Tile drainage causes flashy streamflow response in Ohio watersheds

Samuel A. Miller[1,2], Steve W. Lyon[1,2]

[1]School of Environment and Natural Resources, Ohio State University, Columbus, Ohio

[2]Ohio Agricultural Research & Development Center, Wooster, Ohio

Corresponding Author: Samuel A. Miller, miller.10513@osu.edu

Abstract

Artificial subsurface (tile) drainage is used to increase trafficability and crop yield in much of the Midwest due to soils with naturally poor drainage. Tile drainage has been researched extensively at the field scale, but knowledge gaps remain on how tile drainage influences the streamflow response at the watershed scale. The purpose of this study is to analyze the effect of tile drainage on the streamflow response for 59 Ohio watersheds with varying percentages of tile drainage and explore patterns between the Western Lake Erie Bloom Severity Index to streamflow response in heavily tile-drained watersheds. Daily streamflow was downloaded from 2010-2019 and used to calculated mean annual peak daily runoff, mean annual runoff ratio, the percent of observations in which daily runoff exceeded mean annual runoff (T_{Qmean}), baseflow versus stormflow percentages, and the streamflow recession constant. Heavily-drained watersheds (> 40 % of watershed area) consistently reported flashier streamflow behavior compared to watersheds with low percentages of tile drainage (< 15% of watershed area) as indicated by significantly lower baseflow percentages, T_{Qmean}, and streamflow recession constants. The mean baseflow percent for watersheds with high percentages of tile drainage was 20.9 % compared to 40.3 % for watersheds with low percentages of tile drainage. These results are in contrast to similar research regionally indicating greater baseflow proportions and less flashy hydrographs (higher T_{Qmean}) for heavily-drained watersheds. Stormflow runoff metrics in heavily-drained watersheds were significantly positively correlated to western Lake Erie algal bloom severity. Given the recent trend in more frequent large rain events and warmer temperatures in the Midwest, increased harmful algal bloom severity will continue to be an ecological and economic problem for the

region if management efforts are not addressed at the source. Management practices that reduce the streamflow response time to storm events, such as buffer strips, wetland restoration, or drainage water management, are likely to improve the aquatic health conditions of downstream communities by limiting the transport of nutrients following storm events.

Keywords: tile drainage, agriculture, baseflow, recession analysis, intensively managed landscapes

1. INTRODUCTION

Artificial subsurface (tile) drainage is required for increased crop yield in much of the cropland in the Midwestern U.S. ('Midwest') due to soils with naturally poor drainage capabilities. Tile drains increase soil drainage by removing excess subsurface water that can inhibit plant growth, resulting in lower water tables that increase the trafficability of heavy machinery to operate in farm fields. Tile drains began to be installed in the Midwest during the late 20th century with the initial goal of strategically draining wet areas of farm fields that were susceptible to ponding, but installations are now common throughout the entire field to lower the water table (Blann *et al.*, 2009). Drainage pipes are typically installed between 0.6 – 1.2 m below the surface approximately 10-30 m apart, depending on site-specific soils, crop type, and cost (Skaggs and van Schilfgaarde, 1999). Infiltrated water is captured underground by perforated drainage pipes and routed away from the field into adjacent ditches and streams.

According to the U.S. Department of Agriculture (USDA) National Agriculture Statistics Service (NASS) 2017 Census of Agriculture, 225,024 km^2 of cropland are estimated to have tile drainage with the vast majority occurring in the Midwest (USDA NASS, 2019). The amount of land with tile drainage in the U.S. increased by 28,484 km^2 (14.5%) between 2012 and 2017 (USDA NASS, 2014), with the largest increases occurring in the Midwest. Recent changes to precipitation patterns that generate more frequent large rain events in the Midwest (Williams and King, 2020) may partly explain the growing adoption of tile drainage. Further, as heavy rainfall events are projected to increase in frequency into the future due to climatic change, we can expect an expansion of land under tile drainage globally (Gordon *et al.*, 2017). Understanding how tile drainage impacts the hydrologic response of downstream waterways, and subsequent transport of nutrients, is critical for the development holistic management plans that improve downstream aquatic life and help communities assess flood risks.

However, the streamflow response, and subsequent export of nutrients, from farm fields under tile drainage is complicated to ascertain and predict due to compounding environmental, management, and site-specific soil conditions (Hanrahan *et al.*, 2020). For example, Boland-Brien et al. (2014) reviewed several field studies (< 10 ha) and suggested that tile drainage can cause peak streamflow to decrease when water tables are close to the surface due to clayey soils with low permeability or during high rainfall events. In contrast, peak flows may increase on fields with deeper water tables with drier climates or more permeable soils (Boland-Brien *et al.*, 2014). Such changes in peak flows across large scales could have impacts on timing and magnitudes of flood peaks for downstream communities. In addition, management practices that target particular flow pathways (e.g. reducing surface runoff or reducing tile outlet discharge) could have adverse effects on other nutrient transport mechanisms, and thus have unintended impacts to nutrient loads not initially targeted (Smith *et al.*, 2015). Studies have consistently showed that water exiting tile drains contribute significant amounts of nutrients (e.g. nitrogen and phosphorus) to downstream waterbodies. In Illinois, riverine nitrate flux from tile-drained land was over twice the value compared to non-tile drained land despite higher net nitrogen inputs on non-tile drained land (McIsaac and Hu, 2004). Tile drainage exported 80% of stream nitrogen load, despite only contributing 15-43% of the streamflow in a 122 km^2 watershed in northeast Iowa (Arenas Amado *et al.*, 2017). In a headwater watershed in Ohio (<4 km^2), tile drainage accounted for 47% of total discharge, 48% of dissolved phosphorus, and 40% of total phosphorus (King *et al.*, 2015).

Tile drains have been shown to reduce mean groundwater travel times, which is problematic for example when considering the transport of nitrogen which tends to have higher concentrations in groundwater compared to surface runoff (Schilling et al., 2012). A modeling study on a 74.3 km^2 watershed in north-central Iowa revealed that mean groundwater travel times are more than 150 times faster than those that existed prior to settlement, resulting in the majority of groundwater (>98%) bypassing perennial riparian buffers (Schilling *et al.*, 2015), which drastically reduces the effectiveness of installing stream buffers to reduce nitrogen concentrations (Schilling et al., 2015). A study in western Indiana compared the residence time of baseflow in agricultural and adjacent undisturbed forested watersheds using multiple isotopic tracers (specifically CFC, SF6, ^{36}Cl, and ^{3}H) and suggested that baseflow in the agricultural watershed with tile drainage was controlled by a large contribution of tile drainage and/or soil water with short resdience times (Frisbee *et al.*, 2017). In contrast, Frisbee et al. (2017) concluded that baseflow in the adjacent, undisturbed forested catchments was supported by groundwater with much older residence times (at least 40 years old). Baseflow comprised of large contributions from tile drainage is problematic for the aquatic health of waterways due to the often high concentrations of nutrients measured in tile drainage.

