Estimating first-grade rice production due to high temperature after heading date utilizing the statistical data

Shin FUKUI\textsuperscript{a,b,†}, Yukinaga NISHIHARA\textsuperscript{a,c}, Emi TAMAKI\textsuperscript{d}, Daisuke TAKAHASHI\textsuperscript{e}, Yasushi ISHIGOOKA\textsuperscript{f} and Ryuhei YOSHIDA\textsuperscript{g}

\textsuperscript{a}Faculty of Human Sciences, Waseda University, 2-579-15 Mikajima, Tokorozawa City, Saitama 359-1192, Japan
\textsuperscript{b}Stock Management Group, Research Center for Fisheries Resources, National Research Institute of Fisheries Science, Japan Fisheries Research and Education Agency, 2-12-1 Fukuura, Kanazawa, Yokohama, Kanagawa 236–8468, Japan
\textsuperscript{c}Organization for Regional and Inter-regional Studies, Waseda University, 1–6–1 Nishi-Waseda, Shinjuku, Tokyo 169–8050, Japan
\textsuperscript{d}Faculty of Science and Engineering, Waseda University, 3–4–1 Okubo, Shinjuku, Tokyo 169–8555, Japan
\textsuperscript{e}Faculty of Political Science and Economics, Takushoku University, 3–4–14 Kohinata, Bunkyō, Tokyo 112–8585, Japan
\textsuperscript{f}Institute for Agro-Environmental Sciences, National Agricultural and Food Research Organization, 3–1–3 Kannondai, Tsukuba, Ibaraki 305–8604, Japan
\textsuperscript{g}Faculty of Symbiotic Systems Science, Fukushima University, 1 Kanayagawa, Fukushima City, Fukushima 960–1296, Japan

Abstract

Several eco-physiological process-based crop models have been used in combination with climate models to predict agricultural yield to assess the impact of climate change. However, the quality degradation of rice caused by the influence of climate change is a prevailing problem. Although there is extensive elucidation of the mechanism of the occurrence of white immature grain because of high temperatures resulting in quality degradation, there are fewer studies that incorporate this into their prediction models. In this study, a statistical model to estimate the first-grade rice ratio was developed for three major rice cultivars in Japan. Parameters for a heat-dose index were estimated by employing the particle swarm optimization method and parameters for the statistical model were estimated with the maximum likelihood method. Parameters of the statistical model varied depending on the cultivar variety. It was observed that the statistical model showed varied prediction accuracy for the first-grade rice ratio based on the temperature that was incorporated into model, that is, daily mean, maximum, or minimum temperatures. Our result can generate more accurate predictions of the impact of climate change on rice production, incorporating the farmers’ choice of adaptation to climate change, including the shift in transplanting day.

Key words: Climate change, Cultivar, \textit{Oryza sativa}, Statistical data

1. Introduction

Rice (\textit{Oryza sativa} L.) is one of world’s major crops and the prediction of its yield has significant influence from the food security perspective (GRiSP, 2013). Lately, the impact of climate change on agricultural productivity and food security has attracted wide attention (IPCC, 2014). Accordingly, several eco-physiological process-based crop models have been developed in combination with climate models to predict future yield (Tang et al., 2009; Iizumi et al., 2011; Li et al., 2015). Changes in rice productivity caused by climate change depend on the cultivation area, since an increase in temperature has both positive and negative effects on the growth of a rice plant (Yoshida et al., 2015). Experimental studies, such as the free-air CO\textsubscript{2} enrichment (FACE) experiment or the growth chamber experiment, report that a reduction in fertility leads to a decrease in yield (Matsui et al., 2001; Terao et al., 2005; Jagadish et al., 2007; Hasegawa et al., 2013). Specifically, the physiological responses of a rice plant to high temperatures during the grain filling period result in chalk grain, which reduces the quality of rice. Lately, this phenomenon has been severe in western Japan (Shimoda, 2011). Experimental studies suggest that climate change will affect the quality of future rice yields substantially (Usui et al., 2016), and quality has a critical effect on the price in Japan. To project the socio-economic effects of climate change on agricultural production accurately, an impact assessment must take the quality of the agricultural yield into consideration.

