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Evaluation Of The Use Of DUMPStat To Detect The Impact Of Landfills On Groundwater Quality

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ACF	Autocorrelation Function
ACL	Alternate Concentration Limit
BOD	Biochemical Oxygen Demand
CC	Combined Shewhart-CUSUM Control Chart
COD	Chemical Oxygen Demand
CUSUM	Cumulative Sum
DATCP	Wisconsin Department of Agriculture, Trade and Consumer Protection
DILHR	Wisconsin Department of Industry, Labor, and Human Relations
DMZ	Design Management Zone
DOT	Wisconsin Department of Transportation
DUMPStat	Downgradient Upgradient Monitoring Program Statistics
EPA	United States Environmental Protection Agency
ES	Enforcement Standard
IQR	Interquartile Range
KW	Kruskal-Wallis Test
NR	Natural Resources
PAL	Preventative Action Limit
PL	Prediction Limit
TDS	Total Dissolved Solids
TOC	Total Organic Carbon
TOX	Total Organic Halogen
VOC	Volatile Organic Compounds
WDNR or DNR	Wisconsin Department of Natural Resources

CHAPTER 1

INTRODUCTION

1.1 Objectives

The primary objective of this research is to evaluate the use of the computer program DUMPStat as an alternative or supplement to the use of indicator preventive action limits (PAL) for determining whether a landfill is in compliance with groundwater quality standards.

1.2 Background

Careful monitoring of the impact of landfills on groundwater quality is a critical component of Wisconsin's groundwater protection program. Currently, the Wisconsin Department of Natural Resources (WDNR) administrates the monitoring programs in accordance with Chapter NR 140 of the Wisconsin Administrative Code. This regulation sets two types of groundwater quality standards: preventive action limits (PAL's) and enforcement standards (ES). The lower PAL serves two purposes. First, the PAL is used in design codes so that contamination is prevented through use of stringent designs. Second, the PAL is used as a "trigger" for remedial actions. PAL's are used to prevent contamination but the ES defines when a violation has occurred. If an ES is violated, the landfill is subject to immediate enforcement action. If substances detected in groundwater exceed either the ES or PAL for a health or welfare parameter, the WDNR may set an alternative concentration limit (ACL). The WDNR also sets PAL's for indicator parameters which occur naturally and may indicate contamination. These indicator parameters provide an early warning for possible contamination.

The focus of this research is on PAL's for indicator parameters. NR 140 specifies the PAL for indicator parameters as the mean plus three standard deviations or a minimum increase, based on at least eight background samples. NR 140 does not specify how ACL's are set. However, the WDNR Waste Management Program policy is to use the sample mean plus two sample standard deviations. Consequently, both the indicator PAL and ACL are determined statistically. Also, the indicator PAL and the ACL are both determined on a well specific basis (intrawell) when possible. The health and welfare PAL and ES are uniform across the landfill as well as across the state.

The PAL procedure is set by law and rule while the ACL procedure is set by rule only. The rule can be changed by changing policy and operating procedures but the law can be changed only by an act of the legislature. Since changing the PAL procedure would require a substantial legislative change, this was our focus. Also, the nature of the current statistical procedures is intrawell, so the focus of this research is intrawell.

Gibbons(1994) has developed statistical procedures for analyzing groundwater quality data at landfills. These procedures are included in the statistical package DUMPStat (Downgradient, Upgradient Monitoring Program Statistics), developed by Gibbons and Discerning Systems, Inc. DUMPStat has two intrawell methods which could potentially replace the indicator PAL, prediction limits (PL's) and the combined Shewhart-CUSUM control charts (CC's). The objective of this research focuses on statistical issues, although operational issues are also considered. This report is intended to provide information which the WDNR can use to determine whether or not DUMPStat should be adopted in whole or in part as a tool for assessing groundwater impacts at landfills. Again, we focused on the well specific indicator PAL, since the use of DUMPStat would require a legislative change.

1.3 Project Summary and Organization

In order to evaluate the intrawell DUMPStat algorithms, we proceeded in three steps. First, we applied DUMPStat to indicator parameter data from the Portage County Landfill. From this analysis, we found that the DUMPStat algorithms are far more conservative than the PAL. For indicator parameters, the use of DUMPStat would result in more violations than would the use of PAL's. This would be true for both upgradient and downgradient wells.

Our second step was to test the underlying assumptions of the DUMPStat calculations: independence, stationarity, and normality. These assumptions are not critical to the use of PAL's, as they are not based on statistical significance.

In order to evaluate these assumptions, we tested three indicator parameters for 26 upgradient wells at ten landfills. Normality was rejected at 12 of 26 wells and the assumptions of independence was rejected at 15 of 26 wells. In addition to these assumptions, we tested each well and parameter for trend. For this test, at least 50 percent of the wells and parameters exhibited an upward or downward trend.

The third step in this study was to evaluate how violations of assumptions and presence of trend affects DUMPStat and the use of the indicator PAL. DUMPStat was applied to indicator parameters for the 26 wells at the ten landfills. Next, we determined whether or not each violation was in a data set that rejected normality, rejected independence or exhibited trend. For all parameters combined, we found that over 60 percent of the violations for DUMPStat and PAL were in these data sets.

This report is intended to provide an in depth analysis of the results reported above as well as additional background information. The report is organized in the following manner:

- Chapter one is a simple introduction.
- Chapter two reviews Wisconsin's groundwater monitoring regulations.
- Chapter three reviews all the options available in DUMPStat. Our focus is on intrawell prediction limits and combined Shewhart-CUSUM control charts, however, we discuss in brief the other DUMPStat options.

- Chapter four is the Portage County Landfill case study. In this case study we evaluate all wells using PL's, CC's and PAL's using both eight and 25 background samples.
- Chapter five evaluates the assumptions of parametric tests for 26 upgradient wells at ten landfills. Then we evaluated these wells using PL's, CC's and PAL's. Lastly, we considered how violations of the assumptions affect each statistical test.
- Chapter six is the conclusion and recommendation section.

CHAPTER 2

MONITORING AT WISCONSIN LANDFILLS

2.1 Wisconsin Regulations

As stated in Chapter 1, the primary legislation regulating Wisconsin landfills is NR 140. The purpose of the legislation is:

> "...to establish groundwater quality standards for substances detected in or having a reasonable probability of entering the groundwater resources of the state; to specify scientifically valid procedures for determining if a numerical standard has been attained or exceeded; to specify procedures for establishing points of standards application, and for evaluating groundwater monitoring data; to establish ranges of responses the department may require if a groundwater standard is attained or exceeded; and to provide for exemptions for facilities, practices and activities regulated by the department."

The purpose of Chapter 2 of this report is to outline the regulations of the state, to outline the monitoring requirements, to review the calculations required for PAL, and to show how these requirements relate to intrawell and interwell analysis.

Subchapter III of NR 140 applies only to the DNR while subchapters I and II apply to the DNR as well as the following Wisconsin government agencies:

- Department of Agriculture, Trade and Consumer Protection (DATCP),
- Department of Industry, Labor and Human Relations (DILHR),
- Department of Natural Resources (DNR), and
- Department of Transportation (DOT).

Also, NR 140 applies to facilities and practices which may affect groundwater quality but are regulated by other agencies. However, the regulation does not apply to mining or prospecting activities, which are covered by other regulations.

2.2 Preventive Action Limits and Enforcement Standards

Wisconsin has two water quality standards for each parameter. The preventive action limit (PAL) is the lower of the two; exceedance of this value raises a red flag. The enforcement standard (ES) is the maximum allowable level. NR 140.10 specifies PAL's and ES's for 101 public health related standards. The PAL is ten percent of the ES for parameters with carcinogenic effects. For example, the ES for benzene is 5 micrograms per liter while the PAL for is 0.5 micrograms per liter. For other parameters with mutagenic, teratogenic or interactive effects the PAL is twenty percent of the ES. For example, for cyanide the ES is 200 micrograms per liter and the PAL is 40 micrograms per liter. Similarly, NR 140.12 specifies PAL and ES for parameters having aesthetic or other public welfare concerns. The PAL for these are 50 percent of the ES. For example the ES and PAL for chloride are 250 mg/l and 125 mg/l respectively.

PAL's are calculated for indicator parameters on a well specific basis. These are the parameters that are measured regularly but do not directly affect public health or welfare. For these parameters the PAL is calculated as:

$$PAL = \bar{x} + \max[3s, M] \qquad (2.1)$$

where $\bar{x}$ is the sample mean, s is the sample standard deviation and M is the minimum increase. s and $\bar{x}$ are estimated from a minimum of eight background samples for the particular constituent. Table 2-1 lists the minimum increase, M, for indicator parameters.

Parameter	Minimum Increase, mg/l
Alkalinity	100
Biochemical Oxygen Demand (BOD)	25
Boron	2
Calcium	25
Chemical Oxygen Demand (COD)	25
Magnesium	25
Ammonia Nitrogen	2
Organic Nitrogen	2
Total Nitrogen	5
Potassium	5
Sodium	10
Specific Conductance	200 μmhos/cm
Total Dissolved Solids (TDS)	200
Hardness	100
Total Organic Carbon (TOC)	1
Total Organic Halogen (TOX)	0.25

Table 2-1 Minimum Increase for Indicator Parameters

2.3 Monitoring Requirements

NR 140 covers many of the important factors necessary for environmental protection. However it does not provide specific information regarding the requirements for environmental monitoring for landfills. NR 507 defines the monitoring requirements. The purpose of this rule is:

> "... to help insure that efficient, nuisance-free and environmentally acceptable solid waste management procedures are practiced in this state, to outline environmental monitoring requirements at solid waste facilities and to implement groundwater standards according to NR 140 and ch. 160 stats."

This rule governs all environmental monitoring for solid waste disposal facilities except hazardous waste facilities and mining operations.

Prior to accepting waste, a landfill must have a WDNR approved sampling plan. This plan must include the number and location of all monitoring wells. The number of required monitoring wells is based on the facility size, waste type, design and hydrogeologic or geologic properties. However, each new municipal solid waste landfill (MSW) must have a minimum of four Subtitle D wells.

The baseline monitoring requirements vary depending on the type of waste accepted. For example, the groundwater monitoring requirements for a municipal solid waste landfill are different from a landfill that accepts foundry waste. Table 2-2 lists the detection parameters and sampling frequencies currently required for routine sampling at municipal solid waste landfills. Table 2-3 lists the detection parameters and sampling frequency requirements for other waste types. All proposed landfills must take four samples for all the detection parameters listed in Table 2-2 or 2-3 plus any public health and welfare parameters not included as detection monitoring parameters prior to submittal of the feasibility report. If exemptions to the groundwater standards for public health and welfare are granted in the feasibility determination, four more rounds of sampling for those parameters are required so that an ACL can be calculated and approved as a part of the plan of operation. For detection parameters, the next four samples must be taken before submittal of the plan of operation in order to accumulate a total of eight background samples. Each sample must have a minimum of 30 days between sampling rounds.

Detection Parameters	Frequency for All Wells	Frequency for Sub D. Wells
Alkalinity	Semi-annual	Semi-annual
Chloride	Semi-annual	Semi-annual
COD	Semi-annual	Semi-annual
Field Conductivity	Semi-annual	Semi-annual
Field pH	Semi-annual	Semi-annual
Field Temperature	Semi-annual	Semi-annual
Groundwater Elev.	Semi-annual	Semi-annual
Hardness	Semi-annual	Semi-annual
*VOC Scan	Annual	Semi-annual

Table 2-2 Monitoring Requirements for Municipal Solid Waste Landfills

* A list of VOC parameters for detection monitoring is in Appendix III of NR 507

Waste Type	Detection Parameters	Frequency for All Wells
Municipal Solid Waste	Alkalinity	Semi-annual
Combustor Residue	Boron	Semi-annual
	Cadmium	Semi-annual
	Chloride	Semi-annual
	COD	Semi-annual
	Field Conductivity	Semi-annual
	Field pH	Semi-annual
	Field Temperature	Semi-annual
	Groundwater Elevation	Semi-annual
	Hardness	Semi-annual
	Lead	Semi-annual
	Selenium	Semi-annual
	Sulfate	Semi-annual
Paper Mill Sludge	Ammonia Nitrogen	Semi-annual
	Alkalinity	Semi-annual
	Chloride	Semi-annual
	COD	Semi-annual
	Field Conductivity	Semi-annual
	Field pH	Semi-annual
	Field Temperature	Semi-annual
	Groundwater Elevation	Semi-annual
	Hardness	Semi-annual
	Nitrate + Nitrate as N	Semi-annual
	Sulfate	Semi-annual
Fly or Bottom Ash	Alkalinity	Semi-annual
	Boron	Semi-annual
	COD	Semi-annual
	Field Conductivity	Semi-annual
	Field pH	Semi-annual
	Field Temperature	Semi-annual
	Groundwater Elevation	Semi-annual
	Hardness	Semi-annual
	Sulfate	Semi-annual
		Semi-annual
		Semi-annual
		Semi-annual
Foundry Waste	Alkalinity	Semi-annual
	COD	Semi-annual
	Field Conductivity	Semi-annual
	Field pH	Semi-annual
	Field Temperature	Semi-annual
	Fluoride	Semi-annual
	Groundwater Elevation	Semi-annual
	Hardness	Semi-annual
	Sodium	Semi-annual
Other Solid Waste	As Specified in Writing by the WDNR	

Table 2-3 Monitoring Requirements for Other Solid Waste Landfills

2.4 Responses When a Groundwater Standard is Attained or Exceeded

Wisconsin's rules differ slightly from the U.S. EPA Subtitle D. Subtitle D requires analysis of groundwater samples from designated wells for indicator parameters. These parameters include fifteen metals and VOC's. Wisconsin's approved plan allows for routine monitoring of detection parameters as listed in Table 2-2 and 2-3. Wisconsin's detection monitoring does not include routine metals monitoring. Also, the VOC monitoring is as specified in Table 2-2. If a PAL is exceeded for an indicator parameter, assessment monitoring in accordance with Wisconsin's approved plan may be required.

If the concentration of a substance, including indicator parameters, in groundwater attains or exceeds a PAL this does not automatically lead to assessment monitoring. Sections NR 140.24, NR 140.26 and Chapter NR 508 outline the appropriate responses for exceedances. First, the landfill owner must notify the WDNR in writing of the exceedance. Second, the owner must provide a preliminary analysis of the cause and significance of the concentration. In response the WDNR evaluates the notice and preliminary analysis. The WDNR may require the owner to further assess the cause and significance of the increased concentration and prepare a report evaluating the degree and extent of the problem.

The owner may demonstrate that a reported value represents a false exceedance of the groundwater standard. While reviewing this information the WDNR may look at a number of different items to determine the cause and significance of the exceedance. They may consider:

- the location of the monitoring well;
- the specific characteristics of the site;
- the nature of the substances involved and the likelihood of migration;
- background water quality;
- reliability of sampling data;
- public health, welfare and environmental effects;
- probability that a PAL or ES may be attained or exceeded outside the design management zone (DMZ) of the landfill;
- performance of the facility;
- other known or suspected sources of the substance in the area;
- hydrogeologic conditions;
- extent of groundwater contamination;
- alternate responses.

Within 30 days, if the WDNR does not agree that the exceedance is a false positive, the owner must begin assessment monitoring. If the exceedance is for one of the inorganic compounds listed in Table 2-2 then the WDNR may allow an alternative assessment monitoring plan. Also, an alternate monitoring plan may be approved to include only the parameters that are present in the leachate collection system. If the full assessment monitoring proceeds, all the parameters in Appendix II of NR 507 must be included in the monitoring program. This includes but is not limited to the following:

Public Welfare Parameters	Public Health Parameters
Copper	Arsenic
Manganese	Barium
Sulfate	Cadmium
Zinc	Chromium
	Fluoride
	Lead
	Mercury
	Nitrate + Nitrite (as N)
	Selenium
	Silver
	Antimony
	Beryllium
	Nickel
	Thallium

Table 2-4 Assessment Monitoring Parameters

Assessment monitoring is only one of the options available to the WDNR if a well exceeds a PAL, ES or ACL. The range of responses which the WDNR may take are:

- no action (only for PAL's at NR 140 wells);
- sample wells or require sampling of wells;
- require a change in the monitoring program, including increased monitoring;
- require an investigation of the extent of groundwater contamination;

- require a revision of the operational procedures at the facility, practice or activity;
- require an alternate method of waste treatment of disposal;
- require prohibition or closure and abandonment of a facility, practice or activity;
- require remedial action to renovate or restore groundwater quality;
- revise rules or criteria on facility design, location or management practices.

CHAPTER 3

DUMPStat ALGORITHMS

3.1 Introduction

In the previous chapter we introduced the current groundwater monitoring regulations as enforced by the Wisconsin Department of Natural Resources (WDNR). In this chapter we consider the potential use of DUMPStat as an approach for evaluating groundwater monitoring data at landfill sites. DUMPStat (Downgradient, Upgradient Monitoring Program Statistics) is a statistical package developed by Gibbons. It has five analysis options:

- upgradient versus downgradient (interwell) prediction limits;
- intrawell prediction limits (PL's) and combined Shewhart-CUSUM; control charts (CC's)
- time series plots;
- VOC detection;
- assessment monitoring.

The two intrawell options could potentially replace the indicator PAL. The objective of this research is to evaluate DUMPStat as an alternative to the current methods for calculating the PAL for indicator parameters. The objective of this chapter is to discuss operational issues, to introduce all the options available in DUMPStat, and to take a closer look at the two intrawell options.

3.2 DUMPStat Operation

We found the DUMPStat program easy to use. The program runs well both in Windows 3.11 and Windows 95. We had no installation problems. In addition, the menus are easy to understand and use. The program, in its current form, would be difficult to misuse because all important statistical parameters cannot be changed. For example, the user cannot select the significance level for the prediction limit. Also, the statistical parameters for the combined Shewhart -CUSUM control chart are set and cannot be changed.

The WDNR data was easily merged into the DUMPStat database, with only a few problems. The problems we experienced were with nondetect heavy metals. DUMPStat requires that the nondetect data include detection limits. Some data did not include the detection limit and could not be merged. Most indicator parameter data are above the detection limit. So for our study, merging indicator parameters was not a problem. However, merging large data sets (over 10 Mb) can take over an hour. Merging smaller data sets takes only minutes. In order to shorten merging times, we used a database program to isolate the wells and parameters of interest.

After the data have been merged into the database a few more steps need to be taken to run the DUMPStat options. First, the time window for the background data needs to be defined. Second, the minimum number of background samples needs to be selected (typically eight for indicator parameters). Third, a rare event statistic needs to be selected, either Poisson prediction limits or nonparametric prediction limits. We did not examine parameters that would require use of rare event statistics. Fourth, we decided to identify historical trends, an optional step. Fifth, we isolated the wells and constituents of interest. If these steps are followed most DUMPStat options can be performed.

3.3 DUMPStat Options

DUMPStat has five options for analysis. After merging the data and performing the five steps listed in the previous section these options can be used. The first option is the upgradient versus downgradient prediction limits. The second option includes the intrawell prediction limits (PL's) and combined Shewhart-CUSUM control charts (CC's). This option is the main focus of this study and is discussed below. The third option is the time series plots. This option can be used to plot the concentration versus time for the selected parameters. The fourth option, VOC detection, lists all the selected volatile organic compounds (VOC) above the detection limit. The fifth option is assessment monitoring. For each parameter for which a health or welfare standard is set (by the user), DUMPStat makes a time series plot, determines if any trends exist, and performs a t-test for the last four independent samples. Section NR 140.14 allows the t-test or another valid statistical analysis for the data being considered for health and welfare standards.

3.4 Intrawell Methods

As mentioned previously, the intrawell methods in DUMPStat could potentially replace the use of PAL's for detecting changes in values for indicator parameters. DUMPStat has two methods for intrawell testing: prediction limits (PL's) and the combined Shewhart-CUSUM control charts (CC's).

3.4.1 Prediction Limits

When the prediction limit is used, DUMPStat first removes outliers from the background data using Dixon's test. Next, DUMPStat tests for increasing trend in the background data using Sen's test. Then the prediction limit is calculated as:

$$PL = \overline{x} + s \cdot t_{[1-\alpha, n-1]} \cdot \sqrt{1 + \frac{1}{n}} \tag{3.1}$$

where $\overline{x}$ is the sample mean, s is the sample standard deviation, n is the number of background samples, and $t_{[1-\alpha, n-1]}$ is the t-statistic based on the 1-α confidence level (or α significance level) and n-1 degrees of freedom.

The significance level, α, is the minimum of: 0.01 or

$$\alpha = \sqrt{1 - 0.95^{\frac{1}{k}}}\,. \tag{3.2}$$

where k is the number of future comparisons. From equation 3.2 we can determine that when k is 100, α is the minimum of 0.01 and 0.0226. k will always be less than 100; consequently α will always be 0.01 for intrawell analysis. Further, equation 3.2 is based on one verification resample. We were not able to verify historical results for our analysis. Consequently, DUMPStat only indicated a violation after two consecutive exceedances.

The PL is a logical alternative to the PAL because a limit is set based on the background mean and standard deviation. Similar to the indicator PAL, the PL is compared to future data points. Also, prediction limits and indicator PAL's are better suited for detecting sudden increases in concentration. Unlike the indicator PAL, DUMPStat does not indicate a violation unless the resample or the next sampling round (depending on the verification resampling plan) also violates the PL. The PL procedure outlined here as well as the tests for historical trend and outliers are illustrated in detail with examples in appendix A.

A comparison can be made between the indicator PAL and PL without calculating either. Most of the time, the PL as implemented by DUMPStat will be more conservative and will produce more violations than the indicator PAL. This is true for two reasons. First, the PL does not allow for a minimum increase like the indicator PAL. This minimum increase allows an additional benefit to the landfill owner for indicator parameters with a low variance. Second, the number of standard deviations used to compute the PAL will generally be greater than that used to compute the PL. Consider the second point. The PAL is always three standard deviations above the mean. However, for the PL the number of standard deviations is $t_{[1-\alpha,n-1]} \cdot \sqrt{1+\frac{1}{n}}$. The dependence on n, the number of background samples, is illustrated in Figure 3-1 for a 99 percent confidence level. From this figure, we can see with eight background samples the PL is 3.18 standard deviations above the mean which is almost the same as the indicator PAL. Further, with ten background samples the PL is 2.96 standard deviations above the mean which is essentially the same as the indicator PAL. Looking at Figure 3-1 we can conclude that the PL is more conservative than the PAL for ten or more background samples. From eight to ten background samples the PL is essentially the same as the indicator PAL. Since eight is the minimum number of background samples for indicator parameters the PL will at worst be 0.18 standard deviations above the PAL.

All in all, the PL, as implemented by DUMPStat, is more conservative than the indicator PAL. The PL will cause more violations than the indicator PAL. This could result in additional monitoring or possibly remedial action.

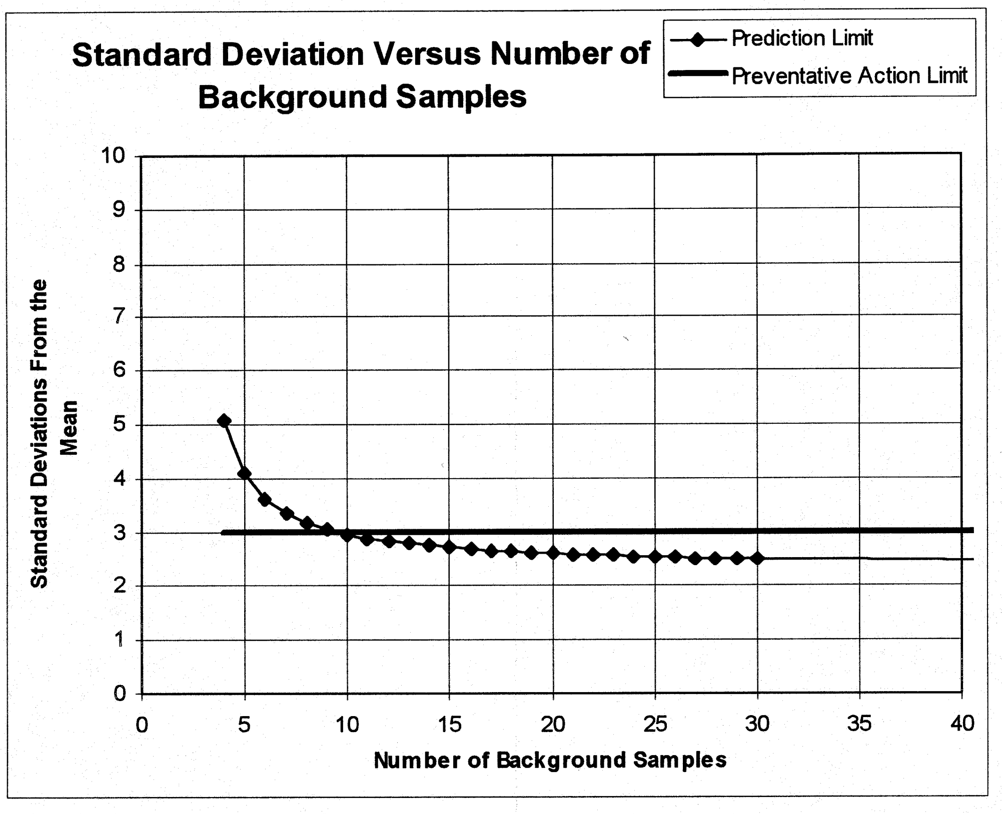


Figure 3-1 Comparison of PAL and PL Based on Number of Background Samples

3.4.2 Combined Shewhart-CUSUM Control Charts

The second intrawell method that could replace the indicator PAL is the combined Shewhart-CUSUM control chart (CC). As its name suggests, the combined Shewhart-CUSUM control chart combines the Shewhart control chart with the CUSUM control chart. The CC can pick up sudden changes as well as long term upward trends in water quality.

The Shewhart control chart is often used in industrial practice. Consider a bolt manufactured with a specified diameter. The diameter of the bolt is assumed to be a random variable. A mean and standard deviation for the bolt diameter can be calculated. The original Shewhart control chart is "out of control" if the bolt diameter is three standard deviations above or below the mean. If the control chart is "out of control" then the problem is considered deterministic. Theoretically, a deterministic problem can be fixed by changing the machinery or the operator. This is very similar to the current indicator PAL. In fact, the WDNR is currently using a one sided Shewhart control chart since the indicator PAL is set three standard deviations above the mean.

The Shewhart test used in DUMPStat is a variation of the original Shewhart control chart. It is a one sided test and the control chart is "out of control" if the sample exceeds the mean by 4.5 standard deviations for eleven or fewer background samples or by 4.0 standard deviations for twelve or more background samples.

The cumulative sum (CUSUM) portion of the control chart is much different. While the Shewhart portion of the control chart detects sudden increases in concentration the CUSUM portion detects steady or slow increases in concentration. The CUSUM, S_i is calculated as

$$S_i = \max[0, (z_i - k) + S_{i-1}] \tag{3.3}$$

where z_i is defined as

$$z_i = \frac{x_i - \bar{x}}{s}, \tag{3.4}$$

$\bar{x}$ is the sample mean, s is the sample standard deviation, and x_i is the concentration of interest. Also, k is a parameter related to the displacement which should be detected quickly (one for eleven or fewer background samples and 0.75 for twelve or more background samples) and S_0=0. The CUSUM portion of the control chart is considered "out of control" if S_i is greater than 4.5 for eleven or fewer samples and 4.0 for twelve or more samples.

Like the prediction limits, the DUMPStat CC does not indicate a violation unless it is confirmed by a resample or the next round of sampling. If a resample is taken it should replace the original value in order to provide an unbiased confirmation of the exceedance for the CC. A complete explanation of the CC is included in Appendix A with a sample calculation.

3.6 Chapter Summary

All in all we found the DUMPStat program easy to install and use. The program has several simple and useful options including: assessment monitoring, time series plotting and VOC detection. DUMPStat also has interwell prediction limits which do not fit well into the WDNR system since intrawell analysis is the preferred method. DUMPStat has two intrawell options: prediction limits and the combined Shewhart-CUSUM control charts. Of these two, the prediction limits are more conservative than the indicator PAL for ten or more background samples. Further, they are essentially the same as the PAL for eight or nine background samples. The combined Shewhart-CUSUM control chart on the other hand is more difficult to evaluate since a limit can only be set for the next sampling round while the prediction limit sets a limit for the next k sampling rounds. In the next chapter we apply these intrawell methods to data from a Wisconsin landfill.

CHAPTER 4

PORTAGE COUNTY CASE STUDY

4.1 Introduction

As previously mentioned, the indicator PAL could potentially be replaced by either of the two DUMPStat intrawell options: prediction limits (PL's) or the combined Shewhart-CUSUM control charts (CC's). In order to examine and compare the effectiveness of the PAL's, PL's and CC's we applied all three methods to the Portage County landfill (license number 2966), a landfill which is not apparently affecting groundwater quality.

We examined both upgradient and downgradient wells using the indicator parameters: alkalinity, hardness and specific conductance. Using box plots, time series plots and a site map we classified each well into one of four categories: up/sidegradient unimpacted; downgradient impact possible; downgradient impact suspected; and downgradient unimpacted. Next for each parameter and each well, we applied the indicator PAL, PL and CC methods. The effectiveness of each method was evaluated using the downgradient impacted wells, while the false positive rate was estimated based on the unimpacted upgradient and sidegradient wells.

Based on this case study we found that the CC's were more conservative than the PL's, and both methods were more conservative than the indicator PAL. That is, the CC and PL would put the landfill in violation much more often than the indicator PAL. This result confirms the arguments made in the third chapter.

In addition, we found an unexpected number of violations at upgradient wells. We used these violations to estimate the false positive rate and we found it to be very high for some unimpacted wells. The high number of violations and high false positive rates led us to question the assumptions of these statistical tests. This issue is considered in Chapter 5.

4.2 Portage County Landfill Characteristics

The Portage County landfill is located approximately in the center of the state of Wisconsin. As stated previously, the landfill has a number of upgradient and sidegradient wells which are not likely to have been impacted by the landfill. The landfill also has a number of downgradient wells. The location of all wells and the direction of groundwater flow are shown on Figure 4-1.

Fifteen of the wells have continuous data from 1983 to the present. Each well has approximately 51 data points for each indicator parameter. Of these fifteen wells, three can be clearly classified as upgradient (W-10, W-11 and W-12). Two of the wells are sidegradient but appear to be beyond the influence of the landfill (W-9 and W-9p). The site has ten clearly downgradient wells (W-17, W-18, W-20, W-20p, W-21, W-21p, W-22, W-22p, W-23 and W-23p). The "p" designates a deep well (piezometer), screened below the water table. These wells are screened in sandy glacial till (in a sand fraction that is coarser than above). The wells without the "p" designation are screened at (or near) the water table which is in fine to very fine sandy glacial till.

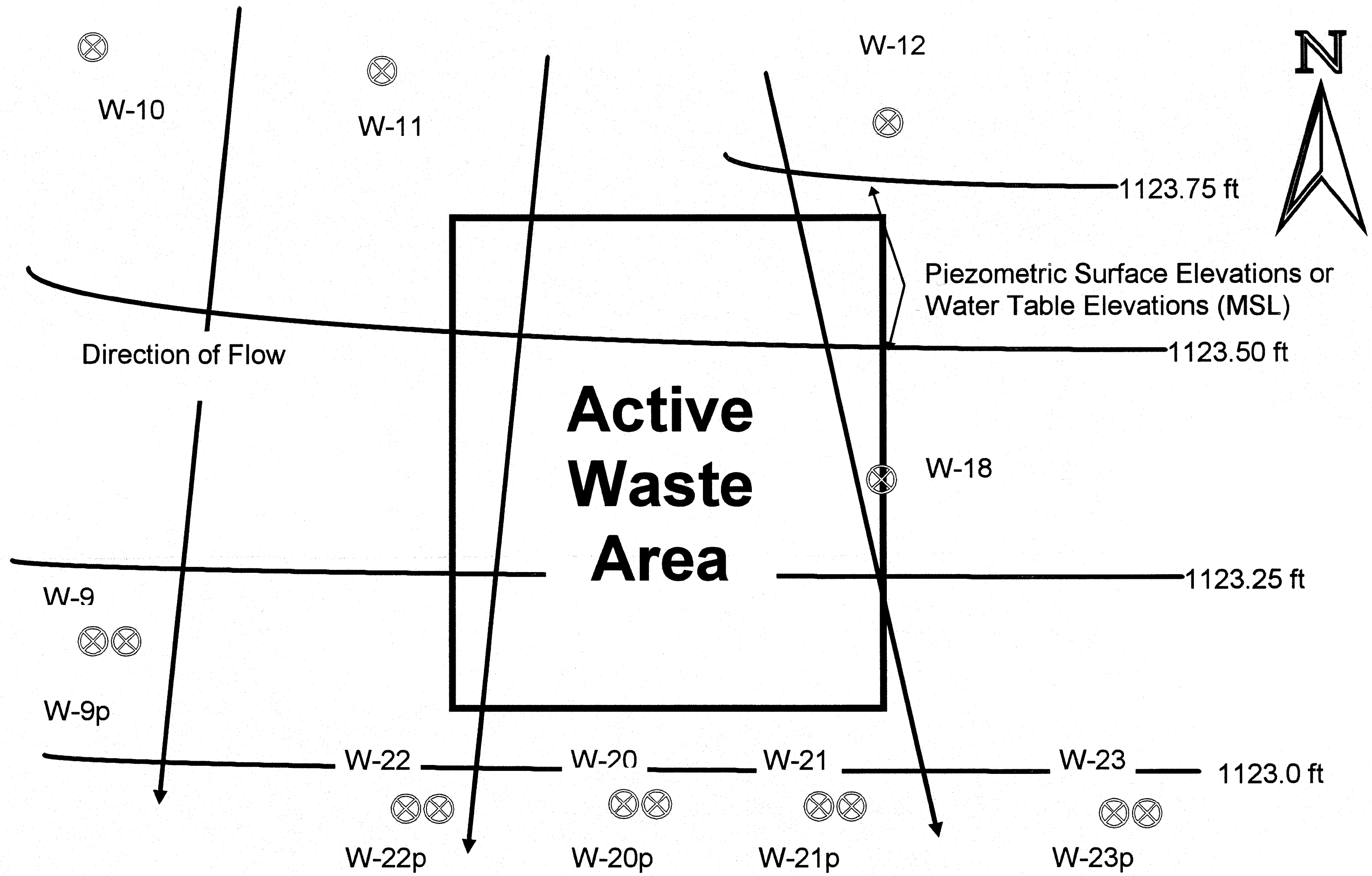


Figure 4-1 Portage County Landfill Well Location Map

4.3 Box Plots and Time Series Plots

As a preliminary step in the evaluation of the landfill, we prepared box plots and time series plots for all wells. These plots were discussed and recommended in the two previous WDNR studies (Goodman, 1987 and Fisher, 1989). These studies suggested that a high median or interquartile range (IQR) may indicate contamination. Similarly, multiple outliers or extreme values may indicate contamination. Box plots for all the wells for a single parameter should be plotted simultaneously. Aside from the box plots, time series plots can be visually inspected for increasing trends. Multiple time series can be plotted on one graph; however, this should be limited to five or fewer wells and one parameter per graph. In addition, at least one upgradient or sidegradient well should be plotted on each graph for comparison.

Figure 4-2, 4-3 and 4-4 show the box plots from the fifteen wells for alkalinity, hardness and specific conductance respectively. The box plots were created by Statistica (1997) and the box plot construction is indicated in Figure 4-5. Time series plots for alkalinity (Figures 4-6, 4-7 and 4-8), hardness (Figures 4-9, 4-10 and 4-11) and specific conductance (Figures 4-12, 4-13 and 4-14) also are given. These box plots and time series plots are based on quarterly samples for each constituent at each well (approximately 51 samples for each parameter). By visually inspecting the box plots, time series plots and well location map, we made some preliminary classifications. Based on these classifications we will compare the effectiveness of the indicator PAL to the PL and CC. The preliminary classifications are:

1. Up/sidegradient unimpacted: W-10, W-11, W-12, W-9 and W-9p
2. Downgradient impact possible: W-17, W-20p, W-21p, W-22 and W-22p
3. Downgradient impact suspected: W-20, W-21 and W-23p
4. Downgradient impacted: W-18 and W-23

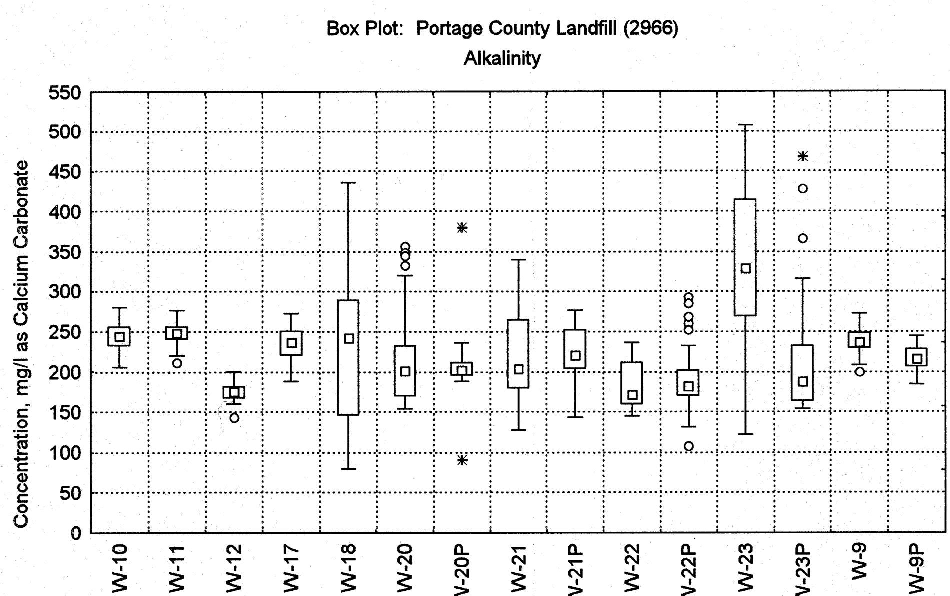


Figure 4-2 Box Plots for Alkalinity

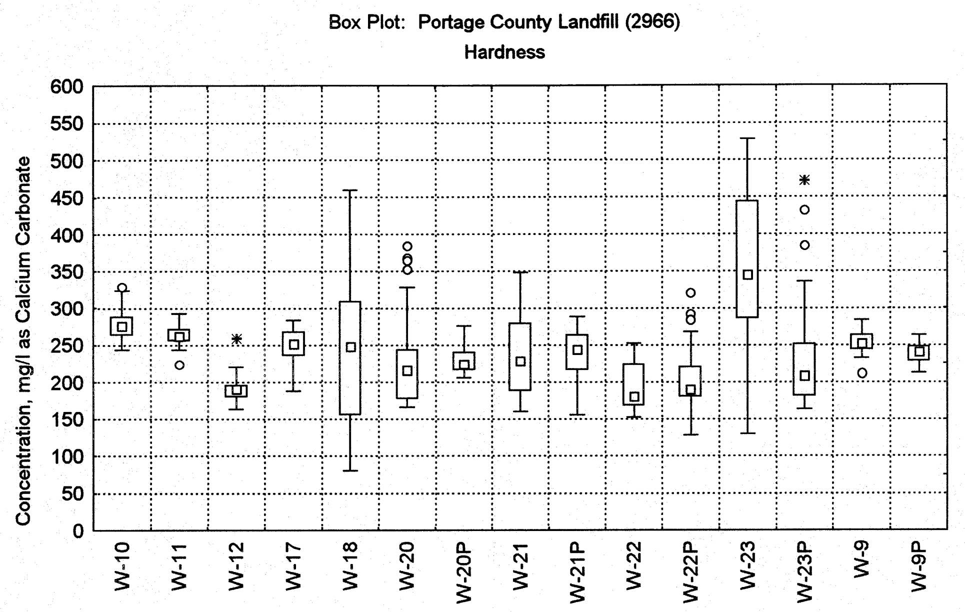


Figure 4-3 Box Plots for Hardness

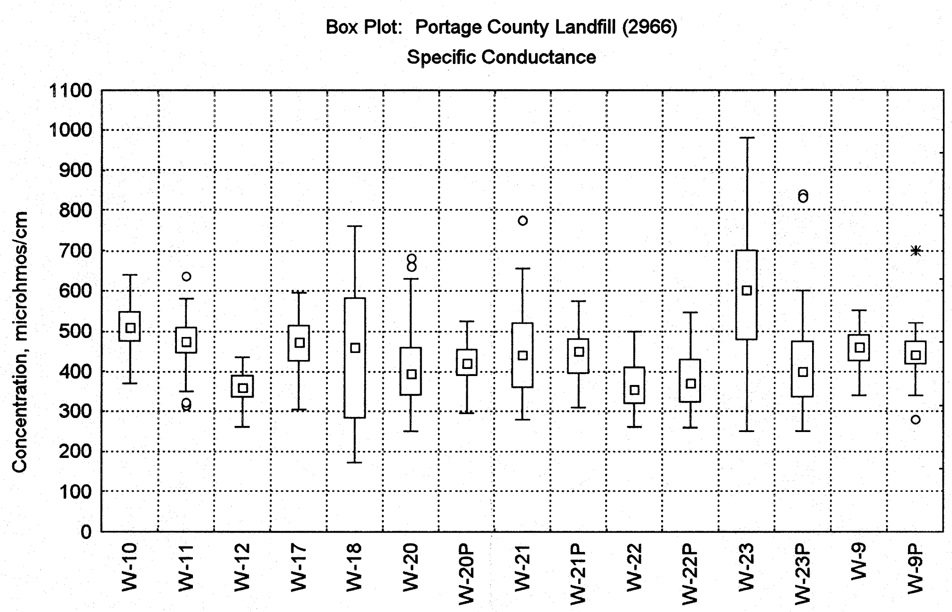


Figure 4-4 Box Plots for Specific Conductance

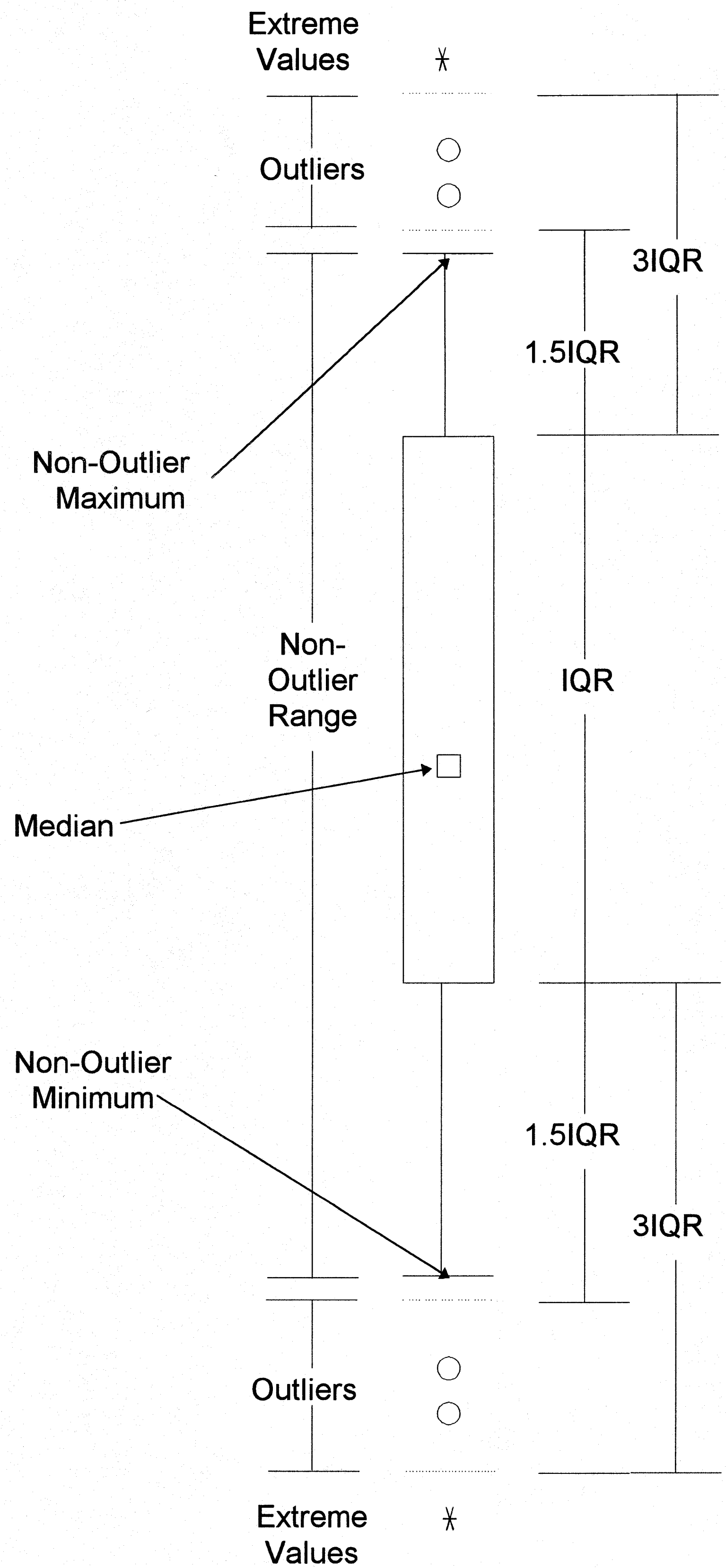


Figure 4-5 Box Plot Construction by Statistica

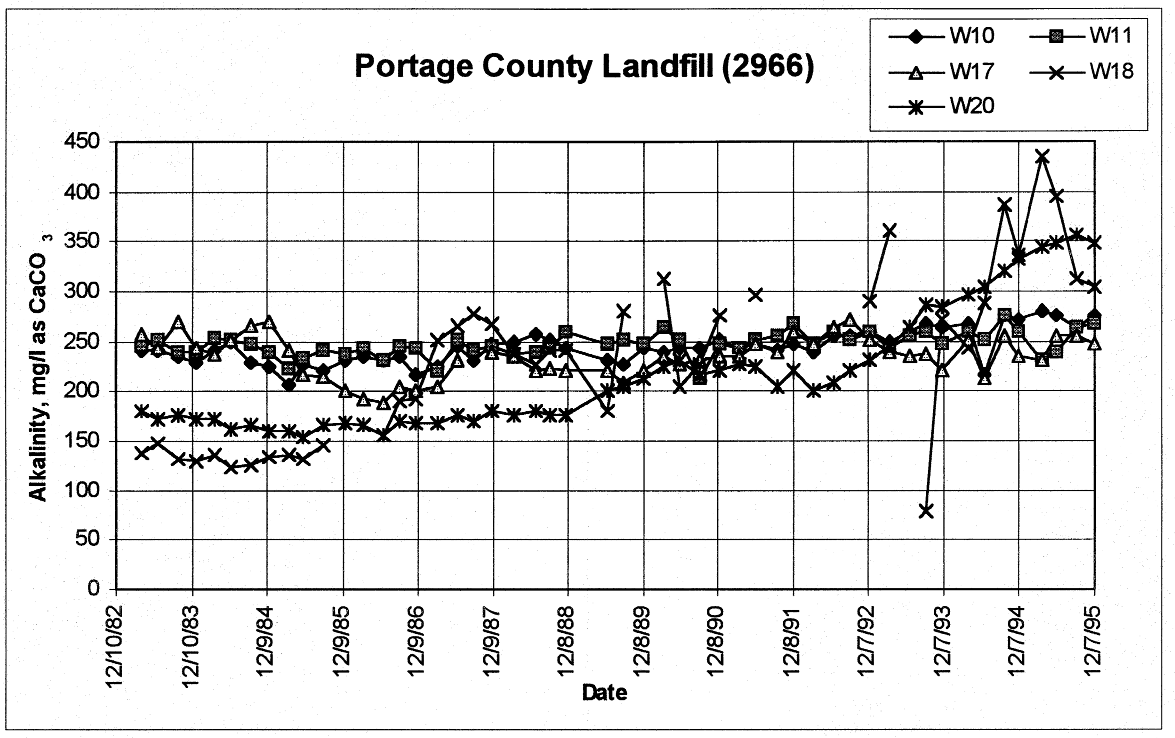


Figure 4-6 Time Series Plots Alkalinity

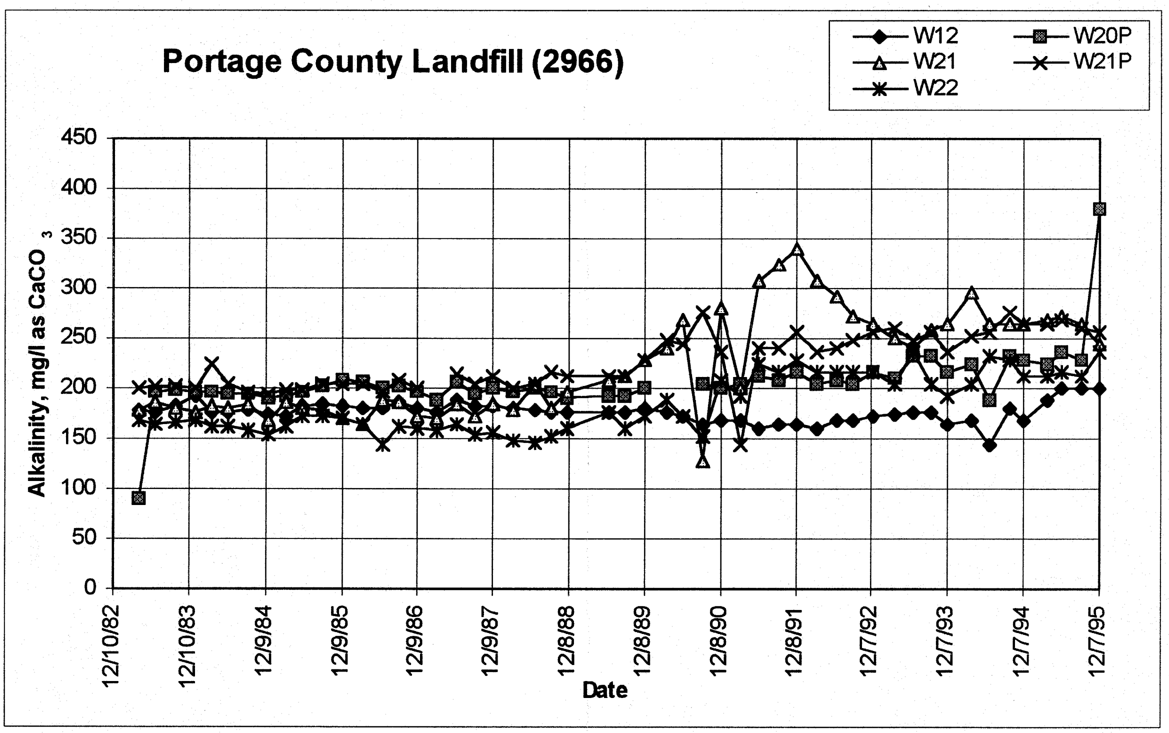
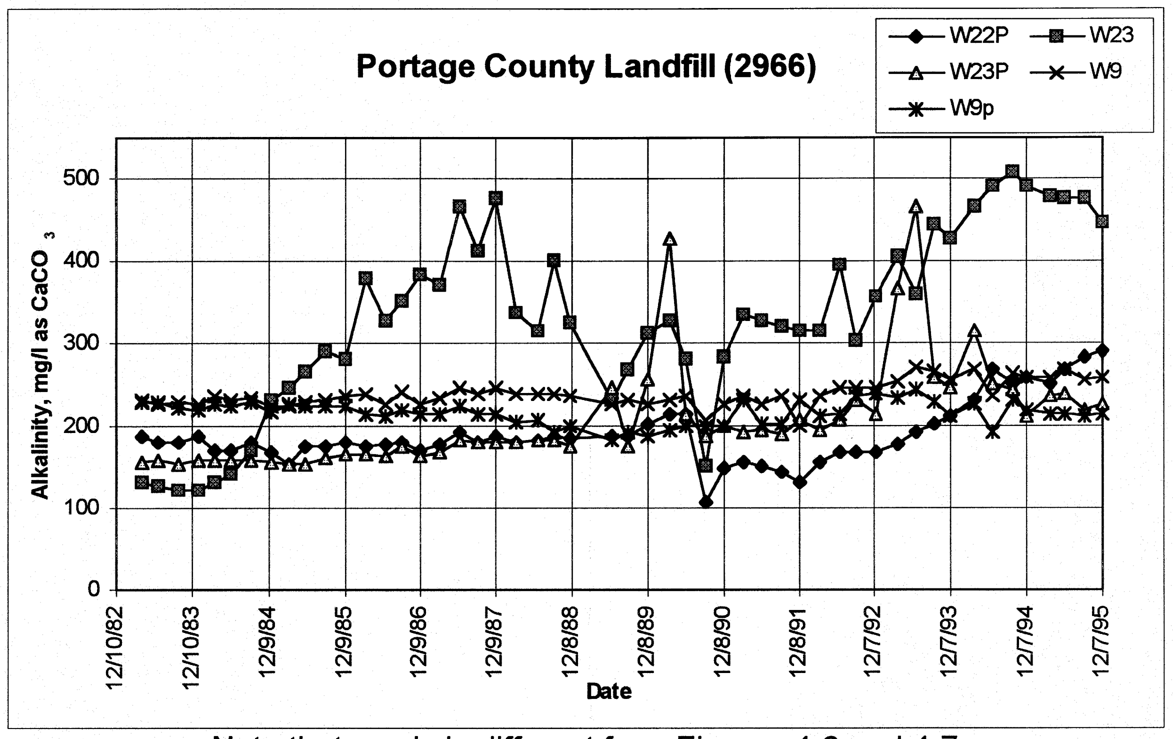


