# INCREASING TRENDS IN PEAK FLOWS IN THE NORTHEASTERN UNITED STATES AND THEIR IMPACTS ON DESIGN 

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#### Abstract

Water management infrastructure is currently designed and operated under the assumption of stationarity (Milly et al, 2008). This assumption implies that both natural and anthropogenic-induced are small enough to be ignored, so that variables like annual peak streamflow do not change over time. Furthermore, flood frequency analysis normally requires that peak flow data is homogeneous, independent and stationary. This paper reveals that annual peak streamflows are not stationary, especially in highly urbanized areas of the country. Nearly all previous research dealing with flood trend detection involved watersheds which were not heavily influenced by humans. We take a different approach by looking for increasing trends at all gaged rivers in the northeastern United States. A hydrologic database of 1,312 gages in the northeastern United States was compiled to analyze trends in instantaneous peak streamflows. After performing a parametric $t$-test on the slope of the linear relationship between the natural log of annual peak streamflow and time, it was determined that approximately 258 gages (19.7\%) indicated positive trends in flood events. Decadal magnification and recurrence reduction factors were developed to investigate how the presence of increasing trends will affect future storm events and return periods. Results indicate that, if trends continue at those sites exhibiting trends, in 10 years, the 10 year storm is reduced, on average, to a 6.1 year storm; the 25 year storm is reduced, on average, to a 13.8 year storm; the 100 year storm is reduced, on average, to a 48.5 year storm. Lastly, impacts of the magnified flow events and reduced return periods are discussed from a design perspective. Our findings reveal remarkably large trends at a small percentage of sites.


## INTRODUCTION

Water management infrastructure is currently designed and operated under the assumption of stationarity (Milly et al, 2008). This assumption implies that both natural and anthropogenic-induced are small enough to be ignored, so that variables like annual peak streamflow do not change over time. There has been much discussion recently in the hydrologic community regarding stationarity and the need to provide accurate flood risk and uncertainty estimates (Lettenmaier, 2008; Stedinger and Griffis, 2008; Brown, 2009). This paper demonstrates that annual peak streamflows are likely not stationary, especially in highly urbanized areas of the northeastern United States and are subject to increasing trends.

This study examines instantaneous annual peak flows in the northeastern United States to evaluate the presence of increasing trends. The goals of the paper are to (1) document the existence of increasing trends in peak flows by performing a parametric $t$-test on the slope of the linear relationship between the natural log of annual peak streamflows and time; (2) develop decadal magnification factors to project future flow rates of major storm events; (3) develop decadal recurrence reduction factors to quantify the change in recurrence interval, or return period, that will occur as a result of increasing trends.

## Review of literature

A vast amount of research has been dedicated to investigating the existence of trends in streamflow. A few examples include Robson et al, 1998; Lins and Slack, 1999; Douglas et al, 2000; Groisman et al, 2001; Burn and Hag Elnur, 2002; McCabe and Wolock, 2002; Hodgkins and Dudley, 2005; Small et al, 2006; Collins, 2009, Petrow and Merz, 2009; Villarini, 2009; and Zariello and Carlson, 2009. Robson et al (1998) found no evidence supporting the existence of increasing trends in annual maximum flows at 890 streamflow gages in the United Kingdom. Lins and Slack (1999) examined whether trends occurred in streamflow over a range of discharge quantiles. They found trends were most prevalent in the annual minimum to median flow categories. Douglas et al (2000) investigated trends in flood and low flows in the United States and found significant increasing trends in low flows in the Upper

