AND logic was used to enforce strict background exclusion. For ENDVI<sub>re</sub> during vigorous growth, OR logic was applied across candidate images, so that a pixel was retained as a maize candidate if it met the ENDVI<sub>re</sub> threshold in at least one cloud-free image within the target stage. This strategy helps reduce omission errors under cloudy conditions, because the vigorous growth stage often coincides with rainy periods in Brazil, Kenya, and parts of China.

The image time windows were adapted to local crop calendars. In Page County, the early, vigorous growth, and harvest windows corresponded to late April–May, July, and October, respectively. In Ukraine, the early-stage window was shifted to May. In Youyi County, the early, vigorous growth, and harvest stages were set to early May, August, and October, respectively, with an additional rice-transplanting window in May. In Fan County, summer maize required a June early-stage window, an August vigorous growth window, and an October harvest window, with additional LSWI constraints in July and October. In Mambore, second-season maize was mapped using March, May, and August windows. In Nandi County, the long-rains maize calendar used April, July, and September windows.

For the transfer experiments, phenology-adaptive refers primarily to the adjustment of temporal windows according to local maize calendars and NDVI-derived stage positions, rather than to unrestricted parameter tuning. The core spectral thresholds were kept unchanged in most regions, and only limited local adjustment was allowed in clearly exceptional cases, such as the C2 LSWI threshold and the K-region ENDVI<sub>re</sub> threshold described above. This setting was used to evaluate whether the same rule logic could be transferred through phenological alignment, rather than through region-specific model retraining.

### 3.5. Accuracy Assessment

Classification accuracy was evaluated using confusion matrices. True positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) were calculated for maize and non-maize classes. Overall accuracy (OA), producer’s accuracy (PA), user’s accuracy (UA), F1-score, and the Kappa coefficient were then computed. PA measures omission error for maize, UA measures commission error among mapped maize pixels, and F1-score summarizes the balance between PA and UA. Kappa was used to assess agreement after

accounting for random consistency, and spatial accuracy patterns were interpreted with reference to established remote-sensing classification assessment principles [52].

$$PA = \frac{TP}{TP + FN} \quad (13)$$

$$UA = \frac{TP}{TP + FP} \quad (14)$$

$$F1 = 2 \times \frac{PA \times UA}{PA + UA} \quad (15)$$

$$Kappa = \frac{OA - P_e}{1 - P_e} \quad (16)$$

$$P_e = \frac{(TP + FP)(TP + FN) + (FN + TN)(FP + TN)}{(TP + TN + FP + FN)^2} \quad (17)$$

Three types of evaluation were conducted. First, classification accuracy was assessed in the six representative study regions. Second, temporal transferability was tested in Fan County from 2020 to 2024 using the same phenology-adaptive logic. Third, spatial transferability was evaluated by applying fixed rules without parameter adjustment to six larger or independent validation regions, including expanded or new regions in the United States, Brazil, China, Kenya, and Ukraine. Finally, the C2 result was compared with three existing high-resolution maize products to evaluate the practical advantage of the proposed method in a complex rotation landscape.

To avoid overly optimistic accuracy estimates, threshold interpretation and accuracy assessment were separated in the experimental design. The proposed method is an expert-rule framework rather than a supervised classifier trained on validation samples. The thresholds were interpreted from representative sample distributions, separability patterns, and phenological knowledge, whereas temporal transfer, spatial transfer, and product-comparison experiments were evaluated using independent years, enlarged or independent regions, and external validation samples that were not used for region-specific model fitting. Because several reference sources are themselves map products rather than uniform field surveys, the resulting accuracies should be interpreted as product-level validation under limited-sample conditions, and potential reference-data uncertainty is discussed in Section 5.5.

