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

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Highlights:

- Stream intermittency datalogger output requires substantial processing
- The STICr R package provides functions to process, analyze, and QAQC this data
- We share a project-wide workflow for creating FAIR stream intermittency data
- In Kansas, STIC data reveal spatial stream intermittency response to geology
- Temporal stream intermittency linked to precipitation and ET at different time lags

Keywords: hydrology, R, non-perennial streams, stream intermittency, Konza Prairie, FAIR data, groundwater

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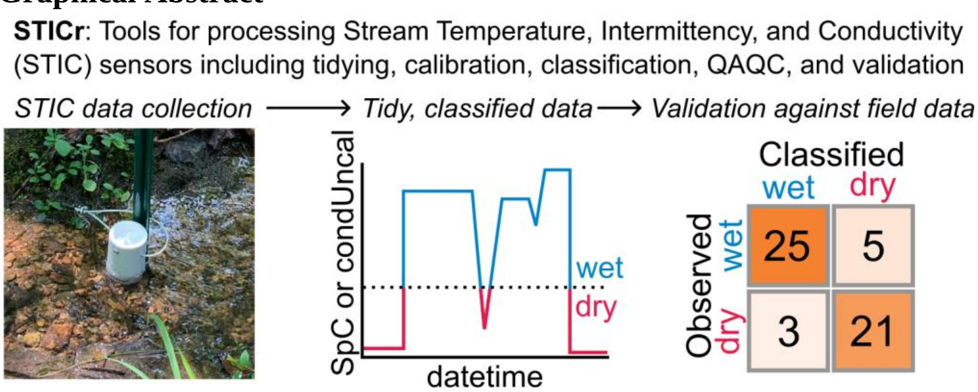
Abstract

Non-perennial streams constitute over half the world's stream miles but are not commonly included in national streamflow monitoring networks. 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 must be processed to generate hydrologically-meaningful data including temperature, conductivity, and interpreted classification of "wet" or "dry" readings at each timestep. To facilitate 'FAIR' (findable, accessible, interoperable, and reusable) stream intermittency science, we present an open-source package, STICr, written in the R language to provide a standardized framework for processing data from STIC loggers. STICr includes functions to tidy data, develop and apply sensor calibrations, classify data into wet/dry readings, and perform quality checks and validation on classified data. We also show a reproducible project-wide data workflow based on STICr for organizing and processing data from over 200 STIC loggers spanning multiple watersheds, years, and research groups, highlighting how interdisciplinary project considerations drive data processing considerations. Using South Fork Kings Creek (Konza Prairie, Kansas, USA) as a case study, we use STICr-processed data to identify spatial and temporal drivers of stream intermittency. For this watershed, stream intermittency is driven by the balance between monthly precipitation inputs and seasonal evapotranspiration fluxes, with spatial patterns of flow durations driven by underlying geology. This demonstrates how STICr can be used to create FAIR stream intermittency data and enable advances in hydrologic and ecosystem science.

Graphical Abstract



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 (Sauquet et al., 2021; Tramblay et al., 2021; Zipper et al., 2021). Locally, the timing and spatial distribution of flow in non-perennial streams influences various ecosystem services (Kaletová et al., 2019; Stubbington et al., 2020), including carbon and nitrogen cycling (Aho et al., 2023; Hale and Godsey, 2019), biological community assemblages (Busch et al., 2024), ecosystem connectivity (Malish et al., 2024), and groundwater recharge (Shanafield and Cook, 2014; Zipper et al., 2022). At regional scales, non-perennial streamflow dynamics ultimately influence the quantity and quality of water available for downstream users (Brinkerhoff et al., 2024). To support effective watershed management, 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., 2020a; Zimmer et al., 2022).

However, non-perennial streams are underrepresented in global stream monitoring networks (Krabbenhoft et al., 2022). To monitor non-perennial flow dynamics, Stream Temperature, Intermittency, and Conductivity (STIC) loggers are a low-cost and rapidly deployable tool. 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 and classified to produce a binary record of water presence or absence. Recently, additional intermittency sensors such as the Smart Rock (Milford and Truong, 2024) have been developed with similar functionality to STIC loggers.

Leveraging data from site-specific studies of stream intermittency into regional to global understanding requires developing findable, accessible, interoperable, and reusable (FAIR; Wilkinson et al., 2016) data on stream intermittency. However, while the field of hydrology has made efforts towards improved open science practices (Hall et al., 2022; Zipper et al., 2019), the discipline has been lagging with respect to FAIR data and computational resources (Reinecke et al., 2022; Stagge et al., 2019). Raw data from STICs and other sensors requires substantial processing to develop a FAIR time series of stream intermittency. Thus, 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 (QAQC) checks on the data.

To advance these goals, we present a new open-source software package (STICr) for tidying and processing STIC logger data. While many R packages exist for working with sensor data, most were developed for specific sensor types (i.e., TDPanalysis for sap flow sensors, Durand, 2020; thermocouple for temperature loggers, Gama, 2015), or to access data from specific locations and programs (i.e., TBEPtools for water quality data in the Tampa Bay, Beck et al., 2021; dataRetrieval for USGS gage and water quality data, DeCicco et al., 2024). Some packages exist to perform specific functions to sensor data regardless of data type (i.e., driftR to address drift in any sensor data, Shaughnessy et al., 2018; sensorQC to perform general QAQC checks and flagging, Read et al., 2015) or for the most commonly used sensor types (i.e., sensorstrings for HOBO, Aquameasure, and Vemco buoy sensors, Dempsey, 2024; microclimloggers for iButton and HOBO pendant sensors, Boersch-Supan and Petry, 2018). However, these packages are not equipped to handle the altered data structure of raw data from STIC sensors. Additionally, few packages exist that contain both functions for processing and tidying data as well as QAQC functions that are sensor-specific. Therefore, STICr provides a FAIR framework for the entire process of data analysis for these increasingly common sensors.

After describing STICr, we 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. We then demonstrate how this can be used to understand links between hydroclimatic processes, geological processes, and spatiotemporal patterns of stream intermittency at the watershed scale, using the South Fork of Kings Creek at Konza Prairie Biological Station as an example.

2. Methods: STICr functionality

The overarching goal of the STICr package is to provide a workflow spanning five data processing steps (Figure 2): (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; units μS/cm); (3) interpreting the conductivity data into a binary "wet/dry" classification, indicating the presence or absence of water at the sensor at each timestep; (4) providing QAQC operations such as correcting negative calibrated conductivity values and flagging anomalous classification points; and (5) validating the classified STIC data and/or calibrated SpC data against field observations. STICr also includes sample datasets showing how these data look at each step in the workflow. 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. In this section, we briefly describe the functionality of core STICr functions including input and output. In Section 3, we then show a project-specific application of this workflow.

