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Flashiness and Flooding of Two Lakes in the Upper Midwest During a Century of Urbanization and Climate Change

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Abstract

Globally, ecosystem services are threatened by increasing urbanization and more variable precipitation patterns driven by climate change. However, how these drivers interact over long-time scales to affect underlying processes remains poorly understood, hindering our ability to predict their long-term consequences. Here, we use long-term data spanning nearly a century to investigate changes in hydrologic attributes for two lakes in the Upper Midwest with urbanizing watersheds. We quantified flashiness—the variability of runoff rate, volume, or stage-level of waterways—to investigate the concurrent impacts of urbanization and climate change on flashiness and flooding potential. Our results indicate that flashiness generally increased for both lakes over the period of 1916–2013, although this overall trend consists of sub-periods of increase and decrease. Increasing impervious surface area has been the stronger driver of flashiness historically; however, our results suggest that the impact of urbanization may reach a threshold, such that saturation effects would cause large magnitude precipitation events to become a relatively stronger driver of flashiness. Increasing flashiness indicates an increase in flooding potential, documented by increases in the 10- and 100-year flood threshold levels as large as 30 cm. Since flashiness is strongly related to the provisioning of multiple ecosystem services, the methodology and results presented here provide a unique approach to gain insight into how non-linear interactions between global change drivers, at multiple time scales, impact the simultaneous provision of multiple services.

Key words: ecosystem service; hydrologic service; freshwater; land use/cover change; climate change; global change drivers; general additive model (GAM); Wisconsin.

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Author Contributions Original project conception and manuscript draft by JU and AK, with subsequent edits by JU, AK, and JQ. Analysis of impervious surface by AK (Figure 5); watershed characteristics by JQ (Figure 1); and statistical models by JU (Figures 2, 3, 4, and 6).

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Introduction

Urbanization and climate change are two of the most significant drivers of global change impacting ecosystems and the provision of ecosystem services critical for human wellbeing (Foley and others 2005; MEA 2005; United Nations 2008). An estimated two-thirds of the world's population will live in cities by 2050 (United Nations 2008); this has major implications because urbanization substantially degrades freshwater quality by increasing human demands for freshwater, replacing land covers with less permeable or impervious covers, and fragmenting natural vegetation (Alberti 2005; Sánchez-Rodriguez and others 2005; Metzger and others 2006; Grimm and others 2008). Climate change is expected to further exacerbate these effects by increasing the frequency and magnitude of heavy rain events, and creating more volatile stormwater runoff (IPCC 2013; WICCI 2011; Doerr and Thomas 2000; Zehe and others 2005). Anticipating the consequences of interactions between urbanization and climate change for ecosystem services depends on understanding how they change underlying hydrologic attributes such as the quantity, quality, and timing of freshwater flows. This remains challenging because it requires integrating complex non-linear relationships between multiple drivers across spatial and temporal scales, but extrapolating from watershed-level hydrologic responses during urbanization may make it possible to encapsulate much of this complexity (Brauman and others 2007; Schneider and others 2012).

A key mechanism linking the influence of urbanization and climate change to the supply of ecosystem services is flashiness, the frequency and rapidity of short-term changes in flow rates, volume of surface runoff, and stage levels of waterways following precipitation events (Poff 1996; Booth and others 2001; Baker and others 2004). As a characteristic of the hydrological regime of a watershed, it is closely associated with the viability of specific ecosystem services, especially regulating services. For example, flashier watersheds or waterbodies often have a higher flooding potential, less ability to attenuate storm water runoff, elevated nutrient loading, and reduced groundwater recharge at local and regional scales (Grimm and others 2008; Pickett and others 2011). Moreover, increased flashiness can negatively impact downstream ecosystems such as wetlands or riparian buffers (Meyer and others 2005; Allan 2004).

As such, we argue that flashiness has the potential to be used as a constituent variable to quantify and monitor a suite of hydrologic attributes simultaneously (Keeler and others 2012). An increase in flashiness may be observable after even minor increases in urbanization, making it valuable as a potential early warning indicator of degradation (Booth 1991; Wenger and others 2009). This has been largely unexplored, despite the widespread availability of long-term water-level data that could be used to quantify changes in flashiness, or the fact that it could serve as an important analytical indicator by which to assess the relative influence of various drivers, including urbanization and climate change, on the hydrologic attributes of a watershed.

Urbanization is known to produce a distinctive suite of physical, chemical, and biological changes in watershed hydrology through various land-use and land-cover changes (Booth 1991; Wenger and others 2009), of which increased flashiness is an important component. It converts many natural covers such as riparian forests and wetlands that would otherwise function to slow hydrologic flow and enhance groundwater infiltration, sediment retention, and nutrient absorption. Soil compaction, ditching and simplification of drainage networks, and increases in impervious surface area also reduce the infiltration capacity of landscapes (Leopold 1968; Poff 1996); this additionally increases surface runoff rates and volumes, ultimately exacerbating these problems and increasing flooding risk (Paul and Meyer 2001; Naiman and Decamps 1997; Fletcher and others 2013). These effects cascade to waterbodies such as lakes or ponds within watersheds, elevating nutrient levels, raising water temperatures, and increasing flashiness (Booth 1991; Carpenter and others 1998; Wenger and others 2009).

Changing precipitation patterns further complicate the effects of urbanization on flashiness, particularly in regions where the frequency and magnitude of heavy rain events are increasing relative to average precipitation (IPCC 2013; WICCI 2011). Extreme precipitation events increase flashiness as a result of soil saturation thresholds (Doerr and Thomas 2000; Zehe and others 2005). As rainfall intensity exceeds infiltration capacity (i.e, reaches a saturation threshold), any additional precipitation will increase the rate and volumes of surface runoff more strongly, driving disproportionately large increases in the stage levels of waterways or waterbodies (Doerr and Thomas 2000; Zehe and others 2005). Thus, projected increases in the variance in precipitation patterns under future climate scenarios will likely increase the flashiness, making runoff and water-level management more challenging.

Changes in flashiness can be difficult to predict given the multitude of factors that altogether influence flow rates. Although there is a well-established mechanistic link between increased flashiness and less permeable or impervious surfaces that replace natural land cover (Leopold 1968; Poff 1996; Naiman and Decamps 1997; Paul and Meyer 2001), much less is known about how climate change might mediate such linkages. In particular, few studies have rigorously teased apart the relative effects of urbanization and shifting climate on flashiness. It is likely that different drivers may dominate during different times; over long time scales, climate and management can affect hydrology and flashiness without changing land cover directly (Fletcher and others 2013). All of these factors are likely to interact with precipitation regimes in ways that are just beginning to be understood (Franczyk and Chang 2009; Poelmans and others 2011).

The objective of our study was to understand the simultaneous impacts of urbanization and changing precipitation patterns on the long-term dynamics of flashiness and flooding. We used several statistical approaches to analyze historical patterns of flashiness, urbanization, and from long-term data for two adjacent watersheds (Lake Mendota and Monona Watersheds, Wisconsin) in the Upper Midwest, USA (Figure 1). Previous work suggests that freshwater ecosystem services have become increasingly compromised during this time period (Wegener 2001; Lathrop and others 2005; Carpenter and others 2005). We quantified changes in flashiness related to urbanization and changing precipitation patterns to specifically address the following questions: (1) How has flashiness changed in Lakes Mendota and Monona Watersheds over the past century? (2) What are the relative importance of urbanization and shifting precipitation patterns in driving changes of flashiness? (3) How do changes in flashiness affect flood potential over time? Finally, we discuss how changes in flashiness may influence lake management decisions and lead to tradeoffs among different hydrologic services. Our statistical approaches are chosen to accommodate the potentially nonlinear nature of changing watershed hydrology. By choosing to work with data from lakes, we hope to bring these water bodies more explicitly into the discussion of flashiness and demonstrate that they are a useful lens through which to investigate the integrated impacts of changes across an entire landscape. Furthermore, the generality of the data that we use in this investigation should make it straightforward to adapt our analyses to other watersheds.