Figure 4-7 Time Series Plots Alkalinity



Note that y-axis is different from Figures 4-6 and 4-7

Figure 4-8 Time Series Plots Alkalinity

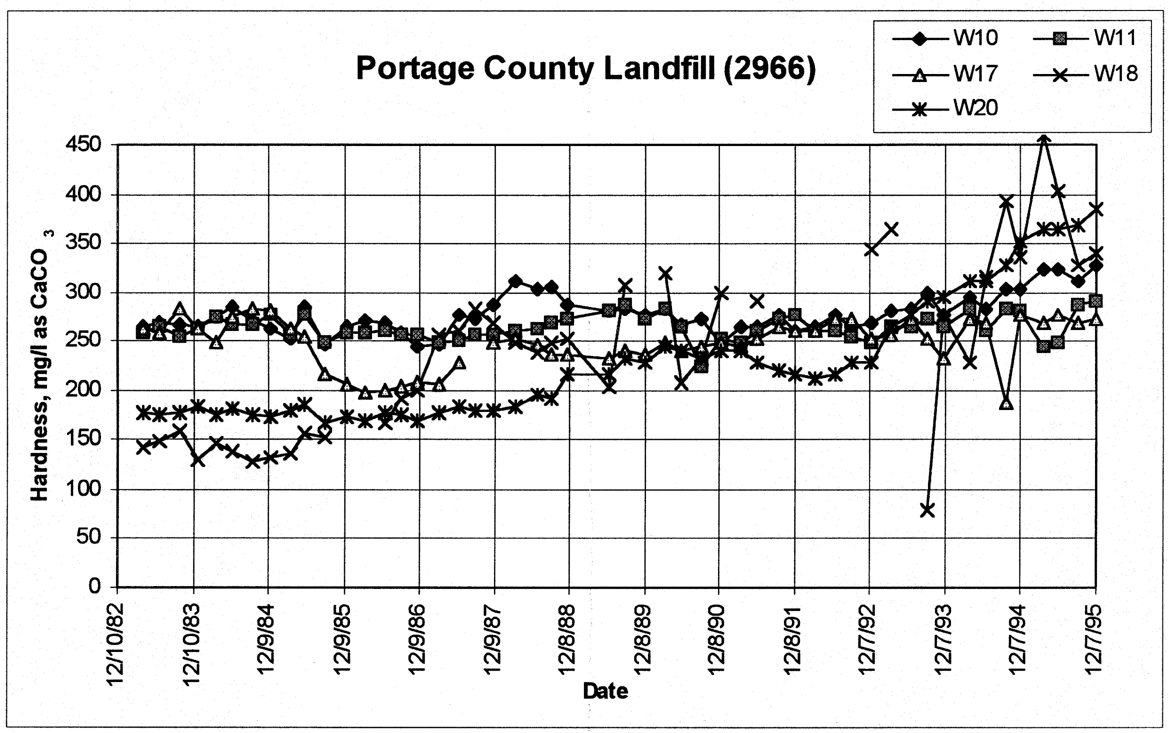


Figure 4-9 Time Series Plots Hardness

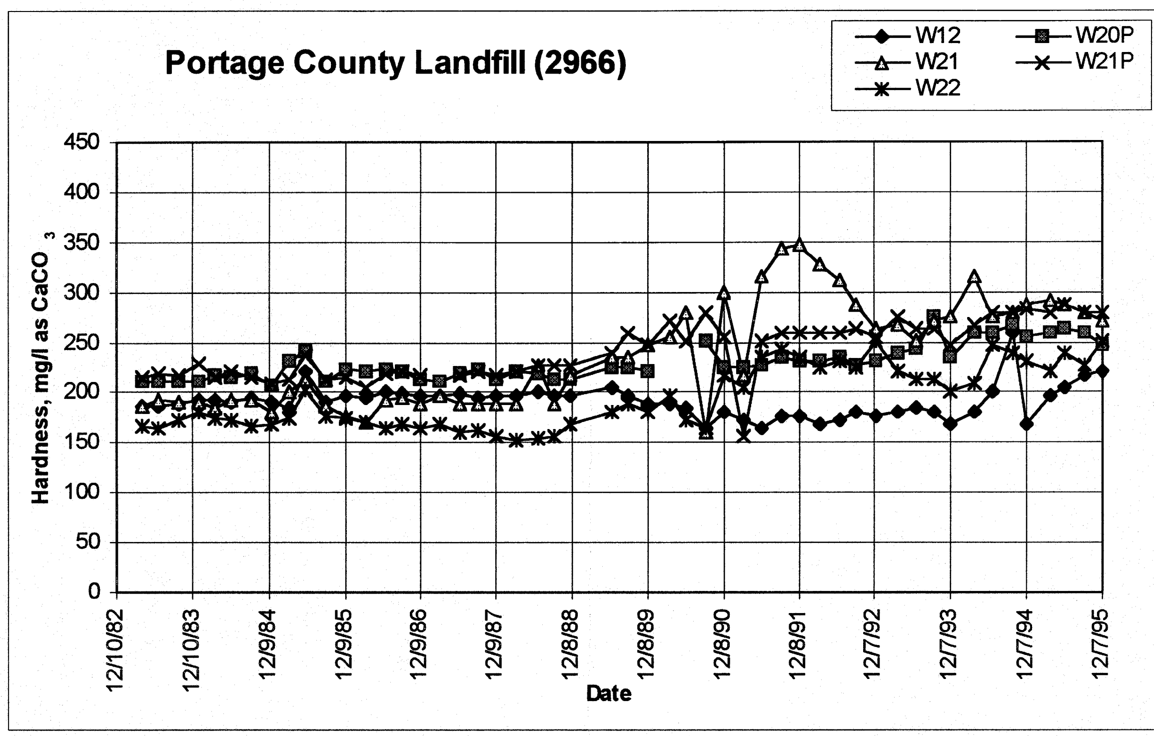
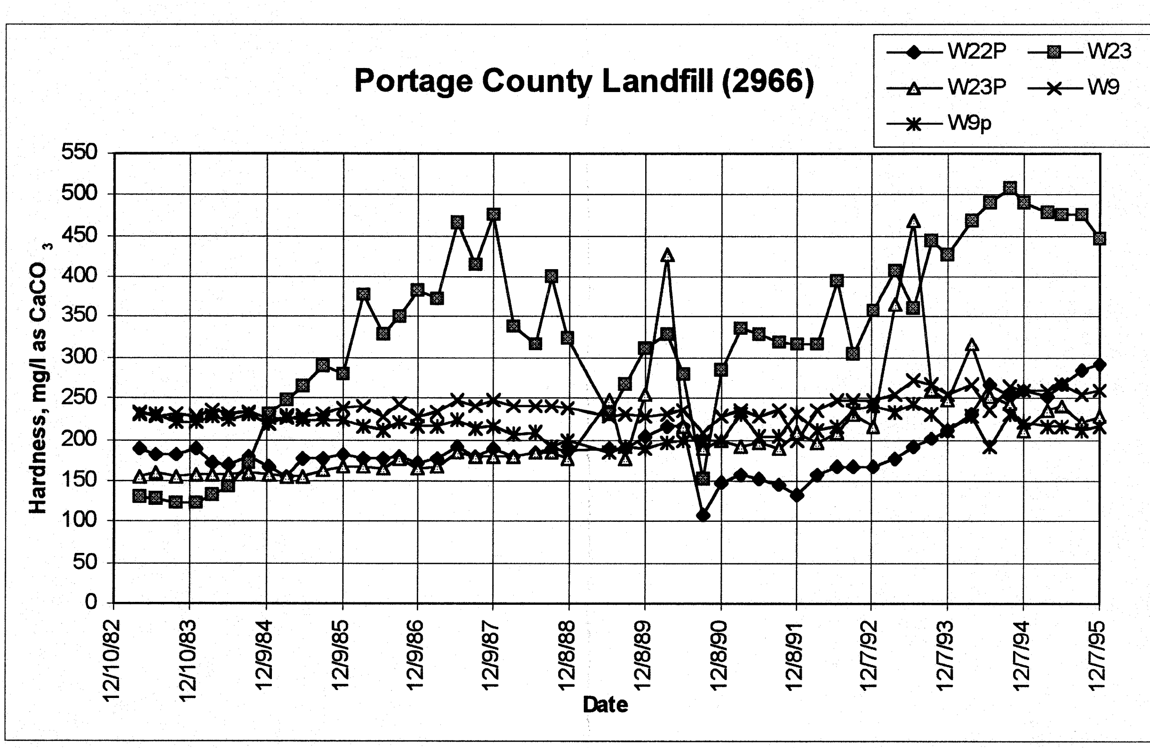


Figure 4-10 Time Series Plots Hardness



Note that y-axis is different from Figures 4-9 and 4-10

Figure 4-11 Time Series Plots Hardness

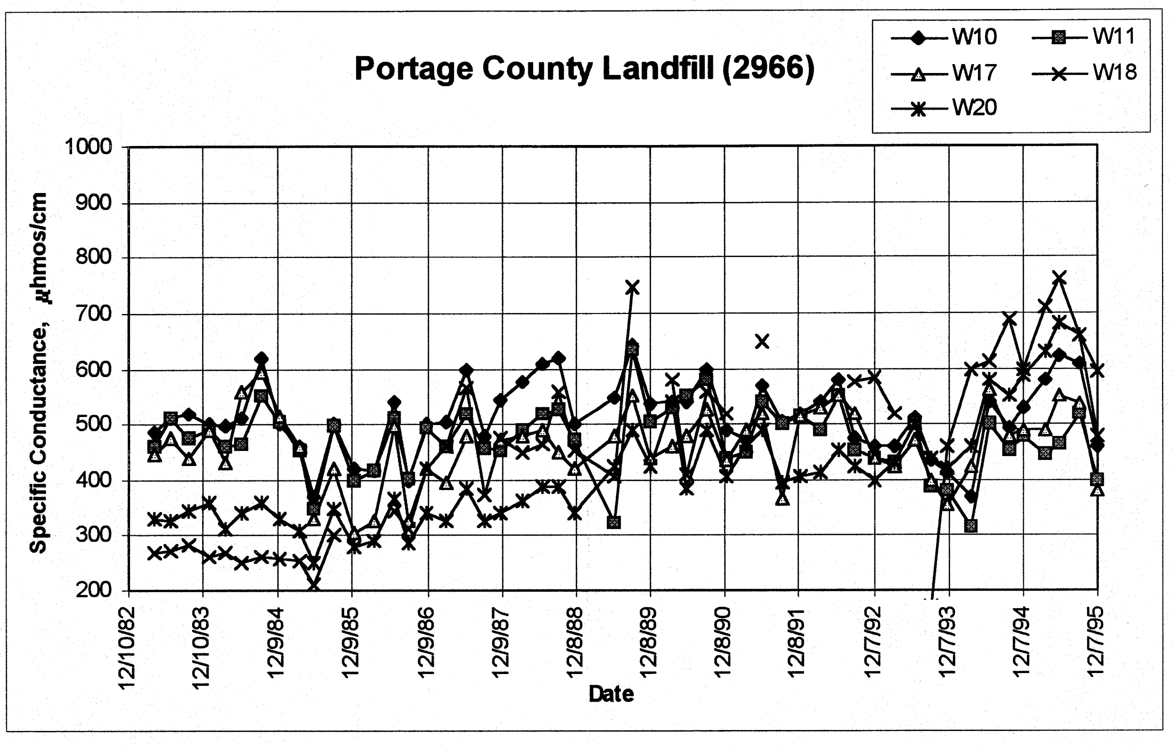


Figure 4-12 Time Series Plots Specific Conductance

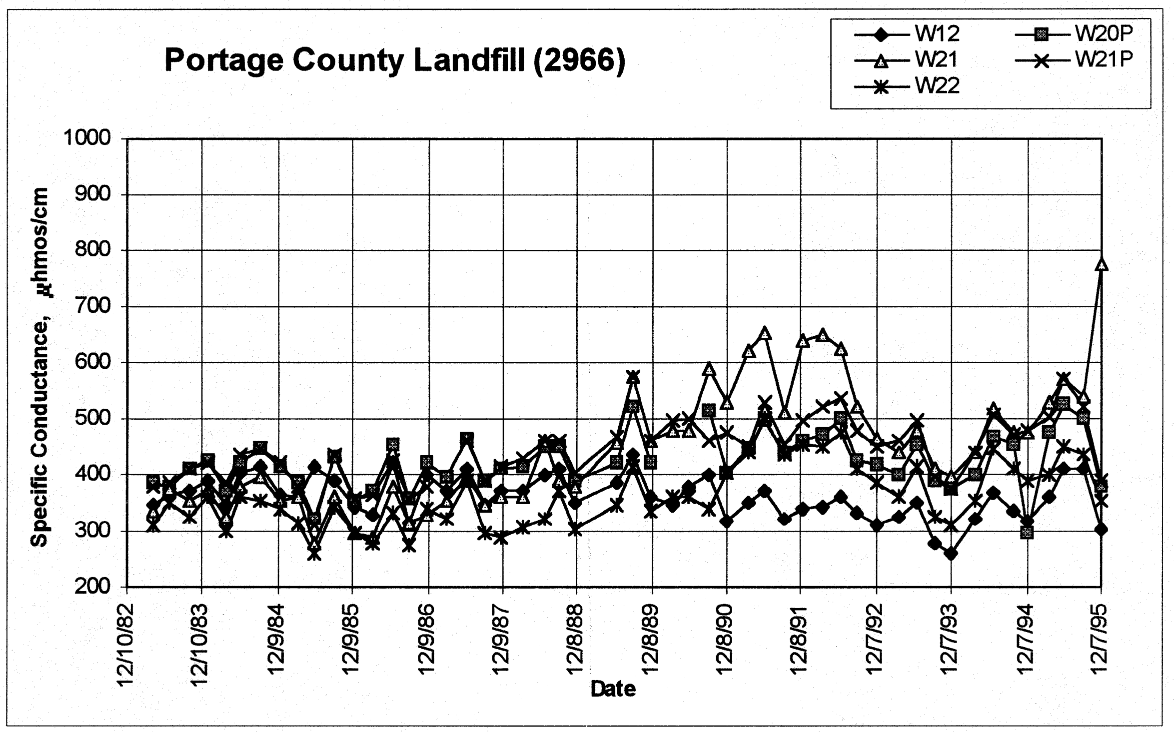


Figure 4-13 Time Series Plots Specific Conductance

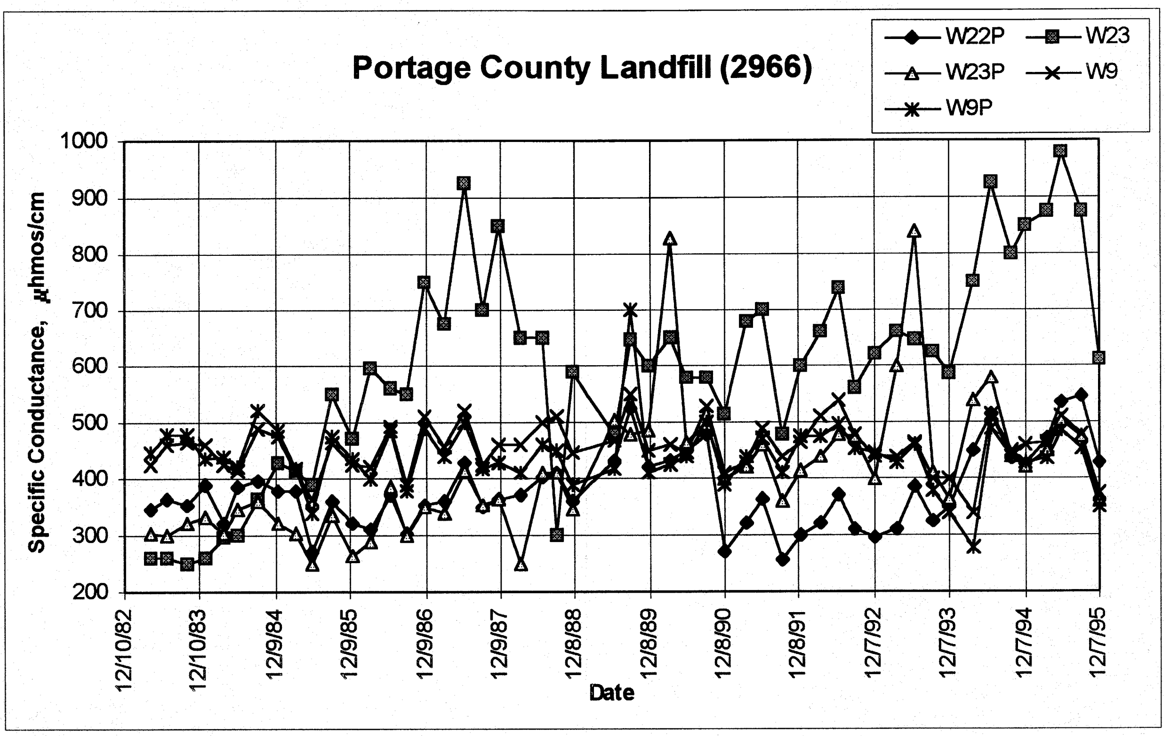


Figure 4-14 Time Series Plots Specific Conductance

4.4 Intrawell Analysis All Wells

Box plots and time series plots, as discussed in the previous section, can be an important tool for groundwater monitoring. In fact, the use of these visual aids may be better than the use of any statistic. However, these visual aids must be used with appropriate statistics governed by law. Currently, the appropriate statistic for alkalinity, hardness and specific conductance is the indicator PAL. The DUMPStat alternatives to the indicator PAL are the PL and CC.

First let us compare the PL to the indicator PAL. Figures 4-15, 4-16 and 4-17 show the indicator PAL and PL for alkalinity, hardness and specific conductance, respectively, based on eight background samples. From these figures we can see the PL is lower for all but a few of wells for each parameter. The PL is higher than the indicator PAL for W-23 for all parameters and for W-20p for alkalinity, because the standard deviation for each is greater than M/3 where M is the minimum increase. Recall (figure 2-1) that the minimum increase for alkalinity, hardness and specific conductance is 100 mg/l, 100 mg/l and 200 μhmos/cm, respectively. So if the variance is above 33.3 mg/l, 33.3 mg/l or 66.7 μhmos/cm for alkalinity, hardness and specific conductance, respectively, the PL will be 3.18 standard deviations above the mean while the indicator PAL will be 3.00 standard deviations above the mean for eight background samples. Otherwise the minimum increase above the mean is set as the indicator PAL which is well above the PL.

We also calculated the PL and indicator PAL based on 25 background samples. As expected, the PL is always less than the indicator PAL. The indicator PAL and PL for 25 background samples are given in Figures 4-18, 4-19 and 4-20 for alkalinity, hardness and specific conductance. For 25 background samples, the PL for parameters with a high variance (over M/3) will be close to the indicator PAL while those with a low variance tend to be much lower than the indicator PAL. Using 25 background samples also produced lower PL than using eight background samples. This result is expected and explained in the last chapter.

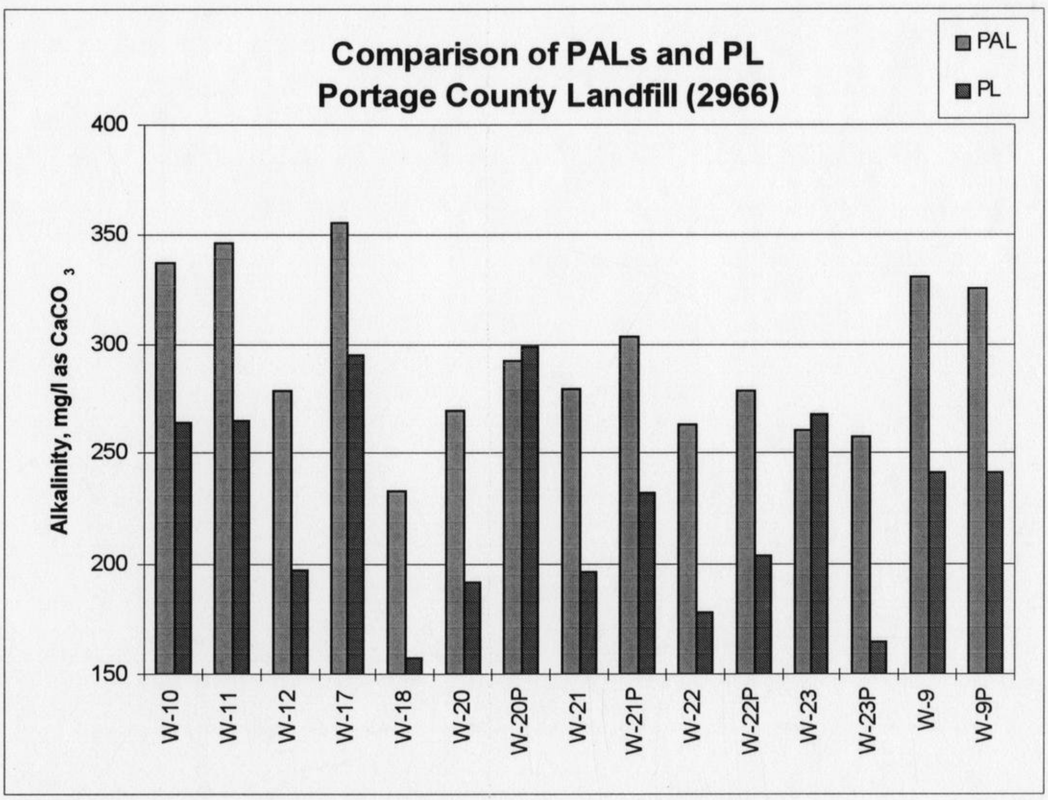


Figure 4-15 PAL and PL for Alkalinity
(8 Background Samples)

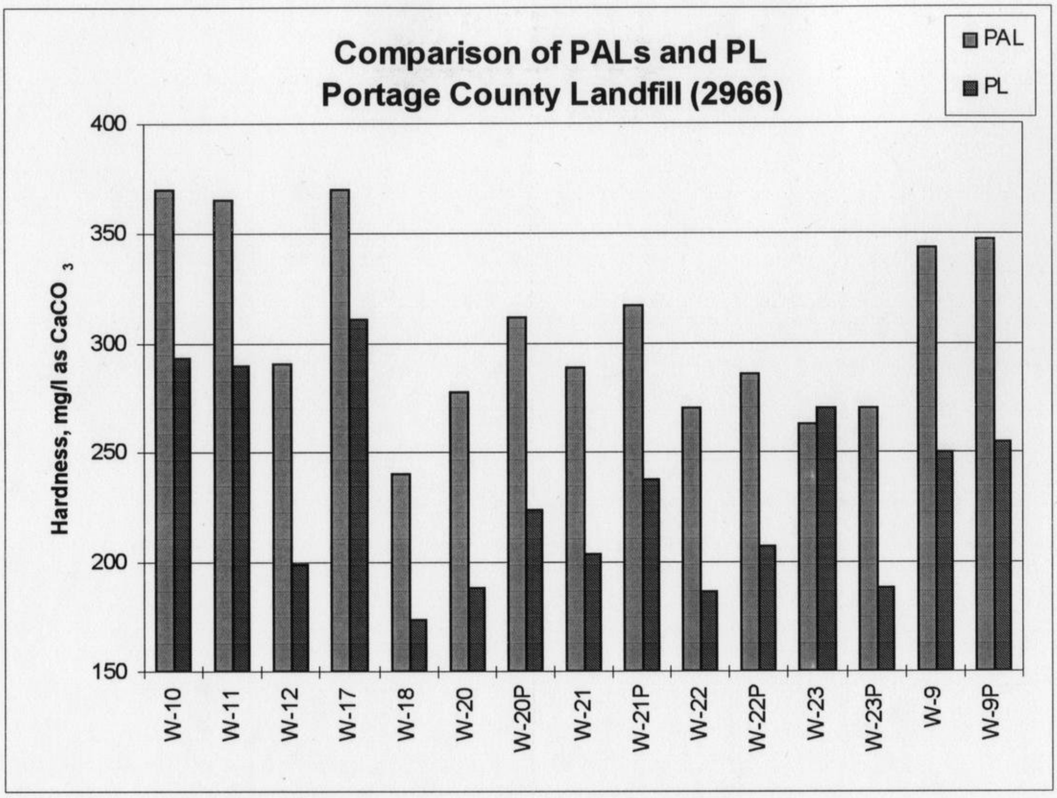


Figure 4-16 PAL and PL for Hardness
(8 Background Samples)

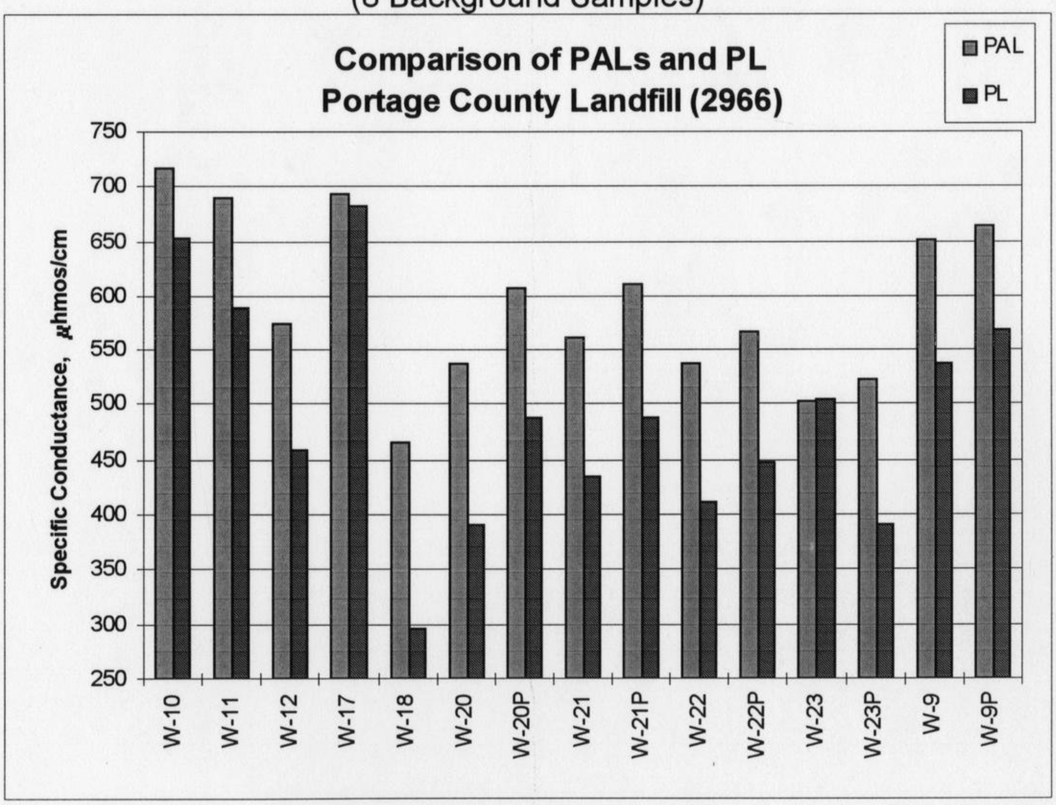


Figure 4-17 PAL and PL for Specific Conductance
(8 Background Samples)

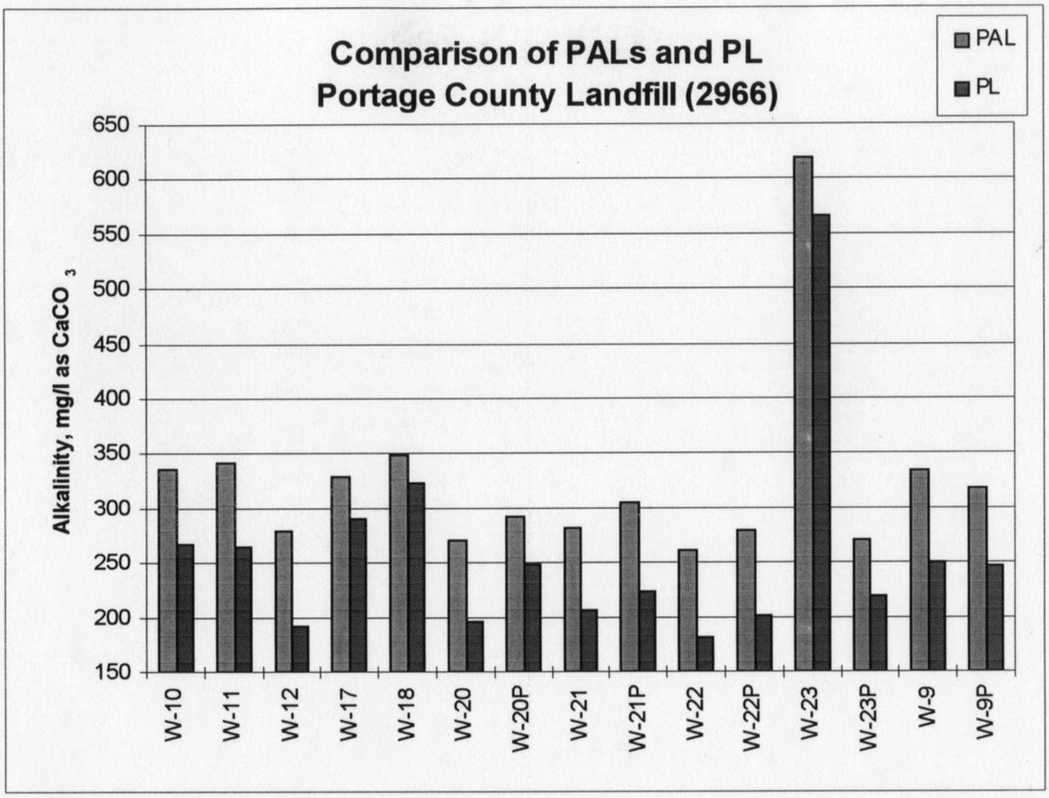


Figure 4-18 PAL and PL for Alkalinity
(25 Background Samples)

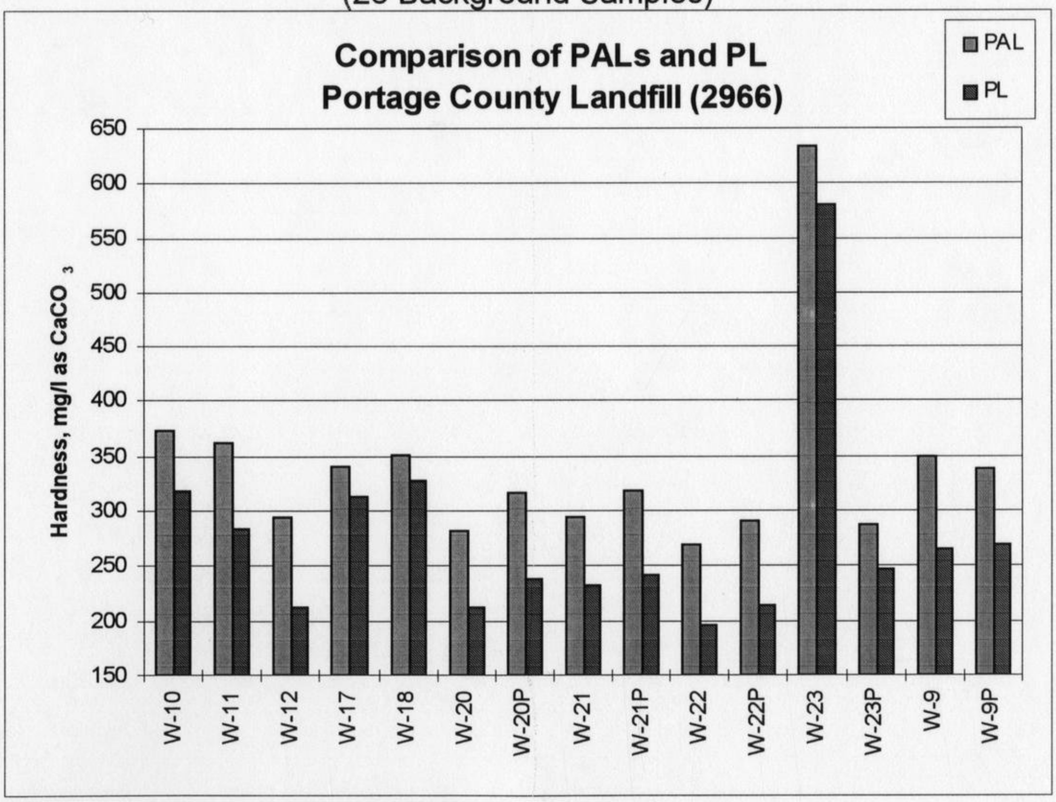


Figure 4-19 PAL and PL for Hardness
(25 Background Samples)

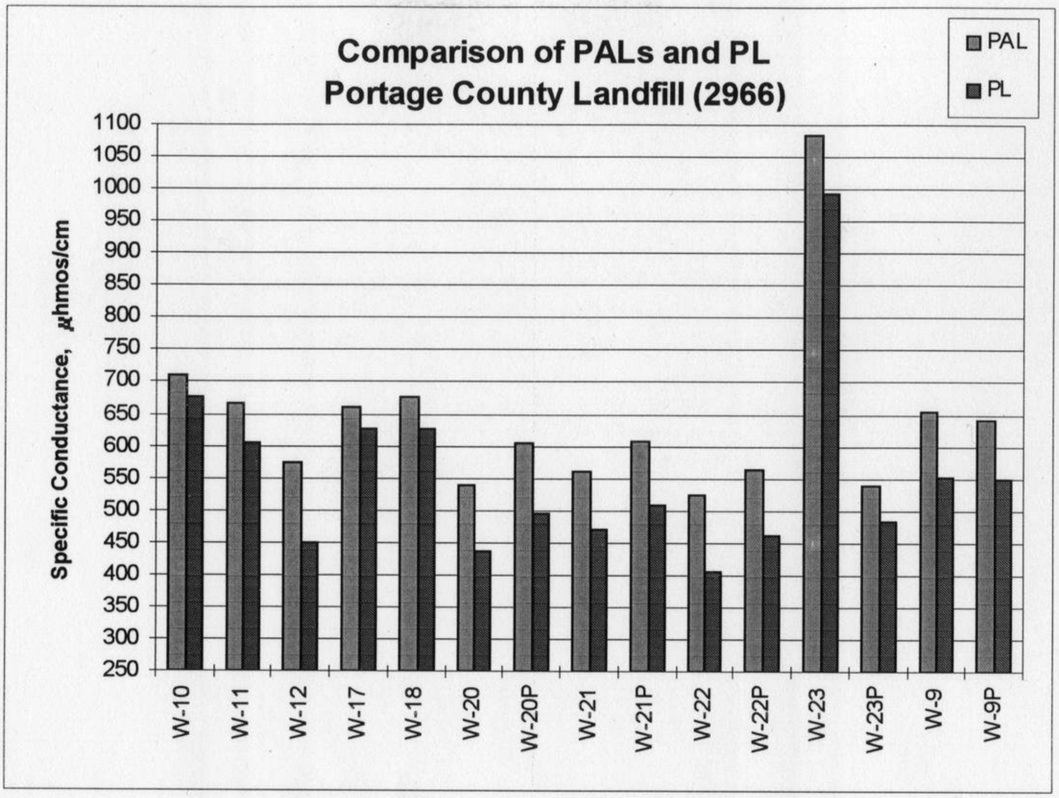


Figure 4-20 PAL and PL for Specific Conductance
(25 Background Samples)

To compare the CC to the indicator PAL, we calculated the number of data points in violation for alkalinity, hardness and specific conductance for each well. This procedure was conducted using both eight and 25 background samples. This analysis was also performed for the PL for comparison. The results from this analysis are listed in Table 4-1 and Table 4-2 for eight and 25 background samples. Figures 4-21 and 4-22 present the total number of violations for each of the parameters for all the wells combined.

From this analysis, we found that the greatest number of violations sitewide (for alkalinity, hardness and specific conductance) was 89 for the PAL with eight background samples and 27 for 25 background samples. The greatest number of violations sitewide for the PL was 308 for eight background samples and 172 violations for 25 background samples. The CC had the highest number violations sitewide with 390 violations for eight background samples and 198 violations for 25 background samples. In other words on a sitewide basis, the PL produced over three times as many violations as the indicator PAL for eight background samples and over six times as many violations based on 25 background samples. Similarly, the CC produced four and seven times as many violations as the indicator PAL for eight and 25 background samples respectively.

	Alkalinity			Hardness			Specific Conductance		
	PAL	PL	CC	PAL	PL	CC	PAL	PL	CC
W-10	0	9	12	0	11	25	0	0	0
W-11	0	3	12	0	1	0	0	1	2
W-12	0	3	2	0	9	28	0	0	0
W-17	0	0	0	0	0	0	0	0	0
W-18	22	28	37	21	28	37	19	31	38
W-20	10	27	26	10	30	30	7	26	28
W-20P	1	1	1	0	22	43	0	6	21
W-21	7	27	28	8	29	31	9	26	27
W-21P	0	23	24	0	27	27	0	12	26
W-22	0	22	23	0	24	27	0	11	20
W-22P	2	12	11	2	16	17	0	8	15
W-23	40	39	42	41	40	42	37	37	41
W-23P	5	38	39	7	36	35	5	27	30
W-9	0	17	28	0	28	41	0	2	0
W-9P	0	1	2	0	7	9	1	1	1

Table 4-1 Number of Data Points in Violation
(Based on Eight Background Samples)

	Alkalinity			Hardness			Specific Conductance		
	PAL	PL	CC	PAL	PL	CC	PAL	PL	CC
W-10	0	7	11	0	3	4	0	0	0
W-11	0	3	15	0	3	4	0	1	1
W-12	0	4	3	0	4	3	0	0	0
W-17	0	0	0	0	0	0	0	0	0
W-18	4	5	27	4	7	26	4	6	26
W-20	10	27	26	10	27	27	7	16	26
W-20P	1	1	5	0	13	20	0	6	20
W-21	6	25	26	7	25	26	9	20	26
W-21P	0	25	25	0	25	26	0	7	26
W-22	0	22	22	0	23	21	0	14	21
W-22P	2	13	11	2	15	14	0	6	15
W-23	0	0	6	0	0	6	0	0	4
W-23P	4	15	26	5	15	27	5	9	26
W-9	0	11	12	0	12	12	0	0	0
W-9P	0	0	2	0	0	0	1	1	11

Table 4-2 Number of Data Points in Violation
(Based on 25 Background Samples)

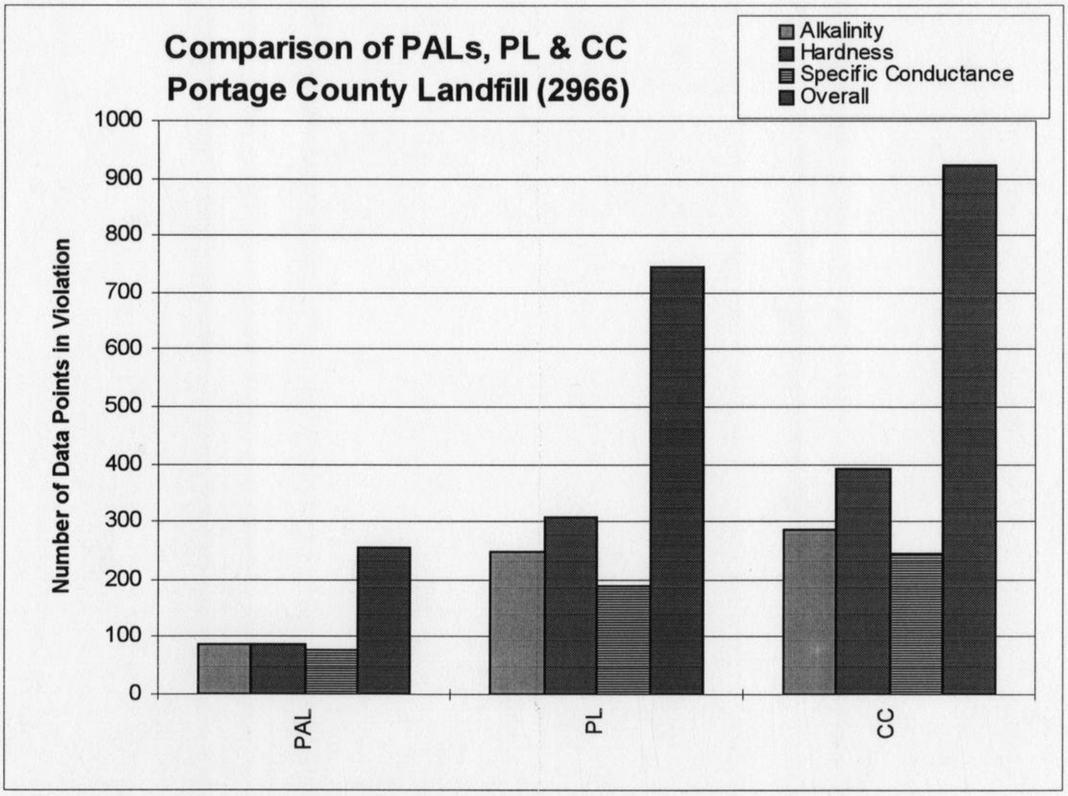


Figure 4-21 Number of Data Points in Violation Sitewide
(Based on Eight Background Samples)

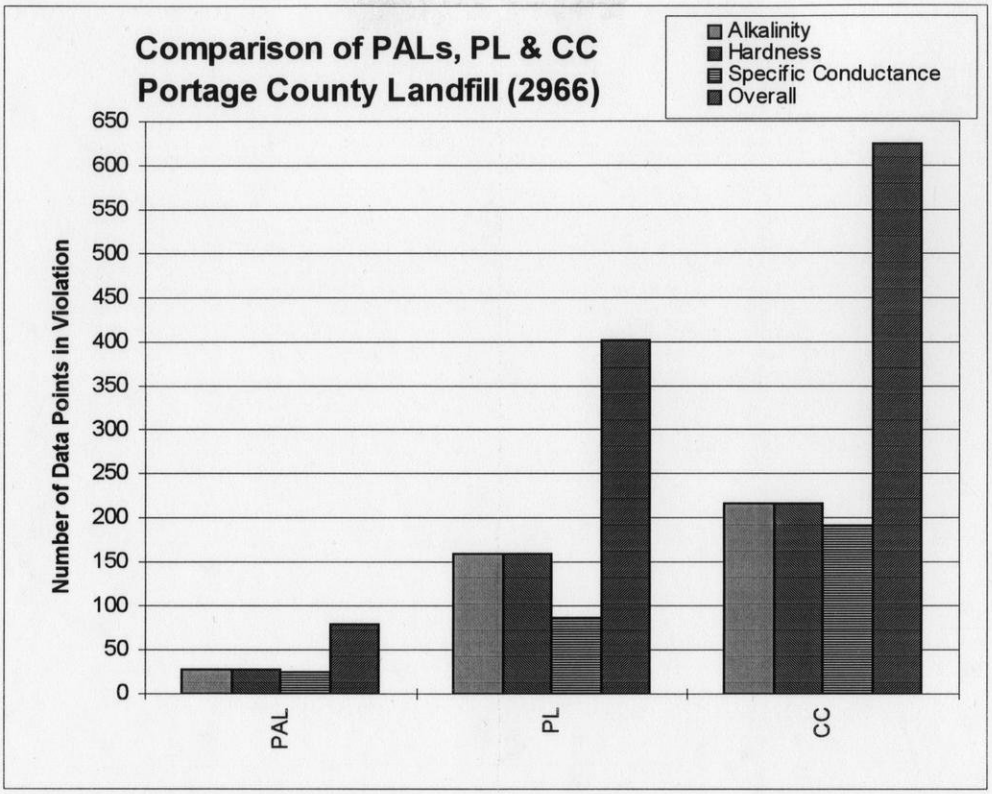


Figure 4-22 Number of Data Points in Violation Sitewide
(Based on Approximately 25 Background Samples)

4.5 Upgradient Wells

As discussed in the previous section, the PL and CC are more conservative than the indicator PAL. Therefore, DUMPStat will produce more violations when compared to the indicator PAL. Because of the increased number of violations, DUMPStat will pick up an impact sooner than the indicator PAL. However, some of these violations are false. In order to evaluate this effect, five wells were considered. All were either upgradient or sidegradient and beyond the influence of the landfill. We estimated the false positive rate by dividing the number of violations by the total number of data points for each parameter for these wells. We performed this analysis based on both eight and 25 background samples.

The results of this analysis are given in Figures 4-23 and 4-24 for alkalinity, hardness and specific conductance. From these plots, one can see that hardness and alkalinity have a higher false positive rate than specific conductance for both eight and 25 background samples. Specifically for the two DUMPStat algorithms, specific conductance had less than a five percent false positive rate for both eight and 25 background samples, while alkalinity and hardness had over a five percent false rate. The worst case was a 40 percent false positive rate for hardness using eight background samples and CC.

Both of the DUMPStat algorithms had higher false positive rates than the indicator PAL. However, CC had the highest false positive rate. With eight background samples, the overall false positive rate was 0.1, 12 and 21 percent for the PAL, PL and CC, respectively. Similarly with approximately 25 background samples, the overall false positive rates improved to 0.1, 6, and 9 percent. We would expect the false positive rates to decrease with more background samples since the mean and standard deviation can be better estimated for upgradient wells. This result is not true for downgradient wells because they may be impacted by the landfill. Hence, the background data for downgradient wells should be selected with care.

