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RESEARCH LETTER

Warming Leads to Lower Rice Quality in East Asia

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Xianfeng Liu^{1,2} , Philippe Ciais² , David Makowski³, and Juan Liang¹ 

Key Points:

- We find a significant decline in rice quality in both China and Japan
- Nighttime temperature is the key driver of rice quality decline
- Climate projections suggest a continuing decreasing trend in rice quality in future

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Supporting Information may be found in the online version of this article.

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Abstract Rice quality, which is intricately connected to market value and human nutrition, is sensitive to weather conditions. However, the relative importance of the different climatic factors is poorly understood, and the impact of climate change on rice quality has been little studied on a large scale. Here, using more than 35 years of rice quality data, we present the first effort to determine the key climate variables driving rice quality in China and Japan. Results show a significant decline in high quality rice rate (HRR, an indicator of rice quality), mainly driven by warm nighttime temperatures when they exceed a critical threshold estimated at 18°C and 12°C in China and Japan, respectively. Climate projections suggest a continuing decreasing trend in HRR under moderate and high emission scenarios by 2100. These findings emphasize the importance of breeding new heat tolerant cultivars to maintain stable rice quality in the future.

Plain Language Summary Food security is not only related to yield, but also to quality, which is closely related to human nutrition and market value. Although crop quality is generally controlled by breed genes, climate change also has an important impact. Unfortunately, existing studies on the impact of climate change on rice quality mostly performed at sites scale, the knowledge on a large scale such as the global or national scale is still limited. This is partly related to the incompleteness of relevant data, and also it is related to the current focus primarily on yield and neglect of quality. Our findings highlight that food security should consider both yield and quality aspects.

1. Introduction

Rice (*Oryza sativa* L.) is one of the most important cereal grains in the world and serves as a staple food source for more than half of the world's population (Zhu et al., 2018). The demand for rice has doubled in the past 50 years and is projected to increase by a further 30% by 2050 (Usui et al., 2016). Rice plays a critical role in global food security, but climate change is calling into question the sustainability of its production (Fu et al., 2023; Xiong et al., 2017). Although rice yield increased considerably during recent decades benefitting from genetic breeding and better management practices, recent studies show that climate change is expected to negatively impact rice production (Zhao et al., 2017; Zhu et al., 2022). Numerous studies have been carried out to assess the impact of climate change on rice yield (Lesk et al., 2016, 2022; Peng et al., 2004), but rice quality has received far less attention, particularly on a large scale. Grain quality is important for both food security and human nutrition especially for those populations that are highly rice-dependent (Zhu et al., 2018). Quality is also taken into account by farmers and consumers when selecting rice cultivars (Sultana et al., 2022). As rice quality is important to many stakeholders, it is important to identify its main climatic drivers.

Rice quality is a combination of several criteria related to milling properties, appearance, palatability and nutritional quality (Fitzgerald et al., 2009; Sultana et al., 2022). The quality criteria related to milling properties and appearance are often considered as the most important as they have a significant influence on rice prices (Ambardekar et al., 2011). Head rice rate (defined as the fraction of milled rice kernels that are three-fourth of the original kernel length after complete milling) is a decisive factor for measuring milled rice quality (Counce et al., 2005), while the grain chalkiness rate (the fraction of rice grains with an opaque portion in white endosperm due to an incomplete accumulation of starch and protein) is a key factor in determining rice appearance quality (Chun et al., 2009; Lanning et al., 2011). Previous studies report that rice quality traits are very sensitive to high temperatures during the grain-filling stage, since high temperature could reduce the rate of photosynthesis and starch accumulation in the grain (Chen et al., 2017). Because of climate change, the frequency of high temperature events tends to increase during the rice growth season in China, especially during the critical flowering and grain filling period of time, which decreases grain transparency, increases chalkiness rate, and reduces head rice rate

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(Ambardekar et al., 2011; Lanning et al., 2011; Morita et al., 2016). Also in Japan, the increased frequency of extremely high temperatures during the ripening phase has led to a deterioration in rice quality, particularly since the turn of the 2000s (Morita et al., 2016).

Hot temperature extremes are projected to increase due to climate change over this century and beyond (IPCC6). Few studies have investigated the potential effects of high temperatures on rice quality in field experiments (Asaoka et al., 1984; Cheng et al., 2003) and model simulations (CAPPELLI & BREGAGLIO, 2021). It was shown that high temperatures have negative impacts on rice quality by decreasing head rice percentage and increasing chalky rice rate with negative consequences on starch and cooking quality (Sreenivasulu et al., 2015; Xiong et al., 2017). A remarkable declining trend in rice quality has already been observed in western Japan and the future global warming associated with climate change is likely to exacerbate such risk (Okada et al., 2009). Among the different variables related to temperature, nighttime temperature is suspected to be a key driver of rice quality (Shi et al., 2016). However, the effect of nighttime temperatures is still poorly understood and has not been quantified on a large scale using a long time series of quality data. Because climate change has increased nighttime temperature more than daytime temperature in several parts of the world (Cooper et al., 2008), it is a critical importance to better quantify the effect of nighttime temperature on both head rice rate and chalkiness. Most studies have focused on rice quality in response to extended periods of high temperature under controlled environmental conditions, and there is limited observed evidence based on field experiments, on-farm surveys and regional statistics. To assess the impact of climate change on rice quality on a large scale and fill an important knowledge gap, we present here the results of the first large-scale assessment of the climate drivers of rice quality variation. Specifically, we use several decades of rice quality data collected in administrative units of China and Japan to (a) analyze the changes in rice quality through time, (b) identify the key weather-related explanatory factors influencing rice quality, and (c) make projections of the impact of future climate changes on rice quality.

