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

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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 to be downloaded here:

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 classifed—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.

The above datasets are those that are described in this document. Additional datasets will be added before the final calibrated model, particularly those that represent drivers of phosphorus export. Phosphorus loads will be the final step in model calibration; because phosphorus loads are dependent on streamflow and sediment loads, phosphorus must be calibrated independently from them. In addition, because most of the water-quality impairments in the basin are related to phosphorus loads, it is important to reserve some datasets to inform the final calibration rather than presuming the *a prior* definition fully explains mechanisms of phosphorus export. Two examples of phosphorus-related datasets that are not described in this document, but will be added prior to final calibration of phosphorus loads, are soil phosphorus concentration estimates and instream baseflow phosphorus concentrations.

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.com owned by the username `dnrwaterqualitymodeling`. 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.

2 Initial Model Construction

2.1 Model Input Data

2.1.1 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 a previously existing watershed dataset[1] based on the National Watershed

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

Boundary Dataset (WBD) that honors the undeveloped geomorphology of the recently glaciated portion of the Wisconsin River basin. We delineated 338 subbasins with an average size of 68 sq. km. ($\sigma = 80$) where larger subbasins were located in areas with fewer water quality impairments and points sources.

2.1.2 Urban Delineation

2.1.3 Point Sources

2.1.4 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. 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).

2.1.5 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) maintained by the USDA-NRCS. For more information about SSURGO data see SSURGO metadata[2]. The SSURGO database is structured by three levels of information: map units, components, and horizons. Horizons are the base 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 an Official Soil 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

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

given. Within the Wisconsin River basin, there are 1,796 map units with an average area of 15 sq. km..

We chose to use the gSSURGO distribution of SSURGO (downloaded on 29 October, 2014). gSSURGO is a version 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; these properties were hydrologic soil group (HSG), albedo, horizon depths, bulk density, available water capacity, organic matter, saturated conductivity, total percentage of clay, silt and sand, K factor, electrical conductivity, calcium carbonate concentrations, pH (1 to 1 in water), and coarse fragment percentage. Of these, the hydrologic soil group and albedo were stored at the component level, while all other properties were stored at the horizon level. For all these properties, the representative value given by SSURGO was used. For more information about these parameters see the SSURGO metadata[3].

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 that impact the hydrologic cycle. This was a two step process: first, components within map units were aggregated together[4], and second, map units were aggregated together based on similarity[5].

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 value given in SSURGO was converted to an organic carbon value by multiplying by the average carbon content of soil organic matter, 50% [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 mapunit was agriculture it was

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

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

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

drained and the first HSG taken; conversely, if the landuse 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. 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.

The aggregation algorithm was not used on every mapunit. It was not necessary to aggregate mapunits with only one component. Additionally, the algorithm requires information on the horizon depths and so could not be applied to those mapunits without this information. Mapunits without this information included water bodies, urban land, landfills, and other miscellaneous disturbed areas.

Using the above aggregation method 48,585 individual soil components were aggregated to 1,603 mapunits. Because the hydrologic response unit (HRU) used in SWAT is derived using unique combinations of land use, slope and soil types, this number of soil mapunits 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 relevant properties. We decided that the most relevant soils information to SWAT is hydrology data, specifically the hydrologic soil group (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 mapunit. Groups of the same HSG were divided into smaller groups, hereafter known as clusters, of homogeneous soil properties, using a clustering algorithm. The mapunits 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 mapunit 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 mapunits with homogeneous soil properties. For this purpose we used Gaussian mixture models to assign mapunits to clusters. The mixture model algorithm we used was 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 mapunits of like hydrologic soil groups (say all mapunits with an HSG of A), while the (unknown) subpopulations are the clusters of mapunits 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 mapunits into 6 clusters, and all of the other HSG classes into 9 clusters.

Each of the 1603 mapunits had data regarding the soil property values at each horizon. In this format it was thought that profile depth would negatively affect the clustering algorithm, e.g., deep soils all clustered together, shallow soils clustered together, 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 mapunit; 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 dominate the clustering algorithm.