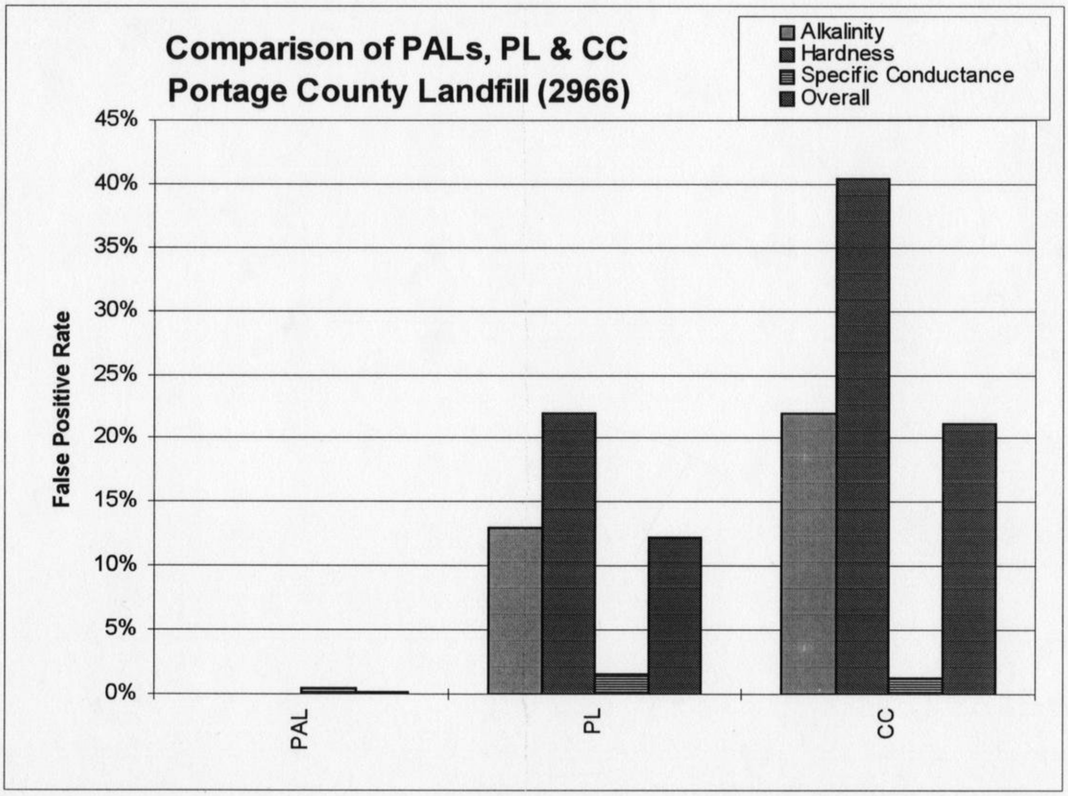


Figure 4-23 False Positive Rate Based on Five Upgradient Wells
(Based on Eight Background Samples)

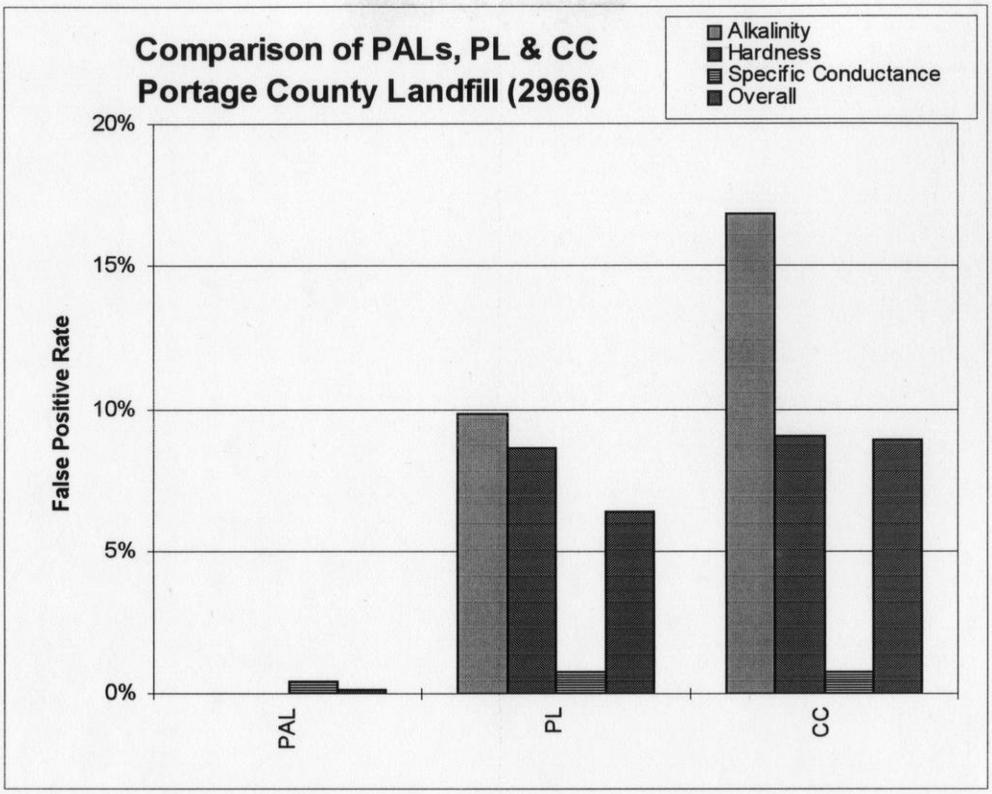


Figure 4-24 False Positive Rate Based on Five Upgradient Wells
(Based on 25 Background Samples)

4.6 Downgradient Wells

The false positive rates for the upgradient wells appear to be high. In addition to determining the false positive rate, we are interested in evaluating the effectiveness of the test. We did this evaluation by examining two downgradient wells which were preliminarily determined to be impacted.

Consider W-18 and W-23 which we determined to be impacted based on box plots and time series plots for alkalinity, hardness and specific conductance.

As noted in Table 4-1, one can see, regardless of the method, that W-23 and W-18 have high numbers of violations based on eight background samples. W-23 has approximately 40 violations (see Table 4-1) for alkalinity, hardness and specific conductance regardless of the test, based on eight background samples. Each method is equally effective for detecting the impact on W-23 since each method indicates 4/5 of the data points are in violation. For W-18 (8 background samples) the PAL, PL and CC have approximately 21, 29, and 37 violations for each parameter. Although the number of violations are different, each test is effective for determining impact.

Based on eight background samples each test was effective for determining impact. However, the same cannot be said for using 25 background samples. Based on 25 background samples, the PL and indicator PAL do not indicate impact for these wells and parameters. Alternatively, the CC indicates a substantial impact for W-18 but not for W-23. This result indicates that background data should be selected with great care. The 25 background samples likely include impacted data which increases the mean and standard deviation and decreases the likelihood of impact detection for all tests.

4.7 Chapter Summary

We have shown that the intrawell DUMPStat algorithms are more conservative than the indicator PAL. In addition, it is clear that the CC will produce more violations than the PL. Each of these methods is effective for determining impact. Of the violations, we noticed some upgradient wells with a substantial number of violations. Consequently, we estimated the false positive rate for the each parameter and statistical test. The false positive rate at these wells for the PL and CC was very high for alkalinity and hardness when compared to the indicator PAL. The number of violations at upgradient wells leads us to question the underlying assumptions of these statistical tests, which will be examined in the next chapter. Regardless of the statistical test or parameter, the selection of background data appears to a very important factor. If too much data is included in the background, all the statistical tests will fail to detect an impact. In the next chapter, we will review the underlying assumptions of these statistical tests.

CHAPTER 5

ASSUMPTIONS FOR INTRAWELL ANALYSIS

5.1 Introduction

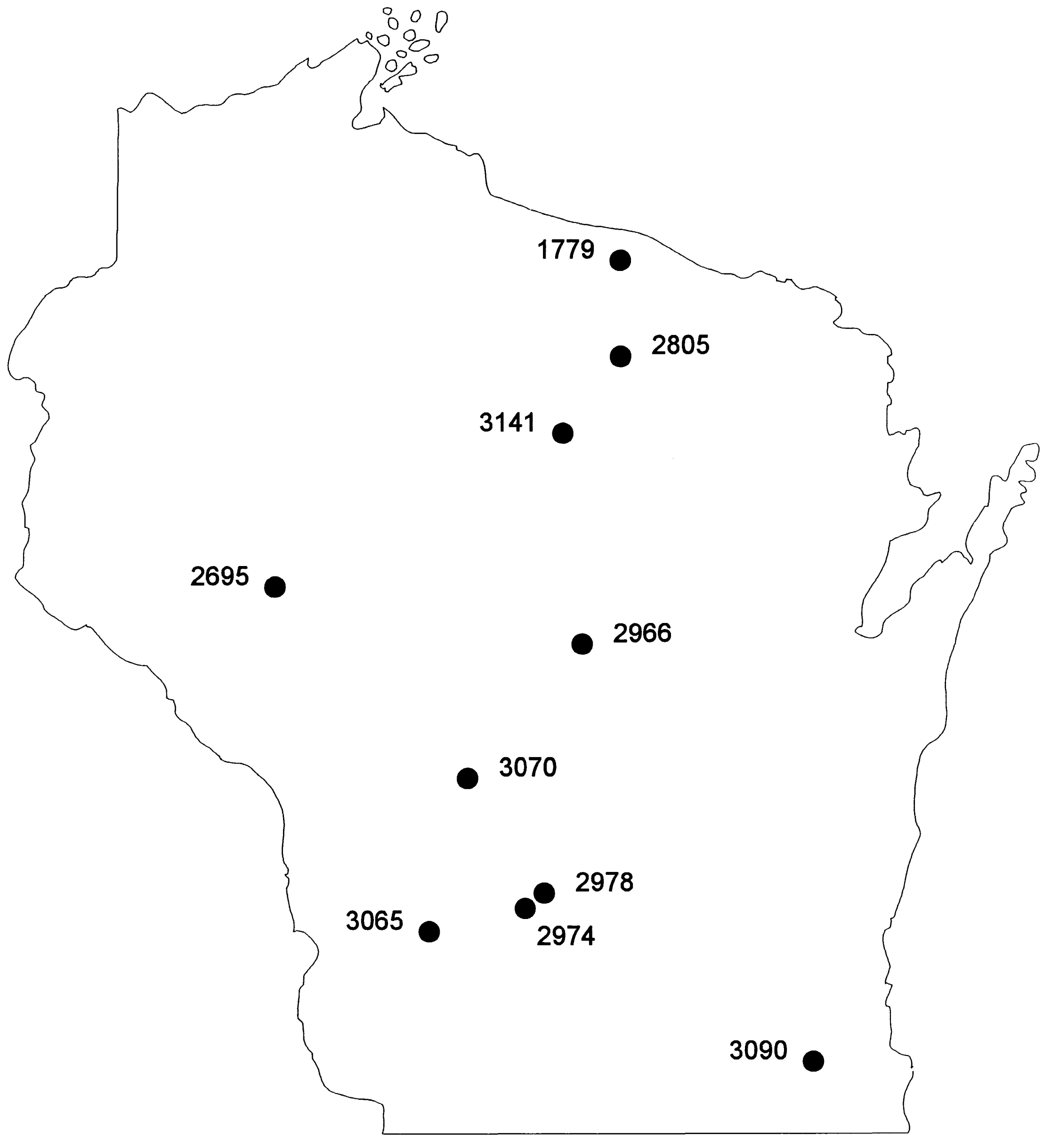
In the previous chapters we examined three statistical tests used for intrawell analysis of indicator parameters including: indicator preventive action limits (PAL), prediction limits (PL) and combined Shewhart-CUSUM control charts (CC). Currently, the PAL is the statistical test mandated by the Wisconsin Administrative Code and enforced by the Wisconsin Department of Natural Resources (WDNR) for indicator parameters. Prediction limits and combined Shewhart-CUSUM control charts are intrawell tests used in the computer program DUMPStat. These tests are potential replacements for the indicator PAL.

In the last chapter we applied the prediction limits and combined Shewhart-CUSUM control charts on data from a Wisconsin landfill and found a large number of false positives. For example, using 25 background samples we found the false positive rate to be over fifteen percent for alkalinity at the Portage County Landfill. In this chapter we investigate when this high incidence of false positives is due to violations of the assumptions; in particular, we explore distributional assumptions and the assumptions of stationarity and independence. These assumptions are investigated using alkalinity, hardness and specific conductance data from 26 upgradient wells at ten Wisconsin landfills.

5.2 Landfill Selection

The locations of the landfills we considered are indicated in Figure 5-1. These landfills cover a majority of the state and are located in a variety of geologic formations. Table 5-1 gives information on each landfill. Most of the landfills accept municipal solid waste (MSW), and three of the landfills accept industrial waste including papermill sludge and foundry waste. The size of these landfills varies from the small Lincoln Landfill (license number 1779), which has a capacity of 0.05 million cubic yards, to the large Troy area landfill (license number 3090), which has a capacity of 3.9 million cubic yards.

Based on site maps provided by the WDNR, we identified 26 wells that were unlikely to have been impacted by these ten landfills. Most of the wells are clearly upgradient. A few are sidegradient wells but are clearly beyond the influence of the landfill. Each of the wells had at least fifteen data points for each of the indicator parameters of interest. The selected wells are listed in Table 5-2.



License Number	Landfill Name	License Number	Landfill Name
1779	Lincoln	2978	Sauk County
2695	Pope & Talbot	3065	City of Richland Center
2805	Oneida County	3070	Juneau County
2966	Portage County	3090	Troy Area
2974	Grede Foundries	3141	Lincoln County

Figure 5-1 Name and Location of Landfills Studied

Table 5-1 Landfill Characteristics for Sites Studied

Landfill (License)	Facility Design	Waste Received	Design Volume (Millions of Cubic Yards)	Site Size (Acres)	Site Life	Year Sampling Began	Number of Upgradient Wells Analyzed
Lincoln (1779)	Natural Attenuation	MSW	0.05	20	1984-1990	1984	2
Pope & Talbot (2695)	Partial Clay Lined Leachate Collection	Papermill Sludge	1.2	19	1976-present	1976	3
Oneida County (2805)	Partial Clay Lined Leachate Collection	MSW Papermill Sludge	1.1	16.3	1979-present	1979	2
Portage County (2966)	Clay Lined Leachate Collection	MSW	1.37	18.6	1984-Present	1983	5
Grede Foundries (2974)	Partial Clay Lined Leachate Collection	Foundry Waste	0.966	19.5	1981-present	1981	2
Sauk County (2978)	Clay Lined Leachate Collection	MSW	1.28	20	1983-Present	1978	3
City of Richland Center (3065)	Clay Lined Leachate Collection	MSW	0.34	7.3	1986-1993	1986	3
Juneau County (3070)	Clay Lined Leachate Collection	MSW	0.42	8	1987-present	1987	1
Troy Area (3090)	Clay Lined	MSW	3.9	26	1987-1996	1987	3
Lincoln County (3141)	Clay Lined Leachate Collection	MSW	0.825	14.6	1987-present	1987	2

License #	Landfill	Common Well #	DNR Well #	Location
1779	Lincoln	MW-1	1	Up
1779	Lincoln	MW-4	104	Up
2695	Pope & Talbot	W-13	11	Up
2695	Pope & Talbot	W-18	18	Up
2695	Pope & Talbot	W-6	3	Up
2805	Oneida County	MW-1	1	Up
2805	Oneida County	MW-126	126	Up
2966	Portage County	W-10	14	Up
2966	Portage County	W-11	16	Up
2966	Portage County	W-12	17	Up
2966	Portage County	W-9	12	Side
2966	Portage County	W-9P	13	Side
2974	Grede Foundries	B-3	103	Up
2974	Grede Foundries	B-5	105	Up/Side
2978	Sauk County	W-30	101	Up
2978	Sauk County	W-30A	102	Up
2978	Sauk County	W-31	103	Up
3065	City of Richland Center	MW-6	106	Up
3065	City of Richland Center	MW-7	107	Side
3065	City of Richland Center	MW-7P	108	Side
3070	Juneau County	OW-5	1	Up
3090	Troy Area	B-1	201	Up
3090	Troy Area	B-1B	203	Up
3090	Troy Area	B-2	204	Up
3141	Lincoln County	M-4	706	Up
3141	Lincoln County	M-9	710	Up/Side

Table 5-2 Selected Wells

5.3 Stationarity, Independence and Trend

Most statistical tests, such as those based on the combined Shewhart-CUSUM control charts or predictions limits are predicated on the assumption that the data are taken from a random sample. Herein random means that the data are independent and identically distributed. In this section, we will determine whether the upgradient alkalinity, hardness and specific conductance data represent random samples. In particular, we will test for two kinds of nonrandomness: nonstationarity; and serial correlation.

For data collected in time, nonstationarity means that the distribution changes in time. Nonstationarity can be due to seasonality of the mean and/or variance or to long-term drift of the mean and/or variance. Figure 5-2 is an example of nonstationarity due to periodic variation in the mean. Figure 5-3 is an example of nonstationarity in variance. Figure 5-4 shows data for which both the mean and variance change in time.

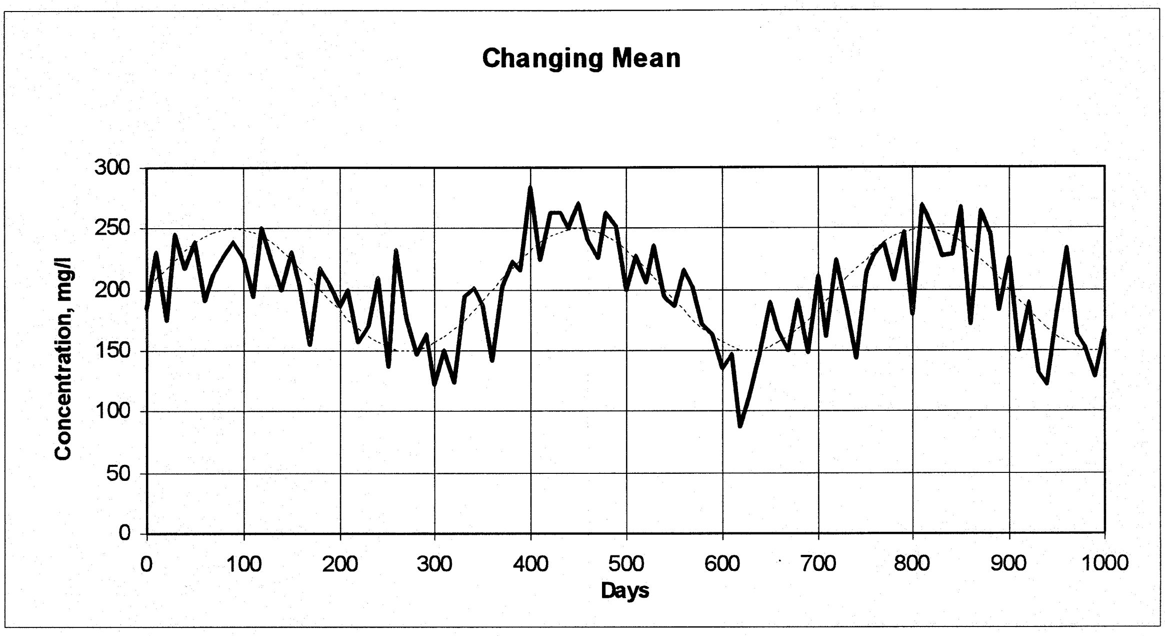


Figure 5-2 Nonstationary Process: Changing Mean

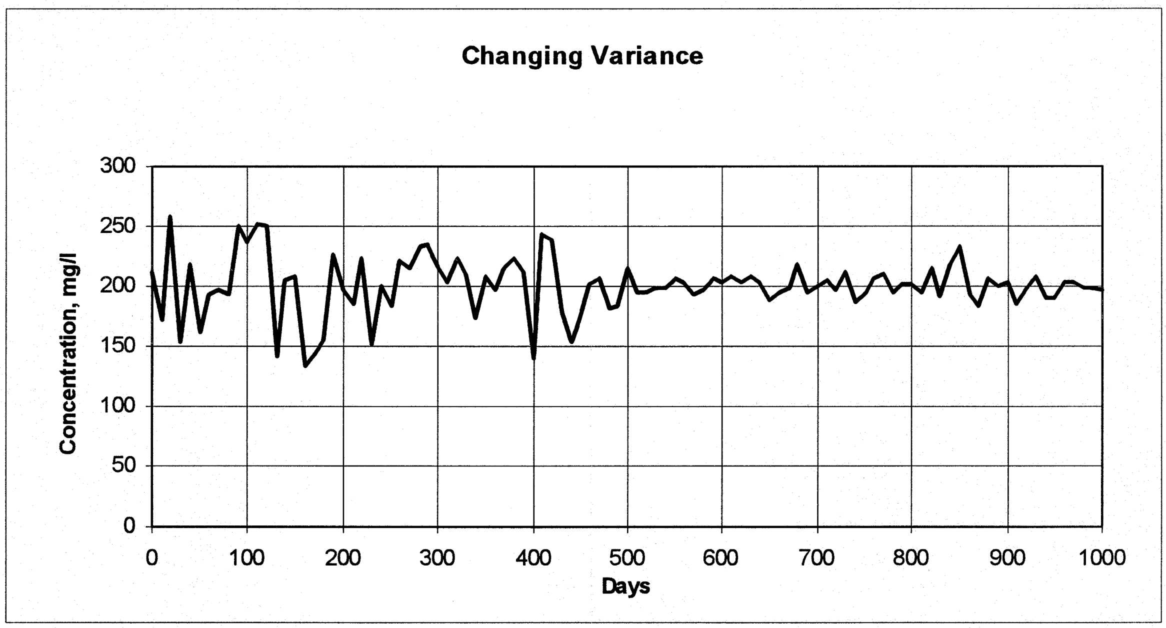


Figure 5-3 Nonstationary Process: Changing Variance

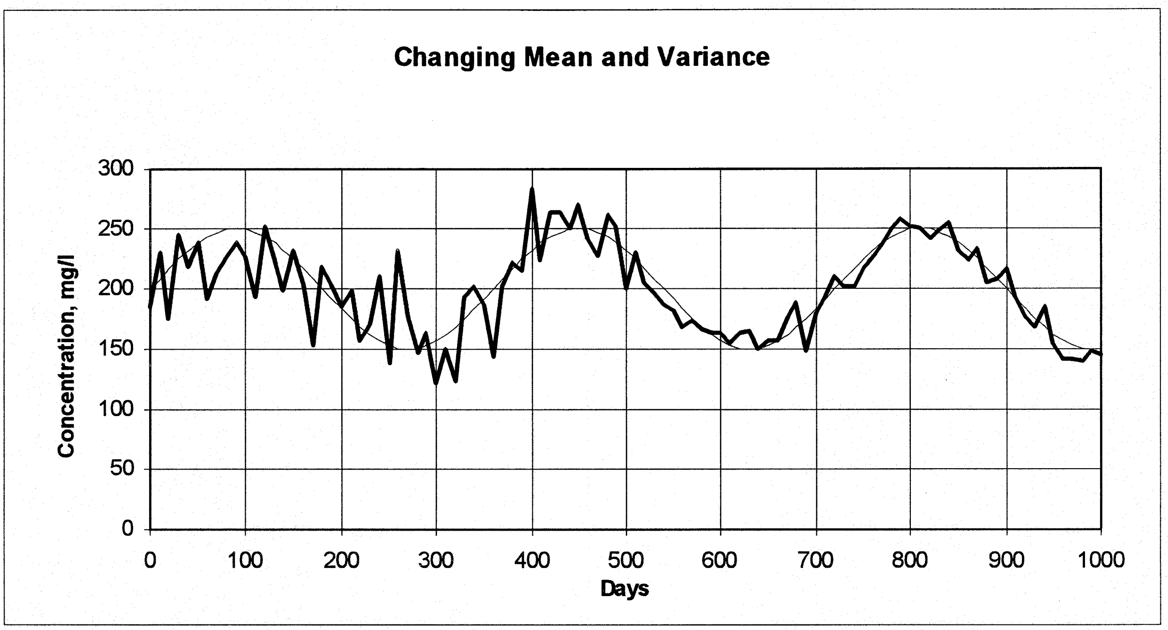


Figure 5-4 Nonstationary Process: Changing Mean and Variance

Figures 5-2 through 5-4 are hypothetical examples of nonstationarity; Figure 5-5 shows an example of apparent nonstationarity of alkalinity data from two wells at the Portage County landfill. These data show apparent variation in the mean and variance. For example, for W-9 the variance for data prior to June 1990 is 38.5 mg/l and after is 374.6 mg/l. The variance of the data from W-9p also appears to increase, although not as significantly as W-9. These wells are clearly beyond the influence of the landfill; hence the apparent nonstationary behavior is not due to contamination by the landfill. Determining the cause of this apparent nonstationarity was beyond the scope of this study. One possibility is consistent measurement error, due to changes in sampling and measurement protocols. Another possibility is that the apparent nonstationarity is due to variation in the flow field at the site.

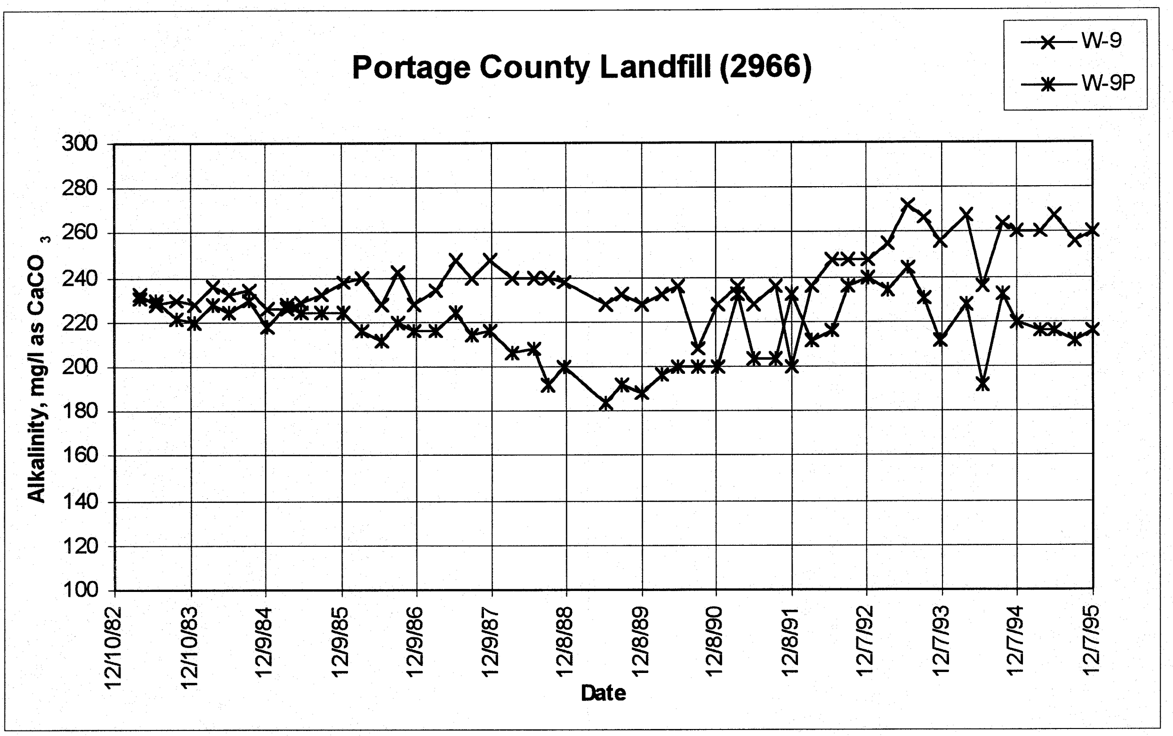


Figure 5-5 Nonstationary Process: Changing Variance

Inspection of all of the time series plots of the water quality data from 26 upgradient wells did not reveal any obvious seasonal behavior. Goodman (1987) and Montgomery et. al. (1987) also found little significant seasonality in groundwater quality data. Consequently, we did not conduct any formal statistical tests for seasonality. Instead, we conducted statistical tests for serial correlation and for linear trends, both of which are causes of nonrandomness. In short datasets, such as those analyzed here, correlation and trend can be confounding. Strictly speaking, serial correlation should only be estimated from stationary data, as the presence of a trend can falsely indicate serial correlation. Similarly, serial correlation can indicate a trend which does not exist. We chose to use tests of both serial correlation and trend to detect nonrandomness. We also tested the data for normality and lognormality, since both prediction limits and combined Shewhart-CUSUM control charts are typically predicated on the assumption of normality or lognormality.

Serial correlation was evaluated using the lag-k autocorrelation coefficient, the correlation coefficient for data points separated by k sampling intervals. This coefficient varies from -1 to +1. For the lag-1 autocorrelation, a positive coefficient indicates high values tend to be followed by high values and low values tend to be followed by low values in the time series. For a negative lag-1 autocorrelation coefficient, the opposite is true.

For our study, we calculated the autocorrelation function coefficient for up to fifteen lags (k=15) depending on the length of the data sets. This analysis was performed for 26 upgradient wells for alkalinity, hardness and specific conductance at ten landfills. We used a five percent significance level for the two sided test. It should be noted that the test procedure offered in Statistica (1997) is slightly different from the procedure used by Goodman (1987). Appendix C outlines the procedure for calculating any lag-k autocorrelation coefficient and it includes a sample calculation.

Before reviewing our results, it is interesting to look at graphical representation of the data. Specifically, a plot for the concentration, C_{i-1}, versus the next concentration, C_i, provides a visual indication of the strength of the lag-1 Autocorrelation coefficient. For perfect positive correlation the plot would be linear with a positive slope. For strong correlation, the plot would show a clustering of the data points with a positive slope. Figures 5-6 and 5-7 show the results for specific conductance for two wells. These two wells show no clustering and no clear slope. The lag-1 autocorrelation coefficient for the data are 0.005 and -0.053 respectively; neither is significant at the 5% level. In contrast, strong lag-1 autocorrelations are shown in Figures 5-8 and 5-9. The positive slopes are clear as well as the clustering of both high values and low values. Lastly, figures 5-10 and 5-11 show strong lag-1 autocorrelations but the high values are more disperse than the low values.

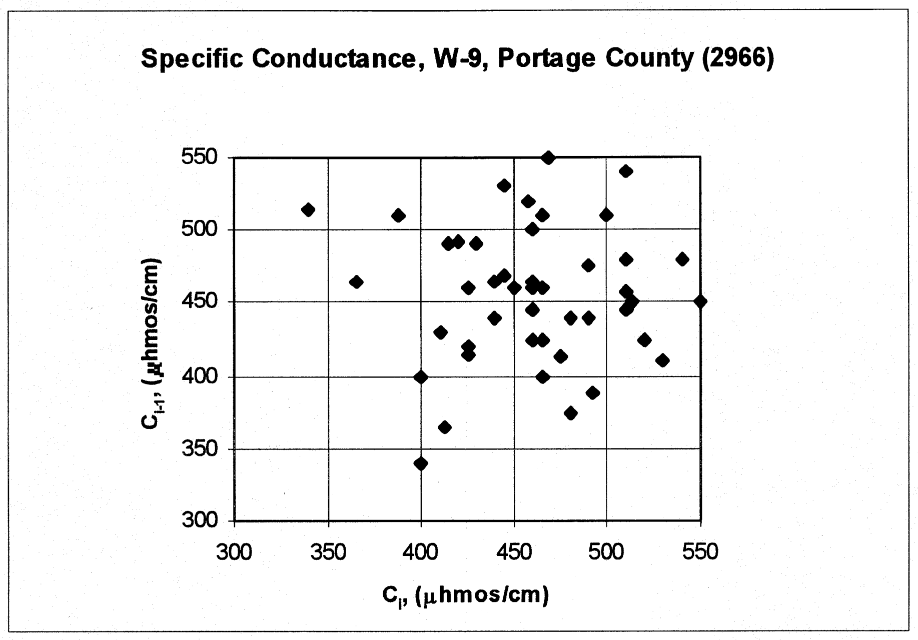


Figure 5-6 No Significant Serial Correlation
(r_1=0.005, p=0.97)

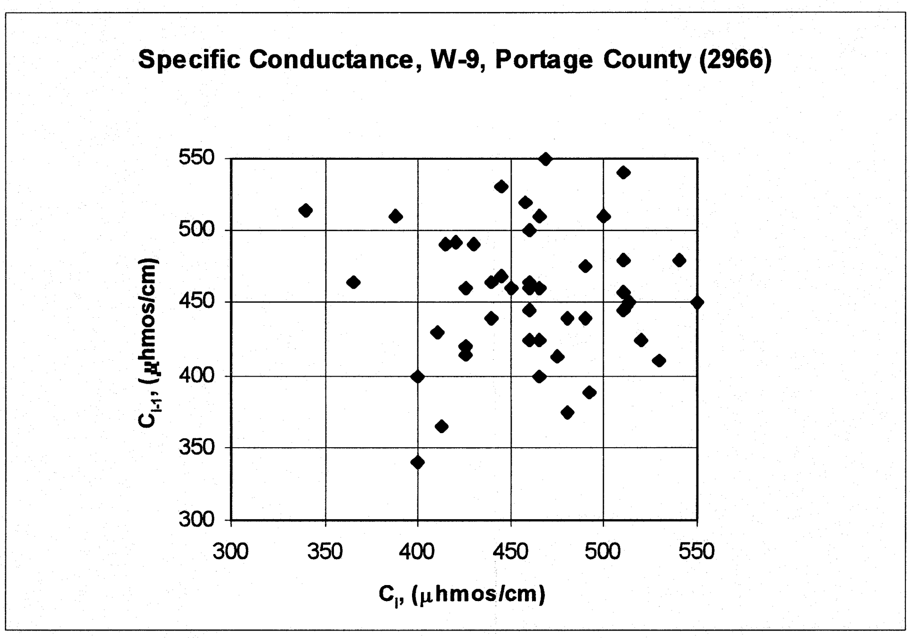


Figure 5-7 No Significant Serial Correlation
(r_1=-0.053, p=0.69)

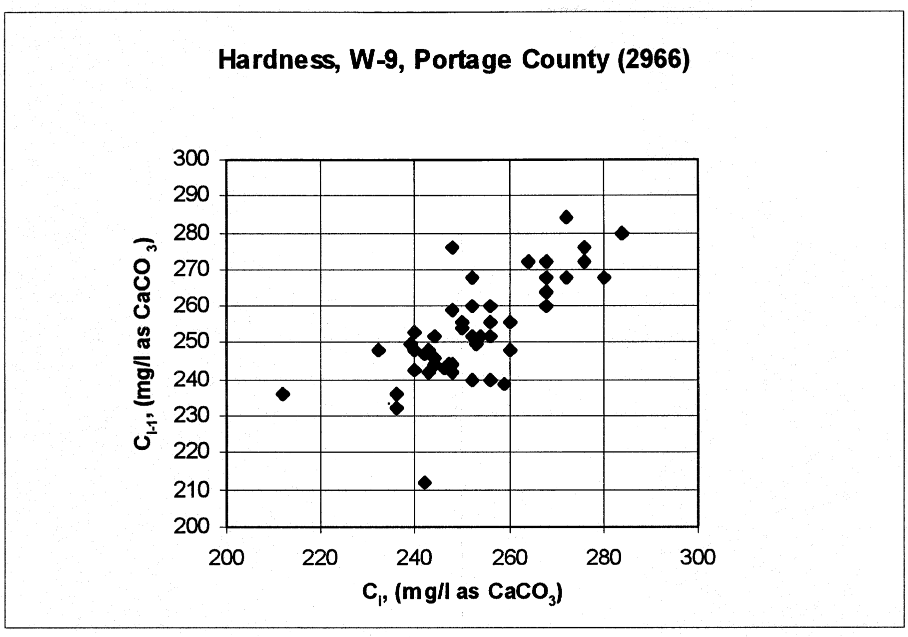


Figure 5-8 Significant Positive Serial Correlation
(r_1=0.716, p=0.000)

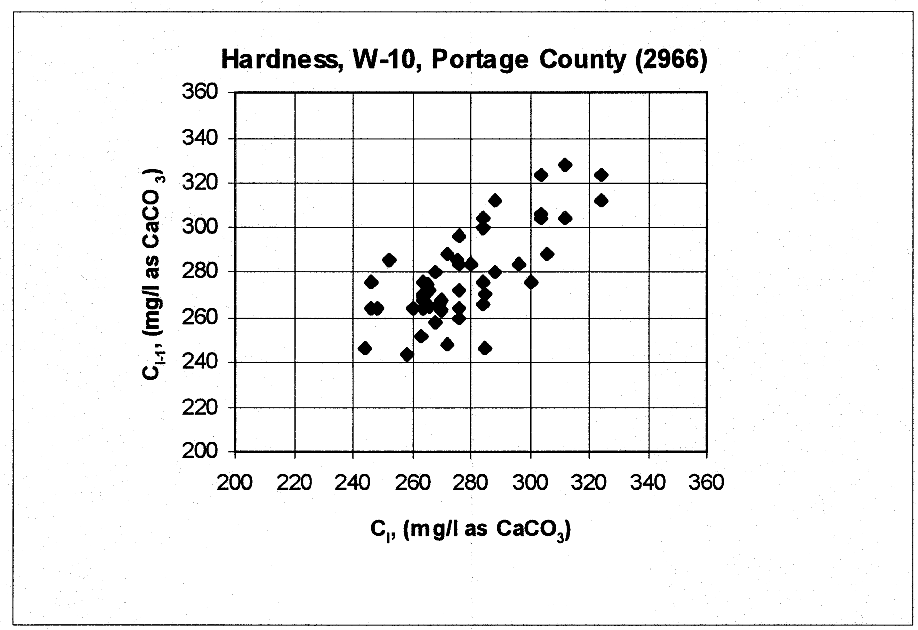


Figure 5-9 Significant Positive Serial Correlation
(r_1=0.676, p=0.000)

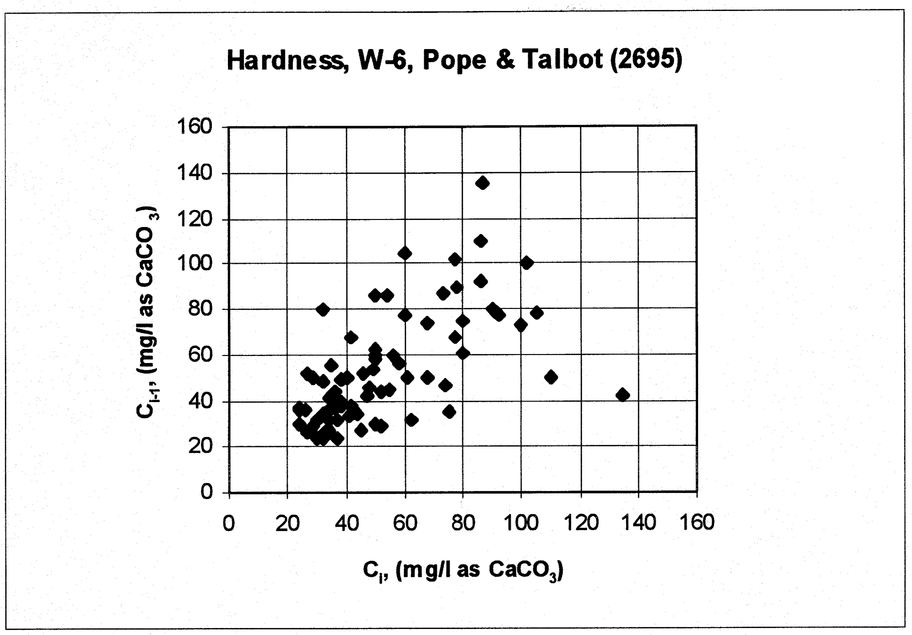


Figure 5-10 Clustering of Lower Values and Dispersion of High Values
(r_1=0.611, p=0.000)

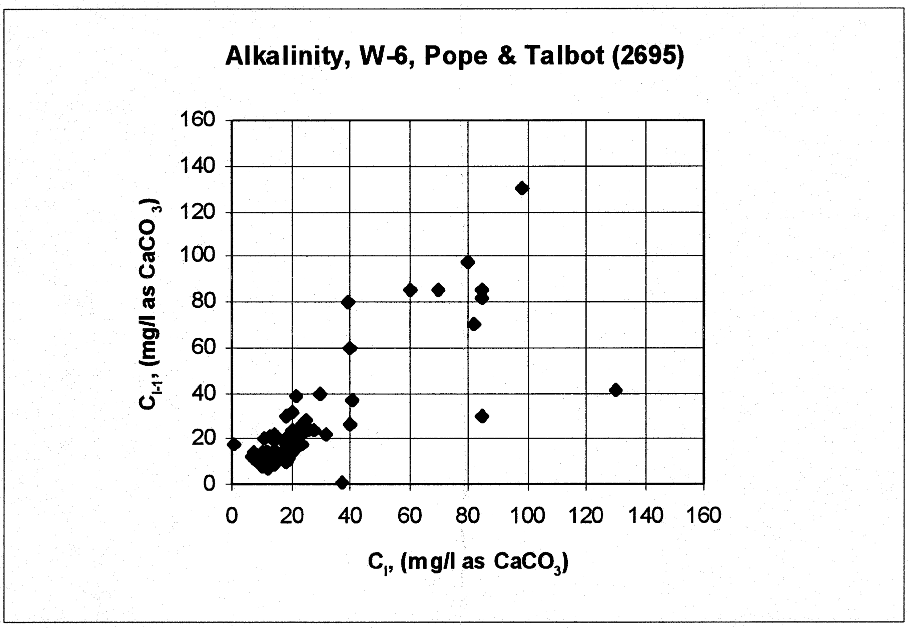


Figure 5-11 Clustering of Lower Values and Dispersion of High Values
(r_1=0.802, p=0.000)

Autocorrelations were displayed in the form of correlograms, plots of the estimated lag-k autocorrelation coefficient as a function of k. Figures 5-12 and 5-13 show an example for which the autocorrelation was insignificant for all fifteen lags calculated. Figures 5-14 and 5-15 show correlograms for which significant correlation persists for a number of lags. It is not surprising that these two correlograms are almost the same. Figure 5-14 is hardness and Figure 5-15 is the alkalinity for the same well. Since this is a carbonate aquifer, we can expect hardness and alkalinity to be similar. Figure 5-16 and 5-17 are also correlograms for the alkalinity and hardness. Here, the correlations decay to zero after eight lags and then become negative (although not significantly). All the correlograms are included in appendix C.

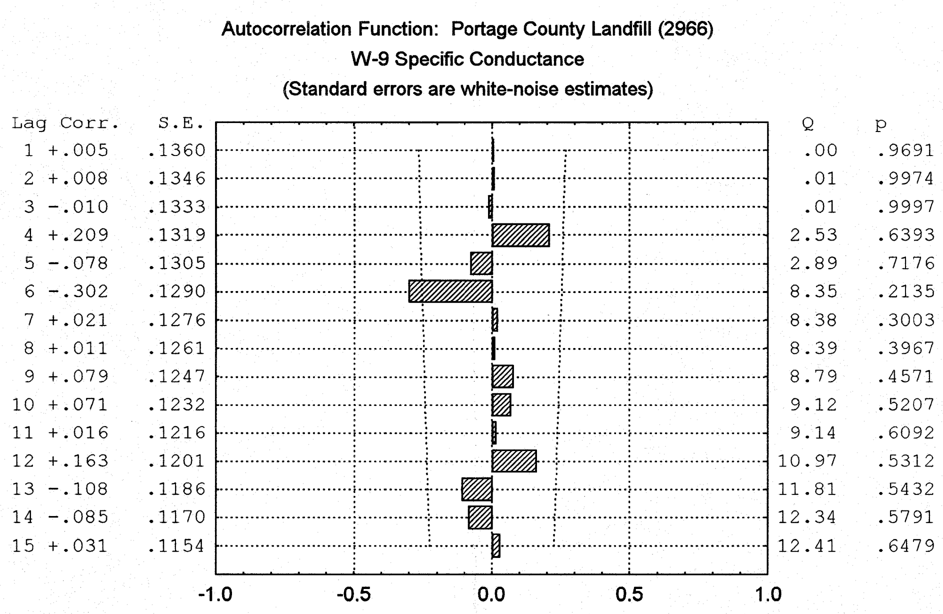


Figure 5-12 Corellogram with Insignificant Autocorrelation

Autocorrelation Function: Portage County Landfill (2966)
W-9P Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	-.053	.1360	.15	.6947
2	-.117	.1346	.91	.6344
3	-.038	.1333	.99	.8038
4	+.191	.1319	3.09	.5433
5	-.154	.1305	4.48	.4821
6	-.155	.1290	5.92	.4318
7	-.002	.1276	5.92	.5486
8	-.008	.1261	5.93	.6552
9	+.071	.1247	6.26	.7140
10	+.106	.1232	7.00	.7250
11	+.004	.1216	7.01	.7986
12	+.095	.1201	7.63	.8133
13	-.094	.1186	8.26	.8260
14	-.071	.1170	8.64	.8536
15	+.120	.1154	9.71	.8375

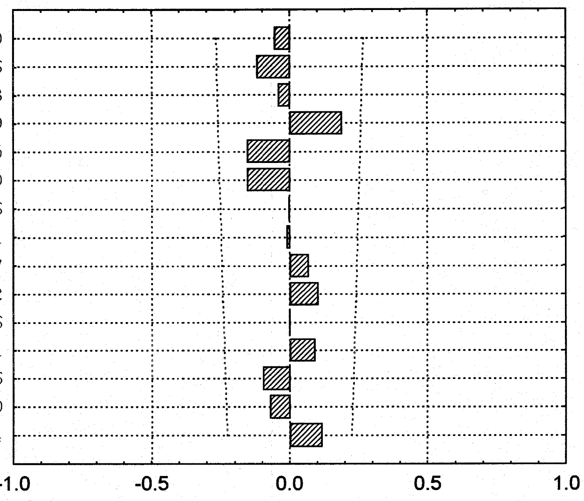


Figure 5-13 Corellogram with Insignificant Autocorrelation

Autocorrelation Function: Pope & Talbot Landfill (2695)
W-6 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.611	.1104	30.65	.0000
2	+.470	.1097	49.01	.0000
3	+.405	.1090	62.80	.0000
4	+.265	.1083	68.81	.0000
5	+.260	.1075	74.66	.0000
6	+.239	.1068	79.68	.0000
7	+.152	.1061	81.74	.0000
8	+.194	.1053	85.12	.0000
9	+.181	.1046	88.11	.0000
10	+.092	.1038	88.90	.0000
11	+.158	.1031	91.26	.0000
12	+.120	.1023	92.62	.0000
13	+.138	.1016	94.48	.0000
14	+.139	.1008	96.39	.0000
15	+.039	.1000	96.54	.0000

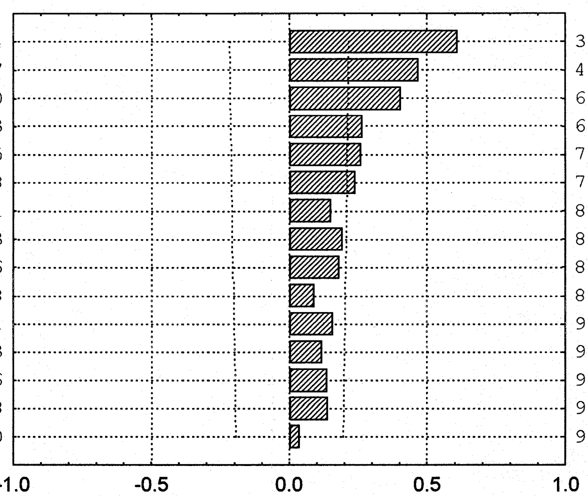


Figure 5-14 Corellogram with Autocorrelation Showing Longer Term Persistence

Autocorrelation Function: Pope & Talbot Landfill (2695)
W-6 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.802	.1104	52.79	.0000
2	+.626	.1097	85.34	.0000
3	+.389	.1090	98.11	.0000
4	+.256	.1083	103.7	.0000
5	+.187	.1075	106.7	.0000
6	+.180	.1068	109.6	.0000
7	+.174	.1061	112.3	.0000
8	+.229	.1053	117.0	.0000
9	+.248	.1046	122.6	.0000
10	+.236	.1038	127.8	.0000
11	+.222	.1031	132.4	.0000
12	+.206	.1023	136.5	.0000
13	+.203	.1016	140.5	.0000
14	+.192	.1008	144.1	.0000
15	+.069	.1000	144.6	.0000

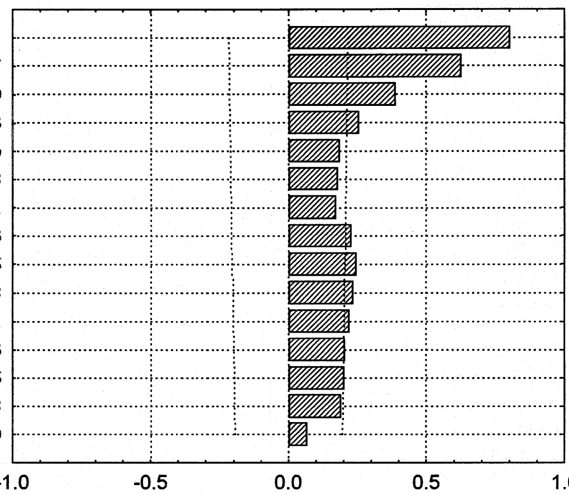


Figure 5-15 Corellogram with Autocorrelation Showing Longer Term Persistence

Autocorrelation Function: Portage County Landfill (2966)
W-9 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.716	.1360	27.70	.0000
2	+.640	.1346	50.28	.0000
3	+.652	.1333	74.20	.0000
4	+.474	.1319	87.13	.0000
5	+.337	.1305	93.80	.0000
6	+.236	.1290	97.15	.0000
7	+.104	.1276	97.81	.0000
8	-.007	.1261	97.82	.0000
9	-.031	.1247	97.88	.0000
10	-.161	.1232	99.58	.0000
11	-.217	.1216	102.8	.0000
12	-.232	.1201	106.5	.0000
13	-.235	.1186	110.4	.0000
14	-.229	.1170	114.3	.0000
15	-.206	.1154	117.5	.0000

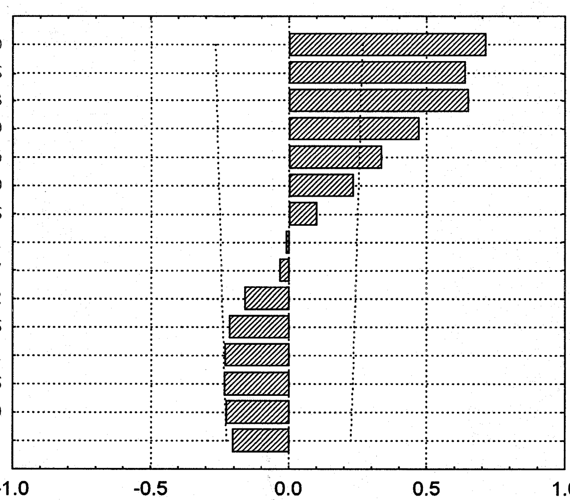


Figure 5-16 Corellogram with Autocorrelation Showing Shorter Term Persistence

Autocorrelation Function: Portage County Landfill (2966)
W-10 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.676	.1360	24.73	.0000
2	+.611	.1346	45.32	.0000
3	+.405	.1333	54.55	.0000
4	+.279	.1319	59.03	.0000
5	+.162	.1305	60.57	.0000
6	+.055	.1290	60.75	.0000
7	+.051	.1276	60.91	.0000
8	-.011	.1261	60.92	.0000
9	-.117	.1247	61.80	.0000
10	-.210	.1232	64.71	.0000
11	-.241	.1216	68.64	.0000
12	-.218	.1201	71.94	.0000
13	-.208	.1186	75.00	.0000
14	-.117	.1170	76.01	.0000
15	-.139	.1154	77.45	.0000

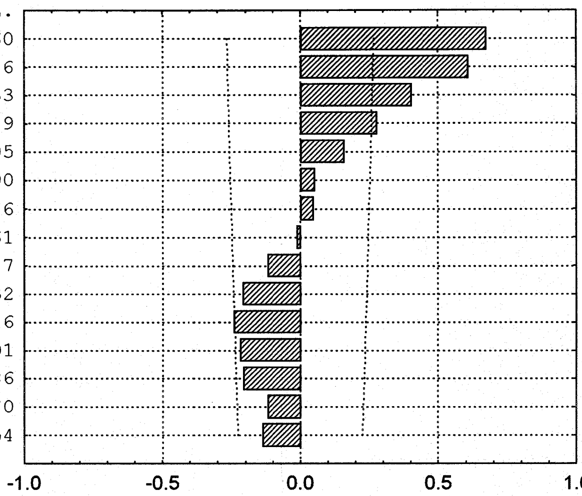


Figure 5-17 Corellogram with Autocorrelation Showing Shorter Term Persistence

Goodman (1987) and Montgomery et. al. (1987) also evaluated serial correlation coefficients of groundwater quality data. Goodman tested for serial correlation using two methods: lag-1 autocorrelation function; and the nonparametric runs test. The results were similar for both tests. For the parameters examined in this study, Goodman (1987) found a smaller proportion of significant lag-1 autocorrelation coefficients: 23, 26 and 24 percent compared to the 62, 65 and 58 percent found in this study for alkalinity, hardness and specific conductance, respectively. Much of the difference may be attributed to differences in record lengths. The average record length in Goodman (1987) was less than three years; in this study the average record length is about thirteen years. Montgomery et. al. (1987) estimated lag-1 autocorrelation coefficients for hardness and specific conductance at two and eight wells, respectively. Of these, only 50% of the hardness data and 25% of the specific conductance data showed significant autocorrelation. The average record length was only about seven years.

