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# Projecting climate change impacts on chalky grain rice in East Kalimantan, Indonesia and implications for heat-tolerant rice variety breeding

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[2]Program Study of Agricultural Science, Faculty of Agriculture, Universitas Mulawarman. Jl. Krayan Kampus Gunung Kelua Gedung C18, Samarinda 75123, East Kalimantan, Indonesia. Tel.: +62-541749159, ♥email: nurhasanah_2710@yahoo.com
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**Abstract.** *Pramana A, Nurhasanah, Sunaryo W, Rusdiansyah, Pranoto, H. 2026. Projecting climate change impacts on chalky grain rice in East Kalimantan, Indonesia and implications for heat-tolerant rice variety breeding. Asian J Agric 10 (1): g100147. https://doi.org/10.13057/asianjagric/g100147.* Rising temperatures associated with climate change are increasing the incidence of Chalky Grain Rice (CGR), reducing grain quality. This study projects future CGR risk and identifies the level of heat-tolerance required for rice varieties to maintain acceptable grain quality under climate change in East Kalimantan, Indonesia. Future CGR incidence was simulated using a temperature-based CGR model combined with bias-corrected climate projections under Representative Concentration Pathway (RCP)2.6 and RCP 8.5 scenarios, along with simulations of rice varietal heat-tolerance under optimistic, median, and pessimistic conditions. Results indicate that even under the low-emission RCP2.6 scenario, most rice-growing areas are projected to exceed the 15% CGR threshold by the 2040s under the optimistic case. Under median conditions, substantially higher CGR levels are projected, particularly under RCP 8.5. To maintain CGR below acceptable limits, rice varieties capable of tolerating temperature increases of approximately 2-3.5°C above current conditions are required by the 2040s, while pessimistic scenarios under both RCPs demand heat-tolerance of up to 4°C. These findings highlight the urgent need to accelerate targeted breeding programs to develop heat-tolerant rice varieties capable of sustaining grain quality, meeting national standards, and remaining resilient under continued climate warming.

**Keywords:** Breeding target, chalky kernels, East Borneo, global warming, grain quality

## INTRODUCTION

Global climate change, driven by Greenhouse Gas Emissions (GHG), pollution, and deforestation, has increasingly disrupted agricultural production, with rice identified as one of the most climate-sensitive staple crops (Zhang et al. 2021; Taratima et al. 2022; Deng et al. 2024). From 2011 to 2020, global surface temperature increased by 0.96-1.20°C compared to the pre-industrial baseline (1850-1900). This trend is also evident in Indonesia, where the highest regional temperature increase between 2013 and 2023 was recorded in East Kalimantan Province, reaching 0.47°C. Future projections warn that, even under the lowest carbon emission scenario, global temperature could rise by 1.5°C by 2040 (IPCC 2023).

Beyond yield losses, elevated temperatures exert a pronounced negative effect on rice grain quality, particularly through the formation of Chalky Grain Rice (CGR). High temperatures during grain filling disrupt starch accumulation in the endosperm, producing loosely packed granules that create air spaces and result in chalky grains, which reduce market value and milling efficiency due to increased grain breakage (Tashiro and Wardlaw 1991; Tabassum et al. 2020; Misra et al. 2021; Shimoyanagi et al. 2021). As visual appearance strongly influences consumer preferences, increased chalkiness significantly limits the commercial acceptability of rice (Cuevas et al. 2016). These quality-related impacts are particularly critical within regulatory frameworks that define market eligibility, underscoring the importance of national rice quality standards.

According to the Indonesian National Standard (SNI), premium rice must have a CGR ratio of no more than 0.5%, while medium 1 and medium 2 grades allow for CGRs of up to 2% and 3%, respectively. When CGR exceeds approximately 15%, rice eating quality declines markedly (Kim et al. 2000), further constraining the ability of producers to meet quality classifications. As elevated temperatures during the critical 20-day period after heading strongly promote CGR development, maintaining compliance with national rice quality standards under future climate scenarios represents a growing challenge for rice production systems (Ishimaru et al. 2020).

In this context, the implications of climate-driven increases in CGR become particularly consequential for rice production systems in East Kalimantan. As rice production is expected to support regional food security, maintaining acceptable grain quality under projected climate change becomes increasingly critical. Elevated temperatures threaten not only yield stability but also the ability of local producers to comply with strict national quality standards, thereby increasing the likelihood of CGR exceeding acceptable limits.

Given these risks and the increasing difficulty of maintaining rice grain quality under rising temperatures, the development of Heat-Tolerant (HT) rice varieties is urgently needed to safeguard grain quality under future climate change. Developing HT rice varieties is widely recognized as one of the most effective strategies for mitigating the effects of rising temperature on CGR (Zhu et al. 2017; Ishimaru et al. 2020; Gann et al. 2021). However, while the importance of heat-tolerance has been widely acknowledged, the specific heat-tolerance thresholds required for rice varieties to maintain CGR below acceptable limits under future climate conditions in Indonesia remain unclear, particularly in terms of the magnitude of temperature increase and the timeframe in which such tolerance will be needed. Because rice breeding is both resource-intensive and time-consuming (Lenaerts et al. 2019), breeding targets must be explicitly aligned with projected climatic conditions. In this context, the present study projects future CGR incidence under RCP2.6 and RCP8.5 scenarios and quantifies the level of heat-tolerance, expressed as temperature increases above current conditions, required in new rice varieties over relevant future periods, thereby providing time-specific and climate-informed benchmarks to support efficient and targeted rice breeding programs in East Kalimantan Province.

## MATERIALS AND METHODS

East Kalimantan Province is located in eastern Borneo, Indonesia, covering approximately 125,000-127,000 km² of land area, in addition to an extensive adjacent marine management zone. The province extends between 113°44′ and 119°00′ E longitude and 2°33′ N and 2°25′ S latitude, straddling the equator and characterized by an equatorial tropical climate. Administratively, East Kalimantan comprises seven regencies and three cities (Figure 1). Spatial datasets, including administrative boundaries, territorial limits, and agricultural land distribution, were obtained from the Indonesian Geospatial Information Agency (*Badan Informasi Geospasial*, BIG). All spatial data were processed using ArcGIS. Agricultural land coordinate points were extracted at a spatial resolution of 2 × 2 km (Table 1).

Temperature data for each coordinate point were obtained from the Copernicus Climate Data Store using the dataset "ERA5 hourly data on single levels from 1940 to present". The data were downloaded for the period 2014 to 2023 to align with the available records from four local observation stations (Figure 4). Although ERA5 primarily provides hourly climate data, daily aggregated datasets are also available. The required variables were downloaded and processed using Python-based scripts to generate daily temperature series.

