Estimations of loads and sources of phosphorus and sediment at ungaged sites in the Wisconsin River basin: preliminary notes on SWAT model configuration

Wisconsin Department of Natural Resources

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Contents

Abbreviations

ArcSWAT	ArcGIS plug-in software for SWAT configuration
CDL	Cropland Data Layer
DEM	Digital Elevation Model
EPA	Environmental Protection Agency
EVAAL	Erosion Vulnerability Assessment for Agricultural Lands
HRU	Hydrologic Response Unit
HSG	Hydrologic Soil Group
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
(g)SSURGO	(gridded) Soil Survey Geographic
SWAT	Soil Water Assessment Tool
TMDL	Total Maximum Daily Load
USDA	United States Department of Agriculture
USGS	United States Geological Survey
USLE	Universal Soil Loss Equation
WBD	Watershed Boundary Dataset
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 Watershed Assessment Model (SWAT) for the estimation of streamflow and sources of sediment and phosphorus in the Wisconsin River basin. It is a technical document that presumes the reader has a high level of familiarity with SWAT and the Wisconsin River TMDL. In fact, it is written specifically to water quality modelers to invite a critical review to 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 may change prior to the release of the final model given new findings 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/`

At a minimum, the basic SWAT configuration includes data for the following:

1. Subbasin delineations
2. Land cover
3. Soil
4. Topographic slope

These elements are used to define discrete model components. Combinations of these elements form discrete units in the model that SWAT defines as hydrologic response units, or HRUs. Each of these elements has been configured for the Wisconsin River SWAT model, and HRUs have been classified—both of these processes are described in this document. HRUs only provide a simple, physical representation of water-quality drivers, and therefore a number of additional datasets were compiled to provide supplemental information to aid in calibrating the model to streamflow, sediment, and phosphorus.

The additional datasets beyond just those for classifying HRUs supply information that are considered *a priori* to describe regionally specific physical and chemical process that impact streamflow and water quality. First and foremost, we compiled daily weather data for a large number of climate stations across the basin—although there is not enough topography within the basin to significantly impact weather, the Wisconsin River flows across enough latitude that the climate in the northern part of the basin is significantly different than that in the southern part. Therefore, a dense network of weather observations was necessary to adequately represent climatic geography. Additionally, the Wisconsin River spans several regions with very different hydrologic properties, mainly related to the storage capacity of the landscape. Specifically, internally draining areas due to recently glaciated landscapes were characterized using a terrain-based methodology, and groundwater flow contribution related to either highly permeable soils or hydrologic springs were characterized by modeling site-specific baseflow contribution with respect to a suite of watershed characteristics. Finally, the Wisconsin River is a highly managed system with many impoundments created for either water storage or generating electricity. Most reservoirs within the basin have monitoring stations located at their outfall—we used these data as well as reservoir geometric properties (e.g., surface areas and volumes) to more accurately model streamflow, sediment, and phosphorus.

Due to extent of data required to configure The Wisconsin River SWAT model, the products described above were created using a series of data processing scripts that can be executed using either the Python or R programming languages. To the extent possible, these scripts have been written in a way that intends to make the data processing transparent and reproducible. However, because the model is not complete in configuration or documentation, in most cases they 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 processing of spatial data. These scripts are publicly available on the website GitHub owned by the username `dnrwaterqualitymodeling`[1]. 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.

[1] `https://github.com/dnrwaterqualitymodeling`

2 Model Configuration

2.1 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 was used to set up the SWAT project and so the file structure was determined by this program.

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 on GitHub[2] website and the WDNR water quality modeling team's page. 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 2.2.7)
- "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[3] and `GeneralizeMergeLandManagementLa` is for creating a map of the land management types of the WRB (see Section 2.3)
- "et" — the scripts contained in the folder pertain to investigating the proper equation for modeling evapotranspiration in the WRB (see Section 2.2.7)
- "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 2.4.4 and 2.4.3)
- "hydrology" — `calculateRunoffUsingBaseflowSeparation.R` is a script for developing a 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.p`

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

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

merged the 2011 Cropland Data Layer (CDL) with the rasterized wetlands, a layer of CRP attributed field boundaries within the 2007 Common Land Unit dataset, and a layer of cranberry land developed by the Wisconsin DNR (see Section 2.2.4.

