Linking groundwater and climate to understand long-term lake level fluctuations in Wisconsin

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Introduction

Understanding long-term variations in water levels for seepage lakes (i.e., closed-basin systems that lack surface inflows or outflows) requires consideration of the role of groundwater, climate and other patterns in driving lake level dynamics. Surface water bodies are tightly linked to the groundwater flow system (Winter 1999), and groundwater can exert substantial influence on the water levels of seepage lakes at both local and regional spatial scales (Almendinger 1990, Novitzki and Devaul 1978). Water level changes in lakes, especially declining water levels, can have substantial socio-economic (Kashian 2008) and ecological (Hayashi and Rosenberry 2002, Gaeta et al. 2014) consequences. In stream environments, understanding streamflow variability across landscapes has been essential to better natural resource management of these ecosystems (Poff et al. 1997), and similar frameworks will also advance groundwater and lake management.

Lake level fluctuations over time reflect both natural (e.g., climate) and human-induced (e.g., groundwater withdrawals) changes to the water budget including inputs and outputs from precipitation and evaporation, surface water inflow and outflow, and groundwater discharge and recharge (Figure 1). During the past decade, an extended drought in Northern Wisconsin resulted in the lowest recorded lake and groundwater levels since 1937 (Watras et al. 2014). Concurrently, water levels in Lake Michigan experienced their lowest levels dating back to 1816. Long-term fluctuations of both groundwater and lake levels are extremely coherent, suggesting that these systems are coupled and influenced by similar drivers (Stow et al. 2008, Watras et al. 2014). Groundwater withdrawals have also dramatically lowered lake levels in the Central Sands area of Wisconsin by reducing groundwater discharge to lakes (Kraft et al. 2012) and further emphasize the tight coupling between groundwater and surface water levels (Almendinger 1990).

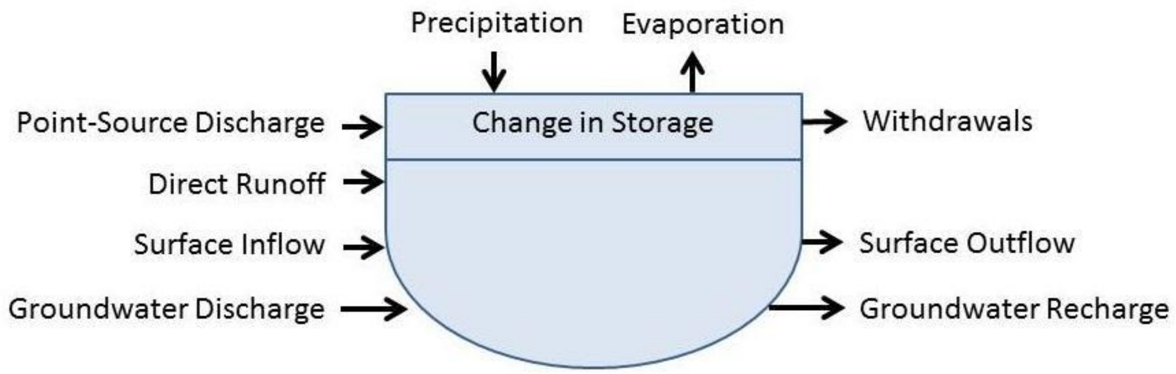

Figure 1. Lake water budget. The water budget for most seepage lakes can be simplified to include precipitation, evaporation, and groundwater discharge and recharge.

Lowered lake levels can desiccate large portions of littoral zone (or nearshore area) habitat, reducing and fragmenting critical ecological habitats. The littoral zone is rich in ecological and biological diversity, often containing dense coarse woody habitats, diverse aquatic plants, benthic macroinvertebrates, fish, and other vertebrates. Much of the lake's primary production occurs in the littoral zone (Vadeboncoeur et al. 2008), and the littoral zone is critical for fish spawning and growth. Drought in northern Wisconsin lowered water levels by 1.1 m on Little Rock Lake, stranding >75% of woody habitat above water, which in turn negatively influenced forage and sport fish (Gaeta et al. 2014). Some of Wisconsin's most endangered aquatic taxa rely specifically on littoral lake habitat types to complete their life-cycle, thus factors leading to degradation of these habitats can be critical conservation considerations. For example, groundwater pumping in the Central Sands stranded piers and boat landings hundreds of feet away from the water line, caused Long Lake to dry up, and threatened an endangered plant that requires fluctuating water levels (US Fish and Wildlife Service 1991, Kraft and Mechenich 2010).

Given the ecological and recreational importance of lake level and its strong coupling with both climate and anthropogenic activities, it is surprising how few lakes are monitored for water levels in the state. Of 15,000 + lakes in Wisconsin, only 41 have at least 10 full years of water level records that we are currently aware of. Initiating lake level monitoring on more lakes across the state is a priority for the WDNR, and this effort is underway as part of the Citizen Lake Monitoring Network. However, many management decisions (e.g., permitting high-capacity wells) cannot wait for new, long-term records to develop. New models linking existing long-term records to short-term monitoring efforts would represent a key resource management tool for Wisconsin. Successful examples of wedding short and long-term water level data exist in other states. For example, Florida administrative code defines minimum lake levels for each lake based on observed or modeled exceedance probabilities (https://www.flrules.org/gateway/ChapterHome.asp?Chapter=40D-8).

