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Designing Rice Cropping Schedules Using a Heading Date Prediction Model: An Integrated Approach for Climate Adaptation, Workload Leveling, and Spatial Optimization

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Abstract

In large-scale rice farming systems, the design of efficient cropping schedules is essential for improving labor management and operational efficiency. However, climate change, including rising temperatures and increased frequency of extreme weather events, has altered crop growth dynamics, making it difficult to achieve optimal management using conventional experience-based scheduling. In addition, the need to distribute operations across numerous fields and optimize labor allocation has increased the complexity of schedule design. In this study, we propose a decision-support method for designing rice cropping schedules using a heading date prediction model and climatological temperature data. The method adjusts transplanting dates based on predicted heading and maturity dates and determines operation periods through both forward and backward scheduling. A case study conducted on a large-scale farming system in Chiba Prefecture demonstrated that the proposed method effectively dispersed the distribution of heading and maturity dates, leading to improved temporal distribution of operations. The standard deviation of heading dates decreased from 11.7 to 8.7 days, indicating a reduction in peak labor demand. The novelty of this study lies in extending a heading date prediction model from growth prediction to practical applications in cropping schedule design and visualization. This approach enables a transition from experience-based planning to data-driven decision-making and contributes to labor distribution in large-scale farming under climate change conditions.

Keywords: rice; cropping schedule; heading date prediction model; climate change adaptation; labor distribution; smart agriculture

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1. Introduction

Rice (*Oryza sativa* L.) is one of the most important crops worldwide and provides food for more than half of the global population [1]. In recent years, increases in mean temperature and the frequency of extreme heat events in major rice-growing regions have been widely reported as consequences of global climate change [2,3]. In Japan, high temperatures during the early growth stages of rice have also become a serious issue [4,5]. Under such changing environmental conditions, it is essential to understand

crop growth stages and to implement cultivation practices at appropriate timings in order to achieve stable production of high-yield and -quality rice [6,7]. In particular, the heading date is a critical growth indicator that serves as a reference for many key operations, including topdressing, pest and disease control, and determining the optimal harvesting time [8].

In Chiba Prefecture, where early-season rice cultivation is practiced under warm climatic conditions, the standard transplanting date is around 20 April, and the average temperature during the rice-growing season (April–August) has shown an increasing trend [9,10]. Under these conditions, recent increases in temperature and frequent abnormal weather events have led to greater interannual variability in crop development. It has been reported that the heading and maturity dates of the rice cultivar 'Koshihikari' have advanced with rising temperatures during the growing period [11]. In addition, large deviations from normal climatic conditions have been frequently observed, resulting in differences in growth stages among years even when transplanting is conducted on the same date in the same region [12].

The major rice cultivars cultivated in Chiba Prefecture are 'Fusaotome', 'Fusakogane', and 'Koshihikari', accounting for 9.2%, 23.5%, and 55.2% of the total planting area, respectively [13]. These cultivars differ in growth characteristics and plant morphology [14]. 'Fusaotome' is classified as an early-maturing cultivar [15], 'Fusakogane' as a medium-maturing cultivar [16], and 'Koshihikari' as a late-maturing cultivar [17]. Therefore, accurate estimation of the heading date for each cultivar is essential not only for timely execution of individual operations but also for effective planning of overall farm management [18]. Consequently, conventional cropping schedules based on experience or previous-year calendars are becoming increasingly insufficient for ensuring appropriate operation timing and labor distribution.

Furthermore, in Chiba Prefecture, farmland consolidation into core farmers has progressed in recent years, leading to the expansion of large-scale farming systems with more than 50 ha of cultivated land [19]. As a result, cropping schedules have become increasingly complex due to expanded planting areas, management of numerous fields, use of multiple cultivars, prolonged transplanting periods, and spatial dispersion of fields. In such large-scale systems, the concentration of heading and maturity periods leads to overlapping operations such as fertilization, pest control, and harvesting, resulting in increased labor demand and competition for machinery use [20]. In addition, the spatial dispersion of the same cultivars across different locations reduces operational efficiency due to increased inter-field movement. Therefore, concentration of growth stages is a major factor causing labor and machinery constraints. These challenges highlight the need for methods that not only track crop development at the field level but also design cropping schedules at the field-group level by considering both temporal distribution of operations and spatial arrangement of fields [21].

To address these challenges, numerous studies have been conducted on heading date prediction in rice [22–26]. Developmental models using temperature and photoperiod as explanatory variables have been established as effective tools for quantitatively evaluating crop growth and have been widely applied for estimating heading dates and supporting optimal management practices [27]. In Chiba Prefecture, heading date prediction models have been developed for major recommended cultivars, enabling predictions tailored to regional cultivation conditions [28]. Furthermore, the authors have developed a cloud-based rice growth prediction system, "Deruta", to provide prediction results in a user-friendly format for farmers and extension services, offering information on heading dates and optimal timing of field operations [29].

In addition, studies on climate-adaptive rice scheduling using such models have been reported, including strategies to mitigate grain quality deterioration [30–32], determination of optimal transplanting dates and cultivar selection [33,34], and optimization of irrigation timing [35]. Moreover, optimization of cropping composition in large-scale rice farming systems has also been investigated [36], and the demand for practical planning tools is increasing [37].

However, most previous studies and systems have focused on predicting heading dates or supporting individual management decisions based on predicted phenology, such as optimal timing of operations or risk avoidance [38,39]. The direct application of prediction results to the design of cropping schedules has not been sufficiently explored [40]. In other words, heading date prediction models have mainly been used as tools for "predicting crop growth" rather than for "designing cropping schedules at the field-group level".

In addition, agricultural production can be regarded as a complex scheduling problem involving constraints such as machinery use and labor availability [41]. However, decision-support methods that comprehensively address temporal and spatial optimization—such as labor distribution, cultivar allocation, and reduction of inter-field movement—have not yet been fully established for large-scale farming systems.

Therefore, this study proposes a decision-support method for designing rice cropping schedules using a heading date prediction model developed in Chiba Prefecture and meteorological data. Based on previous studies [42], the proposed method determines operation timings through both forward and backward scheduling using predicted heading and maturity dates, with either transplanting or harvesting dates as reference points. The results are visualized to enable prior assessment of temporal concentration and dispersion of operations. Furthermore, a case study was conducted on a large-scale farming system in Chiba Prefecture to evaluate the effectiveness of the proposed method in labor distribution, improvement of planning efficiency, and optimization of field arrangement.

2. Materials and Methods

2.1. Overall Framework of the Study

In this study, a decision-support method was developed to design rice cropping schedules by integrating a heading date prediction model with meteorological data. The method consists of three main steps: (1) estimation of heading dates, (2) determination of operation timings, and (3) visualization of cropping schedules (Figure 1).

First, heading dates for each field and cultivar were estimated using a temperature-based prediction model. Next, operation timings were determined in relation to the predicted heading date, using either the transplanting date or the harvesting date as a reference. Both forward and backward calculations were applied depending on the target operation. Finally, the calculated schedules were visualized in tabular and time-series formats, allowing the concentration and distribution of operations to be assessed.

The method was implemented in Microsoft Excel using Visual Basic for Applications (VBA), and the estimation of heading dates and calculation of operation timings were automated. By inputting field-specific conditions such as cultivar, transplanting date, and field area, the system enables batch calculation and visualization for multiple fields. In this study, AMeDAS data were used for designing cropping schedules, while mesh-based agro-meteorological data were used to evaluate the spatial distribution of heading dates, in order to balance practical applicability and spatial analysis.

