Wisconsin Department of Natural Resources
Bureau of Water Quality

Estimations of Loads and Sources of Phosphorus and Sediment at Ungaged Sites in the Wisconsin River Basin

Preliminary Notes on SWAT Model Configuration

Aaron Ruesch
SWAT Modeling Lead
corresponding author
Aaron.Ruesch@wi.gov

David Evans
Water Quality Modeler
DavidM.Evans@wi.gov

Ann Hirekatur
Urban Modeling Lead
Ann.Hirekatur@wi.gov

Laura Rozumalski
Water Quality Modeler
Laura.Rozumalski@wi.gov

WISCONSIN DEPT. OF NATURAL RESOURCES

16 January, 2015

Contents

Abbreviations

ArcSWAT	ArcGIS plug-in software for SWAT configuration
CDL	Cropland Data Layer
DATCP	Department of Agriculture, Trade, and Consumer Protection
DEM	Digital Elevation Model
EPA	Environmental Protection Agency
EVAAL	Erosion Vulnerability Assessment for Agricultural Lands
HUC	Hydrologic Unit Code
HRU	Hydrologic Response Unit
HSG	Hydrologic Soil Group
MS4	Municipal Separate Storm Sewer System
NASS	National Agricultural Statistics Service
NCDC	National Climate Data Center
NED	National Elevation Dataset
NHDPlus	National Hydrography Dataset Plus
NLCD	National Land Cover Dataset
NRCS	Natural Resources Conservation Service
NWIS	National Water Information System
OSD	Official Series Description
PLSS	Public Land Survey System
(g)SSURGO	(gridded) Soil Survey Geographic
SWAT	Soil Water Assessment Tool
TMDL	Total Maximum Daily Load
TSS	Total Suspended Solids
TP	Total Phosphorus
USDA	United States Department of Agriculture
USGS	United States Geological Survey
USLE	Universal Soil Loss Equation
WDNR	Wisconsin Department of Natural Resources
WHDPlus	Wisconsin Hydrography Dataset Plus
WRB	Wisconsin River Basin
WVIC	Wisconsin Valley Improvement Company
WWI	Wisconsin Wetland Inventory

1 Introduction

This document is intended to describe the configuration of the Soil and Water Assessment Tool (SWAT) (Arnold, 1994) for the estimation of streamflow and sources of sediment and phosphorus in the Wisconsin River basin and serves to further define the watershed response model outlined in the Wisconsin River TMDL scope of work (WDNR, 2013). It is a technical document that presumes the reader has a high level of familiarity with SWAT[1] and the Wisconsin River Basin (WRB) Total Maximum Daily Load (TMDL)[2]. It is written specifically to water quality modelers to invite a critical review and ensure the quality of the resulting estimations. The document was written after the model was configured, but before it has been calibrated. Therefore, the methods described here will likely change prior to the release of the final model given new developments during the calibration phase of the project. The model itself is available for download at the following URL:

`ftp://dnrftp01.wi.gov/geodata/wrb_swat/WRB.zip` (512 MB)[3]

Due to the large amount of data required to configure the Wisconsin River SWAT model, the products and data described in this document were created using a series of data processing scripts that can be executed using either the Python or R programming languages, depending upon the script. These scripts are described in Section 2. To the extent possible, these scripts have been written in a way that makes the data processing transparent and reproducible. However, because the model is not complete in configuration or documentation, in some cases the scripts are not annotated to assist in interpretation. Therefore, the reader needs to have a strong understanding of computer programming, Python and R syntax, statistics, and spatial data processing in order to completely understand these scripts. These scripts are publicly available on the website GitHub owned by the username `dnrwaterqualitymodeling`[4]. These scripts can be viewed and downloaded across the history of their development. However, it must be noted that the original datasets used in the processing are not available with the scripts due to limitations in data storage and transfer.

The basic model configuration is described in Section 3. This section describes the methods used to set up the minimum data requirements for a SWAT project. The ArcSWAT program was used to set up the basic SWAT model. It facilitated many of the preliminary spatial data processing tasks that are otherwise difficult to configure manually. These steps included the overlay of the land use, soils, and slope layers to create the hydrologic response units (HRUs), and the creation of the input HRU files needed to run SWAT. Section 3 outlines the data processing steps prior to HRU definition including the following:

[1] http://swat.tamu.edu/
[2] http://dnr.wi.gov/topic/TMDLs/WisconsinRiver/
[3] If the download does not automatically begin or if you are prompted for a password, copy and paste the link into your browser.
[4] https://github.com/dnrwaterqualitymodeling

- climate data processing (Section 3.1)
- SWAT subbasin delineation (Section 3.2)
- HRU definition (Section 3.6), and the components of the HRU definition:
  - land cover data specification (Section 3.3)
  - soil data aggregation (Section 3.4)
  - slope classification (Section 3.5)

The Wisconsin Department of Natural Resources (WDNR) SWAT project team has developed and configured datasets additional to those necessary to create and run a SWAT model. These additional datasets were created for a number of different, often overlapping, reasons as listed below.

- The WRB drains an area of 23,700 km^2 and has significant variation in soils, geologic history, vegetation, and land use. Therefore, additional datasets were created to describe regionally specific physical and chemical processes (Sections 4.1, 4.2, 4.7.2, and 4.7.1).
- The WRB TMDL is a large modeling effort that integrates multiple modeling platforms. We discuss the delineation of urban boundaries that will be modeled separately using the WinSLAMM model (Section 4.3).
- We are incorporating observed data where available. Specifically, we incorporated daily flows monitored at reservoir outlets. We will also describe how we have selected monitoring sites for streamflow calibration. (Sections 4.8 and 4.9).
- Some model parameters were set during the configuration phase of the model development; this was done to save time during the calibration phase and to open these decisions for external review. These parameters may be adjusted during the calibration process, but the estimates set during the configuration phase likely represent better starting points than the default values of the parameters (Sections 4.8, 4.6, 4.7.1, and 4.7.2).

This document represents a description of the configuration for the SWAT model being used in the Wisconsin River Basin TMDL. It must be noted that the SWAT modeling component of the WRB TMDL remains a work in progress and the methods and data described and distributed at this stage may change at a future date because of issues and concerns that may develop during the calibration phase.

2 Model Data Files

The Wisconsin River Basin (WRB) SWAT model distributed for review contains all the files necessary to run the model. The ArcSWAT program (version 2012.10.15) was used to set up the SWAT project and so the file structure was determined by ArcSWAT. The SWAT executable that came bundled with this version of ArcSWAT was SWAT2012 revision 627.

Much of the model configuration was done with the R statistical package (files with a `.r` extension) and the Python scripting language (files ending with `.py`). These scripts can be found at the WDNR water quality modeling team's page on the GitHub[5] website. Below is a brief description of the contents of each code folder and how the scripts inside were used. Included are references and links to sections for further description of methods. The titles of each folder are listed here as they appear on the GitHub site.

- `climate`: contains scripts pertaining to data processing for air temperature, precipitation, relative humidity, solar radiation, and a nearest neighbor algorithm for filling in missing data (see Section 3.1)
- `DEM`: scripts for processing the WRB elevation data from the National Elevation Dataset (NED)
- `LandManagement`: the script `correlateCdlAndDatcpDairy.R` is for validating the predictions of the generalized rotation algorithm[6] and `GeneralizeMergeLandManagementLandCover.R` is for creating a map of the land management types of the WRB (see Section 4.1)
- `et`: the scripts contained in the folder pertain to investigating the proper equation for modeling evapotranspiration in the WRB (see Section 4.6)
- `groundWater`: the script `baseflow_phosphorus.R` contains the processing for estimating the amount of phosphorus from groundwater and the scripts in the `baseFlow` folder contain the files for carrying out the processing and modeling for estimating baseflow contribution to streams (see Section 4.7.2 and 4.7.1)
- `hydrology`: `calculateRunoffUsingBaseflowSeparation.R` is a script for developing basin-wide water balance estimates and formatting the outflows from the basin reservoirs
- `landCover`: the script `mergeWwiWithNass2011.py` was used to reclassify and rasterize the Wisconsin Wetlands Inventory (WWI) into two classes: woody wetlands and herbaceous wetlands. The script `mergeCdlWithWetlandsCrpCranberries.py` merged the 2011 Cropland Data Layer (CDL)

[5] https://github.com/dnrwaterqualitymodeling/wisconsinRiverTMDL/tree/model_setup_public

[6] The generalized rotation algorithm used was the algorithm from within the EVAAL tool. The script can be found here https://github.com/dnrwaterqualitymodeling/EVAAL/blob/master/__EVAAL__.pyt

with the rasterized wetlands, a layer of Conservation Reserve Program (CRP) attributed field boundaries within the 2007 Common Land Unit dataset, and a layer of cranberry bogs developed by the Wisconsin DNR (see Section 3.3)

- `ponds`: these scripts were used in the processing and modeling to derive pond parameters for SWAT (see Section 4.4)

- `soils`: these scripts determine which hydrologic soil group (HSG) to assign to dual HSG map units, aggregate SSURGO data, and process the soil phosphorus data (see Section 3.4)

- `updateParameters`: the script in this folder is used to update the ArcSWAT database with specific data derived in many of the scripts in these folders; they include:

  - Management operations
    - Crop rotations
    - Plant harvest schedule
    - Fertilizer type/amount/schedule
    - Tillage type and schedule
  - Groundwater
    - Baseflow contributions
    - Baseflow phosphorus concentrations
  - Reservoirs, physical properties and daily outflow
  - Internally draining areas (i.e., SWAT wetlands and Ponds)
  - Soil phosphorus concentrations

- `watershedAggregation`: scripts for aggregating the Wisconsin Hydrography Dataset (WHDPlus) watersheds up to the SWAT subbasins (see Section 3.2)

- `wetlands`: script for calculating wetland parameters (see Section 4.5)

- `doc`: contains the raw files for the development and compilation of this document

3 Basic Model Configuration

This section details the basic configuration and data processing steps taken during the development of this SWAT project.

3.1 Climate Station Data

The WRB SWAT model will eventually be calibrated to reduce the error between model estimates and measured data. Measured data of streamflow, sediment concentrations, and phosphorus concentrations were collected between the years of 2002 and 2013. Therefore, we compiled daily climate station data between that period so that measured climate station data would temporally align with streamflow, sediment, and phosphorus measurements.

Daily weather and climate data used in the SWAT model were downloaded from the National Climate Data Center (NCDC) - Global Historic Climate Data Network website[7] (Menne et al., 2012). Weather data include precipitation and temperature. Data sets from 120 different stations were downloaded, from which precipitation data was taken from 74 stations, and temperature from 46. In addition to temperature and precipitation records, we retrieved daily solar radiation, wind speed, and relative humidity data from University of Wisconsin Extension Agricultural Research Stations[8] at Arlington, Hancock, Spring Green, and Marshfield (UWEX, 2014). For both of these sources, the data have gone through quality assurance and quality control procedures.

Not all stations had complete data records covering the entire timeframe being modeled. For time periods missing precipitation or temperature data, the record was supplemented with data from the nearest weather station with data for that time period (Figure 1). Data from neighboring stations was used to fill gaps iteratively until each station had a continuous record of daily observations for the whole model period. For solar radiation, wind speed and relative humidity missing data was generated automatically by the SWAT weather generator which stochastically generates data based on historic weather patterns.

Deterministic models such as SWAT usually perform better with a spin-up period of several years to allow the water budget and other physical and chemical processes of the system to equilibrate. We chose a spin-up period equal in length to the model period of 12 years. For these 12 years, weather was simulated by SWAT using patterns of historic weather between the years of 1961 and 2010. Therefore, the model runs for a total of 24 years (12 spin-up years, and 12 years using measured data). However, as stated above, only the 12 years using measured data are printed.

3.2 Subbasin Delineation

The first step in configuring a SWAT is delineating subbasins. The Wisconsin River is a relatively large area for a TMDL project. Consequently, much of the

[7] ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/daily
[8] http://agwx.soils.wisc.edu/uwex_agwx/awon/

point and non-point load-reduction efforts will occur as nested projects within the overall TMDL framework. Hydrologic and regulatory transitions were used to guide the placement of TMDL subbasin transitions. TMDL subbasins were delineated:

1. to address specific water quality impairments where local water quality does not meet codified standards. Consideration was given to streams that are likely to be impaired, but where sufficient monitoring data do not currently exist.

2. near point source outfalls. Delineations were not required to be at precisely the location of the outfall; if we could assume that streamflow does not significantly increase between the discharge location and the next downstream subbasin division, it was not necessary to further subdivide the subbasin at the discharge location.

3. at locations where water quantity and quality were measured during the model period for use in model calibration.

4. at major transitions of water quality standards, for instance at river impoundments that receive lake criteria.

5. at major hydrologic transitions such as the confluence of two large streams or where there are significant changes in landuse/landcover.

Beyond the above criteria, we made an effort to subdivide the remaining subbasins so that the resulting subbasins are of relatively homogenous area—having similarly sized subbasins results in more accurate timing of peak flows during runoff events.