The objectives of this project were:

1. Compile historical water level and climatic data into a publicly available database
2. Analyze the spatial and temporal coherence of historic water levels
3. Model historic lake levels
4. Characterize hydrologic regimes for all seepage lakes

Historical Water Level Data Compilation

We compiled historical lake level, groundwater level, and climate data for this project. We also gathered lake and watershed characteristic data from the Wisconsin Department of Natural Resources (WDNR) Hydro24K VA database and the Lake multi-scaled geospatial and temporal database (LAGOS, www.lagoslakes.org).

The lake level dataset includes 501 seepage lakes and 535 drainage lakes with a total of 342,319 observations (Figures 2, 3). The data set spans from January 1st, 1900 to December 31st, 2015. The data sources include the United States Geological Survey (USGS), WDNR, North Temperate Lakes-Long Term Ecological Research (NTL-LTER), North Lakeland Discovery Center, Waushara County, and City of Shell Lake. WDNR hosts two lake level data sets: historical lake levels recorded in paper files and modern records collected as part of a recently-initiated citizen monitoring program. The latter is stored in the Wisconsin Surface Water Integrated Monitoring System (SWIMS).

We then embarked on an extensive data compilation and cleaning effort. Some lakes had water level records from multiple sources. We attempted to use the datums from each data source to link records from the same lake together, often extending the period of record for an individual lake. However, many records could not be linked together, resulting in separate water level time series on the same lake. To identify errors or abnormal water level variation, we plotted the time series of each lake level record. We also calculated the water level range and rate of change for each lake level record to further detect lakes with problematic observations. We corrected obvious errors when possible and excluded some observations that appeared to be egregious outliers which could not be rectified using available resources.

The groundwater level dataset includes 964 monitoring wells with about 400,800 observations spanning February 2nd, 1929 to December 31st, 2015 (Figures 2, 3). Data came from USGS, NTL-LTER, and WDNR. The well data downloaded from WDNR is monitored through a joint effort between WDNR, volunteers, and six counties in the Central Sands area (Adams, Marquette, Portage, Waupaca, and Waushara). Data were retrieved from each source and pooled into one data set. As no well was monitored by more than one entity, no further merging operation was conducted. Like lakes, we reviewed time series plots and the range of water levels in each well. All wells in the confined aquifers were discarded as they were severely impacted by human activities and did not reflect natural variation in groundwater levels.

Both the lake and groundwater level data sets were published online through the Environmental Data Initiative.

Data Repositories

Lakes: https://portal.edirepository.org/nis/mapbrowse?packageid=knb-lter-ntl.362.1
Groundwater: https://portal.edirepository.org/nis/mapbrowse?packageid=knb-lter-ntl.363.0

This enhanced data accessibility will benefit future research and management. Now it is much easier for the public to access the historical water level data from WDNR that was previously only available as paper files. This data set also pooled disparate data sets collected by different agencies on 30 lakes, expanding the length and frequency of these records.

The climate data compiled for this project consist of precipitation and evaporation estimates at each lake. The precipitation data are derived from PRISM (PRISM 2004) and evaporation data are from a model developed by Jordan Read (Read et al. 2014). The evaporation model used data from two sources that were stitched together using a linear bias correction approach (White and Toumi, 2013): ZedX Inc. (Bellefonte, PA; Motew and Kucharik, 2013) and the North American Land Data Assimilation System (NLDAS-2; https://ldas.gsfc.nasa.gov/nldas/). The time span of precipitation data is from 1895 to 2015 and the time span of evaporation data is from 1984 to 2015.

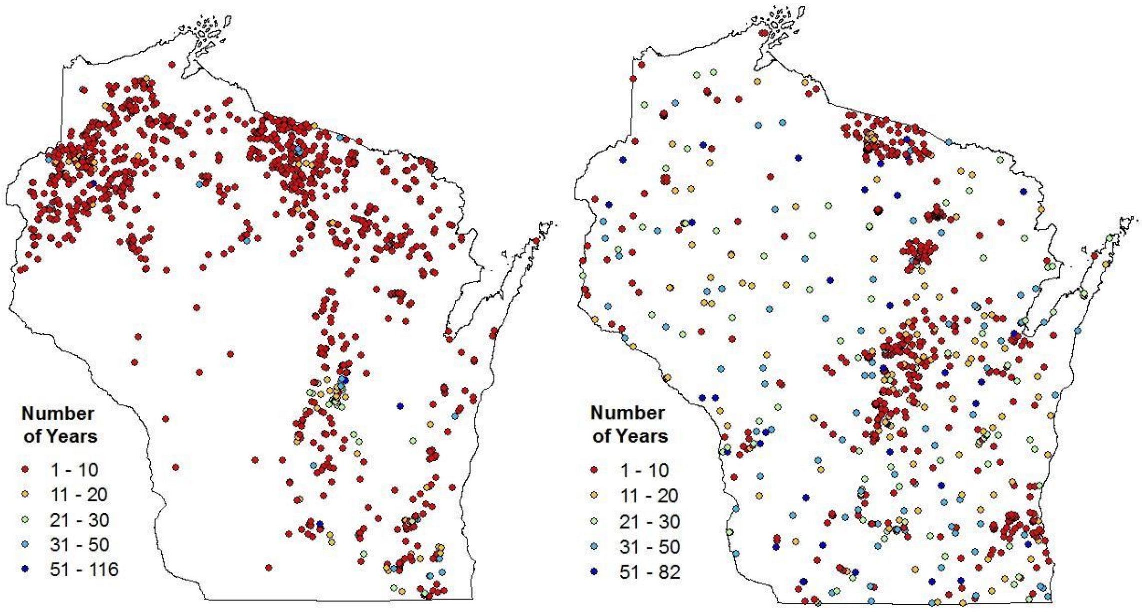

Figure 2. Sites with lake level records (left) and groundwater levels (right). Symbol color indicates the number of years of data for an individual location.

