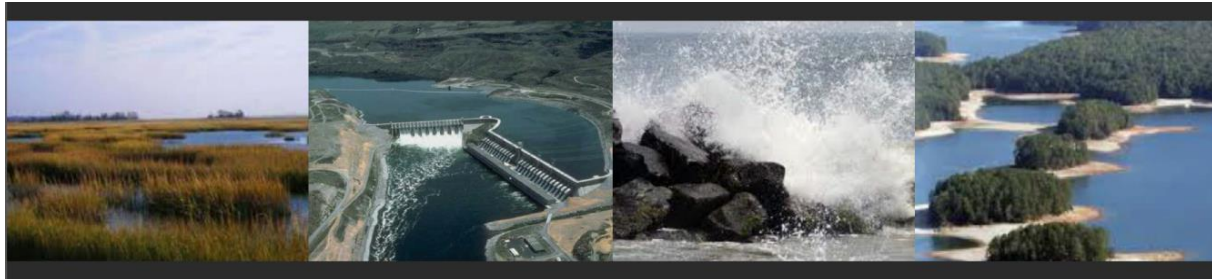




US Army Corps of Engineers Nonstationarity Detection Tool User Guide



User Guide

Version 1.1

January 2016

U.S. Army Corps of Engineers
Climate Preparedness and Resilience Community of Practice
Washington, DC

Abstract: Stationarity, or the assumption that the statistical characteristics of hydrologic time series data are constant through time, enables the use of well-accepted statistical methods in water resources planning and design in which future conditions rely primarily on the observed record. However, recent scientific evidence shows that—in some places, and for some impacts relevant to the operations of the U.S. Army Corps of Engineers (USACE)—climate change and human modifications of the watersheds are undermining this fundamental assumption, resulting in nonstationarity. The purpose of this User Manual is to support the use of Version 1.1 of the USACE Nonstationarity Detection Tool, released in January 2016. The Nonstationarity Detection Tool enables the user to apply a series of statistical tests to assess the stationarity of annual instantaneous peak streamflow data series at any United States Geological Survey (USGS) streamflow gage site with more than 30 years of annual instantaneous peak streamflow records. The tool will aid practitioners in identifying continuous periods of statistically homogenous (stationary) annual instantaneous peak streamflow datasets that can be adopted for further hydrologic analysis. The tool also allows users to conduct monotonic trend analyses on the identified subsets of stationary flow records. The tool facilitates access to USGS annual instantaneous peak streamflow records; does not require the user to have either specialized software or a background in advanced statistical analysis; provides consistent, repeatable analytical results that support peer review processes; and allows for consistent updates over time. The User Manual includes a discussion of the technical concepts incorporated into the Nonstationarity Detection Tool, a description of the user interface, an explanation of how to apply the user interface to execute hydrologic analysis, and a series of examples highlighting how the tool is applied. This user guide does not cover all possible situations one may encounter using the tool. The first step in conducting nonstationarity detection is to carry out data preparation and exploratory data analysis, which are described in detail in Section 3. The Nonstationarity Detection Tool is not a substitute for professional engineering judgment.

Preferred Citation: Friedman, D., J. Schechter, B. Baker, C. Mueller, G. Villarini, and K. D. White. (2016), US Army Corps of Engineers Nonstationarity Detection Tool User Guide. US Army Corps of Engineers: Washington, DC.

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Introduction

Stationarity, or the assumption that the statistical characteristics of hydrologic time series data are constant through time, enables the use of well-accepted statistical methods in water resources planning and design in which future conditions rely primarily on the observed record. Though hydrologic engineers have been aware that this assumption over-simplifies a complex process (e.g., Chow 1964), it was an acceptable assumption for the planning and design of water resources projects where observed records were relatively short and detailed analytical or dynamic representations of physical processes were not available. However, recent scientific evidence shows that—in some places, and for some impacts relevant to the operations of the U.S. Army Corps of Engineers (USACE)—climate change and human modifications of the watersheds are undermining this fundamental assumption, resulting in nonstationarity (Milly, et al., 2008).

The Nonstationarity Detection Tool was developed to support USACE Engineer Technical Letter (ETL) 1100-2-3, *Guidance for Detection of Nonstationarities in Annual Maximum Discharges*, to detect nonstationarities in annual instantaneous peak streamflow data series. Per ETL 1100-2-3, engineers will be required to assess the stationarity of observed streamflow records analyzed in support of hydrologic analysis carried out for USACE planning and engineering decision-making purposes (U.S. Army Corps of Engineers, Forthcoming).

The Nonstationarity Detection Tool enables the user to apply a series of statistical tests to assess the stationarity of annual instantaneous peak streamflow data series at any United States Geological Survey (USGS) streamflow gage site with more than 30 years of annual instantaneous peak streamflow records. The tool will aid practitioners in identifying continuous periods of statistically homogenous (stationary) annual instantaneous peak streamflow datasets that can be adopted for further hydrologic analysis. The tool also allows users to conduct monotonic trend analyses on the identified subsets of stationary flow records. The tool facilitates access to USGS annual instantaneous peak streamflow records; does not require the user to have either specialized software or a background in advanced statistical analysis; provides consistent, repeatable analytical results that support peer review processes; and allows for consistent updates over time.

The purpose of this User Manual is to support the use of Version 1.1 of the Nonstationarity Detection Tool, released in January 2016. The document includes a discussion of the technical concepts incorporated into the Nonstationarity Detection Tool, a description of the user interface, an explanation of how to apply the user interface to execute hydrologic analysis, and a series of examples highlighting how the tool is applied. This user guide does not cover all possible situations one may encounter using the tool. The first step in conducting nonstationarity detection is to carry out data preparation and exploratory data analysis, which are described in detail in Section 3. The Nonstationarity Detection Tool is not a substitute for professional engineering judgment. The Nonstationarity Detection Tool is available at: <https://maps.crrel.usace.army.mil/apex/f?p=257>

1 Technical Background

1.1 Statistical Methods Used in the Nonstationarity Detection Tool

The tool performs nonstationarity detection using the Open Source R statistical programming language (R Development Core Team 2011) and four freely available statistical test packages associated with it: **cpm** (Ross, 2015), **bcp** (Erdman & Emerson, 2007), **ecp** (James & Matteson, 2015), and **trend** (Pohlert, 2015). These packages contain the following sets of statistical methods that the tool uses to detect nonstationarities in annual instantaneous peak streamflow records: likelihood ratio testing, energy-based algorithms, Bayesian Monte-Carlo simulation, and Pettitt tests. Additionally, a custom package developed specifically for this tool executes the Lombard model to test for abrupt and smooth nonstationarities.

1.1.1 Types of Statistical Methods for Nonstationarity Detection

The statistical methods applied within the Nonstationarity Detection Tool are categorized by the type of nonstationarity detected and whether the nonstationarity is representative of a smooth or abrupt change in the statistical properties of the dataset under analysis.

- i. **Type of Nonstationarity** – Methods that only detect differences in the mean will not detect nonstationarities where the mean of the data stays consistent while the variance/standard deviation changes. Likewise, methods that only detect differences in variance/standard deviation will not detect nonstationarities where the mean of the data changes while the variance/standard deviation stays consistent. For this reason, the tool applies several methods that assess nonstationarities in time series datasets driven by changes in the mean, variance/standard deviation, and in the distributional properties of the dataset.
 - a. **Mean-based nonstationarity methods** detect a nonstationarity where there has been a significant change in the average value of the data. The Lombard Wilcoxon, Pettitt, Mann-Whitney, and Bayesian methods are all mean-based.
 - b. **Variance-based nonstationarity methods** detect a nonstationarity where there has been a significant change in the variance/standard deviation of the data. The Mood and Lombard Mood methods are variance-based statistical tests.
 - c. **Distribution-based nonstationarity methods** detect a nonstationarity where there has been a significant change in the underlying distribution of the data, which can be caused by a change in the parameters of the same distribution (e.g. going from one normal distribution to another) or from one distribution type to another (e.g. going from a normal distribution to a beta distribution). The Cramer-Von-Mises, Kolmogorov-Smirnov, LePage, and Energy Divisive methods are distribution-based.
- ii. **Smooth versus Abrupt Nonstationarities** – The methods are also categorized by whether the nonstationarities they detect represent abrupt or smooth changes in the data. Here, a smooth transition refers to a gradual change in the mean, variance/standard deviation, and/or distribution of the annual instantaneous peak streamflows recorded at a USGS gage site. The only methods in the tool that can detect smooth changes in the statistical properties of the datasets under analysis are the smooth Lombard Wilcoxon and smooth Lombard Mood methods. The remaining methods (including the abrupt Lombard Wilcoxon and abrupt Lombard Mood methods) detect abrupt changes in the dataset. Abrupt changes occur at a single point in the record, and separate the period of record into two subsets of data that have one or more of the following: different means, different variances and standard deviations, or different distributions. A record can have multiple abrupt changes, separating it into several subsets of data.

1.1.2 Other Characteristics of Statistical Methods for Nonstationarity Detection

In addition to the categorization of statistical methods described above, there are other defining characteristics associated with the statistical tests applied in the Nonstationarity Detection Tool. These traits should be taken into consideration when interpreting the results generated by the tool, especially when assessing why some methods detected a nonstationarity while other methods did not. The properties associated with each of the statistical tests packaged into the Nonstationarity Detection Tool are described in further detail in Table 1.

- i. Methods are either parametric or non-parametric. If the data used for detection is not normally distributed, which is often the case with annual instantaneous peak streamflow data, then parametric methods are not appropriate. Applying parametric methods to data that is not normally distributed can return inconsistent or incorrect results. The Anderson-Darling Test, which is incorporated into the Nonstationarity Detection Tool, is applied to assess whether or not a given dataset conforms to a normal distribution. The tool application will not apply statistical tests that rely on the assumption of normality, unless the results of the Anderson-Darling Test indicate that the selected annual instantaneous peak streamflow record conforms to a normal distribution. This test only applies to the Bayesian method, which relies on the assumption of normality.
- ii. Methods can detect either single or multiple nonstationarities. The Pettitt method and all of the Lombard methods are only able to detect the single most prominent nonstationarity in a time series. The rest of the methods are able to detect multiple nonstationarities within a single time series.
- iii. For the abrupt methods, results indicating a nonstationarity in the flow record may represent either the start year or the end year of a homogeneous record. Suppose a method detects only one nonstationarity, in 1942. For methods that detect the first year, that means that the period from the start of the record through 1941 is homogenous and the period from 1942 to the end of the record is also homogenous. That is, those methods detect the first year of the second homogenous subseries. For methods that detect the end year, the result “1942” means that the period from the start of the record through 1942 is homogenous and the period from 1943 to the end of the record is homogenous. That is, those methods detect the last year of first homogenous subseries. If a method detects the first year of the second homogenous subseries, then “Yes” appears in the “Detects First Year of Second Subseries” column of Table 1. For guidance on how to account for this difference across methods, refer to Section 3.3.
- iv. Certain statistical methods have strengths and weaknesses that may make them more appropriate to a given application than an alternate statistical test. Depending on the data used, these statistical weaknesses may render a method inappropriate. For example, the Cramer-von-Mises method is not as adept at detecting a change in the mean of a distribution of annual instantaneous peak streamflow records as it is in detecting changes in the extreme values (e.g. minimum, maximum) of a distribution of annual instantaneous peak streamflow records.

1.1.3 Statistical Significance

The Nonstationarity Detection Tool is designed to identify statistically significant nonstationarities in annual instantaneous peak streamflow records. The method for determining statistical significance differs according to the nonstationarity detection method applied as described below. For details about how adjusting the sensitivity parameters for each of the methods affects the output, refer to Table 1 in Section 1.1.5. The parameters can be adjusted using the Sensitivity Parameters on the Nonstationarity Detector and Method Explorer tabs in the tool described in Sections 2.1 and 2.3, respectively.

- i. For the Bayesian method (**bcp**), the tool ensures statistical significance in two ways. First, the tool does not return results if the data undergoing analysis are not normally distributed. Second, the tool does not return nonstationarities if the “posterior probability” that the entire series is

drawn from the same distribution is higher than the posterior probability that different segments of the series are drawn from different distributions. In general, Bayesian statistics generate a posterior probability of end results by combining a prior belief about end results (called a “prior”) with the data. The Bayesian method in the tool develops a prior based on the value in the “Bayesian sensitivity” parameter in the tool (Erdman & Emerson, 2007). The Bayesian sensitivity parameter represents the probability that a nonstationarity is detected in a section of the record given the historical and most recent trends in the record. Values for this parameter can range from 0 to 1. A default level of 0.5 is recommended. A value of 0.5 implies neutrality, meaning it does not favor the presence or absence of a nonstationarity. Higher or lower values would represent favoring the absence (for lower values) or presence (for higher values) of nonstationarities. The user may choose an alternate sensitivity parameter based on professional judgment and experience.

- ii. For both the smooth and the abrupt Lombard methods, the tool performs an overall hypothesis test that the record chosen contains a nonstationarity. For the Lombard Wilcoxon methods, this test checks for a change in mean. The Lombard Mood method checks for a change in variance/standard deviation (Quessy, Favre, Said, & Champagne, 2011). If the hypothesis test returns a true result at the selected level of significance, the Lombard method will return the detected nonstationarity. The selected level of significance for the Lombard methods represents the probability of a Type I error, or the probability of accepting an alternative hypothesis when the null hypothesis is true. In this context, it is the probability of incorrectly asserting that the record contains nonstationarities when in fact it is stationary. The default value for the Lombard method sensitivity in the tool is 0.05, but the user can change this to 0.01 or 0.1. Because they represent accepted probabilities of Type I errors, these values are typically selected as the standard significance threshold within statistical literature. The user may determine an alternate sensitivity parameter using their best judgment.
- iii. The energy divisive method (**ecp**) iteratively detects a nonstationarity, segments the time series according to that non-stationarity, and then detects subsequent nonstationarities. To determine if a nonstationarity is detected at a given point, the method repeatedly performs a statistical test against all previously detected segments to determine if a reasonable level of statistical significance has been achieved. The process continues until it reaches a point that is not statistically significant (James & Matteson, 2015). Similar to other methods, the level of statistical significance is represented as the probability of a Type I error, or the probability of detecting a nonstationarity when none is present. To account for the repeated tests across all possible subsets of the period, a higher level of default sensitivity (0.5) has been chosen to ensure that the method regularly returns at least one nonstationarity. The user can—using professional judgment—adjust the level of statistical significance this method uses by adjusting the accompanying sensitivity parameter.
- iv. For the Pettitt test, the tool returns a single nonstationarity at the point in the dataset where the difference in the mean between the subsets of data prior to and after the nonstationarity has the greatest level of statistical significance (or smallest probability of a Type I error). The significance value must also be below the threshold set in the Pettitt sensitivity parameter. P-values are probabilities of Type I errors, or the probability of accepting an alternative hypothesis when the null hypothesis is true. In this context, it is the probability of incorrectly asserting that there is a nonstationarity when in fact there is none. The default value for the Pettitt sensitivity in the tool is 0.05, but the user can change this to 0.01 or 0.1. Because they represent accepted probabilities of Type I errors, these values are typically selected as the standard significance threshold within statistical literature. The choice of a statistical significance level is determined by professional judgment.
- v. For the Change Point Model (CPM) methods, the algorithm runs the named statistical test (e.g., the Mood test) on the two segments of the time series created by partitioning the record at every possible point in the series to initially detect changes in the mean, variance/standard deviation, or

distribution. After changes are detected, the data is re-examined to determine when these detected changes first occurred in sequence. This process only returns statistically significant results given the sensitivity parameter selected by the user. This sensitivity parameter corresponds to the average number of data points until a Type I error occurs, or the probability of accepting an alternative hypothesis when the null hypothesis is true (Ross, 2015). The recommended default value is 1,000, as that represents the most neutral value in the set of possible values for the sensitivity parameter. However, the user can change this sensitivity parameter to be one of the following values: 370, 500, 600, 700, 800, 900, 1,000, 2,000, 3,000, 4,000, 5,000, 6,000, 7,000, 8,000, 9,000, 10,000, 20,000, 30,000, 40,000 or 50,000. The values for this sensitivity parameter are limited as they are related to a series of precomputed statistical distributions. The choice of an alternate sensitivity parameter may be guided by professional judgment.

If the user has prior knowledge of a nonstationarity in the data (e.g., construction and operation of a dam with significant storage upstream from a stream gage), then that expected nonstationarity could be used as a guide for determining the associated level of significance applied by each of the statistical tests described above. The default levels of significance described above may not be able to detect the known nonstationarity. In this case, the user is advised to adjust the sensitivity parameters associated with each test using professional judgment and experience to ensure they are sensitive enough to detect this known nonstationarity. After adjustments to sensitivity parameters are made, any additional nonstationarities detected could be considered to be equally statistically significant.

Because the abrupt results may represent either the start year or the end year of a homogeneous record, and because each statistical test might be producing slightly different results, the practitioner could combine results from different tests that fall within a five year period in order to segment the time series only once within that five year period. Similarly, when the smooth nonstationarity detection techniques identify a statistical transition period of five years or less, it can be considered indicative of a single nonstationarity. It is up to the user to select the start year within the transition period or amongst an array of nonstationarities that fall within a five year period. If more methods detected a nonstationarity in one year than in the other, then the year with the most concurrence amongst methods is preferred to segment the data. If multiple years have equal concurrence between the statistical methods applied (e.g., two methods detected nonstationarities in each of two consecutive years) then the more recent year could be used to segment the data.

At some sites, the tool may identify multiple clusters of nonstationarity years and/or long periods of time over which the smooth nonstationarity detection techniques indicate statistical instability. Statistically significant results are not necessarily *operationally* significant. It is up to the user to carry out sensitivity analysis using the different nonstationarities identified in the record and/or the periods where the statistics associated with the dataset are unstable to help them decide what period of record is appropriate for subsequent hydrologic analysis.

The Nonstationarity Detection Tool is not a substitute for engineering judgment. Engineers are advised to use their judgment to consider the resilience of the system when incorporating the range of results here in their adopted hydrologic study or design results. Comparison of results generated using a modified portion of the period of record to the results that would have been generated had traditional methods been applied (period of record analysis) is advisable. If, for example, a flow-frequency analysis is carried out in support of mapping the 2% floodplain, and truncating the record produces flow-frequency results which reduce the 2% flood magnitude from the 2% flood magnitude generated by using the entire period of record, then the user could consider relying on traditional analysis techniques (using the entire period of record) at that site for the most resilient characterization of the floodplain.

1.1.4 Length and Continuity of Record

The USGS annual instantaneous peak streamflow datasets available within the Nonstationarity Detection Tool have a minimum of 30 years of record and ideally contain no discontinuities in the peak streamflow record. If the period of record contains significant discontinuities, or if it has been truncated by the user to less than 30 years of data, then detected nonstationarities may be inaccurate. The tool automatically warns the user if there are gaps in the USGS annual instantaneous peak streamflow data record at a given gage site or when statistical tests for nonstationarities are being applied to less than 30 years of record.

The statistical methods used in the Nonstationarity Detection Tool require a continuous record to detect changes in the statistical properties of the flow dataset. If missing data is detected, the tool will omit those years' peak streamflows from the period of record and analyze the remaining data as if it was a single continuous sequence. For example, if a period of record is complete from 1902 to 2002, but the peak streamflow data for 1967 is missing, the tool will shift all observations after 1968 one year earlier to create a single continuous sequence for nonstationarity detection. These scenarios generate a dynamic warning message for the user, because shifting observations may create issues with any nonstationarity issues detected.

In addition to the sensitivity parameters described above, the CPM methods have an additional "CPM Methods Burn-In Period" parameter. The default value for this parameter is 20. This means that any changes in the annual instantaneous peak streamflow data series cannot be detected during the initialization period by these methods until after the twentieth observation (or water year) in the time series. However, the resulting nonstationarities identified by this method may occur prior to this value. This default value represents a good balance between the desire to detect nonstationarities in the early section of the record and the fact that these statistical methods will perform best when given more time to incorporate the variability in the record. Users can adjust this value between 5 and 50 using the "CPM Methods Burn-In Period" slider on the Sensitivity Parameters section of the Nonstationarity Detector tab, which is described in Section 2.1.

1.1.5 Matrix of Statistical Methods for Nonstationarity Detection

Table 1 provides an overview of each of the statistical methods applied by the Nonstationarity Detection Tool. Please note that those methods that share names with established statistical tests are algorithms that apply the named statistical test repeatedly to detect nonstationarities. The algorithms include a check for whether the p-values from their respective tests demonstrate statistically significant results, as detailed in Section 1.1.3.

