STICr: An open-source package and workflow for processing and analyzing data from Stream Temperature, Intermittency, and Conductivity (STIC) loggers

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Abstract

Non-perennial streams constitute over half the world's stream miles, and require hydrologic characterization to understand their flow regimes and impacts on ecosystems and society. Stream Temperature, Intermittency, and Conductivity (STIC) loggers are a widely used tool for studying non-perennial streams because they provide a relatively inexpensive and robust method for characterizing flow presence or absence. However, raw data downloaded from STIC loggers is not immediately suitable for analysis or integration with other datasets and must be processed to generate a usable dataset including temperature, conductivity, and interpreted classification of "wet" or "dry" readings at each timestep. To facilitate rapid, reproducible, and methodologically consistent analyses with STIC data, we present an open-source package written in the R language (STICr) and associated workflow to provide a standardized framework for tidying and processing data from STIC loggers. STICr features include functions to tidy data, develop and apply calibration curves to convert logger output to specific conductivity, classify data into wet/dry readings, and perform quality checks on resulting output data. Using STICr, we demonstrate a reproducible workflow that serves as a project-wide data pipeline for organizing and processing data from over 200 STIC loggers spanning multiple watersheds, years, and research groups. Given the importance of methodologically consistent inter-site and inter-regional comparison in hydrology, as well as a need for increased computational reproducibility in the discipline, we believe that STICr and the associated reproducible workflow represents an important advance for stream intermittency science.

Plain Language Summary

Stream Temperature, Intermittency, and Conductivity (STIC) loggers are small instruments installed in streams that determine whether water is present at a particular location and time. These loggers are used to study streams that periodically dry, which are common worldwide. However, the data downloaded from these loggers is difficult to use and does not immediately show the presence or absence of water. Instead, the loggers read out an electrical conductivity value that must be classified into a "wet" or "dry" reading. We have created an open source software package, called STICr, that performs many of these tasks. In addition to cleaning up the raw data output from STIC loggers and performing the "wet" vs. "dry" classification, the STICr package also provides quality control checks on the data. To show the value of this tool, we give an example of how the STICr package can be used to process data from over 200 STIC loggers over multiple years in a particular scientific project.

1 Introduction

Non-perennial streams represent the majority of flowing water bodies worldwide (Messager et al., 2021), and their prevalence in many regions has increased over the past four decades (Zipper et al., 2021; Sauquet et al., 2021; Tramblay et al., 2021). The timing and spatial distribution of flow in non-perennial streams influences various ecosystem services including carbon cycling (Hale and Godsey, 2019), biodiversity (Meyer et al., 2007), and groundwater recharge (Shanafield and Cook, 2014), and ultimately influences the availability of water for downstream users. To support watershed management in the Anthropocene, accurate and high-resolution *in-situ* measurements of flow intermittence are needed to quantify the hydrologic controls on connectivity and characterize impacts on water quality and society (Shanafield et al., 2020; Zimmer et al., 2022).

Stream Temperature, Intermittency, and Conductivity (STIC) loggers are a low-cost and rapidly deployable tool for monitoring flow intermittence. STICs are created by repurposing the circuitry used for recording light intensity in the widely-available Onset HOBO Pendant temperature and light data logger (model UA-002-64) to provide a relative measurement of electrical conductivity using two external electrodes (Chapin et al., 2014). Since electrical conductivity of water is substantially higher than that of air, conductivity recorded by STIC sensors can be interpreted to produce a binary record of water presence or absence. Since 2014, STIC sensors have become more frequently employed in watershed studies (Fig. 1), owing to their durable and relatively inexpensive design. Recently, additional intermittency sensors such as the Smart Rock (OPEnS, 2022) have been developed with similar functionality to STIC loggers, and would also benefit from open and reproducible data analysis workflows.

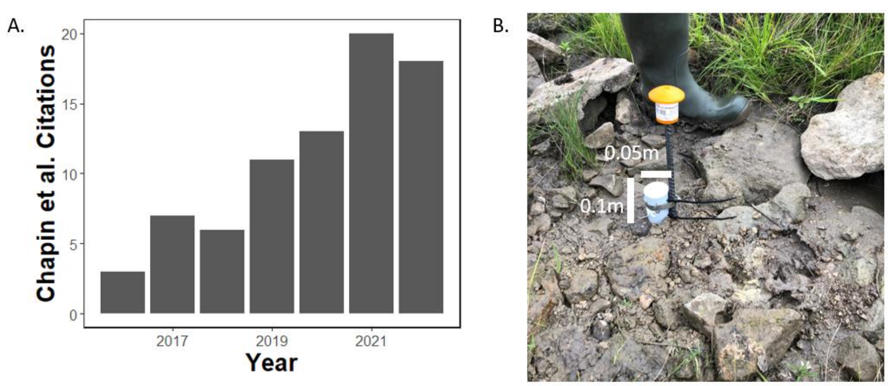

Figure 1: (a) The number of yearly citations of Chapin et al. (2014) from its publication through December 2022. Source: Google Scholar; (b) a STIC sensor deployed in the field.