Methods

Study Area

We studied two lakes in the upper Midwestern U.S., whose watersheds are similar in topology and soil characteristics, but differ in their histories of urbanization. Lake Mendota is the largest of four interconnected lakes along the Yahara River in

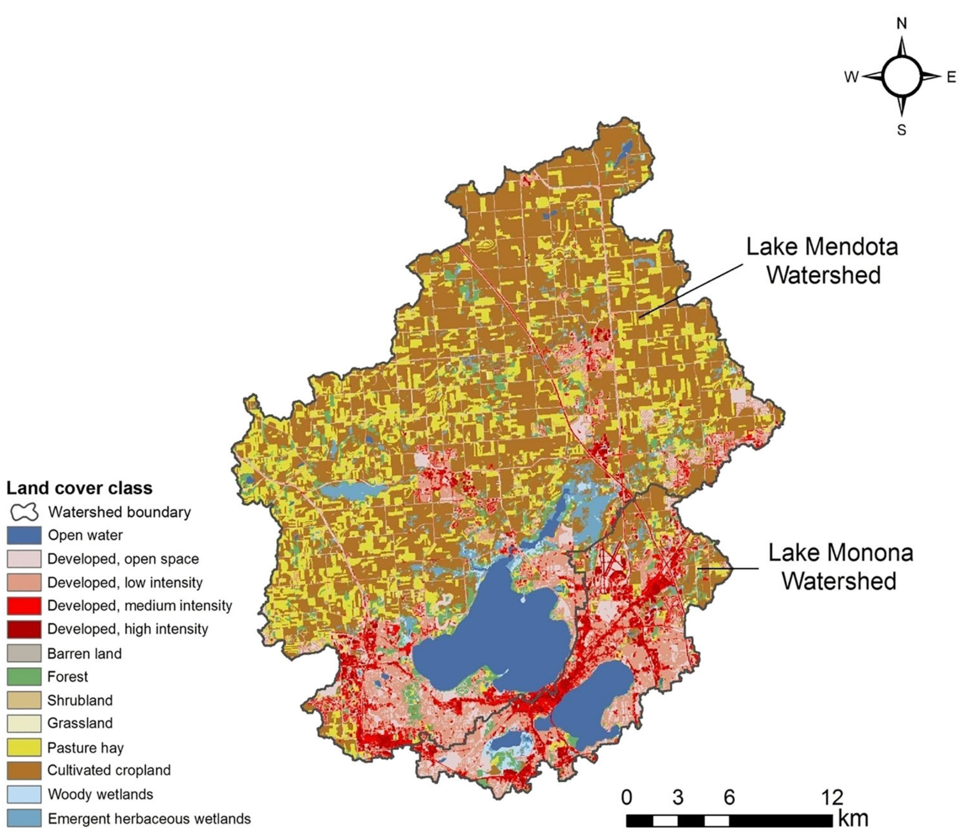

Figure 1. Geographic location and current land use/cover pattern of two studied watersheds: Lake Mendota Watershed and Lake Monona Watershed. Delineations of the watersheds were based on light detection and ranging (LiDAR) elevation, sewer-sheds from the city of Madison and a field-checked basin map from Dane County, Wisconsin. Land use/cover data are derived from National Land Cover Database (NLCD) 2006.

southern Wisconsin (Lathrop 1992). It covers an area of approximately 4000 ha and has a mean depth of 12.7 m. Its watershed drains 549 km^2 and is largely agricultural with row crops and pasture. Originally dominated by a mixture of prairie, oak savanna, woodlands, and wetlands in pre-settlement times (Curtis 1959), this landscape was cleared for agriculture during the mid-1800 s; by about 1870, most of the arable land was in agriculture. It is currently undergoing a rapid transition from agricultural to urban and suburban uses as the city of Madison and surrounding suburbs have increased in size (Dane County Regional Planning Commission 1992). These changes have been linked to eutrophication in Lake Mendota, and the ecological effects have been well-studied within the North Temperate Lakes Long-Term Ecological Research (LTER) Program (Magnuson and others 2006).

Lake Monona is smaller, covering 1320 ha with a mean depth of 8 m, and has the smallest watershed of the four lakes connected by the Yahara, covering 109 km^2. The history of land use/cover transition is very similar to that of Mendota, but a much greater proportion of the Monona watershed is currently urban and suburban covers relative to agriculture. Lake Monona connects to Mendota by a 1.5-km segment of the Yahara River which undergoes a change in elevation of only 1.5 m between the two lakes. Flow rates from Mendota to Monona are controlled by a lock mechanism at the Mendota outlet.

Water-Level and Precipitation Data

We used daily records of precipitation and water level for Lake Mendota and Monona over a historical period beginning in January 1916. Water-level data were obtained from the United States Geological Survey (USGS). These originate from gaging stations at the outlet of lake Mendota at the Tenney locks (43°05′42″N, 89°22′12″W), and the outlet of lake Monona in Brittingham Park (43°03′48″N, 89°23′49″W). Historical precipitation data came from the Midwestern Regional Climate Center. These originate from two different sampling stations, based on the time frame for the data: station Madison WB CITY (ID: 474966) prior to 1943, and station Madison WSO AIRPORT (ID: 474961) for 1943 to present. In each year, the months of January–March and November–December are removed to exclude potential ice-on dates from analyses, based on the median ice-on and ice-off dates of each lake (Wisconsin Climatology Office; available at: http://www.aos.wisc.edu/~sco/). Although snow melt adds additional runoff in the spring, we have no way of accounting for this delayed delivery.

Impervious Surface Quantification

Impervious surface area in each watershed was estimated based on a published empirical relationship with housing united density (HUD) (Lathrop and others 2007). However, the published relationship is based on a watershed with upland forest and recent suburban development, and thereby our estimates may underestimate impervious surface. HUD estimates were derived from decadal census data of Dane county from 1940 to 2000. Census data were imported into ArcGIS 10.0 (ESRI), and all census blocks within each watershed boundary were included in the estimate of HUD. The total HUD for the watershed was converted into an estimate of the percent of impervious surface based on the empirical relationship observed by Lathrop and others (2007), as shown below. The relationship between the percent of impervious surface and HUD was non-linear, with break-point at 1 housing unit per acre.

$$\begin{aligned} &\text{where HUD} < 1.0,\ \text{Percent Impervious} \\ &\quad = 21.5\ \text{HUD} + 0.8 \\ &\text{where HUD} \geq 1.0,\ \text{Percent Impervious} \\ &\quad = 5.7\ \text{HUD} + 13.6 \end{aligned} \tag{1}$$

The percent of impervious surface was converted into area by multiplying with watershed area.

Analysis of Flashiness

The historical data (1916–2013) were analyzed for changes in flashiness in both Lake Mendota and Monona Watersheds using two distinct approaches: by analyzing lake-level variance directly, and by statistically modeling the response of lake level to precipitation. A statistical test for stationary variance was used to answer whether flashiness has changed significantly in either lake. Then we fit general additive models (GAMs) to quantify watershed-level changes indicated by changing flashiness, using lake level as the response and precipitation as the explanatory variable. During the model fitting, we produce three sets of models with different purposes: (1) models without impervious surface that span the time range 1916–2005, with the last eight years reserved for cross-validation between predicted and real lake-level; (2) models with impervious surface data that cover the years 1940–2013 (the full range we have available for this covariate); and (3) models without impervious surface data that cover the years 1940–2103 that serve as ''null'' models to compare against those fitted to the impervious surface data. We assessed how changes in flashiness have affected flooding potential, measured by the likelihood of 10- and 100-year floods. Details of statistical analyses can be found below and in Supplementary Appendix A. This approach is novel in several regards including the following: the use of time series analysis to establish ''baselines'' for the variance in drivers and flashiness, and to use the trend over time as a null model for analytical comparison of the strength of hypothesized drivers; the use of GAMs to account for linear and non-linear patterns of change, and to account for thresholds in variables like soil saturation; and the use of flashiness as an integrative analytical indicator of hydrologic attributes.

Test for Changing Flashiness

Changes in the variance in lake level (i.e, flashiness) were assessed using Engle's test for heteroskedasticity in a time series. We fit a general autoregressive conditional heteroskedasticity (GARCH) model to the daily lake-level data, and compared the fit to the null hypothesis of homogenous variance (Engle 1982). The fitted GARCH models were used to plot the time-dependent magnitude of flashiness for each lake. We calculated 5-year moving-window averages of the daily GARCH fits to make changes in flashiness over longer time scales more apparent.

Statistical Models of Flashiness

Flashiness indicates how a watershed mediates precipitation events of various sizes. This suggests that flashiness can be modeled statistically using lake-level changes as a response to precipitation, and possibly with additional covariates representing the watershed or features of the watershed itself. Using precipitation, percent urban cover, and time as covariates, we fit statistical models of lake-level response for both Mendota and Monona. In its simplest form, our models group the combined effects of different watershed features (e.g., land cover, land use, soil properties) into a generic variable, represented by fitted coefficients on precipitation. Interactions of precipitation with time then account for temporal trends in watershed response. Interactions of impervious surface with precipitation then assess how urbanization specifically has changed the ability of the watershed to mediate precipitation.