Table 1: Statistical Methods Implemented in the Nonstationarity Detection Tool

Statistical Test	Parametric	Type of Nonstationarity	Single or Multiple Nonstationarities	Detected Year		Input Parameters		Strengths/Weaknesses
				Last= Last year of previous, homogeneous subset First= First year of subsequent homogeneous subset		Parameter	Default	
<u>The Change Point Model (CPM)</u>								
Cramer-von-Mises	No	Distributional/Abrupt	Multiple	Last	Burn-In Period	20	Determines how many observations are used for the initialization period. If startup = 20, then changes that occur in the first twenty observations will not be used for changepoint detection. As this parameter is specifically related to the initialization period, the final changepoints detected by this method may occur prior the value supplied by the user. This is used because the statistical tests will have low power for small sample sizes.	This method may be more likely to detect a nonstationarity related to the tails or extremes of a distribution rather than the center of a distribution.
					CPM Sensitivity	1000	Higher values will result in fewer nonstationarities. Must have one of the following values: 370, 500, 600, 700, 800, 900, 1,000, 2,000, 3,000, 4,000, 5,000, 6,000, 7,000, 8,000, 9,000 10,000, 20,000, 30,000, 40,000 or 50,000.	
Kolmogorov-Smirnov	No	Distributional/Abrupt	Multiple	Last	see CPM Cramer-von-Mises			This method may be more likely to detect a nonstationarity related to the center of a distribution rather than the tails or extremes of a distribution.
Mann-Whitney	No	Mean/Abrupt	Multiple	Last	see CPM Cramer-von-Mises			

Statistical Test	Parametric	Type of Nonstationarity	Single or Multiple Nonstationarities	Detected Year		Input Parameters		Strengths/Weaknesses
				Last= Last year of previous, homogeneous subset First= First year of subsequent homogeneous subset	Parameter	Default	Description	
LePage	No	Distributional/Abrupt	Multiple	Last			see CPM Cramer-von-Mises	
Mood	No	Variance / Abrupt	Multiple	Last			see CPM Cramer-von-Mises	
<u>The Lombard Model</u>								
Lombard Wilcoxon	No	Mean/Abrupt	Single	Last	Lombard Sensitivity	0.05	This determines the level of significance at which nonstationarities should be detected. It can also be interpreted as the maximum p-value associated with these nonstationarities. There are a limited number of available sensitivity values due to statistical constraints.	This method does not work well with short time series, or with small changes in magnitude.
		Mean/Smooth						
Lombard Mood	No	Variance/Abrupt	Single	Last	See Lombard Wilcoxon		This method does not work well with short time series, or with small changes in magnitude.	
		Variance/Smooth						
<u>Other Methods</u>								

Statistical Test	Parametric	Type of Nonstationarity	Single or Multiple Nonstationarities	Detected Year		Input Parameters		Strengths/Weaknesses
				Last= Last year of previous, homogeneous subset First= First year of subsequent homogeneous subset	Parameter	Default	Description	
Pettitt	No	Mean/Abrupt	Single	First	Pettitt Sensitivity	0.05	This represents the probability that the nonstationarity detected is a false positive or the p-value associated with the Pettitt test.	
<u>Bayesian Changepoint (BCP)</u>	Yes	Mean/Abrupt	Multiple	Last	Bayesian Sensitivity	0.5	This represents the probability that a nonstationarity is detected in a section of the record. A value of 0.5 implies neutrality, meaning it does not favor the presence or absence of a nonstationarity.	This method does not work well with short time series, or with small changes in magnitude.
<u>Energy-Based Divisive Method (ECP)</u>	No	Distributional/Abrupt	Multiple	First	Energy-Based Sensitivity	0.5	This value represents a change threshold or the probability that the point in question is a nonstationarity. Larger values will yield less nonstationarities.	This method can sometimes detect a series of nonstationarities located in close proximity to one another. These nonstationarities may not all be operationally significant so it is important to examine them carefully.

1.2 Statistical Methods Used for Trend Analysis

The purpose of this section is to outline how the tool performs the detection of monotonic trends within the identified stationary subsets of the record. Detected nonstationarities are used to subdivide the period of record into stationary subsets, each of which are tested for the presence of monotonic trends. Note that the monotonic trend analysis tools is not appropriate for subsets of data with less than 10 years of record. The tool supports not only the detection of monotonic trends, but also indicates whether these trends are positive or negative. All of this analysis takes place within the Trend Analysis tab of the tool, which is described in Section 2.2, with additional detail in Section 3.4. The tool executes three statistical tests to identify and describe monotonic trends: the Mann-Kendall test, the Spearman test, and Sen's slope estimator.

Like all statistical methods, the Mann-Kendall test, Spearman's test, and Sen's slope are more powerful when applied to larger data sets. None of these methods are appropriate for time series that have fewer than ten years of data. This is because the methods may detect trends where there are none with fewer than ten data points. The significance values employed in applying these tests are a choice among standards in statistics. They are held static within the tool, in order to facilitate consistency in the application of these tests across the Corps. In addition to these methods, the tool reports a trend for "parametric statistical methods," which is based on the slope of a simple linear regression line fit using the data.

1.2.1 Mann-Kendall Test for Trend Detection

The tool implements the Mann-Kendall test as a nonparametric measure of trend. The test calculates the Kendall Rank Correlation Coefficient, or Kendall's tau, a value between -1 and 1, where values near -1 suggest monotonically decreasing series of annual instantaneous peak annual streamflow and values close to 1 suggest monotonically increasing series of annual instantaneous peak annual streamflow. The test determines whether the Kendall Rank Correlation Coefficient is significantly different from 0, implying a trend. In the Nonstationarity Detection Tool, the test is implemented using the **trend** package in R (Pohlert, 2015), and the alternative hypothesis—that a trend is apparent—is accepted to be true at the 0.05 significance level.

1.2.2 Spearman's Test for Trend Detection

The tool implements the Spearman test as a second nonparametric measure of trend. Parallel to the Mann-Kendall test, Spearman's test calculates the Spearman Rank Correlation Coefficient, or Spearman's rho, a value between -1 and 1. Values close to -1 suggest strong negative dependence between the two variables (in this case, between time and annual instantaneous peak annual streamflow) and values close to positive one suggest strong positive dependence between two variables. Like the Mann-Kendall test, this test is applied to determine whether the Spearman Rank Correlation Coefficient is significantly different from 0, implying a trend. In the Nonstationarity Detection Tool, the test is implemented using the **trend** package in R (Pohlert, 2015), and the alternative hypothesis—that a trend is apparent—is accepted to be true at the 0.05 significance level.

1.2.3 Sen's Slope Estimator

The tool uses Sen's slope estimator to give the robust, parametric, best-fit line for the annual instantaneous peak streamflow record. Sen's slope is an average of all the slopes between every two points in two-dimensional series. In the case of the Nonstationarity Detection Tool, the two dimensions are time and annual instantaneous peak annual streamflow. The tool implements this calculation with the

trend package in R (Pohlert, 2015). Values for Sen's slope that are greater than zero correspond to an increasing, positive trend. Values less than zero indicate a negative trend. Under the Monotonic Trend Analysis panel, the Sen's slope result is provided as an indication of whether or not a positive or negative trend was detected.

2 User Interface

The Nonstationarity Detection Tool is composed of a landing page (Figure 1) and three tabs, each with its own functionality. The first step in conducting nonstationarity detection is to carry out data preparation and exploratory data analysis, described in detail in Section 3.

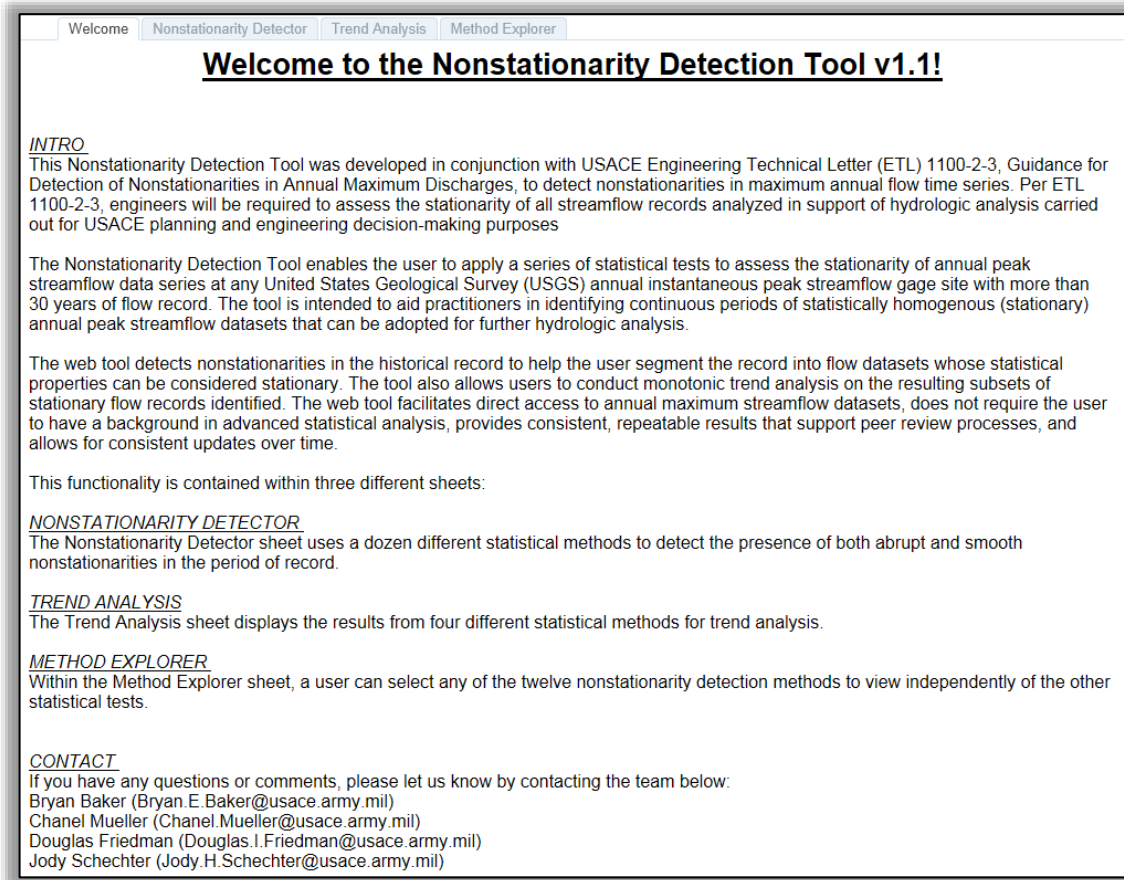


Figure 1. Landing Page for the Nonstationarity Detection Tool

- i. **Nonstationarity Detector** – This is the tab where the practitioner applies the twelve statistical methods described in Section 1.1 to detect nonstationarities in annual instantaneous peak streamflow data from a selected USGS streamflow gage site. This tab allows the user to review the results of these tests for nonstationarities in annual instantaneous peak streamflow datasets, as described in Section 3.3.
- ii. **Trend Analysis** – This tab is where the practitioner performs statistical tests to detect monotonic trends, as described in Section 1.2. The process to apply these tests to both the entire annual instantaneous peak streamflow time series and to stationary subsets of data identified using the Nonstationarity Detector tab is described in Section 3.4.
- iii. **Method Explorer** – This tab allows the practitioner to select a single nonstationarity detection method, rather than viewing the results of all twelve statistical tests concurrently.

2.1 Nonstationarity Detector

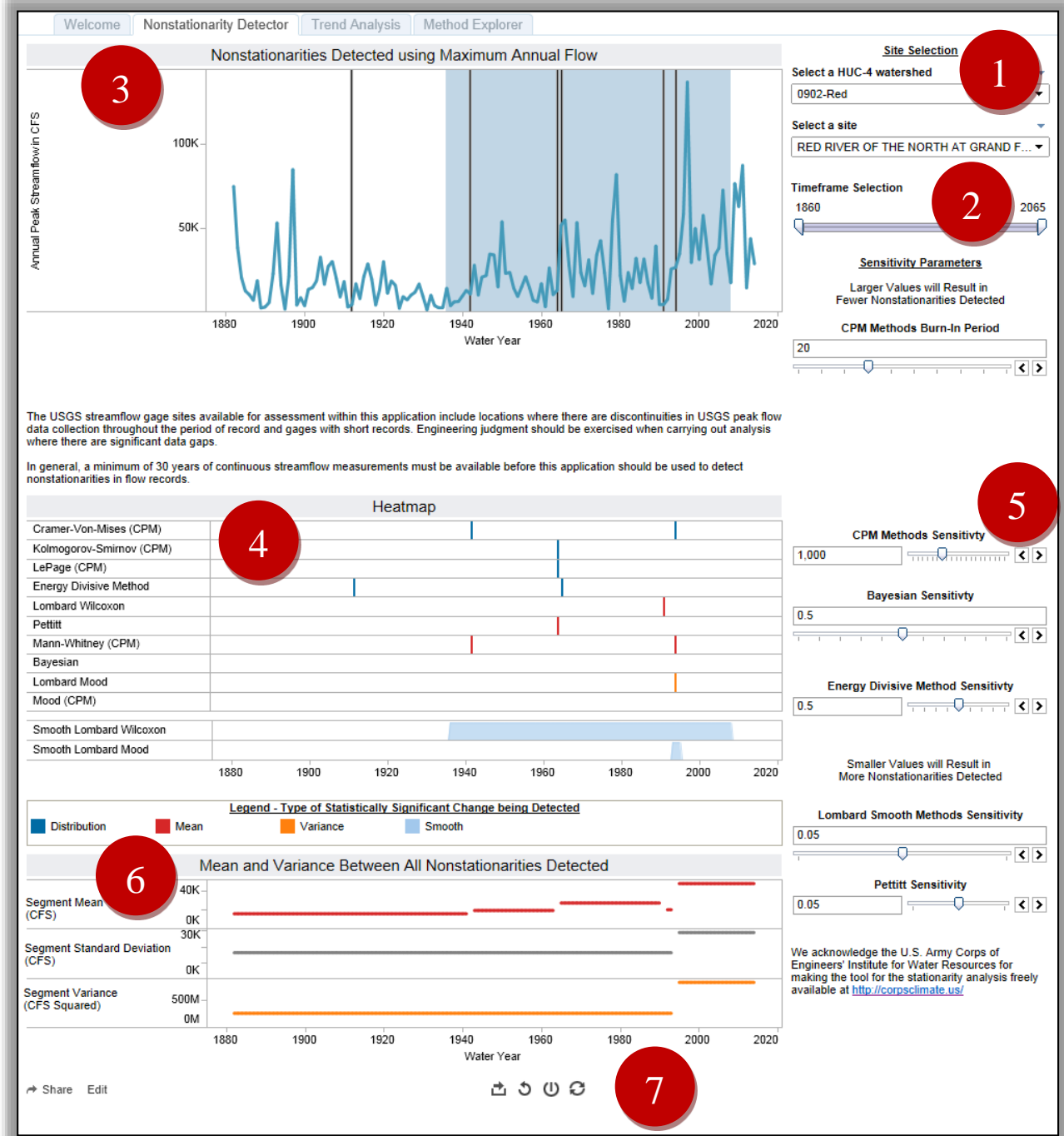


Figure 2. Nonstationarity Detector Tab

The Nonstationarity Detector tab, shown above in Figure 2, displays the results of the methods described in Section 1.1. It has several filters that the practitioner can use to adjust the parameters associated with the methods, which are listed in Section 1.1.5. The components of the tab are discussed below. For guidance on how to interpret the results in this tab, refer to Section 3.

- 1) **Site Selection Dropdown Menus** – Use the dropdown menus indicated by the “1” in Figure 2 to select the HUC-4 watershed and the site name of the USGS gage site to be analyzed. See Section 3.2 for more information.
- 2) **Timeframe Selection** – Adjust this slider, indicated by the “2” in Figure 2, to select the period of record to analyze. See Section 3.2 for details.
- 3) **Nonstationarities Detected using Maximum Annual Flow Graphic** – As indicated by the “3” in Figure 2, the annual instantaneous peak streamflow data series for the site and timeframe selected is graphed along with vertical gray lines representing the abrupt nonstationarities detected in the record. Gradual or smooth nonstationarities detected are shaded in blue. Additional information related to the flow data series can be accessed by hovering over any of the flow series data points, as seen in Figure 3 **Error! Reference source not found.**

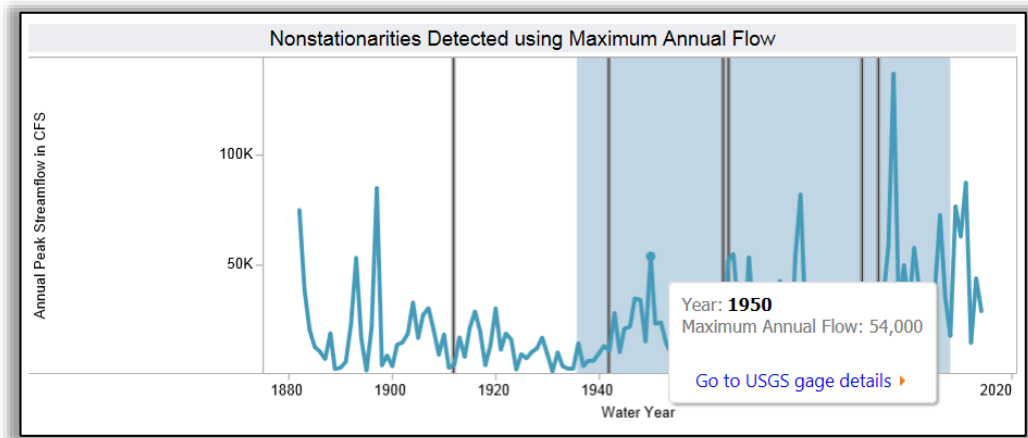


Figure 3. Hover-text of Annual Flow, *Nonstationarities Detected using Maximum Annual Flow Graphic*

Underneath this graphic is a dialog box that will dynamically alert users when they have selected either a period of record containing discontinuities (or missing data) and/or one that is considered too short to accurately detect nonstationarities (less than 30 years of record). These messages (such as the one shown in Figure 4) let users know that when the record is too short, or when there are significant gaps in the flow dataset, there may be issues with the nonstationarities detected.

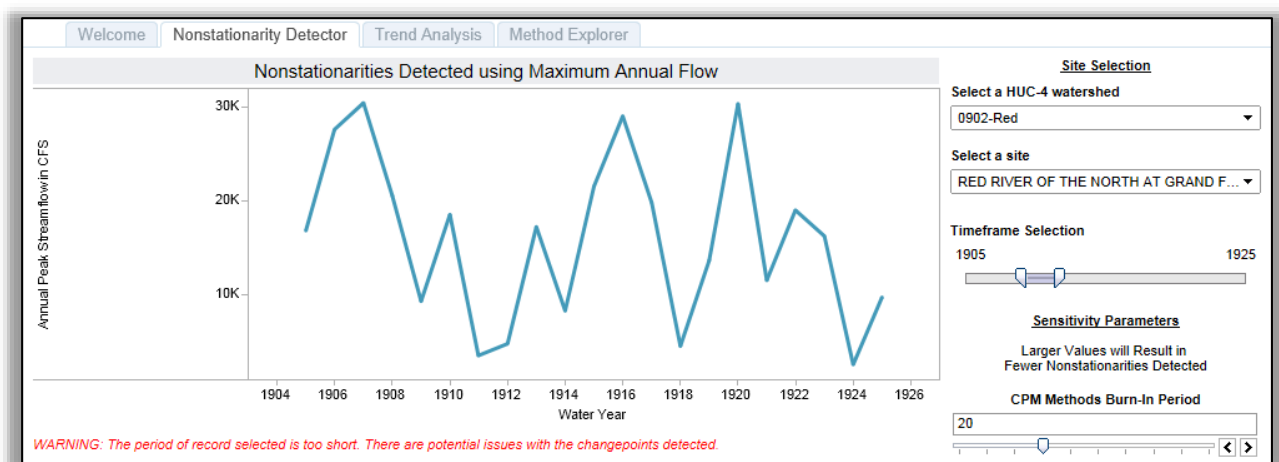


Figure 4. Dynamic Warning Activated on the Nonstationarity Detector Tab

Hovering over any of the vertical gray bars that indicate a nonstationarity in the annual instantaneous peak streamflow record displays a list of the statistical methods used by the tool to detect nonstationarities (see Figure 5). This hover-text indicates whether each of the listed methods detected the nonstationarity indicated by the grey bar, as well as the water year of the nonstationarity. Section 3.3 contains guidance for how to interpret the results displayed in this graphic.