Despite increasing prevalence of STIC loggers for characterizing network connectivity (Jensen et al., 2019) and water quality (Paillex et al., 2020), STIC data in its raw form requires substantial processing to develop a time series of calibrated conductivity and associated wet/dry classification. Given the importance of inter-site and inter-regional comparison in hydrologic studies, there is a need for an open, standardized, and reproducible workflow for tidying STIC data and performing basic processing operations such as calibrating measured conductivity, generating the classified wet/dry dataset, and performing quality assurance and quality control (QA/QC) checks on the data. Additionally, implementing such tools on an open source platform like R will allow studies involving STIC loggers to be more easily reproducible, helping to move water resources science away from the reproducibility problems that have become increasingly evident in recent years (Stagge et al., 2019, Reinecke et al., 2022) and toward an open hydrology framework (Hall et al., 2022). Finally, an open and standardized workflow could decrease the risk of error in the binary classification of STIC conductivity measurements (i.e., incorrectly classifying the conductivity data as wet or dry) through improved and standardized analysis and QA/QC procedures, though local hydrological knowledge and expert opinion will remain crucial in informing site-specific classification and QA/QC checks.

To advance these goals, we present a new open-source software package (STICr) for tidying and processing STIC logger data. We then demonstrate how the package can be used in a project-specific reproducible workflow that involves processing data from many loggers spread across multiple watersheds and research groups to highlight a potential application of the STICr package.

2 STICr package description and examples

The overarching goal of the STICr package is to provide a workflow spanning four data processing steps: (1) "tidying" the raw HOBO output files such that basic data wrangling operations (i.e., subsetting, joining, etc.) can be performed easily; (2) converting the raw conductivity measured by the sensors into calibrated specific conductivity (SpC); (3) interpreting the conductivity data into a binary "wet/dry" classification, indicating the presence or absence of water at the sensor at each timestep; and (4) providing QA/QC operations such as correcting negative calibrated conductivity values and flagging anomalous classification points. After these operations are performed, the resulting data should be application-ready for hydrological analysis and can be more easily integrated with other datasets for analysis.

2.1 Tidying output *(Step 1)*

When the data from a logger is initially downloaded using the Onset HOBOWare proprietary interface and exported as a comma-separated value (CSV) file, it has many characteristics which make it inconvenient for analysis, including logger-specific column names with multiple spaces and punctuation marks, as well as metadata columns which don't represent actual observations. The *tidy_hobo_data* function takes a raw CSV file exported from HOBOware as input and produces a tidy data frame in the R global environment and/or saved as a CSV file, as described below. The input data frame contains three key data columns (date and time of the observation, the uncalibrated conductivity measured by the sensor, and the temperature in degrees Celsius measured by the sensor), which *tidy_hobo_data* preserves in the resulting output data frame. The output data frame has the following columns: *datetime*, which is the date and time of each observation; *condUncal*, which is the uncalibrated conductivity recorded by the STIC (unitless, though reported by Hoboware as "Lux" from the light sensor that is modified to record conductivity); and *tempC*, which is the temperature recorded by the STIC (units: Celsius).

2.2 Converting relative conductivity to specific conductivity *(Step 2)*

While STIC sensors can be used to monitor wet/dry conditions using their raw uncalibrated conductivity output (Jensen et al., 2019; Peirce and Lindsay, 2013), the uncalibrated conductivity recorded by the STICs is a relative indicator that is not directly comparable between sensors. Calibrating the STICs provides more physically meaningful units that are directly comparable between sensors for wet/dry classification and opens new research possibilities for investigating water quality dynamics, for example through high spatiotemporal resolution mapping of solute concentrations (Paillex et al., 2020). Since uncalibrated conductivity is not directly comparable between sensors, it is necessary to develop individual calibration curves for each STIC where SpC is desired and to evaluate the stability of these calibrations throughout the STIC deployment.

