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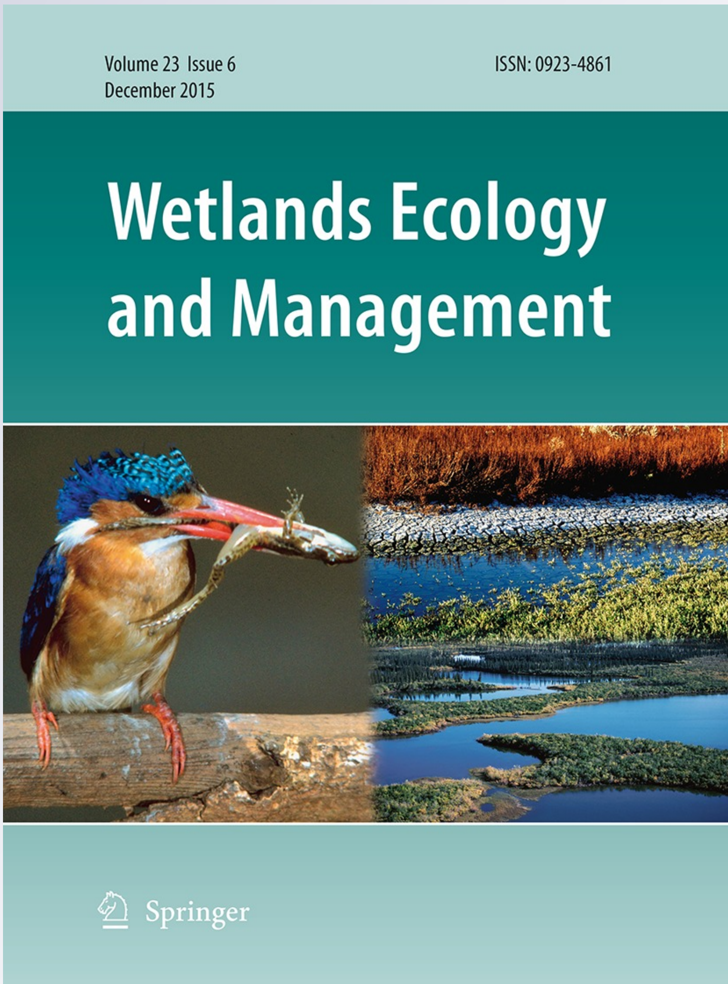

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ORIGINAL PAPER

Automated analysis of temperature variance to determine inundation state of wetlands

Thomas L. Anderson · Jennifer L. Heemeyer · William E. Peterman · Michael J. Everson · Brittany H. Ousterhout · Dana L. Drake · Raymond D. Semlitsch

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Abstract Monitoring the inundation state (wet or dry) of wetlands is critical to understanding aquatic community structure but can be costly and labor-intensive. We tested the ability of temperature data from cost-effective iButton data loggers to reflect the inundation state of wetlands in central Missouri, based on our hypothesis that dry ponds would show greater daily temperature variance than ponds that remained inundated with water. We evaluated this method with two experiments in large outdoor mesocosms, and in existing natural wetlands in which we had deployed iButtons. True inundation state from pond visits was compared to predicted inundation state over different temperature variance thresholds expected to delineate wet or dry ponds. We confirmed that the daily temperature variances of dry iButtons were higher than that of iButtons under water, as expected, but that variance was influenced by factors such as canopy cover. We also describe an automated procedure that can be used to determine whether a pond was wet or dry with greater than 80 % accuracy. Using this approach, changes in inundation state, the number of days wet and dry, and the number of drying and filling events can be calculated. Several caveats are also provided that should be considered prior to using this method to maximize the accuracy in assessing inundation state.

Keywords Drying · Hydroperiod · iButton · Inundation · Pond · Water level · Temperature data logger

William E. Peterman is the corresponding author for technical inquiries.

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Introduction

The amount of time a wetland holds water is an important predictor of species presence, abundance, functional diversity, competitive interactions, predator–prey relationships, and overall aquatic community structure (Pechmann et al. 1989; Semlitsch et al. 1996; Skelly 1996; Wellborn et al. 1996; Babbitt et al. 2003). Further, understanding the temporal duration of wetland inundation is critical for conservation and management, as climate change models predict increased stochasticity in rainfall and temperature, which drive seasonal filling and drying of wetlands (Brooks 2009). However, determining wetland inundation is also one of the most logistically challenging and costly characteristics to measure because it is difficult to precisely capture drying and filling events. Therefore, improving methods that determine these switch points in inundation state are imperative towards improving the temporal resolution of how long wetlands remain wet or dry.