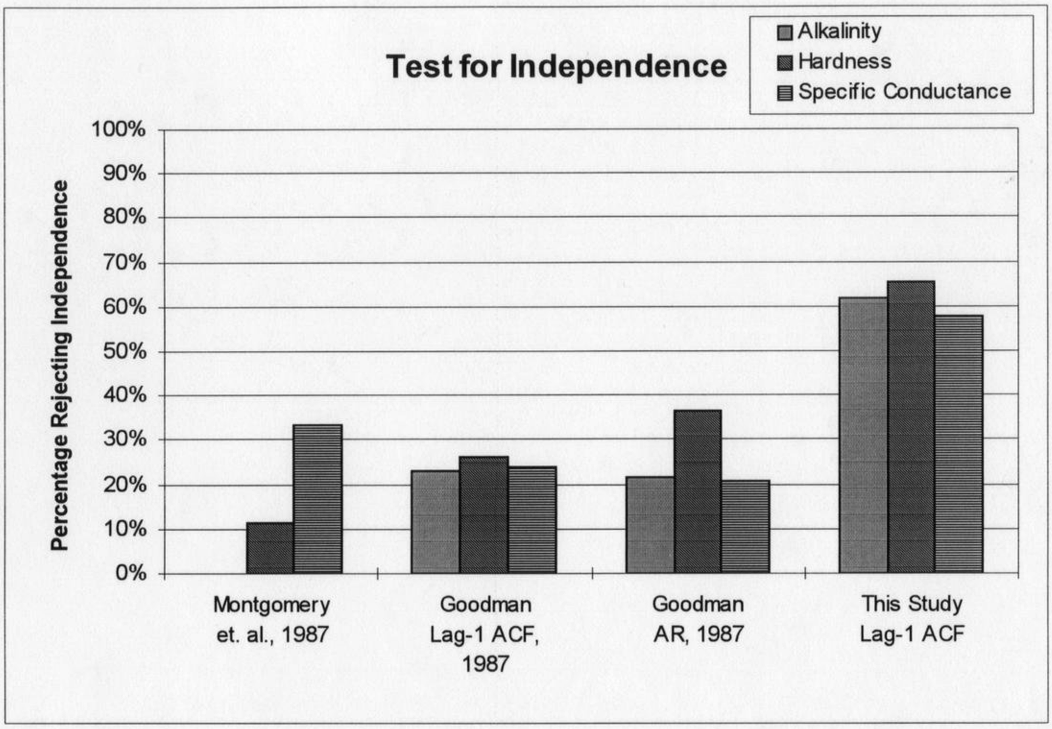


Figure 5-18 Results for Independence Tests

Our study indicates the data for upgradient wells are not random. One or more correlation coefficients for over 50 percent of the data sets are significantly different from zero. In the next section we will test the data for trend.

A number of parametric and nonparametric tests for trend are available. Stoline et. al. (1993) used parametric regression to detect both linear and quadratic downward trends for a superfund site. Frapporti et. al. (1994) used the Spearman rho test to evaluate changing geochemical processes. DUMPStat uses Sen's test to evaluate background data for upward historical trends or the entire data set for upward or downward trends for assessment monitoring. We chose the gamma test, which is a slight variation of the Kendall tau test. The Gamma test and Sen's test procedures are outlined in appendix A.

The results of the gamma test are shown in Figure 5-19, for a significance level of five percent. Overall, at least 50 percent of the wells had a significant trend for alkalinity, hardness and specific conductance. Slightly fewer wells showed trend than autocorrelation for hardness and specific conductance. Slightly more wells exhibited autocorrelation than trend for alkalinity. Further, the breakdown of the gamma trends were 53 percent positive and 47 negative. Figure 5-20 shows the totals for autocorrelation and trend on the same graph.

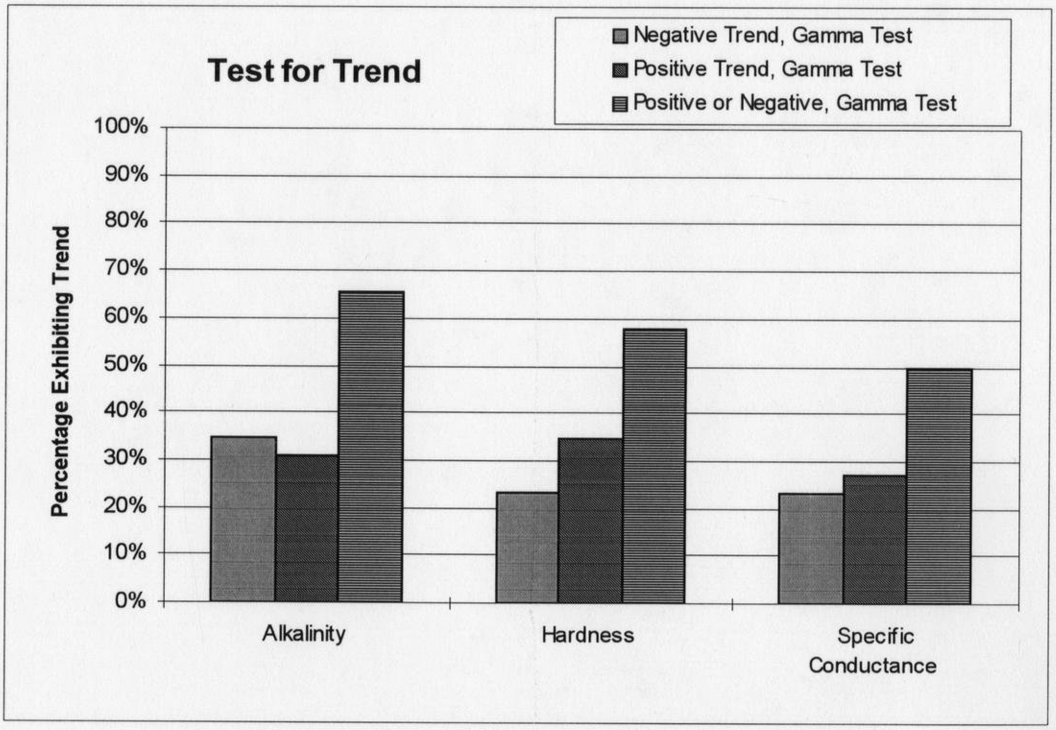


Figure 5-19 Overall Results for Trend Tests

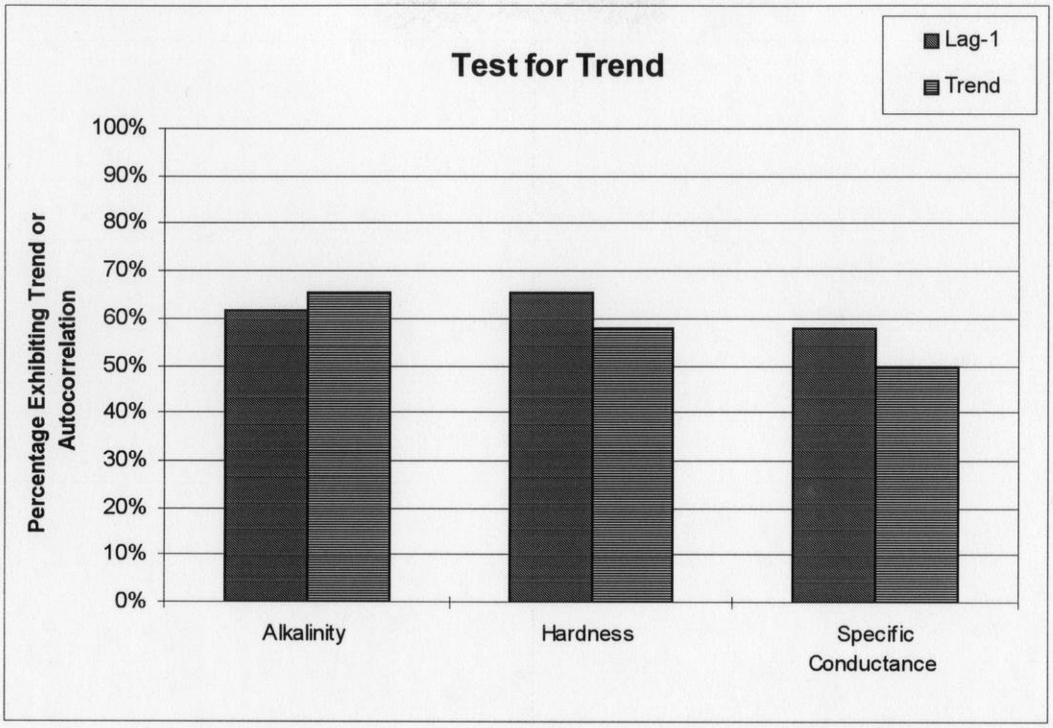


Figure 5-20 Overall Results for Trend and Autocorrelation

5.4 Normality

Prediction limits and combined Shewhart-CUSUM control charts, as used in DUMPStat, are generally predicated on the assumption of normality. A number of tests for normality are suggested in the literature. Gibbons (1994) lists several including:

- Normal Probability Plots
- Shapiro-Wilk Test
- Shapiro-Francia Test
- D'Agostino's Test

- Skewness
- Kolmogorov-Smirnov (mean and variance known) Goodness-of Fit Test
- Kolmogorov-Smirnov with Lilliefors Generalization (uses sample mean and sample standard deviation)

Montgomery et. al. (1987) and Gilbert (1987) suggest:

- Histograms
- Normal Probability Plots
- Chi-Squared Goodness-of-Fit Test
- Skewness

Before applying a test for normality, it is useful to examine histograms of the data. Histograms give qualitative information about data normality. For example, the alkalinity data shown in Figure 5-21 approximately exhibit normal behavior. Other data give a different picture. Figure 5-22 shows sampling data clearly skewed to the right while Figure 5-23 shows data clearly skewed to the left. Although the skewness coefficient would detect non-normal behavior for Figure 5-22 and 5-23 it would not detect the bimodality evident in Figure 5-24.

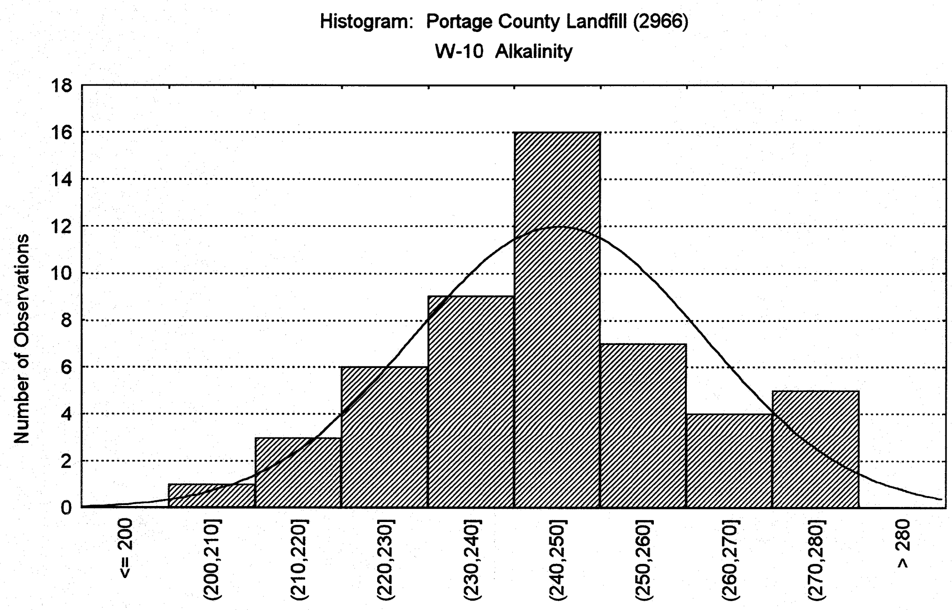


Figure 5-21 Histogram: Groundwater Data Approximately Normal
(51 samples, 0.111 skewness coefficient)

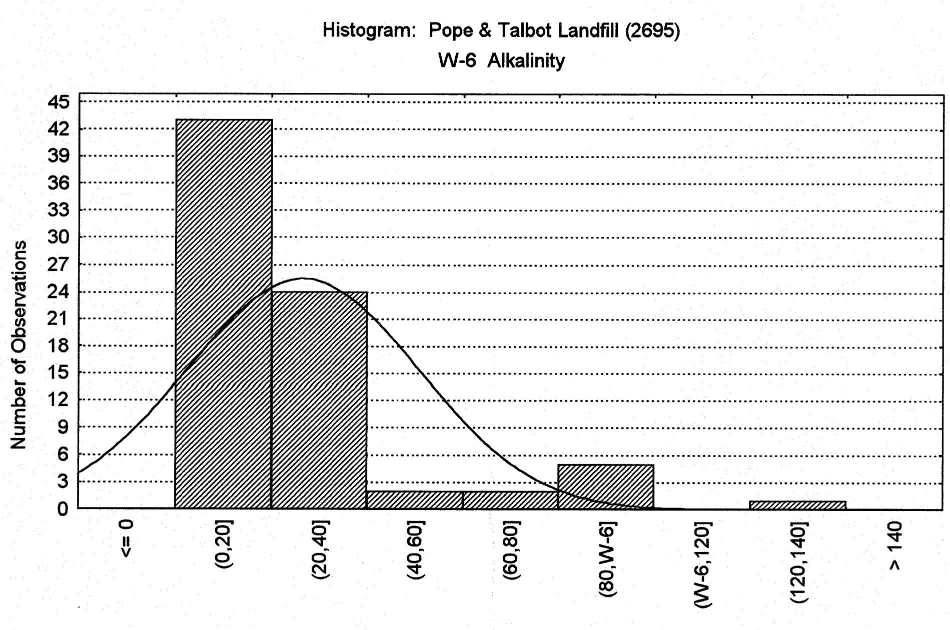


Figure 5-22 Histogram: Groundwater Data Skewed to the Right
(77 samples, 2.294 skewness coefficient)

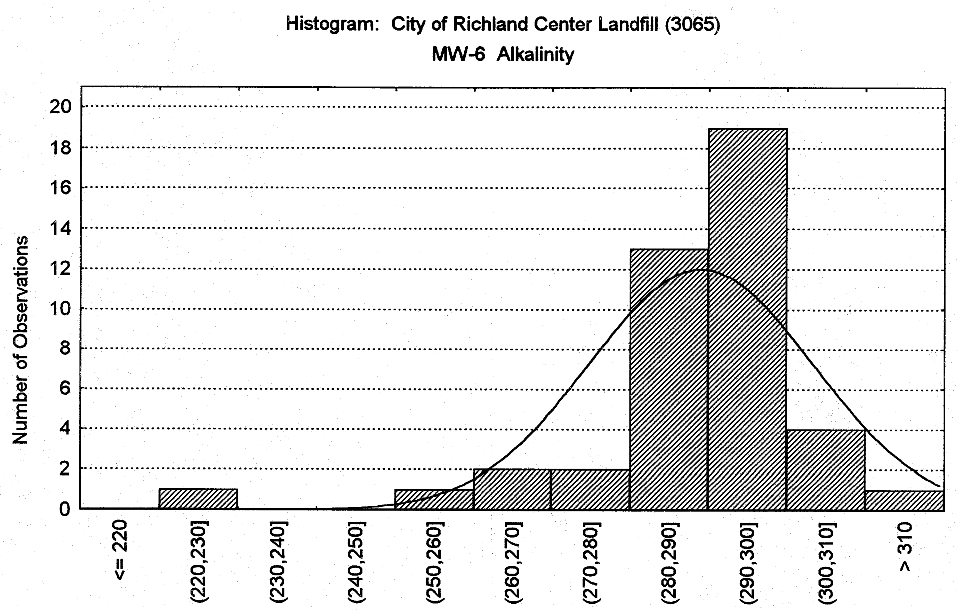


Figure 5-23 Histogram: Groundwater Data Skewed to the Left
(43 samples, -2.470 skewness coefficient)

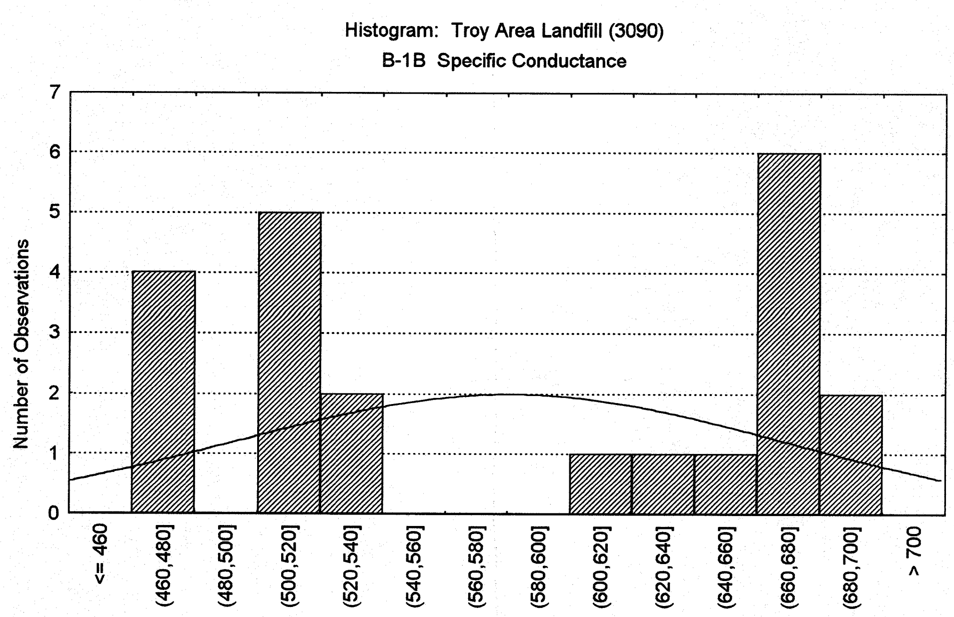


Figure 5-24 Histogram: Groundwater Data Bimodal Zero Skew
(22 samples , -0.029 skewness coefficient)

For a quantitative look at normality we performed two numerical tests: the Shapiro-Wilk (SW) test and the Kolmogorov-Smirnov test (KS). The Lilliefors test procedure was used for the KS test since the mean and variance were not known a priori. For these tests, we analyzed 26 upgradient wells at ten landfills in Wisconsin for normality. For each well we used alkalinity, hardness and specific conductance.

Using a five percent significance level, we found that the KS and SW provided similar results for alkalinity and specific conductance and identical results for hardness. For the SW test, 54, 73 and 54 percent of the wells were rejected for normality for alkalinity, hardness and specific conductance respectively. Similarly for the KS test, 50, 73 and 46 percent of the wells were rejected for normality for alkalinity, hardness and specific conductance. Overall, normality was rejected 60 percent of the time for the SW test and 56 percent of the time for the KS test.

The results from our tests are summarized in Figure 5-25. In addition, this figure compares our results with the results from Montgomery et. al. (1987), Goodman (1987), and Fisher (1989). Note that Montgomery et. al. (1987) did not use alkalinity in any of the tests and only tested three wells for hardness. From Figure 5-25, one can see from all three studies that normality is rejected more often for hardness than for alkalinity and specific conductance. Basically, our study shows that the assumption of normality is frequently violated.

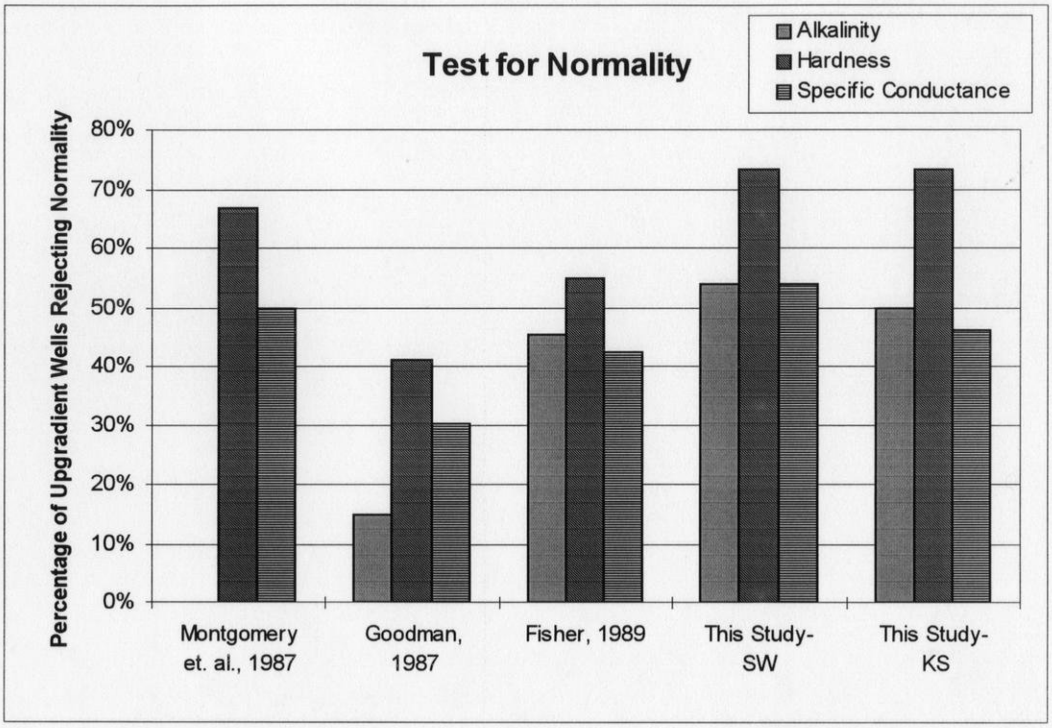


Figure 5-25 Results for Tests of Normality

We also applied the SW test to the log transform of the data. Table 5-3 gives the results of these tests. For the parameters alkalinity, hardness and specific conductance 58, 46 and 61 percent of the wells were rejected for lognormality. This is comparable to the rejection rate of 54, 73 and 54 percent for normality. Also, 46, 46 and 42 percent of the wells were rejected for both normality and lognormality. Alternately, 35, 27 and 27 percent of the wells were not rejected for both normality and lognormality. These results are not encouraging for the use of prediction limits or control charts based on normality or lognormality. In about 50 percent of the cases considered neither assumption appears to be warranted.

	Rejecting Normality	Rejecting Lognormality	Rejecting Both	Not Rejecting Both
Alkalinity	14/26	15/26	12/26	9/26
Hardness	19/26	12/26	12/26	7/26
Specific Conductance	14/26	16/26	11/26	7/26

Table 5-3 Results for Shapiro-Wilk Test for Normality and Lognormality

5.5 How do Violations of Assumptions Affect Parametric Tests?

In previous sections, we found that over 50 percent of the upgradient wells had a significant trend, non-normal distribution or serial correlation. In fact, 93, 100 and 88 percent of the wells were significant for at least one of the three for alkalinity, hardness and specific conductance, respectively. In the case study discussed in the previous chapter, we found that a number of upgradient wells had violations. Further, we found the false positive rate to be higher than expected. In this section, we will use DUMPStat and the indicator PAL to evaluate the same 26 upgradient wells at ten landfills. Again, the parameters alkalinity, hardness and specific conductance will be used. This analysis was performed using eight background samples. After the analysis, we tabulated the number of data points out of compliance. Next, we estimated the false positive rate. Lastly, we determined if the data points that were out of compliance were in data sets exhibiting nonormality, serial correlation, and trend.

Figure 5-26 shows the number of violations for each parameter for all the upgradient wells. Figure 5-27 shows the estimates of the false positive rate based on the same wells. Clearly, the PL and CC indicate a large number of violations in the upgradient data. For all cases, the CC had more violations than the PL and the PL had more violations than the PAL. For instance, alkalinity had 2 ,151 and 202 violations for the PAL, PL and CC, respectively. Since all the data is upgradient, these violations are all false positive results. Overall the false positive rate estimate is 0.7, 10.9, and 21.4 percent for the PAL, PL and CC, respectively.

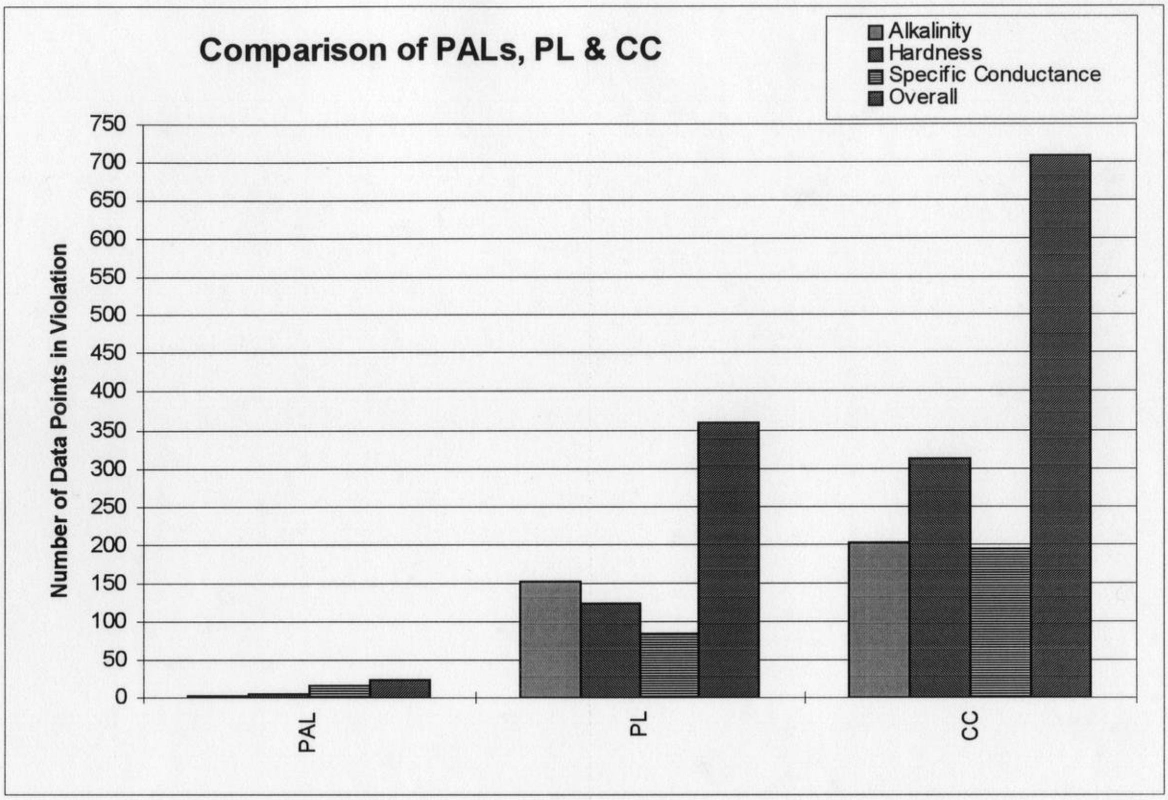


Figure 5-26 Number of Data Points in Violation
(Based on Eight Background Samples)

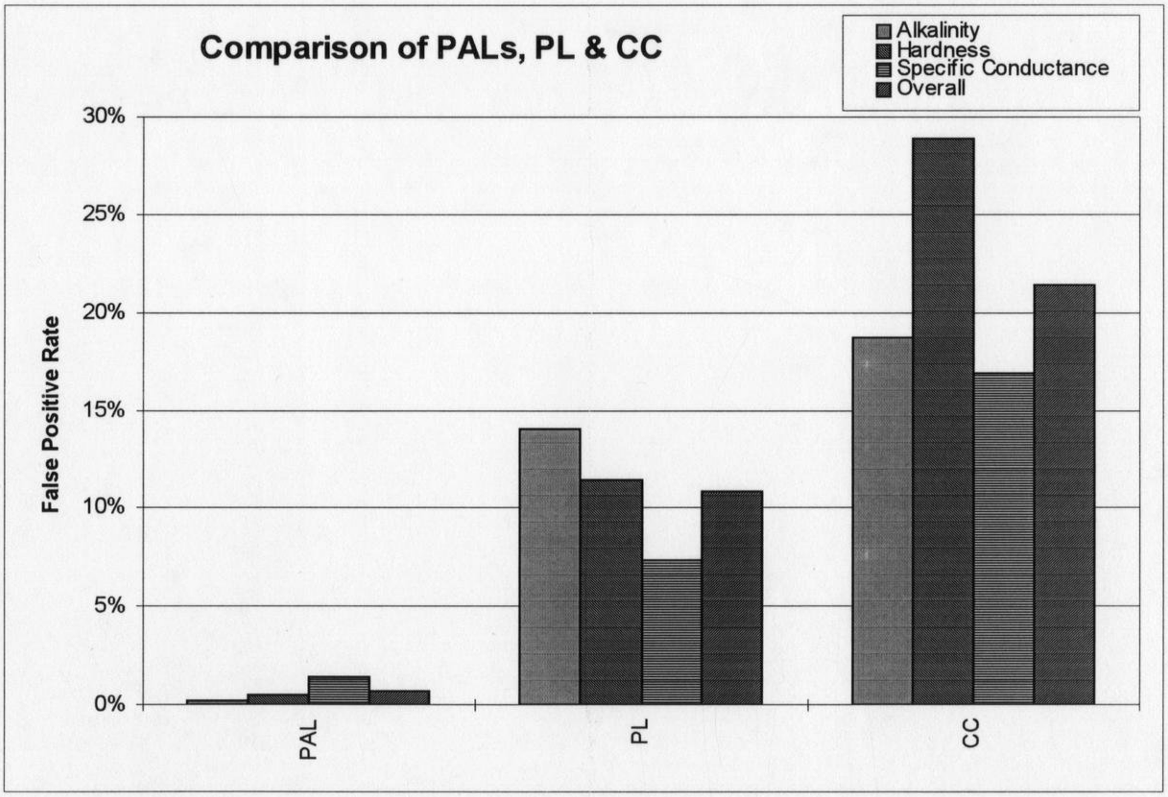


Figure 5-27 False Positive Rate Based on Upgradient Wells
(Based on Eight Background Samples)

How do these false positive results relate to violation of the assumptions of normality and randomness in the indicator PAL, PL and CC. Figure 5-28 shows the percent of PAL exceedances which occur in datasets which exhibit serial correlation, nonormality, or trend. Figures 5-29 and 5-30 show the corresponding plots for PL and CC respectively. Of the PAL violations, 83, 78 and 74 percent of the violations were in data sets showing nonormality, serial correlation or trend respectively. (Note however, that they were close for PAL exceedances for alkalinity and hardness data.) For the PL, at least 65 percent of the violations are in data sets showing nonormality, serial correlation, or trend. For the CC, at least 57 percent of the violations are in data sets violating assumptions. From this, we can conclude data that violates the assumptions is more likely to be out of compliance than in compliance.

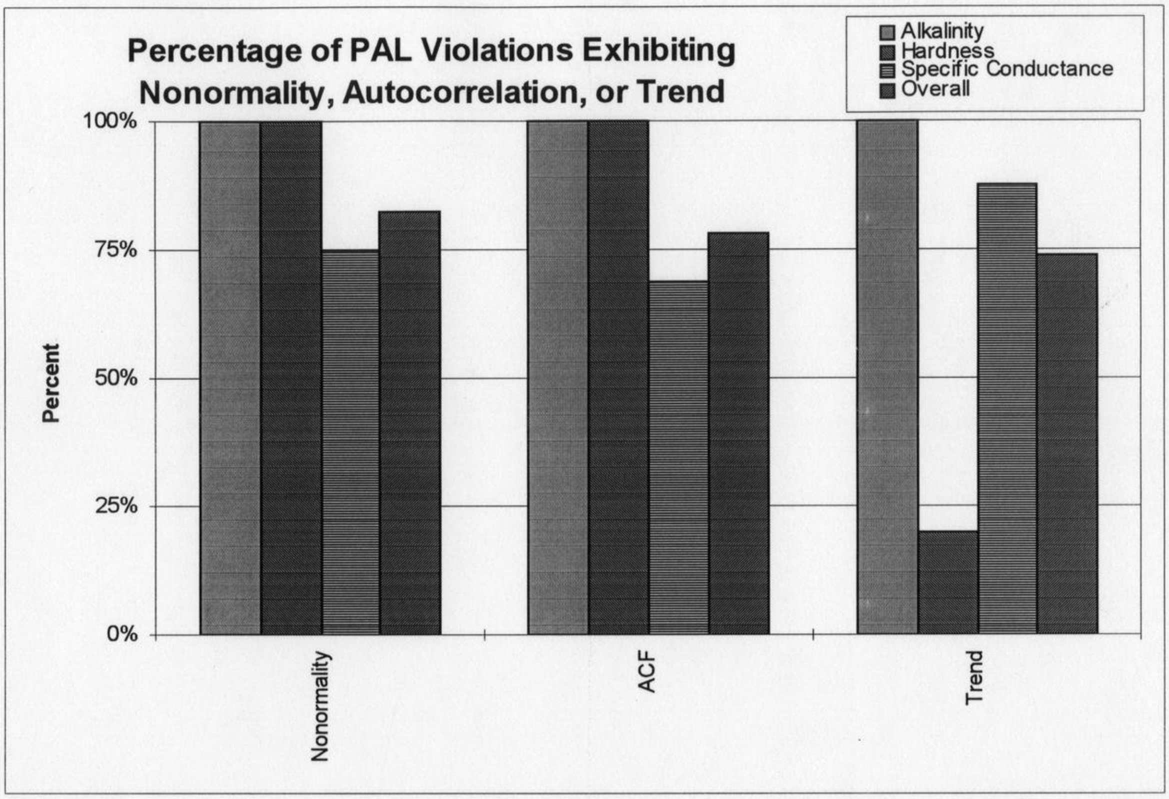


Figure 5-28 Percentages of PAL Violations in Data Sets Deviating from Parametric Assumptions

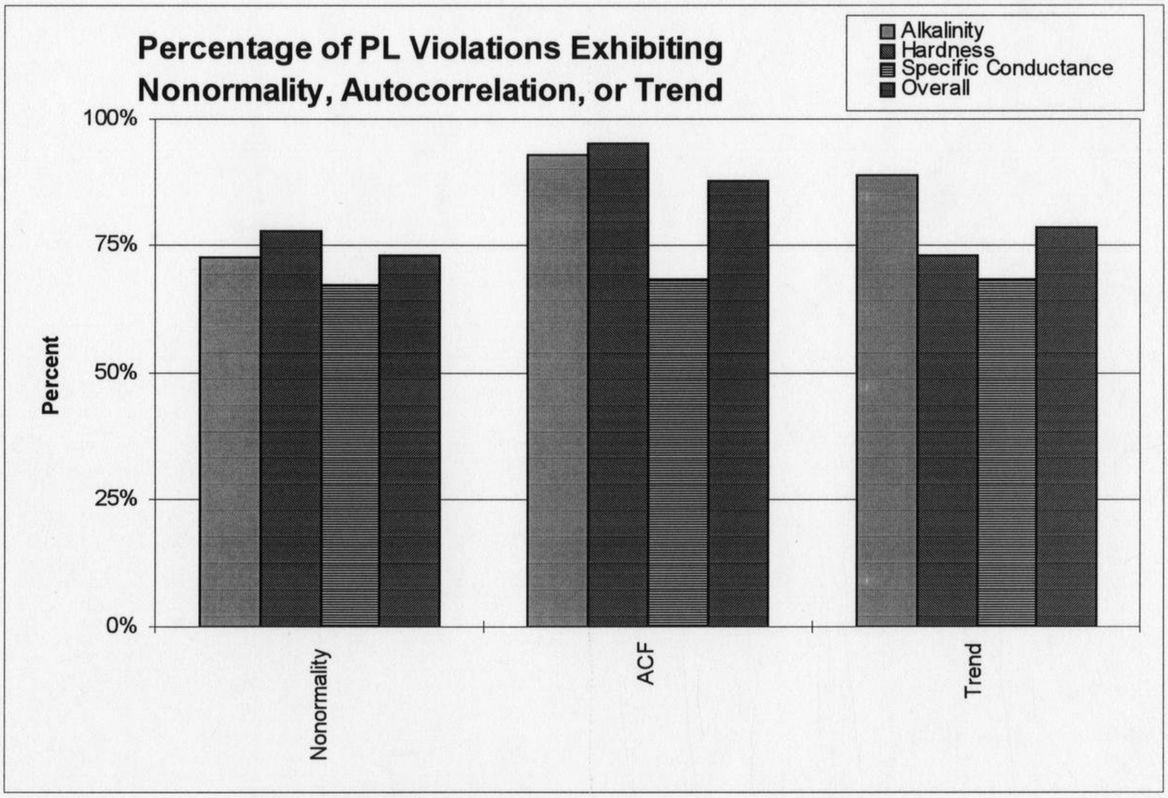


Figure 5-29 Percentages of PL Violations in Data Sets Deviating from Parametric Assumptions

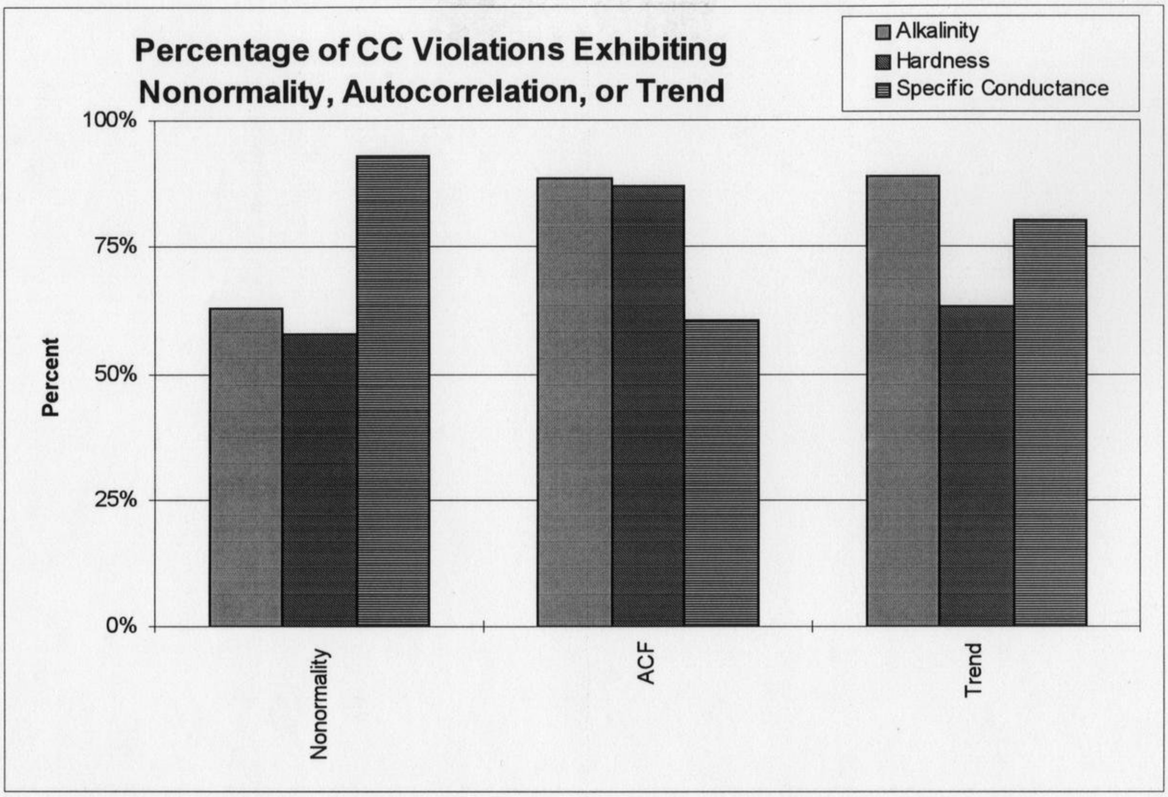


Figure 5-30 Percentages of CC Violations in Data Sets Deviating from Parametric Assumptions

5.6 Chapter Summary

The tests used in DUMPStat assume that the data are random and are normally distributed (or can be normally distributed with a log transformation). Analysis of alkalinity, hardness and specific conductance data for 26 upgradient wells indicated that these assumptions are commonly violated. Over 50 percent of these wells, for each parameter, had a significant autocorrelation coefficient or trend which indicates the data are not random. Also, over 50 percent of the upgradient wells, for each parameter, rejected normality and over 50 percent rejected lognormality.

CHAPTER 6

RECOMMENDATIONS AND CONCLUSIONS

We cannot recommend the use of DUMPStat as a supplement or alternative to the indicator PAL. Use of DUMPStat's methods for intrawell comparison, prediction limits and combined Shewhart-CUSUM control charts, will result in many false indications of contamination. This is true for two reasons. First, DUMPStat's intrawell tests are inherently more conservative than the indicator PAL, except at small sample sizes. Second, the assumptions on which these tests are based, that the data are random samples from normal distributions, are often violated by upgradient landfill monitoring data. Nonrandomness in particular can trigger false indication of contamination.

CHAPTER 7

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APPENDIX A
STATISTICAL TESTS

APPENDIX A
STATISTICAL TESTS

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APPENDIX A
STATISTICAL TESTS

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A1.0 Sen's Test

Reference:

Gibbons, Robert D. Statistical Methods For Groundwater Monitoring. New York: John Wiley & Sons, Inc., 1994.

Sen developed this nonparametric trend test. DUMPStat uses it to identify historical trends if the option is selected in the setup menu. The test estimates the slope of the concentration versus time regression line. According to Gibbons this method is robust to outliers, missing data and nondetects. The required data includes the sample values and the order of the samples in time for a well and constituent.

The one sided hypothesis test is:

Null hypothesis H_0: The data has no upward trend

Alternate hypothesis H_1: The data has an upward trend

A1.1 Test Procedure

First, compute N estimates of the slope Q where

$$N = \frac{n \cdot (n-1)}{2} \quad \text{(A1.1)}$$

and

$$Q = \frac{x_j - x_i}{j - i} \quad \text{(A1.2)}$$

for all combinations of j greater than i where j=(i+1),....n and i=1,....(n-1).

n is the total number of sample points, x_i is the ith sample concentration and x_{j+1} is the jth sample concentration.

Second, rank the N values of Q from smallest to largest. Compute the median slope S, where

$$S = Q_{[(N+1)/2]} \text{ if N is odd} \quad \text{(A1.3)}$$

$$S = Q_{[N/2]} + Q_{[(N+2)/2]} \text{ if N is even} \quad \text{(A1.4)}$$

Third, estimate the variance of S, V[S]. For n>10 the V[S] can be estimated by

$$V[S] = \frac{n \cdot (n-1) \cdot (2n+5) - \sum_{p=1}^{q} t_p \cdot p \cdot (p-1) \cdot (2 \cdot p + 5)}{18} \qquad \text{(A1.5)}$$

where t_p is the number of ties with extent p. For example for $t_4=2$ there are two ties of extent 4. There are two measurements repeated four times each.

Fourth, compute the approximate lower confidence limit which is the Mth smallest value of Q where

$$M = \frac{N - Z_{1-\alpha} \cdot V[S]^{1/2}}{2} \qquad \text{(A1.6)}$$

$Z_{1-\alpha}$ is the lower one sided $(1-\alpha)100$ percent confidence Z statistic for the normal distribution, where α is the significance level of the test.

Lastly, locate the Mth smallest value of Q. Typically, M is not an integer so interpolate to approximate the Mth largest Q. If this interpolated value is greater than zero reject the null hypothesis.

A1.2 Sample Calculation

Compute the number of slope estimates, N

$$N = \frac{10 \cdot 9}{2} = 45$$

Compute slope estimates, Q

Time Period	Sample Concentration									
1	200									
2	210	10.00								
3	225	12.50	15.00							
4	210	3.33	0.00	-15.00						
5	260	15.00	16.67	17.50	50.00					
6	260	12.00	12.50	11.67	25.00	0.00				
7	290	15.00	16.00	16.25	26.67	15.00	30.00			
8	250	7.14	6.67	5.00	10.00	-3.33	-5.00	-40.00		
9	260	7.50	7.14	5.83	10.00	0.00	0.00	-15.00	10.00	
10	300	11.11	11.25	10.71	15.00	8.00	10.00	3.33	25.00	40.00

Table A1.1 Individual Slope Estimates

Now rank the Q values from smallest to largest.

Rank	Q	Rank	Q	Rank	Q	Rank	Q
1	-40	13	5.833	24	10.71	35	15
2	-15	14	6.667	25	11.11	36	16
3	-15	15	7.143	26	11.25	37	16.25
4	-5	16	7.143	27	11.67	38	16.67
5	-3.33	17	7.5	28	12	39	17.5
6	0	18	8	29	12.5	40	25
7	0	19	10	30	12.5	41	25
8	0	20	10	31	15	42	26.67
9	0	21	10	32	15	43	30
10	3.333	22	10	33	15	44	40
11	3	23	10	34	15	45	50
12	5						

Table A1.2 Ranked Slope Estimates

Compute The Median Slope

$$S = Q_{[23]} = 10.00$$

Estimate the variance of S.

$$V[S] = \frac{n \cdot (n-1) \cdot (2n+5) - \sum_{p=1}^{q} t_p \cdot p \cdot (p-1) \cdot (2p+5)}{18} = \frac{10 \cdot 9 \cdot 25 - 1 \cdot 3 \cdot 2 \cdot 11 - 1 \cdot 2 \cdot 1 \cdot 9}{18} = 120.33$$

where n=10 is the number of sample points. Also, the data contains two ties. The first is a two way tie with a concentration of 210. Consequently t_2=1. The second is a three way tie with a concentration of 260. Similarly t_3=1.

For the 99 percent one sided test $Z_{0.99}$=2.33.

Determine the Mth smallest slope estimate Q.

$$M = \frac{N - Z_{1-\alpha} \cdot V[S]^{1/2}}{2} = \frac{45 - 2.33 \cdot 120.33}{2} = 9.72$$

So select the ninth and tenth smallest values for the slope estimate, Q. Then interpolate to get the Mth smallest Q value.

Q_9=0
Q_{10}=3.33
$Q_{9.72}$=2.40

$Q_{9.72}$>0 so the reject null hypothesis that trend is zero (the data may have an upward trend).

A2.0 Dixon's Test

Reference:

Gibbons, Robert D. Statistical Methods For Groundwater Monitoring. New York: John Wiley & Sons, Inc., 1994.

Dixon developed this test for possible outliers. According to Gibbons (1994), Dixon's Test can be used where a small number of outliers are suspected. DUMPStat searches for outliers in the background data. If outliers are included in the background data, the control limit could be set too high or too low. This influences the false positive and false negative rate.

The two sided hypothesis test is:

Null hypothesis H_0: The data set contains no outliers

Alternate hypothesis H_1: The data set contains outliers

A2.1 Test Procedure

To perform the test, first rank the data from smallest to largest. Second, calculate the Dixon statistic for the highest and lowest values in the data set. Table A.2.1 shows the Dixon statistics based on the number of sample values, n.

n	Highest Value	Lowest Value
3-7	$\frac{X_n - X_{n-1}}{X_n - X_1}$	$\frac{X_2 - X_1}{X_n - X_1}$
8-10	$\frac{X_n - X_{n-1}}{X_n - X_2}$	$\frac{X_2 - X_1}{X_{n-1} - X_1}$
11-13	$\frac{X_n - X_{n-2}}{X_n - X_2}$	$\frac{X_3 - X_1}{X_{n-1} - X_1}$
14-25	$\frac{X_n - X_{n-2}}{X_n - X_3}$	$\frac{X_3 - X_1}{X_{n-2} - X_1}$

Table A2.1 Dixon's Test Statistic Equations

Lastly compare these statistics with the critical Dixon's statistics provided in Table A2.2. The test may be repeated if additional outliers are suspected. However, this may increase the probability that a data point is removed unnecessarily. The probabilities in Table A2.2 are for a single test for outliers.

n	5%	1%	n	5%	1%
3	0.941	0.988	14	0.546	0.641
4	0.765	0.889	15	0.525	0.616
5	0.642	0.780	16	0.507	0.595
6	0.560	0.698	17	0.490	0.577
7	0.507	0.637	18	0.475	0.561
8	0.554	0.683	19	0.462	0.547
9	0.512	0.635	20	0.450	0.535
10	0.477	0.597	21	0.440	0.524
11	0.576	0.679	23	0.421	0.505
12	0.546	0.642	24	0.413	0.497
13	0.521	0.615	25	0.406	0.498

Table A2.2 Critical Values for Dixon's Statistic

A2.2 Sample Calculation

Rank	Sample Concentration
1	2.00
2	210
3	210
4	225
5	250
6	260
7	260
8	260
9	290
10	3000

Table A2.3 Sample Data for Dixon's Test

n=10 therefore use $\frac{x_n - x_{n-1}}{x_n - x_2}$ and $\frac{x_2 - x_1}{x_{n-1} - x_1}$ for the high value and low value Dixon statistic. The corresponding results are

x_{n-1}=2.90 x_n=3000

x_2=210 x_1=2.00

The Dixon statistic for the upper value is

$$\frac{x_n - x_{n-1}}{x_n - x_2} = \frac{3000 - 290}{3000 - 210} = 0.971$$

The Dixon statistic for the lower value is

$$\frac{x_2 - x_1}{x_{n-1} - x_1} = \frac{210 - 2.00}{290 - 2.00} = 0.722$$

The critical Dixon Statistic with a one percent false positive rate is 0.597. Since both Dixon statistics calculated above the critical Dixon statistic, reject the null hypothesis. Consequently, the highest and lowest value in the data set should be removed prior to calculating the mean, standard deviation, PAL, prediction limit or control chart.

A3.0 Intrawell Shewart-CUSUM Control Charts

Reference:

Gibbons, Robert D. Statistical Methods For Groundwater Monitoring. New York: John Wiley & Sons, Inc., 1994.

The Shewart-CUSUM control chart is one intrawell option available in DUMPStat. This method combines the Shewart control chart which can detect immediate releases, and the CUSUM control chart which can detect gradual releases. The data in order of measurement are required for this analysis.

DUMPStat notifies the user of historical trends using Sen's test and removes outliers using Dixon's test. Procedures and examples of these tests are included in A1.0 and A2.0.

The one sided hypothesis test is:

Null hypothesis H_0: The well is not in violation

Alternate hypothesis H_1: The well is in violation

A3.1 Test Procedure

DUMPStat selects three Shewart-CUSUM control chart parameters.

n	k	SCL	h
$n < 12$	1.0	4.5	4.5
$n \geq 12$	0.75	4.0	4.0

Table A3.1 Shewart-CUSUM Control Chart Parameters

n is the number of background samples. The user may set the minimum number of n to 4, however, Gibbons and the WDNR recommend a minimum of 8 background samples. k is a parameter related to the displacement that should be quickly detected. h is value which the CUSUM will be compared. SCL is the number of standard deviations the Shewart will be compared. These values are slightly more conservative than the EPA recommendations.

