

International Journal of Advanced Biochemistry Research



ISSN Print: 2617-4693
ISSN Online: 2617-4707
NAAS Rating (2026): 5.29
IJABR 2026; SP-10(5): 403-410
www.biochemjournal.com
Received: 06-03-2026
Accepted: 10-04-2026

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Thermal and rainfall sensitivity with stage wise optimum temperature of rice in Ranchi, Jharkhand

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DOI: <https://www.doi.org/10.33545/26174693.2026.v10.i5Se.8397>

Abstract

Eight consecutive Kharif seasons (2017-2024) of field experiments evaluated phenophase-specific optimum temperature, thermal and rainfall sensitivity of three rice varieties (Sahbhagi Dhan, Naveen, MTU1010) under three sowing dates (D1: 05 June, D2: 15 June, D3: 25 June) at Birsa Agricultural University, Ranchi, Jharkhand. Optimum mean temperature (Topt), absolute (S, kg ha⁻¹ °C⁻¹) and relative (Srel, % °C⁻¹) thermal sensitivity coefficients and standardised rainfall sensitivity indices (β) were estimated across five phenological intervals. Naveen sown on D2 recorded the highest yield (4, 610.5 kg ha⁻¹), followed by MTU1010/D3 (4, 155.8 kg ha⁻¹) and Sahbhagi Dhan/D1 (3, 892.1 kg ha⁻¹). Topt peaked during flowering-milking and milking-grain filling (26.03-28.40 °C) and declined toward maturity (24.65-25.35 °C). Thermal sensitivity was nearly universally very high (|S| > 200 kg ha⁻¹ °C⁻¹). Under D1, Sahbhagi Dhan and Naveen showed strongly negative Srel at sowing-vegetative (-8.60% to -11.32% °C⁻¹), 2.7- to 3.5-fold larger than the global rice warming penalty (-3.2% °C⁻¹), while MTU1010 showed contrasting positive sensitivity at milking-grain filling (+11.60% °C⁻¹), revealing variety-level divergence in thermal response within the same sowing window. Under D2-D3, sensitivity shifted to strongly positive at vegetative-flowering and flowering-milking (+4.17% to +9.92% °C⁻¹) for Sahbhagi Dhan and Naveen, indicating yield benefits from moderate reproductive-stage warming. Rainfall sensitivity was equally stage-dependent: milking-grain filling caused the strongest negative responses under D1 (β = -0.65 in Naveen, R² = 0.424), while grain filling-maturity showed positive sensitivity under D3 (β = +0.53 to +0.57). Phenophase-specific rainfall timing governed yield outcomes more decisively than seasonal totals and mid-June sowing (D2) consistently optimised both thermal and moisture conditions, supporting it as a practical climate-smart adaptation for humid subtropical eastern India.

Keywords: Optimum temperature, phenophases, temperature sensitivity, rice, heat stress, sowing date, rainfall sensitivity, crop-weather relationship, humid subtropics, climate-smart agriculture

1. Introduction

Rice (*Oryza sativa* L.) is the world's most critical staple food crop, sustaining more than half of the global population and supplying over 21% of daily caloric intake worldwide [1]. Global rice demand is projected to rise by approximately 35% by 2035, driven by population growth and shifting dietary preferences [2]. Yet the capacity to meet this demand is increasingly threatened by climate change. Between 2022 and 2023, global rice production declined by an estimated 300, 000 tonnes compared to the preceding year, with major producing countries recording significant yield losses attributable to climatic disruptions [3]. Global mean surface temperatures have already risen by approximately 1.1 °C above pre-industrial levels and projections suggest a further increase of 1.5-4.8 °C by 2100, with the frequency and intensity of heat extremes increasing disproportionately in major rice-growing regions of South and Southeast Asia [4].

Temperature is one of the most dominant abiotic factors governing rice growth, development and yield formation. Each 1 °C increase in global mean temperature is projected to reduce rice yield by approximately 3.2% globally and by up to 5.2% per °C as measured in field warming experiments [5]. In India alone, the world's second-largest rice producer, climate-driven yield losses prompted a nationwide rice export ban in 2023, causing international prices to rise by ~20% and amplifying food security concerns across import-dependent nations [4, 6]. Temperature sensitivity of rice is not uniform across its life cycle.