Missouri, North Central and Ohio Valley. They found no evidence of trends in flood flows. Groisman et al (2001) documented an increase in spring heavy precipitation events over the eastern United States, which indicates with high probability that an increase in high streamflows has occurred during the twentieth century in the eastern United States. Burn and Hag Elnur (2002) tested 248 catchments in Canada and found decreasing trends in annual maximum flow in the south and increasing trends in the north. They also found increasing trends in March and April flows. McCabe and Wolock (2002) documented statistically significant upward trends across the United States for annual minimum and annual median flows. Hodgkins and Dudley (2005) found significant increases over time in various annual percentile flows for 22 gages in New England, indicating that flows increased over time at many streams in New England. However, the increase was not enough to cause significant increases in annual mean flows. Small et al (2006) analyzed trends in 218 basins across the eastern half of the United States and found that the annual mean and low flows increased over the period 1948-1997. They found no evidence of increasing trends in high flows. Collins (2009) reported statistically significant trends in annual flood series at 6 gages in New England. Petrow and Merz (2009) studied 145 gages in Germany and detected significant increasing trends in flood flows in $28 \%$ of the gages tested. Villarini et al (2009) examined annual maximum instantaneous peak discharges from 50 stations in the continental United States and found no overall monotonic temporal patterns in the data. In a USGS study by Zarriello and Carlson (2009), a peak flow analysis was performed at 10 streamflow gaging stations in Massachusetts to determine the magnitude of various flood return intervals in order to characterize the magnitude of an April 2007 "nor’easter". It was determined that the magnitude of flood flow for a given return interval calculated based on actual periods of record were greater than flood magnitudes calculated from flood insurance studies.

The literature review above indicates that increasing trends in low and median flows are well-documented; however, there remains a discrepancy in the research regarding trends in peak flows as some studies found no evidence of increasing trends in peak flows (Robson, 1998; Lins and Slack, 1999; Douglas et al, 2000; Small, 2006; Villarini, 2009) while other studies documented existence of such trends (Groisman, 2001; Burn and Hag Elnur, 2002; Collins, 2009; Petrow and Merz, 2009). Of the these nine studies, three account for spatial correlation and one study employs the use of gages with regulated flows. This study attempts to eliminate the discrepancy and document the existence of increasing trends in peak flows in the eastern United States.

The existence of increasing trends in peak flows will have a major impact on water infrastructure. Peak flows are used to estimate flood frequency, as recommended by the federal interagency Guidelines for Determining Flood Flow Frequency - Bulletin 17B (IACWD, 1981). Bulletin 17B is the standard procedure for flood frequency estimation in the United States and is employed for a multitude of planning and design procedures. When performing a flood frequency analysis, the measured discharge signal must be stationary, as dictated by Bulletin 17B (IACWD, 1981). However, the presence of increasing trends implies a nonstationary discharge signal. As Beighley and Moglen (2002) point out, if the nonstationary signal is not identified, then the appropriate steps to account for the signal cannot be taken. This results in flood frequency relationships that will tend to under predict flood magnitudes, which can lead to the under design of hydraulic structures, such as bridges, culverts, and dams. Zarriello and Carlson (2009) observed large differences in their calculates of flood flow magnitudes for various return intervals compared to results from existing regional equations and flood insurance studies, indicating a need to update region analyses and equations for estimate flood magnitude in Massachusetts. The impacts of increasing trends in peak flows are further quantified in the Results section of this paper, where magnification factors and recurrence reduction factors are developed.

## METHODS

## Data

A compilation of instantaneous annual peak flows was obtained from the U.S. Geological Survey (USGS) National Water Information System (NWIS) for 1,312 streamflow gages in the northeastern U.S. Sites selected included 377 gages from the New England region and 935 gages from the Mid-Atlantic region, as shown in Figure 1. Record length was the sole criteria used for gage selection: minimum record length of 20 years was required for a stream gage to be included in this study. Continuous data was not a requirement for inclusion. Maximum record length was 108 years. Average record length was 50 years. Drainage areas ranged from $0.28 \mathrm{mi}^{2}$ to $27,100 \mathrm{mi}^{2}$.

Previous research on identifying trends in streamflow utilized gages with predominantly natural streamflow. Several studies on trends in streamflows [Vogel et al, 1996; Lins and Slack, 1999; Douglas et al, 2000; Small et al, 2006; Collins, 2009] employed gages selected from the USGS Hydro-Climatic Data Network (HCDN). This dataset was
developed to analyze climate sensitivity and is appropriate only for research related to climate. Watersheds in this dataset have minimal water withdrawals and transfers and are relatively free from land use changes and other anthropogenic influence. This study documents that to show the widespread existence of increasing trends in peak flows, particularly in relation to increasing urbanization, it is necessary to include gages subject to anthropogenic influences. Therefore, the HCDN data set was not used in this study; rather, gages were selected by record length alone, as discussed above.


Figure 1: Stations investigated for increasing trends in peak flows.

