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ARTICLE

Water and air temperature impacts on rice (*Oryza sativa*) phenology

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Abstract

Air temperature (T_a) is commonly used for modeling rice phenology. However, since the growing point of rice is under water during the vegetative and the early part of the reproductive period, water temperature (T_w) is likely to have a greater influence on crop developmental rates than T_a during this period. To test this hypothesis, we monitored T_w, T_a, and crop phenology in three commercial irrigated rice fields in California, USA. Sampling locations were set up on along a transect from the water inlet into the field. (Water warms up as it moves into the field.) T_a averaged 22.7 °C across sampling locations within each field, but average seasonal T_w increased from 22 °C near the inlet to 23.4 °C furthest away from the inlet. Relative to T_w furthest from the inlet, low T_w near the inlet delayed time to panicle initiation (PI 5 days) and heading (HD 8 days) and the appearance of one yellow hull on the main stem panicle (R7 9 days). Using T_w instead of T_a when the active growing point is under water until booting (midway between PI and HD) in a thermal time model improved accuracy (root-mean-square error, RMSE) for predicting time to PI by 2.5 days and HD by 1.6 days and R7 by 1.8 days. This model was further validated under more typical field conditions (i.e., not close to cold water inlets) in six locations in California. Under these conditions, average T_w was 2.6 °C higher than T_a between planting and booting, primarily due to higher daily maximum T_w values. Using T_w in the model until booting improved RMSE by 1.2 days in predicting time to HD. Using T_w instead of T_a during this period could improve the accuracy of rice phenology models.

Keywords Rice · Water temperature · Developmental rate · Phenology · Crop models

Introduction

Temperature is the primary environmental factor affecting crop development (Gao et al. 1992; Yin et al. 1996), although some crops (or varieties) are also sensitive to photoperiod (Yin et al. 1997; Yin and Kropff 1998). Rice is typically grown under flooded field conditions, and water temperature (T_w) has been shown to affect plant developmental rate (Roel et al. 2005; Shimono et al. 2007a), leaf photosynthesis (Shimono et al. 2004; Kuwagata et al. 2008), growth rate (Shimono et al. 2002), spikelet sterility (Satake et al. 1988; Shimono et al. 2007b), and yield (Roel et al. 2005). In terms of developmental rate, since the shoot apex (where different organs are formed) is located under water during much of the growing season, initial development is likely to be more affected by water temperature (T_w) than by air temperature (T_a) (Satake et al. 1988; Confalonieri et al. 2005). After the panicle has differentiated at the base of the shoot, its position rises due to internode elongation, and roughly midway between panicle initiation and heading (i.e., booting stage), the panicle rises above the water surface at which point the growing point is more influenced by T_a rather than T_w (Shimono et al. 2005).

The difference between T_w and T_a can be particularly pronounced in temperate climates, where T_w is generally higher than T_a before canopy closure due to heating from incident solar radiation (Shimono et al. 2002, 2005). In northern Japan, Tanaka (1962) reported that early season minimum T_w was 5 °C higher than minimum T_a and that maximum T_w was 10 °C higher than maximum T_a. The difference between T_w and T_a is less after canopy closure when most of the solar radiation is intercepted by the leaves. Sameshima (2004) studied the developmental stages of rice grown in the field over several years in northern Japan and showed that the variation in the

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developmental stages among years could not be explained well with T_a, and suggested that this might be due to the difference in solar radiation among years affecting the relationship between T_w and T_a.

Phenology models are important components of crop growth models (Zhang and Tao 2013; Espe et al. 2016a) that have been widely used for evaluating crop responses to climate change (Mall and Aggarwal 2002; Yao et al. 2007; Wang et al. 2014), ecosystem productivity (White et al. 2009), yield gaps (van Ittersum et al. 2013; van Wart et al. 2013; Espe et al. 2016b), field management options (Awan et al. 2014), and to estimate the benefit of technological change (Hijmans et al. 2003). In phenology models, the rate of crop development for photoperiod insensitive varieties is typically modeled as a response to thermal time accumulation (Gao et al. 1987; Sharifi et al. 2017). Common rice models such as Oryza2000 (Bouman and van Laar 2006) and CERES-Rice (Alocilja and Ritchie 1991; Jones et al. 2003) use T_a to compute thermal time accumulation. Given the importance of T_w, it has been proposed to use it as an environmental variable in rice phenology models (Confalonieri et al. 2005; Shimono et al. 2007a), but this is not a common practice.

Our objective was to evaluate the use of T_w and T_a on prediction accuracy of a rice phenology model. We hypothesized that since the growing point of rice is under water for the vegetative and the early part of the reproductive period, water temperature (T_w) will have a greater influence on crop developmental rates than T_a during this period. This hypothesis was tested using field data from nine locations and a rice phenology model.