Kawasaki and Uehida (2016) evaluate the economic impact of climate change on rice production after considering future quality changes. They suggested that climate change affects farmers’ revenues negatively because of a decrease in quality, even though the rise in temperatures may result in a higher yield. However, their statistical model does not take the changes in farmers’ choice into consideration and hence, they ignore the farmers’ adaptation to climate change, such as the substitution of different cultivars and shifting the transplanting day combined with cultivar choice. By contrast, Ishigooka et al. (2017) illustrate the effect of climate change on the ratio of production of first-grade quality rice, and propose that the results of conducting crop models across Japan, combined with global circular models (GCMs), the production of the highest quality of rice grain as defined by the Ministry of Agriculture, Forestry and Fisheries (MAFF) of Japan, could be mitigated
by the cultivar choice and the shift of the transplanting day. They calculate the Heat-Dose (HD) index, to demonstrate the geographic distribution of the potential risk of quality reduction as a result of future climate change. The HD index is defined as the cumulative temperature exceeding a threshold temperature during the grain filling period after the heading (flowering) of the rice plant. This index has been used as an indicator of heat stress intensity for assessing the effect of temperature on crop production or quality (Rane and Nagarajan, 2004; Farooq et al., 2011). Morita (2008) reveals that white immature grain was observed when the daily mean temperature, averaged over the 20 days after the heading date, exceeded 27°C. Nagahata et al. (2006) report that the HD with a threshold temperature of 26°C explained the generation of white immature grain in the growth chamber experiment with a japonica rice cultivar Koshikihari by manipulating the exposure period under high-temperatures (33°C during day time and 26°C during night time). Ishigooka et al. (2017) utilize this HD index for the simulation of a crop model by fixing the exposure period to 20 days. However, according to Morita (2008), several other meteorological factors can be contenders for the HD index, such as the daily maximum temperature average during the grain filling period, solar radiation, and so on. In fact, Okada et al. (2011) estimate the effect of daily minimum temperature and solar radiation on rice quality using a prefectural scale in Kyushu, western Japan, without taking into consideration the cultivar’s characteristics. Masutomi et al. (2015) propose a statistical model explaining the chalky grain rice focusing on a cultivar “Sai-no-kagayaki” from field experimental data but they fixed the exposure period under high-temperatures. Thus, there is no predictable model of the relationship between the HD index and the production of first-grade rice if the cultivar is altered as an adaptation to climate change.

This study aims to explain rice quality by constructing a prediction model utilizing gridded meteorological data and public statistical first-grade rice ratio (FGRR) data. Specifically, we estimate the threshold of high-temperature and the exposure period for HD using the observed FGRR, by validating the statistical model between the HD index and FGRR.

2. Materials and Method

2.1 Heat-Dose Index

Based on earlier studies (Nagahata et al., 2006; Ishigooka et al., 2011, 2017), we defined the Heat-Dose index (hereafter HD as variable) as the following equation;

$$HD = \sum_j \sum_{hday} \max ((T_{hday} - T_h), 0) S_j / S_i,$$

(1)

where $i$, $j$, $hday$, $xdays$, $T_{hday}$, $T_h$, $S_j$, and $S_i$ denote the prefecture, a grid within prefecture $i$, heading date of prefecture $i$, high-temperature exposure period, daily mean temperature of grid $j$, threshold temperature for heat stress, land use ratio for paddy fields in the grid, and total paddy field area in prefecture $i$, respectively. For calculating HD, that is, the Heat-Dose index on the prefectural scale, we first calculated the HD of each grid using the gridded meteorological data and prefectoral crop calendar. Then, based on the paddy field ratio, we derived $HD_o$ integrating the weighted average of $HD$ by each grid.