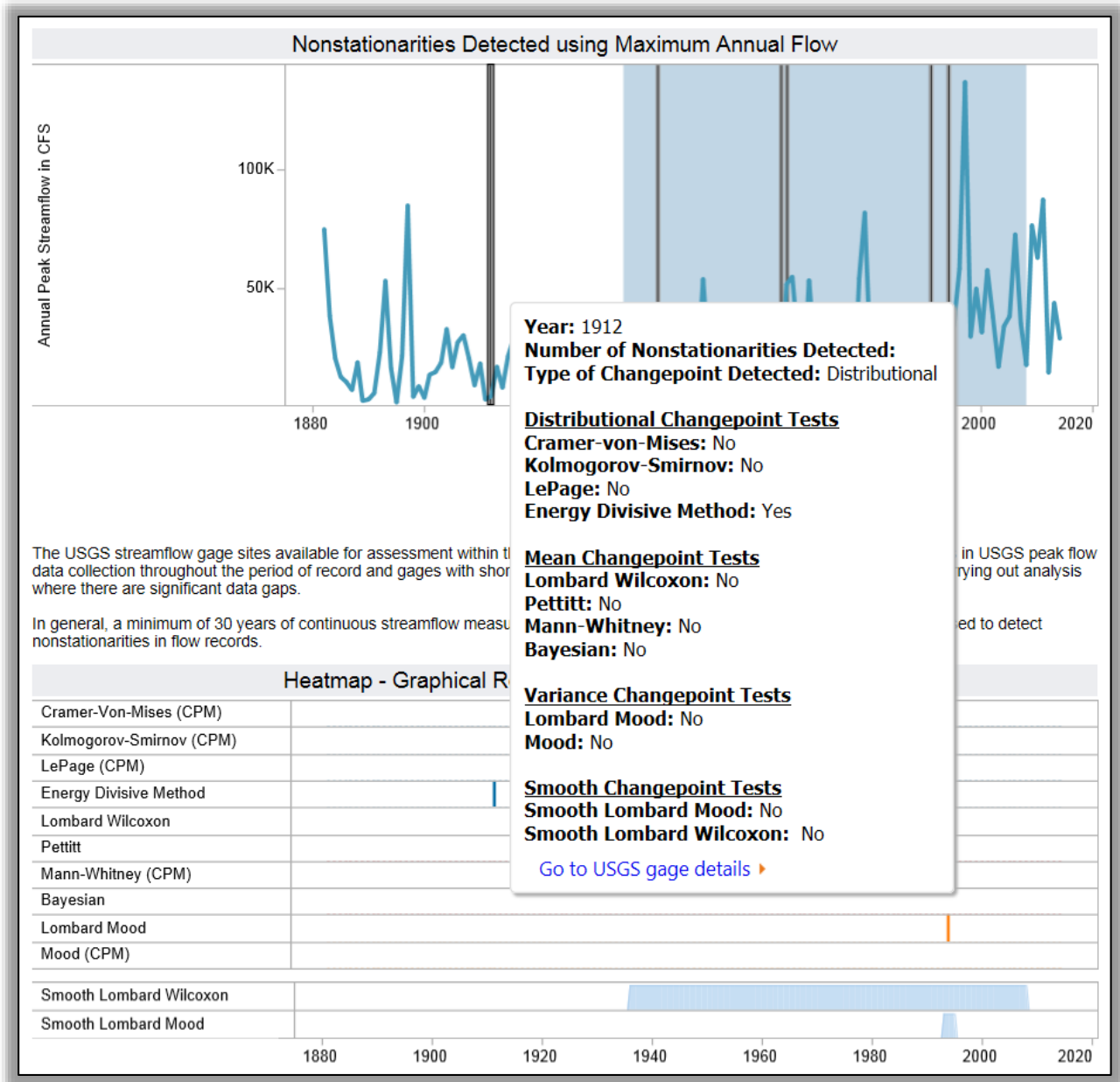


Figure 5. Hover-text of Abrupt Nonstationarity, on the *Nonstationarities Detected using Maximum Annual Flow* Graphic

- 4) **Heatmap Graphic** – This graphic, indicated by the “4” in Figure 2, displays a tick mark for each nonstationarity detected by each method. The color of the mark corresponds to the type of nonstationarity each test is targeted to detect: mean, variance/standard deviation, or distribution

(discussed in Section 1.1.1). The transitions in the statistical properties of the datasets, indicated by the smooth Lombard detection techniques, are indicated by continuous blue fill. As shown in Figure 6, hovering over the tick marks displays the water year associated with the nonstationarity detected. Refer to Table 1 to determine whether the year shown is the first or last in a homogeneous data set as this varies by method.

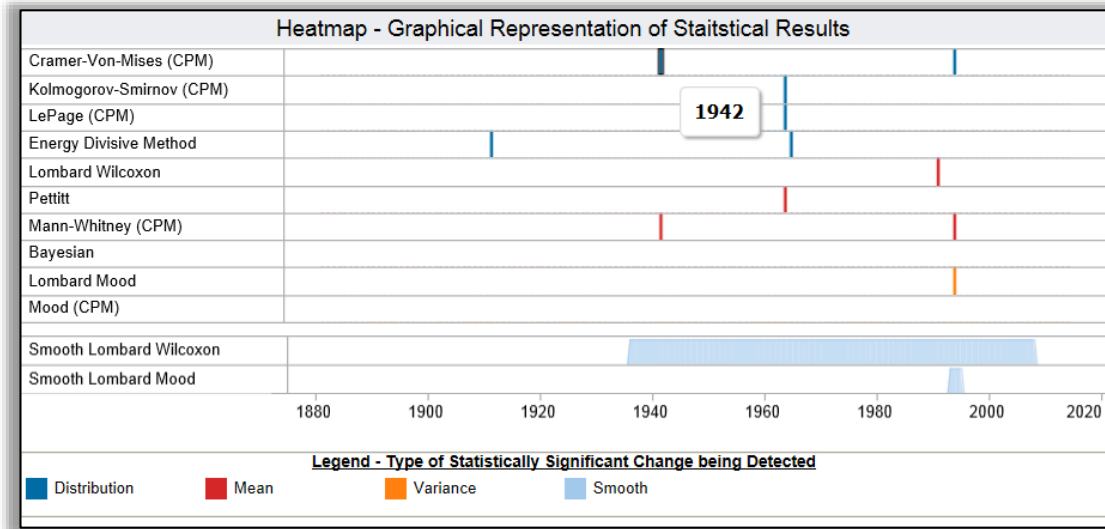


Figure 6. Hover-text for Tick Marks in the Heatmap Graphic

- 5) **Sensitivity Parameters** – The sliders and controls indicated by the “5” in Figure 2 provide the user with the ability to change the sensitivity of each family of nonstationarity detection methods. These parameters are described in Sections 1.1.3 and 1.1.4, and appear in the matrix in 1.1.5. They are set to the suggested default parameters for each statistical method. These default parameters could be adjusted, using engineering judgment, if the user has reason to believe, based on a priori knowledge, that the statistical tests are not sensitive enough at the default values to detect known nonstationarities in the time series.
- 6) **Mean and Variance Between All Nonstationarities Detected Graphic** – This graphic, indicated by the “6” in Figure 2, provides the mean, standard deviation, and variance for the subsets of data for each homogenous period of flow data (between each of the nonstationarities detected). Each of these measures is presented with their associated units of measurement and is color coded to match the associated type of nonstationarity in the Heatmap Graphic. Note that, although the units for mean and standard deviation are the same, the units associated with sample variance are squared. This information can be used to determine the relative changes in mean or variance/standard deviation associated with each of the nonstationarities detected, as described in Section 3.3.
- 7) **Page controls**– The symbols indicated by the “7” in Figure 2, provide page controls for the tab. From the left, the first symbol allows the user to export the results, the second reverts to the original information shown on the tab, the third allows the user to make multiple updates without waiting for the screen to refresh each time, and the last is to refresh data for the view. The export options are to export the page as an image, a text file, a crosstab (Excel) file, or as a pdf. If the screen refresh is paused (third button), it will be replaced with a different icon (the vertical line will rotate clockwise 90 degrees) as a reminder to push the button again to refresh the screen.

2.2 Trend Analysis

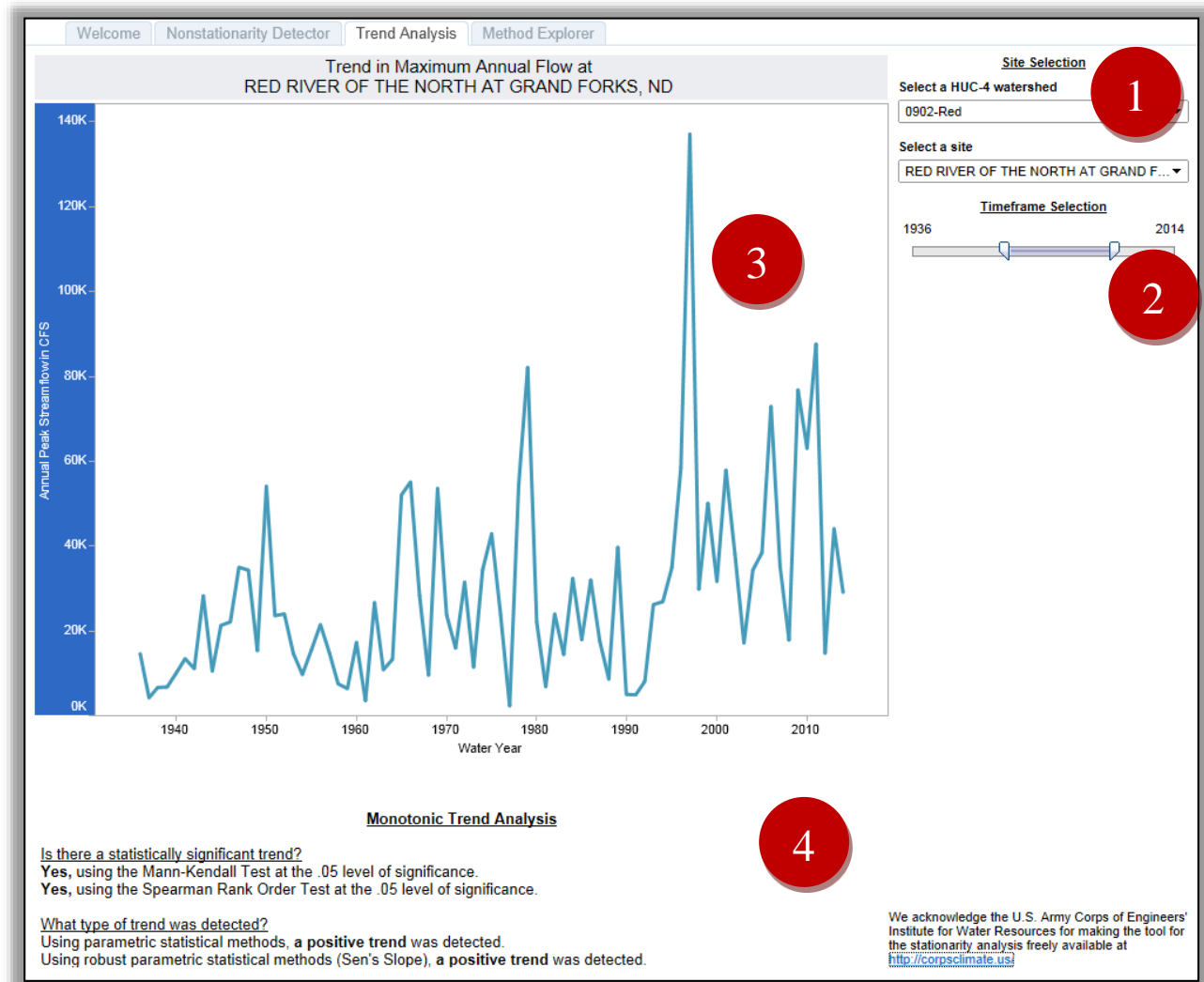


Figure 7. Trend Analysis Tab

The Trend Analysis tab displays the results from the statistical methods for trend analysis, described in Section 1.2. The page control (#7 on Figure 2) are the same for this tab. The other components in this tab, shown in Figure 7, are described below. For guidance on how to use the tab to detect monotonic trends, refer to Section 3.4.

- 1) **Site Selection Dropdown Menus** – These dropdown menus, indicated by the “1” in Figure 7, allow the user to select the HUC-4 watershed and the specific USGS gage within that watershed on which to perform the analysis.
- 2) **Timeframe Selection Slider** – To select the period of record to analyze, adjust the slider indicated by the “2” in Figure 7 (detailed instructions are found in Section 3.2).
- 3) **Trend in Maximum Annual Flow Graphic** – This graph, indicated by the “3” in Figure 7, displays the annual instantaneous peak streamflow time series for the USGS site and timeframe selected.

Underneath this graphic is a dialog box that will dynamically alert users when they have selected a period of record containing discontinuities (or missing data) and/or one that is considered too short to accurately detect monotonic trends in the time series (less than 10 years of record). These messages (such as the one shown in Figure 8) let users know that there may be issues with the trends detected in the selected timeframe.

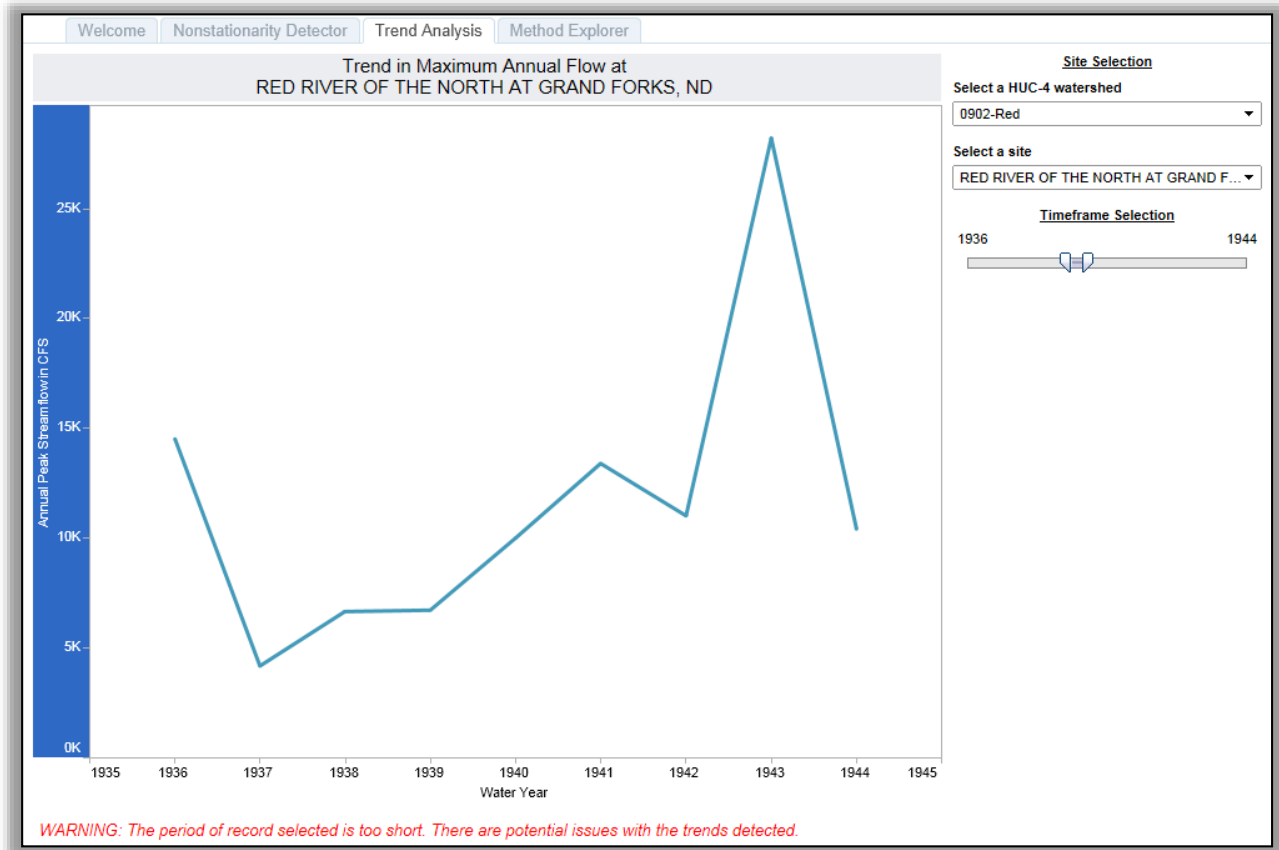


Figure 8. Dynamic Warning Activated on the Trend Analysis Tab

- 4) **Monotonic Trend Analysis Panel** – This panel (indicated by the “4” in Figure 7 and magnified in Figure 9) provides the following statistical information about the detection of monotonic trends in the portion of the annual instantaneous peak streamflow record displayed on the tab:
 - a. **Tests for Statistically Significant Monotonic Trends:**
 - i. **Segment Trend Result Mann-Kendall** – A Mann-Kendall test for the presence of a monotonic trend is performed on the series in view, and the result is displayed using a significance level of 0.05. For details regarding the Mann-Kendall test, refer to Section 1.2.1.
 - ii. **Segment Trend Result-Spearman** – A rank order Spearman test for the presence of a monotonic trend is performed on the series in view, and the result is displayed using a significance level of 0.05. For details regarding Spearman’s test, refer to Section 1.2.2.
 - b. **Assessment of Trend Type (Negative vs. Positive Trend)**
 - i. **Segment Parametric Trend Line Direction** – This represents whether the trend displayed is positive or negative. The trend is positive when the annual instantaneous peak streamflow increases as time moves forward. The trend is negative when the annual instantaneous peak streamflow decreases as time

moves forward. This assessment is based on the slope of a simple linear regression line fit using the data.

- ii. **Segment Robust Parametric Trend Line Direction** – This assessment is interpreted the same way as the Segment Parametric Trend Line Direction, discussed above, but it uses Sen’s Slope estimator—the average of all slopes of the lines that can be drawn between every pair of points in the dataset. For details regarding Sen’s Slope, refer to Section 1.2.3.

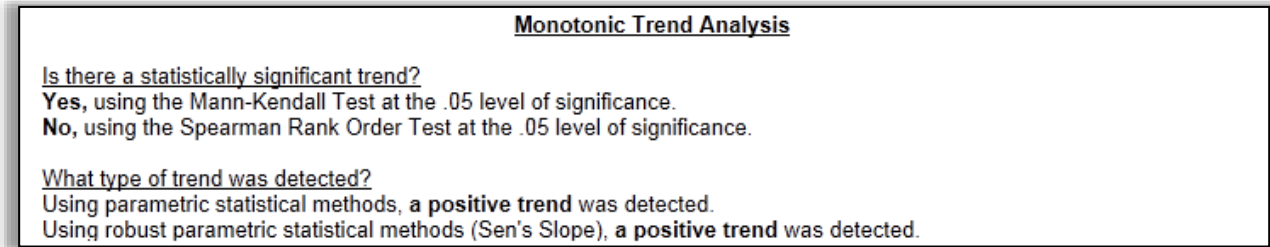


Figure 9. Monotonic Trend Analysis Panel of the Trend Analysis Tab

2.3 Method Explorer

The Method Explorer tab allows a user to select any of the twelve nonstationarity detection methods listed in Section 1.1.5 to view independently of the other statistical tests. This tab can be used to examine the effects of adjustments to the sensitivity parameters associated with one test and the impacts of these adjustments on the results. The page control (#7 on Figure 2) are the same for this tab. The other components of the Method Explorer tab are described below.

- 1) **Method Selection Dropdown Menu** – Select one of the twelve statistical methods used for detecting nonstationarities using the dropdown menu indicated by the “1” in Figure 10.
- 2) **Timeframe Selection Slider** – Adjust the slider indicated by the “2” in Figure 10 to select the portion of the period of record to analyze. Refer to Section 3.2 for more information.
- 3) **Nonstationarities Detected using [Method Name] at [Site Name] Graphic** – This graphic, indicated by the “3” in Figure 10, shows the annual instantaneous peak streamflow record for the site and time selected. If the method selected in the Method Selector detected any nonstationarities, then those are also indicated in the graphic. As shown in Figure 10, abrupt nonstationarities are indicated by vertical, gray lines. Nonstationarities detected by smooth detection methods are shaded in blue, as seen in Figure 11. As seen in Figure 12, additional information related to the streamflow record or detected nonstationarities can be accessed by hovering over any of the flow data points and clicking on the [Go to USGS gage details](#) link.

Underneath this graphic is a dialog box that will dynamically alert users when they have selected a period of record containing discontinuities (or missing data) and/or one that is considered too short to accurately detect nonstationarities (less than 30 years). These messages—such as the one shown in Figure 13—let users know that there may be issues with the nonstationarities detected in the selected period of record.

- 4) **Mean and Variance Between Nonstationarities Detected with [Method Name] Graphic** – This graphic, indicated by the “4” in Figure 10, provides the mean, standard deviation, and variance for the subsets of data for each homogenous period of flow data (between each of the nonstationarities detected by the method selected in the Method Selection menu). This

information can be used to determine the relative changes in mean, standard deviation, or variance associated with each of the nonstationarities detected. As with the Nonstationarity Detector Tab, please note that the segment graph only displays the associated changes in these measures for abrupt nonstationarities.

5) **Sensitivity Parameters** – The sensitivity parameters associated with the chosen nonstationarity detection method are provided in the portion of the tab indicated by the “5” in Figure 10. The practitioner can view the effect of adjusting these parameters on the nonstationarities detected by this method by sliding the indicators on the scales to the right or left.

