Taking account of water temperature effects on phenology improves the estimation of rice heading dates: Evidence from 758 field observations across Japan

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Abstract

Water temperature ($T_w$) plays a key role in growth and development of plants inhabiting flooded environment, but most phenology models use air temperature ($T_a$) for phenology prediction. Gaps between $T_w$ and $T_a$ are known to differ regionally, but regional differences in the importance of using $T_w$ for phenology prediction are not known. This study attempts to determine whether the use of $T_w$ improves the prediction of heading time, by using 758 field observations across Japan and estimated $T_w$ from a nationwide weather database (MeteoCrop Database). We have confirmed that the use of $T_w$ improved the accuracy of prediction by 1.0–2.4 days as measured by the root-mean-square error, but the degree of improvement was similar at 23–41% across different latitudes, altitudes, or planting times, likely because the $T_w$-$T_a$ difference is highly variable even at similar latitudes or altitudes. The models proposed here and the nationwide database of future climate projection will help to reduce the uncertainty in predicting crop calendar for a range of climatic conditions.

Key words: Crop survey data, Developmental Index, Heading prediction, Oryza sativa, Phenology model

1. Introduction

Rice (Oryza sativa L.) is one of the most important crops in the world, feeding about half of the world’s population and being cultivated in varied climate regions. About three-quarters of the global rice output is produced under flood-irrigated conditions (GRiSP, 2013). Because the meristems of the shoot are submerged before the stem elongation stage, which takes place after panicle formation, water temperature ($T_w$) affects the growth, development, and yield of lowland irrigated rice (Shimono et al., 2002; 2007).

Accurately predicting crop phenology is an essential component of crop yield under variable weather and changing climate conditions. A number of rice phenology models have been proposed for improvement, differing in structures and forcing variables (reviewed by van Oort et al., 2011; Zhang and Tao, 2013), but phenology prediction is still one of the major sources of uncertainties in rice yield prediction (Li et al., 2015). In all phenology models, temperature is a major driver for crop development, and most models use air temperature ($T_a$) as a driving variable, whereas few models use $T_w$ for phenology prediction. However, $T_w$ can be different from $T_a$, depending on several meteorological factors, even if $T_a$ is similar (Ohta and Kimura, 2007; Kuwagata et al., 2008).

The difference between $T_a$ and $T_w$ is a source of uncertainties in phenology prediction, as indicated by Dingkuhn et al. (1995) for the arid conditions in the Sahel and by Shimono et al. (2007) for the cool climate of Hokkaido. These studies clearly indicate that there is a need to incorporate $T_w$ for better phenology and yield prediction. Nevertheless, the use of $T_w$ has not been widely adopted in phenology models partly because of the limited availability of $T_w$ data and of the lack of awareness of potential biases in the prediction when only accounting for $T_a$.

$T_w$ varies depending on the heat balance in the soil-water-plant-atmosphere continuum and, therefore, can be variable even within a small spatial scale, and observations are too limited to allow us to evaluate the effects of $T_w$ regionally. Recently, however, the authors’ group have developed a meteorological database called MeteoCrop Database (DB) (http://metecrop.dc.affrc.go.jp/) that includes $T_w$ estimated using meteorological observations from weather stations based on the heat balance method (Kuwagata et al., 2011) for the past 30 to 40 years across Japan. This database provides us with opportunities to make $T_w$ a feasible alternative to $T_a$ in simulating plant growth and development.

According to physical theory, the $T_w$-$T_a$ difference can become greater in areas where solar radiation is high, vapor pressure deficit is low, and wind speed is low. These conditions are often found in cool climate or arid regions. The two previous papers (Dingkuhn et al., 1995; Shimono et al., 2007) that showed the importance of $T_w$ in lowlands were indeed conducted about arid or cool climates. On the other hand, rice is grown in areas with different climatic conditions ranging from tropical to cool temperate conditions, even within Japan. However, we are not fully aware how the $T_w$-$T_a$ difference causes biases in phenology prediction depending on the environmental conditions. Based on the $T_w$-$T_a$ differences, we hypothesized that, improvement in

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phenology prediction using \( T_w \) is greater in relatively cool regions such as high latitudinal and altitudinal areas in Japan. By testing this hypothesis, we can identify the areas/or conditions where the use of \( T_w \) for the forcing variable is effective.