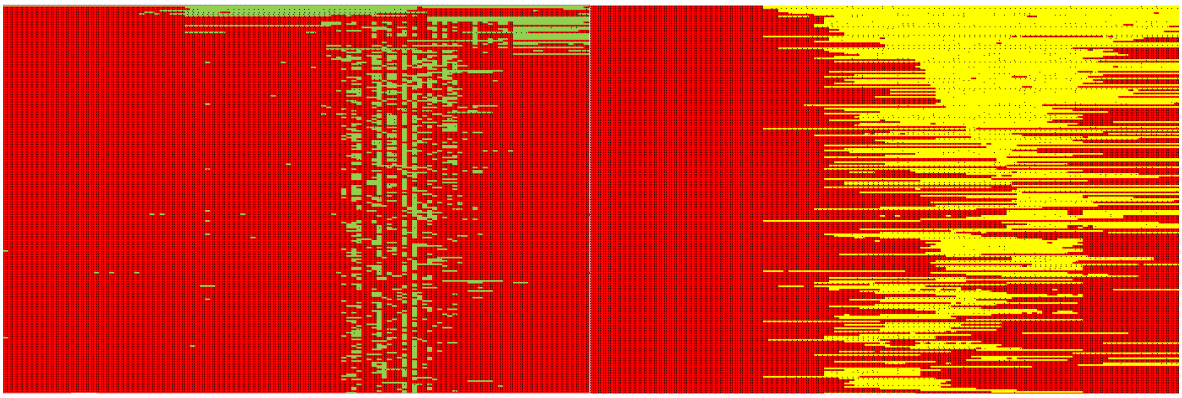

Figure 3. Spatial and temporal coverage of lake level (left) and groundwater level (right) data from the early 1900s to present. Rows represent individual monitoring sites and columns monitoring years. Green or yellow cells represent available data at the site-year and red represents no data.

Spatial and Temporal Coherence of Historic Water Levels

We investigated the spatial and temporal coherence of water levels across Wisconsin to inform our lake level modeling approach. The ultimate goal of this research is to characterize the hydrological regime of the lakes in Wisconsin. A lake's historical water level could be predicted using historical water level data from the lake itself and/or adjacent lakes and wells. However, we did not whether lakes and wells near one another fluctuate in unison nor how to define "adjacent" lakes and wells if there is spatial and temporal synchrony. Besides supporting the decision-making in model building, recognizing the spatial and temporal coherence of lakes and wells can also provide insight into the interaction between surface water and groundwater in Wisconsin.

Approach

Coherence analysis of the lakes and wells was conducted to delineate hydrological regions across the state. We applied the kernel k-means clustering method to group lakes and wells with similar water level variation patterns together using Dynamic Time Warping as a dissimilarity metric (sensu Lottig et al. 2017). The analysis includes both drainage and seepage lakes, as well as groundwater monitoring wells. The time series water level data were retrieved from multiple sources and compiled in one dataset. Then for each lake and well, its average water level in each year during the open water season (i.e., the time period from May 15th to November 15th, was calculated).

Clustering approaches to identify common trends in time series data require a complete time series with no missing data. If gaps in time series exist, those gaps are often filled in using a variety of different approaches including interpolation or mean value replacement. Here, we rely on a Dynamic Time Warping algorithm (Lottig et al. 2017) that can cluster time series even if gaps exist in the time series without the need to fill in the gaps to create complete time series. In order to understand the maximum amount of missing data feasible within a time series while still deriving clusters similar to the complete time series, we used a data-driven approach to determine an acceptable data missing rate. Briefly, a set of water level observations without any missing data was extracted from the water level datasets described above that included data from 41 lakes between 2002 and 2015. Observations were randomly removed from the time series to create three additional datasets with 10%, 20%, 30% and 40% of the data missing. We compared the fidelity of the cluster results at each data missing rate and determined that a missing rate of 20% returned approximately the same result as the full dataset. Therefore, we allowed a missing rate of up to 20% when selecting water level records for coherence analysis.

We analyzed the entire dataset to determine the time period that maximized the number of water level observations while maintaining a maximum missing data rate of 20%. The resulting dataset derived for coherence analysis through time series clustering included 52 lakes and 115 wells from 2001 to 2015. This data subset is of sufficient length to capture the 13-year cycle observed by Watras et al. (2014) and covers most of Wisconsin. We applied dynamic time warping (DTW) to measure the distance, i.e., the similarities of members within the same clusters and the dissimilarities of members from other clusters. This is a method first developed for speech recognition (Sakoe et. al.1990). In comparison to other dissimilarity metrics, DTW can not only deal with missing data but also aligns time series that are slightly asynchronous. In our analysis, we set the time lag as ±1 year to account for possible lags of responses to the hydrological drivers. The number of clusters was determined by comparing the within-cluster DTW distances to DTW distances from random clusters and choosing the number of clusters where the difference was maximal or asymptotes.