## Trend Detection

Hydrological data are often strongly non-normal, which means that tests assuming an underlying normal distribution can be inadequate for trend detection (Kundzewicz and Robson, 2004). However, flood flows are known to be accurately represented by a log normal distribution, as indicated in Bulletin 17B Guidelines for Determining Flood Flow Frequency. Therefore, a log-normal distribution was assumed and applied to peak flow data for the 1,312 streamflow gages analyzed in this study. One of the most important issues in frequency analysis is the selection of an appropriate probability distribution for a set of hydrological data (Heo et al, 2008). To test the goodness-of-fit of the lognormal distribution of flood flows, a probability plot correlation coefficient (PPCC) hypothesis test was conducted on sites exhibiting statistically significant trends. The PPCC test is a simple yet powerful way to evaluate how well data agree with an assumed probability distribution as its population (Heo et al, 2008). Here the lognormal PPCC test was applied at those sites exhibiting statistically significant trends. Results of a $5 \%$ level PPCC test indicate that a majority of sites with statistically significant trends pass the test for normality, as summarized in Table 1 below.

Table 1: Lognormal Probability Plot Correlation Coefficient (PPCC) Test Results for Instantaneous Annual Maximum Flood Flow at Sites Exhibiting Statistically Significant Trends

| Region | No. of <br> sites <br> tested | No. of sites <br> passing PPCC <br> test | \% of sites <br> passing PPCC <br> test | No. of sites <br> failing <br> PPCC test | \% of sites <br> failing PPCC <br> test |
| :--- | :---: | :---: | :---: | :---: | :---: |
| New England region | 88 | 73 | $83.0 \%$ | 15 | $17.0 \%$ |
| Mid-Atlantic region | 170 | 150 | $88.2 \%$ | 20 | $11.8 \%$ |
| Both regions | 258 | 223 | $86.4 \%$ | 35 | $13.6 \%$ |

Peak flows were evaluated using linear regression to investigate presence of increasing trends. The regression model, given by Equation 1, was applied at each site to determine if there was a linear relationship between the natural logarithm of peak flows and time.

$$
\begin{equation*}
\ln \left(\mathrm{Q}_{\mathrm{t}}\right)=\alpha+\beta \cdot \mathrm{t}+\varepsilon \tag{1}
\end{equation*}
$$

$\ln \left(\mathrm{Q}_{\mathrm{t}}\right)=$ natural logarithm of peak flow in year $t$
$\alpha=$ intercept parameter
$\beta=$ slope magnitude and direction
$t=$ year
$\varepsilon=$ model residuals
The slope term, $\beta$, represents the direction and magnitude of the trend. Statistical significance of each trend was estimated using a parametric $t$ test at a 5\% significance level. To carry out the statistical test, the null and alternative hypotheses were defined. The null hypothesis, $\mathrm{H}_{0}$, assumes that peak flows are not increasing over time and there is no trend $(\beta=0)$ present in the data. The alternative hypothesis, $\mathrm{H}_{\mathrm{a}}$, assumes that a trend is present and increasing over time. In performing the statistical test, it was assumed that the null hypothesis is true, $\beta=0$.

The significance level, $5 \%$ for this study, expresses the probability that the null hypothesis is incorrectly rejected and measures whether the test statistic ( $\beta$ in this case) is very different from the range of values expected for the null hypothesis. (Kundzewicz and Robson, 2004). For this study, the parametric $t$ test determined if the slope was significantly ( $p<0.05$ ) different from zero. Time series plots for several gages exhibiting statistically significant increasing trends are shown in Figures 2a-d.


Figure 2a: Eightmile River at North Plain, CT



Figure 2b: Beaver Kill at Cooks Falls, NY


Figure 2c: S. Branch Newton Creek at Haddon Heights, NJ
Figure 2d: Nanticoke River near Bridgeville, DE

## Serial Correlation

An analysis of temporal, or serial, correlation illustrates the degree to which variables in a time series, like peak flows, are dependent upon each other (Lye, 1994). A site is said to exhibit serial correlation if peak flow in a given year is impacted by previous or future peak flows. The presence of positive serial correlation can also lead to a higher probability of incorrectly rejecting the null hypothesis of no trend. This inflates the number of sites exhibiting statistically significant trends and distorts the analysis of what is causing the trends.