Determination of wetland inundation state (wet or dry) can be both work-intensive and financially prohibitive. Monitoring the inundation state of small wetlands is often accomplished with a staff gauge ($20–60 US depending on length, style and supplier), which is manually monitored daily to monthly to record the water level (Pechmann et al. 1989; Babbitt et al. 2003; Gamble and Mitsch 2009). Automated water level sensors, which function either by a float or pressure measurement system, can also be used to monitor water levels (e.g. Onset Computer Corp., Bourne, MA USA = $300–$600 US; Remote Data Systems, Inc., Navassa, NC USA = $750–1500.00). These devices are capable of monitoring a variety of depths ranging from 0–80 m and have been successfully used to monitor ponds and other waterways (Korfel et al. 2010; Correa-Araneda et al. 2012). Although effective, monitoring a large number of wetlands may not be feasible either due to the expense of automated water level sensors or time needed to check multiple staff gages at regular intervals.

Temperature data loggers may provide a useful and inexpensive way to assess inundation state at a large number of wetlands, reducing both the cost and time intensive nature of the previously reviewed methods. Sowder and Steel (2012) found that temperature fluctuations in water were greatly reduced compared to air fluctuations, due to the former's greater specific heat capacity (Oke 2002). Therefore, if loggers are placed at the deepest section of a wetland, extreme switches in temperature variance should capture changes in inundation state. Several relatively inexpensive temperature loggers now exist, including waterproof options (e.g. HOBO Pendant, Onset, Bourne, MA, USA = $42 per unit; iBWetland, AlphaMac, Ste-Julie, QC, Canada = $40 per unit for 100–999 units). iButton temperature data loggers (DS1921G, Maxim Integrated Products, San Jose, CA USA = $17 per unit for 200 units) have become popular in ecological studies (Angilletta Jr. and Krochmal 2003; Hubbart et al. 2005). For aquatic monitoring, iButtons are able to be submerged with the application of a coating of Plasti Dip plastic tool dip (Plasti Dip, Plasti Dip International, Blaine, MN, USA; Grayson and Dorcas 2004; Roznik and Alford 2012).

The objective of our study was to test the ability of plasticized iButton temperature data loggers to monitor the inundation state (wet or dry) of wetlands. We investigated whether pond inundation state could be captured and predicted based on differences in daily temperature variance between water and air (Sowder and Steel 2012). By determining these switch points in inundation state, summation of the total number of days that a data logger is inundated can be used to determine the temporal aspect of hydroperiod. We also provide a user-friendly method for automating analyses of inundation state from large quantities of iButton data (Online Appendix A).

Methods

Experimental Study 1

We conducted a short-term experiment in plastic outdoor experimental mesocosms (1.52 m diameter, 0.6 m depth; hereafter, tanks) which examined whether differences in temperature variance could be used to detect a switch in inundation state. Thermocron iButtons (model DS1921G, 1.8 cm diameter, precision: 0.5 °C, accuracy: ±1 °C) were placed in an ongoing study that had begun in October 2011 (see Anderson and Semlitsch 2014). Tanks were filled with 1000 l of water (47 cm depth) and 2 kg of dry leaf litter. Six iButtons were dipped three times each in PlastiDip and allowed to dry (Grayson and Dorcas 2004; Roznik and Alford 2012). Two iButtons were then placed on the bottom of each of three tanks at the beginning of the experiment. The iButtons had been programmed to record the temperature every 4 h starting at 1500 h, the predicted hottest part of the day, thus providing a baseline of water temperature variance. We started three treatments beginning on 10 July 2012 with one tank per treatment, and all tanks were approximately 18 cm in water depth. Two iButtons were removed from one tank and placed on bare ground, simulating a pond that had dried (i.e. switch in inundation state). One tank was kept at a water depth of 18 cm, and one tank was raised from a water depth of 18 to 47 cm. The experiment was terminated on 16 July. We calculated a daily variance in water temperature based on the six data points gathered daily by each iButton for each tank.