2.2 Statistical Modeling of First-Grade Rice Ratio (FGRR) from HD index

To predict the relationship between the HD index of the rice plant and the FGRR (hereafter FGRR as variable) on a prefectoral scale, the statistical model is formulated as follows.

$$\logit (\text{FGRR}) = a \ \text{HD} + b,$$

(2)

where $i$ denotes each prefecture, and $a$ and $b$ are coefficients of the statistical model. The parameter $a$ denotes how the HD index derived from eq. (1) affects the degradation of FGRR, so that FGRR decreases as HD increases if $a$ takes a negative value. The parameter $b$ represents the upper limitation of the FGRR estimation if $\text{HD}=0$. The maximum likelihood method using the Newton method was adopted to determine the coefficients. It was assumed that FGRR followed a binomial distribution from the variable $\text{FGRR}$ derived by our statistical model, and the model was sampled 100 times for simplicity because information about the number of times the quality check had been conducted was unavailable. We divided the prefectoral FGRR data into two datasets to conduct cross validation; one was used for calibrating the coefficients of the model, and the other was used for validating the model precision. Specifically, FGRR data for odd years were used for calibration, and the data for even years were used for validation. The opposite pattern was also applied. When the Newton method failed to calculate the coefficients, the other initial setting for the Newton method was applied. After determining the coefficients $a$ and $b$ in our statistical model by using statistical FGRR data for calibration, they were validated for the accuracy of the estimation by deriving the root mean square error (RMSE) value between statistical FGRR and calculated FGRR using the other dataset for validation.

2.3 Statistical Data

To develop a model that estimates the first-grade rice production based on meteorological factors, the yearly ratio data of first-grade rice (yearly FGRR) production were collected (MAFF, 2015, 2019a). These statistical data report the FGRR on a prefectural scale. The statistics of major cultivars from each prefecture published by the Organization of Stable Rice Supply of Japan (2018) were utilized. The focus was on the major rice cultivars in Japan (Koshihikari, Hitomebore, and Hinohikari), and we chose prefectures where the cultivation of one of the three varieties accounts for 70% or more of the total production of the prefecture (Table 1). The three rice varieties are widely cultivated in Japan as shown in Figure 1. The reduction in rice quality is not singularly caused by the white immature grain caused by high temperatures. In some cases, insect damage could be the cause. In this study, we explain the rice quality by high temperature exposure assuming that the white immature grain is the primary factor of quality degradation, because the primary reason for quality degradation in 2018, 2016, 2013, 2012, and 2010 was white immature grain (29.0%, 26.4%, 28.5%, 23.5%, and 38.6% of the reason for quality degradation, respectively) (MAFF, 2019b). Many cases of white immature grain yield caused by high temperature were reported in Japan after 2000, therefore we analyzed from 2006 to 2018. MAFF (2019b) published the heading date for each prefecture.
Table 1. Target prefectures according to cultivar, including available data by year.

| Cultivar | Sample size | Prefecture | Year       |
|----------|-------------|------------|------------|
| Koshihikari | 106         | Ibaraki    | 2006–2018  |
|           |             | Tochigi    | 2006–2014  |
|           |             | Chiba      | 2006, 2009, 2010, 2012 |
|           |             | Niigata    | 2006–2018  |
|           |             | Toyama     | 2006–2018  |
|           |             | Ishikawa   | 2006–2017  |
|           |             | Fukui      | 2006       |
|           |             | Yamanashi  | 2010–2018  |
|           |             | Nagano     | 2006–2018  |
|           |             | Mie        | 2006–2018  |
|           |             | Shimane    | 2006–2010, 2012 |
| Hitomebore | 27          | Iwate      | 2012–2016  |
|           |             | Miyagi     | 2006–2018  |
|           |             | Okinawa    | 2010–2018  |
|           |             | Osaka      | 2010–2013, 2015–2018 |
|           |             | Nara       | 2007–2009, 2012, 2013, 2015–2018 |
|           |             | Nagasaki   | 2007, 2008 |
|           |             | Oita       | 2006–2018  |

Fig. 1. Target prefectures in Japan. Prefectures that are colored black, dark gray, and light gray on the map are those where the Koshihikari, Hitomebore, and Hinohikari cultivars, respectively, account for 70% or more of the total production of the prefecture.