A common estimate of serial correlation is the lag-k autocorrelation coefficient, $\rho_{\mathrm{k}}$, where $k$ is the lag between observations. The lag-1 autocorrelation coefficient was evaluated for each gage exhibiting a statistically significant trend using Equation 2.

$$
\begin{equation*}
\rho_{1}=\frac{\sum_{t=1}^{n-1}\left(Q_{t}-\bar{Q}\right)\left(Q_{t+1}-\bar{Q}\right)}{\sum_{t=1}^{n}\left(Q_{t}-\bar{Q}\right)^{2}} \tag{2}
\end{equation*}
$$

where $n$ is the sample size, $Q_{t}$ is flow in year $t$, and $\mathbb{Q}$ is mean flow. Results of the serial correlation analysis are shown in Figure 3. Approximately 27\% of the sites with statistically significant trends exhibited serial correlation.


Figure 3: Lag-1 autocorrelation coefficients for 1,312 streamflow gages in the northeastern United States.

## RESULTS

Figure 4 identifies gages with statistically significant increasing trends using a 5\% level test. Overall, 19.7\% of sites investigated show evidence of increasing trends. These results were consistent with Collins (2009), who analyzed 28 gages in New England for increasing trends and found that 6 gages (21.4\%) exhibited statistically significant trends at the $p<0.05$ level.

Figure 5 summarizes the periods of record for sites exhibiting statistically significant trends. In reviewing Figure 5, it is evident that sites with shorter periods of record comprise a large portion of the sites exhibiting statistically significant trends.


Figure 4: Location of stations with increasing trends in peak flows in the northeastern United States


Figure 5: Distribution of periods of record for gages with statistically significant trends

## Impacts of Trends

While much research has been devoted to analyzing trends in hydrologic data and their causes, little consideration is given to the impacts of such trends and their real-world implications. Trends can have a profound effect on the results of flood frequency estimates and can undermine the usefulness of the concept of a static return period (Petrow and Merz, 2009). In this study, we quantify the impacts of increasing trends in peak flows on return periods and common storm events. Two measures of increasing trends were developed to quantify the impacts on engineering design, prediction, and management: flood magnification factors and recurrence reduction factors.

## Flood Magnification Factors

A flood magnification factor, $M$, was developed for each site exhibiting statistically significant increasing trends. A magnification factor is defined as the ratio of the $T$ year flood (where $T$ could be the $2-, 10-, 25-$, 50 -, or $100-\mathrm{yr}$ flood) at a given site $\Delta t$ years into the future compared to the current $T$ year flood at time $t$. The magnification factor represents how much the magnitude of a given storm event today, such as the 100 -year storm, should be increased to accurately represent the magnitude of the storm event at some time in the future. Magnification factors, $M$, were developed using the quantile function, as shown in the following derivation:

$$
\begin{equation*}
\mathrm{M}=\frac{\mathrm{Q}(\mathrm{p}, \mathrm{t}+\Delta \mathrm{t})}{\mathrm{Q}(\mathrm{p}, \mathrm{t})} \tag{3}
\end{equation*}
$$

Where $Q(p, t)$ is the quantile function corresponding to a particular exceedance probability $p$ at time $t ; Q(p, t+\Delta t)$ is the quantile function at time $t+\Delta t$, and $\Delta t$ is number of years into the future for which the magnification factor is calculated. For example, when calculating decadal magnification factors in the present year of 2009, $\Delta t$ is 10 years. For a log normal distribution, the quantile function $Q(p)$ is defined as:

$$
\begin{align*}
& \mathrm{Q}(\mathrm{p})=\mathrm{e}^{\left(\mu_{\mathrm{y}}+\mathrm{z}_{\mathrm{p}} \cdot \sigma_{\mathrm{y}}\right)}  \tag{4}\\
& \text { where } \quad \mu_{\mathrm{y}}=\alpha+\beta \cdot \mathrm{t} \\
& \mathrm{y}=\ln (\mathrm{Q})  \tag{5}\\
& \alpha=\text { intercept } \\
& \beta=\text { slope } \\
& \mathrm{t}=\text { time } \\
& \sigma_{\mathrm{y}}=\text { standard deviation of } \mathrm{y}=\ln (\mathrm{Q}) \\
& \mathrm{Z}_{\mathrm{p}}=\text { quantile of a normal random variable }
\end{align*}
$$

Substituting Equations 4 and 5 into Equation 3 leads to:

$$
\begin{equation*}
M=\frac{e^{\left(\alpha+\beta(t+\Delta t)+z_{p} \cdot \sigma_{y}\right)}}{e^{\left(\alpha+\beta t+z_{p} \cdot \sigma_{y}\right)}} \tag{6}
\end{equation*}
$$

Which simplifies to:

$$
\begin{equation*}
M=e^{\beta \cdot \Delta t} \tag{7}
\end{equation*}
$$

Figure 6 illustrates the numerical and geographical range of decadal magnification factors.