The next two functions provided in the package, *get_calibration* and *apply_calibration*, develop a calibration curve from laboratory calibration data and apply it to the raw data to convert the uncalibrated unitless conductivity recorded by the logger into physically meaningful specific conductivity (SpC; units µS/cm). In STICr, the *get_calibration* function takes a data frame containing calibration data for a specific logger and outputs a model object, which can then be used as an argument in the *apply_calibration* function to generate the SpC values. The input STIC calibration data frame must contain columns with the following names: *standard*, referring to the SpC value (in µS/cm) of a known standard in which the logger was submerged for calibration, and *condUncal*, referring to the corresponding measured conductivity logged by the STIC when submerged in the solution. The *get_calibration* function includes two options for developing calibration curves, *linear* and *exponential*. Finally, *get_calibration* returns a fitted model object relating SpC to the uncalibrated conductivity values measured by the STIC, which can then be passed to the *apply_calibration* function to calculate an SpC time series for the STIC's period of record. The function works by using the model object along with the *predict* function from base R to produce a column of SpC values from the uncalibrated conductivity values for each individual logger. The function returns the same tidied data frame as the input, with the addition of an *SpC* column.

2.3 Classifying wet/dry conditions *(Step 3)*

The *classify_wetdry* function concerns the main purpose of STIC loggers, which is creating a binary "wet or dry" time series indicating the presence or absence of water at each measurement timestep. The principle behind generating this data set is that conductivity (either uncalibrated or SpC) will be at or near zero when the external electrodes of the sensor are in contact with air and will be at a high value if the electrodes are in contact with water. Despite the simplicity of this concept, there are a number of confounding factors that complicate this binary classification. One such factor is that, depending on factors such as the range of stream water conductivity conditions and sensor drift, one may have a difficult time interpreting where the cutoff is. Additionally, the loggers may become buried in moist soil, giving an "intermediate" conductivity value that is challenging to interpret. To this end, we provide multiple classification options in this *classify_wetdry* function to help address some of these confounding factors, as well as offer users methods that will work best in their particular study areas.

The *classify_wetdry* function takes a tidied STIC data frame as input, such as one generated by *tidy_hobo_data* or *apply_calibration.* The user can then decide what column they would like to use for classification using the *classify_var* input. While our workflow (detailed in Section 3) uses SpC for wet/dry classification, if the user does not have calibration data available for their loggers, they may use the original *condUncal* column generated from *tidy_hobo_data*. There are then three choices of *method* for classification, including defining an absolute threshold, using a percentage of the observed maximum value as a threshold (Warix et al., 2021), or using the y-intercept of the fitted model developed in *get_calibration* as a first-order approximation (Kindred, 2022). The choice of the classification variable, method, and threshold are important decisions and may vary widely in different environments, as typical SpC values in a system can vary widely due to physiographic and environmental factors (Wilde and Radtke, 1998). To guide these decisions, we recommend performing a sensitivity analysis with the calibrated data that shows how a summary statistic (such as the agreement in classification with independent field observations or the total proportion of sensors in a network showing wet readings at each time step) changes using different thresholds (Fig. S1) to guide the selection of the threshold value. Ultimately, *classify_wetdry* returns the same input data frame provided to the function with the addition of a new column called *wetdry*, which contains the character value "wet" or "dry" for every timestep.

2.4 Quality assurance/quality control *(Step 4)*

The remaining functions provided in the STICr package address QA/QC and manual inspection of the processed data. The function *QAQC_stic_data* addresses QA/QC of processed STIC data by providing users with the option for flagging and/or correction of three common anomalous scenarios. The first of these are instances when the calibrated SpC is negative, which indicates an issue with the application of the calibration data to the field measurements. Most often the uncalibrated value associated with a negative SpC is 0, indicating a high-confidence dry reading. As such, the function gives users the option to both flag negative SpC with the character "N", for "Negative", and/or correct these values to 0. The second scenario that the user can flag is occurrences when calibrated SpC value is outside the range of calibration standards (e.g. the calibrated SpC was estimated at 1200 µS/cm, but the highest concentration standard used during calibration was 1000 µS/cm). These cases are flagged with the character code "O", for "Outside". Finally, the function includes an argument that inspects the classified binary time series for potentially suspect anomalies in which relatively few consecutive "wet" or "dry" readings are surrounded by many consecutive opposite readings both before and after. The anomaly detection takes as input two parameters: *window_size* is a numeric argument specifying the number of observations that the anomaly must be surrounded by in order to be flagged, and *anomaly_size* specifies the maximum of a clustered group of points that will be flagged as an anomaly. Such anomalies are assigned the character code "A", for "Anomaly". Since non-perennial streams can exhibit diel cycling between wet and dry conditions (Graham et al., 2013), defining the appropriate *window_size* and *anomaly_size* require knowledge of the site's expected stream drying regime (i.e., Price et al., 2021). The *classify_wetdry* function returns the same input data frame provided to the function with the addition of a new column called *QAQC*, which contains the flagging character codes ("N", "O", and "A") that the user specified.