First, compute the mean, $\bar{x}$, based on the background data where

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{A3.1}$$

Second, calculate the standard deviation, s, based on the background data where

$$s = \sqrt{\frac{\sum_{i=1}^{n} x_i - \bar{x}}{n-1}} \tag{A3.2}$$

Third, calculate the z score for all i=1,2....N where

$$z_i = \frac{x_i - \bar{x}}{s} \tag{A3.3}$$

and N is the total number of samples both background and beyond.

Fourth, calculate the CUSUM, S, for all i=1,2....N where

$$S_i = \max[0, (z_i - k) + S_{i-1}] \tag{A3.4}$$

and

$S_0=0$

The Shewart-CUSUM control chart is out of control if during a sampling period $S_i \geq h$ or $z_i \geq SCL$. This must be verified by the next round of sampling before action is required.

A3.2 Sample Calculation

For the data listed below use the first 8 samples for the background. Compute the Shewart-CUSUM control chart based on the entire sample.

Time Period	Sample Concentration	Time Period	Sample Concentration
1	200	7	240
2	210	8	250
3	225	9	260
4	210	10	310
5	260	11	320
6	260	12	260

Table A3.2 Sample Data for Shewart-CUSUM Control Chart

Calculate the mean and standard deviation based on the eight background samples. The results are listed in Table A3.3. Also, the three Shewart-CUSUM control chart parameters are listed.

Mean, $\bar{x}$	231.875
Standard Deviation, s	23.895
k	1
h=SCL	4.5
Number of Background, n	8
Total Samples, N	12

Table A3.3 Mean, Standard Deviation and Shewart-CUSUM Control Chart Parameters

Calculate z_i and S_i based on equations A3.3 and A3.4. Displays of the control chart in graphical and tabular form are included in table A3.4 and figure A3.1.

Time Period, i	Sample Concentration, x_i	Shewart z_i	CUSUM S_i	Control Chart Status
1	200	-1.33	0.00	In Control
2	210	-0.92	0.00	In Control
3	225	-0.29	0.00	In Control
4	210	-0.92	0.00	In Control
5	260	1.18	0.18	In Control
6	260	1.18	0.35	In Control
7	240	0.34	0.00	In Control
8	250	0.76	0.00	In Control
9	260	1.18	0.18	In Control
10	310	3.27	2.45	In Control
11	320	3.69	5.13	Out of Control (Hit)
12	260	1.18	5.31	Out of Control (Verified Hit)

Table A3.4 Tabular Shewart-CUSUM Control Chart

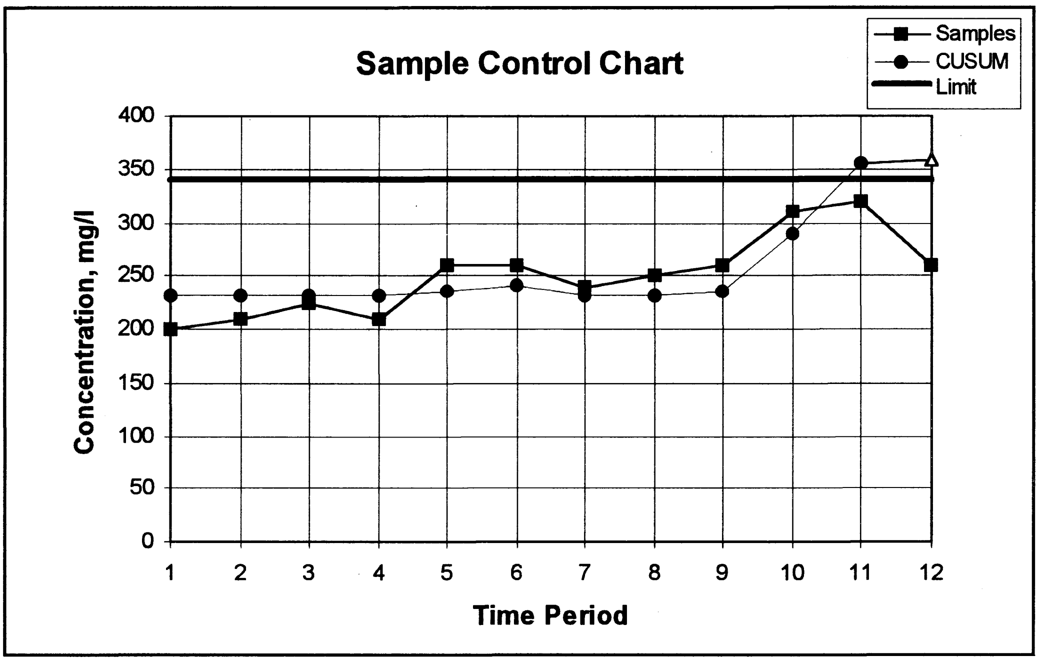

Figure A3.1 Graphical Shewart-CUSUM Control Chart

Note the eleventh concentration is out of control for the CUSUM portion of the control chart. This is verified on the twelfth sample. Therefor action should be taken.

A4.0 Intrawell Prediction Limits

Reference:

Gibbons, Robert D. Statistical Methods For Groundwater Monitoring. New York: John Wiley & Sons, Inc., 1994.

The prediction limit is one intrawell option available in DUMPStat. This method is detects immediate releases faster than the Shewart-CUSUM control charts but cannot detect slow or gradual releases. The data in order of measurement are required for this analysis.

DUMPStat notifies the user of historical trends using Sen's test and removes outliers using Dixon's test. Procedures and examples of these tests are included in A1.0 and A2.0.

The one sided hypothesis test is:

Null hypothesis	H_0: The well not in violation
Alternate hypothesis	H_1: The well is in violation

A4.1 Test Procedure

First, select α as the minimum of 0.01 or $\alpha = \sqrt{1 - 0.95^{\frac{1}{k}}}$ for one verification resample. For this study pass 1 of 1 resamples was selected from the setup menu for the verification resampling plan. Other verification resampling plans can be selected in the DUMPStat setup menu. k is the number of future comparisons to be made.

Second, compute the intrawell prediction limit, PL, as:

$$PL = \bar{x} + s \cdot t_{[1-\alpha, n-1]} \cdot \sqrt{1 + \frac{1}{n}} \qquad \text{(A4.1)}$$

where $\bar{x}$ is the mean and s is the standard deviation of the background data (see equations A3.1 and A3.2). n is the number of background data points. $t_{[1-\alpha, n-1]}$ is the student's upper one sided t statistic based on n-1 degrees of freedom and a 1-α confidence level (see table A4.1 on the next page).

n-1	$t_{0.99}$	n-1	$t_{0.99}$
1	31.82054	17	2.566936
2	6.964523	18	2.552382
3	4.54071	19	2.539488
4	3.746956	20	2.527977
5	3.364931	21	2.517649
6	3.142664	22	2.508326
7	2.997957	23	2.499865
8	2.896457	24	2.492159
9	2.821438	25	2.485111
10	2.76377	26	2.478627
11	2.718078	27	2.472664
12	2.680996	28	2.467141
13	2.650311	29	2.46202
14	2.624493	30	2.457266
15	2.602481	50	2.403274
16	2.583488	31999	2.326463

Table A4.1 Student's t Statistics Based on n-1 Degrees of Freedom and a 99 Percent Confidence Level

Third compare the prediction limit to the data of interest. If the data exceeds the prediction limit two consecutive times the well is in violation.

A4.2 Sample Calculation

Compute the prediction limit based on the first eight background samples (n=8). See if samples nine through twelve exceed the prediction limit.

Time Period	Sample Concentration	Time Period	Sample Concentration
1	200	7	240
2	210	8	250
3	225	9	260
4	210	10	300
5	260	11	320
6	260	12	322

Table 4.2 Sample Data for Prediction Limit

There are four future samples therefor k=4. Consequently, α is the minimum of 0.01 and $\alpha = \sqrt{1-0.95^{\frac{1}{k}}} = \sqrt{1-0.95^{\frac{1}{4}}} = 0.113$.

Select $t_{[0.99,7]}$=2.997957 from Table 4.2.

For the background data the mean, $\overline{x}$, is 231.875 and the standard deviation, s, is 23.895.

$$PL = \overline{x} + s \cdot t_{[1-\alpha, n-1]} \cdot \sqrt{1+\frac{1}{n}} = 231.9 + 23.9 \cdot 2.998 \cdot \sqrt{1+\frac{1}{8}} = 307.9$$

The eleventh and twelfth samples exceed the prediction limit. The well may not be in compliance and action should be taken.

A5.0 Gamma Test

References:

Kendall, M.G, and Jean Dickenson Gibbons. Rank Order Correlation. New York: Oxford University Press, 1990.

Statsoft, Inc. Statistica for Windows [Computer Program and Manual]. Tulsa, Oklahoma: Statsoft, Inc., 1997.

The Gamma test is a nonparametric trend test. It is equivalent to the Kendall tau, except that ties are explicitly taken into account. The Gamma test yields exactly the same results as the Kendall tau type b, except the calculation of the gamma statistic removes the ties from the denominator of the statistic. Like Sen's test the Gamma test is robust to outliers missing data and nondetects. The required data includes the sample values and the order of the samples in time for a well and constituent.

Null hypothesis H_0: The data has no upward trend

Alternate hypothesis H_1: The data has an upward or downward trend

A5.1 Test Procedure

First, compute **N** values of the $\text{sgn}(x_j\text{-}x_i)$ where

$$N = \frac{n \cdot (n-1)}{2} \qquad \text{(A5.1)}$$

and

$$\text{sgn}(x_j - x_i) = \begin{cases} +1 & \text{if} \quad x_j - x_i > 0 \\ 0 & \text{if} \quad x_j - x_i = 0 \\ -1 & \text{if} \quad x_j - x_i < 0 \end{cases} \qquad \text{(A5.2)}$$

for all combinations of j greater than i where j=(i+1),....n and i=1,....(n-1). n is the total number of sample points, x_i is the ith sample concentration and x_{j+1} is the jth sample concentration.

Second, calculate the Mann-Kendall statistic, S as

$$S = \sum_{1}^{n-1}\sum_{i+1}^{n} \operatorname{sgn}(x_j - x_i) \qquad \text{(A5.3)}$$

Basically, this is the sum of the +1 and -1 values calculated in equation A5.2. If S is zero, no trends exist.

Third, calculate the gamma statistic as,

$$\gamma = \frac{S}{N - \sum_{p=1}^{q} t_p \cdot \frac{p}{2} \cdot (p-1)} \qquad \text{(A5.4)}$$

where t_p is the number of ties with extent p. For example for t_4=2 there are two ties of extent four. There are two measurements repeated four times.

Fourth, estimate the variance of S, V[S]. For n>10 the V[S] can be estimated by

$$V[S] = \frac{n \cdot (n-1) \cdot (2n+5) - \sum_{p=1}^{q} t_p \cdot p \cdot (p-1) \cdot (2 \cdot p + 5)}{18} \qquad \text{(A5.3)}$$

Fifth, for n>10 the z statistic can be estimated for the two sided normal test by

$$z = \begin{cases} \dfrac{S-1}{V[S]^{\frac{1}{2}}} & \text{if} \quad S > 0 \\ 0 & \text{if} \quad S > 0 \\ \dfrac{S+1}{V[S]^{\frac{1}{2}}} & \text{if} \quad S < 0 \end{cases} \qquad \text{(A5.4)}$$

Sixth, compare z value with two sided z value with a 95 percent confidence level. Therefor if $|z| > 1.96$ then reject the null hypothesis. The data may have a trend.

A5.2 Sample Calculation

Compute the number of sgn(x_j-x_i) values, **N**

$$N = \frac{10 \cdot 9}{2} = 45$$

Compute sgn(x_j-x_i)

Time Period	Sample Concentration									
1	200									
2	210	1								
3	225	1	1							
4	210	1	0	-1						
5	260	1	1	1	1					
6	260	1	1	1	1	0				
7	290	1	1	1	1	1	1			
8	250	1	1	1	1	-1	-1	-1		
9	260	1	1	1	1	0	0	-1	1	
10	300	1	1	1	1	1	1	1	1	1

Table A5.1 Individual sgn(x_j-x_i) for Gamma Test

Calculate the Mann-Kendall statistic, S by adding all the 1's, 0's and -1's in Table A1.1.

$$S = \sum_{1}^{n-1} \sum_{i+1}^{n} \operatorname{sgn}(x_j - x_i) = 36 \cdot 1 + 4 \cdot 0 + 5 \cdot -1 = 31$$

Calculate the gamma statistic, γ

$$\gamma = \frac{S}{N - \left[\sum_{p=1}^{q} t_p \cdot \frac{p}{2} \cdot (p-1) \right]} = \frac{31}{45 - \left[1 \cdot \frac{2}{2}(2-1) + 1 \cdot \frac{3}{2}(3-1) \right]} = 0.75$$

Estimate the variance of S,

$$V[S] = \frac{n \cdot (n-1) \cdot (2n+5) - \sum_{p=1}^{q} t_p \cdot p \cdot (p-1) \cdot (2p+5)}{18} = \frac{10 \cdot 9 \cdot 25 - 1 \cdot 3 \cdot 2 \cdot 11 - 1 \cdot 2 \cdot 1 \cdot 9}{18} = 120.33$$

S>0 so calculate z, based on equation 5.4.

$$z = \frac{S-1}{V[S]^{\frac{1}{2}}} = \frac{31-1}{120.33^{\frac{1}{2}}} = 2.735 > 1.96$$

Reject the null hypothesis. The data may have an upward trend.

A6.0 Autocorrelation Function

References:

Box, E. P. and G. M. Jenkins. Time Series Analyis Forecasting and Control. San Francisco: Holden Day, 1976.

Kendall, M.G. and Ord, J. K. Time Series. New York: Oxford University Press, 1990.

Statsoft, Inc. Statistica for Windows [Computer Program and Manual]. Tulsa, Oklahoma: Statsoft, Inc., 1997.

The autocorrelation or serial correlation coefficient relates a series of data with itself shifted by a lag of k observations. This is a test of independence. The required data includes the sample values and the order of the samples in time for a well and constituent.

Null hypothesis H_0: The data does not have autocorrelation

Alternate hypothesis H_1: the data has autocorrelation

A6.1 Test Procedure

The autocorrelation function, r_k, may be estimated as

$$r_k = \frac{c_k}{c_0} \qquad \text{(A6.1)}$$

where

$$c_k = \frac{1}{N}\sum_{i=1}^{N-k}(x_i - \bar{x})(x_{i+k} - \bar{x}) \qquad \text{(A6.2)}$$

is the estimate of the autocovariance and $\bar{x}$ is the mean of the data. k is the number of the lag. In this study a k is one was used. Also, i=1,2....(N-k).

Assuming the series is a white noise process (all the autocorrelations are zero), the standard error of the autocorrelation function, $SE[r_k]$ can be estimated by:

$$SE[r_k] = \sqrt{\frac{1}{N} \cdot \frac{N-k}{N+2}} \qquad \text{(A6.3)}$$

Lastly, calculate the normal z statistic and compare it to the two sided tabulated value at the 95 percent confidence level (1.96). If z>1.96 then reject the null hypothesis.

$$z = \frac{r_k}{SE[r_k]} \qquad \text{(A6.4)}$$

A6.2 Sample Calculation

Calculate the autocorrelation function for the following data.

Time Period	Sample Concentration
1	222
2	210
3	200
4	220
5	240
6	260
7	280
8	300
9	320
10	340

Table A6.1 Sample Data for Autocorrelation Function

Calculate the autocovariance functions, c_o and c_1.

$$c_1 = \frac{1}{N}\sum_{i=1}^{9}(x_i - \bar{x})(x_{i+1} - \bar{x}) = \frac{1}{10}\big[(222 - 255.2)(210 - 255.2) + (210 - 255.2)(200 - 255.2) +$$

$$\ldots(320 - 255.2)(340 - 255.2)\big] = 1343.7$$

Similarly,

$$c_0 = 1651.4$$

From these calculate the lag-1 autocorrelation function, r_1.

$$r_1 = \frac{c_1}{c_0} = \frac{1343.7}{1651.4} = 0.814$$

Now, estimate the standard error of the autocorrelation function

$$SE[r_k] = \sqrt{\frac{1}{N}\cdot\frac{N-k}{N+2}} = \sqrt{\frac{1}{10}\cdot\frac{10-1}{10+2}} = 0.075$$

Next, compute the standard normal variate, z

$$z = \frac{r_k}{SE[r_k]} = \frac{0.814}{0.075} = 10.85 > 1.96$$

This z value is greater than 1.96 so reject the null hypothesis. The data may have serial correlation and the assumption of independence is in question.

APPENDIX B
GAMMA TEST RESULTS

APPENDIX B
GAMMA TEST RESULTS

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B1.1 Lincoln Landfill (1779)

Alkalinity

	Valid N	Gamma	Z	p-level
MW-1	19	-0.31	-1.85	0.065
MW-4	19	-0.77	-4.48	7E-06

Hardness

	Valid N	Gamma	Z	p-level
MW-1	19	-0.37	-2.14	0.032
MW-4	20	-0.7	-4.22	2E-05

Specific Conductance

	Valid N	Gamma	Z	p-level
MW-1	46	0.131	1.248	0.212
MW-4	22	-0.75	-4.79	2E-06

B1.2 Pope & Talbot Landfill (2695)

Alkalinity

	Valid N	Gamma	Z	p-level
W-13	66	0.638	7.526	5E-14
W-18	52	-0.08	-0.79	0.43
W-6	77	0.206	2.609	0.009

Hardness

	Valid N	Gamma	Z	p-level
W-13	66	0.261	2.99	0.003
W-18	52	0.449	4.634	4E-06
W-6	77	-0.15	-1.96	0.05

Specific Conductance

	Valid N	Gamma	Z	p-level
W-13	60	0.364	4.098	4E-05
W-18	46	0.365	3.564	4E-04
W-6	71	0.235	2.896	0.004

B1.3 Oneida County Landfill (2805)

Alkalinity

	Valid N	Gamma	Z	p-level
MW-1	15	0.096	0.497	0.619
MW-126	16	-0.08	-0.38	0.702

Hardness

	Valid N	Gamma	Z	p-level
MW-1	15	-0.06	-0.3	0.761
MW-126	16	-0.19	-1.02	0.31

Specific Conductance

	Valid N	Gamma	Z	p-level
MW-1	69	0.414	4.937	8E-07
MW-126	17	-0.46	-2.53	0.011

B1.4 Portage County Landfill (2966)

Alkalinity

	Valid N	Gamma	Z	p-level
W-10	51	0.555	5.659	2E-08
W-11	51	0.378	3.797	1E-04
W-12	51	-0.24	-2.36	0.018
W-9	51	0.452	4.542	6E-06
W-9P	51	-0.11	-1.16	0.247

Hardness

	Valid N	Gamma	Z	p-level
W-10	51	0.357	3.629	3E-04
W-11	51	0.132	1.335	0.182
W-12	51	-0.08	-0.84	0.399
W-9	51	0.435	4.426	1E-05
W-9P	51	-0.08	-0.85	0.395

Specific Conductance

	Valid N	Gamma	Z	p-level
W-10	51	0.059	0.608	0.543
W-11	51	-0.07	-0.75	0.456
W-12	51	-0.27	-2.8	0.005
W-9	51	0.059	0.595	0.552
W-9P	51	-0.08	-0.81	0.421

B1.5 Grede Foundries Landfill (2974)

Alkalinity

	Valid N	Gamma	Z	p-level
B-3	56	-0.3	-3.18	0.001
B-5	51	-0.6	-6.13	9E-10

Hardness

	Valid N	Gamma	Z	p-level
B-3	56	0.221	2.389	0.017
B-5	52	0.237	2.441	0.015

Specific Conductance

	Valid N	Gamma	Z	p-level
B-3	56	0.081	0.882	0.378
B-5	51	0.058	0.599	0.549

B1.6 Sauk County Landfill (2978)

Alkalinity

	Valid N	Gamma	Z	p-level
W-30	48	-0.29	-2.89	0.004
W-30A	48	-0.45	-4.45	9E-06
W-31	47	-0.3	-2.97	0.003

Hardness

	Valid N	Gamma	Z	p-level
W-30	48	-0.2	-1.99	0.046
W-30A	48	-0.3	-2.98	0.003
W-31	48	-0.29	-2.87	0.004

Specific Conductance

	Valid N	Gamma	Z	p-level
W-30	48	-0.22	-2.17	0.03
W-30A	48	-0.21	-2.09	0.036
W-31	48	-0.18	-1.8	0.072

B1.7 City of Richland Center Landfill (3065)

Alkalinity

	Valid N	Gamma	Z	p-level
MW-6	43	0.339	3.152	0.002
MW-7	43	0.02	0.189	0.85
MW-7P	42	0.278	2.558	0.011

Hardness

	Valid N	Gamma	Z	p-level
MW-6	43	-0.01	-0.11	0.915
MW-7	43	0.289	2.717	0.007
MW-7P	43	0.059	0.55	0.582

Specific Conductance

	Valid N	Gamma	Z	p-level
MW-6	43	0.117	1.069	0.285
MW-7	43	0.249	2.312	0.021
MW-7P	42	0.249	2.29	0.022

B1.8 Juneau County Landfill (3070)

Alkalinity

	Valid N	Gamma	Z	p-level
OW-5	35	0.435	2.777	0.009

Hardness

	Valid N	Gamma	Z	p-level
OW-5	35	0.681	5.34	7E-06

Specific Conductance

	Valid N	Gamma	Z	p-level
OW-5	35	0.454	2.931	0.006

B1.9 Troy Area Landfill (3090)

Alkalinity

	Valid N	Gamma	Z	p-level
B-1	32	-0.37	-2.79	0.005
B-1B	21	0.077	0.485	0.627
B-2	30	0.197	1.524	0.128

Hardness

	Valid N	Gamma	Z	p-level
B-1	32	-0.22	-1.75	0.081
B-1B	21	0.043	0.272	0.785
B-2	30	0.244	1.882	0.06

Specific Conductance

	Valid N	Gamma	Z	p-level
B-1	33	-0.55	-4.49	7E-06
B-1B	22	0.214	1.388	0.165
B-2	31	0.137	1.078	0.281

B1.10 Lincoln County Landfill (3141)

Alkalinity

	Valid N	Gamma	Z	p-level
M-4	32	0.218	1.737	0.082
M-9	30	-0.5	-3.83	1E-04

Hardness

	Valid N	Gamma	Z	p-level
M-4	32	0.309	2.457	0.014
M-9	30	0	0	1

Specific Conductance

	Valid N	Gamma	Z	p-level
M-4	32	0.191	1.513	0.13
M-9	30	-0.07	-0.52	0.605

APPENDIX C
AUTOCORRELATION TEST RESULTS

APPENDIX C
AUTOCORRELATION TEST RESULTS

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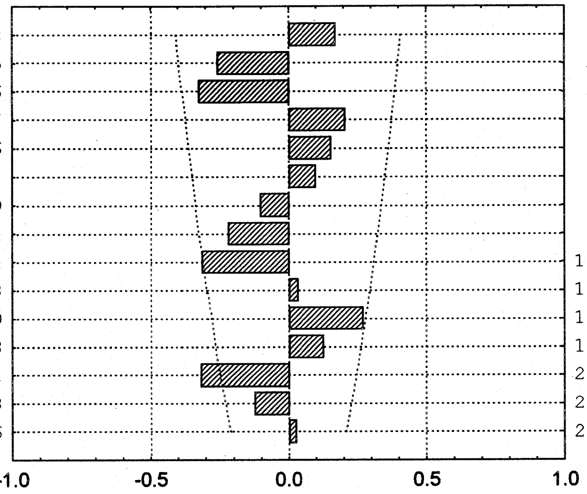
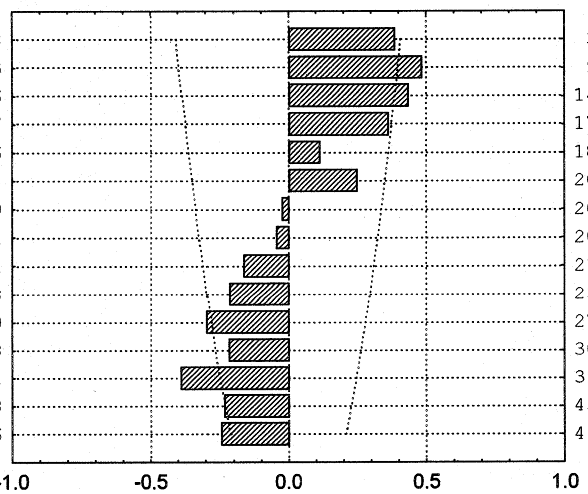
Autocorrelation Function: Lincoln Landfill (1779)
MW-1 Alkalinity
(Standard errors are white-noise estimates)



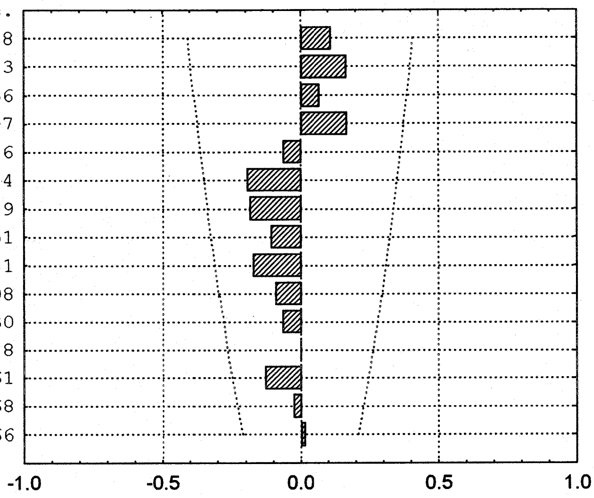
Lag	Corr.	S.E.	Q	p
1	+.173	.2078	.69	.4045
2	-.259	.2023	2.34	.3110
3	-.325	.1966	5.08	.1662
4	+.208	.1907	6.27	.1801
5	+.157	.1846	6.99	.2212
6	+.101	.1784	7.31	.2928
7	-.100	.1719	7.65	.3644
8	-.219	.1651	9.40	.3095
9	-.314	.1581	13.36	.1471
10	+.036	.1508	13.42	.2014
11	+.271	.1430	17.01	.1077
12	+.128	.1348	17.91	.1184
13	-.318	.1261	24.28	.0287
14	-.123	.1168	25.38	.0311
15	+.029	.1066	25.45	.0443

Autocorrelation Function: Lincoln Landfill (1779)
MW-4 Alkalinity
(Standard errors are white-noise estimates)



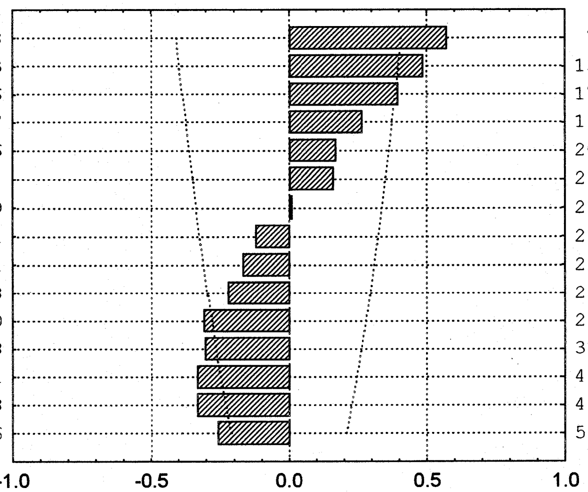
Lag	Corr.	S.E.	Q	p
1	+.389	.2078	3.50	.0614
2	+.486	.2023	9.26	.0098
3	+.437	.1966	14.20	.0027
4	+.366	.1907	17.88	.0013
5	+.117	.1846	18.28	.0026
6	+.252	.1784	20.28	.0025
7	-.021	.1719	20.29	.0050
8	-.043	.1651	20.36	.0091
9	-.163	.1581	21.43	.0109
10	-.215	.1508	23.45	.0092
11	-.297	.1430	27.77	.0035
12	-.216	.1348	30.35	.0025
13	-.390	.1261	39.91	.0001
14	-.233	.1168	43.88	.0001
15	-.244	.1066	49.14	.0000

Autocorrelation Function: Lincoln Landfill (1779)
MW-1 Hardness
(Standard errors are white-noise estimates)



Lag	Corr.	S.E.	Q	p
1	+.112	.2078	.29	.5887
2	+.168	.2023	.98	.6118
3	+.071	.1966	1.11	.7737
4	+.170	.1907	1.91	.7520
5	-.065	.1846	2.03	.8443
6	-.190	.1784	3.17	.7873
7	-.183	.1719	4.30	.7446
8	-.106	.1651	4.71	.7877
9	-.172	.1581	5.90	.7501
10	-.089	.1508	6.25	.7939
11	-.067	.1430	6.47	.8403
12	+.003	.1348	6.47	.8906
13	-.128	.1261	7.49	.8751
14	-.025	.1168	7.54	.9121
15	+.016	.1066	7.56	.9403

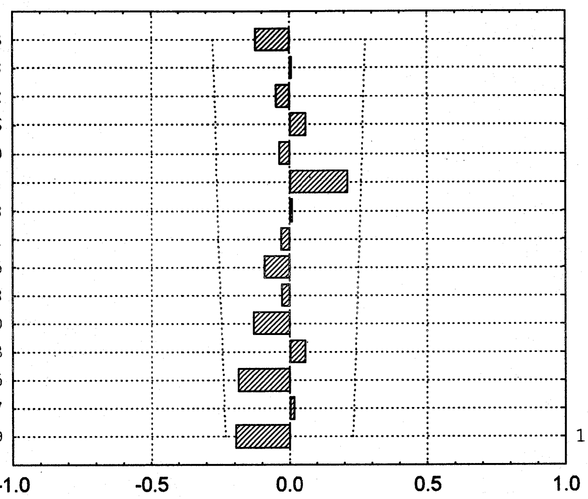
Autocorrelation Function: Lincoln Landfill (1779)
MW-4 Hardness
(Standard errors are white-noise estimates)



Lag	Corr.	S.E.	Q	p
1	+.574	.2078	7.63	.0057
2	+.488	.2023	13.46	.0012
3	+.397	.1966	17.52	.0006
4	+.269	.1907	19.51	.0006
5	+.172	.1846	20.38	.0011
6	+.163	.1784	21.21	.0017
7	+.010	.1719	21.21	.0035
8	-.120	.1651	21.74	.0054
9	-.167	.1581	22.86	.0065
10	-.221	.1508	25.01	.0053
11	-.310	.1430	29.71	.0018
12	-.304	.1348	34.79	.0005
13	-.333	.1261	41.77	.0001
14	-.332	.1168	49.85	.0000
15	-.258	.1066	55.70	.0000

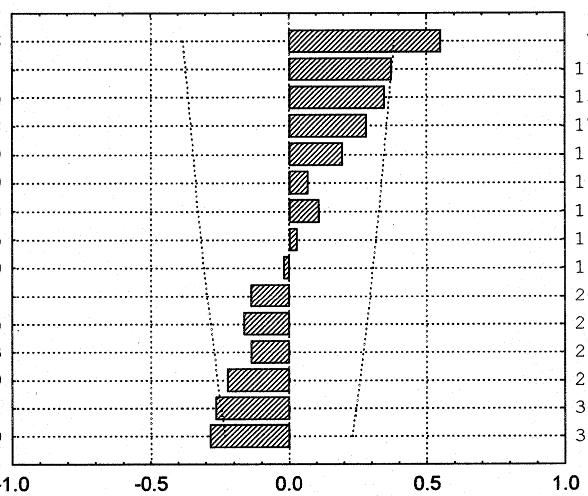
Autocorrelation Function: Lincoln Landfill (1779)
MW-1 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	-.121	.1413	.73	.3916
2	+.008	.1398	.74	.6916
3	-.048	.1382	.86	.8354
4	+.063	.1366	1.07	.8987
5	-.037	.1350	1.15	.9500
6	+.215	.1334	3.74	.7122
7	+.010	.1318	3.74	.8089
8	-.028	.1301	3.79	.8757
9	-.088	.1285	4.26	.8935
10	-.026	.1268	4.30	.9327
11	-.130	.1250	5.38	.9112
12	+.062	.1233	5.63	.9334
13	-.185	.1215	7.95	.8468
14	+.019	.1197	7.97	.8906
15	-.194	.1179	10.69	.7745

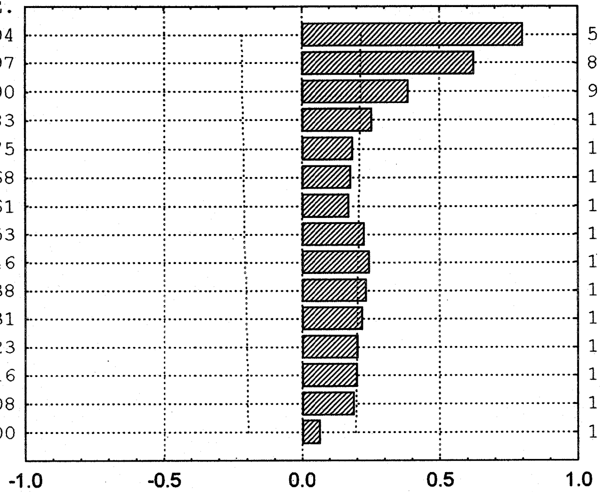


Autocorrelation Function: Lincoln Landfill (1779)
MW-4 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.552	.1956	7.97	.0048
2	+.375	.1911	11.82	.0027
3	+.349	.1865	15.32	.0016
4	+.285	.1818	17.78	.0014
5	+.198	.1769	19.03	.0019
6	+.073	.1719	19.21	.0038
7	+.112	.1668	19.66	.0064
8	+.031	.1615	19.70	.0116
9	-.017	.1560	19.71	.0198
10	-.139	.1504	20.56	.0244
11	-.163	.1445	21.83	.0257
12	-.139	.1383	22.84	.0291
13	-.224	.1319	25.71	.0186
14	-.265	.1251	30.20	.0072
15	-.286	.1180	36.10	.0017

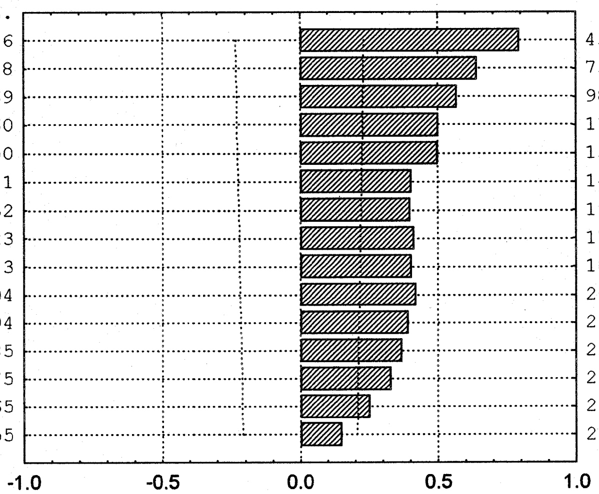


Autocorrelation Function: Pope & Talbot Landfill (2695)
W-6 Alkalinity
(Standard errors are white-noise estimates)



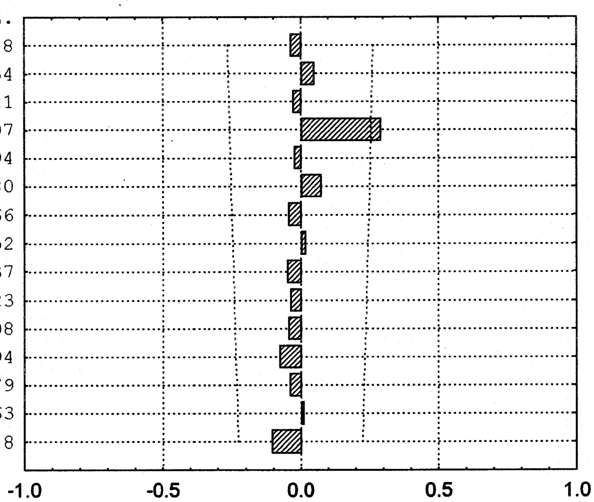
Lag	Corr.	S.E.	Q	p
1	+.802	.1104	52.79	.0000
2	+.626	.1097	85.34	.0000
3	+.389	.1090	98.11	.0000
4	+.256	.1083	103.7	.0000
5	+.187	.1075	106.7	.0000
6	+.180	.1068	109.6	.0000
7	+.174	.1061	112.3	.0000
8	+.229	.1053	117.0	.0000
9	+.248	.1046	122.6	.0000
10	+.236	.1038	127.8	.0000
11	+.222	.1031	132.4	.0000
12	+.206	.1023	136.5	.0000
13	+.203	.1016	140.5	.0000
14	+.192	.1008	144.1	.0000
15	+.069	.1000	144.6	.0000

Autocorrelation Function: Pope & Talbot Landfill (2695)
W-13 Alkalinity
(Standard errors are white-noise estimates)



Lag	Corr.	S.E.	Q	p
1	+.797	.1186	45.15	.0000
2	+.643	.1178	75.01	.0000
3	+.569	.1169	98.76	.0000
4	+.502	.1160	117.5	.0000
5	+.499	.1150	136.3	.0000
6	+.406	.1141	149.0	.0000
7	+.401	.1132	161.5	0.000
8	+.414	.1123	175.1	0.000
9	+.404	.1113	188.3	0.000
10	+.420	.1104	202.7	0.000
11	+.393	.1094	215.7	0.000
12	+.369	.1085	227.2	0.000
13	+.329	.1075	236.6	0.000
14	+.253	.1065	242.3	0.000
15	+.152	.1055	244.4	0.000

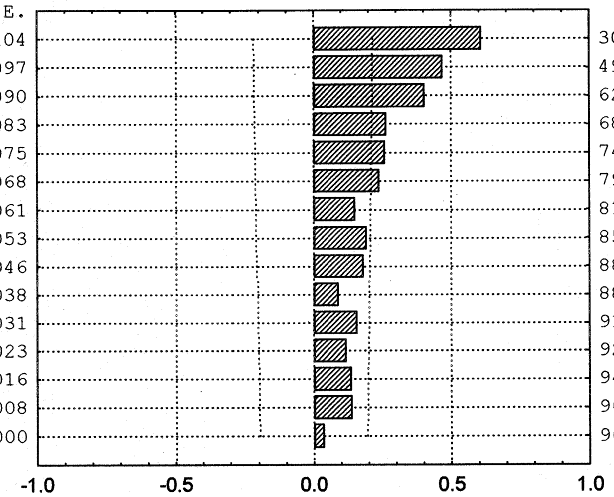
Autocorrelation Function: Pope & Talbot Landfill (2695)
W-18 Alkalinity
(Standard errors are white-noise estimates)



Lag	Corr.	S.E.	Q	p
1	-.036	.1348	.07	.7892
2	+.053	.1334	.23	.8913
3	-.027	.1321	.27	.9651
4	+.293	.1307	5.28	.2594
5	-.022	.1294	5.31	.3790
6	+.077	.1280	5.67	.4606
7	-.043	.1266	5.79	.5644
8	+.019	.1252	5.81	.6682
9	-.048	.1237	5.96	.7439
10	-.036	.1223	6.05	.8114
11	-.044	.1208	6.18	.8614
12	-.078	.1194	6.60	.8828
13	-.039	.1179	6.71	.9165
14	+.010	.1163	6.72	.9451
15	-.104	.1148	7.53	.9411

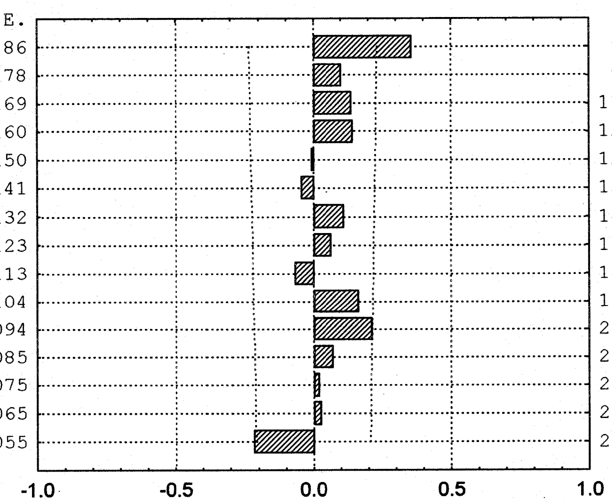
Autocorrelation Function: Pope & Talbot Landfill (2695)
W-6 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.611	.1104	30.65	.0000
2	+.470	.1097	49.01	.0000
3	+.405	.1090	62.80	.0000
4	+.265	.1083	68.81	.0000
5	+.260	.1075	74.66	.0000
6	+.239	.1068	79.68	.0000
7	+.152	.1061	81.74	.0000
8	+.194	.1053	85.12	.0000
9	+.181	.1046	88.11	.0000
10	+.092	.1038	88.90	.0000
11	+.158	.1031	91.26	.0000
12	+.120	.1023	92.62	.0000
13	+.138	.1016	94.48	.0000
14	+.139	.1008	96.39	.0000
15	+.039	.1000	96.54	.0000



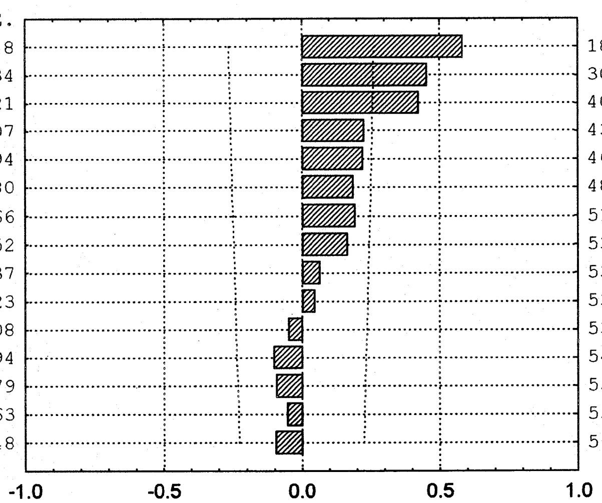
Autocorrelation Function: Pope & Talbot Landfill (2695)
W-13 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.358	.1186	9.10	.0026
2	+.104	.1178	9.88	.0072
3	+.141	.1169	11.33	.0101
4	+.144	.1160	12.88	.0119
5	-.007	.1150	12.88	.0245
6	-.043	.1141	13.02	.0427
7	+.113	.1132	14.03	.0508
8	+.065	.1123	14.36	.0729
9	-.068	.1113	14.74	.0985
10	+.167	.1104	17.02	.0739
11	+.213	.1094	20.83	.0352
12	+.074	.1085	21.29	.0464
13	+.023	.1075	21.33	.0666
14	+.028	.1065	21.40	.0918
15	-.217	.1055	25.63	.0422



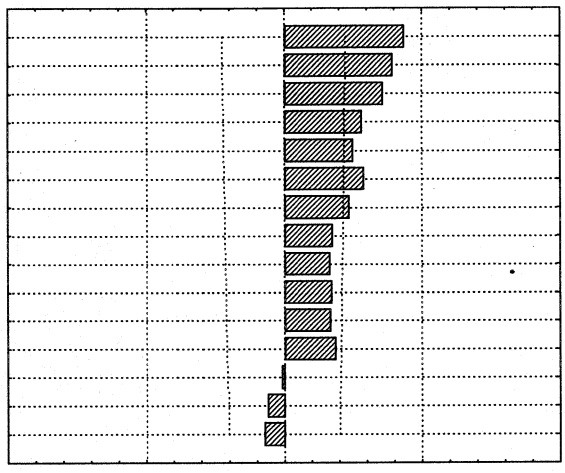
Autocorrelation Function: Pope & Talbot Landfill (2695)
W-18 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.585	.1348	18.87	.0000
2	+.455	.1334	30.48	.0000
3	+.424	.1321	40.80	.0000
4	+.228	.1307	43.83	.0000
5	+.224	.1294	46.83	.0000
6	+.188	.1280	48.99	.0000
7	+.196	.1266	51.39	.0000
8	+.169	.1252	53.21	.0000
9	+.069	.1237	53.53	.0000
10	+.049	.1223	53.69	.0000
11	-.047	.1208	53.84	.0000
12	-.100	.1194	54.54	.0000
13	-.092	.1179	55.15	.0000
14	-.055	.1163	55.37	.0000
15	-.094	.1148	56.05	.0000



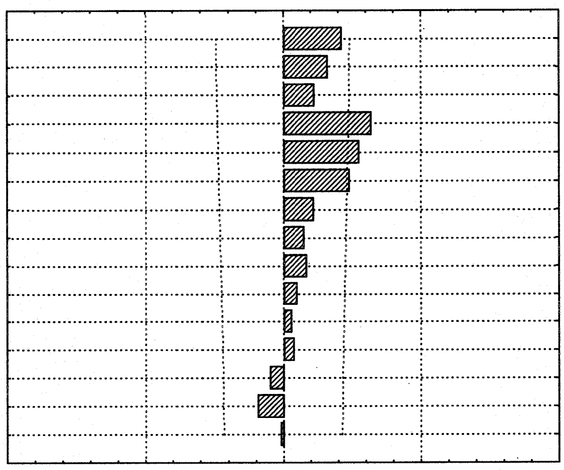
Autocorrelation Function: Pope & Talbot Landfill (2695)
W-6 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.436	.1147	14.44	.0001
2	+.396	.1139	26.51	.0000
3	+.360	.1131	36.64	.0000
4	+.285	.1123	43.07	.0000
5	+.252	.1114	48.18	.0000
6	+.291	.1106	55.12	.0000
7	+.239	.1098	59.84	.0000
8	+.176	.1090	62.46	.0000
9	+.168	.1081	64.87	.0000
10	+.176	.1073	67.56	.0000
11	+.171	.1064	70.13	.0000
12	+.190	.1056	73.37	.0000
13	-.009	.1047	73.37	.0000
14	-.062	.1038	73.73	.0000
15	-.072	.1029	74.22	.0000



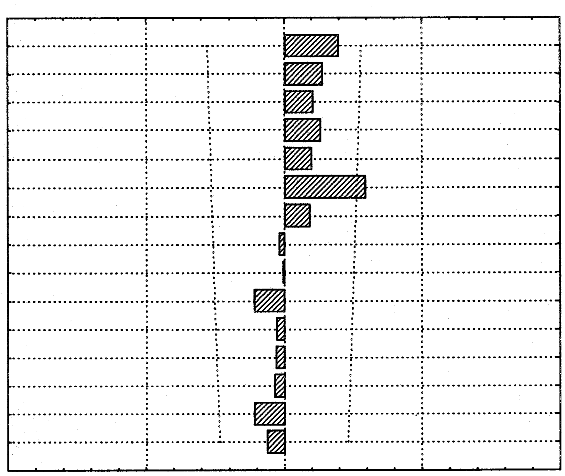
Autocorrelation Function: Pope & Talbot Landfill (2695)
W-13 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.213	.1240	2.96	.0851
2	+.163	.1230	4.73	.0942
3	+.114	.1219	5.61	.1324
4	+.321	.1209	12.67	.0130
5	+.276	.1199	17.99	.0030
6	+.242	.1188	22.12	.0012
7	+.113	.1177	23.05	.0017
8	+.078	.1167	23.49	.0028
9	+.088	.1156	24.07	.0042
10	+.053	.1145	24.28	.0069
11	+.031	.1134	24.36	.0113
12	+.040	.1123	24.48	.0175
13	-.047	.1111	24.66	.0256
14	-.091	.1100	25.35	.0313
15	-.008	.1088	25.36	.0454



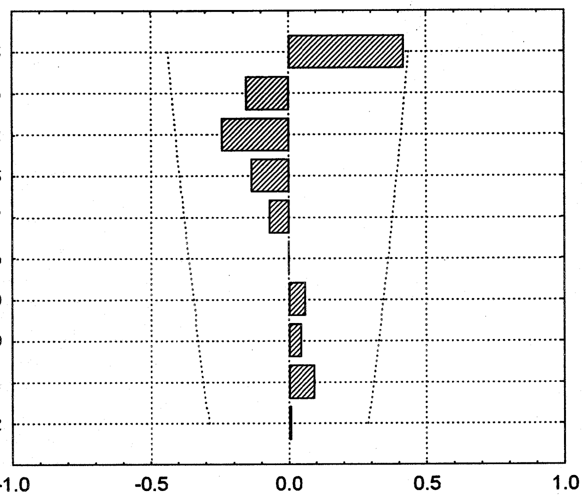
Autocorrelation Function: Pope & Talbot Landfill (2695)
W-18 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.200	.1428	1.96	.1613
2	+.142	.1412	2.97	.2267
3	+.108	.1396	3.57	.3120
4	+.135	.1379	4.52	.3399
5	+.103	.1363	5.09	.4051
6	+.297	.1346	9.97	.1261
7	+.097	.1329	10.50	.1620
8	-.018	.1312	10.52	.2305
9	-.004	.1294	10.52	.3101
10	-.107	.1277	11.22	.3408
11	-.027	.1259	11.26	.4214
12	-.028	.1241	11.32	.5021
13	-.033	.1223	11.39	.5782
14	-.108	.1204	12.20	.5902
15	-.063	.1185	12.49	.6418



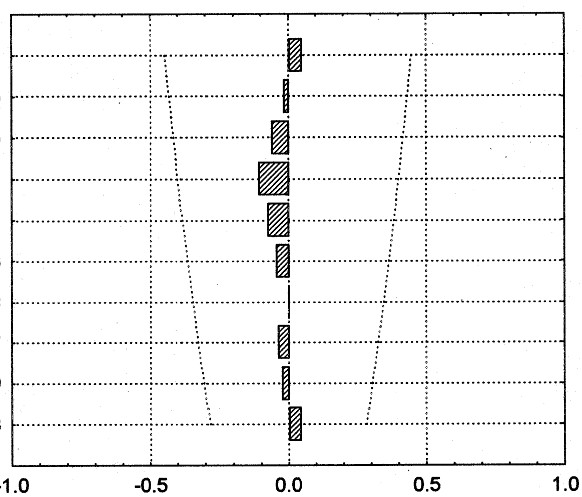
Autocorrelation Function: Oneida County Landfill (2805)
MW-1 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.422	.2226	3.59	.0581
2	-.155	.2155	4.11	.1284
3	-.241	.2082	5.44	.1420
4	-.135	.2006	5.90	.2071
5	-.071	.1927	6.03	.3032
6	+.001	.1845	6.03	.4197
7	+.063	.1760	6.16	.5212
8	+.047	.1669	6.24	.6205
9	+.095	.1574	6.60	.6782
10	+.009	.1472	6.61	.7618



