hatchR: A toolset to predict when fish hatch and emerge

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- ⁷ keywords: developmental phenology, effective value model, R, Shiny

Abstract

Understanding the timing of key life history events is necessary for managing and conserving populations. Historically, models to predict hatch and emergence timing for fishes were difficult to employ in wild settings 10 because average incubation temperature was needed as the primary parameter in predictive models. However, 11 recent improvements to these techniques reworked models such that they could be applied in wild environments 12 as long as users had data for when adult fish spawned and a record of average daily temperature over the course 13 of development. Despite these improvements, their application remains limited due to few parameterizations 14 for varying species, being largely limited to Salmonids. Here we present hatchR, a software ecosystem that 15 allows users to predict hatch and emergence timing for wild fishes, as well as additional tools to aid in those 16 analyses. hatchR allows users to leverage popular historic parameterizations for phenological models or to 17 easily implement custom parameterizations using data not included in the package. hatchR is distributed in 18 two forms—an open source R package for maximum customization and as an HTML graphical-user-interface 19 web application for individuals not familiar with scripting languages. To demonstrate potential uses, we 20 present two case studies as likely applications for this software. hatch promises to open many exciting 21 avenues in research and management of fishes during their early life history.

23 Introduction

As primarily poikilothermic organisms, the development and growth of fishes is tightly linked with the temperature of their ambient environment. This close relationship has allowed researchers to generate statistical models that allow the prediction of developmental phenology with high accuracy and precision. These models were typically developed in aquaculture settings and their initial formulations were not applicable to wild populations because they assumed a constant temperature over the course of development (Alderdice & Velsen, 1978; Beacham & Murray, 1990; McPhail & Murray, 1979). However, Sparks et al. (2019) reformulated this approach as an "Effective Value model", in which the input was daily average temperature after a parent spawned and fish would either hatch or emerge when effective values cumulatively summed to one.

The resulting effective value approach has now been widely applied in Salmonids for which parameterizations from aquaculture were readily available—for example, Pacific Salmon (*Oncorhynchus spp.*) models developed by Beacham & Murray (1990) have been applied to various species and populations (Adelfio, Wondzell, Mantua, & Reeves, 2019, 2024; Kaylor et al., 2021) while models developed for Bull Trout (*Salvelinus confluentus*) by McPhail & Murray (1979) were extended by Austin, Essington, & Quinn (2019). Despite growing popularity, applications have been largely limited within Salmonids, presumably because parameterizations for such models already existed due to their wide use in aquaculture and their general popularity as sport and commercial fish.

To bridge the gap between the application of one-off effective value model applications within individual studies and the lack of parameterization for other species, we developed the software ecosystem, hatchR. Specifically, hatchR allows users to input standard raw or summarized temperature data sets that are commonly collected in wild settings, run basic checks on those data, use built-in parameterizations like those from Beacham & Murray (1990) or Sparks, Westley, Falke, & Quinn (2017), develop custom models from their own or published temperature and phenological data, and predict hatch and emergence timing using these models in the effective value framework.

To widen the user application of these methods, we distribute two user-interfaces for **hatchR**. The first is a R package ("R" (n.d.)) distributed via CRAN that allows users the most customizable application for these methods. The R package is especially powerful as it allows users to automate their analyses over multiple variables such as phenology type, multiple spawn dates, or different habitats with varying thermal regimes. These variable approaches are outlined in the package documentation on **hatchR**'s website. Alternatively, we also distribute a Shiny application (Chang et al. (2024)) in the form of an HTML-based web tool to interact with many of **hatchR**'s functions in a graphical-user-interface. The Shiny app trades-off some of automative power for user simplicity, while still allowing users to leverage much of the functionality of **hatchR**'s R package. Below, we present the basic overview of the software and multiple case studies of how it may be applied.

58 ## Warning: package 'lubridate' was built under R version 4.4.1

Package Overview

hatchR is meant to primarily be a tool for predicting phenology. In this sense, we limit functionality to these applications and provide minimal data checking and plotting help. This decision is in part driven by the diversity of data types that users may import and the difficulty in addressing all those data types with respect to various data checks. In other words, we expect users to know their data better than we do and to check it accordingly. We do provide two basic data check functions discussed in the Checking Data section. Similarly, we provide limited functionality for plotting results, but provide examples of how to build custom visualizations from output, specifically in R. For the Shiny application, we provide a base output plot, but the ability to download your results for custom plotting in software of the user's choice. Finally, we provide brief summaries of general applications of hatchR below (Figure 1), but encourage users to visit articles hosted

on the software webpage that extensively outline primary functions and applications, especially automating the application of predicting phenology across multiple variables.

