

SWMPPr: An R Package for Retrieving, Organizing, and Analyzing Environmental Data for Estuaries

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Abstract

Standardized monitoring programs have vastly improved the quantity and quality of data that form the basis of environmental decision-making. One example in the United States is the System Wide Monitoring Program (SWMP) that was implemented in 1995 by the federally-funded National Estuarine Research Reserve System (NERRS). This program has provided two decades of continuous monitoring data at over 140 fixed stations in 28 estuaries. SWMP data have been used in a variety of applications with the general objective of describing dynamics of estuarine ecosystems to better inform effective coastal management. However, simple tools for processing and evaluating the increasing quantity of data provided by the monitoring network have prevented broad-scale comparisons between systems and, in some cases, simple trend analysis of water quality parameters at individual sites. I describe SWMPPr, an open-source R package, for use with SWMP environmental data. The package provides several functions that facilitate data retrieval, organization, and analysis of time series data to describe water quality, weather, and nutrient dynamics in the reserve estuaries. Previously unavailable functions for estuaries are also provided to estimate rates of ecosystem metabolism using the open-water method. Tools included with the SWMPPr package have facilitated a cross-reserve comparison of trends, including simple evaluation of changes over time and comparisons of patterns in primary productivity. Overall, the package provides an effective approach to link quantitative information with analysis tools that will greatly inform management programs aimed at coastal protection and restoration.

Introduction

The development of low-cost, automated sensors that collect data in near real-time has enabled a proliferation of standardized environmental monitoring programs [1, 2]. These programs provide access to invaluable sources of data that can be used to address a variety of research and management objectives. Applications from automated remote sensors are numerous for aquatic environments with notable examples including prediction of harmful algal blooms and toxicants in freshwater systems [3], development of a hydrometeorological monitoring network to support flash flood warning programs [4], and a national marine buoy network covering large portions of the open ocean and coastal zones of the United States [5]. Automated remote monitoring

programs offer several advantages over traditional site-specific, field-based methods including streamlining of data acquisition, minimizing human error, and reducing the overall cost of the collection process [1]. However, the increasing quantity of available information to address relevant questions has contributed to the growth of ‘big data’ where analyses are limited by computational requirements and identifying the signal from the noise rather than the availability of information. A greater focus on synthesis, exploratory-based analytical techniques, and interpretation have characterized the use of data from automated monitoring programs [6, 7].

An important monitoring network for coastal environments in the United States is the National Estuarine Research Reserve System (NERRS)¹. This network represents 28 estuarine reserves from different biogeographic regions that were chosen to address multiple goals for long-term research, monitoring, education, and stewardship in support of coastal management. As part of this effort, the System Wide Monitoring Program (SWMP)² was implemented in 1995 at over 140 stations at the reserves to provide a robust, long-term monitoring system for water quality, weather, and land-use/habitat change. The SWMP network has provided a continuous source of data collected at near real-time with the intent to evaluate natural and anthropogenic causes of spatiotemporal variation in environmental condition and ecosystem function. These data have been applied both for evaluations of relevant characteristics at individual reserves (e.g., [8, 9]) and differences between reserves (e.g., ecosystem metabolism [10, 11], tidal characteristics [12], dissolved oxygen [13]). However, no cross-reserve comparisons have been conducted within the last decade despite the online availability of current SWMP data. NERRS researchers and staff have also expressed a need for quantitative analysis tools to evaluate trends in water quality time series given the quantity and quality of data provided by SWMP [14].

This article describes a software package that was developed to address research needs of the NERRS program using the open-source statistical programming language R [15]. SWMP_r (pronounced ‘swamper’) is an R package that contains functions for retrieving, organizing, and analyzing estuary monitoring data from the System Wide Monitoring Program. Functions provided by SWMP_r address many of the common issues working with large datasets created from automated sensor networks, such as data pre-processing to remove unwanted information, combining data from different sources, and exploratory analyses to identify key parameters of interest. Additionally, a cross-reserve comparison of water quality trends and current ecosystem metabolism estimates is provided to illustrate potential applications using the functions in this package. The software is provided specifically for use with NERRS data, although many of the applications are relevant for addressing common challenges working with large datasets.

SWMP overview and data retrieval

Four core data elements are collected through the SWMP monitoring network: abiotic monitoring data, biotic observations, habitat and land use mapping, and sentinel monitoring. Only the abiotic data are monitored continuously with automated sensor networks, whereas the remaining elements involve field surveys or mapping products that differ between reserves given site-specific requirements. As such, the SWMP_r package is developed for the continuous abiotic monitoring network that represents a majority of the SWMP data and, consequently, the most challenging to evaluate. Abiotic elements monitored at each reserve include water quality (water temperature, specific conductivity, salinity, dissolved oxygen concentration, dissolved oxygen

¹<http://www.nerrs.noaa.gov/>

²<http://nerrs.noaa.gov/RCDefault.aspx?ID=18>

saturation, depth, pH, turbidity, chlorophyll fluorescence), weather (air temperature, relative humidity, barometric pressure, wind speed, wind direction, photosynthetically active radiation, precipitation), and nutrient data (orthophosphate, ammonium, nitrite, nitrate, nitrite + nitrate, chlorophyll a). Each reserve has no less than four water quality stations and one weather station at fixed locations. Water quality and weather data are collected at 15 minute intervals, whereas nutrient data are collected monthly at each water quality station. All data are made accessible through the Centralized Data Management Office (CDMO) web portal³, where multiple quality assurance/quality control (QAQC) measures are used to screen the information for accuracy and reliability. The final data include all timestamped observations including relevant QAQC flags with the appropriate qualifier.

The CDMO web portal was established to support priority areas of SWMP that focus on the continuation and advancement of data management. As such, CDMO provides access to over 35 million water quality, weather, and nutrient records that have been authenticated through systematic QAQC procedures. Prior to any data request to the CDMO, the location, parameter type, and date ranges need to be identified based on the analysis needs. All stations in the SWMP network are identified by a 7 or 8 character name that specifies the reserve, station, and parameter type. For example, 'apaebwq' is the water quality identifier ('wq') for the East Bay station ('eb') at the Apalachicola reserve ('apa'). Similarly, a suffix of 'met' or 'nut' would specify the weather (meteorological) or nutrients station. All reserve names, stations, and date ranges for each parameter type can be viewed on the CDMO website. Alternatively, the `site_codes` (all sites) or `site_codes.ind` (single site) functions provided by the SWMP package can be used to view the same information. As noted below, the computer's IP address must be registered with CDMO before using the data retrieval functions in SWMP. Web services⁴ are provided by CDMO for direct access to SWMP data through http requests, in addition to standard graphical user interface options for selecting data. The data retrieval functions in SWMP are simple calls to the existing retrieval functions on CDMO web services. For example, the `site_codes` function in SWMP uses the `exportStationCodesXMLNew` function from the web services to retrieve metadata for all the SWMP sites. The text below describes the data retrieval functions in more detail, including all other functions available in SWMP.

Structure of the SWMP package

Installing the package

The SWMP package was developed for use with the R (\geq v3.0.0) statistical programming language [15]. The SWMP package can be downloaded from the Comprehensive R Archive Network (CRAN)⁵ by executing the following commands at the R console prompt. The package is loaded in the workspace using the `library` command.

```
> install.packages('SWMP')
> library(SWMP)
```

The SWMP package was developed by considering a standard workflow that categorizes the functions as one of three steps based on their intended use: retrieving, organizing, and analyzing. Functions for retrieving are used to import the data into R

³<http://cdmo.baruch.sc.edu/>

⁴<http://cdmo.baruch.sc.edu/webservices.cfm>

⁵<http://cran.r-project.org/web/packages/SWMP/index.html> for the CRAN release, the development version can be installed from <https://github.com/fawda123/SWMP>.

Table 1. Retrieval functions available from the SWMP_r package. Full documentation for each function is in the help file (e.g., execute `?all_params` at the command line).