In our previous study, we proposed the use of common variety trials to estimate the phenology parameters for rice cultivars ("Performance Tests for Recommended Varieties of Rice (October 2010)" (PTRV) database, compiled by the National Agriculture and Food Research Organization (NARO)). The data were obtained from national or prefectural research stations all over Japan; however, agricultural experimental stations are not necessarily representative of the whole rice-growing regions. As an alternative to this database, we used the data collected from the standard lot survey by the Production, Marketing and Consumption Statistics Division, Minister’s Secretariat, Ministry of Agriculture, Forestry and Fisheries, Japan, conducted for crop production statistics, where variety information and cropping history data are obtained. We selected 758 datasets for a dominant cultivar, Koshihikari, for the period from 1995 to 2008. Coupling the statistical survey data and the MeteoCrop DB that provides the water temperatures of the paddy fields allows us to test how the use of \( T_w \) might improve phenology prediction in farmers’ fields.

In this study, we firstly estimated the phenology parameters based on \( T_w \). They were then tested against 758 field observations collected from areas with diverse growing conditions across Japan. Goodness of fit was analyzed on the climatic zones to determine whether phenology prediction biases could be greater in some particular climate.

2. Materials and Methods

2.1 Meteorological data

We obtained \( Ta \) and \( Tw \) data from the MeteoCrop DB (http://meteocrop.dc.affrc.go.jp/). This database uses nationwide weather data obtained from about 150 meteorological offices and about 850 Automated Meteorological Data Acquisition System (AMeDAS) stations (Kuwagata et al., 2011), and it estimates \( Ta \), from \( Tw \) atmospheric and vapor pressure, wind speed, solar, and downward longwave radiations, assuming that the energy balance between the ground surface and the atmosphere is in an equilibrium state (Kuwagata et al., 2008). Actual \( Ta \) is also influenced by the leaf area because shading alters the energy balance. In the MeteoCrop DB, \( Ta \) is estimated under a full canopy cover condition and no-vegetation conditions. Here, we used \( Ta \) without vegetation because the effects of growth and development are most significant before the canopy cover when the shoot meristems are under the water surface.

To demonstrate how the difference between \( Ta \) and \( Tw \) varies depending on the climatic zones, we chose six sites from the MeteoCrop DB, covering a range of climatic conditions across Japan (Table 1). At each site, we extracted data for a month during the transplanting period from 1995 to 2010.

For the crop phenology modeling, the daily temperature was required as one of the input data, and we used the average of the maximum and the minimum temperature of a day as the \( Ta \) of the day. We used two different types of data about rice crop phenology: one is the trial test data of several cultivars for estimating the parameters of the crop phenology model, and the other is the crop developing records for the crop situation index for model validation. In both cases, \( Ta \) and \( Tw \) were obtained from the MeteoCrop DB. Following the methodology by Fukui et al. (2015), we obtained the meteorological data for each trial test from the nearby AMeDAS station for estimating the parameters of the phenology model. For the validation of the model, we used the temperature data of each recording point of crop development from the nearby meteorological station.

2.2 Phenology model

We used a modified version of the phenology model of Yin et al. (1997) as described in Fukui et al. (2015). Briefly, the phenological development is described using the developmental index \((DVI)\), \( DVI \) ranges from 0 to 2, with the crop stages indicated as follows: 0—seedling emergence; 1—heading (flowering); and 2—maturity. It is calculated by integrating the daily developmental rate, \( DVR(\text{day}^{-1}) \), as follows:

\[
DVI = \sum_{i=0}^n DVR_i, \tag{1}
\]

