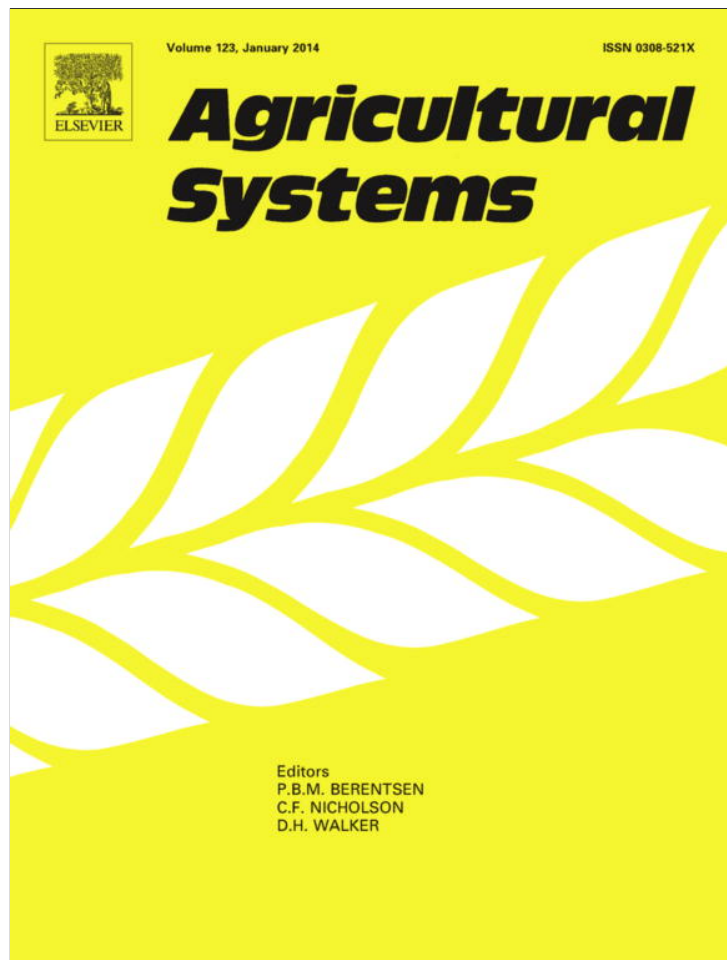


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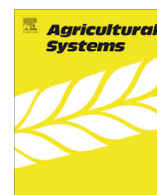
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## Site-specific, real-time temperatures improve the accuracy of weed emergence predictions in direct-seeded rice systems



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## ABSTRACT

The efficacy of crop management is highly sensitive to the timing of operations. This study tested the hypothesis that using site-specific, real-time temperatures to predict weed emergence at the regional scale can improve the timing of weed management in stale-seedbed and drill-seeded rice (*Oryza sativa*) relative to the use of regional emergence averages that incorporate the spatiotemporal variability. First, thermal models of emergence for smallflower umbrella sedge (*Cyperus difformis*) and watergrass (*Echinochloa* spp.), two of the most problematic weeds in California's direct-seeded rice system, were developed from field-scale observations made across 3 sites and 2 years. The models predicted smallflower umbrella sedge and watergrass emergence in an independently collected dataset with accuracy [root mean square error (RMSE) = 21% emergence and 1.3 d; model efficiency index (EF) = 0.80; and RMSE = 14% emergence and 2.2 d; EF = 0.88, respectively]. Subsequently, in order to quantify the degree to which spatially and temporally precise temperatures affect predicted emergence at the regional scale, the models were applied to a daily regional temperature dataset precise to 2 km × 2 km. For each species, the number of days to emergence was simulated for 48 dates (April 15–June 1), 9 years (2003–2011), and 193 locations in the Sacramento Valley rice growing region (83,376 total emergence predictions per species). The variability of the resulting emergence predictions due to the intra-annual, inter-annual and spatial heterogeneity of temperatures was measured with a linear model. Each of the spatiotemporal effects affected the emergence predictions ( $P < 0.001$ ), with the temporal effects (intra- and inter-annual variability) having the greatest impact on predicted emergence. In management terms, using site-specific, real-time temperatures to predict weed emergence would have improved the timing of weed management by as much as 14 days for smallflower umbrella sedge and 12 days for watergrass when compared to using regionally-specific averages that ignored spatiotemporal variability for the simulated period. These results argue for further efforts to merge phenological models with spatiotemporally-specific environmental data in order to improve their accuracy when applied to real-time management decisions.

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### 1. Introduction

In any cropping system, the timing of weed control is crucial to its efficacy (Swanton and Murphy, 1996). Much effort has been made to predict the timing of key developmental stages of weeds as a means of maximizing the impact of management events aimed at their control (Holst et al., 2007). Weed emergence is a key phenological event that is primarily explained by temperature and moisture (Bradford, 2002; Grundy and Mead, 2000). Where water is not limiting (e.g. irrigated cropping systems), accumulation of temperatures within a weed's physiologically relevant range (thermal time) can alone predict germination and early growth with

accuracy (Grundy, 2003). With the growing availability of environmental data at ever-finer spatial and temporal resolutions (Hart et al., 2009; Hijmans et al., 2005), the potential exists to improve the accuracy of phenological models applied at regional scales by improving the precision of their input data (Kriticos and Leriche, 2010; Miller et al., 2004, 2007; Shaw, 2005). Therefore, as the driving variable in weed emergence models, the precision of the temperature input may affect the accuracy of an applied model as much or more as the model parameterization itself.

Rice (*Oryza sativa*) is the most widely consumed staple food in the world (Maclean et al., 2002), and weeds are the major biological constraint to its productivity (Ni et al., 2000). Weed control represents a significant portion of input costs and management effort in rice cropping systems (Pandey et al., 1999). As a semi-aquatic plant, rice has been transplanted and grown under

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flooded conditions for millennia, primarily as a means of weed suppression (Rao et al., 2007). However, the diminishing availability of water and labor, combined with improvements in herbicide and mechanization technology are leading to an increase in direct-seeded rice systems across the world (Farooq et al., 2011). Because weed and rice plants emerge in closer temporal proximity in direct-seeded than in transplanted systems, weed competition is generally greater in direct-seeded rice (Hill et al., 1994). As a result, weed control in direct-seeded rice systems is a research priority of growing importance (Rao et al., 2007).