Experimental Study 2

We conducted this experiment from 4 September to 4 October 2014 in the same location as Experiment 1 using identical experimental tanks. We placed four tanks in the shade on the edge of a forest where they received little to no direct sunlight, and placed four tanks in an open field with full sunlight (Online Appendix B). We filled all tanks to a starting depth of 40 cm.

iButtons were placed at four heights (32, 24, 16 and 8 cm) on a upright meter stick which was placed in the center of each tank (Online Appendix B). The meter sticks were held upright in tanks by fastening them to a piece of PVC piping that was laid across the top of the tanks. iButtons were dipped three times each in PlastiDip, and housed in plastic mesh held together with zip ties. They were then duct taped to the meter stick to keep the iButtons stationary during the experiment (Online Appendix B). All iButtons were programmed to record temperatures at 4 h intervals (starting at 1500 h).

We manually lowered the water level in all tanks with buckets every 4 days, resulting in five different water depths (36, 28, 20, 12 and 4 cm). On 10 September 2014, we recorded water depths of all tanks prior to a rainstorm. After the rain ended, the tanks were lowered back to their pre-rainfall depth of 40 cm. At a depth of 4 cm, all iButtons were exposed to the air. The tanks were then filled by adding 8 cm of water from a garden hose every 4 days to the same respective heights until the water height reached 36 cm again. Actual water levels were recorded prior to and after every water depth change.

Field study

We conducted field assessments of iButtons at Fort Leonard Wood (FLW) military base in southern Central Missouri. For this study, we focused on wetlands with varying hydroperiods within a 7140 ha section of FLW. These wetlands ranged from small (1 m^2) road-side ditches to large (>2 ha) fishing ponds, with most of them being constructed as wildlife ponds. The average surface area of the ponds used in this study was 0.0591 ha ($\pm$0.16 SD).

We deployed iButtons in ponds at FLW from July 2012–December 2012 (n = 159) and February–July 2013 (n = 79). As in the experimental studies, each iButton was dipped three times in PlastiDip and set to record temperature at 4 h intervals. To prevent them from being tampered with by animals or lost in the wetlands, we put the iButtons in wire mesh cages (approx. 2.5 cm diameter, 10 cm length, 3 mm mesh). The mesh cages with the iButtons inside were then affixed to bamboo stakes and deployed.

We placed one iButton in each pond, although the within-pond location varied depending on depth and size of the pond, and thus the water depth over each iButton varied. When possible, the iButton was placed at the predicted deepest location (i.e., where water would remain the longest in the event of drying), and the cage placed flush with the benthic substrate. In many of the constructed ponds, the deepest location was next to the berm. For ponds where the deepest point was inaccessible, the iButton was placed as deep as possible when wading out into the pond with hip waders. While this was ineffective at capturing true inundation state for these large permanent ponds, iButtons placed in this manner recorded the shoreline receding/advancing over the course of the study, thus capturing the desired effect of a change in inundation state.

An additional four iButtons were placed on bamboo stakes 60 cm above the ground (hereafter Air iButtons) on the basin margin of four ponds that also had an iButton submerged in water. These Air/Water iButton pairs allowed for a comparison of temperature variance at individual ponds, and provided for a similar comparison of temperature variance to Experiment 1 under more natural conditions. The amount of shading the Air/Water iButtons received was not controlled for in this study; three of the Air iButtons were under substantial canopy cover but the fourth was in open habitat. Both Air and Water iButtons were similarly coated in PlastiDip. At all pond visits, we recorded whether the pond had water and if the iButton was underwater.

Analysis

Our primary metric to determine inundation state of each pond was the daily temperature variance (s^2), computed from the six measurements recorded by each iButton. We expected that high daily variance would be associated with dry ponds, and low variance with wet ponds, due to the buffering capacity of water to fluctuations in ambient air temperatures (Sowder and Steel 2012). We visually compared the daily temperature variance for both experiments, and the paired Air and Water iButtons at our field site. However, we did not know a priori what the difference between and air and water temperature variance would have to be to delineate wet and dry ponds. Therefore, we initially compared seven different temperature variance "thresholds" (i.e. ponds were predicted to be dry when the daily temperature variance exceeded each of these values) against the confirmed true inundation state from each pond visit. The variance threshold values were haphazardly chosen from actual daily temperature variances recorded by iButtons verified to be underwater when ponds were visited.

