Temperature loggers capture intraregional variation of inundation timing for intermittent ponds

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Abstract

Hydroperiod, or the amount of time a lentic waterbody contains water, shapes communities of aquatic organisms. Precise measurement of hydroperiod features such as inundation timing and duration can help predict community dynamics and ecosystem stability. In areas defined by high spatial and temporal variability, fine-scale temporal variation in inundation timing and duration may drive community structure, but that variation may not be captured using common approaches including remote sensing technology. Here, we provide methods to accurately capture inundation timing by fitting hidden Markov models to measurements of daily temperature standard deviation collected from temperature loggers. We describe a rugged housing design to protect loggers from physical damage and apply our methods to a group of intermittent ponds in southeastern Arizona, showing that initial pond inundation timing is highly variable across a small geographic scale (~50km^2). We also compare a 1-logger (pond only) and 2-logger (pond + control) design and show that, although a single logger may be sufficient to capture inundation timing in most cases, a 2-logger design can increase confidence in results. These methods are cost-effective and show promise in capturing variation in intraregional inundation timing that may have profound effects on aquatic communities, with implications for how these communities may respond to hydroperiod alteration from a changing climate.

1. Introduction

For water-dependent organisms, hydroperiod – or the amount of time a lentic waterbody holds water – plays a critical role in population and community dynamics (De Meester et al., 2005). Dispersal decisions (Tournier et al., 2017), fitness (Johnson et al., 2013; Rogers & Chalcraft, 2008), reproductive success (Ryan & Winne, 2001), survival (Acosta & Perry, 2001), and source-sink dynamics (Ruetz III et al., 2005; Werner et al., 2007) are all influenced by hydroperiod. Hydroperiod is also an important predictor of community composition (Razgour et al., 2010; Skelly, 1997; Waterkeyn et al., 2008) and diversity (Schriever et al., 2015; Schriever & Williams, 2013; Stendera et al., 2012), and thus may influence ecosystem stability. Specific components of hydroperiod, such as inundation timing or stability, influence species density and richness (Florencio et al., 2020; Kneitel, 2014) and may play a key role in determining reproductive success of aquatic organisms such as amphibians (Paton & Crouch III, 2002).

The wide-ranging effects of hydroperiod on individual organisms, populations, and ecological communities necessitate tools to enable fine-scale measurement and monitoring of the timing, frequency, and duration of hydroperiod events in temporary lentic waters. Such tools will play an important role in predicting how hydroperiods may change in response to future water use and climate scenarios – and how organisms that rely on these habitats will fare. Satellite remote sensing tools such as Synthetic Aperture Radar (Bourgeau-Chavez et al., 2005; Hong et al., 2010) and Landsat imagery (DeVries et al., 2017; Díaz-Delgado et al., 2016; Murray-Hudson et al., 2015) enable wetland hydroperiod assessment over multi-year or multi-decade periods and covering 10s to 1000s km^2. The accuracy of these methods continues to improve with advances in image analytical techniques that provide information on surface water presence and area at a sub-pixel level (Halabisky et al., 2018). Unmanned aerial systems (i.e., drones) can also provide high-resolution spatial and temporal data, particularly for specific regions (e.g. Levy & Johnson, 2021). Despite these promising advances, the temporal grain of remotely sensed data remains coarse for most remotely sensed datasets. For example, Landsat captures images at a spatial resolution of 30 meters every 16 days (Irons et al., 2012; Ozesmi & Bauer, 2002). In many regions, inundation of intermittent lentic habitat may occur over hours or days. Temporal resolution on the order of 2-4 weeks may miss important fine-scale differences in pond inundation timing, particularly in regions with unpredictable spatial patterns of precipitation that drive a patchwork of inundation dates. More recently, new earth observation products continue to refine the temporal grain size of satellite data, with some providing daily or sub-weekly observations (Lefebvre et al., 2019). Spatial resolution of new commercial products offer sub-meter resolution in some cases (e.g., Planet Team 2021). Though these products do not have the historical breadth of Landsat, they offer much higher spatial and temporal resolution for more recent years. However, challenges remain. Some remotely-sensed hydroperiod data can be obscured by cloud and/or canopy cover, decreasing temporal resolution from a few days to longer periods. This may be particularly challenging if inundation timing co-occurs with periods of high cloud cover. Though commercial products are often available at no charge for researchers with particular affiliations, data in these cases is often limited in format, spatial extent, or resolution. For full access, project budgets often must accommodate product costs.

Temperature and conductivity sensors are used increasingly in both lotic and lentic systems to provide fine-scale spatial and temporal hydroperiod measurements (Anderson et al., 2015; Arismendi et al., 2017; Jaeger & Olden, 2012). Daily temperature variance is typically lower in water than in air, and comparison of daily temperature variance provides a reliable proxy for inundation state (Sowder & Steel, 2012). A rapid drop in daily temperature variance can reliably measure the precise timing of an inundation event (Anderson et al., 2015; Arismendi et al., 2017). For example, Anderson et al. (2015) tested the ability of temperature sensors to accurately predict inundation states both in natural wetlands and in controlled mesocosms. The authors deployed temperature sensors for two six-month periods in ponds over a 7140 ha area that varied in size and depth. They demonstrated that daily temperature variance reflected pond filling and drying events, with higher variance in dry ponds and in control sensors placed on the ground outside of ponds, and they determined an approximate variance threshold to predict inundation states. Arismendi et al. (2017) placed paired temperature sensors and electrical resistors in temporary streams and found that using daily temperature standard deviation more accurately predicted inundation states than mean hourly or daily temperature measurements.

Hidden Markov models (HMMs) can be used to identify shifting trends in time series data (e.g. high temperature variance associated with dry states and low temperature variance associated with wet states) while accounting for temporal autocorrelation and are useful tools for modeling climatic data (reviewed in Srikanthan & McMahon, 2001). Arismendi et al. (2017) demonstrated the ability of these algorithms to predict wetland inundation states and found that fitting 2-state HMMs to temperature standard deviations led to accurate predictions of shifts from wet to dry states in ephemeral streams.

Here, we describe methods for deployment and data analysis of an array of temperature loggers to monitor inundation state of intermittent ponds in the San Rafael Valley of Arizona, USA. These methods are applicable to a range of temporary lentic habitats, especially where logistical challenges may necessitate use of on-the-ground measurements rather than remotely sensed data. The objectives of this study were: 1) design a sturdy, low cost, and low maintenance housing unit for temperature sensor deployment in remote and rugged terrain; 2) deploy paired sensors (one within the target pond and one outside the pond) to monitor hydroperiod inundation states in temporary ponds; 3) evaluate inundation states using HMMs, comparing inundation date inference between 1-logger (pond only) and 2-logger (pond + control) experimental design; 4) compare observed and inferred inundation state recorded during in-person visits to ponds. Overall, our findings point to the utility of temperature loggers as a cost-effective, low profile tool in uncovering ecologically relevant spatiotemporal differences in intraregional inundation timing. This is particularly useful in regions with highly localized precipitation events that drive small-scale differences in spatiotemporal hydroperiod dynamics.

2. Methods

2.1 Study area

We deployed paired temperature loggers (one within and one outside each pond) in 16 intermittent ponds in the Coronado National Forest, located within the Huachuca Mountains Canelo Hills (HMCH) region and San Rafael Valley of southeastern Arizona, USA in June and July 2018 (Figure 1). The HMCH region is part of the Madrean Sky Islands, with an elevation range of approximately 1150 m to 2880 m. Habitat composition includes cienega wetlands, semi-arid grasslands and thorn-scrub, and evergreen and coniferous woodlands. The climate of this region is semi-arid, with up to half of the annual rainfall occurring during the summer monsoon season (Sheppard et al., 2002). Rain events during the monsoon season are typically short in duration, high in intensity, and seasonally predictable but spatially variable (Goodrich et al., 2008). Ponds in the region were originally constructed to provide water for livestock and are often called "stock tanks"; these ponds are now surrogating for aquatic habitat lost to human activities and support a range of aquatic species (Rosen & Schwalbe 1998; Storfer et al. 2014; Mims et al. 2016). We selected ponds based on historical hydroperiod data that indicated they were generally intermittent and tended to have longer (>1 month) duration wetted phases (Parsley et al., 2020).