The approximately 200,000 ha of rice grown in California's Sacramento Valley has long been direct-seeded. California rice has among the highest number of herbicide resistant weed species in the United States (Heap, 2012) due, in part, to a reliance on herbicides for weed control and soils that offer limited options in terms of crop rotation (Hill et al., 1994; Pittelkow et al., 2012). As a response to the growing problem of herbicide resistant weeds (Fischer et al., 2000; Osuna et al., 2002), the use of stale seedbed and drill-seeded systems with intermittent early-season flooding has been investigated in recent years (Pittelkow et al., 2012). These establishment systems attempt to diversify the weed recruitment environment and herbicides used while also improving the timing and efficacy of herbicide applications, thereby reducing selection pressure for herbicide resistance as well as reducing the overall usage of herbicides (Fischer et al., 2009).

In both establishment systems, a moist, primarily aerobic seedbed rapidly recruits problematic weeds such as watergrass (*Echinochloa phyllopogon* and *Echinochloa oryzoides*) and smallflower umbrella sedge (*Cyperus difformis*) (Pittelkow et al., 2012), which are resistant to a broad range of herbicides and cause the most economic damage in the California rice system (Fischer et al., 2000; Osuna et al., 2002). In the stale seedbed system, once maximum weed emergence has been attained, a broad-spectrum herbicide for which resistance has not yet evolved (such as glyphosate) is applied to the weed foliage. The field is subsequently flooded, and rice is seeded aerially without further seedbed disturbance. A post-emergence herbicide (such as propanil) can be used later to control weeds that might escape the stale seedbed treatment. The drill seeded system typically employs propanil and pendimethalin to control watergrass with multiple resistance. These herbicides are usually mixed and applied to the non-flooded seedbed after a critical growth threshold is reached and prior to the permanent flood (CRPW, 2011). Further management details for these systems can be found in Pittelkow et al. (2012), Linquist et al. (2008) and in Section 2 of this paper. Both systems have shown promise as alternatives to the conventional establishment systems in terms of weed control and rice yield (Pittelkow et al., 2012).

Despite the promise of these systems, their efficacy is sensitive to the timing of herbicide applications. Also, in the case of the stale seedbed, planting of rice must be delayed to allow for weed emergence and sufficient foliage exposure to the herbicide application. This affects rice variety choice and introduces late season risk of low temperature induced spikelet sterility (blanking) if rice is planted too late in the season (Board and Peterson, 1980). As a result, information on the timing of weed emergence and early growth in alternative stand establishment systems is necessary for farmers to be able to implement effective weed management.

Hart et al. (2009) combined surface measured climate variables with remote sensed climate variables to interpolate maximum and minimum air temperatures (among other variables) on a 2 km × 2 km grid throughout California. Data are available on a daily interval between 2003 and the present day (COMET, 2012). Preliminary analysis of these interpolations indicated that temperature is relatively uniform across the Sacramento Valley rice growing region for the majority of the growing season. However,

early in the growing season [during the weed recruitment period for alternative establishment systems (April 15–June 1)], the accumulation of thermal time may vary across space and time due to orographically induced climate variation caused by the presence of the Sutter Buttes (Wright et al., 2006) and the inter-annual variability of climate phenomena such as El Niño–Southern Oscillation (Dettinger et al., 2004). Further, the base temperature (lowest temperature required for physiological activity) for smallflower umbrella sedge germination is greater than average nighttime lows during the period of interest, which is in contrast to base temperature estimates for watergrass germination (Boddy et al., 2012; Pedroso, 2012). As such, the spatial and temporal distribution of physiologically relevant temperatures may not be uniform among weed species.

This study employed a historical simulation to test the hypothesis that the use of site-specific, real-time temperatures to predict rice weed emergence can improve the timing of weed management in stale-seedbed and drill-seeded systems relative to management decisions informed by average regional emergence over the same period. The objectives of the study were threefold. The first was to develop and validate thermal-unit driven emergence models for smallflower umbrella sedge and watergrass based on field-scale observations. The second objective was to apply these models with a regional temperature data set accurate to 2 km × 2 km (COMET, 2012) in order to predict emergence across 9 years of historical data. The final objective was to quantify the degree to which the intra-annual, inter-annual and spatial variability affected the simulated emergence in order to illustrate the value of using site-specific, real-time data to inform decision support tools.