Figure 6: Decadal magnification factors for 258 streamflow gages

## Recurrence Reduction Factors

The existence of increasing trends in peak flows has a strong effect on calculations of return periods. A return period (also known as recurrence interval or exceedance interval) is defined as the average time interval between actual occurrences of hydrological events of a given or greater magnitude (IACWD, 1981). An increasing trend will accelerate, or shorten, the time interval between hydrological events. To demonstrate the impact of trends on return periods, Recurrence Reduction Factors (RRFs) were developed. RRFs are defined by Equation 8:

$$
\begin{equation*}
\mathrm{RRF}=\frac{\mathrm{T}_{2}}{\mathrm{~T}_{1}} \tag{8}
\end{equation*}
$$

Where $T_{1}$ is the return period with an exceedance probability $p_{1}$ for a storm event today and $T_{2}$ is the return period with an exceedance probability $p_{2}$ for a storm event occurring at some time $\Delta t$ years in the future. In this study, we calculate decadal RRFs with $\Delta t=10$ years. Recurrence reduction factors provide insight as to how a return period today (like the 10-, 25-, and 100-year storms) will be reduced in the future if observed trends were to continue at those sites.

Today's return period $T_{1}$ is defined as:

$$
\begin{equation*}
\mathrm{T}_{1}=\frac{1}{\mathrm{p}_{1}} \tag{9}
\end{equation*}
$$

Where $p_{1}$ is a known exceedance probability. The associated quantile function is $\mathrm{Q}\left(\mathrm{p}_{1}, \mathrm{t}_{1}\right)$. In $\Delta t$ years, the return period becomes:

$$
\begin{equation*}
\mathrm{T}_{2}=\frac{1}{\mathrm{p}_{2}} \tag{10}
\end{equation*}
$$

With a quantile function of $\mathrm{Q}\left(\mathrm{p}_{2}, \mathrm{t}_{2}\right)$ and unknown exceedance probability, $p_{2}$. By setting the quantile functions equal to each other and manipulating terms, an estimate of the reduced return period can be obtained, as shown below. Recall that the quantile function is given by Equation 4.

$$
\begin{gather*}
\mathrm{Q}\left(\mathrm{p}_{1}, \mathrm{t}_{1}\right)=\mathrm{Q}\left(\mathrm{p}_{2}, \mathrm{t}_{2}\right)  \tag{11}\\
\mathrm{e}^{\left(\mu_{\mathrm{y}}+\mathrm{z}\left(\mathrm{p}_{1}\right) \cdot \sigma_{\mathrm{y}}\right)}=\mathrm{e}^{\left(\mu_{\mathrm{y}}+\mathrm{z}\left(\mathrm{p}_{2}\right) \cdot \sigma_{\mathrm{y}}\right)}  \tag{12}\\
\mathrm{e}^{\left(\alpha+\beta \cdot \mathrm{t}_{1}+\mathrm{z}\left(\mathrm{p}_{1}\right) \cdot \sigma_{\mathrm{y}}\right)}=\mathrm{e}^{\left(\alpha+\beta \cdot \mathrm{t}_{2}+\mathrm{z}\left(\mathrm{p}_{2}\right) \cdot \sigma_{\mathrm{y}}\right)} \tag{13}
\end{gather*}
$$

After taking the natural log of both sides of the equation and cancelling terms, Equation 14 is generated:

$$
\begin{equation*}
\beta \cdot \mathrm{t}_{1}+\mathrm{z}\left(\mathrm{p}_{1}\right) \cdot \sigma_{\mathrm{y}}=\beta \cdot \mathrm{t}_{2}+\mathrm{z}\left(\mathrm{p}_{2}\right) \cdot \sigma_{\mathrm{y}} \tag{14}
\end{equation*}
$$