where \( i \) is the number of days after transplanting. In this model,

| Place       | Latitude (°N) | Longitude (°E) | Altitude (m) | Temperature (°C) | Solar radiation (W m\(^{-2}\)) | Downward longwave radiation (W m\(^{-2}\)) | Relative humidity (%) | Windspeed (m s\(^{-1}\)) |
|-------------|---------------|----------------|--------------|------------------|-------------------------------|------------------------------------------|-----------------------|-------------------------|
| Asahikawa   | 43.76         | 142.37         | 119.8        | 12.2             | 207                           | 311                                       | 66.3                  | 1.98                    |
| Niigata     | 37.91         | 139.05         | 1.9          | 16.8             | 214                           | 338                                       | 68.8                  | 2.74                    |
| Tateo       | 36.06         | 140.12         | 25.2         | 17.2             | 199                           | 347                                       | 75.9                  | 1.88                    |
| Suwa        | 36.04         | 138.11         | 760.1        | 15.4             | 215                           | 330                                       | 68.8                  | 2.36                    |
| Miyazaki    | 31.94         | 131.41         | 9.2          | 16.4             | 198                           | 334                                       | 69.1                  | 2.29                    |
| Ishigakijima| 24.34         | 124.16         | 5.7          | 21.0             | 158                           | 374                                       | 73.2                  | 2.98                    |

* Each meteorological factor was an average value during a month and the missing values were removed.

** Major transplanting day is in March at Ishigakijima, in April at Miyazaki, and in May at the other points.

*** Downward longwave radiation was estimated from \( Tw \), solar radiation, atmospheric pressure, and vapor pressure (for details, see Kuwagata et al. (2011)).

**** Windspeed was adjusted to the value at 2.5 m height from the ground.
the calculation starts from the transplanting, and DVI at transplanting (DVItp) is given by
\[ DVItp = 0.1 + Fp \cdot SAC, \]  
where \( Fp \) is a coefficient and \( SAC \) is an integer indicating the seedling age class. Here, we focused on the duration from transplanting to heading (flowering). For the initial setting of DVI at transplanting, see Fukui et al. (2015). The DFR is a function of temperature and photoperiod as follows:
\[ DFR = \frac{f(T)p(L)}{G}, \]  
where \( T \) is the daily temperature (\( T_s \) or \( T_r \)) (°C) and \( L \) is the day length (h). The parameter \( G \) is the minimum number of days required from emergence to heading under optimum conditions. The functions \( f(T) \) and \( g(L) \) represent the response to temperature and day length on crop development, respectively. The response to temperature is given by the following equation (Yin et al., 1997):
\[ f(T) = \left\{ \begin{array}{ll} \frac{T-T_{\min}}{Topt-T_{\min}} & \text{if } T_{\min} < T < Topt \\ 0 & \text{if } T < T_{\min} \text{ or } T > Topt \end{array} \right. \]  
where \( T_{\min} \) and \( Topt \) are the minimum and maximum temperatures, below or above which we assume that the development of rice does not proceed, respectively, and \( Topt \) is the optimum temperature. \( T_{\min} \) and \( Topt \) are fixed at 8.0 °C and 42.0 °C, respectively (Yin et al., 1997). In the original model, \( T_s \) was used throughout the growing season, but \( T_r \) was a major determinant during the early developmental stages. In this study, we therefore initially used \( T_r \) as a temperature variable and, from a given DVI onward, \( T_r \) to drive the temperature function. The DVI at which the temperature variable switches from \( T_s \) to \( T_r \) (DVIsw) is not known and, thus, is estimated as in the following section. The parameter \( \alpha \) is the sensitivity coefficient, which determines the response to temperature.
The response to photoperiod is given by
\[ g(L) = \left\{ \begin{array}{ll} \left( \frac{L}{L_{\min}} \right)^{\gamma} & \text{if } L_{\min} < L < L_{max} \\ 1 & \text{if } L > L_{max} \end{array} \right. \]  
where \( L_{min} \) and \( L_{max} \) are the minimum and maximum day lengths, and are fixed at 10 h and 24 h, respectively. The parameter \( \gamma \) is the sensitivity coefficient for the response to photoperiod. If we estimate the phenological parameter including DVIsw, we face the difficulty of finding out the reasonable parameter set because of the combinatorial explosion. To avoid it, we set the given value for DVIsw as 0.2, 0.3, …, 0.7 (0.1 stepwise from 0.2 to 0.7) for estimating the other parameters (\( Fp, G1, \alpha, \beta, \) and \( Topt \)), which were estimated by the method described in Fukui et al. (2015).