The vegetative stage benefits from moderate warmth (optimal temperature ~28-30 °C) for canopy development and dry matter accumulation, while reproductive stages — panicle initiation, flowering and grain filling — are far more vulnerable to temperature extremes [7]. At the flowering stage, exposure to temperatures above 33-35 °C for even one to two hours during anthesis triggers irreversible spikelet sterility through pollen desiccation, impaired anther dehiscence and disrupted fertilisation [8]. During grain filling, temperatures exceeding 26-27 °C shorten the grain-filling duration, reduce starch biosynthesis rates and lower 1,000-grain weight, collectively compressing final yield [9, 10].

(10) (10) demonstrated that growing-season temperature is a key statistical predictor of inter-annual yield variability in major cereals, explaining 30% or more of year-to-year fluctuations in global average yields. Subsequent work has refined this understanding by showing that crop yield responses to temperature are highly stage-specific: the same degree of warming can be neutral or even beneficial during early vegetative growth but catastrophic during the reproductive window [4, 8]. This body of literature largely emerged from temperate, irrigated, or controlled-environment systems and their direct applicability to rainfed humid subtropical ecosystems of South Asia, where erratic monsoon timing superimposes moisture stress on already challenging thermal regimes, remains poorly characterised. Adjusting sowing dates is widely recognised as one of the most accessible and low-cost agronomic strategies to synchronise crop phenology with favourable thermal and moisture windows, thereby buffering the impact of climate variability on yield [11]. In the Eastern Indo-Gangetic Plain (EIGP) of India, a region encompassing the humid subtropical states of Jharkhand, Bihar and Odisha, sowing date decisions are closely intertwined with the onset and cessation of the south-west monsoon, which delivers ~85% of the annual rainfall in the June-September window. Early sowings risk exposing the crop to pre-monsoon heat build-up during establishment, while late sowings may push grain filling into cooler, drier post-monsoon conditions that limit productivity [12].

Despite the agronomic importance of this region, long-term empirical evidence quantifying how sowing date modulates phenophase-specific temperature sensitivity across multiple rice varieties under field conditions remains limited. Most crop-weather studies from India have either been conducted at a single location and season [7], relied on simulation modelling without multi-year field validation [11], or focused on temperature thresholds for spikelet sterility without resolving the continuous sensitivity coefficient across the full crop cycle [4]. Similarly, the role of phenophase-specific rainfall beyond total seasonal accumulation in shaping yield outcomes has received scant attention at the variety × sowing date level in humid subtropical settings [6, 13].

A key knowledge gap exists across three dimensions: how temperature and rainfall effects vary by individual growth stage rather than the whole season; how the direction and strength of sensitivity shifts with sowing date; and whether commercially grown varieties differ in their thermal and moisture responses. No multi-year, multi-variety field study has addressed all three together under humid subtropical conditions of eastern India.

Therefore, this study quantifies phenophase-specific temperature and rainfall sensitivity of rice grain yield across

varieties and sowing dates, with three specific objectives: (i) to estimate stage-wise optimum temperatures (T_{opt}) using quadratic regression; (ii) to identify the most temperature-sensitive phenophase and quantify the sensitivity coefficient (S , $\text{kg ha}^{-1} \text{ } ^\circ\text{C}^{-1}$); and (iii) to assess phenophase-specific rainfall-yield relationships to identify moisture-critical growth windows.

The study makes four novel contributions: it provides the first multi-year, field-based characterisation of stage-resolved thermal sensitivity across three varieties in the humid subtropical eastern Indo-Gangetic Plain; it documents a sowing-date-driven directional shift in sensitivity from negative under early sowing to positive under mid-to-late sowing, not previously reported at this resolution in India; it identifies flowering-milking as the most rainfall-critical stage, offering actionable targets for irrigation management; and it generates robust, biologically consistent estimates to support climate-smart cultivar recommendations, sowing calendar optimisation and crop model parameterisation under projected warming.

2. Materials and Methods

2.1. Experimental Site, Design and Crop Management

Field experiments were conducted at Birsa Agricultural University, Ranchi, Jharkhand, India (23.17°N, 85.19°E; 625 m msl) under humid subtropical climatic conditions across eight consecutive cropping seasons from 2017 to 2024. A factorial randomised block design (FRBD) with three replications was adopted to evaluate three rice (*Oryza sativa* L.) varieties viz. Sahbhagi Dhan, Naveen and MTU1010 sown under three sowing dates: D1 (05 June), D2 (15 June) and D3 (25 June). Daily meteorological data comprising maximum temperature (T_{max}), minimum temperature (T_{min}) and rainfall (mm) were systematically recorded across five key phenological stages: panicle initiation, 50% flowering, milking, grain filling and physiological maturity.