After the locations of subbasin outfalls were identified, we delineated the contributing area upstream of each. ArcSWAT will automatically delineate model subbasins, but because of our specific reasons for creating subbasins outlined above, we manually created the SWAT subbasins by aggregating the WHDPlus dataset (Diebel et al., 2013), which contains subcatchments within the Hydrologic Unit Code (HUC) 12 basins (which are standard watersheds created and maintained by the United States Geologic Survey [USGS]). We delineated 338 subbasins with an average size of 68 km^2 (standard deviation = 80 km^2); larger subbasins were located in areas with fewer water quality impairments and points sources. This size is smaller than the average HUC12 watershed (84 km^2), which is the scale at which TMDL implementation strategies are typically evaluated.

3.3 Land Cover

The composite land cover developed for the SWAT model input began with the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) 2011 Cropland Data Layer (CDL) for Wisconsin (USDA-NASS, 2011). The layer, originally created to provide agricultural information for the major crops to the USDA Agricultural Statistics Boards, provides a raster-based, geo-referenced data layer that defines growing-season land cover at a cell resolution of 900 m^2 for Wisconsin using satellite imagery from a variety of satellites (USDA-NASS, 2011). For non-agricultural land cover, the CDL relies on the United States Geological Survey (USGS) National Land Cover Database (NLCD) 2006. The 2011 USDA NASS CDL was selected because that year had improved accuracy statistics when compared to other years, and there were no flooding or drought events within the growing season. To improve CDL wetland definition, mainly related to the misclassification of forested wetlands, Wisconsin Wetlands Inventory (WWI) information was integrated into the 2011 CDL. The WWI coverage provides the geographic extent of wetlands that have been digitized from aerial photography, verified through photo interpretation, and compared against soil surveys, topographic maps, and previous wetland inventories (WDNR, 1991).

3.4 Soil Data Aggregation

Soils are a critical part of the SWAT modeling framework; properties such as texture, hydraulic conductivity, and available water capacity play a critical role in determining system hydrology . We used the county-scale Soil Survey Geographical Database (SSURGO) (USDA-NRCS, 2014). For more information about SSURGO data see the SSURGO metadata[9]. The SSURGO database is structured in three levels of information: map units, components, and horizons (Figure 3). Horizons are the fundamental unit of soil in SSURGO, and are therefore where the majority of soil information is stored in the database. Components are aggregations of horizons that represent a full soil profile, typically conforming to the Official Series Description (OSD). Map units are discrete polygons drawn on a map (originally mapped at scales from 1:12,000 to 1:63,360) that contain one or more components that are stored non-spatially in the database—that is, only a list of components and their percent composition of the map unit is given.

We chose to use the gSSURGO distribution of SSURGO. gSSURGO is a form of the SSURGO database that is packaged in a more convenient form for coarse scale projects such as the WRB TMDL. The tabular data representing the components and horizons were joined together so that each component had the data required for the SWAT model (Table 1). For all these properties, the representative value given by SSURGO was used.

HRU definition in a SWAT model is a balance of incorporating the most important pieces of information without overloading it with redundant or insignificant information—a modeler should represent every process that controls the system, however an overloaded model requires more computational resources, which may not be feasible to acquire. To reduce the number of HRUs in the model and generally create a simpler and more efficient model, we aggregated soils together based on similarity of several key properties that impact the hydrologic cycle. This was a two step process: first, components within map units

[9] http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey

were aggregated together,[10] and second, map units were aggregated together based on similarity[11] (Figure 2).

Several changes were made to the dataset before aggregation, in order to facilitate processing. Soil organic carbon content is required by SWAT, but is given by SSURGO as soil organic matter. The percent organic matter value given in SSURGO was converted to percent organic carbon by multiplying by 50% which is the generally accepted average carbon content of soil organic matter (Brady and Weil, 2004). The HSG is denoted as a letter in SSURGO, either A through D, or if the soil has different characteristics when drained, as two letters, A/D, B/D or C/D, the former is if the soil is drained (i.e. through tiling or ditching), while the latter is the drainage class of soil in its natural state. In order to average the different components it was necessary to convert these letters into numbers; groups A through D were converted to 1 through 4 to correspond with increasingly wetter drainage conditions. Once a number was obtained for the HSG, it was treated as any other soil property in the aggregation process, then rounded to the nearest integer, and converted in the same manner to a letter once the aggregation was finished. For those components with dual HSGs, we assumed that if half of the area in the map unit was agriculture it was drained and the first HSG taken. Conversely, if the land use was not majority agriculture then it was assumed to not be drained and the "D" designation was chosen. There is no evidence to suggest that this assumption accurately represents the properties of these soils in reality—rather, the 50% threshold was chosen simply to give favor to the dominant condition. A more informed approach may be used in future developments of the model.

The first aggregation step was to aggregate components by map unit to conform to the SWAT soils data structure. The data structure for soils in SWAT does not directly conform to SSURGO data structure, mainly that there is no analogue to the SSURGO *component* level in SWAT—in other words, soils in SWAT cannot be subdivided (Figure 4). Similar to Gatzke et al. (2011), who aggregated SSURGO data for a SWAT model, we aggregated components by computing component-weighted averages of each soil property for any given depth of soil from the soil surface to the average depth. These averages were computed using the `slab` function in the `aqp` package in R (Beaudette et al., 2013). We used this algorithm to apply a depth weighted average to each horizon, while also weighting the percent composition of each component. The depth and number of horizons of the aggregated soil profile produced by this algorithm must be specified before processing. The depth was calculated as a weighted mean of the full depths of soil profile in each of the components, with the weights equal to the percent composition of each component. As the number of horizons was assumed not to matter as much as the maximum depth, an arbitrary number of five horizons was chosen for the aggregation algorithm.

Using the above aggregation method 48,585 individual soil components were

[10] https://github.com/dnrwaterqualitymodeling/wisconsinRiverTMDL/blob/model_setup_public/soils/step1_aggregate_gSSURGO.R

[11] https://github.com/dnrwaterqualitymodeling/wisconsinRiverTMDL/blob/model_setup_public/soils/step2_aggregate_gSSURGO.R

aggregated to 1,603 map units. Because the HRUs used in SWAT were derived using unique combinations of land use, slope and soil types, this number of soil map units is still too many for efficient computation and so the second step of the soils data configuration was necessary to further reduce the number of soil types.

Other researchers have aggregated soil types by their taxonomic class (Gatzke et al., 2011) but Soil Taxonomy, the soil classification system of the US, primarily classifies based on soil morphology and not necessarily on properties relevant to SWAT. We decided that the most relevant soils information to SWAT is hydrology data, specifically the HSG, which has a large impact on the soil curve number. With this consideration, aggregation was based around (and so preserved) the HSG of the map unit. Groups of the same HSG were divided into smaller groups (hereafter known as clusters) of homogeneous soil properties. The map units within each of these clusters were then averaged together to create an average profile for that homogeneous set of soils. These averages were then used as the soil types for the HRU definitions and the SWAT modeling.

To begin, each map unit (each of which is an aggregation of components, as described above) was placed into one of four groups according to its hydrologic soil group, A, B, C or D. To subdivide these groups further, a clustering algorithm was used to objectively create clusters of map units with homogeneous soil properties. For this purpose, we used Gaussian mixture models to assign map units to clusters. The mixture model approach we used was implemented within the `Mclust` function in the `mclust` package in R (Fraley et al., 2012). A mixture model is a probabilistic model for representing the presence of subpopulations within an overall population. In our case, the overall population would be the group of map units of similar hydrologic soil groups (i.e., all map units with an HSG of A), while the (unknown) subpopulations are the clusters of map units with similar distributions of soil properties (such as a clusters of sandier soils, shallow soils, or slow saturated conductivity). Using the default settings of the function, we clustered all of the A HSG map units into 6 clusters, B HSG map units had 8 clusters, and C and D both had 9 clusters.

In order to use the clustering function we had to put our data in a format in which it could be used by the `Mclust` function. We calculated horizon depth-weighted averages of each soil property for each map unit, essentially collapsing the soil profile down to one aggregate horizon with average properties. Profile depth was still considered in the clustering algorithm using the total depth of the profile.

After each map unit had been assigned to a cluster, the map units within each cluster were aggregated together to form a composite or average soil profile. The same soil profile aggregation algorithm (Beaudette et al., 2013) used to aggregate several components together in the first step was used to combine the soil profiles of a cluster into one composite soil profile. In this implementation, each map unit was given equal weight in the aggregation algorithm.

Not every map unit was included in the clustering procedure. Several of the soil property fields of the SSURGO dataset were not populated or commonly had "no data" values, these properties were not used in the clustering process so the spurious zeros would not influence the algorithm (Table 1). These properties were coarse fragments, calcium carbonate, and electrical conductivity. Albedo and pH were also excluded from the clustering algorithm. Mapunits that had no HSG designation were not included, nor were map units that did not have information on the soil properties of the horizons. Examining these excluded map units revealed that they were generally disturbed landscapes or those without a significant soil layer such as pits, landfills, urban or made land, rock outcrops, and water. These miscellaneous map units were all grouped together as one cluster with the exception of water. All water map units were collapsed into one using properties described in the default ArcSWAT SSURGO database[12].

A total of 35 soil classes were distilled from this process. An example of the properties of each cluster are shown in Table 3 and the number of map units in each cluster can be found in Table 2. The hydrologic soil groups and the clusters within these groups are displayed in Figure 5, which shows the relative variability of soil properties of map units that were aggregated to clusters.

3.5 Slope Classification

Topographic features are characterized at the subbasin level in SWAT. Using ArcSWAT software, we created a slope grid within the same grid domain as our basin-wide DEM (900 m^2 resolution). The slopes for each subbasin were grouped into five quantile classes. Each class contained approximately equal numbers of grid cells whose value fell within the range of values of each bin. These bins in degrees were 0.0–0.5, 0.5–1.5, 1.5–3.0, 3.0–5.8, and > 5.8 (or, in percent, 0–0.87, 0.87–2.62, 2.62–5.24, 5.24–10.2 and > 10.2).

3.6 HRU Definition

The hydrologic response units in SWAT are defined by unique combinations of land use, soils, and slope class and are unique for every subbasin. If every combination were honored, there would be many tens of thousands of HRUs and the model would take an impractical amount of time to run while having a number of functional redundancies within it. To reduce the number of HRUs, ArcSWAT allows for the removal of small HRUs; by setting a minimum threshold for each landcover, soils, and slope class, we reduced the number of overall HRUs. First, if a given landcover covered less than 1% of a subbasin, we excluded it and proportionally reallocated the remaining landcovers so that they would add to 100%. Second, within the remaining landcovers, if a given soil type covered less than 25% of a landcover class, it was excluded and reallocated in the same way as landcover. Finally, within the remaining landcover/soil combinations, if a given slope class covered less than 50% of a landcover/soil combination, it was excluded and reallocated. This means that only the dominant slope class is used for a given landcover/soil combination. This iterative method of exclusion resulted in 4,400 HRUs; a manageable number for performing calibrations and yet detailed enough where there is little data resolution lost.

[12] http://swat.tamu.edu/media/63316/SWAT_US_SSURGO_Soils.zip

4 Additional Model Configuration

This section details some of the additional data configuration that was done in the WRB SWAT model. This configuration was not necessary for the model to run but was done to better represent actual conditions in the Wisconsin River basin.

4.1 Agricultural Land Management

The representation of agriculture is particularly important in the WRB where agriculture covers nearly 25% of the watershed. When combined with other variables such as precipitation, soils, and slope, certain agricultural practices can contribute significant loads of sediment and phosphorus to receiving waters. The SWAT model provides the opportunity to distinguish between land cover and land management. One of SWAT's strengths, and one of the primary reasons it was selected for the WRB TMDL modeling effort, is its ability to model variability in land management on a daily time step.

The objective of this effort was to develop and implement a methodology to define agricultural management by integrating geospatial data and analysis, local knowledge from county land and water conservation staff, private agronomists, and field data. The methodology was applied to agricultural landcover within the WRB. The result is a spatial layer that defines spatiotemporal variability of agricultural land management, such as rotation, tillage, and nutrient application for any given 900 mi^2 pixel in the basin-wide grid. All methods included in Section 4.1 are fully described in the WDNR Land Cover and Agricultural Management Definition Report (WDNR, 2014).

No unified dataset existed with data related to changes in tillage practices, fertilizer application, timing of the fertilizer application, etc. Local knowledge became essential as county and regional experts were brought together to supply this missing information and develop a regionally-specific dataset at the scale of a Public Land Survey System (PLSS) quarter section. A balance was struck between relying on satellite imagery and relying on local knowledge. The satellite imagery is trusted (with overall accuracies between 84 and 91%[13]) to spatially identify rotation types better than a local expert, but the local experts were trusted to inform the satellite-identified rotation with the land management information. Transect data collected in the field provided us with a validation dataset to verify data provided from counties.

4.1.1 Tillage

The types of tillage practiced on farms was reported to the WDNR by county conservation staff and local experts. Tillage practices were mapped by county staff as the dominant pattern within any given PLSS quarter section. For each PLSS quarter section, tillage timing (e.g., spring or fall) and type (e.g., chisel disk or moldboard plow) was reported across a 6-year crop rotation. We used

[13] http://www.nass.usda.gov/research/Cropland/metadata/meta.htm

transect survey data collected by county staff to confirm the reported tillage types and timing. For example, fall tillage is predominant in the north central WRB and spring tillage is predominant in the southern WRB—a deviation from this pattern would flag it for further confirmation, which was mainly from professional agronomists working within the region.