Results & Interpretation

Analysis of the data resulting from generating 10 sets of clusters (1 through 10) suggest the presence of two distinct clusters (Figure 3) that separate lakes and groundwater wells along a north/south gradient (Figure 3). The patterns separating the two regions highlight the

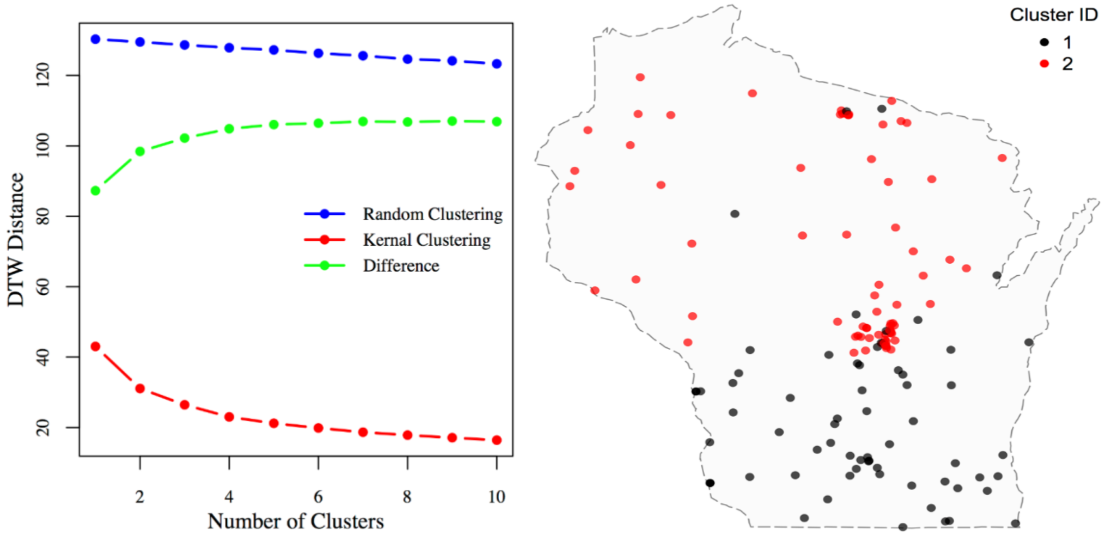

Figure 3. Comparison of DTW distances estimated by kernal clustering (red), random clustering (blue) and the difference between approaches (green; left panel). Location of lakes and groundwater that share similar long-term patterns based on time series clustering of water level records (right panel).

extensive drought in northern Wisconsin and the more recent higher than average precipitation years in southern Wisconsin (Figure 4).

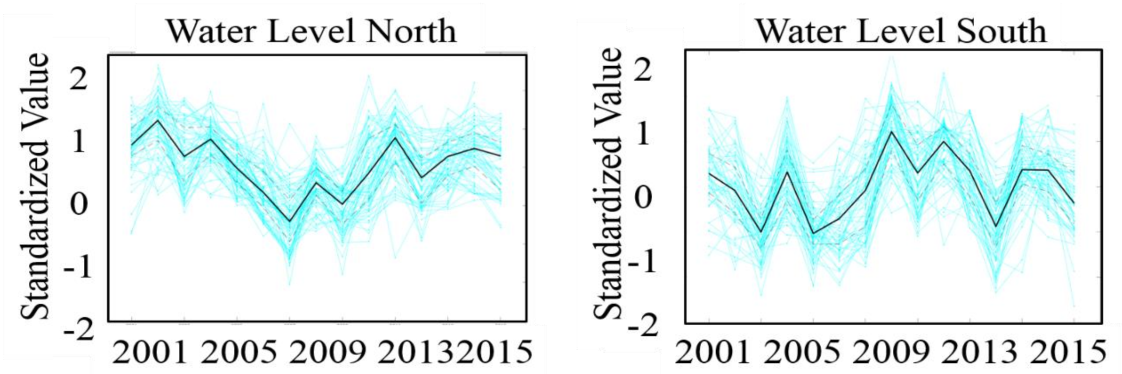

Figure 4. Water level patterns for both lakes and ground waters for the two clusters shown in Figure 3. Light blue lines are individual time series, the black line is group median value.

We used random forest models to help understand what ecological context variables might explain why these groups of lakes and groundwater wells shared similar long-term water level patterns. Variables used to predict cluster association include site-specific information (e.g., lake vs well), watershed land use information, soil types and soil characteristics, and climate. Climate variables characterizing precipitation were able to classify 89% of the lakes between the northern and southern groups. The two most important variables were the 30-year mean annual precipitation and the cumulative precipitation deviation from the 10-year rolling mean. Additionally, it is important to note that the site type (i.e., lake or groundwater well) was not important for understanding the long-term water level patterns. These results highlight that climate (precipitation) is one of the strongest drivers of water levels across the state of Wisconsin and that both lake and groundwater levels respond similarly to precipitation patterns at multiple spatial and temporal scales.

While the long-term water level data does not exist to assess if these clusters change depending on the time period or time span the data covers, we suspect that given the strong climate signal from precipitation observed here, periods of converging and diverging patterns should emerge. We would expect similar water level patterns to be observed across the entire state if similar precipitation patterns are observed. On the other hand, if precipitation patterns differ amongst regions for a significant period, we would expect the water level patterns to differ in a similar matter as well for that region.