2. Materials and Methods

2.1. Data

Rice quality data. Rates of head rice is considered as a major quality criterion (Sultana et al., 2022). An increase in the head rice rate indicates enhanced rice quality, and vice versa. Although the criteria for defining head rice vary between China and Japan, they are consistent over time and space within their respective countries. According to the Chinese national standard 'GB/T21719-2008', head rice is milled rice kernels that are three-fourth of the original kernel length after complete milling. Head rice rate refers to the mass ratio of head rice to the overall rice sample, which significantly affects rice quality. The China head rice rate data is obtained from China National Rice Research Institute. China has a variety of rice-growing systems, including southern dual cropping rice, Yangtze River basin, medium-cultivation rice, and northern single cropping rice, covering almost all rice cropping patterns in the world. The datasets are collected from each province in China. The measurement data of each province includes multiple samples taken on different types of rice and then averaged. We deleted all the sterile samples before calculating the head rice rate for each province. The time span of head rice rate is from 1985 to 2020, but most missing data occurred before 2000.

Appearance quality includes size, shape, color, transparency, and chalkiness. Herein, chalkiness and grain shape are the main indicators affecting appearance quality. Among various appearance qualities, chalkiness is of primary concern since it affects the milling, eating, and cooking properties (Sultana et al., 2022). In Japan, the first grade quality rice (%) is selected not based on length, but based on the thickness of brown rice (husked but unmilled grains) and chalkiness, because Japan grows short grains. First grade quality rice should contain at least 70% high-quality grains (Ohtsubo et al., 1993). The first grade quality rice rate during 1979–2018 is retrieved from the Ministry of Agriculture, Forestry and Fisheries of Japan (MAFF), which is different from the head rice rate in China. In the paper, we use high quality rice rate (HRR) to denote head rice rate in China and first grade rice in Japan. To account for the difference of quality definitions between China and Japan, we analyze the time trend of HRR and establish a random forest model separately for the two countries.

Rice phenological data. Rice phenology information including planting date, heading date and harvest date is used to determine the critical period considered to compute the climate inputs. In China, we retrieved the phenology data from Luo et al. (2020). We selected the harvest date from each province for single rice, early rice, and late rice. The harvest date of Japan is obtained from Inoue et al. (2020).

We also download the “Monthly Growing Area Grids for 26 irrigated and rain fed crops, or the total of irrigated and rain fed crops” data set from https://www.uni-frankfurt.de/45218031/Data_download_center_for_MIRCA2000. Both “The crop_03_irrigated_12.flt.gz” and “The crop_03_rainfed_12.flt.gz” were extracted, since crop three is rice according to the data description. We first merge the rain-fed and irrigated rice area to obtain the annual rice planting area, and then intersect the rice planting areas of multiple years to obtain the final spatial distribution of rice paddy in China and Japan.

Historical climate data. ERA5-Land, produced by the European Center for Medium-Range Weather Forecasts (ECMWF), is a global reanalysis dataset that provides a wide range of variables on the Earth's land surface for the period from 1979 to the present day. The main advantage of ERA5-Land compared to ERA5 stays in its horizontal resolution, which is enhanced globally to 9 km compared to 31 km (ERA5). The temporal resolution is hourly and monthly. In this study, we retrieved hourly datasets including air temperature, dew point temperature, precipitation, solar radiation during 1979–2020 for China and Japan area (Muñoz-Sabater et al., 2021). The dataset can be downloaded from <https://cds.climate.copernicus.eu/>. We first converted the hourly data to daily data to obtain the minimum temperature (nighttime temperature, NT), daytime vapor pressure deficit (VPD), daily solar radiation (SR), daily precipitation (PR). Then we extracted seven different datasets covering different time periods to identify the most influential period of climate factor on rice quality, specifically (a) between harvest date-10 days and harvest date; (b) between harvest date-20 days and harvest date; (c) between harvest date-30 days and harvest date; (d) between harvest date-40 days and harvest date; (e) between harvest date-20 days and harvest date-10 days; (f) between harvest date-30 days and harvest date-20 days and (g) between harvest date-40 days and harvest date-30 days for China and Japan, respectively (Figure S1 in Supporting Information S1). We calculate the average NT/VPD over various time periods preceding the harvest date, while for PR and SR, we calculate their cumulative values over the same time periods. The above seven different datasets are used to train seven different models for China and Japan separately, and the best model is selected based on the criteria of root-mean-square error (RMSE) estimated by year-by-year cross validation (see below for details). In China, typical rice cropping systems include a single cropping system (e.g., single rice) in the northern region (northeast China) and a double cropping system (e.g., early rice and late rice) in south China (Li et al., 2018). The climatic background covered by these two rice cropping systems are different. Therefore, we calculated the climate variables using the harvest date of each cropping system in China.