4.1.2 Inorganic Fertilizers

A starter fertilizer application was changed from 0.22 to 0.17 $tons \cdot ha^{-1} \cdot yr^{-1}$ with an NPK composition of 20-10-18. This was done following the suggestions from a panel of WDNR staff, faculty from the University of Wisconsin, private agronomists, manure haulers, and crop consultants.

A nitrogen auto-fertilization routine was added to SWAT's management operations. This operation applies nitrogen in order to minimize plant stress due to nitrogen limitation and therefore maintain proper plant growth. This assumption may not be realistic; as a result, the model should not be used to assess nitrogen loads in surface waters.

4.1.3 Manure

Manure application type (e.g., stored and applied as a liquid or applied frequently as a solid) and timing (e.g., spring or fall if liquid manure) were reported to the WDNR by county staff and local experts in the same way tillage information was collected.

Similar to past SWAT applications, cattle inventories were used to validate the amount of manure application reported by the counties, as well as the extent of dairy rotation identification (Baumgart, 2005; Freihoefer and McGinley, 2007; Timm and McGinley, 2011). SWAT uses dry weight values for manure application, so reported values of liquid and solid manure were converted to dry weight values in kg/ha. The conversion process required dry weight percentages of each solid and liquid manure. Based on previous research 6% dry weight for liquid manure and 24% dry weight for solid manure were used (Jokela and Peters, 2009; Laboski and Peters, 2012; USDA-NRCS, 2006). Based on the Department of Agriculture, Trade, and Consumer Protection (DATCP) dairy manure estimation calculator[14], it was assumed that liquid manure has the same density as water (8.34 lbs/gal).

4.1.4 Crop Rotations

Generalized rotations were created by using rules to classify five years of cropland information, as described in WDNR, 2014. The generalized rotations were entered into a database where each activity was stored for a 6-year period. In total, 15 rotations (11 dairy, 3 cash grain, and 1 potato/vegetable) were created for the WRB, based on the data from the CDL, information from county and regional staff, NASS census data, and information from our meeting with

[14] http://datcp.wi.gov/uploads/Farms/pdf/NMTrainingYKnowHowMuchYouHaul.pdf

agronomists. Each of the 15 rotations had three variations, each a result from offsetting the rotation period (described further below), resulting in 45 rotations that were incorporated into the SWAT model (WDNR, 2014).

We found it necessary to randomize rotations for several different reasons. Firstly, locations where corn was grown continuously for the five year period were randomly classified as either a cash grain rotation or a dairy rotation. Using long-term records in the Pleasant Valley watershed in south-central Wisconsin, we found that when corn was being grown continuously over a 5-year period, it was equally likely to be a cash grain operation or a dairy rotation. Additionally, several of the counties provided non-spatial information about how manure was handled: it was estimated that about 50% of producers used liquid storage while the other 50% were daily haulers. The manure management types were randomly assigned to the dairy rotations for those counties.

If each land use was given the same rotation sequence, the artificial landscape would represent all the same crop being grown in any given year. This was considered an issue especially for the corn silage years of the dairy rotations. If all of the dairy rotations were growing corn silage in the same year, there could be unreasonably large spikes in runoff and erosion during that year. To remedy this issue, rotations of identical management operation schedules were offset by two years, creating three different rotation sequences for each rotation/tillage/fertilizer combination (Table 6).

4.2 Soil Phosphorus

Soil Phosphorus concentrations were obtained through the University of Wisconsin Soil Testing Laboratory [15]. Soil phosphorus concentrations were aggregated by county by the soil laboratory for each year from 1974 to the present. We chose the annual average soil concentration nearest the beginning of the model spin-up period, 1995, to establish prior concentrations. Subbasin-level soil phosphorus concentrations were estimated by calculating an area-weighted average of intersecting counties within a subbasin. The soil testing laboratory receives almost exclusively agricultural soils, to reflect this bias in the soil phosphorus data, only agricultural HRUs were given the subbasin average concentration, while the non-agricultural HRUs were given SWAT's default concentration (5 mg P/Kg). This default concentration is assumed to equilibrate over the 12-year model spin-up period. Soluble phosphorus concentrations were estimated as half of the reported phosphorus using the Bray-1 method measured with a spectrophotometer (Vadas and White, 2010). Organic phosphorus concentrations were estimated by assuming that phosphorus constitutes 0.85% of organic material measured by loss of weight upon ignition (Havlin et al., 2005). SWAT allows soil phosphorus values to be set at every soil horizon, in our case we changed the soil phosphorus values only for the first horizon, the rest were left at the default values.

[15] http://uwlab.soils.wisc.edu/

4.3 Urban Area Model

The simulation of urban areas within the WRB will be completed using the Source Loading and Management Model for Windows (WinSLAMM v10.0). Urban runoff volumes, total suspended solid (TSS) loads and total phosphorus (TP) loads exported from WinSLAMM will be incorporated into the watershed response model (SWAT) as point source discharges. Areas within the WRB modeled in WinSLAMM comprise the urban model area. The urban model area was not modeled using SWAT, that is these areas were removed from the data layers input into SWAT. See Table 7 and Table 8 for the specific data files from which boundaries were derived. The extent of the urban model area is defined as

1. Cities and villages, excluding the following areas:
   (a) Large, contiguous non-urbanized[16], undeveloped areas located within the municipal limits of a city or village
   (b) Areas mapped as open water[17] within the municipal limits of a city or village
   (c) Undeveloped[18] floodplain islands[19] within the municipal limits of a city or village
2. Urbanized areas within townships that have a permitted Municipal Separate Storm Sewer System (MS4)
3. State Department of Transportation right-of-way located within an urbanized area, and county transportation right-of-way located within an urbanized area of a county that has a permitted MS4

Data sets used to define the urban model area layer include the published statewide data listed in Table 7 and data provided by individual permitted MS4s.

4.3.1 Urban Model Area Reach-shed Delineation

The urban model area draining to each TMDL reach was delineated according to outfall and outfall shed mapping, rather than SWAT subbasin boundaries, for urban model areas located within permitted MS4s that provided the WDNR with the aforementioned mapping data. For unpermitted MS4s, and permitted MS4s that provided the aforementioned mapping data, SWAT subbasin boundaries were used to delineate urban model reach-sheds, Table 9 lists all mapping data provided by permitted MS4s that was used to delineate reach-sheds within the urban model area.

[16] "Urbanized areas" is defined herein as an area classified as "urbanized" by the 2010 Decennial Census. For the purpose of this document "urbanized area" and "urban model area" are not the same.

[17] According to the USGS National Hydrography Dataset

[18] Based on visual inspection of 2010 Wisconsin Regional Orthophotography Consortium.

[19] Areas completely surrounded on all sides by areas mapped as open water.

4.4 Ponds

The SWAT model simulates rainfall storage using the *ponds*, *wetlands*, and *potholes* functions, where ponds and wetlands are defined at the subbasin level and potholes are defined at the HRU level. Due to the large scope of the WRB SWAT, we chose to model rainfall storage using both ponds and wetlands, conceding that HRU-level storage was too detailed and did not match the scale of analysis. The ponds routine is used to simulate storage of internally drained ponds or lakes, and the wetlands routine is used to simulate smaller depressions that either manifest in true wetlands, or at least function as seasonal capture zones.

The ponds function in SWAT requires a minimum input of geometric properties and hydraulic conductivity, with a number of additional parameters to control sediment and chemical processes. We calculated geometric properties using a combination of WHDPlus (Diebel et al., 2013), the Wisconsin 1:24k Hydrography Geodatabase[20], the Wisconsin Lake Book (WDNR, 2009), and terrain analysis. We set hydraulic conductivity to zero, reserving it as a calibration parameter.

The geometric properties for the lakes themselves, as required by SWAT, are the fraction of the subbasin that drains to a pond, principal and emergency storage volume, and principal and emergency surface area. The principal/emergency jargon are adopted from reservoir management, but here are taken to mean *normal* conditions and conditions that would cause the internally drained lake to overtop, respectively. Normal surface areas were extracted from the Wisconsin Hydrography Geodatabase. The Wisconsin Hydrography Geodatabase was digitized from USGS topographic maps, so we assume that the interpretation of the aerial photography associated with the USGS topography maps was representative of normal conditions. We also assume that normal surface area matches normal volumes that were taken directly from Wisconsin Lakes (WDNR, 2009).

If normal volumes were not listed in Wisconsin Lakes (WDNR, 2009), at least the maximum depth of the lake typically was. For those lakes where volume was not listed, we predicted their volume based on a fitted regression using maximum depth ($p < 0.001$) and surface area ($p < 0.001$) as predictors (Figure 6).

$$\boldsymbol{V} = e^{-0.1+1.1\cdot\ln(\boldsymbol{A})+0.6\cdot\ln(\boldsymbol{D})} \tag{1}$$

If maximum depth was not available, we fitted a separate regression using only surface area. (Figure 6).

$$\boldsymbol{V} = e^{0.7+1.3\cdot\ln(\boldsymbol{A})} \tag{2}$$

In the above equations, $\boldsymbol{V}$ is the volume of any given lake in $acre \cdot feet$, $\boldsymbol{A}$ is surface area in acres, and $\boldsymbol{D}$ is maximum depth in feet.

The contributing area of each pond was estimated using WHDPlus. WHDPlus includes a polygon feature class of watersheds of each hydrographic unit in

[20] http://dnr.wi.gov/maps/gis/datahydro.html

the Wisconsin Hydrography Geodatabase. Stream-type hydrographic units are confluence-bounded reaches that are further subdivided by changes in hydrology "type" (e.g., transition from stream to wetland gap). Lake-type hydrographic units are any lake greater than five acres. The watersheds of all lake-type hydrographic units defined as "landlocked" were selected, and the sums of the areas of these watersheds were used to define the percent of each subbasin that flows to a pond.

Emergency volume and surface area were estimated using terrain analysis. We simulated overtopping of ponds by "filling" the DEM—filling the DEM raises the elevation of grid cells within internally draining areas until the landscape simulates overtopping of internally draining areas. Once the DEM was filled, we calculated the elevation difference of each filled grid cell that intersected the internally draining area associated with the landlocked lake (Figure 7). To calculate emergency volume, we summed the elevation differences and multiplied by the grid cell area. This was done for each landlocked hydrographic unit in WHDPlus, and summarized for each of the 338 subbasins in the WRB.

$$V_{max,s} = \sum_{l=1}^{m} \sum_{c=1}^{n} (\Delta e_c \cdot 900)_l \tag{3}$$

Emergency volumes of all ponds within a given subbasin $V_{max,s}$ were calculated using the above equation where l represents a landlocked lake within a subbasin, c is a grid cell associated with the internally drained area of a landlocked lake, Δe_c is the elevation difference between the original DEM and the filled DEM for any grid cell c, and 900 is equal to the area in meters of all grid cells in the DEM.

4.5 Wetlands

SWAT considers wetlands in a manner very similar to how it considers ponds, the difference only being one additional parameter in ponds, NDTARG. There were several parameters that needed to be calculated for the basin's wetlands and these were the same as for ponds: the fraction of each subbasin composed of wetlands, the normal and maximum surface areas, and the normal and maximum volumes.

These parameters were calculated for each subbasin using a terrain-based approach. A digital elevation model (DEM) was filled using the Fill function in ArcGIS, filling all of the sink areas and causing all simulated water to run off of the landscape. The original DEM was subtracted from the filled DEM to derive a surface of the depth of internally drained areas or sinks. This sinks layer shows the internally drained areas for the basin.

The areas classified by the CDL as herbaceous wetlands, woody wetlands, and cranberries were considered to be areas where wetland vegetation is likely to be found. If wetland vegetation exists it can be assumed that the landscape has a consistent wetland hydrology, enough that it is expressed in the vegetation. The intersection or overlap of the sinks layer and the wetland vegetation, as identified by the CDL, was considered to be the principal wetland surface area. To calculate principal storage volume, we assumed an average water depth for any given wetland to be 0.5 m, and then multiplied this by the principal surface area. For emergency surface area, we used the union of CDL wetlands and sink areas. The emergency storage volume was calculated by summing the volumes of sinks and adding that to the principal storage volume. The maximum wetland surface area was divided by the subbasin area to derive the fraction of the subbasin that contributes to wetlands. Contributing areas to wetlands can be seen in Figure 8.

There are precedents to using a terrain-based approach to defining wetland areas in SWAT. Almendinger and Murphy (2007) considered internally drained areas as wetlands (as identified by remote sensing[21]) if they were not connected to the main channel and lakes were considered ponds in their SWAT model. Wetlands, identified through remote sensing, were considered SWAT wetlands only if they occur on the main channel. Similarly, Kirsch et al. (2002) considered internally drained areas as wetlands in SWAT if they overlapped with remotely-sensed-defined wetlands; if they did not, they were considered ponds. Almendinger and Ulrich (2010) modeled closed internal depressions as wetlands and open (those draining to the main channel) as ponds.

4.6 Evapotranspiration Equation

The method selected to model potential evapotranspiration is used across all subbasins within the model. The three methods to choose from include the Hargreaves, the Penman-Monteith, and the Priestley-Taylor equations. We determined which method would work best by evaluating the percent bias and the Nash-Sutcliffe model efficiency coefficient when comparing modeled water yield to observed water yield at 20 sites across the basin. Without calibrating the initial model, Penman-Monteith outperformed the other two methods in both Nash-Sutcliffe coefficient and percent bias (Table 5). See Figure 9 for maps of the quality metrics for each of the different evapotranspiration equations. The Penman-Monteith equation is an energy balance and aerodynamic formula that computes water evaporation from vegetated surfaces. The equation estimates evapotranspiration rates based on solar radiation, temperature, wind speed, and relative humidity.