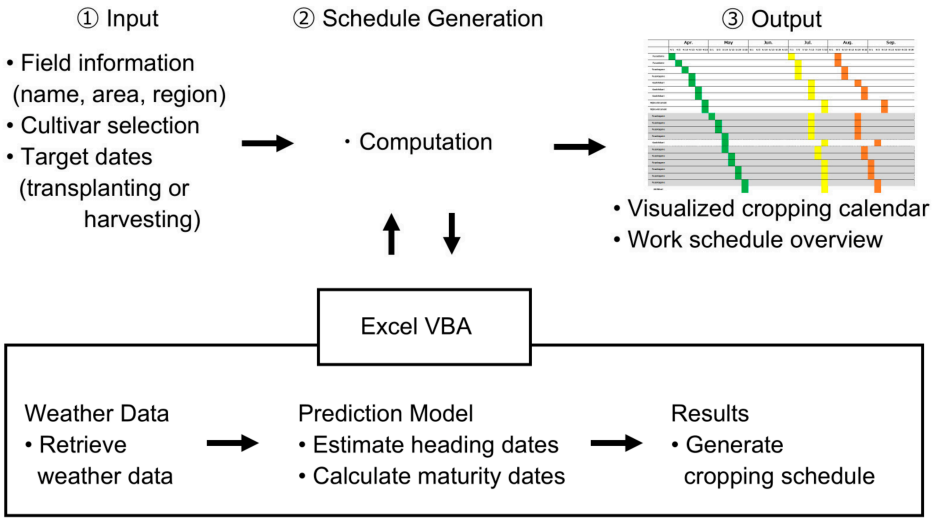


Figure 1. System architecture and workflow of the rice cropping schedule support system. This figure illustrates the overall structure of the proposed system. Field information, cultivar selection, and target dates (transplanting or harvesting) are provided as inputs, and scheduling is performed using Excel VBA. A prediction model based on weather data estimates heading and maturity dates, and the results are visualized as a cropping calendar and work schedule.

2.2. Visualization of Spatial Distribution of Heading Dates Using Mesh Agro-Meteorological Data

To examine spatial variation in heading dates under changing climatic conditions, mesh agro-meteorological data provided by NARO were used [43]. These data consist of daily mean air temperature with a fixed spatial resolution, allowing analysis that reflects regional differences in meteorological conditions.

The analysis was conducted for Chiba Prefecture. A uniform transplanting date (20 April) was applied to all grid cells, and heading dates were estimated using the prediction model. Two temperature scenarios were considered: climatological normal conditions and recent temperature conditions (2025). The differences between these scenarios were used to evaluate changes in heading dates.

This analysis was not directly used for cropping schedule calculation but was treated as a supplementary analysis to illustrate the spatial distribution of heading dates and their variation.

2.3. Heading Date Prediction Model

In this study, heading dates were predicted using a developmental model originally proposed by Horie and Nakagawa (1990) [22] and subsequently modified for rice cultivation conditions in Chiba Prefecture by Mochizuki et al. (2017) [28]. The model estimates crop development based on daily mean air temperature and day length and has been applied to major rice cultivars grown in Chiba Prefecture. The cultivar-specific parameter values developed by Mochizuki et al. (2017) [28] were adopted in this study. These parameters were estimated using multi-year field observations collected in Chiba Prefecture and have been applied to major rice cultivars grown in the region.

The model uses a developmental index (DVI) to represent crop developmental progress. DVI is a dimensionless index, where the value at transplanting is set to 0.2 and heading is assumed to occur when DVI reaches 1.0. Crop development progresses through the accumulation of daily developmental rates (DVRs), which are calculated as functions of temperature and photoperiod.

The DVI is calculated as follows:

$$DVI(n) = \sum_{i=0}^{n} DVRi$$

(When $L < Lc$)

$$DVRi = \frac{1}{G} \cdot \frac{1 - exp\{B(L - Lc)\}}{1 + \exp\{-A(T - Th)\}}$$

(When day length is equal to or longer than the critical day length)

$$DVRi = 0\ ,\ DVI(0) = 0.2$$

(Heading occurs on day h after transplanting)

$$DVI(h) > 1 > DVI(h-1)$$

where DVI(n) is the developmental index on day n after transplanting, and DVRi is the developmental rate on day i after transplanting. The variable n denotes the number of days after transplanting, whereas i represents the summation index used to accumulate daily developmental rates from transplanting to day n. T is the daily mean air temperature (°C), and L is the day length (h).

When the day length is shorter than the critical day length (Lc), DVR is calculated as a function of both temperature and photoperiod. When the day length is equal to or longer than Lc, crop development is assumed to cease and DVR is set to zero.

The model includes five cultivar-specific parameters (G, A, Th, B, and Lc) that describe crop responses to temperature and photoperiod. Here, G is a parameter related to the minimum duration from transplanting to heading, A and B are coefficients determining the shapes of the temperature and photoperiod response functions, respectively, Th is the threshold temperature for development, and Lc is the critical day length.

Table 1 presents the parameter values used for each cultivar.

Table 1. Parameter values of the heading date prediction model for each rice cultivar used in this study.

Cultivar	Parameter				
	G	**A**	**Th**	**B**	**Lc**
Fusaotome	59.6	0.298	17.5	0.587	18.2
Fusakogane	55.5	0.249	17.8	0.514	18.1
Koshihikari	47.8	0.283	17.7	0.283	17.8
Akihikari	49.1	0.254	17.6	0.456	17.6

The model was originally developed using mesh agro-meteorological data provided by NARO [43]. However, access to these data may be limited in practical applications. Therefore, the use of AMeDAS data provided by the Japan Meteorological Agency was also examined.

A previous study [29] validated the heading date prediction model under field conditions using AMeDAS data and reported a root mean square error (RMSE) of 2.99 days (Figure S1), which falls within the generally accepted accuracy range of ±3 days for practical rice cultivation management. These results indicate that the model provides sufficient accuracy for use in cropping schedule design and decision support.

2.4. Temperature Data Used for Heading Date Simulation

When using AMeDAS data for heading date simulation, it has been pointed out that climatological normal values (30-year averages) do not adequately reflect recent warming trends, leading to increased prediction errors [44]. In addition, an analysis of representative temperature datasets showed that, across 10 major AMeDAS stations in Chiba Prefecture, the recent 10-year average temperature was approximately 1 °C higher than the climatological normal (1990–2020) during the rice-growing period (April–September). Furthermore, the 10-year average showed closer agreement with observed temperatures in recent years than the climatological normal [44].

Based on these findings, the recent 10-year average temperature was used in this study to better reflect current warming conditions in heading date simulations.

2.5. Calculation of Operation Timings

In this study, cropping schedules were designed using the heading date as a reference. Heading dates were obtained either from the prediction model or by backward calculation from the maturity date. Two approaches were applied: forward calculation based on the transplanting date and backward calculation based on the harvesting date (Figure 2). In the forward calculation, the heading date was estimated from the transplanting date using the prediction model. In the backward calculation, the heading date and transplanting date were estimated in reverse from the harvesting date.