Function	Description
<code>all_params</code>	Retrieve up to 100 records ^a starting with the most recent at a given station, all parameters. Wrapper to <code>exportAllParamsXMLNew</code> function on web services.
<code>all_params_dtrng</code>	Retrieve up to 1000 records of all parameters within a given date range for a station. Optional argument for a single parameter. Wrapper to <code>exportAllParamsDateRangeXMLNew</code> .
<code>import_local</code>	Import files from a local path. The files must be in a specific format, such as those returned from the CDMO using the zip downloads option.
<code>import_remote</code>	Import site data from an independent server. These files have been downloaded from CDMO up to December 2014, processed using SWMP _r functions, and uploaded to an Amazon server for quicker import into R.
<code>single_param</code>	Retrieve up to 100 records for a single parameter starting with the most recent at a given station. Wrapper to <code>exportSingleParamXMLNew</code> function on web services.
<code>site_codes</code>	Metadata for all stations, wrapper to <code>exportStationCodesXMLNew</code> function on web services.
<code>site_codes_ind</code>	Metadata for all stations at a single site, wrapper to <code>NERRFilterStationCodesXMLNew</code> function on web services.

^a Server limits prevent retrieving more records in a single request.

as a `swmpr` object class. Functions for organizing and analyzing the data provide methods for working with a `swmpr` object. An additional group of ‘miscellaneous’ functions are included as helpers for the main functions. The following describes the package structure, beginning with the retrieval functions, a description of the `swmpr` object returned after retrieval, and, finally, the organizing and analyzing functions.

Data retrieval

Three approaches can be used to import SWMP data into R, either through direct download or by importing local data (Table 1). First, functions from the package can be used to import the data directly from the online server using CDMO web services. To do so, the IP address for the computer making the request must be registered with CDMO.⁶ The `site_codes` or `site_codes_ind` functions can be used to view the available metadata after a computer is registered with CDMO.

```
> # retrieve metadata for all sites
> site_codes()
>
> # retrieve metadata for a single site
> site_codes_ind('apa')
```

Due to rate limitations on the CDMO server, the retrieval functions return a limited number of records. The functions are more useful for evaluating short time periods,

⁶Follow instructions here: <http://cdmo.baruch.sc.edu/webservices.cfm>

although these functions could be used iteratively (i.e., with `for` loops) to obtain longer time series. Data retrieval functions to access the CDMO include `all_params`, `all_params_dtrng`, and `single_param`: `all_params` returns the most recent records of all parameters at a station, `all_params_dtrng` returns all records within a date range for all parameters or a single parameter, and `single_param` is identical to `all_params` except that a single parameter is requested.

```
> # all parameters for a station, most recent
> all_params('hudscwq')
>
> # get all parameters within a date range
> all_params_dtrng('hudscwq', c('09/10/2012', '02/8/2013'))
>
> # get single parameter within a date range
> all_params_dtrng('hudscwq', c('09/10/2012', '02/8/2013'),
+   param = 'do_mgl')
>
> # single parameter for a station, most recent
> single_param('hudscwq', 'do_mgl')
```

A second approach for importing SWMP data into R uses the `import_remote` function. This method imports site data from an independent server where SWMP data have been downloaded previously and uploaded as `swmpr` objects in RData binary format. This approach is advantageous because the files can be imported very quickly and an IP address does not need to be registered. The files include almost all available SWMP data for each site up to December 2014. However, the files will not be regularly updated and CDMO should always be used for the most recent and accurate data. The files can be accessed by copying the URL to a web browser with the site name and file extension (e.g., <https://s3.amazonaws.com/swmpalldata/acebbnut.RData>, see the Supporting Information) or by using the function as follows.

```
> # import a file from an independent server
> import_remote('acebbwq')
```

A third approach for data retrieval is to use the `import_local` function to import data into R that are locally available after downloading from CDMO. This approach is most appropriate for large, specific data requests. The `import_local` function is designed for data from the zip downloads⁷ feature in the advanced query section of the CDMO. The function may also work using data from the data export system,⁸ although this feature has not been extensively tested. The zip downloads feature is an easy way to obtain data from multiple stations in one request. The downloaded data will be in a compressed folder that includes multiple .csv files by year for a given data type (e.g., `apacpwq2002.csv`, `apacpwq2003.csv`, `apacpnut2002.csv`, etc.). The `import_local` function can be used after the folder is decompressed.

Occasionally, duplicate time stamps are present in the raw data. The `import_local` function handles duplicate entries differently depending on the data type (water quality, weather, or nutrients). For water quality and nutrient data, duplicate time stamps are simply removed. Note that nutrient data often contain replicate samples with similar but not identical time stamps within the span of a few minutes. Replicates with unique time stamps are not removed but can be further processed using `rem_reps`. Weather data prior to 2007 may also contain duplicate time stamps at frequencies for hourly

⁷<http://cdmo.baruch.sc.edu/aqs/zips.cfm>

⁸<http://cdmo.baruch.sc.edu/get/export.cfm>

(denoted as '60') and daily ('144') averages, in addition to 15 minute frequencies. Only duplicate values at 15 minutes are averaged for weather data.

```
> # import local data for apaebmet
>
> # this is an example path with the decompressed csv files
> path <- 'C:/my_path/'
>
> # import, do not include file extension
> import_local(path, 'apaebmet')
```

The swmpr object class

All data retrieval functions return a **swmpr** object that includes relevant data and several attributes describing the dataset. The data include a **datetimestamp** column in the appropriate timezone for a station and additional parameters for a given data type (weather, nutrients, or water quality). Corresponding QAQC columns for each parameter are also returned if provided by the initial data request. The attributes for a **swmpr** object include **names** of the dataset, **row.names** of the dataset, **class** (character string indicating **swmpr** and **data.frame**), **station** (7 or 8 characters identifying the station), **parameters** (character vector of data columns, e.g., 'do_mgl'), **qaqc.cols** (logical T or F if present or not), **date_rng** (POSIXct vector of minimum/maximum dates), **timezone** (text string in country/city format, standard time only), and **stamp_class** (class of **datetimestamp** vector, POSIXct or Date). Attributes of a **swmpr** object can be viewed as follows.

```
> # import data
> dat <- import_remote('apadbwq')
>
> # view all attributes of dat
> attributes(dat)
>
> # view a single attribute of dat
> attr(dat, 'station')
```

The **swmpr** object class was created for use with the organizing and analyzing functions. This object-oriented approach is standard for R (i.e., the S3 object system, [16]), such that specific methods for a generic function are developed for the object class. A **swmpr** object also secondarily inherits methods from the **data.frame** class, such that common **data.frame** methods also apply to **swmpr** objects. Available methods for the **swmpr** class are described below and can also be viewed:

```
> # view available methods for swmpr class
> methods(class = 'swmpr')
```

A sample dataset can be downloaded for use with the examples below.⁹ This dataset has an identical format as the data returned from the zip downloads feature of the CDMO. Processed versions of the raw data are also included with the package as binary data files (RData). These include **swmpr** objects for four stations at Apalachicola Bay: **apacpnut**, **apacpwq**, **apadbwq**, and **apaebmet**. Information for each file can be viewed in the help documentation (e.g., **?apacpnut**).

⁹<https://s3.amazonaws.com/swmpexdata/zip-ex.zip>

Table 2. Organizing functions available from the SWMP package. Full documentation for each function is in the help file (e.g., execute `?comb.swmpr` at the command line).

Function	Description
<code>comb.swmpr</code>	Combines <code>swmpr</code> objects to a common time series using <code>setstep</code> , such as combining the weather, nutrients, and water quality data for a single station. Only different data types can be combined.
<code>qaqc.swmpr</code>	Remove QAQC columns and remove data based on QAQC flag values for a <code>swmpr</code> object. Only applies if QAQC columns are present.
<code>qaqcchk.swmpr</code>	View a summary of the number of observations in a <code>swmpr</code> object that are assigned to different QAQC flags used by CDMO. The output can be used to inform further processing.
<code>rem_reps.swmpr</code>	Remove replicate nutrient data that occur on the same day. The default is to average replicates.
<code>setstep.swmpr</code>	Format data from a <code>swmpr</code> object to a continuous time series at a given timestep. The function is used in <code>comb.swmpr</code> and can also be used with individual stations.
<code>subset.swmpr</code>	Subset by dates and/or columns for a <code>swmpr</code> object. This is a method passed to the generic <code>subset</code> function provided in the base package.