4.7 Groundwater

4.7.1 Groundwater Inflow (Baseflow)

In SWAT, the relative contribution of streamflow as baseflow is determined by the ALPHA_BF parameter and can be adjusted for each subbasin. An effort was made to regionalize this variable to account for the wide variations in baseflow conditions across the WRB. A regression model was fitted that relates baseflow

[21]Specifically, the remotely sensed imagery was from the WISCLAND data set; a dataset of landcover determined from LANDSAT imagery.

to upstream watershed characteristics. Then this model was used to predict ALPHA_BF at ungaged sites in the WRB[22]. In order to construct a model relating baseflow contribution to watershed characteristics it was necessary to obtain observed values of baseflow. The Baseflow Program (Arnold et al., 1995) was used to estimate baseflow from daily streamflow data. All monitoring stations in Wisconsin (USGS, 2014) that met the requirements of the Baseflow Program were used, excluding sites with upstream watersheds less than 50 km^2 or greater than 1,000 km^2 (Arnold et al., 2000).

This algorithm requires continuous daily observations of streamflow for at least one year, from which it determines the baseflow contribution from the hydrograph. After the observed data were downloaded, they were processed to ensure that only contiguous periods of streamflow of at least one year were used in the routine. For this analysis gaps of up to nine days were allowed in the record and still considered contiguous. If a monitoring site had a gap(s), of longer than nine days, it was split at the gaps into separate records and each part assessed as to whether it contained at least a year of data. Therefore, it was possible for a monitoring site to have several periods of contiguous streamflow records. If a record spanned less than one year of data it was not used in the analysis.

The Baseflow Program was run at each USGS gage site and the program output, which is the ALPHA_BF parameter in SWAT, was computed (Arnold et al., 1995). This smoothing algorithm produces several outputs, one for each successive pass of the smoothing filter. The final pass (third and smoothest) was used in the regression model. For sites with multiple records, the Baseflow program values were averaged, weighting the values by the length of the record. The end result was an ALPHA_BF value for each monitoring station that satisfied the requirements for the Baseflow Program filtering algorithm.

The resulting ALPHA_BF estimates from the Baseflow Program were site-specific, and thus were only valid for upstream subbasins. To parameterize ALPHA_BF for ungaged subbasins, we fit a multiple linear regression model to predict Bflow using upstream watershed characteristics. Data regarding the landscape characteristics of the watershed for each monitoring station were retrieved from WHDPlus (Diebel et al., 2013). Additionally, the Environmental Protection Agency's (EPA) Ecoregion boundaries level III were used as a categorical predictor. We tested a suite of geologic, soil, and topographic watershed characteristics that could potentially affect baseflow by calculating Pearson correlation coefficients and visually analyzing scatterplots. We made an effort to avoid overfitting and multicollinearity by excluding collinear predictors. The final model was selected based on R^2 (Figure 10). We used residual plots to examine evidence of model bias. The best model (eq. 4) used average slope of watershed, average permeability, and the EPA ecoregion boundaries. The ecoregion boundaries were used as a factor on the watershed slope term. The ecoregion term with slope was meant to allow for the expression of the effect

[22] The code used to carry out these and the following tasks is available here: `https://github.com/dnrwaterqualitymodeling/wisconsinRiverTMDL/tree/model_setup_public/groundWater/baseFlow`

of slope on the baseflow contribution in different regions in the WRB ()e.g., different slope terms for the Driftless Area and the Central Sands).

$$\boldsymbol{A} = \beta_0 + \beta_1 \boldsymbol{E_1} \boldsymbol{S} + \beta_2 \boldsymbol{E_2} \boldsymbol{S} + \beta_3 \boldsymbol{E_3} \boldsymbol{S} + \beta_4 \boldsymbol{E_4} \boldsymbol{S} + \beta_4 \boldsymbol{P} \tag{4}$$

Where $\boldsymbol{A}$ represents the SWAT ALPHA_BF parameter controlling baseflow, $\boldsymbol{P}$ is average surface permeability of the watershed, $\boldsymbol{S}$ is the average slope of the watershed, while $\boldsymbol{E_x}$ are dummy variables denoting one of four ecoregion within the WRB (i.e., the slope term of $\boldsymbol{S}$ varies by ecoregion).

This model was used to predict the ALPHA_BF for every small watershed in the WHDPlus dataset. An area weighted average of these small watersheds was taken for each SWAT subbasin to aggregate the ALPHA_BF predictions. These values were used to update ALPHA_BF in the groundwater files for each subbasin. The resulting distribution of the ALPHA_BF parameter in the WRB can be found in Figure 11.

4.7.2 Baseflow Phosphorus

The baseflow component of background phosphorus is not simulated by default in SWAT and so the parameter controlling soluble phosphorus in groundwater (GW_SOLP) needs to be populated manually. Rather than estimating a value of baseflow phosphorus concentrations for the whole WRB, we attempted to regionalize this parameter. In the Wisconsin River Basin SWAT model, we used values of reference baseflow phosphorus from a USGS study of nutrient concentrations in wadeable streams in Wisconsin (Robertson et al., 2006a). In their study, Robertson et al. (2006a) used a multiple linear regression equation to predict reference phosphorus in nutrient boundaries known as "environmental phosphorus zones", which they use as a way of dividing the state into smaller homogeneous regions. These zones were derived in an earlier study by Robertson et al. (2006b).

For each of the phosphorus zones, the percent land area in agricultural use and percent land in urban use was calculated along with the number of point sources. Using these variables, a multiple linear regression model predicting the concentration of phosphorus was fitted. To represent the scenario where human impact is negligible, the values of the predictors of this model (all of which represent human impact) are set to zero. With the predictors set to zero (i.e., model intercept), the predicted value of the model is the median phosphorus concentration when human impact is zero (Equation 5). The SWAT subbasins were overlaid with the phosphorus zones, and the predicted reference phosphorus was calculated for each subbasin using an area-weighted average. These reference phosphorus levels were input into SWAT using the groundwater soluble phosphorus parameter.

$$\boldsymbol{P} = e^{\beta_0 + \beta_1 \boldsymbol{A} + \beta_2 \boldsymbol{U} + \beta_3 log_{10}(\boldsymbol{O})} \tag{5}$$

Here, $\boldsymbol{A}$, $\boldsymbol{U}$, and $\boldsymbol{O}$ are the percent of the watershed in agricultural and urban landuse and the number of point source outfalls, respectively. When these are set to zero, the equation reduces to simply:

$$\boldsymbol{P} = e^{\beta_0} \tag{6}$$

The resulting distribution of the groundwater phosphorus in the WRB can be found in Figure 12.

Robertson et al. (2006a) intend their background phosphorus values to estimate median phosphorus concentration in streams when there is no human impact in the watershed. They do not specifically estimate the groundwater or baseflow contribution to reference phosphorus concentration. We assume that the median reference phosphorus estimate is an accurate estimate of baseflow phosphorus concentration because a landscape under natural conditions (that is one without human impact) will experience much less runoff, and that the median estimate represents low-runoff conditions (USDA-NRCS, 1986). Due to a lack of appropriate monitoring data, we are left to assume that this is our best estimate of baseflow phosphorus. However, as the development of the model progresses, we may discover patterns in the output phosphorus loads that provide insight into the quality of this assumption.

4.8 Reservoir Outflow

The Wisconsin River basin is a highly managed system with many reservoirs and hydroelectric dams. To calibrate the water budget of the SWAT model, we forced flow to match observed flow at impoundments where flow is measured. We assume that if flow is not measured, then the impoundment outfall flows with the run of the river. We forced flow to match observed values at the sites of 22 impoundments within the WRB (Table 10).

Reservoir geometries were taken from the WDNR Statewide Dam Database[23]. Principal volumes, emergency volumes, principal surface areas, and dam locations (Table 10) were taken from the columns MAX_STORAGE_ACFT_AMT, NORM_STORAGE_ACFT_AMT, IMPOUND_AC_AMT, and LL_LAT_DD_AMT and LL_LAT_DD_AMT, respectively. Estimates of emergency surface area do not exist for all reservoirs. It was therefore assumed that emergency surface area is 50% greater than principal surface area.

Outflow of all SWAT subbasins with reservoirs were forced to daily flow measurements. Daily flow measurements were compiled from the USGS National Water Information System (NWIS) (USGS, 2014) and the Wisconsin Valley Improvement Company (WVIC) (personal communication with Peter Hansen). For each daily time series, we inspected the hydrograph and only used data from dams that clearly regulated flow. If the hydrograph did not appear as though the dam regulated flow, we did not force outflow of the associated subbasin to the daily observed time series, but rather estimated flow in the same way we estimate flow at the outflow of all ungaged subbasins.

[23] http://dnr.wi.gov/topic/Dams/documents/StatewideDamData.zip

4.9 Streamflow calibration sites

Stream flow will be calibrated to daily discharge data using data from USGS gaging stations throughout the WRB (Figure 13). Subbasins in the WRB SWAT model were delineated at the pour point of each USGS gage site. Table 11 lists the gages that were used for various subbasins and the years of data that will be used for calibration. Not all gages within the WRB will be used as calibration points. The discharge records for all gages will be analyzed to only include sites where discharge was not regulated by dams or other human impoundments or affected by impervious surfaces from human development. Gages that exhibited a regulated hydrograph will not be used for calibration.

5 Conclusion

The methods described here illustrate the preliminary framework used to configure the WRB SWAT model. The parameters calculated for this initial SWAT configuration represent a basic level of detail for known, or well-estimated values that represent physical processes within the basin. These parameters do not fully represent hydrologic processes within the WRB—a number of parameters have been reserved for calibration, or future estimation as we learn more about the hydrologic system during the calibration phase of the project. During the calibration phase, we may find that parts of the model configuration described in this document are inappropriate or inaccurate. Although it is good practice to limit the number of adjusted parameters for the sole purpose of model-fitting, the parameters that were estimated using the methods described in this document may change as we compare the model results to measured data. If these parameters change during the calibration phase, they will likely be adjusted to preserve regional patterns and processes.

We made every effort to configure the model in the most robust and accurate way possible. We accounted for the scale of the WRB analysis in the spatial and temporal data configuration, and thus it was necessary to ignore certain phenomena (e.g., septic systems and barnyards). The project team is only midway through the complete development and now invite review and comments that may improve the development and accuracy of the model.

6 Tables

Table 1: Soil attributes used in SWAT and the methods used to cluster SSURGO map units. The listed soil attributes are all soil properties used in SWAT. Not all these properties were used to cluster soil map units. The aggregation method is the aggregation function used to simplify the properties used in the clustering algorithm. Also listed are the original tables where the soil properties are located in SSURGO.

Variable	Used in clustering?	Aggregation method	SSURGO table	Column name
Albedo dry	Yes	surface horizon	component	albedodry_r
Available water capacity (cm/cm)	Yes	depth-weighted mean	chorizon	awc_r
Bulk density (g/cm^3)	Yes	depth-weighted mean	chorizon	dbovendry_r
Calcium carbonate (%)	No	depth-weighted mean	chorizon	caco3_r
Clay (%)	Yes	depth-weighted mean	chorizon	claytotal_r
Electric conductivity (dS/m)	No	depth-weighted mean	chorizon	ec_r
Horizon depth (mm)	Yes	Sum of all horizons	chorizon	hzdepb_r
Hydrologic soil group	Yes	category*	component	hydgrp_r
Organic carbon (%)	Yes	depth-weighted mean	chorizon	cbn_r
pH	No	depth-weighted mean	chorizon	ph1to1h2o_r
Rock fragments (%)	No	depth-weighted mean	chfrags	fragvol_r
Sand (%)	Yes	depth-weighted mean	chorizon	sandtotal_r
Saturated conductivity ($\mu m/sec$)	No	depth-weighted mean	chorizon	ksat_r
Silt (%)	Yes	depth-weighted mean	chorizon	silttotal_r
USLE** erodibility	Yes	surface horizon	chorizon	usle_kwfact

**Prior to clustering, map units were first categorized by Hydrologic Soil Group (HSG).*

***Universal Soil Loss Equation*

Table 2: Number of mapunits in each cluster.

Cluster Number	A	B	C	D
1	33	79	51	36
2	72	50	42	17
3	57	152	18	15
4	45	41	11	15
5	54	284	36	9
6	32	120	16	12
7	NA	68	12	6
8	NA	70	25	11
9	NA	NA	6	10

Table 4: Climate stations providing temperature and precipitation data for the Wisconsin River Basin. The number of subbasins using each climate station and the corresponding area are given.

