ChinaRiceCalendar-Seasonal Crop Calendars for Early, Middle, and Late Rice in China

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Abstract. Long-time series and large-scale rice calendar datasets provide valuable information for agricultural planning and field management in rice-based cropping systems. However, current regional-level rice calendar datasets do not accurately distinguish between rice seasons in China, causing uncertainty in crop model simulation and climate change impact analysis. Based on satellite remote sensing data, we extracted transplanting, heading, and maturity dates of early-, middle-, and late-season rice across China from 2003 to 2022, and established a multi-season rice calendar dataset named ChinaRiceCalendar. Overall, the ChinaRiceCalendar dataset shows a good agreement with field-observed phenological dates of early, middle, and late rice in Chinese Agricultural Meteorological Stations (AMSs). According to the calendar data from 2003 to 2022 in China, the transplanting dates for early, middle, and late rice shifted by +0.7, -0.7, and -5.1 DOY/decade, respectively; the heading date for early, middle, and late rice shifted by -0.5, +2.7, and -0.6 DOY/decade, respectively; the maturity date for early, middle, and late rice shifted by -0.7, +3.8, and -1.6 DOY/decade, respectively. The ChinaRiceCalendar can be utilized to investigate and optimize the spatio-temporal structure of rice cultivation in China under climate and land-use change.

1 Introduction

As one of the major food crops, rice feeds nearly half of the world's population (Nelson and Gumma, 2015; Fahad et al., 2019). In the context of climate change, continued warming is projected to result in shorter crop growth periods, lower rice productivity, and food insecurity in the Asian monsoon region

(Carleton, 2017; Zhao et al., 2017; IPCC, 2022). Revealing changes in rice phenology will facilitate timely adjustment of planting time, rice cultivars, and cropping systems under global warming (Waha et al., 2013; Wang et al., 2022; Wang et al., 2024). Moreover, a dynamic rice calendar with key phenological dates is integral to agricultural monitoring and farmer support systems (Laborte et al., 2017; Fritz et al., 2019; Mishra et al., 2021). Large-scale rice calendars can contribute to more reliable simulations of crop growth and yield at regional and global scales (Franke et al., 2020).

Satellite remote sensing is an effective tool for detecting long-term trends in crop phenology at the regional scale (Xiao et al., 2006; Kotsuki and Tanaka, 2015; Luo et al., 2020; Gao and Zhang, 2021; Mishra et al., 2021). Crop phenology detection methods based on remote sensing vegetation indices (VIs) can be categorized into threshold, inflection point, and shape model approaches. The threshold approaches assume that a development stage begins when the VI value exceeds a predefined threshold (Jönsson et al., 2004; Boschetti et al., 2009; Pan et al., 2015; Guo et al., 2016). The inflection point approaches reconstruct the VI time-series curve by filter smoothing or function fitting, and then corresponds the maxima, minima, and inflection points on the curve to the key phenological events (Zhang et al., 2003; Sakamoto et al., 2005; Sun et al., 2009; Wang et al., 2019). The shape model approaches fit observed VI time-series curves by geometric scaling a robust standard VI time-series curve for the specific crop to identify development stages (Sakamoto et al., 2010; More et al., 2016; Zeng et al., 2016; Sakamoto et al., 2018). In addition to the methods based on time series of VIs, there are also rule-based algorithms that integrate multiple approaches and indicators to detect crop phenology, such as the PhenoRice algorithm proposed by Boschetti et al. (2017). The PhenoRice algorithm, which combines the advantages of threshold and inflection point approaches, utilizes the Enhanced Vegetation Index (EVI), the Normalized Difference Flood Index (NDFI), and the land surface temperature (LST) to estimate rice planting dates. The PhenoRice algorithm excels at extracting rice phenology in multiple cropping systems and has been widely used in East Asia, South Asia, Southeast Asia, and Europe (Busetto et al., 2019; Liu et al., 2020; Mishra et al., 2021). However, the performance of the PhenoRice algorithm depends on the division of rice seasons, which requires expert knowledge about rice-based cropping systems in different regions (Mishra et al., 2021).

In China, there are at least three rice-growing seasons (early, middle, and late seasons) in diverse rice-based cropping systems (e.g., single-rice, double-rice, rice-wheat, rice-rapeseed, and rice-vegetable systems) (Frolking et al., 2002; Qiu et al., 2003; Cao et al., 2021; He et al., 2021). Generally, early, middle, and late-season rice in China are transplanted around Day Of Year (DOY) 80-130, DOY 130-180, and DOY 180-230, respectively. Their typical maturity dates align with DOY 160-220, DOY 240-290, and DOY 270-330, respectively. Although field observations are important data sources for studying rice calendars in different growing seasons, they are usually limited by spatial and temporal discontinuities (Zhao et al., 2016; Wang et al., 2017). Therefore, previous studies have typically utilized satellite remote sensing products to establish rice calendar datasets at the regional scale (Shihua et al., 2014; Liu et al., 2019; Bai and Xiao, 2020; Luo et al., 2020; Mishra et al., 2021). Nevertheless, these calendar datasets based on satellite remote sensing do not rationally classify rice growing seasons across China. For example, the dataset ChinaCropPhen1km only distinguishes between early and late rice in double-rice systems (Luo et al., 2020); the assumptions of the dataset RICA about rice heading dates in different seasons do not correspond to the realities in China (Mishra et al., 2021); Shen et al. (2023) produced high-resolution distribution maps of single-season rice but did not explore multiple rice cropping systems. Early-, middle- and late-season rice in China are not only planted at different times, but also have distinguishing varietal characteristics, such as different temperature and photoperiod sensitivities (Zong et al., 2021). Thus, a crop calendar that accurately classifies rice seasons will provide reliable data for agricultural models to calibrate crop parameters at the variety level. Moreover, effective identification of different rice seasons will help analyze the response and adaptation of rice phenology to climate change.

Therefore, to address the shortcomings of the existing rice calendar datasets in China, we attempted to improve the PhenoRice algorithm and use satellite remote sensing data to (1) establish crop calendars for early, middle, and late rice in China; (2) validate the extracted rice calendars in different growing seasons; and (3) explore the spatio-temporal changes of rice calendar dates in major agricultural zones across China from 2003 to 2022.

2 Data and Methodology

2.1 Study area

We selected seven agricultural zones in China as the study area: the Northeast Plain (NP), Huanghuaihai Plain (HP), Loess Plateau (LP), Middle and Lower Yangtze River Region (MLY), South China Region (SC), Yunnan-Guizhou Plateau (YGP), and Sichuan Basin and Surrounding Region (SCS) (Fig. 1). Due to limited hydrothermal resources, the NP and HP zones mainly cultivates single-season rice. Early, middle, and late rice exist in different cropping systems in the MLY zone. The SC zone has a higher cropping frequency than other zones and usually cultivates rice twice a year. Parts of Hainan Province cultivates rice three times a year. Agricultural zoning data were obtained from Resources and Environment Science and Data Center (https://www.resdc.cn/data.aspx?DATAID=275).