Materials and methods

Field experiments

Two sets of field trials were used to evaluate the effect of T_a and T_w on rice phenology. The first was a cold water gradient study conducted in 2014 to directly analyze the effect of T_a and T_w on crop development and develop a model to account for the effects of both T_a and T_w. The second set of field trials was part of the University of California Cooperative Extension (UCCE) variety trials conducted in six locations, where T_a, T_w, and 50% heading date were recorded. Data from this trial were used to validate the model developed from the cold water gradient study. The variety M-206 was used in all studies. M-206 is not photoperiod sensitive and is a medium grain temperate *japonica* variety that is planted in approximately 50% of California rice fields (Espe et al. 2016a).

Cold water gradient study

A cold water gradient study was conducted in three fields in Butte County, California, in 2014. In many fields in this county, the T_w of the irrigation water at the field inlet is relatively low (Roel et al. 2005), between 2 and 3 °C (Table 1), and the water warms up as it moves into the field due to solar radiation; thus, the cold water area is typically restricted to a few ha near the inlet. This condition allows for an analysis of the effects of T_w on crop phenology under conditions where everything else (i.e., T_a, crop management) is the same. In each field, we identified five sampling locations (L1–L5) along a transect moving away from the inlet (L1 being near the inlet and having the lowest T_w and L5 being furthest from inlet and having the highest T_w). The distance between these locations varied between fields but averaged about 20 m. Throughout the season, T_w was measured in all locations, while T_a was measured only in L1 and L5 locations. HOBO 2x External Temperature data loggers (Onset; http://www.onsetcomp.com/products/data-loggers/u23-003) were set up before the fields were flooded and recorded the temperature every hour. The T_w sensors were placed 3 cm above the soil surface and the T_a sensors 120 cm above the soil surface and were enclosed in a HOBO Solar Radiation Shield Mounting-RS3 (Onset; http://www.onsetcomp.com/products/mounting/rs3). The fields were all water seeded as is typical for California, in which the field is first flooded and then seeded by airplane. The fields remained flooded throughout the season until about 3 weeks before harvest when the fields were drained in preparation for harvest. In order to maintain the floodwater height in the field, water continually flowed into the field except for brief periods when the floodwater in the field needed to be lowered for some reason (e.g., herbicide applications).

In all fields and locations, the rice growth staging system described by Counce et al. (2000) was used to identify three developmental stages: panicle initiation (PI or R0), 50% heading (HD or R3), and the appearance of one yellow hull on the main stem panicle (R7). Crop growth stage data were collected every 2 days during the periods of interest. PI was defined as when a dark green circle (i.e., "*green ring*") formed below the last initiated leaves of the culm and initiated panicle. HD was defined as the time when 50% of the panicles were fully exerted, which occurs 1–3 days before flowering (R4) in rice (De Datta 1981; Counce et al. 2015). Counce et al. (2000) indicated that physiological maturity occurs between R7 and R8 (when one brown hull appears on the main stem panicle); however, for this study, we measured R7 (based on our observation R7 is about 2 weeks before physiological maturity) as a proxy for physiological maturity because it was more objectively identifiable than R8. The booting stage, which occurs between PI and HD, is also important for this study as that is the stage in which the

Table 1 Mean air (T_a) and water (T_w) temperatures for the three fields and locations in the 2014 cold water gradient study

Field	Location	Planting	T_a			T_w			Days to reach		
			PL-PI (°C)	PI-HD (°C)	HD-R7 (°C)	PL-PI (°C)	PI-HD (°C)	HD-R7 (°C)	PI (days)	HD (days)	R7[a] (days)
Cold water 1	L1	7 May	23.0	24.5	23.8	22.1	22.9	22.1	56	90	110
	L2		–	–	–	22.4	23.0	22.2	54	87	108
	L3		–	–	–	22.8	23.0	22.5	54	85	106
	L4		–	–	–	23.3	23.0	22.3	51	83	103
	L5		22.7	24.2	23.7	23.7	23.2	22.4	51	80	101
Cold water 2	L1	4 May	22.8	24.9	23.5	22.4	22.7	21.9	59	88	109
	L2		–	–	–	23.0	23.1	21.8	57	86	109
	L3		–	–	–	23.2	24.0	22.0	56	83	105
	L4		–	–	–	23.4	24.4	22.0	54	81	102
	L5		22.5	24.5	23.6	24.4	24.4	22.2	54	81	99
Cold water 3	L1	8 May	22.8	24.1	23.3	21.1	22.1	21.5	57	95	111
	L2		–	–	–	21.7	22.2	21.7	56	95	111
	L3		–	–	–	22.2	22.5	20.7	56	88	108
	L4		–	–	–	22.3	22.5	20.7	53	86	105
	L5		22.5	24.5	23.2	22.9	22.5	21.0	51	84	103

T_a was only measured for L1 and L5 locations. Temperature data are averaged across different growth stages: planting (PL), panicle initiation (PI), 50% heading (HD), and R7

[a]R7 is the growth stage marked by the appearance of one yellow hull on the main stem panicle. We used it as a proxy for physiological maturity; however, true physiological maturity occurs between R7 and R8

panicle which is sensitive to ambient temperature moves upward through the main stem and changes from being below to above the water line (Confalonieri et al. 2005).