Effective value models

Effective value models were created by Sparks et al. (2019) to implement developmental models in wild environments for Sockeye Salmon (*O. nerka*). The need for their creation arose because historic models, specifically those in Beacham & Murray (1990), only considered the average incubation temperature during development and, for wild fishes, average incubation temperature was impossible to estimate because it was unknown when fish hatched even if adult spawn timing was known. To address this, Sparks et al. (2019) used the reciprocal of the formulation of model 2 from Beacham & Murray (1990) and assigned an effective value for every day of development using the daily average temperature.

The model follows the general format of:

$$EffectiveValue_i = 1/exp(log_ea - log_e(Temperature_i - b))$$

Where i is the daily value and a fish hatches or emerges when the cumulative sum of effective values reaches

$$\sum_{i=1}^{n} EffectiveValue_i = 1$$

The effective value model framework is the basis for the phenological models in **hatchR**, both in the included model_table in the package (though model_table includes more complex models developed by Beacham & Murray (1990)), as well as for custom models users can fit with fit_model(). Specifically, model_table includes parameterizations from Beacham & Murray (1990), Sparks et al. (2017), and Austin et al. (2019) (who extended McPhail & Murray (1979)).

87 Data format

Water temperature data sets collected for wild environments are often either 1.) already summarized by day
(i.e., mean daily temperature) or, 2.) in a raw format from something like a HOBO TidbiT where readings
are taken multiple times per day, which can be summarized into a mean daily temperatures. Alternatively,
new statistical models like that of Siegel, Fullerton, FitzGerald, Holzer, & Jordan (2023) could be similarly
implemented.

Fundamentally, **hatchR** assumes you have input data with two columns: a date column, giving the date (and often time) of a temperature measurement, and a temperature column, giving the associated temperature measurement (in centigrade). Other columns are okay to include, but these two columns (with any column name—just without spaces) are required. Data is expected to be formatted similar to Table 1.

Table 1: Example temperature data for use in hatchR.

date	temperature
2000-01-01	2.51
2000-07-01	 16.32
2000-12-31	3.13

hatchR assumes you've checked for missing records or errors in your data as it will function with gaps, so
 it's important to go through the data checks discussed below, as well as your own validity checks. hatchR

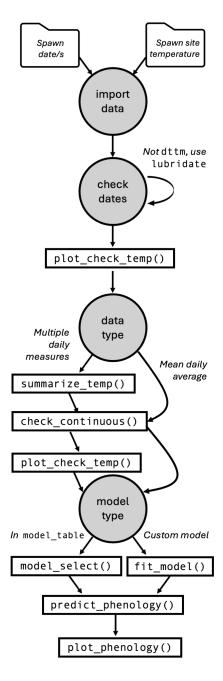


Figure 1: hatchR workflow. Data inputs are represented by folders, data processes by filled circles, hatchR functions as plain text rectangles, and decisions choices as italicized text.

can use values down to freezing (e.g, 0 °C), which returns extremely small effective values, and time to hatch or emerge could extend to a year or more. In these cases, we suggest users consider how much of that data type is reasonable with their data.

For users choosing to implement **hatchR** in R, data can be imported from any format the user chooses, as long as users can eventually coerce their data into a **dataframe** or **tibble** format, in which each row represents a single record. For the Shiny application, users must have their data stored as a .csv (comma separated values) file for upload, which can easily be exported using datasheet software like Microsoft Excel or Google Sheets.

107 Checking Data

hatch is built assuming data will be analyzed as daily average temperatures. Despite that assumption, raw data (e.g., as outputted by HOBO loggers) can be used and hatch includes functionality to summarize those data into a format that is usable (only in R, it must be summarized for the Shiny app), as well as provides functions for basic visual and programmatic data checks to make sure outliers or missing data are at least brought to user's attention.

We demonstrate the utility of the summary and check functions summarize_temp(), plot_check_temp(), and check_continuous() using a simulated year-long data set (year_sim, the dimensions of the data and first 6 rows are shown) with temperature readings every thirty minutes.

```
#year_sim data dimensions
dim(year_sim)
```

```
16 ## [1] 17568 2
```

```
#fist 6 rows of year_sim
head(year_sim)
```

```
##
                         date
                                    temp
117
   ## 1 2000-07-01 00:00:00
                                8.318573
118
      2 2000-07-01 00:29:55
                               9.309468
119
   ## 3 2000-07-01 00:59:50 14.676125
120
   ## 4 2000-07-01 01:29:45 10.211525
121
   ## 5 2000-07-01 01:59:40 10.387863
122
   ## 6 2000-07-01 02:29:35 15.145195
123
```

First, we recommend checking imported data for any outliers or strange inputs using plot_check_temp() (Figure 2).