The *validate_stic_data* function takes a data frame with field observations of wet/dry status and SpC and generates both a confusion matrix for the wet/dry observations and a scatterplot comparing estimated SpC from the STICs to field-measured values. The general purpose of the function is to test the accuracy of both the SpC conversion and classification. The input data frame of field observations must include a *datetime* column, as well as a column labeled *wetdry* consisting of the character strings "wet" or "dry" (as in the processed STIC data itself). Additionally, if field data on SpC was collected (e.g., with a sonde), this should be included as a third column called *SpC*, and units should be in µS/cm. The function then compares these field observations with closest-in-time STIC time series data. If only wet/dry observations are included in the input, then output will consist of a confusion matrix showing the number of correct readings as well as false positives and negatives. If field-measured SpC is included, the function will also output a scatterplot with STIC-measured SpC on the x-axis and field-measured SpC on the y-axis for the number of field observations available.

The final QA/QC function is called *test_threshold*. This function is intended to allow the user to visually assess the effects of classification threshold uncertainty on STIC classification. Its two inputs are the model object used to calibrate SpC, as well as a classified STIC data frame. The output is a time series plot of classified wet/dry observations through time using three different absolute classification thresholds: the y-intercept of the fitted model developed in *get_calibration*, the y-intercept plus one standard error, and the y-intercept minus one standard error (following Kindred, 2022).

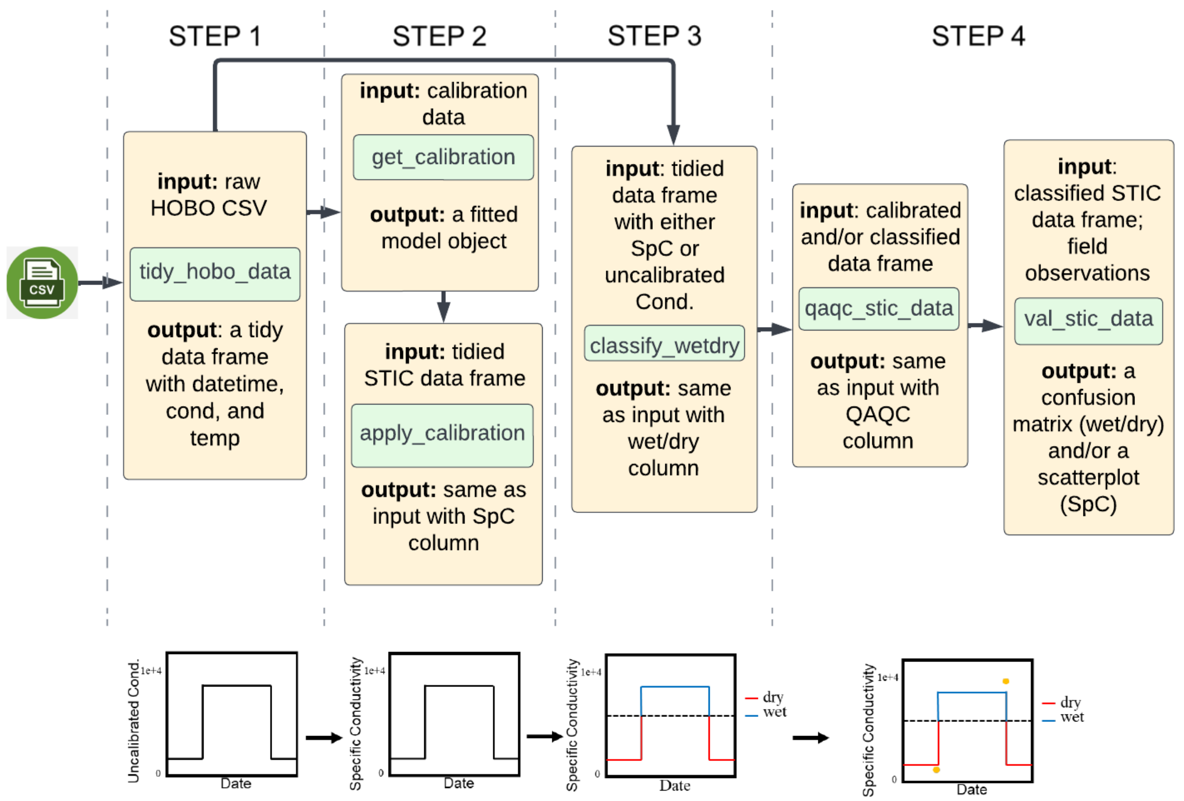

Figure 2: (a) Workflow diagram for the functions provided in the STICr *package, delineated by steps 1-4 described above; (b) Graphs of the STIC data at four stages in the workflow. First, a time series of the original uncalibrated conductivity data is shown. Then, the same time series is shown, but the y-axis has been calibrated to SpC units (µS/cm). Then, an SpC time series is shown again, colored by its binary wet/dry classification. Finally, the classified time series is shown again with field SpC measurements indicated with dots.*