Model development and simulations

Phenology model

The DD10 phenology model (Counce et al. 2015) calibrated by Sharifi et al. (2017) for California rice systems (hereafter DDCA) was used for phenology simulations. In DDCA, the developmental rate is modeled as a function of thermal time accumulation. A given amount of thermal time (°Cd) is required to reach a given developmental stage. The thermal time accumulated in each time step (in this case, $t = 1$ day) is calculated as follows:

$$\mathrm{TT}_t = \max(0, [0.5(T_{\max} + T_{\min}) - T_{\mathrm{b}}]) \tag{1}$$

$$T_{\min} = T_l \quad \text{if} \quad T_{\min} > T_{\mathrm{l}}$$

$$T_{\max} = T_{opt} \quad \text{if} \quad T_{\max} > T_{\mathrm{opt}}$$

where TT is the thermal time at time *t*, $T_{\max}$ is the daily maximum temperature, $T_{\min}$ is the daily minimum temperature, T_{b} is the base temperature, T_{l} is the lower threshold, and T_{opt} is the optimum threshold. Thus, there is no development if the daily average temperature is below T_{b}, and there is no increase in the development for daily maximum temperatures above $\mathrm{T_{opt}}$ or for daily minimum temperatures above $\mathrm{T_l}$.

Model temperature parameters: T_{a} versus T_{w}

Sharifi et al. (2017) calibrated and validated the DDCA for M-206 using T_{a}. The "cardinal temperatures" are $T_{\mathrm{b}} = 11.7$ °C, $T_{\mathrm{l}} = 13.1$ °C, and $T_{\mathrm{opt}} = 29.9$ °C, and a thermal time threshold of 454 °Cd is required to reach PI, 178 °Cd for PI to booting, 356 °Cd for PI to HD, and 203 °Cd for HD to R7. For the purposes of this model, we assumed the critical booting period (where the emerging panicle moves from below to above the water surface) occurred midway between PI and HD, that is 178 °Cd after PI.

Model simulations

Cold water gradient study

The effect of using T_{w}, T_{a}, or a combination of both on model performance was assessed using three modeling approaches (TA, TW, and TWA) and data from the cold water gradient study. In the TA model runs, thermal time was calculated using only T_{a}. This was the control treatment in our study as T_{a} is typically used in phenology models. We used the averaged T_{a} of L1 and L5 from each field as they did not differ, which was expected given that all locations in a field were within 100 m of each other. In the TW approach, T_{w} was used. For the TWA runs, the model was set to use T_{w} until booting stage (i.e., when the growing point is under water), 178 °Cd after PI, and T_{a} after that.

The prediction accuracy of each model was evaluated for the time to PI, HD, and R7 using the root-mean-square error (RMSE), which was calculated as:

$$\mathrm{RMSE} = \left[n^{-1} \sum (P - O)^2\right]^{0.5} \tag{2}$$

where n is the number of observations, P is the predicted duration (days), and O is the observed duration (days).

Validation field trials

The models developed using cold water gradient data (TA, TW, and TWA) were validated using data collected from separate field trials conducted under typical field conditions in 2015. Data were collected from the University of California Cooperative Extension (UCCE) variety field trials which were set up in six counties in the Sacramento Valley. Trials were set up as a randomized complete block design with four replicates. All varieties (we used only M-206) in these trials were water seeded with individual varieties being hand broadcast into defined plots (3 × 6 m). Planting dates were between April 27 and May 11. All fields were managed according to commercial practices. T_{a} and T_{w} were collected using the same instrumentation as described above for the cold water gradient fields; however, the only phenological data collected from these studies were HD. For the model runs, booting was set to 178 °Cd after PI, similar to cold water gradient study.

Results

Cold water gradient study

Temperature gradients and crop phenology

Across fields, the T_{a} of locations L1 and L5 was 22.9 and 22.6 °C, respectively (Table 1). Among fields, there was a little difference in mean T_{a}, while T_{w} was lowest in Field 3 and highest in Field 2. In all fields, T_{w} increased from L1 to L5 following the direction of the water moving into the field from the inlet (as expected). On average across fields, the L5 mean T_{w} was 1.8 °C higher than L1 between PL and PI and 0.8 °C from PI to HD. However, after HD T_{w} was similar for all locations (< 0.1 °C difference). Reflecting changes in T_{w}, the time to PI, HD, and R7 was delayed moving from L5 toward L1. Delay in development occurred primarily between PL and HD (Table 1).

Averaged across fields and relative to L5, PI was delayed by 5.6 days for L1, 4.6 days for L2, 2 days for L3, and 1.6 days for L4. Similarly, HD was delayed by 9 days for L1, 7.6 days for L2, 5.6 days for L3, and 1.6 days for L4. The delay in R7 was similar to the delay in HD.

Maximum and minimum T_w

Comparing the two extreme locations (L1 vs. L5) in all fields indicates that it was the maximum water temperature that led to higher mean T_w in the warmer T5 location (Fig. 1). Daily minimum T_w was similar for L1 and L5 throughout the season. However, before booting stage, the maximum T_w at L1 was, on average, 4 °C below the maximum T_w at L5. From booting to R7, there was a little difference in T_w between locations.