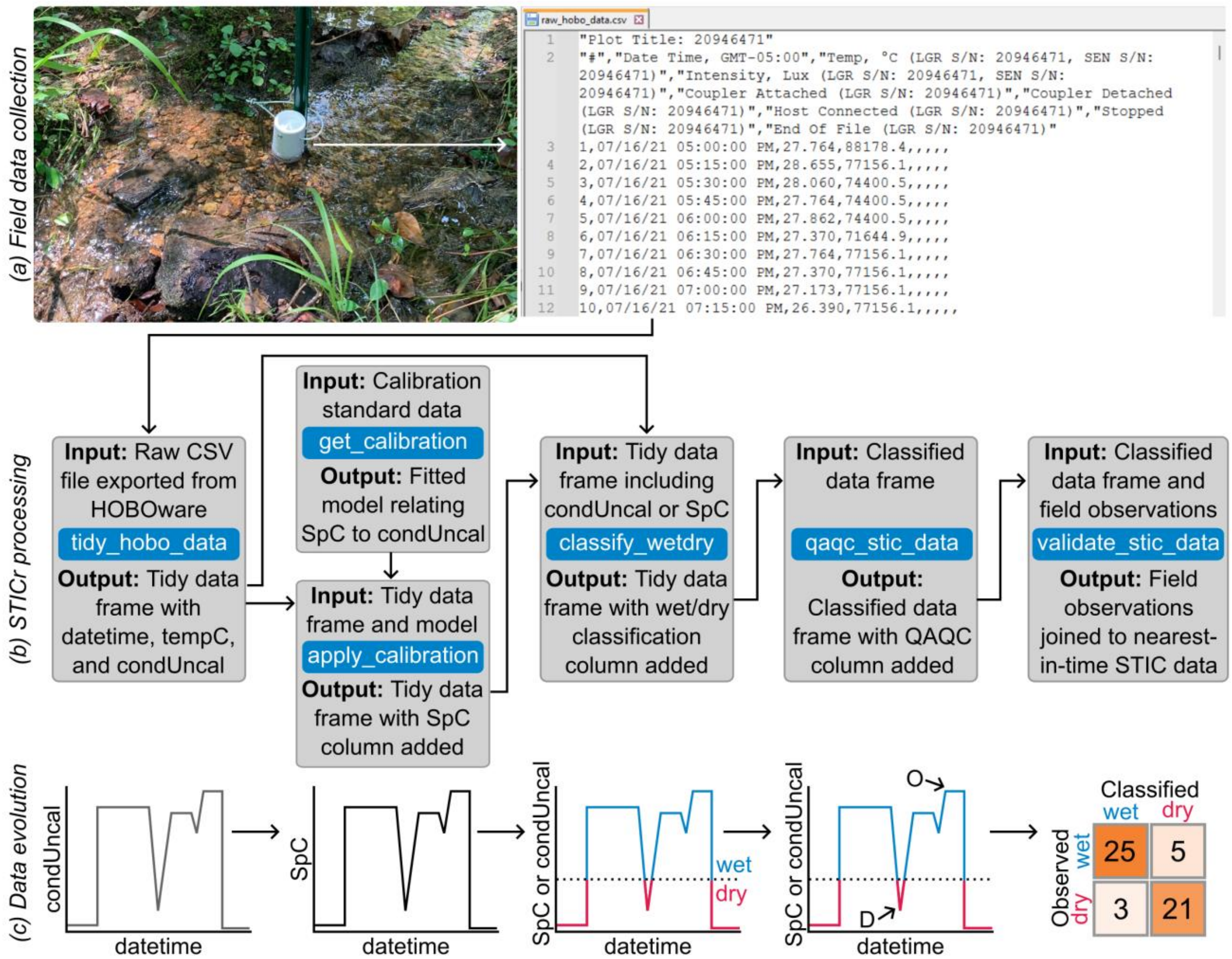


Figure 1. STICr functionality from data collection to validation. (a) Raw data collection, including a STIC logger deployed at a field site [photo credit: D.M. Peterson] and the resulting data output format from the proprietary HOBOware software. (b) Core STICr functions shown in blue boxes, including input/output data and potential interlinkages among functions to create a processing workflow. (c) Visual depiction of how STIC data evolves as it moves through the STICr processing workflow. Variable names used in the figure include datetime = date and time of STIC reading, tempC = temperature in degrees Celsius, condUncal = uncalibrated relative conductivity logged by STIC, and SpC = specific conductivity.

2.1 Step 1: Tidying output

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 that make it inconvenient for analysis, including logger-specific column names with multiple spaces and punctuation marks, as well as metadata columns that do not represent actual observations (Figure 2a; example raw file available at https://samzipper.com/data/raw_hobo_data.csv). 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 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 relative 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 Step 2 (optional): Calculation of Specific Conductivity (SpC)

Since STIC sensors are created from a modified light sensor, their conductivity data output is uncalibrated conductivity (*condUncal*), which is not a physically meaningful unit. Since STIC sensors can be used to monitor wet/dry conditions using their raw uncalibrated conductivity (Jensen et al., 2019), the calibration step is optional, but STIC calibration can provide more physically meaningful units (specific conductivity, or *SpC*) that are directly comparable between sensors and opens new research possibilities for investigating water quality dynamics, for example through high spatiotemporal resolution mapping of solute concentrations (Paillex et al., 2020).

In STICr, this is accomplished through two functions: *get_calibration*, which develops a calibration curve from laboratory calibration data, and *apply_calibration*, which applies the calibration curve to the tidied raw data to convert the *condUncal* recorded by the logger into physically meaningful *SpC*. In STICr, the *get_calibration* function takes a data frame containing calibration data for a specific logger and outputs a fitted model object in R which relates lab-measured *SpC* to STIC-measured *condUncal*. Currently, *get_calibration* creates a linear regression model, though other functional forms could be incorporated into the package in the future. This model object can be inspected to evaluate fit statistics (R^2, slope, intercept, etc.), uncertainty, and other properties useful to assess the performance of the calibration. The input STIC calibration data must be a data frame object with the following attribute labels: *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. Typically separate calibrations are required for each STIC sensor; a standard operating procedure (SOP) for STIC sensor calibration is provided in Burke et al. (2024).

The fitted model produced by *get_calibration* can then be passed as an input argument to the *apply_calibration* function, along with the tidied data generated in Step 1, to convert the STIC time series of *condUncal* to *SpC* using the *predict.lm* function from the ‘stats’ package for R. The function returns the same tidied data frame as the input, with the addition of an *SpC* column.

2.3 Step 3: Classifying wet/dry conditions

The *classify_wetdry* function underlies 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 *condUncal* or *SpC*) will be at or near zero when the 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 several confounding factors that complicate this binary classification. These factors include the range of stream water conductivity conditions or the possibility that loggers may become buried in moist soil, both of which may lead to difficulty in interpreting where the cutoff is.

STICr's *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 project-specific workflow (detailed in Section 3) uses *condUncal* for wet/dry classification – since we did not have calibration data available for all STIC sensors – the *SpC* column can also be used. To account for the confounding factors described above, there are three choices of *method* for classification: (1) *"absolute",* where the user must specify an absolute threshold of the classification variable; (2) *"percent",* where the user specifies a percentage of the observed maximum value of the classification variable as a threshold (Warix et al., 2021), which can help account for sensor-specific differences in *condUncal* readings; or (3) *"y-intercept"*, in which the y-intercept of the fitted model developed in *get_calibration* is used as a first-order approximation of the threshold (Bilbrey, 2024; Kindred, 2022). For each of these methods, values of the classification variable above the threshold are interpreted as wet and below the threshold are interpreted as dry.

The choice of the classification variable, method, and thresholds are important decisions and may vary widely in different environments, as typical *SpC* values in streams can span orders of magnitude across freshwater systems due to physiographic and environmental factors (Bolotin et al., 2023). In describing our project-specific case study, we show how a sensitivity analysis and validation process can be used to determine an appropriate classification threshold and evaluate the potential frequency and direction of misclassification errors (Section 3.4). Alternately, separate thresholds for each sensor could be developed and implemented using the STICr functionality. 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 string "wet" or "dry" for every timestep.