Earth system models. To gain additional insights on the impact of future climate on rice quality, we analyze the response of rice quality to future climate by using the output from five earth system models participating in the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP), namely GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, UKESM-0-LL (Table S1 in Supporting Information S1). The daily historical simulation datasets (1979–2020) and the future simulation datasets (2020–2100) for three shared socioeconomic pathways (ssp126, ssp370 and ssp585 are retrieved from <https://data.isimip.org/>). These model outputs have been bias corrected.

2.2. Methods

Detection of rice quality change. We implemented the SEN trend analysis method as it is nonparametric, does not require any distributional assumption, and is robust to measurement errors and outliers (Liu et al., 2020; Sen and Kumar, 1968). According to this method, the trend is defined as

$$\beta = \text{median}\left(\frac{x_j - x_i}{j - i}\right) \forall j > i \quad (1)$$

where β is the HRR trend, x_i and x_j are the values of the HRR at time i and j . All pairs x_i and x_j are considered in turn (with $j > i$), and the median value is computed. A value $\beta > 0$ indicates that the HRR is increasing, while a value $\beta < 0$ indicated that the HRR is showing a decreasing trend. The Mann-Kendall (MK) test (non-parametric) was implemented to test the statistical significance of the trend, at a level of 5%.

Calculation of Vapor Pressure Deficit. The VPD commonly estimates as the difference between the saturation vapor pressure (SVP) and actual vapor pressure (AVP) (Yuan et al., 2019). The empirical formula is as below:

$$VPD = SVP - AVP \quad (2)$$

$$SVP = 0.6108 \times e^{\frac{17.27T_a}{T_a + 237.3}} \quad (3)$$

$$AVP = 0.6108 \times e^{\frac{17.27T_d}{T_d + 237.3}} \quad (4)$$

where, *SVP* and *AVP* are saturated vapor pressure and actual vapor pressure, respectively. T_a and T_d are air temperature and dew point temperature, respectively.

Quantifying the effect of predictors on rice quality. The random forest (RF) model was used to quantify the impact of climate variables on rice quality. In order to select the most relevant climate predictors, we reviewed the available literature on the effect of climate on rice quality. The climate variables mentioned in the literature are nighttime temperature, daytime temperature, diurnal temperature, daily averaged temperature, hot days (above 30°C/35°C), precipitation, precipitation frequency, soil moisture, solar radiation, cloud cover, relative humidity, daytime vapor pressure deficit, Transpiration, and CO₂. These variables were chosen due to their relevance to rice growth. Then we calculated the correlation coefficients between these climate variables and rice quality to find the most relevant climate variables. This approach led us to select nighttime temperature, daytime temperature, precipitation, solar radiation, cloud cover, daytime VPD, and CO₂ as candidates.

We use different combinations of these predictors to build random forest models, and features are selected based on the model performance (prediction accuracy and R²) when added to models (recursive feature elimination). We first ran a random forest model with all predictor variables included, and the predictor variables were ranked according to their permutation importance. The model was then rerun with the least important variable removed from the model, and this process was repeated until the three most important predictor variables remained. Then, the model was rerun with the next most important variable added back in, and the variable was selected in the model if it led to an increase in R². This process was repeated until all predictor variables had been added back into the model, and the variable combination with the highest R² value was selected for the final model. Finally we obtained the best model features including nighttime temperature, solar radiation, precipitation, and daytime VPD. Considering each province in China and Japan has different climate, soil types, hydrothermal conditions, and cultivars, we also include the coordinates (latitude + longitude) of each province as a feature in our model, in order to capture the local crop characteristics, soil characteristics, and farming practices and improve the robustness of the model projections.

Specifically, we used the seven datasets defined above (covering different periods of the growing season) to build separate random forest models (i.e., seven models for China and seven models for Japan) (see historical climate data section). The algorithm employed in this study for model development consists of two loops: the outer loop and the inner loop. Specifically, the original datasets are partitioned into training and testing sets in the outer loop (1 year of data is removed at each iteration and allocated to the testing set). The training set in the inner loop is utilized for model building, followed by model selection based on internal validation metrics. Within the inner loop, the training set is further divided into calibration and validation sets using the leave-one-group-out cross validation technique. Meanwhile, the testing set in the outer loop is used to assess the model's predictive performance. This approach ensures that the test set remains unseen by the model during the development process. Three hyperparameters were tuned: the number of trees, the maximum depth of a tree, and the number of features (input variables) tested at each node. The optimal combination of the three hyperparameters was found with a grid search approach. The grid was defined as follows: the number of trees ranged from 1,000 to 2,500 with an interval of 50, the maximum tree depth ranged from 2 to 10, and the number of features ranged 1 to 6. After conducting all the possible combinations and tests, we found that the best performances were obtained with a number of trees of 2,000, the maximum depth of 12, and a number of features of 3. The groups were defined by the different years (e.g., 1979–2018). The predictions derived from the cross-validation procedure were used to produce scatter plots comparing predictions and observations, and compute the R² and RMSE. Data analysis was carried out using the Python 3.9 packages Sklearn, SciPy, Matplotlib, Numpy.