Data organizing

The organize functions are used to clean or prepare the imported data for analysis, including viewing and removal of QAQC flags, subsetting, combining replicate nutrient observations, creating a standardized time series, and combining data of different types (Table 2).

The `qaqc` function is a simple screen to retain observations from the data with specified QAQC flags.¹⁰ Each parameter in the imported `swmpr` object will have a corresponding QAQC column of the same name with the added prefix `f_` (e.g., `do_mgl`, `f_do_mgl`). Values in the QAQC column range from -5 to 5 to indicate the QAQC flag that was assigned by CDMO during initial processing. The QAQC function is used to remove observations in the raw data with given flags, with the default option to retain only values with the 0 QAQC flag (i.e., passed initial CDMO checks). Additionally, simple filters are used to remove obviously bad values, e.g., wind speed values less than zero or pH values greater than 12. Erroneous data entered as -99 are also removed. The function returns the original data with the QAQC columns removed and NA (not available) values for observations that do not meet the criteria specified in the function call.

```
> # qaqc screen for a swmpr object, retain only '0'
```

¹⁰CDMO flags: <http://cdmo.baruch.sc.edu/data/qaqc.cfm>


```
> qaqc(dat)
>
> # retain all data regardless of flag
> qaqc(dat, qaqc_keep = NULL)
>
> # retain only '0' and '-1' flags
> qaqc(dat, qaqc_keep = c(0, -1))
```

Viewing the number of observations for each parameter that are assigned to a QAQC flag may be useful for deciding how to process the data with `qaqc`. The `qaqcchk` function can be used to view this information.

```
> # view the number of observations in each QAQC flag
> qaqcchk(dat)
```

Raw nutrient data obtained from the CDMO will usually include replicate samples that were taken within a few minutes of each other. The `rem_reps.swmpr` function combines nutrient data that occur on the same day to preserve an approximate monthly time step. The `datetimestamp` column will always be averaged for replicates, but the actual observations will be combined based on the user-supplied function which defaults to the mean. Other suggested functions include the `median`, `min`, or `max`. The entire function call, including treatment of NA, values should be passed to the `FUN` argument (see the examples). The function is meant to be used after `qaqc` processing, although it works with a warning if QAQC columns are present.

```
> # get nutrient data
> data(apacpnut)
> dat <- apacpnut
> dat <- qaqc(dat)
>
> # remove replicate nutrient data
> rem_reps(dat)
>
> # use different function to aggregate replicates
> func <- function(x) max(x, na.rm = T)
> rem_reps(dat, FUN = func)
```

A subset method added to the existing generic `subset` function in R is available for `swmpr` objects. This function is used to subset the data by date and/or a selected parameter. The date can be a single value or as two dates to select records within the range. The former case requires a binary operator as a character string passed to the argument, such as `>` or `<=`. The subset argument for the date(s) must also be a character string of the format YYYY-mm-dd HH:MM for each element (e.g., `'2007-01-01 06:30'`). Be aware that an error may be returned using this function if the subset argument is in the correct format but the calendar date does not exist, e.g. `'2012-11-31 12:00'`. Finally, the function can be used to remove rows and columns that do not contain data.

```
> # import data
```



```

> data(apaebmet)
> dat <- apaebmet
>
> # select two parameters from dat
> subset(dat, select = c('rh', 'bp'))
>
> # subset records greater than or equal to a date
> subset(dat, subset = '2013-01-01 0:00', operator = '>=')
>
> # subset records within a date range
> subset(dat, subset = c('2012-07-01 6:00', '2012-08-01 18:15'))
>
> # subset records within a date range, select two parameters
> subset(dat, subset = c('2012-07-01 6:00', '2012-08-01 18:15'),
>   select = c('atemp', 'totsorad'))
>
> # remove rows/columns that do not contain data
> subset(dat, rem_rows = T, rem_cols = T)

```

The **setstep** function formats a **swmpr** object to a continuous time series at a given time step. This function is not necessary for most stations but can be useful for combining data or converting an existing time series to a set interval. The first argument of the function, **timestep**, specifies the desired time step in minutes starting from the nearest hour of the first observation. The second argument, **differ**, specifies the allowable tolerance in minutes for matching existing observations to the defined time steps in cases where the two are dissimilar. Values for **differ** that are greater than one half the value of **timestep** are not allowed to prevent duplication of existing data. Likewise, the default value for **differ** is one half the time step. Time steps that do not match any existing data within the limits of the **differ** argument are not discarded, although a corresponding data value will not be assigned.

```

> # import, qaqc removal
> data(apadbwq)
> dat <- qaqc(apadbwq)
>
> # convert time series to two hour intervals
> # tolerance of +/- 30 minutes for matching existing data
> setstep(dat, timestep = 120, differ = 30)
>
> # convert a nutrient time series to a continuous time series
> # then remove empty rows and columns
> data(apacpnut)
> dat_nut <- apacpnut
> dat_nut <- setstep(dat_nut, timestep = 60)
> subset(dat_nut, rem_rows = T, rem_cols = T)

```

The **comb** function is used to combine multiple **swmpr** objects into a single object with a continuous time series at a given step. The **timestep** function is used internally such that **timestep** and **differ** are accepted arguments for **comb**. All arguments must be called explicitly since an arbitrary number of **swmpr** objects can be used as input. The function combines data by creating a master time series that is used to iteratively merge all **swmpr** objects. The time series for merging depends on the value passed to the **method** argument. Passing **union** to **method** will create a time series that is continuous from the earliest and latest dates for all input objects. Passing **intersect** to **method** will create a time series that is continuous from the set of dates that are shared between

all input objects. Finally, a seven or eight character station name passed to `method` will merge all data based on a continuous time series for the specified station, which must be present in the input data. Currently, combining identical data types from different stations is not possible (e.g., two water quality stations from the same reserve).

```
> # get nut, wq, and met data as separate objects
> data(apacpnut)
> data(apacpwq)
> data(apaebmet)
> swmp1 <- apacpnut
> swmp2 <- apacpwq
> swmp3 <- apaebmet
>
> # combine nut and wq data by union
> comb(swmp1, swmp2, method = 'union')
>
> # combine nut and wq data by intersect
> comb(swmp1, swmp3, method = 'intersect')
>
> # combine nut, wq, and met data by nut time series, two hour time step
> comb(swmp1, swmp2, swmp3, timestep = 120, method = 'apacpnut')
```

Data analysis

The analysis functions range from general purpose tools for time series analysis to more specific functions for working with continuous monitoring data in estuaries (Table 3). The general purpose tools are `swmpr` methods that were developed for existing generic functions in the R base installation or relevant packages. These functions include `swmpr` methods for `aggreswmp`, `filter`, and `approx` to deal with missing or noisy data and more general functions for exploratory data analysis, such as `plot`, `lines`, and `hist` methods. Decomposition functions, `decomp` and `decomp_cj`, are provided as relatively simple approaches for decomposing time series into additive or multiplicative components. Functions to estimate and plot ecosystem metabolism from combined water quality and weather data are provided by the `ecometab` and `plot_metas` functions. The analysis functions may or may not return a `swmpr` object depending on whether further processing with `swmpr` methods is possible from the output.