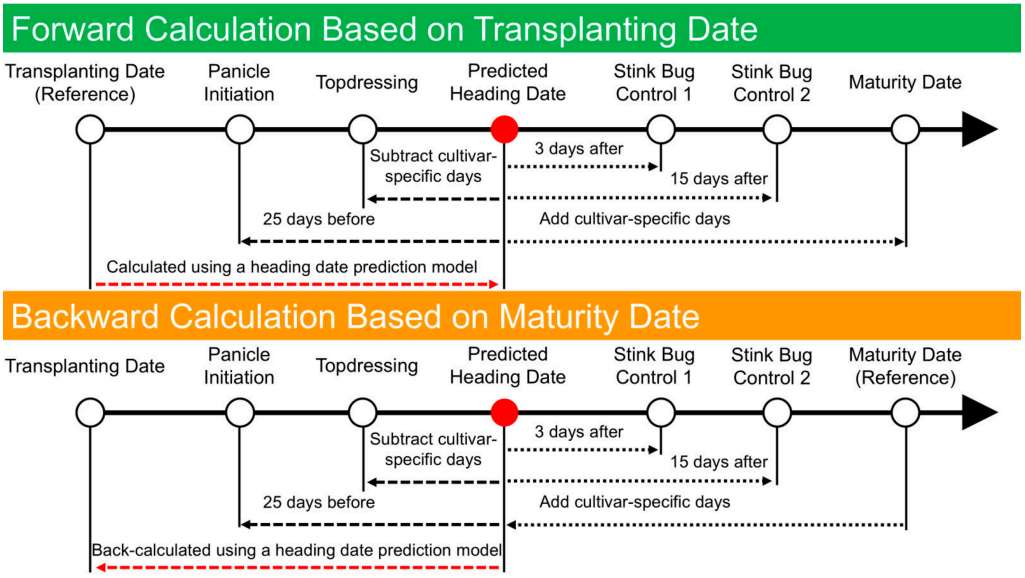


Figure 2. Conceptual diagram of forward calculation based on transplanting date and backward calculation based on maturity date for cropping schedule design. The (**upper panel**) shows forward calculation using the transplanting date as a reference, and the (**lower panel**) shows backward calculation using the maturity date as a reference. In both approaches, management operations are scheduled based on relative days from the predicted heading date. In the forward calculation, the heading date is estimated using a prediction model from the transplanting date, and subsequent operations and maturity date are determined using cultivar-specific parameters. In the backward calculation, the heading date is estimated by subtracting cultivar-specific days from the maturity date, and the transplanting date is then back-calculated. This framework enables consistent cropping schedule design regardless of the reference date used. Green and orange headers indicate the forward and backward calculation frameworks, respectively. Red circles denote the predicted heading date, and red dashed lines indicate the periods calculated using the heading date prediction model.

Based on the distributions of heading and maturity dates obtained by these methods, the effect of temporal distribution of operations was evaluated.

The timing of individual operations (e.g., topdressing and pest control) can be set as relative days from the heading date according to cultivation guidelines in Chiba Prefecture [8,29]. Therefore, the proposed method can be extended to a range of management practices. In addition, operation periods were determined by considering the operational capacity of agricultural machinery and facilities, including rice transplanters, harvesters, and drying facilities. The required number of working days for each operation was calculated based on the target area and daily operational capacity, and these constraints were incorporated into the schedule design process.

The system does not automatically optimize field allocation using a geographic clustering algorithm. Instead, users evaluate alternative cropping scenarios based on heading date predictions and visualization functions and manually adjust cultivar allocation and field arrangement according to management objectives such as workload leveling and spatial consolidation.

2.6. Case Study Setting

To evaluate the effectiveness of the proposed method, a case study was conducted on a large-scale rice farming system in Chiba Prefecture. The target farm operates in Kimitsu, Futtsu, and Sodegaura cities, with a total cultivated area of 111 ha and 626 fields, and grows multiple rice cultivars.

In this study, cropping schedules were generated based on the actual planting conditions of the farm and compared with the farm's conventional cropping schedule. The conventional schedule was the actual schedule used by the farm manager and was developed based on experience, previous management practices, and operational considerations, including transplanting dates, cultivar allocation, and field arrangement.

The evaluation focused on the concentration of operations, the dispersion of heading dates, and the time required for schedule planning.

AMeDAS data from Kisarazu, located near the study area, were used. Field layout maps and spatial visualization of cropping arrangements were prepared using QGIS.

Paddy soils in Chiba Prefecture are mainly classified as gley lowland soils, with soil pH generally ranging from weakly acidic to neutral, around pH 6 [45]. Since extreme soil pH conditions were not assumed in the study fields, the effect of soil pH on the simulation results was considered to be limited.

2.7. Evaluation Indices

To evaluate cropping schedules, several indices based on the distribution of heading dates were used.

First, the standard deviation of heading dates was calculated to evaluate the degree of dispersion. A larger standard deviation indicates greater dispersion of heading dates and, therefore, better temporal distribution of operations. The standard deviation was calculated based on heading dates converted into numerical day values.

Second, the peak concentration of heading dates was calculated to assess the degree of operational concentration. This index was defined as the proportion of fields heading on the day with the highest frequency, relative to the total number of fields. A higher value indicates that operations are concentrated on a specific day.

Finally, the duration of the heading period was calculated as the number of days from the first to the last heading date. These indices were used to compare the proposed method with conventional cropping schedules in terms of dispersion and concentration of operations.

3. Results

3.1. Advancement of Heading Dates and Changes in Spatial Distribution Under Climate Change

To examine the effects of climate change on rice heading dates, heading dates were estimated under climatological normal conditions and recent temperature conditions (2025) using the spatial visualization method described in Section 2.2. The target cultivars were the early-maturing 'Fusaotome', the medium-maturing 'Fusakogane', and the late-maturing 'Koshihikari', with a uniform transplanting date of 20 April. Figure 3 shows the spatial distribution of heading dates under both conditions.

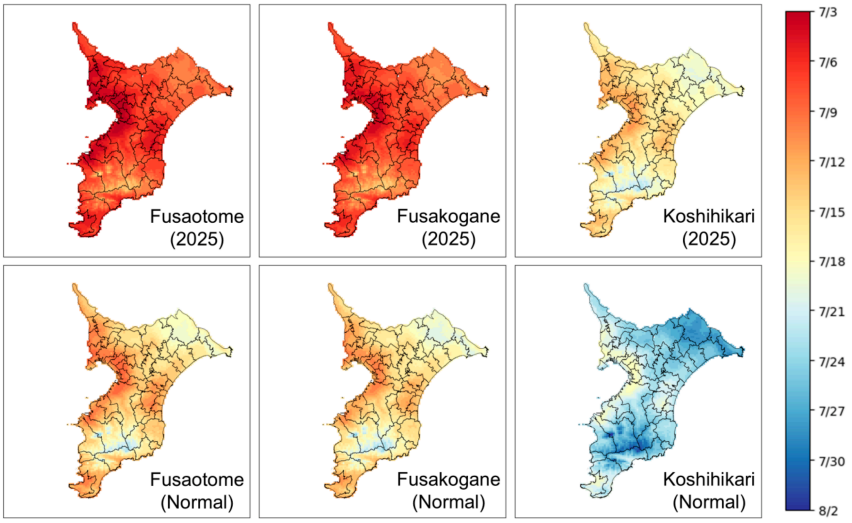


Figure 3. Spatial distribution of heading dates for three rice cultivars in Chiba Prefecture under 2025 and climatological normal conditions. Heading dates were estimated using a rice phenology model. The (**upper panels**) show results based on meteorological conditions in 2025, while the (**lower panels**) represent those based on climatological normals. The cultivars analyzed were Fusaotome, Fusakogane, and Koshihikari. A common color scale was applied across all panels, where colors indicate calendar dates of heading derived from days after transplanting. In this study, the climatological normal was defined as the 30-year average. The range of heading dates was unified across all panels, spanning from 3 July to 2 August.