2.2 Data

2.2.1 Satellite Imagery

MODIS (Moderate Resolution Imaging Spectroradiometer) remote sensing data are widely used in crop phenology detection because of their excellent performance in temporal and spatial continuity (Reed et al., 1994; Zhang et al., 2003; Zhao et al., 2011; Son et al., 2013). We selected two MODIS EVI products for the study area during 2003–2022: MOD13Q1 (TERRA data) and MYD13Q1 (AQUA data) (https://doi.org/10.5067/MODIS/MOD13Q1.061). Because the TERRA and AQUA data are based on the synthetic period of moving eight days from each other, the time series of the two 16-day products of MOD13Q1 and MYD13Q1 have a temporal resolution of 8 days (Boschetti et al., 2017). The red (ρ_{RED}) and near-red (ρ_{SWIR}) bands of MOD13Q1 and MYD13Q1 were used to calculate the Normalized Flooding Index (NDFI) (Eq. 1). The Pixel Reliability, Usefulness Index, and Blue Band Reflectance from MOD13Q1/MYD13Q1 were used to assess data quality. The Land Surface Temperature (LST) product MOD11A2 (https://doi.org/10.5067/MODIS/MOD11A2.061) were employed to estimate land surface temperature during rice planting.

$$NDFI = \frac{\rho_{RED} - \rho_{SWIR}}{\rho_{RED} + \rho_{SWIR}} \quad (1)$$

All above raster data were downloaded and spatially aggregated to 1km resolution by the Google Earth Engine (GEE) platform and the Python package of Geemap (Wu, 2020).

2.2.2 Validation Data

We collected field observations including transplanting, heading, and maturity dates of early, middle (single-season), and late rice between 2003 and 2013 from 338 Agricultural Meteorological Stations (AMSs, https://data.cma.cn/) in China. Moreover, we compared ChinaRiceCalendar with other multi-season and regional-scale calendar datasets, including the RiceAtlas dataset based on the agricultural statistics (Laborte et al., 2017), the ChinaCropPhen1km dataset based on the Global Land Surface Satellite (GLASS) leaf area index (LAI) products (Luo et al., 2020), and the RICA dataset based on the MOD13Q1/MYD13Q1 products (Mishra et al., 2021).

2.2.3 Additional Data

Cropland data were obtained from the International Geosphere-Biosphere Program (IGBP) classification of the MODIS land cover product (MCD12Q1) from 2003 to 2022 (https://doi.org/10.5067/MODIS/MCD12Q1.006). Digital elevation model (DEM) data used to create a terrain mask were obtained from the Shuttle Radar Topography Mission (SRTM, https://srtm.csi.cgiar.org). Both data are resampled to a spatial resolution of 1 km.

2.3 Methodology

The technology roadmap of this study is shown in Fig. 2.

2.3.1 Data pre-processing

The data pre-processing in the study falls into three steps:

1. The signal of agronomic flooding was used to help identify the rice transplanting period, but non-agricultural wetlands may have similar flooding signals to paddy fields (Dong and Xiao, 2016; Han et al., 2022). Thus, the annual cropland extent from 2003 to 2020 was used to establish a cropland mask to screen the cropland pixels of the MODIS EVI data.

2. Given that too high an elevation or too great a slope is unsuitable for paddy rice cultivation (Gumma et al., 2011; Dong and Xiao, 2016), only the image pixels with an elevation below 2600 m and a slope less than 8° were selected to extract rice calendars (Han et al., 2022).

3. To reduce the impacts of cloud contamination, we deleted the image pixels with reflectance greater than 0.2 in the blue band (Xiao et al., 2006).

2.3.2 Estimation of rice area and cropping calendar

We combined the PhenoRice algorithm (Boschetti et al., 2017) with a growing season division method (Kong et al., 2022) to extract rice pixels and cropping calendars in different growing seasons. Firstly, we identified possible crop heading periods based on a weighted-smoothed EVI time-series curve in each image pixel. Then we input the possible heading periods into the PhenoRice algorithm to divide potential growing seasons and check if the corresponding EVI time series belongs to rice. Lastly, we estimated rice planting, heading, and maturity dates and categorized them into early-, middle-, and late-season calendars according to the respective transplanting and maturity times.

① **Divide potential growing seasons**: The PhenoRice algorithm requires a pre-specification of rice heading periods in different growing seasons to extract the corresponding VI time series. To reduce the uncertainty caused by the artificial division of growing seasons, we employed the *phenofit* R package developed by Kong et al. (2022) to identify possible heading periods in each image pixel. 1) The weighted Whittaker method in the *phenofit* R package was employed to smooth the MODIS-EVI time series (Kong et al., 2022). The Whittaker smoothing function can robustly capture seasonal signals with little noise interference, and it is widely used to identify crop phenology (Atzberger and Eilers, 2011; Bush et al., 2017). The curve fitting mainly relies on information from good-quality points, but also extracts the limited information available from the marginal- and bad-quality points. During the rough fitting to the EVI time series, we categorized the data quality of the observations according to their Quality Control (QC) information (SummaryQA of MOD13A1) and assigned weights of 1.0, 0.5, and 0.2 to the good-, marginal-, and bad-quality VI observations, respectively. 2) Following Kong et al. (2022), the possible heading date (peak point date) in each crop season was identified by the smoothed EVI time series, based on the rules that only one peak value is inside a growing season and two trough values define a growing season. 3) The possible heading periods (peak point dates ± 16 days) detected in each image pixel were input into the PhenoRice algorithm to generate the potential growing seasons.

② **Check if the pixel belongs to a rice-cultivated area**: Whether the pixel belongs to a rice cultivated area during the selected growing season is checked using the following procedure (Boschetti et al., 2017): 1) Compare the observed maximum, and minimum EVI values with the corresponding thresholds for paddy fields (EVI_{max_th}, *and* EVI_{min_th}) to reduce misclassification problems with evergreen forests and non-vegetative areas; 2) Check for the existence of a maximum inflection point on the EVI curve, which must show a consistent increasing trend before the maxima and a consistent decreasing trend after the maxima. The time interval between the inflection points of the minimum and maximum EVI values during the season must fall within the range of rice vegetative growing periods [*vl1*, *vl2*]; 3) Check if the meteorological conditions on the day of the minimum are favourable for rice crop establishment based on a MODIS-LST value above a specified threshold (LST_{th}); 4) Detect a flood signal (NDFI ⩾ *minndfi*) within a time window (*winfl*) centred on the minimum; 5) Check if there is a consistent increase in EVI observed after the minimum; 6) Check if EVI decreases by more than *decrth*% of the amplitude of the min-max range in a time window after the maxima (*windecr*). Only if all the above requirements are satisfied, the selected growing season in the pixel is labelled as a rice season. The PhenoRice parameters used in the study were calibrated by the phenological observations from the AMSs in China (Table 1).