Station	Precipitation		Temperature	
	# of Subbasins	Area (km^2)	# of Subbasins	Area (km^2)
USC00478018	NA	NA	7	1012
USC00475364	17	2013	10	959
USC00473405	4	955	4	955
USC00478241	NA	NA	19	814
USC00479236	6	782	5	753
USC00478171	11	1049	7	752
USC00478324	NA	NA	5	735
USC00475164	9	846	8	717
USC00473182	NA	NA	4	631
USC00477121	NA	NA	10	630
USC00472447	NA	NA	7	589
USC00470456	NA	NA	3	583
USC00475786	5	581	5	581
USC00471155	NA	NA	5	565
US1WIAD0002	NA	NA	4	535
US1WILN0002	NA	NA	3	517
USC00476122	5	503	4	482
US1WIMN0004	NA	NA	12	474
USC00477349	1	443	1	443
US1WIMT0003	NA	NA	3	438
USC00475516	6	432	6	432
USC00475178	20	674	14	407
USC00470239	2	430	4	375
USC00475120	28	1186	9	373
USC00477113	4	545	3	368

Continued on next page

Table 4 – *Continued from previous page*

Station	Precipitation		Temperature	
	# of Subbasins	Area (km^2)	# of Subbasins	Area (km^2)
US1WIMT0001	NA	NA	2	364
USC00477480	8	461	5	358
USC00472314	22	1176	12	351
USW00054903	6	450	2	341
US1WION0006	NA	NA	1	308
US1WIWD0001	NA	NA	5	308
USC00477142	12	1192	6	292
USW00094985	12	626	2	278
USC00479319	9	478	5	271
USC00472973	8	792	4	257
US1WIWD0004	NA	NA	8	247
USC00470516	10	277	8	246
US1WIPT0001	NA	NA	3	227
USC00470308	3	200	3	200
US1WICB0004	NA	NA	2	189
USC00478288	NA	NA	4	183
USC00476518	NA	NA	3	176
US1WIWD0002	NA	NA	4	159
USC00473654	15	495	4	145
USC00475255	11	856	3	144
USC00473636	1	142	1	142
USC00477115	2	234	1	141
USC00474790	4	139	4	139
US1WIMT0004	NA	NA	3	129
USC00477140	NA	NA	3	122
US1WION0002	NA	NA	2	113
USC00471970	6	192	5	111
USC00477319	5	278	2	110
USC00474422	NA	NA	3	104
USC00476796	3	129	2	94
USC00477118	NA	NA	1	93
USC00474383	NA	NA	1	82
USC00477052	9	266	3	78
USC00476718	3	186	1	65
USC00474424	11	374	1	61
USW00014897	21	1665	1	61
USC00473650	2	101	1	54
USC00476357	3	87	1	51
USW00004826	11	853	3	43
US1WICB0005	NA	NA	1	35
US1WIMN0001	NA	NA	2	34

Continued on next page

Table 4 – *Continued from previous page*

Station	Precipitation		Temperature	
	# of Subbasins	Area (km^2)	# of Subbasins	Area (km^2)
USC00479345	NA	NA	2	29
US1WIVL0007	NA	NA	2	28
USC00479335	5	184	1	27
US1WISK0002	NA	NA	1	18
USC00478969	NA	NA	1	17
US1WISK0005	NA	NA	1	8
USC00473651	1	44	0	0
USC00476838	1	156	0	0
USC00207812	1	24	NA	NA
USC00476859	4	234	NA	NA
USC00477997	4	133	NA	NA
USR0000MWAT	1	82	NA	NA
USR0000WANT	4	366	NA	NA
USW00004803	2	392	NA	NA

Table 3: Soil property data for the first horizon of each cluster. Total depth is the depth of entire profile, not just the horizon. Abbreviations: D_B is bulk density, AWC is available water capacity, K_{sat} is saturated conductivity, C is carbon percentage, clay is percentage of clay-size particles, and sand is percentage of sand size particles.

Soil Class	Total Depth (mm)	D_B (g/cm^3)	AWC (cm/cm)	K_{sat} ($\mu m/s$)	C (%)	Clay (%)	Sand (%)
A1	1525	0.00	0.46	125.37	37.25	0.00	0.00
A2	1521	1.58	0.10	185.52	0.61	6.25	83.37
A3	1528	1.63	0.09	267.17	0.61	3.77	84.64
A4	1455	1.30	0.27	185.29	17.88	2.21	44.51
A5	1806	1.58	0.14	243.14	4.24	4.59	71.70
A6	1523	1.65	0.07	271.49	0.47	3.49	93.86
B1	1520	1.55	0.18	50.53	0.94	12.48	47.51
B2	1537	1.50	0.22	27.17	0.93	19.04	12.22
B3	1520	1.59	0.13	94.29	0.68	8.55	70.05
B4	1544	1.58	0.12	195.90	2.00	6.71	75.42
B5	1523	1.52	0.20	42.73	1.07	13.44	38.50
B6	1578	1.45	0.20	50.08	5.19	11.79	36.19
B7	1533	1.57	0.15	40.36	1.61	6.84	62.35
B8	2003	1.51	0.22	27.73	0.74	18.15	12.74
C1	1521	1.55	0.20	27.66	0.90	12.32	29.21
C2	1520	1.56	0.18	36.30	0.92	11.11	49.20
C3	1710	1.60	0.18	24.39	0.74	20.46	27.03
C4	1520	1.58	0.14	52.02	0.97	10.45	62.91
C5	1732	1.51	0.19	54.78	3.14	9.04	41.07
C6	1526	1.49	0.22	27.46	1.23	16.13	14.31
C7	1529	1.63	0.13	274.05	2.88	6.00	76.92
C8	1583	1.49	0.20	26.05	1.04	20.47	23.93
C9	2072	1.41	0.18	64.26	4.88	5.00	55.33
D1	1520	1.52	0.18	69.54	2.53	13.67	46.29
D2	1521	0.95	0.40	68.93	34.45	1.64	5.50
D3	760	1.36	0.19	29.40	1.48	17.53	34.80
D4	1520	1.61	0.17	52.55	0.84	14.04	51.78
D5	1813	1.66	0.18	16.90	2.36	28.73	20.09
D6	1552	1.43	0.26	215.82	15.40	2.66	41.92
D7	1520	0.00	0.40	66.00	38.75	0.00	0.00
D8	1520	1.39	0.24	27.71	4.35	22.94	8.00
D9	1797	1.25	0.20	50.65	5.10	7.76	39.68
W	25	0.00	0.00	600.00	0.00	0.00	0.00
X	417	1.78	0.02	157.56	0.49	5.86	78.24

Table 5: Different evapotranspiration equations and their percent bias and Nash-Sutcliffe coefficients.

ET Method	Percent bias	Nash-Sutcliffe
Hargreaves	204.730	-17.873
Penman-Monteith	30.645	-4.491
Priestley-Taylor	42.090	-5.089

Table 6: The agricultural land cover classes represented within SWAT are shown here with the class of land use and land management. The rotation codes are Cg=corn grain, Cs=corn silage, So=soybean, Po=potato, Vg=vegetable, A=Alfalfa, O/A=oats/alfalfa. Tons are English tons. Note that the SWAT Landuse is a code used by SWAT and is a placeholder for unique agricultural practices and are not truly representative of the landcover and is only included here for reference.

SWAT Landuse	Type	Definition
SWHT	Dairy	Cg-Cs-O/A-A-A-A - Spring Chisel - 10,000 ga/acre/year Liquid Manure
WWHT	Dairy	O/A-A-A-A-Cg-Cs - Spring Chisel - 10,000 ga/acre/year Liquid Manure
DWHT	Dairy	A-A-Cg-Cs-O/A-A - Spring Chisel - 10,000 ga/acre/year Liquid Manure
RYE	Dairy	Cg-Cs-O/A-A-A-A - Spring Chisel - 25 tons/acre/year Solid Manure
BARL	Dairy	O/A-A-A-A-Cg-Cs - Spring Chisel - 25 tons/acre/year Solid Manure
OATS	Dairy	A-A-Cg-Cs-O/A-A - Spring Chisel - 25 tons/acre/year Solid Manure
RICE	Dairy	Cg-O/A-A-A-A-A - Spring Chisel - 25 tons/acre/year Solid Manure
PMIL	Dairy	A-A-A-A-Cg-O/A - Spring Chisel - 25 tons/acre/year Solid Manure
TIMO	Dairy	A-A-Cg-O/A-A-A - Spring Chisel - 25 tons/acre/year Solid Manure
BROS	Dairy	Cg-Cs-O/A-A-A-A - Fall Chisel - 10,000 ga/acre/year Liquid Manure
BROM	Dairy	O/A-A-A-A-Cg-Cs - Fall Chisel - 10,000 ga/acre/year Liquid Manure
FESC	Dairy	A-A-Cg-Cs-O/A-A - Fall Chisel - 10,000 ga/acre/year Liquid Manure
BLUG	Dairy	Cg-Cs-O/A-A-A-A - Fall Chisel - 25 tons/acre/year Solid Manure
BERM	Dairy	O/A-A-A-A-Cg-Cs - Fall Chisel - 25 tons/acre/year Solid Manure
CWGR	Dairy	A-A-Cg-Cs-O/A-A - Fall Chisel - 25 tons/acre/year Solid Manure
WWGR	Dairy	Cs-Cs-O/A-A-A-A - Fall Chisel - 10,000 ga/acre/year Liquid Manure
SWGR	Dairy	O/A-A-A-A-Cs-Cs - Fall Chisel - 10,000 ga/acre/year Liquid Manure
RYEG	Dairy	A-A-Cs-Cs-O/A-A - Fall Chisel - 10,000 ga/acre/year Liquid Manure
RYER	Dairy	Cs-Cs-O/A-A-A-A - Fall Chisel - 25 tons/acre/year Solid Manure
RYEA	Dairy	O/A-A-A-A-Cs-Cs - Fall Chisel - 25 tons/acre/year Solid Manure
SIDE	Dairy	A-A-Cs-Cs-O/A-A - Fall Chisel - 25 tons/acre/year Solid Manure

Continued on next page

Table 6 – *Continued from previous page*

SWAT Landuse	Type	Definition
BBLS	Dairy	Cs-Cs-O/A-A-A-A - Fall MB Plow - 10,000 ga/acre/year Liquid Manure
LBLS	Dairy	O/A-A-A-A-Cs-Cs - Fall MB Plow - 10,000 ga/acre/year Liquid Manure
SWCH	Dairy	A-A-Cs-Cs-O/A-A - Fall MB Plow - 10,000 ga/acre/year Liquid Manure
INDN	Dairy	Cs-Cs-O/A-A-A-A - Fall MB Plow - 25 tons/acre/year Solid Manure
ALFA	Dairy	O/A-A-A-A-Cs-Cs - Fall MB Plow - 25 tons/acre/year Solid Manure
CLVS	Dairy	A-A-Cs-Cs-O/A-A - Fall MB Plow - 25 tons/acre/year Solid Manure
CLVR	Dairy	Cg-Cs-O/A-A-A-A - Fall MB Plow - 10,000 ga/acre/year Liquid Manure
CLVA	Dairy	O/A-A-A-A-Cg-Cs - Fall MB Plow - 10,000 ga/acre/year Liquid Manure
SOYB	Dairy	A-A-Cg-Cs-O/A-A - Fall MB Plow - 10,000 ga/acre/year Liquid Manure
CWPS	Dairy	Cg-Cs-O/A-A-A-A - Fall MB Plow - 25 tons/acre/year Solid Manure
MUNG	Dairy	O/A-A-A-A-Cg-Cs - Fall MB Plow - 25 tons/acre/year Solid Manure
LIMA	Dairy	A-A-Cg-Cs-O/A-A - Fall MB Plow - 25 tons/acre/year Solid Manure
LENT	Cash Grain	Cg-Cg-So-Cg-Cg-So - Fall Chisel/Spring Disk
PNUT	Cash Grain	So-Cg-Cg-So-Cg-Cg - Fall Chisel/Spring Disk
FPEA	Cash Grain	Cg-So-Cg-Cg-So-Cg - Fall Chisel/Spring Disk
PEAS	Cash Grain	Cg-So-Cg-So-Cg-So - Fall Chisel/Spring Disk
SESB	Cash Grain	So-Cg-So-Cg-So-Cg - Fall Chisel/Spring Disk
COTS	Cash Grain	Cg-So-Cg-So-Cg-So - Fall Chisel/Spring Disk
COTP	Cash Grain	Cg-So-Cg-So-Cg-So - No Till
SGBT	Cash Grain	So-Cg-So-Cg-So-Cg - No Till
POTA	Cash Grain	Cg-So-Cg-So-Cg-So - No Till
SPOT	Potato/Vegetable	Po-Vg-Vg-Po-Vg-Vg - Deep Till Potato Years/Cultivate Vegetable Years
CRRT	Potato/Vegetable	Vg-Po-Vg-Vg-Po-Vg - Deep Till Potato Years/Cultivate Vegetable Years

Table 7: Statewide datasets used to define urban model area extent.

Model Area	Dataset
City and Village Municipal limits	TIGER 2010 Minor Civil Divisions ("State–based") with PL 94-171 Attributes
Urbanized Areas	TIGER 2010 Urban Areas Western Great Lakes
Open Water	Open water features (i.e. lakes, reservoirs, wide streams and rivers) as defined by the USGS 1:24,000 National Hydrography Dataset

Table 8: Municipal limits used to define the extent of major urban areas in the urban model area.

Model Area	Dataset
Marathon County City/Village/Town Limits	Marathon County Planning and Zoning
City of Baraboo Municipal Limits	City of Baraboo Public Works/Engineering
City of Marshfield Municipal Limits	City of Marshfield Engineering
City of Wisconsin Rapids Municipal Limits	City of Wisconsin Rapids Engineering

Table 9: Mapping data provided by permitted Municipal Separate Sewer System (MS4s) used to delineate urban model area reach-sheds.