A GAM framework was used to explore fits. This framework is useful because it allows both parametric and non-parametric terms to be combined in the same model. At the extreme where all terms are parametric, the GAM becomes a linear model. Details and comparisons of linear models and GAMs are given in Supplementary Appendix A, but here we give a conceptual overview of the model covariates. We explore both parametric and non-parametric fits to take advantage of the strengths of each approach. Non-parametric terms may be more successful at representing changes across multiple time scales resulting from the combination of gradual trends that emerge as a result of land-use conversion, and abrupt changes resulting from management decisions. In contrast, the strength of parametric representations is then their ability to average across the many short-term, non-linear fluctuations and more clearly represent any overall, long-term trend that may be present. The explicit inclusion of both parametric and non-parametric model fitting within the bounds of the same analytical exercise emphasizes the utility of this approach in assessing the relative contribution of drivers that occur across multiple scales in a long-term dataset.

Precipitation is the primary driver of lake-level increase. It contributes to lake level on the same day as an event, as well as on subsequent days following the initial input as runoff gradually reaches the lake from the surrounding watershed. The lake level of any given day is then determined from precipitation of the current day, as well as precipitation from a number of previous days. This leads to several lag terms of precipitation.

Threshold effects of soil saturation become increasingly important as the total amount of precipitation increases during a single event, and across multiple-day events. This leads to a non-linear increase in the effect of precipitation on lake level as it accumulates during these events. Threshold response is captured naturally in GAMs by non-parametric terms, and can be incorporated into linear models through exponential (squared) coefficients.

The proximity and topography of Mendota and Monona make it likely that their lake levels are interdependent, although this is more likely to be true for Monona, which is downstream from Mendota. To account for this, we included terms for current day lake level of the other lake, as well as lags over a number of previous days.

The ability of hydrologic services to mediate precipitation effects on lake level can be impacted by numerous changes in watershed characteristics. By including a generic variable of ''time,'' and allowing our covariates to interact with time, we capture the simultaneous effects of all relevant changes: replacing time with only percent impervious surface accounts for the influence of only that particular feature. Thus, we produce two distinct sets of models: one with the generic change in time representing overall watershed change, and the other with percent impervious surface area of the watershed as the driver of change.

The decision to include or exclude terms in all models was based on minimizing the Akaike Information Criterion (AIC) (Akaike 1973; Guisan and others 2002). The AIC is effective for all linear models including GAMs (Wood 2006). We first attempted to find the best linear model of lake-level response for Mendota and Monona in each of the three scenarios outlined previously (time since 1916, impervious surface since 1940, time since 1940). Once this model was determined, we proceeded to replace parametric terms with the analogous non-parametric terms. Decisions to retain a smooth fit over a parametric fit were made based on changes in the AIC.

Drivers of Flashiness

Flashiness in lake level is driven by changes in hydrologic attributes driven by watershed-level changes in land use/cover, as well as more variable precipitation patterns. To separate these effects, we partition flashiness (variance in lake-level response $R_i(t)$) into an amplifying/dampening effect of watershed and an effect of the variance in precipitation patterns. At the watershed level, flashiness should be damped through such mechanisms as groundwater infiltration and stormwater retention; as these abilities decline, flashiness should increase. Consider a linear model of lake level including current day of precipitation, its interaction with time, an effect of opposite lake, and a first-order autoregressive term: $R_i(t) = u_i + \beta_1$ rain0 + $\delta_1 t$*rain0 + $\kappa_1 R_i(t-1)$. The total variance of this model can be written as

$$\mathrm{var}(R_i) = \frac{T_1^2 \mathrm{var(rain)} + \gamma^2 \mathrm{var(R_j)}}{1 - \kappa^2} \quad (2)$$

The coefficients β_1 and δ_1 have been incorporated into an overall time effect given by $T_1^2 = (\beta_1 + \delta_1 t)^2$. That is, T_1^2 indicates the extent to which watershed characteristics amplify ($T_1^2 > 1$) or dampen ($T_1^2 < 1$) the underlying variance in precipitation. Comparing variability in a baseline period to subsequent periods amounts to taking the ratio of Eq. (1) calculated for each time period. After subtracting $\mathrm{var}(R_j)$ and subscripting variables assuming decades at the beginning and end of the dataset, the ratio of variances becomes

$$\frac{\mathrm{var_{hi}(R_i)}}{\mathrm{var_{bas}}(R_i)} - \frac{\mathrm{var_{hi}(R_j)}}{\mathrm{var_{bas}}(R_j)} = \frac{T_{\mathrm{hi}}^2 \mathrm{var_{hi}(rain)}}{T_{\mathrm{bas}}^2 \mathrm{var_{bas}(rain)}} \quad (3)$$

Thus, the ratio $V_{\mathrm{hi}} \equiv \mathrm{var_{hi}}(R_j)/\mathrm{var_{bas}}(R_j)$ is partitioned into the proportionate change due to variance in precipitation (changed by a factor of V_{hi}), and the ratio $T_{\mathrm{hi}} \equiv T_{\mathrm{hi}}^2/T_{\mathrm{bas}}^2$ gives the proportionate change in an amplifying/dampening effect of watershed changes (changed by a factor of T_{hi}). Although we have demonstrated this calculation for a linear model, it is equally valid for GAMs because terms still satisfy the same linearity properties.

Since changes in flashiness may not be monotonic over time but consist of multiple peaks, we identified periods of peak flashiness in the overall time-series and analyzed them separately. To identify periods of peak flashiness, we used the results of the GARCH models to establish an overall, mean lake-level variance for each lake. Then a period of baseline flashiness was identified relative to the overall mean by finding the longest continuous period with an average variance below the overall mean. Periods of peak flashiness were identified when average variance was above the overall mean.

Flood Potential Analysis

Flood potential is an indication of the likelihood that lake level will exceed a defined stage height. Greater flashiness results in a greater potential for floods. We explored this relationship using a standard approach to quantify flood potential; we created an annual flood series based on historical data by identifying the peak flow lake level for each year, and ranked them in order of magnitude (U.S. Geological Survey 1982). The frequency of measured lake levels was well-modeled by a log-normal distribution, and thus, we followed the convention of fitting a Pearson Type III (Gamma) distribution to the frequency of log-maxima (i.e, floods) through direct calculation of the first three moments (mean, variance, and skew) (Foster 1924; USGS 1982). The fitted distribution gives flooding potential through the exceedance probabilities; i. e, the probability that a peak lake level exceeds a pre-defined threshold. Specifically, we identify lake levels with likelihoods of 0.01 (1%) and 0.1 (10%), corresponding to the 100- and 10-year flood thresholds.

To account for the expected non-stationarity in exceedance probabilities resulting from changing flashiness, we calculated time-dependent exceedance probabilities with a moving-window approach. Given a certain window width, w, we calculated exceedance probabilities for each time period (year $n + w$) for all n beginning at $n = 1$. We set w based on time scales suggested by the fitted GARCH model; thus if the variance was homogenous, then w was the length of the entire dataset. Our final results then showed 100- and 10-year flood thresholds as a function of time, as opposed to a single value summarizing the entire time period of 1916–2013.

Results

Long-Term Changes in Flashiness

The flashiness of both Lake Mendota and Monona Watersheds was significantly time dependent ($P < 0.001$ for both lakes). The fitted GARCH models were used to plot daily changes in variance or flashiness (Figure 2, gray lines), as well as longer term trends reflected by the 5-year moving average of daily variance (Figure 2, dark lines) in both watersheds. The GARCH models anticipated intermediate-term trends in Mendota, where large spikes at the daily time-scale typically signaled shifts toward greater flashiness, as revealed by the moving-window averages. This relationship was less obvious for Lake Monona, where the overall volatility of the GARCH model suggested that shifts in flashiness occurred rapidly.

Lake Mendota and Monona had overlapping periods of baseline flashiness, and shared peak periods beginning in the early 1990 s (Figure 2, dotted lines). Otherwise, the overall trends in flashiness for the two lakes differed markedly. Flashiness in Mendota fluctuated at baseline levels until approximately 1964, and afterwards increased within distinct sub-peaks. Monona had already reached a period of peak flashiness at the beginning of the time series, dropped to baseline levels in the early 1940s and became flashier again in the early 1990s, concurrent with the most recent increasing trend for Mendota.

Statistical Models of Flashiness

Mendota and Monona shared a number of overarching similarities in the way that lake level responds to rain, as reflected by similarities in the explanatory variables that were retained in fitted models. Precipitation from up to 4 days in the past has a significant effect in lake levels. The ability of each watershed to mediate precipitation from a certain day changed over time, reflected by the significant rain lag and time interactions in the models. Precipitation that occurred over multiple days effected lake level more than precipitation on any single day; this is evidenced by positive interactions between lags, which indicate that the magnitude of change in lake level was larger when precipitation followed previous events.