2.4 Gridded cell and Paddy Field Land Use

Gridded meteorological data, with a range of 10 km², was used to calculate the prefectural scale HD index. This study defined grid cells with paddy-field ratios smaller than 1% from the National Land Numerical Information database (MLITT, 2012) as non-paddy areas and excluded them from the analysis. The geographical distribution of paddy fields calculated in 2006 was applied and incorporated throughout the analysis period, following the method used by Yoshida et al. (2015). The Mesh-AMeDAS observation (Seino, 1993; Ohno et al., 2016), developed by the National Institute for Agro-Environmental Sciences Japan, was used to calculate the accumulated temperature for the paddy fields from 2006 to 2018. The observed meteorological data coordinated with the second-order mesh (spatial resolution is approximately 10 km²) was derived from the gridded daily meteorological data set with the third-order resolution (approximately 1 km²).

2.5 Algorithm for Parameter Estimation

Comparing the RMSE values derived from several \( (\text{xdays}, T_0) \) parameter sets, the parameters having the smallest RMSE can be determined for calculating the HD index. The particle swarm optimization algorithm (Kennedy and Eberhart, 1995), a heuristic optimization method, was utilized to identify the parameter sets with the smallest RMSE. Particles that are characterized by the parameter set \( (\text{xdays}, T_0) \) were set to 1000, and optimization was performed 1000 times to converge the particles’ characteristics. The 1000 particles were each assigned a parameter set \( (\text{xdays}, T_0) \), and particles were assigned their own HD index. Next, parameter set \( (a, b) \) was determined for each particle using calibration data, and RMSEs were derived. A candidate of the parameter set \( (\text{xdays}, T_0) \) that had the smallest RMSE value was chosen for one procedure of optimization and the other particles were conditioned into the \( (\text{xdays}, T_0) \) parameter set based on the candidate parameter.

2.6 Comparing the accuracy of the statistical model using different meteorological elements

As mentioned in the Introduction, earlier studies have suggested that several meteorological factors could negatively affect the quality of the rice yield. The other parameter sets were estimated based on the HD index that was determined by the daily maximum, mean, and minimum temperatures during the \( \text{xdays} \) after the heading day. The accuracy of estimation by RMSE values derived from the statistical models were compared utilizing the assumption in previous studies using the daily mean temperature \( (\text{xdays}, T_0) = (20, 26.0{\degree}\text{C}) \) and the result derived from our statistical model using the daily mean temperature. Parameters of the statistical model with \( (\text{xdays}, T_0) = (20, 26.0) \) were determined by maximum likelihood method using the same data for the calibration procedure. Additionally, the accuracy of estimation between three statistical models was examined using the daily minimum, mean, and maximum temperatures.