6)

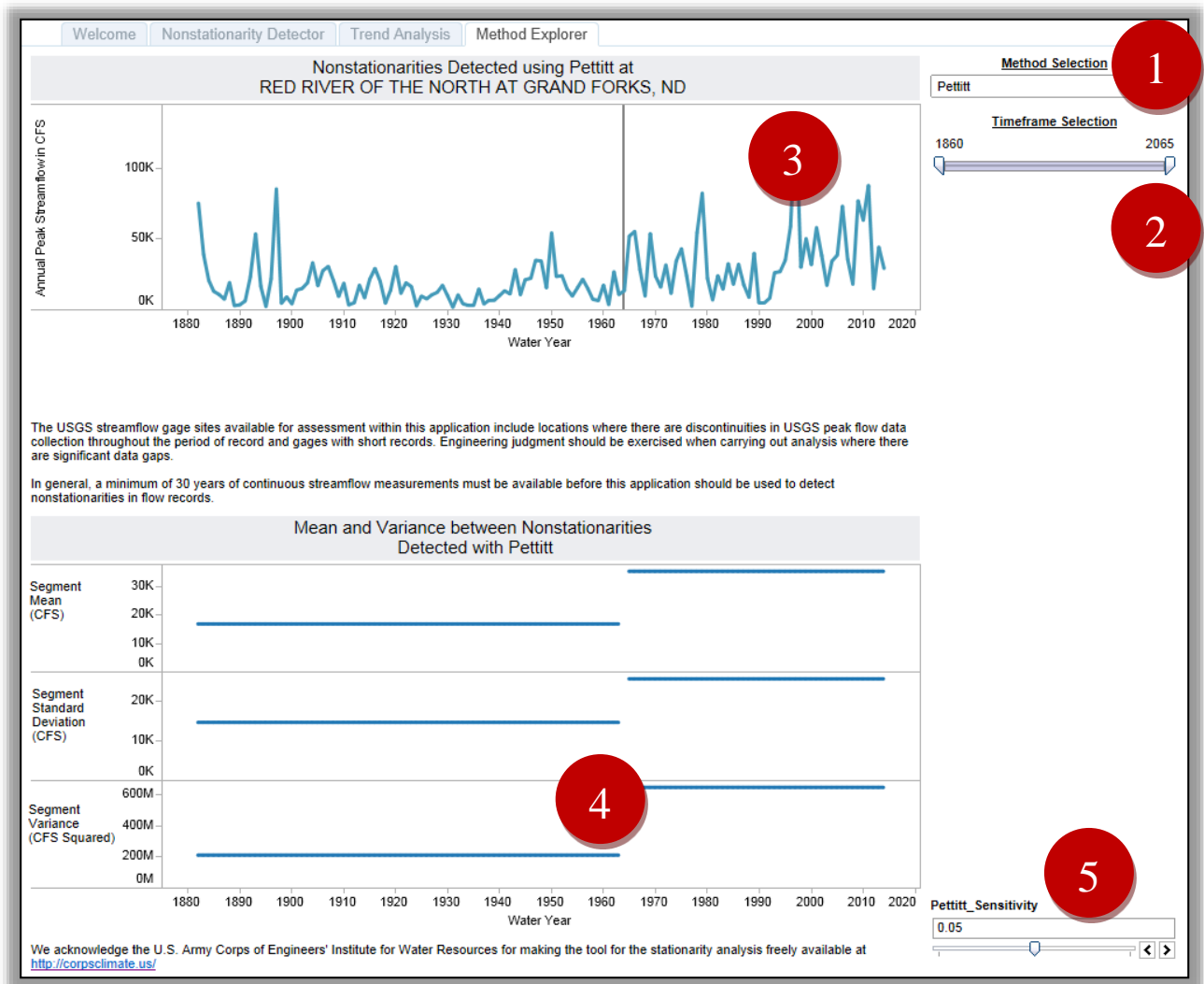


Figure 10. Method Explorer Tab

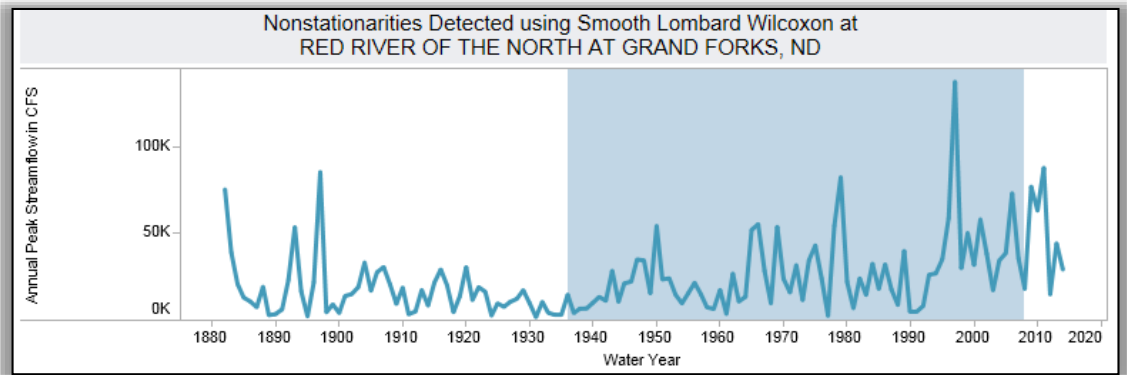


Figure 11. Nonstationarities Detected using Smooth Lombard Wilcoxon at Red River of the North at Grand Forks, ND Graphic: Smooth Transition

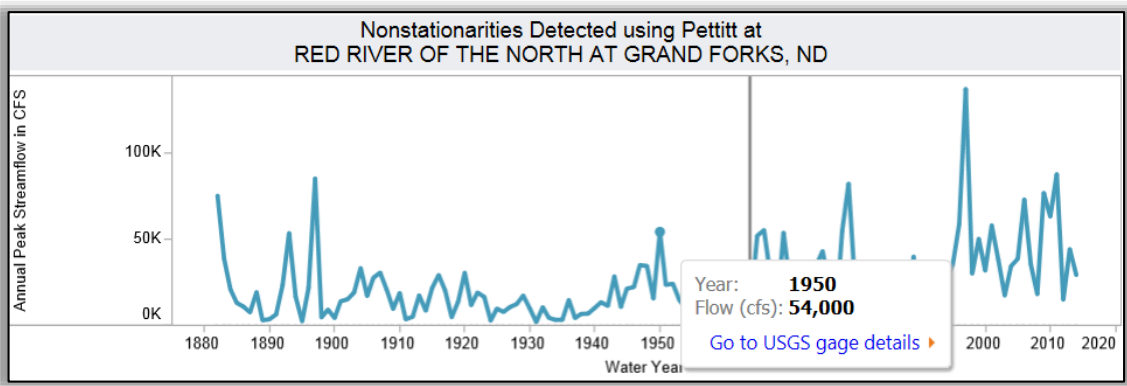


Figure 12. Nonstationarities Detected using Pettitt at Red River of the North at Grand Forks, ND Graphic: Hover-text

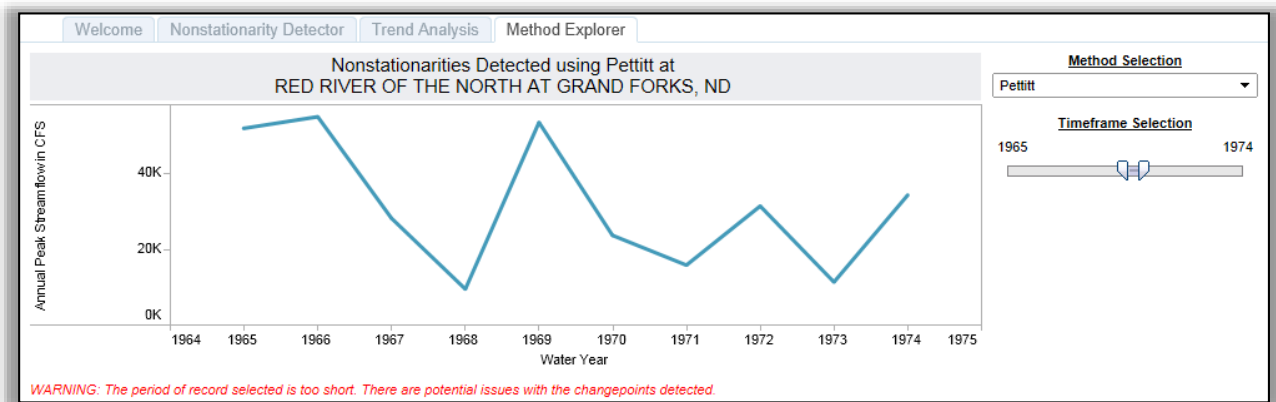


Figure 13. Dynamic Warning Activated on the Method Explorer Tab

3 Detecting and Interpreting Nonstationarities

3.1 Data Preparation and Exploratory Analysis

The first step in conducting Nonstationarity detection is to carry out data preparation and exploratory data analysis. During this step, the practitioner identifies whether there is a priori knowledge of a nonstationarity in the streamflow record and assesses the availability/quality of the annual instantaneous peak streamflow data under consideration for analysis. Listed below are sources of information and relevant tools available to the practitioner to complete this step.

- i. The USGS provides information that can be used for data preparation and exploratory data analysis. This data is presented as part of the metadata associated with each USGS streamflow gage recording site. The Nonstationarity Detector tab contains a direct link to the USGS webpage for the selected streamflow gage site. As shown in Figure 14, this link can be accessed by hovering over the blue annual instantaneous peak streamflow data displayed in the *Nonstationarities Detected using Maximum Annual Flow* graphic, and then clicking on the Go to USGS gage details link displayed in the hover-text that appears.

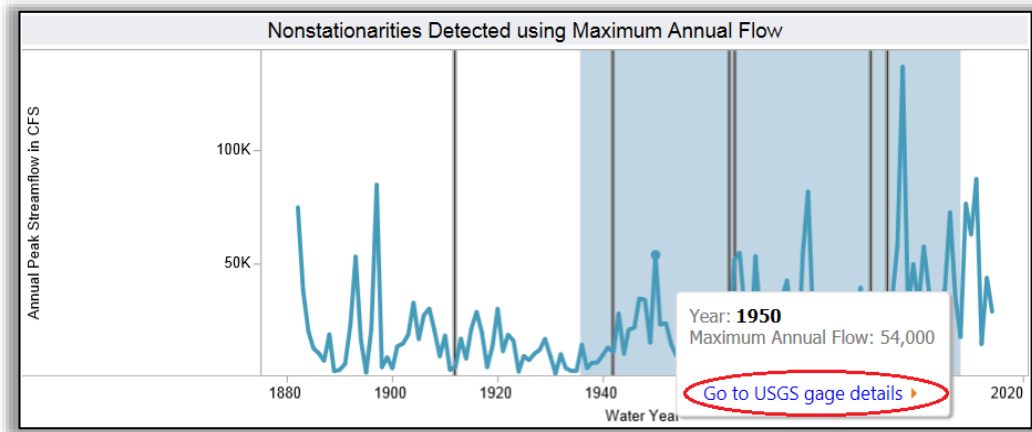


Figure 14. Link to the USGS Gage Details Webpage

The USGS Water-Year Summary report is another source of metadata available for each station of interest. An example of this report is displayed in Figure 15, below.

USGS
science for a changing world

USGS Water-Year Summary 2015

05054000 RED RIVER OF THE NORTH AT FARGO, ND

LOCATION - Lat 46°51'40", long 96°47'00" referenced to North American Datum of 1927, in NW 1/4 NE 1/4 sec.18, T.139 N., R.48 W., Cass County, ND, Hydrologic Unit 09020104, 0.7 mi upstream of Midtown Dam, 25 mi upstream from mouth of Sheyenne River, and at mile 453.

DRAINAGE AREA - 6,800 mi², approximately.

SURFACE-WATER RECORDS

PERIOD OF RECORD - **DAILY DISCHARGE--June 1901 to current year**, Published as "at Moorhead, MN.", 1901. Monthly discharge only for some periods, published in WSP 1308.

PERIOD OF RECORD.--DAILY GAGE-HEIGHT--October 2000 to current year.

REVISED RECORDS - WSP 1308: 1902-4, 1906-7, 1910-14, 1916, 1918, 1924. WSP 1388: 1905-6, 1917-20(M), 1935(M), 1938-39(M), 1943.

GAGE - Water-stage recorder and concrete control from October 1, 1962 to present, datum of gage is 861.8 ft above National Geodetic Vertical Datum of 1929. **Previous locations and datums are as follows:**

Staff gage on timber breakwater of old Front Street bridge (now Main Avenue) 1.8 mi downstream from May 27, 1901 to August 31, 1914. Datum was 860.75 ft above NGVD of 1929.

Staff gage on trees above former dam 1.0 mile downstream from September 1, 1914 to July 31, 1928. Datum was 871.1 ft above NGVD of 1929.

Staff gage in vicinity of Fargo Municipal Water Plant 1.0 mile downstream from August 1, 1928 to April 11, 1959. Datum was 867.4 ft above NGVD of 1929.

Continuous recorder in concrete stilling well on downstream side of Interstate 94 bridge 2.0 mile upstream from April 12, 1959 to September 30, 1960. Datum was 867.4 ft above NGVD of 1929.

Continuous recorder in Fargo Municipal Water Plant at current location from October 1, 1960 to September 30, 1962. Datum was 867.4 ft above NGVD of 1929.

REMARKS - 10/01/13-09/30/14: **Records good except for estimated daily discharges, which are poor.**

REGULATION.--Flow regulated by: Orwell Reservoir, flood storage capacity, 13,300 acre-ft at elevation 1,070 ft above mean sea level, adjustment of 1912; **Mud Lake**, flood storage capacity, 78,600 acre-ft at elevation 981 ft above mean sea level, adjustment of 1912; **Lake Traverse**, flood storage capacity, 75,100 acre-ft at elevation 981 ft above mean sea level, adjustment of 1912; **and numerous other controlled lakes, ponds and several powerplants.**

DIVERSIONS.--Figures of daily discharge do not include diversions to cities of Fargo and Moorhead, MN, from the Sheyenne River.

Information about gage period of record

Gage description and previous gage locations

Data quality remarks

Comments related to upstream regulation

Figure 15. Gage Description on USGS Website – Water Year Summary 2015

The USGS also provides information related to data quality and regulation for each individual water year for each site, which can be accessed by viewing the USGS Peak Streamflow page for a site. Along with the annual instantaneous peak streamflow magnitudes, the USGS provides “Peak Streamflow Qualification Codes;” these are displayed in Figure 16.

Peak Streamflow for North Dakota

Click to hide state-specific text

USGS 05054000 RED RIVER OF THE NORTH AT FARGO, ND

Available data for this site Surface-water: Peak streamflow GO

Cass County, North Dakota
 Hydrologic Unit Code 09020104
 Latitude 46°51'40", Longitude 96°47'00" NAD27
 Drainage area 6,800 square miles
 Gage datum 861.8 feet above NGVD29

Output formats

Table
Graph
Tab-separated file
peakfo (watstore) format
Reselect output format

Water Year	Date	Gage Height (feet)	Stream-flow (cfs)
2004	Jun. 03, 2004	20.47	5,430 ⁶
2005	Jun. 18, 2005	28.18	9,810 ⁶
2006	Apr. 05, 2006	37.13	19,900 ⁶
2007	Jun. 08, 2007	30.84 ²	13,500 ⁶
2008	May 05, 2008	19.50 ²	4,840 ⁶
2009	Mar. 28, 2009	40.84	29,500 ⁶
2010	Mar. 21, 2010	36.99	21,200 ⁶
2011	Apr. 09, 2011	38.81	27,700 ⁶
2012	Mar. 18, 2012	17.83	4,120 ⁶
2013	Apr. 30, 2013	33.18 ²	16,200 ⁶
2014	Jun. 23, 2014	27.85	10,400 ⁶

Peak Gage-Height Qualification Codes.

- 1 -- Gage height affected by backwater
- 2 -- Gage height not the maximum for the year
- 3 -- Gage height at different site and(or) datum
- 6 -- Gage datum changed during this year

Peak Streamflow Qualification Codes.

- 1 -- Discharge is a Maximum Daily Average
- 2 -- Discharge is an Estimate
- 6 -- Discharge affected by Regulation or Diversion
- 7 -- Discharge is an Historic Peak

Figure 16. Peak Streamflow Qualification Codes – USGS website

Note that in addition to using the information presented by the USGS related to data quality and regulatory history at a USGS site, the user is advised to seek out other resources to fully understand the hydrologic properties of the watershed under study. This includes contacting local

water resources experts who might have additional insight into the hydrologic properties of drainage basin upstream of the site under investigation and into the quality of the data collected at the site for any given year in the period of record.

- ii. The “waterData” package for the R programming language by Ryberg and Vecchia (2012) and the USACE Hydrologic Engineering Center’s HEC-DSSVue (available at: <http://www.hec.usace.army.mil/software/hec-dssvue/downloads.aspx>) both contain useful toolsets that can be applied to handle and examine USGS data. Becoming familiar with these applications would be beneficial and would support the data preparation and exploratory data analyses steps.
- iii. Annual peak streamflow data series can be visually inspected within the *Nonstationarities Detected using Maximum Annual Flow* graphic of the Nonstationarity Detector tab (see Figure 2).

3.2 Select a USGS Site and Timeframe for Nonstationarity Detection

In order to use the Nonstationarity Detection Tool tab to analyze a site, the user must first select the correct HUC-4 watershed and site name from the Site Selection dropdown menus on the right side of the tab (shown below in Figure 17; see Figure 2 to locate these menus in the context of the entire tab).

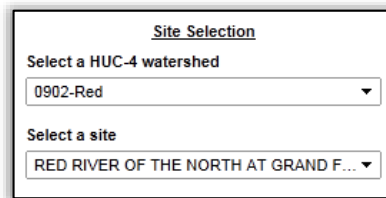


Figure 17. Nonstationarity Detector USGS Site Selection

Note that the watershed and site name can be selected by manually searching through the list or by typing a partial name of the HUC-4 watershed or site. The tool will display a filtered list of options matching the input name, shown in Figure 18 below.

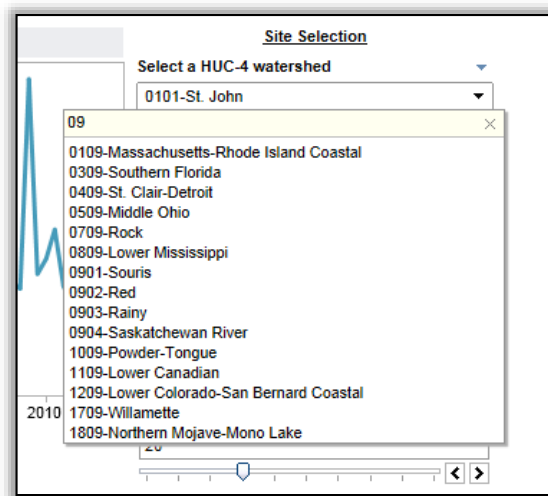


Figure 18. Site Selection Filtered Results

Please note that if the site in question has less than 30 years of annual instantaneous peak streamflow data, the tool will not allow the user to select it for analysis. A sample set of less than 30 years has too few data points to produce meaningful results using the statistical tests selected to detect nonstationarities in annual instantaneous peak streamflow datasets. The annual instantaneous peak streamflow data

displayed in the graphic should be consistent with the annual instantaneous peak streamflow data series available on the USGS website.

After selecting a site, the practitioner evaluate whether the site’s record is continuous. If there is a gap in the annual instantaneous peak streamflow time series (the blue line) shown in the *Nonstationarities Detected using Maximum Annual Flow* graphic, then the record does not have information for the intervening years. An example of this is shown in Figure 19.

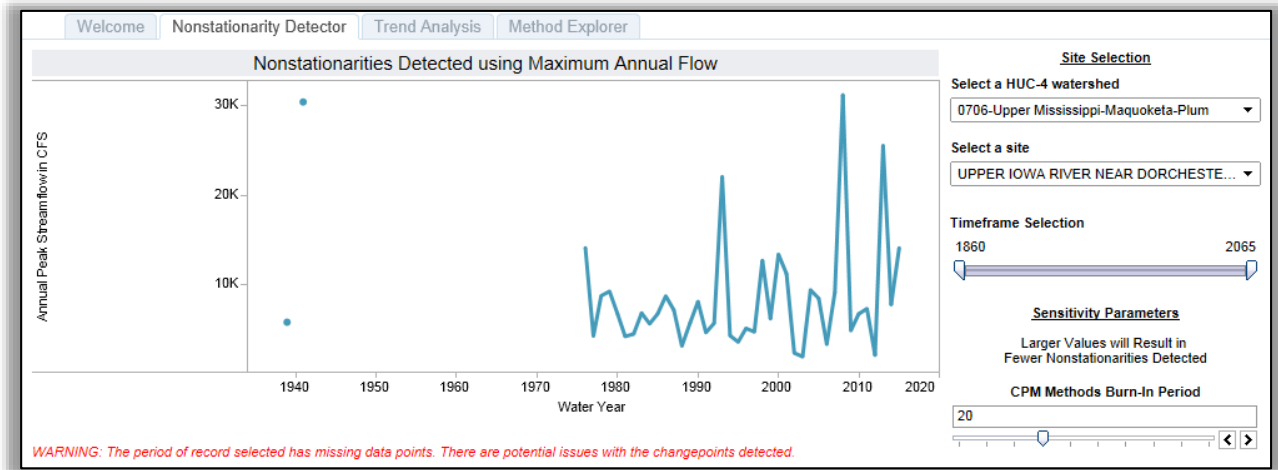


Figure 19. A Discontinuity in the Record, shown in the *Nonstationarities Detected using Maximum Annual Flow* Graphic

When a significant discontinuity exists in the flow series, the Timeframe Selection slider can be used to truncate the record so that only the most recent, continuous portion of the period of record, based on the water year, is displayed. There are two ways to use the Timeframe Selection slider, which is located below the Site Selection dropdown menus, on the right side of each tab. (See Figure 20; to locate the slider in the context of the tab, see Figure 2.) They are discussed below.

- i. The user can drag the sliders to the appropriate start and end dates, as seen in Figure 20.