2.4 Step 4: Quality assurance/quality control (QAQC)

Once the STIC data are classified, the *qaqc_stic_data* function provides several options for typical QAQC procedures for stream intermittency data. The *qaqc_stic_data* takes in a classified data frame, as produced by the *classify_wetdry* function, and allows the user to select different QAQC options that they may want to evaluate. Currently, there are three QAQC inspections available:

(1) Negative SpC values, 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 *qaqc_stic_data* function gives users the option to set any negative *SpC* value to 0 and, if so, flag the data with the character “C”, for “Corrected”.

(2) Conductivity value 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). This QAQC flag is produced in the *apply_calibration* step when the fitted model is applied to the time series of STIC data. In this case, the data are flagged with the character code “O”, for “Outside”, but the value of SpC is not changed. As shown in Section 3.3, these data can be highly suspect when compared to field observations, so this flag is critical for potential interpretations of STIC *SpC* data.

(3) Short-term deviation in STIC classification data (e.g., a single “wet” data point surrounded by many “dry” data points before and after), likely indicating a potential sensor or classification anomaly. 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 *deviation_size* specifies the maximum of a clustered group of points that will be flagged as an anomaly. Such anomalies are assigned the character code “D”, for “Deviation”. Since non-perennial streams can exhibit diel cycling between wet and dry conditions (Hale et al., 2024; Newcomb and Godsey, 2023; Warix et al., 2023), defining the appropriate *window_size* and *anomaly_size* require knowledge of the site’s expected stream drying and wetting regimes and typical local stream intermittency dynamics (Price et al., 2024, 2021).

The *qaqc_stic_data* 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 (“C”, “O”, and “D”) that the user specified.

2.5 Step 5: Validation

The *validate_stic_data* function takes a data frame with field observations of wet/dry status and (optionally) measured SpC and aggregates STIC sensor data for these variables for STIC validation. 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 independent field data on SpC were collected (e.g., with a sonde), this should be included as a third column in the observation data frame called *SpC*, and units should be in μS/cm. The *validate_stic_data* function then identifies the closest-in-time STIC sensor data (within a user-specific maximum allowed time range) and joins the relevant *wetdry, SpC,* and *QAQC* data collected by the STIC. Ultimately, this produces a new dataframe with columns for both the field observations (*wetdry_obs*, *SpC_obs*) and the corresponding STIC reading (*condUncal_STIC*, *wetdry_STIC*, *SpC_STIC*, *QAQC_STIC*). These data can then be used for a variety of different validation steps, such as accuracy assessments, sensitivity analyses, and checking of calibration performance. Examples of each of these validation applications from the AIMS project are shown in Section 3.

3. Case study: Integration into project-wide reproducible workflow

3.1 Stream intermittency in a cross-institution interdisciplinary project

Although the functions provided in STICr provide details 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 for organizing and processing STIC data for the *Aquatic Intermittency effects on Microbiomes in Streams* (AIMS) project, which includes over 200 STIC loggers from nine watersheds and multiple universities, investigators, and students over a multi-year period (Figure 2; Peterson et al., 2023). AIMS is a multidisciplinary National Science Foundation-funded project (award OIA-2019603) 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, methodologically consistent stream intermittency data from STIC loggers form the scientific backbone of this project to interpret variations in stream dissolved organic carbon export (Bilbrey, 2024), microbiome dynamics, macroinvertebrate community structure, and many other datasets being collected. This need for consistency in processing, analysis, and QAQC 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.

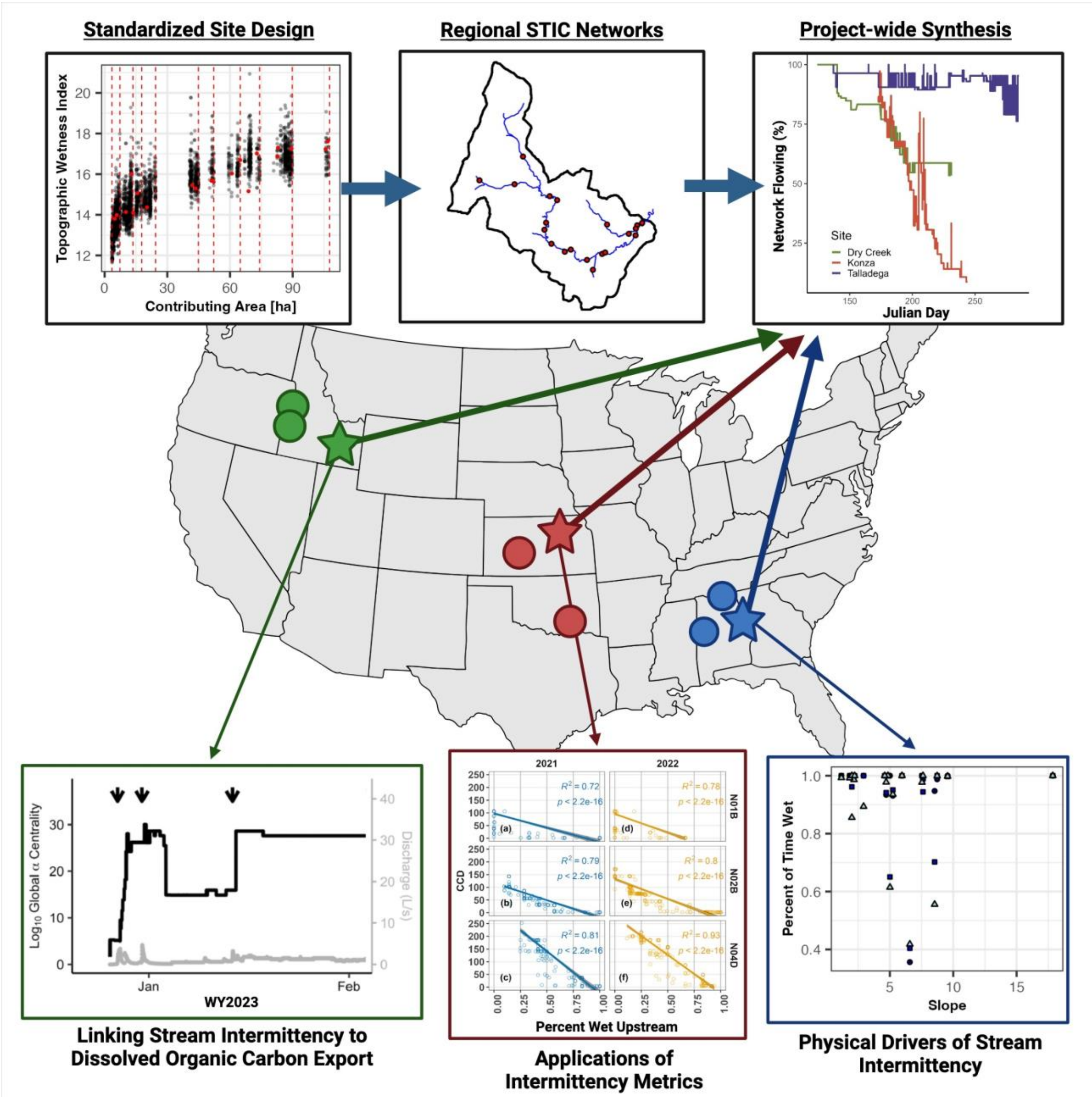


Figure 2. Design and application of STIC data for the AIMS project. Each of the circles/stars on the map is a study watershed where AIMS has deployed STIC sensors to monitor stream intermittency. The sequence of plots along the top shows how a standardized site design, using topographic wetness index and contributing area, was used to distribute the sensors within each watershed, and this consistent approach allows for cross-site synthesis research. The graphs along the bottom show examples of region-specific analyses that connect STIC data to other datasets being collected in the project. Top row figure sources, from left to right: Peterson; Peterson; Kraft et al. (in prep). Bottom row figure sources, from left to right: Bilbrey (2024), Ramos et al. (in prep), Peterson et al. (in prep).