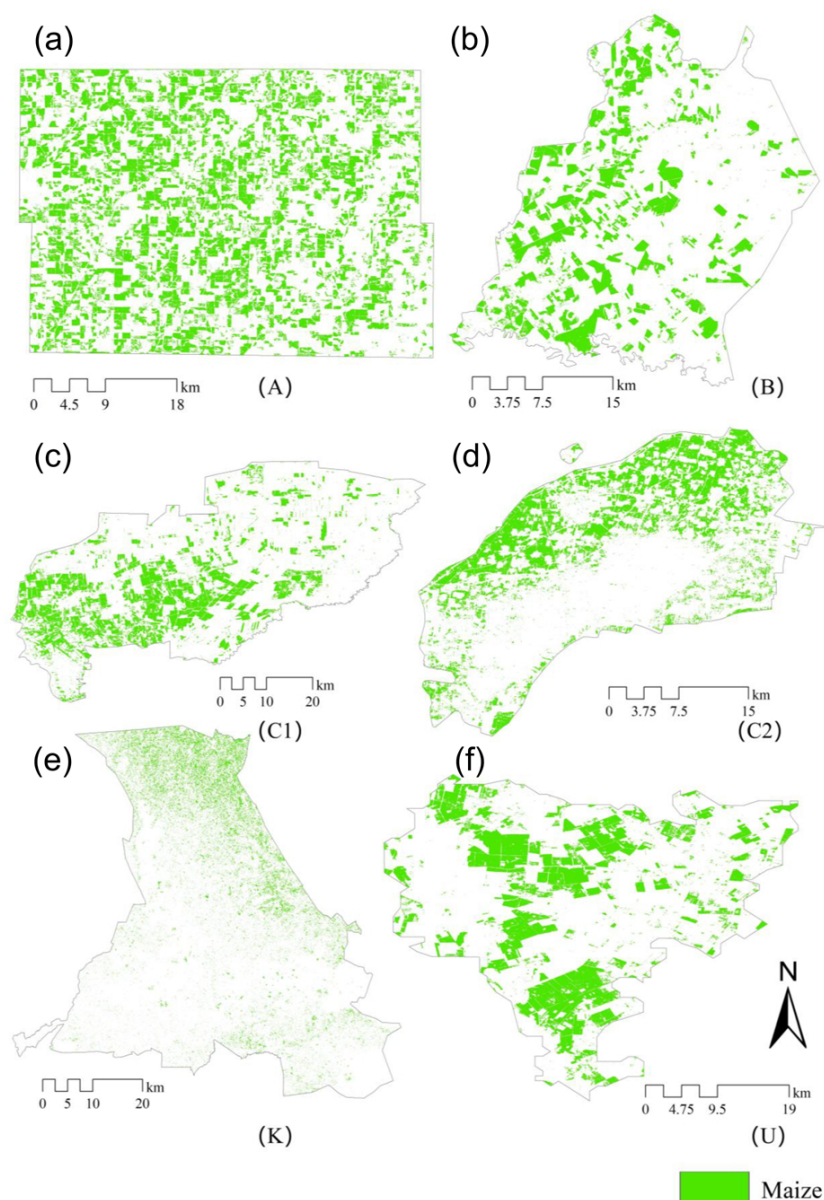
## 4. Results

### 4.1. Maize Mapping in the Six Representative Regions

The proposed ENDVIre-based decision rules produced maize maps with clear regional patterns (Figure 9). In Page County, Youyi County, and Yahotyn Raion, maize fields formed relatively continuous patches consistent with mechanized single-season agriculture. In Mambore and Fan County, maize was interspersed with soybean, wheat, and other rotation crops, resulting in more fragmented spatial patterns. In Nandi County, mapped maize patches were smaller and more dispersed because of smallholder management, topographic variation, and mixed-cropping backgrounds.

Accuracy metrics confirmed that the model performed well across the six regions (Table 2). OA ranged from 85.40% to 96.60%. The average OA, F1-score, and Kappa coefficient were 93.27%, 93.14%, and 0.8652, respectively. Mambore achieved the highest OA (96.60%) and F1-score (96.74%), with a UA of 98.82%, indicating few commission errors. Youyi County and Yahotyn Raion also showed F1-scores above 93%, demonstrating that the method is reliable in single-season maize systems with clear phenology. Fan County

achieved balanced PA and UA values of 94.94%, suggesting that ENDVIre and LSWI jointly reduced confusion with soybean and rice in a rotation region.



**Figure 9.** Maize classification results in the six representative study regions: (a) Page County, Iowa, USA (A); (b) Mambore, Parana, Brazil (B); (c) Youyi County, Heilongjiang, China (C1); (d) Fan County, Henan, China (C2); (e) Nandi County, Kenya (K); and (f) Yahotyn Raion, Kyiv Oblast, Ukraine (U). This figure is intended to demonstrate the regional mapping performance of the proposed ENDVIre-based decision rules across contrasting agroecosystems.