Based on this initial assessment, we found that the proportion of incorrect predictions were affected by the variance threshold that was tested, where higher variance thresholds resulted in more ponds being incorrectly predicted to be wet and lower variance thresholds incorrectly predicted more ponds to be dry, and that pond area, depth and canopy closure influenced the number of incorrect predictions (Online Appendix C). We then examined whether temperature variance assessed over multiple days would improve detection of a switch in inundation state. We implemented and automated a multi-day assessment of daily temperature variance within R (R Development Core Team 2014), and provide the code and a complete description in Online Appendix A. As implemented, this method provides user flexibility in determining four separate criteria, including the daily temperature variance threshold, a moving window to assess daily variance across, whether to use the mean or variance of the daily variances within that window, and how many consecutive days the variance threshold must be crossed for a change in inundation state to be identified. For example, if the variance threshold was set to 20, a moving window specified to 5 days, and the consecutive day criteria was 3 days, a pond would be considered dry if the variance in temperature over 5 days was greater than 20 for three consecutive shifts in the moving window (i.e. 3 days). Importantly, because we are able to identify dates of filling and drying (i.e. switches in inundation), the number of days between each event can be used to calculate temporal durations of wet and dry for each wetland.

Based on the visits to each pond where we could visually verify inundation state, we optimized what values should be used for the four parameters to accurately predict inundation state. Specifically, we tested all combinations of moving window size (2–15 by 1), variance threshold (2–30 by 2), consecutive days (1–5 by 1), and threshold calculation method for summarizing daily variance within the moving window (mean or variance) for a total of 2250 unique parameter combinations. The combination of assessment criteria values that maximized sensitivity (percent positive results correctly predicted, i.e. wet ponds to be wet) and specificity (the percent negative results correctly predicted negative, i.e. dry ponds to be dry) was determined to be the optimal combination. We also performed this optimization on the data from Experiment 2 for the open and shaded tanks separately. Then, using these optimized values, we compared how well the automated procedure could identify the known switches in inundation state as each iButton was exposed to the air. We also calculated an average predicted duration of inundation for each depth and compared it to the actual time period of inundation.

Results

Air–water differences in temperature variance

Experiment 1

Data from all six iButtons were successfully downloaded. Over the 60 days leading up to experimental treatments, mean daily variance (s^2) in water temperature across all tanks was 9.4 ± 5.8 SD. The temperature variance immediately and drastically increased for the iButtons placed on the ground ($s^2 \geq 80$), whereas the variance of the iButtons in the tank with 18 cm and the tank that was raised to 47 cm of water remained relatively constant and well below the values for the iButtons on the ground (Fig. 1a). The tank that was filled from 18 to 47 cm also decreased in temperature variance compared to the tank that remained at a depth of 18 cm (mean $s^2 = 4.1 \pm 2.7$ SD and 10.4 ± 4.4 SD, respectively).