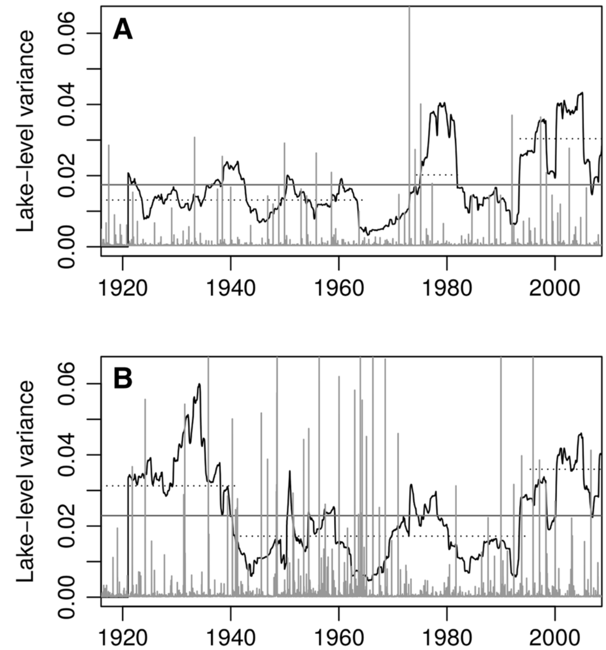

Figure 2. Flashiness—defined as the lake-level variance—as a function of time for both (**A**) Mendota and (**B**) Monona. *Vertical gray lines* are the variance as a function of time at each day in the dataset predicted from fitted GARCH models of each lake. *Solid black lines* give the variance calculated with a 5-year moving window. *Horizontal lines* correspond to average variances for certain periods, with the solid gray lines as overall averages of the variance. Both (**A**) Mendota and (**B**) Monona were divided into regions of baseline variance (*dotted horizontal lines*, below the average) and two peak variance regions (*dotted horizontal lines*, above the average). Flashiness is time dependent in both lakes. In Mendota, it appears to be increasing in the last 40 years. Monona is initially flashy, decreases, and then begins to increase in the last 20 years.

One of the best predictors of lake level is actually lake level itself. This is reflected in the autocorrelation structure of the models; lake level over previous days provides a lot of information about current lake level. In the case of Monona, lake level was also dependent on Mendota lake level on previous days, reflecting the fact that Monona is downstream from Monona. Although it might be possible for Monona to also influence Mendota lake level in extreme cases, by overflowing back along their adjoining tributary, we found no statistical evidence of this, since none of the Monona

Table 1. The Best-fit Models for Mendota and Monona Lake-level Response, Showing Both the Fully Non-parametric Best-Fit GAM, and an ''Equivalent'' Parametric Model

Mendota				Monona			
GAM		**Parametric**		**GAM**		**Parametric**	
Term	Edf/ estimate ± SE	Term	Estimate ± SE	Term	Edf/ estimate ± SE	Term	Estimate ± SE
Intercept	849.7 ± 3.7E−4***	Intercept	849.7 ± 3.7E−4***	Intercept	845 ± 3.4E−4***	Intercept	845 ± 3.4E−4***
s(time)	2**	Time	2.56E−7 ± 8.9E−8**	s(time)	7.918***	Time	−1.92E−7 ± 9.2E−8*
s(rain0)	3.224***	rain0	4.13E−2± 5.4E−3***	s(rain0)	4.089***	rain0	2.62E−2 ± 5.7E−3***
s(rain1)	4.217***	rain1	1.63−2 ± 5.4E−3**	s(rain1)	3.334	rain1	4.8E−2 ± 5.8E−3***
s(rain2)	1***	rain2	2.2E−2 ± 5.4E−3***	s(rain2)	2.61	rain2	−9.2E−3 ± 5.8E−3
s(rain3)	1***	rain3	1.69E−2 ± 5.4E−3**	s(rain3)	1	rain3	−1.08E−3 ± 5.8E−3
s(rain4)	1.745***	rain4	−3.83E−5 ± 2.7E−3	s(rain4)	1	rain4	6.54E−3 ± 2.8E−3*
s(menr1)	4.492***	menr1	1.02 ± 7.5E−3***	s(monr1)	4.681***	monr1	1.08 ± 8.7E−3***
s(menr2)	4.026***	menr2	−6.65E−3 ± 1.1E−2	s(monr2)	2.707***	monr2	−2.74E−2 ± 1.3E−2*
s(menr3)	2.75***	menr3	1.91E−4 ± 1.1E−2	s(monr3)	4.707***	monr3	−1.47E−2 ± 1.3E−2
s(menr4)	1***	menr4	−1.01E−2 ± 1.1E−2	s(monr4)	1	monr4	6.24E−4 ± 1.2E−2
s(menr5)	1***	menr5	3.47E−3 ± 1.1E−2	s(monr5)	1**	monr5	−2.8E−2 ± 1.2E−2*
s(menr6)	1***	menr6	−2.71E−2 ± 6.7E−3***	s(monr6)	2.773	monr6	3.43E−3 ± 1.2E−2
te(rain0,time)	40.362***	rain0*time	3.21E−7 ± 4.8E−7	s(monr7)	1.93***	monr7	−2.9E−2 ± 8.3E−3***
te(rain1,time)	7.595***	rain1*time	3.06E−6 ± 4.8E−7***	s(menr0)	4.793***	menr0	5.96E−1 ± 7.8E−3***
te(rain2,time)	1.545***	rain2*time	−2.02E−6 ± 4.8E−7**	s(menr1)	4.802***	menr1	−6.5E−1 ± 1.2E−2***
te(rain3,time)	5.805***	rain3*time	−1.65E−6 ± 4.8E−7***	s(menr2)	4.635***	menr2	2.73E−2 ± 1.3E−2*
te(rain4,time)	9.47***	rain4*time	4.67E−7 ± 2.5E−7	s(menr3)	1	menr3	8.5E−3 ± 1.3E−2
te(rain0,rain1)	9.277***	rain0*rain1	2.14E−2 ± 2.57E−3***	s(menr4)	3.399	menr4	−9.41E−3 ± 1.3E−2
te(rain1,rain2)	5.417***	rain1*rain2	8.97E−3 ± 2.58E−3***	s(menr5)	1	menr5	1.95E−2 ± 1.3E−2
te(rain2,rain3)	2.773***	rain2*rain3	6.82E−3 ± 2.6E−3**	s(menr6)	2.472	menr6	−1.7E−3 ± 1.3E−2
		rainsq0	−9.33E−3 ± 3.1E−3**	s(menr7)	1.001***	menr7	2.48E−2 ± 8.6E−3**
		rainsq1	1.21E−2 ± 3E−3***	te(rain0,time)	24.204***	time*rain0	6.77E−7 ± 4.23E−7
		rainsq2	−7.46E−3 ± 3.0E−3*	te(rain1,time)	68.327***	time*rain1	−2.69E−6 ± 4.3E−7***
		rainsq3	−6.01E−3 ± 3E−3*	te(rain2,time)	7.537***	time*rain2	−3.25E−7 ± 4.3E−7
		time*rainsq0	3.17E−7 ± 2.6E−7	te(rain3,time)	13.721***	time*rain3	−4.31E−7 ± 4.3E−7
		time*rainsq1	−2.88E−7 ± 2.53E−7	te(rain4,time)	7.715**	time*rain4	−8.4E−7 ± 2.1E−7***
		time*rainsq2	1.15E−6 ± 2.5E−7***	te(rain0,rain1)	7.125***	rain0*rain1	1.82E−2 ± 2.8E−3***
		time*rainsq3	7.41E−7 ± 2.6E−7**	te(rain1,rain2)	3.764***	rain1*rain2	−1.31E−3 ± 2.8E−3
				te(rain2,rain3)	2.07*	rain2*rain3	6.15E−4 ± 2.8E−3
						rainsq0	−7.89E−3 ± 3.4E−3*
						rainsq1	−8.99E−3 ± 3.4E−3**
						rainsq2	5.75E−3 ± 3.4E−3.
						rainsq3	−2.03E−3 ± 3.4E−3**
						time*rains0	3.14E−7 ± 2.3E−7