2.2 Sensors, housing units, and deployment

We selected a waterproof temperature logger with the capacity for battery replacement by the user for longevity (company: Onset, Bourne, MA, USA; model: HOBO Pendant, MX2201; diameter: 3.35 cm; temperature range: -20 @C to 50@C; temperature precision: ± 0.5@C; cost: $54.00 USD; data retrieval: Bluetooth, battery: user replaceable CR2032 3V lithium). Our study region is remote with rugged terrain, and deployed equipment is exposed to variable weather, UV exposure, and potential tampering from humans, wildlife, or livestock. The intermittent ponds in our study region are visited frequently by cattle, and equipment must be able to withstand trampling or tampering. With this in mind, we designed a rugged housing unit to protect temperature loggers from damage and ensure long-term durability (Figure S1). We placed a logger inside a PVC junction box (hereafter called the housing unit) with two nuts between the box and the lid for increased air or water flow. The logger moved freely inside the housing unit to increase the chance that it remained submerged (i.e., fell to the lowest point within the housing unit) if disturbed after deployment. The housing unit was connected to a concrete tie or other secure post (e.g., a metal fence post marking edges of allotments) via a 3/32" (2.381 mm) galvanized, uncoated steel cable strung through the holes of the junction box. We fastened the cable by swaging a crimping sleeve. We provide a complete list of specifications for tools and materials in Table S1.

At each of the 16 ponds, we deployed one logger at the approximate deepest point of fill within the tank (the pond logger) and one logger approximately 10 m outside of the high-water mark for the pond (the control logger). Where possible, we placed control loggers in sunny, shade-free areas in order to most closely match conditions and exposure of the pond logger. If the pond basin consisted of fine clay or silt, we placed the housing unit on a flat rock partially buried to sit flush with the ground and to avoid it becoming buried in silt upon pond inundation. We then secured the housing unit to an existing fence post (typically a metal T post) or to a concrete tie using steel cable looped through the housing. We used a mallet to drive concrete ties completely into the ground for protection of livestock. Finally, we covered units with loosely stacked rocks to minimize livestock tripping risk and to help camouflage units to avoid tampering (Figure S2). Loggers recorded temperature at 15-minute intervals with Bluetooth set to manual (i.e., not continuously seeking a signal), resulting in an estimated 3.2-year battery life for each logger. We visited ponds three times after sensor deployment: 31 Jul – 2 Aug 2018, 31 Mar - 3 April 2019, and 21 – 27 June 2019 (time of data retrieval). During each site visit, we evaluated logger function, cleared any mud or sediment in the rugged housing units, and replaced disturbed rock piles (Figure S3).

2.3 Prediction of pond inundation states using hidden Markov models

We used hidden Markov models (HMMs) to detect temporal shifts in daily temperature standard deviations (tSDs) measured from the temperature sensors, which can be used to infer pond filling and drying events.

The simplest HMMs partition datasets into 2 categories; in our study, the two categories represent distinct wet and dry states. However, Anderson et al. (2015) showed that seasonal fluctuation, canopy cover, pond vegetation, and water depth can influence temperature variance readings from temperature loggers placed in wetland basins, and that loggers in relatively deeper water have lower variance than those in shallower water. Use of HMMs with >2 states can help resolve this variation among dry-wet states, improving classifications. We therefore fit both 2-state and 3-state HMMs to both of our datasets, with the former modeling a simple scenario of distinct dry and wet states, and the latter factoring in the potential for additional wet, dry, or intermediate damp states.

In order to test whether a single logger (e.g., one in a pond without a control outside the pond) is sufficient to capture inundation states, we also compared two different datasets for each study site: one using temperature data from the paired pond and control loggers, calculated by subtracting the tSDs of the pond loggers from the tSDs of control loggers (wherein a value of 0 indicates no difference in daily tSD between the pond and air temperatures), and another using tSDs from pond loggers only.

We used a custom script in R v3.6.1 (R Development Core Team, 2018) to calculate tSDs measured by each temperature logger. We then used the package depmixS4 v1.4.0 (Visser & Speekenbrink, 2010) in R to fit HMMs. Because applying HMMs forces each dataset into the designated number of states, even in the absence of a true wet state, we used the HMM parameter estimates to determine appropriate tSD thresholds to designate each state as "wet" or "dry" for both datasets. We then compared the predicted states to the known states of the ponds during our four site visits (Tables S2 and S3).

3. Results and Discussion

3.1 Assessment of housing unit performance

We retrieved data from 30 (n = 14 pond loggers, n = 16 control loggers) of the 32 loggers deployed, with two pond loggers underwater at the time of collection. We downloaded temperature data for the entire study period (between 1 July 2018 and 21 June 2019) for 26 loggers. Four pond loggers at sites T1, T2, T8, and T13 failed due to a potentially faulty logger backing design that was addressed by the manufacturer during the time between initial deployment and site visits in June 2019; all pond loggers were replaced by the manufacturer, and replacements were deployed following data retrieval in June 2019. No subsequent issues emerged (0% failures) using loggers with the updated backing for other experiments during which loggers were submerged in water for months at a time (M.C. Mims, unpublished data).

Overall, we found that the logger housing design successfully protected the loggers from physical damage, even when disturbed by cattle, but there were some considerations and limitations. Careful placement of loggers in the deepest point in the pond is imperative for accurate hydroperiod estimation. At site T11, we observed that the pond logger did not appear to be placed at the lowest point within the pond, as was intended. We observed very shallow water pooled in another location near the logger in summer 2019 that dried a few days later. Therefore, the data collected from this logger may not accurately reflect the pond inundation state. Additionally, rock piles placed on top of the rugged housing likely affected absolute temperature readings. Though rock color or density may have had differential effects among loggers, we suspect the variation among loggers was likely low overall. Furthermore, because this method considers tSD rather than absolute temperature, we do not anticipate these differences had substantial effects on results.

Another potential issue with our physical design was the accumulation of sediment or other debris within the rugged housing unit that interfered with temperature readings from the pond loggers at sites A14, T4, T9, and T17 (see Figure S3 for example). Although we have relatively high confidence in inundation timing, drying dates were less precise largely due to the accumulation of sediment in the housing unit. At site A14, mud was discovered in the logger housing on 31 March 2019 and was cleared. In the days preceding 31 March 2019, the temperature standard deviations from the pond logger were considerably lower than those from the control logger at this site, despite a lack of water in the pond, resulting in the paired pond-control model falsely predicting that the pond was in a wet state. After the sediment was cleared, the difference in these tSDs decreased to nearly zero, and the paired pond-control model correctly designated the pond state as dry. Mud and debris found inside the rugged housing of the pond loggers at sites T4 and T9 in late June likely caused the tSDs of these pond loggers to remain low relative to those of the control loggers even after drying, leading to false wet predictions in the paired pond-control models. In addition, we occasionally observed animals inside housing units, including several salamanders inside the housing for the pond logger at site T9 (Figure 2).

To improve drying date precision, the housing unit design would likely need to exclude sediment, which is difficult to do without making other compromises. Solutions for avoiding the issue of sediment in rugged housing units, and the subsequent decoupling of pond and control data, include packing the housing unit with insulation or other material that would not allow sediment to enter. However, this can lead to issues such as a buoyant housing unit and may affect the temperature readings if the material is a good insulator.

3.2 Comparison of 2- versus 3-state hidden Markov models and determination of wet state threshold values

Although 2-state HMMs have been applied in past work (Arismendi et al., 2017), we found that 2-state HMMs appeared to over- or underestimate inundation duration for several ponds or predict additional wet states when we were confident that the ponds were dry (Figure S4). Using 3-state HMMs and subsequently combining multiple wet or dry states provided more accurate and consistent state predictions between pond only and paired pond-control datasets (Tables S2, S3). Therefore, we focused our analyses on results from the 3-state HMMs, which allow for the potential for seasonal variation in daily tSDs and intermittent wet-dry states (e.g., damp) and account for potential uncertainty due to wet sediment or other factors (see Figure 3 for examples).

For the paired pond-control dataset, we used a wet state threshold of -2.0°C, meaning that the daily tSDs measured by the pond sensors were at least 2.0°C lower on average than those measured by the control sensors. This -2.0°C threshold minimized the number of false dry state predictions. It did result in a false wet prediction for T17, but this was likely due to sediment in the pond sensor housing that may have affected the reading. A more conservative threshold of -2.2°C falsely predicted T12 as dry (Table S3).