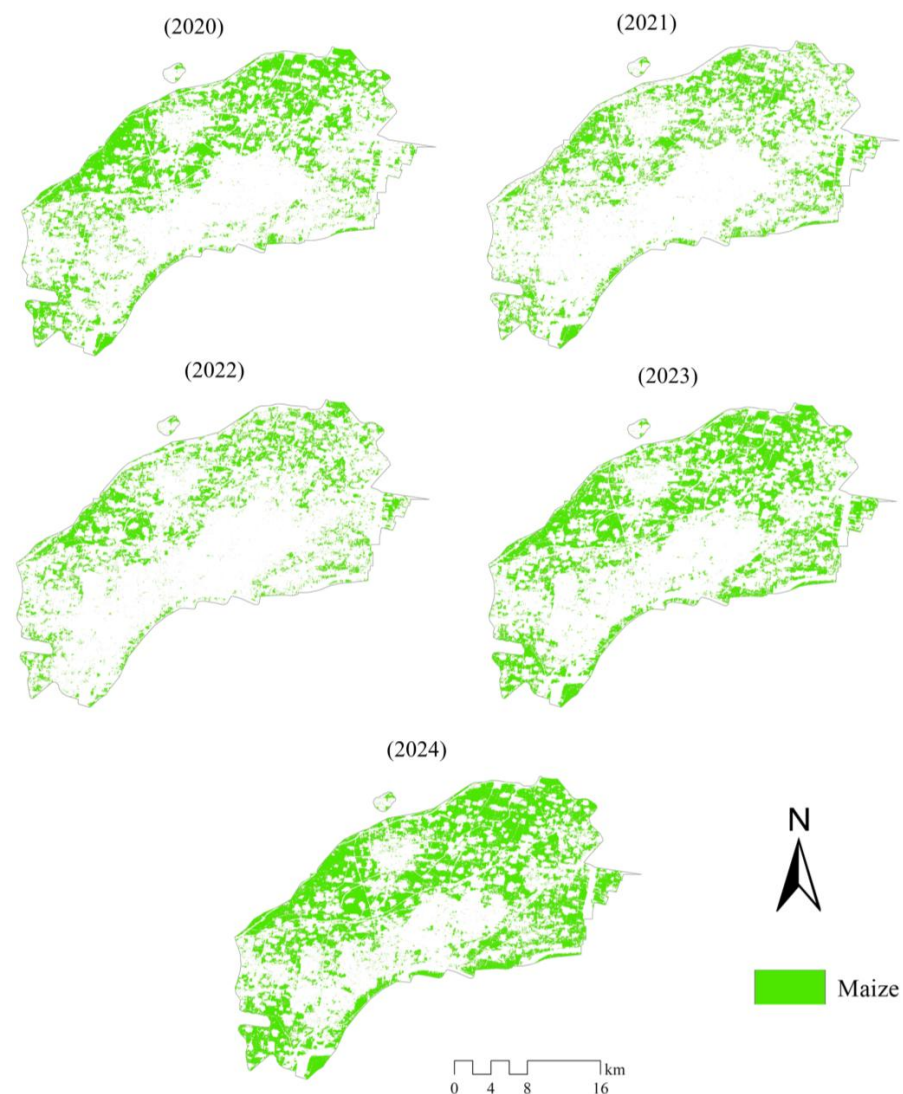
**Table 2.** Classification accuracy in the six representative study regions.

| Region | Class           | Confusion Matrix: Maize | Confusion Matrix: Non-Maize | PA (%) | UA (%) | OA (%) | F1 (%) | Kappa  |
|--------|-----------------|-------------------------|-----------------------------|--------|--------|--------|--------|--------|
| A      | Maize/non-maize | 230/24                  | 13/232                      | 94.65  | 90.55  | 92.59  | 92.55  | 0.8518 |
| B      | Maize/non-maize | 252/3                   | 14/231                      | 94.74  | 98.82  | 96.60  | 96.74  | 0.9319 |
| C1     | Maize/non-maize | 231/14                  | 6/249                       | 97.47  | 94.29  | 96.00  | 95.85  | 0.9199 |
| C2     | Maize/non-maize | 225/12                  | 12/251                      | 94.94  | 94.94  | 95.20  | 94.94  | 0.9037 |
| K      | Maize/non-maize | 207/32                  | 41/220                      | 83.47  | 86.61  | 85.40  | 85.01  | 0.7079 |
| U      | Maize/non-maize | 233/11                  | 20/236                      | 92.09  | 95.49  | 93.80  | 93.76  | 0.8760 |

Nandi County had the lowest accuracy, with OA of 85.40% and PA of 83.47%, indicating omission of some true maize fields. The lower performance is consistent with the presence of small fields, mixed pixels, intercropping, and heterogeneous non-maize backgrounds. Nevertheless, UA remained 86.61%, suggesting that the mapped maize patches were generally credible even though some fields were missed. These results indicate that, in highly fragmented smallholder landscapes, pixel-based optical rules may need to be combined with finer-resolution imagery, object- or parcel-level post-processing, local sample refinement, and SAR features to reduce omission errors.

#### 4.2. Temporal Generalization from 2020 to 2024

Temporal transferability was tested in C2, a winter-wheat–summer-maize rotation region, for five consecutive years (Figure 10 and Table 3). OA ranged from 89.80% to 96.80%, and all years except 2021 had F1-scores above 91%. These results indicate that the phenology-adaptive rule model can accommodate interannual variation in crop growth and image availability when stage-aligned windows are used.