3 Integration into reproducible workflow

Although the functions provided in STICr allow users to address basic tidying and processing operations, their arguments and functionality remain relatively general to allow users to adapt and integrate them into reproducible workflows that fit their specific needs. Here, we provide an example of how these functions are used in a reproducible workflow that serves as a project-wide pipeline for organizing and processing data from over 200 STIC loggers from nine watersheds over a multi-year period. The *Aquatic Intermittency effects on Microbiomes in Streams* (AIMS) project is a multidisciplinary National Science Foundation-funded project whose goal is to collect and integrate high resolution datasets on the hydrology, biogeochemistry, and microbial ecology of intermittent streams in multiple regions of the US. As such, inter-site and inter-regional comparisons of methodologically consistent stream intermittency data from STIC loggers form the scientific backbone of this project. This need for consistency in processing, analysis, and QA/QC of STIC data across sites and regions, as well as the need to integrate this data with other project-specific data sets (e.g., optical water quality sensors, pressure transducers, etc.), led to the development of STICr and an AIMS-specific STIC data pipeline.

3.1 Data Collection

The first step is the collection of high-quality field data. While the focus of this paper is data analysis, we briefly offer several recommended best practices for field deployment to ensure high data quality. Prior to deployment, we recommend carefully calibrating the loggers using multiple solutions of known SpC that exceed the range of expected conditions in the field. We recommend a minimum of four calibration points encompassing the full range of SpC values that the STIC will likely encounter during its field deployment, including a dry calibration point when the STIC is exposed to the air rather than submerged in water. Calibrating the loggers provides a strong foundation for threshold estimation and classification steps because uncalibrated conductivity is not comparable across loggers and using a calibrated value as a threshold greatly improves the consistency of threshold identification and classification. During deployment, the sensors should be placed in the stream thalweg with the sensor's electrodes just off the streambed to capture shallow flow. We typically place the sensor within a couple millimeters of the streambed, unless rapid sedimentation is expected, in which case positioning further above the streambed helps prevent sensor burial. Along the thalweg, specific sensor locations should be targeted based on the desired hydrologic indicators for the study, for example avoiding pools if the goal is to record the expansion and contraction of the surface water network in the catchment (Jensen et al., 2019) or targeting pools if the goal is to characterize the persistence of water in the network. The STICs should be visited regularly to check for erosion or sediment deposition, and to record a field observation of the wet/dry status and SpC which can be used for validation. Finally, data from the sensors should be downloaded and sensors should be maintained on a regular schedule. We recommend downloading data and changing sensor batteries every 6 to 9 months. To assist with evaluation of the STIC data, we have also developed some qualitative data categories, which are included in the Supplemental Information.

3.2 Data processing workflow

The processing workflow consists of five scripts written in R that make use of the *STICr* package through specific applications of these general functions combined with additional project-specific requirements such as data naming and formatting conventions. The scripts described in the following section are available on GitHub (https://github.com/christopherwheeler/AIMS_stic_pipeline; Wheeler, 2022). While our analysis focuses on the widely used STIC sensor, apart from the *tidy_hobo_data* function, each of the functions and scripts we develop can also be modified to work with data from other stream intermittency sensors such as the Smart Rock.

The first script in the AIMS pipeline, *Tidy_Calibrate_Classify_Data.R*, tidies the raw data, calibrates the uncalibrated conductivity readings to SpC units, then classifies the data into a binary wet/dry time series using SpC. After each step, the resulting data sets are saved as intermediate working files. Due to the large number of loggers in use on this project and their different maintenance and download timelines, we perform the tidying, calibration, and classification on an entire folder of files that represents one "round" of STIC downloads at a particular site, which produces one CSV file per site, per download. We use a CSV file relating the serial number of the STIC logger to its project-specific site name (corresponding to its watershed position), as well as a file containing all of the SpC calibration data grouped by serial number, as indices to perform the necessary operations. This script also uses data contained within the CSVs to automate naming the output files according to the project-specific convention, which contains the logger serial number, site/region codes, and the start and end dates for the download period in YYYYMMDD format.