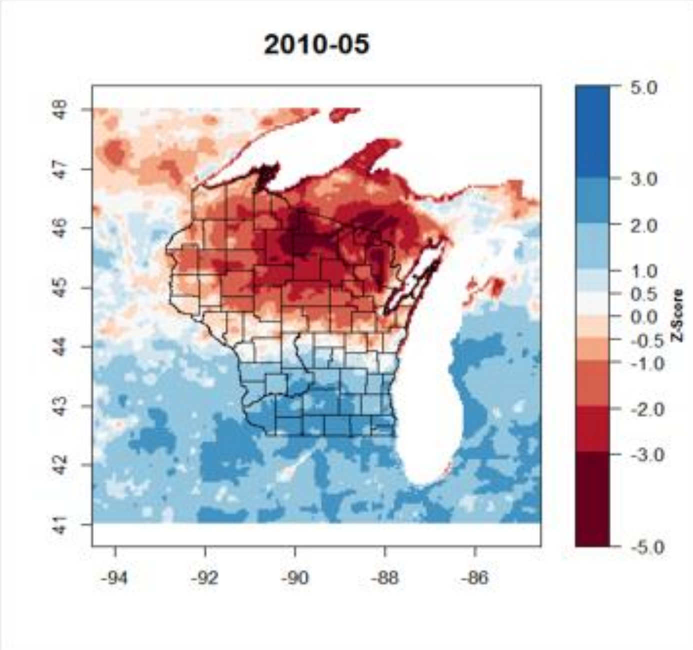

Figure 5. Example of North/South gradient in precipitation across the state of Wisconsin that correlates with the division between the North/South patterns of lake and groundwater levels.

Modeling Historic Lake Levels

We explored reconstructing historical water levels using two different approaches. The first approach was to rely on the strong correlation between water levels and precipitation (Goal #2) and the second approach was to build a mechanistic-based model similar to Watras et al. 2014 and reconstruct water levels using both precipitation and evaporation data.

Empirical Model Using Historic Precipitation Data

Given the strong correlations observed between precipitation patterns and observed lake levels (Goal #2), we quantified the relationship between precipitation and water levels in seepage lakes (i.e., lakes with closed basins) whereby:

$$y_{tj} = ppt_{tj} + \varepsilon_j$$

To assess the relationship, we fit a Bayesian Hierarchical model as follows:

$$y_i \sim N\left(a_{j(i)} + B_{j(i)}x_i, \sigma_j^2\right), for\ i = 1, \ldots n$$

$$\begin{pmatrix} a_j \\ B_j \end{pmatrix} \sim N\left(\begin{pmatrix} u_a \\ u_B \end{pmatrix}, \begin{pmatrix} \sigma_a^2 & \rho\sigma_a\sigma_B \\ \sigma_a\ \sigma_B & \sigma_B^2 \end{pmatrix}\right), for\ j = 1, \ldots j$$

$$\sigma_j \sim N\left(u_a, \omega_\sigma^2\right), for\ j = 1, \ldots j$$

where y_i is the observation *i* of change in lake water level from lake *j*; x_i is the precipitation from lake *j*; α_j and β_j are the intercept and slope for lake *j*, respectively; μ_α is the population-average intercept and μ_β is the population average slope; $\sigma_a^2$and $\sigma_B^2$are the variances of the intercepts and slopes, respectively; and $\rho\sigma_\alpha\sigma_\beta$ describes the covariance between α_j and β_j with ρ describing the correlation between α_j and β_j. σ_j is the lake-specific residual variance with a mean μ_α and variance ω_σ^2.

Precipitation was represented in the model as the cumulative deviation of monthly precipitation (cmdev) from an eight-year rolling mean (*sensu* Smail personal communication). Though precipitation is an important factor, applying raw precipitation data could lead to several problems. The most critical issue with the raw data is that they can only show isolated rainfall instances at each time point and therefore fail to capture the deficit and surplus of the precipitation budget. If there were a significant amount of precipitation in previous years, i.e., there is a surplus in the water budget, one dry year might not cause an immediate negative impact on the water level. By the same logic, one wet year may not be able to make up for the consequence of a long-term drought and fail to increase the lake level. The cumulative values which are the sums of the precipitation data between a certain time period can deal with this problem by reflecting the influence of the past precipitation. Lake-specific precipitation data was derived from PRISM spatial coverages.

In total 40 different lakes had sufficient temporal coverage (8+ years of data) and precipitation ranges to assess the relationship between cmdev and lake - specific water levels (Figure 6). There were strong linear relationships between lake water level and cmdev for each discrete lake (Figure 6) that were well characterized by the hierarchical linear models. Resultant predictions of lake specific water levels generally closely approximated observed water levels (Figure 7). On average the slope between cmdev and the lake water level was approximately 1.2 but varied from approximately 0.5 to 4. This variation in slopes provided challenges for extrapolating the knowledge gained from these study lakes to other lakes across the state of Wisconsin.