Table 1. continued

Mendota				Monona			
GAM		Parametric		GAM		Parametric	
						time*rainsq1	1.25E−6 ± 2.4E−7***
						time*rainsq2	−1.05E−7 ± 2.4E−7
						time*rainsq3	1.08E−7 ± 2.3E−7
	AIC : −56427.97		AIC : −56133.88		AIC : −44369.82		AIC : −43729.09
s(imperv.men)	4.73**	Imperv.men	−8.16E−4 ± 3.3E−2	s(imperv.mon)	1*	Impervmon	−0.041 ± .015**
	AIC: −43148.9		AIC:−42756.29		AIC:−32115.92		AIC: −31542.87
s(time.1940)	5.97**	Time.1940	6.57E−8 ± 1.3E−7	s(time.1940)	1	Time.1940	−4.56E−7 ± 1.6E−7**
	AIC: −43030.97		AIC: −42779.22		AIC:−32102.5		AIC: −31543.57

In each lake, the AICs were comparable between both models (Mendota: AIC = −56427.97 and −56133.88; Monona −44369.82 and −43729.09 for GAM and parametric). Also shown are the AIC values for two additional sets of models, calculated by replacing time either with % impervious surface area, or by time since 1940. The terms that were retained during model selection were similar across both lakes, and across both model types. The terms rainn refers to rain, lagged by n is in days. A notable difference between lakes was the dependence of Monona lake level on Mendota lake level.
*Significance codes:*** <2e¯16, ** 0.001, * 0.01, . 0.05.*
s() smooth function of one term, te() smooth function of interaction, rainn Precipitation at lag n, menrn Mendota lake-level response at lag n, monrn Monona lake-level response at lag n, rainsqn (Preciptation at lag n)^2, imperv.men Mendota impervious surface, impver.mon Monona impervious surface, time.1940 models with time starting 1940.

lake-level terms were retained in the Mendota model.

In terms of the performance of parametric versus non-parametric models, both Mendota and Monona were fit well by both types (Table 1, Figure 3), but AIC was always lower for fully non-parametric models (GAMs) (Mendota AIC = −56427.97, Monona AIC = −44369.82) and was comparable for parametric models (−56133.88 and −43729.09). In most cases, the average influence of explanatory variables (i.e, impervious surface, time, precipitation) could be inferred from parametric fits (Table 1), which provided qualitatively similar results to non-parametric fits (e.g., Supplementary Figure A1). In the case that non-parametric fits reduced to 1 degree of freedom (DF), the parametric fits can be regarded as essentially equivalent. However, estimates in the parametric models were not always significant, while the non-parametric fits were; this affects the ability to use parametric terms to infer covariate effects (Supplementary Appendix A).

The GAMs predicted lake level during cross-validation (Figure 3). However, there was a notable bias in each lake toward matching positive spikes in lake-level response, although not representing periods when lake level was below average. This is likely due to the lack of explanatory variables corresponding to mechanisms that drive lake level down, such as drought or manipulation through opening the locks on Lake Mendota. Although we fit models to account for drought by including subsequent days without precipitation as an explanatory variable, these terms did not decrease model AIC or improve the cross-validation (Figure 3).

Lake-Level Response to Precipitation

Both lakes respond the most strongly to recent precipitation (Table 1: rain0: rain 0 days past, rain1: rain 1 day past), but this response increased through time. Precipitation from previous days (Table 1: rain2: rain 2 days past to rain4: rain 4 days past) has always had an effect on lake level that is smaller, but this effect decreased for both Lake Mendota and Monona over the time period of our data (Table 1, parametric models, rain$n$*time interactions). Thus, precipitation that falls in the watershed reaches the lake more quickly than it once did.

These trends are also supported by the non-parametric fits in the GAM models, but this is more difficult to see. To aid interpretation, we summarize the GAM fits for each lag of precipitation by plot-

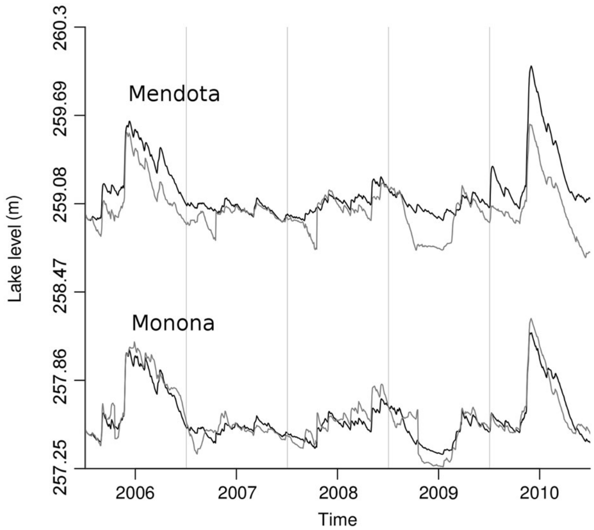

Figure 3. The predicted response given by the best-fit GAM of lake Mendota and lake Monona (*dark line*) is positioned over the actual lake-level data (*gray lines*). Vertical lines denote the beginning of a new year. In each case, AIC values suggest good fits (Mendota AIC = −56427.97, Monona AIC = −44369.82). However, certain shortcomings of the model are visible, the most notable being the inability of the Mendota GAM to capture the sharpest drops in lake level.

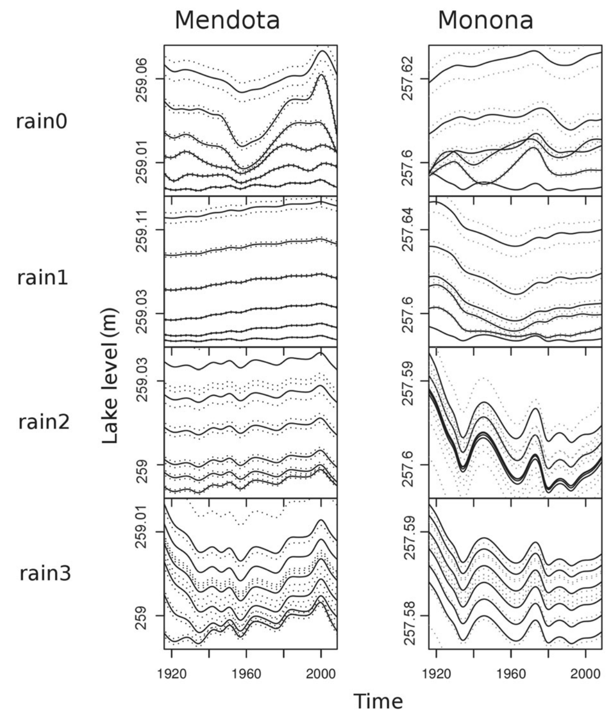

Figure 4. Contour plots showing the change through time of lake-level response to precipitation events of increasing magnitude, predicted by the best-fit GAM of lakes Mendota and Monona. Prediction intervals are given around each contour (*dotted lines*). Each contour is produced by fixing precipitation at a given interval, allowing time to increase starting from 1916, and fixing all other explanatory variables at mean values. The contours begin at the mean precipitation value of 2.6 mm and increment by 1 standard deviation (7.6 mm) from the previous curve. The magnitude of the response is relative to average lake levels of 258.99 and 257.56 m for Mendota and Monona, respectively.

ting the effect of each precipitation lag (Table 1: s(rain*n*), *n* = 0–3, where *n* is in units of days and te(rain*n*, time) for interactions) on lake level as a function of time (Figure 4). Multiple curves were plotted in each panel to create a contour plot. Each curve on a plot represents the response of lake level to precipitation events of increasing magnitude, starting from the mean precipitation value (2.7 mm), incremented by 1 standard deviation (7.6 mm). All other explanatory variables were held constant at mean values.

Here again it is clear that both Mendota and Monona responded most to recent precipitation events (i.e, rain0 or rain1) (Figure 4, first and second rows). Lake-level response across contours (±1SD) was non-linear for Mendota and Monona; thus, given a constant increment in the amount of precipitation (7.6 mm), the relative change in lake level tended to increase with larger precipitation events (Figure 4).

Otherwise, lake-level response to precipitation has developed differently for Mendota and Monona through time. For Mendota, lake level has continued to respond more strongly to rain from the current day (rain0) up to 2 days past (rain2). Meanwhile, precipitation from 3 to 4 days past (rain3 and rain4) has had a weaker effect on lake level through time. For Lake Monona, lake-level response to precipitation from the current day (rain0) has increased overall, while rain from all previous days has had a weaker and weaker effect. The response of Monona's lake level to previous day's rain (rain1) is more difficult to interpret; it shows a decreasing response of Monona lake level for the first half of the twentieth century, but has gradually increased since the 1960s.