2.2. Computation of Mean Temperature

For each phenological stage, the mean temperature (T_{mean} ; °C) was computed as the arithmetic mean of daily maximum (T_{max} ; °C) and minimum (T_{min} ; °C) temperatures, following the standard procedure widely adopted in crop-weather analysis [14, 15]:

$$T_{mean} = (T_{max} + T_{min}) / 2 \quad (1)$$

where T_{mean} is the phenophase-specific mean temperature (°C), T_{max} is the daily maximum temperature (°C) and T_{min} is the daily minimum temperature (°C). This widely used metric effectively characterises the thermal environment experienced by the crop during each developmental stage.

2.3. Estimation of Optimum Temperature

The optimum temperature (T_{opt} ; °C) for grain yield at each phenological stage was estimated by fitting a quadratic polynomial regression of grain yield (Y ; kg ha^{-1}) on phenophase mean temperature (T ; °C) for each variety × sowing date combination [10, 14, 15]:

$$Y = \beta_0 + \beta_1 \cdot T + \beta_2 \cdot T^2 + \varepsilon \quad (2)$$

where Y is the grain yield (kg ha^{-1}); T is the phenophase mean temperature ($^{\circ}\text{C}$); β_0 is the intercept; β_1 and β_2 are the linear and quadratic regression coefficients, respectively; and ε is the random error term. The T_{opt} was derived analytically by differentiating Equation [2] with respect to T and equating the first derivative to zero:

$$T_{\text{opt}} = -\beta_1 / (2 \cdot \beta_2) \quad (3)$$

To be biologically valid, a T_{opt} estimate must meet two conditions: (i) $\beta_2 < 0$, confirming a concave-downward parabola indicating a genuine yield maximum and (ii) T_{opt} fell within the observed range of Tmean for that specific phenophase-sowing date combination, preventing extrapolation beyond the measured thermal domain. When these parameters were not met because of limited inter-annual thermal variation across the eight-year observational record, the empirical T_{opt} was reported as the observed Tmean that corresponded to the maximum grain production in that combination [10].

2.4. Phenophase-Specific Temperature Sensitivity of Grain Yield

The sensitivity of grain yield to phenophase-specific temperature was quantified by estimating the slope coefficient from a simple ordinary least-squares (OLS) linear regression of grain yield (Y; kg ha^{-1}) on phenophase mean temperature (T; $^{\circ}\text{C}$) for each variety $\times$ sowing date combination [10, 16].

$$Y = \alpha + S \cdot T + \varepsilon \quad (3)$$

where Y is the grain yield (kg ha^{-1}); T is the phenophase mean temperature ($^{\circ}\text{C}$); α is the regression intercept (kg ha^{-1}); S is the temperature sensitivity coefficient ($\text{kg ha}^{-1} ^{\circ}\text{C}^{-1}$), representing the change in grain yield per unit increase of 1 $^{\circ}\text{C}$ in mean temperature; and ε is the residual error term. A negative S indicates a yield penalty (heat stress) per unit warming, while a positive S shows a yield advantage as temperature rises. Regression slopes were classified as Very High = $|S| > 200$; High = $|S| 100\text{--}200$; Moderate = $|S| 50\text{--}100 \text{ kg ha}^{-1} ^{\circ}\text{C}^{-1}$ [17]. The phenophase exhibiting the maximum absolute sensitivity value ($|S|_{\text{max}}$) was identified as the most temperature-sensitive developmental stage for each variety $\times$ sowing date combination.

Relative sensitivity (S_{rel}) was calculated as:

$$S_{\text{rel}} = (S / \text{mean yield}) \times 100 (\% ^{\circ}\text{C}^{-1}) \quad (5)$$

where S = temperature sensitivity coefficient ($\text{kg ha}^{-1} ^{\circ}\text{C}^{-1}$). Model fit was assessed using the coefficient of determination (R^2), calculated as [18]:

$$R^2 = 1 - (SS_{\text{res}} / SS_{\text{tot}}) \quad (6)$$

where $SS_{\text{res}} = \sum (Y_i - \hat{Y}_i)^2$ is the residual sum of squares and $SS_{\text{tot}} = \sum (Y_i - \bar{Y})^2$ is the total sum of squares. The student's t-test was used to determine statistical significance at $p < 0.05$, $p < 0.01$ and $p < 0.001$. Given the eight-year observational record ($n = 8$ per sowing group; degrees of freedom = 6), statistical power was naturally limited. As a result, temperature sensitivity was predominantly evaluated using the magnitude ($|S|$) and

direction of regression slopes, as well as their biological consistency across varieties and sowing dates, as recommended by (10) (10) and Rezaei *et al.* (2015) [16].