2.3 Model parameterization
To estimate the model parameters, we used the (October 2010) PTRV database, compiled by NARO (Japan), as in our previous paper (Fukui et al., 2015). We extracted datasets for the cultivar Koshihikari, the most widely planted cultivar in Japan. As many as 1284 records were available for Koshihikari, and we used the dates of planting and heading in addition to planting times and nursery conditions. In principle, the parameters except DVIsw were estimated following the method described in Fukui et al. (2015). Briefly, we used genetic algorithm to minimize the sum of squared difference between the observed and modeled number of days for the transplanting-heading period. From the 1284 records, we extracted 10 sample datasets each with \( N = 50 \) records and estimated parameter sets with the minimum squared error for each sample dataset. Each parameter set was then cross-validated with the nine other datasets, and we selected the one with the minimum RMSE (see Fukui et al., 2015 for details). To determine the sensitivity of the goodness of fit to DVIsw, we estimated the parameter values for \( Fp, G1, \alpha, \beta, \) and \( Topt \) at different DVIsw values, ranging from 0.2 to 0.7 at 0.1 intervals.

2.4 Independent model testing
For the model with estimated parameters against independent data sets, we used data obtained from the nationwide crop survey for crop statistics (CSCS) for the period between 1995 and 2010, extracted from the standard lot survey by the Production, Marketing and Consumption Statistics Division, Ministry’s Secretariat, Ministry of Agriculture, Forestry and Fisheries, Japan. The methods of the survey are detailed in http://www.maff.go.jp/e/tokei/kikaku/nenji_e/89nenji/pdf/n157_160.pdf (last accessed on 21 August 2016). Briefly, the survey is principally for crop production statistics. Yield surveys are conducted for randomly chosen fields from the rice-growing regions every year, and representative cultivar, crop management, and crop calendar data are collected at fixed standard points (standard lots). We selected datasets for the cultivar Koshihikari, which were obtained within a 10-km radius from the nearest meteorological observation stations and within an altitude difference of 30 m. Collectively, 758 datasets were available for the present analysis. To examine the effect of environmental conditions on the performance of the models, we classified field sites into latitudes or altitudes.

3. Results
3.1 Regional characteristics of the \( T_r-T_s \) difference
To examine the difference between \( T_r \) and \( T_s \) in widely different climatic zones, we chose six meteorological sites from the MeteorCrop DB (Table 1) and extracted a 30-day data after the respective transplanting time. As is well known, \( T_r \) was generally higher than \( T_s \); the \( T_r-T_s \) difference averaged 2 °C across six sites (Fig. 1). The \( T_r-T_s \) difference tended to be smaller where \( T_r \) was higher, but that for the Tateno site with an intermediate \( T_r \) level, but with the highest humidity and lowest wind speed (represented by the square symbol in Fig. 1), it was as large as that for the coolest site, Asahikawa. Ishigakijima showed almost no difference between \( T_s \) and \( T_r \) partly because of the relatively high \( T_r \) and weak solar radiation. At each site, however, day-to-day standard deviation in the \( T_r-T_s \) difference was about 2 °C, suggesting that the \( T_r-T_s \) difference varies substantially at each site.
3.2 Estimated phenological parameters

Table 2 shows the estimated parameters of the phenological model for each $DVI_{sw}$, along with the root-mean-square error (RMSE) values derived from the difference between the observed and the modeled number of days to heading, using the PTRV database. The RMSE value was smallest at a $DVI_{sw}$ value of 0.5, but the changes in RMSE with $DVI_{sw}$ were small.

3.3 Performance of the phenology model utilizing $T_a$
3.3.1 Independent tests against the nationwide crop survey data

The same parameter sets for different $DVI_{sw}$ values were applied to the 758 field observations selected from the nationwide crop survey. The RMSE values decreased when the temperature variable was switched from $T_r$ to $T_a$ at $DVI_{sw}=0.4$, which was similar to that estimated with the PTRV database (Fig. 2a). The improvement in RMSE was 1 day, compared to that with the model that used $T_r$ only. We used the parameters with the model using only $T_r$ estimated by Fukui et al. (2015), which were $(F_p, G_1, \alpha, \beta, \text{and } T_{opt})=(0.03, 36.56, 1.11, 3.43, \text{and } 34.64, \text{respectively})$.