To calibrate ERA5 temperature data, observed temperature records from stations operated by the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG) in East Kalimantan, namely Berau, Samarinda, and Balikpapan, were used. Because no BMKG stations are located in the upstream western regions of East Kalimantan, observational data from the North Barito station in Central Kalimantan Province were used to calibrate temperature data for Mahakam Ulu and West Kutai Regencies.

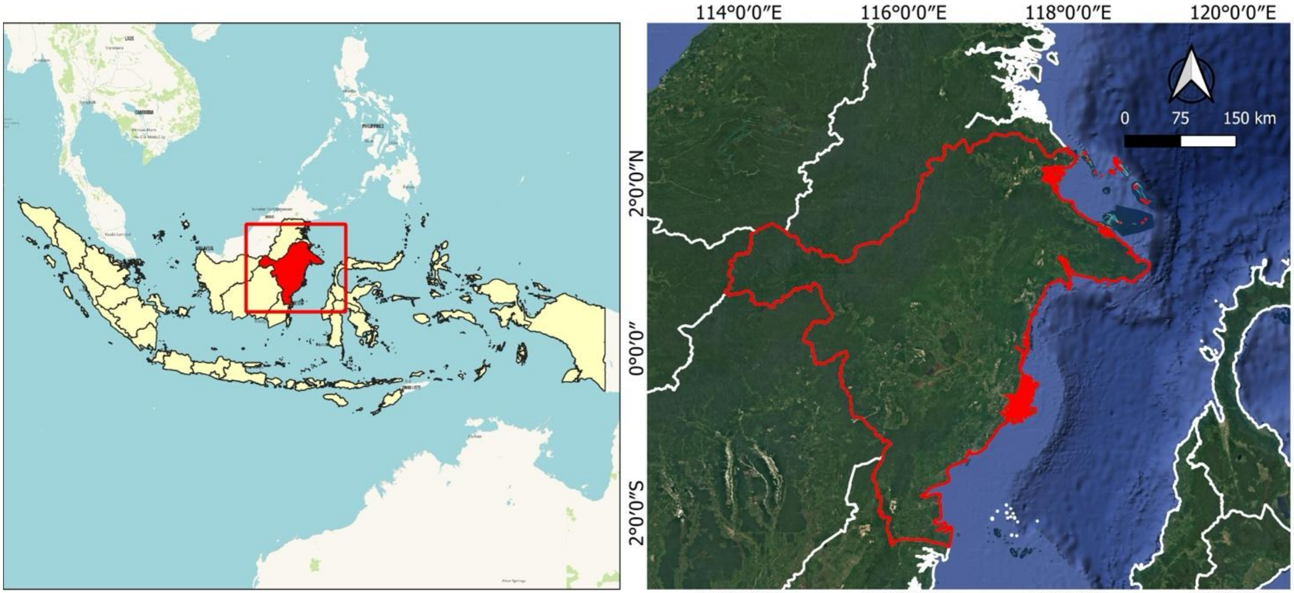

**Figure 1.** Map of the study area in East Kalimantan Province, Indonesia

ERA5 data were bias-corrected using the Quantile Mapping (QM) method according to the following equation (Heo et al. 2019):

$$Qm(t) = Fo^{-1} \{ Fs [ Qs(t) ] \} \quad [1]$$

Where, Qm(t): Bias-corrected data at time t, Qs(t): Predicted data at time t, Fs: Cumulative Distribution Function (CDF) of the simulated data, $Fo^{-1}$: Inverse CDF of the observed data from BMKG observed stations (Berau, Samarinda, Balikpapan, and North Barito).

The calibrated datasets were subsequently used to correct biases in future temperature projections derived from the General Circulation Model (GCM) MPI-M-MPI-ESM-LR under RCP2.6 and RCP8.5 scenarios. Future projections were obtained from the Earth System Grid Federation (ESGF) through the Coordinated Regional Climate Downscaling Experiment (CORDEX) framework. The CORDEX Southeast Asia (SEA-22) dataset was selected to represent regional climate conditions. The ESGF–CORDEX framework provides coordinated and accessible global climate model outputs suitable for climate impact assessments (Han and Choi 2021).

GCM data under RCP2.6 and RCP8.5 were processed using the Climate Model Data for Hydrologic Modeling (CMhyd) tool, which has been widely applied for extraction and bias correction of temperature and precipitation data (Nile et al. 2018; Yeboah et al. 2022). CMhyd generates simulated climate datasets corresponding precisely to the locations of observation gauges. Therefore, bias correction was performed individually for each coordinate point to ensure consistency between simulated and observed datasets (Mukheef et al. 2024).

Climate models often produce systematic deviations from observed time series, which necessitates bias correction. In this study, CMhyd was used to extract and correct simulated GCM data, as summarized in Figure 2.

The bias-corrected temperature data for each regency were validated using two statistical performance metrics: Root Mean Square Error (RMSE) (Eq. 2) and Percent Bias (PBIAS) (Eq. 3) (Mukheef et al. 2024). Observational temperature data were used to assess the accuracy of the bias-corrected simulations.

$$RMSE = \sqrt{[ \Sigma_i(Qobs - Qsim)^2 / n ]} \quad [2]$$
$$PBIAS = \Sigma_i(Qobs - Qsim) / \Sigma_i(Qobs) \quad [3]$$

Where, Qobs: Observed data, Qsim: Predicted data, n: Number of observations

RMSE reflects the standard deviation between predicted and observed values, with lower values indicating better model performance. PBIAS measures the average tendency of simulated data relative to observed data. Negative PBIAS values indicate overestimation, whereas positive values indicate underestimation. The optimal PBIAS value is 0. According to Mukheef et al. (2024), PBIAS values within ±5 are generally considered acceptable.Based on validated, bias-corrected climate datasets for each regency, CGR incidence was estimated using a temperature-based statistical model developed by Masutomi et al. (2015, 2019a, b). The model describes the empirical relationship between elevated air temperature during the grain-filling stage and chalkiness occurrence, which is highly sensitive to temperature. CGR was calculated for each 2 km × 2 km grid cell across East Kalimantan using daily temperature inputs.

The model formulation is expressed as:

$$I = \max \{ 0, KT (T_{20} - (Tcrit + THT)) \} \quad [4]$$

Where, I: Incidence of CGR (%), $T_{20}$: Average daily temperature during 20 days following the flowering date (°C), Tcrit: Threshold temperature at which CGR starts to appear (°C), KT: Temperature sensitivity parameter (%/°C), THT: Heat-tolerance parameter of the variety (°C).