There are no obvious outliers but since each day has 48 records, we need to summarize it to daily mean temperature with summarize_temp() and then check for missing days with check_continuous(). We also recommend using plot_check_temp() again on the summarized data (though leave out the resulting plot for space efficiency in this manuscript).

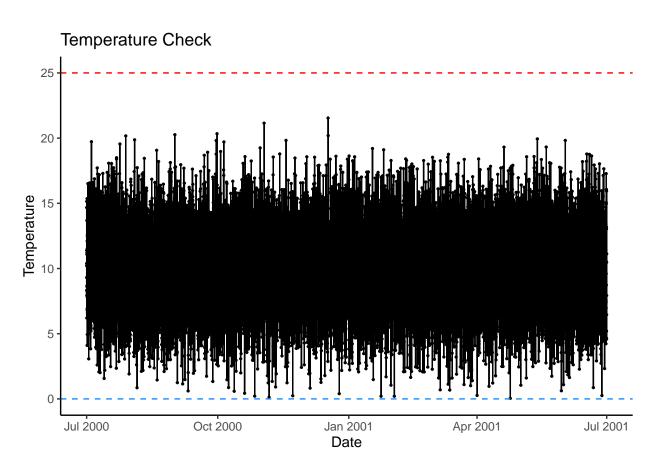


Figure 2: Output of hatchR function plot_check_temp(), which is used as a visual data check on the raw year_sim data set. Users can set custom thresholds for minimum and maximum temperatures (dashed lines).

130 ## [1] 365 2

i No breaks were found. All clear!

```
## Warning: ! Data not continuous
## i Breaks found at rows:
## i 100
```

135 Model Selection

Users can either use Salmonid models from model_table or generate custom models suing fit_model() in both R and Shiny deployments of hatchR. As discussed, the models in model_table are included because parameterizations already existed in the literature, however, these parameterizations are limited to Pacific Salmon and Bull Trout (though see Quinn (2018) pg. 183 for numerous other Salmonids). Additionally, we limit available models in model_table because they are well vetted models, with experimental ranges spanning 2-17 °C. Custom models we demonstrate later with fit_model() have much narrower parameterization ranges and, as such, we choose to keep those models out of model_table so as to require users to consider whether the custom models they are parameterizing fit the data over which they are predicting.

To widen the application of the effective value approach, we include a fit_model() function, which is species agnostic (as long as development generally follows the power law). The function fit_model() uses data in which average incubation temperature (°C) and days to phenological event (as two vectors) are the inputs.

The function estimates parameter coefficients for log_ea and b using stats::nls()

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149 Fitting models for other fishes

We demonstrate how the fit_model() function may be used to create custom parameterizations for species beyond the Salmonids in the model_table included in the package. We include parameterizations from three warm-water species to demonstrate the fit_model() utility for fishes beyond the scope of the original effective value approach. These parameterizations are for commonly cultured sportfishes including Smallmouth Bass (Micropterus dolomieu) (Webster, 1948), Channel Catfish (Ictalurus punctatus) (Small & Bates, 2001), and Lake Sturgeon (Acipenser fulvescens) (Smith & King, 2005). We show parameterization for just Smallmouth Bass here for concision, but the full code set for all species is available at in the paper.Rmd in the project GitHub.

We demonstrate the utility of this approach by creating a random thermal regime with an ascending thermograph with a mean temperature of 16 °C, parameterizing models for each species, and demonstrating days to hatch and developmental period for each species with the random thermal regime (Figure 3).