③ **Estimate rice planting, heading, and maturity dates**: The rice calendar dates were estimated in the detected rice pixels within the rice seasons. On the EVI time-series curve, the onset date of the field growth period corresponds to the date of the minimum point closest to the retained maximum; the heading time corresponds to the date of the retained maximum point; the maturity date corresponds to the date when the EVI declined by *decrth*% of the amplitude of the min-max range. Additionally, the study categorized the detected rice calendars into early, middle, and late seasons based on their respective range of transplanting and maturity dates in each province (Table 2).

2.3.3 Data validation

Taking AMS field observations as benchmarks, we evaluated the accuracy of rice calendar dates derived from four multi-season rice calendars: ChinaRiceCalendar, ChinaCropPhen1km, RiceAtlas, and RICA. These regional rice calendars can be divided into 2 categories: raster datasets (ChinaRiceCalendar and ChinaCropPhen1km) and district-level datasets (RiceAtlas and RICA). For ChinaRiceCalendar and ChinaCropPhen1km, we sought the nearest rice pixel around each AMS site for data pairing. In instances where there was no corresponding rice pixel within a 4 km radius around an AMS site, the site was excluded from the analysis. Also, we conducted a comparison between district-level rice calendars obtained from RiceAtlas and RICA, juxtaposed with AMS data distributed within the respective districts. Two criteria were used to evaluate the accuracy of the estimated rice areas and cropping dates in each season, namely Root Mean Squared Error (RMSE, Eq. (2)) and R^2 (Eq. (3)):

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{true_i} - \mathrm{est_i})^2} \tag{2}$$

$$\mathrm{R}^2 = \left(\frac{\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{est_i} - \overline{\mathrm{est}})(\mathrm{true_i} - \overline{\mathrm{true}})}{\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{est_i} - \overline{\mathrm{est}})^2}\sqrt{\sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{true_i} - \overline{\mathrm{true}})^2}}\right)^2 \tag{3}$$

where $\mathrm{true_i}$ is the true value in the ith province or AMS; $\mathrm{est_i}$ is the corresponding estimated value; $\overline{\mathrm{est}}$ and $\overline{\mathrm{true}}$ denote the mean of the estimated and true values, respectively; N is the number of provinces or AMSs.

Additionally, in order to investigate the historical shifts of rice phenological dates in China, we analyzed the trends of rice planting, heading, and maturity dates at the county level by a Sen+Mann-Kendall trend analysis at a significance level of 0.05. The trend analysis method is detailed in Gocic et al. (2013).

3 Result

3.1 Validation of ChinaRiceCalendar

The key phenological dates estimated in the study show high consistency with the data from AMSs (Fig. 3). The R^2 between rice phenological dates from ChinaRiceCalendar and AMSs is 0.95. The R^2 between ChinaRiceCalendar and AMS data for transplanting, heading, and maturity dates in China is 0.91, 0.88, and 0.90, respectively. The RMSEs of transplanting, heading, and maturity dates in ChinaRiceCalendar are approximately 14 days. The R^2 between rice phenological dates from

ChinaRiceCalendar and AMS data for early, middle, and late rice is 0.91, 0.94 and 0.90, respectively.

Also, we calculated the RMSE of the estimated rice cropping dates in the seven agricultural regions in China (Fig. 4). Overall, the estimated rice calendars are more accurate in northern China than in the south. For early-season rice, the RMSE average of the estimated cropping dates is 12.73, 12.43, and 14.53 days in the MLY, SC, and YGP, respectively. For middle-season rice, the range of the RMSEs in the seven agricultural regions is from 4.74 days in the HP to 14.34 days in the YGP. For late-season rice, the RMSE average of the estimated cropping dates is 13.90, 17.54, and 14.25 days in the MLY, SC, and YGP, respectively.

3.2 Comparison with other calendar datasets

Using AMS field observations as benchmarks, the RMSE of rice phenological dates obtained from ChinaRiceCalendar, ChinaCropPhen1km, RiceAtlas, and RICA is 13.8 days, 15.0 days, 17.9 days, and 22.6 days, respectively. According to the accuracy evaluation at the seasonal level (Fig. 5), ChinaRiceCalendar is the only dataset where the RMSE does not exceed 15 days across three rice seasons. Compared with the ChinaRiceCalendar dataset, ChinaCropPhen1km exhibits suboptimal performance in early-rice seasons (RMSE=18days), RiceAtlas underperforms in middle-rice seasons (RMSE=22days), and RICA falls short in both middle- and late-rice seasons (RMSE>30days). Overall, ChinaRiceCalendar demonstrates superior accuracy in the estimated rice calendars compared to ChinaCropPhen1km, RiceAtlas, and RICA at the annual and seasonal levels in China.

3.3 Spatial distribution of rice phenological dates

According to the spatial distribution of the detected rice areas during 2003~2022, early and late rice were mainly grown in southern China, while middle rice was widely planted in China from south to north (Figs. 6 and 7). The spatial variations of rice phenology were significant in early, middle, and late seasons. In the NP, HP, and LP, middle rice was transplanted around DOY150, flowered around DOY230, and matured around DOY270. In the YGP, the mean transplanting date was approximately DOY100 for early rice, DOY150 for middle rice, and DOY195 for late rice; the mean heading date for early, middle, and late rice was DOY170, DOY230, and DOY250, respectively; the mean maturity date was approximately DOY200 for early rice, DOY260 for middle rice, and DOY290 for late rice. In the MLY, the mean transplanting date was approximately DOY120 for early rice, DOY160 for middle rice, and DOY200 for late rice; the mean heading date was approximately DOY190 for early rice, DOY230 for middle rice, and DOY250 for late rice; the mean maturity date was DOY210 for early rice, DOY260 for middle rice, and DOY290 for late rice. In the SC, the mean transplanting date was approximately DOY100 for early rice and DOY220 for late rice; the mean heading date was approximately DOY170 for early rice and DOY270 for late rice; the mean maturity date was approximately DOY200 for early rice and DOY300 for late rice. For rice in the SCS, the mean transplanting, heading, and maturity dates were approximately DOY130, DOY220, and DOY250, respectively.

3.4 Temporal changes in rice phenological dates

Based on the trend analysis of rice phenological dates from 2003 to 2022 in China (Fig. 8), the mean transplanting dates for early, middle, and late rice shifted by +0.74, -0.68, and -5.12 DOY/decade, respectively; the mean heading dates for early, middle, and late rice shifted by -0.51, +2.73, and -0.60 DOY/decade, respectively; the mean maturity dates for early, middle, and late rice shifted by -0.67, +3.75, and -1.62 DOY/decade, respectively. The detected shifts in rice phenological dates during 2003~2022 depended on the agricultural region (Fig. 9). For middle-season rice in the Northeast Plain (NP), 76% of the counties showed a significant or slight advance in transplanting dates, while 71% of the counties showed a significant or slight delay in maturity dates. In the Middle and Lower Yangtze River Region (MLY), 59%, 66%, and 72% of the rice-producing counties showed a significant or slight delay in transplanting, heading, and maturity dates of middle rice, respectively. In the Sichuan Basin and Surrounding Region (SCS), 79%, 86%, and 80% of the rice-producing counties showed a significant or slight delay in transplanting, heading, and maturity dates of middle rice, respectively. In the Yunnan-Guizhou Plateau (YGP), 77%, 67%, and 59% of the rice-producing counties showed a significant or slight delay in transplanting, heading, and maturity dates of middle rice, respectively. In the Huanghuaihai Plain (HP) and the Loess Plateau (LP), rice phenological dates did not show a consistent or significant trend. For early-season rice, transplanting tends to be delayed, but maturity tends to be earlier in the Southern China Region (SC). In most parts of China, the detected trends in early rice phenological dates were not significant during 2003~2022. For late-season rice in China, 64% of the counties showed a significant or slight advance in transplanting dates, whereas 64% of the counties showed a significant or slight delay in heading and maturity dates.