- "ponds" — these scripts were used in the processing and modeling to derive pond parameters for SWAT (see Section 2.4.1
- "soils" — scripts for determining which hydrologic soil group (HSG) to assign to dual HSG map units, for aggregating SSURGO data, and processing the soil phosphorus data (see Section 2.2.5
- "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 2.2.1)
- "wetlands" — script for calculating wetland parameters (see Section 2.4.2)

2.2 Model Input Data

2.2.1 Subbasin Delineation

To estimate sources of pollutants in a river, the first step is to delineate subbasins. The size of each subbasin is critical to water quality improvement following model development—they should be small enough that water quality improvement plans can address specific pollutant sources, while large enough that model results appropriately match the scale of model inputs and calibration data. Ultimately, the size of each subbasin depends on what the project is intending to achieve by simulating water quality, and therefore requires communication with water quality policy staff and watershed planners.

The Wisconsin River is a relatively large area for a TMDL project, and therefore much of the point and non-point load-reduction efforts will occur as nested projects within the overall TMDL framework. Each subbasin was scaled to a size that watershed managers and stakeholder groups can realistically account for and assess downstream improvements in water quality related to implementation of upstream best management practices.

In addition to the above guidelines, hydrologic and regulatory transitions were used to guide placement of subbasin transitions. TMDL subbasins were delineated:

1. to address specific water-quality impairments where local water quality does not meet codified standards; this is an EPA mandate for de-listing of water quality impairments. Consideration was given to streams that were estimated to be impaired, but where monitoring data does not exist to prove it.

2. near point source outfalls; delineations were not required to be at precisely the location of the outfall, but rather close enough that flow could be accurately estimated by proportionally scaling modeled flow by upstream contributing area.

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.

After the locations of subbasin outfalls were identified, we delineated the contributing area upstream of each. Rather than re-creating contributing areas from a DEM using ArcSWAT, we chose to aggregate contributing areas based on the Wisconsin Hydrography Dataset Plus[4] (WHDPlus, modeled after NHDPlus) which honors the undeveloped geomorphology of the recently glaciated portion of the Wisconsin River basin. We delineated 338 subbasins with an average size of 68 km2 ($\sigma = 80$ km2) where larger subbasins were located in areas with fewer water quality impairments and points sources.

2.2.2 Urban Delineation

2.2.3 Point Sources

2.2.4 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

[4] `ftp://dnrftp01.wi.gov/geodata/hydro_va_24k`

of Agriculture [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 30x30m for Wisconsin using satellite imagery from a variety of satellites (USDA, 2011). For non-agricultural land cover, the USDA NASS 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 the landcover definition, 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).

2.2.5 Soils

Soils are a critical part of the SWAT modeling framework; they determine many surface hydraulic properties such as texture, hydraulic conductivity, and available water capacity. We used the county-scale Soil Survey Geographical Database (SSURGO) [NRCS, 2014]. For more information about SSURGO data see SSURGO metadata[5]. The SSURGO database is structured by three levels of information: map units, components, and horizons, see Figure 2. 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 GIS users. 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. For more information about these parameters see the SSURGO metadata[6].

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, we aggregated soils together based on similarity of several key properties

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

[6] http://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2_053631

that impact the hydrologic cycle. This was a two step process: first, components within map units were aggregated together,[7] and second, map units were aggregated together based on similarity,[8] see figure 1.

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 organic matter (percent) 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 latter of which is the natural state of the soil if not artificially drained (e.g., through tiling or ditching) while the former is if the soil is drained. 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 and 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.

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 analog to the SSURGO *component* level in SWAT—in other words, soils in SWAT cannot be subdivided, see Figure 3. 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 depthGatzke et al. [2011], Beaudette et al. [2013]. 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. This achieved a robust average of the soil properties for each horizon, while also accounting for differing compositions 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 by using the weighted mean of the depths of the components, with the weights equal to the percent composition of each component. As the number of horizons was not seen 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 aggregated to 1,603 map units. Because the HRU used in SWAT is derived

[7] `https://github.com/dnrwaterqualitymodeling/wisconsinRiverTMDL/blob/master/soils/step1_aggregate_gSSURGO.R`

[8] `https://github.com/dnrwaterqualitymodeling/wisconsinRiverTMDL/blob/master/soils/step2_aggregate_gSSURGO.R`

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, classifies largely based on soil morphology and not necessarily on SWAT relevant properties. We decided that the most relevant soils information to SWAT is hydrology data, specifically the HSG, which has a large impact on the curve number calculation. 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, using a clustering algorithm. 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.

Each map unit 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 and robustly 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 algorithm we used was implemented within the `Mclust` function in the mclust package [Fraley et al., 2012] in R. 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 like hydrologic soil groups (say 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 cluster of sandier soils, shallow soils or slow saturated conductivity). Using the default settings of the function, the algorithm clustered all of the A HSG map units into 6 clusters, B HSG map units had 8 clusters and C and D had 9 clusters.