Under climatological normal conditions, heading dates varied among regions, with 'Fusaotome' distributed from early to late July, 'Fusakogane' around mid-July, and 'Koshihikari' from late July to early August. In contrast, under the 2025 temperature conditions, heading dates advanced across all regions and cultivars, generally by several days to about one week.

The overall range of heading dates shifted from 8 July to 2 August under normal conditions to 3 July to 24 July under the 2025 conditions. The earliest heading date advanced by approximately 5 days, while the latest heading date advanced by approximately 9 days.

Differences among cultivars were also observed. The advancement was relatively small for the early-maturing cultivar 'Fusaotome', whereas larger shifts were observed for 'Fusakogane' and 'Koshihikari', with the greatest advancement found in 'Koshihikari'.

In addition to temporal changes, spatial patterns were also maintained. Although regional differences in heading dates were observed under both conditions, some areas consistently showed relatively later heading. Under the 2025 conditions, these spatial differences remained, while the overall distribution shifted earlier.

These results indicate that recent temperature increases have accelerated rice development, leading to systematic advancement of heading dates. This suggests that conventional experience-based cropping schedules may not be sufficient under current conditions and supports the need for the proposed prediction-based planning approach.

3.2. Visualization of Cropping Schedules Based on Heading Date Prediction

In this study, an Excel-based tool was developed to automatically generate and visualize cropping schedules using the heading date prediction model. By inputting field information (field name, area, and location), cultivar, and a reference date (transplanting date or harvesting date), the tool estimates heading and maturity dates through forward or backward calculation and outputs the corresponding operation timings. The tool was also designed to allow adjustment of schedules considering operational constraints such as machinery capacity and facility conditions.

Figure 4 presents cropping schedules generated using the proposed tool and those based on the conventional experience-based approach, shown as calendar-style time-series diagrams. The horizontal axis represents the date, and the vertical axis represents cultivar and field groups. Transplanting (green), heading (yellow), and harvesting (orange) periods are indicated using color coding.

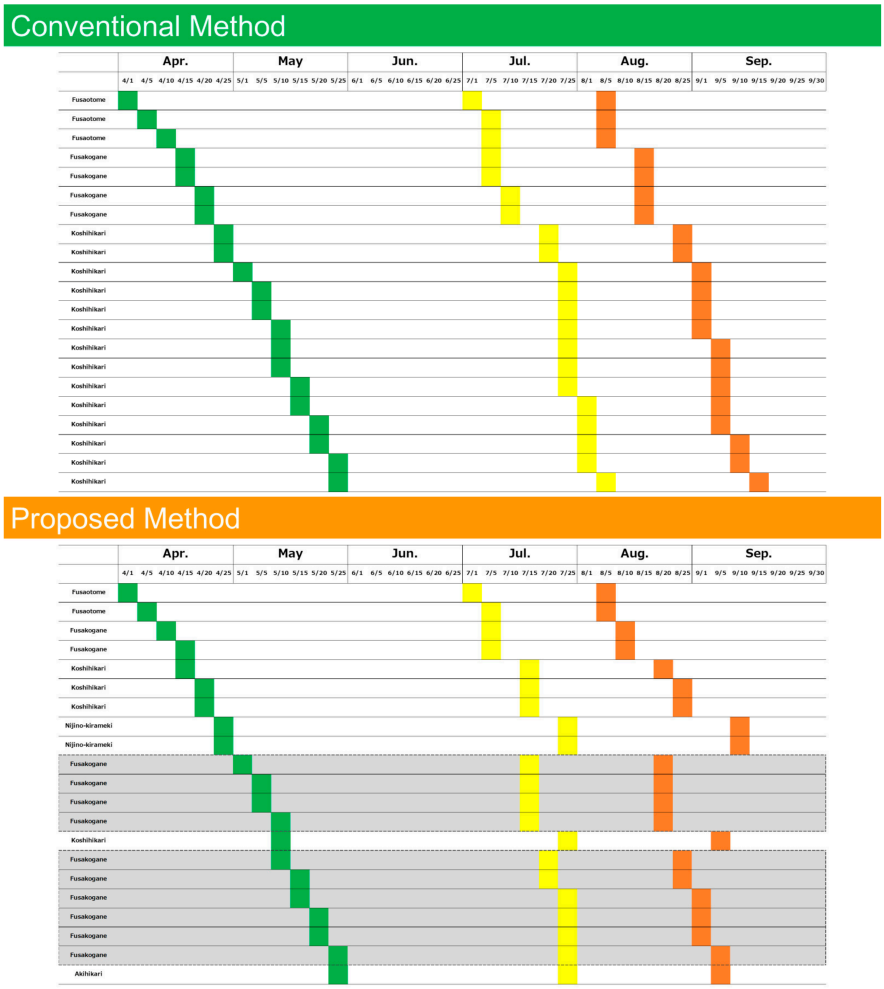


Figure 4. Comparison of cropping schedules between the conventional and proposed methods. The (**upper panel**) shows the conventional method, and the (**lower panel**) shows the proposed method. The horizontal axis represents calendar dates, and the vertical axis represents fields and cultivars. Green, yellow, and orange indicate transplanting, heading, and maturity periods, respectively. In the conventional method, heading and maturity dates are concentrated within limited periods, whereas in the proposed method, these periods are more evenly distributed, contributing to workload leveling and improved operation scheduling. Dashed gray boxes indicate field groups assigned using backward scheduling to fill scheduling gaps that could not be resolved by forward scheduling alone. Note that the results were originally calculated on a daily basis but are aggregated into half-month periods for visualization purposes.

In the conventional approach, heading and maturity periods were concentrated within a limited time window, resulting in overlapping operations. In contrast, in the proposed approach using the tool, adjustment of transplanting dates led to a more dispersed distribution of heading and maturity dates, reducing the overlap of operations. In particular, the distribution of heading dates was spread across multiple periods, which visually reduced the concentration of peak workload.

In addition to the preliminary cultivar 'Akihikari', the proposed method was further evaluated using 'Nijino-kirameki', which exhibits a similar heading date to 'Koshihikari' but requires approximately 10 additional days to reach maturity [46].

The results demonstrated that even when cultivars with different developmental characteristics were combined, the dispersion of heading and maturity dates was appropriately maintained.

This suggests that the proposed method is not limited to specific cultivars and can be applied to cropping systems involving cultivars with diverse growth characteristics.

These results show that visualizing cropping schedules makes it possible to identify potential concentration of operations in advance and to design schedules that consider workload distribution. In addition, the tool enables cropping schedules, which were previously dependent on experience, to be designed in a more quantitative and reproducible manner.

3.3. Temporal Distribution of Operations Based on Heading Date Prediction

Figure 5 shows the distribution of heading dates. In the conventional approach, heading dates were concentrated in early July, with a pronounced peak observed on a specific day (maximum 16.3% of all fields). In contrast, in the proposed approach, heading dates were distributed over multiple days, and the peak value decreased to 15.5%. The standard deviation decreased from 11.7 days in the conventional approach to 8.7 days in the proposed approach, indicating a reduction in variability of heading dates. The weighted mean date was similar between the two approaches, with 19 July for the conventional approach and 18 July for the proposed approach, suggesting that the overall timing of heading was largely unchanged.