3. Results

3.1 Estimated parameter sets for three different cultivars using daily mean temperature

The estimated parameter sets, coefficients of the statistical model using the daily mean temperature, and the RMSE as the accuracy of the model are shown in Table 2. Note that the RMSEs in Table 2 were derived using all sample appeared in Table 1, which are different from RMSEs of validation.
data in the procedure of parameter estimation. The threshold temperature \( T_b \) for the Koshihikari cultivar, of 24.56°C, was lower than the threshold temperature, of 26.0°C, determined in the previous studies (Nagahata et al., 2006; Ishigooka et al., 2011, 2017). Additionally, the exposure period was longer than 20 days as mentioned in previous studies (Morita, 2008). The threshold temperature was higher, and the exposure period is longer for the Hitomebore cultivar than that of Koshihikari. For the Hinohikari cultivar, the threshold temperature was lower, and the exposure period was longer than that of Koshihikari. The statistical model for FGRR using the threshold temperature and exposure period \((xdays, T_b) = (20, 26.0)\) was derived, and the RMSE between the observed and estimated values of FGRR was 14.03%. The RMSE derived using the estimated parameters in this study \((xdays, T_b) = (33, 24.56)\) was 13.38%, indicating that our method could improve the accuracy of predictions. Figure 2 shows the relationship between the observed FGRR and calculated FGRR for the (a) Koshihikari, (b) Hitomebore, and (c) Hinohikari cultivars. For the Koshihikari cultivar, as shown in Fig. 2 (a), the FGRR estimated by the statistical model using \((xdays, T_b) = (20, 26.0)\) tends to be overestimated whereas the observed FGRR value is within the range (20–40). This trend is suppressed by using the estimated parameters in this study. The prediction accuracy of our model was better than the statistical model using \((xdays, T_b) = (20, 26.0)\) for the Hitomebore cultivar, except for the very low FGRRs. For the Hinohikari cultivar, our method could improve the accuracy of predictions in the range of high FGRR values. Figure 3 shows the relationship between the FGRR and HD index derived in this study for the three cultivars. The statistical models derived from parameters estimated by our method (top panels in Fig. 3) have less biases than those using \((xdays, T_b) = (20, 26.0)\) (bottom panels in Fig. 3) in all cultivars. Especially, the prediction errors where the FGRR becomes large in the range of small HD index values are suppressed by our method.

### Table 2. Estimated parameters using daily mean temperature for FGRR and their accuracy.

| Variety   | Parameters for Heat Dose | Parameters for statistical model | RMSE (%) |
|-----------|--------------------------|---------------------------------|----------|
|           | \(xdays\) | \(T_b\) (°C) | \(a\) | \(b\) |         |
| Koshihikari | 33        | 24.56           | -0.021 | 2.372 | 13.38   |
|           | 20        | 26.00           | -0.058 | 2.286 | 14.03   |
| Hitomebore | 38        | 25.10           | -0.028 | 2.186 | 11.38   |
|           | 20        | 26.00           | -0.103 | 1.994 | 14.73   |
| Hinohikari | 45        | 20.50           | -0.012 | 1.828 | 19.33   |
|           | 20        | 26.00           | -0.039 | 0.691 | 20.81   |

3.2 Estimated parameter sets using daily temperatures and the accuracy of the statistical model

The results of the FGRR estimation by the statistical model using daily maximum or minimum temperatures are shown in Table 3. As seen in this table, the statistical models using the daily maximum temperature could not estimate reasonable parameters for the Hitomebore and Hinohikari cultivars. By contrast, the statistical models using the daily minimum temperature could estimate the FGRR based on the RMSE values. Figure 4 shows the accuracy of each statistical model for the FGRR using daily mean, maximum, and minimum temperatures for the Koshihikari cultivar. The daily maximum temperature statistical model improved the accuracy of prediction where the observed FGRR has high values for the Koshihikari. The estimated FGRR was improved in the daily minimum temperature statistical model where the observed FGRR values are within the range (20%–60%). As a result, the model with the daily minimum temperature has the lowest RMSE value (Table 3). Figure 5 shows the accuracy of each statistical model for the FGRR using daily mean and daily minimum temperatures for the Hitomebore and Hinohikari cultivars. Similar to Koshihikari, the statistical models using daily minimum temperature could improve the accuracy where observed FGRR values are low compared with the model using daily mean temperature for the Hitomebore (Fig. 5a). For the Hinohikari, the statistical models using daily minimum temperature improved the FGRR in the overall range (Fig. 5b).