Each of the 1603 map units had data regarding the soil property values at each horizon. In this format it was thought that profile depth would have undue influence over the clustering algorithm, that is deep soils would cluster together and shallow soils cluster together regardless of the nature of the other properties, causing clusters to be entirely governed by depth. To remedy this issue, depth weighted averages of the horizons were taken to derive one value per soil property for each map unit; essentially collapsing the soil profile down to one aggregate horizon. Profile depth was still considered in the clustering algorithm by keeping the profile depth as a property and so in this way it is represented but does not dominate the clustering 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, which we did not use in the cluster analysis.

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. Those map units designated as miscellaneous were aggregated into one soil profile as the other clusters were, while the water map units were not aggregated. The miscellaneous grouping was assigned an HSG by converting the letter designation into an ordinal integer (that is A, B, C, D to 1, 2, 3, 4) and the average was taken, rounded to the nearest integer, and converted back to a letter, which happened to be B. Following SWAT convention, the water units were given an HSG of D, and assigned an albedo of 0.23, and a saturated conductivity of 600.

A total of 35 soil classes were distilled from this process. An example of the properties of each cluster can be seen 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 4. This figure shows the relative variability for each soil property for each cluster.

Soil Phosphorus concentrations were obtained through the University of Wisconsin Soil Testing Laboratory [9]. 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 so 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 6-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 (correspondence with Phillip Barak, needs citation). Soil phosphorus estimates are not included in the SWAT model provided—they will be included during the phosphorus calibration phase.

[9] `http://uwlab.soils.wisc.edu/`

2.2.6 Topographic Slope

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 m2 resolution). The slopes for each subbasin were grouped into five quantile classes. Each class contained approximately equal numbers of gridcells whose value fell wihin 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.

2.2.7 Climate

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. Data sets from 120 different stations were downloaded, from which precipitation data was taken from 74 stations, and temperature from 46. Weather data include precipitation and temperature. Climate data included solar radiation, wind speed, and relative humidity.

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 that did have data for that time period. For time periods missing climate data, the record was not supplemented with data from another station. Instead, the recommended option for SWAT is to allow the model to generate these values. The generated values were used for all missing solar radiation, wind speed, and relative humidity data.

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 Preistley-Taylor methods. 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. The three methods compared were Hargreaves, Penman-Monteith, and Preistley-Taylor. Without calibrating the initial model, Penman-Monteith outperformed the other two methods in both Nash-Sutcliffe coefficient and percent bias, table 5.

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.

2.3 Agricultural Land Management

The representation of agriculture is particularly important in the WRB where agriculture covers nearly 25% of the watershed, and when combined with other variables such as precipitation, soils, and slope, agriculture can be a significant contributor of sediment and phosphorus delivery 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 and 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 described in Section 2.3 are fully described in [WDNR, 2014].

2.3.1 Tillage

No unified dataset existed with data related to crop rotations such as 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 quarter section level. A balance was struck between relying on satellite imagery and relying on local knowledge. The satellite imagery is trusted (with confidence percentages around 95%) 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 tillage information by crop type. The tillage information from the transects was compared with the information that the county/regional staff provided. The tillage information was very dense and there was not consistent naming of the tillage types by county.

The general tillage types and timing were interpreted by looking at the predominant tillage by crop type. This data corroborated what we heard from county staff, which was that fall tillage is predominant in the north central WRB and that spring tillage is predominant in the southern WRB. Note that the tillage reported is for all crop types under all rotations for each county.

2.3.2 Inorganic Fertilizer

The starter fertilizer applications in SWAT were changed from 0.22 to 0.17 $tons \cdot ha^{-1} \cdot yr^{-1}$. This was done in accordance to the suggestion from a panel of WDNR staff, faculty from the University of Wisconsin, private agronomists, manure haulers, and crop consultants.

2.3.3 Manure

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 dry manure 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, NRCS 2006). Based on the DATCP dairy manure estimation calculator, it was assumed that there are 8.34 pounds of dry weight per gallon of liquid manure.

2.3.4 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 the 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 agronomists. Each of the 15 rotations had three variations, resulting in 45 rotations that were incorporated into the SWAT model [WDNR, 2014].

We found it necessary to randomize several of the rotation types and 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. This was done because county experts had explained that when corn was being grown year after year 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.