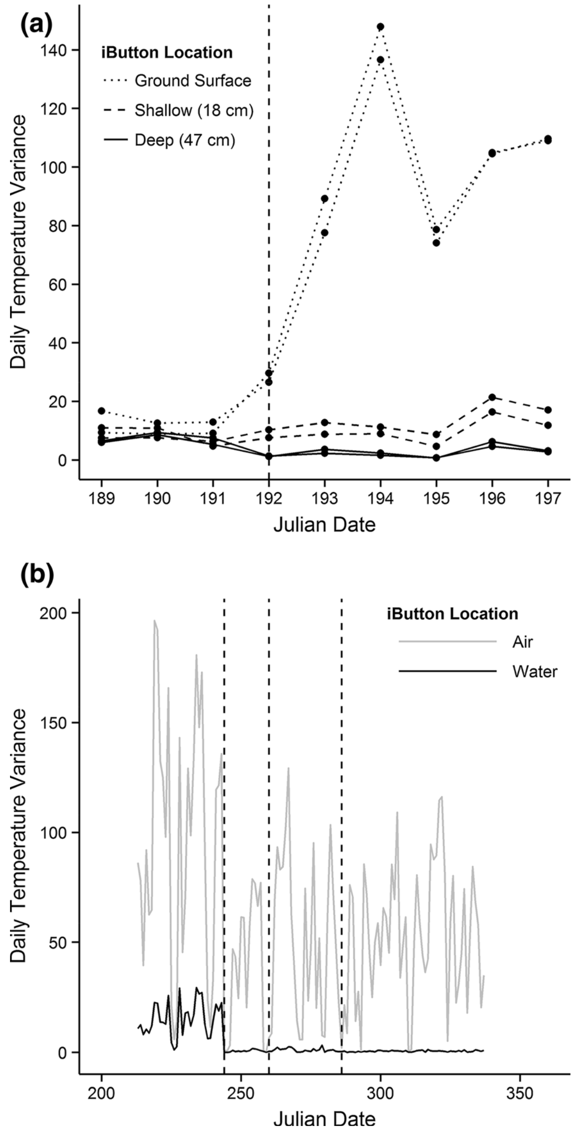

Fig. 1 Differences between daily temperature variance in air and water from **a** Experiment 1 and **b** field deployment. **a** Daily temperature variance of iButtons placed on bare ground (*dotted*), 18 cm of water (*dashed line*) and 47 cm of water (*solid line*). The first *vertical dashed line* indicates the start of the experiment. Prior to that *line*, all iButtons were in tanks of water with a depth of 18 cm. Each *line* indicates one iButton. **b** An example of daily temperature variance is shown from an iButton placed 60 cm in the air (*gray line*) and an iButton within the water (*black line*). *Vertical dashed lines* indicate rainfall events

Paired air–water iButtons: field study

We obtained data from three ponds that had paired Air/Water iButtons (from the five pairs, one water iButton failed to record data and another could not be recovered). All three ponds were dry during the summer of 2012 when the iButtons were deployed. Two of the ponds filled on 31 August 2012 when 3.7 cm of rain fell, resulting in a shift to near 0 in temperature variance (Fig. 1b). Compared to the Water iButtons, Air iButtons maintained a high daily variance. Inundation was delayed in the third pond as the iButton was placed closer to the pond edge due to logistical constraints, but had a daily variance near 0 after rain completely filled the pond on 12 October (0.79 cm rainfall) while the paired Air iButton continued to have high daily variance in temperature.

Experiment 2

Data from all 28 iButtons were successfully downloaded. All iButtons showed higher variance when they were exposed to the air (Fig. 2). The iButtons placed at the shallowest depth (height = 32 cm) showed the highest values of mean daily variance that was also maintained the longest duration. The deepest iButton (height = 8 cm) showed the least change; only after these iButtons were exposed to the air did the mean variance begin to increase, and was quickly reduced after iButtons were re-inundated 4 days later. Daily temperature variance was also greater in open canopy tanks (Fig. 2a) compared to tanks in the shade, which showed lower variances and had fewer fluctuations (Fig. 2b).

Field study and automated assessment

Of the 159 iButtons that were deployed in summer 2012, 130 were recovered from the field, and data were successfully downloaded from 95 of them (27 % failure rate of iButtons that were recovered). We had reduced failure and increased download success for the deployment from February–July 2013 (18 % failure of 79 iButtons, 100 % recovered).

Based on the optimization procedure for February–July 2013, sensitivity and specificity were maximized for ponds at FLW when we assessed the variance of daily variance over an 11 day moving window, and determined drying and filling when variance switched over/under a threshold of 22 for two consecutive days. Using these values resulted in 82 % of ponds being correctly predicted to be dry when they were verified as dry, and 87 % of ponds correctly predicted to be