Lake-Level Response to Impervious Surface Area

The amount of impervious surface area increased in both Lake Mendota and Lake Monona Watersheds between the years 1940 and 2000 (Figure 5). It increased from 49.5 km^2 (8.2%) in 1940–1975.7 km^2 (12.6%) in 2000, and increased from 35.8 km^2 (16.3%) to 63.7 km^2 (28.9%) for lakes Mendota and Monona, respectively. However, the relative percent increase in impervious surface was greater in the Lake Monona than Mendota

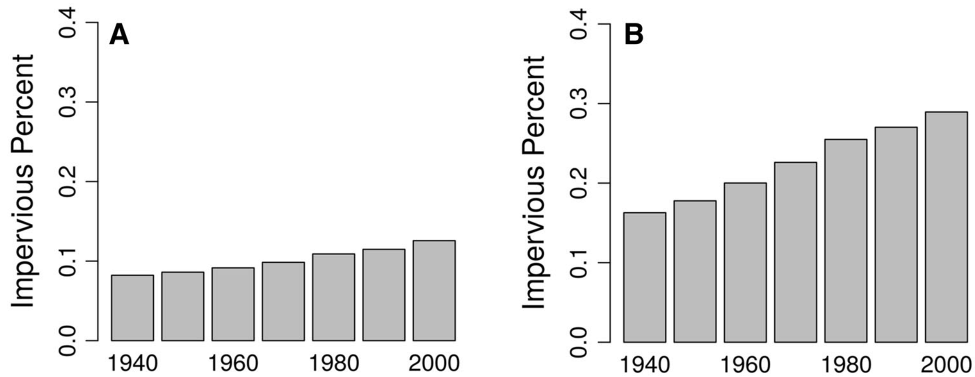

Figure 5. The percent of impervious surface area in the (**A**) Mendota and (**B**) Monona watersheds since 1940. The Mendota watershed covers an area of 602 km^2, and the Monona watershed is 220 km^2 in extent. The Mendota watershed has increased from 8.2% in 1940 to 12.6% impervious in 2000, whereas the Monona watershed has increased from 16.3% impervious in 1940 to 28.9% impervious as of 2000.

Watershed, although the watershed area of Lake Mendota is larger than Monona (602 km^2 vs. 220 km^2).

Model comparison clearly indicates that land use dominates long-term changes in lake hydrologic behavior. Percent impervious surface area in a watershed was a significant predictor of lake-level response, according to both the models. It explained the change in lake-level response since 1940 in both Lake Mendota and Monona (Table 1, AIC = −43148.9 and -28867.44). GAMs where the linear effect of time was replaced with percent impervious surface area as an explanatory variable had lower AIC values (imperv.men, imperv.mon versus time.1940: −43148.9 vs. −43030.97 for Mendota, −32115.92 vs. −32102.5 for Monona, Table 1). This suggests that the percentage of impervious surface area provides a better predictive model of lake-level response.

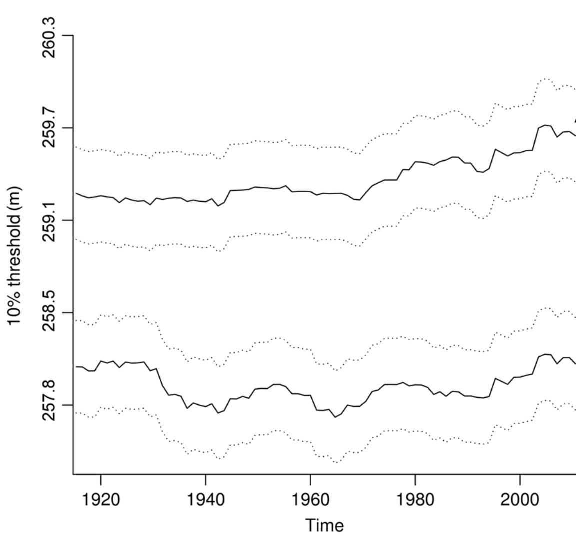

Figure 6. The change in 10-year (10%) flood levels and standard errors with respect to time for (**A**) Mendota and (**B**) Monona. Values are calculated as a combination of annual flood and partial flood series (yielding 30 total independent peaks) across a 10-year moving window. The 10-year level gives the peak lake level that should be observed in a 10-year interval. Higher values indicate that the largest peak observed in a 10-year period has increased.

Drivers of Flashiness

Overall, flashiness was driven more strongly by watershed-level changes than by changes in precipitation patterns. One baseline and two peak periods of flashiness were identified by the GARCH models and used to analyze the relative importance of these drivers. In Lake Mendota, the baseline variance was 0.013 m. The variance of the first (1974–1982) and second (1993-present) peak periods increased to 0.020 and 0.030 m, respectively. During the first peak period, the variance due to precipitation increased by a factor of $V_{\mathrm{hi},1} = 1.145$, whereas the amplifying effect of watershed changes increased by a factor of $T_{\mathrm{hi},1} = 1.350$. In the second peak, the variance in precipitation is greater than the baseline by a factor of $V_{\mathrm{hi},2} = 1.323$, and the amplifying effect due to watershed changes is greater by a factor of $T_{\mathrm{hi},2} = 1.487$.

Similar to Lake Mendota, our results in Lake Monona showed a more pronounced effect of watershed changes in most peaks, as compared to the influence of changing precipitation patterns. Here, the baseline variance was 0.017 m, compared to variances of 0.031 and 0.036 m for the peaks at the beginning of the dataset and the peak emerging later in 1995. The variance in the first peak is driven by the amplifying effect of watershed changes, which is greater than the baseline by a factor of $T_{\mathrm{hi},1} = 2.588$; the variance in precipitation is actually lower over this period by a factor of $V_{\mathrm{hi},1} = 0.918$. In the second peak, the increase in overall variance is due to increases in both variance in precipitation by a factor of $V_{\mathrm{hi},2} = 1.308$ and the amplifying effect of watershed changes by a factor of $T_{\mathrm{hi},2} = 1.528$. Thus, this approach allows one to assess the amplification in flashiness caused by drivers like precipitation or land use compared to a baseline based on historical data.

Flooding Likelihood

The likelihood of flooding increased through time for both Lake Mendota and Monona (Figure 6). Both 10-year (10%) and 100-year (1%) flooding thresholds have generally increased through time for Mendota, but have fluctuated around an average level for Monona. In the early 1920s, the 10-year threshold was 259.26 m for Mendota, reaching 259.64 m by the end of the twentieth century. These thresholds change little over time for Lake Monona, beginning at 258.11 m in the early 1920 s and reaching 258.17 m by the end of the twentieth century. The 100-year flood threshold follows the same patterns as the 10-year threshold in both lakes, with the magnitude of change by approximately 0.18 and 0.23 m in Mendota and Monona, respectively.

Discussion

Flashiness has increased in both Lake Mendota and Lake Monona over the last century (Figure 2) resulting from both urbanization of land-use/land-cover types, and regional shifts in precipitation patterns driven by climate change. The increase in flashiness is strongly correlated with an increase in impervious surface area, (Table 1; Figure 5) which has changed the dynamics of precipitation runoff by both increasing the total volume of water entering the lakes, and shifting the timing so that most runoff reaches the lakes in a short-time period (i.e, rain lags 0 days past and 1 days past, Figure 4). These changes in runoff dynamics suggest that specific hydrologic attributes related to the regulation of flow quantity and timing have been compromised. As a result, the likelihood of floods generally considered to be large enough to damage property (the 10-y and 100-year thresholds) has increased (Figure 6). For Lake Mendota, the 10-year flood level in the twenty first century (259.64 m) has exceeded its 100-year flood level for the beginning of the twentieth century (259.44 m); Mendota now has a 10% chance of reaching lake levels that it previously had only a 1% chance of reaching. Over the time period studied, these changes in flashiness and flooding potential have been driven more strongly by land-use and land-cover changes within the watershed than by changing precipitation pattern in both lakes ($T_{\mathrm{hi},1} > V_{\mathrm{hi},1}$ and $T_{\mathrm{hi},2} > V_{\mathrm{hi},2}$); however, as discussed below, we also found evidence that more variable precipitation could eventually become the stronger driver.