Rearranging Equation 14 yields:

$$
\begin{equation*}
\beta\left(\mathrm{t}_{2}-\mathrm{t}_{1}\right)=\sigma_{\mathrm{y}} \cdot\left(\mathrm{z}\left(\mathrm{p}_{1}\right)-\mathrm{z}\left(\mathrm{p}_{2}\right)\right) \tag{15}
\end{equation*}
$$

Substituting $\Delta t=t_{2}-t_{1}$ and rearranging terms results in:

$$
\begin{equation*}
\mathrm{p}_{2}=\Phi \mathrm{z}\left(\mathrm{p}_{1}\right)-\frac{\beta \cdot \Delta \mathrm{t}}{\sigma_{\mathrm{y}}} \tag{16}
\end{equation*}
$$

Where $\Phi$ is the normal cumulative density function. Standard statistical tables in software packages like Microsoft Excel can be used to solve Equation 16 for $p_{2}$, an exceedance probability for $\Delta t$ years into the future. Values for $p_{2}$ are then substituted into Equation 10 to generate revised values of $T_{2}$. The range of values of $T_{2}$ is illustrated in Figure 7. The 10 year storm is reduced, on average, to a 6.1 year storm; the 25 year storm is reduced, on average, to a 13.8 year storm; the 100 year storm is reduced, on average, to a 48.5 year storm.

Decadal Recurrence Reduction Factors Northeastern United States


Figure 7: Range of reduced recurrence intervals for the 10-, 25-, and 100-yr storm

## DISCUSSION

While attribution of trend is not the primary goal here, the link between trend presence and urbanization is briefly explored through data analysis and the use of Geographic Information Systems (GIS). Sites investigated and sites exhibiting statistically significant increasing trends are overlaid on census data in Figures 8 and 9. Findings are summarized by state in Table 2.

In reviewing Figures 8 and 9 and Table 2, there appears to be a link between population density and trend presence. The states with the highest population densities (Massachusetts, Rhode Island, Connecticut, New Jersey, and Maryland) are closely correlated with the states exhibiting the highest percentage of gages with statistically significant trends. More than 30\% of gages investigated in Rhode Island (37.5\%), Connecticut (31.1\%), and Delaware (37.5\%) exhibited statistically significant trends. Not only does Connecticut show evidence of statistically significant trends, the state also exhibits the largest trend magnitudes of the thirteen states investigated. More than 20\% of gages investigated in New Jersey (22.4\%), Maryland (24.0\%), and New Hampshire (25.4\%) exhibited statistically significant trends. It is surprising to note that while Massachusetts has the fourth highest population density in the United States, only $17.6 \%$ of sites exhibited statistically significant trends. This is similar to the percentage of gages in Pennsylvania (17.8\%) exhibiting statistically significant trends, even though Pennsylvania’s population density ( 278 persons per sq. mi.) is about one-third of Massachusetts' population density (833 persons per sq. mi.).

Table 2: Results of trend analysis by state

| State | Number of <br> gages <br> investigated | Number of <br> gages with <br> trends $(\boldsymbol{p}<\mathbf{0 . 0 5 )}$ | \% of gages <br> with trends <br> $(\boldsymbol{p}<\mathbf{0 . 0 5 )}$ | 2008 population <br> density (persons <br> per sq. mi.) |
| :--- | ---: | ---: | ---: | ---: |
| Maine | 63 | 10 | $15.9 \%$ | 43.0 |
| New Hampshire | 63 | 16 | $25.4 \%$ | 147.0 |
| Vermont | 66 | 11 | $16.7 \%$ | 67.0 |
| Massachusetts | 91 | 16 | $17.6 \%$ | 833.0 |
| Connecticut | 103 | 32 | $31.1 \%$ | 723.0 |
| Rhode Island | 16 | 6 | $37.5 \%$ | 1016.0 |
| New York | 210 | 41 | $19.5 \%$ | 414.0 |
| Pennsylvania | 213 | 38 | $17.8 \%$ | 278.0 |
| New Jersey | 165 | 37 | $22.4 \%$ | 1181.0 |
| Delaware | 16 | 6 | $37.5 \%$ | 448.0 |
| Maryland | 104 | 25 | $24.0 \%$ | 580.0 |
| Virginia | 172 | 18 | $10.5 \%$ | 197.0 |
| West Virginia | 16 | 0 | $0.0 \%$ | 75.0 |

The impact of urbanization on trend presence is further investigated using land cover data in Figures 10 and 11. In Figure 10, gages with increasing trends are overlaid on land cover; in Figure 11, impervious area is extracted from the land cover data. These figures indicate that development, particularly impervious area, may affect the presence of trends.