To extrapolate the relationships quantified here to other lakes, we tested a variety of model selection approaches to explain the variation in among lake slopes and ecological context variables including black box approaches such as random forest. For ease of interpretation, we have chosen to rely on linear models. These analyses were driven by semi-informed decisions about what ecological context variables may be important factors influencing water level changes in lakes and their response precipitation. The ecological

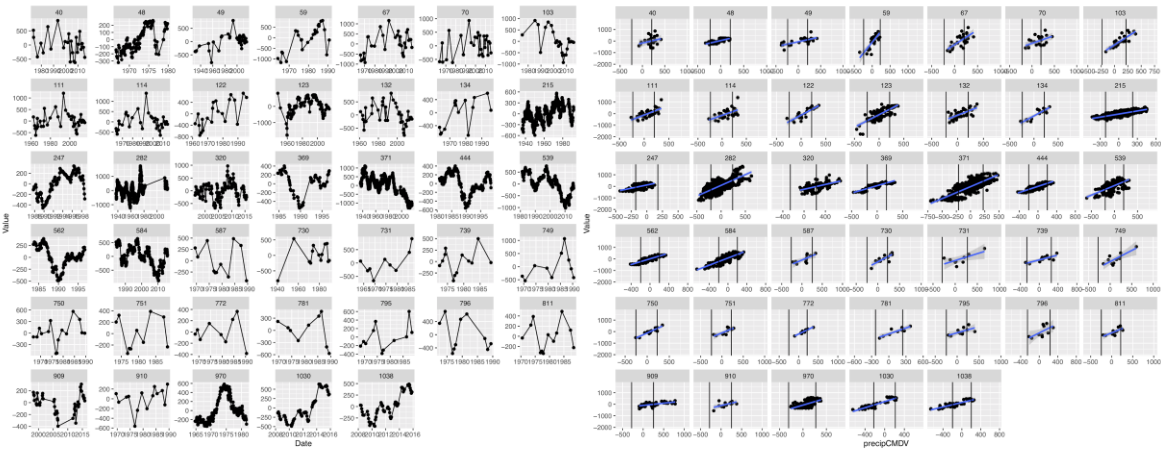

Figure 6. Lake water level time series for 40 lakes (left) used to quantify the relationship between cumulative monthly precipitation deficit (cmdev) and lake water level (right).

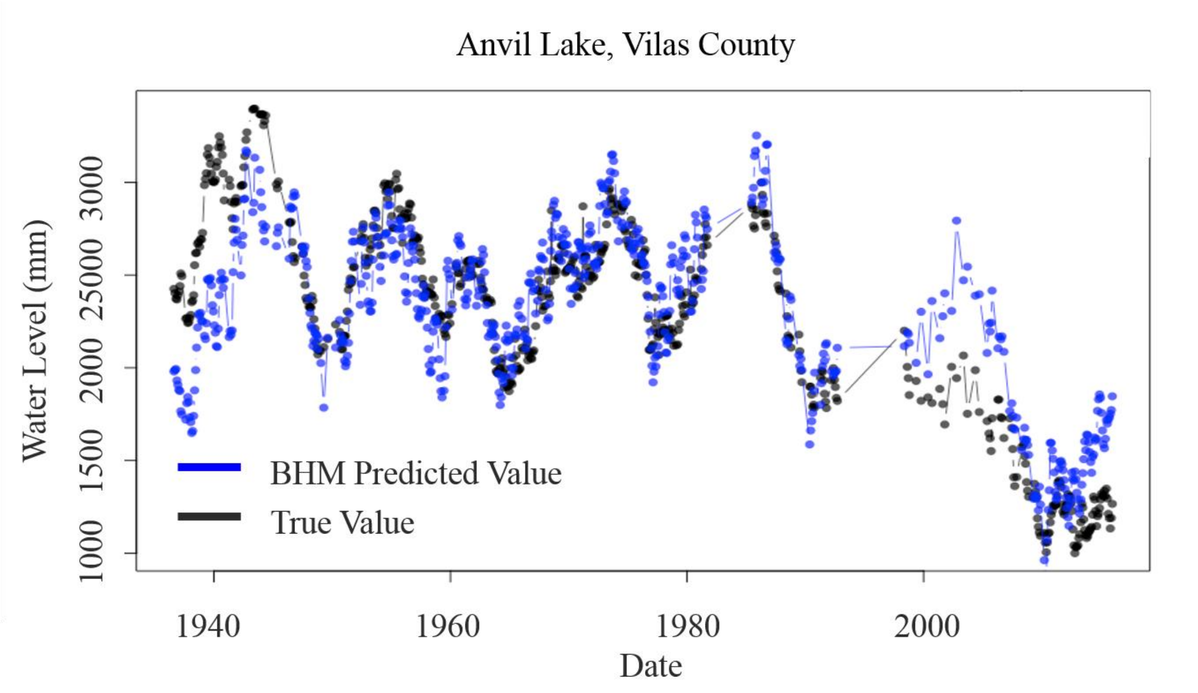

Figure 7. Time series of water levels from Anvil lake and modeled water levels based on the lake specific Bayesian hierarchical model.

context variables used to understand the variation in the slope of the relationships among lakes between water levels and precip observed above included the following variables: Max lake depth, soil permeability, soil Darcy value, conductivity, the difference between lake elevation and maximum watershed elevation, the lake area, and percent riparian forest. Forest land type was chosen for the land-use variable because it is strongly correlated with other variables. We also chose to use land-use characteristics calculated for the riparian zone (30m buffer) around the lake.