Upon fitting 3-state HMMs to the pond-only dataset, we found that a threshold between 2.9°C to 3.3°C minimized the number of false dry states for most ponds (Table S2, Table S3). This threshold is slightly lower than that proposed by Anderson et al. (2015), who determined that using daily temperature variances cutoffs between 13 and 15 (corresponding to tSDs between 3.6°C and 3.9°C) for the wet state provided the most accurate predictions of pond inundation states in their field experiments. Within our pond-only dataset, using a less conservative tSD threshold of 3.5°C decreased the accuracy leading to a false wet state prediction for pond T15U. For pond T8, the state with the highest average temperature standard deviation (~2.8°C) fell below our wet state cutoff of 3.0°C (Table S5). Because we knew that the pond was dry at two timepoints in this state (during logger deployment and logger retrieval), we decreased the wet state threshold to 2.7°C for this particular pond and considered the average tSD of 2.8°C to reflect a dry state.

To further define a "reliable" wet state prediction from our HMMs, we also required that the pond remain in a given state for a minimum of 5 consecutive days. We chose this cutoff based on site observations in early August 2018, during which ponds T17 and T20 had short predicted wet states of 7 and 5 days in July respectively and both showed evidence of prior inundation despite being dry at the time of our visit. Pond A14 also had a predicted wet state of 4 days in mid-July but showed no evidence of earlier inundation in early August (Table S2, Table S3).

3.3 Comparison of 1 (pond-only) versus 2 (paired pond-control) logger design

Under the wet state criteria defined above, 3-state HMMs for the pond-only model accurately predicted inundation states for 92% of site visits for the 14 ponds. The paired pond-control model, which used combined data from the loggers inside and outside of each pond, accurately predicted inundation states for 90% of sites visits. Most of the incorrect state predictions were likely due to sediment or additional debris accumulating within the rugged housing units, which was more likely to affect precision of drying dates rather than initial inundation timing.

Models using temperature data from pond loggers alone predict inundation timing that closely aligned with those using paired pond-control logger data, indicating that a single logger design may be sufficient to capture inundation timing of longer-duration events (Table S5, Figure 4). However, control logger data may help alleviate some of the wet state false-positives, particularly when the standard deviation of daily air temperature is relatively low or issues such as sediment in rugged housing units occur. For example, earlier inundation dates are predicted for several ponds by the pond-only model relative to the paired pond-control model. This may be a true wet state, or the coincident low temperature standard deviations measured by the control loggers may have simply resulted in lower variance in the temperature on those days. For site T13, the state was correctly predicted as wet by the paired pond-control model, but not by the pond-only model in April 2019. While we did observe water in the pond at this time, the water level was just at the base of the rock pile covering the logger housing, which may explain the discrepancies between the models. In cases such as this when shallow water is present, the 2-logger design may help to increase the probability of detecting inundation. Predicting pond drying may require an array of pond loggers situated at different heights within the pond to capture this fine-scale variation or a different type of sensor, such as pressure transducers. But considerations exist for the pond-control logger model as well. For example, pond-only models predicted wet states for most ponds in the winter months (between December and February) that were not predicted by the paired pond-control models. The relatively low tSDs of the loggers in the winter months may be due to snow accumulation on top of the control loggers.

3.4 Pond inundation regimes

Based on HMM estimates, ponds varied in both initial timing and duration of inundation (Figure 4), with initial inundation dates ranging from 10 July 2018 to 7 August 2018, over a small geographic area (Figure 1). Eleven of the fourteen ponds in our study had at least one predicted wet state during our monitoring period. Ten of these ponds had wet states predicted from both datasets. Based on the state predictions by both models, ponds in the central range of our study area filled first, with ponds T8, T9, T12, and T13 all inundated between 10 - 17 July 2018. Ponds in the northern and southern portions of the study area had more variation in their initial inundation dates, which were predicted to occur between late July and mid-August (Table S6, Figure 1, Figure 4).

Inundation dates inferred from pond-only and pond-control models largely aligned (Figure 4). Only pond T20 was predicted to have a wet state by one model (the pond-only model) and not the other. The presence of vegetation at the perimeter of the pond and mud inside the housing of the T20 pond logger during our visit in April 2019 suggest that the pond may have been inundated with water at some point during logger deployment. Visual inspection of the T20 temperature standard deviation readings revealed a slight difference between August and October 2018. Ponds T11 and T15U, which had no predicted inundation dates, also showed slightly lower readings from the pond loggers relative to the control loggers at certain points in the monsoon season and had mean state values close to but slightly above our wet state thresholds. It is possible that some water accumulated in these ponds and that our wet state threshold for the HMMs lacked the sensitivity to capture these low signals. The tSD threshold may need to be adjusted to increase precision in cases where small amounts of water accumulate for durations shorter than 5 days.

3.5 Broader applications and considerations

The methods we present are relevant and applicable to temporary lentic habitats in a wide range of regions, particularly where logistical challenges constrain the data available for hydroperiod monitoring. For example, temperature sensor-derived hydroperiod inference may be particularly useful for ponds or wetlands that can have high canopy cover (e.g., some Carolina bays (Sharitz, 2003) or vernal pools (Brooks, 2004)) or other considerations that may make remote sensing difficult, particularly across multiple sites. Temperature sensors may also be helpful in regions where drone activity is discouraged or prohibited, thus limiting targeted, fine-scale aerial data acquisition. This includes national parks, wildlife sanctuaries, or areas where drone flight is otherwise prohibited (for example, drone operation is not logistically feasible in our study region due to restrictions by the United States Border Patrol). Our proposed methods are relatively low-cost and low-maintenance, making them accessible for even small-scale research grants. The long battery life of the sensors and high durability of the design make them ideal for deploying in remote areas. However, we suggest that users visit deployment sites at least once a year, particularly before major seasonal inundation events.

Some scenarios may necessitate modifications to the current design, including components and deployment. For example, complex bathymetry of wetlands may call for the use of more than one temperature sensor to detect hydroperiod inundation, particularly when distinct areas of the temporary habitat have meaningful ecological differences (Chandler, 2017). If longer battery life is desired, the temporal resolution of measurements could also be adjusted to capture temperature data in less frequent intervals. Additionally, users may consider alternative sensor designs. For example, conductivity sensors offer an alternative to temperature loggers. However, custom modifications required to create conductivity sensors can be time-consuming or, if outsourced, may result in units that are >2 times the cost of temperature loggers. Additionally, conductivity sensors may suffer from the same issues related to poor or imprecise detection of drying patterns due to water trapped in sediments. Temperature measurements offer data that are biologically meaningful (temperature as well as presence/absence of water) and that may address multiple needs depending on the objectives of a study. Pressure transducers would likely capture drying dynamics more accurately and are available for as low as ~$300 per sensor (e.g., Onset HOBO Water Level Data Logger, U20L-01). However, the physical dimensions of pressure transducers would require modifications to the current rugged housing unit design, and the additional cost would result in approximately a four-fold reduction in the number of sensors obtained for the same budget. An additional consideration is the ability of sensors to withstand extreme temperatures. The temperature sensors in our design have a range of -20 to 50°C in water; anticipated temperatures outside this range would likely necessitate a different sensor model and may be an important consideration for high-latitude study regions. Finally, deployment methods for the housing unit and sensor may need to be modified depending upon the substrate of the habitat. For example, mud or other soft sediment may require a T-post or similar support structure rather than buried concrete ties depending upon the depth of the soft substrate.

4. Conclusions

Precise measurement of pond inundation timing can be essential for studies of ecological and hydrological dynamics, particularly in areas with fine-scale variation in climate, where limited water supply may be crucial in shaping population and community dynamics. In this study, we observed an approximate 4-week difference in initial inundation timing between ponds within a small geographic range (~50km^2), which is a substantial portion of the aquatic stage for many aquatic organisms that rely on these ponds to complete their life cycle (e.g., amphibians: Mims et al., 2020; Moore et al., 2020); these intraseasonal differences in inundation timing may thus have major implications for community composition and species turnover in these habitats. Fine-scale hydrological data such as those presented herein provide valuable information about dynamic water regimes that can improve conservation strategies by identifying potential refugees for plants and wildlife and can also aid in planning for human adaptation in response to the changing climate.

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Figure Legends

Figure 1. Study ponds (N=14) in the Huachuca Mountains-Canelo Hills region of southeastern Arizona (reference map inset). Colors indicate pond initial fill dates, ranging from 17 July 2018 (T8, 9, 12, and 13) to 25 August 2018 (T2). Initial fill dates were calculated from paired pond-control Hidden Markov models, where inundation was defined as a period of 5 or more consecutive days with the daily temperature standard deviation measured by the pond logger was at least 2°C less than that of the control logger. UTM coordinates (NAD 83) indicate position of each corner of the map.