Model accuracy for cases without heat-tolerant varieties (THT = 0) was validated by Masutomi et al. (2019a, b). In this study, THT was introduced to evaluate the effect of Heat-Tolerant (HT) varieties. When $T_{20} \leq Tcrit + THT$, I = 0; otherwise, I increases linearly with $T_{20}$ according to KT (Masutomi et al. 2023). For example, when THT = 1, the effective threshold temperature increases by 1°C, reducing CGR incidence compared with THT = 0. This represents the introduction of a variety with 1°C greater heat-tolerance. In this study, nine HT levels were evaluated: 0, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, and 4.0°C. Although previous studies indicate that Tcrit and KT vary among rice varieties (Takimoto et al. 2019), such variability was not explicitly incorporated due to analytical complexity, following the approach of Masutomi et al. (2023).

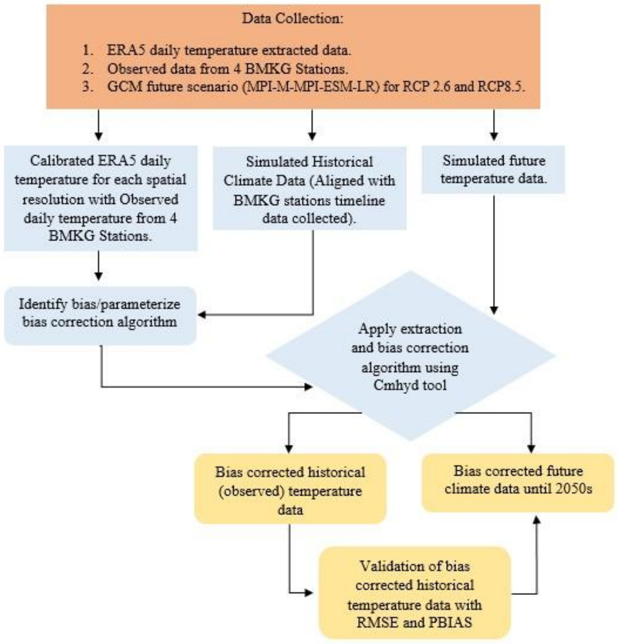

**Figure 2.** General methodological framework for correcting biases in downscaled climate data obtained from GCM

**Table 1.** Framework of assessment: Estimation and analysis

| Item | Estimation | Analysis |
|---|---|---|
| Area | East Kalimantan Province | |
| Spatial Resolution | 2 km | Potential rice-growing area |
| Year | 2011-2050 | 2020s, 2030, 2040s |
| RCP | RCP2.6, RCP8.5 | RCP2.6, RCP8.5 |
| GCM | MPI-M-MPI-ESM-LR | OPT, MED, PES |
| CGR Model | 100 parameters sets | |
| Heat-Tolerant (HT) | 0, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5, 4.0 | |

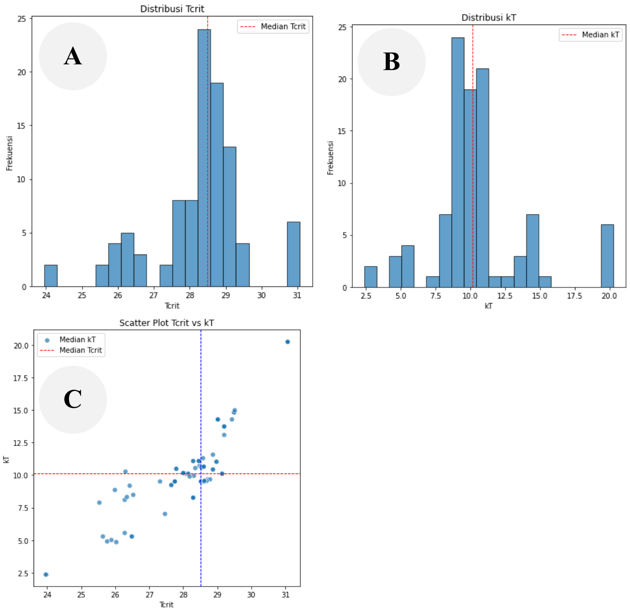

**Figure 3.** Frequency of $T_{crit}$ [ºC](A), $K_T$ [%/ºC](B), and plots of 100 sets (C) of the parameters (red and blue dot line indicates the median value)

The parameters Tcrit and KT were statistically estimated based on observed I and $T_{20}$ values. To account for model uncertainty, 100 parameter sets were generated using bootstrap resampling (Efron 1979) (Figure 3). Each bootstrap sample was used to recalibrate the model parameters, and the resulting parameter sets were propagated through the CGR model using projected temperature data, generating a range of possible CGR outcomes rather than a single deterministic estimate. A general threshold temperature of 27°C was applied, with an upper limit based on experimental data (Tashiro and Wardlaw 1991). Optimal parameter values were obtained by minimizing the error between observed and estimated I using the Downhill Simplex method (Nelder and Mead 1965).

The assessment framework was applied consistently across space, time, and climate scenarios (Table 1). The analysis covered East Kalimantan Province (Figure 1) at a spatial resolution of 2 km. CGR incidence was estimated annually for 2011 to 2050 and subsequently aggregated into decadal periods: the 2020s, 2030s, and 2040s. Bias-corrected climate projections under RCP2.6 and RCP8.5 were analyzed. Climate uncertainty was represented by evaluating the 10th, 50th, and 90th percentiles of projected temperature data, corresponding to optimistic (OPT), median (MED), and pessimistic (PES) scenarios.

To evaluate adaptation through varietal improvement, CGR estimation was repeated for HT rice varieties with tolerance levels ranging from 0 to 4°C. This framework enabled systematic assessment of the potential of HT varieties to reduce CGR risk under future climate.

## RESULTS AND DISCUSSION

### Observed historical temperature trends

Temperature observations from four stations in East Kalimantan and Central Kalimantan, namely Berau, Samarinda, Balikpapan, and North Barito, show an overall increasing trend from 2014 to 2023 (Figure 4). At the Berau observation station, the average temperature increase reached 0.54°C over this period. However, a noticeable decline in temperature was observed after 2020.

This temporary decrease is consistent with studies indicating that global lockdowns during the COVID-19 pandemic produced short-term environmental effects, including reductions in carbon emissions and air pollutants. Global $CO_2$ emissions reportedly declined by approximately 6% in 2020, largely due to reduced fossil fuel consumption in the transportation and industrial sectors (Tollefson 2020). In several regions, including China and Europe, nitrogen dioxide ($NO_2$) concentrations decreased by about 30%, leading to improved air quality (Tollefson 2020). These findings illustrate how abrupt changes in human activity can influence atmospheric conditions and surface temperature, although the effect was temporary, followed by a rebound in temperature trends at the Berau, Balikpapan, and North Barito stations.