The dairy and cash grain rotation types covered such a large area that we considered that it would be a potential problem for the SWAT model if all every year a significant portion of the landscape was growing all the same crop. 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 staggered as to what their starting crop would be, that is each would be offset from the other by two years. In this way variations in crop effects would be smoothed out.

2.4 Other Model Configurations

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 function is used to simulate storage of internally drained ponds or lakes, and the wetlands function is used to simulate smaller depressions that either manifest in true wetlands, or at least function as seasonal capture zones.

2.4.1 Ponds

The ponds function in SWAT requires geometric properties and hydraulic conductivity at the very least, with a number of additional paramaters to control sediment and chemical processes. We calculated geometric properties using a combination of WHDPlus (NEEDS CITATION), the Wisconsin 1:24k Hydrography Geodatabase(NEEDS CITATION), the Wisconsin Lake Book [Wisconsin Department of Natural Resources 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 percent 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. Normal surface areas were extracted from the Wisconsin Hydrography Geodatabase (NEEDS CITATION). 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 Wisconsin Department of Natural Resources [2009].

If normal volumes were not listed in Wisconsin Lakes Wisconsin Department of Natural Resources [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 5).

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

If maximum depth was not available, we fitted a seperate regression using only surface area. (Figure 5).

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

In the above equations, $\boldsymbol{V}$ is the volume of any given lake in $acre \cdot feet$, $\boldsymbol{A}$ is its surface area in acres, and $\boldsymbol{D}$ is its 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 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 5 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 6). 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.

2.4.2 Wetlands or Internally Draining Areas

SWAT considers wetlands in a manner very similar to how it considers ponds, the difference only being in the outflow calculation. That said 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 using a topography-based approach and were calculated by individual subbasin. A digital elevation model (DEM) was filled using a 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 sink layer provided the starting point for the wetlands layer.

The areas identified by the USDA-NASS's Cropland Data Layer (CDL) as herbaceous and woody wetlands and cranberry were considered to be areas where wetland vegetation is likely to be found. If wetland vegetation exists it can be assumed that that landscape has a consistent wetland hydrology, consistent 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 normal wetland area. From this the normal surface area was calculated. The depth of the sinks were used as the depth of water in the wetland areas and this was multiplied by the normal surface area to calculate the normal volume. For maximum surface area, all sinks were considered to be wetland areas, regardless of their relationship with the wetland vegetation map. The area of the sinks was considered the maximum surface area. The maximum surface area was multiplied by the sink depth to derive the maximum volume. The maximum wetland surface area was divided by the subbasin area to derive the fraction of the subbasin that is wetland.

There are precedents to using a topography-based approach to defining wetland areas in SWAT; several studies conducted in the midwest are discussed here. Almendinger and Murphy [2007] considered internally drained areas as wetlands (as identified by remote sensing[10]) 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.

2.4.3 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 model was constructed relating baseflow to local watershed characteristics and then this model was used to create a local value of ALPHA_BF based upon local conditions.[11]

In order to construct a model relating baseflow contribution to watershed characteristics it was necessary to obtain observed values of baseflow. Bflow, a baseflow separation program, [Arnold et al., 1995] was used to determine baseflow from daily streamflow data. The observed streamflow data were retrieved from the USGS National Water Information System (NWIS) [Survey, 2014] on 27 August, 2014. All monitoring stations in Wisconsin that met the requirements of the Bflow separation 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

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

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

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, or gaps, 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.

Each record of streamflow was analyzed using the SWAT Bflow filter [Arnold et al., 1995]. This smoothing algorithm produces several estimates of ALPHA_BF, one for each successive pass of a smoothing filter; for every record, the final pass (third and smoothest) was used. For sites with multiple records, the ALPHA_BF 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 Bflow filtering algorithm.

To estimate ALPHA_BF for all SWAT subbasins in the WRB, we fit a multiple linear regression model to predict ALPHA_BF using upstream watershed characteristics. Data regarding the landscape characteristics of the watershed for each monitoring station were retrieved from the Wisconsin DNR's Wisconsin Hydrography Dataset Plus (WHDPlus) [Diebel et al., 2013]. Additionally, the EPA's Ecoregion boundaries level III were also 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 parameters based on correlation coefficients. The final model was selected based on R^2. We used residual plots to examine evidence of model bias. The best model 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 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.

[Table of model terms?]

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.

2.4.4 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. 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, they 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 log concentration of phosphorus was constructed. 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. 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 P parameter.

[map of baseflow P]

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 [SCS, 1986].

2.4.5 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 observed at the sites of 24 impoundments within the WRB (Table 6).