**Figure 10.** Cross-year maize mapping results in the C2 region from 2020 to 2024. The figure highlights the temporal stability of the phenology-adaptive rules under interannual variation in image availability and crop growth conditions.

**Table 3.** Cross-year classification accuracy in the C2 region.

| Year | Class           | Confusion Matrix: Maize | Confusion Matrix: Non-Maize | PA (%) | UA (%) | OA (%) | F1 (%) | Kappa  |
|------|-----------------|-------------------------|-----------------------------|--------|--------|--------|--------|--------|
| 2020 | Maize/non-maize | 232/19                  | 14/235                      | 94.31  | 92.43  | 93.40  | 93.36  | 0.8680 |
| 2021 | Maize/non-maize | 248/8                   | 43/201                      | 85.22  | 96.88  | 89.80  | 90.66  | 0.7952 |
| 2022 | Maize/non-maize | 218/17                  | 24/241                      | 90.08  | 92.77  | 91.80  | 91.40  | 0.8357 |
| 2023 | Maize/non-maize | 236/12                  | 4/248                       | 98.33  | 95.16  | 96.80  | 96.72  | 0.9360 |
| 2024 | Maize/non-maize | 229/21                  | 11/239                      | 95.42  | 91.60  | 93.60  | 93.48  | 0.8720 |

The lowest OA occurred in 2021 (89.80%). In that year, PA was 85.22% and UA was 96.88%, indicating a strong omission pattern with few commission errors. Image-quality analysis suggested that the maize silking-to-grain-filling window suffered from heavy cloud contamination, leaving insufficient clear optical observations. Although the OR logic for ENDVIre reduced omission relative to a strict multi-date rule, residual cloud, cloud shadow, and interpolation uncertainty still caused some maize fields to be missed. The 2023 result was the best, with OA of 96.80%, F1-score of 96.72%, and Kappa of 0.9360.

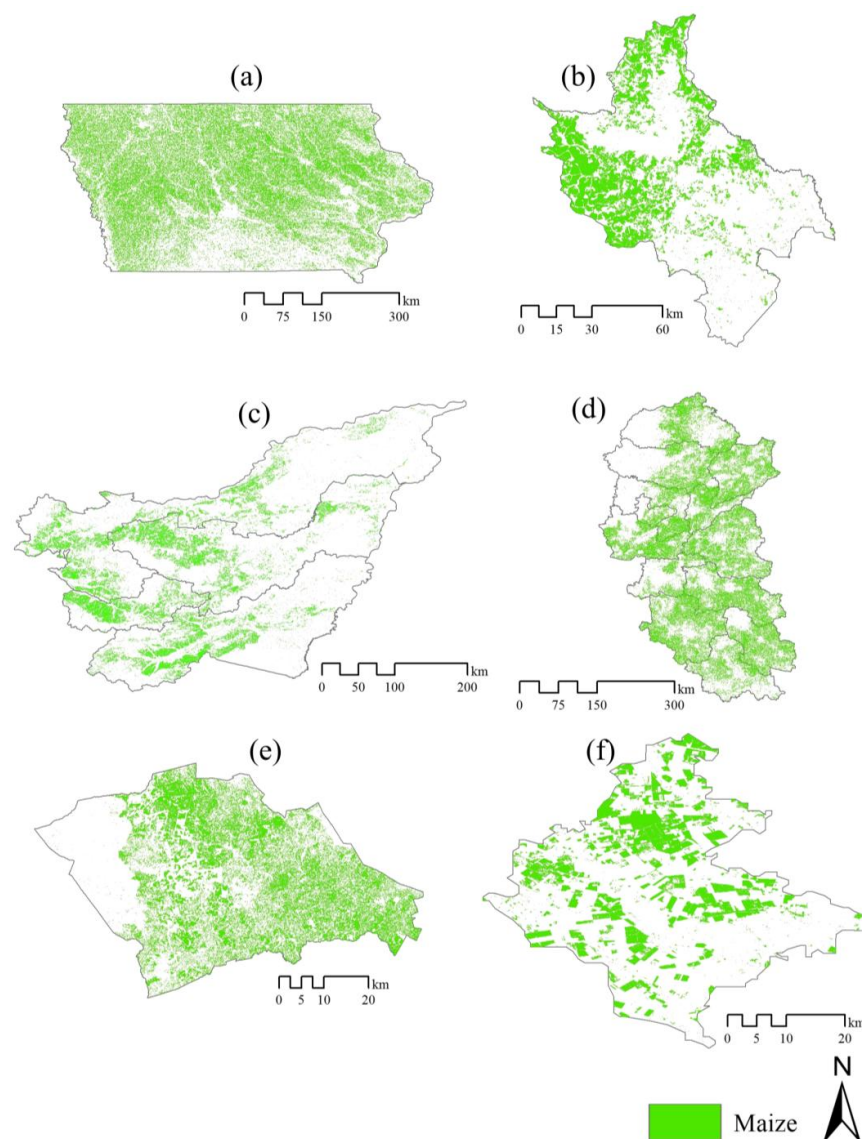
Specifically, the 2021 C2 silking-to-grain-filling window was affected by insufficient clear Sentinel-2 observations. Two July observations contained large invalid areas after cloud and cloud-shadow masking, and two August observations were affected by residual cloud contamination. This reduced the number of usable observations in the ENDVIre decision window and increased omission errors for maize pixels whose peak canopy signal was not captured.