Figure 2. Three-state hidden Markov model predictions for pond T9 using (a) pond-only dataset, and (b) paired pond-control dataset. (c) Photos from site visits (dates correspond with stars in (a)), in which observed pond inundation state was dry at the time of sensor deployment (1 July 2018), wet during a return visit the following spring (3 April 2019), and dry at the time of sensor retrieval (24 June 2019). Though we observed no standing water on 24 June 2019, the pond supported vegetation, and we found salamanders in the sensor housing unit (inset photo; possibly contributing to different predicted states on 24 June 2019). Colors indicate temporal state predictions for each pond (pink=dry, blue=wet) and lines represent daily temperature standard deviation (tSD) measurements from pond logger (black lines) and control logger (grey lines).

Figure 3. Inundation state predictions by 3-state hidden Markov models (HMMs). Shown are marginal distributions and predicted inundation timing for select ponds that (a) became inundated for long durations during the study period, (b) filled for relatively shorter durations, and (c) had no predicted wet state. Left

panels represent marginal distributions and right panels represent HMM estimates from paired pond-control models (top) and pond-only models (bottom). Shading on HMM graphs indicate temporal state predictions for each pond (pink=dry, blue=wet) and lines represent temperature standard deviation (tSD) measurements from control loggers (grey lines) and pond loggers (black lines). Dashed lines indicate wet state thresholds (3.0°C for the pond only dataset and -2.0°C difference for the paired dataset).

Figure 4. Hidden Markov model (HMM) pond inundation predictions. Lines show daily tSDs measured by pond loggers (black) and control loggers (grey). Rectangles represent wet days predicted by HMMs from single pond loggers (light green), by paired pond-control loggers (light blue), and by both models (dark blue). Grey shading indicates a predicted dry/damp state and lack of shading indicates no data due to logger failure.

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Temperature loggers capture intraregional variation of inundation timing for intermittent ponds

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ABSTRACT

Hydroperiod, or the amount of time a lentic waterbody contains water, shapes communities of aquatic organisms. Precise measurement of hydroperiod features such as inundation timing and duration can help predict community dynamics and ecosystem stability. In areas defined by high spatial and temporal variability, fine-scale temporal variation in inundation timing and duration may drive community structure, but that variation may not be captured using common approaches including remote sensing technology. Here, we provide methods to accurately capture inundation timing by fitting hidden Markov models to measurements of daily temperature standard deviation collected from temperature loggers. We describe a rugged housing design to protect loggers from physical damage and apply our methods to a group of intermittent ponds in southeastern Arizona, showing that initial pond inundation timing is highly variable across a small geographic scale (~50km^2). We also compare a 1-logger (pond only) and 2-logger (pond + control) design and show that, although a single logger may be sufficient to capture inundation timing in most cases, a 2-logger design can increase confidence in results. These methods are cost-effective and show promise in capturing variation in intraregional inundation timing for a range of temporary lentic habitats that may have profound effects on aquatic communities, with implications for how these communities may respond to hydroperiod alteration from a changing climate.

Key Words: temporary ponds, hydroperiod, HOBO Pendant logger, temperature sensor, hidden Markov models, American Southwest, aquatic, desert

1. Introduction

For water-dependent organisms, hydroperiod – or the amount of time a lentic waterbody holds water – plays a critical role in population and community dynamics (De Meester et al., 2005). Dispersal decisions (Tournier et al., 2017), fitness (Johnson et al., 2013; Rogers & Chalcraft, 2008), reproductive success (Ryan & Winne, 2001), survival (Acosta & Perry, 2001), and source-sink dynamics (Ruetz III et al., 2005; Werner et al., 2007) are all influenced by hydroperiod. Hydroperiod is also an important predictor of community composition (Razgour et al., 2010; Skelly, 1997; Waterkeyn et al., 2008) and diversity (Schriever et al., 2015; Schriever & Williams, 2013; Stendera et al., 2012), and thus may influence ecosystem stability. Specific components of hydroperiod, such as inundation timing or stability, influence species density and richness (Florencio et al., 2020; Kneitel, 2014) and may play a key role in determining reproductive success of aquatic organisms such as amphibians (Paton & Crouch III, 2002).

The wide-ranging effects of hydroperiod on individual organisms, populations, and ecological communities necessitate tools to enable fine-scale measurement and monitoring of the timing, frequency, and duration of hydroperiod events in temporary lentic waters. Such tools will play an important role in predicting how hydroperiods may change in response to future water use and climate scenarios – and how organisms that rely on these habitats will fare. Satellite remote sensing tools such as Synthetic Aperture Radar (Bourgeau-Chavez et al., 2005; Hong et al., 2010) and Landsat imagery (DeVries et al., 2017; Díaz-Delgado et al., 2016; Murray-Hudson et al., 2015) enable wetland hydroperiod assessment over multi-year or multi-decade periods and covering 10s to 1000s km^2. The accuracy of these methods continues to improve with advances in image analytical techniques that provide information on surface water presence and area at a sub-pixel level (Halabisky et al., 2018). Unmanned aerial systems (i.e., drones) can also provide high-resolution spatial and temporal data, particularly for specific regions (e.g. Levy & Johnson, 2021). Despite these promising advances, the temporal grain of remotely sensed data remains coarse for most remotely sensed datasets. For example, Landsat captures images at a spatial resolution of 30 meters every 16 days (Irons et al., 2012; Ozesmi & Bauer, 2002). In many regions, inundation of intermittent lentic habitat may occur over hours or days. Temporal resolution on the order of 2-4 weeks may miss important fine-scale differences in pond inundation timing, particularly in regions with unpredictable spatial patterns of precipitation that drive a patchwork of inundation dates. More recently, new earth observation products continue to refine the temporal grain size of satellite data, with some providing daily or sub-weekly observations (Lefebvre et al., 2019). Spatial resolution of new commercial products offer sub-meter resolution in some cases (e.g., Planet Team 2021). Though these products do not have the historical breadth of Landsat, they offer much higher spatial and temporal resolution for more recent years. However, challenges remain. Some remotely-sensed hydroperiod data can be obscured by cloud and/or canopy cover, decreasing temporal resolution from a few days to longer periods. This may be particularly challenging if inundation timing co-occurs with periods of high cloud cover. Though commercial products are often available at no charge for researchers with particular affiliations, data in these cases is often limited in format, spatial extent, or resolution. For full access, project budgets often must accommodate product costs.

Temperature and conductivity sensors are used increasingly in both lotic and lentic systems to provide fine-scale spatial and temporal hydroperiod measurements (Anderson et al., 2015; Arismendi et al., 2017; Jaeger & Olden, 2012). Daily temperature variance is typically lower in water than in air, and comparison of daily temperature variance provides a reliable proxy for inundation state (Sowder & Steel, 2012). A rapid drop in daily temperature variance can reliably measure the precise timing of an inundation event (Anderson et al., 2015; Arismendi et al., 2017). For example, Anderson et al. (2015) tested the ability of temperature sensors to accurately predict inundation states both in natural wetlands and in controlled mesocosms. The authors deployed temperature sensors for two six-month periods in ponds over a 7140 ha area that varied in size and depth. They demonstrated that daily temperature variance reflected pond filling and drying events, with higher variance in dry ponds and in control sensors placed on the ground outside of ponds, and they determined an approximate variance threshold to predict inundation states. Arismendi et al. (2017) placed paired temperature sensors and electrical resistors in temporary streams and found that using daily temperature standard deviation more accurately predicted inundation states than mean hourly or daily temperature measurements.

Hidden Markov models (HMMs) can be used to identify shifting trends in time series data (e.g. high temperature variance associated with dry states and low temperature variance associated with wet states) while accounting for temporal autocorrelation and are useful tools for modeling climatic data (reviewed in Srikanthan & McMahon, 2001). Arismendi et al. (2017) demonstrated the ability of these algorithms to predict wetland inundation states and found that fitting 2-state HMMs to temperature standard deviations led to accurate predictions of shifts from wet to dry states in ephemeral streams.

Here, we describe methods for deployment and data analysis of an array of temperature loggers to monitor inundation state of intermittent ponds in the San Rafael Valley of Arizona, USA. These methods are applicable to a range of temporary lentic habitats, especially where logistical challenges may necessitate use of on-the-ground measurements rather than remotely sensed data. The objectives of this study were: 1) design a sturdy, low cost, and low maintenance housing unit for temperature sensor deployment in remote and rugged terrain; 2) deploy paired sensors (one within the target pond and one outside the pond) to monitor hydroperiod inundation states in temporary ponds; 3) evaluate inundation states using HMMs, comparing inundation date inference between 1-logger (pond only) and 2-logger (pond + control) experimental design; 4) compare observed and inferred inundation state recorded during in-person visits to ponds. Overall, our findings point to the utility of temperature loggers as a cost-effective, low profile tool in uncovering ecologically relevant spatiotemporal differences in intraregional inundation timing. This is particularly useful in regions with highly localized precipitation events that drive small-scale differences in spatiotemporal hydroperiod dynamics.