Reservoir geometries were taken from the WDNR Statewide Dam Database[12]. Principal volumes, emergency volumes, principal surface areas, and dam locations (Table 6) 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. No estimates of emergency surface area exists for all reservoirs; it was therefore assumed that emergency surface area is 50% greater than principal surface area.

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

Outflow of all SWAT subbasins with reservoirs were forced to daily flow measurements. Daily flow measurements were compiled from the USGS NWIS [Survey, 2014] and the Wisconsin Valley Improvement Company (WVIC) (personal communication with Peter Hansen). For each daily time series, we inspected its 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.

2.4.6 Streamflow calibration sites

Stream flow will be calibrated to daily discharge data aggregated to monthly mean using data from USGS gaging stations throughout the WRB. Subbasins in the WRB SWAT model were delineated at the pour point of each USGS gage site. Table 7 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 or affected by human development. Gages that exhibited an altered hydrograph will not be used for calibration.

3 Conclusion

The methods described here illustrate a 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 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 by a scalar to preserve regional patterns and processes.

As the project team is only midway through the complete development of the WRB SWAT model, we invite comments that may improve our conceptualization of the model. If comments are provided by reviewers, it is important to note that adjustments can only be made if it is clear that the adjustments will not substantially bias the model results. Also to note, recommended adjustments should match the scale of analysis, in geographic and data resolution. For example, we cannot incorporate adjustments that represent processes at the scale of an agricultural field, nor can we incorporate adjustments to highly specific agricultural land management such as specific planting dates during a particularly warm spring.

4 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 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
B9	1521	1.37	0.22	27.11	1.32	20.30	9.76
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 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)
US1WIAD0002	-	-	4	535
US1WICB0004	-	-	2	189
US1WICB0005	-	-	1	35
US1WILN0002	-	-	3	517
US1WIMN0001	-	-	2	34
US1WIMN0004	-	-	12	474
US1WIMT0001	-	-	2	364
US1WIMT0003	-	-	3	438
US1WIMT0004	-	-	3	129
US1WION0002	-	-	2	113
US1WION0006	-	-	1	308
US1WIPT0001	-	-	3	227
US1WISK0002	-	-	1	18
US1WISK0005	-	-	1	8
US1WIVL0007	-	-	2	28
US1WIWD0001	-	-	5	308
US1WIWD0002	-	-	4	159
US1WIWD0004	-	-	8	247
USC00207812	1	24	-	-
USC00470239	2	430	4	375
USC00470308	3	200	3	200
USC00470456	-	-	3	583
USC00470516	10	277	8	246
USC00471155	-	-	5	565
USC00471970	6	192	5	111
USC00472314	22	1176	12	351
USC00472447	-	-	7	589
USC00472973	8	792	4	257
USC00473182	-	-	4	631
USC00473405	4	955	4	955
USC00473636	1	142	1	142
USC00473650	2	101	1	54
USC00473651	1	44	0	0
USC00473654	15	495	4	145
USC00474383	-	-	1	82
USC00474422	-	-	3	104
USC00474424	11	374	1	61
USC00474790	4	139	4	139
USC00475120	28	1186	9	373
USC00475164	9	846	8	717
USC00475178	20	674	14	407
USC00475255	11	856	3	144
USC00475364	17	2013	10	959
USC00475516	6	432	6	432
USC00475786	5	581	5	581
USC00476122	5	503	4	482
USC00476357	3	87	1	51
USC00476518	-	-	3	176
USC00476718	3	186	1	65
USC00476796	3	129	2	94
USC00476838	1	156	0	0
USC00476859	4	234	-	-
USC00477052	9	266	3	78

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
Preistley-Taylor	42.090	-5.089

Table 6: 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.

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	Castle Rock Flowage	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 Mohawkson	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 7: U.S. Geological Survey (USGS) gage sites chosen for streamflow calibration. Excluded sites from Figure **??** are not included here.