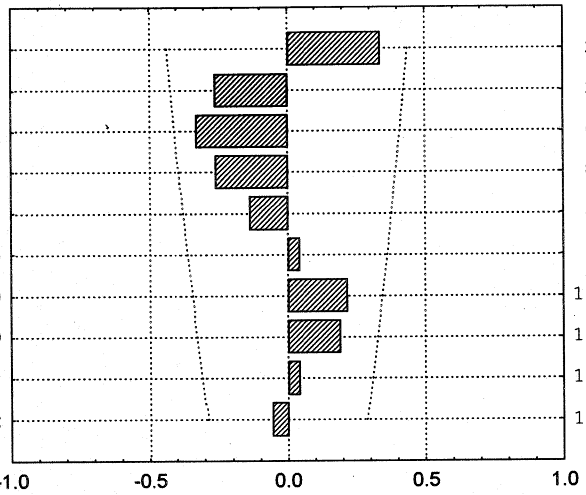
Autocorrelation Function: Oneida County Landfill (2805)
MW-126 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.052	.2282	.05	.8196
2	-.015	.2205	.06	.9722
3	-.060	.2125	.14	.9871
4	-.105	.2041	.40	.9824
5	-.076	.1954	.55	.9901
6	-.042	.1863	.60	.9964
7	+.001	.1768	.60	.9990
8	-.035	.1667	.65	.9996
9	-.021	.1559	.67	.9999
10	+.047	.1443	.77	.9999



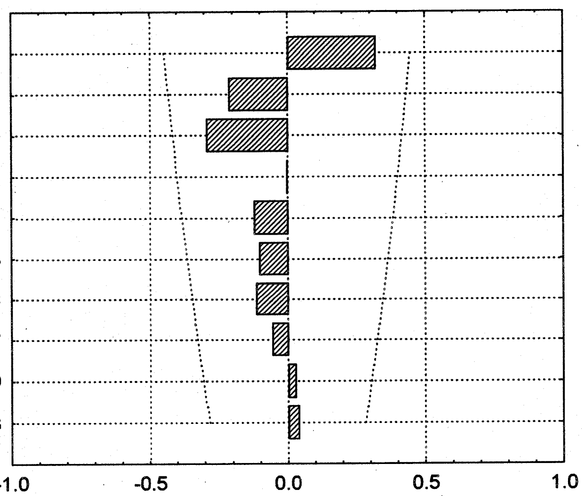
Autocorrelation Function: Oneida County Landfill (2805)
MW-1 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.340	.2226	2.33	.1271
2	-.264	.2155	3.83	.1476
3	-.329	.2082	6.33	.0966
4	-.262	.2006	8.03	.0905
5	-.138	.1927	8.54	.1287
6	+.046	.1845	8.61	.1969
7	+.219	.1760	10.16	.1800
8	+.194	.1669	11.51	.1746
9	+.044	.1574	11.59	.2377
10	-.057	.1472	11.74	.3030



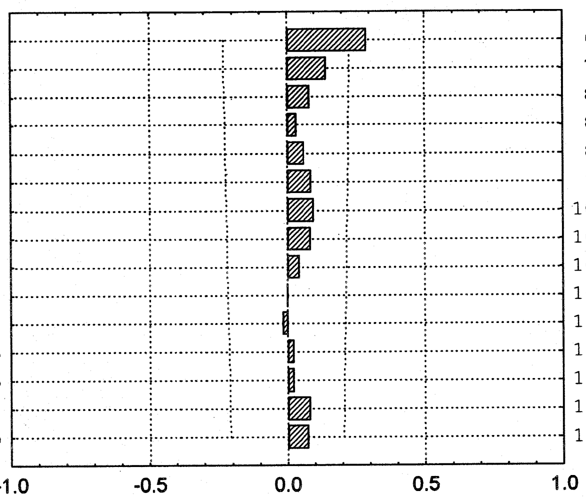
Autocorrelation Function: Oneida County Landfill (2805)
MW-126 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.323	.2282	2.01	.1566
2	-.211	.2205	2.92	.2317
3	-.293	.2125	4.82	.1853
4	-.002	.2041	4.82	.3060
5	-.119	.1954	5.20	.3925
6	-.101	.1863	5.49	.4830
7	-.112	.1768	5.89	.5531
8	-.056	.1667	6.00	.6472
9	+.032	.1559	6.04	.7357
10	+.044	.1443	6.14	.8038



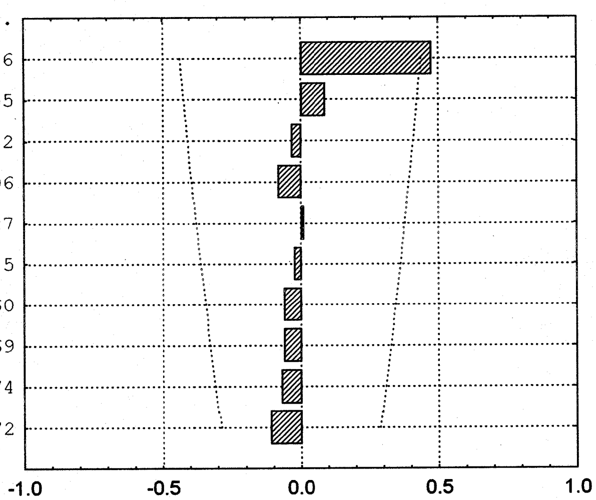
Autocorrelation Function: Oneida County Landfill (2805)
MW-1 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.291	.1170	6.21	.0127
2	+.145	.1162	7.76	.0206
3	+.085	.1153	8.30	.0401
4	+.035	.1144	8.40	.0780
5	+.064	.1136	8.72	.1209
6	+.089	.1127	9.35	.1551
7	+.099	.1118	10.13	.1814
8	+.087	.1109	10.75	.2165
9	+.045	.1100	10.91	.2818
10	+.001	.1091	10.91	.3644
11	-.016	.1082	10.93	.4488
12	+.024	.1073	10.98	.5303
13	+.024	.1063	11.04	.6078
14	+.085	.1054	11.69	.6314
15	+.079	.1045	12.25	.6598



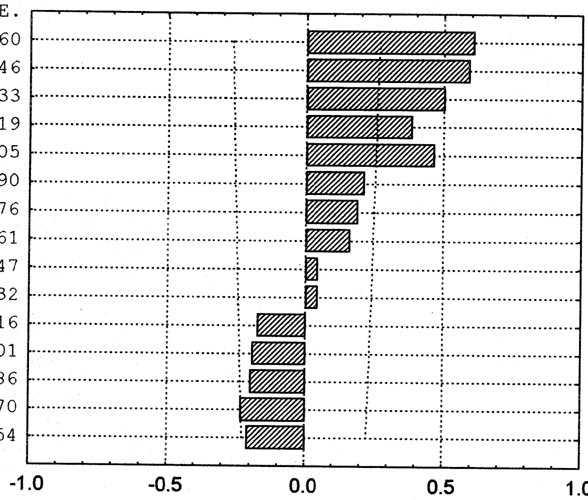
Autocorrelation Function: Oneida County Landfill (2805)
MW-126 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.476	.2226	4.58	.0323
2	+.091	.2155	4.76	.0925
3	-.031	.2082	4.78	.1885
4	-.082	.2006	4.95	.2925
5	+.010	.1927	4.95	.4217
6	-.021	.1845	4.97	.5482
7	-.061	.1760	5.09	.6493
8	-.062	.1669	5.23	.7332
9	-.071	.1574	5.43	.7952
10	-.107	.1472	5.96	.8188



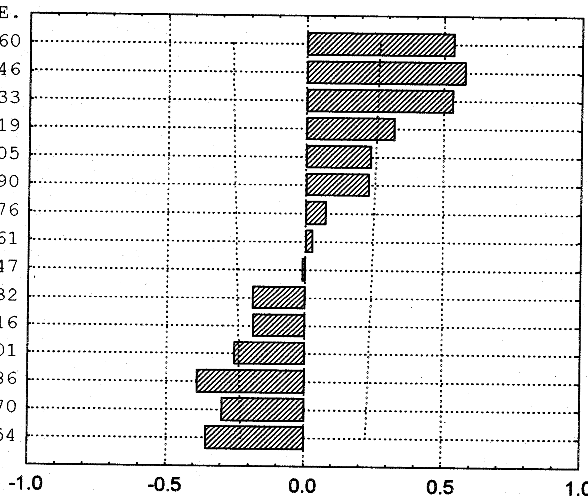
Autocorrelation Function: Portage County Landfill (2966)
W-9 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.610	.1360	20.11	.0000
2	+.594	.1346	39.56	.0000
3	+.505	.1333	53.90	.0000
4	+.385	.1319	62.43	.0000
5	+.466	.1305	75.22	.0000
6	+.213	.1290	77.95	.0000
7	+.192	.1276	80.23	.0000
8	+.164	.1261	81.91	.0000
9	+.048	.1247	82.06	.0000
10	+.047	.1232	82.20	.0000
11	-.172	.1216	84.20	.0000
12	-.189	.1201	86.67	.0000
13	-.197	.1186	89.43	.0000
14	-.233	.1170	93.38	.0000
15	-.210	.1154	96.69	.0000



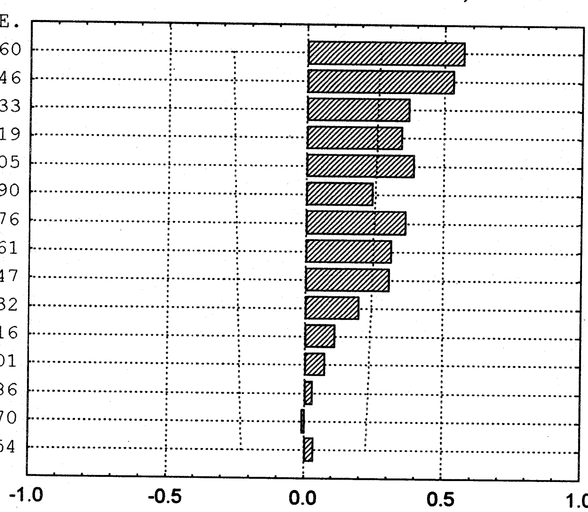
Autocorrelation Function: Portage County Landfill (2966)
W-9P Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.537	.1360	15.61	.0001
2	+.577	.1346	33.99	.0000
3	+.533	.1333	50.00	.0000
4	+.324	.1319	56.02	.0000
5	+.240	.1305	59.42	.0000
6	+.232	.1290	62.66	.0000
7	+.077	.1276	63.03	.0000
8	+.029	.1261	63.08	.0000
9	-.009	.1247	63.08	.0000
10	-.186	.1232	65.37	.0000
11	-.185	.1216	67.67	.0000
12	-.254	.1201	72.13	.0000
13	-.388	.1186	82.82	.0000
14	-.298	.1170	89.33	.0000
15	-.356	.1154	98.83	.0000

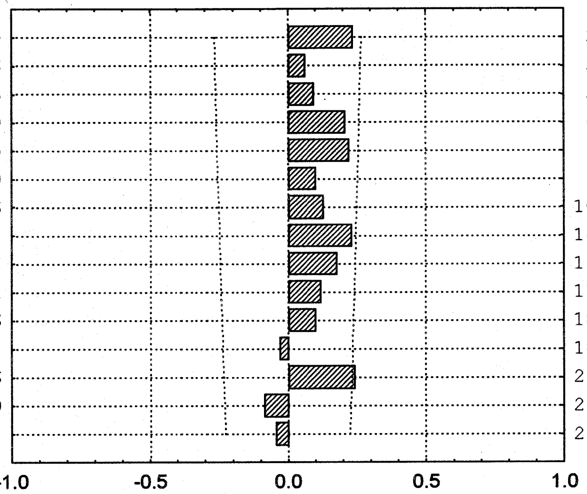


Autocorrelation Function: Portage County Landfill (2966)
W-10 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.572	.1360	17.70	.0000
2	+.535	.1346	33.48	.0000
3	+.374	.1333	41.37	.0000
4	+.349	.1319	48.40	.0000
5	+.393	.1305	57.49	.0000
6	+.244	.1290	61.07	.0000
7	+.366	.1276	69.28	.0000
8	+.315	.1261	75.53	.0000
9	+.306	.1247	81.57	.0000
10	+.199	.1232	84.17	.0000
11	+.113	.1216	85.04	.0000
12	+.075	.1201	85.43	.0000
13	+.032	.1186	85.50	.0000
14	-.009	.1170	85.51	.0000
15	+.037	.1154	85.61	.0000

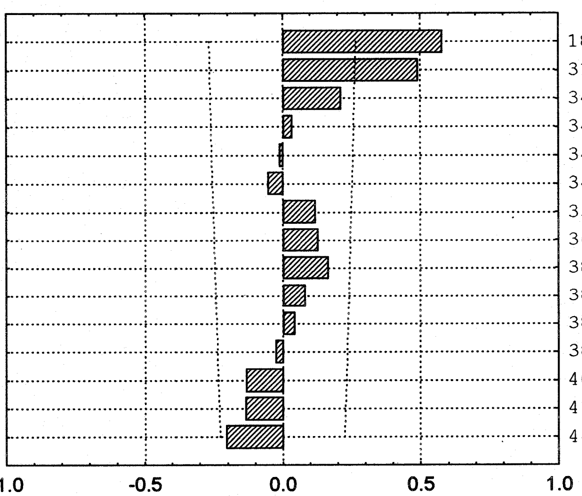


Autocorrelation Function: Portage County Landfill (2966)
W-11 Alkalinity
(Standard errors are white-noise estimates)



Lag	Corr.	S.E.	Q	p
1	+.238	.1360	3.07	.0797
2	+.065	.1346	3.30	.1919
3	+.095	.1333	3.81	.2825
4	+.209	.1319	6.32	.1766
5	+.224	.1305	9.26	.0990
6	+.104	.1290	9.91	.1285
7	+.131	.1276	10.97	.1401
8	+.233	.1261	14.39	.0723
9	+.180	.1247	16.47	.0577
10	+.122	.1232	17.46	.0649
11	+.103	.1216	18.17	.0778
12	-.030	.1201	18.23	.1090
13	+.244	.1186	22.46	.0487
14	-.087	.1170	23.01	.0601
15	-.043	.1154	23.15	.0810

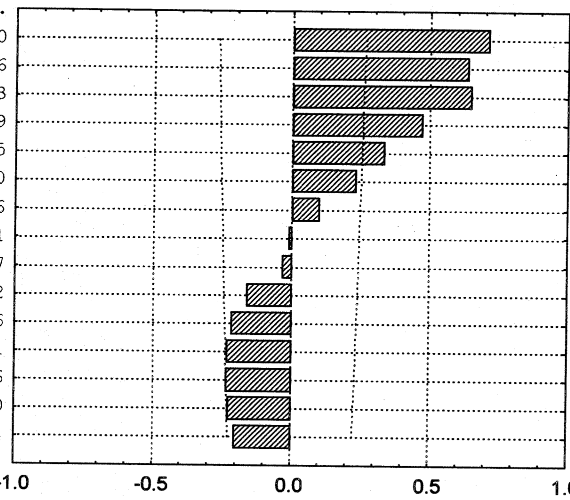
Autocorrelation Function: Portage County Landfill (2966)
W-12 Alkalinity
(Standard errors are white-noise estimates)



Lag	Corr.	S.E.	Q	p
1	+.582	.1360	18.29	.0000
2	+.493	.1346	31.70	.0000
3	+.215	.1333	34.30	.0000
4	+.036	.1319	34.38	.0000
5	-.011	.1305	34.39	.0000
6	-.053	.1290	34.56	.0000
7	+.122	.1276	35.46	.0000
8	+.130	.1261	36.53	.0000
9	+.168	.1247	38.33	.0000
10	+.084	.1232	38.79	.0000
11	+.046	.1216	38.94	.0001
12	-.023	.1201	38.98	.0001
13	-.134	.1186	40.25	.0001
14	-.135	.1170	41.57	.0001
15	-.204	.1154	44.71	.0001

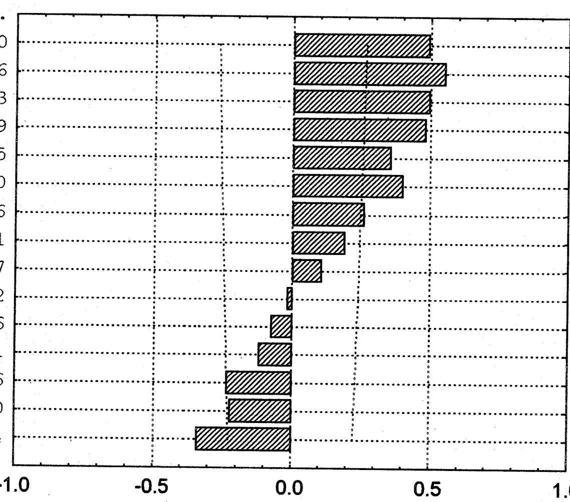
Autocorrelation Function: Portage County Landfill (2966)
W-9 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.716	.1360	27.70	.0000
2	+.640	.1346	50.28	.0000
3	+.652	.1333	74.20	.0000
4	+.474	.1319	87.13	.0000
5	+.337	.1305	93.80	.0000
6	+.236	.1290	97.15	.0000
7	+.104	.1276	97.81	.0000
8	-.007	.1261	97.82	.0000
9	-.031	.1247	97.88	.0000
10	-.161	.1232	99.58	.0000
11	-.217	.1216	102.8	.0000
12	-.232	.1201	106.5	.0000
13	-.235	.1186	110.4	.0000
14	-.229	.1170	114.3	.0000
15	-.206	.1154	117.5	.0000



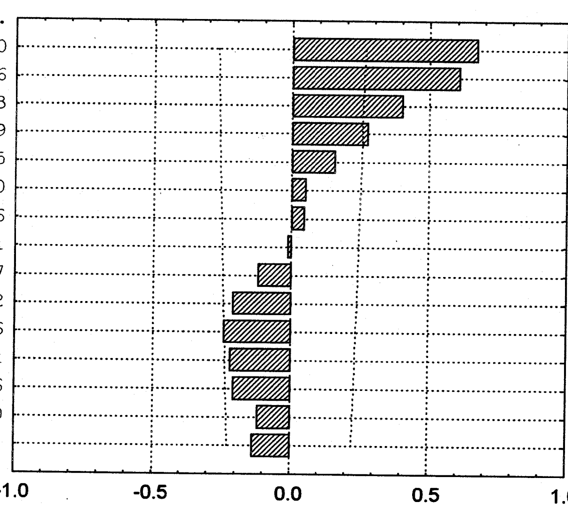
Autocorrelation Function: Portage County Landfill (2966)
W-9P Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.495	.1360	13.24	.0003
2	+.553	.1346	30.09	.0000
3	+.496	.1333	43.94	.0000
4	+.483	.1319	57.35	.0000
5	+.358	.1305	64.89	.0000
6	+.402	.1290	74.58	.0000
7	+.263	.1276	78.83	.0000
8	+.194	.1261	81.20	.0000
9	+.109	.1247	81.97	.0000
10	-.016	.1232	81.98	.0000
11	-.076	.1216	82.37	.0000
12	-.118	.1201	83.34	.0000
13	-.235	.1186	87.26	.0000
14	-.224	.1170	90.93	.0000
15	-.341	.1154	99.68	.0000



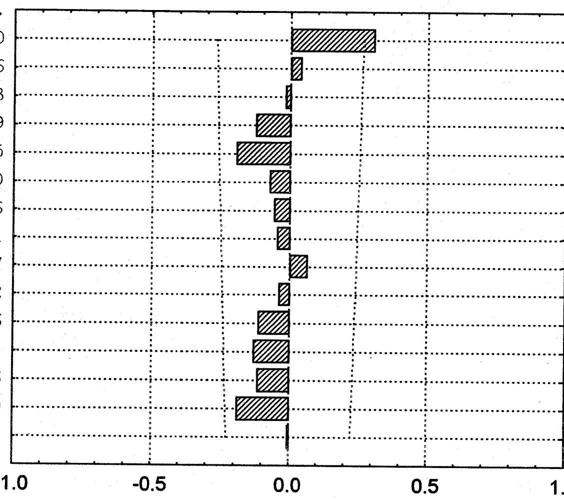
Autocorrelation Function: Portage County Landfill (2966)
W-10 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.676	.1360	24.73	.0000
2	+.611	.1346	45.32	.0000
3	+.405	.1333	54.55	.0000
4	+.279	.1319	59.03	.0000
5	+.162	.1305	60.57	.0000
6	+.055	.1290	60.75	.0000
7	+.051	.1276	60.91	.0000
8	-.011	.1261	60.92	.0000
9	-.117	.1247	61.80	.0000
10	-.210	.1232	64.71	.0000
11	-.241	.1216	68.64	.0000
12	-.218	.1201	71.94	.0000
13	-.208	.1186	75.00	.0000
14	-.117	.1170	76.01	.0000
15	-.139	.1154	77.45	.0000



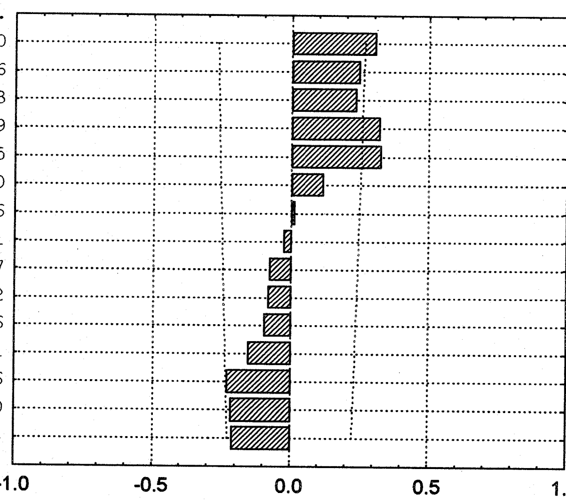
Autocorrelation Function: Portage County Landfill (2966)
W-11 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.308	.1360	5.12	.0237
2	+.042	.1346	5.21	.0738
3	-.016	.1333	5.23	.1560
4	-.122	.1319	6.08	.1930
5	-.192	.1305	8.25	.1428
6	-.073	.1290	8.57	.1991
7	-.057	.1276	8.77	.2693
8	-.042	.1261	8.89	.3519
9	+.068	.1247	9.18	.4208
10	-.035	.1232	9.26	.5073
11	-.111	.1216	10.09	.5222
12	-.129	.1201	11.25	.5075
13	-.113	.1186	12.16	.5148
14	-.186	.1170	14.68	.4006
15	-.003	.1154	14.68	.4749



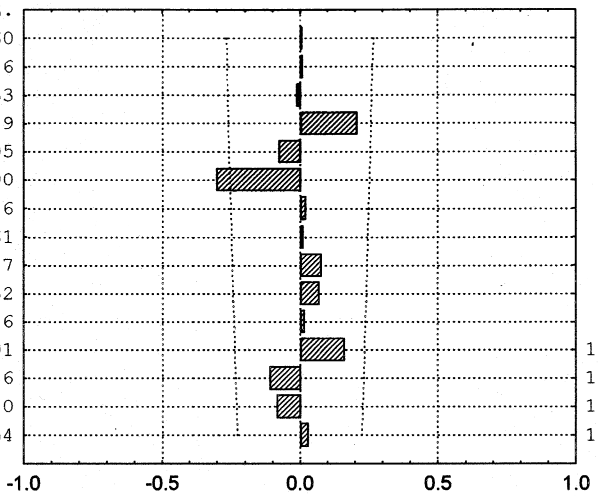
Autocorrelation Function: Portage County Landfill (2966)
W-12 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.308	.1360	5.11	.0237
2	+.250	.1346	8.57	.0138
3	+.237	.1333	11.74	.0083
4	+.324	.1319	17.77	.0014
5	+.327	.1305	24.07	.0002
6	+.120	.1290	24.94	.0004
7	+.012	.1276	24.95	.0008
8	-.025	.1261	24.99	.0016
9	-.078	.1247	25.38	.0026
10	-.083	.1232	25.83	.0040
11	-.094	.1216	26.43	.0056
12	-.154	.1201	28.07	.0054
13	-.230	.1186	31.84	.0025
14	-.217	.1170	35.28	.0013
15	-.213	.1154	38.68	.0007



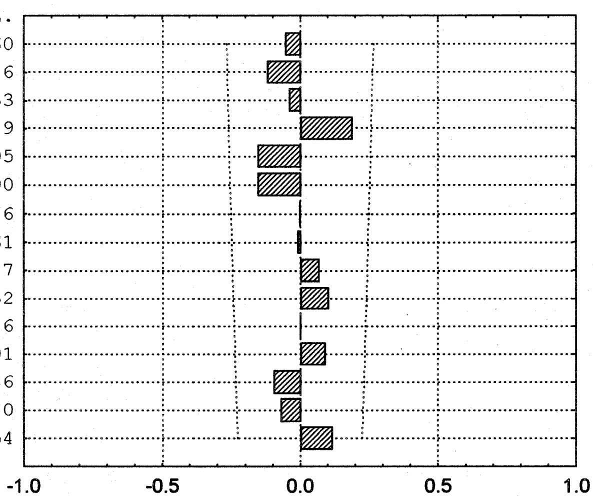
Autocorrelation Function: Portage County Landfill (2966)
W-9 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.005	.1360	.00	.9691
2	+.008	.1346	.01	.9974
3	-.010	.1333	.01	.9997
4	+.209	.1319	2.53	.6393
5	-.078	.1305	2.89	.7176
6	-.302	.1290	8.35	.2135
7	+.021	.1276	8.38	.3003
8	+.011	.1261	8.39	.3967
9	+.079	.1247	8.79	.4571
10	+.071	.1232	9.12	.5207
11	+.016	.1216	9.14	.6092
12	+.163	.1201	10.97	.5312
13	-.108	.1186	11.81	.5432
14	-.085	.1170	12.34	.5791
15	+.031	.1154	12.41	.6479



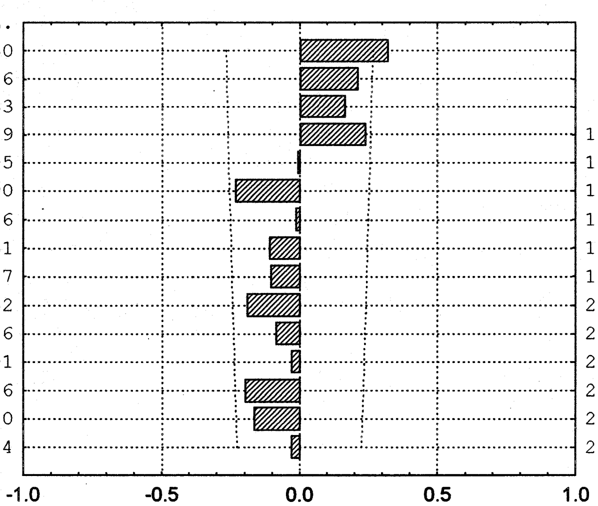
Autocorrelation Function: Portage County Landfill (2966)
W-9P Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	-.053	.1360	.15	.6947
2	-.117	.1346	.91	.6344
3	-.038	.1333	.99	.8038
4	+.191	.1319	3.09	.5433
5	-.154	.1305	4.48	.4821
6	-.155	.1290	5.92	.4318
7	-.002	.1276	5.92	.5486
8	-.008	.1261	5.93	.6552
9	+.071	.1247	6.26	.7140
10	+.106	.1232	7.00	.7250
11	+.004	.1216	7.01	.7986
12	+.095	.1201	7.63	.8133
13	-.094	.1186	8.26	.8260
14	-.071	.1170	8.64	.8536
15	+.120	.1154	9.71	.8375



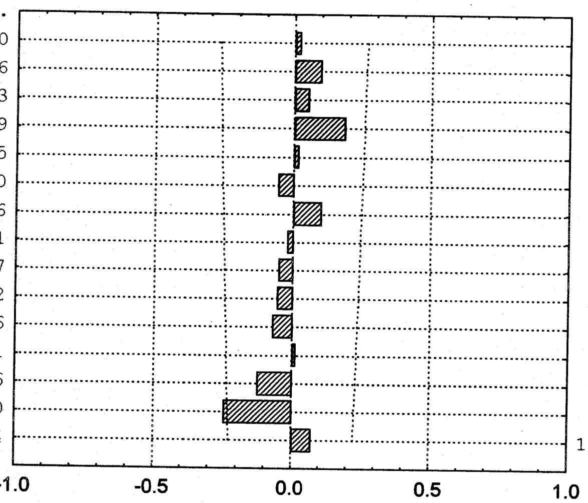
Autocorrelation Function: Portage County Landfill (2966)
W-10 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.323	.1360	5.64	.0175
2	+.214	.1346	8.17	.0168
3	+.168	.1333	9.77	.0207
4	+.242	.1319	13.13	.0107
5	-.007	.1305	13.14	.0222
6	-.232	.1290	16.38	.0119
7	-.012	.1276	16.39	.0218
8	-.107	.1261	17.10	.0291
9	-.104	.1247	17.80	.0376
10	-.190	.1232	20.18	.0276
11	-.086	.1216	20.68	.0369
12	-.029	.1201	20.73	.0545
13	-.199	.1186	23.55	.0355
14	-.164	.1170	25.53	.0297
15	-.028	.1154	25.59	.0426



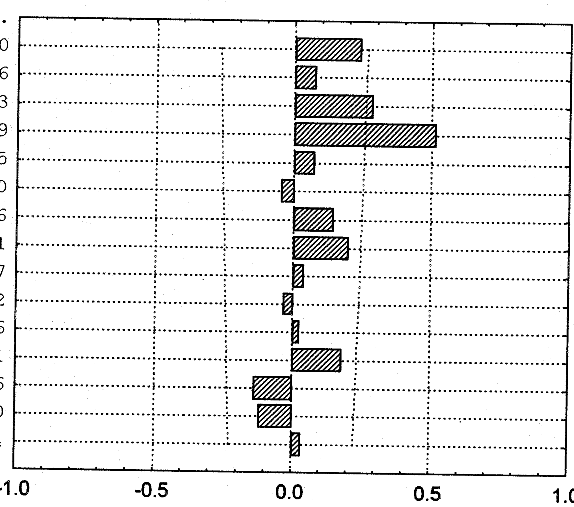
Autocorrelation Function: Portage County Landfill (2966)
W-11 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.025	.1360	.03	.8554
2	+.100	.1346	.59	.7451
3	+.057	.1333	.77	.8568
4	+.188	.1319	2.81	.5909
5	+.019	.1305	2.83	.7267
6	-.055	.1290	3.01	.8079
7	+.106	.1276	3.69	.8143
8	-.017	.1261	3.71	.8820
9	-.048	.1247	3.86	.9201
10	-.054	.1232	4.05	.9448
11	-.071	.1216	4.40	.9567
12	+.013	.1201	4.41	.9748
13	-.124	.1186	5.50	.9625
14	-.243	.1170	9.83	.7748
15	+.074	.1154	10.24	.8043



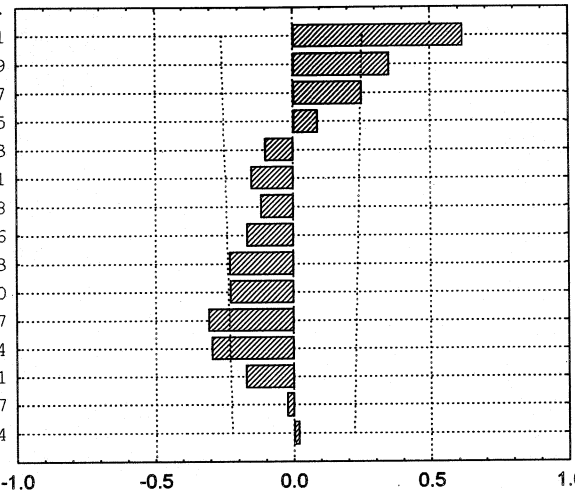
Autocorrelation Function: Portage County Landfill (2966)
W-12 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.242	.1360	3.17	.0752
2	+.081	.1346	3.53	.1714
3	+.287	.1333	8.15	.0430
4	+.515	.1319	23.38	.0001
5	+.078	.1305	23.74	.0002
6	-.043	.1290	23.85	.0006
7	+.148	.1276	25.19	.0007
8	+.204	.1261	27.80	.0005
9	+.042	.1247	27.91	.0010
10	-.031	.1232	27.97	.0018
11	+.028	.1216	28.03	.0032
12	+.181	.1201	30.30	.0025
13	-.139	.1186	31.66	.0027
14	-.117	.1170	32.66	.0032
15	+.036	.1154	32.75	.0051



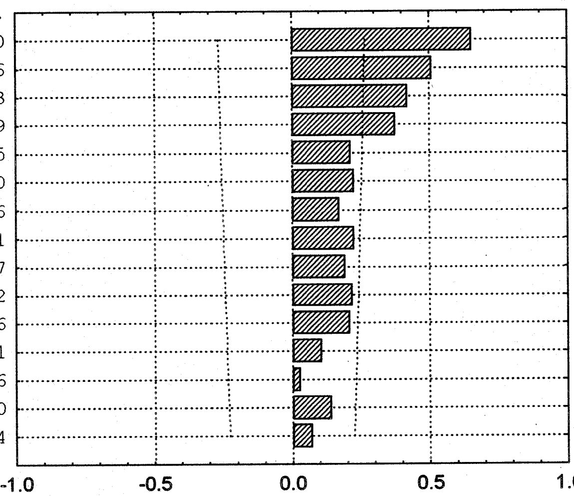
Autocorrelation Function: Grede Foundries Landfill (2974)
B-3 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.621	.1301	22.77	.0000
2	+.354	.1289	30.29	.0000
3	+.253	.1277	34.21	.0000
4	+.095	.1265	34.78	.0000
5	-.099	.1253	35.40	.0000
6	-.151	.1241	36.88	.0000
7	-.115	.1228	37.76	.0000
8	-.167	.1216	39.65	.0000
9	-.230	.1203	43.29	.0000
10	-.228	.1190	46.96	.0000
11	-.307	.1177	53.78	.0000
12	-.294	.1164	60.18	.0000
13	-.173	.1151	62.44	.0000
14	-.022	.1137	62.48	.0000
15	+.022	.1124	62.52	.0000



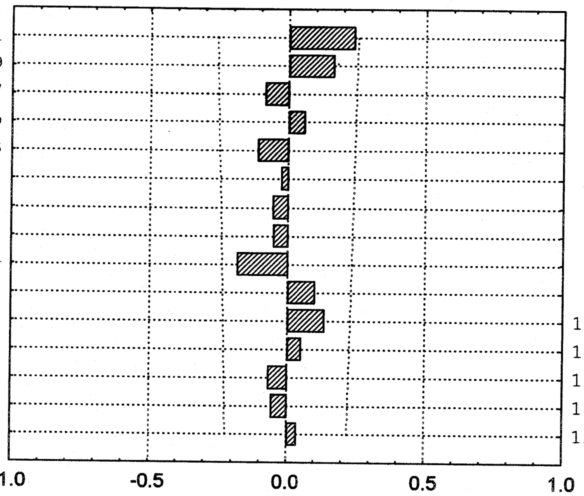
Autocorrelation Function: Grede Foundries Landfill (2974)
B-5 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.656	.1360	23.24	.0000
2	+.509	.1346	37.51	.0000
3	+.422	.1333	47.52	.0000
4	+.377	.1319	55.69	.0000
5	+.215	.1305	58.40	.0000
6	+.227	.1290	61.49	.0000
7	+.173	.1276	63.34	.0000
8	+.227	.1261	66.57	.0000
9	+.193	.1247	68.97	.0000
10	+.218	.1232	72.10	.0000
11	+.210	.1216	75.09	.0000
12	+.109	.1201	75.91	.0000
13	+.029	.1186	75.97	.0000
14	+.142	.1170	77.45	.0000
15	+.072	.1154	77.84	.0000



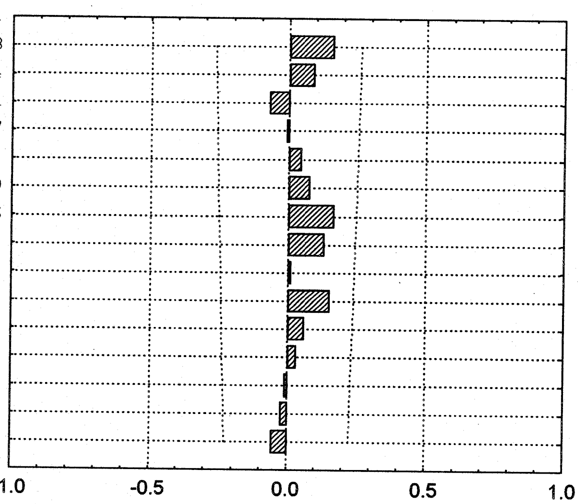
Autocorrelation Function: Grede Foundries Landfill (2974)
B-3 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.243	.1301	3.49	.0619
2	+.168	.1289	5.19	.0747
3	-.084	.1277	5.62	.1317
4	+.064	.1265	5.87	.2087
5	-.108	.1253	6.61	.2511
6	-.023	.1241	6.65	.3548
7	-.054	.1228	6.84	.4458
8	-.050	.1216	7.01	.5355
9	-.178	.1203	9.21	.4181
10	+.104	.1190	9.98	.4427
11	+.137	.1177	11.33	.4158
12	+.055	.1164	11.55	.4821
13	-.068	.1151	11.90	.5359
14	-.057	.1137	12.15	.5939
15	+.039	.1124	12.28	.6580



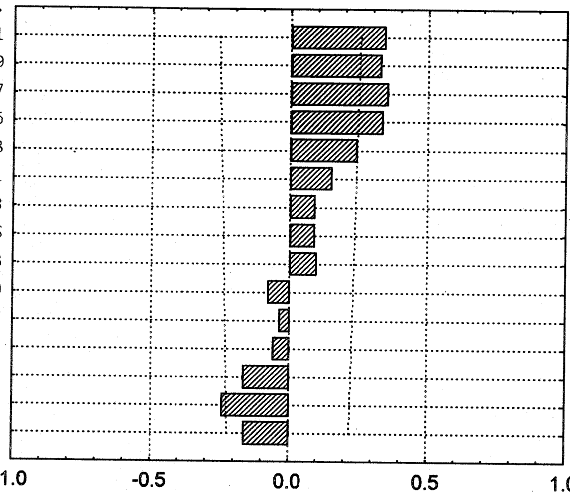
Autocorrelation Function: Grede Foundries Landfill (2974)
B-5 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.162	.1348	1.45	.2283
2	+.095	.1334	1.96	.3761
3	-.071	.1321	2.24	.5238
4	-.005	.1307	2.24	.6911
5	+.047	.1294	2.38	.7950
6	+.079	.1280	2.76	.8385
7	+.167	.1266	4.50	.7202
8	+.133	.1252	5.63	.6887
9	+.011	.1237	5.64	.7756
10	+.154	.1223	7.22	.7045
11	+.061	.1208	7.47	.7596
12	+.033	.1194	7.55	.8192
13	-.008	.1179	7.55	.8713
14	-.021	.1163	7.59	.9096
15	-.058	.1148	7.84	.9300



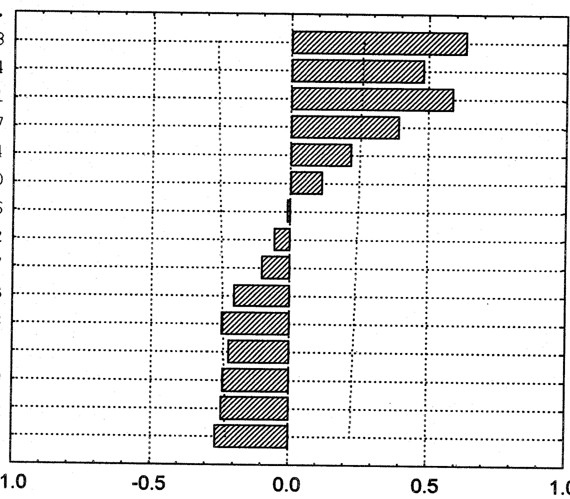
Autocorrelation Function: Grede Foundries Landfill (2974)
B-3 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.344	.1301	6.97	.0083
2	+.330	.1289	13.53	.0012
3	+.356	.1277	21.29	.0001
4	+.337	.1265	28.38	.0000
5	+.244	.1253	32.18	.0000
6	+.154	.1241	33.72	.0000
7	+.095	.1228	34.31	.0000
8	+.095	.1216	34.92	.0000
9	+.102	.1203	35.64	.0000
10	-.078	.1190	36.07	.0001
11	-.033	.1177	36.14	.0002
12	-.060	.1164	36.41	.0003
13	-.166	.1151	38.50	.0002
14	-.242	.1137	43.03	.0001
15	-.162	.1124	45.11	.0001



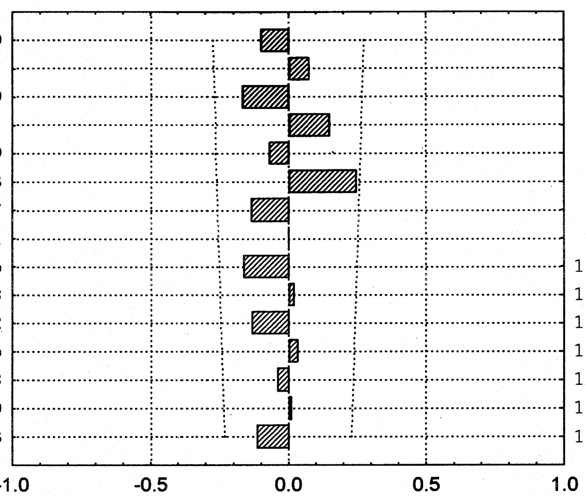
Autocorrelation Function: Grede Foundries Landfill (2974)
B-5 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.638	.1348	22.43	.0000
2	+.484	.1334	35.56	.0000
3	+.590	.1321	55.51	.0000
4	+.396	.1307	64.67	.0000
5	+.223	.1294	67.64	.0000
6	+.119	.1280	68.51	.0000
7	-.008	.1266	68.51	.0000
8	-.057	.1252	68.72	.0000
9	-.099	.1237	69.36	.0000
10	-.200	.1223	72.05	.0000
11	-.244	.1208	76.11	.0000
12	-.219	.1194	79.47	.0000
13	-.240	.1179	83.61	.0000
14	-.244	.1163	88.00	.0000
15	-.265	.1148	93.33	.0000



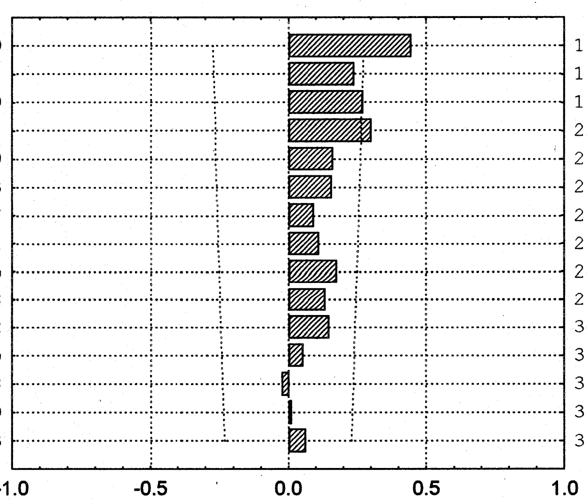
Autocorrelation Function: Sauk County Landfill (2978)
W-30 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	-.099	.1399	.50	.4800
2	+.077	.1384	.81	.6674
3	-.168	.1369	2.31	.5112
4	+.152	.1354	3.57	.4676
5	-.070	.1339	3.84	.5729
6	+.249	.1323	7.38	.2870
7	-.135	.1307	8.46	.2941
8	+.003	.1291	8.46	.3902
9	-.164	.1275	10.11	.3415
10	+.023	.1258	10.14	.4279
11	-.133	.1242	11.30	.4189
12	+.035	.1225	11.38	.4967
13	-.038	.1208	11.48	.5706
14	+.009	.1190	11.49	.6474
15	-.112	.1173	12.40	.6485



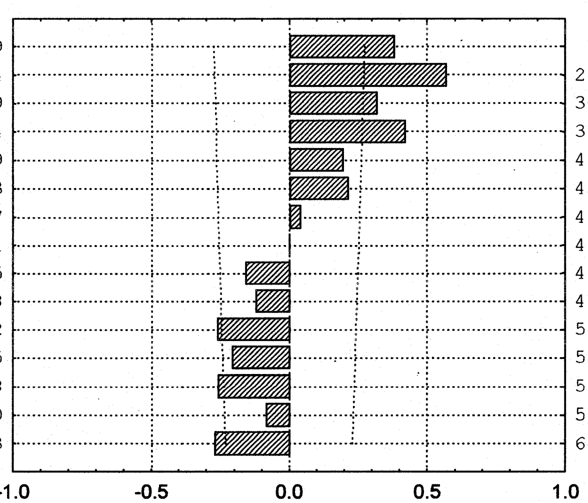
Autocorrelation Function: Sauk County Landfill (2978)
W-30A Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.447	.1399	10.20	.0014
2	+.241	.1384	13.22	.0014
3	+.272	.1369	17.17	.0007
4	+.302	.1354	22.16	.0002
5	+.162	.1339	23.63	.0003
6	+.159	.1323	25.07	.0003
7	+.094	.1307	25.59	.0006
8	+.112	.1291	26.35	.0009
9	+.178	.1275	28.31	.0009
10	+.134	.1258	29.45	.0011
11	+.150	.1242	30.91	.0011
12	+.054	.1225	31.10	.0019
13	-.022	.1208	31.13	.0032
14	+.010	.1190	31.14	.0053
15	+.065	.1173	31.45	.0077



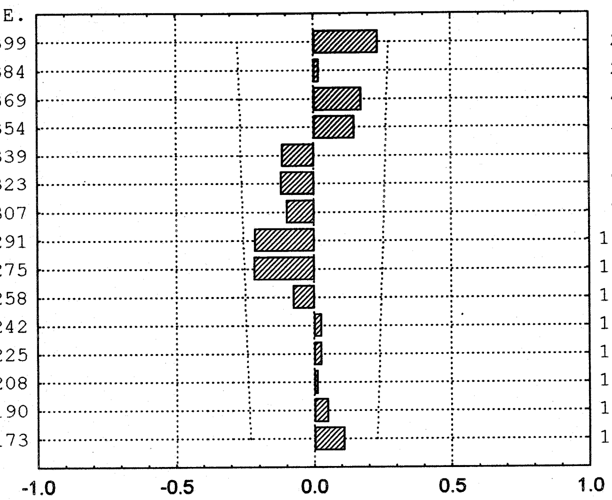
Autocorrelation Function: Sauk County Landfill (2978)
W-31 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.384	.1399	7.53	.0061
2	+.571	.1384	24.52	.0000
3	+.322	.1369	30.05	.0000
4	+.423	.1354	39.81	.0000
5	+.197	.1339	41.98	.0000
6	+.217	.1323	44.68	.0000
7	+.043	.1307	44.78	.0000
8	+.001	.1291	44.78	.0000
9	-.159	.1275	46.34	.0000
10	-.120	.1258	47.24	.0000
11	-.262	.1242	51.69	.0000
12	-.208	.1225	54.56	.0000
13	-.257	.1208	59.11	.0000
14	-.085	.1190	59.62	.0000
15	-.269	.1173	64.88	.0000



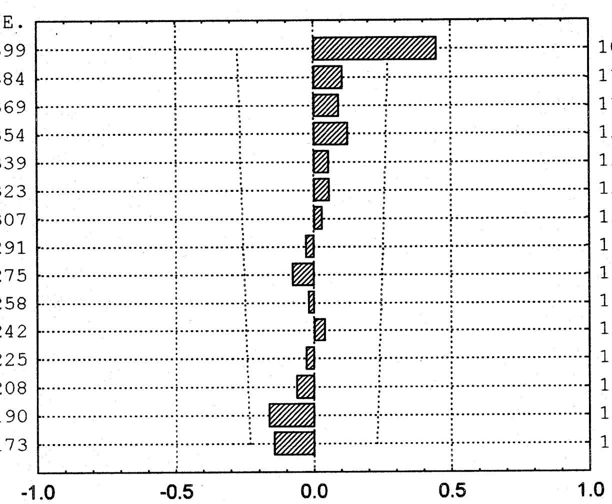
Autocorrelation Function: Sauk County Landfill (2978)
W-30 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.238	.1399	2.90	.0886
2	+.023	.1384	2.93	.2314
3	+.177	.1369	4.59	.2042
4	+.152	.1354	5.85	.2107
5	-.112	.1339	6.55	.2561
6	-.117	.1323	7.33	.2911
7	-.095	.1307	7.86	.3447
8	-.215	.1291	10.63	.2234
9	-.217	.1275	13.53	.1401
10	-.074	.1258	13.88	.1787
11	+.030	.1242	13.94	.2366
12	+.029	.1225	13.99	.3012
13	+.013	.1208	14.01	.3735
14	+.052	.1190	14.20	.4353
15	+.111	.1173	15.10	.4443



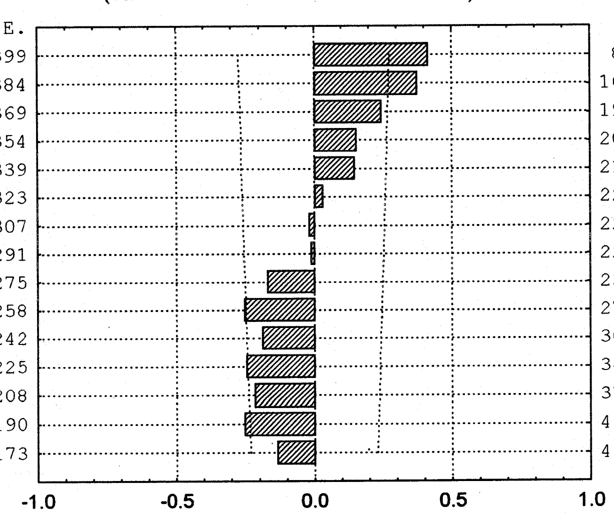
Autocorrelation Function: Sauk County Landfill (2978)
W-30A Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.451	.1399	10.36	.0013
2	+.110	.1384	11.00	.0041
3	+.096	.1369	11.49	.0093
4	+.128	.1354	12.39	.0147
5	+.059	.1339	12.58	.0277
6	+.062	.1323	12.80	.0463
7	+.033	.1307	12.87	.0755
8	-.026	.1291	12.91	.1151
9	-.078	.1275	13.28	.1505
10	-.017	.1258	13.30	.2076
11	+.044	.1242	13.42	.2667
12	-.026	.1225	13.47	.3361
13	-.063	.1208	13.73	.3928
14	-.163	.1190	15.62	.3371
15	-.145	.1173	17.15	.3103



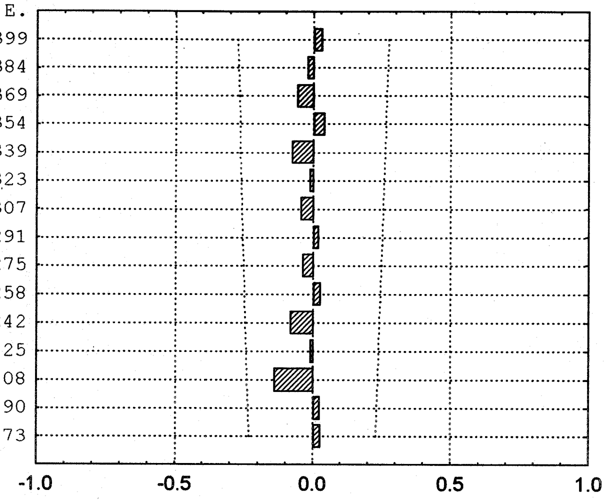
Autocorrelation Function: Sauk County Landfill (2978)
W-31 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.415	.1399	8.79	.0030
2	+.376	.1384	16.18	.0003
3	+.247	.1369	19.43	.0002
4	+.156	.1354	20.76	.0004
5	+.149	.1339	21.99	.0005
6	+.033	.1323	22.06	.0012
7	-.018	.1307	22.07	.0025
8	-.010	.1291	22.08	.0048
9	-.170	.1275	23.87	.0045
10	-.255	.1258	27.96	.0018
11	-.186	.1242	30.21	.0015
12	-.246	.1225	34.24	.0006
13	-.216	.1208	37.43	.0004
14	-.253	.1190	41.96	.0001
15	-.136	.1173	43.29	.0001