2.5. Effect of Rainfall on Grain Yield

The relationship between cumulative seasonal rainfall and grain yield was quantified for each variety $\times$ sowing date combination using the Pearson correlation coefficient (r) and OLS linear regression. Total seasonal rainfall ($\text{Rain}_{\text{Total}}$; mm) was computed as the cumulative sum of rainfall recorded across all five phenological stages:

$$\text{Rain}_{\text{Total}} = \text{Rain}_{\text{S-Veg}} + \text{Rain}_{\text{Veg-Flow}} + \text{Rain}_{\text{Flow-Milk}} + \text{Rain}_{\text{Milk-GFill}} + \text{Rain}_{\text{GFill-Mat}} \quad (7)$$

where $\text{Rain}_{\text{S-Veg}}$, $\text{Rain}_{\text{Veg-Flow}}$, $\text{Rain}_{\text{Flow-Milk}}$, $\text{Rain}_{\text{Milk-GFill}}$ and $\text{Rain}_{\text{GFill-Mat}}$ represent cumulative rainfall (mm) during the sowing-vegetative, vegetative-flowering, flowering-milking, milking-grain filling and grain filling-maturity stages, respectively.

Phenophase-wise rainfall sensitivity was assessed by computing the standardised OLS regression coefficient (β ; dimensionless) of grain yield on phenophase-specific rainfall for each variety $\times$ sowing date combination, following the elasticity-based sensitivity framework of Lobell and Burke (2010) [19] as adapted by Deb *et al.* (2023) [20].

$$\beta = (dY/SDY) / (dR/SDR) \quad (8)$$

where dY and dR are the changes in yield and rainfall, respectively and SDY and SDR are their standard deviations. Both variables were standardised to zero mean and unit variance prior to regression, enabling direct comparison of sensitivity magnitude across phenophases with differing rainfall scales. A positive β indicates a yield benefit from phase rainfall, while a negative β denotes a yield penalty. Model fit was assessed using R^2 and statistical significance was tested at $p < 0.05$, $p < 0.01$ and $p < 0.001$ using the student's t-test. Given the eight-year record ($n = 8$; $\text{df} = 6$), biological consistency of the direction and magnitude of β across varieties and sowing dates was prioritised over formal significance thresholds, as recommended by (10) (10) and Rezaei *et al.* (2015) [16]. All analyses were performed in R (version 4.5.1) using the `lm()` function and visualisations were produced with `ggplot2`.

3. Results

3.1. Optimum Temperature and Grain Yield under Optimal Sowing Dates

The stage-wise optimum temperatures (T_{opt}) and corresponding mean grain yields for each variety under their respective optimum sowing dates are listed in Table 1. Naveen sown on D2 (15 June) achieved the highest mean grain yield ($4,610.5 \text{ kg ha}^{-1}$), with T_{opt} ranging from $24.95 ^{\circ}\text{C}$ at grain filling-maturity (GM) to $28.40 ^{\circ}\text{C}$ at flowering-milking (FM). MTU1010 under D3 (25 June) recorded $4,155.8 \text{ kg ha}^{-1}$, with T_{opt} declining from $27.40 ^{\circ}\text{C}$ at sowing-vegetative (SV) to $24.65 ^{\circ}\text{C}$ at GM. Sahbhagi Dhan under D1 (05 June) produced the lowest yield ($3,892.1 \text{ kg ha}^{-1}$), with T_{opt} ranging from $25.35 ^{\circ}\text{C}$ (GM) to $28.03 ^{\circ}\text{C}$ (MG). Across all varieties, T_{opt} was consistently highest during FM and MG ($26.03\text{--}28.40 ^{\circ}\text{C}$) and lowest at GM ($24.65\text{--}25.35 ^{\circ}\text{C}$).

3.2. Phenophase-Specific Temperature Sensitivity of Grain Yield

The most temperature-sensitive phenological intervals and their corresponding absolute (S , $\text{kg ha}^{-1} \text{ }^{\circ}\text{C}^{-1}$) and relative (S_{rel} , $\% \text{ }^{\circ}\text{C}^{-1}$) sensitivity coefficients are summarised in Table 2 and illustrated in Fig. 1.