### Performance of bias-correction climate projections

The RMSE values for bias-corrected Tmax ranged from 0.606 to 1.031 across regions, indicating close agreement with the observed Tmax series (Table 2). The corresponding PBIAS values for the corrected Tmax ranged from 0.003 to 0.030 (Table 3), demonstrating minimal deviation between corrected and observed Tmax data. For Tmin, RMSE values were generally low across regions, although slightly higher variability was observed in Kutai Barat under RCP2.6. PBIAS values for corrected Tmin remained within acceptable limits across all regions, with minor overestimation and underestimation. Because the optimal PBIAS value is 0, the small absolute values observed in this study indicate satisfactory performance. According to Mukheef et al. (2024), PBIAS values within ±5 are considered acceptable. Overall, the bias-corrected Tmax and Tmin datasets show good agreement with observations across all regions under both RCP2.6 and RCP8.5, with low RMSE and PBIAS values confirming reliable model performance despite minor regional deviations.

### Projected CGR incidence without heat-tolerant varieties (HT0)

Table 4 and Figure 5 summarizes the average incidence of Chalky Grain Rice (CGR) across East Kalimantan from the 2020s to the 2040s under RCP2.6 and RCP8.5 when Heat-Tolerant (HT) rice varieties are introduced. In the absence of heat-tolerance (HT0), CGR incidence increased markedly over time under both emission pathways, with consistently higher values under RCP8.5 than under RCP2.6. The lowest incidence of CGR, recorded at 28.8% under RCP2.6 with HT0 in the 2020s OPT case, shows that all potential rice-growing areas experiencing severe CGR (Figure 6). This temporal increase reflects the cumulative effect of rising temperatures, with CGR incidence under RCP2.6 increasing from 31.9% in the 2020s to 38.1% in the 2040s, while under RCP8.5 it rose from 37.1% to 45.9% over the same period. Progressive introduction of HT varieties substantially reduced CGR incidence in all decades and under both RCPs, with reductions becoming more pronounced as the level of heat-tolerance increased.

### Impact of introducing heat-tolerant varieties

The introduction of Heat-Tolerant (HT) rice varieties substantially reduced CGR incidence across decades and emission scenarios (Table 4 and Figure 5). In the median case for the 2040s, introducing a variety with 1°C additional Heat-Tolerance (HT1) reduced CGR incidence from 38.1% to 27.9% under RCP2.6 and from 45.9% to 35.8% under RCP8.5. However, the magnitude of reduction decreased as tolerance levels increased, indicating diminishing marginal returns.

Under RCP2.6 in the 2040s median case, the reduction between HT1 and HT2 was 10.1 percentage points, whereas the reduction between HT2 and HT3 was 9.1 percentage points. Although reductions remain substantial, each additional increment in tolerance yields progressively smaller gains.

**Table 2.** Performance of bias-corrected Tmax and Tmin datasets, RMSE for both scenarios

| Variable | Region | RCP2.6 | RCP8.5 |
|---|---|---|---|
| Tmax | Berau | 0.988 | 0.606 |
| | Kutai Timur | 0.960 | 0.565 |
| | Bontang | 0.925 | 0.520 |
| | Kutai Kartanegara | 0.885 | 0.496 |
| | Kutai Barat | 1.031 | 0.477 |
| | Mahakam Ulu | 0.837 | 0.424 |
| | Samarinda | 0.939 | 0.530 |
| | Balikpapan | 0.824 | 0.399 |
| | Paser | 0.802 | 0.345 |
| | PPU | 0.814 | 0.388 |
| Tmin | Berau | 0.087 | 0.077 |
| | Kutai Timur | 0.143 | 0.125 |
| | Bontang | 0.117 | 0.152 |
| | Kutai Kartanegara | 0.144 | 0.133 |
| | Kutai Barat | 0.736 | 0.085 |
| | Mahakam Ulu | 0.140 | 0.102 |
| | Samarinda | 0.160 | 0.190 |
| | Balikpapan | 0.121 | 0.163 |
| | Paser | 0.140 | 0.111 |
| | PPU | 0.136 | 0.148 |

**Table 3.** Performance of bias-corrected Tmax and Tmin datasets, PBIAS for both scenarios

| Variable | Region | RCP2.6 | RCP8.5 |
|---|---|---|---|
| Tmax | Berau | 0.030 | 0.018 |
| | Kutai Timur | 0.029 | 0.017 |
| | Bontang | 0.028 | 0.016 |
| | Kutai Kartanegara | 0.027 | 0.015 |
| | Kutai Barat | 0.030 | 0.014 |
| | Mahakam Ulu | 0.025 | 0.003 |
| | Samarinda | 0.028 | 0.015 |
| | Balikpapan | 0.026 | 0.012 |
| | Paser | 0.025 | 0.011 |
| | PPU | 0.026 | 0.012 |
| Tmin | Berau | 0.003 | 0.018 |
| | Kutai Timur | 0.004 | 0.005 |
| | Bontang | 0.004 | 0.006 |
| | Kutai Kartanegara | 0.005 | 0.005 |
| | Kutai Barat | -0.025 | 0.003 |
| | Mahakam Ulu | 0.006 | 0.004 |
| | Samarinda | 0.006 | 0.007 |
| | Balikpapan | 0.004 | 0.006 |
| | Paser | 0.005 | 0.004 |
| | PPU | 0.005 | 0.006 |

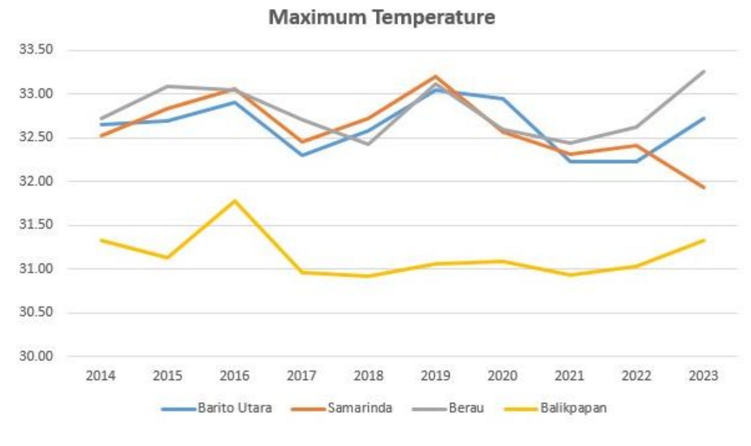

**Figure 4.** Annual temperature trends at four stations in East Kalimantan and Central Kalimantan (Berau, Samarinda, Balikpapan, and North Barito), Indonesia, from 2014 to 2023