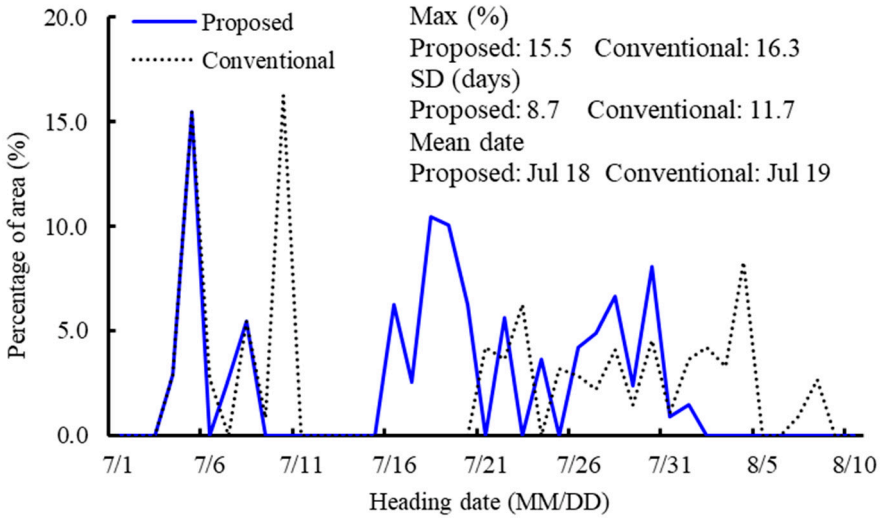


Figure 5. *Cont.*

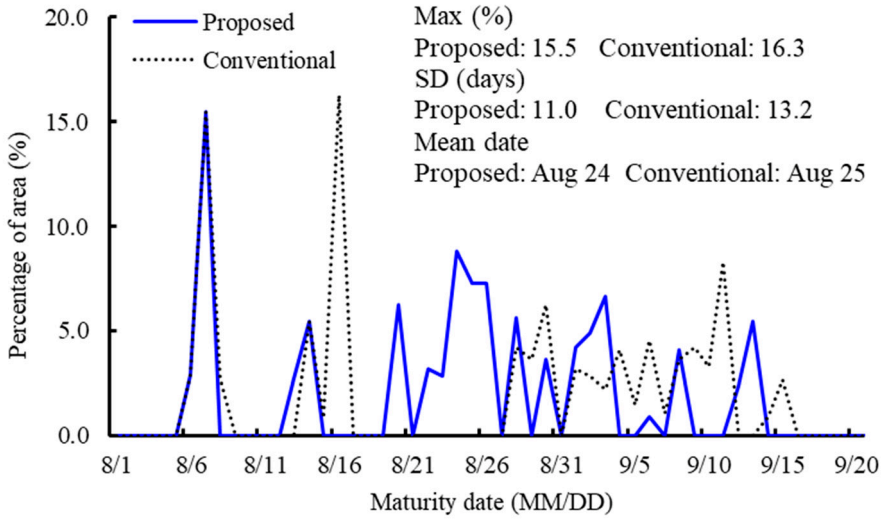


Figure 5. Comparison of temporal distributions of heading and maturity dates between the conventional and proposed methods. The (**upper panel**) shows heading dates, and the (**lower panel**) shows maturity dates as the percentage of area over time. The horizontal axis represents calendar dates, and the vertical axis represents the percentage of area (%). The solid blue line indicates the proposed method, and the dotted black line indicates the conventional method. The proposed method reduces peak values (Max) and standard deviation (SD), indicating a more distributed schedule. In contrast, the mean dates remain nearly unchanged, suggesting that workload leveling is achieved without significantly altering the cropping calendar.

Figure 5 also shows the distribution of maturity dates. In the conventional approach, maturity dates tended to be concentrated in mid-August and later, with a peak value of 16.3%. In contrast, in the proposed approach, maturity dates were distributed over a wider period, and the peak value decreased to 15.5%. The standard deviation decreased from 13.2 days in the conventional approach to 11.0 days in the proposed approach, indicating reduced variability. The weighted mean date was 25 August for the conventional approach and 24 August for the proposed approach, again showing little difference in the average timing.

These results indicate that the proposed approach reduces peak concentration while maintaining the overall timing of heading and maturity. This suggests that the method contributes to a more even temporal distribution of operations and may help to alleviate peak labor demand.

3.4. Optimization of Spatial Cropping Arrangement by District

Figure 6 compares field allocation under the conventional and proposed cropping plans. Under the conventional method (Figure 6a), three cultivars (Fusaotome, Fusakogane, and Koshihikari) were distributed across the study area, resulting in a spatially fragmented arrangement of cultivars within districts.

In contrast, the proposed method (Figure 6b) allocated cultivars while considering heading date distribution and operation scheduling. As a result, fields planted with the same cultivar were spatially clustered within districts, creating a simpler field arrangement and reducing the dispersion of cultivars across the study area.

Such spatial clustering is expected to improve operational efficiency by reducing travel distance between fields and facilitating continuous field operations. These results suggest that the proposed tool can support spatial cropping design that considers both temporal workload distribution and field operation efficiency under large-scale farming conditions.

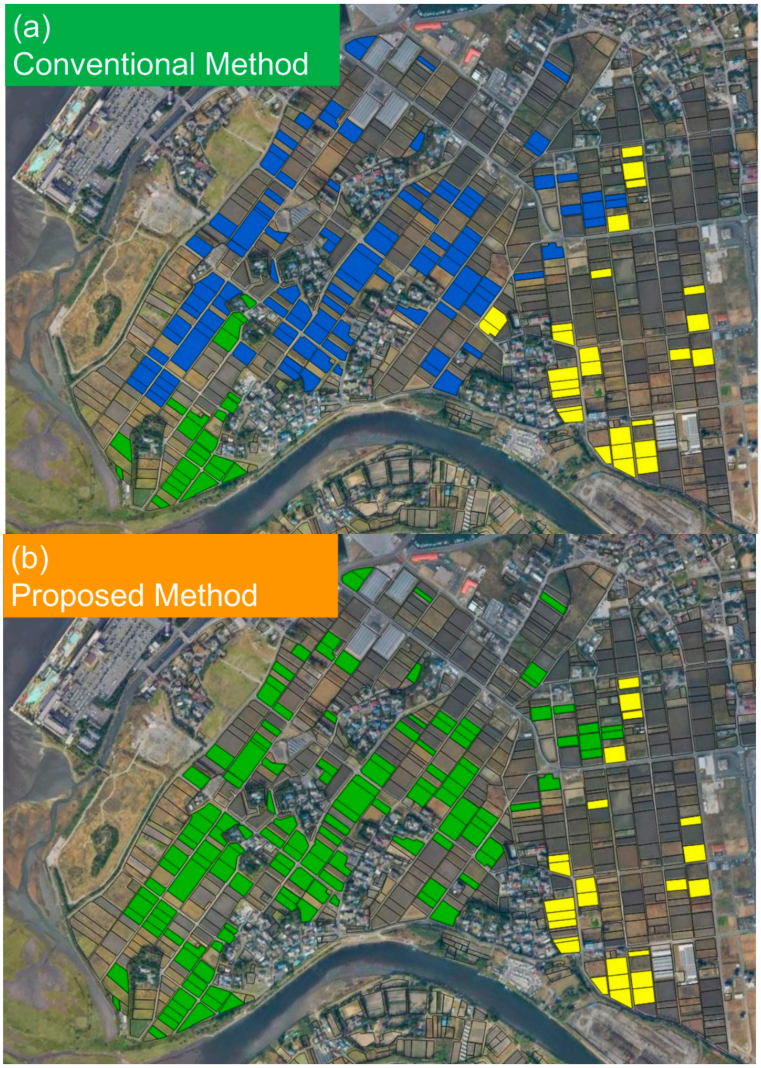


Figure 6. Comparison of field allocation between the conventional and proposed cropping plans. (**a**) Conventional Method. (**b**) Proposed Method. Green, blue, and yellow indicate Fusaotome (early-maturing), Fusakogane (medium-maturing), and Koshihikari (late-maturing), respectively. Under the conventional method, cultivars were spatially intermixed within districts, whereas the proposed method resulted in greater spatial clustering of cultivars within districts.