2. Methods

2.1 Study area

We deployed paired temperature loggers (one within and one outside each pond) in 16 intermittent ponds in the Coronado National Forest, located within the Huachuca Mountains Canelo Hills (HMCH) region and San Rafael Valley of southeastern Arizona, USA in June and July 2018 (Figure 1). The HMCH region is part of the Madrean Sky Islands, with an elevation range of approximately 1150 m to 2880 m. Habitat composition includes cienega wetlands, semi-arid grasslands and thorn-scrub, and evergreen and coniferous woodlands. The climate of this region is semi-arid, with up to half of the annual rainfall occurring during the summer monsoon season (Sheppard et al., 2002). Rain events during the monsoon season are typically short in duration, high in intensity, and seasonally predictable but spatially variable (Goodrich et al., 2008). Ponds in the region were originally constructed to provide water for livestock and are often called "stock tanks"; these ponds are now surrogating for aquatic habitat lost to human activities and support a range of aquatic species (Rosen & Schwalbe 1998; Storfer et al. 2014;

Mims et al. 2016). We selected ponds based on historical hydroperiod data that indicated they were generally intermittent and tended to have longer (>1 month) duration wetted phases (Parsley et al., 2020).

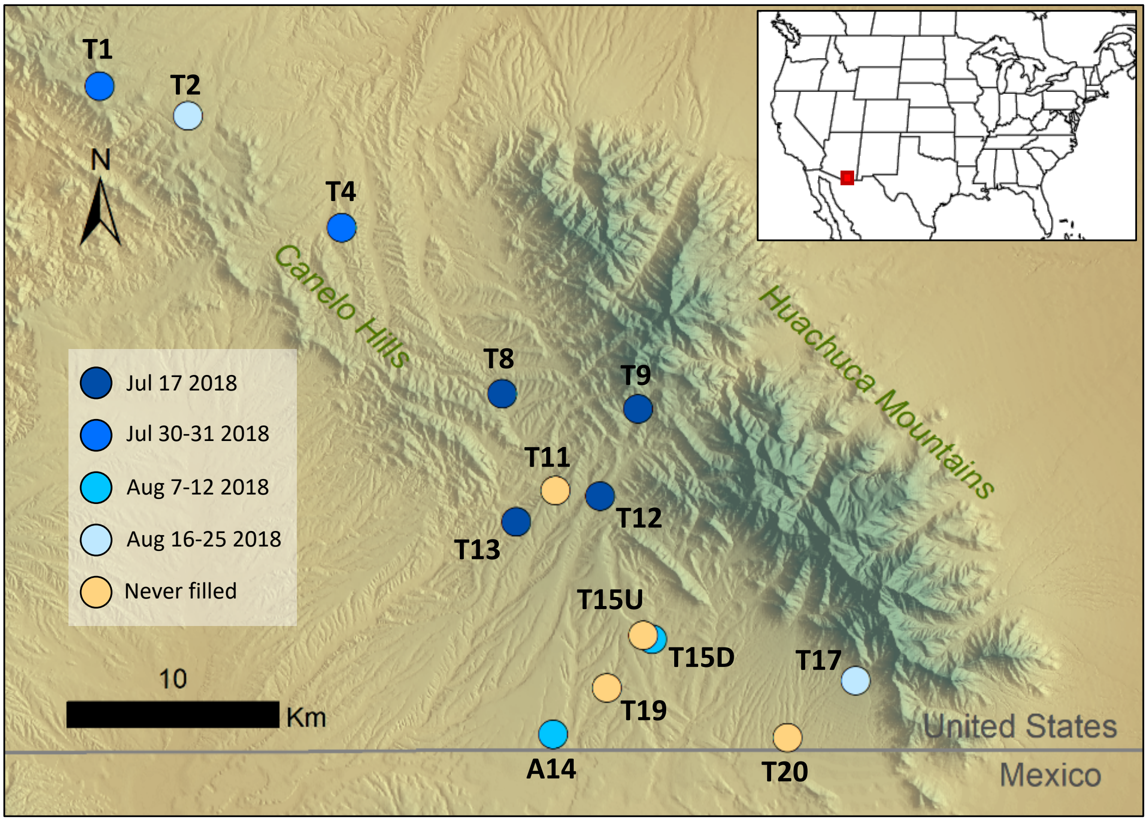

Figure 1. Study ponds (N=14) in the Huachuca Mountains-Canelo Hills region of southeastern Arizona (reference map inset). Colors indicate pond initial fill dates, ranging from 17 July 2018 (T8, 9, 12, and 13) to 25 August 2018 (T2). Initial fill dates were calculated from paired pond-control Hidden Markov models, where inundation was defined as a period of 5 or more consecutive days with the daily temperature standard deviation measured by the pond logger was at least 2°C less than that of the control logger. UTM coordinates (NAD 83) indicate position of each corner of the map.

2.2 Sensors, housing units, and deployment

We selected a waterproof temperature logger with the capacity for battery replacement by the user for longevity (company: Onset, Bourne, MA, USA; model: HOBO Pendant, MX2201; diameter: 3.35 cm; temperature range: -20 ˚C to 50˚C; temperature precision: ± 0.5˚C; cost: $54.00 USD; data retrieval: Bluetooth, battery: user replaceable CR2032 3V lithium). Our study region is remote with rugged terrain, and deployed equipment is exposed to variable weather, UV exposure, and potential tampering from humans, wildlife, or livestock. The intermittent ponds in our study region are visited frequently by cattle, and equipment must be able to withstand trampling or tampering. With this in mind, we designed a rugged housing unit to protect temperature loggers from damage and ensure long-term durability (Figure S1). We placed a logger inside a PVC junction box (hereafter called the housing unit) with two nuts between the box and the lid for increased air or water flow. The logger moved freely inside the housing unit to increase the chance that it remained submerged (i.e., fell to the lowest point within the housing unit) if disturbed after deployment. The housing unit was connected to a concrete tie or other secure post (e.g., a metal fence post marking edges of allotments) via a 3/32" (2.381 mm) galvanized, uncoated steel cable strung through the holes of the junction box. We fastened the cable by swaging a crimping sleeve. We provide a complete list of specifications for tools and materials in Table S1.

At each of the 16 ponds, we deployed one logger at the approximate deepest point of fill within the tank (the pond logger) and one logger approximately 10 m outside of the high-water mark for the pond (the control logger). Where possible, we placed control loggers in sunny, shade-free areas in order to most closely match conditions and exposure of the pond logger. If the pond basin consisted of fine clay or silt, we placed the housing unit on a flat rock partially buried to sit flush with the ground and to avoid it becoming buried in silt upon pond inundation. We then secured the housing unit to an existing fence post (typically a metal T post) or to a concrete tie using steel cable looped through the housing. We used a mallet to drive concrete ties completely into the ground for protection of livestock. Finally, we covered units with loosely stacked rocks to minimize livestock tripping risk and to help camouflage units to avoid tampering (Figure S2). Loggers recorded temperature at 15-minute intervals with Bluetooth set to manual (i.e., not continuously seeking a signal), resulting in an estimated 3.2-year battery life for each logger. We visited ponds three times after sensor deployment: 31 Jul – 2 Aug 2018, 31 Mar - 3 April 2019, and 21 – 27 June 2019 (time of data retrieval). During each site visit, we evaluated logger function, cleared any mud or sediment in the rugged housing units, and replaced disturbed rock piles (Figure S3).

2.3 Prediction of pond inundation states using hidden Markov models

We used hidden Markov models (HMMs) to detect temporal shifts in daily temperature standard deviations (tSDs) measured from the temperature sensors, which can be used to infer pond filling and drying events. The simplest HMMs partition datasets into 2 categories; in our study, the two categories represent distinct wet and dry states. However, Anderson et al. (2015) showed that seasonal fluctuation, canopy cover, pond vegetation, and water depth can influence temperature variance readings from temperature loggers placed in wetland basins, and that loggers in relatively deeper water have lower variance than those in shallower water. Use of HMMs with >2 states can help resolve this variation among dry-wet states, improving classifications. We therefore fit both 2-state and 3-state HMMs to both of our datasets, with the former modeling a simple scenario of distinct dry and wet states, and the latter factoring in the potential for additional wet, dry, or intermediate damp states.