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

5 Figures

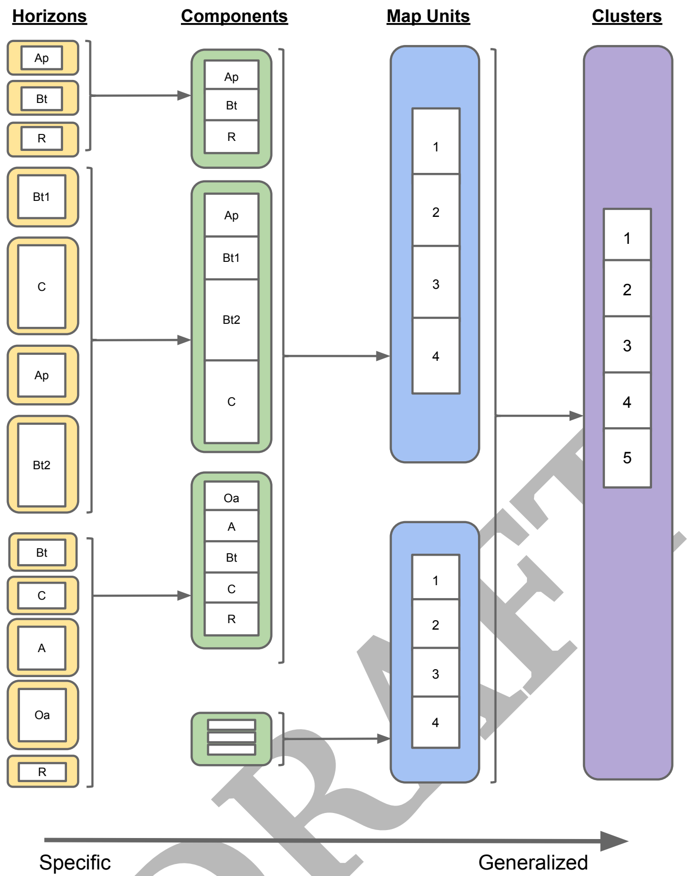

Figure 1: Flow diagram of the soil aggregation process. Horizons are grouped together according to which component they belong. Components are grouped together according to which map unit they belong. A weighted average is calculated, based upon the component percentage. Mapunits are grouped together 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.

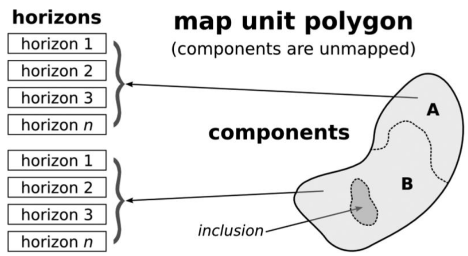

Figure 2: Schematic diagram of SSURGO data structure Gatzke et al. [2011]
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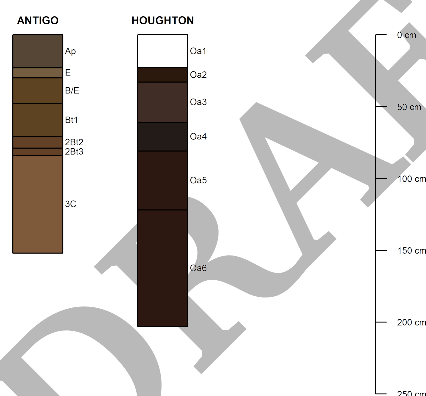


Figure 3: Schematic diagram of SSURGO map unit. Antigo and Houghton are each components within the map unit. Within each map unit are varying numbers of components with varying horizon depths (e.g., Ap and O1 are the surface horizons for Antigo and Houghton respectively. Components were aggregated to map units by averaging soil properties (e.g., percent sand) horizontally across horizons.