3.5. Evaluation of Workload and Planning Efficiency

Cropping schedules generated using the proposed and conventional approaches were evaluated in terms of workload and planning efficiency.

In the conventional approach, heading and maturity dates were concentrated within a limited period, resulting in overlapping operations on the same day and temporary increases in workload. In contrast, in the proposed approach, the distribution of cropping periods reduced daily overlaps of operations, allowing tasks to be carried out over multiple days. This contributed to improved continuity of operations and greater flexibility in planning.

In addition, in the present case study, the time required for cropping schedule planning was reduced from approximately four days with two operators under the conventional approach to about three hours using the proposed tool, indicating a substantial reduction in labor for planning.

These results indicate that the proposed approach reduces overlap of operations while improving both workload distribution and planning efficiency.

4. Discussion

4.1. Quantitative Significance of Temporal Distribution of Operations

In this study, adjustment of cropping schedules based on heading date prediction resulted in a more dispersed distribution of both heading and maturity dates. In the conventional approach, heading dates were concentrated in early July, with a maximum proportion of 16.3% on a single day. In contrast, the proposed approach distributed heading dates across multiple days, reducing the peak to 15.5%. In addition, the standard deviation decreased from 11.7 days to 8.7 days, indicating a reduction in variability.

A similar trend was observed for maturity dates, where the standard deviation decreased from 13.2 days to 11.0 days. The weighted mean dates for both heading and maturity remained nearly unchanged compared with the conventional approach. This indicates that temporal distribution was achieved without substantially altering the overall timing of the cropping period.

These results suggest that the proposed approach does not simply shift cropping periods earlier or later, but rather reduces the concentration of operations while maintaining the overall structure of the cropping schedule. The dispersion of operation timing has direct implications for labor management. In the conventional approach, the concentration of heading and harvesting within a short period may require simultaneous operations across multiple fields, potentially leading to delays and increased risk of quality deterioration. In contrast, the proposed approach distributes operations over multiple days, which can reduce daily workload and improve continuity and manageability of field operations.

Such effects are particularly important in large-scale farming systems. As the number of fields and total cultivated area increase, concentration of operations can lead to constraints in both labor and machinery use. The present results indicate that cropping schedule design based on heading date prediction can help alleviate these constraints by distributing workload more evenly.

Furthermore, recent temperature increases have generally advanced heading dates, resulting in earlier heading compared with climatological normal conditions. Such changes are difficult to address using conventional experience-based planning and may increase the risk of concentrated operations. Therefore, the importance of quantitatively capturing variation in heading dates and incorporating it into cropping schedule design is expected to increase. The proposed method provides a practical approach for supporting decision-making under such changing climatic conditions.

4.2. Significance of Spatial Optimization in Cropping Schedule Design

In addition to adjusting cropping schedules based on heading date prediction, this study demonstrated that incorporating spatial field arrangement enables cultivar aggregation at the district level. In conventional practices, expansion of farm size and accumulation of cropping history often lead to dispersed allocation of the same cultivar across multiple districts. Such arrangements increase inter-field travel distance and complicate operation routes, thereby reducing operational efficiency.

In contrast, the proposed method considers operation sequence and efficiency and designs cropping schedules to group the same cultivar within each district. As a result, cultivars were spatially aggregated at the district level, forming a layout that reduces inter-field movement and allows more continuous field operations.

This type of spatial optimization differs from simple adjustment of operation timing. It can be interpreted as an integrated farm management design that combines the temporal dimension (cropping period) with the spatial dimension (field arrangement). In this sense, the proposed method simultaneously achieves temporal distribution of operations and

spatial organization of fields, enabling a level of combined optimization that is difficult to achieve using conventional experience-based approaches.

Field dispersion tends to become more pronounced as farm size increases and can directly reduce operational efficiency in large-scale systems. The present results suggest that cropping schedule planning based on heading date prediction can contribute to more rational field arrangement, leading to improved operational efficiency and reduced labor burden.

In addition, spatial aggregation of cultivars may facilitate the integration of management operations such as fertilization, pest control, and harvesting. When the same cultivar is concentrated within a district, field conditions become more uniform, which can simplify decision-making and input management.

Overall, the proposed method provides a practical approach for optimizing spatial arrangement in cropping schedule design and improving operational efficiency in large-scale farming systems.

4.3. Practical Implications and Novelty of the Proposed Framework

The proposed framework demonstrated practical applicability for cropping schedule planning in large-scale rice farming systems. Compared with conventional planning approaches, the tool reduced the time required for schedule development and enabled intuitive visualization of operation timing through Gantt charts, thereby facilitating decision-making and information sharing among stakeholders.

The novelty of this study lies in integrating heading date prediction, cropping schedule design, and visualization into a single decision-support framework. While heading date prediction models have traditionally been used for growth forecasting and operation scheduling, the proposed method extends their application to farm-level planning and field allocation. By simultaneously considering temporal workload distribution and spatial field arrangement, the framework transforms heading date prediction from a forecasting tool into a practical planning and management tool.

In addition, the framework may be applicable to rice seed production, where sufficient temporal separation of heading dates is required to maintain varietal purity [47]. These features highlight the practical value of the proposed approach for supporting data-driven farm management.

4.4. Limitations and Future Perspectives

Several limitations should be noted. First, the proposed method depends on the accuracy of heading date prediction and may be affected by uncertainties in meteorological conditions and input data. However, because the primary objective is the relative optimization of cropping schedules rather than exact prediction of heading dates, deviations of several days are unlikely to substantially reduce its effectiveness.

Second, this study evaluated the method under a limited range of climatic conditions, and its robustness under diverse weather patterns and extreme climate events has not yet been fully examined. In addition, field-specific factors and operational constraints, such as labor availability, machinery capacity, and field conditions, were simplified in the present analysis.

Future research should evaluate the framework under actual farm conditions and further assess its applicability across different climatic regions and cropping systems. Field trials involving multiple commercial farms are currently underway and are expected to provide further evidence of the practical effectiveness of the proposed method.

In addition, future work should quantify the economic benefits of the proposed framework, including labor savings, machinery utilization efficiency, and reductions in operational costs under actual farm conditions.

In practical farming, transplanting dates may vary by several days due to weather conditions or seedling growth. Based on the characteristics of the heading date prediction model reported in previous studies [28,29], a one-day shift in transplanting date generally results in a change of approximately 0–1 day in the predicted heading date. Therefore, small variations in transplanting date are unlikely to substantially affect the overall distribution of heading dates or the effectiveness of workload leveling. Nevertheless, quantitative evaluation of the sensitivity of the proposed framework to transplanting date variability warrants further investigation.

Although the present study focused on rice cultivation in Chiba Prefecture, the overall framework is not limited to a specific region, cultivar, or crop. The proposed approach may be applicable to other regions and crops, provided that suitable developmental models and meteorological data are available. This flexibility suggests potential for broader application of the framework in agricultural planning and management.