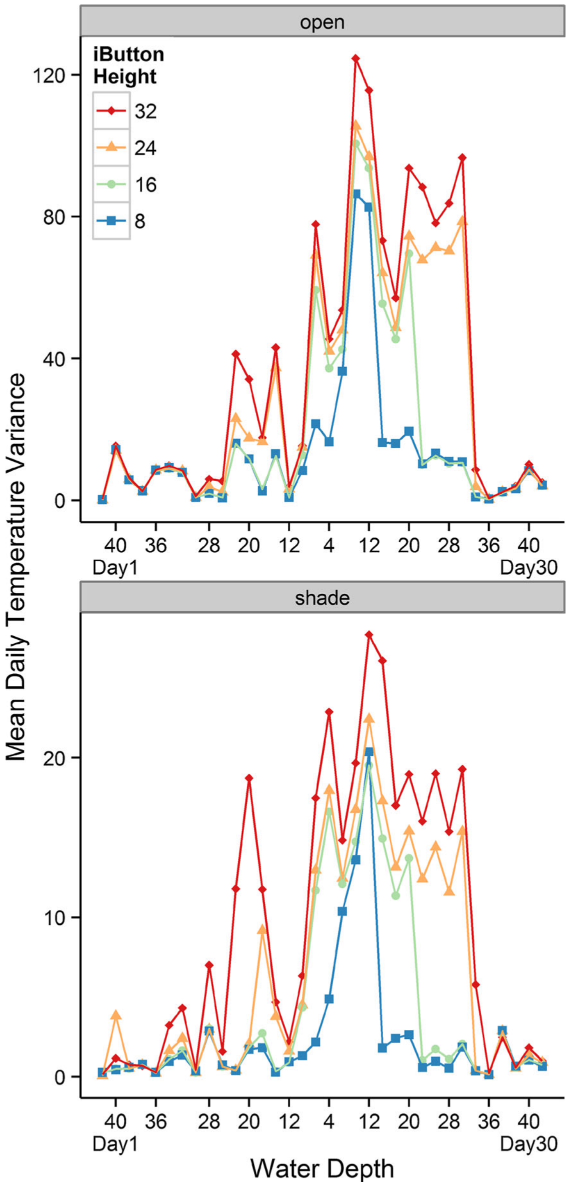

Fig. 2 Mean daily temperature variance of iButtons placed at four heights within outdoor experimental tanks in Experiment 2. Each *dot* represents the average of the iButtons at each height in the four tanks. The x-axis shows the categorical variable water depth, which initially was 40 cm, decreased to 4 cm, and finally raised back to 40 cm. Each depth of water was held for a period of 3 days, except for the increase from 28 to 36 which was 4 days. Note the difference in y-axis ranges among the *open* and *shaded panels*

filled when they were actually filled. Predictions of inundation state were more accurate in the spring than in the summer (overall averages of 84 vs. 54 %). For some combinations of user-specified criteria, predictions of inundated ponds were 100 % accurate in the spring. Predictions were less accurate in the summer, especially when predicting ponds to be dry; accuracy ranged from 18 to 82 % across all combinations of variance thresholds and window sizes. The optimization procedure produced similar results of accuracy for the July–December 2012 deployment (sensitivity: 96 %, specificity: 84 %). Similar to both experiments, iButtons that were permanently inundated showed little to no variance and were always predicted to be wet (Fig. 3a). Ponds that were dry and incorrectly predicted to be wet were shaded either from canopy (Fig. 3b–e) or in pond vegetation (Fig. 3c), likely due to less variability in temperature in shaded habitats. Ponds that were wet but incorrectly predicted as dry were almost always shallow, completely open canopy, and/or had small basin sizes (Online Appendix C).

The optimization procedure for Experiment 2 resulted in greater than 80 % accuracy of both sensitivity and specificity. When using these optimized values, the automated procedure resulted in predicted drying and filling dates that were all within one day of the true inundation switches in the shaded treatment (Table 1). For the open canopy tanks, use of the optimized parameters resulted in less precise prediction of the drying date for iButtons that were lower in height (i.e. deeper in the water), but still accurately predicted filling dates within a day or two (Table 1). Twenty-four of the 28 iButtons had only two predicted changes in inundation state, matching reality; the other four each had an extra dry/fill event.

Discussion

Our data indicate that assessing temperature variance can accurately predict the inundation state of wetlands, and the use of inexpensive temperature data loggers may be highly effective when frequent site visits or expensive equipment are not viable options. The paired water–air iButtons in the field, as well as both experiments show iButtons in the air maintained higher temperature variances than iButtons in the water. Using the automated procedure, we were able to correctly predict the inundation state of wetlands with an average of >80 % accuracy, and up to 100 % under certain conditions (e.g. spring vs. summer). We also verified our automated method could predict