3.2 STIC data collection best practices

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, and we have published SOPs on STIC deployment, maintenance, and calibration (Burke et al., 2024; Godsey et al., 2024). 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. As shown below (Section 3.4), STIC SpC estimates outside of the calibration range tend to perform quite poorly. 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. STICs can be re-calibrated as frequently as needed, for example during periods when they are being collected for download and redeployment. During deployment, the sensors should be placed in the stream thalweg with the sensor's electrodes just off the streambed to capture shallow flow (shown in Figure 1a). We typically place the sensor within two 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 (Godsey et al., 2024). 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 by other team members and researchers outside the project, we developed qualitative data quality categories, which are detailed in Appendix 1.

3.3 Using STICr to create a FAIR data workflow

The AIMS STIC processing workflow (Figure 3; available on GitHub, https://github.com/HEAL-KGS/AIMS_stic_pipeline) consists of five scripts written in R that make use of the *STICr* package by integrating the generalized functionality of STICr with additional project-specific requirements such as data naming and formatting conventions. 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 (Milford and Truong, 2024).

The AIMS pipeline is set up within the *STIC_00_ControlScript.R* script. In this script, the user defines the location of key files such as exported HOBO CSV data, a look-up table that links STIC serial numbers to specific field monitoring sites, calibration standard information, and paths to save output files and figures. Information from this control script is then read into each of the following four scripts that carry out sequential processing steps:

- *STIC_01_Tidy+Calibrate+ClassifyData.R* carries out the bulk of the processing, including the loading/tidying of raw HOBO CSV data (Step 1; Section 2.1), getting and applying the calibration to calculate *SpC* if available (Step 2; Section 2.2), and classifying the STIC data to create the *wetdry* column (Step 3; Section 2.3). 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 set of STIC downloads at a particular site, which produces one CSV file per site, per download. We use a look-up table CSV file relating the serial number of the STIC logger to its project-specific site name (corresponding to its watershed position) 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 date/time for the download period in YYYMMDD HH:MM:SS format.

- *STIC_02_QAQCdata.R* conducts both automated and manual QAQC steps. Automated steps include the corrections for negative estimated SpC values ("C" flag), identification of SpC values outside the range of standards used for calibration ("O" flag), and detection of deviations/anomalies in the classified time series ("D" flag). There is also a manual step in which the qualitative rating criteria are determined based on the conditions described in Appendix 1, which is streamlined through the importing of digitized STIC metadata sheets from field data collection efforts and the automated creation of diagnostic graphs and tables with information from the STIC sensor (i.e., classified wetdry conditions, SpC, and condUncal) and corresponding field observations from the corresponding period. Plots produced by this script include time series of classified STIC *condUncal*, *tempC*, and *SpC* data, color-coded by wet/dry classification, which can be used for additional checks on classification performance. For example, the STIC daily temperature range is typically greater when the STIC is dry and exposed to the atmosphere than when it is when the STIC is wet and thermal variability is dampened by the water. Therefore, paired inspection of the temperature, conductivity, and classification data can be used to assess potential misclassification issues.
- *STIC_03_CombineData+PlotTimeseries.R* collects the classified and QAQCed data for each site across all download periods to produce a single CSV file, and associated summary plots, of all available data for each site. This script does not use any STICr functionality, but is necessary because different STIC loggers are used at the same site during different deployments.
- *STIC_04_Validate+Finalize.R* script compiles field observations and uses *validate_stic_data* to create the validation data frame, which is then plotted in various ways including a confusion matrix, sensitivity to threshold choice for wetdry classification, and overall accuracy. This script also creates additional data columns and saves the data into individual CSV files for each site and year to align with the AIMS project-wide data formatting standards. These are the files that are posted to HydroShare (Zipper et al., 2024).

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.

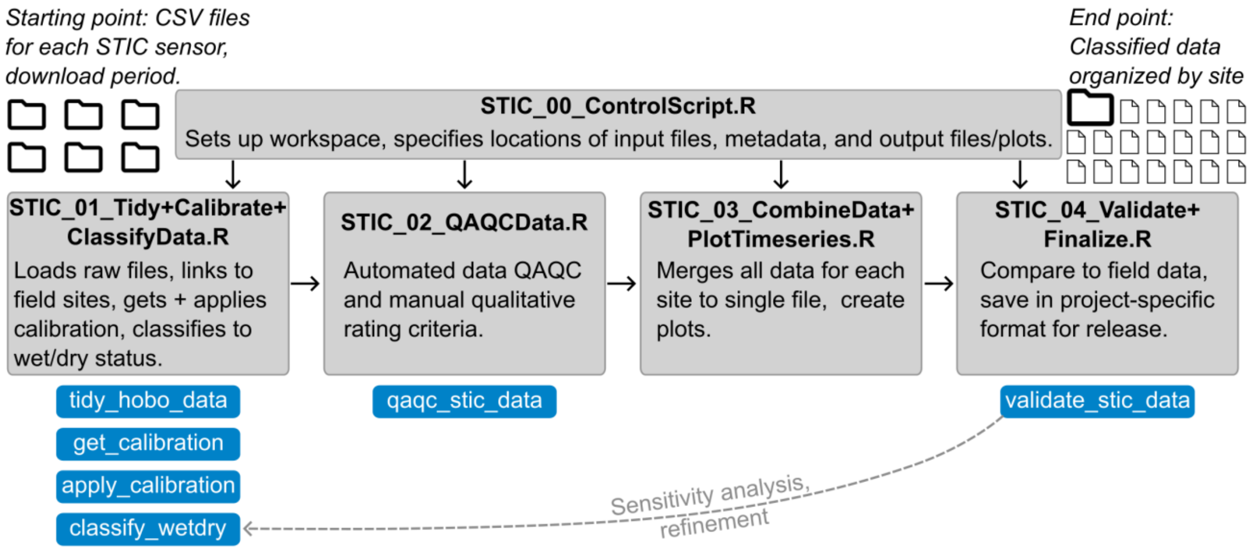


Figure 3. STICr as part of a project-wide data processing workflow. The starting point of the workflow is a set of raw CSV files exported from HOBOware for each STIC download period. Each processing script is shown in a gray box with a summary of key steps, and STICr functions used in each script are shown beneath in blue. The end point is a classified and organized set of files for each site.