Under D1 (05 June), Sahbhagi Dhan and Naveen exhibited very high negative sensitivity at sowing-vegetative, with S values of -334.71 and $-497.33 \text{ kg ha}^{-1} \text{ }^{\circ}\text{C}^{-1}$ and S_{rel} of -8.60% and $-11.32\% \text{ }^{\circ}\text{C}^{-1}$ respectively. MTU1010 showed a different response as its peak sensitive phenophase under D1 was milking-grain filling, with a positive coefficient ($S = +431.94 \text{ kg ha}^{-1} \text{ }^{\circ}\text{C}^{-1}$; $S_{\text{rel}} = +11.60\% \text{ }^{\circ}\text{C}^{-1}$), highlighting variety-level divergence in thermal response under the same sowing window.

Under D2 (15 June), the vegetative-flowering interval was the most sensitive stage for Sahbhagi Dhan and Naveen, with positive S values of $+377.23$ and $+357.06 \text{ kg ha}^{-1} \text{ }^{\circ}\text{C}^{-1}$ and S_{rel} of $+9.74\%$ and $+7.74\% \text{ }^{\circ}\text{C}^{-1}$ respectively. MTU1010 under D2 showed a positive moderate response at flowering-milking ($S = +164.77 \text{ kg ha}^{-1} \text{ }^{\circ}\text{C}^{-1}$; $S_{\text{rel}} = +4.17\% \text{ }^{\circ}\text{C}^{-1}$).

Under D3 (25 June), Sahbhagi Dhan and Naveen recorded peak positive sensitivity at flowering-milking ($S = +380.71$ and $+191.96 \text{ kg ha}^{-1} \text{ }^{\circ}\text{C}^{-1}$; $S_{\text{rel}} = +9.92\%$ and $+4.45\% \text{ }^{\circ}\text{C}^{-1}$), while MTU1010 showed maximum negative sensitivity at sowing-vegetative ($S = -281.17 \text{ kg ha}^{-1} \text{ }^{\circ}\text{C}^{-1}$; $S_{\text{rel}} = -6.77\% \text{ }^{\circ}\text{C}^{-1}$). The wide S_{rel} range across all combinations (-11.32% to $+9.92\% \text{ }^{\circ}\text{C}^{-1}$) reflects strong sowing-date mediation of thermal impact on yield.

3.3. Effect of Seasonal Rainfall on Grain Yield

Seasonal rainfall ranged from 781 mm to 1797 mm across years and sowing dates, yet total accumulation did not linearly govern yield outcomes, rainfall timing across phenophases proved far more decisive. The standardised sensitivity index (β) heatmap (Fig. 2) and phenophase-wise summary (Table 3) consistently show that reproductive stages were the most rainfall-sensitive across all varieties and sowing windows.

Under D1 (05 June), milking-grain filling was the most sensitive phenophase for all three varieties, with Naveen recording the strongest negative response ($\beta = -0.65$), followed by Sahbhagi Dhan ($\beta = -0.49$) and MTU1010 ($\beta = -0.43$). Flowering-milking showed similarly strong negative sensitivity ($\beta = -0.59, -0.46$ and -0.40 for Naveen, Sahbhagi Dhan and MTU1010, respectively). It is indicating that excess rainfall across consecutive reproductive stages consistently depressed yield, likely through lodging, poor pollination and disease pressure. Early-season rainfall showed a slight positive association ($\beta = +0.10$ to $+0.18$), while vegetative-flowering remained negligible.

D2 (15 June) showed the most dampened sensitivity profile. Reproductive stage penalties persisted but were considerably weaker. Flowering-milking β ranged from -0.22 to -0.32 and milking-grain filling from -0.08 to -0.24 , making D2 the most stable sowing window against rainfall-driven yield variability.

Under D3 (25 June), a clear sign reversal emerged at grain filling-maturity, where all varieties recorded positive β values (Naveen: $+0.57$; Sahbhagi Dhan and MTU1010: $+0.53$), reflecting supplementary benefit of residual post-monsoon rainfall during terminal grain development. Despite this, mid-season stages remained strongly negative.

Milking-grain filling reached $\beta = -0.51, -0.46$ and -0.38 and flowering-milking $\beta = -0.38, -0.35$ and -0.30 for Sahbhagi Dhan, MTU1010 and Naveen, respectively, confirming that the reproductive stage rainfall penalty is a cross-variety phenomenon independent of sowing date. Among all combinations, Naveen under D1 returned the highest R^2 for milking-grain filling ($R^2 = 0.424$), indicating rainfall variability in this phase alone explained $\sim 42\%$ of inter-annual yield variation, which is the strongest single-phase moisture control in the dataset (Table 3). Although none of the β values attained formal significance (all $p > 0.05$), the directional consistency across varieties and sowing dates provides strong biological evidence that phenophase-specific rainfall timing, not seasonal totals, drives yield variability in this system.