Thermal time accumulation

Using T_w to calculate thermal time led to an increased accumulation along the temperature gradient mainly during PL to PI with a little difference after PI (Fig. 2). Averaged across fields, the daily thermal time accumulation rate was 7.9 °Cd^{-1} at L1 and 9.6 °Cd^{-1} at L5 during PL to PI (Fig. 3). When thermal time accumulation at L5 reached 499 °Cd (PI), thermal time accumulation was 106 °Cd lower at L1, 71 °Cd at L2, 42 °Cd at L3, and 22 °Cd at L4 (Fig. 3). After PI, thermal time accumulation rates were similar for all locations.

T_w and T_a in phenology models

In all cold water gradient fields, TWA had the highest prediction accuracy (lower RMSE) (Table 2). Averaged across fields, the TA (control) RMSE was 5.9 days for PI, 5.2 days

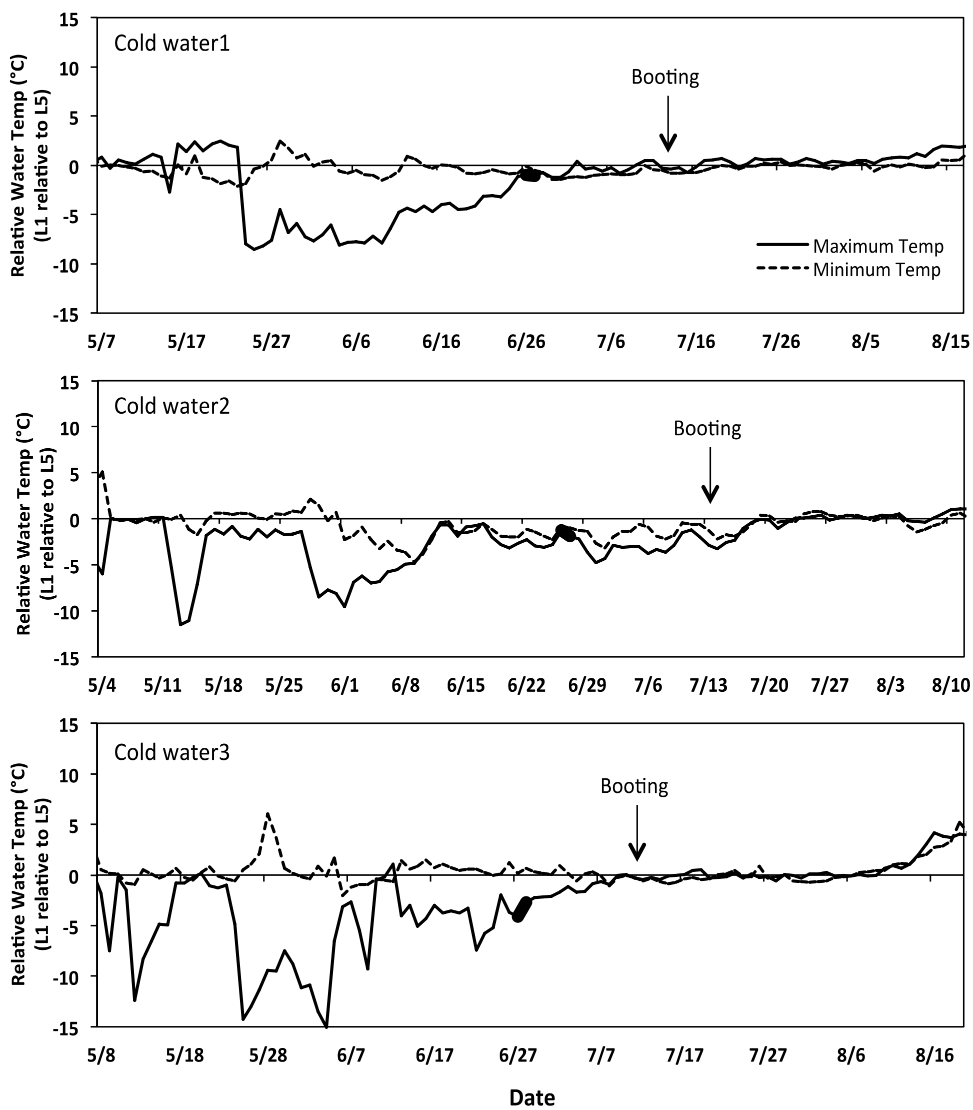

Fig. 1 Maximum and minimum water temperature (T_w) for the L1 and L5 locations in the cold water study. For each field, maximum and minimum T_w for the L1 (coldest) location is shown relative to the L5 (warmest). For example, when the solid line is −5 °C below the flat horizontal line, the maximum temperature at that time for the L1 location was 5 °C cooler than the L5 location. The filled circle marks the time of panicle initiation stage, and down arrow indicates when booting occurred at L1 location