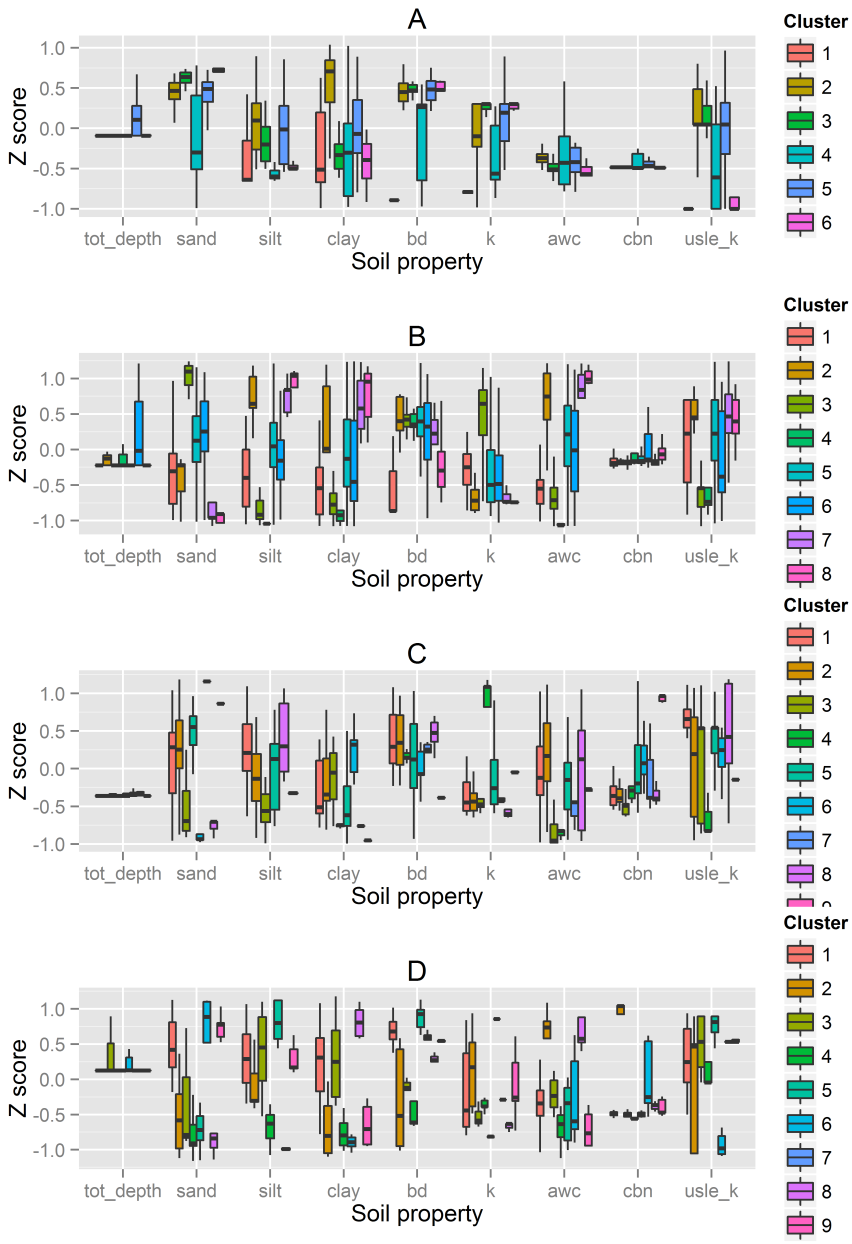


Figure 4: Boxplots showing the variability of soil properties within the final set of soil clusters. The letter above each plot denotes hydrologic soil group (HSG). Each color represents a cluster of map units. The Z score for each soil property is reported as $Z = X - \mu/\sigma$ where X is the value 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.

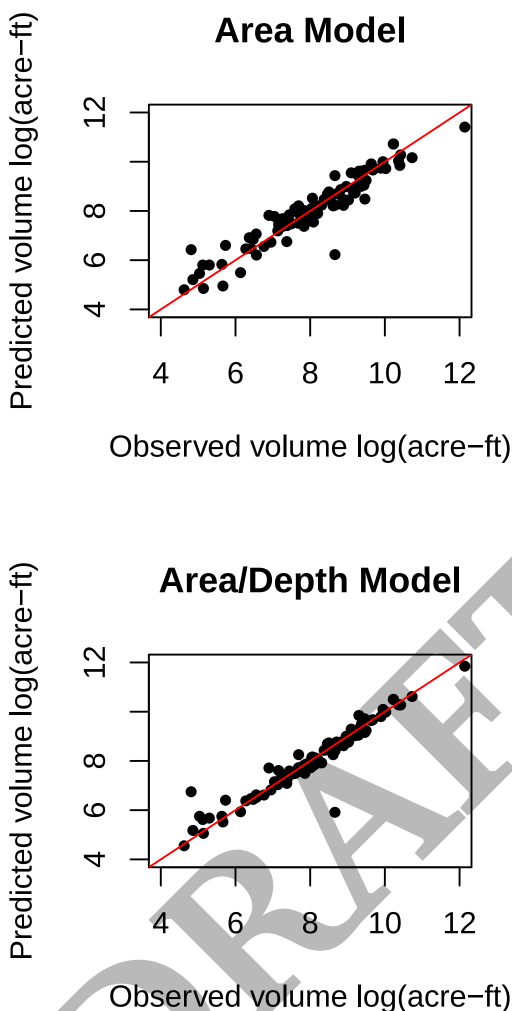


Figure 5: Scatterplots of observed versus predicted lake volumes used to parameterize geometric properties of ponds in SWAT. The area/depth model used lake surface area and maximum depth to predict lake volume and the area model used only lake surface area to predict its volume. The area/depth model explains 92% of the variability in volumes and the area model explains 89% of the variability in volumes.