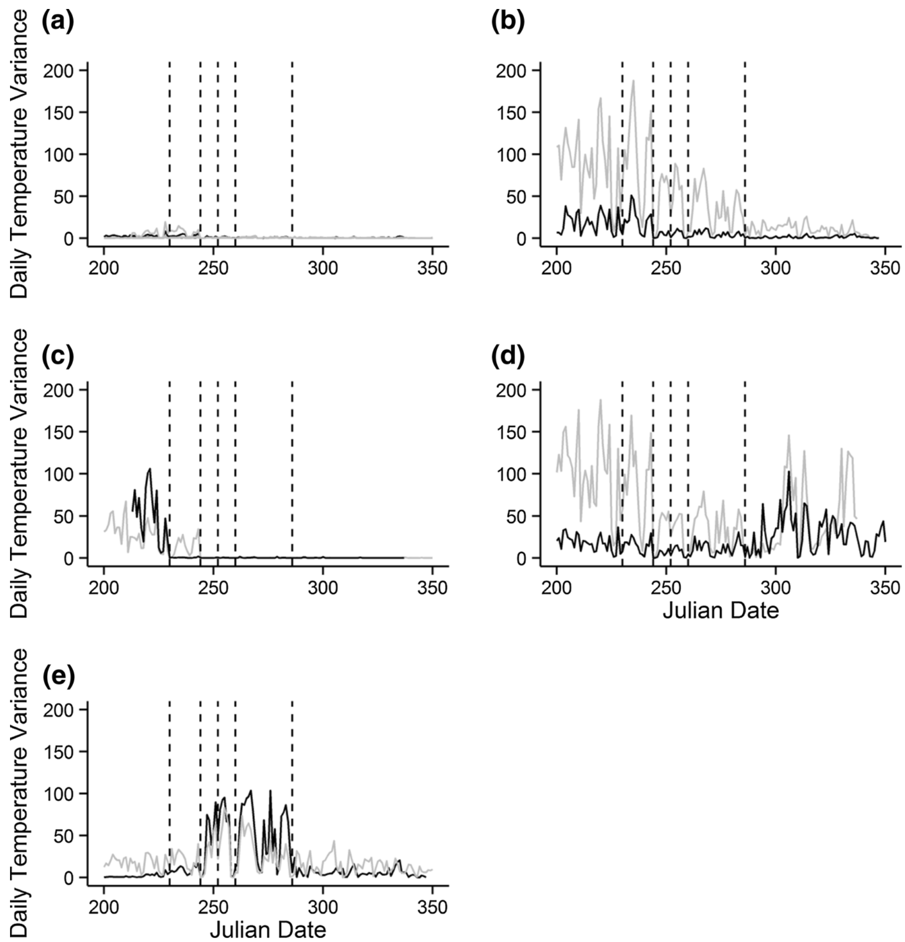

Fig. 3 Examples of temperature variance profiles for ponds with different characteristics. *Vertical dashed lines in all panels* indicate rainfall events. *Gray lines* indicate ponds with open canopy cover, and *black lines* indicate closed canopy ponds. **a** Ponds with a permanently wet inundation state. **b** Two ponds varying in canopy closure that became inundated at different times in fall 2012. **c** Two ponds varying in canopy closure that filled in fall 2012, and had 100 % cover in cattails. **d** Two ponds varying in canopy closure that fluctuated often in inundation state. **e** Two ponds varying in canopy closure where pond shoreline receded over the iButton (i.e. dried) and then became inundated again in fall 2012

Table 1 Actual and predicted dates of drying and filling for Experiment 2

iButton height	Drying date		Fill date		Inundation (days)	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
Shade						
32	9/11/2014	9/11/2014	10/3/2014	10/1/2014	4	6
24	9/14/2014	9/15/2014	9/30/2014	10/1/2014	10	10
16	9/17/2014	9/18/2014	9/26/2014	9/27/2014	17	17
8	9/20/2014	9/20/2014	9/23/2014	9/24/2014	23	22
Open						
32	9/11/2014	9/11/2014	10/3/2014	10/1/2014	4	6
24	9/14/2014	9/12/2014	9/30/2014	9/28/2014	10	10
16	9/17/2014	9/13/2014	9/26/2014	9/27/2014	17	12
8	9/20/2014	9/13/2014	9/23/2014	9/24/2014	23	15

The optimized parameters were: Shade treatment, variance threshold = 3, continuous days = 1 day, window size = 2 days; Open treatment, variance threshold = 15, continuous days threshold exceeded = 3, window size = 3 days. "Shade" is the shaded treatment, and "Open" is the open canopy treatment. iButton height is in cm. Inundation is calculated by summing the number of days that were wet or dry, both for actual and predicted dates drying/filling dates generally within 1 or 2 days of actual switches in inundation state, resulting in a close match to the actual duration. The information gained from these changes in pond inundation state can be used to further understand how the inundation aspect of wetland hydroperiod influences community structure (Wellborn et al. 1996).