Baseflow proportions can be used to assess hydrologic impacts of land use and conservation practices and have been found to be strongly correlated to legacy nutrient concentrations; thus, baseflow estimations provide a first approximation of stream vulnerability to legacy nutrients (Tesoriero *et al.*, 2013). Tile drainage was demonstrated to increase the proportion of baseflow to receiving streams in Iowa (Schilling and Libra, 2003; Schilling and Helmers, 2008; Boland-Brien et al., 2014), but a gap remains understanding the relationship between tile drainage and baseflow in other regions, particularly in regions with different soil and precipitation characteristics, such as Ohio. Baseflow proportions are generally thought to increase in larger or flatter watersheds as groundwater tends to be the main contributor to streamflow. According to Boland-Brien et al. (2014), while watersheds in Iowa with large proportions of tile drainage tended to have larger baseflow proportions compared to non-tiled watersheds, the variability of baseflow percentage with watershed size was much lower for watersheds with large proportions of tile drainage compared to non-tiled watersheds which exhibited an increase in baseflow proportion with watershed size. Boland-Brien et al. (2014) found that tile drainage had a similar homogenizing effect on all flow regimes, where heavily tile-drained watersheds showed little to no variability in streamflow response across a range of drainage areas compared to watersheds with a smaller proportion of tile drainage that exhibited larger variability in streamflow response when considering various streamflow metrics across a range of watershed sizes, which is expected for natural systems.

In addition to baseflow assessments, hydrograph recession analysis has proven to be a helpful mathematical exercise that estimates the potential change in the storage-discharge relationship for a particular watershed. Recession analysis can be used to evaluate storm responses and thus infer storage properties and mean residence times (e.g. Troch et al., 2013). For example, Schilling and Helmers (2008) found the master recession curves for tile-drained watersheds in Iowa to be more linear compared to less-tiled watersheds that showed a non-linear recession, typical of natural systems where hydraulic conductivity deceases with depth. They suggested that downstream hydrograph recession may be controlled by longer recession times from tiled regions, but also found inconsistent recession coefficients between tiled and non-tiled regions and advocated for additional research in this field. Boland-Brien et al. (2014) also performed streamflow recession analysis on watersheds with varying percentages of tile drainage across Iowa and concluded that tiled regions were less flashy compared to non-tiled regions based on master recession curve analysis.

Clearly, tile drainage can have confounding impacts on hydrological response depending on scale and the combination of physical and climatic characteristics considered. Given an emphasis in the literature on tile drainage impacts to streamflow response in Iowa (e.g., Schilling and Helmers, 2008; Boland-Brien et al., 2014; Schilling et al., 2015; Arenas Amado et al., 2017), we wondered how tile drainage impacts hydrological response under other landscapes and climatic conditions? As such, the goal of this study is to assess the impact of tile drainage on the streamflow response of Ohio watersheds with varying percentages of tile drainage. The shallow, poorly-drained soils of Ohio provide an excellent contrast to those in Iowa, which tend to be deeper and coarser, thus have different drainage tendencies. We used an automated baseflow separation technique combined with hydrograph recession analysis to determine if the effects of tile drainage on the storage-discharge relationship are evident at the watershed scale and postulate the consequences for downstream nutrient transport. To this latter aspect, phosphorous loads from March to July have recently been identified as a major driver of the severity of HABs in the western Lake Erie basin (Baker *et al.*, 2019), which is where the majority of tile drainage occurs in Ohio. Therefore, we focused on this critical time period in order to isolate the effects of tile drainage from heavily-drained watersheds in the western Lake Erie basin on hydrograph partitioning that could be exacerbating HAB severity by creating a quicker hydrologic connection between agricultural fields and adjacent streams.

2. MATERIALS AND METHODS

2.1 Data

Daily mean streamflow for each study watershed was downloaded from 2010 – 2019 for 59 United States Geologic Survey (USGS) stream gaging stations in Ohio using the R package 'dataRetrieval' (De Cicco and Hirsch, 2014). The station ID for each stream gage is included as supplementary material. Streamflow was converted to area-weighted runoff ('runoff') using the total watershed area and daily time interval. The time period of data considered was selected to match with the responses from the recent county-level tile drainage census data used to generate AgTile-US (Valayamkunnath *et al.*, 2020). Monthly PRISM precipitation data from the same period (i.e. 2010 – 2019) was aggregated to watershed boundaries to determine mean monthly and annual precipitation for each study watershed (PRISM Climate Group, 2019).

The 59 study watersheds were selected based on streamflow record and limited hydrological modifications using the following criterion: (1) had at least eight years of complete data from 2010 - 2019, with each year having at least 90% daily streamflow records available, (2) had less than 6 major dams, (3) were located at least 5 miles downstream of dams, (4) had less than 25% developed land, (5) had at least 25% agricultural land, and (6) had area less than 2,000 km^2 (Falcone, 2011). The watershed size limitation was suggested as a threshold in which the effects of tile drainage were likely to become less apparent due to channelization and in-stream attenuation (Boland-Brien *et al.*, 2014). These 59 watersheds were split into three roughly equal groups with increasing proportions of tile drainage to evaluate the mean streamflow response for watersheds with low (< 15 % area), medium (15% - 40% area), and high (> 40% area) amounts of tile drainage.

Watershed characteristics and boundaries were obtained from the GAGES-II dataset (Falcone, 2011). For each of the 59 watersheds in Ohio, a 30-m resolution tile drainage map (AgTile-US) was aggregated to calculate the percent of each watershed under tile drainage (Valayamkunnath *et al.*, 2020). This dataset was generated using soil drainage information, topographic slope, and county-level tile drainage census data for the most-likely tile-drained area of the contiguous United States. Accuracy across the Midwest ranges from 82.7% to 93.6% (Valayamkunnath *et al.*, 2020). The raster dataset is available in binary format, where 1 indicates tile-drained land and 0 indicates undrained land. For each watershed, the percent of tile drainage was calculated by summing the total amount of tile-drained area divided by the total watershed area.

2.2 Runoff metrics

To evaluate the effects of tile drainage on streamflow response, we calculated several of the runoff metrics suggested by Boland-Brien et al. (2014) including runoff ratio, mean annual peak runoff, and the percent of time daily runoff exceeded mean annual runoff (Tq_{mean}). Runoff ratios were calculated by dividing annual runoff by annual precipitation from PRISM and multiplying the result by 100 to have ratios expressed as a percent. To evaluate the impact of tile drainage on peak runoff conditions, we calculated mean annual peak daily runoff for each watershed considered. The final metric considered the percent of time daily runoff exceeded mean annual runoff, T_{Qmean}, which measures the flashiness of the hydrograph (Konrad and Booth, 2002). As such, a low value corresponds to a flashier response and a high value suggests a more dampened hydrograph. Differences in runoff metrics were compared among the three drainage categories using the Tukey test and Pearson's correlation coefficient. All significant results are considered when $p < 0.05$.