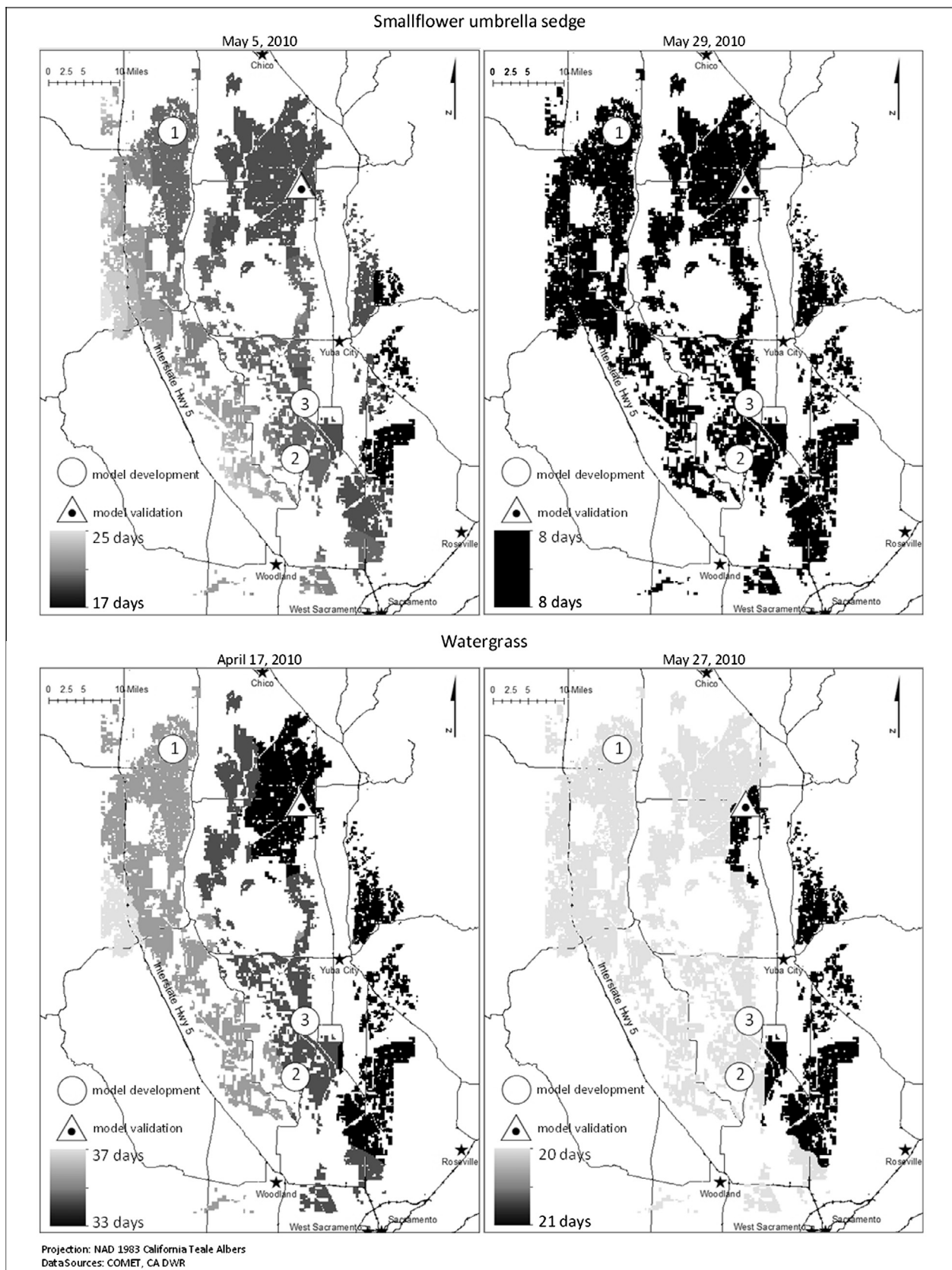
## 2. Methodology

### 2.1. Model development: data collection

In 2010 and 2011 emergence of smallflower umbrella sedge and watergrass was observed in three rice fields where their presence had been confirmed the previous growing season. One of the fields (location 1: 39°33'51"N, –122°4'14"W) was managed as a stale seedbed, while the other two fields (location 2: 38°53'43"N, –121°43'43"W; and location 3: 39°00'35"N, –121°42'29"W) were drill seeded fields (see Fig. 1). Fields were 8.1–11.2 ha in size. The soils in two of the three fields were Mollisols (locations 1 and 3) and the other was a Vertisol (location 2).

Although overall crop management differs between stale seedbed and drill seeded fields in California rice, both management systems employ irrigation flushes during the first 2–4 weeks of the growing season to encourage the rapid emergence of weeds, which are then eliminated via post-emergence herbicide application. As a result, water management during the period of observation was similar between the three fields and resulted in a moist to near-saturated soil surface during the periods of observation.

Following pre-season tillage [which included passes with a chisel plow, disc, tri-planer, and soil roller (stale seedbed) or drill-seeder], 4–8 main plots per field were established in areas of substantial weed infestation as reported by the growers. Main plots were 5 × 10 m in size and were bisected lengthwise by an elevated 6 m wooden plank that served as an observation platform to prevent soil surface disturbance within the plot. Air temperature (1.5 m above the soil surface) was recorded at the center of the main plot at 15 min intervals via a shielded Onset Hobo U23 Pro v2 External Temperature Data Logger. Soil temperature at 2 cm depth was also recorded at the same interval with the same equipment in the center of the plot. Each main plot contained four 0.3 m × 0.3 m subplots, situated at least 1 m apart and established



**Fig. 1.** Image depicts the spatial variability of simulated days-to-emergence for selected start dates. The dates represent the species-specific maximum and minimum spatial variability of emergence predictions for all start dates from April 15 to June 1 during the 2010 season. Emergence was simulated using Eq. (1), the parameters presented in Table 1, and air temperatures interpolated on a 2 km × 2 km grid for areas under rice cultivation in the Sacramento Valley (193 total locations). The sites where development and validation of the emergence models occurred are also depicted.

in areas that were representative of the main plot emergence on the first day that emergence was observed.

Emergence observations were made daily in 2011 and every 1–2 days in 2010 beginning from the first irrigation event (the “start date”) until no further increases in emergence had occurred for at least 3 days. The number of seedlings in each subplot was counted as soon as the seedlings were visually identifiable by species. Generally, this was the first day of emergence for smallflower umbrella sedge (<0.5 cm in shoot height) and 1–2 days after initial emergence (approximately 1 cm in shoot height) for watergrass. Given their abundance, smallflower umbrella sedge seedlings were not removed, but recounted, while watergrass seedlings were removed after being counted. Daily subplot totals were recorded on an absolute basis and then calculated as a proportion of the maximum (smallflower umbrella sedge) or total (watergrass) number of plants counted in the subplot during the entire observation period. Proportional emergence for the main plot was calculated as the mean of the proportional emergence for the four subplots on a given day of observation. In one field (location 1), observations were made in both 2010 and 2011, while in locations 2 and 3 counts were made in 2010 and 2011, respectively. This resulted in a total of 4 site-year and 63 site-day observations per species.

A validation dataset was collected in 2010 at a site located 33–62 km from the other fields (39°27'3"N, –121°43'9"W; see Fig. 1). At this site, observations were made as described before but every 5–7 days in two basins (3.2 and 1.5 ha in size) with stating dates 2 weeks apart for a total of 5 site-day observations for smallflower umbrella sedge and 8 site-day observations for watergrass.