The best model for extrapolating the slope between lake water level and cmdev was:

water_level = elevation_difference + Forest*Darcy

	Estimate	Std. Error	Pr(>|t|)
(Intercept)	4.223e-01	3.542e-01	0.241
elevation_difference	1.924e-02	6.592e-03	0.006
forest	1.214e-02	7.003e-03	0.092
DARCY	-5.720e-03	1.645e-03	0.001
forest:DARCY	1.117e-04	3.061e-05	0.001

The overall model explained 49.1% of the variation in the slope of the relationship between cmdev and water level between lakes ($p < 0.001$). In order to limit the potential of extrapolating beyond the bounds of the training dataset, we limited lakes that were extrapolated to have elevation differences between 5 and 62 m, forest landcover between 2 and 88 percent, and Darcy estimates between -502 and 5.

Mechanistic Model Using Precipitation and Evaporation Data

The second approach we explored for understanding how climate and groundwater interact to influence water levels in lakes was through the use of recursive time series models. Changes in closed basin (seepage) lake water levels (S) can be described by:

$$S_t = S_{(t-1)} + P_{(t-1)} - E_{(t-1)} - \beta * S_{(t-1)}$$

where S is the lake stage (cm), P is precipitation (cm), E is lake evaporation (cm), and ϐ is a coefficient accounting for stage-specific groundwater outflow (i.e., loss of lake water to groundwater) after Watras et al. (2014). The precipitation data are derived from PRISM (PRISM 2004) and evaporation data are from a model developed by Jordan Read (Read et al. 2014). Lake-specific ϐ values were estimated using a grid-search algorithm that minimized the root mean squared error values between the predicted and observed water levels for each individual lake. A one-year time step was used in the model, and lakes had to have at least 20 years of data for quantifying ϐ values. In total, 20 lakes met this criterion for estimating a lake-specific ϐ value. Groundwater outflow ranged from 22 - 43 cm/yr (mean = 35 cm/yr). The average value of groundwater outflow was consistent with those observed by Watras et al. (2014).

As with the empirical approach above, lake-specific ϐ values were extrapolated to seepage lakes that lacked water level observations needed for directly calculating a ϐ value. We used the same set of predictor variables as described above to help identify the ecological context variables that explain the among lake variation in ϐ. The best model for extrapolating the slope between lake water level and cmdev was:

ϐ = Lake Elevation + Lake Max Depth + Conductivity

Estimate	Std. Error	Pr(>|t|)

(Intercept)	1.699e-02	5.669e-03	0.009
Lake Elevation	6.266e-05	1.249e-05	0.001
Max Depth	-1.844e-04	4.074e-05	0.001
Conductivity	2.118e-05	1.101e-05	0.072

The overall model explained 72.3% of the variation in lake specific б values ($p < 0.001$). In order to limit the potential of extrapolating beyond the bounds of the training dataset, we limited lakes that were extrapolated to have maximum depths between 12 and 67 m, lake elevations between 256 and 517 m, and conductivity between 16 and 412 us/cm. In total, б were extrapolated for 312 lakes. Average groundwater outflow was 36 cm/yr (range 24 - 48 cm/yr).

Statewide Seepage Lake Hindcasted Water Levels

In total, water levels were hindcasted for 316 seepage lakes using a combination of either or both approaches described above depending on the availability of driver data for each model (Figure 8). In general, there was close agreement between water levels hindcasted using the empirical and mechanistic models (See Supplementary Document #1). While the overall patterns in annual water levels were similar between both approaches, water levels hindcasted using the empirical model tended to be more accurate (RMSE = 33.6 cm) relative to the mechanistic model (RMSE = 44.3 cm; Figure 9).

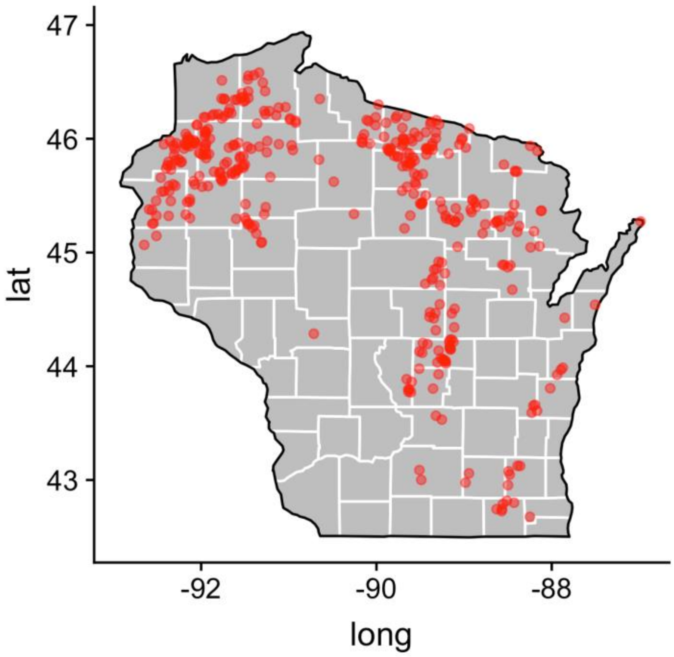

Figure 8. Map of seepage locations that have hindcasted water levels.

In addition to generating more accurate predictions of seepage lake water levels, the empirical model is advantageous in the applications explored here because it only requires precipitation data instead of both precipitation and evaporation data which must be either directly measured or modeled using complicated process-based models (see Read et al. 2014). Visual analysis of the differences between hindcasted and observed water levels suggest that, while the agreement is generally good (Figure 9), patterns have the potential to deviate substantially at times (See Supplementary Document #1). Further research is needed to better understand the dynamics of lakes in which water levels do not appear to track climate.