Daily baseflow was calculated from the total daily runoff hydrograph using the R package 'lfstat' (Koffler *et al.*, 2016) following methodology from Tallaksen and van Lanen (2004) and WMO (2008). This procedure was developed for rainfall regimes with a typical runoff response in hours or days and partitions the hydrograph into delayed and quick components by identifying turning points of runoff minima for each non-overlapping five-day period. Turning points are joined by straight lines to obtain the baseflow hydrograph. Daily stormflow was subsequently calculated by subtracting daily baseflow from daily total runoff. A baseflow index (BFI) was then calculated by dividing baseflow by total runoff, expressed as a percent.

All runoff metrics were calculated from daily records and summarized to mean annual and monthly values to assess potential seasonality effects. Further, a time period of particular interest for the study area is from March – July, for which runoff (and nutrient loads) have been shown to be critical for determining HAB severity in the western Lake Erie Basin (Baker *et al.*, 2019). For this reason, we calculated runoff metrics by averaging daily values for these months in watersheds with high (> 40% area) amounts of tile drainage. In addition, we calculated the day of calendar year in which 50% of annual runoff occurs to evaluate the effect that annual streamflow timing had on bloom severity. Runoff metrics were compared to the Western Lake Erie Bloom Severity Index, calculated by the United States National Oceanic and Atmospheric Administration based on algal bloom biomass, to evaluate relationships between streamflow response and HAB severity.

To assess how water is stored and released following storm events, we performed hydrograph recession analyses for each of the watersheds considered in this study. The calculation of the recession constant required selecting an analytical expression to fit to the recession curve, determining the typical recession period, and optimizing the recession parameters (WMO, 2008). We used the R package 'lfstat' to determine recession rates (Koffler *et al.*, 2016). The recession curve was modelled using an exponential equation assuming a single linear reservoir where storage is proportional to outflow:

$$Q_t = Q_o e^{\left(\frac{-t}{C}\right)} \quad (1)$$

where Q_t is total runoff at time t; Q_o is total runoff at the beginning of the recession period (t=0), and C is the recession constant [time], which is the number of days needed for runoff to decrease one log cycle. The recession curve plots as a straight line with slope -1/C on a semi-logarithmic plot of t versus $\ln Q_t$. Both master recession curve (MRC) and individual recession segments (IRS) methods require criteria for selecting recession segments and the period of discharge to disregard following peak runoff to avoid selecting times of rapid response following a rainfall event that were not caused by groundwater discharge. For both analyses, a minimum segment length of five days was chosen and recession segments began at least two days after peak flood discharge and after runoff was below a Q25 threshold (i.e. the highest 25% of runoff following peak flood discharge was omitted). The MRC method constructs a single mean recession curve, while in the IRS method a recession model is fit to each segment and the recession constant C, is determined as the mean value of individual recession segments.

3. Results

3.1 Watershed characteristics

According to the AgTile-US dataset (Valayamkunnath *et al.*, 2020), mean areal coverage of tile drainage for the watersheds analyzed in this study was 27.8% and ranged from 0.5% to 61.0%. Watersheds were split into three roughly equal groups to compare the mean streamflow response: low (< 15% tile drained, n = 18), medium (15% - 40% tile drained, n = 24), and high (>40% tile drained, n = 17) (Figure 1). Watersheds in the medium and high drainage categories were located primarily in northwestern Ohio, while watersheds in the low drainage category were spread out throughout the state. Mean watershed size was similar for all three drainage categories (Table 1). There was a significant positive relationship with agricultural land and tile drainage (Pearson's r = 0.86, $p < 0.001$, Figure 2a, Table 1) and a significant negative relationship with mean watershed slope and tile drainage (Pearson's r = -0.77, Figure 2b, Table 1). Tile drainage was significantly positively correlated to clay content (Pearson's r = 0.54, Figure 2c, Table 1) and significantly negatively correlated to the depth of the seasonally high water table provided in the GAGES-II dataset (Pearson's r = -0.71, Figure 2d, Table 1; Falcone, 2011). [Insert Figure 1] [Insert Figure 2] [Insert Table 1]

3.2 Precipitation

Mean annual precipitation (PRISM Climate Group, 2019) for the 59 watersheds over the ten-year period (2010-2019) was 1109 mm and ranged from 945 mm in 2010 to 1465 mm in 2011. Mean annual precipitation was significantly greater for the low drainage category (1160 mm) compared to the medium (1099) or high drainage (1067 mm) categories (Table 2). On average across all 59 watersheds, spring and summer months (April – September) were wetter than fall and winter months (October – March). The five-month period from March – July contributed 50% of annual precipitation in high drainage watersheds.

For high drainage watersheds June had the most precipitation (133 mm), followed by May (123 mm) and July (111 mm), while January had the least precipitation (60 mm), followed by February (66 mm) and December (70 mm). In medium drainage watersheds June had the most precipitation (132 mm) followed by May (115 mm) and July (111 mm), while January had the least precipitation (63 mm), followed by February (72 mm) and October (79 mm). For low drainage watersheds June had the most precipitation (140 mm), followed by July (113 mm) and May (111 mm), while January had the least precipitation (71 mm), followed by February (80 mm) and November (83 mm). [Insert Table 2]

3.3 Runoff metrics

Mean annual runoff for the 59 watersheds from 2010 – 2019 was 435 mm and ranged from 298 mm in 2012 to 717 mm in 2011. Mean annual runoff was significantly greater for the low drainage category (469 mm) compared to the medium (429 mm) and high drainage (407 mm) categories (Table 2). On average, across all 59 watersheds winter and spring months (January – June) produced more runoff compared to summer or fall months (July – December). The five-month period from March – July contributed 57% of annual runoff in high drainage watersheds.

For high drainage watersheds March had the most runoff (59 mm), followed by April (56 mm) and June (44 mm), while August had the least runoff (6 mm), followed by September (7 mm) and October (12 mm). In medium drainage watersheds March had the most runoff (64 mm) followed by April (59 mm) and February (49 mm), while September had the least runoff (8 mm), followed by August (9 mm) and October (13 mm). For low drainage watersheds March had the most runoff (71 mm), followed by April (65 mm) and February (57 mm), while August and September had the least runoff (13 mm), followed by October (16 mm).