Our study highlights the importance of watershed characteristics for hydrologic flashiness of lakes. The Mendota watershed is dominated by agriculture, and thus a greater proportion of rainfall will be first intercepted, infiltrated, and absorbed in the soil. This should reduce runoff and peak flows, and generate time lags on lake-level response (Bennett and others 1999). For Mendota, this is evidenced in the way that runoff is distributed through the first several lags of precipitation (i.e, rain0–4: rain 0–4 days past; Table 1; Figure 4). Comparison with Lake Monona also highlights the role of land-cover types. Here, the watershed has been more than 15% covered by impervious surface since the 1920 s, corresponding to a runoff threshold proposed by Arnold and Gibbons (1996). The strong role of urban land cover is reflected in the threshold that Monona lake-level response to immediate precipitation events (rain 0) reaches at this time, and the simultaneous decrease in lake-level response to later events (rain1 and greater; Table 1; Figure 4). Additionally, increasing urbanization in the Mendota watershed (Figure 6) is concurrent with an increase in the magnitude of lake-level response to previous day's rain (rain1) and current rain (rain0). Although differences in watershed size are also reflected in the importance of particular lags in either lake (that is, the importance of rain1 for Mendota lake level, versus rain0 on Monona lake level), clearly other explanations are needed for the various characteristics of lake-level response we observed.

The changes in hydrologic flashiness of lakes that were identified in this study point to major implications for ecosystem services. Increased flashiness over time might lead to an overall decline in the regulation of water flow and water quality services, as evidenced by increased risk of flooding and degradation of lake clarity (Lathrop and others 2005; Carpenter and others 1998, 2005). Although management strategies could be implemented to alter flashiness and enhance certain services, unintended consequent tradeoffs may occur Lovell and Taylor (2013). For example, in the case of Lake Mendota and Monona, the lock system currently in place at the Mendota outflow would allow lake levels to be maintained below their current average to buffer against rapid changes and reduce the potential for flooding. However, the current lake levels reflect a mandate by the Wisconsin Department of Natural resources designed to facilitate recreational boating, and spring spawning of game fish species. Thus any attempt to reduce average lake levels and decrease flashiness to mitigate flooding potentials would directly impact recreational ecosystem services and fish communities, especially considering that management to reduce variance can actually lead to declines in ecosystem resilience in the long term (Carpenter and others 2015). Furthermore, the linkage between lakes indicates that this management solution can only be effective locally; attempts to reduce flashiness in Lake Mendota push the problem to downstream lakes such as Monona, creating spatial tradeoffs in flooding potential (Rodríguez and others 2006).

In our study system, the increasing magnitude and frequency of precipitation events may eventually surpass urbanization as the major driver of flashiness. When soil is fully saturated, any additional rainfall will turn into runoff and drive more rapid increases in lake level (Bronstert and others 2002). This is reflected in Figure 4 for both lakes; the increased spacing in contour lines over constant increments in precipitation means that larger precipitation events lead to increasingly larger changes in lake level. In this scenario, the increased likelihood that soil saturation thresholds are surpassed (WICCI 2011) means that traditional management strategies designed to counteract the effects of increased impervious surface area, such as restoring riparian buffers and promoting green infrastructure, might ultimately seem ineffective in their goal of reducing flashiness and flooding potential. Thus, the efficacy of solutions designed to rehabilitate watershed hydrology will be complicated by shifts in the relative importance of urbanization and precipitation over time.

We focused our analyses on the statistical relationship between precipitation, impervious surface, and flashiness. This limits our ability to interpret trends in flashiness because other forms of land-cover change or management decisions might also influence lake-level response. As such, we do not have explanations for certain features of the results, such as the two sub-peaks of flashiness in Lake Mendota within the overall trend. Such finer-scale trends may be a result of changes in management policy related to water regulation within the watershed (for example, a change in the magnitude or location of wastewater output). The topologies of tributaries and internal basins of lake watersheds also contribute to lake-level response; for Mendota and Monona, the elevation change between watersheds is slight and the lakes are connected at a very short distance, making it possible that lake-level responses are more interdependent than our models allow. Their floodplains are not well defined, which makes them likely to spread horizontally for substantial distances—filling wetlands and even moving water back up tributaries—before increasing lake levels notably. Wetlands and riparian buffers are known to be important to influence watershed flashiness and deliver hydrological services, and even small changes in their percent cover can have disproportionate impacts (Brauman and others 2007; Zedler 2003). In the Monona Watershed as much as 63% of wetlands were lost prior to 1938, which likely contributed to increased flashiness; wetland loss from the Mendota watershed, however, was not significant after 1970, when flashiness in Mendota increased most rapidly.

Another important contribution of our methodology is to use a relatively common dataset to investigate the simultaneous effects of two different drivers on flashiness—an important hydrologic attribute that serves as an indicator or watershed characteristics. Our approach is readily applicable to other watersheds and could also facilitate the assessment of implications on ecosystem services from changes in flashiness, especially those related to the quantity and timing of freshwater availability. Despite the way that this approach averages over landscape heterogeneity within a watershed, it was able to identify a clear signal of impervious surface in the change in lake flashiness over time. Additionally, it was able to differentiate this signal from that of shifting precipitation patterns, thus making it possible to unmask the various effects of single drivers (Gillon and others 2015).

Conclusion

Our results showed that urbanization has been a dominant driver of flashiness, relative to climate effects, over the past century. Although it is widely acknowledged in the literature that increased impervious surface leads to increased flashiness and flood probability, our results provide additional support by separating the confounding effects of climate, and assessing their relative contributions. The fact that land use is a stronger driver suggests that classic strategies for rehabilitating watershed hydrology such as reducing imperviousness, or increasing riparian buffers like wetlands, may be effective options to buffer against future climate changes (Qiu and Turner 2015; Turner and others 2013). On the other hand, the effects of urbanization may reach a threshold such that saturation effects would cause large magnitude precipitation events (as anticipated with future climate changes) to be a stronger drivers of flashiness.

Quantifying long-term changes in flashiness reveals the complicated interactions between urbanization and climate change that affect the hydrologic attributes of regional watersheds, and thus their capacity to sustain important ecosystem services. Increased flashiness may make it more likely that flooding will occur, while also reducing groundwater levels through reduced infiltration times. This simultaneous change in hydrological attributes has been reported previously, and identified as a driver of decreased health in multiple ecosystem services simultaneously (Qiu and Turner 2013; Maes and others 2013), thus supporting the idea that ecosystem services are usually bundled together (Foley and others 2005; Raudsepp-Hearne and others 2010). We have suggested that flashiness may be useful as a constituent variable due to its relationship with multiple ecosystem services, but this remains to be investigated in more depth. However, there is much to be gained because flashiness can be easily measured with commonly available, long-term datasets. Thus, there is potential for our study to enhance the successful long-term management of multiple ecosystem services simultaneously.

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REFERENCES

Akaike H. 1973. Information theory and an extension of the maximum likelihood principle. International Symposium on Information Theory, 2nd, Tsahkadsor, Armenian SSR, pp 267–81.

Alberti M. 2005. The effects of urban patterns on ecosystem function. Int Reg Sci Rev 28:168–92.

Allan JD. 2004. Landscapes and riverscapes: the influence of land use on stream ecosystems. Ann Rev Ecol Evol Syst 35:257–84.

Arnold CL Jr, Gibbons CJ. 1996. Impervious surface coverage. J Am Plan Assoc 62:243.

Baker DB, Richards RP, Loftus TT, Kramer JW. 2004. A new flashiness index: Characteristics and applications to Midwestern rivers and streams. J Am Water Resour Assoc 40:503–22.

Bennett EM, Reed-Andersen T, Houser JN, Gabriel JR, Carpenter SR. 1999. A phosphorus budget for the Lake Mendota watershed. Ecosystems 2:69–75.

Booth DB. 1991. Urbanization and the natural drainage system—impacts, solutions, and prognoses. Inst Environ Stud 7:93–118.

Booth DB, Karr JR, Schauman S, Konrad CP, Morley SA, Larson MG, Henshaw PC, Nelson EJ, Burges SJ. 2001. Urban stream rehabilitation in the Pacific Northwest. Wash Water Resour 12:1–11.

Brauman KA, Daily GC, Duarte TK, Mooney HA. 2007. The nature and value of ecosystem services: an overview highlighting hydrologic services. Ann Rev Environ Resour 32:67–98.

Bronstert A, Niehoff D, Bürger G. 2002. Effects of climate and land-use change on storm runoff generation: present knowledge and modelling capabilities. Hydrol Process 16:509–29.

Buja A, Hastie T, Tibshirani R. 1989. Linear smoothers and additive models. Ann Stat 17:453–510.

Carpenter SR, Caraco NF, Correll DL, Howarth RW, Sharpley AN, Smith VH. 1998. Nonpoint pollution of surface waters with phosphorus and nitrogen. Ecol Appl 8:559–68.

Carpenter SR, Lathrop RC, Nowak P, Bennett EM, Reed T, Soranno PA. 2005. The ongoing experiment: restoration of Lake Mendota and its watershed. Long-Term Dyn Lakes Landsc 25:236–56.