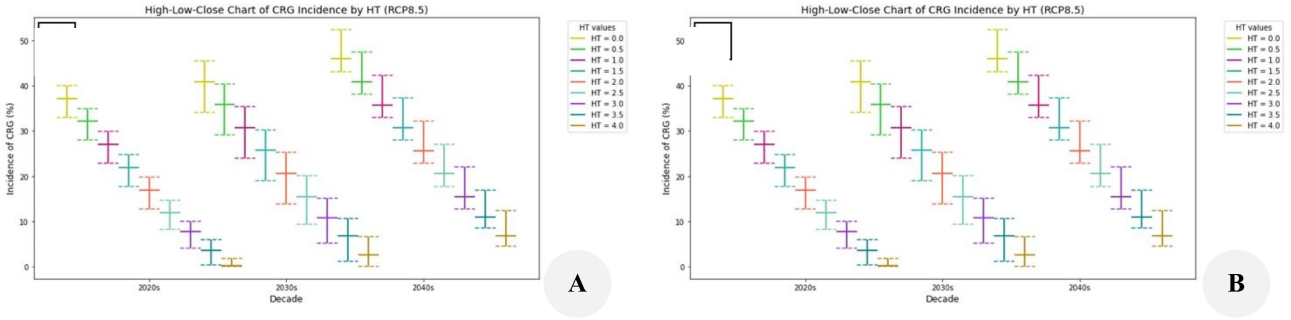

**Figure 5.** Average CGR incidence (%) across East Kalimantan from the 2020s to 2040s under A. RCP2.6 and B. RCP8.5 for HT levels 0 to 4

Spatial analysis for the 2040s further supports these findings (Figures 7 and 8). Under RCP2.6, the introduction of HT varieties with 3°C to 4°C tolerance eliminated high-CGR areas under both optimistic and median scenarios. In contrast, under RCP8.5, particularly in the median case, high-incidence areas persisted even with 4°C tolerance, although their spatial extent decreased (Figure 9). These patterns confirm diminishing effectiveness beyond 3°C to 4°C tolerance, especially under pessimistic projections where core CGR hotspots remain.

Under the optimistic (OPT) scenario, both RCP2.6 and RCP8.5 projections show that CGR incidence declines to below 5% following the introduction of varieties with 4°C tolerance. However, Berau Regency exhibited a distinct spatial response under RCP8.5, where CGR incidence remained predominantly above 5% compared with other regencies. This localized persistence is consistent with the higher historical warming trend observed in Berau (Figure 5), suggesting that stronger local thermal stress reduces the relative effectiveness of heat-tolerance.

Under the pessimistic scenario in the 2040s, the spatial extent of high CGR incidence expanded under both RCPpathways. Even with 3°C tolerance, affected regions continued to grow. Consequently, varieties with 4°C heat-tolerance would be required to effectively control CGR incidence under these conditions (Figure 9).

At the provincial scale, increasing tolerance from HT0 to HT1 reduced CGR incidence by more than 10 percentage points in the 2040s median case. However, tolerance levels above 3°C provided progressively smaller provincial-scale benefits, while CGR incidence in several areas remained above 15% (Table 4 and Figure 9).

From a breeding perspective, achieving more than 3°C heat-tolerance is technically demanding and typically requires multigenic improvement and extensive multi-environment testing. A tolerance increase of 1°C to 2°C is more consistent with current breeding pipelines using conventional methods supported by marker-assisted selection or genomic selection. In contrast, achieving 4°C tolerance, as required under pessimistic mid-century projections, would necessitate accelerated breeding cycles, broader genetic introgression, and sustained national investment in rice improvement programs.

### Temperature variablity in East Kalimantan from 2014-2023

The temporary decrease in temperature observed after 2020 is consistent with studies indicating that global lockdowns during the COVID-19 pandemic produced short-term environmental effects, including reductions in carbon emissions and air pollutants. Global $CO_2$ emissions reportedly declined by approximately 6% in 2020, largely due to reduced fossil fuel consumption in the transportation and industrial sectors (Tollefson 2020). In several regions, including China and Europe, nitrogen dioxide ($NO_2$) concentrations decreased by about 30%, leading to improved air quality (Tollefson 2020). These findings illustrate how abrupt changes in human activity can influence atmospheric conditions and surface temperature, although the effect was temporary, followed by a rebound in temperature trends at the Berau, Balikpapan, and North Barito stations.

### Implications of rising CGR for rice quality and market standards

Despite the substantial reductions in CGR incidence achieved through the introduction of Heat-Tolerant (HT) varieties (Table 4), the projected CGR levels under baseline and low-tolerance conditions remain a serious concern for rice quality. Even under the RCP2.6 scenario in the 2020s with HT0, CGR incidence exceeds 15% (Table 4), a level known to significantly reduce eating quality and consumer acceptance (Kim et al. 2000). Experimental evidence shows that cooked rice containing 0 to 4% CGR exhibits superior texture compared with rice containing 15% CGR, highlighting the importance of maintaining low chalkiness to preserve grain quality (Kim et al. 2000). Rice kernels with higher proportions of CGR tend to have lower amylose content and higher water absorption than vitreous kernels. After cooking, cells in vitreous kernels are tightly packed and well aligned, whereas such structural organization is not observed in chalky kernels. Rice samples without chalky kernels receive higher scores for appearance, texture, and overall quality than samples containing 15% chalky kernels. The inferior texture of chalky rice may be associated with increased air spaces and a higher water absorption index in chalky kernels.

This quality challenge is further intensified by Indonesia's stringent rice quality standards, which set maximum CGR thresholds at 0.5% for Premium, 2% for

Medium 1, and 3% for Medium 2 grades (BPSIP Lampung 2023). When compared with projected CGR levels exceeding 15% even under HT0 in the RCP2.6 scenario, these regulatory limits reveal a substantial gap between acceptable market standards and climate-affected production outcomes. Consequently, even modest increases in CGR may lead to disproportionate economic and food-security constraints for farmers in East Kalimantan, particularly in their ability to supply high-quality rice. This mismatch between consumer quality requirements and climate-driven CGR risks reinforces the importance of HT varietal development as a key adaptation strategy for maintaining rice quality under future warming conditions.

### Efficacy and limits of heat-tolerant varieties

Figures 4 to 8 and Table 4 indicate that introducing HT rice varieties can substantially reduce CGR incidence across climate scenarios, with the largest reductions achieved at lower tolerance levels. In the MED scenario during the 2040s, increasing heat-tolerance by 1°C (HT1) reduces CGR incidence by approximately 10 to 11% under both RCP2.6 and RCP8.5, demonstrating that relatively modest genetic gains can produce meaningful improvements in grain quality at the provincial scale. This finding is consistent with previous studies showing that chalky grain formation increases sharply when grain-filling temperatures exceed critical thresholds of around 26-27°C, implying that even small improvements in heat-tolerance can substantially mitigate grain quality losses (Lin et al. 2010). Similarly, studies on heat-tolerant rice cultivars have demonstrated that varietal improvement can significantly reduce chalkiness, although the magnitude of reduction depends strongly on the level of thermal stress experienced during grain filling (Guo et al. 2025). Under optimistic (OPT) conditions, deploying HT varieties with up to 4°C tolerance reduces CGR incidence to below 5% across most regencies. However, spatial analyses reveal persistent hotspots, such as Berau Regency, where stronger local thermal stress limits the effectiveness of heat-tolerance in fully mitigating CGR risk.