Mean annual runoff ratio for the 59 study watersheds from 2010 – 2019 was 39.1% and ranged from 33.6% in 2010 to 47.8% in 2018. There was a significant positive relationship between mean annual runoff ratio and mean annual precipitation among all 59 watersheds (Pearson's r = 0.48). Despite significantly greater mean annual precipitation and runoff for the low drainage category, mean annual runoff ratio was the same among all drainage categories (Table 2). Mean annual runoff ratio was not significantly correlated to tile drainage (Figure 3a) or watershed area (Figure 4a) for any of the drainage categories considered. Peak daily runoff was similar among all drainage categories and not significantly correlated to tile drainage (Figure 3b; Table 2). Peak daily runoff was significantly negatively correlated to watershed area for the medium (Pearson's r = -0.67) and high (Pearson's r = -0.76) drainage categories, but not for the low drainage category (Figure 4b). [Insert Figure 3] [Insert Figure 4]

The percent of time in which mean daily streamflow was greater than mean annual streamflow (T_{Qmean}) was significantly negatively correlated to tile drainage (Pearson's r = -0.57, Figure 3c, Table 2). A lower T_{Qmean} value implies a flashier hydrograph response for the high drainage category watersheds. There was a significant positive relationship between watershed area and T_{Qmean} for the medium (Pearson's r = 0.47) and high (Pearson's r = 0.51) drainage categories, but not for the low drainage category (Figure 4c). The mean annual baseflow index (BFI) was significantly negatively correlated to tile drainage (Pearson's r = -0.58, Figure 3d, Table 2). The mean annual BFI for the high drainage category was 20.9% compared to 40.3% for the low drainage category. Conversely, watersheds with a high percentage of tile drainage had significantly higher stormflow proportions compared to watersheds with low to medium percentages of tile drainage. There was no significant relationship between watershed area and BFI for any of the drainage categories (Figure 4d).

Both MRC and IRS techniques for hydrograph recession analysis revealed a significant negative correlation between recession constants and tile drainage (Pearson's r = -0.45, Figs. 5a; Pearson's r = -0.46, Figure 5c, Table 2). There was no significant relationship with watershed area and recession constant using either MRC or IRS methods for any of the drainage categories (Figs. 5b & 5d). Both MRC and IRS recession constants were significantly positively correlated to annual BFI (Pearson's r = 0.89), T_{Qmean} (Pearson's r = 0.70), and average soil permeability (Pearson's r = 0.79) (Falcone, 2011). These relationships suggest a flashier hydrograph response from watersheds with higher percentages of tile drainage and poorer drainage capabilities. [Insert Figure 5]

It should be noted that the March – July BFI was similar to the annual BFI and was significantly lower for the high drainage category watersheds (Table 2). In addition, the amount of March – July stormflow as a percentage of total annual runoff was significantly positively correlated to tile drainage (Pearson's r = 0.58, Figure 6a). The amount of annual runoff from March – July stormflow approached 50% for watersheds with high percentages of tile drainage, while the percent of total annual runoff from March – July stormflow in watersheds with low percentages of tile drainage was around 30%. [Insert Figure 6]

We compared runoff metrics from the high drainage category watersheds, which predominantly drain into western Lake Erie, to the Western Lake Erie Bloom Severity Index and found mean March – July total stormflow (mm) to be the best predictor of bloom severity for all of the runoff metrics (Pearson's r = 0.90, Figure 6b). The March – July stormflow runoff ratio (i.e. the ratio of total stormflow to total precipitation during March – July) was also highly positively correlated to bloom severity (Pearson's r = 0.87, Figure 6c), unlike the March – July baseflow runoff ratio that did not show any correlation (Figure 6c). Another runoff metric that was highly correlated to the bloom severity index was the mean day of year in which 50% of annual runoff occurred (Pearson's r = 0.89, Figure 6d). Recent years with the highest bloom severity index (>10) observed 50% of annual streamflow in June, while years with less severe blooms saw 50% of annual streamflow occurring much earlier in the year.

4. Discussion

4.1 Comparison with other studies across the Midwestern U.S.

Our results on the streamflow response of watersheds with varying percentages of tile drainage in Ohio are markedly different from previous studies conducted in Iowa watersheds. We showed a significant negative relationship between tile drainage percent and mean annual baseflow index (BFI) (Figure 3d) and a significant positive relationship between tile drainage percentage and Mar-Jul total stormflow (Figure 6a) for 59 watersheds in Ohio. This is in contrast to extensive research performed with Iowa watersheds that showed an increase in baseflow proportions with tile drainage percentage (Schilling and Libra, 2003; Schilling and Helmers, 2008; Boland-Brien et al., 2014). This should not come as a surprise since previous work showed a linear relationship between rainfall and tile drainage in which 12.6% of rainfall was recovered in tile drainage in Iowa, compared to 22.2% in Ohio (Logan *et al.*, 1980). According to 30-year climate normal, the watersheds used our study have significantly greater mean annual precipitation (979 mm) compared to Iowa watersheds (869 mm) analyzed by Boland-Brien et al. (2014) (Falcone, 2011). In the Midwest, Ohio and Iowa roughly represent two end-members in terms of the meteorological and physical characteristics of watersheds with high percentages of tile drainage; thus, it is fair to assume that tile drainage could result in greater baseflow or stormflow proportions, depending on site-specific meteorological and physical conditions.

When our results are compared to the work from Boland-Brien et al. (2014) - who calculated similar runoff metrics - it is clear that large percentages of tile drainage can cause a notably different hydrologic response at the watershed scale in terms of baseflow and stormflow proportions and the general flashiness behavior. Boland-Brien et al. (2014) reported a mean BFI of 67% for the Iowa watersheds considered with a high degree of tile drainage (>50%), compared to 22% reported for the high drainage category (>40%) in our Ohio study. The mean annual runoff ratio was notably higher for watersheds analyzed in our study (39%) compared to those by Boland-Brien et al. (2014) (28%). In addition, our results suggest T_{Qmean} and the recession constants indicate flashier streamflow behavior in watersheds with high amounts of tile drainage compared to the Iowa watersheds that showed the opposite trend. Given low drainage category watersheds had significantly greater mean annual precipitation and runoff (Table 2), we would usually expect to observe a significantly greater mean annual runoff ratio and peak daily runoff for the low drainage category. However, there were no significant difference between mean annual runoff ratio or peak daily runoff for any of the drainage categories, suggesting medium and high drainage category watersheds had greater mean annual runoff ratios and peak daily runoff than expected. All of these results suggest an increasing percentage of tile drainage leads to flashier watersheds in Ohio.