4 Uncertainties in ChinaRiceCalendar

This study used MODIS remote sensing data to extract rice phenological dates in various growing seasons in China. The MODIS remote sensing products have an appropriate temporal resolution, long time series, and good time consistency for analyzing changes in rice calendars at the regional scale. Moreover, the MODIS data are easy to obtain and process on the GEE platform, allowing for automated and timely updating of the calendar dataset. Nevertheless, discerning early- and late-rice pixels is more difficult than identifying middle-rice pixels in MODIS data, resulting in lower accuracy of the detected rice calendars in southern China (MLY, SC, SCS, YGP) than in northern China (NP, HP, LP).

There are several factors leading to the incomplete identification of rice pixels in early and late seasons in southern China. Firstly, the pixel-based detection of rice areas may be interfered with by the contamination of clouds, aerosols, and water vapor, especially during the monsoon season when late rice is transplanted (Xiao et al., 2005; Xiao et al., 2014; Clauss et al., 2016; Mishra et al., 2021). Because synthetic aperture radar (SAR) can penetrate through clouds, subsequent studies could combine optical and SAR images to avoid the impacts of clouds (Shen et al., 2023a). Utilizing geostationary satellite observations to increase the temporal frequency of remote sensing data may also be an effective way to improve accuracy of rice calendars (Shen et al., 2023b). Secondly, diverse multi-cropping systems, complex topography, and the fragmentation of croplands in southern China make the pixel detection for early and late rice more challenging (Dong and Xiao, 2016). Producing satellite remote sensing data with higher spatial resolution and integrating multiple data sources from satellite-airborne-ground observations will facilitate real-time monitoring of rice cropping areas at the regional scale (Zheng et al., 2022; Sun et al., 2023). Additionally, the PhenoRice algorithm falls short in detecting rice pixels in rainfed or upland rice systems due to the absence of clear agronomic flooding signals. In China, rice is mainly planted in flooded paddy fields (Luo et al., 2022), which mitigates the problems of detecting rainfed or upland rice. Last but not least, precisely corresponding the image pixels from the MODIS dataset to the Agricultural Meteorological Stations remains a challenge during data validation. In the future, it would be beneficial to conduct a quantitative assessment to determine the representativeness of the MODIS pixels surrounding the AMS site.

In this study, we improved the method of growing season division in the PhenoRice algorithm. We also attempted to remove non-paddy pixels and reduce the impacts of low-quality data on the reconstruction of EVI time-series curves. Although the local tuning of the PhenoRice algorithm parameters could further improve the results, we employed a single configuration of EVI threshold values (EVI_{max_th}, EVI_{min_th}, $Wind_{ecr}$, and dec_{th}) in the PhenoRice algorithm across China because automated methods that perform robustly are essential for developing timely information about crop calendars over large extents (Mishra et al., 2021). Subsequently, we will try to automate the generation and updating of ChinaRiceCalendar based on the 'rgee' package (Aybar et al., 2023).

5 Data Availability

ChinaRiceCalendar is a raster dataset with 1-km spatial resolution. The dataset falls into two parts: detected rice pixel data (*_rice_pixels.tif) and county-level rice calendar data (*_county_level.tif). The spatial reference system of the dataset is WGS_1984_UTM_Zone_49N. The dataset currently includes mean calendar dates during five periods: 2003~2007, 2008~2012, 2013~2017, 2018~2022, and 2003~2022. ChinaRiceCalendar is available at https://doi.org/10.7910/DVN/EUP8EY (Liu et al., 2023).

6 Conclusions

Utilizing MODIS time series data, we established a multi-season rice calendar dataset named ChinaRiceCalendar, encompassing transplanting, heading, and maturity dates of early, middle, and late rice in China from 2003 to 2022. The rice phenological dates within ChinaRiceCalendar, estimated through the enhanced PhenoRice algorithm, exhibit strong alignment with field observations collected by Agricultural Meteorological Stations across China. The R^2 values between ChinaRiceCalendar and field data for early, middle, and late rice consistently surpass 0.90, with RMSE values below 15 days in three rice seasons. According to the calendar data from 2003 to 2022, the transplanting dates for early, middle, and late rice shifted by +0.7, -0.7, and -5.1 DOY/decade, respectively; the heading date for early, middle, and late rice shifted by -0.5, +2.7, and -0.6 DOY/decade, respectively; the maturity date for early, middle, and late rice shifted by -0.7, +3.8, and -1.6 DOY/decade, respectively. In summary, ChinaRiceCalendar stands as a reliable dataset for investigating and optimizing the spatio-temporal dynamics of rice cultivation in China, particularly in the context of climate and land-use changes.

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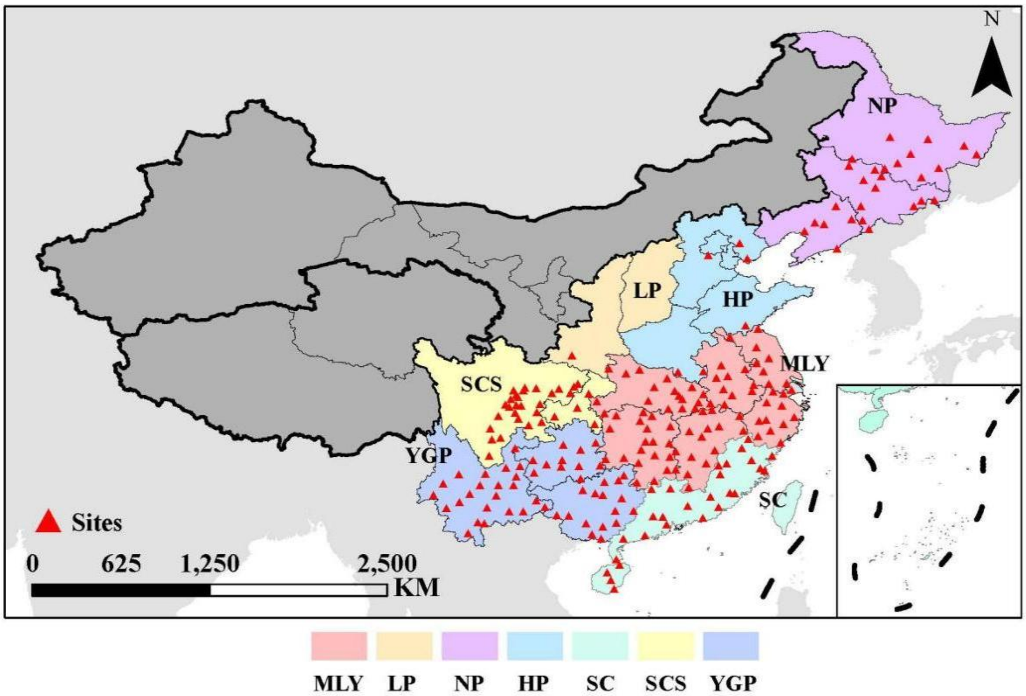