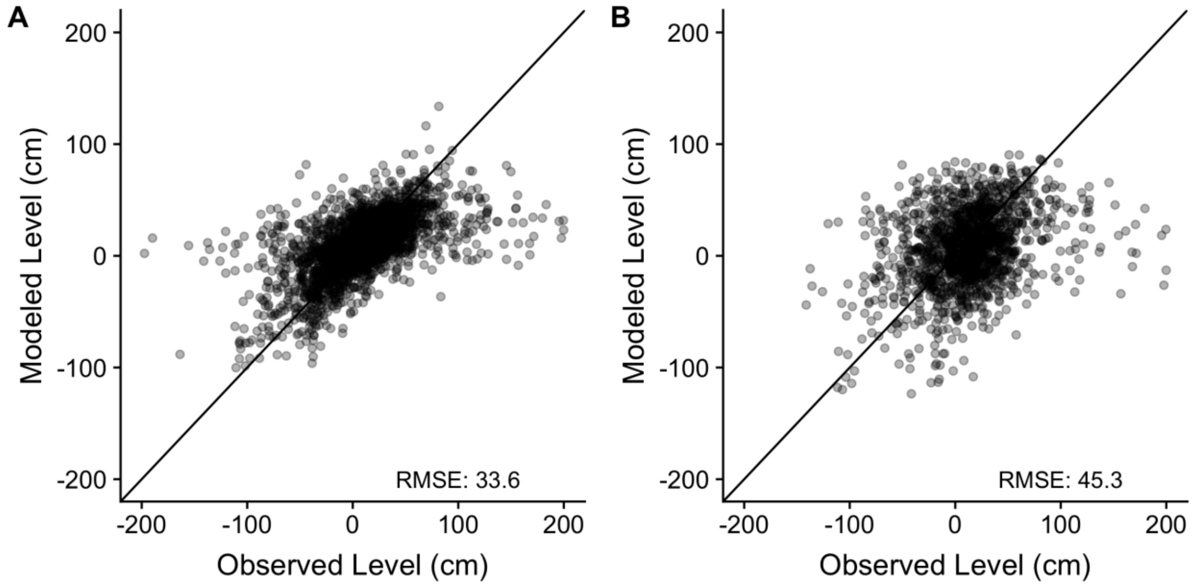

Figure 9. Comparison of observed and hindcasted water levels for the empirical (A) and mechanistic seepage lake water level models.

Seepage Lake Hydrologic Regimes

Hindcasting water levels over long periods of time (since the 1920s) provides an opportunity to begin placing water levels within a lake's hydrologic regime instead of simply the period of the current record (Figure 10). Across all lakes with empirical (precipitation based) water level predictions, 20% of the time lake stage equaled or exceeded 26 cm above the long-term average (range 9 to 54cm) and 70% of the time it equaled or exceeded -19 cm (range -45 to -6cm). Thus, on average for lakes considered in this study, water levels were typically +/- 0.25m 50% of the time for any given lake.

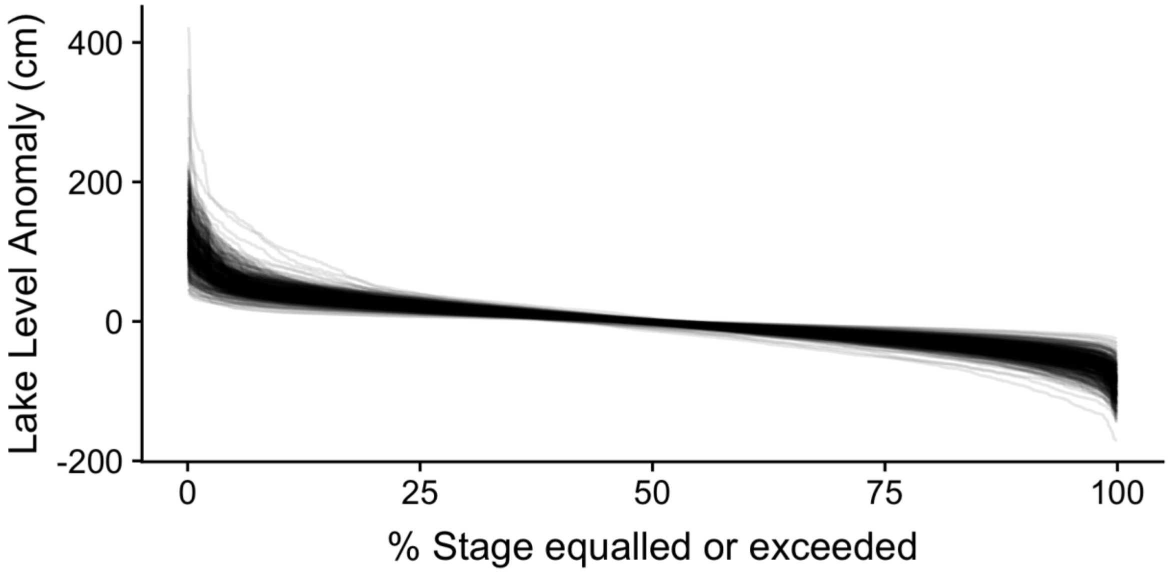

Figure 10. Stage exceedance curves for seepage lakes with hindcasted water levels.

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