Note the R^2 fit from the models below. You can see they generally all preform well and are in line with values from model 2 of Beacham & Murray (1990).

```
#model fits
smb_mod$r_squared; cat_mod$r_squared; sturgeon_mod$r_squared

## [1] 0.9868067

## [1] 0.9433598

## [1] 0.9217358
```

Predicting Phenology and Output

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To illustrate model selection and phenology prediction we will recreate a small portion of the analysis done by Sparks et al. (2019) using the woody_island data set included in this package. We will predict both hatch and emergence timing, so we will obtain a model expression for each using model_select(), which calls built-in models from model table.

```
sockeye_hatch_mod <- model_select(
  author = "Beacham and Murray 1990",
  species = "sockeye",
  model = 2,
  development_type = "hatch"
)</pre>
```

We can now use our model expressions to predict when sockeye would hatch and emerge at Woody Island in 1990. First we predict hatch timing using predict_phenology():

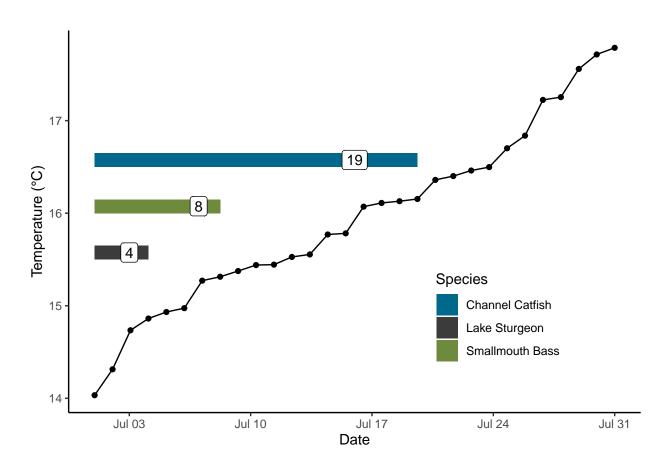


Figure 3: Predicted days to hatch for three warmwater species with custom parameterizations using a random thermal regime with an ascending thermograph with a mean temperature of 16 $^{\circ}$ C over 30 days.

```
WI_hatch <- predict_phenology(
  data = woody_island,
  dates = date,
  temperature = temp_c,
  spawn.date = "1990-08-18",
  model = sockeye_hatch_mod
)</pre>
```

And then look at the returned object to see days to hatch and development period:

```
WI_hatch$days_to_develop
```

174 ## [1] 74

WI hatch\$dev.period

```
175 ## start stop
176 ## 1 1990-08-18 1990-10-30
```

177 Understanding your results

The output from predict_phenology() includes a lot of information. If we look at our WI_hatch object we see there are multiple elements stored in a list which can be accessed using the \$ operator.

```
str(WI_hatch)
```

WI_hatch\$days_to_develop outputs the predicted days to develop.

WI_hatch\$dev.period is a 1x2 dataframe with the dates corresponding to when your fish's parent spawned (which you input with predict_phenology(spawn.date = ...)) and the date when the fish is predicted to develop.

WI_hatch\$ef_table is a $n \times 5$ tibble (n = number of days to hatch or emerge) and the columns are a row index, the date, each day's temperature and effective value, and the cumulative sum of the effective values. The ef_table object is meant to serve as the basis for users to make custom figures for their data beyond the functionality we discuss below.

WI_hatch\$model_specs provides details about the model used for predicting phenology, which varies depending on if the model was generated from model_select() or fit_model(), but most importantly contains the model expression (e.g., the formula) used for prediction.

191 Plotting phenology

hatchR has a built in function, plot_phenology(), that allows users to visualize their phenology results (Figure 4). The plot visualizes three specific components: 1.) the temperature regime over which you are predicting, 2.) the cumulative sum of effective values, and 3.) the effective value for each day in your prediction span. The function allows you to output various figures based on your interests, but defaults to a figure with all information and the corresponding labels.

```
plot_phenology(WI_hatch)
```

74 days to develop Fish spawned: 1990–08–18; fish developed: 1990–10–30 Temperature; Scaled cumulative EF value; Daily EF value (x100) 12.5 10.0 2.5 Sep Oct Nov

Figure 4: Output of plot_phenolgy() function using predicted hatch time from woody_island data set.

Date

$_{_{197}}$ Case Study 1

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A common management scenario where developmental phenology might be useful would be trying to understand if fish might be free-moving before some management action. For instance, will fish have emerged from redds when a stream section has been opened to grazing or road work?

In this scenario, we will consider the road work example and Bull Trout, a threatened fish in the United
States under the Endangered Species Act (Nolfi, Melbihess, Fisher, & Ellis, 2024), and the Crooked River, a
key Bull Trout population in the Boise River watershed. In this hypothetical scenario, the Forest Fisheries
Biologist wants to know if fish will likely be out of the gravel and free-swimming by June 1st as Bull Trout
are particularly sensitive to sediment. In this system, it is expected that Bull Trout will be done spawning by
the end of September, so we'll consider the last possible spawn date as September 30th.