#### 4.3. Spatial Transferability Across Independent Regions

The model was further transferred without parameter adjustment to six larger or independent validation regions (Figure 11 and Table 4). These regions included the Iowa maize-belt core, Jatai in Brazil, an expanded Sanjiang Plain region in Northeast China, the Huang-Huai-Hai Plain core region, Trans Nzoia County in western Kenya, and Orzhyskyi in the Ukrainian forest steppe. The transfer experiments covered large mechanized fields, double-season systems, summer-maize rotations, tropical highlands, and short-season temperate systems.

OA values ranged from 87.40% to 95.40%. The expanded Sanjiang Plain and Ukrainian forest steppe transfer regions showed the highest and most stable performance, with OA values of 95.38% and 95.40%, respectively. PA and UA were balanced in the Sanjiang Plain, indicating that the rules transferred well within a similar ecological zone. The Iowa transfer experiment achieved OA of 92.72% and Kappa of 0.8544; UA was slightly lower than PA, suggesting that some soybean fields still resembled maize during vigorous growth. In Jatai, OA was 94.20% and UA reached 96.81%, indicating effective separation of second-season maize from other land covers. The Huang-Huai-Hai transfer region achieved OA of 92.86%, confirming the applicability of phenology-aligned rules to summer maize even though its calendar differs from spring maize.

The Kenya transfer region had the lowest OA (87.40%) and PA (84.50%). The pattern again suggests maize omission in smallholder and mixed-cropping landscapes. Nevertheless, the model captured the broad spatial distribution of maize. Overall, the spatial-transfer experiments show that the ENDVIre-based method is robust where field boundaries and phenology are clear, while small fields, mixed planting, and background heterogeneity remain important limitations.



**Figure 11.** Spatial-transfer maize mapping results in six larger or independent validation regions: (a) Iowa, USA; (b) Jatai, Brazil; (c) expanded Sanjiang Plain, Northeast China; (d) Huang-Huai-Hai Plain core region, China; (e) Trans Nzoia County, Kenya; and (f) Orzhytskyi, Ukraine. The figure evaluates spatial transferability by applying the same rule logic to larger or independent regions after phenological-window alignment.

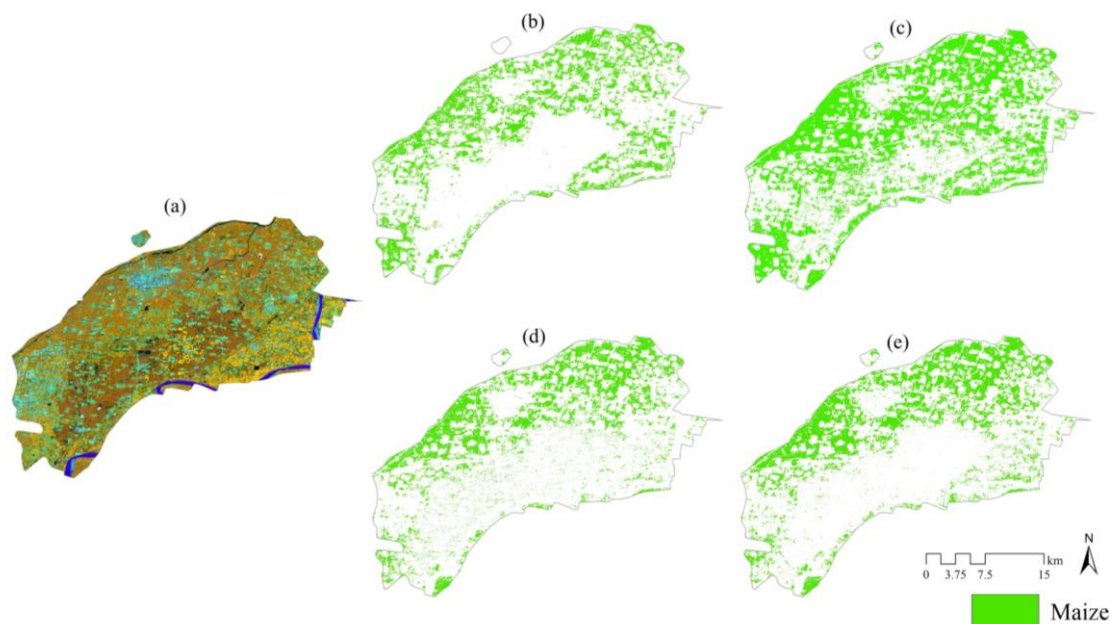
**Table 4.** Spatial-transfer classification accuracy. Regions a–f correspond to Iowa, Jatai, expanded Sanjiang Plain, Huang-Huai-Hai Plain core, Trans Nzoia, and Orzhytskyi, respectively.