Fig. 1 Study area and distribution of Agricultural Meteorological Stations (AMSs) in China

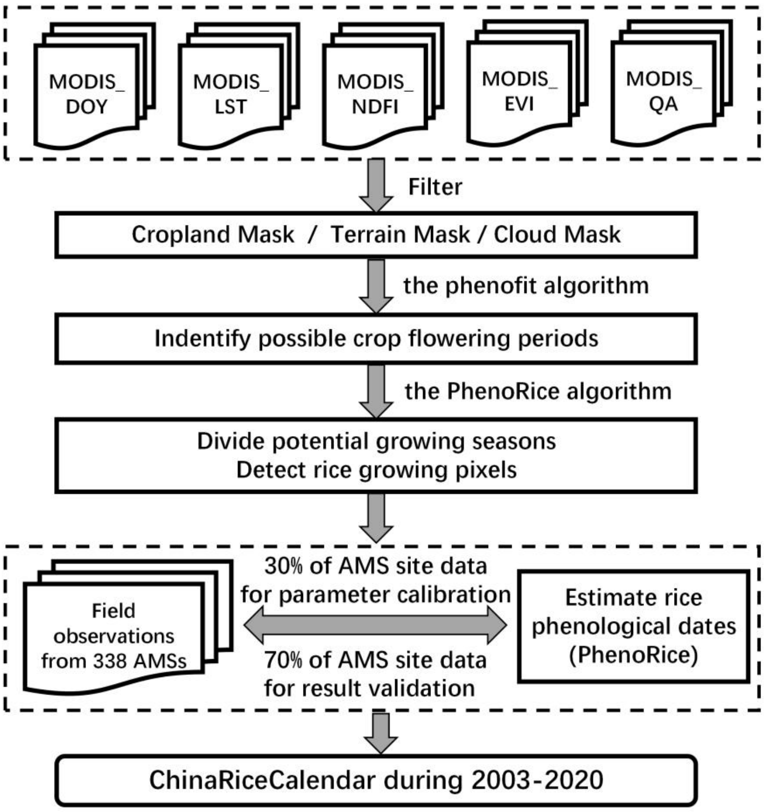

Fig. 2 Technology roadmap for this study

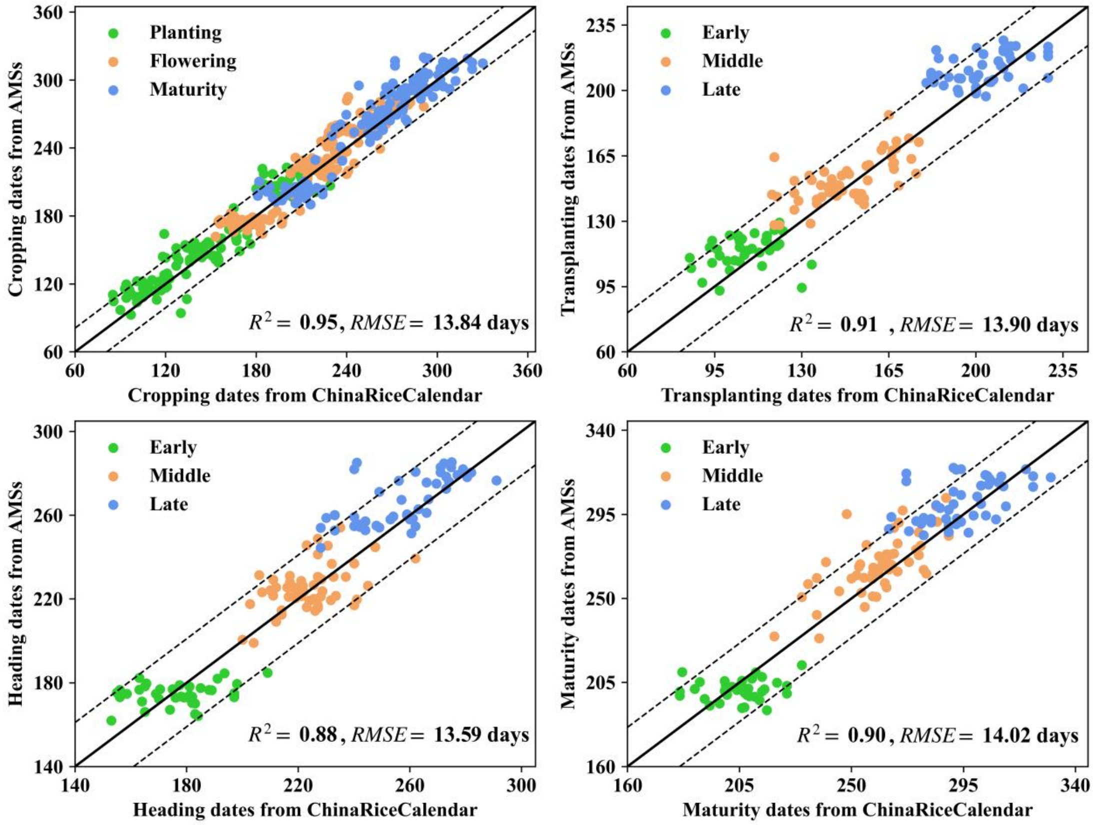

Fig. 3 Comparison of rice phenological dates between ChinaRiceCalendar and AMS data at the site scale (dashed lines are ±21 days)

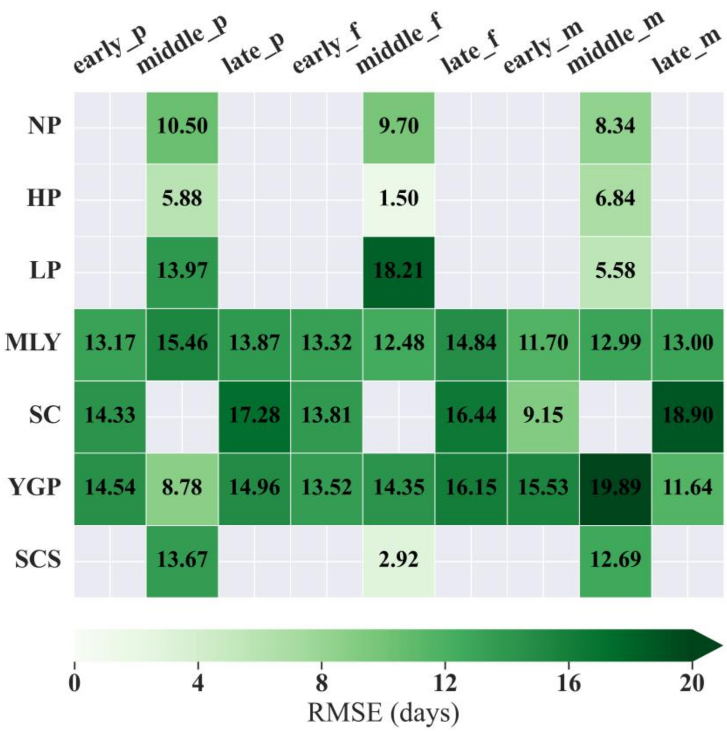

Fig. 4 RMSEs of rice phenological dates between ChinaRiceCalendar and AMS data in main agricultural regions