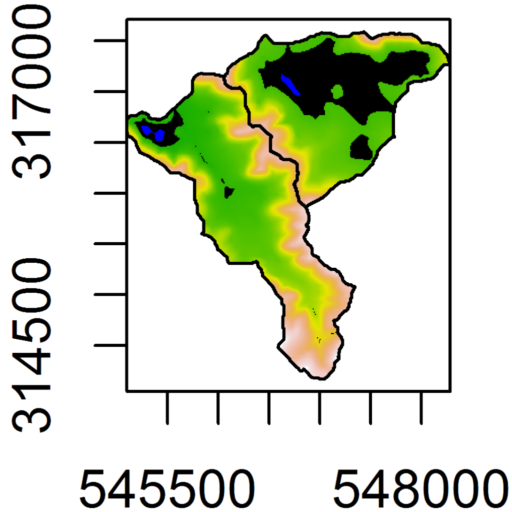
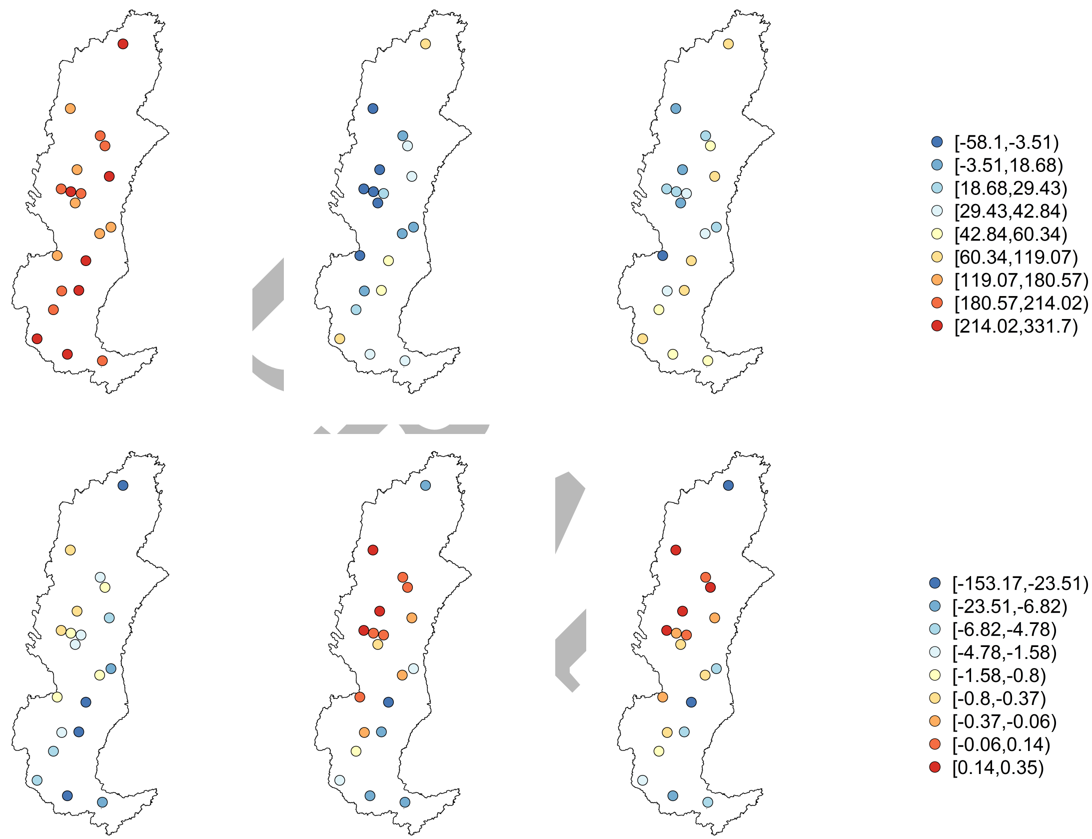


Figure 6: Example image of a filled digital elevation model (DEM) used to estimate maximum storage volume and surface area of landlocked lakes for parameterizing geometries of ponds in SWAT. The green to white gradient represents elevation from low to high. Blue polygons are landlocked lakes. Black polygons 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.


[-58.1,-3.51)
[-3.51,18.68)
[18.68,29.43)
[29.43,42.84)
[42.84,60.34)
[60.34,119.07)
[119.07,180.57)
[180.57,214.02)
[214.02,331.7)
[-153.17,-23.51)
[-23.51,-6.82)
[-6.82,-4.78)
[-4.78,-1.58)
[-1.58,-0.8)
[-0.8,-0.37)
[-0.37,-0.06)
[-0.06,0.14)
[0.14,0.35)

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