4. Discussion

Topt was phenophase-specific and variety-dependent, peaking at $28.40 \text{ }^{\circ}\text{C}$ during flowering-milking in Naveen/D2 and declining toward maturity ($24.65\text{--}25.35 \text{ }^{\circ}\text{C}$) across all varieties. This is consistent with known thermal sensitivity of carbohydrate accumulation during grain filling [9] and reproductive impairment above $33 \text{ }^{\circ}\text{C}$ [8].

The most prominent finding was the sowing-date-driven directional reversal of temperature sensitivity. Under D1, Sahbhagi Dhan and Naveen showed very high negative sensitivity at sowing-vegetative ($S_{\text{rel}} = -8.60\%$ to $-11.32\% \text{ }^{\circ}\text{C}^{-1}$), which is 2.7 to 3.5-fold larger than the global rice warming penalty of $-3.2\% \text{ }^{\circ}\text{C}^{-1}$ [5]. It is reflecting pre-monsoon heat stress suppressing early establishment. MTU1010 diverged markedly, showing peak positive sensitivity at milking-grain filling ($S = +431.94 \text{ kg ha}^{-1} \text{ }^{\circ}\text{C}^{-1}$; $S_{\text{rel}} = +11.60\% \text{ }^{\circ}\text{C}^{-1}$), suggesting this variety may possess relatively greater early-season heat tolerance, possibly through deeper root architecture or stronger osmotic adjustment, while remaining thermally responsive during later grain development. Though physiological characterisation studies would be needed to confirm this mechanism. This variety-level divergence under the same sowing window cautions against applying uniform thermal response assumptions across varieties in climate adaptation planning.

Under D2 and D3, sensitivity shifted to strongly positive at vegetative-flowering and flowering-milking ($S_{\text{rel}} = +4.17\%$ to $+9.92\% \text{ }^{\circ}\text{C}^{-1}$), suggesting moderate warming during reproductive development remains within beneficial thresholds below the critical spikelet sterility temperature of $35 \text{ }^{\circ}\text{C}$ [21]. This directional shift is largely absent from global meta-analyses that report uniformly negative warming responses [4, 23] and the wide S_{rel} range (-11.32% to $+9.92\% \text{ }^{\circ}\text{C}^{-1}$) confirms that a single global sensitivity estimate cannot capture stage- and sowing-specific variability. Modest R^2 values ($0.043\text{--}0.210$) further indicate that temperature explains only a fraction of inter-annual yield variability, with other factors such as rainfall distribution and solar radiation contributing substantially.

Rainfall timing governed yield outcomes more decisively than total seasonal accumulation, consistent with findings from Indian monsoon rice systems [6, 13]. Under D1, milking-grain filling exerted the strongest negative rainfall influence across all varieties ($\beta = -0.49$ to -0.65), with Naveen showing the highest explained variance ($R^2 = 0.424$) moisture variability in this single phase accounted for over 40% of inter-annual yield fluctuation. Excess rainfall during

consecutive reproductive stages likely intensified disease pressure, caused physical lodging and impaired pollination [22]. D2 showed the most checked and balanced rainfall sensitivity profile across all phenophases, reinforcing its status as the most climate-stable sowing option with direct implications for irrigation scheduling. Under D3, a positive reversal at grain filling-maturity ($\beta = +0.53$ to $+0.57$) reflects supplementary benefit of residual post-monsoon rainfall during terminal grain development when monsoon withdrawal otherwise limits moisture availability. That mid-season reproductive stages remained strongly negative even under D3 confirms the rainfall penalty during these phases

is a cross-variety phenomenon independent of sowing date. Overall, Naveen/D2 emerged as the most productive combination, with higher reproductive-stage T_{opt} indicating greater heat buffering capacity. The convergence of both thermal and rainfall sensitivity analyses on D2 dampened negative thermal sensitivity, moderate and balanced rainfall penalties and avoidance of both pre-monsoon heat stress and mid-season waterlogging risk. It makes mid-June sowing the most robust adaptation recommendation under current and near-future climate conditions in this region, consistent with broader Indo-Gangetic Plain policy guidance [11, 24].