## 2.2. Model development: statistical analysis

Using the ‘nlme’ package (Pinheiro et al., 2011) in R 2.11.1 (2010), a non-linear, mixed-effects model was fit to proportional emergence and base-temperature modified air temperature (thermal units) using the sigmoidal function:

$$E = 1 / (1 + \exp[-(TU - TU_{50\%}) / E_{rate}]) \quad (1)$$

where  $E$  = emergence;  $TU$  = cumulative thermal units;  $TU_{50\%}$  = cumulative thermal units at 50% emergence; and  $E_{rate}$  = rate of emergence (Eq. (1)), as in Chauhan and Johnson (2009b). Thermal units ( $TU$ ) were determined by subtracting a base-temperature ( $BT$ ) from the air temperature measurements ( $T$ ) and summing the results cumulatively over time ( $t$ , days):

$$TU = \sum_i^n \max[(T_i - BT)] \Delta t_i \quad (2)$$

for  $\Delta t_i = 15$  min and  $TU$  such that, if  $T_i < BT$ ,  $(T_i - BT) = 0$  (McMaster and Wilhelm, 1997). Base temperatures were initialized at 17.5 °C for smallflower umbrella sedge (Pedroso, 2012) and 9.3 °C for watergrass (Boddy et al., 2012). The resulting  $TU$  accumulation was matched to observed proportional emergence for each plot. The fixed parameters  $TU_{50\%}$  and  $E_{rate}$  were fit iteratively via maximum likelihood and an autoregressive correlation structure to account for the repeated nature of the measurements. The effects on  $TU_{50\%}$  of site-year were designated as random. Subsequently, base temperatures were incrementally modified 0.05 °C in both positive and negative directions. The resulting models were iteratively compared for significant differences using a 1 degree of freedom chi-squared distribution test on the log-likelihood difference. A range of base temperature values resulting in models that were not significantly different ( $P < 0.025$ ) from the best fit was determined. The midpoint of this range was designated as the base temperature and used to fit a final model for each weed species. Independently

distributed errors and normality were assessed graphically via Q–Q, residual–predicted, and lagged residual–residual plots.

Using spatially and temporally specific maximum and minimum daily air temperature interpolations accurate to 2 km × 2 km (Hart et al., 2009; COMET, 2012), thermal units were calculated according to the double triangle method (Roltsch et al., 1999; Sevacherian et al., 1977) for the dates and location where the validation dataset was collected. The parameters from the aforementioned models were combined with the spatiotemporally specific thermal units to produce emergence predictions for comparison with the validation dataset. Subsequently, the root mean square error (RMSE) and modeling efficiency index (EF) of the predicted versus observed values were calculated as in Loague and Green (1991) such that a perfect model fit would result in a RMSE = 0 and an EF = 1.

## 2.3. Spatiotemporal simulation

Using the species-specific parameter results from the aforementioned thermal-unit-driven emergence models and the double triangle thermal unit calculation method (Roltsch et al., 1999; Sevacherian et al., 1977), the number of days to emergence was predicted for each location on a 2 km × 2 km grid in the Sacramento Valley rice growing region. There were 193 location-specific COMET (2012) air temperatures where rice was grown in the Sacramento Valley for all years from 2003 to 2011 ( $n = 9$ ) and all dates from April 15 to June 1 ( $n = 48$ ). This totaled 83,376 spatiotemporally specific emergence predictions per species. The data was retrieved and manipulated with PHP. Predicted, proportional emergence was rounded to 1 at 0.99, and the number of calendar days that had elapsed between emergence = 0 (the “start date”) and emergence = 1 was designated as the “days-to-emergence” for each location-year-date combination.

Spatial variability was analyzed in the following manner. For each location, a species-specific days-to-emergence prediction ( $n = 193$ ) was projected in NAD 1983–California Teale Albers, interpolated via the inverse distance weighted method, and clipped to represent only those areas where rice was grown in 2010 according to the California Department of Water Resources (CDWR, 2012) using the ArcMAP10 version of ArcGIS mapping software (ESRI, 2011). Visual color delineations were created by calculating the number of predicted days-to-emergence between the minimum and maximum values and grouping locations by shade according to their distance from the minimum value in 1 day increments. The spatial lag distance (distance at which two randomly selected points in the population are uncorrelated) and the correlation structure of these data were determined visually using variogram plots.

Spatial and temporal variability was further characterized statistically using the ‘lm’ function of the base package and the ‘lme’ function of the ‘nlme’ package (Pinheiro et al., 2011) in R 2.11.1 (2010). First, a simple linear model was fit to the species-specific simulation results by apportioning the variance of the spatiotemporally-specific days-to-emergence responses according to the grouping factors “start date”, “year” and “location” to account for the intra-annual, inter-annual, and spatial variability, respectively. After confirming the significance ( $P < 0.001$ ) of the grouping factors via one-way ANOVA, for each start date from April 15 to June 1, a linear, mixed-effects model was fit to the data such that the variance in days-to-emergence was explained by the fixed effect of “location” and the random effect of “year.” The effect of location incorporated a spherical correlation structure with a lag distance initialized at 50 km based on the aforementioned variogram plots of the mean spatial variability across all start dates and years. In addition to the models fit to each start date during the period of interest, for each location, a mean days-to-emergence for all start

**Table 1**  
Parameter values and associated errors for mixed, non-linear regressions fit, using the sigmoidal in Eq. (1), to observations of smallflower umbrella sedge (*Cyperus difformis*) and watergrass (*Echinochloa* spp.) emergence across 2 years and 3 sites in rice fields managed with early-season irrigation flushes.  $TU_{50\%}$  = thermal time to 50% emergence;  $E_{rate}$  = rate of emergence; BT (°C) = base temperature. See Fig. 2 for graphical representation.

Smallflower umbrella sedge				Watergrass							
Fixed effects			Random effects	Fixed effects			Random effects				
Parameter	value ± standard error	95% Confidence interval	P-value	Standard deviation ( $TU_{50\%}$ )	Parameter	value ± standard error	95% Confidence interval	P-value	Standard deviation ( $TU_{50\%}$ )		
$TU_{50\%}$	28.02 ± 3.85	16.55–46.85	<0.001	Year	7.20	$TU_{50\%}$	106.47 ± 6.91	82.09–135.95	<0.001	Year	7.26
$E_{rate}$	0.67 ± 0.08	0.52–0.81	<0.001	Site	7.20	$E_{rate}$	17.14 ± 1.30	14.63–19.65	<0.001	Site	8.16
BT (°C)	15.55	15.10–16.00	<0.05	Residual	0.05	BT (°C)	8.88	8.50–9.25	<0.05	Residual	0.07

dates from April 15 to June 1 was calculated. These data were analyzed with the same mixed effect model as the individual start dates (fixed effect = spatially autocorrelated location; random effect = year) to determine the overall proportional variance attributable to location during the period of rice establishment. Independently distributed errors and normality were assessed graphically via Q–Q and residual–predicted plots.