To interpret the RF outcome, we used SHAP values (Shapley Additive explanation) (LUNDBERG & LEE, 2017). SHAP values are a way of interpreting machine learning models based on information theory. The SHAP values determine the contributions of the different inputs to the deviations of the model predictions from the mean predicted value. SHAP values were produced for all model inputs and all HRR data included in the dataset. Also, Accumulative Local Effect (ALE) has been implemented following the algorithm described below (APLEY &

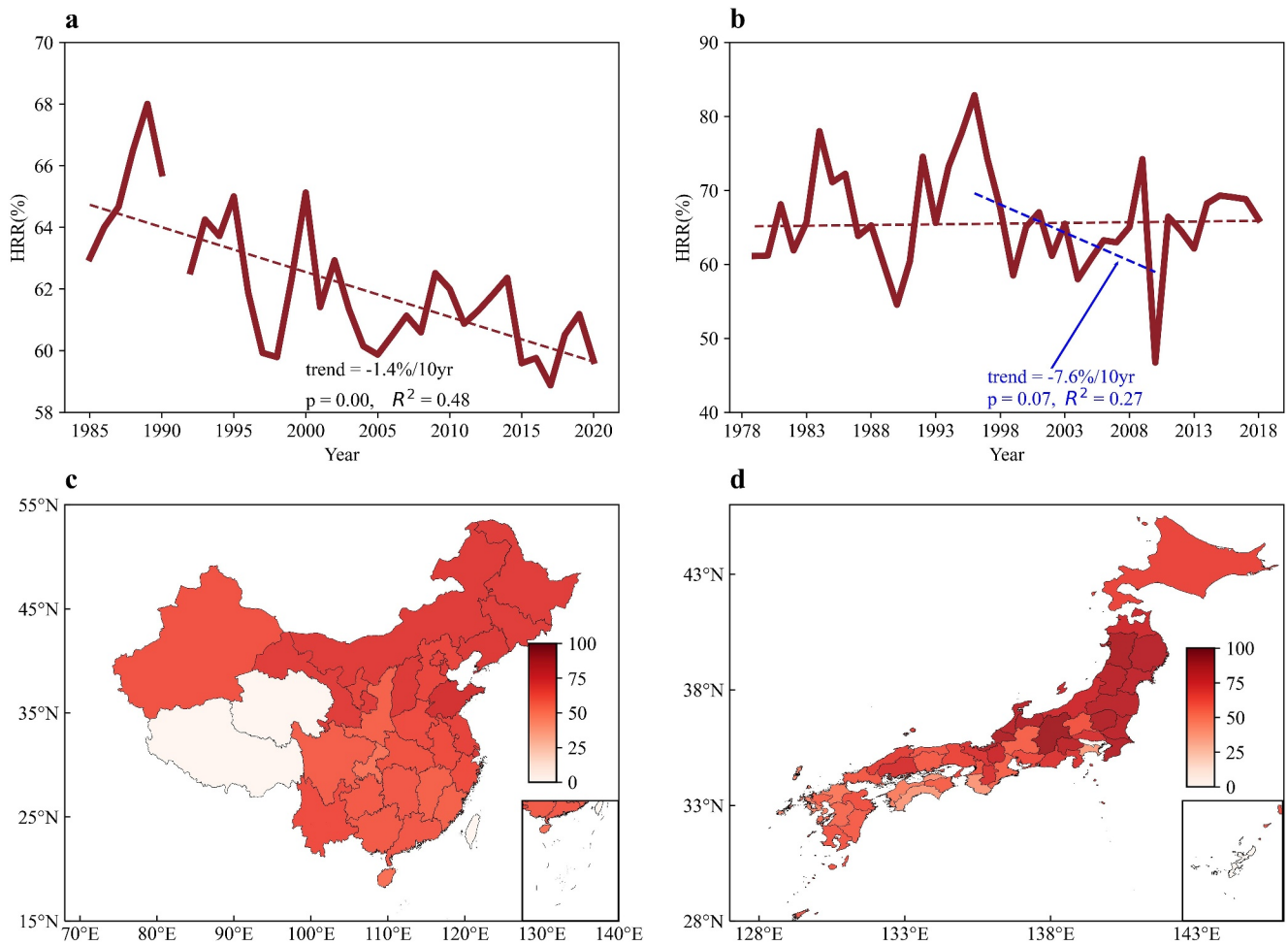


Figure 1. Spatiotemporal variations in HRR in China and Japan. Interannual variations in head rice rate across China (a) and Japan (b) during 1985–2020 and 1979–2018, respectively. Spatial distribution of multiyear average HRR in China (c) and Japan (d). Both China and Japan are spatial auto-correlation in HRR ($p < 0.05$).