Since different STIC loggers are used at the same site during different deployments and the same STIC may be deployed at different locations over the course of the project, data from the same locations over multiple download periods must be combined such that the final data folder contains only one file per site. This operation is performed in the script, *Combine_Data.R*. This script makes use of the *Purrr* package (Henry and Wickham, 2020) to combine data from the same STIC locations over the entire period of record to generate a complete time series for each location. An important part of this step is the use of an index data frame to match logger-specific serial numbers to locations for each time period, as described in the preceding step. This is because loggers are often switched out or replaced while downloading, resulting in multiple serial numbers associated with a given watershed location. Next, the third script (*Finalize_Data.R*) implements project-specific QA/QC requirements and generates the final data files, which are then shared with all collaborators. This includes generating a QA/QC column in the final data frame with character codes representing various QA/QC flags described above in section 2.

The final script in the pipeline (*Make_Markdown.R*) uses iteration to create a PDF-formatted RMarkdown data summary file (e.g., Fig. S2) for each of the final data files for manual, visual QA/QC checks of the final data. The documents include an SpC time series for the entire period of record, colored by its binary designation, with an additional point showing a field SpC measurement if available. This is followed by a temperature time series, as well as a map showing the location of that particular logger. Finally, each document contains a scatterplot of field SpC measurements versus their corresponding STIC readings, which the point representing that particular logger indicated. Overall, the AIMS STIC data workflow shows one instance of how the generalized STICr functions can be utilized for the automation of project-specific tasks.

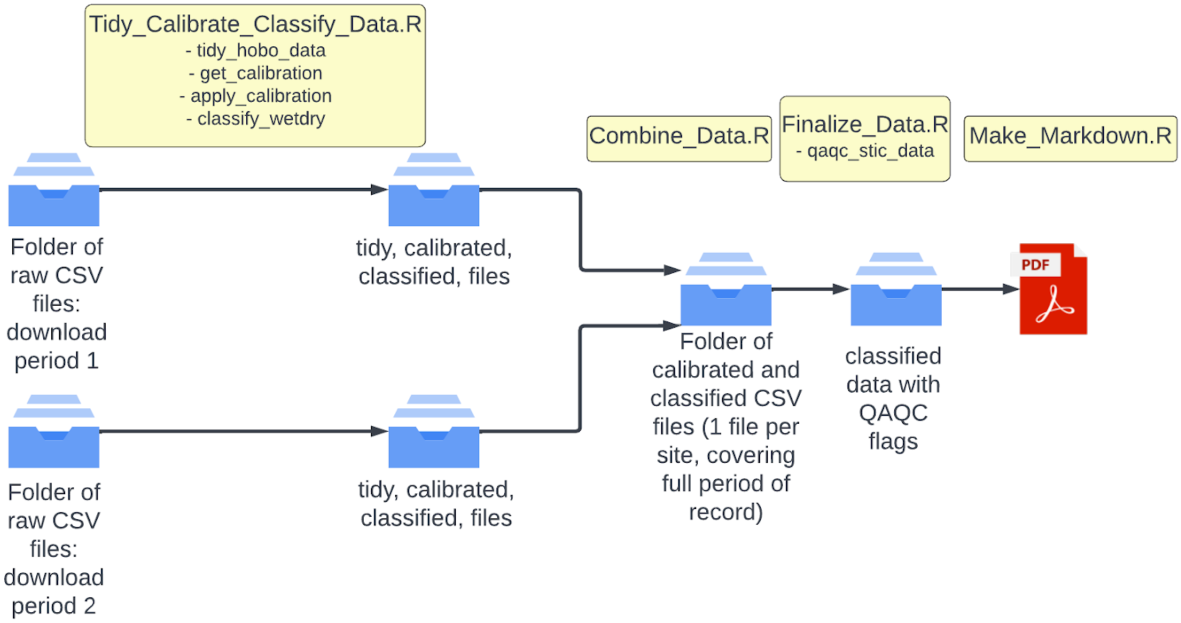

Figure 3: Workflow diagram for the AIMS STIC pipeline; Capitalized names with .R extension represent scripts in the workflow; Lower case names below represent STICr functions applied in the script.

4 Future needs

Although the package presented here represents an important first step toward an open and reproducible framework for stream intermittency sensors, it is an ongoing, open-source package with multiple additional pathways for future improvements. One major aspect that remains is the incorporation of additional options in the *classify_wetdry* function such as more sophisticated classification algorithms, as well as multivariate approaches that make better use of the high-resolution temperature data provided by STIC loggers. A second potential area for expansion of the package is the inclusion of additional tools for summarizing the resulting STIC data, for example increased plotting functionality and functions that could provide summary statistics (such as wet network proportion) for a group of sensors for a given time period. Finally, the package currently relies on manual reading and export of data from the proprietary HOBOware format to a machine-readable CSV format, and development of a programming-based approach to read in the HOBOware files directly would enhance reproducibility and efficiency. As an open-source package, we encourage STIC users to make suggestions for improvements as issues on the package's GitHub page and contribute code they develop for their own analyses.