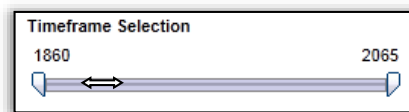


Figure 20. Dragging Sliders on the Timeframe Selection

- ii. The user can click on the start or end year, displayed above the slider, and then type the appropriate year into the textbox that appears, as displayed in Figure 21 **Error! Reference source not found.**

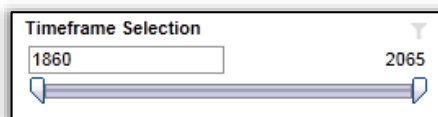


Figure 21. Typing Year of Reference before using Slider

iii. To show all timeframe values, click on the filter icon above the end year, as shown in Figure 22.

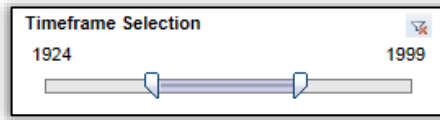


Figure 22. Click on the Filter Icon to Show All Timeframe Selection Values

As shown in Figure 23, once the sliders have been adjusted, the *Nonstationarities Detected using Maximum Annual Flow* graphic will refresh to display the selected period of record.

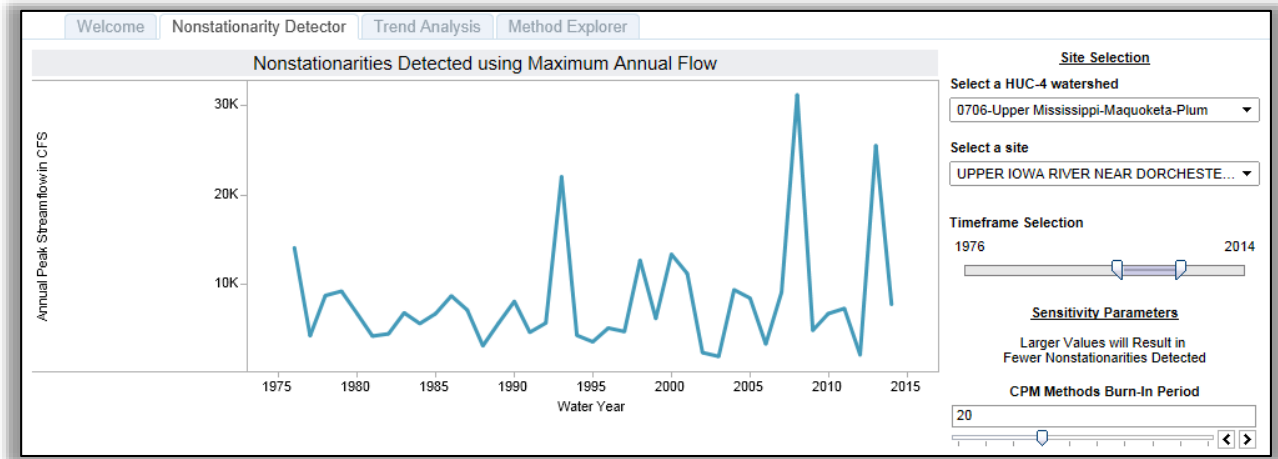


Figure 23. *Nonstationarities Detected using Maximum Annual Flow* Graphic, with Timeframe Truncated to Remove Discontinuity in the Flow Record

3.3 Nonstationarity Detection

The Nonstationarity Detector Tab will automatically apply all of the methods described in Section 1.1.1 and outlined in Table 1 to the selected annual instantaneous peak streamflow time series, and the tool will display all statistically significant results on the *Nonstationarities Detected using Maximum Annual Flow* graphic and the associated Heatmap (see Figure 2). For examples of how to apply these criteria when making decisions about whether or not to segment data based on nonstationarities detected by the methods in the tool, refer to Chapter 4.

3.3.1 Identifying Nonstationarities for Segmentation of the Data Using the Web Application

It is up to the user to determine which, if any, of the statistically significant nonstationarities identified by the Nonstationarity Detection Tool may be used to segment the data for hydrologic analysis. The user often seeks to find a balance between identifying both a homogenous flow record and one that is long enough to be representative of the natural variation in maximum flow magnitudes at the site. It is advisable to assess the relative “strength” of any nonstationarities detected to identify “strong” nonstationarities for use in further analyses.

A “strong” nonstationarity is one for which there is a consensus among multiple nonstationarity detection methods, robustness in detection of changes in statistical properties, and relatively large change in the

magnitude of a dataset's statistical properties. Output from the Nonstationarity Detection Tool offers insight into the following three key criteria related to each identified nonstationarity, which can be used to help the user select a homogenous dataset that can be used for hydrologic analysis.

- i. A nonstationarity that is detected can be considered strong if it is detected by two or more detection methods of the same type (e.g. mean or variance/standard deviation or distribution). This represents **consensus** that a statistically significant nonstationarity occurs at a given point in a flow record. If consensus cannot be found for a given year or short period of time, then it is reasonable to discount it.

To analyze whether there is consensus among the methods, assess the Heatmap graphic to determine if multiple tests targeted at identifying nonstationarities using the same statistical property are identifying a nonstationarity in a given year or short period of time. An example of consensus is displayed in Figure 24. Both the LePage and Energy Divisive methods are indicating statistically significant changes in the overall distributional properties of the dataset in the mid-nineteen sixties. This represents consensus in terms of detecting a change in the overall distributional properties of the dataset. Similarly, in the mid-sixties, the Lombard Wilcoxon and Pettitt tests are identifying statistically significant changes in the mean of the dataset. This represents consensus in terms of detecting a change in the mean of the dataset.

- ii. A statistically significant nonstationarity can be considered **robust** when tests targeting changes in two or more different statistical properties (mean, variance/standard deviation and/or overall distribution) are indicating a statistically significant nonstationarity (for example, the distributional CPM LePage tests, as well as the Lombard Mood and the CPM-Mood tests for changes in variance/standard deviation are identifying a nonstationarity). While a robust nonstationarity is not necessarily stronger, it represents a multifaceted change in the record. This can be taken into consideration when deciding which portion of the period of record to use in order to perform hydrological analysis.

To determine whether the nonstationarity is robust, examine the column associated with the year of the nonstationarity in the Heatmap graphic for multi-colored tick marks indicating that tests targeting changes in different statistical properties are identifying nonstationarities. As shown in Figure 24, in addition to demonstrating consensus, the nonstationarity identified in the mid-nineteen sixties can be considered robust because statistical tests targeting both changes in the mean and the overall distributional properties of the dataset are identifying statistically significant nonstationarities.

- iii. An identified nonstationarity is also associated with a given **magnitude** of change in the mean or standard deviation/variance in the annual instantaneous peak streamflow datasets prior to and after the identified nonstationarity. Nonstationarities that are produced by greater changes in the statistical properties of the datasets before and after the identified nonstationarities may be important to take into consideration when performing subsequent hydrological analysis.

The user is advised to review the *Mean and Variance Between All Nonstationarities Detected* graphic on the Nonstationarity Detector tab to view changes in the statistical properties of the subsets of flow record associated with each identified statistically significant nonstationarity (see Figure 25).

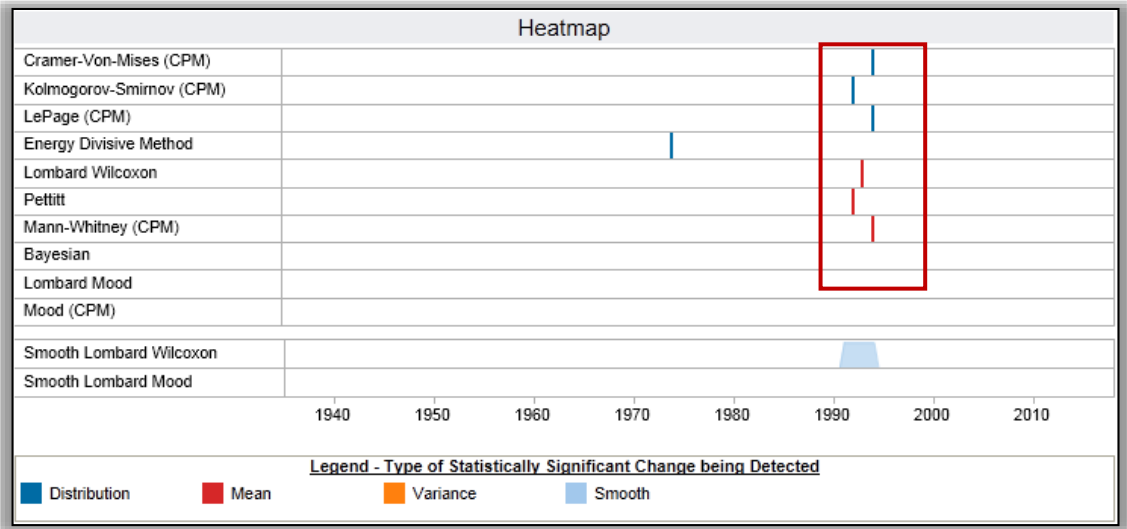


Figure 24. Robust Nonstationarity in the Nonstationarity Detector Heatmap Graphic

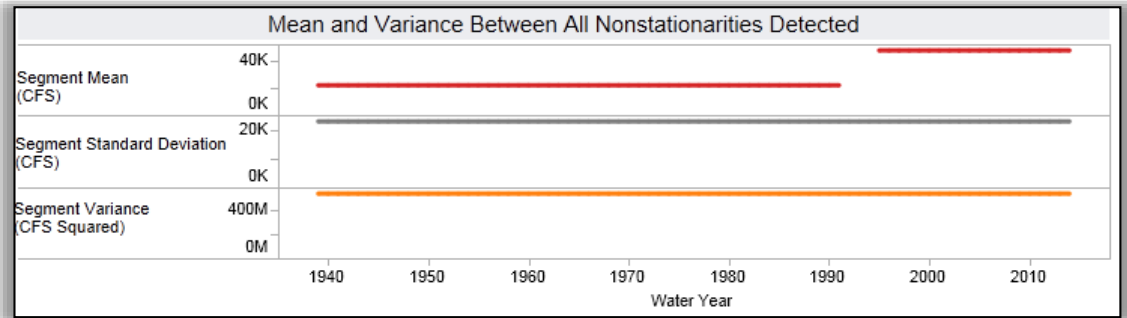


Figure 25. Mean and Variance Between All Nonstationarities Detected Graphic Displaying Magnitudes of Changes

3.3.2 Hydrologic Applications and Identifying Nonstationarities

The detection of multiple nonstationarities within a short span is partly due to differences between how each method detects and identifies nonstationarity years. Some methods detect the last year of a homogenous period, while others identify the first year of a subsequent homogenous period (Table 1). Where the various abrupt statistical methods detect statistically significant nonstationarities within five years of one another, or if the smooth Lombard method detects a transition period over which the statistical properties of the dataset are changing that is less than 5 years long, the user is encouraged to “combine” those to be representative of a single nonstationarity in the flow record. To select which year to use as the representative nonstationarity year for the last year of a homogeneous period, consider the following criteria:

- If more methods detected a nonstationarity in one year than in the other, then the year with more concurrence is best suited to segment the data.
- If multiple years have equal concurrence among the methods (e.g., two methods detected nonstationarities in each of two consecutive years) then the more recent year is a more appropriate choice to segment the data.

When there are multiple, unique, strong nonstationarities detected throughout the period of record, and/or a long period of smooth statistical change detected (via the Lombard Smooth methods), it is recommended that the user carry out sensitivity analyses using all potential periods of record, including the period over which the Lombard model might be detecting a smooth change and the entire period of record of available data including any valid historical data. Note that even if a single, strong, statistically significant nonstationarity is identified, a sensitivity analysis could still be carried out using the entire period of record including any valid historical data.

It is important to consider that a shorter flow record is less representative of the natural variability that exists within hydrometeorological data series. This adds uncertainty to the analysis, and ought to be characterized alongside the presentation of results. For flow-frequency analyses, this can be accomplished by displaying confidence limits. The user is balancing the need to identify a homogenous flow record with the need to identify one that is long enough to be representative of the natural variation in maximum flow magnitudes at the site.

As part of the analysis, the user is advised to assess the sensitivity of the results to altering the period of record used for analyses, and whether the observed trend is expected to persist into the future. The following sensitivity tests are recommended if nonstationarities are detected:

- Conduct a sensitivity analysis using the period of record following all statistically significant, “strong” nonstationarities identified within an annual instantaneous peak streamflow dataset.
- If the smooth Lombard model identifies a long (greater than 5 years) period where the statistical properties of the dataset are in flux, which also transects the portion of the period of record following other abrupt, “strong” nonstationarities, an additional sensitivity analysis could be conducted including the portion of the period of record identified as in flux by the smooth Lombard model. For example, if the period of record is 1902-2014 and the smooth Lombard model identifies the period 1938-1970 as being in flux, a sensitivity analysis could be conducted using the period of record from 1938-2014.
- The case where the smooth Lombard method is indicating that the statistical properties associated with long portions of a dataset are gradually changing will be addressed in greater detail in future updates to the tool.
- A sensitivity analysis could be conducted to assess the differences between the results generated using a truncated record for analysis versus applying traditional methods that incorporate all available flow data (period of record analysis).

Engineers use their judgment and experience to consider the resiliency of the system when incorporating the range of results produced by conducting the sensitivity analysis described above in their adopted hydrologic design or study results.

3.4 Monotonic Trend Analysis

If nonstationarities are detected, the Mann-Kendall test and the Spearman test is then be applied to check for the presence of monotonic trends in the identified subsets of statistically homogenous flow datasets under consideration for analysis. Monotonic trend analysis are not appropriate for a homogenous subset of data containing less than ten years. If no statistically significant nonstationarities are identified within an annual instantaneous peak streamflow dataset, then the entire period of record could be assessed for monotonic trends.

The Timeframe Selection slider on the right side of the Trend Analysis tab is used to select the timeframe associated with each subset of homogenous streamflow data identified by the Nonstationarity Detection Tool. If no statistically significant nonstationarities were identified, then the entire period of record may be used. Note that the nonstationarities identified in the proceeding section can be assumed to be representative of the end year of a homogenous subset, so the start year of each subsequent homogenous subset would be the water year following an adopted nonstationarity. For example, if the continuous period of record is 1902-2014, and a single nonstationarity is detected in water year 1942, then the final homogenous subset of data would be defined as 1943-2014. As shown in Figure 26, the results from the Mann-Kendall and Spearman tests, and an indication of whether the monotonic trends detected are increasing or decreasing, will be displayed below the flow series.

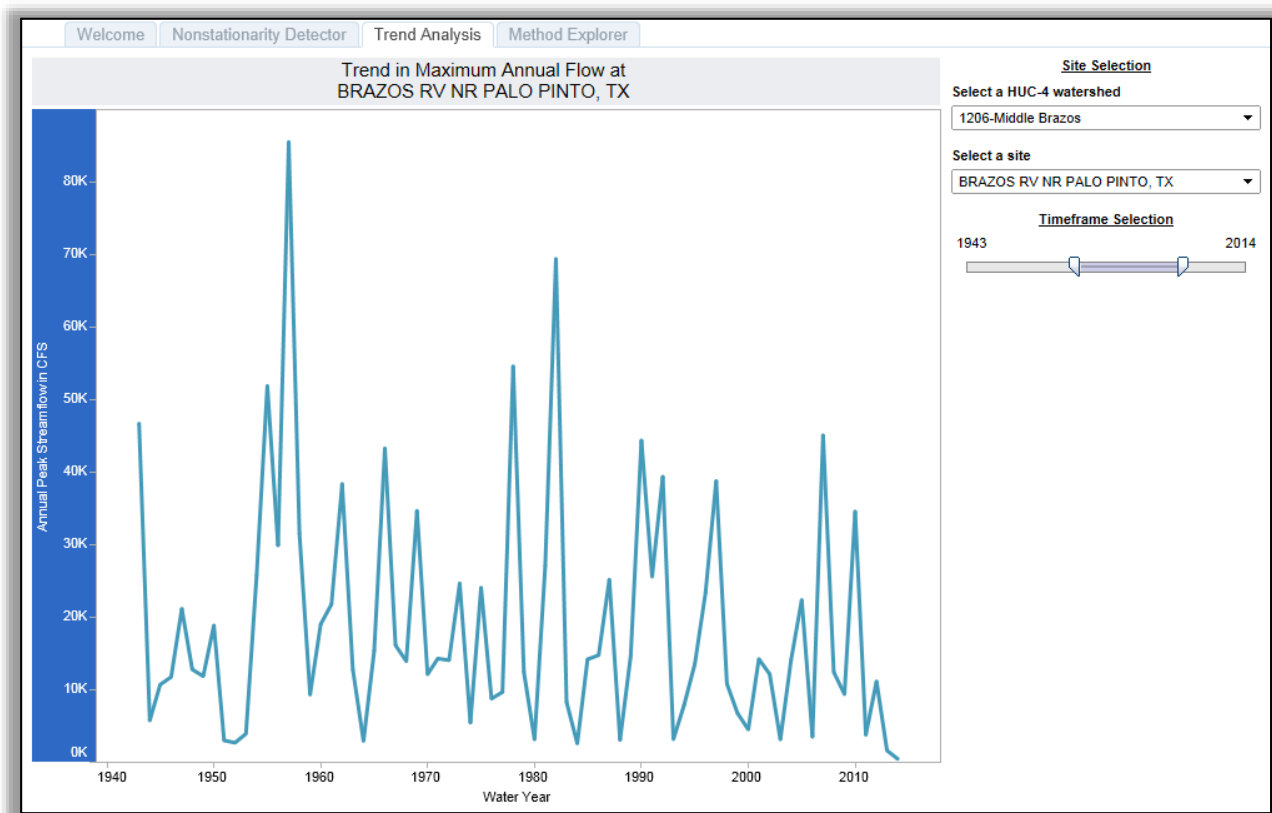


Figure 26. Trend Analysis for Period between Nonstationarities detected in 1943 and 2013

At a minimum, this process is repeated for all segments of the time series being considered for hydrologic analyses. For example, if the full time series extends from 1921–1982, and the practitioner finds nonstationarities in 1932 and 1970, then the periods from 1933–1982, and 1971–1982 are candidates to be examined for monotonic trends. If the practitioner used the Lombard smooth tests to identify a long period over which the statistical properties of the dataset appear to be in flux, it is appropriate to assess that portion of the period of record for monotonic trends. If, in the example described above, the Lombard smooth test identifies the period from 1937-1967 as being in flux, than an additional test for monotonic trends could be conducted between 1937 and 1982. To gain additional insight into the dataset being analyzed the user could also examine the portions of the period of record prior to identified changepoints (1921-1932 and 1921-1970 in the example above), as long as the periods of record are of sufficient length.

The assessment of monotonic trends will provide the user with further insight into the trends observed within the statistical properties of the flow data. The test results do not support attribution of the trend; engineering judgment is required to determine whether the trend is likely to persist in the future. If a monotonic trend is detected, this implies that the time series still may not meet the assumption of stationarity. This finding would be documented and the users continue to apply engineering judgment when carrying out hydrologic analysis. The case where monotonic trends are still detected after statistically identified nonstationarities have been accounted for will be addressed in greater detail in future versions of the tool.

4 Examples

4.1 Simple Analysis (with a priori knowledge)

USGS ID 08089000 Brazos River near Palo Pinto, Texas

This example demonstrates how to use the Nonstationarity Detection Tool to detect nonstationarities in an annual instantaneous peak streamflow record where there is a priori knowledge that a nonstationarity may exist in the record. The flow data used in this example was collected at the USGS gage site located on the Brazos River near Palo Pinto, Texas (USGS ID 08089000). Annual peak streamflows recorded on the Brazos River near Palo Pinto are known to be impacted by upstream regulation.

4.1.1 Exploratory Analysis

Figure 27 shows the annual instantaneous peak streamflow time series obtained from the USGS website. A visual examination of this time series suggests that there have been changes in the annual instantaneous peak streamflow record over the past 90 years. In particular, the values prior to the 1940s are on average higher than later years. Examination of the metadata associated with this record (available at: <http://wdr.water.usgs.gov/wy2013/pdfs/08089000.2013.pdf>) indicates that the construction of the Possum King Lake project was completed around 1941. This is also supported by the application of the USGS Peak Streamflow Qualification Code “6” (“Discharge affected by Regulation or Diversion”) to instantaneous peak streamflow data starting in 1941. Based on this information, a priori knowledge exists that an abrupt change occurred in the early nineteen forties due to construction of the Morris Sheppard Dam, which impounds Possum King Lake. Therefore, the next step in the analysis is to formally test whether a nonstationarity exists in the annual instantaneous peak streamflow record observed at Palo Pinto in the early forties.