In order to test whether a single logger (e.g., one in a pond without a control outside the pond) is sufficient to capture inundation states, we also compared two different datasets for each study site: one using temperature data from the paired pond and control loggers, calculated by subtracting the tSDs of the pond loggers from the tSDs of control loggers (wherein a value of 0 indicates no difference in daily tSD between the pond and air temperatures), and another using tSDs from pond loggers only.

We used a custom script in R v3.6.1 (R Development Core Team, 2018) to calculate tSDs measured by each temperature logger. We then used the package depmixS4 v1.4.0 (Visser & Speekenbrink, 2010) in R to fit HMMs. Because applying HMMs forces each dataset into the designated number of states, even in the absence of a true wet state, we used the HMM parameter estimates to determine appropriate tSD thresholds to designate each state as "wet" or "dry" for both datasets. We then compared the predicted states to the known states of the ponds during our four site visits (Tables S2 and S3).

3. Results and Discussion

3.1 Assessment of housing unit performance

We retrieved data from 30 (n = 14 pond loggers, n = 16 control loggers) of the 32 loggers deployed, with two pond loggers underwater at the time of collection. We downloaded temperature data for the entire study period (between 1 July 2018 and 21 June 2019) for 26 loggers. Four pond loggers at sites T1, T2, T8, and T13 failed due to a potentially faulty logger backing design that was addressed by the manufacturer during the time between initial deployment and site visits in June 2019; all pond loggers were replaced by the manufacturer, and replacements were deployed following data retrieval in June 2019. No subsequent issues emerged (0% failures) using loggers with the updated backing for other experiments during which loggers were submerged in water for months at a time (M.C. Mims, unpublished data).

Overall, we found that the logger housing design successfully protected the loggers from physical damage, even when disturbed by cattle, but there were some considerations and limitations. Careful placement of loggers in the deepest point in the pond is imperative for accurate hydroperiod estimation. At site T11, we observed that the pond logger did not appear to be placed at the lowest point within the pond, as was intended. We observed very shallow water pooled in another location near the logger in summer 2019 that dried a few days later. Therefore, the data collected from this logger may not accurately reflect the pond inundation state. Additionally, rock piles placed on top of the rugged housing likely affected absolute temperature readings. Though rock color or density may have had differential effects among loggers, we suspect the variation among loggers was likely low overall. Furthermore, because this method considers tSD rather than absolute temperature, we do not anticipate these differences had substantial effects on results.

Another potential issue with our physical design was the accumulation of sediment or other debris within the rugged housing unit that interfered with temperature readings from the pond loggers at sites A14, T4, T9, and T17 (see Figure S3 for example). Although we have relatively high confidence in inundation timing, drying dates were less precise largely due to the accumulation of sediment in the housing unit. At site A14, mud was discovered in the logger housing on 31 March 2019 and was cleared. In the days preceding 31 March 2019, the temperature standard deviations from the pond logger were considerably lower than those from the control logger at this site, despite a lack of water in the pond, resulting in the paired pond-control model falsely predicting that the pond was in a wet state. After the sediment was cleared, the difference in these tSDs decreased to nearly zero, and the paired pond-control model correctly designated the pond state as dry. Mud and debris found inside the rugged housing of the pond loggers at sites T4 and T9 in late June likely caused the tSDs of these pond loggers to remain low relative to those of the control loggers even after drying, leading to false wet predictions in the paired pond-control models. In addition, we occasionally observed animals inside housing units, including several salamanders inside the housing for the pond logger at site T9 (Figure 2).

To improve drying date precision, the housing unit design would likely need to exclude sediment, which is difficult to do without making other compromises. Solutions for avoiding the issue of sediment in rugged housing units, and the subsequent decoupling of pond and control data, include packing the housing unit with insulation or other material that would not allow sediment to enter. However, this can lead to issues such as a buoyant housing unit and may affect the temperature readings if the material is a good insulator.

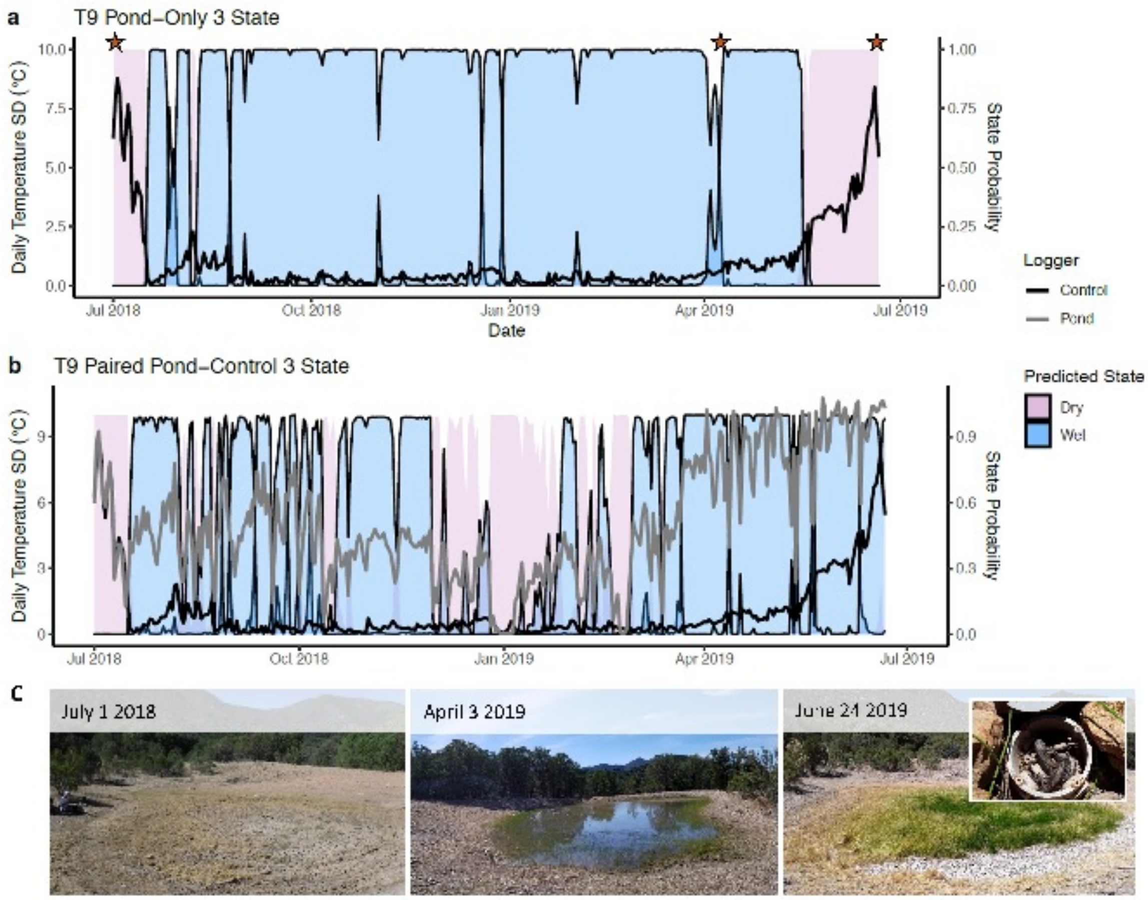

Figure 2. Three-state hidden Markov model predictions for pond T9 using (a) pond-only dataset, and (b) paired pond-control dataset. (c) Photos from site visits (dates correspond with stars in (a)), in which observed pond inundation state was dry at the time of sensor deployment (1 July 2018), wet during a return visit the following spring (3 April 2019), and dry at the time of sensor retrieval (24 June 2019). Though we observed no standing water on 24 June 2019, the pond supported vegetation, and we found salamanders in the sensor housing unit (inset photo; possibly contributing to different predicted states on 24 June 2019). Colors indicate temporal state predictions for each pond (pink=dry, blue=wet) and lines represent daily temperature standard deviation (tSD) measurements from pond logger (black lines) and control logger (grey lines).

3.2 Comparison of 2- versus 3-state hidden Markov models and determination of wet state threshold values

Although 2-state HMMs have been applied in past work (Arismendi et al., 2017), we found that 2-state HMMs appeared to over- or underestimate inundation duration for several ponds or predict additional wet states when we were confident that the ponds were dry (Figure S4). Using 3-state HMMs and subsequently combining multiple wet or dry states provided more accurate and consistent state predictions between pond only and paired pond-control datasets (Tables S2, S3). Therefore, we focused our analyses on results from the 3-state HMMs, which allow for the potential for seasonal variation in daily tSDs and intermittent wet-dry states (e.g., damp) and account for potential uncertainty due to wet sediment or other factors (see Figure 3 for examples).