Bias in the model prediction, defined here as the averaged difference between the simulated and the observed number of days, was negative, indicating that the simulated heading date was generally earlier than the observed one (Fig. 2b). Bias was also sensitive to changes in $DVI_{sw}$: It was least negative at $DVI_{sw}=0.4$, but mostly negative with $T_r$ (Fig. 2b, Table 3).

Table 2. The estimated parameters and results of cross-validation test.

| $DVI_{sw}$ | $\alpha$ | $T_{opt}$ (°C) | $G_1$ (day) | $\beta$ | $F_p$ | TP-HD* | RMSE** (day) | Bias*** |
|-----------|---------|----------------|-----------|--------|------|--------|-------------|---------|
| 0.2       | 1.16    | 34.81          | 35.14     | 3.74   | 0.03 | 4.72   | 0.94        |
| 0.3       | 1.53    | 31.46          | 31.80     | 4.98   | 0.03 | 4.56   | -0.01       |
| 0.4       | 1.17    | 35.00          | 35.86     | 4.62   | 0.03 | 4.52   | 0.95        |
| 0.5       | 1.27    | 34.83          | 35.61     | 3.74   | 0.03 | 4.49   | 0.12        |
| 0.6       | 1.31    | 35.00          | 34.44     | 3.87   | 0.03 | 4.62   | 0.03        |
| 0.7       | 1.40    | 33.14          | 31.87     | 4.99   | 0.03 | 4.71   | -0.22       |

* TP and HD represent the transplanting day and heading day, respectively.
** Root mean squared error using data from "Performance Tests for Recommended Varieties of Rice (October 2010)" database.
*** Bias is the mean of differences between estimated and observed values.
3.3.2 Residual analysis under different climate zones

The RMSE or bias values by different altitudes showed that model estimates improved if $T_w$ was used in both high- and low-altitude sites (Table 3). The best estimate in terms of RMSE and bias was obtained at $DVI_{sw}=0.4$, consistently across different altitudes. The model performances by latitudes demonstrated that RMSE and bias in the high-latitude sites ($>37^\circ$N) were least at $DVI_{sw}=0.4$, as was found in the nationwide datasets (Table 3).

![Graph](image)

**Table 3.** RMSE and biases (in days) each phenology model under several regional and early cultivation conditions.

| Altitude          | RMSE   | Bias    | $T_a$ | $T_w$ | Number of records | RMSE ratio ($T_a/T_w$)*** |
|-------------------|--------|---------|-------|-------|-------------------|--------------------------|
| All records*      | RMSE   | Bias    | 0.2   | 0.3   | 0.4               | 0.5                      | 0.6                      | 0.7                      | 758                      | 0.75                     |
| Higher Altitude** | RMSE   | Bias    | 3.6   | 2.9   | 3.0               | 2.7                      | 3.1                      | 3.0                      | 2.8                      | 40                       | 0.73                     |
| Lower Altitude**  | RMSE   | Bias    | -2.4  | -1.2  | -1.5              | -0.5                     | -1.5                     | -1.2                     | -0.9                     | 125                      | 0.77                     |
| Northern Latitude | RMSE   | Bias    | 4.9   | 4.2   | 4.1               | 3.8                      | 4.4                      | 4.4                      | 4.1                      | 57                       | 0.63                     |
| Southern Latitude | RMSE   | Bias    | -3.6  | -2.4  | -1.9              | -1.2                     | -2.8                     | -2.7                     | -2.0                     | 59                       | 0.59                     |
| Early Transplanting| RMSE   | Bias    | 6.0   | 5.0   | 6.7               | 5.3                      | 3.6                      | 3.5                      | 6.1                      | 62                       | 0.70                     |

* Data from the nationwide crop survey for crop statistics were used for this model performance test.
** The latitudinal range was set between 36.0°N and 36.5°N.
*** DOY, day of year.
**** RMSE for $T_w$ was from the model with $DVI_{sw}$ that had the smallest RMSE.
Fig. 3. Relationship between the transplanting day in day of year (DOY) and the latitude of the planted point. The symbol indicates the latitude range; open triangles indicate >37° N, closed triangles indicate <32° N, and open circles indicate a latitude between 32° N and 37° N.