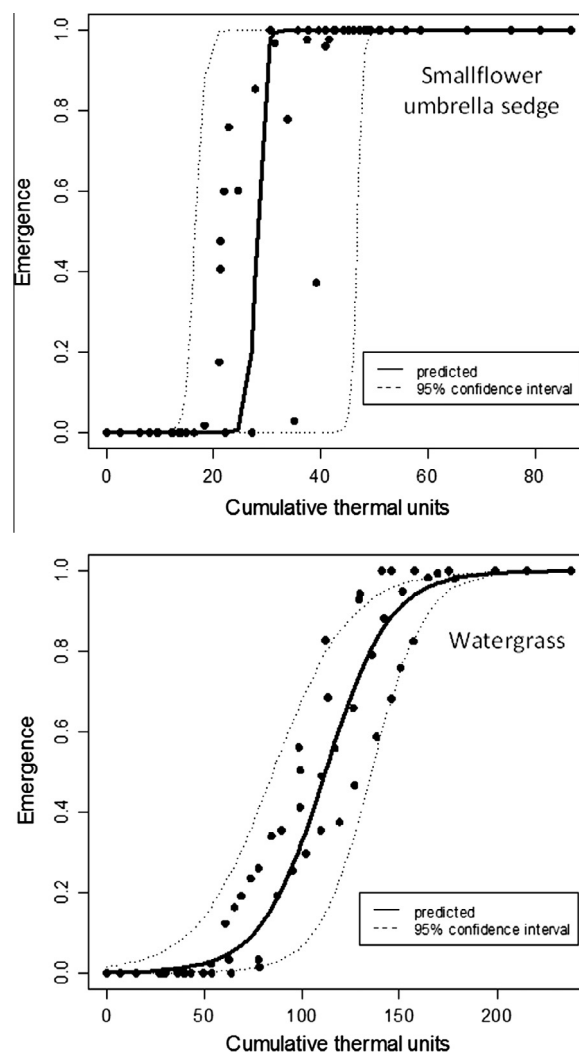
### 3. Results

#### 3.1. Temperature based emergence models

Although both soil and air temperatures were recorded at the plot level, under the saturated but predominantly aerobic soil conditions which emergence observations were recorded, air temperatures provided a more consistent model fit across experimental units (data not shown) and were therefore used to fit the emergence models. Smallflower umbrella sedge emerged more quickly than watergrass, and its emergence was more variable. A base temperature range of 15.10–16.00 °C provided the best fit of the sigmoidal (Eq. (1)) to observed smallflower umbrella sedge emergence (Table 1). Meanwhile, a range of 8.50–9.25 °C resulted in the best fit for watergrass (Table 1). In addition to the higher base temperature, smallflower umbrella sedge required fewer cumulative thermal units to achieve 50% emergence ( $TU_{50\%} = 28.02 \pm 3.85$ ) than watergrass ( $TU_{50\%} = 106.47 \pm 6.91$ ) and exhibited a more rapid rate of emergence as well (Table 1; Fig. 2). Additionally, the proportional variability of the year-specific site effect was greater for smallflower umbrella sedge than for watergrass (standard deviation of  $TU_{50\%} = 7.20/28.02$  and  $8.16/106.47$ , respectively) (Table 1), which is, in part, a result of the narrower thermal unit window (distance between the base temperature and the daily high temperature) for smallflower umbrella sedge relative to watergrass. Lending confidence to the parameterization reported here, the modeled emergence for both species largely agreed with the observed emergence in the independently collected validation dataset, resulting in RMSE values of 21% emergence and 1.3 days and 14% emergence and 2.2 days, and EF values of 0.80 and 0.88 for smallflower umbrella sedge and watergrass, respectively (Table 2). It should be noted that a second cohort of smallflower umbrella sedge was observed emerging later in the season after the permanent flood, and this emergence is not captured by our model.

#### 3.2. Multi-year, regional weed emergence simulation for the period of rice establishment

When the models reported in Table 1 and Fig. 2 were applied to the multi-year, multi-start date, and multi-location temperature dataset, the spatial and temporal precision of the temperatures greatly influenced the predictions. For both smallflower umbrella sedge and watergrass, the simulated days-to-emergence were



**Fig. 2.** Observed and predicted emergence of smallflower umbrella sedge (*Cyperus difformis*) and watergrass (*Echinochloa* spp.) in rice fields with flushed early-season irrigation management. Observations represent site-day means from 4 site-year combinations. Emergence was modeled using a mixed, non-linear model and the sigmoidal in Eq. (1). See Table 1 for presentation of associated model parameters.

affected by intra-annual, inter-annual and spatial variability according to a simple linear model of the effects ( $P < 0.001$ ). Holding intra-annual variability constant, modeling inter-annual variability as a random effect, and accounting for spatial autocorrelation also resulted in an effect of location on the number of days to emergence ( $P < 0.001$ ). Across all starting dates from April 15 to June 1, the mean days-to-emergence among locations ranged from 19.6 to 8.8 days and 31.9 to 20.4 days for smallflower

**Table 2**

Observed and predicted percent emergence (%) for smallflower umbrella sedge (*Cyperus difformis*) and watergrass (*Echinochloa* spp.). Observed data was collected independently of model development (see Fig. 1 for locations). Predicted data was produced using the models presented in Fig. 2 and Table 1. RMSE = root mean square error; EF = model efficiency index. A perfect model fit would result in a RMSE = 0 and an EF = 1.