For the paired pond-control dataset, we used a wet state threshold of -2.0°C, meaning that the daily tSDs measured by the pond sensors were at least 2.0°C lower on average than those measured by the control sensors. This -2.0°C threshold minimized the number of false dry state predictions. It did result in a false wet prediction for T17, but this was likely due to sediment in the pond sensor housing that may have affected the reading. A more conservative threshold of -2.2°C falsely predicted T12 as dry (Table S3).

Upon fitting 3-state HMMs to the pond-only dataset, we found that a threshold between 2.9°C to 3.3°C minimized the number of false dry states for most ponds (Table S2, Table S3). This threshold is slightly lower than that proposed by Anderson et al. (2015), who determined that using daily temperature variances cutoffs between 13 and 15 (corresponding to tSDs between 3.6°C and 3.9°C) for the wet state provided the most accurate predictions of pond inundation states in their field experiments. Within our pond-only dataset, using a less

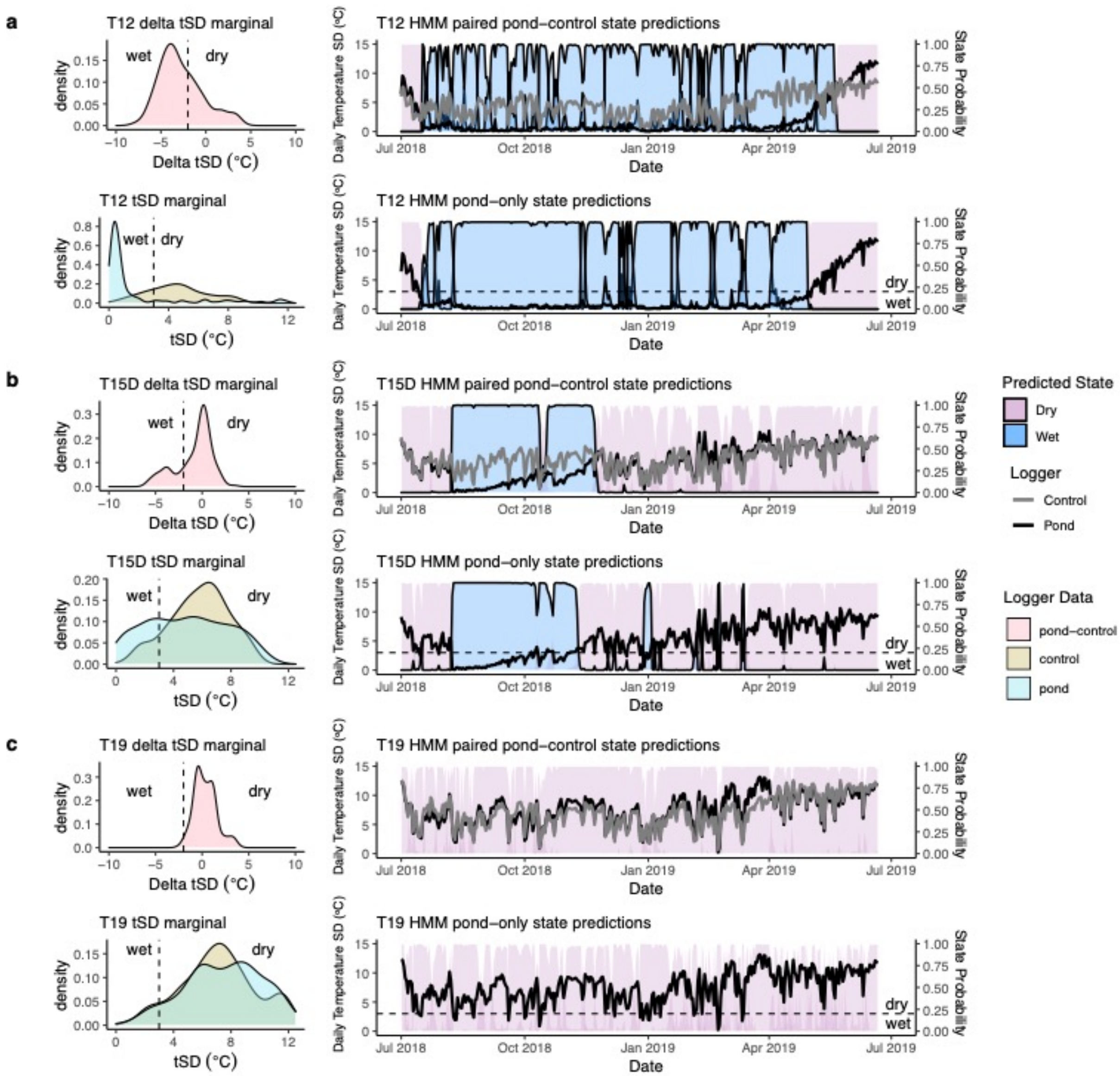

Figure 3. Inundation state predictions by 3-state hidden Markov models (HMMs). Shown are marginal distributions and predicted inundation timing for select ponds that (a) became inundated for long durations during the study period, (b) filled for relatively shorter durations, and (c) had no predicted wet state. Left panels represent marginal distributions and right panels represent HMM estimates from paired pond-control models (top) and pond-only models (bottom). Shading on HMM graphs indicate temporal state predictions for each pond (pink=dry, blue=wet) and lines represent temperature standard deviation (tSD) measurements from control loggers (grey lines) and pond loggers (black lines). Dashed lines indicate wet state thresholds (3.0°C for the pond only dataset and -2.0°C difference for the paired dataset).

conservative tSD threshold of 3.5°C decreased the accuracy leading to a false wet state prediction for pond T15U. For pond T8, the state with the highest average temperature standard deviation (~2.8°C) fell below our wet state cutoff of 3.0°C (Table S5). Because we knew that the pond was dry at two timepoints in this state (during logger deployment and logger retrieval), we decreased the wet state threshold to 2.7°C for this particular pond and considered the average tSD of 2.8°C to reflect a dry state.

To further define a "reliable" wet state prediction from our HMMs, we also required that the pond remain in a given state for a minimum of 5 consecutive days. We chose this cutoff based on site observations in early August 2018, during which ponds T17 and T20 had short predicted wet states of 7 and 5 days in July respectively and both showed evidence of prior inundation despite being dry at the time of our visit. Pond A14 also had a predicted wet state of 4 days in mid-July but showed no evidence of earlier inundation in early August (Table S2, Table S3).

3.3 Comparison of 1 (pond-only) versus 2 (paired pond-control) logger design

Under the wet state criteria defined above, 3-state HMMs for the pond-only model accurately predicted inundation states for 92% of site visits for the 14 ponds. The paired pond-control model, which used combined data from the loggers inside and outside of each pond, accurately predicted inundation states for 90% of sites visits. Most of the incorrect state predictions were likely due to sediment or additional debris accumulating within the rugged housing units, which was more likely to affect precision of drying dates rather than initial inundation timing.

Models using temperature data from pond loggers alone predict inundation timing that closely aligned with those using paired pond-control logger data, indicating that a single logger design may be sufficient to capture inundation timing of longer-duration events (Table S5, Figure 4). However, control logger data may help alleviate some of the wet state false-positives, particularly when the standard deviation of daily air temperature is relatively low or issues such as sediment in rugged housing units occur. For example, earlier inundation dates are predicted for several ponds by the pond-only model relative to the paired pond-control model. This may be a true wet state, or the coincident low temperature standard deviations measured by the control loggers may have simply resulted in lower variance in the temperature on those days. For site T13, the state was correctly predicted as wet by the paired pond-control model, but not by the pond-only model in April 2019. While we did observe water in the pond at this time, the water level was just at the base of the rock pile covering the logger housing, which may explain the discrepancies between the models. In cases such as this when shallow water is present, the 2-logger design may help to increase the probability of detecting inundation. Predicting pond drying may require an array of pond loggers situated at different heights within the pond to capture this fine-scale variation or a different type of sensor, such as pressure transducers. But considerations exist for the pond-control logger model as well. For example, pond-only models predicted wet states for most ponds in the winter months (between December and February) that were not predicted by the paired pond-control models. The relatively low tSDs of the loggers in the winter months may be due to snow accumulation on top of the control loggers.