Furthermore, integration of pre-season cropping schedule design with crop growth prediction systems based on observed weather data [29] may further improve adaptability to interannual climatic variability and support both pre-season planning and in-season management.

5. Conclusions

This study proposed a decision-support framework for rice cropping schedule design by integrating a heading date prediction model with meteorological data. The proposed method enabled the adjustment and visualization of cropping schedules based on predicted heading dates.

The case study demonstrated that the proposed approach reduced the concentration of heading and maturity dates while maintaining the overall cropping calendar. In addition, consideration of spatial field allocation enabled cultivar consolidation, which may contribute to improving operational efficiency in large-scale rice farming systems.

The proposed framework extends the application of heading date prediction models from growth forecasting to farm-level planning and management. Although further validation under diverse climatic and operational conditions is required, the method provides a practical approach for supporting cropping schedule design and decision-making in rice production.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/agronomy16121157/s1, Figure S1. Relationship between observed and predicted heading dates for three rice cultivars (Fusaotome, Fusakogane, and Koshihikari) using AMeDAS data. The dashed line indicates the 1:1 relationship, and the solid lines indicate the ±3-day range. The root mean square error (RMSE) was 2.99 days. Reproduced from Aoki et al. [29].

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References

1. He, X.; Batáry, P.; Zou, Y.; Zhou, W.; Wang, G.; Liu, Z.; Bai, Y.; Gong, S.; Zhu, Z.; Settele, J.; et al. Agricultural Diversification Promotes Sustainable and Resilient Global Rice Production. *Nat. Food* **2023**, *4*, 788–796. [CrossRef]
2. Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Masson-Delmotte, V., Zhai, P., Pirani, A., Eds.; Cambridge University Press: Cambridge, UK, 2021. Available online: https://www.ipcc.ch/report/ar6/wg1/ (accessed on 1 April 2026).
3. Wassmann, R.; Jagadish, S.V.K.; Sumfleth, K.; Pathak, H.; Howell, G.; Ismail, A.; Serraj, R.; Redona, E.; Singh, R.K.; Heuer, S. Regional Vulnerability of Climate Change Impacts on Asian Rice Production and Scope for Adaptation. *Adv. Agron.* **2009**, *102*, 91–133. [CrossRef]
4. Ishii, A.; Kuroda, E.; Shimono, H. Effect of High Water Temperature during Vegetative Growth on Rice Growth and Yield under a Cool Climate. *Field Crops Res.* **2011**, *121*, 88–95. [CrossRef]
5. Jagadish, S.V.K.; Murty, M.V.R.; Quick, W.P. Rice Responses to Rising Temperatures—Challenges, Perspectives and Future Directions. *Plant Cell Environ.* **2015**, *38*, 1686–1698. [CrossRef]
6. Counce, P.A.; Keisling, T.C.; Mitchell, A.J. A Uniform, Objective, and Adaptive System for Expressing Rice Development. *Crop Sci.* **2000**, *40*, 436–443. [CrossRef]
7. Peng, S.; Tang, Q.; Zou, Y. Current Status and Challenges of Rice Production in China. *Plant Prod. Sci.* **2009**, *12*, 3–8. [CrossRef]
8. Chiba Prefecture; Chiba Prefectural Agriculture and Forestry Technology Council. *Standard Rice Cultivation Technology System*; Chiba Prefecture: Chiba, Japan, 2014; pp. 165–175. (In Japanese)
9. Yoshimoto, M.; Sakai, H.; Ishigooka, Y.; Kuwagata, T.; Ishimaru, T.; Nakagawa, H.; Maruyama, A.; Ogiwara, H.; Nagata, K. Field Survey on Rice Spikelet Sterility in the Hot Summer of 2018 in Chiba and Ibaraki. *J. Agric. Meteorol.* **2021**, *77*, 262–269. [CrossRef]
10. Mochizuki, A. Effects of Global Warming Climate Change on Rice Paddy Cultivation in Chiba Prefecture and Research on the Countermeasures. In Proceedings of the 37th Meeting of the Kanto Branch of the Crop Science Society of Japan, Chiba, Japan, 2 December 2022; pp. 4–7. (In Japanese with English summary) [CrossRef]
11. Yanai, K.; Arihara, K. Relationships between Meteorological Trends over the Past 20 Years and Growth Stages and Yield of Rice 'Koshihikari' in Chiba Prefecture. In Proceedings of the 25th Meeting of the Kanto Branch of the Crop Science Society of Japan, Chiba, Japan, 3 December 2010; pp. 10–11. (In Japanese with English summary) [CrossRef]
12. Ota, K. Relationship between Temperature, Dry Matter Production, Yield of Paddy Rice and Appearance of Brown Rice in Chiba Prefecture in Recent Years. In Proceedings of the 104th Meeting of the Kanto Branch of the Crop Science Society of Japan, Tokyo, Japan, 4 December 2015; pp. 10–11. (In Japanese with English summary) [CrossRef]
13. Chiba Prefecture. *Horticulture and Agricultural Production in Chiba Prefecture*; Chiba Prefecture: Chiba, Japan, 2025; p. 26. (In Japanese)
14. Chiba Prefecture. *Characteristics of Recommended Rice Cultivars in Chiba Prefecture*; Chiba Prefecture: Chiba, Japan, 2025; p. 4. (In Japanese)
15. Watanabe, T.; Arihara, K.; Nishikawa, Y. Establishment of Cultivation Methods for the New Rice Cultivar 'Fusaotome'. *Jpn. J. Crop Sci.* **2000**, *69*, 500–506. (In Japanese with English summary) [CrossRef]
16. Shinoda, M.; Koyama, Y. Characteristics and Cultivation Methods of Rice Cultivar "Chiba 28" ("Fusakogane"). *Bull. Chiba Prefect. Agric. For. Res. Cent.* **2007**, *6*, 85–94. (In Japanese with English summary)
17. Ota, K.; Otaguro, T.; Mochizuki, A.; Kusakawa, T. Grain Yield and Dry Matter Production Characteristics of Rice Cultivar 'Tsubusuke' When Transplanted Late: A Comparison with 'Koshihikari'. *Bull. Chiba Agric. For. Res. Cent.* **2022**, *14*, 19–26. (In Japanese with English summary) [CrossRef]
18. Peng, S.; Huang, J.; Sheehy, J.E.; Laza, R.C.; Visperas, R.M.; Zhong, X.; Centeno, G.S.; Khush, G.S.; Cassman, K.G. Rice Yields Decline with Higher Night Temperature from Global Warming. *Proc. Natl. Acad. Sci. USA* **2004**, *101*, 9971–9975. [CrossRef]
19. Tsuruoka, Y. Management of Production Technology in Large-Scale Rice Farming Businesses. *Spec. Res. Bull. Chiba Prefect. Agric. For. Res. Cent.* **2015**, *6*, 1–67. (In Japanese with English summary) [CrossRef]
20. Plessen, M.G. Coupling of Crop Assignment and Vehicle Routing for Harvest Planning in Agriculture. *arXiv* **2019**, arXiv:1703.08999. [CrossRef]