ZHU, 2020). Local Effects (LE) for each quantile bin have been calculated by measuring the average change in prediction upon substituting observed abundance of a feature, with right and left bin border values. ALEs for each quantile are calculated by adding up all the previous LEs and centering the result to make the average effect of each taxon zero. ALE plots are a faster and unbiased alternative to partial dependence plots. We use alepython package to calculate ALE plot.

3. Results

3.1. Changes in Rice Quality in East Asia

In the following, we collected high quality rice rate (HRR) data defined as the head rice rate in China, and the first quality rice rate in Japan. On average over all sites and years, HRR is $62.14\% \pm 2.13\%$ in China, with some differences between groups of rice cultivars in China where late rice has the highest HRR ($63.52\% \pm 3.62\%$), followed by single rice ($63.16\% \pm 1.97\%$), and by early rice ($53.16\% \pm 4.943\%$). A significant quality decline is observed in China over the 1985–2020 period (Figure 1), with quality decrease rate of $-1.45\%/10$ years ($p < 0.01$). In China, the lowest HRR was observed in 2004 (58.88%). In Japan, the average first quality rate is $66.03\% \pm 6.67\%$. Although no significant time trend in HRR is found in Japan over the whole time period (1979–2018), a negative trend is detected during the sub period 1996–2010, with an estimated decrease rate of $-7.6\%/10$ years ($p = 0.07$). In Japan, the between-year variability of HRR is strong, with HRR varying from 46.72% to 82.84% (Figure 1).

Spatially, the maps shown in Figures 1c and 1d reveal a negative north-south gradient in China, with higher HRR in the northern rice plantation regions, for example, Heilongjiang, Jilin, Liaoning and Shandong provinces, and lower HRR in the southern rice plantation regions, for example, Hainan, Guangdong, Guangxi and Chongqing province. A similar north-south gradient is observed in Japan, with the exception of Hokkaido where HRR is lower than just further south (Figure 1). The spatial distribution of HRR in China and Japan both present a significant spatial auto-correlation ($p < 0.05$).

3.2. Nighttime Temperature Is a Major Driver of Rice Quality

To identify and quantitatively evaluate the response of rice quality to climatic factors, a machine learning random forest algorithm was used to reconstruct HRR based on NT, SR, PR, VPD and the coordinates of each administrative unit (prefectures in Japan, provinces in China, see Method section). We first extracted climate data preceding the observed harvest dates across rice paddy areas for each province, then we built random forest models predicting HRR before the harvest date. Seven model variants based on different sets of predictors (see Method section) were tested by year-by-year cross validation, and we found that climate data averages during 40 days before harvest led to the best predictive performances for HRR in both China and Japan. For the best model (model_4), the year-by-year cross-validated R^2 and RMSE are equal to 0.42% and 6.5% in China, and to 0.44% and 15.8% in Japan, respectively (Figures S2-S8 in Supporting Information S1). All the following analyses are based on these models.

Using the Shapley values (see Methods), we determined the contributions of the different climatic inputs to the deviations of the model predictions from the mean predicted value. In China, the results reveal that high NT values tends to decrease HRR, while low NT values increase HRR (Figures 2a and 2b). SR is the second most important contributor to HRR deviations, with lower SR values associated with higher HRR values. For Japan, results also indicate that high NT have a negative impact on HRR, while other inputs have weaker impacts. Overall, the nighttime temperature appears to be the dominant climate driver of HRR for both China and Japan.

To further describe the response of HRR to these climate inputs, we computed the ALE values (APLEY & ZHU, 2020) that describe the shapes of the average relationships between the climate variables and the HRR predictions. For China, the ALE plot shows that HRR is decreasing with increasing NT when this temperature exceeds 18°C. For Japan, the critical threshold of NT is lower, about 12°C (Figures 2c and 2d). The distribution of NT shows a marginal increase in days above these thresholds from the first part of the study period to the second part, but a large increase is projected in the future under SPP5-85 (Figures 2e and 2f), indicating a higher risk of quality decline in the future. The ALE plot also reveals that SR and PR have a negative effect on HRR in China (Figure S9 in Supporting Information S1). However, in Japan, these two inputs first have positive effects on HRR and then negative effects when pre-harvest SR and PR exceed 460 MJ-m⁻² and 200 mm, respectively. In China, the effect of VPD is smaller and cancels out when VPD exceeds 1 kPa. In Japan, HRR increases with VPD when VPD is below 0.5 kPa, but then slightly decrease when VPD is higher than this threshold.