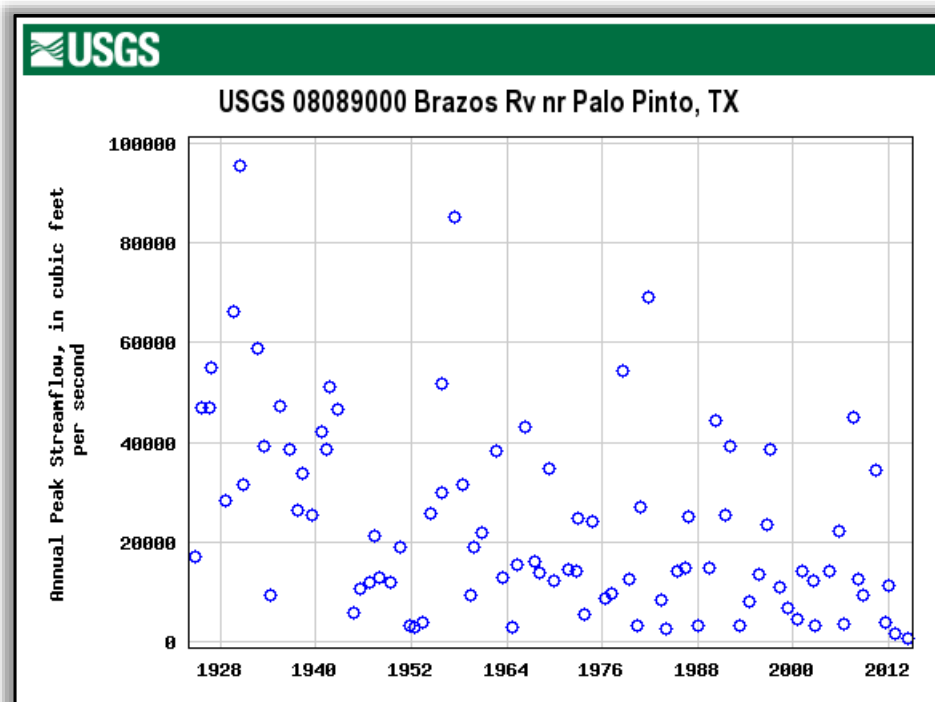


Figure 27. Annual peak streamflow time series for the Brazos River near Palo Pinto in Texas (USGS ID 08089000)

4.1.2 Select a USGS Site and Timeframe for Nonstationarity Detection

On the Nonstationarity Detector tab, the user selects a HUC-4 watershed and a site—for this example, “1206-Middle Brazos” and “BRAZOS RV NR PALO PINTO, TX”—from the Site Selection dropdown menus located to the right of the *Nonstationarities Detected using Maximum Annual Flow* graphic (Figure 28). Because the annual instantaneous peak streamflow record at this gage site is continuous, the timeframe does not need to be adjusted before carrying out analysis.

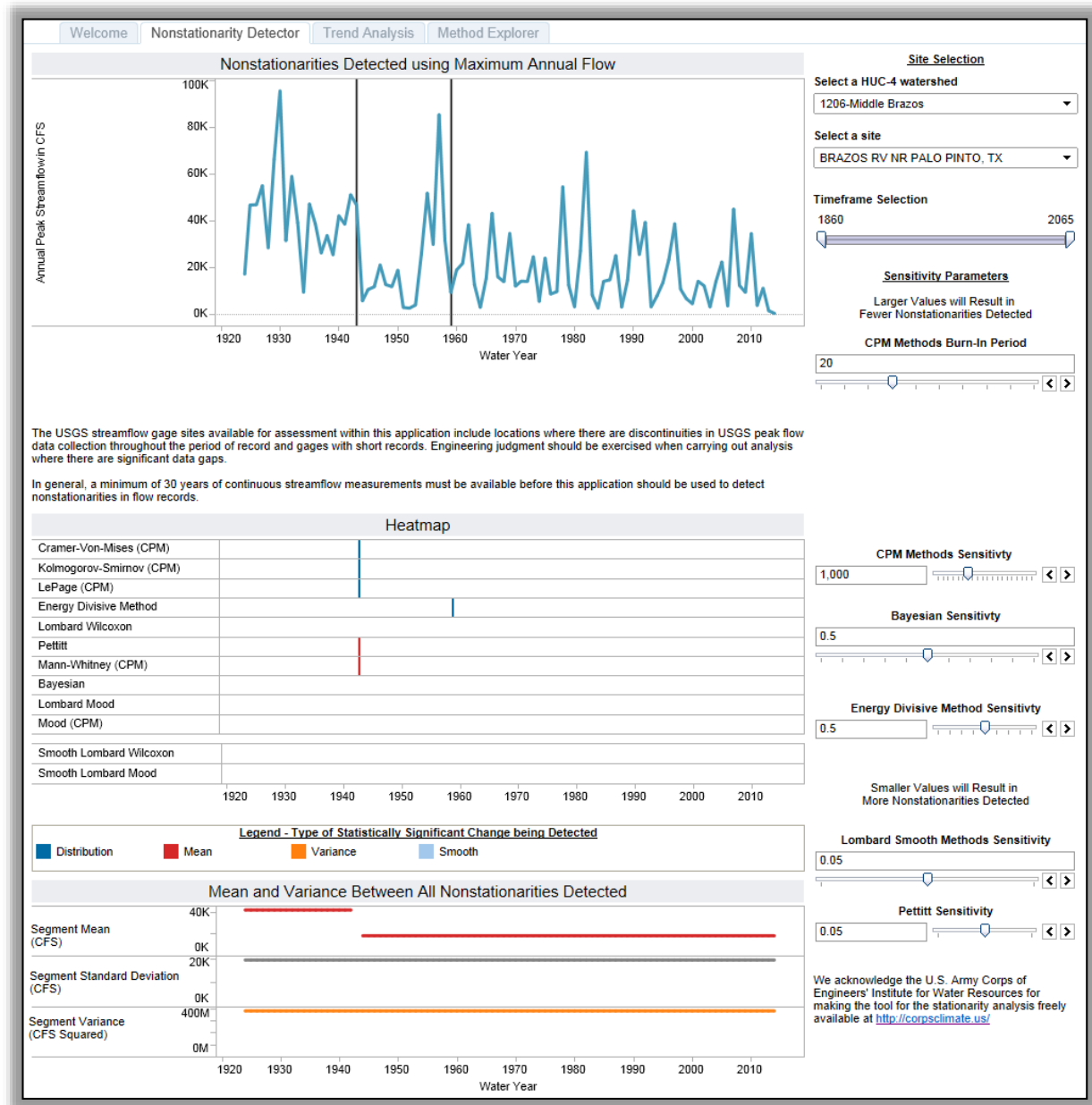


Figure 28. Nonstationarity Detector Tab for the Brazos River near Palo Pinto in Texas (USGS ID 08089000)

Nonstationarity Detection

As shown in Figure 28, the twelve nonstationarity detection methods contained in the tool collectively detected nonstationarities in two different years. To determine the types of changes detected by these methods, the user can hover over the vertical bars in the top graph to reveal the year and the statistical methods that detected the change (see Figure 29).

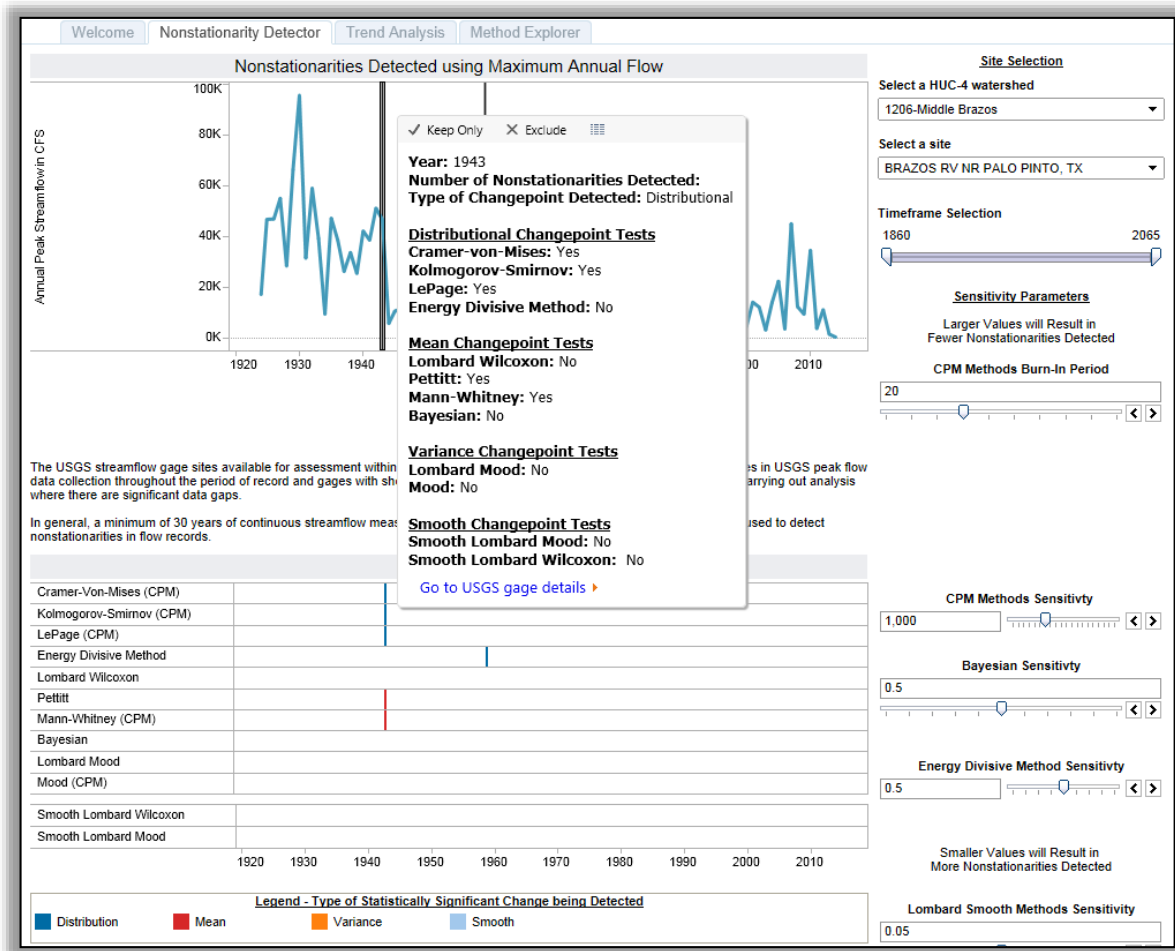


Figure 29. Detailed Results for the Nonstationarity Detected in 1942 for the Brazos River near Palo Pinto in Texas (USGS ID 08089000)

These results are also presented in the Heatmap. The color scheme associated with the tick marks shows that the detection methods are identifying nonstationarities driven by changes in the overall statistical distribution of the data and in the mean. An evaluation of the strength of the nonstationarities follows:

1. **Consensus:** The relative strength of a detected nonstationarity can be determined by looking at the level of consensus between different methods targeted at detecting the same type of nonstationarities (variance/standard deviation, mean, or overall distribution) in a flow data series. The statistically significant nonstationarity detected in 1943 has consensus among three methods that detect a change in distribution and between two methods that detect a change in mean.

Due to the way the Pettit statistical test is performed (Table 1), the nonstationarity detected by the Pettit method in 1943 is appropriate for 1942. However, where the various abrupt statistical methods detect statistically significant nonstationarities within five years of one another, the user is

encouraged to “combine” those to be representative of a single nonstationarity in the flow record. Consequently, the changepoint detected by the Pettitt test is considered indicative of the same nonstationarity being detected in 1943 by the other methods. The nonstationarity detected in 1959 lacks consensus because it was only detected by a single method.

2. **Robustness:** The Heatmap graphic in Figure 28 shows that multiple nonstationarity detection methods detected nonstationarities in the mean and the overall distributional properties of the dataset in the early nineteen forties. Consequently, the nonstationarity detected in the early forties can be considered representative of “robust” changes in the statistical properties of the flow dataset under analysis.
3. **Magnitude:** Using the segmented *Mean and Variance Between All Nonstationarities Detected* graphic displayed at the bottom of the Nonstationarity Detector tab (shown in Figure 30), users can examine the differences in the mean and variance/standard deviation associated with the average of subsets of annual instantaneous peak streamflow data prior to and after detected nonstationarities. As could be expected due to the construction of a dam designed to mitigate flood flows, the nonstationarities detected by the statistical tests targeted at detecting changes in the mean correspond to relatively large changes in the mean annual instantaneous peak streamflow between each of the nonstationarities identified. Between 1942 and 1944, the mean annual instantaneous peak streamflow decreases from approximately 42,000 cfs to 19,000 cfs.

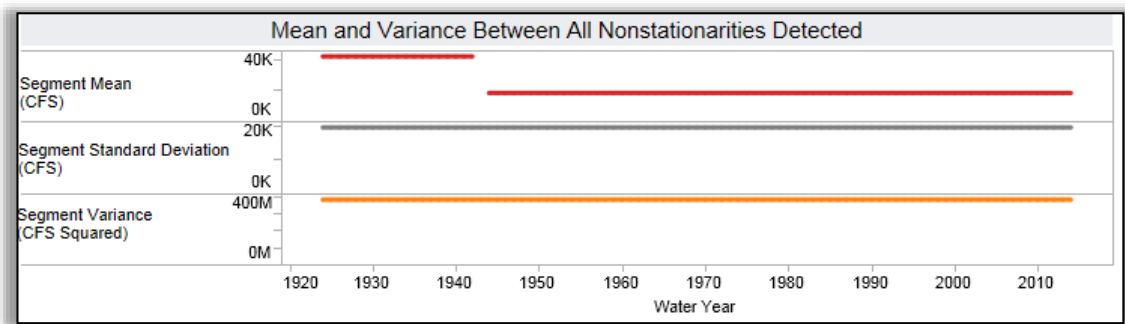


Figure 30. Mean and Variance Between All Nonstationarities Detected Graphic for the Brazos River near Palo Pinto in Texas (USGS ID 08089000)

In this example, the default sensitivity values facilitated the detection of the known nonstationarity in 1943. Consequently, the default sensitivity parameters were adopted for analysis. If the web tool had failed to detect the known nonstationarity in the period of record using the default sensitivity parameters, the user could take steps to incrementally adjust the sensitivity of the tests until the known nonstationarity is detected. Any other nonstationarities detected after these sensitivity parameters are adjusted are considered equally significant. If the user feels it is necessary to adjust the default parameters to identify a known nonstationarity based on prior knowledge, this would be documented and the sensitivity parameters applied recorded.

Where there is a prior knowledge of a specific water management feature becoming operational, the user considers both local knowledge of when the homogenous operating period at the structure commenced and the nonstationarity that the detection tool is identifying when selecting a homogenous period of record for analysis. Deference is given to the known homogenous operating period when several consecutive years are indicated by the tool. For example if two of the nonstationarity detection methods are indicating 1941 as a nonstationarity year, one nonstationarity detection method is detecting 1942 as a nonstationarity year, and the district engineer indicates that the reservoir was not filled until after the

spring of 1942, the adopted period of record for hydrologic analysis would be 1943-2014, because this reflects homogenous operation of the reservoir.

4.1.3 Monotonic Trend Analysis

The next portion of the analysis consists of assessing the subsets of homogenous data for monotonic trends. Because one statistically significant nonstationarity—with consensus among different methods—was detected (1943), the user divides the data into two statistically stationary (homogenous) segments or periods of record based on the single nonstationarity identified:

- 1924-1942 (Before Morris Sheppard Dam)
- 1943-2014 (After Morris Sheppard Dam)

To assess monotonic trends within the record, the user can navigate to the “Trend Analysis” tab, shown in Figure 31, where the tool performs multiple statistical tests to detect the presence of monotonic trends within the annual instantaneous peak streamflow data series. Adjusting the timeframe to look for trends within each of the two stationary subsets of the period of record, as described in Section 3.2, yields the results shown in Figure 32:

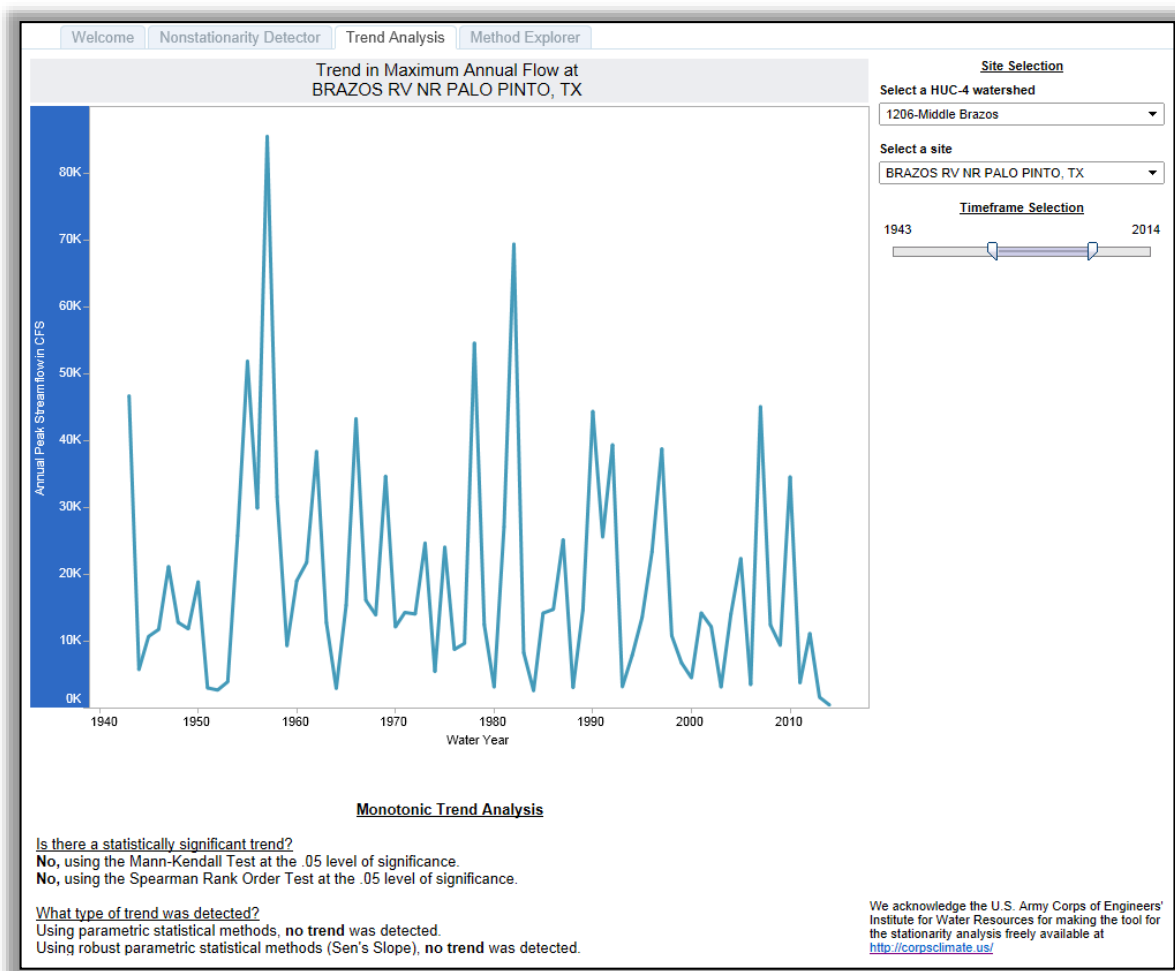


Figure 31. Trend Analysis Page for the Brazos River near Palo Pinto in Texas (USGS ID 08089000)

a. 1924-1942 (Before Morris Sheppard Dam)

<u>Monotonic Trend Analysis</u>
<u>Is there a statistically significant trend?</u> No, using the Mann-Kendall Test at the .05 level of significance. No, using the Spearman Rank Order Test at the .05 level of significance.
<u>What type of trend was detected?</u> Using parametric statistical methods, no trend was detected. Using robust parametric statistical methods (Sen's Slope), no trend was detected.

b. 1943-2014 (After Morris Sheppard Dam)

<u>Monotonic Trend Analysis</u>
<u>Is there a statistically significant trend?</u> No, using the Mann-Kendall Test at the .05 level of significance. No, using the Spearman Rank Order Test at the .05 level of significance.
<u>What type of trend was detected?</u> Using parametric statistical methods, no trend was detected. Using robust parametric statistical methods (Sen's Slope), no trend was detected.

Figure 32. Monotonic trend analysis results for a) 1924-1942 and b) 1943-2014.

The results indicate that, if the dataset is separated into statistically homogenous subsets of flow data prior to and after the construction of the Morris Dam, there is not an overall, statistically significant, monotonic trend in the annual instantaneous peak streamflow record for Brazos River.

4.1.4 Application to Hydrologic Analysis

The results of the assemblage of nonstationarity detection methods applied using the Nonstationarity Detection Tool strongly supports the notion that the distributions in the two sub-series (pre- and post-dam) are different. Although the construction of the dam was completed in 1941, the Nonstationarity Detection Tool identifies a nonstationarity in the statistical properties of the dataset in 1943. This is likely because although the dam was constructed in 1941, it likely took a few years for the reservoir to fill and for “normal” operation to commence. For this reason, engineering judgment and a knowledge of reservoir operation/history is important when conducting hydrologic analysis. For the purpose of this example, it will be assumed that normal reservoir operation was initiated in 1943.