The `aggreswmp` function aggregates parameter data for a `swmpr` object by set units of time. This function is most useful for aggregating noisy data to evaluate trends on longer time scales or to simply reduce the size of a dataset. Data can be aggregated by years, quarters, months, weeks, days, or hours by a predefined function, which defaults to the mean. A `swmpr` object is returned for the aggregated data, although the `datetimestamp` vector will be converted to a date object if the aggregation period is a day or longer. Days are assigned to the date vector if the aggregation period is a week or longer based on the `round` method for `IDate` objects created in the `data.table` package [17]. Additionally, the method of treating NA values for the aggregation function should be noted since this may greatly affect the quantity of data that are returned, particularly for nutrient data.

```
> # get data
> data(apacpwq)
> dat <- qaqc(apacpwq)
>
> # get mean DO by months
> aggreswmp(dat, 'months', params = c('do_mgl'))
```

Table 3. Analysis functions available from the SWMPPr package. Full documentation for each function is in the help file (e.g., execute `?aggreswmp.swmpr` at the command line).

Function	Description
<code>aggreswmp.swmpr</code>	Aggregate <code>swmpr</code> objects for different time periods - years, quarters, months, weeks, days, or hours. The aggregation function defaults to the mean.
<code>aggremetab.swmpr</code>	Aggregate metabolism data from a <code>swmpr</code> object. This is primarily used within <code>plot_metab</code> but may be useful for simple summaries of raw metabolism data.
<code>ecometab.swmpr</code>	Estimate ecosystem metabolism for a combined water quality and weather dataset using the open-water method.
<code>decomp.swmpr</code>	Decompose a <code>swmpr</code> time series into trend, seasonal, and residual components. This is a simple wrapper to <code>decompose</code> [18]. Decomposition of monthly or daily trends is possible.
<code>decomp_cj.swmpr</code>	Decompose a <code>swmpr</code> time series into grandmean, annual, seasonal, and events components. This is a simple wrapper to <code>decompTs</code> in the <code>wq</code> package [19]. Only monthly decomposition is possible.
<code>hist.swmpr</code>	Plot a histogram for a <code>swmpr</code> object.
<code>lines.swmpr</code>	Add lines to an existing plot created with <code>plot.swmpr</code> .
<code>na.approx.swmpr</code>	Linearly interpolate missing data (NA values) in a <code>swmpr</code> object. The maximum gap size that is interpolated is defined by the arguments.
<code>plot.swmpr</code>	Plot a univariate time series for a <code>swmpr</code> object. The parameter name must be specified.
<code>plot_metab.swmpr</code>	Plot ecosystem metabolism estimates after running <code>ecometab</code> on a <code>swmpr</code> object.
<code>plot_summary.swmpr</code>	Create summary plots of seasonal/annual trends and anomalies for a water a single paramter of interest.
<code>smoother.swmpr</code>	Smooth <code>swmpr</code> objects with a moving window average. Window size and sides (e.g., centered) can be specified, passed to <code>filter</code> .

Time series can be smoothed to better characterize a signal independent of noise (Fig. 1). Although there are many approaches to smoothing, a moving window average is intuitive and commonly used. The `smoother` function can be used to smooth parameters in a `swmpr` object using a specified window size with arguments passed to the `filter` function from the base installation. The `window` argument specifies the number of observations included in the moving average where larger windows result in greater smoothing. The `sides` argument specifies how the average is calculated for each observation. Setting `sides = 1` will filter observations within the window that are previous to the current observation, whereas `sides = 2` will filter observations within the window centered at zero lag from the current observation. As before, the `params` argument specifies which parameters to smooth.

```
> # import data, qaqc and subset
> data(apadbwq)
> dat <- qaqc(apadbwq)
> dat <- subset(dat, select = 'do_mgl',
+ subset = c('2012-07-09 00:00', '2012-07-24 00:00'))
>
> # smooth
> dat_smooth <- smoother(dat, window = 50, params = 'do_mgl')
>
> # plot raw and smoothed
> plot(dat)
> lines(dat_smooth, col = 'red', lwd = 2)
```

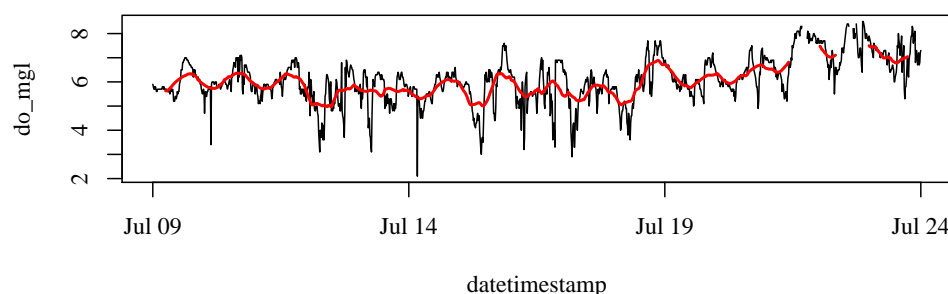


Fig. 1. Raw and smoothed dissolved oxygen data for a two-week period after using the `smoother` function.

A common issue with any statistical analysis is the treatment of missing values. Missing data can be excluded from the analysis, included but treated as true zeroes, or interpolated based on similar values. In either case, an analyst should have a strong rationale for the chosen method. A common approach implemented in the `SWMP` package is linear interpolation using the `na.approx` function (Fig. 2). A simple curve fitting method is used to create a continuous set of records between observations separated by missing data. However, the ability of the interpolated data to approximate actual trends is related to the maximum gap size between observations with missing data. Interpolation between larger gaps are less likely to resemble patterns of an actual parameter, whereas interpolation between smaller gaps are often more accurate. An upper limit on the maximum gap size to interpolate trends depends on the

characteristics of the dataset such that a trial and error approach is appropriate for most applications. The `maxgap` argument passed to `na.approx` defines the maximum gap size for interpolation and the following illustrates use of different maximum values to fill missing data.

```
> # get data, qaqc and subset
> data(apadbwq)
> dat <- qaqc(apadbwq)
> dat <- subset(dat, select = 'do_mgl',
+ subset = c('2013-01-22 00:00', '2013-01-26 00:00'))
>
> # interpolate, maxgap of 10 records
> fill1 <- na.approx(dat, params = 'do_mgl', maxgap = 10)
>
> # interpolate maxgap of 30 records
> fill2 <- na.approx(dat, params = 'do_mgl', maxgap = 30)
>
> # plot for comparison
> par(mfrow = c(3, 1))
> plot(dat, main = 'Raw')
> plot(fill1, col = 'red', main = 'Interpolation - maximum gap of 10 records')
> lines(dat)
> plot(fill2, col = 'red', main = 'Interpolation - maximum gap of 30 records')
> lines(dat)
```

The disaggregation of time series into additive or multiplicative components that can be attributed to separate sources of variance is another common application for trend analysis. The `decomp` function is a simple wrapper to `decompose` [18] that separates a time series into components describing a trend, cyclical variation (e.g., daily or annual), and the remainder (Fig. 3). An additive decomposition assumes that the cyclical component of the time series is stationary (i.e., the variance is constant), otherwise a multiplicative decomposition can be used. The `frequency` argument describes the periodicity of the cyclical parameter in units of the native time step. For example, the `frequency` for a parameter with daily periodicity would be 96 if the time step is 15 minutes ($4 * 24$). The frequency of a parameter with annual periodicity at a 15 minute time step would be 35040 ($4 * 24 * 365$). For simplicity, character strings of 'daily' or 'annual' can be supplied in place of numeric values, although any number can be used to identify an arbitrary cyclical component. A starting value of the time series must be supplied in the latter case that indicates the sequence in the cycle for the first observation (e.g., 1 if the first observation is at sunrise for a diurnal cycle).¹¹ Use of the `setstep` function is also required to standardize the time step prior to decomposition.

```
> # get data
> data(apadbwq)
> swmp1 <- apadbwq
>
> # subset for daily decomposition
> dat <- subset(swmp1, subset = c('2013-07-01 00:00', '2013-07-31 00:00'))
>
> # decomposition and plot
> test <- decomp(dat, param = 'do_mgl', frequency = 'daily')
> plot(test)
```

¹¹The value is passed to the `ts` function, <https://stat.ethz.ch/R-manual/R-devel/library/stats/html/ts.html>