3.3. Projecting Future Impacts of Climate Change on Rice Quality

Under the mitigation emission scenario (SSP126), future projections show a slightly decreasing trend in HRR both in China and Japan (Figures 3a and 3b), leading to a decline in quality of about -1.5% and -0.5% in China and Japan from 2020 to 2100, respectively. Under the moderate and higher emission scenarios (SSP370 and SSP585), the decreasing trends become stronger, particularly after 2050. The expected HRR decline is stronger in China than in Japan, indicating that a decline of quality exceeding -5% is plausible in 2100 in China, which poses a substantial challenge for adapting cultivars to future climate conditions. Spatially, future HRR (2071-2100 in comparison with 1981-2010) under SSP8.5 are projected to decline across all provinces in China, with stronger declines anticipated in south China, where the main rice cultivation regions are located (Figure 3c). In Japan, the projected HRR changes show a strong spatial variability. In this country, a decline of HRR is anticipated in most prefectures but with several exceptions, in particular in the northern part of the country (Hokkaido) (Figure 3d).

4. Discussion

Although existing studies have documented the impact of temperature on rice quality traits locally in a few sites, our study is the first to assess the effect of climate change at a large scale, covering two major rice producers. The influence of climate change factors on rice production in China is related to the region and the type of rice

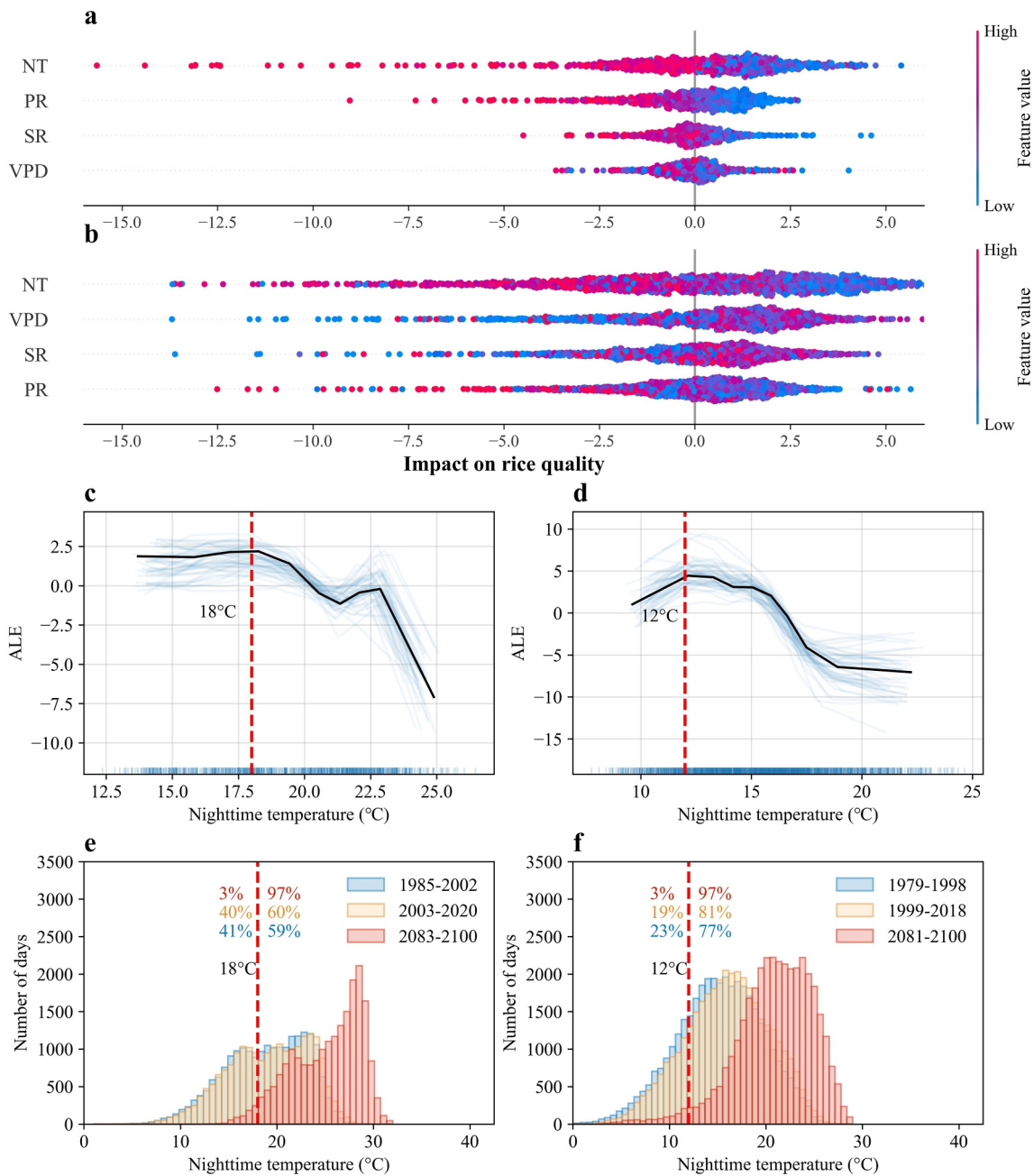


Figure 2. SHAP and ALE plots of random forest model. Contributions of the climate inputs to the predicted HRR in China (a) and Japan (b). These contributions are expressed in SHAP values. The SHAP values determine the contributions of the different inputs to the deviations of the model predictions from the mean predicted