A priori knowledge of the existence of abrupt changes allows for testing differences in the distribution generating the records before and after the year of the known nonstationarity. In the preceding example, USGS metadata provided information about the construction of a dam in 1941. Engineering practice generally considers that because the flow record is impacted by regulation, design flood estimation for the present might not be appropriate using the entire period of record. There are two ways to address this issue: the pre-1943 period can be excluded from analysis; or, preferably, the pre-1943 period can be adjusted to be reflective of current basin conditions using a reservoir model. A monotonic trend analysis was applied to assess both the non-regulated portion of the period of record at this site and the current, regulated condition at this site. As expected, the monotonic trend analysis returned no significant trends within the homogenous subset of data prior to and post the construction of the water management structure. Thus, the 1924–1942 and the 1943-2013 subsets of the period of record can be considered stationary. Further analyses rely on current USACE guidance: Engineer Manual (EM) 1110-2-1417, Flood-Runoff Analysis (1994) and EM 1110-2-1413, Hydrologic Analysis of Interior Areas (1987). Engineering judgment can consider the resiliency of the system when incorporating the range of results produced by conducting the sensitivity analysis described above in the adopted hydrologic design or study results..

4.2 Complex Analysis (without a priori knowledge)

USGS ID 05082500 Red River of the North at Grand Forks, North Dakota

4.2.1 Problem Statement

Consider the case in which there is no a priori knowledge of the existence of an abrupt change in the annual instantaneous peak streamflow data series. This more complex example is based on the annual instantaneous peak streamflow for the Red River of the North at Grand Forks, North Dakota (USGS ID 05082500). Figure 33 shows the annual instantaneous peak streamflow time series obtained from the USGS. There is a substantial amount of drainage area between Grand Forks, North Dakota and any upstream water control structures. Consequently, there is no prior knowledge indicating that there is a nonstationarity within the streamflow record at Grand Forks.

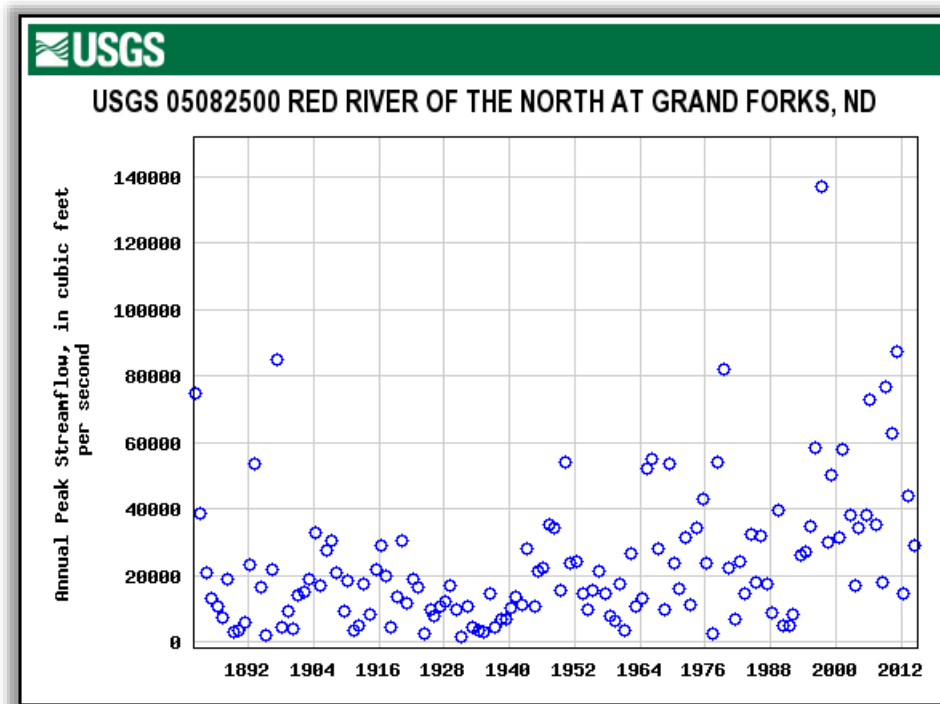


Figure 33. Annual peak streamflow time series for the Red River of the North at Grand Forks, ND (USGS ID 05082500)

The Nonstationarity Detection Tool was applied to check for nonstationarities within the streamflow record at Grand Forks, North Dakota.

4.2.2 Select a USGS Site and Timeframe for Nonstationarity Detection

As before, select the HUC-4 watershed—"0902-Red" and site name—"RED RIVER OF THE NORTH AT GRAND FORKS, ND"—from the Site Selection dropdown menus. In this case, the timeframe does not need to be adjusted because the gage contains a continuous dataset for the entire period of record (see Figure 34).

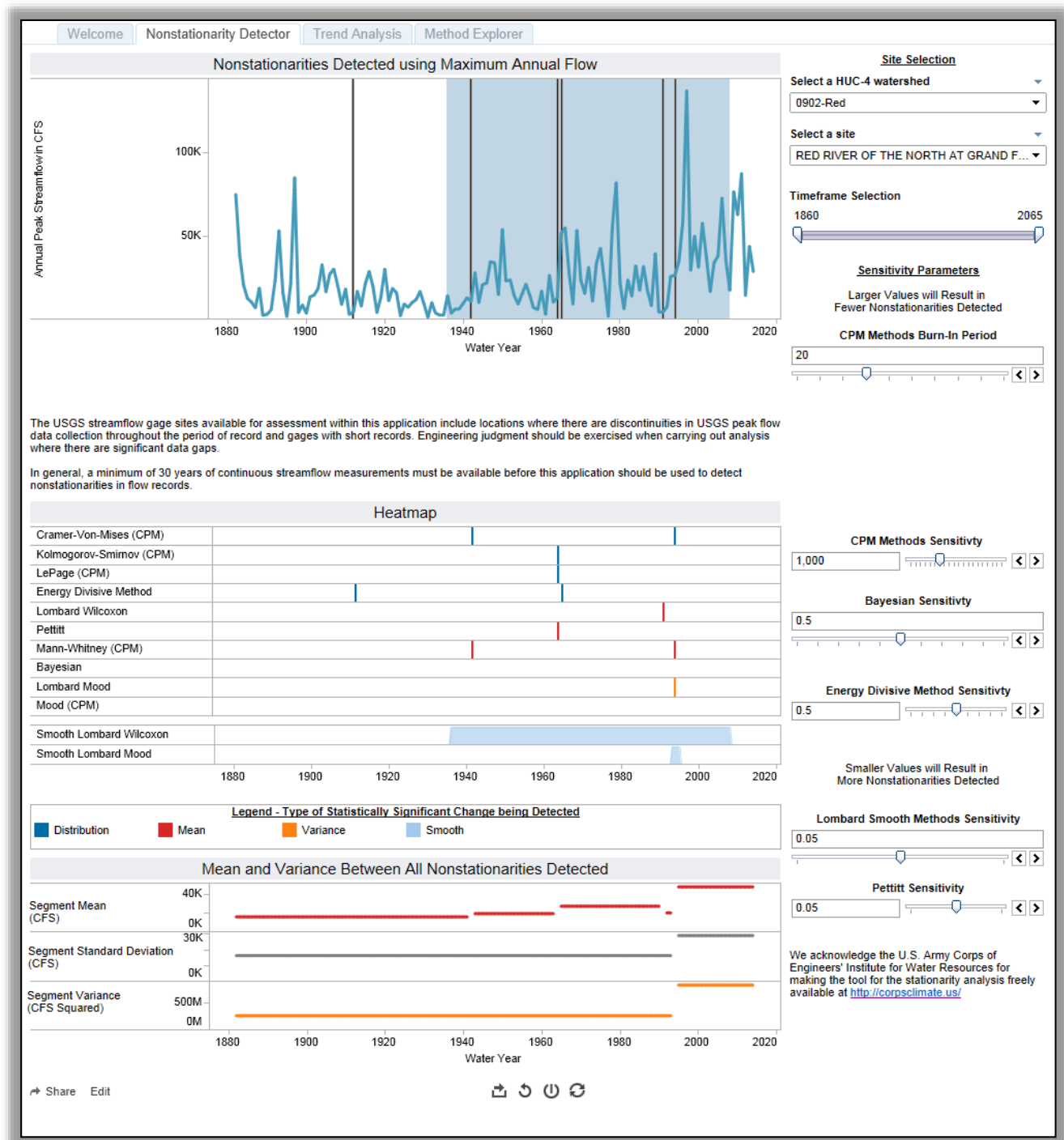


Figure 34. Nonstationarity Detector Tab for the Red River of the North at Grand Forks, ND (USGS ID 05082500)

4.2.3 Nonstationarity Detection

As can be seen in the *Nonstationarities Detected using Maximum Annual Flow* graphic in Figure 34, the detection tool identified several nonstationarities, both abrupt (grey vertical lines) and smooth (blue shading), within the annual instantaneous peak streamflow record at Grand Forks.

As with the first example, hovering over the vertical bars in the *Nonstationarities Detected using Maximum Annual Flow* graphic indicates the exact year when an abrupt nonstationarity was detected, along with a list of the statistical tests that detected the change in the statistical properties of the flow record. This information is also presented using the color coded tick marks in the Heatmap, with one tick mark—color coded by the type of nonstationarity detected—for each year in which an abrupt change was detected.

As seen in Figure 34, the Smooth Lombard Wilcoxon method also detects smooth changes in the mean of the annual instantaneous peak streamflow extending from 1936-2008 and the Smooth Lombard Mood method detects a smooth transition in sample variance/standard deviation of the annual instantaneous peak streamflow extending from 1993-1995. The output of the Smooth Lombard tests indicate that the statistics associated with the flow record at Grand Forks are in flux over these periods of time. Because the smooth Lombard Mood result indicates a transitional period of five years or less, it can be compared directly to the abrupt nonstationarities indicated by the other techniques. It is analogous to an abrupt nonstationarity in 1995. The longer duration transitional period (1936-2008) identified by the Smooth Lombard Wilcoxon method must be considered independently.

Because the clusters of nonstationarities detected between 1964-1965 and 1991-1995 fall within five year periods, these clusters can be analyzed as two statistically significant nonstationarities. An evaluation of the strength of the nonstationarities follows:

1. **Consensus:**

- a. 1964-1965: There is consensus between the LePage, Kolmogorov-Smirnov, and Energy Divisive methods which indicate changes in the distributional properties of flow datasets.
- b. 1993-1995: There is consensus between the abrupt Lombard Wilcoxon and Mann-Whitney methods, which detect changes in the mean associated with flow datasets.

2. **Robustness:** As can be seen in the Heatmap in Figure 34, both of these nonstationarities can be considered robust. The nonstationarity detected between 1993 and 1995 is indicated by statistical tests that target changes in mean, variance/standard deviation, and overall distribution. The nonstationarities detected between 1964-1965 are indicated by statistical tests that target changes in mean and the overall statistical distribution of the datasets being assessed.

3. **Magnitude:** Using the Mean and Variance Between All Nonstationarities Detected graphic, located at the bottom of the Nonstationarity Detector tab (Figure 34), the nonstationarities detected in the 1960s correspond to changes of about 8,000 cfs in the mean of the annual instantaneous peak streamflow. The nonstationarity detected in 1990s corresponds to a change of 21,000 cfs in the mean, 13,000 cfs in the standard deviation, and 560,000,000 cfs² in the variance of the annual instantaneous peak streamflow.

Because the nonstationarities detected between 1964-1965 and 1991-1995 demonstrate consensus, can be considered robust, and represent appreciable changes in the mean and variance/standard deviation associated with each subset of data the engineer can conclude that there are two, strong statistically significant nonstationarities within the dataset.

Within the period 1964-1965 the majority of nonstationarities are detected in 1964. Consequently, **1964** can be adopted as the representative nonstationarity year for this period. Within the period 1993-1995, the majority of nonstationarities are detected in **1994**. Note that if, for example, two methods were detecting nonstationarities in 1993 and two methods were detecting nonstationarities in 1995 the user would adopt

1995 as the end of the homogenous period because it is the more recent year. The selected nonstationarity years are assumed to be the end year of each homogenous subset identified.

The tool detected an extended, gradual change in the variance/standard deviation **between 1936 and 2008**. This provides additional context for future analyses and alerts users that the stationarity assumption may not necessarily hold throughout this entire period.

It is recommended that the default sensitivity values be adopted for analysis. Consequently, for this example application, default sensitivity parameters were applied. If the user chooses to alter the sensitivity parameters associated with the statistical tests executed by the web application, the new parameters could be recorded, and a description of how sensitivity parameters were modified could be included in report documentation.

4.2.4 Monotonic Trend Analysis

The next portion of the analysis consists of assessing the subsets of data for monotonic trends. Given these results, a user would divide the data into five segments or periods of record based on the three nonstationarities identified:

- 1882-1964
- 1965-2014
- 1882-1994
- 1995-2014
- 1936-2014

To assess monotonic trends within these subsets of the flow record, the user can navigate to the Trend Analysis tab, where the tool performs multiple statistical tests to detect the presence of monotonic trends in the annual instantaneous peak streamflow record, as seen in Figure 35.

Adjusting the timeframe to look for trends within each of the five subsets of the period of record yields the results shown in Figure 35.

The results indicate that there were no statistically significant trends in annual instantaneous peak streamflow in any of the first four subsets of data (1882-1964, 1965-2014, 1882-1994, and 1995-2014). As expected, there was a statistically significant, positive monotonic trend detected in the portion of period of record following the onset of the smooth transition detected by the Lombard Wilcoxon test (1936-2014).

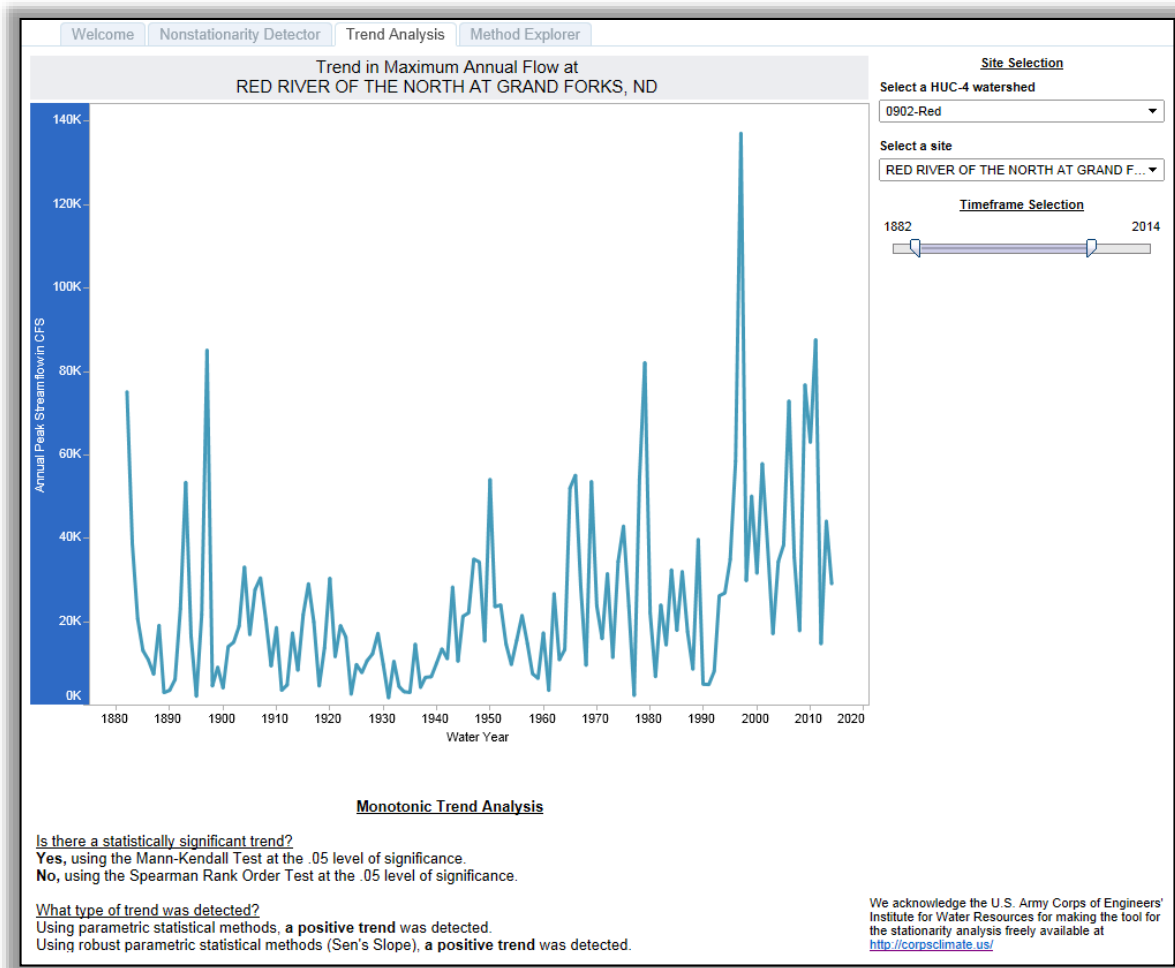


Figure 35. Trend Analysis Tab for the Red River of the North at Grand Forks, ND (USGS ID 05082500)

a. 1882-1964

Monotonic Trend Analysis

Is there a statistically significant trend?

No, using the Mann-Kendall Test at the .05 level of significance.

No, using the Spearman Rank Order Test at the .05 level of significance.

What type of trend was detected?

Using parametric statistical methods, **no trend** was detected.

Using robust parametric statistical methods (Sen's Slope), **no trend** was detected.

b. 1965-2014

Monotonic Trend Analysis

Is there a statistically significant trend?

No, using the Mann-Kendall Test at the .05 level of significance.

No, using the Spearman Rank Order Test at the .05 level of significance.

What type of trend was detected?

Using parametric statistical methods, **no trend** was detected.

Using robust parametric statistical methods (Sen's Slope), **no trend** was detected.

c. 1882-1994

Monotonic Trend Analysis

Is there a statistically significant trend?

No, using the Mann-Kendall Test at the .05 level of significance.

No, using the Spearman Rank Order Test at the .05 level of significance.

What type of trend was detected?

Using parametric statistical methods, **no trend** was detected.

Using robust parametric statistical methods (Sen's Slope), **no trend** was detected.

d. 1995-2014

Monotonic Trend Analysis

Is there a statistically significant trend?

No, using the Mann-Kendall Test at the .05 level of significance.

No, using the Spearman Rank Order Test at the .05 level of significance.

What type of trend was detected?

Using parametric statistical methods, **no trend** was detected.

Using robust parametric statistical methods (Sen's Slope), **no trend** was detected.

e. 1936-2014

Monotonic Trend Analysis

Is there a statistically significant trend?

Yes, using the Mann-Kendall Test at the .05 level of significance.

Yes, using the Spearman Rank Order Test at the .05 level of significance.

What type of trend was detected?

Using parametric statistical methods, **a positive trend** was detected.

Using robust parametric statistical methods (Sen's Slope), **a positive trend** was detected.

Figure 36. Trend Analysis Tab for the Red River of the North at Grand Forks, ND (USGS ID 05082500): a) 1882-1964, b) 1965-2014, c) 1882-1994, d) 1995-2014, and e) 1936-2014.

4.2.5 Application to Hydrologic Analysis

Because there are multiple “strong” statistically significant nonstationarities identified within the annual instantaneous peak streamflow record observed at Grand Forks, North Dakota, design flood estimation for the present might not be appropriate using the entire period of record. If one were to use the entire period of record, recurrence intervals would inaccurately reflect the risk of occurrence associated with a given flood magnitude. To carry out hydrologic analysis, the flow record could be truncated to the portion of the period of record following a “strong” and statistically significant nonstationarity.

As in the previous example, a shorter flow record is less representative of the natural variability that exists within hydrometeorological data series. This adds uncertainty to the analysis, which can be characterized alongside the presentation of results (e.g., by confidence limits). Periods of record adopted for hydrologic analysis generally have a minimum record length of 30 years. Consequently, the period of record after the 1994 nonstationarity (1995-2014) may not be acceptable for use. The user could seek to find a balance between identifying both a homogenous flow record and one that is long enough to be representative of the natural variation in maximum flow magnitudes at the site.

When there are multiple nonstationarities detected with consensus, and/or a long period of smooth statistical change (via Lombard) detected, it is recommended that the user carry out sensitivity analyses using all potential periods of record, including the period over which the Lombard model might be detecting a smooth change and the entire period of record of available data. Note that even if a single, strong, statistically significant nonstationarity is identified, a sensitivity analysis using the entire period of record is advisable. As part of the analysis, the user could assess the sensitivity of the results to altering the period of record used for analyses and whether the observed trend is expected to persist into the future.

For the Red River of the North at Grand Forks, ND, the following sensitivity tests could be carried out in support of nonstationarities detected in the unregulated record:

1. A sensitivity analysis using the period of record following the “strong,” statistically significant nonstationarity identified within the annual instantaneous peak streamflow record for which there is greater than 30 year of subsequent observations using the period of record from 1965-2014.
2. Because the smooth Lombard Wilcoxon model identifies a long (greater than 5 years) period where the statistical properties of the dataset are in flux, and because this transitional period transects the portion of the period of record following the other abrupt, “strong” nonstationarities, an additional sensitivity analysis could be conducted using the period of record from 1936 to 2014. This contains the portion of the period of record identified as in flux by the smooth Lombard model. The case where the smooth Lombard method is indicating that the statistical properties associated with long portions of a dataset are gradually changing will be addressed in greater detail in future versions of the tool.
3. A sensitivity analysis could be conducted to assess the differences between the results generated using the truncated records described above (1965-2014, and 1936-2014) for analysis versus applying traditional methods that incorporate all available flow data (1882-2014 and any historical flood events).