Cumulative thermal units	Observed emergence (%)	Predicted emergence (%)	95% Confidence interval (%)	Observed days (d)	Predicted days (d)
<i>Smallflower umbrella sedge</i>					
3.2	0	<1	<1–<1	3	3
22.7	0	<1	<1–95	11	11
52.3	53	100	7–100	7	4
61.1	100	100	100–100	18	18
92.5	100	100	100–100	12	12
RMSE = 21% emergence; 1.3 days EF = 0.80					
<i>Watergrass</i>					
13.5	0	<1	<1–3	3	3
67.1	0	9	3–21	11	6
91.8	58	30	10–62	7	9
145.3	70	91	62–99	18	17
166.2	80	97	82–100	12	10
223.5	100	100	99–100	17	17
237.2	100	100	99–100	26	26
283.2	100	100	100–100	21	21
RMSE = 14% emergence; 2.2 days EF = 0.88					

umbrella sedge and watergrass, respectively (Fig. 3, Table 3). During this period, the effect of location resulted in a standard error in the emergence prediction of 2.4–1.0 days for smallflower umbrella sedge and 1.8–0.6 days for watergrass (Fig. 3, Table 3). Meanwhile, the standard deviation for the random effect of year ranged from 6.8 to 2.7 days and 5.1 to 1.6 days for smallflower umbrella sedge and watergrass, respectively (Fig. 3, Table 3). While days-to-emergence generally decreased with increasing temperatures between April 15 and June 1 (Fig. 3), the large intra-annual temperature variability enabled exceptions to this trend (e.g., as illustrated in Fig. 4, smallflower umbrella sedge required fewer days to emerge on April 27, 2011 than on May 9, 2011).

Among location, start date and year, the temporal (intra- and inter-annual) effects explained the greatest proportion of the variability (Fig. 3, Table 3). Nonetheless, the effect of location on the number of days to emergence explained approximately 11% of the modeled variability in smallflower umbrella sedge emergence ( $F$ -value = 14.23(location)/129.23(intercept)) and 4.5% of the modeled variability in watergrass emergence ( $F$ -value = 21.01(location)/468.8(intercept)) across means of the entire period of rice establishment for all years simulated. This spatial heterogeneity of predictions varied intra-annually with the lag distance (distance at which two randomly selected points in the population are uncorrelated) averaging 60.8 km but ranging from 45.0 to 161.4 km for smallflower umbrella sedge and averaging 45.0 km but ranging from 24.1 to 79.1 km for watergrass across the 125 × 70 km region of interest (Table 3).

In management terms, in the most extreme cases within the years given in Figs. 1 and 4 (2010 and 2011), using site-specific, real-time temperatures to predict emergence resulted in an improvement in accuracy of 14 days for smallflower umbrella sedge and 12 days for watergrass compared to applying the average emergence for the simulated period (Table 3).

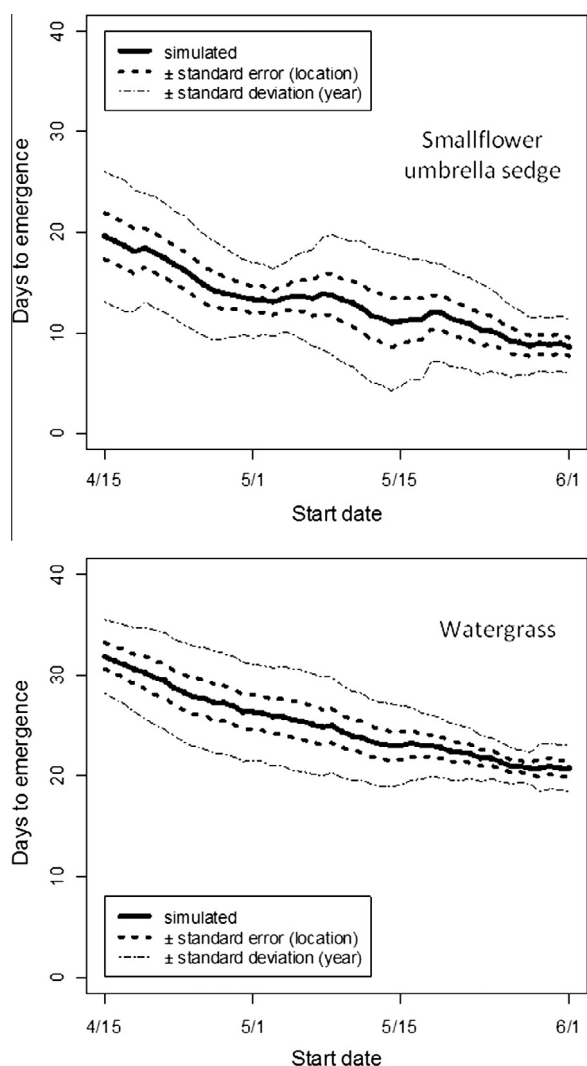
#### 4. Discussion

Although soil temperatures are what seeds experience and are predominantly used to model weed emergence (Forcella et al., 2000), the use of physiologically relevant air temperatures in the empirical models reported here was effective in explaining large portions of the variability (Fig. 2). If the cumulative thermal units derived from both soil and air temperatures had not been as

closely correlated as they were in this experiment (data not shown), air temperature might not be as appropriate an input variable. However, in this case, air-temperature driven models resulted in agreement with the independently collected validation data (Table 2), further confirming the general utility of the thermal time approach to empirical weed emergence modeling (Bradford, 2002; Grundy and Mead, 2000; Leguizamón et al., 2005; Masin et al., 2010).

A wide range of base temperatures (6.5–13.85 °C) has been reported for early development of *Echinochloa* spp. (Gardarin et al., 2009; Masin et al., 2010; Steinmaus et al., 2000; Swanton et al., 2000; Wiese and Binning, 1987). However, only recently have base temperature ranges been estimated for smallflower umbrella sedge and watergrass germination that are specific to the biotypes of California's rice growing region (Boddy et al., 2012; Pedroso, 2012). Using these recent germination estimates to initiate the model fitting procedure narrowed the maximum likelihood region (Lindstrom and Bates, 1990) and resulted in base temperature ranges for the field observations of both smallflower umbrella sedge and watergrass emergence (Table 1) that agreed with the base temperatures for germination developed at the laboratory scale by Boddy et al. (2012) and Pedroso (2012). This agreement may be due to the fact that the "emergence" observed in this study was primarily comprised of the germination events modeled by Boddy et al. (2012) and Pedroso (2012) plus a small degree of early growth. Nevertheless, emergence is governed by a complex set of environmental interactions, which are best understood via more comprehensive experimental methodologies than those employed here (see Boddy et al., 2012).