value. SHAP values were produced for all model inputs and all HRR data included in the dataset (each point in the figure corresponds to one specific data and one model input). A positive (negative) SHAP value for a given input indicates that this input contributed to increase (decrease) HRR. Colors indicate the values of the inputs (low values in blue and high values in red, ranging from the lowest to highest values in the dataset). The climate variables considered are nighttime temperature (NT), solar radiation (SR), precipitation (PR), vapor pressure deficit (VPD). The most (least) important inputs according to the mean absolute SHAP are at the top (bottom). Responses of HRR to nighttime temperature estimated by accumulated local effect (ALE). Panel c and d show the HRR responses to nighttime temperature (NT) in China (c) and Japan (d), respectively. Panel e and f show the corresponding distribution of nighttime temperature during the harvest date and harvest date-40 days in China (e) and Japan (f), respectively. In Panel e and f, the projected nighttime temperature is from five ISIMIP climate models with daily bias corrected output, and the SSP5-85 is used here.

cultivation including mainly dual cropping rice (i.e., early rice and late) and single cropping rice (single rice or medium rice). Indica rice cultivars are earlier than Japonica cultivars. Also, early rice typically has a shorter growing season (90–120 days) and a higher nighttime temperature than single rice (120–150 days) or late rice

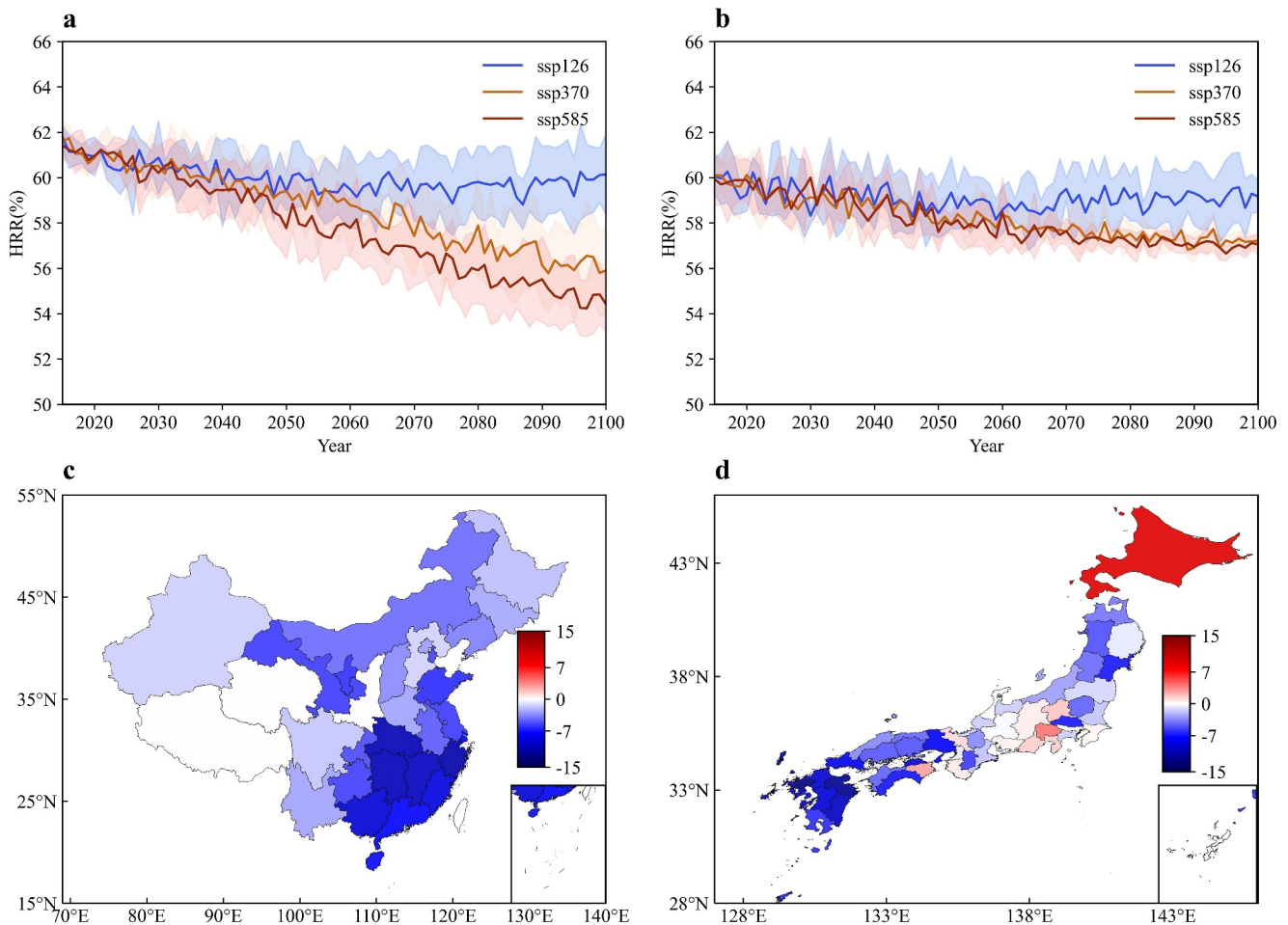


Figure 3. Future projected changes in HRR in China (a) and Japan (b) until 2100 under different Shared Socioeconomic Pathways. Error bars represent standard deviation over different climate models. Spatial distributions of future projected HRR changes (2071–2100 in comparison with 1981–2010) for each province in China (c) and Japan (d) under SSP585.