At the same time, the results indicate diminishing marginal returns as heat-tolerance increases. While the transition from HT0 to HT1 produces the largest reduction in CGR, subsequent increases, for example from HT2 to HT3, deliver progressively smaller gains. This pattern is particularly evident under MED and PES conditions, where CGR incidence often remains above 15% despite higher tolerance levels. This pattern is consistent with genetic evidence showing that chalkiness is a complex polygenic trait controlled by numerous Quantitative Trait Loci (QTLs) and strong genotype-environment interactions, which constrain the rate of achievable genetic improvement (Yao et al. 2020). From a breeding perspective, these findings suggest that targeting 1 to 2°C improvements in heat-tolerance offers the most efficient balance between achievable CGR reduction and breeding feasibility, whereas increasing tolerance beyond 3°C provides limited additional benefits relative to the escalating biological complexity and resource demands required to achieve such gains. These findings are also aligned with global assessments indicating that climate warming substantially increases chalky grain occurrence, thereby reinforcing the importance of combining varietal improvement with broader adaptation strategies in rice production systems (Liu et al. 2025).

**Table 4.** Average incidence (%) of CGR for the whole of East Kalimantan from the 2020s to 2040s under RCP2.6 (top) and RCP8.5 (bottom) when nine HT varieties are introduced from HT0 to HT4. Values on the left of the parentheses represent the median (MED) case; values in parentheses represent the optimistic (OPT) and pessimistic (PES) cases

| | | RCP2.6 | |
|---|---|---|---|
| **HT** | **2020s** | **2030s** | **2040s** |
| 0.0 | 31.9 (28.8, 36.1) | 35.6 (28.3, 42.6) | 38.1 (32.7, 47.1) |
| 0.5 | 26.8 (23.7, 31.1) | 30.5 (23.3, 37.5) | 33.0 (27.6, 42.1) |
| 1.0 | 21.8 (18.7, 26.0) | 25.5 (18.2, 32.5) | 27.9 (22.5, 37.0) |
| 1.5 | 16.7 (13.6, 20.9) | 20.4 (13.1, 27.4) | 22.9 (17.5, 31.9) |
| 2.0 | 11.6 (9.0, 15.9) | 15.3 (8.5, 22.3) | 17.8 (12.4, 26.9) |
| 2.5 | 7.4 (5.0, 11.1) | 10.7 (4.4, 17.3) | 12.9 (8.2, 21.8) |
| 3.0 | 3.4 (1.3, 7.0) | 6.5 (0.7, 12.7) | 8.7 (4.1, 16.8) |
| 3.5 | 0.2 (0.0, 2.9) | 2.5 (0.0, 8.6) | 4.6 (0.6, 12.4) |
| 4.0 | 0.0 (0.0, 0.1) | 0.0 (0.0, 4.4) | 1.0 (0.0, 8.2) |

| | | RCP8.5 | |
|---|---|---|---|
| **HT** | **2020s** | **2030s** | **2040s** |
| 0.0 | 37.1 (33.0, 40.0) | 40.9 (34.2, 45.5) | 45.9 (43.1, 52.4) |
| 0.5 | 32.1 (27.9, 34.9) | 35.8 (29.1, 40.4) | 40.8 (38.0, 47.3) |
| 1.0 | 27.0 (22.8, 29.9) | 30.7 (24.0, 35.3) | 35.8 (33.0, 42.3) |
| 1.5 | 21.9 (17.8, 24.8) | 25.7 (19.0, 30.3) | 30.7 (27.9, 37.2) |
| 2.0 | 16.9 (12.7,19.8) | 20.6 (13.9, 25.2) | 25.6 (22.8, 32.1) |
| 2.5 | 11.9 (8.3, 14.7) | 15.5 (9.4, 20.2) | 20.6 (17.8, 27.1) |
| 3.0 | 7.7 (4.1, 10.1) | 10.9 (5.2, 15.1) | 15.5 (12.8, 22.0) |
| 3.5 | 3. (0.4, 6.0) | 6.7 (1.2, 10.7) | 11.0 (8.7, 17.0) |
| 4.0 | 0.2 (0.0, 1.9) | 2.6 (0.0, 6.6) | 6.9 (4.5, 12.5) |

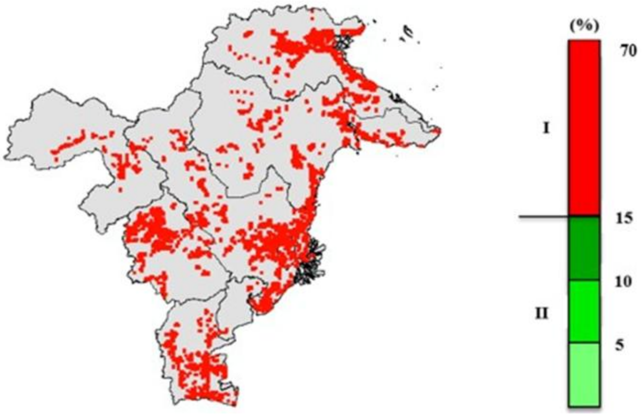

**Figure 6.** Spatial distribution of CGR incidence (%) across East Kalimantan, Indonesia, in the 2020s under HT0. Grids that do not contain rice fields or where rice is not cultivated are shown in grey. A 15% incidence of CGR serves as the dividing threshold between the first and second grades. The percentage of CGR exceeds 15%, the rice's eating quality decreases significantly (Kim et al. 2000)