MS4 Name	Outfall Mapping	Outfall Drainage Area Mapping	Source of Mapping Data	Contact
Baraboo	baraboo_outfalls.shp	stormbasins.shp	City of Baraboo	Tom Pinion
Kronenwetter	Figure 3 - Village MS4 Map-Vierbicher.pdf	Figure 3 - Village MS4 Map-Vierbicher.pdf	Village of Kronenwetter	Duane Gau
Marshfield	Outfalls	StormBasin*	City of Marshfield	Thomas Turchi
Merrill	2011 STORM SEWER MAP.dwg	2011 STORM SEWER MAP.dwg	Becher-Hoppe (on behalf of the City of Merrill)	Tonia Speener
Mosinee	Outfalls	Basins**	AECOM (on behalf of the City of Mosinee)	Daniel Rossiter
Rib Mtn	Outfalls	Project_basins***	Schoen Engineering (on behalf of Rib Mtn)	Kurt Schoen
Rothschild	Rothchild_basins	Rothchild_basins****	Village of Rothschild	Tim Vergara
Schofield	Outfalls.shp	Watersheds.shp	Becher-Hoppe (on behalf of the City of Schofield)	Archie Becher/ Kevin King
Wausau	MS4DrainageBasins.shp	StormOutfalls.shp	City of Wausau	Sean Gehin
Weston	NA	sti_districts.shp	Village of Weston	Michael Wodalski
Wisconsin Rapids	WIRapids_Outfalls.shp	MajorDrainageBasin.shp; MinorDrainage-Basin.shp	City of Wisconsin Rapids	Nick Dums

**Extracted from TMDL Sotrm Sewer and City Limits Data.mpk*
***Feature class within Mad_Slamm_Data.mdb*
****Feature class within Rib_Mountain_TMDL_data_Export.mdb*
*****Feature class within Rothchild.gdb*

Table 10: Geometries of Wisconsin River Basin reservoirs, where PVOL is principal volume, EVOL is emergency volume, PSA is principal surface area, and ESA is emergency surface area (data taken from Wisconsin Department of Natural Resources Dam Database, http://dnr.wi.gov/topic/Dams/documents/StatewideDamData.zip)

Dam name	Impoundment	PVOL ($ha \cdot m$)	EVOL ($ha \cdot m$)	PSA (ha)	ESA (ha)
Petenwell	Petenwell Flowage	40,125	67,484	9,324	13,986
Castle Rock	Castle Rock Flowage	21,222	38,441	5,649	8,474
Prairie Du Sac	Lake Wisconsin	14,796	23,831	3,642	5,463
Big Eau Pleine	Big Eau Pleine Reservoir	12,619	16,899	2,764	4,146
Willow River Reservoir	Willow Reservoir	9,350	12,532	3,091	4,636
Dubay	Lake Dubay	6,833	12,582	2,692	4,039
Rainbow Reservoir	Rainbow Flowage	6,167	7,294	1,815	2,723
Rice	Lake Nokomis, Rice River Flow	5,119	7,894	1,795	2,692
Kilbourn	Kilbourn Flowage	2,282	4,441	756	1,134
Spirit River Reservoir	Spirit River Flowage	2,146	3,454	848	1,272
Biron	Biron Flowage	2,011	2,798	860	1,291
Tomahawk	Lake Mohawksin	1,974	3,145	773	1,159
Rothschild	Lake Wausau	1,665	2,652	776	1,164
Stevens Point	Wisconsin River Flowage	1,468	1,850	847	1,271
Kings	Lake Alice	1,295	1,628	554	831
Mosinee	Mosinee Flowage	740	1,480	402	603
Buckatahpon	Buckatahpon	370	765	433	650
Rhinelander	Boom Lake And Thunder Lake	358	543	246	370
Lower Ninemile	Lower Ninemile	345	518	349	524
Sevenmile	Sevenmile	259	567	217	325
Little Saint Germain	Little Saint Germain	222	740	417	625
Merrill	Lake Alexander	74	136	66	100

Table 11: U.S. Geological Survey (USGS) gage sites chosen for streamflow calibration. Excluded sites from Figure 13 are not included here; the values in the "Number" column correspond to the labels in the figure.

Number	Site name	USGS ID	Drainage area (km^2)	Daily records	Start Date	End Date
2	Muskellunge Cr-Muskellunge L Outlet	05390680	12	3987	1-Jan-2002	30-Nov-2012
8	Spirit River at Spirit Falls	05393500	211	4383	1-Jan-2002	31-Dec-2013
9	Prairie River	05394500	477	4383	1-Jan-2002	31-Dec-2013
11	Pine River	05395063	306	1327	16-Apr-2010	2-Dec-2013
12	Big Rib River	05396000	785	1553	1-Oct-2009	31-Dec-2013
13	Eau Claire River	05397500	971	4383	1-Jan-2002	31-Dec-2013
15	Big Eau Pleine River	05399500	580	4383	1-Jan-2002	31-Dec-2013
16	Fenwood Creek	05399550	96	1553	1-Oct-2009	31-Dec-2013
17	Freeman Creek	05399580	69	1522	1-Oct-2009	30-Nov-2012
18	Little Eau Pleine River	05400220	414	1325	16-Apr-2010	30-Nov-2013
19	Plover River at Hwy 66	05400513	430	1371	1-Apr-2010	31-Dec-2013
22	Mill Creek at Hwy PP	05400718	329	1344	1-Apr-2010	4-Dec-2013
24	Tenmile Creek	05401050	190	4383	1-Jan-2002	31-Dec-2013
25	Big Roche a Cri Creek	05401556	370	1310	1-May-2010	30-Nov-2013
26	Yellow River at Babcock	05402000	557	4383	1-Jan-2002	31-Dec-2013
27	Yellow River at Necedah	05403000	1272	1341	1-May-2010	31-Dec-2013
28	Lemonweir River	05403500	1313	1341	1-May-2010	31-Dec-2013
30	West Branch Baraboo River at Hillsboro	05404116	101	4138	1-Jan-2002	30-Apr-2013
31	Baraboo River at Reedsburg	054041665	1002	884	1-Jul-2011	30-Nov-2013
32	Baraboo River near Baraboo	05405000	1577	4383	1-Jan-2002	31-Dec-2013

7 Figures

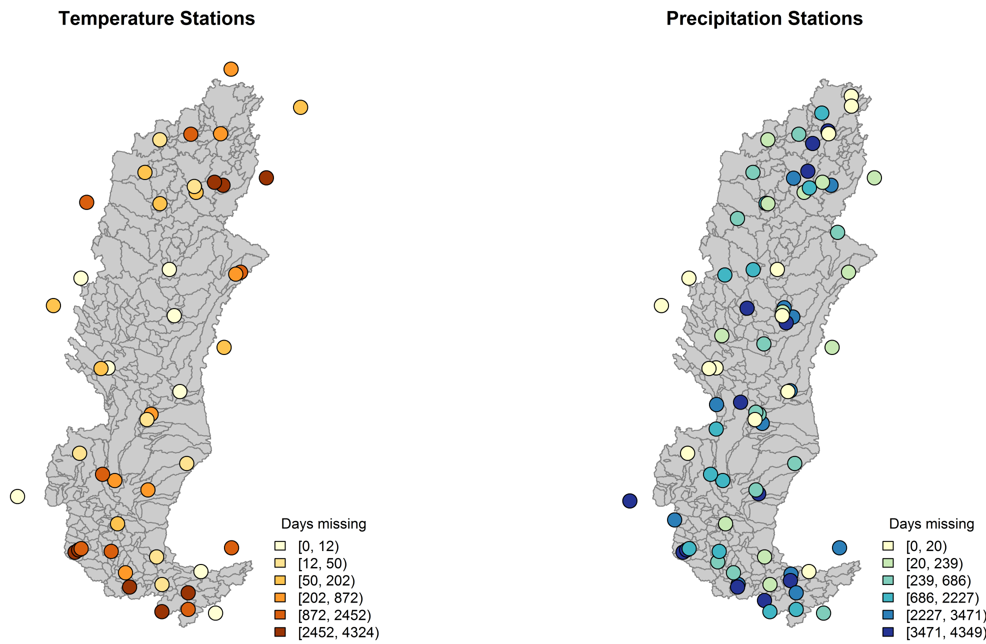


Figure 1: Maps displaying the climate stations used for in the SWAT model. Stations are colored according the number of days missing in the record.

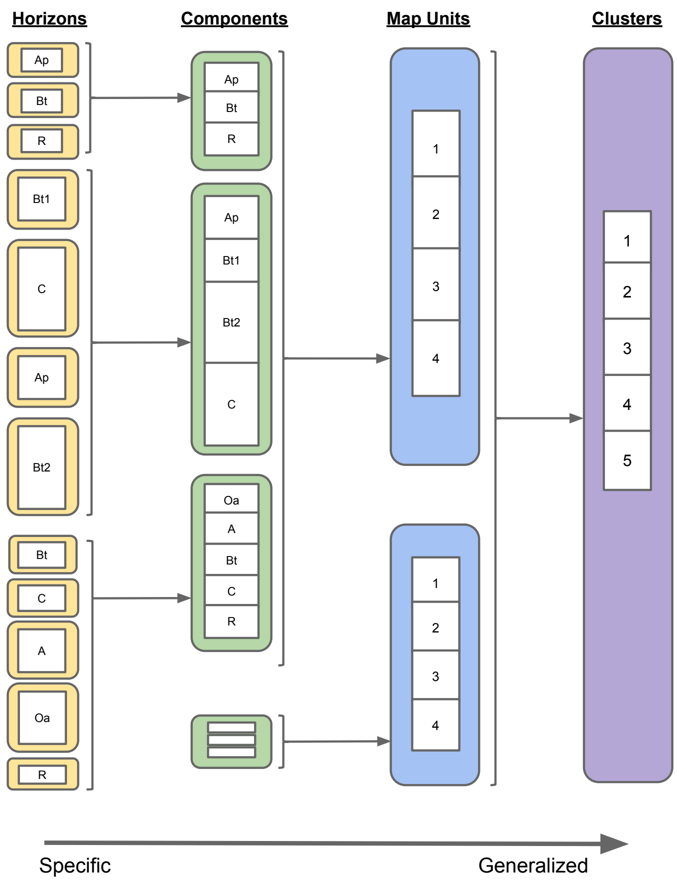


Figure 2: Flow diagram of the soil aggregation process. Horizons are grouped together according to which component they belong. Components are grouped together according to which map unit they belong. A weighted average is calculated, based upon the component percentage. Mapunits are grouped together according to hydrologic soil group and are then assigned to a cluster based on a clustering algorithm. Clusters are created by aggregated map units together using a depth-weighted average of soil properties for each horizon.

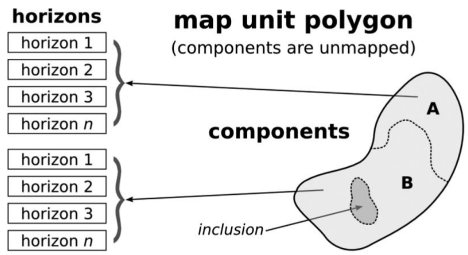


Figure 3: Schematic diagram of SSURGO data structure Gatzke et al. (2011)
.

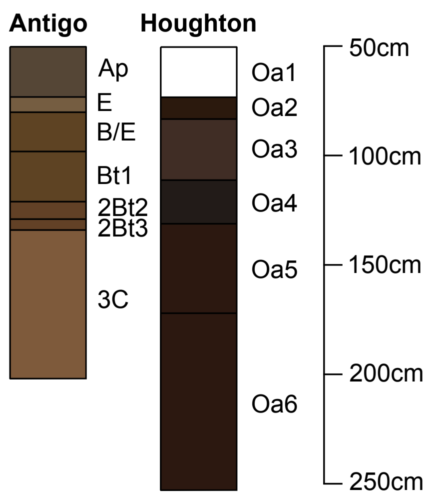


Figure 4: Schematic diagram of SSURGO map unit. Antigo* and Houghton are each components within the map unit. Within each map unit are varying numbers of components with varying horizon depths (e.g., Ap and O1 are the surface horizons for Antigo and Houghton respectively. Components were aggregated to map units by averaging soil properties (e.g., percent sand) horizontally across horizons.
*https://www.youtube.com/watch?v=Qe6I5GB_5iI