21. Ansarifar, J.; Akhavizadegan, F.; Wang, L. Scheduling Planting Time through Developing an Optimization Model and Analysis of Time Series Growing Degree Units. *arXiv* **2022**, arXiv:2207.00745. [CrossRef]
22. Horie, T.; Nakagawa, H. Modelling and Prediction of Developmental Process in Rice. I. Structure and Method of Parameter Estimation of a Model for Simulating Developmental Process toward Heading. *Jpn. J. Crop Sci.* **1990**, *59*, 687–695. (In Japanese with English summary) [CrossRef]
23. Horie, T.; Nakagawa, H.; Centeno, H.G.S.; Kropff, M.J. The Rice Simulation Model SIMRIW and Its Testing. In *Modeling the Impact of Climate Change on Rice Production in Asia*; Matthews, R.B., Kropff, M.J., Bachelet, D., van Laar, H.H., Eds.; CAB International: Wallingford, UK, 1995; pp. 95–139.
24. Gao, L.; Jin, Z.; Huang, Y.; Zhang, L. Rice Clock Model: A Computer Model to Simulate Rice Development. *Agric. For. Meteorol.* **1992**, *60*, 1–16. [CrossRef]
25. Yin, X.; Kropff, M.J.; McLaren, G.; Visperas, R.M. A Nonlinear Model for Crop Development as a Function of Temperature. *Agric. For. Meteorol.* **1995**, *77*, 1–16. [CrossRef]
26. Yin, X.; Kropff, M.J.; Horie, T.; Nakagawa, H.; Centeno, H.G.S.; Zhu, D.; Goudriaan, J. A Model for Photothermal Responses of Flowering in Rice. I. Model Description and Parameterization. *Field Crops Res.* **1997**, *51*, 189–200. [CrossRef]
27. Nakagawa, H. Crop Management Support Systems Delivering Agricultural Information Using Meteorological Data. *JATAFF J.* **2018**, *6*, 13–17. (In Japanese)
28. Mochizuki, A.; Yoshida, H.; Tsuruoka, Y. Prediction of the Rice Growth Stage with Mesh Agricultural Meteorological Data in Chiba Prefecture: II. A Model to Predict Heading Stage Based on Daily Photoperiod and Temperature. *Jpn. Crop Sci. Kanto Branch* **2017**, *32*, 26–29. (In Japanese with English summary) [CrossRef]
29. Aoki, Y.; Mochizuki, A.; Tsuruoka, Y. Prediction of Rice Growth in Chiba Prefecture from Weather Data by Cloud Compu-ting. *Agric. Inf. Res.* **2023**, *32*, 38–45. (In Japanese with English abstract) [CrossRef]
30. Okada, M.; Iizumi, T.; Hayashi, Y.; Yokozawa, M. Projecting Climate Change Impacts on Rice Quality and Yield in Japan. *J. Agric. Meteorol.* **2011**, *67*, 263–272. [CrossRef]
31. Yoshida, R.; Fukui, S.; Shimada, T.; Hasegawa, T.; Ishigooka, Y.; Takayabu, I.; Iwasaki, T. Adaptation of Rice to Climate Change through a Cultivar-Based Simulation: A Possible Cultivar Shift in Eastern Japan. *Clim. Res.* **2015**, *64*, 275–290. [CrossRef]
32. Yoshida, R.; Nishihara, Y.; Takahashi, D. Climate-Induced Risk Assessment of Future Rice Production Value in the Tohoku and Kyushu Regions, Japan. *J. Agric. Meteorol.* **2024**, *80*, 99–110. [CrossRef]
33. Nemoto, M.; Hamasaki, T.; Sameshima, R.; Kumagai, E.; Ohno, H.; Wakiyama, Y.; Maruyama, A.; Goto, S.; Ozawa, K. Probabilistic Risk Assessment of the Rice Cropping Schedule for Central Hokkaido, Japan. *J. Appl. Meteorol. Climatol.* **2012**, *51*, 1644–1658. [CrossRef]
34. An, K.; Kim, S.; Shin, S.; Min, H.; Kim, S. Optimized Supply Chain Management of Rice in South Korea: Location–Allocation Model of Rice Production. *Agronomy* **2021**, *11*, 270. [CrossRef]
35. Liu, J.; Chang, F.; Wang, X.; Kang, M.; Lu, C.; Wang, C.; Hu, S.; Li, Y.; Ma, L.; Su, H. Smart Irrigation Scheduling for Crop Production Using a Crop Model and Improved Deep Reinforcement Learning. *Agriculture* **2025**, *15*, 2569. [CrossRef]
36. Ishikawa, T.; Naito, T.; Naito, J.; Furuwata, K.; Yoshinaga, S. Improvement of Cultivar Composition in Data-Driven Large-Scale Rice Cultivation with Field-Specific Datasets. *Jpn. J. Crop Sci.* **2024**, *93*, 57–66. (In Japanese with English summary) [CrossRef]
37. Ishikawa, T.; Yoshinaga, S.; Shimizu, Y.; Naito, T.; Naito, J. Creation of a Web Application Using "Shiny" to Visualize Large-Scale Rice Production. *Jpn. J. Crop Sci.* **2026**, *95*, 85–90. (In Japanese with English summary) [CrossRef]
38. Van Oort, P.A.J.; Saito, K.; Zwart, S.J.; Shrestha, S. A Simple Model for Simulating Heat-Induced Sterility in Rice as a Function of Flowering Time and Transpirational Cooling. *Field Crops Res.* **2014**, *156*, 303–312. [CrossRef]
39. Zhou, H.; Chen, X.; Li, M.; Shi, C.; Jiang, M. Simulation Model for Assessing High-Temperature Stress on Rice. *Agronomy* **2024**, *14*, 900. [CrossRef]
40. Brinkhoff, J.; McGavin, S.L.; Dunn, T.; Dunn, B.W. Predicting Rice Phenology and Optimal Sowing Dates in Temperate Regions Using Machine Learning. *Agron. J.* **2023**, *116*, 871–885. [CrossRef]
41. Sørensen, C.G.; Bochtis, D.D. Conceptual Model of Fleet Management in Agriculture. *Biosyst. Eng.* **2010**, *105*, 41–50. [CrossRef]
42. Aoki, Y.; Mochizuki, A.; Kuwata, C. Development of a Planting Schedule Planning Support Tool Based on a Rice Heading Date Prediction Model in Chiba Prefecture. *Jpn. Crop Sci. Kanto Branch* **2025**, *40*, 10–13. (In Japanese with English summary) [CrossRef]
43. Ohno, H.; Sasaki, K.; Ohara, G.; Nakazono, K. Development of Grid Square Air Temperature and Precipitation Data Compiled from Observed, Forecasted, and Climatic Normal Data. *Clim. Biosph.* **2016**, *16*, 71–79. [CrossRef]
44. Aoki, Y.; Mochizuki, A.; Kuwata, C. Effect of Differences in the Number of Years Used for Calculating Average Temperature on Prediction Results of Rice Heading Period. *Jpn. Crop Sci. Kanto Branch* **2023**, *38*, 44–47. (In Japanese with English summary) [CrossRef]
45. Chiba Prefecture. *Current Status and Changes in Agricultural Soils in Chiba Prefecture: Results of the 9th Soil Survey (2017–2020)*; Chiba Prefecture: Chiba, Japan, 2023; p. 20. (In Japanese)

46. Fukushima, A. Effects of varieties, fertilization methods, and transplanting time on yielding ability in rice—Analysis using the rice variety "Nijino-kirameki". *Jpn. J. Crop Sci.* **2022**, *91*, 303–314. [CrossRef]
47. Chiba Prefecture; Chiba Prefectural Agriculture and Forestry Technology Council. *Rice Seed Production Cultivation*, 4th ed.; Chiba Prefecture: Chiba, Japan, 2023; p. 17. (In Japanese)

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