Several of the soil property fields of the SSURGO dataset did not seem to be 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. These properties were coarse fragments, calcium carbonate, and electrical conductivity. Further, we believe that several of the soil properties used by SWAT were not as important as others and so these properties were also excluded from the clustering algorithm; these variables were pH and albedo.

Not every mapunit was included in the clustering procedure. Those mapunits that did not have hydrologic soil group were not included, nor were mapunits that did not have information on the soil properties of the horizons. These included the same miscellaneous mapunits as were excluded from the aggregation algorithm used in aggregating components to the mapunit level: pits, landfills, urban or made land, and rock outcrops. These miscellaneous mapunits were grouped by their non-soil/no-property status. Water polygons were also not included in the clustering analysis.

The same soil profile aggregation algorithm [Beaudette et al., 2013] used to aggregate several components together in the first part of the configuration was used to combine the soil profiles of a cluster into one composite soil profile. In this implementation each mapunit was given equal weight in the aggregation algorithm. Those mapunits designated as miscellaneous were aggregated into one soil profile as the other clusters were, while the water mapunits were not aggregated. The miscellaneous grouping was assigned a hydrologic soil group 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 by to the appropriate hydrologic soil group designation, which happened to be B. Following SWAT convention, the water units were given an HSG of D, and assigned an albedo of 0.23, a saturated conductivity of 600.

A total of 35 soil classes were distilled from this process. A sample of the properties are found in table 1.

Soil Phosphorus concentrations were obtained through the University of Wisconsin Soil Testing Laboratory [6]. 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. Because the phosphorus samples analyzed at the soils laboratory are strongly bias toward samples on agricultural fields, only agricultural HRUs were given the subbasin average concentration, while non-agricultural HRUs within each subbasin were given the default concentration (5 mg P/kg) and 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 constitues 0.85% of organic material measured by loss of weight upon ignition (correspondence with Phillip Barak, needs citation).

2.1.6 Topographic Slope

2.1.7 Climate

The text files contain largely the same data as the database files, however, the text files contain a time series where any gaps in the raw data have been filled by data from the nearest climate station. If that nearest weather station was also missing data for that period, the next closest weather station's data was used to fill the gaps.

The format of the database files is the Date, the daily maximum and the daily minimum, in Celsius for temperature and millimeters for precipitation. The value -99 means that there was no data for that day. The text files were formatted specifically for ArcSWAT. The first line contains the starting date of the model simulation, in the format yyyymmdd (19900101 or 1 January, 1990). Each row after this contains minimum and maximum daily temperature or precipitation. All the dates in the warm-up period until the beginning of the model period (1 January, 2002) are given the value of -99, thus the first 12 years do not have climate data, but are represented in the text files for SWAT input.

The climate data used in the SWAT model was provided for the US EPA contractors (Limnotech). This data was retrieved on 13 August, 2014 from the National Climate Data Center - Global Historic Climate Data Network.