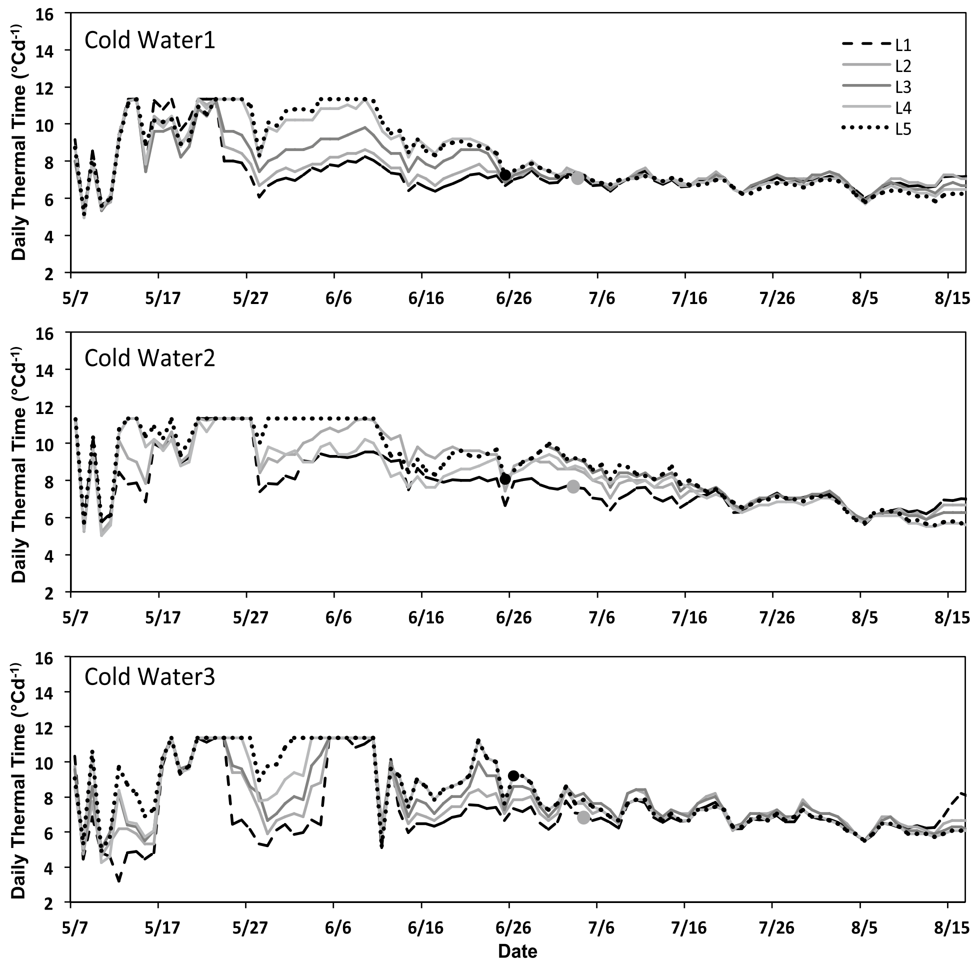

Fig. 2 Water temperature (T_w). Daily thermal time °Cd^{-1} accumulation (Eq. 1) for all locations (L1–L5) in the cold water gradient study. The black filled circle marks the time of panicle initiation stage at L5 and gray for L1

for HD, and 5.4 days for the R7 stage. For the TW, the RMSE was improved by 2.5 days as compared to TA model for estimating PI; however, RMSE increased by 9.5 days for HD and 22.4 days for R7 stage. The TWA and TW model results were similar for estimating PI as both models used T_w. Relative to the TA, the TWA model improved RMSE by 1.6 days for HD and by 1.8 days for R7.

Field validation studies

In the 2015 field validation studies, planting dates ranged from April 27 to May 11 and time to heading from 78 to 87 days (Table 3). There was a little difference among locations in mean T_w and T_a across stages.

Across fields, the average T_w was 2.6 °C higher from PL to booting than T_a; however, after booting, it was 1.6 °C lower than T_a (Table 3). Minimum T_w was higher than minimum T_a by 4–5 °C, and this difference remained relatively constant across the season. In contrast, maximum T_w was higher than maximum T_a by 1.8 °C from PL to booting, but after booting the maximum T_w was 8 °C lower than T_a (Table 3).

The changing relationship between T_w and T_a is shown more clearly in Figs. 4 and 5. Across the season, the difference between average T_w and T_a gradually decreased between PL and booting, while between booting and R7 it increased, with T_w being lower than T_a (Fig. 4). Looking at the cause of this change by examining maximum and minimum temperatures indicates that it is the change in maximum temperatures that is responsible. For the first 20 days of the season maximum T_w averaged about 6 °C greater than maximum T_a, after which T_w in relationship to T_a declined and by the end of the season averaged about 10 °C less than T_a (Fig. 5).

Using these data and running the models to simulate time to HD, we found that using TWA increased predication accuracy by 1.4 days compared to TA. RMSE for TW decreased accuracy with 7.4 days as compared to TA (Table 4).