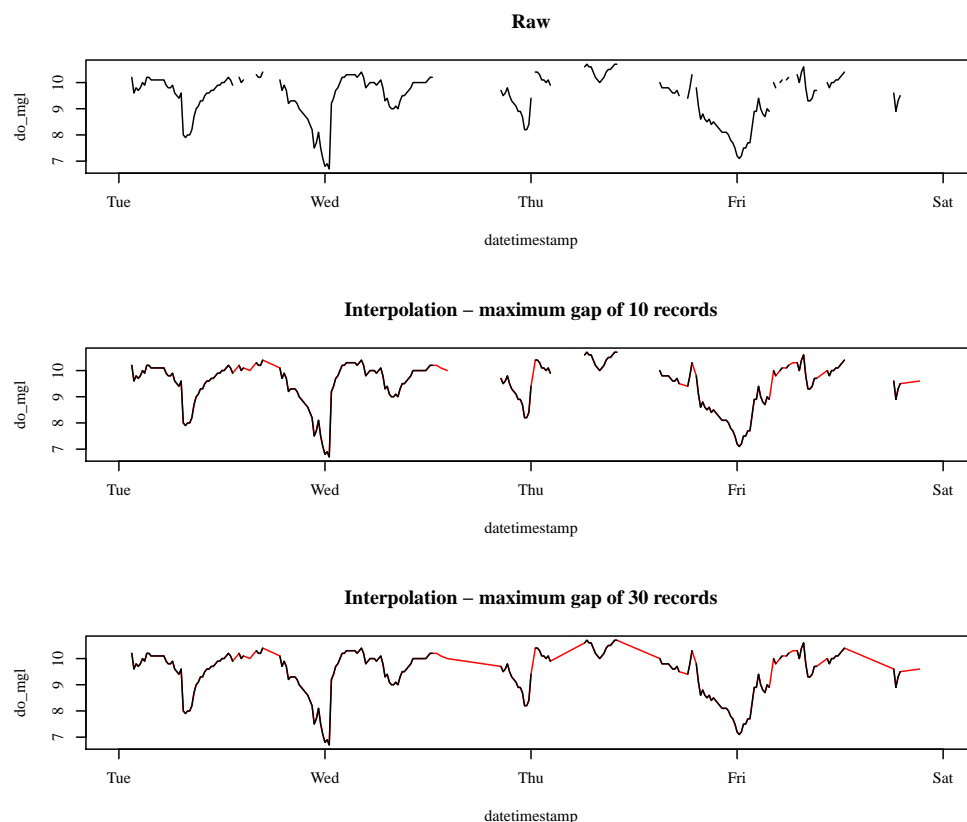


Fig. 2. Examples illustrating use of the `na.approx` function to fill gaps of different sizes in a dissolved oxygen time series for a four day period.

An alternative approach to time series decomposition is provided by the `decomp_cj` function, which is a simple wrapper to the `decompTs` function in the `wq` package [19, 20]. The `decomp_cj` function provides only a monthly decomposition, which is appropriate for characterizing relatively long-term trends. This approach works best for nutrient data that are typically obtained on a monthly cycle. The function will also work with continuous water quality or weather data but note that the data must first be aggregated on the monthly scale before decomposition. Additionally, the time series is decomposed into the grandmean, annual, seasonal, and events components, as compared to trend, seasonal, and random components for the `decomp` function described above. For both, the random or events components, respectively, can be considered anomalies that do not follow the trends in the remaining categories. Additional arguments passed to `decompTs` can be used with `decomp_cj`, such as `startyr`, `endyr`, and `type`. Values passed to `type` are `mult` (default) or `add`, referring to multiplicative or additive decomposition. Fig. 4 shows the results from the `decomp_cj` function applied to a multi-year chlorophyll time series.

```
> # get data
```

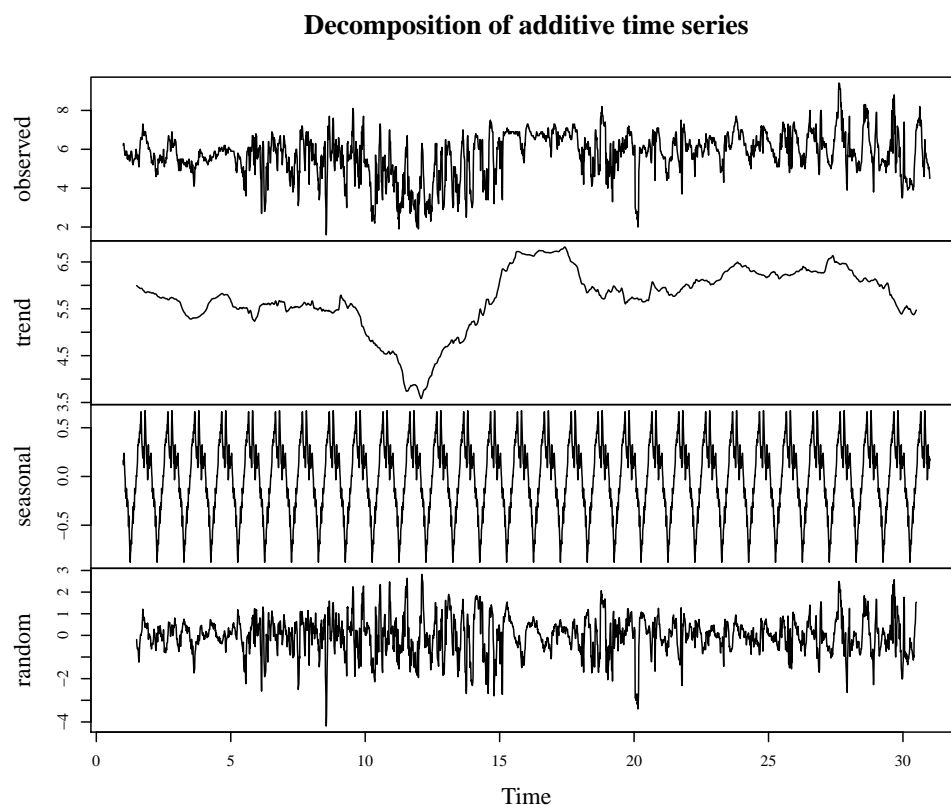


Fig. 3. An additive decomposition of dissolved oxygen into a trend, seasonal, and random component using the `decomp` function.

```
> data(apacpnut)
> dat <- apacpnut
> dat <- qaqc(dat, qaqc_keep = NULL)
>
> # decomposition of chl
> decomp_cj(dat, param = 'chla_n')
```

Detailed exploratory graphics are also useful for evaluating general trends in observed data. Several graphics showing seasonal and annual trends for a single SWMP parameter can be obtained using the `plot_summary` function (Fig. 5). The plots include monthly distributions, monthly anomalies, and annual anomalies in multiple formats. Anomalies are defined as the difference between the monthly or annual averages from the grand mean for the parameter. An interactive web application [21] that uses this function is available for viewing results of any parameter at all SWMP sites (see the Supporting Information).

```
> ## import data
> data(apacpnut)
> dat <- qaqc(apacpnut)
>
> ## plot
> plot_summary(dat, param = 'chla_n', years = c(2007, 2013))
```