Base map from U.S. Geological Survey and MassGIS data sources, NAD83 projection
Figure 8: Comparison of trend magnitude and population density for Maine, New Hampshire, Vermont, Massachusetts, Rhode Island and Connecticut


Base map from U.S. Geological Survey and MassGIS data sources, NAD83 projection
Figure 9: Comparison of trend magnitude and population density for New York, New Jersey, Pennsylvania, Delaware, Maryland, Virginia, and West Virginia


Figure 10: Land use in the northeastern United States


Figure 11: Impervious area in the northeastern United States

Investigation of trend magnitude is also important, as magnitude provides an indication as to where infrastructure efforts should be focused to address increasing peak flows. To determine if basin size affects trend magnitude, drainage area is plotted again trend magnitude (slope, $\beta$ ) in Figure 12. In examining Figure 12, it appears there may be a relationship between drainage area and trend magnitude. The sites with larger drainage areas ( $\sim \geq 10 \mathrm{sq} . \mathrm{mi}$ ) seem to exhibit smaller trend magnitudes, as compared to sites with small drainage areas. This is not surprising, if one considers that large basins are less likely to be urbanized. Table 3 provides a summary of the trend detection results in the context of drainage area size.


Figure 12: Comparison of drainage area and trend magnitude
Table 3: Summary of trend detection results and drainage area

| Region | Total number <br> of sites <br> investigated | Total <br> number of <br> sites with <br> $\mathrm{DA} \leq 10$ <br> $\mathrm{mi}^{2}$ | Number of <br> \% sites <br> with DA <br> $\leq 10 \mathrm{mi}^{2}$ | \% of sites <br> sites with <br> statistically <br> significant <br> trends | with <br> statistically <br> significant <br> trends | Number <br> of sites <br> with trend <br> where DA <br> $\leq 10 \mathrm{mi}^{2}$ | $\%$ of sites <br> with trend <br> where DA <br> $\leq 10 \mathrm{mi}^{2}$ |
| :--- | ---: | ---: | ---: | ---: | ---: | ---: | :---: |
| New <br> England | 376 | 76 | $20.2 \%$ | 88 | $23.4 \%$ | 34 | $38.6 \%$ |
| Mid- <br> Atlantic | 936 | 209 | $22.3 \%$ | 170 | $18.1 \%$ | 50 | $29.4 \%$ |
| Regions <br> combined | 1312 | 285 | $21.7 \%$ | 258 | $19.6 \%$ | 84 | $32.6 \%$ |

Of the total number of sites investigated (1312 gages), 285 sites, or $21.7 \%$, have drainage areas less than or equal to $10 \mathrm{mi}^{2}$. Trend detection revealed that 258 sites, or $19.6 \%$, exhibited statistically significant trends; almost one-third $(32.6 \%)$ of these sites with trends have a drainage area less than or equal to $10 \mathrm{mi}^{2}$. Sites with statistically significant trends and drainage area less than or equal to $10 \mathrm{mi}^{2}$ are shown in Figure 13. Many of these sites are located in highly urbanized areas, including Connecticut, eastern New York, New Jersey, and Maryland. Connecticut seems to have the largest number of sites with trends and drainage area less than $10 \mathrm{mi}^{2}$.


Figure 13: Sites exhibiting statistically significant trends with drainage areas less than $10 \mathrm{mi}^{2}$
From an economic perspective, the presence of increasing trends in flood flows has dramatic implications. In 2007, the Red Cross estimated that floods kill more than 100 people per year, on average, and are responsible for $\$ 4.6$ billion in damage in the United States each year (Red Cross, 2007). With documented existence of increasing peak flows, some may draw the conclusion that flood damage will also increase and more people will be killed. While this statement contains some truth, it also negates the idea that society has considerable remaining potential to reduce its vulnerability to floods (Pielke and Downton, 2000). In Pielke and Downton's study on precipitation and damaging floods in the United States (Pielke and Downton, 2000), they found that increased precipitation is associated with increased flood damage. However, they also found that increasing population growth and wealth are also associated with increased flood damage. They concluded that much of the flood-related damages in recent decades can be attributed to numerous human choices. Examples of human choices that impact flood-related damages include continued increase of populations in and around flood-prone areas, destruction of flood-storing wetlands, increases in impervious areas, and implementation of policies that allow or encourage development in flood plains (i.e. subsidies for roads and bridges) (Pielke, 1999).