3.4 South Fork Kings Creek (Konza Prairie, Kansas, USA) STIC data

In this case study, we demonstrate an example of the implementation of STICr within the project-wide reproducible workflow to assess spatial and temporal patterns of stream intermittency in the South Fork Kings Creek watershed (Kansas, USA). This watershed is the core AIMS study watershed for the Great Plains region and is fully within the Konza Prairie Biological Station, which is host to a Long Term Ecological Research (LTER) site and is part of the National Ecological Observatory Network (NEON). Streamflow in the watershed is highly intermittent and characterized by a 'fill-and-spill' hydrology controlled by subsurface storage dynamics (Costigan et al., 2015). Subsurface hydrological processes are highly complex at the site due to the merokarst landscape typical of the Flint Hills ecoregion, which consists of thinly interbedded limestones (which act as aquifers through dissolution and fracture networks) and mudstones (which act as aquitards, but are highly fractured and likely leaky) (Macpherson, 1996; Vero et al., 2018). Overall, groundwater contributes a large portion of total streamflow (Hatley et al., 2023) but groundwater flowpaths are relatively rapid and grow longer as the stream network dries (Swenson et al., 2024). The spatial patterns of stream-aquifer interactions are complex, as water is exchanged between the stream and specific limestone units only in highly localized settings where limestones outcrop onto the streambed (Gambill et al., 2024) and the watershed groundwater system has complex potentiometric surfaces that are not exclusively driven by stream-aquifer interactions (Sullivan et al., 2020). While the ecoregion is native grassland, woody vegetation encroachment has expanded rapidly over the past several decades despite watershed burning and grazing, and has led to a decrease in annual streamflow despite increasing precipitation (Keen et al., 2024; Sadayappan et al., 2023).

While this past work suggests potential spatial and temporal heterogeneity in streamflow dynamics, these studies have primarily focused on the outlets of four subwatersheds within South Fork Kings Creek that have streamflow gaging stations as part of the LTER program. In AIMS, we installed STIC sensors at 50 distributed locations within the South Fork Kings Creek watershed in May 2021, and data included in this study cover a three-year period from May 2021 to May 2024. A detailed description of site selection is presented in Swenson et al. (2024). Briefly, some locations were identified based on local hydrologic site knowledge (such as the locations of springs and confluences) while others were randomly distributed to span a range of topographic wetness index (TWI) and drainage area (Figure 2), which past work has shown to be an important control over stream intermittency elsewhere (Warix et al., 2021). These locations were designed to balance project-wide goals related to hydrology, biogeochemistry, microbiology, and ecology, and therefore were not exclusively targeted towards stream intermittency efforts, but were driven by the overarching project goal of capturing a gradient of stream intermittency and hydrologic connectivity. At each site, the STIC was installed at the thalweg of a local channel high point, such as the top of a riffle sequence, so that a "wet" STIC reading would correspond to a connected stream network at that location (as opposed to the persistence of pools at the site). Most, but not all, STICs were calibrated before deployment and STICs were downloaded and maintained approximately every 6-9 months. During these visits, and at other opportunistic occasions when project members were collecting other field data at the sites, we collected field observations including wet/dry status and independent stream water SpC, for a total of 333 field observations that can be used for validation. The STIC field data collection followed the best practices described in Section 3.2 and data were processed using the workflow described in Section 3.3.

3.5 STIC data sensitivity analysis and validation

For the South Fork Kings Creek, we conducted an iterative sensitivity analysis and validation to determine the appropriate threshold for wet/dry classification. Since we did not have calibration data for all STIC sensors, we used *condUncal* for classification. To select the *condUncal* threshold used to identify wet and dry sensor readings in *classify_wetdry*, we conducted a sensitivity analysis by evaluating agreement with observations using unitless *condUncal* thresholds every 100 from a low value of 100 to a high value of 100,000. At each threshold, we calculated overall classification accuracy (percent of field observations that agree with the closest-in-time STIC wet/dry classification), the percentage of dry field observations that were misclassified as wet, and the percentage of wet field observations that were misclassified as dry (Figure 4). We found that variability in the *condUncal* threshold had a relatively small influence on the overall classification accuracy, which is consistent with the strong conductivity contrast between air and water. However, there was an important trade-off with the type of misclassification errors, with lower *condUncal* threshold associated with a greater wet bias (dry observations misclassified as wet) and higher *condUncal* thresholds associated with a greater dry bias (wet observations misclassified as dry). For South Fork Kings

Creek, we selected a *condUncal* threshold of 700, which had a slightly lower overall classification accuracy (84.7%) than the peak we found (max overall accuracy of 88.3% at a *condUncal* threshold of 29,000), but minimized the difference between wet and dry misclassification errors. This threshold was selected after consultation with other project members who plan to use the STIC data in their analysis to best balance the potential types of misclassification errors and avoid either dry or wet bias in the STIC data, demonstrating the important role of project-wide communication in developing hydrological datasets for interdisciplinary research goals. In practice, the best classification threshold willy likely vary between sensors, watersheds, and/or regions due to variability in sensor construction and different conductivities of stream water. Therefore, overall classification accuracy could be improved by developing sensor-specific wet/dry classification thresholds where resources permit, which was completed for some AIMS watersheds. STICr provides a useful set of tools to select this threshold, apply it to the STIC data, and evaluate its accuracy.

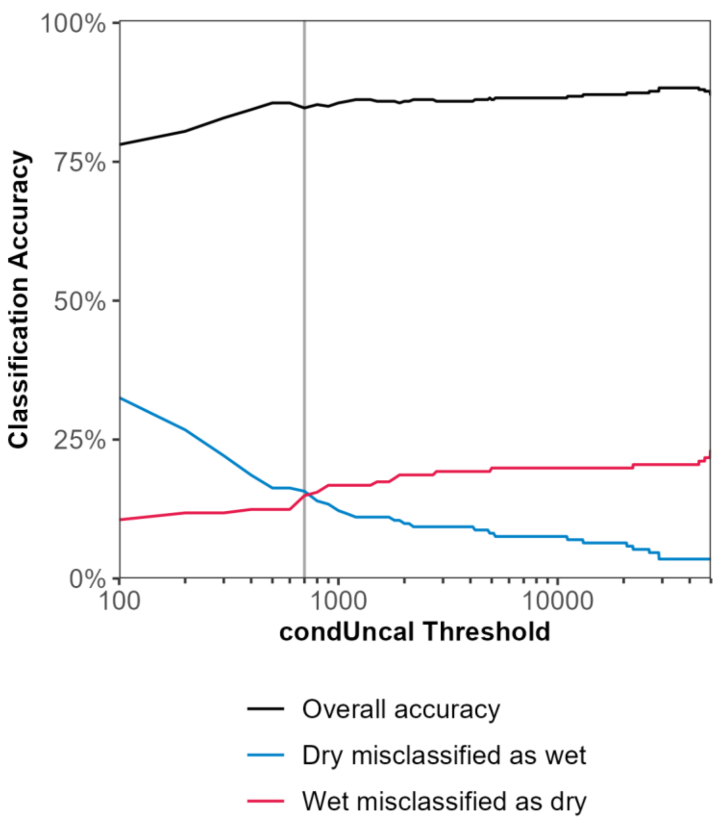


Figure 4. Selecting optimal classification threshold for the South Fork Kings Creek (Konza Prairie) watershed. This figure shows the overall classification accuracy as well as the proportion of different types of misclassification errors as a function of the condUncal threshold used in the classify_wetdry function. The gray vertical line (condUncal = 700) was used for watershed-wide classification.