While the results reported here confirm that temperature is a determining environmental variable for weed emergence, large portions of the variability are unexplained by temperature alone (see 95% confidence intervals in Table 1 and Fig. 2). Osmotic potential has also been widely shown to influence seed germination (Bradford, 2002; Forcella et al., 2000), including for smallflower umbrella sedge (Chauhan and Johnson, 2009a,b; Pedroso, 2012) and *Echinochloa* spp. (Boddy et al., 2012; Boyd and van Acker, 2004). Soil moisture and osmotic potential were not measured in the fields or accounted for in the models reported here. They were, however, controlled to a certain extent by selecting fields for observation where early-season water was managed similarly (periodic flushes to ensure moist but predominantly aerobic



**Fig. 3.** Simulated days-to-emergence for each start date from April 15 to June 1 and the associated error due to the effects of location and year for smallflower umbrella sedge (*Cyperus difformis*) and watergrass (*Echinochloa* spp.). Data includes 9 years (2003–2011) of temperature data precise to 2 km × 2 km in locations where rice is grown in the Sacramento Valley (193 total locations). Simulated values are summarized in Table 3.

conditions). Nevertheless, it is likely that portions of the unexplained variability in these emergence models are due to differences in osmotic conditions between sites and years. Finally, it should be mentioned that a single-parameter, temperature-based model developed under a narrow set of management circumstances must be cautiously applied in non-analogous situations (e.g. a continuously flooded field).

The relative differences in emergence parameters between the two weeds are indicative of their distinct competitive strategies

**Table 3**  
Summary of simulated days (d) to emergence for each start date from April 15 to June 1 and the associated error due to the effects of location and year for smallflower umbrella sedge (*Cyperus difformis*) and watergrass (*Echinochloa* spp.) as modeled via linear mixed effects models. Data includes 9 years (2003–2011) of temperature data precise to 2 km × 2 km in locations where rice is grown in the Sacramento Valley (193 total locations). See Fig. 3 for graphical representation of simulation data.

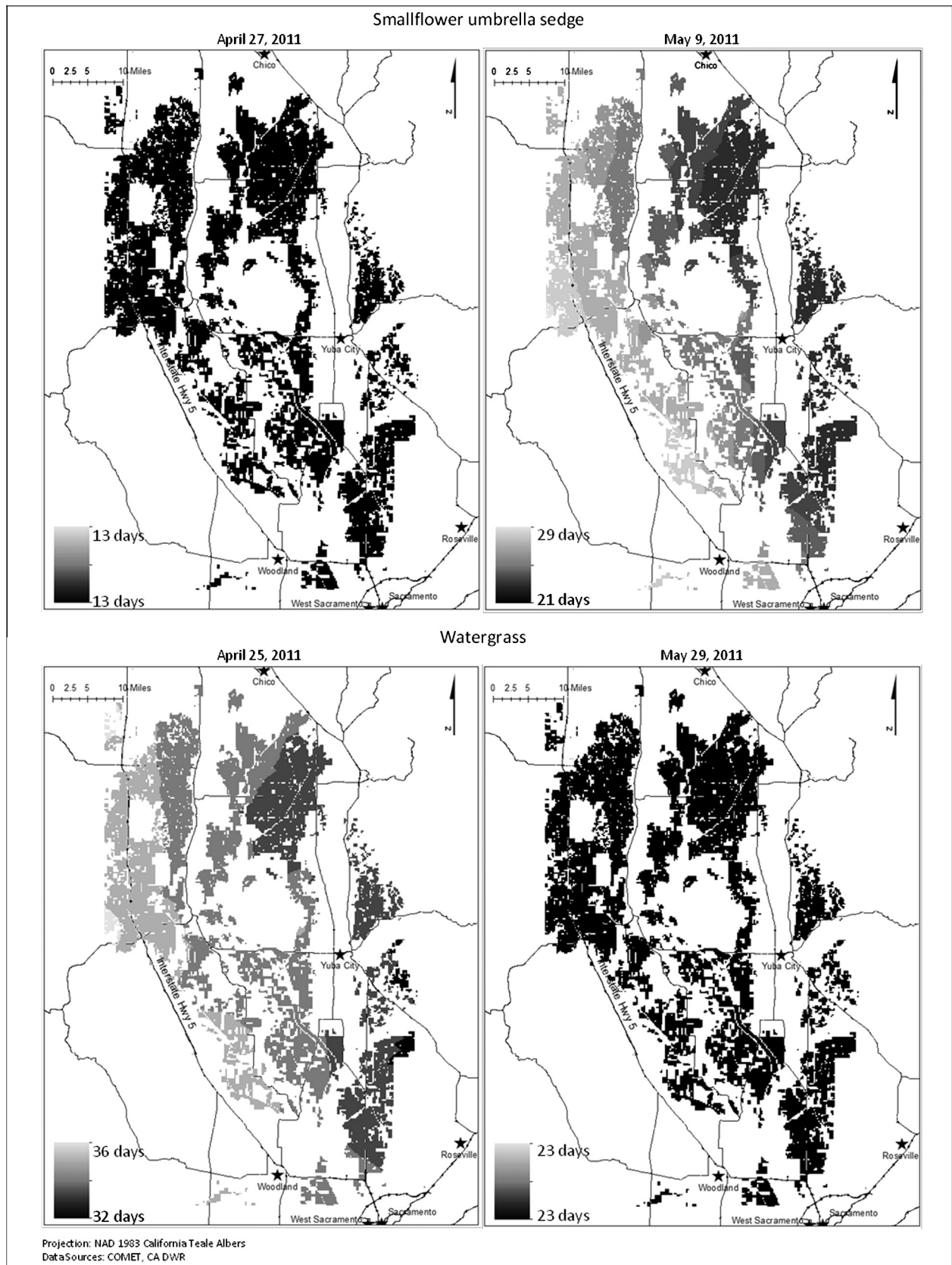
Effect	Smallflower umbrella sedge		Watergrass	
	Range	Mean	Range	Mean
Start date (intercept)	19.56–8.77 d	13.04 d	31.89–20.44 d	25.0 d
Location (standard error)	2.41–0.96 d	1.73 d	1.81–0.58 d	1.37 d
Year (standard deviation)	6.82–2.69 d	4.89 d	5.11–1.60 d	3.9 d
Lag distance <sup>a</sup>	45–161.4 km	60.8 km	24.1–79.1 km	45.0 km