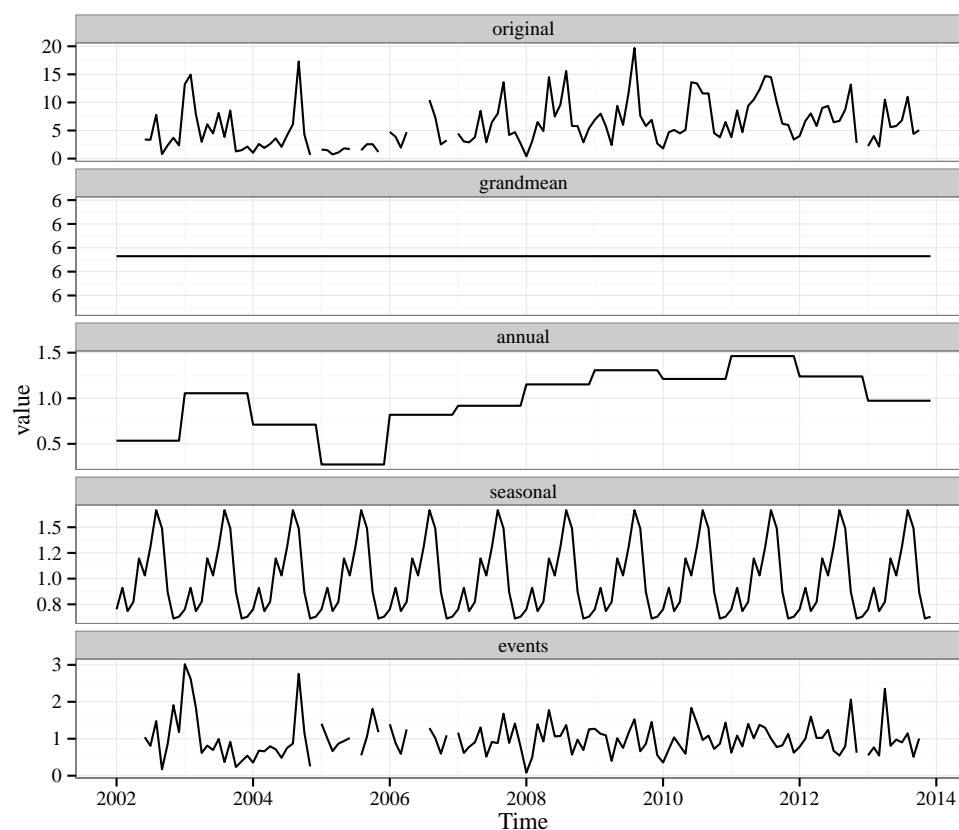



Fig. 4. Additive decomposition of a multi-year chlorophyll time series into the grandmean, annual, seasonal, and events components using the `decomp_cj` function.

Finally, estimates of ecosystem metabolism provide a measure of overall system productivity to evaluate whether an ecosystem is a net source or sink of organic material. The open-water method [22] is a common approach to quantify metabolism using a mass balance equation that describes the change in dissolved oxygen over time from the balance between photosynthetic and respiration processes, corrected using an empirically constrained air-sea gas diffusion model [23,24]. The diffusion-corrected dissolved oxygen (DO) flux estimates are averaged separately over each day and night of the time series. The nighttime average DO flux is used to estimate respiration rates, while the daytime DO flux is used to estimate net primary production. To generate daily integrated rates, respiration rates are assumed constant such that hourly nighttime DO flux rates are multiplied by 24. Similarly, the daytime DO flux rates are multiplied by the number of daylight hours, which varies with location and time of year, to yield net daytime primary production. Respiration rates are subtracted from daily net production estimates to yield gross production rates. The metabolic day is considered the 24 hour period between sunsets on two adjacent calendar days

The `ecometab` function is used to implement the open-water method with a combined water quality and weather dataset [25]. Several assumptions must be met for a valid interpretation of the results. First, the DO time series is assumed to be a sample of the same water mass over time. Tidal advection may have a significant influence on the time series, which can contribute to a significant amount of noise in metabolic estimates. The extent to which tidal advection influences the dissolved oxygen signal depends on various site-level characteristics and an intimate knowledge of the site may

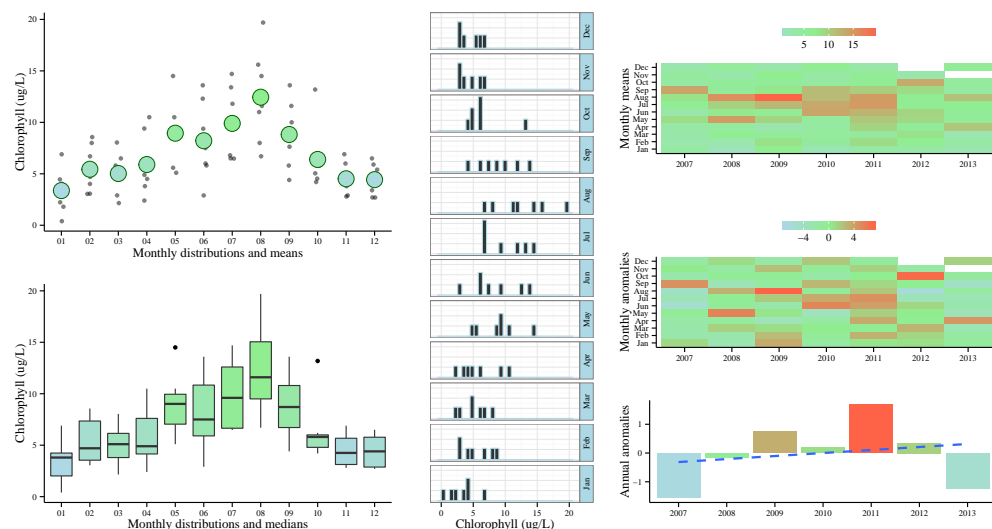


Fig. 5. Summaries of a multi-year chlorophyll time series using the `plot_summary` function. Summaries include monthly distributions (means on top left, quantiles on bottom left), monthly histograms (center), monthly means by year (top right), deviation from monthly means (middle right), and annual trends as deviations from the grand mean (bottom right)

be required. Second, areal rates for gross production and total respiration are based on volumetric rates normalized to the depth of the water column at the sampling location, which is assumed to be well-mixed, such that the water quality sensor is reflecting the integrated processes in the entire water column (including the benthos). Water column depth is calculated as the mean value of the depth variable across the time series in the `swmpr` object. Depth values are floored at one meter for very shallow stations and 0.5 meters is also added to reflect the practice of placing sensors slightly off of the bottom. Third, the air-sea gas exchange model is calibrated with wind data either collected at, or adjusted to, wind speed at 10 m above the surface. The metadata should be consulted for exact height. Other assumptions may apply and relevant resources should be consulted to ensure appropriate application of the open-water method (see [26, 27]).

The following is an example that shows use of the function from a combined water quality and weather data set. Monthly aggregations of the raw, daily estimates are plotted using `plot_metab` (Fig. 6).

```
> ## import water quality and weather data
> data(apadbwq)
> data(apaebsmet)
>
> ## qaqc, combine
> wq <- qaqc(apadbwq)
> met <- qaqc(apaebsmet)
> dat <- comb(wq, met)
>
> ## estimate metabolism
> res <- ecometab(dat, trace = FALSE)
> plot_metab(res)
```

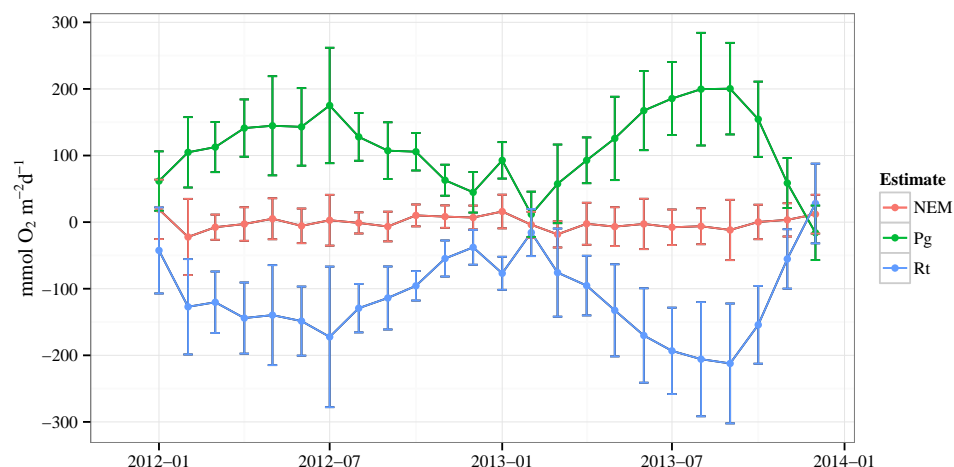


Fig. 6. Monthly means (95% confidence) of ecosystem metabolism estimates (net ecosystem metabolism, gross production, and total respiration) for combined water quality and weather data for two years at Apalachicola Bay, Florida.