Overall, the total classification accuracy was 84.7% and had relatively balanced data between correctly classified wet/dry conditions (137 and 145 correctly classified observations, respectively) and incorrectly classified wet/dry errors (24 and 27 observation errors, respectively) (Figure 5a). Of the 24 wet observations that were misclassified as dry, 13 of them had a *condUncal* reading of 0, suggesting that the misclassification was caused by the STIC being out of the water, for example due to channel erosion or migration. For the remaining wet observations misclassified as dry, a lower classification threshold could have fixed the issue, suggesting potential value from sensor-specific accuracy assessments and classification threshold determination.

However, the agreement between field-measured SpC values and calibrated STIC observed SpC data was poor, with much higher SpC values estimated from the STICs than observed in the field-measured SpC. This comparison demonstrates the value of our QAQC procedures, as screening out any data points flagged with a "C" (meaning negative SpC values were obtained after calibration) or an "O" (meaning the calibrated SpC was outside the range of standards) eliminates the most extreme SpC values, which are shown as gray circles in Figure 5b. The remaining data points are distributed close to the 1:1 line (slope = 0.998), though the overall coefficient of determination remains relatively low ($R^2 = 0.20$) compared to lab fits to calibration standards, which generally had an $R^2 > 0.9$. The lower agreement compared to field could be due to issues with the STIC calibrations (such as calibration drift through time), issues with the STIC *condUncal* raw data (such as biofouling of the STIC electrodes during deployment which could influence conductivity), or issues with the field observations (such as errors in portable water quality sondes used to measure SpC). Through this validation process, we can constrain the potential applications of STIC-derived SpC data and identify potential opportunities to improve future calibration and data collection practices.

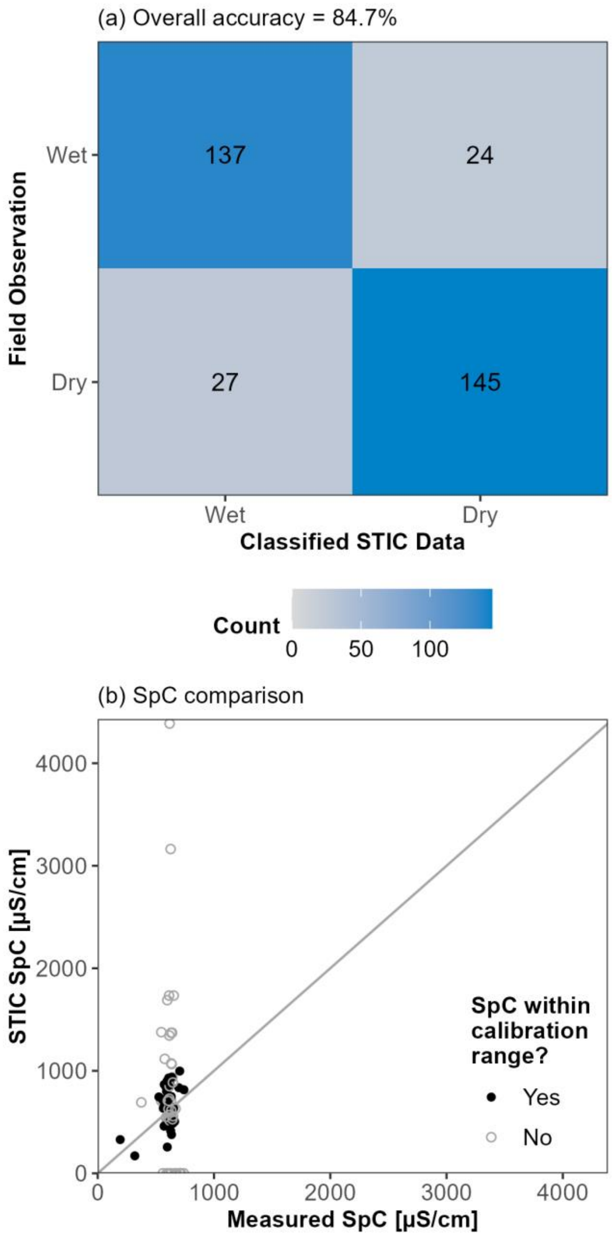


Figure 5. STIC data validation from the South Fork Kings Creek (Konza Prairie) watershed. (a) Confusion matrix showing classification accuracy. The numbers correspond to the total number of observations in each quadrant. (b) Scatterplot showing calibrated SpC accuracy.

3.5 Spatial and temporal intermittency dynamics

Our STIC data collection, which was motivated by the goal to develop improved understanding of spatial patterns of stream intermittency at a watershed scale (Section 3.1), revealed both spatial and temporal of stream intermittency dynamics in South Fork Kings Creek. Spatially, we observed that the South Fork Kings Creek watershed generally has the wettest conditions (greatest percent of time wet) in the middle reaches of the westernmost subwatersheds in the study area, while conditions are drier in the upstream and downstream portions and easternmost subwatersheds (Figure 6). The locations with the greatest flow persistence are associated with portions of the stream network where past work has found significant local contributions from limestone aquifers and the stream channel, while downstream areas with less flow persistence are associated with potential areas of loss from the aquifer into the stream (Gambill et al., 2024). Since flow at the watershed outlet tends to be dominated by groundwater (Hatley et al., 2023), but with relatively high fractions of young water (water that fell as precipitation within the past three months; Swenson et al., 2024), this supports the important role of fill-and-spill dynamics within specific limestone aquifers as key controls over flow persistence not just at the watershed outlet, as shown by Costigan et al. (2015), but also at fine spatial resolution within the stream network.

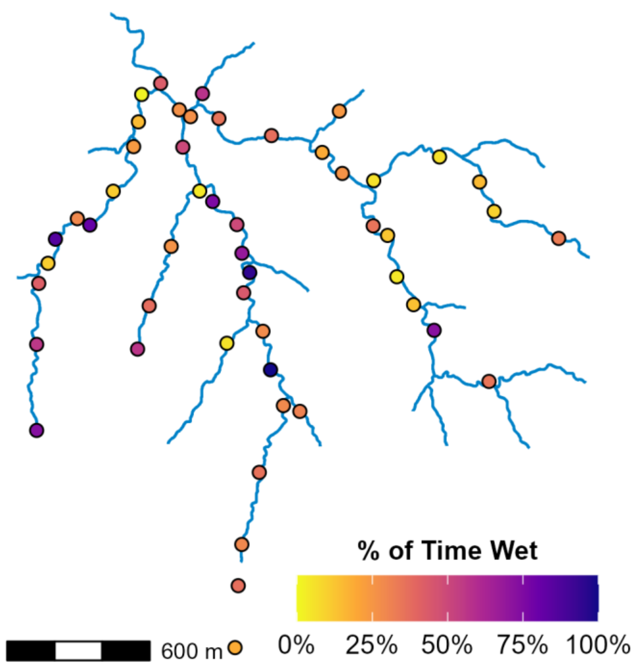


Figure 6. Spatial patterns of stream intermittency. Map of the South Fork of Kings Creek STIC monitoring network, colored by the percentage of time that each STIC was classified as wet conditions for the May 2021 to May 2024 period of record.