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**Fig. 2.** The accuracy of the FGRR statistical model. The clear and black dots are the prediction by our statistical model using the estimated parameter for \((xdays, T_b)\) in this study and that using the parameters proposed by previous studies, that is, \((xdays, T_b) = (20, 26.0)\), respectively. Each panel shows the result of one cultivar; that is, (a) Koshihikari, (b) Hitomebore, and (c) Hinohikari.
Fig. 3. The relationship between the FGRR and Heat-Dose (HD) index. The panels in the top row represent the result derived from our method and those in the bottom row represent the results using the parameter \((x_{days}, T_a) = (20, 26.0)\). The left, middle, and right columns represent the results of the Koshihikari, Hitomebore, and Hinohikari cultivars, respectively. The horizontal axis represents the HD index derived from each parameter and the vertical axis represents the observed FGRR. The solid line represents the logistic function of the statistical model.

Table 3. Estimated parameters using daily maximum and minimum temperatures and their accuracy.

| Variety       | Daily temperature | Parameters for Heat Dose | Parameters for statistical model | RMSE (%) |
|---------------|-------------------|--------------------------|----------------------------------|----------|
|               |                   | \(x_{days}\) | \(T_a (\degree C)\) \(a\) \(b\) |          |
| Koshihikari   | maximum           | 37          | 19.80                       | -0.009   | 4.626    | 14.28    |
|               | minimum           | 33          | 24.22                       | -0.117   | 1.900    | 11.92    |
| Hitomebore    | maximum           | 22          | 35.86                       | 0.000    | 0.694    | 25.14    |
|               | minimum           | 22          | 24.80                       | -0.157   | 1.711    | 10.97    |
| Hinohikari    | maximum           | 10          | 36.25                       | 0.000    | 0.114    | 25.19    |
|               | minimum           | 9           | 13.30                       | -0.048   | 4.175    | 16.79    |

4. Discussion and Conclusion

This study constructed a statistical model to estimate the FGRR for the three major rice cultivars in Japan. Parameters for the HD index, estimated by particle swarm optimization using the actual prefectural data of FGRR from 2006 to 2018, differed from those declared in previous studies where the HD index is derived by the daily mean temperature averaged over the 20 days after the heading date exceeded 26\(\degree C\) (Nagahata et al., 2006; Morita, 2008). The estimated parameters differed for each cultivar. The accuracy of the FGRR estimated by the statistical model conducted with estimated parameters in this study was slightly improved when compared with the model that uses the parameters proposed in the previous study (Nagahata et al., 2006). The parameters were plausible to use for the estimation of FGRR because the index derived in the previous study was based on experimental data using the Koshihikari cultivar. The estimation accuracies for the Hitomebore and Hinohikari cultivars were also improved. This implies that the difference in sensitivity to high temperature for each cultivar would result in quality deterioration. Therefore, when predicting the quality of rice yield, the evaluation of the effect of climate change would be inaccurate if the specific characteristics of each cultivar are ignored. The framework of our method can contribute to the adaptation to climate change on rice production by providing statistical models for each cultivar.
Specifically, for the Koshihikari cultivar, the estimate of the high temperature exposure period from the heading date was longer and the threshold temperature was lower than that derived in the previous study, regardless of which daily temperature was used. This suggests that if the HD index is used for predicting the FGRR in field conditions, the exposure period becomes a range of 30–40 days, which is around the ripening period of this cultivar, in contrast to experimental manipulation where the growing environment is constant. The exposure period and threshold temperature of this study partially support the evaluation by Tashiro and Wardlaw (1991) that milky rice is produced when the daily mean temperature exceeds 24°C beginning 7 days after the heading date to maturity. In this study, we also performed statistical modeling for daily maximum and minimum temperatures. Parameter $b$ in Table 2 of our model, the intercept of eq (2), was higher than that of previous studies, and the prediction range widens toward high FGRRs with the statistical model using the daily maximum temperature. Additionally, the model using daily minimum temperature is effective for predicting in the range where the FGRR largely decreases. The daily minimum temperature is usually observed at night, therefore our result supports the claim by Ambardekar et al. (2011) that an increase in the nighttime air temperature contributes to the generation of chalky grain. Tashiro and Wardlaw (1991) also suggest that milky white grains are produced when the air temperature exceeds 27°C and white immature grains are frequently produced when the air temperature exceeds 30°C. As a result of this study, using daily maximum temperature relatively good quality rice yield, in other words the low degree of heat dose, can be modeled and using daily minimum temperature low-quality rice yield, i.e., the high degree of heat dose, can be modeled. Because of the characteristics of the logit equation, the extremely high or low values of FGRR were saturated for the estimation. FGRR prediction by daily minimum temperature is inaccurate if the observed FGRR is higher than 86.99%, as the value was derived from eq. (2) where HD = 0. FGRR combining the HD by daily minimum and maximum temperatures can be predicted using parameter $b$, the intercept value of eq. (2), and RMSE in Table 3. The RMSE was 11.81%, when the estimation of FGRR switched from prediction by daily maximum temperature to that by the daily minimum temperature, where FGRR by the daily