Table 4. Miscellaneous functions available from the SWMP package. Most are used within the main functions above but may be useful for customized evaluations of SWMP data. Full documentation for each function is in the help file (e.g., execute `?calckl` at the command line).

Function	Description
<code>calckl</code>	Estimate the reaeration coefficient for air-sea gas exchange. Used in the <code>ecometab</code> function.
<code>map_reserve</code>	Create a map of all stations in a reserve using the <code>ggmap</code> package.
<code>metab_day</code>	Identify the metabolic day for each approximate 24 period in an hourly time series. Used in the <code>ecometab</code> function.
<code>param_names</code>	Returns column names as a list for the parameter types (nutrients, weather, or water quality). Includes QAQC columns with <code>f_</code> prefix. Used in the data retrieval functions.
<code>parser</code>	Parses HTML returned from CDMO data requests. Used in the retrieval functions.
<code>swmpr</code>	Creates a <code>swmpr</code> object class. Used in the data retrieval functions.
<code>time_vec</code>	Converts time vectors to <code>POSIXct</code> objects with the appropriate time zone for a site. Used in the data retrieval functions.

Miscellaneous functions

Several additional functions are provided that do not fit the above categories (Table 4). These functions are generally used within the main functions but may be useful for more customized evaluation of SWMP data.

For brevity, only the `reserve_map` function is discussed. This function can be used to create a map with all stations at a reserve using functions in the `ggmap` package [28]. The current function is limited to Google maps of four types that can be set with the

`map_type` argument: terrain (default), satellite, roadmap, or hybrid. The `zoom` argument may have to be chosen through trial and error depending on the spatial extent of the reserve. See the help documentation for the `ggmap` function for more info on `zoom`.

```
> # plot the stations at Jacques Cousteau reserve
> map_reserve('jac')
```



Fig. 7. Locations of all sites at the Jacques Cousteau reserve using the `map_reserve` function.

Applications using the SWMP_r package

The ability to evaluate environmental characteristics between estuaries within the NERRS program has been greatly improved using functions in the SWMP_r package. This section describes three examples using the SWMP_r package to illustrate the improved ability to synthesize and evaluate multi-year time series of estuarine data. First, the open-water method for estimating metabolism was applied to nearly all co-located water quality and weather sites at each NERRS reserve using all years of available data. The results are provided primarily to illustrate ease of use of the functions and secondarily to provide an update on metabolism estimates using the most recent SWMP data. Caffrey [10] and Caffrey [11] applied the open-water method to estimate ecosystem metabolism using five years of water quality observations at two sites at each of the NERRS reserves. The air-sea gas exchange model also assumed a constant value for the reaeration coefficient, whereas the current `ecometab` function provides a more accurate estimate by including weather data in the calculation (see Caffrey et al. [25] for details).

Water quality and weather observations from January 1995 to December 2014 for all NERRS sites were obtained through a bulk data request using the zip downloads

feature of CDMO. All csv files for each station were imported into R using the `import_local` function, processed using the `setstep` and `qaqc` functions, then saved locally as binary RData files.¹² This resulted in a single `swmpr` object for each parameter at each site. All files were then uploaded to a remote server for online access. An additional R script¹³ was executed that retrieved and processed water quality and weather data at each reserve to estimate metabolism. Two water quality sites with the longest time series at each reserve were used. Mean annual values at each site, organized by region, are shown in Fig. 8, whereas decadal comparisons are shown in Table 5. All sites were generally net heterotrophic across the range of observations (i.e., sink of organic matter, in agreement with Caffrey [10]), although differences were observed in early (i.e., 1995–2004) as compared to recent (2005–2014) time periods. Overall, the results indicate that between-region and within-site differences in metabolism are apparent and varying by time period, such that a more comprehensive evaluation of factors that influence metabolic rates is needed. More importantly, use of the data retrieval, synthesis, and analysis functions to create the results illustrates the utility provided by the SWMP package.

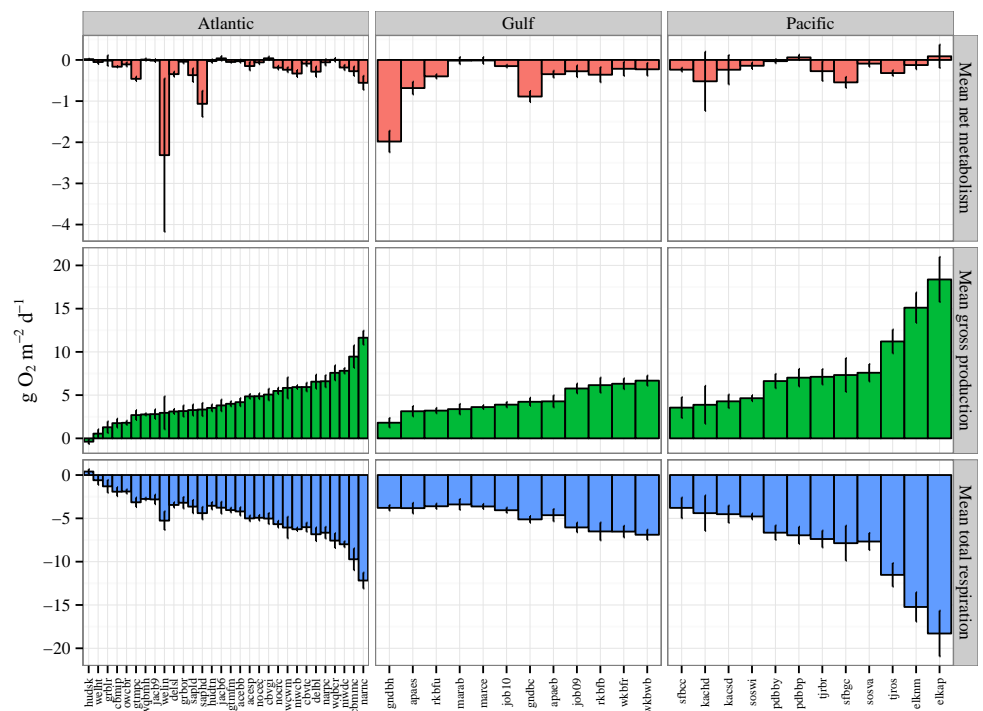


Fig. 8. Aggregated estimates of net metabolism, gross production, and total respiration for two sites at each NERES reserve. Values are daily integrated estimates as mean annual values averaged across all years with 95% confidence intervals. Two sites were chosen from each reserve that had the longest available time series. Sites were assigned to regions based on approximate geographic coordinates.

The second and third examples are two interactive web applications [21] created using the SWMP package that illustrate summaries and comparisons of SWMP data (see the Supporting Information). The first web application evaluates trends in SWMP data within and between sites using an interactive map. Trends between reserves can be

¹²Data processing script: https://github.com/fawda123/swmp_rats/blob/master/R/dat_proc.R

¹³Metabolism processing script: <https://gist.github.com/fawda123/4fc51c2cb86341ed9291>

Table 5. Trends in metabolism for two sites at each of the NERRS reserves. Values are averages of mean annual estimates for each period of observation (1994-2004 and 2005-2014). Bold values indicate an increase from the first period, whereas italic values indicate a decrease. Sites were assigned to regions based on approximate geographic coordinates.