Discussion

Despite many studies evaluating the effect of T_w on rice growth and yield (Shimono et al. 2002; Roel et al. 2005), little attention has been given to its effect on phenological

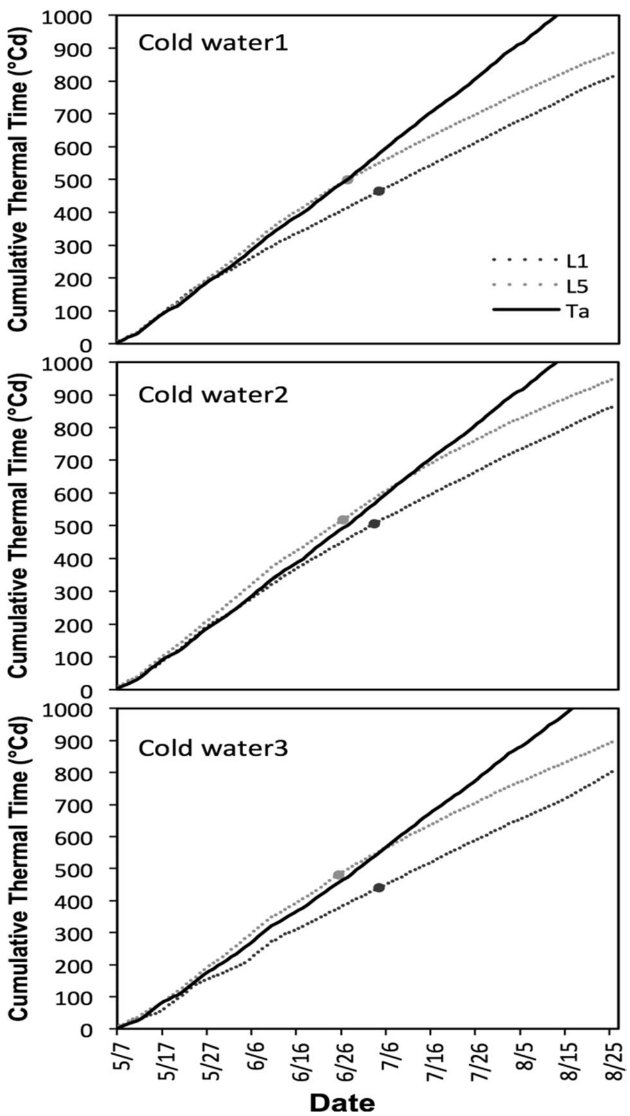

Fig. 3 Cumulative thermal time °Cd based on water temperature (T_w) for L1 and L5 locations in each cold water gradient study field. T_a shows the cumulative thermal time °Cd based on air temperature in each field. The filled circle marks the time of panicle initiation in L1 and L5 locations

development. The cold water gradient study supported our hypothesis and showed that T_w had a greater influence on phenological development than T_a from planting to booting, while after booting, crop development was primarily influenced by T_a. This was illustrated by more rapid crop development in warm water field locations as opposed to cold water locations while T_a being the same (Table 1). The physiological reason for this is likely that the shoot apex, which is the most sensitive to changes in ambient temperature, is located under the water until booting and thus affected by T_w, not T_a (Tanaka 1962; Shimono et al. 2005; Confalonieri et al. 2005).

Table 2 Model simulation results for cold water gradient study showing prediction accuracy (RMSE) to panicle initiation (PI), heading (HD), and R7

Field	*n*	Model	RMSE_PI (days)	RMSE_HD (days)	RMSE_R7[a] (days)
Cold water 1	5	TA	5.1	7.2	5.6
	5	TW	3.2	15.3	28.3
	5	TWA	3.2	2.5	4.0
Cold water 2	5	TA	5.5	5.4	5.7
	5	TW	2.8	19.5	31.8
	5	TWA	2.8	5.4	3.7
Cold water 3	5	TA	7.3	2.9	5.0
	5	TW	4.1	11.3	23.2
	5	TWA	4.1	2.8	2.8
Mean cold water		TA	5.9	5.2	5.4
		TW	3.4	15.4	27.8
		TWA	3.4	3.6	3.5

TA used T_a and TW used T_w for the entire season; however, TWA used T_w until booting and T_a from booting to R7

[a]R7 is marked by the appearance of one yellow hull on the main stem panicle and was used as a proxy for physiological maturity; however, true physiological maturity occurs between R7 and R8

Shimono et al. (2002) suggested that under field conditions, T_w differed from T_a, and these differences were magnified in temperate climates. Our results from the six validation field studies, which represent typical California rice fields, show a consistent difference among fields between T_w and T_a; however, this difference changes during the season. Specifically, the average T_w during the first 60–70 days after planting was higher than average T_a, after which T_a was higher than T_w (Fig. 5). The main source of the seasonal variation between T_w and T_a was maximum temperature, not minimum temperature. The minimum T_w was about 4–5 °C higher than T_a throughout the season. For example, during the first 20 days of the season maximum T_w was about 6 °C higher than maximum T_a, after which T_w, relative to T_a, and by the end of the season T_w was about 10 °C lower than T_a. At approximately 40 days after planting maximum T_w was similar to maximum T_a. This reduction in maximum temperature difference between T_w and T_a was likely due to an increased leaf area and radiation captured by the canopy. During the first 2–3 weeks after planting, plants were small and there was little shading of the water by the rice plants; however, plant growth increases rapidly after about 3 weeks (start of tillering) (Shimono et al. 2007a) with complete canopy closure typically occurring between 40 and 50 days after planting, after which maximum T_w fell below maximum T_a (Fig. 5a, b).