We demonstrate this first case study using the graphical user interface portion of the hatchR ecosystem found at https://elifelts.shinyapps.io/hatchR demo/. Users will first upload their data with the Import Data window, which requires them to select their file on their personal computer, provide the program with the columns corresponding for dates and temperatures, and then provide the format in which dates are coded (e.g., year-month-day or day-month-year). Data used in this case study are from the crooked_river data set. It is included as a demo data set in Shiny, but can also be written out from the package or accessed at https://github.com/bmait101/hatchR/blob/master/extdata/crooked river.csv/. Once data is uploaded the program automatically plots the user's data using plot_check_temp() in the background and provides them the outputted graphical check. After uploading and checking data, the user switches to the Model Phenology window. In this circumstance, we use the preloaded parameterization for bull trout from Austin et al. (2019) with the Existing button for model selection, which the user selects with the various drop down options in the menu. After the model is selected, the user can choose multiple spawn dates from the interactive calendar provided. We show results for spawning for September 30th as indicated in the example above. Once dates are chosen, a table entry for each spawn date is outputted in the Phenology Summaries tab and corresponding plot with data from each spawn date in the Timeline Plot tab. Output from predicting phenology and the resulting figure are downloadable from their respective tabs. The process is demonstrated in the included supplementary video file???, but the interface is described more completely on hatchR's Shiny website.

In this example we expect the last fish out of the gravel well before the June 1st date and the manager could allow road work in this area without worrying about sediment disturbance to fish developing in the gravel.

Tase Study 2

For the second example, we will again use Bull Trout, but demonstrate a much more complex application for the purpose of showing the full flexibility of the programmatic application of **hatchR**. In this scenario we will use data from Isaak, Luce, Chandler, Horan, & Wollrab (2018) (included **idaho** data set), which includes temperature data from 226 sites across the major upper Columbia River headwater watersheds in Idaho. For this approach we winnow putative bull trout spawning sites by filtering for sites with mean August temperature </= 13 °C in accordance with thresholds from Isaak, Young, Nagel, Horan, & Groce (2015). For the resulting 139 sites we will demonstrate predicting hatch timing in these putative Bull Trout spawning habitats.

We need to setup our models and data for this analysis, which we don't demonstrate here for the sake of concision, however they are demonstrated in paper.Rmd included in the GitHub repository for hatchR. After the setup, we can easily map predict_phenology() across all putative spawning sites and three spawn dates (September 1-Early Spawning, September 15-Peak Spawning, and September 31-Late Spawning), the results of which are presented in Figure 5.

```
hatch_res <- isaak_summ_bt |>
mutate(
```

```
dev_period = map2(
    summ_obj, spawn_dates, # map across our site object and spawn dates
    predict_phenology,
    temperature = daily_temp,
    model = bt_hatch,
    dates = date
    ) |>
    map_df("dev.period") |> # pull out just dev.period results
    list()
    ) |>
    select(site, dev_period) |> # just select the columns we want
    unnest(cols = c(dev_period)) |> # unnest everything
    mutate(days_to_hatch = stop - start) # make a new column of days to hatch
```

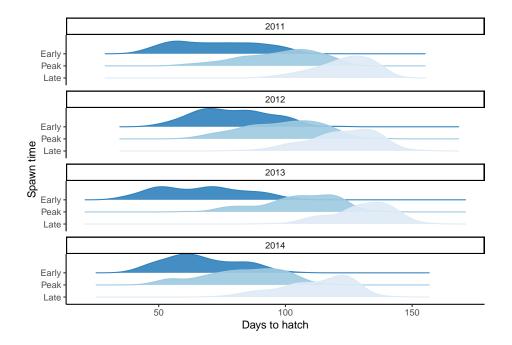


Figure 5: Predicted days to hatch for 139 putative bull trout populations over three spawning periods (Early = September 1, Peak = September 15, Late = September 30) and four years of temperature data.

Discussion

With hatchR we present a software ecosystem that bridges the analytical gap of predicting developmental phenology for wild fishes and develops a formal framework for applying effective value models from user-provided parameterizations. To do so, the software is bundled in two forms, a fully customizable R package, especially useful for running repetitive or complex analyses and a graphical-user-interface designed for ease of use and tasks that may only run once or a handful of times. Both applications allows users to import their data, run basic data checks, and apply historic model parameterizations for Salmonids or create their own species- or population specific parameterizations. Additionally, we provide substantial documentation on the hatchR website (https://bmait101.github.io/hatchR/) to walk users through basic to advanced applications of the two platforms.