<sup>a</sup> Distance at which two randomly selected points in the population are uncorrelated.

and help to explain differences in the proportional variability between the two species. Smallflower umbrella sedge can complete its vegetative and reproductive stages in roughly one third of the time required by rice (Chauhan and Johnson, 2009a); meanwhile the phenology of watergrass from emergence to heading closely mimics that of the rice plant (Yamasue, 2001). The rapid life-cycle and narrower range between its base temperature and the daily maximum temperatures would tend to exacerbate temperature-related variability in smallflower umbrella sedge emergence. In contrast, the slower rate of watergrass development and larger range between its base temperature and daily maximum temperatures would provide a larger temporal interval over which to integrate temperature-related variability relative to smallflower umbrella sedge. Indeed, such differential effects of temperature-related variability between the two species are demonstrated by the greater proportional variability observed for the time to 50% emergence (Fig. 2, Table 1) and the year-specific effect of site for smallflower umbrella sedge (Table 1). The simulation results, which held the error from the emergence models constant and only considered the variable effects of temperature over space and time, illustrate this difference in absolute terms (number of days) as well. Both the means and the maxima of the ranges of variability due to the effects of year and the location were greater for smallflower umbrella sedge than for watergrass (Fig. 3, Table 3). Additionally, the lag distance (Table 3) and the absolute difference between predicted days-to-emergence (e.g. Figs. 1 and 4) were more variable for the simulated smallflower umbrella sedge emergence relative to watergrass.

Interspecific differences aside, the simulations demonstrate that spatiotemporally precise temperature inputs greatly affect weed emergence predictions at the regional scale. Between the earliest and latest starting dates considered, based solely on changing the intra-annual starting date from April 15 to June 1, the 9-year average regional emergence predictions changed by as much as 10.8 and 11.5 days for smallflower umbrella sedge and watergrass, respectively (Fig. 3, Table 3). In addition, during this same period of interest, the standard deviation for the inter-annual variability was as high as 6.8 and 5.1 days (Fig. 3, Table 3). Although the spatial variability was small in proportion to the temporal variability, it was highly significant nonetheless ( $P < 0.001$ ), with the standard error for the effect of location as high as 2.4 and 1.8 days (Fig. 3, Table 3) across all years. Furthermore, the lag distance estimates indicated that, on average, emergence predictions were improved by spatially explicit temperatures when locations were at least 61 and 45 km apart for smallflower umbrella sedge and watergrass, respectively (Table 3). Due to the size of the dataset, it was not computationally possible (due to memory limitations) to test for an interaction between spatial and temporal effects directly. However, the wide range of lag distances during the periods of interest (Table 3), the changing magnitude of the effect of location across the intra-annual simulation period (Fig. 3), and the changing spatial distribution of emergence predictions at various points in time (Figs. 1 and 4) indicate a possible interaction.





**Fig. 4.** Image depicts the spatial variability of simulated days-to-emergence for selected start dates. The dates represent the species-specific maximum and minimum spatial variability of emergence predictions for all start dates from April 15 to June 1 during the 2011 season. Emergence was simulated using Eq. (1), the parameters presented in Table 1, and air temperatures interpolated on a 2 km × 2 km grid for areas under rice cultivation in the Sacramento Valley (193 total locations).

The simulation results are, to a degree, intuitively obvious: a temperature-bound process will clearly vary in warmer or cooler regions, years, or parts of the growing season. What is less obvious is how greatly the processes can vary within the spatiotemporal scales reported here. In practical terms, each effect modeled from the simulation results (location, year and start date) influenced the predicted days-to-emergence by days on its own (Fig. 3, Table 3), and, in extreme cases, by weeks when combined (Figs. 1 and 4). Compared to using a species-specific average emergence to guide weed management recommendations for this region and period of interest, management that is informed by site-specific, real-time temperatures used to predict weed emergence would be better timed. For weed management strategies that depend on precision timing for weed control, such improvements could greatly influence the utility of decision support tools and, by extension, the success or failure of a weed control strategy.

For example, a rice grower trying to optimize the timing of smallflower umbrella sedge control in the coolest part of the Sacramento Valley would have had to wait 12 days for emergence if flushing began on May 2, 2011, 17 days if flushing began 1 day later, and 29 days if it began 1 week later. A year earlier, the same grower would have seen emergence occur in 15, 16 and 22 days on the same starting dates. Meanwhile, a grower in the warmest part of the valley would have seen smallflower umbrella sedge emergence in 11, 11 and 21 days on those same dates in 2011. Further, if the original grower had used the 9-year regional average (13 days; Table 3) to anticipate smallflower umbrella sedge emergence, s/he would have been more than a week off in 2 of the 6 instances. In contrast to the general trend toward warmer temperatures and faster emergence as the season progresses (Fig. 3), in this example the slower emergence occurred later in the season. This somewhat counterintuitive result demonstrates that, because emergence is a thermally, not temporally, regulated process, where temperatures are heterogeneous, emergence will more become more predictable if the source of variability is explicitly incorporated into the predictive tool. Thus, recommendations based on average emergence that ignore spatiotemporal variability will result in management timing that could be easily improved upon by recommendations that are informed by site-specific, real-time data.

## 5. Conclusion

Characterizing heterogeneity across temporal and spatial scales is a fundamental problem of ecology (Levin, 1992) and agronomic weed management (Shaw, 2005). The results presented here are a quantitative illustration of the degree to which spatiotemporally precise inputs can improve the accuracy of even a simple phenological model. Farmers using stale-seedbed and drill-seeded rice establishment systems to recruit weeds would improve the timing and efficacy of their herbicide applications by predicting weed emergence via site-specific, real-time temperatures. Further efforts are needed to merge site-specific environmental data with weed emergence and other phenological models in order to produce decision support tools that are both more accurate and more immediately applicable to individual farmers and land managers.

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