5 Conclusions

In this note, we introduced STICr, an open-source R package for working with data from STIC loggers. The package includes functions for tidying of the raw data, calibration of uncalibrated conductivity to physically-meaningful SpC in µS/cm, classification of conductivity into a binary data frame representing flow presence of absence, and performing QA/QC operations and some corrections to the classified data frame. We also described a data pipeline for STIC sensors deployed in the AIMS project that applies the STICr functions in a more specific framework, allowing for comparison with other data collected as part of the project. This package represents an important advance toward open and reproducible hydrologic analysis in the study of non-perennial streams.

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Availability Statement

The code and associated data used in this manuscript are available via GitHub (https://github.com/HEAL-KGS/STICr) during the review process and will be submitted to CRAN concurrent with the revision process.

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Supporting Information for

STICr: An open-source package and workflow for processing and analyzing data from Stream Temperature, Intermittency, and Conductivity (STIC) loggers

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Introduction

Figure S1 is an example of the type of plot that could be used as part of a sensitivity analysis to determine the choice of an absolute "wet" or "dry" classification threshold. Data comes from a 3-month period (June through end of August 2021) at Konza Prairie Biological Station (near Manhattan, KS). The summary metric used is wet network proportion (the proportion of total sensors recording a "wet" reading at each timestep). Figure S2 is an example of a portion of a PDF-formatted RMarkdown data summary document produced by the *Make_Markdown.R* script described in section 3.2. Data is from an individual STIC sensor at Konza Prairie.

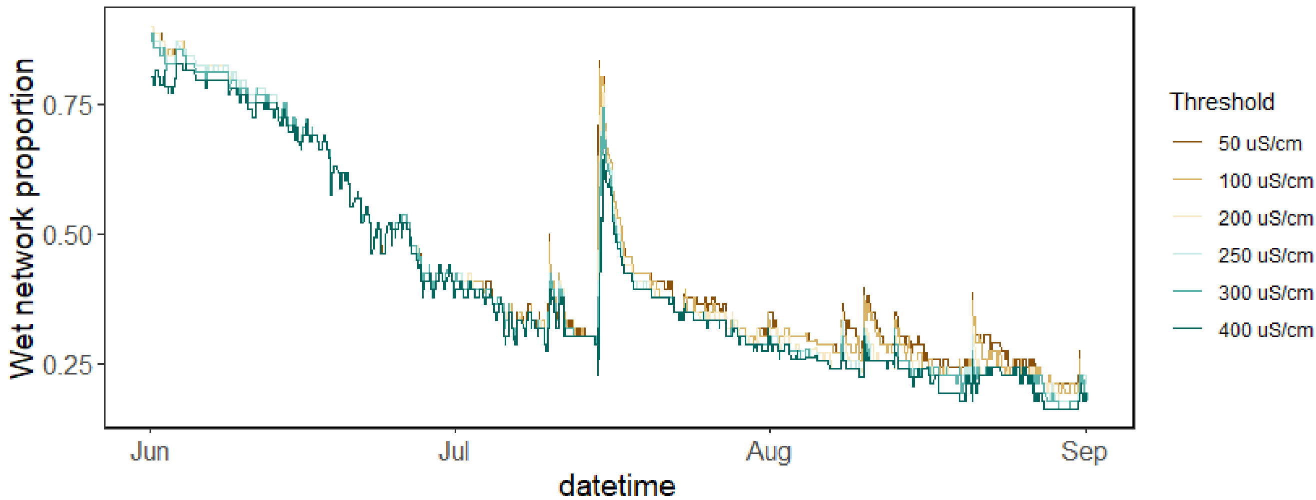
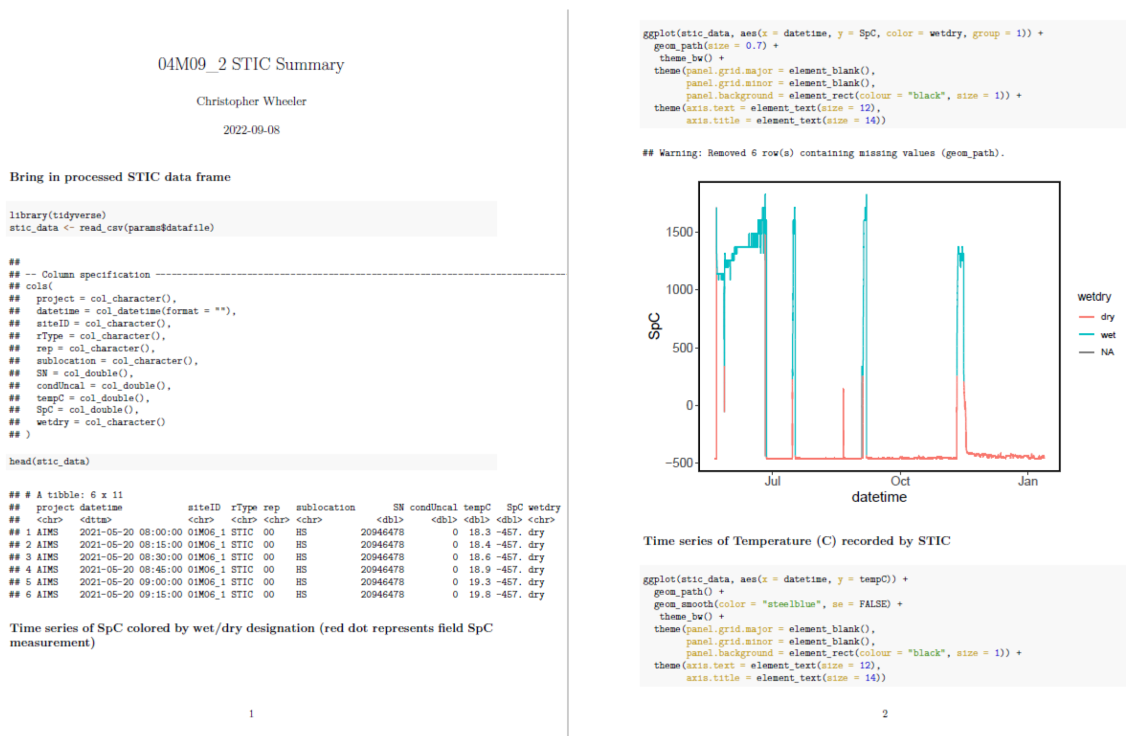