Of course, the watersheds analyzed by Boland-Brien et al. (2014) were substantially larger (average area of 1,666 km^2) compared to the ones presented in this study (average area of 605 km^2), which likely partially explains the larger observed BFI in Iowa watersheds. This difference, however, does not explain the opposite trend observed between the relationship of percent tile drainage and runoff metrics. Despite similar soil textures (i.e. sand, silt, clay percentages) between our watersheds and the ones presented in Boland-Brien et al. (2014), the Ohio watersheds showed significantly greater soil bulk density (1.54 g/cm^3) compared to the Iowa watersheds (1.44 g/cm^3) (Falcone, 2011). The lower bulk density values observed in Iowa favor faster infiltration rates compared to Ohio, which likely results in greater groundwater recharge and smaller proportions of stormflow in Iowa. In fact, the Ohio watersheds analyzed in this study had a significantly greater percent of soils in hydrologic group C (62%), characterized by moderately fine or fine texture, slow soil infiltration rates with layers impeding the downward movement of water (Falcone, 2011). In contrast the Iowa watersheds had a significantly lower percent of soils in hydrologic group C (16%) and were dominated by soils in hydrologic group B, characterized by moderately deep, coarse, well drained soils with moderate infiltration rates. Another substantial difference between the two areas is the depth to seasonally high water table, which was significantly smaller for the Ohio watersheds (which averaged 0.80 m) compared to the Iowa watersheds (which averaged 1.23 m) (Falcone, 2011). Tile drains installed in Ohio fields with slow soil infiltration rates and shallow water tables creates a more direct response to rainfall events observed in tile drainage outlets compared to installations in fields with moderate infiltration rates and deeper water tables since soil bulk density typically increases with depth.

Another major difference in hydrologic response of Ohio and Iowa watersheds to varying percentages of tile drainage was the homogenization of all runoff metrics with high percentages of tile drainage reported by Boland-Brien et al. (2014). While our study watersheds with high percentages of tile drainage did not show a relationship with drainage area for mean annual runoff ratio or mean annual BFI, we found significant correlations between drainage area and T_{Qmean} (Figure 4c) and peak daily runoff (Figure 4d) for the medium and high tile drainage category watersheds, but not for the low drainage category watersheds. In contrast, drainage area was not correlated to any of the runoff metrics for the low drainage category (Figure 4). As mentioned before, larger watersheds typically show higher percentages of baseflow and a more attenuated streamflow response as groundwater contributions increase (Price, 2011). However, the influence of geological conditions on streamflow response will be most apparent during dry conditions when baseflow contributions are high (Cross, 1949). Since the low drainage category watersheds are more dispersedly located throughout Ohio (Figure 1), it is possible the geological conditions are more variable for these watersheds compared to the medium or high drainage categories, which are predominantly located in northwest Ohio and likely have more similar geological conditions.

4.2 Implications for nutrient transport

The agricultural economic benefits of tile drainage are accompanied with environmental and economic costs associated with impaired water quality. Water exiting tile drain outlets transport agricultural pollutants (e.g. nitrogen, phosphorous, pesticides) downstream which can accumulate leading to hypoxic zones and harmful algal blooms (HABs), with detrimental effects to human and aquatic systems (Diaz, 2001). Harmful algal blooms are not unique to Ohio and have become a global problem in recent decades (Ho *et al.*, 2019). The environmental consequences of HABs are difficult to remediate and can negatively impact tourism, recreation, property values, wildlife, and commercial fishing. In August of 2014, elevated microcystin toxin levels associated with a HAB resulted in 400,000 residents left without drinking water. In Lake Erie, the world's largest walleye fishery, summer-long HABs can result in $5.6 million in lost fishing expenditures alone (Wolf *et al.*, 2017).

Tile drainage is thought to reduce surface runoff, therefore improve soil stability and limit the amount of erosion and particulate nutrient concentrations exporting via surface runoff.

While nutrient concentrations measured in tile drainage are often low during low discharge periods, elevated nutrient concentrations have been measured during high discharge periods, proving that tile drains can act as effective conduits for nutrient export from agricultural fields (Dils and Heathwaite, 1999). Numerous studies have showed a strong surface connection to tile drainage through macropores and other preferential flow paths (Stamm et al., 1998; Smith et al., 2015; Williams et al., 2016; Macrae et al., 2019), and thus potential to transport nutrients applied to the soil surface. In addition, recent research suggests storm events can accelerate the subsurface transport of particulate and dissolved nutrient species (Jiang *et al.*, 2021).

The results reported in this study suggest that Ohio watersheds with large percentages of tile drainage could be exacerbating the problem with downstream nutrient transport due to increases in total stormflow amounts and proportions (Figure 3d; Figure 6a). In fact, recent HAB severity observed in the western Lake Erie basin was significantly correlated to March-July stormflow amounts (Figure 6b). It should be noted that one of the strongest correlations of watershed attributes from the GAGES-II dataset with tile drainage percentage were estimates of applied nitrogen (Pearson's $r = 0.79$) and phosphorus (Pearson's $r = 0.70$) from agricultural censuses (Falcone, 2011). This should not be surprising given the strong correlation between agriculture and tile drainage (Figure 2a) but emphasizes the role that watersheds with high percentages of tile drainage, and higher percentages of stormflow, play in the downstream transport of nutrients.

Direct HAB remediation is costly and involves either physical, chemical, or biological control measures, but will not help mitigate future severe HABs. If left uncontrolled, HABs in Lake Erie are estimated to cost Canada alone \$5.3 billion over the next 30 years (Smith *et al.*, 2019), thus targeting conservation efforts at the source could prove to be cost-effective. A combination of both nutrient and water management practices are probably needed to improve downstream aquatic conditions (Hanrahan *et al.*, 2019). In Ohio, soil test phosphorus concentrations were found to be linearly related to dissolved concentration loads in tile-drained fields, thus soil test phosphorus can be a good screening method to identify fields at risk for greater phosphorus loss (Duncan *et al.*, 2017). Limiting fertilizer application prior to spring storm events or incorporating fertilizer into the soil structure could help to reduce the downstream transport of nutrients from tile-drained fields (Williams *et al.*, 2016). The strong positive correlation between the timing of 50% of annual streamflow and HAB severity (Figure 6d) supports an earlier application of fertilizer to avoid excess nutrient transport during large late-spring storms which could be contributing to more severe HABs when water temperatures are greater.

Conservation practices that decrease the hydrologic response time to storm events in Ohio watersheds could benefit the aquatic health of downstream communities (e.g. buffer strips, wetland restoration). Restoring 5-10% of the 4,000 km^2 Great Black Swamp in the Maumee River basin could reduce phosphorus loading by 18-37% (Mitsch, 2017). Another technique that could decrease the hydrologic response time and thus greatly reduce the export of nutrient loads from agricultural fields is drainage water management, which has been shown to significantly reduce annual tile drainage discharge and subsequent nutrient loads (e.g. Williams et al., 2015). Through drainage water management, tile drainage outlets can be manipulated at the edge of field to reduce discharge during winter fallow periods and times in which field accessibility is not imperative.