From a temporal perspective, the classified STIC data reveals a highly dynamic watershed that is rarely completely wet and never completely dry (Figure 7a). Stream wetting tends to be flashy, with immediate increases in the wet STIC proportion associated with precipitation events, and then more gradual recessions back to a relatively consistent baseline of ~10-20% wet STICs, which are primarily concentrated in the middle portions of the watershed (Figure 6). To investigate climatic drivers of intermittency, we obtained daily meteorological data from the Konza Prairie LTER (Nippert, 2024) and daily watershed-average evapotranspiration (ET) data from OpenET, which provides satellite-derived estimates of daily ET for the western US (Melton et al., 2022; Volk et al., 2024), and tested the linear correlation between each of these climatic drivers summed over time lags ranging from 1 to 365 days. This reveals that temporal patterns of network-scale stream intermittency are strongly associated with the atmospheric water supply (precipitation) and losses (ET) at different timescales. The best predictive relationships for wet STIC proportion occur when precipitation is summed over the prior 27 days ($R^2 = 0.59$; Figure 7b, Figure 7e) and when ET is summed over the prior 290 days ($R^2 = 0.57$; Figure 7c, Figure 7f). A simple multiple linear regression model using these two variables as predictors can explain 75% of the overall variability in wet STIC proportion (Figure 7d), with a significant ($p < 0.05$) positive relationship to 27-day summed precipitation and a significant negative relationship to 290-day summed ET.

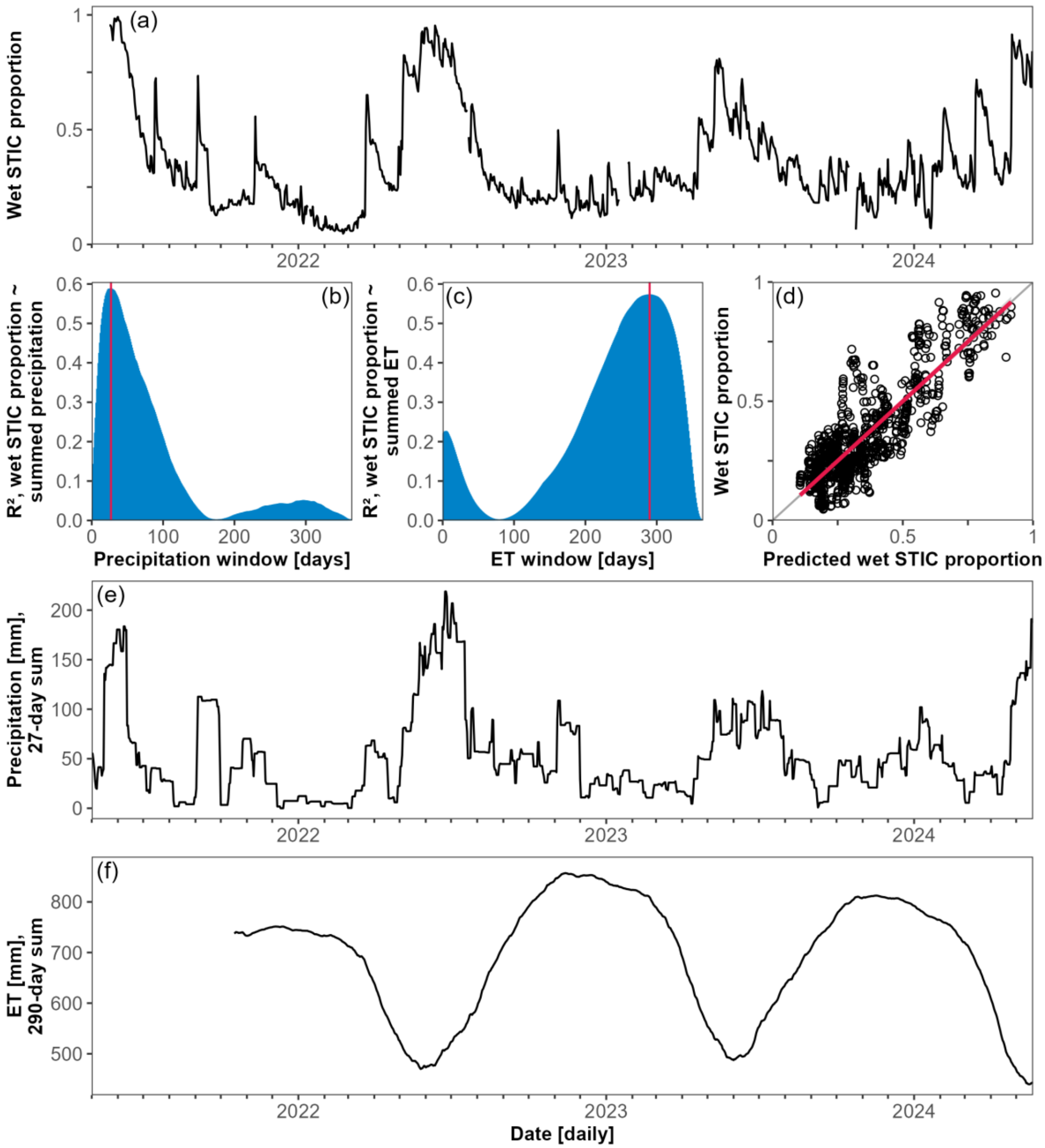


Figure 7. Temporal patterns and drivers of stream intermittency. (a) Daily wet STIC proportion for the May 2021 – May 2024 period (tick marks show months). R^2 of a linear relationship between the proportion of wet STICs and (b) summed precipitation and (c) summer ET for different windows. (d) Predicted wet STIC proportion as a function of precipitation over the preceding 27-day window (best for from panel b; $R^2 = 0.59$) and ET over the preceding 290-day window (best for panel c; $R^2 = 0.57$), with gray line showing 1:1 relationship and red line showing linear best fit (overall $R^2 = 0.75$). Daily time series of (e) summed 27-day precipitation and (f) summer 290-day ET.

4. Discussion

4.1 STICr functionality and future development 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 package with several opportunities for improvement. First, while the *classify_wetdry* function allows for several different approaches to differentiate wet and dry sensor data, it does not currently take advantage of temperature data, which is an additional dataset recorded by STIC sensors that can be used for identifying dry and wet periods (Constantz et al., 2001). Second, STIC data can often have gaps due to sensor malfunction or loss, which can lead to difficulties in calculated derived metrics that depend on complete data such as communication distance (Aho et al., 2023), longitudinal connectivity (Zimmer and McGlynn, 2018), or active drainage density (Godsey and Kirchner, 2014). Work elsewhere has suggested that stream network length is often hierarchical, meaning that sites dry and rewet in a typical order (Botter et al., 2021; Botter and Durighetto, 2020), and integrating this concept into STICr as a potential gap-filling approach (with appropriate flags in the QAQC column) would improve STICr's ability to develop spatially and temporally complete datasets of stream intermittency (Durighetto et al., 2023). Third, 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 address these needs and/or make additional suggestions for improvements as issues on the package GitHub page (https://github.com/HEAL-KGS/STICr/issues) and contribute code they develop for their own analyses.