Table 1: Stage-wise optimum temperature (T_{opt} , °C) and mean grain yield of rice varieties under optimum sowing dates

Variety	Optimum Sowing Date	Mean Yield (kg ha ⁻¹)	Topt (°C)				
			SV	VF	FM	MG	GM
Sahbhagi Dhan	D1 (June 05)	3892.1	26.39	26.50	27.00	28.03	25.35
Naveen	D2 (June 15)	4610.5	27.75	28.30	28.40	26.25	24.95
MTU1010	D3 (June 25)	4155.8	27.40	26.30	26.03	25.70	24.65

SV = Sowing-Vegetative; VF = Vegetative-Flowering; FM = Flowering-Milking; MG = Milking-Grain Filling; GM = Grain Filling-Maturity.

Table 2: Most temperature-sensitive phenological interval, absolute sensitivity coefficient (S, kg ha⁻¹ °C⁻¹), relative sensitivity (Srel, % °C⁻¹) and R² for rice varieties across sowing dates

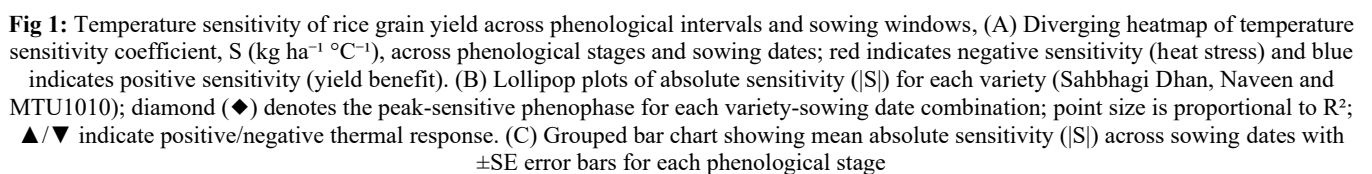
Variety	Sowing Date	Most Sensitive Phenophase	S (kg ha ⁻¹ °C ⁻¹)	Srel (% °C ⁻¹)	R ²	Direction	Magnitude
Sahbhagi Dhan	D1 (June 05)	Sowing-Vegetative	-334.71	-8.60	0.106	Negative	Very High
Sahbhagi Dhan	D2 (June 15)	Vegetative-Flowering	+377.23	+9.74	0.145	Positive	Very High
Sahbhagi Dhan	D3 (June 25)	Flowering-Milking	+380.71	+9.92	0.177	Positive	Very High
Naveen	D1 (June 05)	Sowing-Vegetative	-497.33	-11.32	0.210	Negative	Very High
Naveen	D2 (June 15)	Vegetative-Flowering	+357.06	+7.74	0.083	Positive	Very High
Naveen	D3 (June 25)	Flowering-Milking	+191.96	+4.45	0.043	Positive	High
MTU1010	D1 (June 05)	Milking-Grain Filling	+431.94	+11.60	0.197	Positive	Very High
MTU1010	D2 (June 15)	Flowering-Milking	+164.77	+4.17	0.053	Positive	High
MTU1010	D3 (June 25)	Sowing-Vegetative	-281.17	-6.77	0.102	Negative	Very High

S = absolute temperature sensitivity coefficient (kg ha⁻¹ °C⁻¹); Srel = relative sensitivity = (S / mean yield) × 100 (% °C⁻¹). Magnitude: Very High = |S| > 200; High = |S| 100-200; Moderate = |S| 50-100 kg ha⁻¹ °C⁻¹. Srel enables direct comparison with global meta-analyses (e.g. Zhao *et al.*, 2017: -3.2% °C⁻¹; Gallé & Katzenberger, 2024).

Table 3: Most rainfall-sensitive phenophase, sensitivity index (SI) and coefficient of determination (R²) of rice varieties under different sowing dates

Sowing Date	Variety	Most Sensitive Phenophase	SI	R ²
D1 (June 05)	Sahbhagi Dhan	Milking-Grain Filling	-0.492	0.242
	Naveen	Milking-Grain Filling	-0.651	0.424
	MTU1010	Milking-Grain Filling	-0.428	0.183
D2 (June 15)	Sahbhagi Dhan	Sowing-Vegetative	0.306	0.093
	Naveen	Flowering-Milking	-0.322	0.104
	MTU1010	Flowering-Milking	-0.263	0.069
D3 (June 25)	Sahbhagi Dhan	Grain Filling-Maturity	0.525	0.276
	Naveen	Grain Filling-Maturity	0.567	0.321
	MTU1010	Grain Filling-Maturity	0.534	0.285

SI = Rainfall sensitivity index; R² = Coefficient of determination.