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

Table 1: 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	1525.30	0.00	0.46	125.37	37.25	0.00	0.00
A2	1520.55	1.58	0.10	185.52	0.61	6.25	83.37
A3	1528.08	1.63	0.09	267.17	0.61	3.77	84.64
A4	1454.86	1.30	0.27	185.29	17.88	2.21	44.51
A5	1805.87	1.58	0.14	243.14	4.24	4.59	71.70
A6	1522.91	1.65	0.07	271.49	0.47	3.49	93.86
B1	1520.00	1.55	0.18	50.53	0.94	12.48	47.51
B2	1537.39	1.50	0.22	27.17	0.93	19.04	12.22
B3	1520.09	1.59	0.13	94.29	0.68	8.55	70.05
B4	1544.18	1.58	0.12	195.90	2.00	6.71	75.42
B5	1522.91	1.52	0.20	42.73	1.07	13.44	38.50
B6	1577.51	1.45	0.20	50.08	5.19	11.79	36.19
B7	1533.33	1.57	0.15	40.36	1.61	6.84	62.35
B8	2002.61	1.51	0.22	27.73	0.74	18.15	12.74
B9	1521.05	1.37	0.22	27.11	1.32	20.30	9.76
C1	1521.39	1.55	0.20	27.66	0.90	12.32	29.21
C2	1520.00	1.56	0.18	36.30	0.92	11.11	49.20
C3	1710.42	1.60	0.18	24.39	0.74	20.46	27.03
C4	1520.44	1.58	0.14	52.02	0.97	10.45	62.91
C5	1731.63	1.51	0.19	54.78	3.14	9.04	41.07
C6	1526.38	1.49	0.22	27.46	1.23	16.13	14.31
C7	1529.74	1.63	0.13	274.05	2.88	6.00	76.92
C8	1583.62	1.49	0.20	26.05	1.04	20.47	23.93
C9	2072.00	1.41	0.18	64.26	4.88	5.00	55.33
D1	1520.21	1.52	0.18	69.54	2.53	13.67	46.29
D2	1521.23	0.95	0.40	68.93	34.45	1.64	5.50
D3	760.00	1.36	0.19	29.40	1.48	17.53	34.80
D4	1520.00	1.61	0.17	52.55	0.84	14.04	51.78
D5	1813.33	1.66	0.18	16.90	2.36	28.73	20.09
D6	1552.68	1.43	0.26	215.82	15.40	2.66	41.92
D7	1520.00	0.00	0.40	66.00	38.75	0.00	0.00
D8	1520.00	1.39	0.24	27.71	4.35	22.94	8.00
D9	1796.86	1.25	0.20	50.65	5.10	7.76	39.68
W	25.00	0.00	0.00	600.00	0.00	0.00	0.00
X	416.77	1.78	0.02	157.56	0.49	5.86	78.24

We chose an evapotranspiration method by evaluating percent bias and Nash-Sutcliffe coefficients when comparing modeled water yield to observed water yield at 20 sites acroos the basin. The three methods compared were Hargreaves, Penman-Monteith, and Preistley-Taylor. Without calibrating the initial model, Penman-Monteith outperformed the other 2 methods in both Nash-Sutcliffe coefficient and percent bias.

Table 2: 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.

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

2.2 Agricultural Land Management

2.2.1 Crop Rotations

2.2.2 Rotation Randomization

2.2.3 Tillage

For a detailed description of tillage definitions, see WDNR Land Management Report[7].

2.2.4 Inorganic Fertilizer

Starter fertilizer, 20-10-18 N-P-K applied at 150 lbs/acre/year (consult SWAT manual to convert to proper units).

2.2.5 Manure

For a detailed description of manure definitions, see see WDNR Land Management Report[7].

[7] http://dnr.wi.gov/topic/TMDLs/documents/WisconsinRiver/Technical/WRBLndManagmntJuly2014.pdf

2.3 Other Model Configurations

2.3.1 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 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 maxiumum volumes.

These parameters were calculated using a topography-based approach for each 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 difference between the filled DEM and the original DEM was a layer showing the internally drained areas for the basin or sinks, i.e., those areas that are not immediately connected to surface waters. 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 were wetland vegetation is likely to be occur. 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 and the area of the sinks were considered the maximum surface area. The max 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 is precedent to using a topography-based approach to defining wetland areas in SWAT. Almendinger and Murphy [2007] considered internally drained areas as wetlands (as identified by WISCLAND) if they were not connected to the main channel and lakes as ponds in their SWAT model. Wetlands, identified through WISCLAND, were considered SWAT wetlands only if they occur on the main channel. Similarly, Kirsch et al. [2002] consider internally drained areas as wetlands if they overlapped with WISCLAND 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. This configuration closely matches the methodology being used in the Wisconsin River basin.

2.4 Groundwater Inflow (Baseflow)

The SWAT parameter ALPHA_BF controls the proportion baseflow to each subbasin reach. In order to regionalize (get a more local value for) this parameter, we retrieved daily stream flow data from the USGS http://nwis.waterdata.usgs.gov/nwis/dv

site. We selected all streams in Wisconsin larger than 19.3 m^3 and smaller than 386 m^3. This was done following WHO? Sites were also filtered so that they had at least a minimum of one year of contiguous flow data.

2.5 Reservoir Outflow

3 Conclusion

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