4.2 Integration into interdisciplinary research projects

Using STICr, we demonstrate how a workflow can be developed to create FAIR and standardized stream intermittency data (Figure 3) for a project spanning multiple watersheds, institutions, and personnel (Figure 2). Since each watershed had different personnel, sensor deployment and maintenance timelines, and ability to access sites, the modular approach enabled by STICr allowed for the development of consistent processing workflows with site-specific modifications where needed as the project evolved. Given the increasing interdisciplinary collaboration around non-perennial stream research, hydrological flow intermittence data is increasingly of interest to researchers in disciplines such as ecology (Allen et al., 2020; Datry et al., 2018; DelVecchia et al., 2022), and biogeochemistry (Price et al., 2024; Ward et al., 2019; Zimmer et al., 2022). Here, we demonstrate how STICr's functionality can be used to carry out sensitivity analyses and validations that quantify the impacts of different hydrologic data processing decisions on potential classification errors (Figure 4). These types of decisions are often hidden in derived data products, and we show how STICr provides a quantitative framework that researchers can use to gather feedback and make collaborative decisions about data processing steps that meet the needs of eventual data users from other disciplines. Additionally, the standardized approach to QAQC flagging allows future users of the data, whether within or beyond the project, to make important data filtering decisions and interpretations based on their research questions and data needs (Figure 5).

4.3 Evaluating spatial and temporal stream intermittency dynamics

We also present a brief case study demonstrating how data processed using STICr can be used to assess spatial and temporal dynamics of stream intermittency in the South Fork Kings Creek watershed (Kansas, USA). We documented complex spatial patterns in watershed-scale stream intermittency (Figure 6), with the greatest wetness in the middle portion of the watershed and drier conditions upstream and downstream. We interpret these spatial patterns to be driven by localized stream-aquifer exchange that are ultimately controlled by the intersection of different limestone units with the stream channel (Gambill et al., 2024; Macpherson, 1996; Vero et al., 2018). This finding supports work done in sedimentary river systems documenting fine-scale variation in stream-aquifer exchange driven by streambed properties (Noorduijn et al., 2014; Shanafield et al., 2020b), and suggests that flow at the watershed outlet may not always be a direct indicator of hydrologic function, and associated water quality outcomes. As a result, network-scale stream connectivity indicators such as active channel length (Botter et al., 2021) and communication distance (Aho et al., 2023), informed by data from stream intermittency sensors like STICs, will likely play a critical role in determining the drivers of water quantity and quality impacts of non-perennial streams – a major open question in hydrologic research (Shanafield et al., 2020a; Zimmer et al., 2022).

Our investigation of temporal dynamics showed a time-varying meteorological response to controlling hydroclimatic variables, with a shorter (27-day) correlation with precipitation and a longer (290-day) correlation with ET in the watershed. These two timescales combined to produce rapid, precipitation event-driven wetting superimposed on a seasonal wetting and drying pattern created by the cumulative water use of vegetation throughout the summer and fall. This sheds light on climatic controlling the wetting and drying regime at this site, which have strong potential impacts on biogeochemical and ecological function (Price et al., 2024, 2021), and can vary at fine spatial scales (Sabathier et al., 2023). Both climate and land cover are changing in the region, with a long-term increasing precipitation trend counteracted by increased ET due to woody vegetation encroachment (Sadayappan et al., 2023). There is increasing evidence that non-perennial stream ecosystems can be characterized by alternative ecohydrological stable states (Ayers et al., 2024; Dodds et al., 2023; Heffernan, 2008; Zipper et al., 2022) with nonlinear trajectories of change (Kar et al., 2024), suggesting that the interactions among concurrent changes in precipitation and ET could drive regime shifts to novel hydrologic regimes in the future.

5. Conclusions

In this study, we introduced STICr, an open-source R package for working with Stream Temperature, Intermittency, and Conductivity (STIC) data. STICr includes a variety of functions for tidying, calibrating, QAQCing, and validating STIC data in order to advance FAIR stream intermittency data. We then provided a case study showing how STICr can be incorporated into a workflow for processing STIC data on a cross-regional interdisciplinary project, and how STICr capabilities related to validation and sensitivity analysis can be used to make data processing decisions that prioritize the needs to future data users. The stable version of STICr is currently available on the Comprehensive R Archive Network (CRAN; https://cran.r-project.org/package=STICr) and the development version is available on GitHub (https://github.com/HEAL-KGS/STICr) and we welcome contributions from the community.

For the South Fork Kings Creek watershed (Kansas, USA), we used the data produced by this workflow to show spatial and temporal dynamics of stream intermittency over a three-year study period. We found that the watershed stays wettest for the longest duration in the middle and western portions, which are areas where outcropping limestone aquifers intersect the aquifer. At the network-scale, we show that the proportion of the network that is wet at a daily timestep can be well-predicted by precipitation over an approximately monthly timescale (27 days) and ET over a longer period (290 days) that is associated with the cumulative water uptake by plants over the growing season. Combined, these timescales lead to rapid increases in hydrologic connectivity in response to precipitation events and gradual recessions in response to seasonal network drying. The functions here, and associated shared workflows, provide a valuable basis for developing FAIR stream intermittency datasets and advancing links between non-perennial stream hydrology and other disciplines.

Software and data availability

- STICr:
  - Release version (v1.1): https://cran.r-project.org/package=STICr
  - Development version: https://github.com/HEAL-KGS/STICr
- AIMS STIC processing workflow: https://github.com/HEAL-KGS/AIMS_stic_pipeline
- South Fork Kings Creek raw STIC data: http://www.hydroshare.org/resource/77d68de62d6942ceab6859fc5541fd61 (Zipper et al., 2024)
- Code and data used to generate the figures in this manuscript: https://github.com/samzipper/AIMS_STIC_GP
  - This will be placed into a repository with a DOI at the time of manuscript acceptance so a DOI-ed dataset will be included in the final manuscript

CRediT authorship contribution statement

SZ: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing-Original Draft, Writing-Review & Editing

CTW: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing-Original Draft, Writing-Review & Editing

DMP: Methodology, Software, Visualization, Writing-Review & Editing

SCC: Data curation, Methodology, Software, Writing-Review & Editing

SEG: Funding acquisition, Methodology, Supervision, Writing-Review & Editing

KA: Funding acquisition, Methodology, Writing-Review & Editing

Declaration of competing interest

The authors declare no competing financial interests or personal relationships that could appear to influence the work reported in this paper.

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Appendix 1: STIC qualitative rating criteria

The following definitions were adopted by the AIMS project to rate the quality of STIC data for a given download period:

- **Excellent**: STIC was (1) calibrated prior to deployment, <u>and</u> (2) stayed operational throughout 95% of the download period, <u>and</u> (3) was not displaced from streambed (i.e., the external electrodes were within 1 cm from stream bed at the time of download indicating minimal erosion/deposition), <u>and</u> (4) data from sensor roughly agree with field observations of wet/dry (i.e., >1000 Lux sensor reading on day of removal corresponds to field observations of water at STIC).
- **Good**: (1) STIC stayed operational throughout the entire download period, <u>and</u> (2) the external electrodes were within 1 cm from stream bed at the time of download, <u>and</u> (3) data from sensor roughly agree with field observations of wet/dry, <u>but</u> (4) the STIC was not calibrated prior to deployment.
- **Fair**: (1) STIC stayed operational throughout 75% or more of the download period, <u>and</u> **(2)** data roughly agree with field observations, <u>and/or</u> (3) the external electrodes were between 1-3 cm from streambed at the time of download.
- **Poor**: (1) STIC stayed operational throughout less than 75% of the download period, <u>and/or</u> (2) the external electrodes were >3 cm from streambed at the time of download, <u>and/or</u> (3) data does NOT agree with field observations.

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