The presence of increasing trends in peak flows further supports the theory commonly referred to as the "death of stationarity." Increasing trends demonstrate that the statistics of historical streamflow records are changing over time. In an editorial to the Journal of Water Resources Planning and Management (in press, 2010) Dr. Casey Brown states that the death of stationarity implies that the reliability associated with any storm event is in fact, not very reliable. Brown demonstrates the concept of reliability using the example of a flood control system design to withstand a 100-year flood, stating that the 100-year flood "is the flood that is estimated to have a $1 \%$ chance of being equaled or exceeded in a given year and consequently having a reliability of $99 \%$ and probability of failure of $1 \%$ in any given year." However, the methods used to determine the value of the 100-year flood are based on assumptions of stationarity; with the death of stationarity, the assumptions underlying the calculation of the storm value and its associated probability are violated. Therefore, the probability of failure (i.e. equaling or exceeding that storm value) is not accurate or reliable.

The death of stationarity presents many obstacles in the design of water infrastructure. For example, the Federal Emergency Management Agency (FEMA) maintains maps of various flood zones, including the 100-year floodplain. These zones are defined according to flood risk and are used to prepare flood insurance studies, which determine if flood insurance is required for residential homeowners. The 100-year floodplain is calculated from past flood records and is therefore subject to substantial errors with respect to the probabilities of future floods (Pielke, 1999). As new flood events occur that add to the historical record, the 100-year floodplain is subject to redefinition. However, the regulatory definition of the 100-year floodplain, as determined by the flood insurance study, is difficult to change (Pielke, 1999) and can take decades to revise. This leads to stationary depictions of the 100-year floodplain on physical maps, which become outdated and inaccurate as new flood events occur that add to the historical record.

## CONCLUSIONS

This study explored trend magnitudes and their consequences for all USGS gages in the Northeastern United States with a period of record greater than twenty years. Almost $20 \%$ of gages investigated in the northeastern United States exhibited statistically significant ( $\mathrm{p}<0.05$ ) increasing trends. If historic trends were to continue for approximately $20 \%$ of the sites in the Northeastern United States that exhibited statistically significant trends, we expect the following remarkable results for those sites:

1) The 10 year storm will be reduced, on average, to a 6.1 year storm; the 25 year storm will be reduced, on average, to a 13.8 year storm; the 100 year storm will be reduced, on average, to a 48.5 year storm.
2) Flood magnitudes will increase, on average, by almost $17 \%$.

Findings from this study are consistent several recent studies on trends in hydrologic data. Burn and Hag Elnur (2002) found a greater number of trends in Canadian catchments than are expected to occur by chance. Collins (2009) found increasing trends in 25 out of 28 annual flood series comprised of predominantly natural streamflow in New England. Groisman et al. (2001) found an increasing trend for high discharge, particularly in the eastern part of the United States. Hodgkins and Dudley (2005) investigated 27 streamflow gages considered to be free of substantial human influences in New England; while they found no significant changes over time in the annual mean streamflows, they did note significant increases over time on various annual percentile streamflows, including minimum, $25^{\text {th }}$ percentile, median, $75^{\text {th }}$ percentile, and maximum flows at 22 of the 27 stations. They conclude that flows have increased over time at many streams in New England. Petrow and Merz (2009) detected significant trends in flood flows for a considerable fraction of 145 discharge gages in Germany. In most cases, the trends were increasing. They concluded that flood hazard in Germany increased during the last 50 years, particularly due to an increased flood frequency.

The presence of large and statistically significant trends across a majority of the eastern United States challenges the traditional assumption that flood series are independent and identically distributed random variables (Olsen et al, 1999). This suggests that flood risk is changing over time in the eastern United States and that water management agencies need to reconsider their standards for flood frequency analysis to account for fluctuation sin flood risk over time. Regardless of what is causing trends, the issue of non-stationarity needs to be a primary focus of public policy.

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