Figure S1. Example Time series of wet network proportion calculated using six different SpC threshold values. This is one example of analysis used to guide the determination of a classification threshold for a given site.



04M09_2 STIC Summary

Christopher Wheeler

2022-09-08

Bring in processed STIC data frame

```
library(tidyverse)
stic_data <- read_csv(params$datafile)
```

```
##
## -- Column specification ----------------------------------------------------------
## cols(
##   project = col_character(),
##   datetime = col_datetime(format = ""),
##   siteID = col_character(),
##   rType = col_character(),
##   rep = col_character(),
##   sublocation = col_character(),
##   SN = col_double(),
##   condUncal = col_double(),
##   tempC = col_double(),
##   SpC = col_double(),
##   wetdry = col_character()
## )
```

```
head(stic_data)
```

```
## # A tibble: 6 x 11
##   project datetime            siteID  rType rep   sublocation       SN condUncal tempC   SpC wetdry
##   <chr>   <dttm>              <chr>   <chr> <chr> <chr>          <dbl>     <dbl> <dbl> <dbl> <chr>
## 1 AIMS    2021-05-20 08:00:00 01M06_1 STIC  00    HS          20946478         0  18.3 -457. dry
## 2 AIMS    2021-05-20 08:15:00 01M06_1 STIC  00    HS          20946478         0  18.4 -457. dry
## 3 AIMS    2021-05-20 08:30:00 01M06_1 STIC  00    HS          20946478         0  18.6 -457. dry
## 4 AIMS    2021-05-20 08:45:00 01M06_1 STIC  00    HS          20946478         0  18.9 -457. dry
## 5 AIMS    2021-05-20 09:00:00 01M06_1 STIC  00    HS          20946478         0  19.3 -457. dry
## 6 AIMS    2021-05-20 09:15:00 01M06_1 STIC  00    HS          20946478         0  19.8 -457. dry
```

Time series of SpC colored by wet/dry designation (red dot represents field SpC measurement)

1

```
ggplot(stic_data, aes(x = datetime, y = SpC, color = wetdry, group = 1)) +
  geom_path(size = 0.7) +
   theme_bw() +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(colour = "black", size = 1)) +
  theme(axis.text = element_text(size = 12),
        axis.title = element_text(size = 14))
```

```
## Warning: Removed 6 row(s) containing missing values (geom_path).
```


Time series of Temperature (C) recorded by STIC

```
ggplot(stic_data, aes(x = datetime, y = tempC)) +
  geom_path() +
  geom_smooth(color = "steelblue", se = FALSE) +
   theme_bw() +
  theme(panel.grid.major = element_blank(),
        panel.grid.minor = element_blank(),
        panel.background = element_rect(colour = "black", size = 1)) +
  theme(axis.text = element_text(size = 12),
        axis.title = element_text(size = 14))
```

2

Figure S2. Example of the first two pages of a PDF-formatted RMarkdown data summary document produced by the *Make_Markdown.R* script.