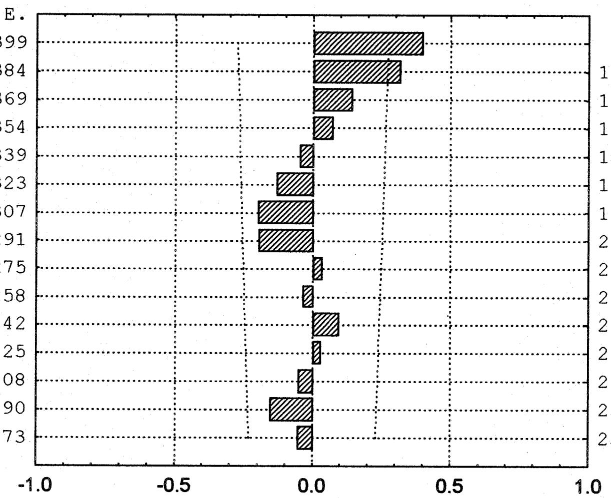
Autocorrelation Function: Sauk County Landfill (2978)
W-30 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.033	.1399	.06	.8108
2	-.018	.1384	.08	.9631
3	-.058	.1369	.26	.9679
4	+.042	.1354	.35	.9860
5	-.077	.1339	.69	.9837
6	-.011	.1323	.69	.9946
7	-.042	.1307	.80	.9975
8	+.023	.1291	.83	.9991
9	-.036	.1275	.91	.9996
10	+.028	.1258	.96	.9999
11	-.083	.1242	1.41	.9997
12	-.009	.1225	1.41	.9999
13	-.140	.1208	2.76	.9987
14	+.027	.1190	2.81	.9994
15	+.028	.1173	2.86	.9997



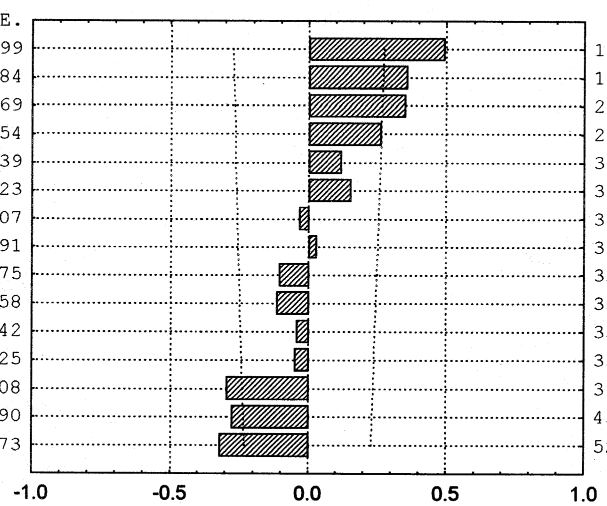
Autocorrelation Function: Sauk County Landfill (2978)
W-30A Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.400	.1399	8.18	.0042
2	+.318	.1384	13.45	.0012
3	+.144	.1369	14.56	.0022
4	+.075	.1354	14.87	.0050
5	-.045	.1339	14.98	.0104
6	-.131	.1323	15.96	.0140
7	-.197	.1307	18.23	.0110
8	-.195	.1291	20.52	.0085
9	+.037	.1275	20.61	.0145
10	-.033	.1258	20.67	.0235
11	+.099	.1242	21.31	.0303
12	+.032	.1225	21.38	.0451
13	-.051	.1208	21.56	.0627
14	-.155	.1190	23.25	.0564
15	-.056	.1173	23.48	.0746



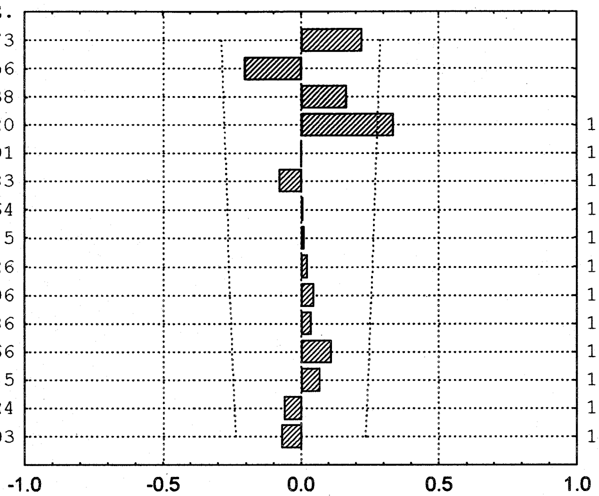
Autocorrelation Function: Sauk County Landfill (2978)
W-31 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.494	.1399	12.48	.0004
2	+.360	.1384	19.25	.0001
3	+.354	.1369	25.92	.0000
4	+.265	.1354	29.75	.0000
5	+.122	.1339	30.59	.0000
6	+.156	.1323	31.98	.0000
7	-.031	.1307	32.03	.0000
8	+.032	.1291	32.10	.0001
9	-.104	.1275	32.76	.0001
10	-.113	.1258	33.56	.0002
11	-.039	.1242	33.66	.0004
12	-.048	.1225	33.81	.0007
13	-.295	.1208	39.80	.0001
14	-.277	.1190	45.20	.0000
15	-.321	.1173	52.68	.0000



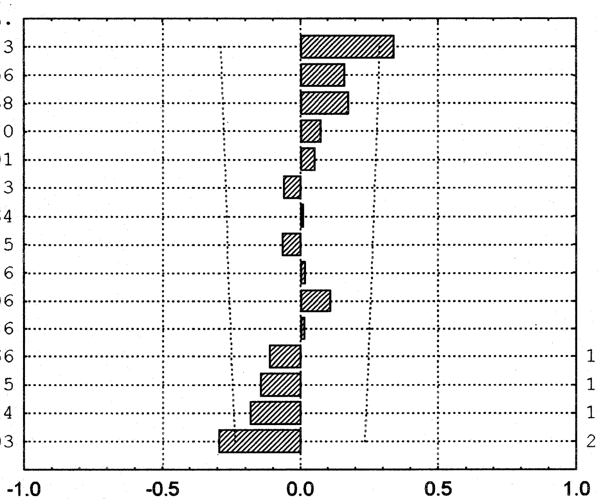
Autocorrelation Function: City of Richland Center (3065)
MW-6 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.224	.1473	2.32	.1279
2	-.204	.1456	4.28	.1176
3	+.169	.1438	5.66	.1296
4	+.337	.1420	11.28	.0236
5	+.004	.1401	11.28	.0461
6	-.080	.1383	11.62	.0711
7	+.007	.1364	11.62	.1138
8	+.011	.1345	11.63	.1687
9	+.025	.1326	11.66	.2331
10	+.048	.1306	11.80	.2990
11	+.037	.1286	11.88	.3728
12	+.112	.1266	12.67	.3936
13	+.071	.1245	12.99	.4485
14	-.062	.1224	13.24	.5075
15	-.070	.1203	13.58	.5577



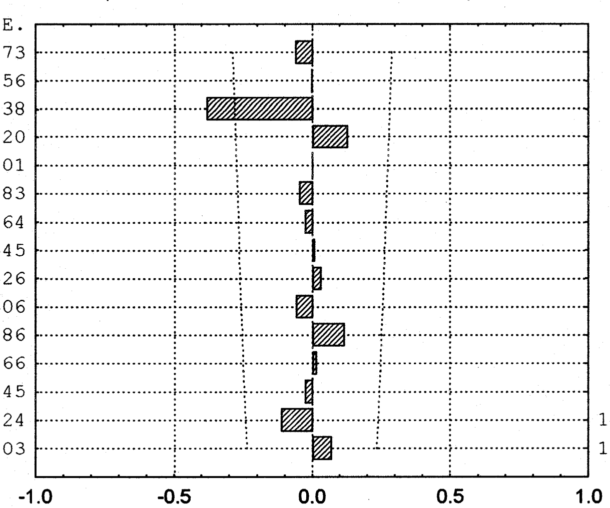
Autocorrelation Function: City of Richland Center (3065)
MW-7 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.342	.1473	5.40	.0201
2	+.165	.1456	6.68	.0354
3	+.176	.1438	8.19	.0423
4	+.078	.1420	8.49	.0753
5	+.054	.1401	8.64	.1245
6	-.060	.1383	8.83	.1836
7	+.010	.1364	8.83	.2649
8	-.067	.1345	9.08	.3355
9	+.018	.1326	9.10	.4281
10	+.112	.1306	9.83	.4554
11	+.015	.1286	9.84	.5445
12	-.109	.1266	10.58	.5649
13	-.146	.1245	11.95	.5317
14	-.180	.1224	14.11	.4418
15	-.295	.1203	20.12	.1673



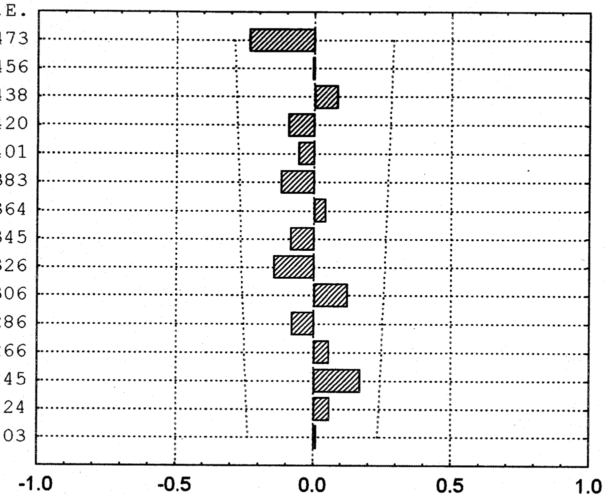
Autocorrelation Function: City of Richland Center (3065)
MW-7P Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	-.061	.1473	.17	.6799
2	-.002	.1456	.17	.9183
3	-.382	.1438	7.23	.0648
4	+.130	.1420	8.07	.0890
5	+.002	.1401	8.07	.1524
6	-.045	.1383	8.18	.2253
7	-.024	.1364	8.21	.3145
8	+.007	.1345	8.21	.4129
9	+.034	.1326	8.28	.5065
10	-.060	.1306	8.49	.5815
11	+.120	.1286	9.36	.5891
12	+.014	.1266	9.37	.6712
13	-.024	.1245	9.41	.7416
14	-.110	.1224	10.22	.7458
15	+.074	.1203	10.59	.7807



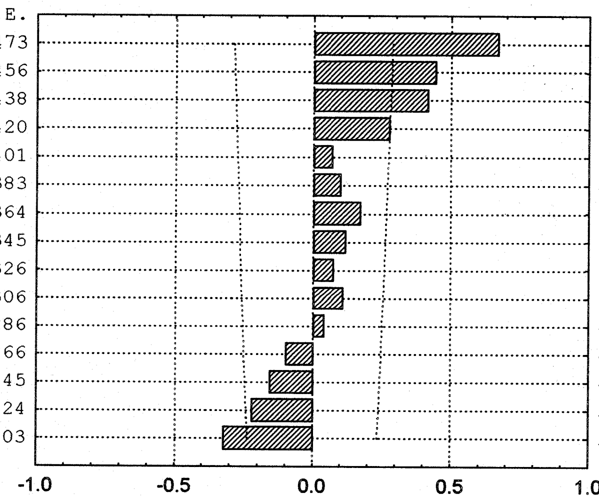
Autocorrelation Function: City of Richland Center (3065)
MW-6 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	-.235	.1473	2.54	.1113
2	-.005	.1456	2.54	.2812
3	+.089	.1438	2.92	.4042
4	-.090	.1420	3.32	.5050
5	-.056	.1401	3.49	.6254
6	-.117	.1383	4.20	.6496
7	+.045	.1364	4.31	.7434
8	-.084	.1345	4.70	.7892
9	-.145	.1326	5.89	.7508
10	+.125	.1306	6.81	.7430
11	-.080	.1286	7.20	.7828
12	+.059	.1266	7.42	.8289
13	+.172	.1245	9.33	.7474
14	+.062	.1224	9.59	.7914
15	+.010	.1203	9.60	.8442



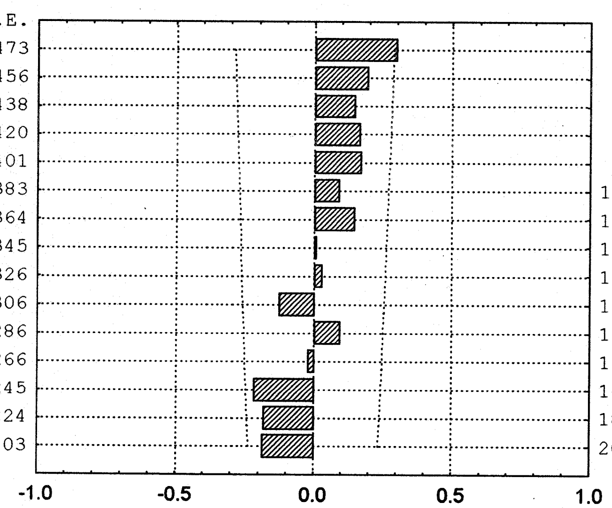
Autocorrelation Function: City of Richland Center (3065)
MW-7 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.673	.1473	20.90	.0000
2	+.447	.1456	30.34	.0000
3	+.418	.1438	38.80	.0000
4	+.279	.1420	42.67	.0000
5	+.073	.1401	42.94	.0000
6	+.104	.1383	43.51	.0000
7	+.176	.1364	45.18	.0000
8	+.121	.1345	45.98	.0000
9	+.078	.1326	46.33	.0000
10	+.113	.1306	47.07	.0000
11	+.042	.1286	47.18	.0000
12	-.095	.1266	47.75	.0000
13	-.157	.1245	49.33	.0000
14	-.222	.1224	52.61	.0000
15	-.323	.1203	59.82	.0000



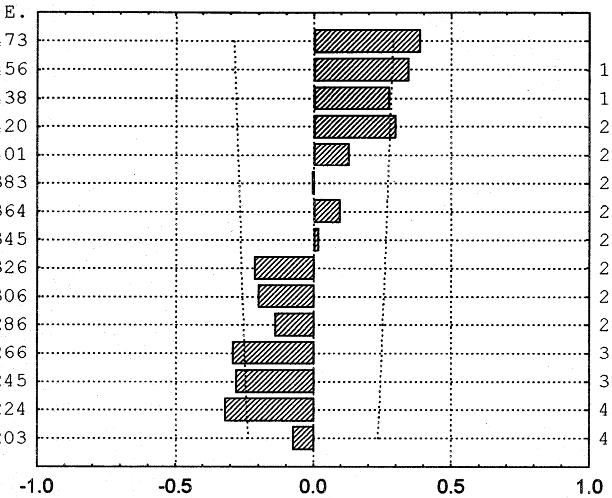
Autocorrelation Function: City of Richland Center (3065)
MW-7P Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.300	.1473	4.14	.0419
2	+.197	.1456	5.96	.0508
3	+.149	.1438	7.04	.0706
4	+.169	.1420	8.45	.0764
5	+.172	.1401	9.95	.0767
6	+.095	.1383	10.42	.1079
7	+.151	.1364	11.64	.1130
8	+.009	.1345	11.65	.1678
9	+.031	.1326	11.70	.2307
10	-.126	.1306	12.64	.2446
11	+.098	.1286	13.22	.2793
12	-.019	.1266	13.24	.3517
13	-.217	.1245	16.28	.2347
14	-.180	.1224	18.43	.1881
15	-.185	.1203	20.79	.1436



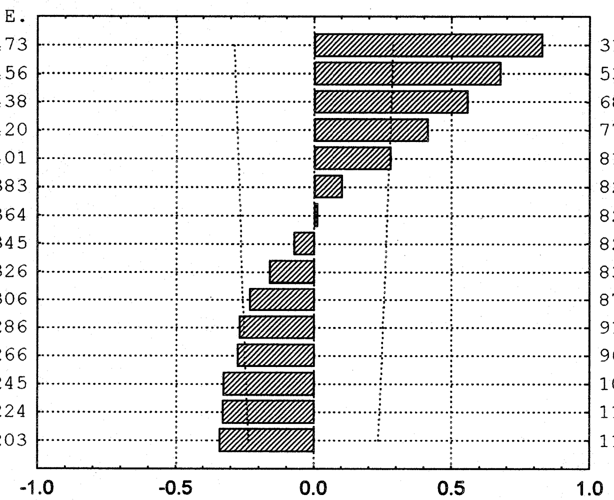
Autocorrelation Function: City of Richland Center (3065)
MW-6 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.388	.1473	6.93	.0085
2	+.345	.1456	12.56	.0019
3	+.277	.1438	16.27	.0010
4	+.300	.1420	20.74	.0004
5	+.131	.1401	21.61	.0006
6	-.004	.1383	21.61	.0014
7	+.099	.1364	22.13	.0024
8	+.021	.1345	22.16	.0046
9	-.215	.1326	24.78	.0032
10	-.200	.1306	27.13	.0025
11	-.140	.1286	28.32	.0029
12	-.292	.1266	33.66	.0008
13	-.283	.1245	38.81	.0002
14	-.321	.1224	45.69	.0000
15	-.076	.1203	46.09	.0001



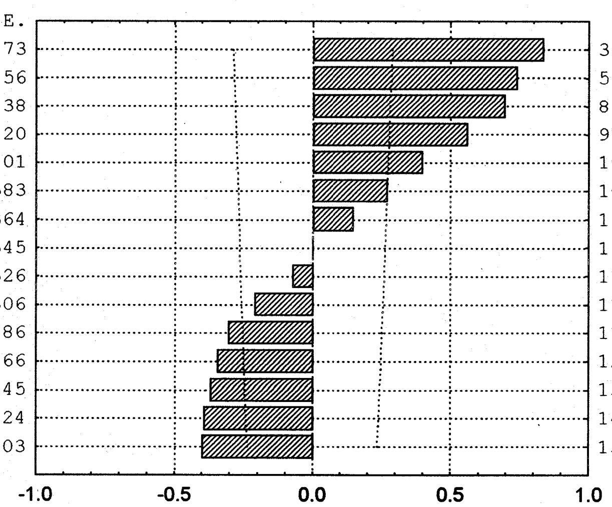
Autocorrelation Function: City of Richland Center (3065)
MW-7 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.831	.1473	31.83	.0000
2	+.681	.1456	53.74	.0000
3	+.559	.1438	68.84	.0000
4	+.415	.1420	77.39	.0000
5	+.281	.1401	81.41	.0000
6	+.106	.1383	82.01	.0000
7	+.012	.1364	82.01	.0000
8	-.074	.1345	82.32	.0000
9	-.162	.1326	83.81	.0000
10	-.234	.1306	87.01	.0000
11	-.270	.1286	91.40	.0000
12	-.277	.1266	96.20	.0000
13	-.328	.1245	103.1	.0000
14	-.329	.1224	110.4	.0000
15	-.342	.1203	118.5	.0000



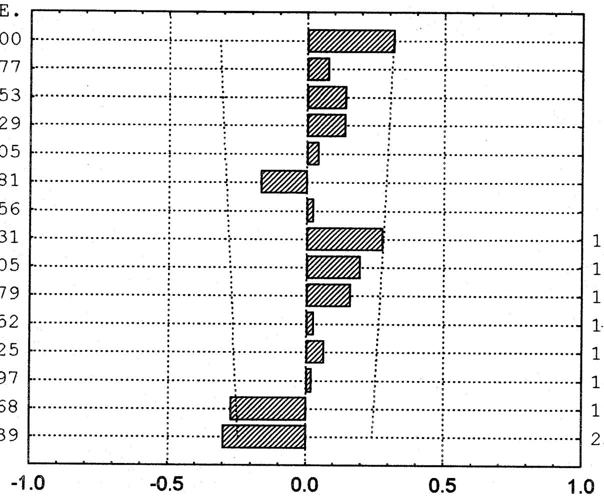
Autocorrelation Function: City of Richland Center (3065)
MW-7P Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.839	.1473	32.40	.0000
2	+.744	.1456	58.50	.0000
3	+.699	.1438	82.11	.0000
4	+.562	.1420	97.80	.0000
5	+.400	.1401	106.0	.0000
6	+.272	.1383	109.8	.0000
7	+.150	.1364	111.1	.0000
8	+.003	.1345	111.1	.0000
9	-.074	.1326	111.4	.0000
10	-.209	.1306	113.9	.0000
11	-.303	.1286	119.5	.0000
12	-.345	.1266	126.9	.0000
13	-.369	.1245	135.7	.0000
14	-.393	.1224	146.0	.0000
15	-.400	.1203	157.1	.0000



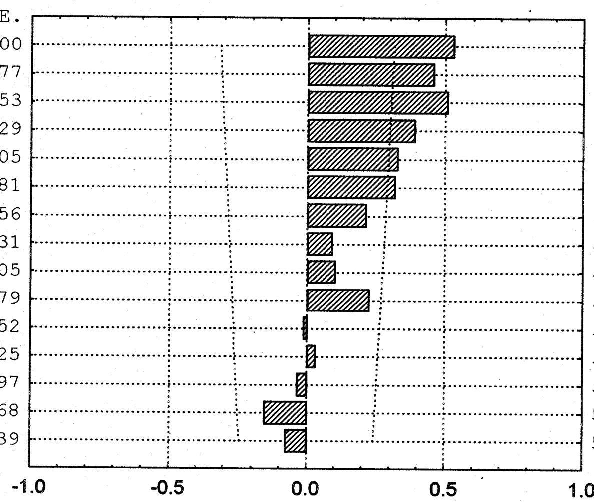
Autocorrelation Function: Juneau County Landfill (3070)
OW-5 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.319	.1600	3.97	.0463
2	+.082	.1577	4.24	.1200
3	+.144	.1553	5.10	.1646
4	+.143	.1529	5.98	.2008
5	+.045	.1505	6.07	.2995
6	-.165	.1481	7.31	.2932
7	+.027	.1456	7.34	.3940
8	+.280	.1431	11.17	.1923
9	+.197	.1405	13.14	.1565
10	+.163	.1379	14.53	.1501
11	+.028	.1352	14.58	.2027
12	+.069	.1325	14.85	.2500
13	+.023	.1297	14.88	.3152
14	-.273	.1268	19.51	.1463
15	-.300	.1239	25.36	.0454



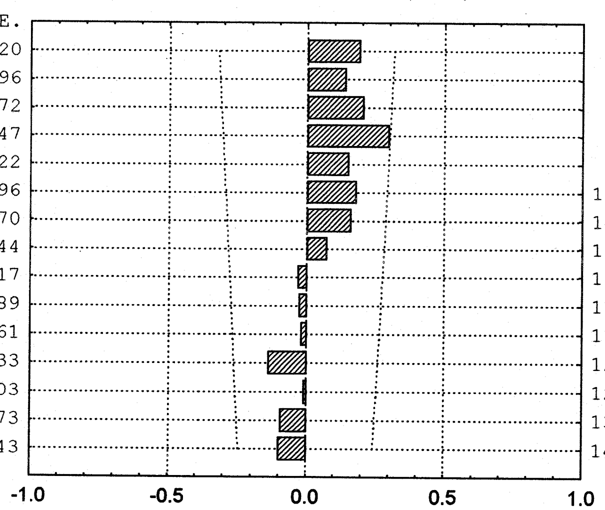
Autocorrelation Function: Juneau County Landfill (3070)
OW-5 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.532	.1600	11.07	.0009
2	+.460	.1577	19.59	.0001
3	+.512	.1553	30.45	.0000
4	+.394	.1529	37.07	.0000
5	+.331	.1505	41.92	.0000
6	+.321	.1481	46.60	.0000
7	+.217	.1456	48.82	.0000
8	+.094	.1431	49.26	.0000
9	+.105	.1405	49.82	.0000
10	+.229	.1379	52.58	.0000
11	-.011	.1352	52.58	.0000
12	+.034	.1325	52.65	.0000
13	-.033	.1297	52.71	.0000
14	-.155	.1268	54.20	.0000
15	-.077	.1239	54.59	.0000



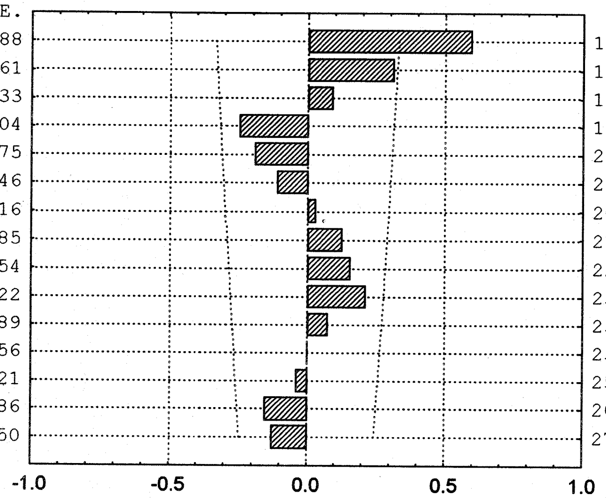
Autocorrelation Function: Juneau County Landfill (3070)
OW-5 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.193	.1620	1.42	.2334
2	+.142	.1596	2.21	.3307
3	+.208	.1572	3.96	.2653
4	+.300	.1547	7.73	.1021
5	+.154	.1522	8.75	.1194
6	+.183	.1496	10.25	.1147
7	+.164	.1470	11.49	.1189
8	+.075	.1444	11.76	.1625
9	-.030	.1417	11.80	.2249
10	-.023	.1389	11.83	.2968
11	-.016	.1361	11.84	.3757
12	-.138	.1333	12.91	.3757
13	-.008	.1303	12.91	.4545
14	-.091	.1273	13.42	.4938
15	-.097	.1243	14.03	.5231



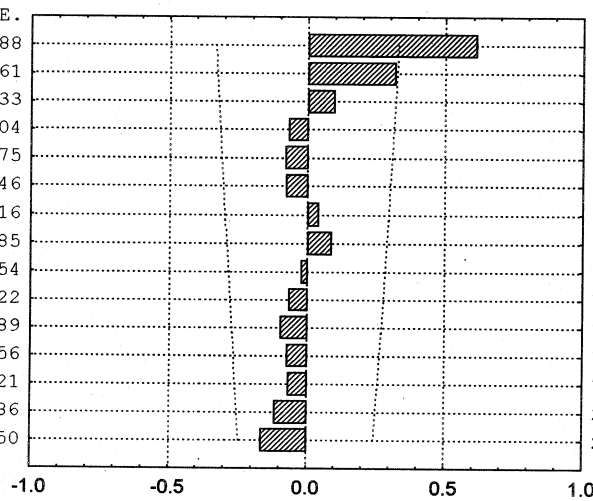
Autocorrelation Function: Troy Area Landfill (3090)
B-1 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.597	.1688	12.53	.0004
2	+.315	.1661	16.13	.0003
3	+.095	.1633	16.47	.0009
4	-.246	.1604	18.83	.0009
5	-.189	.1575	20.27	.0011
6	-.107	.1546	20.75	.0020
7	+.030	.1516	20.79	.0041
8	+.129	.1485	21.54	.0059
9	+.159	.1454	22.73	.0068
10	+.214	.1422	25.01	.0053
11	+.077	.1389	25.31	.0082
12	+.003	.1356	25.31	.0134
13	-.039	.1321	25.40	.0205
14	-.155	.1286	26.86	.0201
15	-.128	.1250	27.90	.0222



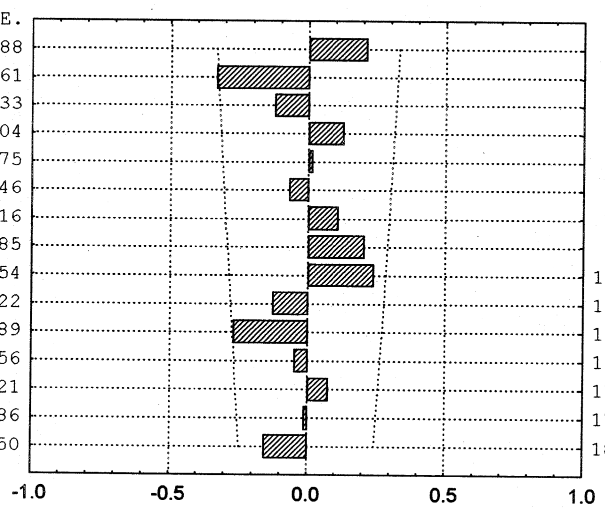
Autocorrelation Function: Troy Area Landfill (3090)
B-1B Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.616	.1688	13.30	.0003
2	+.320	.1661	17.02	.0002
3	+.100	.1633	17.40	.0006
4	-.067	.1604	17.57	.0015
5	-.080	.1575	17.83	.0032
6	-.077	.1546	18.08	.0061
7	+.042	.1516	18.16	.0113
8	+.092	.1485	18.54	.0175
9	-.019	.1454	18.56	.0293
10	-.067	.1422	18.78	.0432
11	-.094	.1389	19.24	.0571
12	-.074	.1356	19.53	.0766
13	-.068	.1321	19.80	.1005
14	-.114	.1286	20.58	.1129
15	-.167	.1250	22.36	.0988



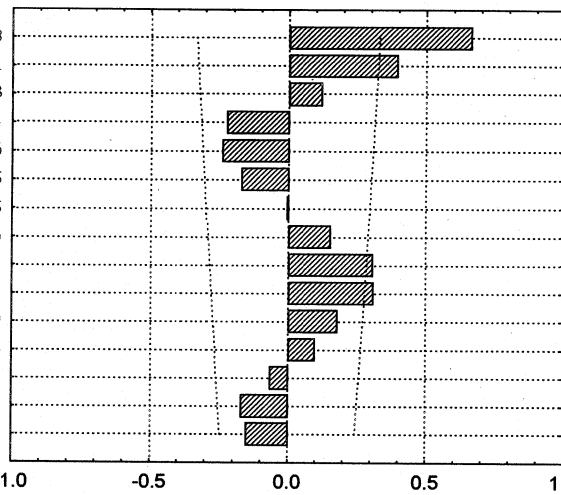
Autocorrelation Function: Troy Area Landfill (3090)
B-2 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.213	.1688	1.60	.2065
2	-.333	.1661	5.61	.0605
3	-.118	.1633	6.13	.1053
4	+.132	.1604	6.81	.1465
5	+.015	.1575	6.82	.2347
6	-.069	.1546	7.02	.3194
7	+.112	.1516	7.56	.3728
8	+.207	.1485	9.50	.3019
9	+.242	.1454	12.26	.1990
10	-.127	.1422	13.06	.2202
11	-.268	.1389	16.79	.1142
12	-.045	.1356	16.90	.1534
13	+.077	.1321	17.24	.1886
14	-.011	.1286	17.25	.2432
15	-.155	.1250	18.79	.2233



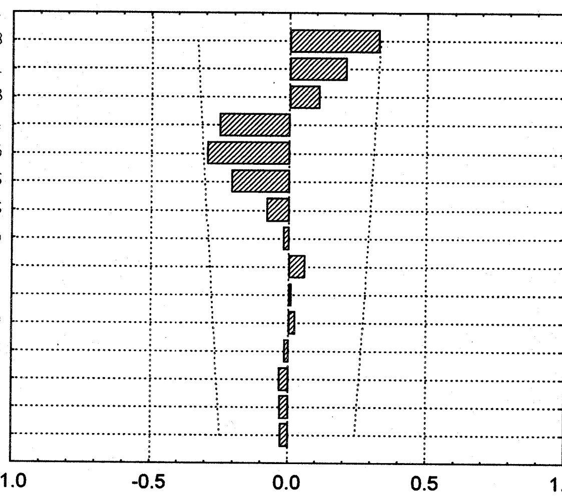
Autocorrelation Function: Troy Area Landfill (3090)
B-1 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.666	.1688	15.56	.0001
2	+.398	.1661	21.29	.0000
3	+.125	.1633	21.87	.0001
4	-.225	.1604	23.84	.0001
5	-.240	.1575	26.16	.0001
6	-.171	.1546	27.38	.0001
7	-.004	.1516	27.38	.0003
8	+.156	.1485	28.48	.0004
9	+.310	.1454	33.02	.0001
10	+.313	.1422	37.86	.0000
11	+.182	.1389	39.58	.0000
12	+.101	.1356	40.14	.0001
13	-.067	.1321	40.39	.0001
14	-.170	.1286	42.13	.0001
15	-.151	.1250	43.60	.0001



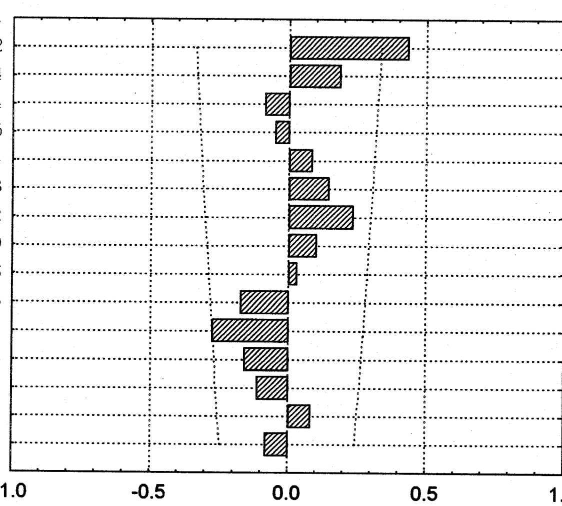
Autocorrelation Function: Troy Area Landfill (3090)
B-1B Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.328	.1688	3.77	.0523
2	+.209	.1661	5.35	.0689
3	+.113	.1633	5.83	.1202
4	-.252	.1604	8.29	.0815
5	-.297	.1575	11.84	.0371
6	-.208	.1546	13.65	.0338
7	-.081	.1516	13.94	.0523
8	-.017	.1485	13.95	.0831
9	+.063	.1454	14.14	.1176
10	+.011	.1422	14.14	.1667
11	+.026	.1389	14.18	.2235
12	-.012	.1356	14.18	.2892
13	-.031	.1321	14.24	.3573
14	-.029	.1286	14.29	.4285
15	-.027	.1250	14.33	.5003



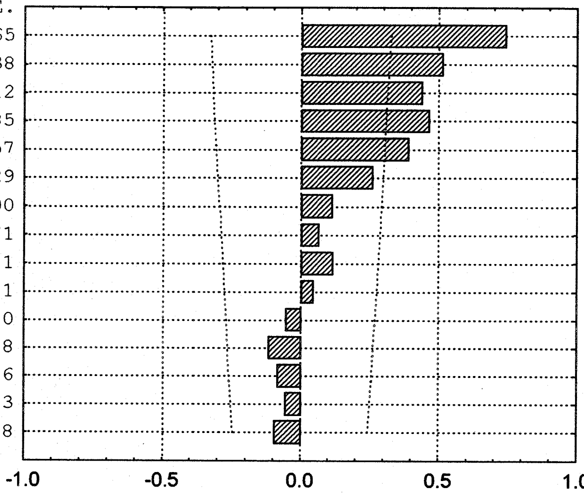
Autocorrelation Function: Troy Area Landfill (3090)
B-2 Hardness
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.435	.1712	6.44	.0111
2	+.188	.1684	7.69	.0214
3	-.087	.1654	7.96	.0468
4	-.048	.1625	8.05	.0897
5	+.087	.1594	8.35	.1379
6	+.149	.1563	9.27	.1592
7	+.238	.1532	11.69	.1114
8	+.105	.1499	12.18	.1435
9	+.035	.1466	12.23	.2005
10	-.171	.1433	13.67	.1889
11	-.276	.1398	17.55	.0927
12	-.159	.1363	18.91	.0908
13	-.110	.1326	19.60	.1058
14	+.086	.1289	20.04	.1289
15	-.082	.1251	20.47	.1548



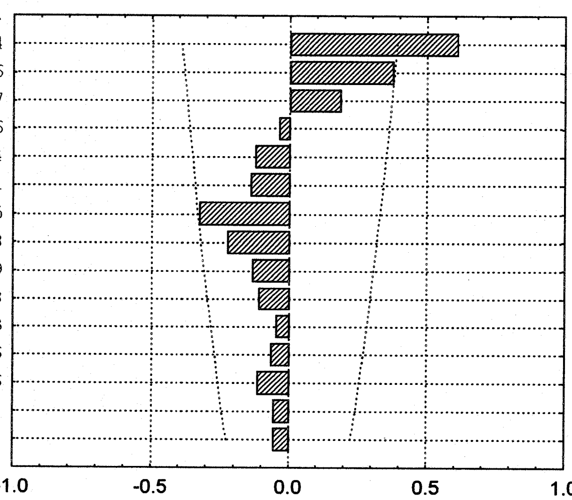
Autocorrelation Function: Troy Area Landfill (3090)
B-1 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.745	.1665	20.01	.0000
2	+.515	.1638	29.90	.0000
3	+.441	.1612	37.39	.0000
4	+.468	.1585	46.11	.0000
5	+.392	.1557	52.44	.0000
6	+.263	.1529	55.40	.0000
7	+.118	.1500	56.02	.0000
8	+.068	.1471	56.24	.0000
9	+.121	.1441	56.94	.0000
10	+.047	.1411	57.05	.0000
11	-.054	.1380	57.20	.0000
12	-.115	.1348	57.93	.0000
13	-.084	.1316	58.34	.0000
14	-.057	.1283	58.54	.0000
15	-.094	.1248	59.11	.0000



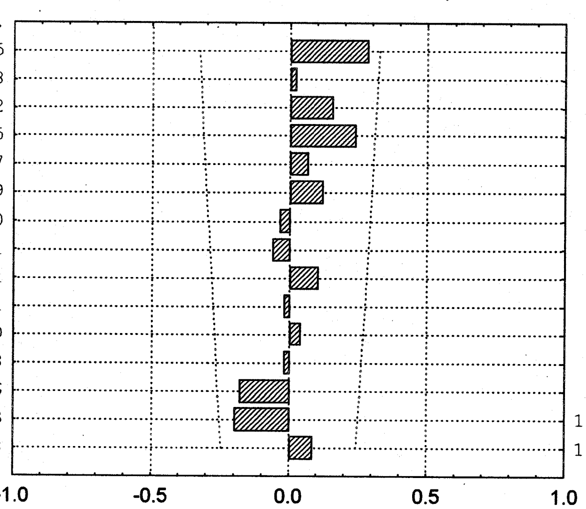
Autocorrelation Function: Troy Area Landfill (3090)
B-1B Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.613	.1994	9.45	.0021
2	+.380	.1946	13.25	.0013
3	+.189	.1897	14.25	.0026
4	-.035	.1846	14.28	.0065
5	-.124	.1794	14.76	.0115
6	-.140	.1741	15.40	.0174
7	-.326	.1685	19.14	.0078
8	-.223	.1628	21.02	.0071
9	-.134	.1569	21.75	.0097
10	-.109	.1508	22.26	.0138
11	-.045	.1443	22.36	.0218
12	-.066	.1376	22.59	.0315
13	-.113	.1306	23.34	.0379
14	-.056	.1231	23.54	.0520
15	-.058	.1151	23.80	.0687



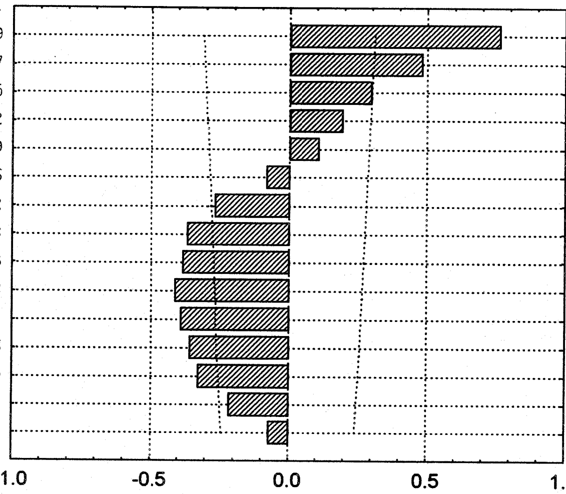
Autocorrelation Function: Troy Area Landfill (3090)
B-2 Specific Conductance
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.287	.1665	2.97	.0847
2	+.024	.1638	2.99	.2239
3	+.159	.1612	3.97	.2648
4	+.242	.1585	6.29	.1783
5	+.069	.1557	6.49	.2613
6	+.124	.1529	7.15	.3075
7	-.033	.1500	7.19	.4090
8	-.061	.1471	7.37	.4977
9	+.108	.1441	7.93	.5417
10	-.018	.1411	7.94	.6345
11	+.043	.1380	8.04	.7097
12	-.018	.1348	8.06	.7805
13	-.176	.1316	9.85	.7062
14	-.199	.1283	12.26	.5855
15	+.088	.1248	12.75	.6215



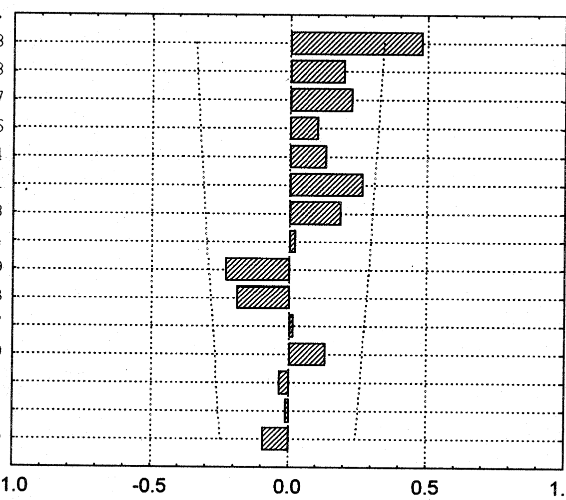
Autocorrelation Function: Lincoln County Landfill (3141)
M-4 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.765	.1579	23.47	.0000
2	+.484	.1557	33.13	.0000
3	+.301	.1535	36.97	.0000
4	+.195	.1512	38.63	.0000
5	+.109	.1489	39.17	.0000
6	-.083	.1466	39.49	.0000
7	-.266	.1442	42.90	.0000
8	-.367	.1418	49.61	.0000
9	-.383	.1393	57.16	.0000
10	-.411	.1368	66.18	.0000
11	-.391	.1342	74.65	.0000
12	-.359	.1316	82.08	.0000
13	-.327	.1290	88.52	.0000
14	-.216	.1262	91.44	.0000
15	-.073	.1235	91.79	.0000

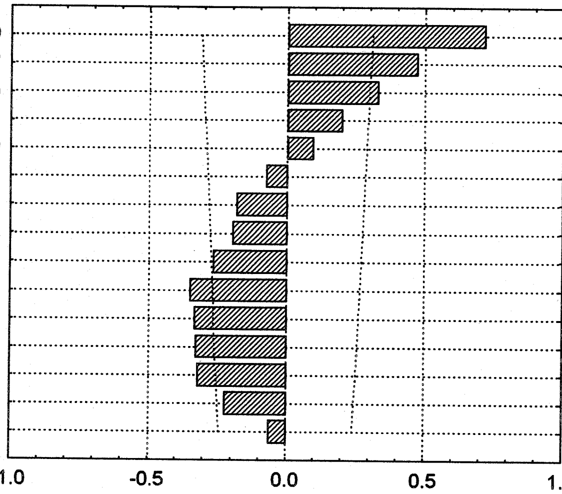


Autocorrelation Function: Lincoln County Landfill (3141)
M-9 Alkalinity
(Standard errors are white-noise estimates)

Lag	Corr.	S.E.	Q	p
1	+.481	.1738	7.67	.0056
2	+.200	.1708	9.03	.0109
3	+.228	.1677	10.88	.0124
4	+.106	.1646	11.29	.0235
5	+.135	.1614	12.00	.0348
6	+.268	.1581	14.86	.0214
7	+.190	.1548	16.36	.0220
8	+.023	.1514	16.39	.0372
9	-.231	.1479	18.83	.0267
10	-.187	.1443	20.51	.0248
11	+.015	.1407	20.53	.0387
12	+.135	.1369	21.50	.0435
13	-.033	.1331	21.56	.0626
14	-.010	.1291	21.57	.0880
15	-.091	.1250	22.11	.1052

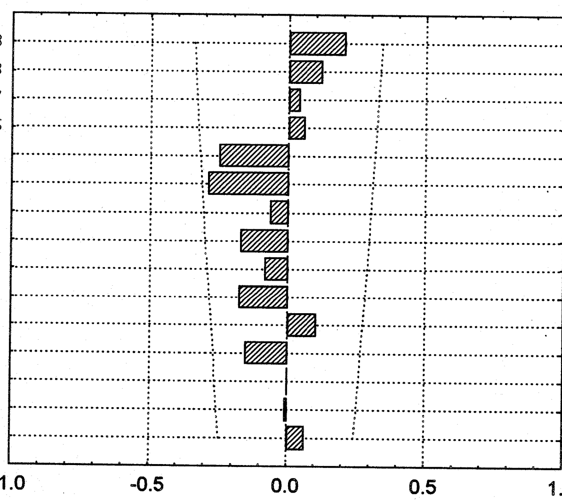


Autocorrelation Function: Lincoln County Landfill (3141)
M-4 Hardness
(Standard errors are white-noise estimates)



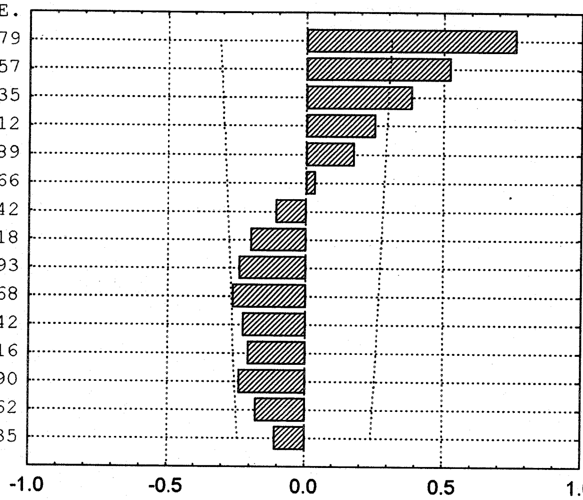
Lag	Corr.	S.E.	Q	p
1	+.720	.1579	20.80	.0000
2	+.473	.1557	30.03	.0000
3	+.333	.1535	34.75	.0000
4	+.202	.1512	36.53	.0000
5	+.098	.1489	36.96	.0000
6	-.075	.1466	37.22	.0000
7	-.179	.1442	38.77	.0000
8	-.196	.1418	40.67	.0000
9	-.265	.1393	44.28	.0000
10	-.349	.1368	50.80	.0000
11	-.333	.1342	56.96	.0000
12	-.329	.1316	63.21	.0000
13	-.321	.1290	69.40	.0000
14	-.224	.1262	72.54	.0000
15	-.065	.1235	72.81	.0000

Autocorrelation Function: Lincoln County Landfill (3141)
M-9 Hardness
(Standard errors are white-noise estimates)



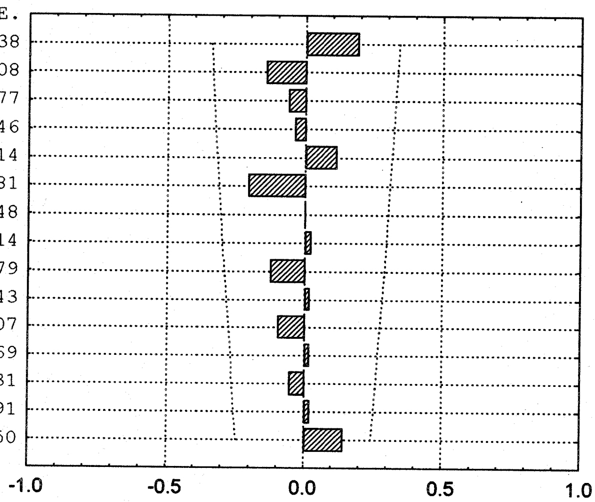
Lag	Corr.	S.E.	Q	p
1	+.208	.1738	1.43	.2314
2	+.125	.1708	1.96	.3746
3	+.042	.1677	2.03	.5668
4	+.061	.1646	2.17	.7053
5	-.249	.1614	4.55	.4726
6	-.288	.1581	7.86	.2483
7	-.064	.1548	8.03	.3298
8	-.171	.1514	9.31	.3172
9	-.082	.1479	9.62	.3824
10	-.174	.1443	11.07	.3524
11	+.108	.1407	11.66	.3897
12	-.153	.1369	12.90	.3763
13	+.003	.1331	12.90	.4554
14	-.007	.1291	12.90	.5340
15	+.067	.1250	13.19	.5874

Autocorrelation Function: Lincoln County Landfill (3141)
M-4 Specific Conductance
(Standard errors are white-noise estimates)



Lag	Corr.	S.E.	Q	p
1	+.765	.1579	23.43	.0000
2	+.526	.1557	34.84	.0000
3	+.386	.1535	41.15	.0000
4	+.254	.1512	43.98	.0000
5	+.177	.1489	45.39	.0000
6	+.036	.1466	45.45	.0000
7	-.105	.1442	45.98	.0000
8	-.197	.1418	47.91	.0000
9	-.239	.1393	50.86	.0000
10	-.264	.1368	54.58	.0000
11	-.225	.1342	57.39	.0000
12	-.208	.1316	59.89	.0000
13	-.240	.1290	63.36	.0000
14	-.177	.1262	65.33	.0000
15	-.109	.1235	66.10	.0000

Autocorrelation Function: Lincoln County Landfill (3141)
M-9 Specific Conductance
(Standard errors are white-noise estimates)



Lag	Corr.	S.E.	Q	p
1	+.194	.1738	1.24	.2652
2	-.144	.1708	1.95	.3776
3	-.061	.1677	2.08	.5557
4	-.035	.1646	2.13	.7123
5	+.118	.1614	2.66	.7521
6	-.204	.1581	4.33	.6319
7	+.004	.1548	4.33	.7408
8	+.024	.1514	4.36	.8234
9	-.122	.1479	5.04	.8311
10	+.018	.1443	5.05	.8877
11	-.094	.1407	5.49	.9049
12	+.019	.1369	5.51	.9386
13	-.052	.1331	5.67	.9574
14	+.021	.1291	5.69	.9736
15	+.145	.1250	7.04	.9565