4.3 Limitations and future research needs

One of the main limitations to our analyses was accurately selecting appropriate watersheds to compare the hydrologic response. The medium and high drainage category watersheds analyzed in this study are primarily located in northwest Ohio, while the low drainage category watersheds are scattered more throughout the state. Thus, the low drainage category watersheds have more variable soil properties, land cover, and precipitation patterns compared to the medium and high drainage category watersheds. In addition, some of the low drainage category watersheds have much greater mean slope (>4 %) and forest cover, thus the processes leading to the observed streamflow response in these low drainage category watersheds are likely quite different compared to the medium or high drainage category watersheds or the remaining low drainage category watersheds with lower mean watershed slope (< 4%). We performed the same analyses after removing the steepest watersheds (> 4% mean watershed slope, n = 13), which tended to be located in eastern and southern Ohio and none of the results changed, suggesting that our results and interpretations presented are robust across a range of tile drainage percentage for Ohio watersheds.

Another limitation for this study was relying on the modeled tile drainage dataset (Valayamkunnath *et al.*, 2020) for accurate identification of land drained by subsurface tiles. While recent advancements using thermal infrared sensors deployed with drones have provided adequate representation of tile delineation at agricultural fields (Allred *et al.*, 2018), it is currently unrealistic to obtain this information at the scale of the watersheds analyzed in this study. In Ohio, the total land area in the AgTile-US dataset is within 0.22 % of the total tile drained area reported in the USDA Census of Agriculture. However, neither of these datasets are able to provide information on whether drainage water management is implemented. For this reason, we assumed that drainage water management did not contribute substantially to the tile drained land or that drainage water management is uniformly practiced throughout the study watersheds, thus would not impact any particular watershed or drainage category.

Baseflow is a fairly ambiguous term but is generally thought to be representative of the water that sustains streamflow in between storms. In contrast, stormflow (i.e. quickflow, Hewlett and Hibbert, 1967) is a term used to represent the remaining streamflow not accounted for in baseflow. While mathematical baseflow separation techniques have been used since the early 20th century, more recently, chemical and isotopic mass-balance methods have become a popular alternative to mathematical approaches and are generally considered to be more physically-based due to incorporating chemical and/or isotopic information (Schilling and Helmers, 2008; Tesoriero et al., 2013; Frisbee et al., 2017; Schilling et al., 2019). However, mathematical approaches continue to be used widespread due to fewer data requirements, with only stream discharge being needed to perform baseflow separation (Schilling and Helmers, 2008; Boland-Brien et al., 2014; Schilling and Jones, 2019). Since the calculations for baseflow and stormflow used in this study are strictly based on the shape of the hydrograph, mathematical derivations of these terms cannot differentiate the geographic sources or ages and residences times of these two hydrograph sources. For example, under dry conditions tile drainage is likely composed of primarily baseflow derived from relatively older groundwater, whereas during wet storm conditions tile drainage could be comprised from a mixture of older groundwater and younger rainfall event water. Thus, the water discharging from tile drainage cannot be assumed to be entirely baseflow or stormflow. Additional research utilizing unique tracer signatures would be valuable for assessing the relative age of stream water and discharge from tile drainage outlets and downstream rivers and lakes.

5. Conclusion

This study analyzed the effect of tile drainage on various runoff metrics for 59 Ohio watersheds. We used a recently developed 30-m resolution tile drainage dataset to calculate the percentage of tile drainage in each watershed. Our results indicate that high percentages of tile drainage (> 40% of watershed area) result in significantly greater percentages of stormflow and a flashier hydrograph response in general, which contrasts with similar studies conducted in Iowa that showed increases in baseflow percentages and less flashy hydrographs for heavily tiled watersheds. Using baseflow and recession analysis, watersheds with high percentages of tile drainage consistently reported flashier behavior compared to watersheds with low percentages of tile drainage. The total amount of March – July stormflow and the stormflow proportion during this time was significantly positively correlated to western Lake Erie harmful algal bloom severity during the study period (2010-2019).

Increases in stormflow proportions, or the fast-varying portion of the hydrograph, are problematic for the downstream transport of nutrients and could be linked to exacerbated harmful algal bloom severity in Lake Erie observed in recent years. Given the recent trend in more frequent large rain events and warmer temperatures in the Midwest, increased harmful algal bloom severity will continue to be an ecological and economic problem for the region if management efforts are not addressed at the source. Management practices that reduce the hydrologic response time to storm events, such as buffer strips, wetland restoration, or drainage water management, are likely to improve downstream aquatic health conditions by limiting the transport of nutrients after storm events.

ACKNOWLEDGEMENTS

We thank Nandita Basu for providing helpful comments on an earlier draft of the manuscript. Funding was provided by the Ohio Department of Higher Education's Harmful Algal Bloom Research Initiative (Award 105335).

DATA AVAILABILITY

All data sources (streamflow, precipitation, watershed characteristics, tile drainage) are available publically. Code is available from the corresponding author upon reasonable request.

REFERENCES

Allred B, Eash N, Freeland R, Martinez L, Wishart DB. 2018. Effective and efficient agricultural drainage pipe mapping with UAS thermal infrared imagery: A case study. *Agricultural Water Management* **197**: 132–137 DOI: 10.1016/j.agwat.2017.11.011

Arenas Amado A, Schilling KE, Jones CS, Thomas N, Weber LJ. 2017. Estimation of tile drainage contribution to streamflow and nutrient loads at the watershed scale based on continuously monitored data. *Environmental Monitoring and Assessment* **189** (9) DOI: 10.1007/s10661-017-6139-4

Baker DB, Johnson LT, Confesor RB, Crumrine JP, Guo T, Manning NF. 2019. Needed: Early-term adjustments for Lake Erie phosphorus target loads to address western basin cyanobacterial blooms. *Journal of Great Lakes Research* **45** (2): 203–211 DOI: 10.1016/j.jglr.2019.01.011

Blann KL, Anderson JL, Sands GR, Vondracek B, Blann KL, Anderson JL, Sands GR, Vondracek B, Blann KL, Anderson JL, et al. 2009. Effects of Agricultural Drainage on Aquatic Ecosystems: A Review. *Critical Reviews in Environmental Science and Technology* **39** (11): 909–1001 DOI: 10.1080/10643380801977966

Boland-Brien SJ, Basu NB, Schilling KE. 2014. Homogenization of spatial patterns of hydrologic response in artificially drained agricultural catchments. *Hydrological Processes* **28** (19): 5010–5020 DOI: 10.1002/hyp.9967

De Cicco LA, Hirsch RM. 2014. The dataRetrieval R package: 1–26

Cross WP. 1949. The relation of geology to dry−weather stream flow in Ohio. *Eos, Transactions American Geophysical Union* **30** (4): 563–566 DOI: 10.1029/TR030i004p00563

Diaz RJ. 2001. Overview of Hypoxia around the World. *Journal of Environment Quality* **30** (2):

275–281

Dils RM, Heathwaite AL. 1999. The controversial role of tile drainage. *Water Science Technology* **39** (12): 55–61

Duncan EW, King KW, Williams MR, Labarge G, Pease LA, Smith DR, Fausey NR. 2017. Linking Soil Phosphorus to Dissolved Phosphorus Losses in the Midwest. *Agricultural & Environmental Letters*: 1–5 DOI: 10.2134/ael2017.02.0004

Falcone J. 2011. GAGES-II: Geospatial Attributes of Gages for Evaluating Streamflow. Reston, Virginia.