In the application of using effective value models **hatchR** and the user make some key assumptions. Particu-

larly, numerous studies have indicated that stressful environmental conditions can cue fish to prematurely hatch or emerge from their environment. These include water quality like dissolved oxygen, pH, or salinity, pathogens, and even mechanical agitation (reviewed in Quinn (2018) and Cowan et al. (2024)). Moreover, while the **hatchR** provides point estimates for developmental phenology, spawning and developmental within populations of fishes both occur as distributions as opposed single events Mason (1976) and we encourage users to either predict phenology using early, peak, and late frameworks (e.g., 5th, 50th, and 95th quantiles) or with real or modeled distributions. Another factor that could bias estimates from these models is that temperatures used from sensors do not reflect the geomorphic properties in the environment where eggs are developing such that they may be too cold or warm Geist et al. (2002).

To date, the application of the effective value framework has largely focused using species-specific models to predict phenology in wild environments (see Adelfio et al. (2024), Austin et al. (2019)). However, we emphasize that the statistical relationships at the basis of these models are fundamentally reaction norms, meaning that both the intercept and slope of the responses of fishes to temperature are reflective of family- or population-level genetic variation, genetic x environment responses, or may be indicative of phylogenetic differences among species (West-Eberhard (2003)). For instance, while Sparks et al. (2017) did not find differences in the rates of development between the focal populations of their study, they did observe family-level genetic x environment interactions across different thermal regimes. Similarly, when they reparameterized their models using fish from western Alaska, they found differences in both the slope and intercept of the model relative to the original parameterization from Beacham & Murray (1990), notably derived from multiple Canadian stocks. The western Alaskan fish generally developed more slowly than their southerly counterparts, consistent with cogradient variation (Conover, Duffy, & Hice (2009), Sparks, Kraft, Blackstone, McNickle, & Christie (2022)). In this sense, we encourage users not to only think about the end points of these models (days to development) but also how the statistical relationships they are premised on inform our understanding of micro- and and macro-evolutionary processes.

BRYAN check the below

The models presented in hatchR can be further customized in multiple ways beyond the use-cases provided above. For instance, while our models are fit to predict hatch or emergence timing, they could be used to predict other developmental stages prior to the initiation of external feeding like eye-up or other embryological developmental stages (Velsen (1980)) or Some example from a non-salmonid, maybe initiation of pelagic-larval or riverine current dispersal. Additionally, while fit_model() relies on non-linear modeling platform, predict_phenology() only requires users to pass a model expression, so if users preferred a different model fit than the non-linear option provided (as long as it integrates daily temperature), they could pass a different expression into predict_phenology() for additional customization. Finally, while hatchR was designed specifically for fishes, we expect other polikilothermic organisms such as reptiles, amphibians, or invertebrates would develop in accordance with the power law and these developmental models could be extended to other organisms beyond fishes.

« Conclusion

hatch bridges the analytical gap for the prediction of developmental phenology for fishes in wild environments. It provides basic data checks and summarization, options for existing or custom model parameterization, and simple to complex phenology prediction frameworks. Importantly, it extends the effective value framework developed by Sparks et al. (2019) to a generalizable tool that can be applied to any fish species or population as long as the appropriate source data are available, which can easily be collected in aquaculture settings. We present basic applications for how hatch may be used, with additional and more detailed examples provided on the software's website. hatch is designed for applied and basic applications in which users can engage with the resource in a programmatic environment or a point-and-click Shiny app. We expect we have only demonstrated a small suite of the applications hatch may be used for and encourage the user community to creatively build on the framework developed here.

299 Acknowledgements

- We thank Laura Koller for her help designing the **hatchR** logo. Dan Isaak provided useful discussion about model development and temperature data sets.
- The views expressed in this manuscript are those of the authors and do not necessarily represent the views or policies of USFS or USFWS. Any mention of trade names, products, or services does not imply an endorsement by the U.S. government, USFS, or USFWS. USFS and USFWS do not endorse any commercial products,

305 services or enterprises.

Conflicts of Interest

The authors declare no known conflicts of interest.

Data Availability

hathcR is fully open source and reproducible. Source code and data can be found at https://github.com/ bmait101/hatchR/. The latest version will be archived upon acceptance of the manuscript.

Ethics Statement

All data was derived from pre-published sources or created synthetically.

313 Funding

314 The authors declare no funding sources.

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