Fig. 4. Relationship between the transplanting day in day of year (DOY) and the model biases; the model using $T_a$ in (a), that using $T_w$ with $DVI_{sw}=0.04$ in (b), and that using $T_w$ with $DVI_{sw}=0.05$ in (c). The coefficient of each regression was statistically significant ($p < 0.01$). The meanings of the symbols are the same as those in Fig. 3.
In the low-latitude sites (<32°N), the best estimates in terms of RMSE were obtained at $DVI_{sw}=0.5$ or 0.6. Likewise, bias was least negative at $DVI_{sw}=0.6$. The RMSE improvements in heading estimates with $T_{e}$ compared to those with $T_{w}$ were about 40% and were similar in both high- and low-latitude sites.

The differences in latitudes reflected not only the temperature and day length conditions but also the transplanting time. As clearly shown in Fig. 3, transplanting is generally earlier in the warm south. Time of planting could become a source of prediction bias in our model. In fact, the model estimates were significantly earlier than the observed heading stage for the datasets with earlier transplanting, particularly when we used $T_{e}$ or when $DVI_{sw}$ was small (Fig. 4a and b). This also reflected a greater RMSE value for the early transplanting practices (Table 3). Nonetheless, taking account of $T_{w}$ effects reduced both RMSE and bias even for early transplanting by about 30% at $DVI_{sw}=0.6$ (Table 3). Bias also became less negative (Table 3), and the model residual showed a weaker relation with transplanting day (Fig. 4c and d).

4. Discussion

We hypothesized that incorporating the effect of $T_{e}$ on crop development would improve phenology model prediction for time of heading, a key developmental event for crop growth and management practices in relatively cool regions, because the $T_{e}$-$T_{w}$ difference is expected to be higher under low temperature conditions. Our analysis of the regional characteristics of $T_{e}$ during a month after transplanting using the MeteoCrop DB confirmed that $T_{e}$ was higher than $T_{w}$ by, on average, 2 °C and that the difference between $T_{e}$ and $T_{w}$ was generally greater in the high-latitude areas (Table 1 and Fig. 1). This is basically because of the low vapor pressure deficit under low temperature ranges, which reduces latent heat flux (evaporation) from the water to the air, compared to that under higher temperatures.

The results of the phenology prediction against 758 field observations across Japan demonstrated that the use of $T_{e}$ improved the accuracy of the prediction by 1.0–2.4 days as measured by the RMSE (Table 3). However, the degree of improvement was similar at 23–41% across different latitudes, altitudes, or planting times (Table 3), suggesting that incorporating $T_{e}$ is effective and contributes to model improvements in different climates. This may be related to the fact that the $T_{e}$-$T_{w}$ difference could be variable even at similar latitudes or altitudes, depending on the other climatic factors, such as relative humidity and wind speed, and even solar radiation also affects the $T_{e}$-$T_{w}$ difference. For instance, Tateno, located in a mid-latitude zone, showed as large a $T_{e}$-$T_{w}$ difference as that of Ashikawa because of its high humidity and low wind speed (Fig. 1). Variation in these climatic factors is a source of large day-to-day variation in the $T_{e}$-$T_{w}$ difference in each site, as shown by the long standard deviations (vertical bars in Fig. 1).