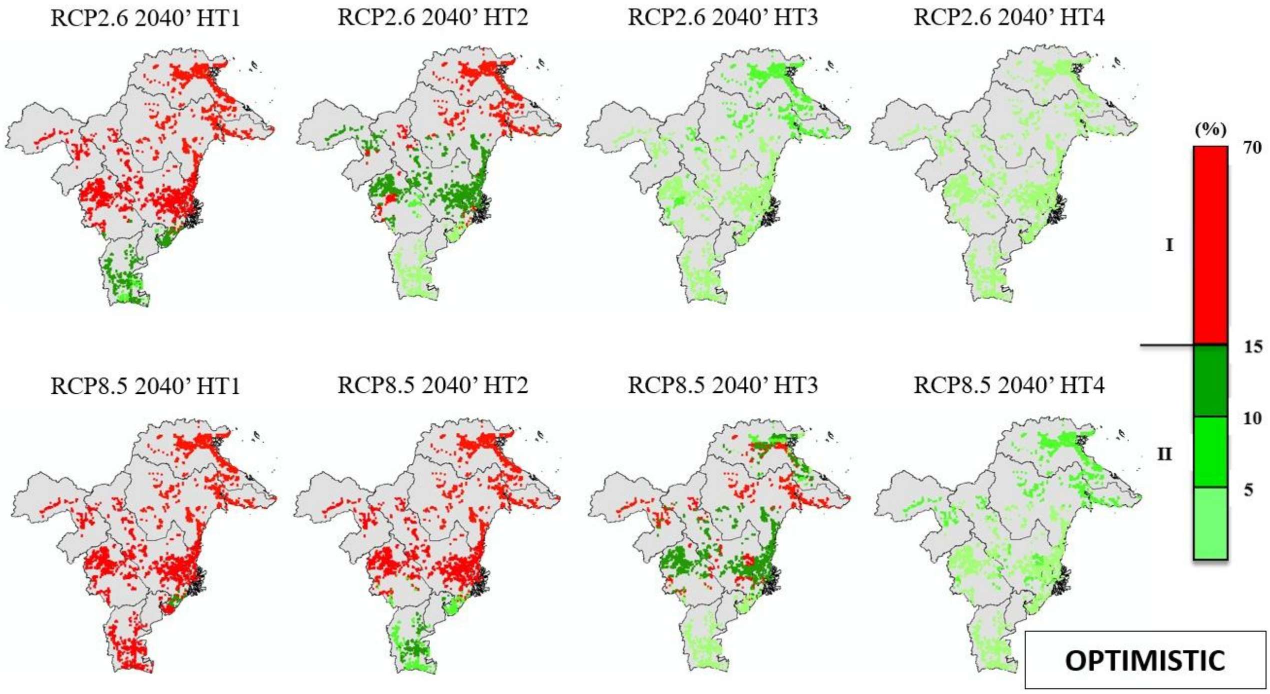

**Figure 7.** Incidence [%] of CGR in the 2040s in the OPT case with HT0 to HT4 under RCP2.6 (top) and RCP8.5 (bottom)

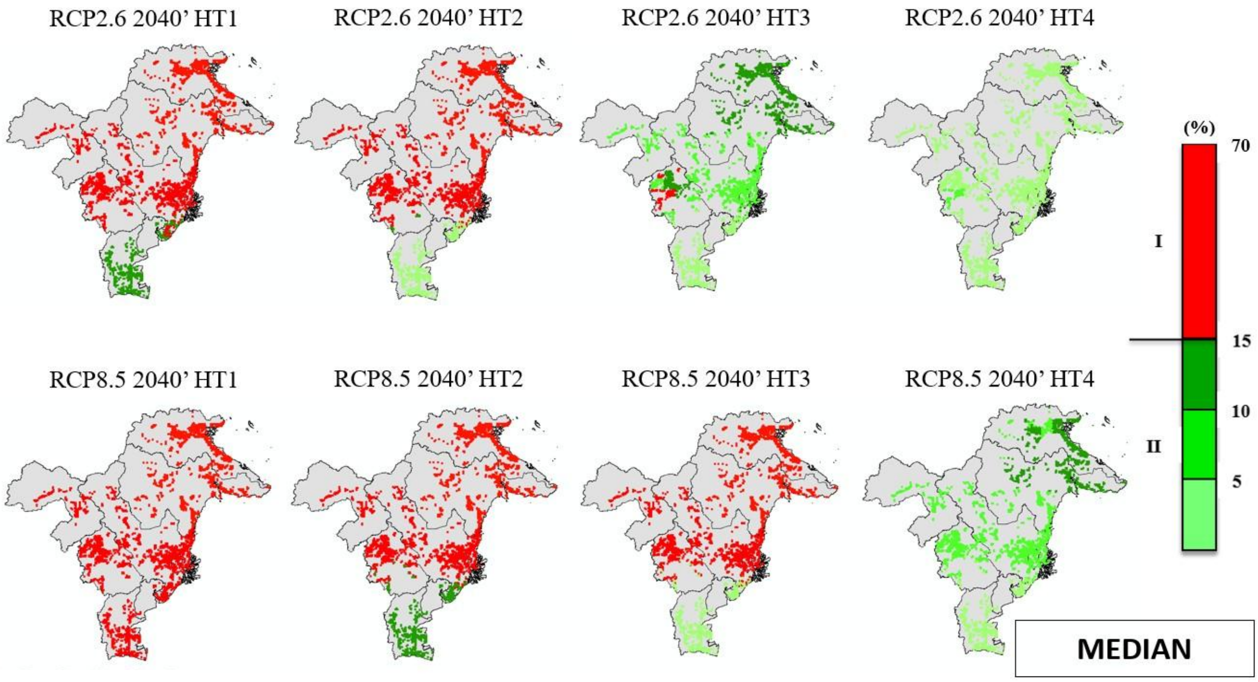

**Figure 8.** Incidence [%] of CGR in the 2040s in the MED case with HT0 to HT4 under RCP2.6 (top) and RCP8.5 (bottom)

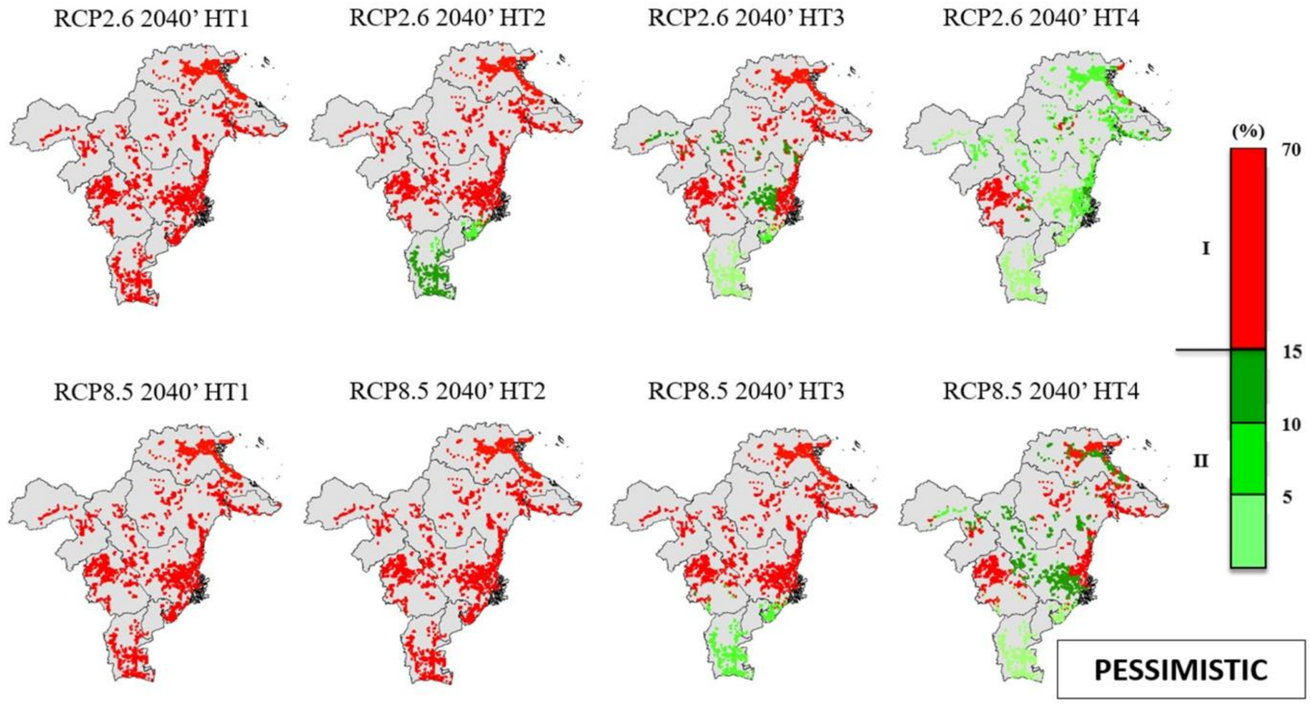

**Figure 9.** Incidence [%] of CGR in the 2040s in the PES case with HT0 to HT4 under RCP2.6 (top) and RCP8.5 (bottom)

## Deriving practical breeding targets

The current breeding targets are based on projections for the 2040s (Figures 7 to 9), considering different climate scenarios, including RCP2.6 and RCP8.5. A prerequisite for this assessment is defining an acceptable CGR incidence threshold. Table 5 presents the resulting breeding targets for HT rice varieties.

Under the moderate emission scenario (MED), HT varieties capable of tolerating an additional 3°C will need to be developed and deployed by the 2040s under RCP8.5, whereas an increase of 2.5°C will be sufficient under RCP2.6. This indicates that more advanced HT varieties will be required under RCP8.5 than under RCP2.6 by the 2040s. Under the pessimistic scenario (PES), HT varieties with a 4°C increase in heat-tolerance will need to be bred and introduced by the 2040s for both RCP2.6 and RCP8.5. However, in certain locations (Figure 9), many areas still exhibit CGR incidences above 15% even after the introduction of HT4 varieties. These findings indicate that varietal improvement alone may be insufficient in some high-risk areas and that broader climate mitigation and adaptive management strategies are also required.

## Improving CGR traits through plant breeding

The results demonstrate that introduction of HT rice varieties substantially reduces CGR incidence across East Kalimantan, yet the benefits show clear diminishing marginal returns as tolerance levels increase (Table 4, Figures 7-9). From an agricultural adaptation perspective, these modelling results indicate that heat-tolerant varietal development should be prioritized as a core adaptation strategy, particularly in areas identified as high-risk CGR zones. From a breeding perspective, these findings align with established priorities in rice improvement, where grain quality is second only to yield (Huang et al. 1998). Chalkiness, although influenced by amylose content and governed partly by the Waxy (Wx) gene encoding GBSSI, is a complex polygenic trait involving strong environmental interactions (Deng et al. 2022; Li et al. 2023; Bowen et al. 2024; Ouyang et al. 2026). Achieving HT levels of ~2-3°C is therefore consistent with what current breeding pipelines can realistically deliver within one to two decades through conventional breeding supported by Marker-Assisted Selection (MAS) and SSR markers (Gao et al. 2016; Das et al. 2017), making this tolerance range a realistic medium-term adaptation target. In contrast, targeting 4°C tolerance required under pessimistic 2040s scenarios would necessitate accelerated breeding cycles, broader genetic introgression, and sustained investment, highlighting the urgency of aligning HT breeding targets with both agronomic feasibility and market-driven grain quality standards. HT varietal development should be implemented alongside complementary adaptation measures, such as adjustment of planting calendars and spatial targeting of suitable cultivation areas, to maximize the effectiveness of climate adaptation strategies in rice production systems (Ji et al. 2024).