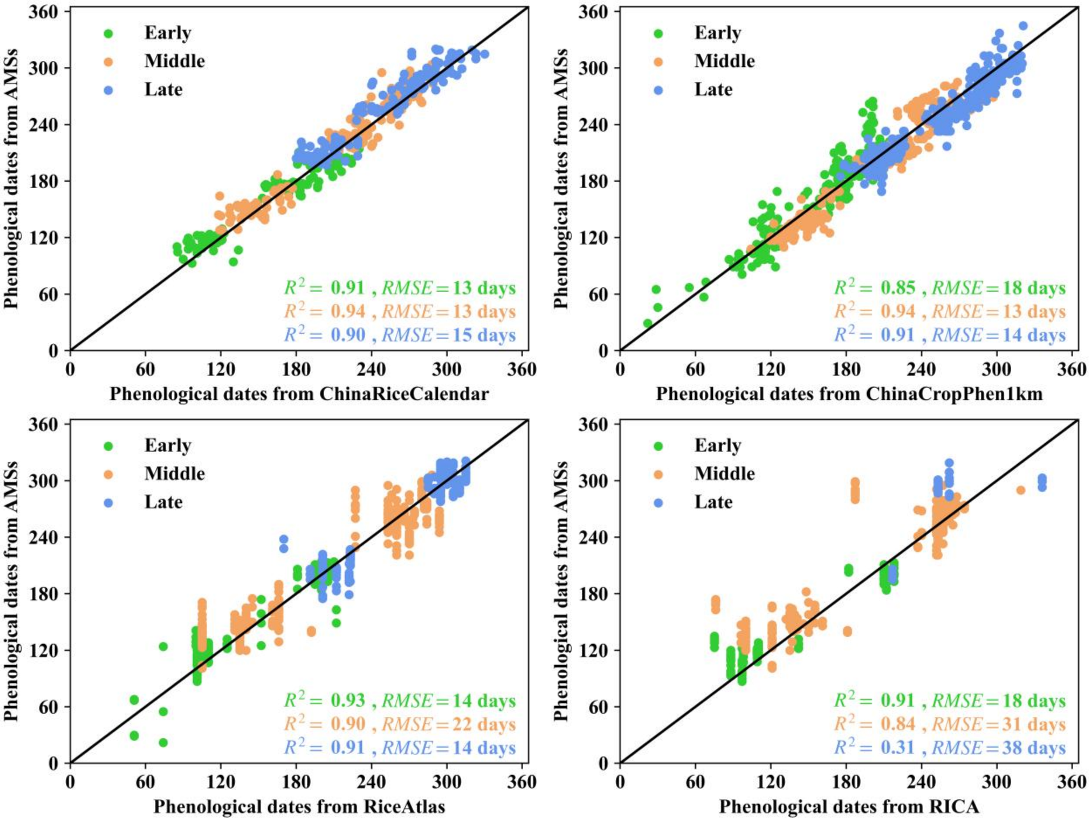

Fig. 5 Comparison of rice phenological dates between calendar datasets and AMS data at the site scale in early (green), middle (orange), and late (blue) seasons.

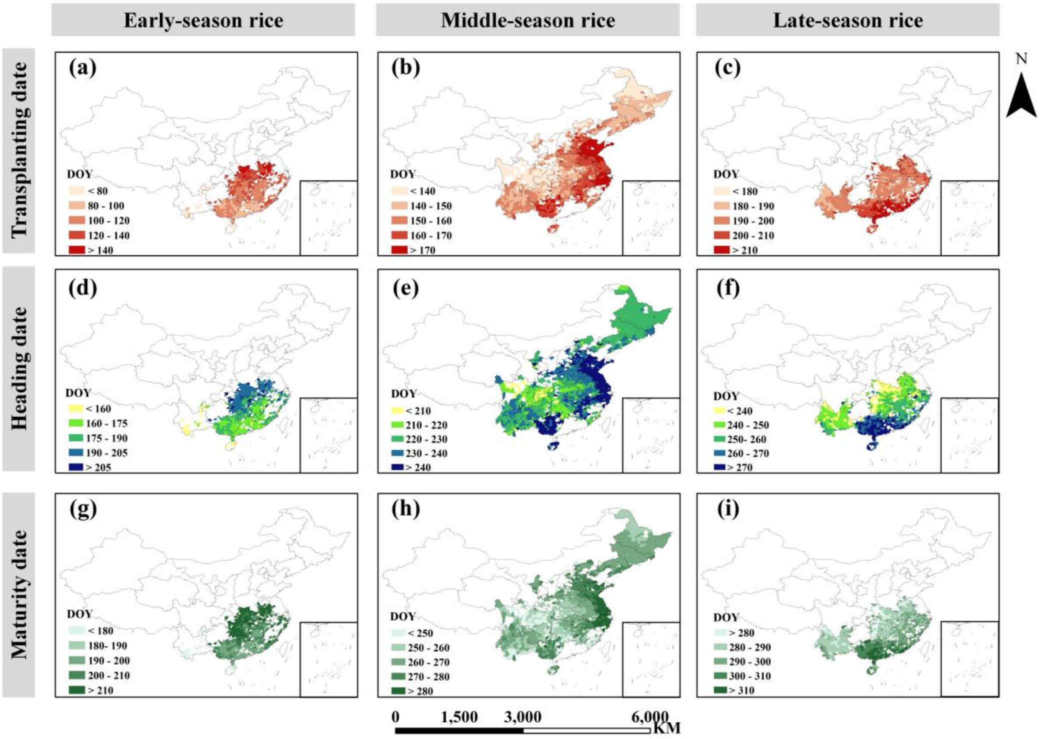

Fig. 6 Rice phenological dates at the county scale between 2003 and 2022 (a: early-rice transplanting dates; b: middle-rice transplanting dates; c: late-rice transplanting dates; d: early-rice heading dates; e: middle-rice heading dates; f: late-rice heading dates; g: early-rice maturity dates; h: middle-rice maturity dates; i: late-rice maturity dates)