The precision of the phenology prediction using $T_{e}$ depended on the timing of the switching from the $T_{e}$-sensitive period to the $T_{w}$-sensitive period ($DVI_{sw}$). The best estimates were obtained with $DVI_{sw}=0.4$ or 0.5 (Table 3, Fig. 2). This developmental stage roughly corresponds to the late vegetative growth period, prior to panicle initiation, which typically occurs between $DVI=0.6$ and $DVI=0.7$ (Hasegawa et al., unpublished data). This is somewhat earlier than the timing used by Dingkuhn et al. (1995) or Shimono et al. (2007), who used $T_{e}$ for the phenology estimates until the booting or heading stage. Shoot meristems are submerged under water before the stem elongation stage, and ample evidence exists that $T_{e}$ has a strong influence on phenology even after the shoot meristems rise above the water surface (Shimono et al., 2002). This may be partly because we used the $T_{e}$ estimated for the no-vegetation conditions. This tends to overestimate the $T_{e}$-$T_{w}$ difference as the canopy cover increases, so the estimated $T_{e}$ after panicle initiation may not represent well the actual temperature conditions. In general, the gap between $T_{e}$ and $T_{w}$ becomes smaller as the canopy develops (Iwakiri, 1964), so $T_{e}$ may be closer to the temperatures around the shoot meristem. Using $T_{e}$ under a canopy cover would be a better alternative to $T_{w}$ without vegetation, but prediction errors associated with the dynamics of plant canopy cover may be another source of uncertainties. The estimation with $T_{e}$ under a canopy cover will be made available when the heat balance module is combined with the comprehensive crop growth models.

Independent testing of the phenology model against 758 datasets demonstrated that the model generally predicted earlier dates of heading than the observed ones (Fig. 2b). The reasons for the negative bias are not clear, but this is unrelated to the method of parameter estimation because we did not observe apparent bias when the parameters were estimated using the PTRV datasets (Table 2). The reasons for the negative bias are not clear, but this is unrelated to the method of parameter estimation because we did not observe apparent bias when the parameters were estimated using the PTRV datasets (Table 2). Two sources of errors might be involved: (1) difference in planting methods and measurements between the data for model parameterization and the data for independent testing, and (2) difference in weather conditions between the survey plot and the nearest weather stations.

We used two crop databases in this study: the PTRV database for model parameterization and the CSCS database for independent testing. The PTRV data were obtained from the agricultural research stations, where manual transplanting is commonly practiced for the variety trials, whereas the CSCS data were collected from farmers’ paddy fields, where mechanical transplanting is the common practice. Uprooting or transplanting shocks could be more pronounced with mechanical transplanting, which can delay the heading dates for a few days even when the climatic conditions are unchanged. Models parameterized with the manual planting could underestimate the days to heading with greater transplanting shocks by mechanical transplanting. Measurements for the heading dates on stations were generally made based on detailed plant-based observations, whereas those in the CSCS data were made based on field-based observations. The difference in the observation methods could be another source of error.

We used meteorological data collected from the nearest weather stations for the survey plot for testing the model. Because weather stations are often located in urban areas and some urbanization effects are expected, $T_{e}$ measured at weather stations could be higher than that at the survey plots, which are typically located in rural areas. For example, Kuwagata et al. (2014) reported a difference in $T_{e}$ of as large as 1 °C between paddy fields and a nearby
weather station during the rice-growing season. This could also be a reason for the bias in the model prediction.

The models showed generally poorer estimates for early planting practices (Table 3). This could be related to how the models were parameterized. In this study, we followed the method we proposed in our previous study (Fukui et al., 2015), where we chose datasets for parameterization randomly from several areas, recorded in the PTVR dataset across Japan. With this sampling method, the chances of selecting early planting practices are few, resulting in poor estimates of heading for early planting. Some improvements may be needed for the sampling procedure.

The accurate prediction of phenology prediction is fundamental for determining the impacts of climate change on crop growth, yield, and quality (Craufurd and Wheeler, 2009). We demonstrated improvements in phenology estimates by taking account of $T_v$ in the phenology models in a wide range of climatic conditions. The improvements will be important for phenology prediction in the future because changes in $T_v$ under global warming will likely be different from $T_v$, and the difference will depend on the regions (Ohta and Kimura, 2007; Shimono et al., 2007). Recently, $T_v$ estimates are made available by combining the water temperature estimation model (Kuwagata et al., 2008) and the multiple climate scenarios at more than 900 sites across Japan (Iizumi et al., 2012). The models proposed here and the nationwide database of future climate projection will help to reduce the uncertainty in predicting crop calendar under climate change.

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