| Region | Class           | Confusion Matrix: Maize | Confusion Matrix: Non-Maize | PA (%) | UA (%) | OA (%) | F1 (%) | Kappa  |
|--------|-----------------|-------------------------|-----------------------------|--------|--------|--------|--------|--------|
| a      | Maize/non-maize | 2275/216                | 148/2361                    | 93.89  | 91.33  | 92.72  | 92.59  | 0.8544 |
| b      | Maize/non-maize | 243/8                   | 21/228                      | 92.05  | 96.81  | 94.20  | 94.37  | 0.8840 |
| c      | Maize/non-maize | 2367/122                | 109/2402                    | 95.60  | 95.10  | 95.38  | 95.35  | 0.9076 |
| d      | Maize/non-maize | 2342/180                | 177/2301                    | 92.97  | 92.86  | 92.86  | 92.92  | 0.8572 |
| e      | Maize/non-maize | 229/21                  | 42/208                      | 84.50  | 91.60  | 87.40  | 87.91  | 0.7480 |
| f      | Maize/non-maize | 244/7                   | 16/233                      | 93.85  | 97.21  | 95.40  | 95.50  | 0.9080 |

#### 4.4. Comparison with Existing High-Resolution Maize Products

Product comparison was conducted in the C2 region, where summer maize coexists with winter wheat, rice, soybean, and other crops. Three existing products were compared

with the proposed result: the 30 m China maize dataset of Peng et al. [20], the 10 m annual maize map of Li X et al. [24], and the 10 m maize–soybean map of Li H et al. [25] (Figure 12 and Table 5).



**Figure 12.** Spatial comparison of maize products in the C2 region. Panel (a) presents the Sentinel-2 false-color composite image using the NIR, SWIR1, and red bands as RGB channels. Panels (b–d) correspond to the maize products of Peng et al., Li X et al., and Li H et al., respectively, while panel (e) shows the result obtained in this study.

**Table 5.** Accuracy comparison among high-resolution maize products in the C2 region.

| Product     | Class           | Confusion Matrix: Maize | Confusion Matrix: Non-Maize | PA (%) | UA (%) | OA (%) | F1 (%) | Kappa  |
|-------------|-----------------|-------------------------|-----------------------------|--------|--------|--------|--------|--------|
| Peng et al. | Maize/non-maize | 159/26                  | 78/237                      | 67.09  | 85.95  | 79.20  | 75.36  | 0.5783 |
| Li X et al. | Maize/non-maize | 236/73                  | 1/190                       | 99.58  | 76.38  | 85.20  | 86.45  | 0.7076 |
| Li H et al. | Maize/non-maize | 228/21                  | 9/242                       | 96.20  | 91.57  | 94.00  | 93.83  | 0.8799 |
| This study  | Maize/non-maize | 225/12                  | 12/251                      | 94.94  | 94.94  | 95.20  | 94.94  | 0.9037 |

The proposed method achieved OA of 95.20%, F1-score of 94.94%, and Kappa of 0.9037. Peng et al.’s product showed a clear omission pattern, with PA of 67.09%, and visually missed maize areas in the southeastern part of the region. Li X et al.’s product had very high PA (99.58%) but low UA (76.38%), indicating overestimation and commission errors; visual interpretation suggested that some water-rich rice fields or non-maize cropland were incorrectly classified as maize. Li H et al.’s product performed well (OA of 94.00% and F1-score of 93.83%) but was still slightly lower than the proposed method. Because the proposed rules combine ENDVIre and LSWI at phenologically meaningful stages, they balanced omission and commission errors more effectively in this complex rotation system.