Data from the cold water gradient study indicated that when T_w was used until booting and T_a after that, TWA model runs resulted in the highest prediction accuracy across

Table 3 2015 validation field trials showing planting dates, observed days to 50% heading (HD), and average (Tavg), minimum (Tmin), and maximum (Tmax) air (T_a) and water (T_w) temperature during planting to booting (PL-booting) and booting to R7 (booting-R7)

Field	Planting	T_a			T_w			T_a			T_w			Days to HD
		PL-booting			PL-booting[a]			Booting-R7			Booting-R7			
		Tavg (°C)	Tmin (°C)	Tmax (°C)	Tavg (°C)	Tmin (°C)	Tmax (°C)	Tavg (°C)	Tmin (°C)	Tmax (°C)	Tavg (°C)	Tmin (°C)	Tmax (°C)	
Butte	11 May	21.8	15.2	28.3	24.9	19.8	29.9	24.2	17.2	31.3	22.8	22.1	23.5	83
Colusa	27 Apr	23.0	16.0	29.1	25.7	20.6	30.8	23.2	15.7	30.8	21.8	21.0	22.6	78
Glenn	9 May	23.1	16.3	28.9	25.6	21.0	30.2	22.9	15.9	30.0	21.2	20.3	22.1	83
Sutter	8 May	22.3	15.5	29.1	24.8	17.9	31.8	23.0	15.4	30.5	22.3	21.0	23.5	79
Yolo	8 May	22.6	15.2	29.3	25.6	19.3	31.8	23.2	15.3	31.1	21.8	21.0	22.5	87
Yuba	5 May	23.4	16.6	29.2	25.1	20.9	30.3	23.7	15.7	31.8	20.8	20.2	22.5	81
	Mean	22.7	15.8	29.0	25.3	19.9	30.8	23.4	15.9	30.9	21.8	20.9	22.8	82

[a]For the purposes of this model, we assumed the critical booting period (where the emerging panicle moves from below to above the water surface) occurred midway between PI and HD, that is 178 °Cd after PI

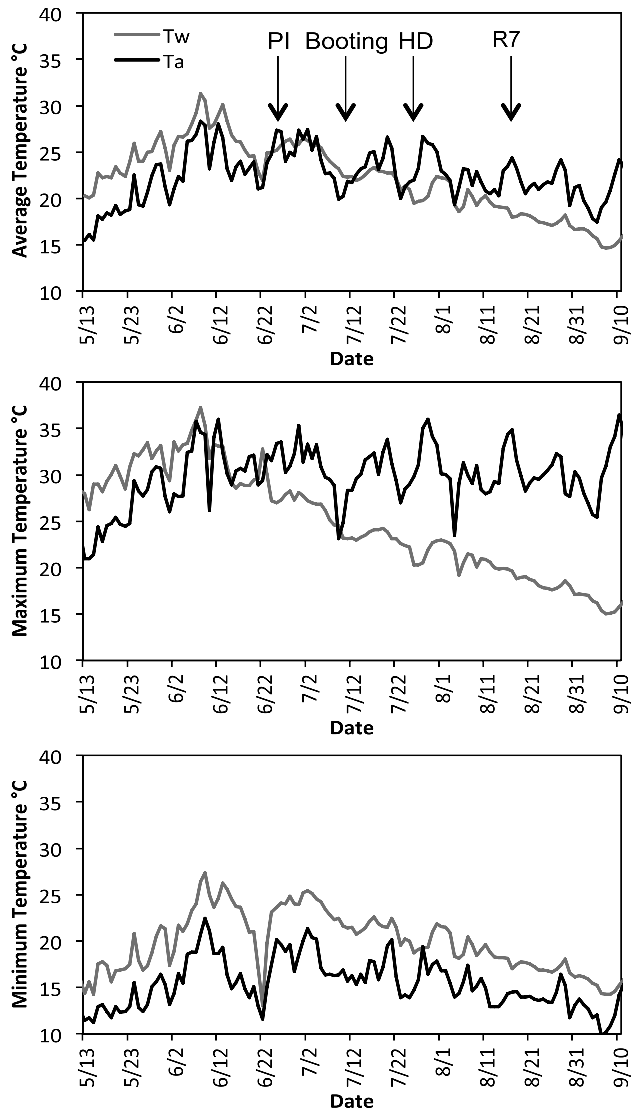

Fig. 4 Average, maximum and minimum water (T_w) and air (T_a) temperatures during 2015 growing season for Glenn field (Table 3). The down arrow indicates the time to panicle initiation (PI), booting, heading (HD), and R7. Booting stage is half-way between PI and HD. The time to PI and R7 was predicted using DDCA calibrated by Sharifi et al. (2017)

all stages compared to either using T_a or T_w for the entire season (Table 2). These results were confirmed in field trails under more typical growing conditions (Table 4). Overall, RMSE for prediction of various stages ranged from 2.5 to 5.4 days using TWA compared to 2.9 to 7.3 days using TA. This represents an improvement in prediction accuracy of roughly 2 days when using both T_w and T_a compared to the standard approach of only using T_a. The temperature parameters used in these models were all calibrated and validated using T_a (Sharifi et al. 2017). Calibrating the models using T_w data would likely further improve the accuracy of these models. The data set we had available was too small to do