Frisbee MD, Meyers ZP, Stewart-Maddox NS, Caffee MW, Bogeholz P, Hughes MN. 2017. What is the source of baseflow in agriculturally fragmented catchments? Complex groundwater/surface-water interactions in three tributary catchments of the Wabash River, Indiana, USA. *Hydrological Processes* **31** (22): 4019–4038 DOI: 10.1002/hyp.11345

Gordon GERJ, John A, Tyndall C. 2017. What would farmers do ? Adaptation intentions under a Corn Belt climate change scenario. *Agriculture and Human Values* **34** (2): 333–346 DOI: 10.1007/s10460-016-9719-y

Hanrahan BR, King KW, Macrae ML, Williams MR, Stinner JH. 2020. Among-site variability in environmental and management characteristics: Effect on nutrient loss in agricultural tile drainage. *Journal of Great Lakes Research* **46** (3): 486–499 DOI: 10.1016/j.jglr.2020.02.004

Hanrahan BR, King KW, Williams MR, Duncan EW, Pease LA, LaBarge GA. 2019. Nutrient balances influence hydrologic losses of nitrogen and phosphorus across agricultural fields in northwestern Ohio. *Nutrient Cycling in Agroecosystems* **113** (3): 231–245 DOI: 10.1007/s10705-019-09981-4

Hewlett JD, Hibbert AR. 1967. Factors affecting the response of small watershed to precipitation in humid areas. *Forest Hydrology*: 275–279 DOI: 10.1177/0309133309338118

Ho JC, Michalak AM, Pahlevan N. 2019. Widespread global increase in intense lake phytoplankton blooms since the 1980s. *Nature* **574** (7780): 667–670 DOI: 10.1038/s41586-019-1648-7

Jiang X, Livi KJT, Arenberg MR, Chen A, Chen K yue, Gentry L, Li Z, Xu S, Arai Y. 2021. High flow event induced the subsurface transport of particulate phosphorus and its speciation in agricultural tile drainage system. *Chemosphere* **263**: 128147 DOI: 10.1016/j.chemosphere.2020.128147

King KW, Williams MR, Fausey NR. 2015. Contributions of Systematic Tile Drainage to Watershed-Scale Phosphorus Transport. *Journal of Environmental Quality* **44** (2): 486–494 DOI: 10.2134/jeq2014.04.0149

Koffler AD, Gauster T, Laaha G, Gauster MT. 2016. Package ‘ lfstat ’: 63

Konrad CP, Booth DB. 2002. Hydrologic trends associated with urban development for selected streams in the Puget Sound Basin, Western Washington. *U.S. Geological Survey Water-Resources Investigations Report 02-4040* Available at: http://catalog.hathitrust.org/Record/003781146%5Cnhttp://hdl.handle.net/2027/mdp.39015051623455

Logan TJ, Randall GW, Timmons DONR. 1980. Nutrient Content of Tile Drainage from Cropland in the North Central Region. *North Central Regional Research Publication 268* **Ohio Agric** (September)

Macrae ML, Ali GA, King KW, Plach JM, Pluer WT, Williams M, Morison MQ, Tang W. 2019. Evaluating Hydrologic Response in Tile-Drained Landscapes: Implications for Phosphorus Transport. *Journal of Environmental Quality* **1355** (July): 1347–1355 DOI: 10.2134/jeq2019.02.0060

McIsaac GF, Hu X. 2004. Net N input and riverine N export from Illinois agricultural watersheds with and without extensive tile drainage. *Biogeochemistry* **70** (2): 251–271 DOI: 10.1023/B:BIOG.0000049342.08183.90

Mitsch WJ. 2017. Solving Lake Erie’s harmful algal blooms by restoring the Great Black Swamp in Ohio. *Ecological Engineering* **108** (September): 406–413 DOI: 10.1016/j.ecoleng.2017.08.040

Price K. 2011. Effects of watershed topography, soils, land use, and climate on baseflow hydrology in humid regions : A review. *Progress in Physical Geography* **35** (4): 465–492

DOI: 10.1177/0309133311402714

PRISM Climate Group OSU. 2019. PRISM Climate Data Available at: http://prism.oregonstate.edu

Schilling KE, Helmers M. 2008a. Effects of subsurface drainage tiles on streamflow in Iowa agricultural watersheds : Exploratory hydrograph analysis. *Hydrological Processes* **4506** (May): 4497–4506 DOI: 10.1002/hyp

Schilling KE, Helmers M. 2008b. Tile drainage as karst: Conduit flow and diffuse flow in a tile-drained watershed. *Journal of Hydrology* **349** (3–4): 291–301 DOI: 10.1016/j.jhydrol.2007.11.014

Schilling KE, Jones CS. 2019. Hydrograph separation of subsurface tile discharge. *Environmental Monitoring and Assessment* **191** (4) DOI: 10.1007/s10661-019-7377-4

Schilling KE, Libra RD. 2003. Increased baseflow in Iowa over the second half of the 20th century1. *Journal of the American Water Resources Association* **39** (4): 851–860

Schilling KE, Gassman PW, Arenas-Amado A, Jones CS, Arnold J. 2019. Quantifying the contribution of tile drainage to basin-scale water yield using analytical and numerical models. *Science of the Total Environment* **657**: 297–309 DOI: 10.1016/j.scitotenv.2018.11.340

Schilling KE, Jindal P, Basu NB, Helmers MJ. 2012. Impact of artificial subsurface drainage on groundwater travel times and baseflow discharge in an agricultural watershed, Iowa (USA). *Hydrological Processes* **26** (20): 3092–3100 DOI: 10.1002/hyp.8337

Schilling KE, Wolter CF, Isenhart TM, Schultz RC. 2015. Tile Drainage Density Reduces Groundwater Travel Times and Compromises Riparian Buffer Effectiveness. *Journal of Environmental Quality* **44** (6): 1754–1763 DOI: 10.2134/jeq2015.02.0105

Skaggs RW, van Schilfgaarde J. 1999. *Agricultural Drainage*. American Society of Agronomy, Crop Science Society of America: Madison, Wisconsin. DOI: 10.2134/agronmonogr38

Smith DR, King KW, Johnson L, Francesconi W, Richards P, Baker D, Sharpley AN. 2015. Surface Runoff and Tile Drainage Transport of Phosphorus in the Midwestern United

States. *Journal of Environmental Quality* **44** (2): 495–502 DOI: 10.2134/jeq2014.04.0176

Smith RB, Bass B, Sawyer D, Depew D, Watson SB. 2019. Estimating the economic costs of algal blooms in the Canadian Lake Erie Basin. *Harmful Algae* **87** (November 2018): 101624 DOI: 10.1016/j.hal.2019.101624

Stamm C, Flühler H, Gächter R, Leuenberger J, Wunderli H. 1998. Preferential Transport of Phosphorus in Drained Grassland Soils. *Journal of Environmental Quality* **27** (3): 515–522 DOI: 10.2134/jeq1998.00472425002700030006x

Tallaksen LM, van Lanen HAJ (eds). 2004. *Hydrological Drought: Processes and Estimation Methods for Streamflow and Groundwater*. Elsevier: Amsterdam, the Netherlands.