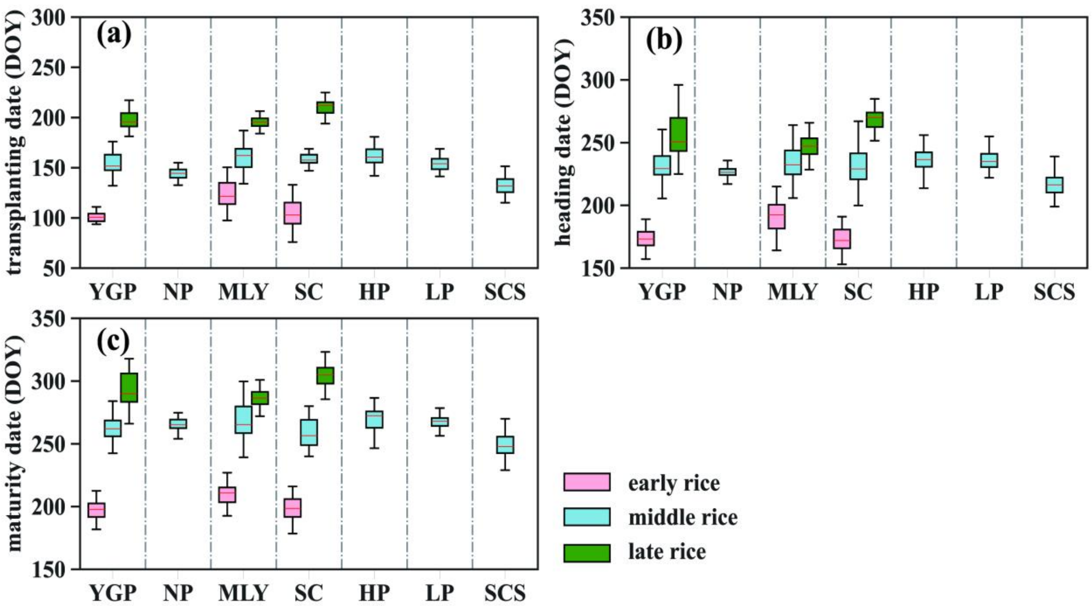

Fig. 7 Rice phenological dates in rice-producing counties between 2003 and 2022 (a: Transplanting dates; b: Heading dates; c: Maturity dates)

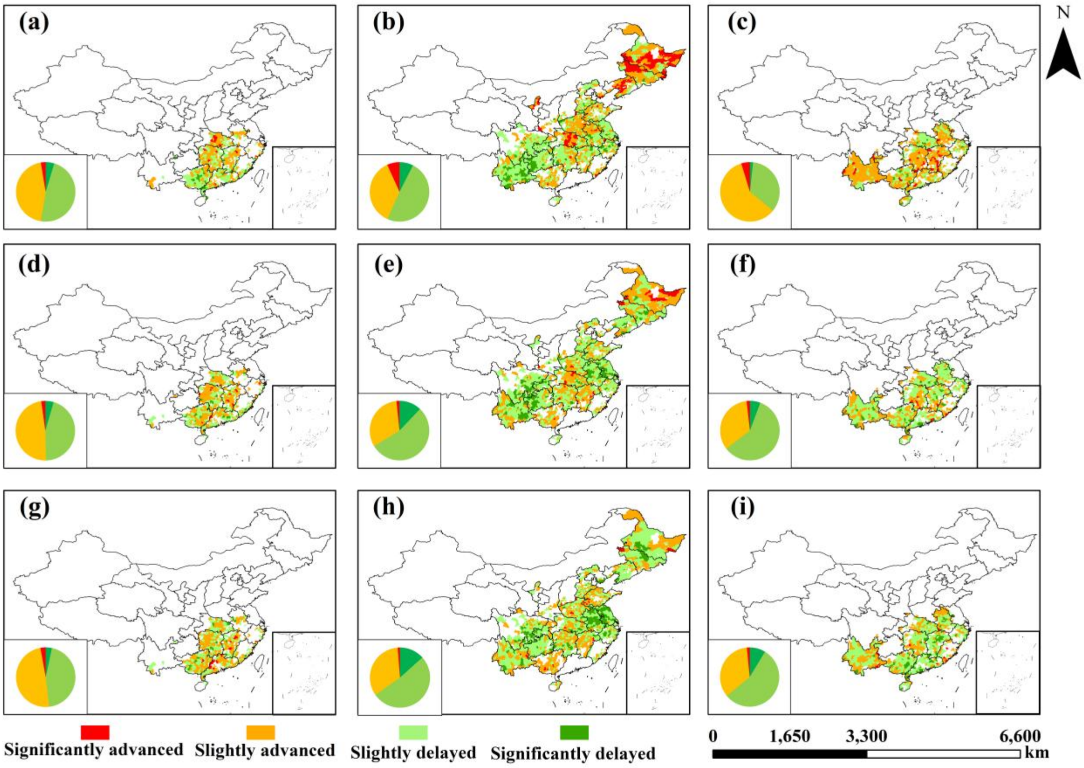

Fig. 8 Temporal trends in rice phenological dates at the county scale from 2003 to 2022 (a: early-rice transplanting dates; b: middle-rice transplanting dates; c: late-rice transplanting dates; d: early-rice heading dates; e: middle-rice heading dates; f: late-rice heading dates; g: early-rice maturity dates; h: middle-rice maturity dates; i: late-rice maturity dates)