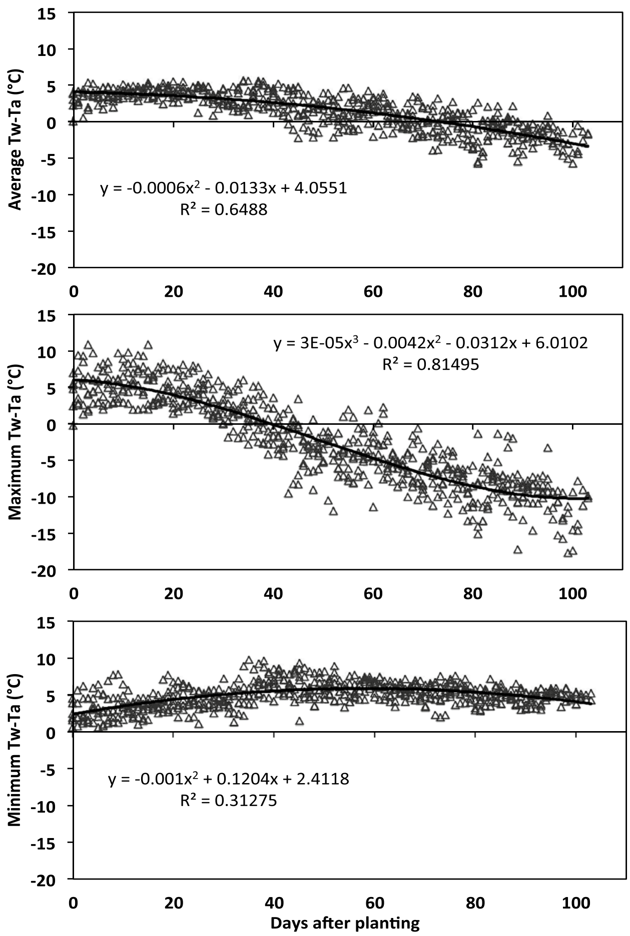

Fig. 5 Water temperature (T_w) relative to air temperature (T_a) for all fields in 2015 validation field trials. Shown are average, maximum, and minimum temperatures

Table 4 Model simulation results for 2015 validation field trials showing prediction accuracy (RMSE) for time from planting to heading (HD)

Field	*n*	Model	RMSE_HD (days)
Validation field trial	6	TA	5.1
	6	TW	12.5
	6	TWA	3.7

TA used T_a and TW used T_w for the entire season; however, TWA used T_w until booting and T_a from booting onward. Data used in the models are summarized in Table 3

this properly; however, this would be a useful area of study in the future.

One problem with the implementation of T_w in rice phenology models is that it is not collected in standard meteorological stations (Shimono et al. 2005). Even if it were, the T_w in rice fields would still need to be estimated through simulation, as T_w is affected by the temperature of the incoming water, water height, and field management. However, models have been developed to estimate T_w based on T_a and other factors such as leaf area, wind speed, and solar radiation (Confalonieri et al. 2005; Ohta and Kimura 2007; Kuwagata et al. 2008). Incorporating T_w estimates from these sorts of models into crop development models may help improve accuracy (Shimono et al. 2005).

Our findings may be of more importance in temperate rice regions than in tropical. While in both regions maximum T_w may be higher than maximum T_a early in the season, in tropical regions it may not have much effect on developmental rates because both maximum T_w and T_a may be higher than T_{opt} and thus would not lead to higher developmental rates. In temperate regions, rice planting typically occurs during a relatively cool time of year with temperatures rising throughout the season. For example, in California rice is typically planted in early May. Average maximum T_a during May is 27.6 °C (CIMIS-Colusa). During May 2015, average maximum T_a was 28.7 °C at our field locations, while the maximum T_w was 30.6 °C. Given that the optimized value for T_{opt} was 32.9 °C (Eq. 1), more thermal time is accumulated using T_w than T_a, which leads to faster developmental rates.

Conclusion

In this study, we found that both T_w and T_a influence rice development but at different times during crop growth. During the first part of the season, when the growing apex is under water, T_w determines developmental rates, while later in the season, it is T_a. Incorporating both T_w and T_a into a rice phenology model increased its accuracy. We found that it was the difference in maximum temperature between T_w and T_a that affected thermal time accumulation and consequently developmental rates. Developing models to better predict T_w in rice fields and using T_w in crop growth models will improve model accuracy.

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