## 5. Discussion

### 5.1. Why ENDVIre Improves Maize Separability

The proposed ENDVIre is designed around the physiological and structural characteristics of maize during the most discriminative part of the growing season. NDVI captures greenness but can saturate when vegetation is dense. In maize–soybean systems, both crops develop high greenness and similar seasonal profiles during mid-summer, which reduces NDVI separability. ENDVIre instead emphasizes the difference between B8A

and B6. Because B8A is more responsive to canopy scattering and B6 remains strongly linked to chlorophyll absorption and red-edge displacement, the index is sensitive to the high-biomass maize canopy that forms during silking and grain filling.

The J-M analysis supports this interpretation. ENDVire showed stronger maize–soybean separability during the vigorous stage than other tested indices, while LSWI was more useful for distinguishing rice from upland crops during water-sensitive periods. The complementary roles of ENDVire and LSWI are important: ENDVire targets structural and chlorophyll-related differences in dense canopies, whereas LSWI captures water-status differences caused by rice transplanting and flooding. This combination explains why the method achieved balanced PA and UA in the C2 rotation region and outperformed or matched existing products.

### *5.2. Phenology Adaptation Rather than Fixed-Date Thresholding*

A central feature of the method is that the rules are linked to phenological stages, not to universal calendar dates. The same physiological stages occur in different months across regions: May–August–October in Northeast China, June–August–October for summer maize in Fan County, March–May–August for second-season maize in Brazil, and April–July–September for long-rains maize in Kenya. Dynamic time-window matching allows the same rule logic to be used after aligning the input imagery to local crop calendars.

This stage-based design also explains the cross-year stability observed in Fan County. Even when weather conditions shift planting and growth timing, the decision rule remains connected to emergence, vigorous growth, and harvest. However, the 2021 result shows that phenology adaptation cannot fully overcome missing optical observations. If the vigorous growth window lacks clear images, ENDVire cannot reliably detect the maize canopy. Thus, optical image availability during key stages is one of the main constraints of the approach.

### *5.3. Transferability and Limits in Different Agricultural Landscapes*

It should be noted that transferability in this study does not mean parameter-free global generalization. Rather, it refers to the application of the same crop-phenology-based rule structure after aligning temporal windows to local maize phenology, while keeping the core spectral thresholds unchanged in most regions. This distinction is important because agricultural similarity is determined not only by climate zone or geographic distance, but also by crop calendars, rotation systems, field size, and image availability.

The spatial-transfer experiments show that the method transfers best among regions with clear crop calendars, large field sizes, and relatively homogeneous management. The expanded Sanjiang Plain, Ukrainian forest steppe, and Iowa maize belt all reached OA values above 92%. The model also performed well in Brazil's second-season maize system after aligning the windows to the local calendar. These results demonstrate that ENDVire-based rules are not restricted to a single climate zone or hemisphere.

Performance decreased in Kenya and other smallholder contexts. This decline is mainly associated with mixed pixels, intercropping, topographic heterogeneity, and highly diverse non-maize backgrounds. In such landscapes, a 10–20 m Sentinel-2 pixel may contain maize mixed with tea, grass, bare soil, or other crops, weakening both ENDVire and LSWI signals. Small fields also increase boundary errors when validation samples are interpreted from imagery. These limitations suggest that the method can still be useful for rapid and interpretable mapping in sample-scarce regions, but further improvements are needed for highly fragmented agricultural systems.

#### 5.4. Relationship to Machine Learning and Deep Learning Approaches

The proposed decision-tree framework is not intended to replace machine-learning or deep-learning models in data-rich regions. Random Forest, Support Vector Machines, CNNs, LSTMs, and Transformer-based time-series models can achieve strong performance when dense, representative, and spatially balanced labels are available. However, the purpose of the present framework is different: it aims to provide a transparent and low-sample alternative for regions where such labels are unavailable or difficult to harmonize. Therefore, the product-level comparison in Section 4.4 should be interpreted as a practical evaluation against existing high-resolution maize products, rather than as a complete model-family comparison under identical training conditions.

Deep learning and advanced machine-learning models can learn complex spatial, spectral, and temporal features from large datasets, but they often require extensive, well-distributed labels and careful domain adaptation [35–40]. By contrast, the proposed ENDVire decision-tree method relies on expert knowledge and a small number of interpretable thresholds. This makes it attractive for regions where ground samples are limited or where transparent rules are preferred for operational adoption.

The method is not intended to replace data-driven models in all cases. Rather, it provides a complementary pathway. It can generate initial maps or pseudo-labels for regions lacking samples, guide sample selection by identifying uncertain areas, and provide phenological constraints for later machine learning or deep learning models. Integrating ENDVire-based stage features with domain adaptation, foundation-model embeddings, or active learning could further improve large-scale maize mapping.