**Table 5.** Breeding targets of Heat-Tolerant (HT) varieties: HT that needs to increase [°C]

| | **RCP2.6** | | | **RCP8.5** | | |
|---|---|---|---|---|---|---|
| | **2020s** | **2030s** | **2040s** | **2020s** | **2030s** | **2040s** |
| OPT | 2 | 2 | 2 | 2.5 | 2.5 | 3.5 |
| MED | 2.5 | 2.5 | 2.5 | 3 | 3 | 4 |
| PES | 2.5 | 3.5 | 4 | 3 | 3.5 | 4 |

Notes: OPT: Optimistic, MED: Median, PES: Pessimistic

### Study limitations and future research

This study provides a regionally relevant, scenario-based assessment of future CGR risk and associated heat-tolerance requirements, offering a useful first-order framework for linking climate projections with rice breeding targets in East Kalimantan. Nevertheless, several simplifying assumptions should be acknowledged. The CGR estimation relies on a temperature-driven model with constant values of temperature sensitivity (KT) and critical threshold (Tcrit). Although this approach enables consistent comparisons across scenarios, it may not fully capture varietal differences or nonlinear responses to heat stress. Heat-tolerance was represented as uniform increments in temperature tolerance, which allows systematic evaluation of adaptation pathways. However, actual genotypic responses are likely to vary according to local climate and management conditions. Therefore, the breeding targets presented here should be interpreted as province-scale guidance rather than precise varietal thresholds. Future research incorporating varietal-specific parameters, together with controlled experiments and multi-location field trials, would refine these projections, improve representation of genotype × environment interactions, and strengthen the applicability of this modeling framework to practical rice breeding and deployment strategies.

In conclusion, this study demonstrates that climate-driven temperature increases pose a substantial and escalating risk to rice grain quality in East Kalimantan by significantly increasing the incidence of chalky grain rice (CGR), thereby challenging compliance with Indonesia's stringent market quality standards. Across climate scenarios, projected CGR levels exceed thresholds associated with marked deterioration in eating quality, even under low-emission pathways, highlighting the high sensitivity of grain quality to warming during the critical grain-filling period. The findings further indicate that the introduction of Heat-Tolerant (HT) rice varieties can substantially reduce CGR incidence, particularly through moderate improvements in heat-tolerance. Increases of approximately 1 to 2°C provide the most efficient reductions in CGR relative to breeding feasibility and resource requirements. However, diminishing marginal returns become evident as tolerance levels rise. Under moderate to pessimistic climate trajectories, CGR risks remain considerable despite higher HT levels, especially in thermally stressed areas. Together, these results indicate that although HT varietal development represents a key adaptation strategy, breeding targets must be aligned with both achievable genetic gains and projected climate pressures. Timely and well-targeted breeding efforts, supported by complementary climate adaptation measures, will be essential to sustain rice quality, maintain market acceptance, and strengthen regional food security under continued warming.

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