Carpenter SR, Brock WA, Folke C, van Nes EH, Scheffer M. 2015. Allowing variance may enlarge the safe operating space for exploited ecosystems. Proc Natl Acad Sci 112:14384–9.

Commission, D. C. R. P. 1992. Yahara-Monona priority watershed plan. Dane County, Madison, Wis.

Curtis JT. 1959. The vegetation of Wisconsin: an ordination of plant communities. Madison: University of Wisconsin Press.

Doerr Stefan H, Thomas Andrew D. 2000. The role of soil moisture in controlling water repellency: new evidence from forest soils in Portugal. J Hydrol 231:134–47.

Engle RF. 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica 50(4):987–1007.

Fewster RM, Buckland ST, Siriwardena GM, Baillie SR, Wilson JD. 2000. Analysis of population trends for farmland birds using generalized additive models. Ecology 81:1970–84.

Fletcher TD, Andrieu H, Hamel P. 2013. Understanding, management and modelling of urban hydrology and its consequences for receiving waters: a state of the art. Adv Water Resour 51:261–79.

Foley JA, DeFries R, Asner GP, Barford C, Bonan G, Carpenter SR, Chapin FS, Coe MT, Daily GC, Gibbs HK et al. 2005. Global consequences of land use. Science 309:570–4.

Foster HA. 1924. Theoretical frequency curves and their application to engineering problem. Trans Am Soc Civil Eng 88(1):142–73.

Franczyk J, Chang H. 2009. The effects of climate change and urbanization on the runoff of the Rock Creek basin in the Portland metropolitan area, Oregon, USA. Hydrol Process 23:805–15.

Gillon S, Booth EG, Rissman AR. 2015. Shifting drivers and static baselines in environmental governance: challenges for improving and proving water quality outcomes. Reg Environ Change 16(3):1–17.

Grimm NB, Faeth SH, Golubiewski NE, Redman CL, Wu J, Bai X, Briggs JM. 2008. Global change and the ecology of cities. Science 319:756–60.

Guisan A, Edwards TC, Hastie T. 2002. Generalized linear and generalized additive models in studies of species distributions: setting the scene. Ecol Model 157:89–100.

Hastie T, Tibshirani R. 1987. Generalized additive models: some applications. J Am Stat Assoc 82:371–86.

IPCC. 2013. Climate change 2013: the physical science basis. In: Stocker TF, Qin D, Plattner G-K, Tignor M, Allen SK, Boschung J, Nauels A, Xia Y, Bex V, Midgley PM, Eds. Contribution of working group i to the fifth assessment report of the intergovernmental panel on climate change. Cambridge: Cambridge University Press.

Keeler BL, Polasky S, Brauman KA, Johnson KA, Finlay JC, O'Neill A, Dalzell B. 2012. Linking water quality and well-being for improved assessment and valuation of ecosystem services. Proc Natl Acad Sci 109(45):18619–24.

Lathrop RC. 1992. Lake Mendota and the Yahara River chain. In: Kitchell JF, Ed. Food web management. New York: Springer.

Lathrop RC, Bradbury K, Halverson B, Potter K, Taylor D. 2005. Responses to urbanization. LakeLine 25:39–46.

Lathrop RG, Tulloch DL, Hatfield C. 2007. Consequences of land use change in the New York-New Jersey highlands, USA: landscape indicators of forest and watershed integrity. Landsc Urban Plan 79:150–9.

Leopold LB. 1968. Hydrology for urban land planning–a guidebook on the hydrologic effects of urban land use. US Geol Surv Circ 554:18.

Lovell ST, Taylor JR. 2013. Supplying urban ecosystem services through multifunctional green infrastructure in the United States. Landsc Ecol 28(8):1447–63.

Maes J, Teller A, Erhard M, Liquete C, Braat L, Berry P, Egoh B, Puydarrieux P, Fiorina C, Santos F et al. 2013. Mapping and assessment of ecosystems and their services. An analytical framework for ecosystem assessments under action. Ecosyst Serv 5:1–58.

Magnuson JJ, Kratz TK, Benson BJ. 2006. Long-term dynamics of lakes in the landscape: long-term ecological research on north temperate lakes. Oxford: Oxford University Press.

Metzger MJ, Rounsevell MDA, Acosta-Michlik L, Leemans R, Schröter D. 2006. The vulnerability of ecosystem services to land use change. Agric Ecosyst Environ 114:69–85.

Meyer Judy L, Paul Michael J, Keith Taulbee W. 2005. Stream ecosystem function in urbanizing landscapes. J North Am Benthol Soc 24(3):602–12.

Millennium Ecosystem Assessment (MEA). 2005. Ecosystems and human well-being. Washington, DC: Island Press.

Naiman RJ, Decamps H. 1997. The ecology of interfaces: riparian zones. Ann Rev Ecol Syst 28:621–58.

Paul MJ, Meyer JL. 2001. Streams in the Urban landscape. Ann Rev Ecol Syst 32:333–65.

Pickett STA, Cadenasso ML, Grove JM, Boone CG, Groffman PM, Irwin E, Kaushal SS, Marshall V, McGrath BP, Nilon CH, Pouyat RV, Szlavecz K, Troy A, Warren P. 2011. Urban ecological systems: scientific foundations and a decade of progress. J Environ Manag 92:331–62.

Poelmans L, Rompaey AV, Ntegeka V, Willems P. 2011. The relative impact of climate change and urban expansion on peak flows: a case study in central Belgium. Hydrol Process 25:2846–58.

Poff N. 1996. A hydrogeography of unregulated streams in the United States and an examination of scale-dependence in some hydrological descriptors. Freshwater Biol 36:71–9.

Qiu J, Turner MG. 2013. Spatial interactions among ecosystem services in an urbanizing agricultural watershed. Proc Natl Acad Sci 110:12149–54.

Qiu J, Turner MG. 2015. Importance of landscape heterogeneity in sustaining hydrologic ecosystem services in an agricultural watershed. Ecosphere 6:1–19.

Raudsepp-Hearne C, Peterson GD, Bennett EM. 2010. Ecosystem service bundles for analyzing tradeoffs in diverse landscapes. Proc Natl Acad Sci 107:5242–7.

Rodríguez JP, Beard TD Jr, Bennett EM, Cumming GS, Cork SJ, Agard J, Dobson AP, Peterson GD. 2006. Trade-offs across space, time, and ecosystem services. Ecol Soc 11:28.

Sánchez-Rodríguez R, Seto KC, Simon D, Solecki WD, Kraas F, Laumann G. 2005. Science plan: urbanization and global environmental change. IHDP report.

Schneider A, Logan KE, Kucharik CJ. 2012. Impacts of urbanization on ecosystem goods and services in the US Corn Belt. Ecosystems 15:519–41.

Turner MG, Donato DC, Romme WH. 2013. Consequences of spatial heterogeneity for ecosystem services in changing forest landscapes: priorities for future research. Landsc Ecol 28:1081–97.

United Nations. 2008. World urbanization prospects: the 2007 revision. New York: Population Division.

U.S. Department of the Interior, Geological Survey, Office of Water Data Coordination. 1982. On Water Data, I. Guidelines for determining flood flow frequency.

Venables WN, Ripley BD. 2002. Modern applied statistics with S. New York: Springer.

Wegener MW. 2001. Long-term land use/cover change patterns in the Yahara Lakes region and their impact on runoff volume to Lake Mendota. University of Wisconsin–Madison.

Wenger SJ, Roy AH, Jackson CR, Bernhardt ES, Carter TL, Filoso S, Gibson CA, Hession WC, Kaushal SS, Martí E, Meyer JL, Palmer MA, Paul MJ, Purcell AH, Ramírez A, Rosemond AD, Schofield KA, Sudduth EB, Walsh CJ. 2009. Twentysix key research questions in urban stream ecology: an assessment of the state of the science. J N Am Benthol Soc 28:1080–98.

Wisconsin's Changing Climate: Impacts and Adaptation. 2011. Wisconsin Initiative on Climate Change Impacts. Nelson Institute for Environmental Studies, University of Wisconsin-Madison and the Wisconsin Department of Natural Resources, Madison, Wisconsin.

Wood SN. 2006. Generalized additive models: an introduction with R. Boca Raton: CRC Press.

Yee TW, Mitchell ND. 1991. Generalized additive models in plant ecology. J Veget Sci 2:587–602.

Zedler JB. 2003. Wetlands at your service: reducing impacts of agriculture at the watershed scale. Front Ecol Environ 1:65–72.

Zehe E, Becker R, Bárdossy A, Plate E. 2005. Uncertainty of simulated catchment runoff response in the presence of threshold processes: role of initial soil moisture and precipitation. J Hydrol 315(1):183–202.