#### 5.5. Limitations and Future Work

Several limitations remain. First, the method depends on clear or sufficiently reliable Sentinel-2 observations during key phenological windows. Persistent cloud cover, cloud shadows, haze, and interpolation errors can reduce PA, as observed in Fan County in 2021. Incorporating Sentinel-1 SAR time series could improve robustness in cloudy regions. Second, fixed thresholds, even when aligned with phenological stages, cannot fully capture differences in local management practices, cultivars, and environmental conditions. Local threshold calibration or probabilistic decision rules could therefore improve regional adaptation. Third, mixed pixels and intercropping remain challenging in smallholder landscapes. Higher-resolution imagery, object-based field boundaries, or super-resolution techniques could help reduce boundary and mixing effects. Fourth, product comparison was conducted only in one complex Chinese rotation region; additional comparisons in Brazil, Africa, and Eastern Europe would further clarify the generality of the proposed method.

The empirical thresholds also require cautious interpretation. They were selected from separability patterns and probability density distributions rather than from a fully data-driven optimization procedure. This design improves interpretability and low-sample applicability, but it also means that thresholds may need recalibration when crop calendars, varieties, irrigation regimes, or background crops differ substantially from the representative regions tested here.

Reference-data uncertainty is another limitation. CDL, MapBiomass, China crop maps, the Nandi crop-type dataset, and KPI-Ukraine maps differ in classification schemes, production methods, and reported accuracies. Although homogeneous pixels and visual checks were used to reduce inconsistencies, these products cannot fully replace synchronized field surveys. Future multi-region validation should include more harmonized in situ samples and sampling-based confidence intervals where feasible.

Future work should focus on three directions. The first is multi-source data fusion, especially the integration of ENDVire with Sentinel-1 backscatter and texture features

to reduce the impact of optical data gaps. The second is uncertainty-aware mapping, in which pixels close to decision thresholds are flagged for manual inspection, active sampling, or model refinement. The third is integration with deep learning and geospatial foundation-model embeddings, using phenological rules as interpretable priors or pseudo-label generators. Such integration could preserve the mechanistic advantages of ENDVIre while improving performance in heterogeneous and cloud-prone agricultural landscapes. In cloud-prone regions, Sentinel-1 VV/VH backscatter, polarization ratios, and temporal texture features could be fused with optical ENDVIre and NDVI through rule-based voting, feature-level stacking, or object-level post-processing. Such microwave–optical fusion would be especially useful for recovering maize signals during the rainy-season vigorous growth window, when optical observations are missing or unreliable.

## 6. Conclusions

This study proposed an ENDVIre-based phenology-adaptive method for maize mapping in representative maize-growing regions under limited-sample conditions. ENDVIre, computed from Sentinel-2 B8A and B6, enhanced the response to maize canopy structure and chlorophyll-related red-edge changes during the silking-to-grain-filling stage. By combining ENDVIre with NDVI-based phenological stage extraction and LSWI-based rice exclusion, the decision-tree model effectively distinguished maize from soybean, rice, wheat, and other non-maize backgrounds.

Across six study regions in the United States, Brazil, China, Kenya, and Ukraine, the method achieved a mean OA of 93.27%, an F1-score of 93.14%, and a Kappa coefficient of 0.8652. Cross-year experiments in Fan County showed stable performance from 2020 to 2024, with OA values ranging from 89.80% to 96.80%. Spatial-transfer tests achieved OA values of 87.40–95.40% across independent regions, suggesting that phenology-aligned rules have practical transfer potential across the tested representative climates, hemispheres, and cropping systems. Product comparison in the Huang-Huai-Hai Plain further showed that the proposed method better balanced omission and commission errors than several existing high-resolution maize products.

These results suggest that ENDVIre-based phenology rules provide an interpretable and practical approach for maize mapping in regions where large training datasets are unavailable. The method is most effective in areas with clear crop calendars and sufficient optical observations, but it remains sensitive to persistent cloud cover and fragmented mixed-cropping systems. Combining ENDVIre with SAR observations, local calibration, and data-driven models offers a promising direction for future large-scale maize monitoring. Therefore, the conclusions should be limited to the tested representative agroecosystems and interpreted as evidence of practical transfer potential, rather than as proof of a universally applicable, parameter-free global maize-mapping model.

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**Data Availability Statement:** The Sentinel-2 imagery used in this study is publicly available through the Copernicus program and Google Earth Engine. Reference products include USDA CDL, Map-

Biomass, China crop maps, Nandi crop-type data, and KPI-Ukraine crop maps. Derived maize maps and code can be made available through a public repository after manuscript acceptance.

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