There are no statistically significant, monotonic trends detected before or after the two nonstationarities identified in 1964 and 1994. The results of the monotonic trend analysis supports the hypothesis that these nonstationarities are appropriate for use in segmenting the dataset into homogenous subsets of data. The only caveat to the conclusion that the 1995-2014 or 1965-2014 record is stationary is the detection of the

Lombard Wilcoxon Smooth nonstationarity detected between 1936 and 2014. The results of the Smooth Lombard Wilcoxon test point to a degree of statistical instability throughout the portion of the period of record between 1936 and 2008.

When a monotonic trend is detected in the dataset adopted for analysis, or when a long, transition period is detected by one of the smooth nonstationarity detection methods within the adopted period of record, the time series may still not meet the assumption of stationarity. If so, these findings are documented, and the user applies engineering judgment when carrying out hydrologic analysis in accordance with current USACE guidance: Engineer Manual (EM) 1110-2-1417, Flood-Runoff Analysis (1994) and EM 1110-2-1413, Hydrologic Analysis of Interior Areas (1987). Engineering judgment can consider the resiliency of the system when incorporating the range of results produced by conducting the sensitivity analysis described above in the adopted hydrologic design or study results.

Given the potential instability in this record, efforts to qualitatively evaluate what might be driving the nonstationarities detected in the flow record are advisable. The guidance presented in USACE Engineering and Construction Bulletin 2014-10, *Guidance for Incorporating Climate Change Impacts to Inland Hydrology in Civil Works Studies, Designs, and Projects*, could be applied to qualitatively assess projected climate trends in the region. Temporal variation in land use practices could be studied using historic land use datasets and aerial imagery. Hydraulic structure inventories could be consulted to assess when both major and minor hydraulic structures were installed throughout the study area.

4.3 No Statistically Significant Nonstationarity Detected

USGS ID 05388250: Upper Iowa River near Dorchester, Iowa

4.3.1 Problem Statement

This example assesses the stationarity assumption as it applies to the annual instantaneous peak streamflow dataset recorded along the Upper Iowa River near Dorchester, Iowa (USGS ID 05388250). Figure 37 shows the annual instantaneous peak streamflow time series obtained from the USGS for gage 05388250. There is no prior knowledge indicating that there might be a nonstationarity within the streamflow record at Dorchester, Iowa.

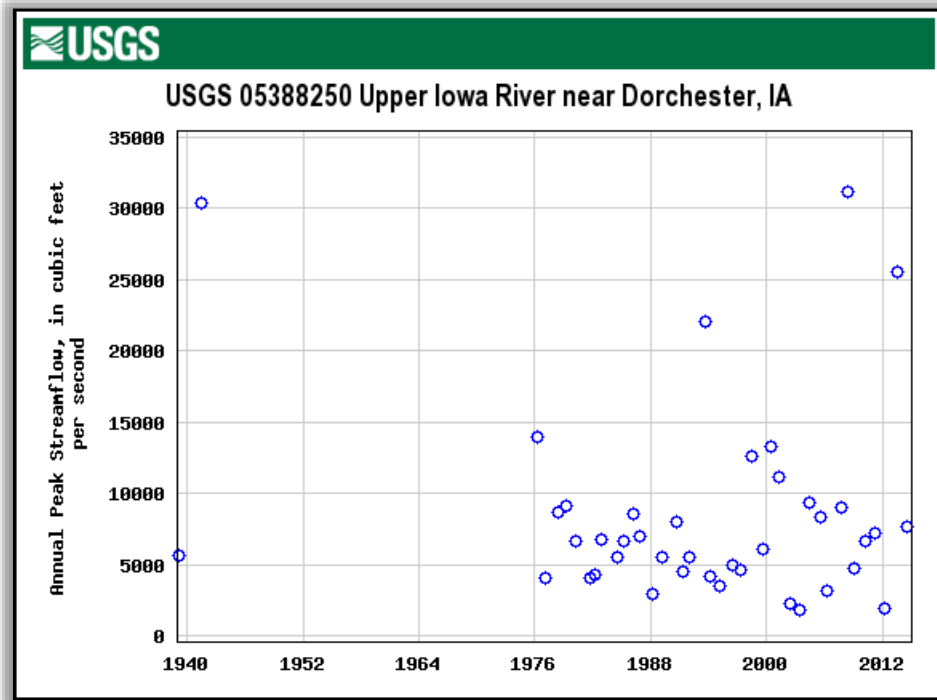


Figure 37. Annual peak streamflow time series for the Upper Iowa River near Dorchester, Iowa (USGS ID 05388250)

4.3.2 Select a USGS Site and Timeframe for Nonstationarity Detection

Using the Site Selection dropdown menus, located on the right side of Nonstationarity Detector tab, the user selects the 0706 Upper Mississippi-Maquoketa-Plum from the “HUC-4 Label” menu and the site of interest—“UPPER IOWA RIVER NEAR DORCHESTER, IA”—from the “Site Name” dropdown. In Figure 38, the annual instantaneous peak streamflow time series in the *Nonstationarities Detected using Maximum Annual Flow* graphic shows missing data between 1941 and 1976.

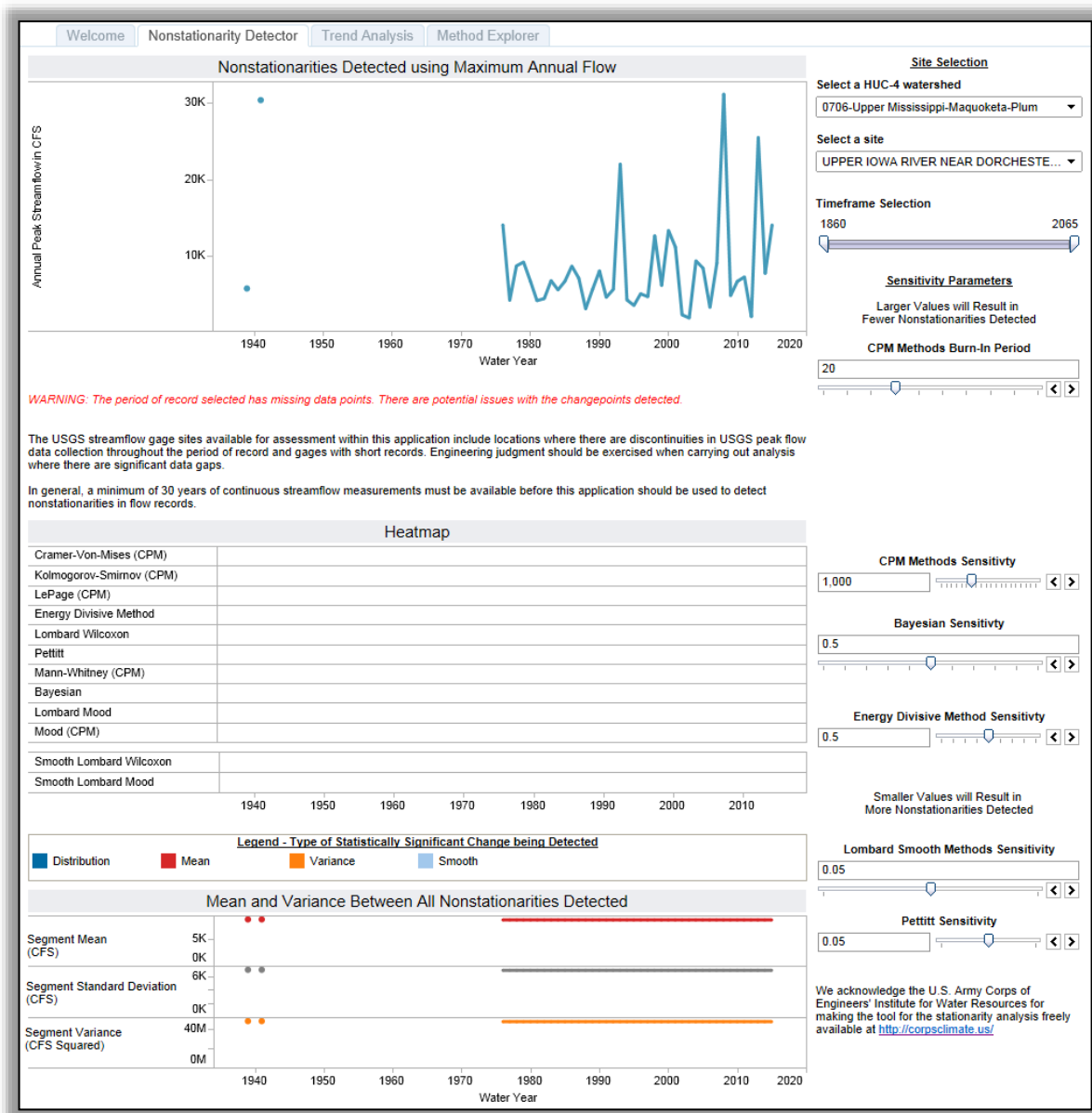


Figure 38. Nonstationarity Detector Tab for the Upper Iowa River near Dorchester, Iowa (USGS ID 05388250) – Without Timeframe Adjustment

Using the Timeframe Selection slider on the right side of the Nonstationarity Detector tab, the user must limit the timeframe selected for analysis to the period with continuous flow data: 1976-2014. Note that changing the timeframe will impact the nonstationarities detected by the tool.

4.3.3 Nonstationarity Detection

Now that the timeframe and site have been selected, the results of the detection analysis can be assessed. As shown in Figure 39, no nonstationarities were detected by the tool for the continuous period of record beginning in 1976. For this example, the default sensitivity parameters were applied. If the user chooses to alter the sensitivity parameters associated with the statistical tests executed by the Nonstationarity Detection Tool, the new parameters would be recorded, and a description of how sensitivity parameters were modified is also included.

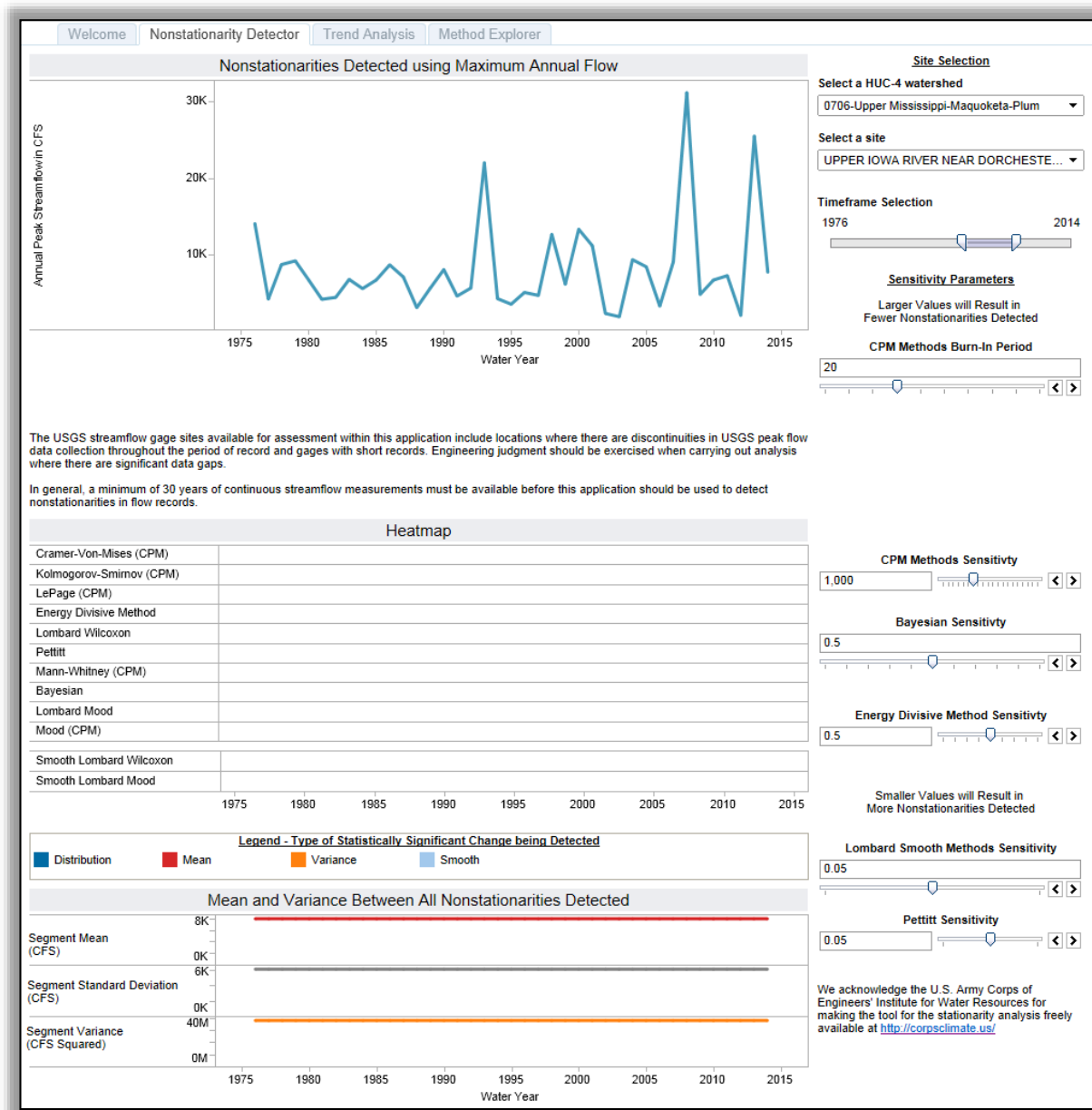


Figure 39. Nonstationarity Detector Tab for the Upper Iowa River near Dorchester, Iowa (USGS ID 05388250) – With Timeframe Adjustment

4.3.4 Monotonic Trend Analysis

The next portion of the analysis consists of assessing the subsets of homogenous data for monotonic trends. In this case, because no nonstationarities were identified for analysis, there is no need to segment the record. The entire period of record is assessed for monotonic trends. As can be seen in Figure 40, there is no statistical evidence of a monotonic trend in the annual instantaneous peak streamflow recorded on the Iowa River near Dorchester, IA.

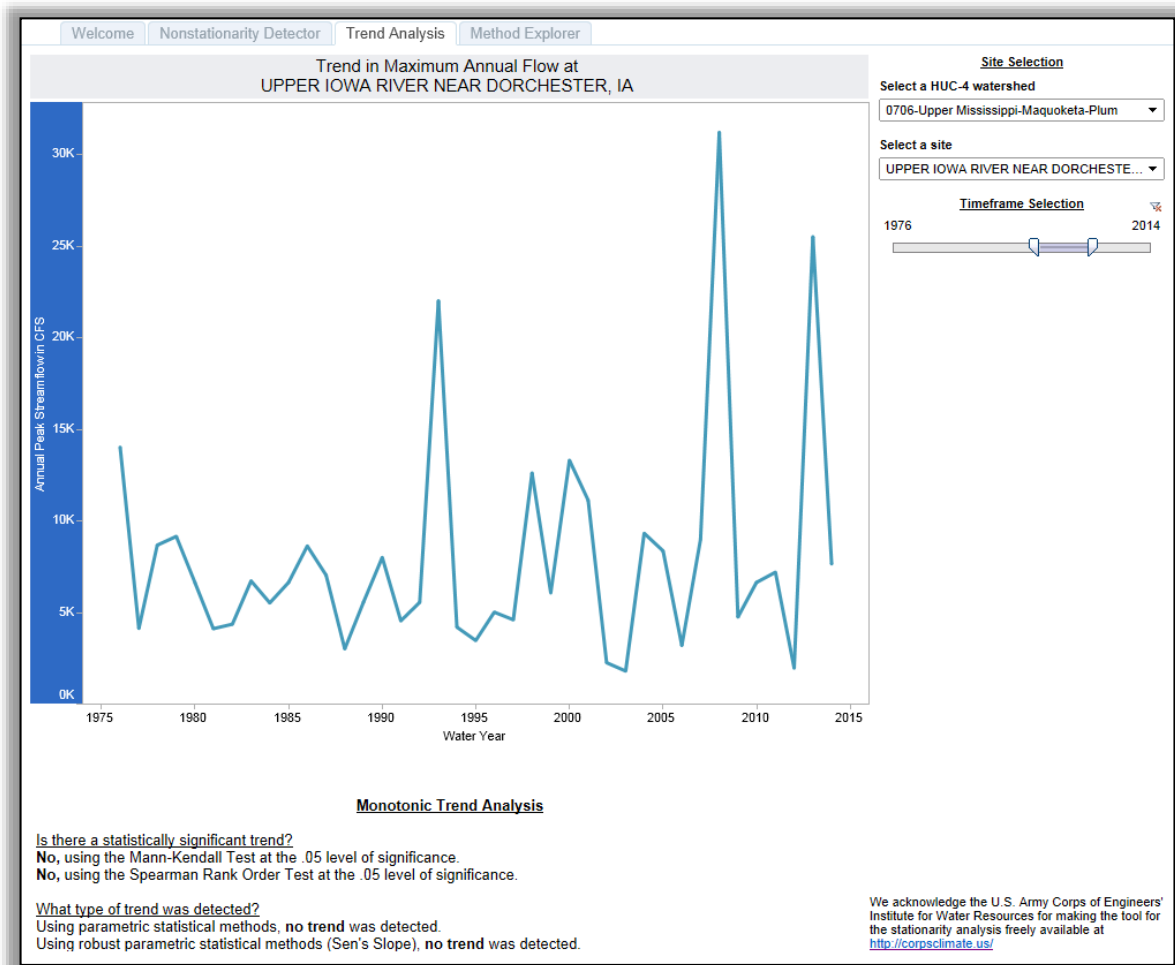


Figure 40. Trend Analysis Tab for the Upper Iowa River near Dorchester, Iowa (USGS ID 05388250)

4.3.5 Application to Hydrologic Analysis

At streamflow gage sites where no nonstationarities are detected, inland hydrologic analysis will continue to be evaluated in the manner described in current USACE guidance: Engineer Manual (EM) 1110-2-1417, *Flood-Runoff Analysis* (1994) and EM 1110-2-1413, *Hydrologic Analysis of Interior Areas* (1987).

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Appendix 1: Glossary of Statistics Terms

Bayesian – In contrast to “Frequentist” statistics, Bayesian statistics interprets probability as a quantity assigned to a state of belief. In the Bayesian view, a probability can be assigned to a hypothesis, which is known as the prior.

Monotonic Trend – A variable increases or decreases consistently over time. This does not imply a linear trend.

Parametric – From a branch of statistics that assumes the sample data comes from a population that follows a probability distribution based on a fixed set of parameters.

Posterior Probability – This is unique to **Bayesian** statistics. It is the outcome of a Bayesian model. A Bayesian assigns a prior probability to a hypothesis, then uses the data to inform the model, before outputting the new state of belief around an event.

Stationarity – The assumption that the statistical characteristics of hydrologic time series data are constant through time.

Type I Error – The probability of accepting an alternative hypothesis when the null hypothesis is true.

Appendix 2: Version Changelog

Version 1.1 changes resulting from review comments of version 1.0

- The tool uses instantaneous streamflow data incorporating those gages for which metadata is available in the database (OBSERVED_TSS). This means that some gages will be unavailable to users initially (e.g. 08246500 Conejos River nr Mogote, CO).
- Missing data points in a period of record are no longer connected by a line. This will help users better determine where the continuous period of record starts and ends. See Upper Iowa River near Dorchester, IA in HUC 706 for an example.
- There is now a dynamic warning box below the tool that alerts users when they have selected a period of record less than ideal for the type of analysis they are conducting (30 years for nonstationarity detection, 10 years for trend detection) and/or when they have selected a discontinuous period of record. These warning messages appear directly below the graphic and emphasize that the user could adjust the period of record to avoid potential issues.
- There is now a static dialog below the main graphics on each of the three tabs that describes the data being shown and reminds the user to use both a long and continuous period of record if possible.
- The sensitivity issues with the abrupt Lombard methods have been resolved. Using the gages and comments provided by the independent reviewers, we were able to determine a revised level of sensitivity for these methods. We are holding the sensitivity parameter for these methods constant to obtain user feedback on the new level of sensitivity before determining an appropriate range of values.
- Some users commented that the CPM Methods were detecting changepoints prior to the startup period that they had supplied. After looking into this issue, we determined that there was a miscommunication about the way in which the CPM Methods function. To address this, we have since updated the language in the user guide and changed the name of the parameter in the tool to avoid confusion. These methods perform two scans of the data. The first scan is to determine if there are any changes in the mean/variance/distribution occur and this is the scan that takes this value into account. A second scan of the data is then made to determine when these changes in the mean/variance/distribution occurred and these are the resulting changepoints displayed. This second scan can sometimes determine that the time at which a change occurred is prior to when it was initially detected in the first scan. For more details and a very helpful graphic, Section 4.2 on Page 13 in this document explains this as well (<http://gordonjross.co.uk/cpm.pdf>).
- The reviewer's version of the tool appeared to crash when the Energy Divisive Method sensitivity was set to 1; this has been resolved.
- The reviewer's version of the tool appeared to calculate the Kolmogorov-Smirnov method incorrectly for a specific HUC; this has been resolved.
- A landing page has been added to the tool. It uses language from the user guide and explains the layout/functionality of each tab. It also provides contact information for the team.