Tesoriero AJ, Duff JH, Saad DA, Spahr NE, Wolock DM. 2013. Vulnerability of streams to legacy nitrate sources. *Environmental Science and Technology* **47** (8): 3623–3629 DOI: 10.1021/es305026x

Troch PA, Berne A, Bogaart P, Harman C, Hilberts AGJ, Lyon SW, Paniconi C, Pauwels VRN, Rupp DE, Selker JS, et al. 2013. The importance of hydraulic groundwater theory in catchment hydrology: The legacy of Wilfried Brutsaert and Jean-Yves Parlange. *Water Resources Research* **49** (9): 5099–5116 DOI: 10.1002/wrcr.20407

USDA NASS. 2014. United States Summary and State Data. *2012 Census of Agriculture* **1** (April 2019) Available at: https://www.nass.usda.gov/Publications/AgCensus/2017/Full_Report/Volume_1,_Chapter_1_US/usv1.pdf

USDA NASS. 2019. United States Summary and State Data. *2017 Census of Agriculture* **1** (April 2019) Available at: https://www.nass.usda.gov/Publications/AgCensus/2017/Full_Report/Volume_1,_Chapter_1_US/usv1.pdf

Valayamkunnath P, Barlage M, Chen F, Gochis DJ, Franz KJ. 2020. Mapping of 30-meter resolution tile-drained croplands using a geospatial modeling approach. *Scientific Data* **7** (257): 1–10 DOI: 10.1038/s41597-020-00596-x

Williams MR, King KW. 2020. Changing Rainfall Patterns Over the Western Lake Erie Basin

(1975 – 2017): Effects on Tributary Discharge and Phosphorus Load. *Water Resources Research* DOI: 10.1029/2019WR025985

Williams MR, King KW, Fausey NR. 2015. Drainage water management effects on tile discharge and water quality. *Agricultural Water Management* **148**: 43–51 DOI: 10.1016/j.agwat.2014.09.017

Williams MR, King KW, Ford W, Buda AR, Kennedy CD. 2016. Effect of tillage on macropore flow and phosphorus transport to tile drains. *Water Resources Research* **52**: 2868–2882 DOI: 10.1002/2015WR017650.Received

WMO. 2008. *Manual on Low-flow Estimation and Prediction : Operational Hydrology Report No.50*.

Wolf D, Georgic W, Klaiber HA. 2017. Reeling in the damages: Harmful algal blooms' impact on Lake Erie's recreational fishing industry. *Journal of Environmental Management* **199**: 148–157 DOI: 10.1016/j.jenvman.2017.05.031

TABLES

Table 1: Mean watershed characteristics for the three drainage categories. Area, Agricultural land, slope, clay, and depth to seasonally high water table from the GAGES-II dataset (Falcone, 2011). Unique letters represent significant differences ($p < 0.05$) using the Tukey Test.

Drainage Category	Number	Area (km^2)	Tile Drainage (%)	Agricultural Land (%)	Slope (%)	Clay (%)	Water Table Depth (m)
Low	18	493 a	4.9 a	42.2 a	5.3 a	27.4 a	1.08 a
Medium	24	655 a	28.5 b	72.6 b	1.3 b	27.9 a	0.80 b
High	17	653 a	51.2 c	82.2 c	0.4 b	33.7 b	0.52 c

Table 2: Mean annual precipitation (PRISM Climate Group, 2019), area-weighted runoff, runoff ratio, peak daily runoff (Peak Q), proportion of time mean daily streamflow is greater than mean annual streamflow (T_{Qmean}), mean annual baseflow index (BFI), March – July BFI, and recession constants from MRC and IRS methods for the three drainage categories during all study years (2010-2019). Unique letters represent significant differences ($p < 0.05$) using the Tukey Test.

Drainage Category	Precip. (mm)	Runoff (mm)	Runoff Ratio (%)	Peak Q (mm/day)	T_{Qmean} (%)	BFI (%)	Mar-Jul BFI (%)	MRC	IRS
Low	1160 a	469 a	40.3 a	17.7 a	27.9 a	40.3 a	41.1 a	6.3 a	7.6 a
Medium	1099 b	429 b	38.9 a	18.3 a	25.7 a	35.6 a	35.8 a	6.5 a	7.5 a
High	1067 b	407 b	38.1 a	19.6 a	22.3 b	20.9 b	22.2 b	3.5 b	4.2 b

FIGURE LEGENDS

Figure 1: Location and drainage category of 59 watersheds used in this study.

Figure 2: Watershed tile drainage (%) versus agricultural land (a), mean watershed slope (b), average value of soil clay content (c), and depth to seasonally high water table (d) (Falcone, 2011).

Figure 3: Mean annual runoff ratio (%) (a), mean annual peak daily runoff (b), percent of observations daily runoff exceeds mean annual runoff (T_{Qmean}) (c), and mean annual baseflow index (BFI) (d) versus watershed tile drainage (%).

Figure 4: Mean annual runoff ratio (%) (a), mean annual peak daily runoff (b), percent of observations daily runoff exceeds mean annual runoff (T_{Qmean}) (c), and mean annual baseflow index (BFI) (d) versus watershed drainage area colored by drainage category.

Figure 5: Recession (MRC) constant versus watershed tile drainage (a) and watershed area (b) colored by drainage category. Recession (IRS) constant versus watershed tile drainage (c) and watershed area (d) colored by drainage category.

Figure 6: March – July stormflow as a percentage of total annual runoff versus tile drainage (a). March – July mean total stormflow (mm) for the high drainage category watersheds vs Western Lake Erie Bloom Severity Index (b). March – July mean stormflow (blue) and baseflow (red) runoff ratio for the high drainage category watersheds vs Western Lake Erie Bloom Severity Index (c). Day of calendar year (DOY) when 50% of annual streamflow occurs for the high drainage category watersheds vs Western Lake Erie Bloom Severity Index (d).