Temperature data loggers such as iButtons are often small, inexpensive, and require little to no monitoring beyond deployment and retrieval. Using iButtons (and likely other loggers) to measure inundation state, however, does come with limitations that should be considered before employing our method. An a priori understanding of factors that influence temperature variance would greatly improve the accuracy, such as sun exposure (e.g. Experiment 2). In the case of open canopy ponds, adjusting the variance threshold to a higher value and with a larger window size should allow for greater water temperature fluctuations and reduce false identification of drying/filling. Conversely, temperature variance in closed canopy ponds would be reduced, and setting a lower variance threshold would be more effective at capturing true filling/drying events. iButtons in ponds with a larger volume of water will also have a decreased variance due to the higher specific heat of water compared to air (Oke 2002). However, ponds that have springs or other connections to the ground water supply may have a below average variance and maintain a more constant water temperature, regardless of volume (Williams 2005). Placement of the loggers within the pond may also influence the variance, especially if iButtons have to be placed in shallower water that fluctuates more with air temperature changes. In large bodies of water, thermocline turnover in the spring and fall may also be a factor that affects temperature variance (Williams 2005). All of these factors require further inquiry into their effects on daily and seasonal temperature measurements, and should be considered prior to deploying temperature data loggers. Furthermore, these constraints are likely not mutually exclusive, and accounting for multiple factors will likely result in greater precision in predicting inundation state. Finally, the wide ranges in accuracy we observed in the automated procedure were due to the optimization procedure searching all possible combinations of input values; when the appropriate/optimized values were selected, predicted inundation state became increasingly accurate. As we optimized across a wide range of pond conditions to obtain the >80 % accuracy, selecting more appropriate input values that reflect certain pond characteristics may be critical and even result in more precise predictions.

Depending upon the study design, automated water level monitors may be more useful because they provide quantitative data on actual water depth whereas our method describes inundation state (i.e. wet vs. dry). However, Experiment 2 shows it may be possible to capture water depth changes if multiple iButtons are used; vertical or horizontal stratification of iButtons could capture shoreline movement and depth changes to get a more detailed picture of the actual hydroperiod. Increasing the number of iButtons may negate their cost savings relative to a water level monitor; however the cheapest water level logger ($300) we found was equivalent to 17 iButtons, 7 HOBO pendants or 7 iBWetland loggers, using unit prices listed in "Introduction" section. Placing four iButtons per pond, it is possible to sample twice as many wetlands as any other method. Physically monitoring each site with infrequent visits would verify correct data logger placement, and supplement the information gained from temperature loggers. However, this may not be feasible on larger landscapes with hundreds of wetlands.

In our initial field deployment, we experienced a high iButton failure rate (27 %) despite the application of a plastic coating. Additionally, we experienced a high rate of iButton loss that was likely due human tampering at our study area. However, subsequent field deployments and both experiments showed reduced or no failures and less loss due to better placement (i.e. hidden from view). While the cause of failures is unknown, the duration which iButtons were left out under natural conditions could potentially impact their functionality. Use of waterproof data loggers would potentially alleviate failure issues due to water damage although there are tradeoffs in monetary costs and benefits gained. Combining manual monitoring with multiple iButtons in a pond basin would be prudent safeguards against iButton failure and the loss of data.

Hydroperiod is often categorized in discrete values for logistical purposes, such as permanent, semi-permanent and ephemeral (e.g. Babbitt et al. 2003; Babbitt 2005; Anderson et al. 2015). The actual number of drying and filling events, as well the actual length of days a wetland holds water can be predicted using our methods, which will improve our understanding of the sensitivity of different species to temporal regimes of inundation. A single drying event that lasts for months compared with several drying/filling events prior to complete re-inundation may have important biological consequences that are minimized when hydroperiod categorization is reduced to ephemeral. Such a fine-scale approach may be increasingly needed, as climate change is predicted to produce shorter inundation periods and more frequent drying events (Brooks 2009).

Despite all of the caveats and circumstances that may make assessment of inundation state more difficult, we have shown that temperature data loggers can be an effective way to capture pond inundation state, and that this approach can be implemented across large landscapes. Examination of daily temperature variance from iButtons has also allowed us to predict inundation state with a relatively high degree of accuracy; however, use in further studies requires careful consideration of limitations and caveats of the approach to maximize effectiveness.

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