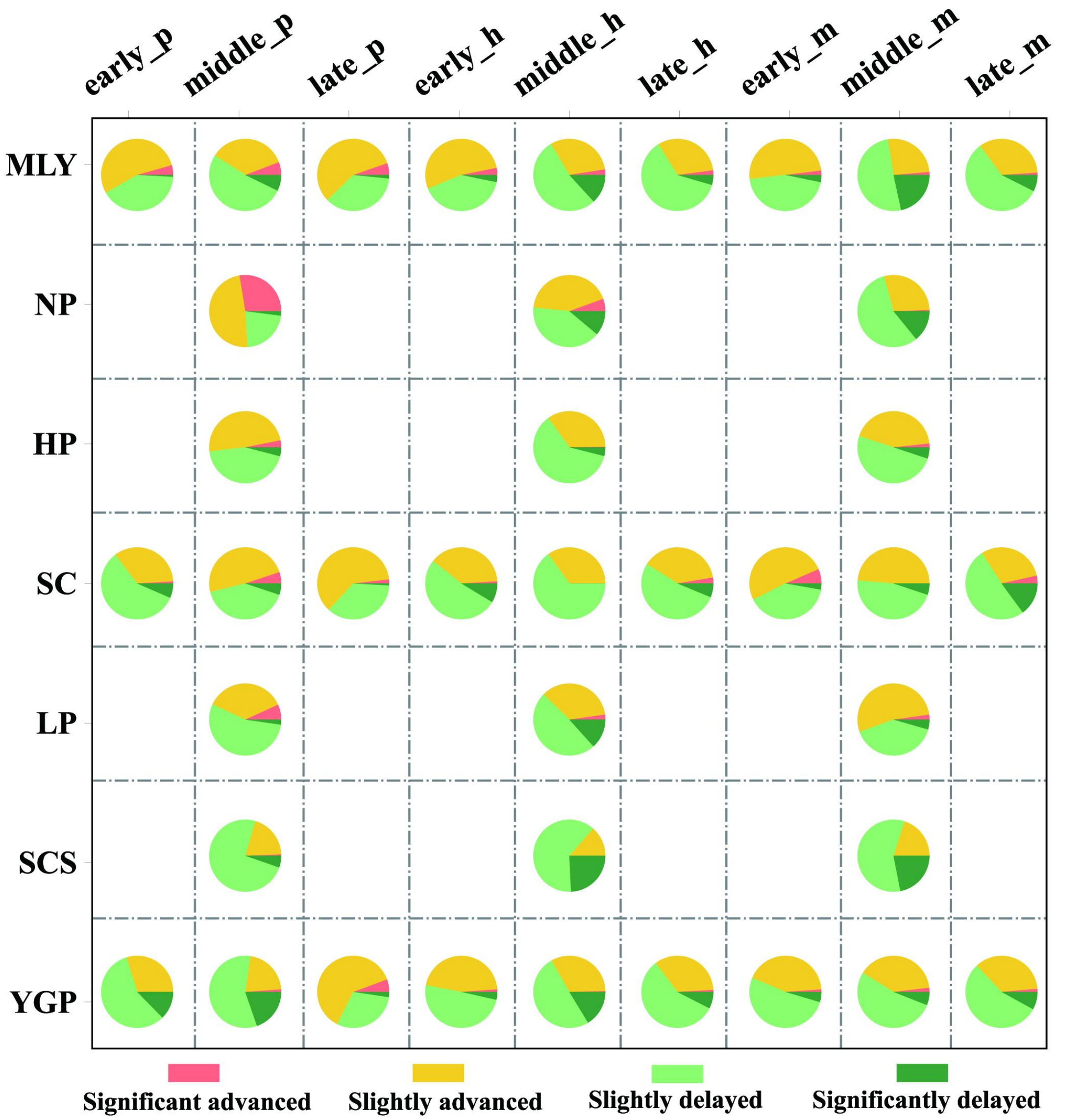

Fig. 9 Temporal trends in rice phenological dates at the regional level from 2003 to 2022 (early_p: early-rice transplanting dates; middle_p: middle-rice transplanting dates; late_p: late-rice transplanting dates; early_h: early-rice heading dates; middle_h: middle-rice heading dates; late_h: late-rice heading dates; early_m: early-rice maturity dates; middle_m: middle-rice maturity dates; late_m: late-rice maturity dates)

Table 1 PhenoRice parameters used in the study (EVI_{max_th}: EVI threshold above which a local maxima can be considered as a peak of a growing season; EVI_{min_th}: EVI threshold below which a local minima min can be considered as a start of a growing season; vl1: shortest vegetative growth length; vl2: longest vegetative growth length; tl1: shortest field growth length; tl2: longest field growth length; LST_{th}: minimum land surface temperature for rice planting; Winfl: time window for capturing flooding signals; minndfi: threshold for NDFI; Win_{decr}: threshold for a decline window after EVI maximum; dec_{th}: percent decrease of EVI after EVI maximum)

Province	EVI_{max_th}	EVI_{min_th}	vl1 (days)	vl2 (days)	tl1 (days)	tl2 (days)	LST_{th} (°C)	Winfl (days)	minndfi	$Wind_{ecr}$ (days)	Dec_{th}
Anhui	0.4	0.25	32	72	64	120	15	24	0	64	0.5
Chongqing	0.4	0.25	64	88	96	136	15	24	0	64	0.5
Fujian	0.4	0.25	24	88	56	128	15	24	0	64	0.5
Guangdong	0.4	0.25	40	96	72	120	15	24	0	64	0.5
Guangxi	0.4	0.25	40	88	72	120	15	24	0	64	0.5
Guizhou	0.4	0.25	56	96	80	152	15	24	0	64	0.5
Hainan	0.4	0.25	56	112	80	128	15	24	0	64	0.5
Hebei	0.4	0.25	56	112	104	152	15	24	0	64	0.5
Heilongjiang	0.4	0.25	56	96	104	136	15	24	0	64	0.5
Henan	0.4	0.25	56	88	96	120	15	24	0	64	0.5
Hubei	0.4	0.25	24	112	56	152	15	24	0	64	0.5
Hunan	0.4	0.25	32	96	56	136	15	24	0	64	0.5
Jiangsu	0.4	0.25	56	88	104	136	15	24	0	64	0.5
Jiangxi	0.4	0.25	32	80	64	120	15	24	0	64	0.5
Jilin	0.4	0.25	56	96	96	136	15	24	0	64	0.5
Liaoning	0.4	0.25	56	96	104	152	15	24	0	64	0.5
Ningxia	0.4	0.25	64	88	112	152	15	24	0	64	0.5
Shaanxi	0.4	0.25	64	88	104	128	15	24	0	64	0.5
Shandong	0.4	0.25	56	80	96	120	15	24	0	64	0.5
Shanxi	0.4	0.25	64	88	104	128	15	24	0	64	0.5
Sichuan	0.4	0.25	56	96	80	160	15	24	0	64	0.5
Yunnan	0.4	0.25	24	112	56	160	15	24	0	64	0.5
Zhejiang	0.4	0.25	32	72	64	128	15	24	0	64	0.5

Table 2 Classification criteria of seasons for detected rice calendars by province in China

Province	Early season		Middle season		Late season	
	Transplanting dates	Maturity dates	Transplanting dates	Maturity dates	Transplanting dates	Maturity dates
Anhui	110~150	190~220	130~180	240~280	190~230	270~320
Chongqing	--	--	110~160	210~280	--	--
Fujian	90~140	180~230	140~170	240~270	180~240	270~330
Guangdong	70~140	170~220	--	--	200~240	280~340
Guangxi	80~130	180~230	140~180	250~290	180~240	280~340
Guizhou	--	--	100~180	220~310	--	--
Hainan	10~80	110~190	140~180	240~280	180~220	280~320
Hebei	--	--	120~190	260~300	--	--
Heilongjiang	--	--	120~170	240~290	--	--
Henan	--	--	130~170	240~270	--	--
Hubei	110~160	170~220	110~180	230~280	180~220	270~330
Hunan	100~140	180~230	130~170	230~280	180~230	260~320
Jiangsu	--	--	150~190	260~310	--	--
Jiangxi	90~140	180~220	130~180	230~390	180~220	270~320
Jilin	--	--	130~170	240~280	--	--
Liaoning	--	--	130~170	260~290	--	--
Ningxia	--	--	120~160	250~290	--	--
Shaanxi	--	--	130~160	250~280	--	--
Shandong	--	--	170~200	270~300	--	--
Shanxi	--	--	140~170	250~280	--	--
Sichuan	--	--	100~170	210~300	--	--
Yunnan	10~90	130~180	90~170	210~310	170~230	260~330
Zhejiang	100~140	180~230	150~190	270~330	190~220	270~330