![Fig. 4](image_url)

**Fig. 4.** The difference in the accuracies of the FGRR statistical model regarding the meteorological element input for the Koshihikari cultivar. Clear circles, clear triangles, and black squares denote the estimation result of the statistical model using the daily mean, maximum, and minimum temperatures, respectively.

![Fig. 5](image_url)

**Fig. 5.** The difference in the accuracies of the FGRR statistical model regarding the meteorological element input for the (a) Hitomebore and (b) Hinohikari cultivars. The clear circles and black squares denote the estimation results of the statistical model using the daily mean and minimum temperatures, respectively.
maximum temperature turns lower than 86.99% (HD by daily maximum temperature reaches 293°C). This combinatory method based on two meteorological elements can be used for the FGRR prediction as a simple prediction model.

The prediction failed to estimate the FGRR correctly through the model using daily maximum temperature for the Hitomebore and Hinohikari cultivars. This could be a result of insufficient data being used to estimate the parameters of the statistical model by our method. By contrast, the model using daily minimum temperature fits the FGRR well, where the quality largely decreases for the Hitomebore cultivar and where the observed FGRR value is within the range (50%~80%) for the Hinohikari cultivar (Fig. 4), so the prediction would fail in the range where the FGRR is slightly lower than 100%. Okada et al. (2011) develop a method to estimate the rice quality in a wide range by using two meteorological elements and explain the deterioration in rice quality by the daily minimum temperature and the accumulated solar radiation during the grain ripening period. In this study, the effect of accumulated solar radiation was not considered, because solar radiation affects the daily mean, maximum, and minimum temperatures resulting in a multi-collinearity problem in regression analysis. The effect of solar radiation on the quality deterioration via the heat dose should be explored in the future.

In this study, we assumed the white immature grain rice as the only indicator for the deterioration in rice quality. However, other factors such as colored grain caused by insect feeding, fulfillment of grain, and crop damage also result in the deterioration of rice quality. Because the period of exposure to high temperature in this study overlaps the active season of the mirid bug, whose activity significantly reduced the quality or rice, our statistical model unintentionally estimates the effects of temperature during the ripening period on FGRR, not only by heat dose but also by the influence of insect damage and disease. Therefore, the prediction of our model might be inaccurate if the response of insects and/or disease microorganisms to environmental conditions changes because of alternative cultivation management. A detailed analysis for quality deterioration in each prefecture will be required to solve this issue. Furthermore, it would be possible to develop a prediction model for quality reduction by each factor. Additionally, the prediction accuracy would be improved by crop statistics with fine spatial-resolution and repetitive numbers or quality checks of factors by a competent authority.

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