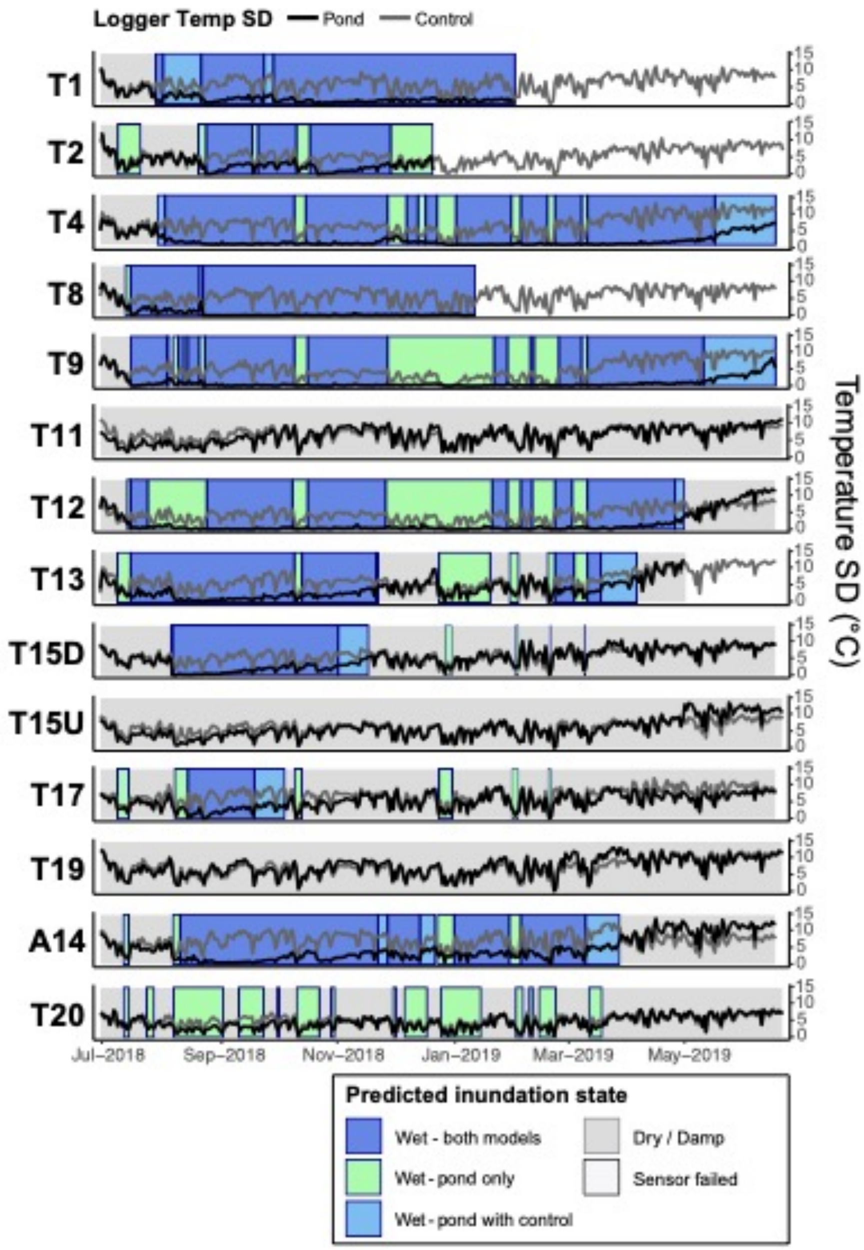

Figure 4. Hidden Markov model (HMM) pond inundation predictions. Lines show daily tSDs measured by pond loggers (black) and control loggers (grey). Rectangles represent wet days predicted by HMMs from single pond loggers (light green), by paired pond-control loggers (light blue), and by both models (dark blue). Grey shading indicates a predicted dry/damp state and lack of shading indicates no data due to logger failure.

3.4 Pond inundation regimes

Based on HMM estimates, ponds varied in both initial timing and duration of inundation (Figure 4), with initial inundation dates ranging from 10 July 2018 to 7 August 2018, over a small geographic area (Figure 1). Eleven of the fourteen ponds in our study had at least one predicted wet state during our monitoring period. Ten of these ponds had wet states predicted from both datasets. Based on the state predictions by both models, ponds in the central range of our study area filled first, with ponds T8, T9, T12, and T13 all inundated between 10 - 17 July 2018. Ponds in the northern and southern portions of the study area had more variation in their initial inundation dates, which were predicted to occur between late July and mid-August (Table S6, Figure 1, Figure 4).

Inundation dates inferred from pond-only and pond-control models largely aligned (Figure 4). Only pond T20 was predicted to have a wet state by one model (the pond-only model) and not the other. The presence of vegetation at the perimeter of the pond and mud inside the housing of the T20 pond logger during our visit in April 2019 suggest that the pond may have been inundated with water at some point during logger deployment. Visual inspection of the T20 temperature standard deviation readings revealed a slight difference between August and October 2018. Ponds T11 and T15U, which had no predicted inundation dates, also showed slightly lower readings from the pond loggers relative to the control loggers at certain points in the monsoon season and had mean state values close to but slightly above our wet state thresholds. It is possible that some water accumulated in these ponds and that our wet state threshold for the HMMs lacked the sensitivity to capture these low signals. The tSD threshold may need to be adjusted to increase precision in cases where small amounts of water accumulate for durations shorter than 5 days.

3.5 Broader applications and considerations

The methods we present are relevant and applicable to temporary lentic habitats in a wide range of regions, particularly where logistical challenges constrain the data available for hydroperiod monitoring. For example, temperature sensor-derived hydroperiod inference may be particularly useful for ponds or wetlands that can have high canopy cover (e.g., some Carolina bays (Sharitz, 2003) or vernal pools (Brooks, 2004)) or other considerations that may make remote sensing difficult, particularly across multiple sites. Temperature sensors may also be helpful in regions where drone activity is discouraged or prohibited, thus limiting targeted, fine-scale aerial data acquisition. This includes national parks, wildlife sanctuaries, or areas where drone flight is otherwise prohibited (for example, drone operation is not logistically feasible in our study region due to restrictions by the United States Border Patrol). Our proposed methods are relatively low-cost and low-maintenance, making them accessible for even small-scale research grants. The long battery life of the sensors and high durability of the design make them ideal for deploying in remote areas. However, we suggest that users visit deployment sites at least once a year, particularly before major seasonal inundation events.

Some scenarios may necessitate modifications to the current design, including components and deployment. For example, complex bathymetry of wetlands may call for the use of more than one temperature sensor to detect hydroperiod inundation, particularly when distinct areas of the temporary habitat have meaningful ecological differences (Chandler, 2017). If longer battery life is desired, the temporal resolution of measurements could also be adjusted to capture temperature data in less frequent intervals. Additionally, users may consider alternative sensor designs. For example, conductivity sensors offer an alternative to temperature loggers. However, custom modifications required to create conductivity sensors can be time-consuming or, if outsourced, may result in units that are >2 times the cost of temperature loggers. Additionally, conductivity sensors may suffer from the same issues related to poor or imprecise detection of drying patterns due to water trapped in sediments. Temperature measurements offer data that are biologically meaningful (temperature as well as presence/absence of water) and that may address multiple needs depending on the objectives of a study. Pressure transducers would likely capture drying dynamics more accurately and are available for as low as ~$300 per sensor (e.g., Onset HOBO Water Level Data Logger, U20L-01). However, the physical dimensions of pressure transducers would require modifications to the current rugged housing unit design, and the additional cost would result in approximately a four-fold reduction in the number of sensors obtained for the same budget. An additional consideration is the ability of sensors to withstand extreme temperatures. The temperature sensors in our design have a range of -20 to 50°C in water; anticipated temperatures outside this range would likely necessitate a different sensor model and may be an important consideration for high-latitude study regions. Finally, deployment methods for the housing unit and sensor may need to be modified depending upon the substrate of the habitat. For example, mud or other soft sediment may require a T-post or similar support structure rather than buried concrete ties depending upon the depth of the soft substrate.

4. Conclusions

Precise measurement of pond inundation timing can be essential for studies of ecological and hydrological dynamics, particularly in areas with fine-scale variation in climate, where limited water supply may be crucial in shaping population and community dynamics. In this study, we observed an approximate 4-week difference in initial inundation timing between ponds within a small geographic range (~50km^2), which is a substantial portion of the aquatic stage for many aquatic organisms that rely on these ponds to complete their life cycle (e.g., amphibians: Mims et al., 2020; Moore et al., 2020); these intraseasonal differences in inundation timing may thus have major implications for community composition and species turnover in these habitats. Fine-scale hydrological data such as those presented herein provide valuable information about dynamic water regimes that can improve conservation strategies by identifying potential refugees for plants and wildlife and can also aid in planning for human adaptation in response to the changing climate.

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