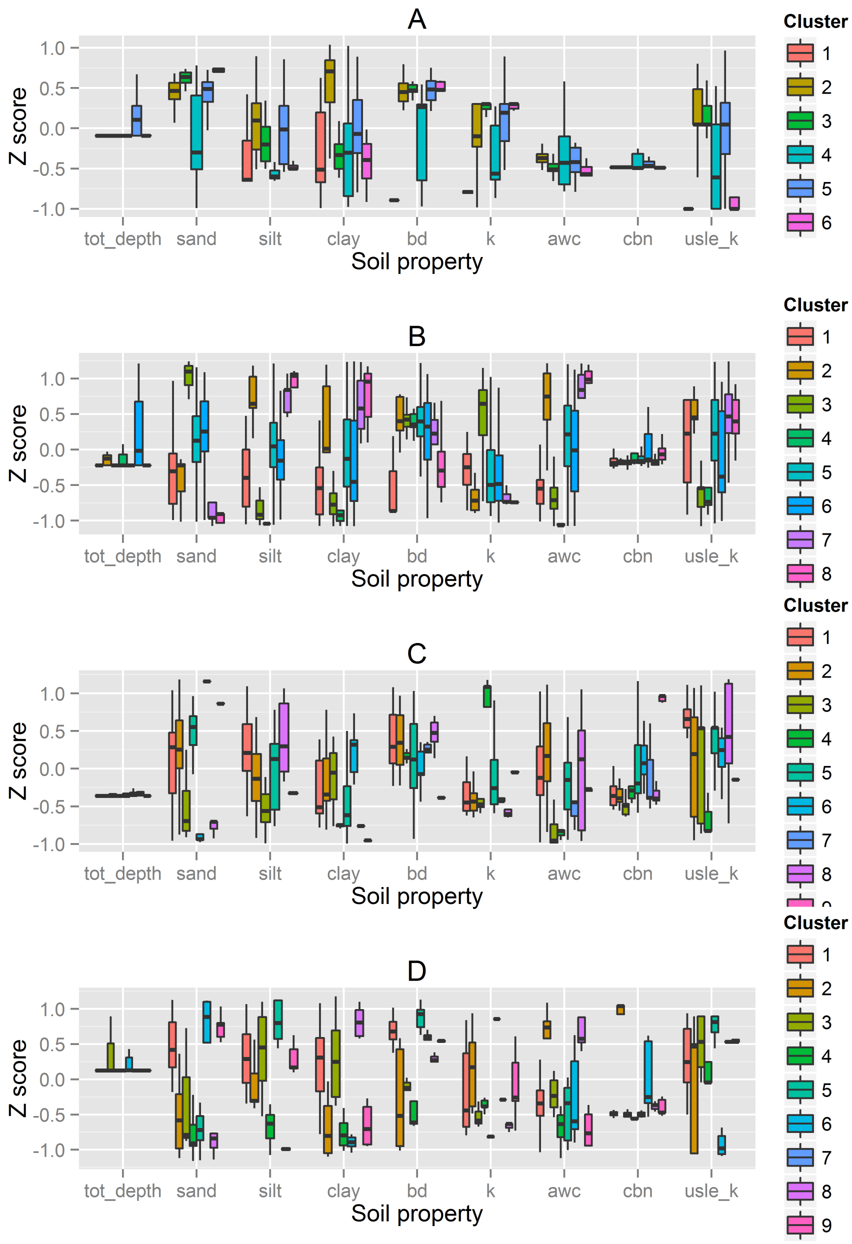
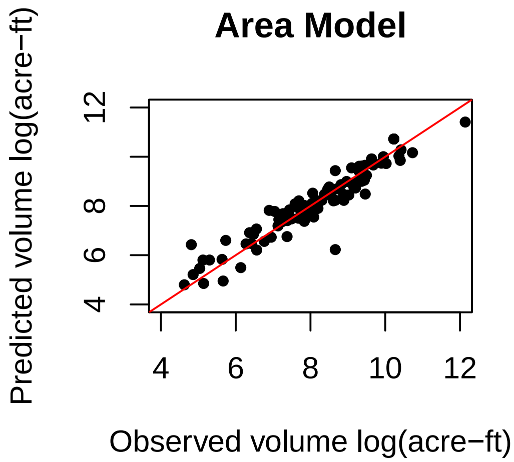


Figure 5: Boxplots showing the variability of soil properties within the final set of soil clusters. The letter above each plot denotes hydrologic soil group (HSG). Each color represents a cluster of map units. The Z score for each soil property is reported as $Z = X - \mu/\sigma$ where X is the value of the soil property, μ and σ are the population mean and standard deviation of a soil property. Outliers were excluded. The x-axis shows soil properties where tot_depth is the soil depth, sand/silt/clay are the percent composition of each texture class, bd is bulk density, k is saturated conductivity, awc is available water capacity, cbn is organic carbon concentration, and usle_k is soil erodibility.



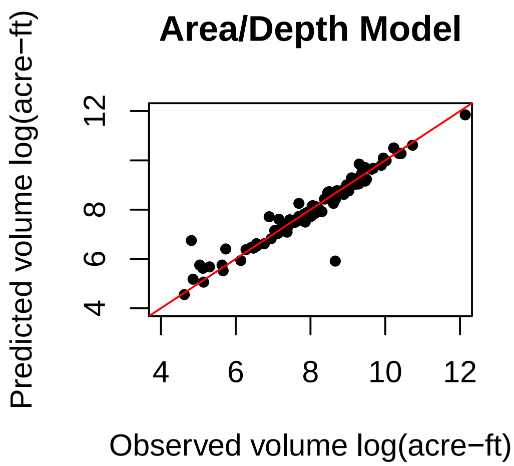


Figure 6: Scatterplots of observed versus predicted lake volumes used to parameterize geometric properties of ponds in SWAT. The area/depth model used lake surface area and maximum depth to predict lake volume and the area model used only lake surface area to predict its volume. The area/depth model explains 92% of the variability in volumes and the area model explains 89% of the variability in volumes.

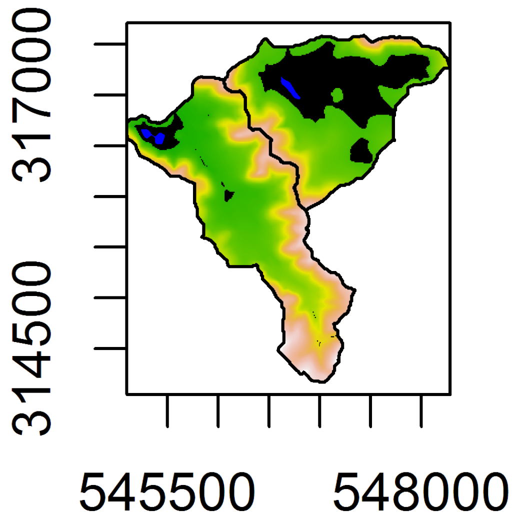


Figure 7: Example image of a filled digital elevation model (DEM) used to estimate maximum storage volume and surface area of landlocked lakes for parameterizing geometries of ponds in SWAT. The green to white gradient represents elevation from low to high. Blue polygons are landlocked lakes. Black polygons are the extent of grid cells associated with the internally draining area that flows to a landlocked lake. Black polygons not intersecting a landlocked lake were not used in surface area and volume calculations. The x and y axes are for scale—they are in units of meters from the origin of the Wisconsin Transverse Mercator projection.

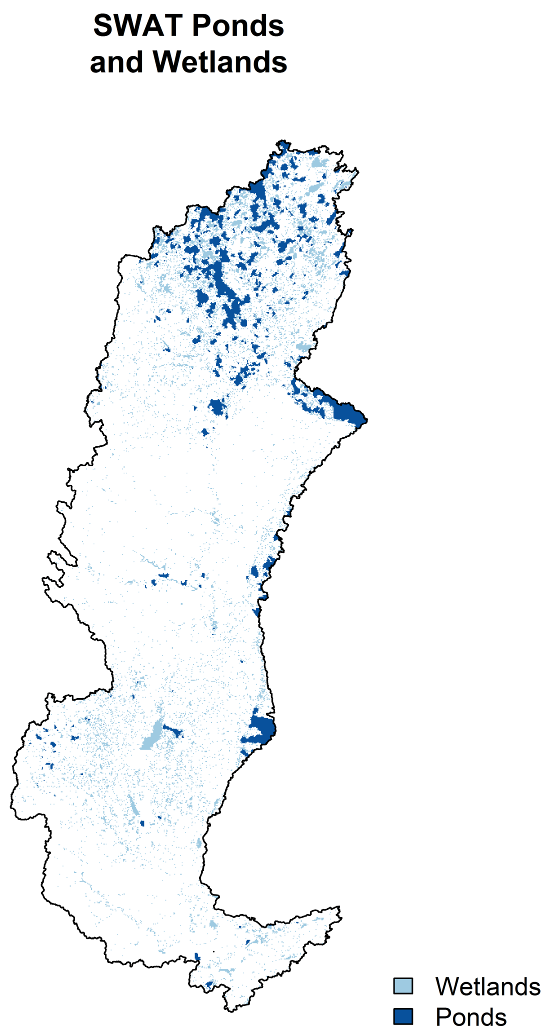


Figure 8: Map showing the contributing area of the SWAT ponds and wetlands in the Wisconsin River Basin.

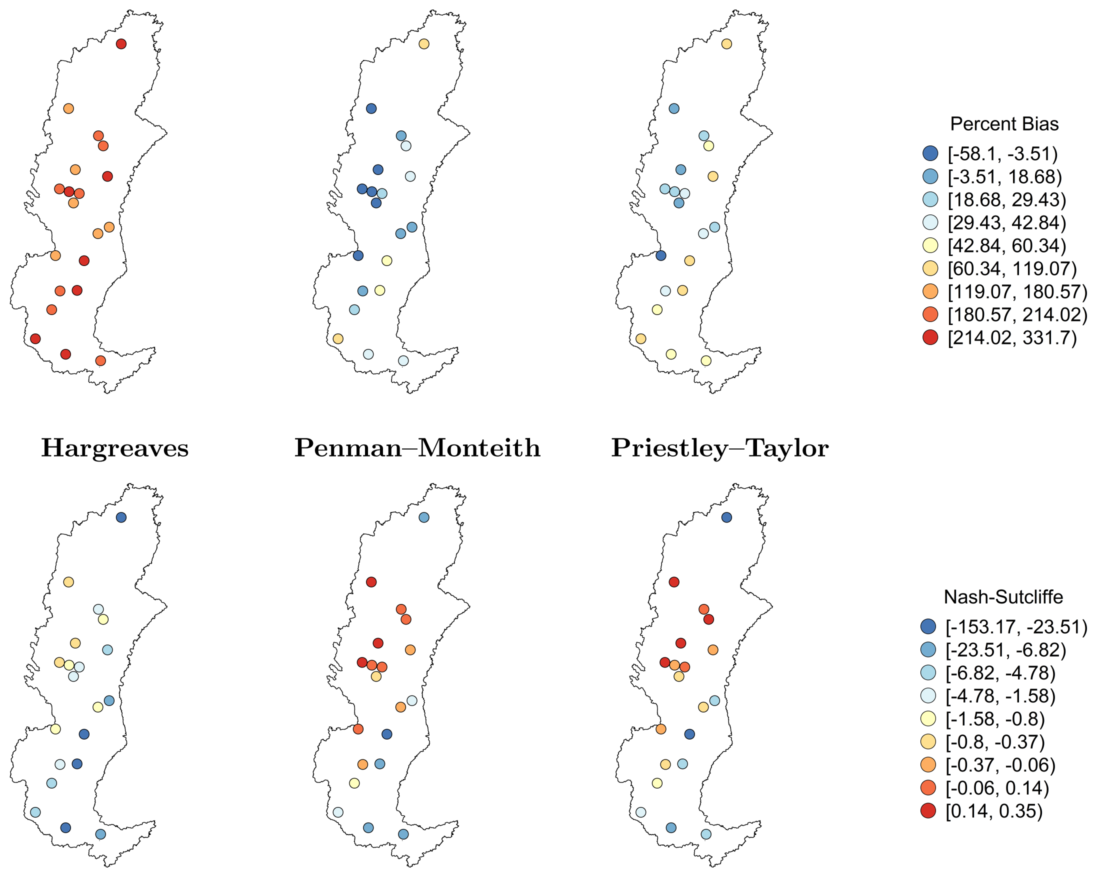


Figure 9: Three evapotranspiration methods were examined, Hargreaves, Penman–Monteith, and Priestley–Taylor (displayed left to right) each of which was assessed for how well the simulated streamflow matched observed streamflow sites, the value of each is displayed in each map. Each method was assessed using percent bias (top three maps) and the Nash-Sutcliffe model efficiency coefficient (bottom three maps). The Penman–Monteith equation provided the best fit to observed streamflow.

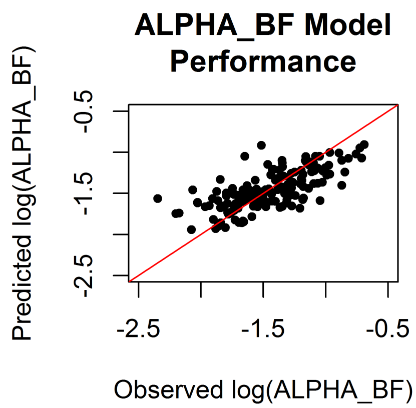


Figure 10: Observed versus predicted ALPHA_BF SWAT parameter. Observed ALPHA_BF was calculated for each USGS gage site (USGS, 2014) by the Baseflow Program (Arnold et al., 1995).