Site	NEM ^a		Pg		Rt	
	1995-2004	2005-2014	1995-2004	2005-2014	1995-2004	2005-2014
Atlantic						
acebb	-0.04	-0.03	5.11	<i>3.81</i>	-5.15	-3.82
acesp	-0.26	-0.1	4.68	4.93	-4.94	<i>-5.03</i>
cbmip	-0.14	<i>-0.17</i>	1.02	1.91	-1.16	<i>-2.08</i>
cbmmc	-0.43	-0.24	6.06	10.13	-6.48	<i>-10.38</i>
cbvgi	0.13	<i>0</i>	6.56	<i>4.47</i>	-6.43	-4.46
cbvte	-0.15	-0.07	5.58	6.07	-5.73	<i>-6.14</i>
delbl	-0.59	-0.16	6.68	<i>6.51</i>	-7.27	-6.67
delsl	-0.37	-0.33	2.84	3.22	-3.21	<i>-3.55</i>
grblr		-0.02		1.28		-1.31
grbor		-0.04		3.16		-3.2
gtmfm	-0.09	-0.04	3.36	4.19	-3.45	<i>-4.23</i>
gtmpc	-0.48	-0.45	1.95	2.91	-2.43	<i>-3.37</i>
hudsk	0.02	<i>0.02</i>	-0.36	<i>-0.39</i>	0.38	0.41
hudtn	-0.03	<i>-0.03</i>	3.75	<i>3.43</i>	-3.78	-3.46
jacb6	0.05	<i>0.03</i>	3.41	3.93	-3.36	<i>-3.89</i>
jacb9	0.01	<i>-0.02</i>	1.8	3.1	-1.79	<i>-3.12</i>
narnc	-0.64	-0.53	12.64	<i>11.33</i>	-13.25	-11.86
narpc	-0.14	-0.03	7.36	<i>6.3</i>	-7.5	-6.32
niwcb	-0.46	-0.28	5.5	6.1	-5.95	<i>-6.38</i>
niwde	-0.13	<i>-0.2</i>	7.28	8.02	-7.41	<i>-8.23</i>
nocec	-0.05	<i>-0.06</i>	4.86	4.88	-4.92	<i>-4.94</i>
nocrc	-0.19	<i>-0.19</i>	5.93	<i>5.31</i>	-6.12	-5.5
owcbr	-0.17	-0.09	1.45	1.9	-1.62	<i>-1.99</i>
owcwm	-0.36	-0.19	7.02	<i>5.36</i>	-7.38	-5.54
saphd	-1.28	-1	1.89	3.77	-3.17	<i>-4.77</i>
sapld	-0.16	<i>-0.43</i>	2.32	3.56	-2.49	<i>-3.99</i>
welht	-0.07	-0.04	0.36	0.63	-0.43	<i>-0.67</i>
welin	-1.87	<i>-2.49</i>	3.61	<i>2.68</i>	-5.48	-5.18
wqbc	-0.01	0.01	8.13	<i>7.41</i>	-8.14	-7.4
wqbmh	0.02	<i>0</i>	2.82	<i>2.76</i>	-2.79	-2.75
Gulf						
apaeb	-0.35	<i>-0.35</i>	4.19	4.31	-4.54	<i>-4.67</i>
apaes	-0.71	-0.67	3.35	<i>3.05</i>	-4.06	-3.73
gndbc	-1.02	-0.88	3.5	4.3	-4.51	<i>-5.18</i>
gndbh	-1.81	<i>-2</i>	2.19	<i>1.77</i>	-4	-3.77
job09	-0.34	-0.25	5.32	5.95	-5.66	<i>-6.2</i>
job10	-0.15	<i>-0.15</i>	3.58	4.03	-3.72	<i>-4.2</i>
marab		-0.02		3.38		-3.4
marce		-0.01		3.62		-3.63
rkbfb	-0.28	<i>-0.37</i>	5.28	6.25	-5.56	<i>-6.62</i>
rkbft	-0.33	<i>-0.41</i>	2.95	3.24	-3.28	<i>-3.64</i>
wkbfr	-0.29	-0.14	6.27	6.35	-6.57	-6.49
wkbwb	-0.29	-0.16	6.81	<i>6.54</i>	-7.1	-6.69
Pacific						
elkap	0.03	0.11	14.7	19.84	-14.67	<i>-19.74</i>
elknm	-0.24	-0.08	11.95	16.37	-12.18	<i>-16.45</i>
kachd	0.2	<i>-0.66</i>	7.31	<i>3.2</i>	-7.12	-3.86
kacsd	-0.06	<i>-0.26</i>	5.15	<i>4.2</i>	-5.21	-4.45
pdbbp	0.01	0.08	6.29	7.31	-6.27	<i>-7.23</i>
pdbby	-0.07	-0.01	8.39	<i>5.92</i>	-8.47	-5.93
sfbcc		-0.24		3.56		-3.79
sfbgc		-0.55		7.32		-7.87
sosva	-0.2	-0.05	6.98	7.83	-7.18	<i>-7.87</i>
soswi	-0.28	-0.08	4.41	4.74	-4.69	<i>-4.82</i>
tjrbr	-1.33	-0.17	7.72	<i>7.06</i>	-9.05	-7.22
tjros	-0.26	<i>-0.34</i>	10.18	11.61	-10.44	<i>-11.96</i>

^aNEM: net ecosystem metabolism, Pg: gross production, Rt: total respiration, all values in g O₂ m⁻² d⁻¹ as annual averages.

viewed using the map, whereas trends at individual sites can be viewed by clicking on a map location. Site-level trends are shown below the map with a simple linear regression to show an increase or decrease in values over time. Trends on the map at each station are plotted as circles that identify the direction and significance of the trend, such that larger points with darker colors indicate a strong trend. The trend direction is blue for decreasing and red for increasing with time. The second application provides graphical summaries of water quality, weather, or nutrient station data at individual stations using the `plot_summary` function. The drop down menus can be used to select the station, date range, and parameter for plotting. The data used for each application are similar to those used to estimate ecosystem metabolism described above and are available in the [Supporting Information](#).

Summary

The ability of management and research programs to address critical environmental issues is highly dependent on the quality of data used to inform decision making. Standardized monitoring programs have vastly improved the ability to evaluate factors that influence a range of conditions, leading to more comprehensive assessments of site-specific characteristics and more informed decisions to manage environmental resources. The System Wide Monitoring Program has provided twenty years of continuous monitoring of environmental characteristics at over over 140 stations within the 28 estuaries of the National Estuarine Research Reserve System. This monitoring network establishes a foundation for more effective coastal management by providing standardized data to address spatiotemporal variation in natural and anthropogenic characteristics that influence environmental condition. Although the data provided by SWMP are unique among coastal observing systems and have been used in a variety of applications [8–10, 12, 13], the capacity of NERRS researchers and staff to more effectively evaluate SWMP data could be greatly improved using the SWMP package.

The SWMP package provides several functions to retrieve, organize, and analyze SWMP data to more effectively address common challenges working with large datasets. The package is designed to augment, rather than replace, existing data retrieval programs by providing a bridge between the raw data and the analysis software through its numerous data retrieval functions (Table 1). Established QAQC methods and data processing techniques are also enhanced with SWMP by functions that filter observations for different QAQC flags (`qaqc`) and subset by selected dates or variables (`subset`). Additionally, cumbersome challenges comparing different datasets are addressed by the `setstep` and `comb` functions that standardize time steps and combine the data. Finally, the analysis functions provide numerous tools to implement common analyses for time series and more specific methods for water quality data. In particular, the `ecometab` function can be used to estimate daily integrated rates of ecosystem metabolism using the open-water method [22, 25]. The above analysis (see [Applications using the SWMP package](#)) provided a cursory update of metabolism estimates for each the NERRS estuaries using recent data to evaluate trends over time. Although further evaluation of the data are needed, particularly regarding assumptions of the open-water method and tidal effects, the results could be used in a more comprehensive evaluation of factors that influence estuary metabolism. Further development of the SWMP package will consider modifying existing and including additional functions to more effectively integrate data analysis with the quality of information provided by SWMP and NERRS.

Supporting Information

Trends in SWMP parameters

Evaluate trends within and between reserves using an interactive map:
https://beckmw.shinyapps.io/swmp_comp

Monthly and annual summary of SWMP parameters

Summarize trends in SWMP parameters for an individual site:
https://beckmw.shinyapps.io/swmp_summary/

SWMP data as R binary files

Quickly access all SWMP data from 1995 through 2014. See the help file for `import_remote` for more information: <https://s3.amazonaws.com/swmpalldata/>

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