(150–170 days), contributing to a lower HRR for early rice. Global warming contributes to shortening the growing season of rice cultivation, but the mechanisms behind the relationship between the length of the growing season and rice quality is still an open question. Although both China and Japan showed a decreasing trend in HRR in the past, China experienced a continuous decline since the mid-1980s, while Japan exhibited a more recent downward trend starting only in the late 1990s. In addition, the projected changes of HRR are different between the two countries. While a decline of -5% of HRR is plausible for China in 2100, the projections are less pessimistic for Japan, especially in the Northern part of the country where an increase of HRR is even possible. The negative impact of climate change for rice quality is thus expected to become stronger for China than for Japan. In China, the spatial sensitivity of HRR to NT ($-1.224\%/^{\circ}\text{C}$) is higher than the temporal sensitivity ($-0.733\%/^{\circ}\text{C}$) (Figure S10 in Supporting Information S1), suggesting a limited adaptation potential for south of China where the quality is already strongly impacted by higher NT.

Although rice quality traits are partly determined by genetics (Zeb et al., 2022), our results show that climate also plays a key role in controlling rice quality and, more specifically, that NT is a key driver of HRR in both China and Japan. Our study demonstrates that future climate change will lead to a substantial decline in rice quality, in particular because NT is expected to increase more than daytime temperature in many parts of the world over the next decades (Shi et al., 2016). Rice cultivation will become challenging in several major producing areas by such asymmetric rise in daytime and nighttime temperatures (Rehmani et al., 2014). A large yield reduction resulting from high NT has been already reported in major rice growing areas across South and Southeast Asia (Peng

et al., 2004; Welch et al., 2010). The possible mechanism is that high NT stress during the filling stage triggers non-uniform filling and impairment in storage biosynthesis, which decrease HRR, increase chalkiness, and reduce gain width in rice, in turn, leading to extensive reduction in economic benefits (Dong et al., 2014; Siddik et al., 2019; Welch et al., 2010). The gaps formed due to aborted starch granule formation are thought to be responsible for making chalky grains more brittle and for forming fissures along the grain. As a result, chalky grains crack easily during grain processing, which decline head rice percentage as a consequence of the increased amount of broken grains (Sreenivasulu et al., 2015). The economic value and the consumer acceptance of a rice variety also depend on rice quality, and hence a reduced rice quality caused by warm nights also lead to economic losses (Jagadish et al., 2014). Our findings highlight the importance of developing new breeding strategies in order to restore the HRR in future warmer climates, especially in China.

This study improves our understanding of climate change on rice quality during the past four decades over the East Asia regions. However, caveats and limitations remain. First, rice quality is influenced by many factors, including but not limited to cultivars, cultivation management, geographical location, but it is difficult to separate the effect of these influencing factors on rice quality given current data availability. To reduce the uncertainty, we used the coordinates (latitude + longitude) of each province as additional features in our models. Thanks to this approach, our models do not assume that the effects of climatic factors are similar in all provinces, while being trained on a large data set. Second, our projections of future rice quality under climate change may be uncertain for the most extreme climate change scenarios, because a small fraction of the climate inputs used under these scenarios are more extreme than the range of climate inputs under current climate conditions. Nevertheless, the percentages of out of range inputs remain lower than 5% in Japan in all scenarios, while it exceeds 15% in China only in the most extreme climate change scenario (SSP 585) (Figure S11 in Supporting Information S1). Third, although our approach allowed us to identify the key climate factors explaining head rice rate changes, the mechanisms behind these effects cannot be inferred from our machine learning models alone. Another limitation is that we did not take into account the possible future adaptations of planting regime and paddy areas under future climate warming. As the definition of head rice rate is different in China and Japan, we built a separate model for China and Japan. Remarkably, we found that nighttime temperature was the dominant climate factor in explaining the change in rice quality in both countries. Our analysis also allowed us to identify critical nighttime temperature thresholds (18°C and 12°C in China and Japan, respectively), above which strong grain quality losses are expected. It should be noted that our understanding of rice quality is limited to a certain extent by the availability of data. Thus we call for a unified rice quality monitoring framework, to monitor global rice quality more efficiently in the future and improve our knowledge of the mechanisms determining rice quality.

5. Conclusions

In summary, for the first time we assess the impact of climate change on rice quality across East Asia. We show that the HRR had decreased in most regions in the past and that a further decline in rice quality is highly plausible during the next decades under both moderate and high emission scenarios by 2100. We also provide robust observed evidence for the dominant role of nighttime temperature in explaining the variability of HRR and were able to identify critical temperature thresholds offering a practical tool to anticipate major impacts of adverse climate conditions on grain quality.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The code used in this analysis is available at *zenodo* via Liu et al. (2024).

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