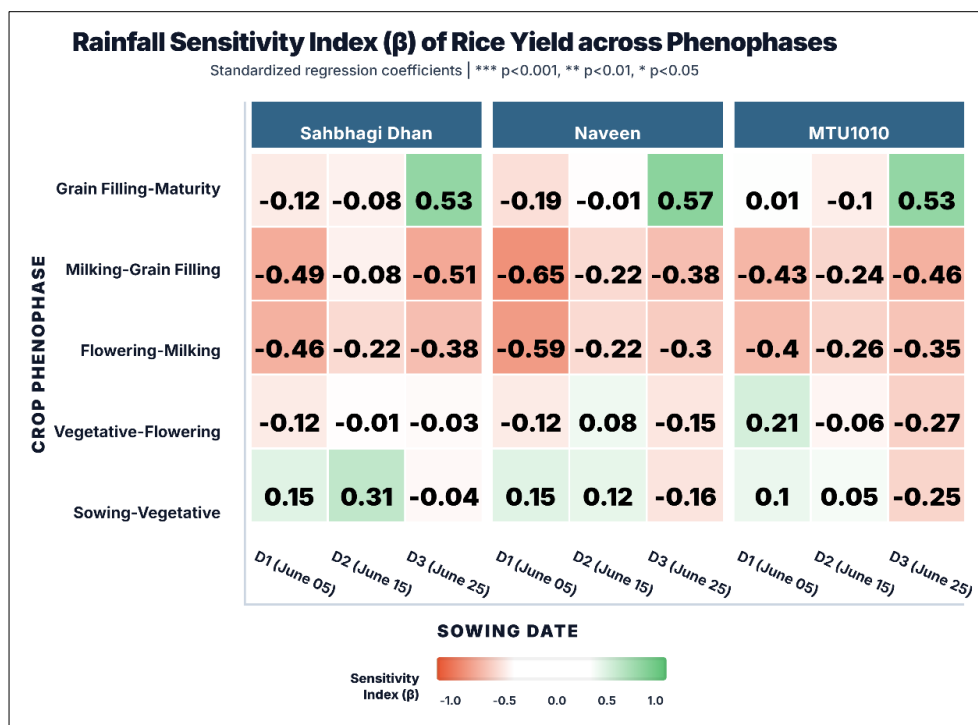


Fig 2: Standardised rainfall sensitivity index (β) of grain yield across phenophases, varieties and sowing dates

5. Conclusion

Thermal and rainfall sensitivity of rice grain yield are not fixed varietal traits but dynamic outcomes governed jointly by phenological stage and sowing window. Both the direction and the peak stage of temperature sensitivity shifted systematically across sowing dates from strongly negative during early-season establishment under June 5 sowing to strongly positive at reproductive stages under mid- and late-June sowing at a magnitude two to three times larger than the global rice warming benchmark. MTU1010's divergent thermal profile further confirms that variety-level responses cannot be generalised. Equally, reproductive-stage rainfall proved more decisive for yield than seasonal totals, with excess moisture during milking and grain filling consistently penalising yield regardless of sowing date. The convergence of dampened thermal and rainfall sensitivity under mid-June sowing (D2), with Naveen as the best-performing variety, identifies this combination as the most climate-resilient option for Kharif rice in the humid subtropical Ranchi region.

The stage-specific sensitivity coefficients generated here provide a quantitative foundation for crop model parameterisation and climate-smart sowing calendar design. Future research should determine critical rainfall thresholds at reproductive stages, elucidate the physiological basis of variety-level divergence in thermal response, and evaluate the stability of these sensitivity profiles under projected monsoon intensification.

6. Author Contributions

Satya Pragyan Kar: Conceptualization, Data collection, Formal analysis, Investigation, Methodology, Visualization, Lab work, Writing - Original Draft.

Dr. Pragyan Kumari: Resources, Software, Supervision, Review & Editing.

Dr. Ramesh Kumar: Supervision, Investigation

Dr. C. S. Singh: Validation, Writing - Review & Editing, Data curation.

Dr. P. Mahapatra: Validation, Writing - Review & Editing, Data curation.

All authors reviewed and approved the final manuscript.

7. Acknowledgements

The authors express their sincere gratitude to the Department of Agricultural Meteorology, Birsa Agricultural University, Kanke, Ranchi, for providing necessary research facilities, software support and technical assistance. The authors also acknowledge the support of the All India Coordinated Research Project on Agrometeorology (AICRPAM) under which the experiment was conducted.

8. Funding

This research was financially supported by the All India Coordinated Research Project on Agrometeorology (AICRPAM). The study was conducted as part of the ongoing research programme under this project.

9. Competing Interests

The authors declare no competing interests.

10. Data Availability

All data supporting the findings of this study are included within the article.

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