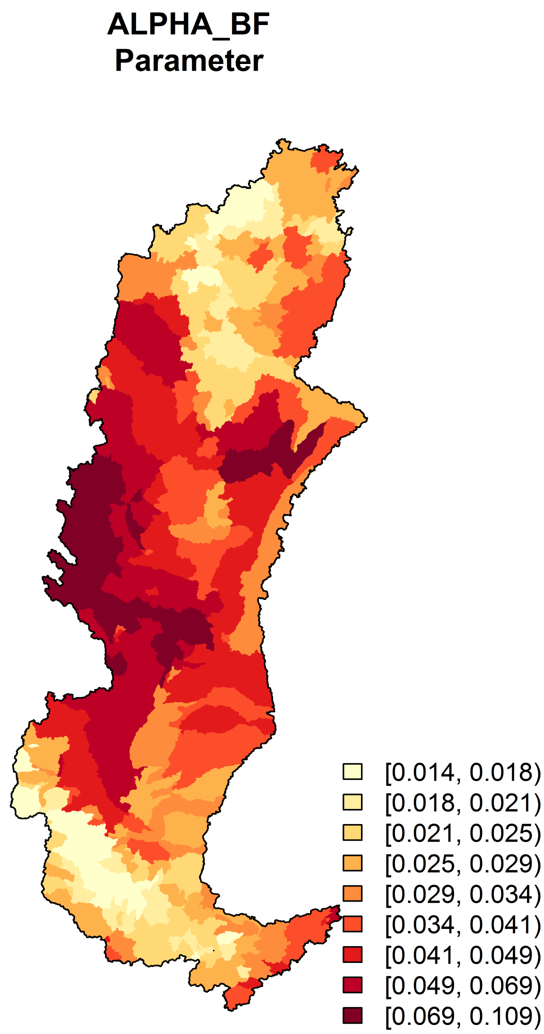


Figure 11: Map showing the predicted ALPHA_BF for each SWAT subbasin. Higher (darker) values indicate a slower response of groundwater to recharge and lighter values indicate greater baseflow.

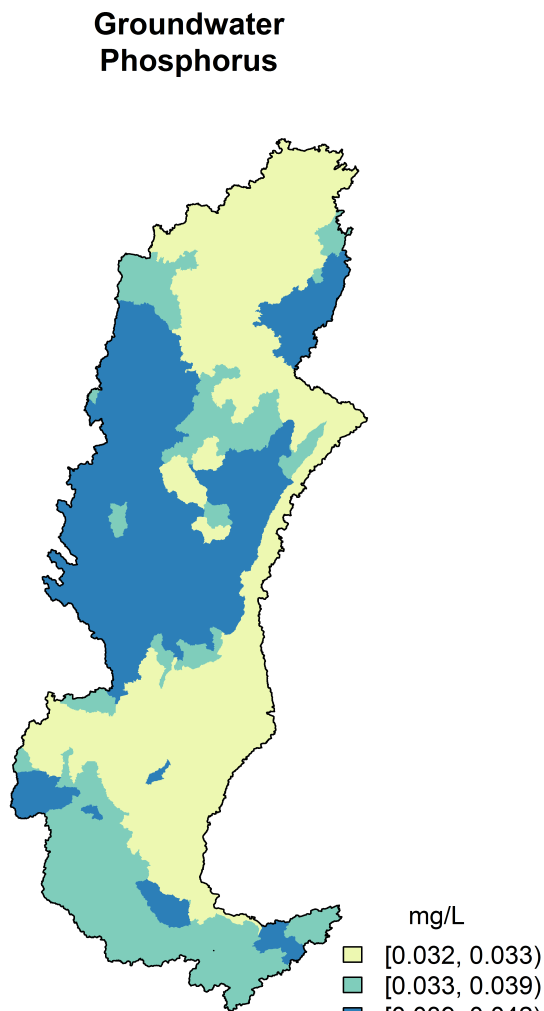


Figure 12: Map showing the estimated concentration of groundwater phosphorus in the Wisconsin River Basin. Values were obtained from Robertson et al. (2006b)

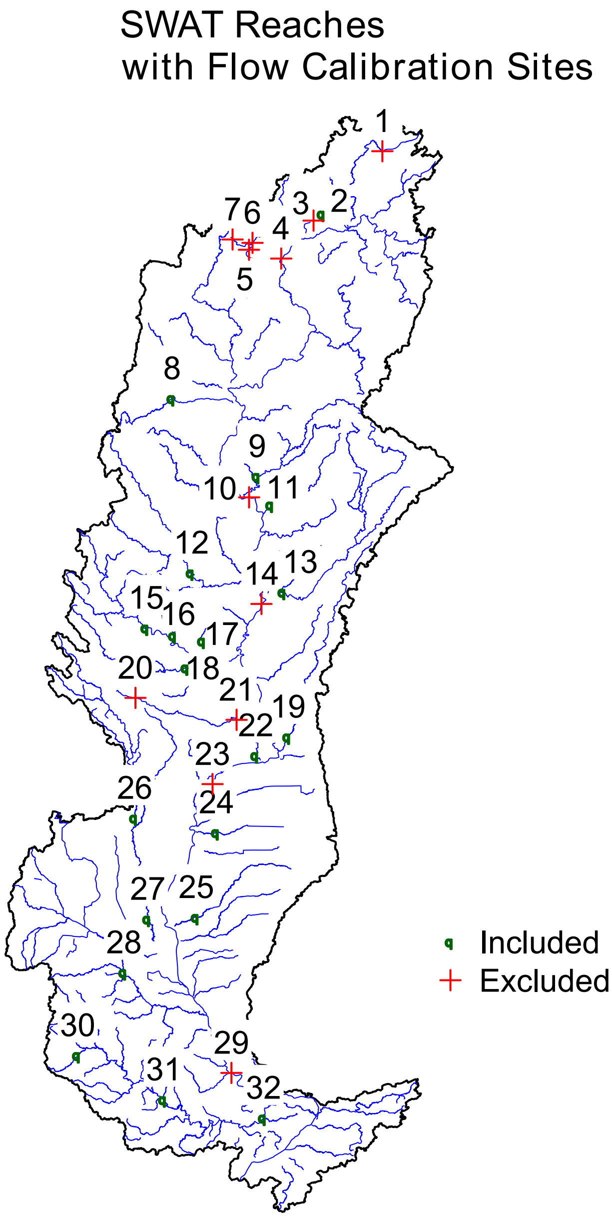


Figure 13: Flow monitoring sites. The sites marked "Included" are currently considered calibration sites. Those marked "Excluded" are downstream of reservoirs or other structures that regulate flow and so are not used for calibration. For more detailed information see Table 11.

References

J. E. Almendinger and M. S. Murphy. Constructing a SWAT model of the Willow River watershed, western Wisconsin. Technical report, Report to Legislative Commission on Minnesota Resources, St. Paul, MN, 2007. URL http://www.smm.org/static/scwrs/tapwaters_willowriver2.pdf.

J. E. Almendinger and J. M. Ulrich. Constructing a SWAT model of the Sunrise River watershed, eastern Minnesota. Technical report, St. Croix Watershed Research Station, Marine on St. Croix, MN, 2010. URL http://www.smm.org/static/scwrs/tapwaters_sunrise.pdf.

J. G. Arnold. *SWAT (Soil and Water Assessment Tool)*. Grassland, Soil and Water Research Laboratory, USDA, Agricultural Research Service, 1994.

J. G. Arnold, P. M. Allen, R. Muttiah, and G. Bernhardt. Automated base flow separation and recession analysis techniques. *Groundwater*, 33(6):1010–1018, 1995.

J. G. Arnold, R. S. Muttiah, R. Srinivasan, and P. M. Allen. Regional estimation of base flow and groundwater recharge in the Upper Mississippi River basin. *Journal of Hydrology*, 227(1):21–40, 2000.

P. Baumgart. Source allocation of suspended sediment and phosphorus loads to Green Bay from the Lower Fox River subbasin using the Soil and Water Assessment Tool (SWAT). Technical report, Prepared for Oneida Tribe of Indians of Wisconsin and Science and Technical Advisory Committee of the Green Bay Remedial Action Plan (RAP), 2005. URL http://www.uwgb.edu/watershed/reports/related_reports/load-allocation/lowerfox_tss-p_load-allocation.pdf.

D. E. Beaudette, P. Roudier, and A. T. O'Geen. Algorithms for quantitative pedology: A toolkit for soil scientists. *Computers & Geosciences*, 52:258–268, 2013.

N. C. Brady and R. R. Weil. *Elements of the nature and property of soils*. Pearson Education, New Jersey, 2004. ISBN 0130481038x.

M. Diebel, D. Menuz, and A. Ruesch. 1:24k hydrography attribution data. Technical report, Wisconsin Department of Natural Resources, 2013. URL ftp://dnrftp01.wi.gov/geodata/hydro_va_24k. Accessed 21 October, 2013.

C. Fraley, A. E. Raftery, T. B. Murphy, and L. Srucca. `mclust` version 4 for r: Normal mixture modeling for model-based clustering, classification, and density estimation. Technical Report 597, University of Washington, 2012. URL https://www.stat.washington.edu/research/reports/2012/tr597.pdf.

A. Freihoefer and P. McGinley. Mead Lake watershed sediment and nutrient export modeling. Technical report, Center for Watershed Science and Education, University of Wisconsin—Stevens Point, 2007. URL https://www.uwsp.edu/cnr-ap/watershed/Documents/mlw_swat.pdf.

S. E. Gatzke, D. E. Beaudette, D. L. Ficklin, Y. Luo, A. T. O'Geen, and M. Zhang. Aggregation strategies for SSURGO data: effects on SWAT soil inputs and hydrologic outputs. *Soil Science Society of America Journal*, 75 (5):1908–1921, 2011.

John Havlin, James D Beaton, Samuel L Tisdale, and Werner L Nelson. *Soil fertility and fertilizers: An introduction to nutrient management*. Pearson Prentice Hall Upper Saddle River, NJ, 7 edition, 2005.

B. Jokela and J. Peters. Dairy manure nutrients: variable but valuable, 2009. URL http://www.soils.wisc.edu/extension/wfapmc/dbsearch.php?yr=2009&auth=jokela&submit=Go.

K. Kirsch, A. Kirsch, and J. G. Arnold. Predicting sediment and phosphorus loads in the Rock River basin using SWAT. *Transactions of the ASAE*, 45 (6):1757–1769, 2002.

C. Laboski and J. Peters. Nutrient application guidelines for field, vegetable, and fruit crops in Wisconsin. Technical Report A2809, University of Wisconsin—Extension, 2012.

M. J. Menne, I. Durre, B. Korzeniewski, S. McNeal, K. Thomas, X. Yin, S. Anthony, R. Ray, R. S. Vose, B. E. Gleason, and T. G. Houston. Global Historical Climatology Network - Daily (GHCN-Daily). National Oceanic and Atmospheric Administration National Climatic Data Center (NCDC), 2012. URL ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/daily/. Accessed 13 August, 2014.

Natural Resources Conservation Service, Bureau of Water Quality, United States Department of Agriculture. The Gridded Soil Survey Geographic (gssurgo) database for Wisconsin, 2014. URL http://datagateway.nrcs.usda.gov. Accessed 29 October, 2014.

United States Department of Agriculture. Wisconsin conservation planning. Technical Report Note WI-1, Natural Resources Conservation Service, 2006.

United States Department of Agriculture. National agricultural statistics service cropland data layer, 2011. URL http://nassgeodata.gmu.edu/CropScape/. Accessed 1 May, 2013.

Wisconsin Department of Natural Resources. Wisconsin Wetlands Inventory. Technical Report WZ022-92, Bureau of Watershed Management, 1991. URL http://dnr.wi.gov/topic/wetlands/inventory.html. Accessed 9 August, 2012.

Wisconsin Department of Natural Resources. Wisconsin River Total Maximum Daily Load Technical Scope of Work. Technical report, Bureau of Water Quality, 2013. URL http://dnr.wi.gov/topic/TMDLs/documents/WisconsinRiver/Technical/WIRiverTMDLTechScope2013.pdf.

University of Wisconsin Extension. UW Extension Ag Weather, 2014. URL http://agwx.soils.wisc.edu/uwex_agwx/awon/. Accessed 05 November, 2014.

D. M. Robertson, D. J. Graczyk, P. J. Garrison, W. Lizhu, G. LaLiberte, and R. Bannerman. Nutrient concentrations and their relations to the biotic integrity of wadeable streams in Wisconsin. Technical Report 1722, United States Geological Survey, 2006a. URL http://pubs.usgs.gov/pp/pp1722/pdf/PP_1722.pdf.

D. M. Robertson, D. A. Saad, and D. M. Heisey. A regional classification scheme for estimating reference water quality in streams using land-use-adjusted spatial regression-tree analysis. *Environmental Management*, 37(2):209–229, 2006b.

United States Geological Survey. National water information system, 2014. URL http://waterdata.usgs.gov/nwis/. Accessed 27 August, 2014.

A. Timm and P. McGinley. SWAT model for Mill Creek, Portage and Wood Counties—Wisconsin. Technical report, Center for Watershed Science and Education. University of Wisconsin—Stevens Point, 2011.

United States Department of Agriculture. Urban hydrology for small watersheds. Technical Report TR-55, Natural Resources Conservation Service, Conservation Engineering Division, 1986. URL http://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/stelprdb1044171.pdf.

P. A. Vadas and M. J. White. Validating soil phosphorus routines in the SWAT model. *Transactions of the ASABE*, 53(5):1469–1476, 2010. ISSN 0001-2351.

Wisconsin Department of Natural Resources. Wisconsin lakes. Technical Report PUB-FH-800, Bureau of Fisheries and Habitat Management, 2009.

Wisconsin Department of Natural Resources. Land cover and agricultural management definition within the Upper Wisconsin River basin. Technical report, Bureau of Water Quality, 2014. URL http://dnr.wi.gov/topic/TMDLs/documents/WisconsinRiver/Technical/WRBLndManagmntJuly2014.pdf.