APPENDIX D
DUMPStat RESULTS: PORTAGE COUNTY CASE STUDY

APPENDIX D
DUMPStat RESULTS: PORTAGE COUNTY CASE STUDY

Table of Contents

8 Background Samples

25 Background Samples

2966 Case Study: Table 1

Summary Statistics and Intermediate Computations for Intra-Well Prediction Limits

Constituent	Units	Well	N	Mean	SD	Factor	Limit
Alkalinity	mg/L	W-10	8	236.925	8.505	3.180	263.967
	mg/L	W-11	8	246.175	5.847	3.180	264.767
	mg/L	W-12	8	178.975	5.762	3.180	197.297
	mg/L	W-17	8	255.063	12.611	3.180	295.160
	mg/L	W-18	8	133.425	7.492	3.180	157.247
	mg/L	W-20	8	169.975	6.804	3.180	191.608
	mg/L	W-20P	8	181.863	36.830	3.180	298.968
	mg/L	W-21	8	179.225	5.555	3.180	196.889
	mg/L	W-21P	8	202.875	9.156	3.180	231.989
	mg/L	W-22	8	162.713	4.847	3.180	178.123
	mg/L	W-22P	8	178.738	7.835	3.180	203.649
	mg/L	W-23	8	147.662	37.709	3.180	267.565
	mg/L	W-23P	8	157.438	2.129	3.180	164.206
	mg/L	W-9	8	230.787	3.388	3.180	241.559
	mg/L	W-9P	8	225.287	4.934	3.180	240.977
Conductivity	MICR	W-10	8	517.875	42.549	3.180	653.166
	MICR	W-11	8	489.375	31.332	3.180	589.000
	MICR	W-12	8	374.875	26.107	3.180	457.885
	MICR	W-17	8	493.625	59.457	3.180	682.677
	MICR	W-18	8	265.750	9.603	3.180	296.284
	MICR	W-20	8	338.000	16.759	3.180	391.287
	MICR	W-20P	8	406.250	25.600	3.180	487.649
	MICR	W-21	8	361.250	23.414	3.180	435.698
	MICR	W-21P	8	410.000	24.495	3.180	487.885
	MICR	W-22	8	337.125	23.000	3.180	410.256
	MICR	W-22P	8	366.625	25.629	3.180	448.116
	MICR	W-23	8	302.500	63.552	3.180	504.573
	MICR	W-23P	8	323.500	21.119	3.180	390.650
	MICR	W-9	8	451.875	26.984	3.180	537.674
	MICR	W-9P	8	463.125	33.374	3.180	569.243
Hardness	mg/L	W-10	8	269.663	7.325	3.180	292.953
	mg/L	W-11	8	265.525	7.539	3.180	289.496
	mg/L	W-12	8	190.213	2.801	3.180	199.119
	mg/L	W-17	8	269.512	13.027	3.180	310.934
	mg/L	W-18	8	140.488	10.463	3.180	173.756
	mg/L	W-20	8	177.800	3.283	3.180	188.238
	mg/L	W-20P	8	211.762	3.913	3.180	224.203
	mg/L	W-21	8	188.600	4.837	3.180	203.979
	mg/L	W-21P	8	216.787	6.418	3.180	237.194

* - Insufficient Data
** - Detection Frequency < 25%
*** - Zero Variance

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2966 Case Study: Table 1 - Continued

Summary Statistics and Intermediate Computations for Intra-Well Prediction Limits

Constituent	Units	Well	N	Mean	SD	Factor	Limit
Hardness	mg/L	W-22	8	170.525	5.152	3.180	186.908
	mg/L	W-22P	8	186.075	6.602	3.180	207.067
	mg/L	W-23	8	154.075	36.476	3.180	270.056
	mg/L	W-23P	8	170.787	5.405	3.180	187.975
	mg/L	W-9	8	243.600	2.209	3.180	250.624
	mg/L	W-9P	8	247.488	2.382	3.180	255.061

* - Insufficient Data
** - Detection Frequency < 25%
*** - Zero Variance

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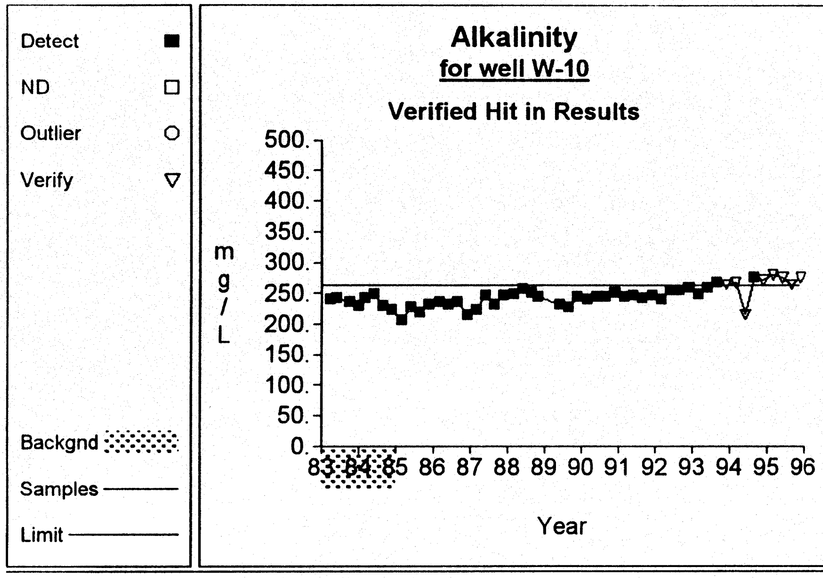
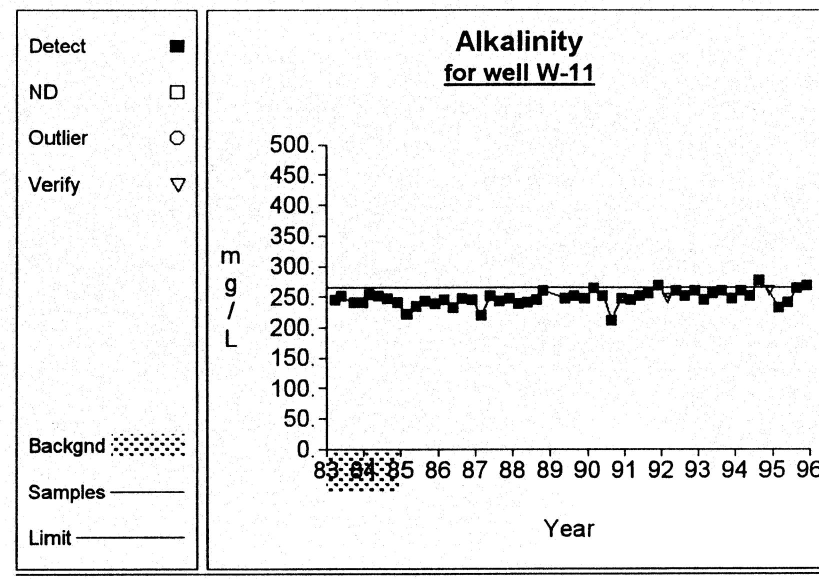
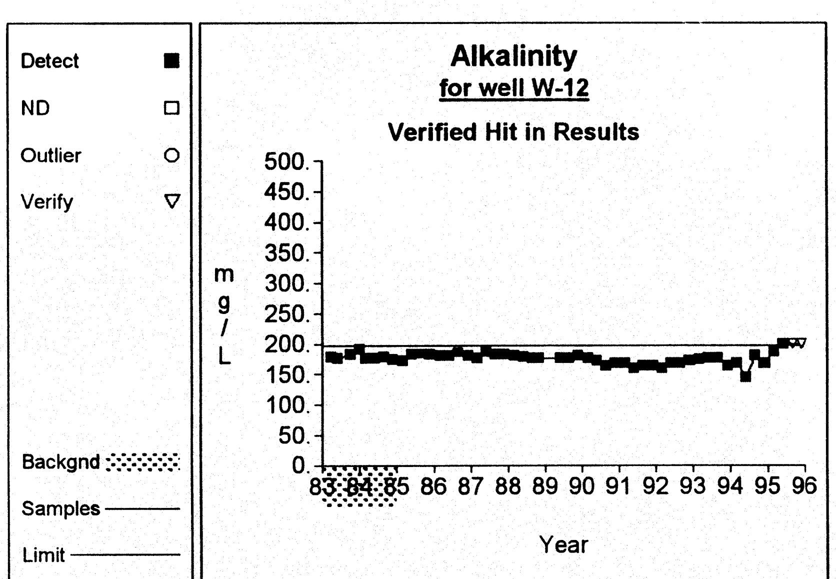
2966 Case Study: Intra-Well Prediction Limits



Graph 1



Graph 2



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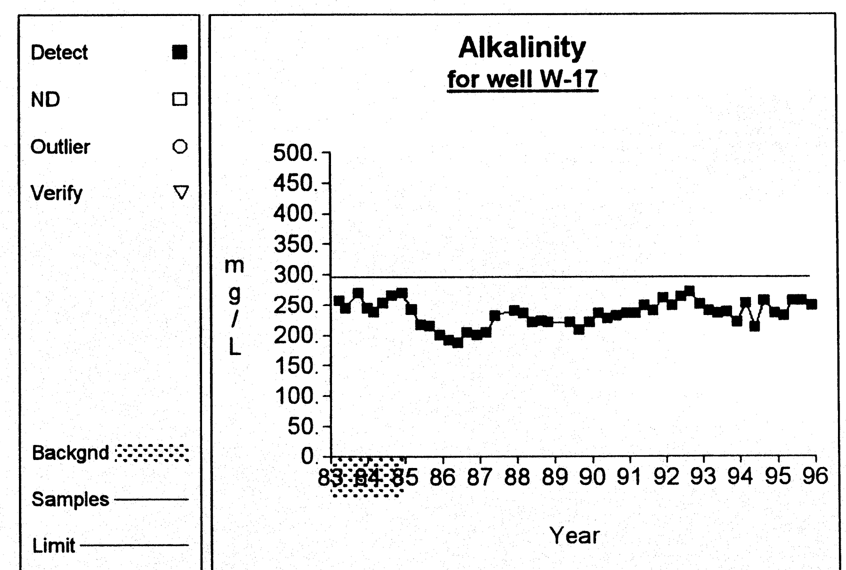

Graph 4

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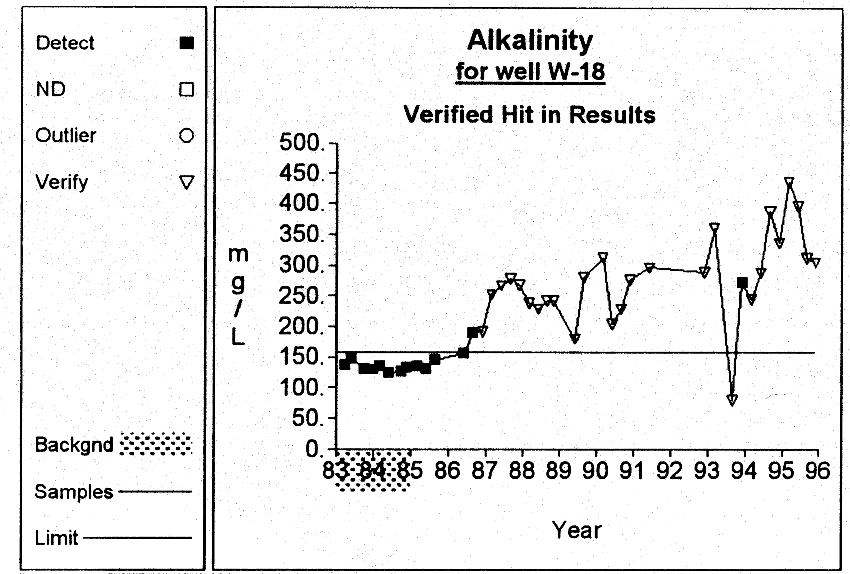
2966 Case Study: Intra-Well Prediction Limits



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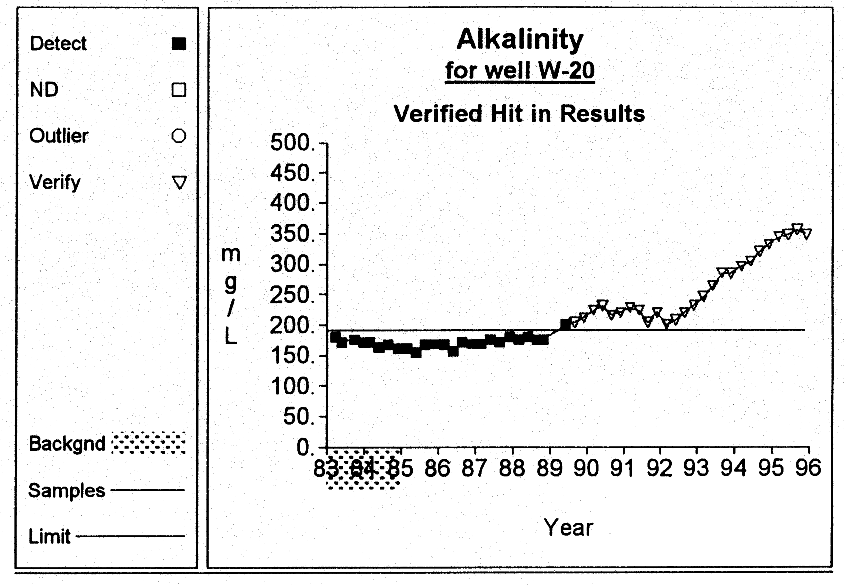
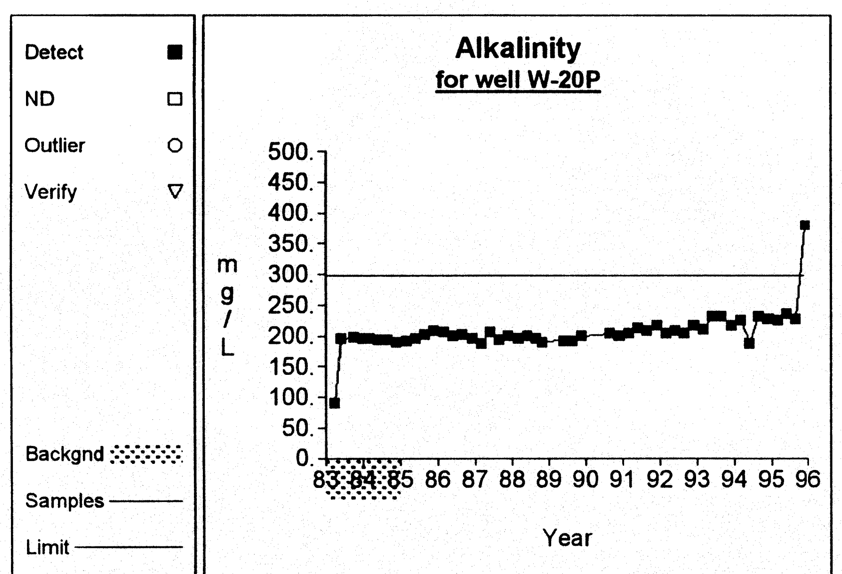


Graph 6



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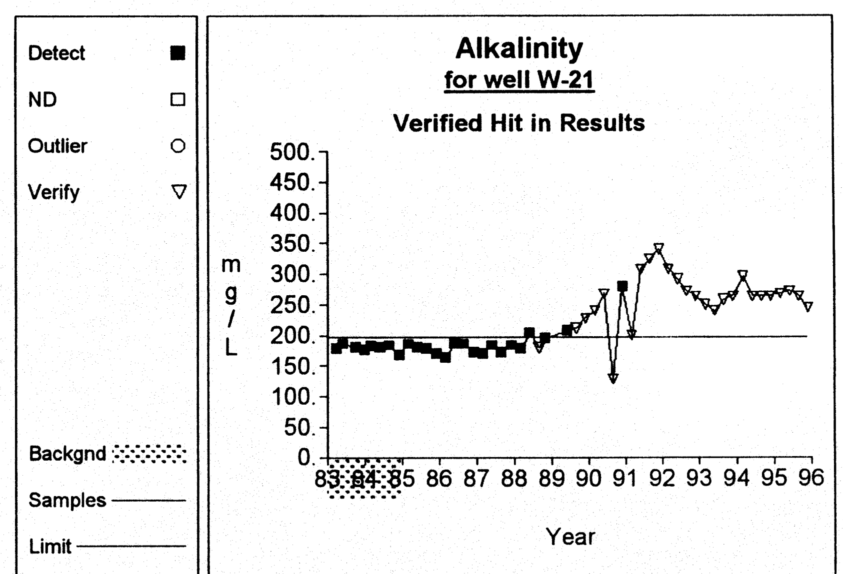

Graph 8

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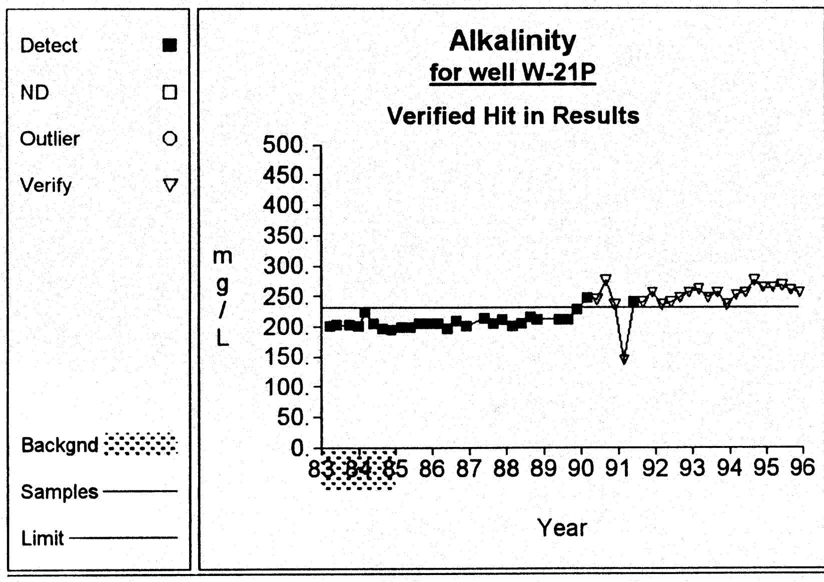
2966 Case Study: Intra-Well Prediction Limits



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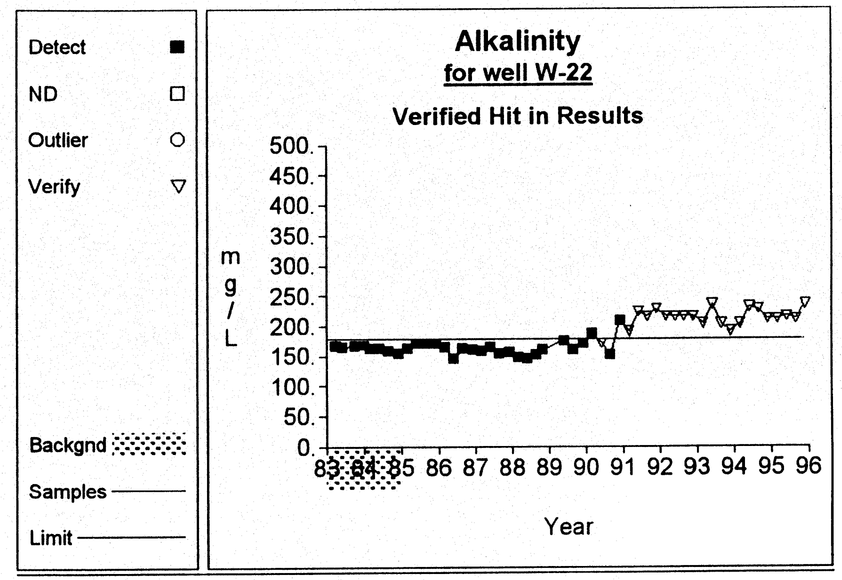

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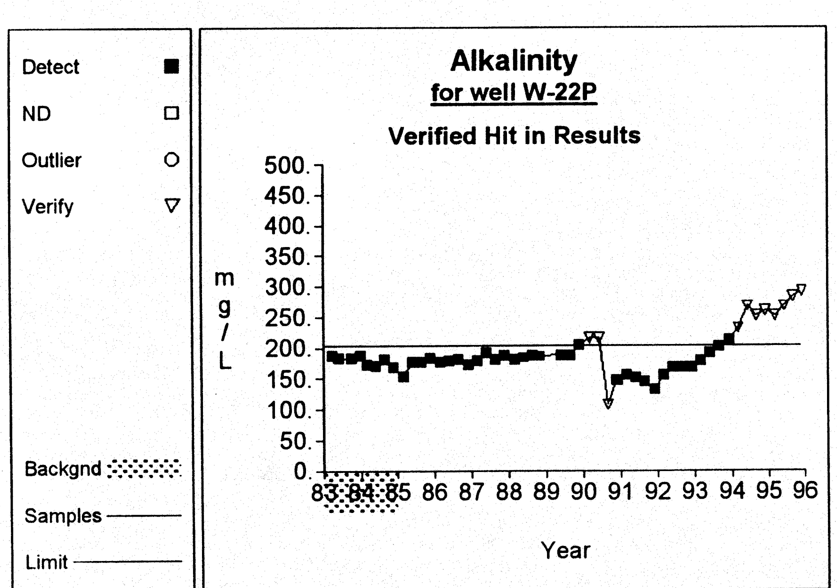
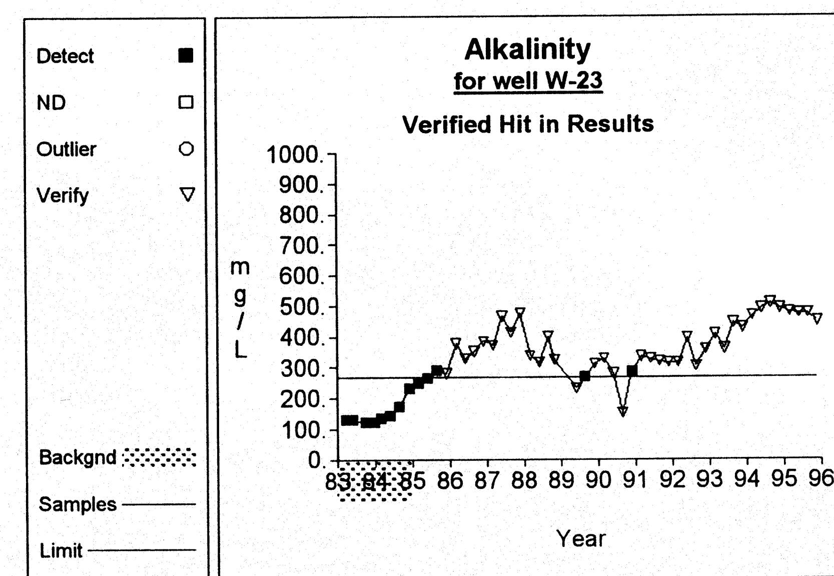


Graph 11



Graph 12

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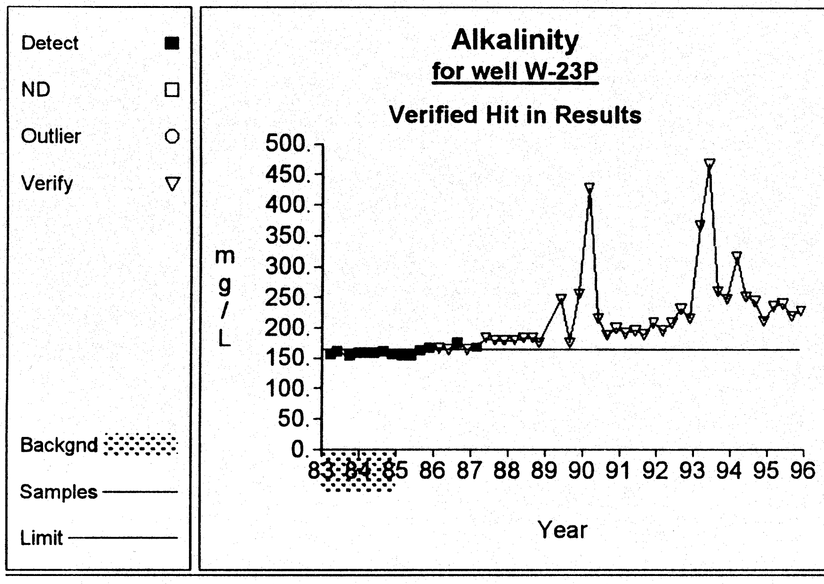
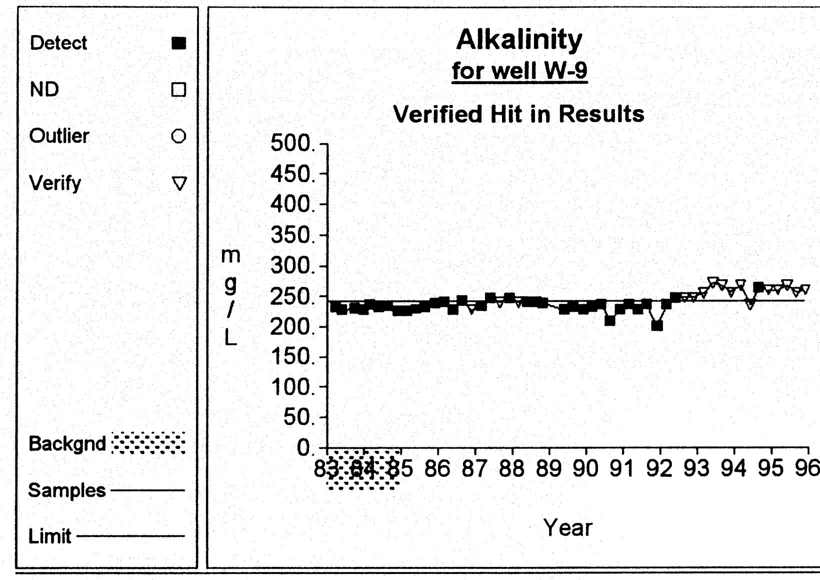
2966 Case Study: Intra-Well Prediction Limits



Graph 13



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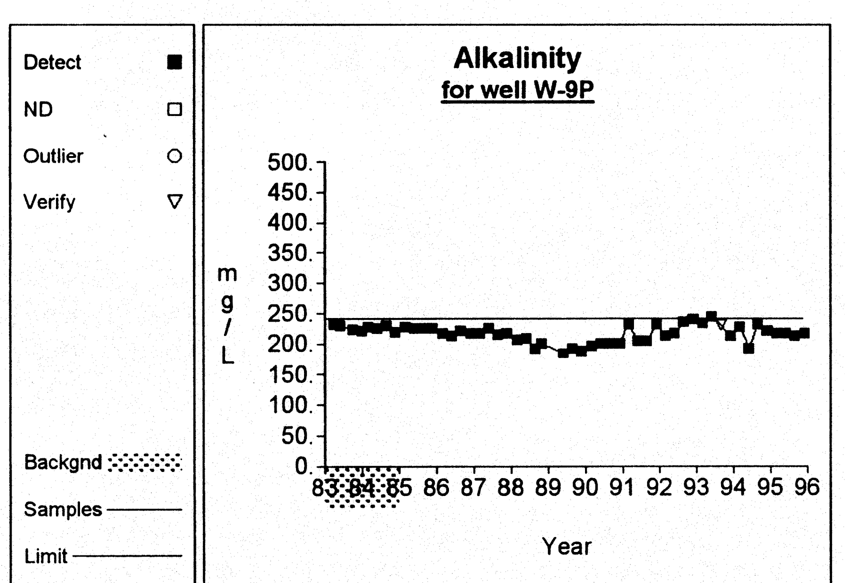

Graph 15

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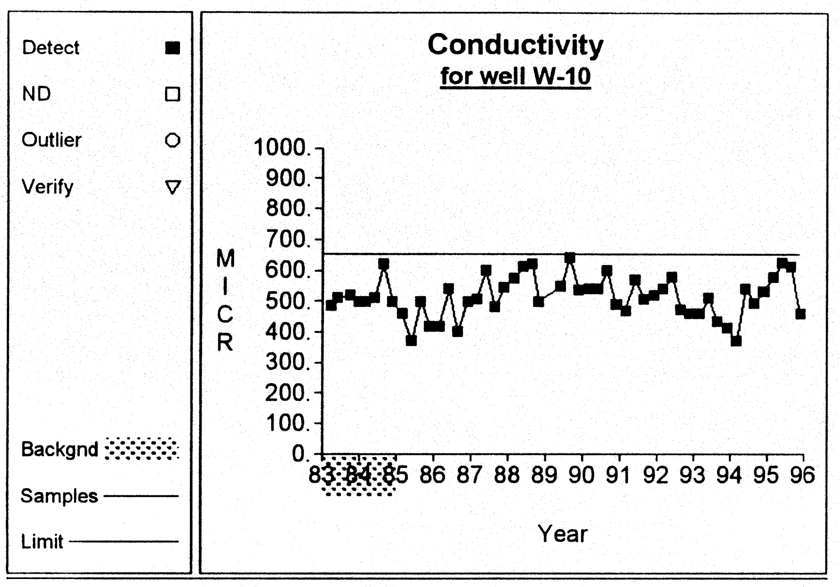
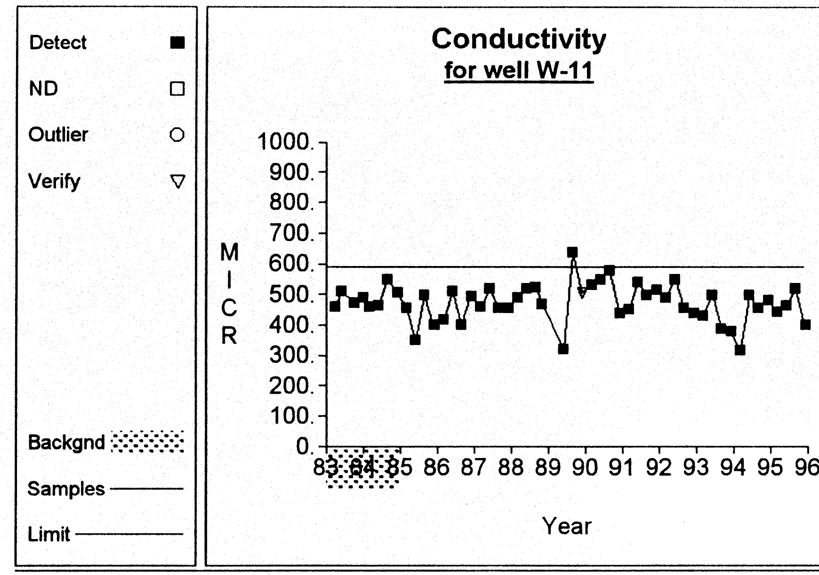
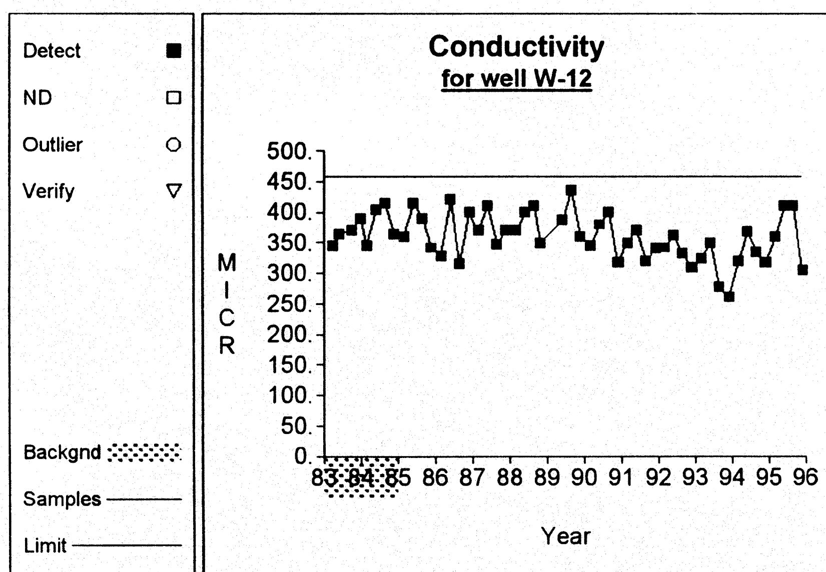
2966 Case Study: Intra-Well Prediction Limits



Graph 16



Graph 17



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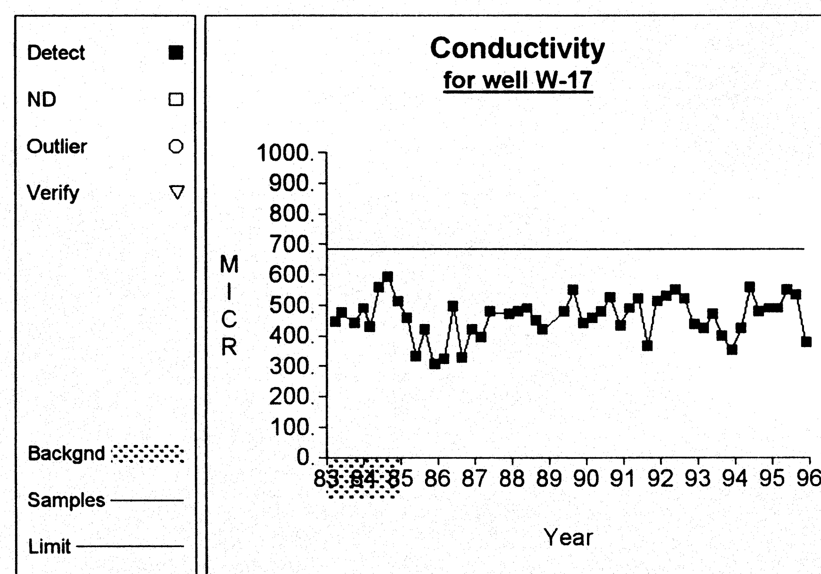

Graph 19

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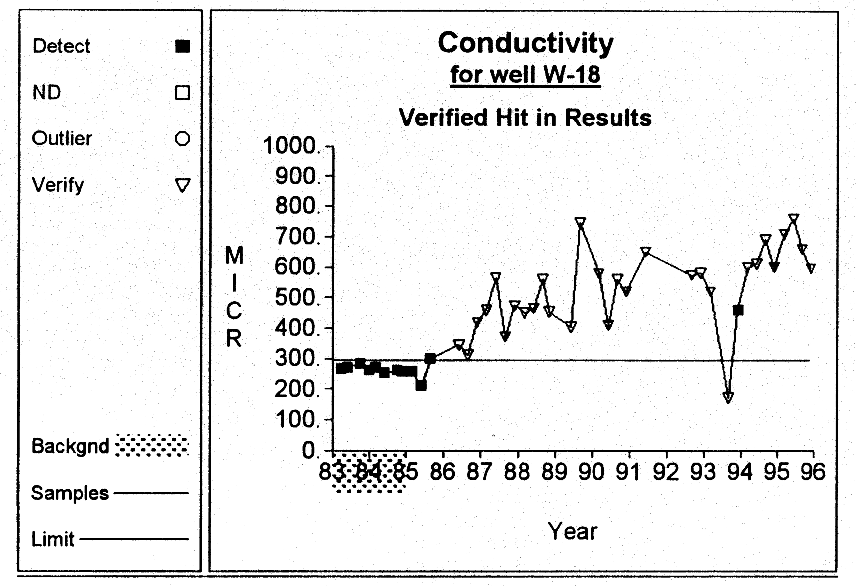
2966 Case Study: Intra-Well Prediction Limits



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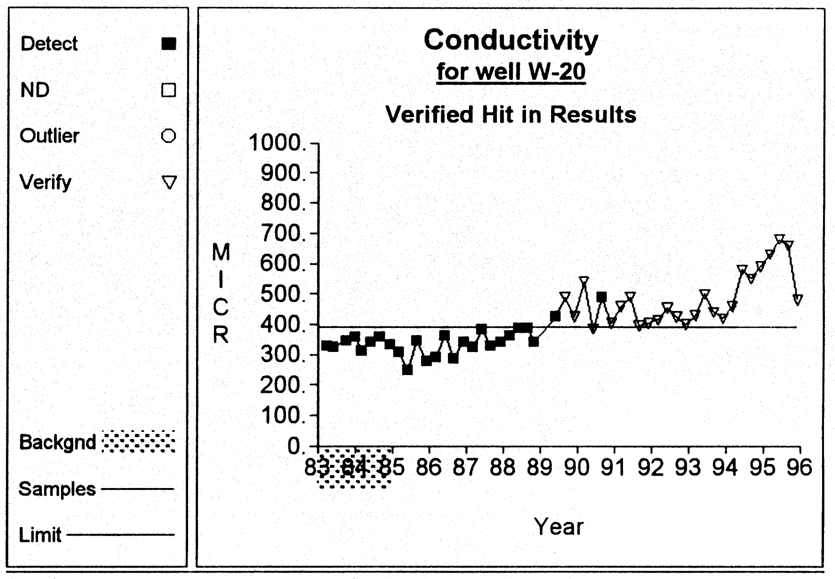
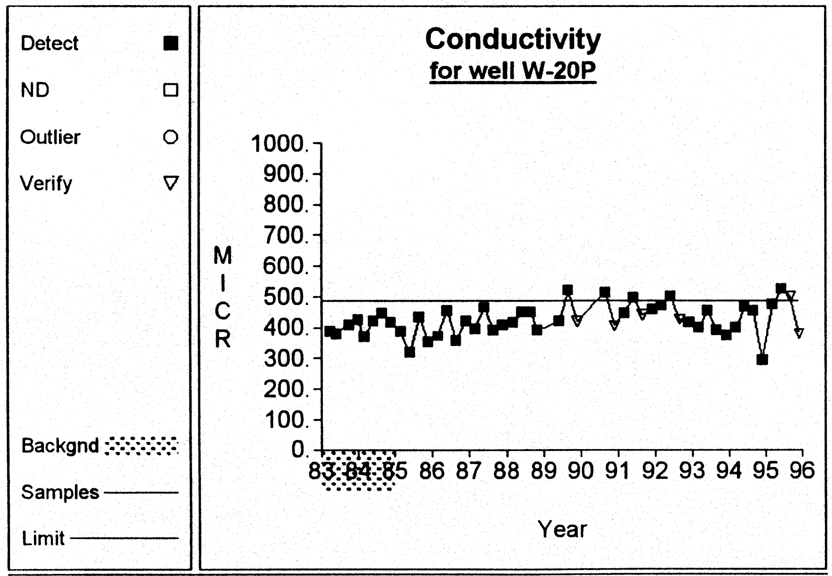
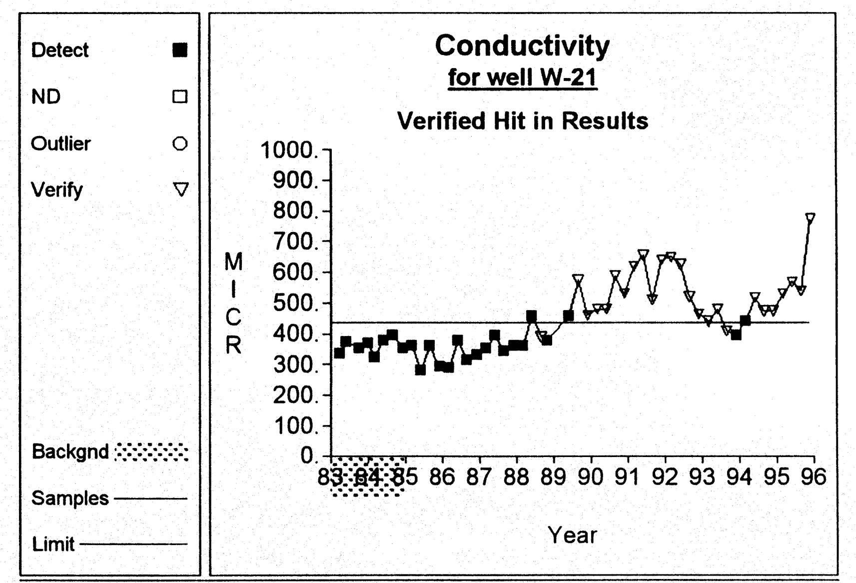


Graph 21



Graph 22



Graph 23

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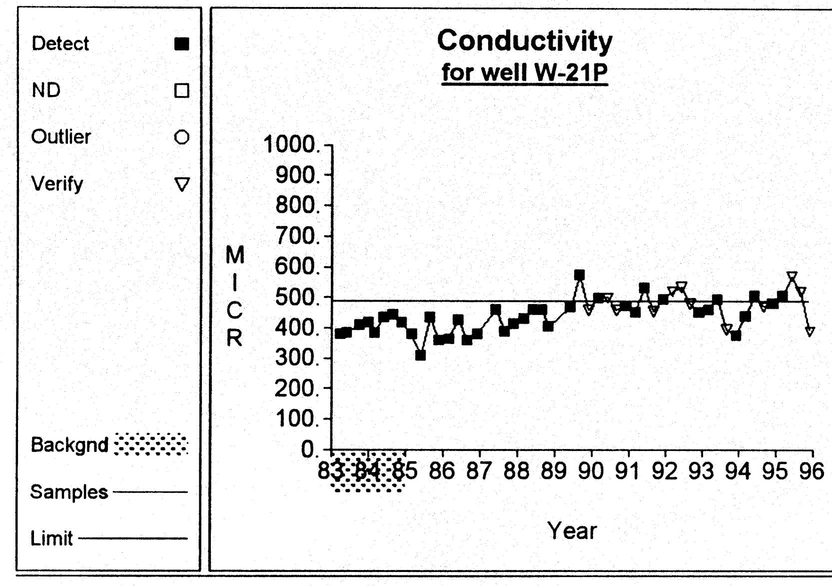
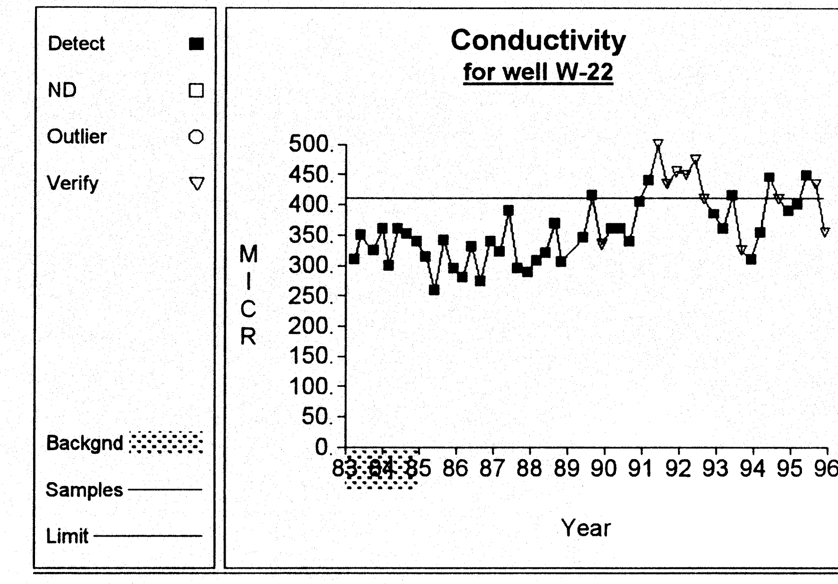
2966 Case Study: Intra-Well Prediction Limits



Graph 24



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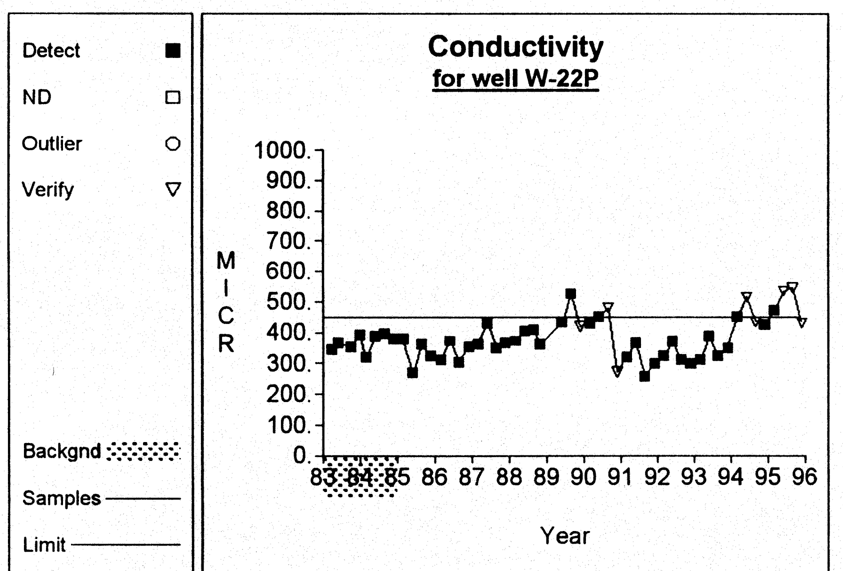

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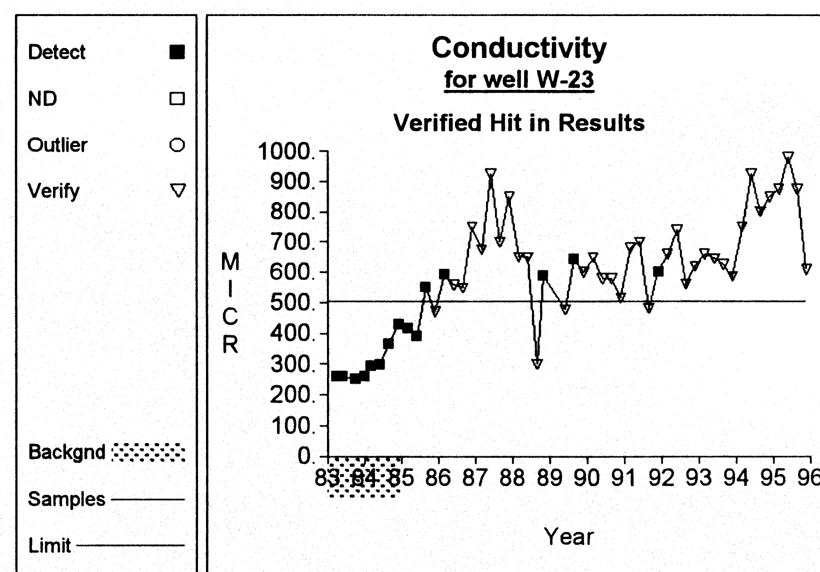

Graph 27

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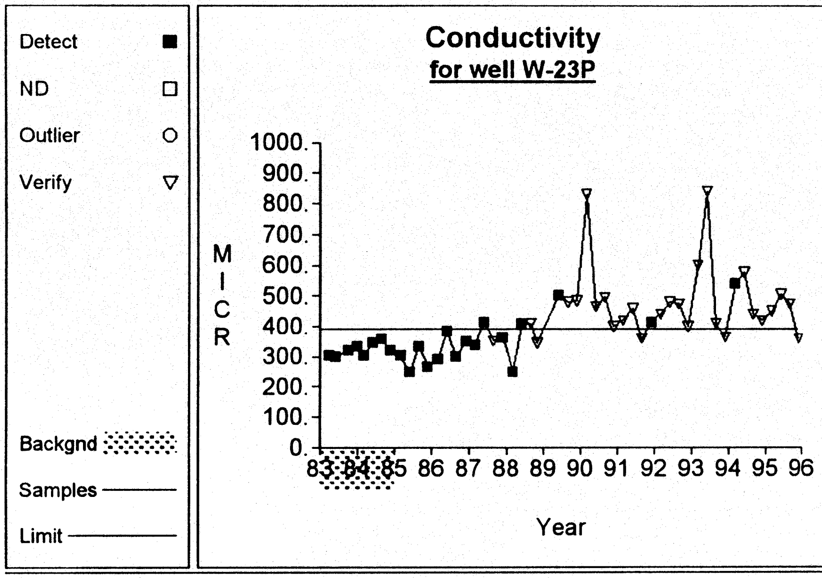
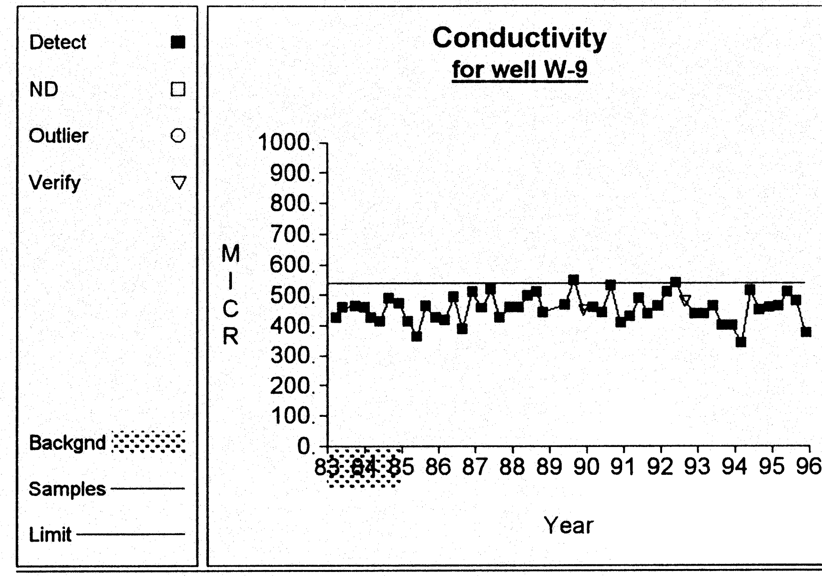
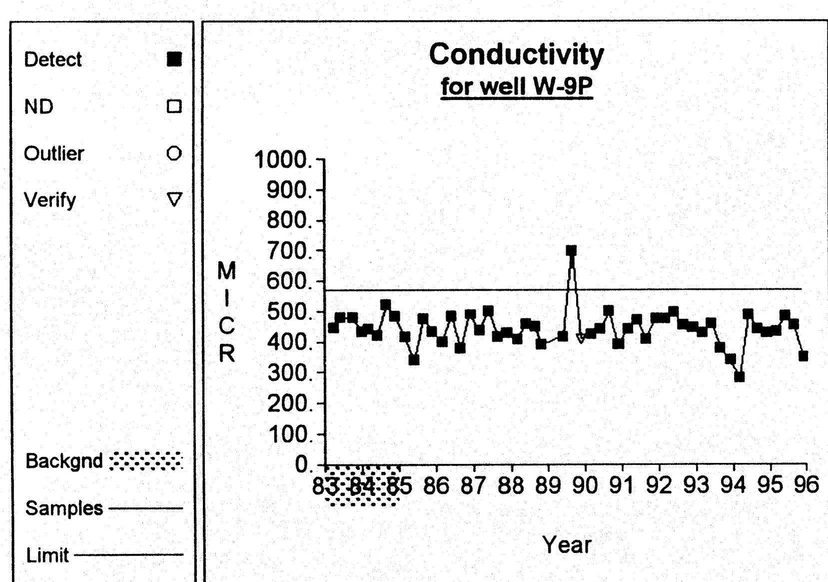
2966 Case Study: Intra-Well Prediction Limits



Graph 28



Graph 29



Graph 30

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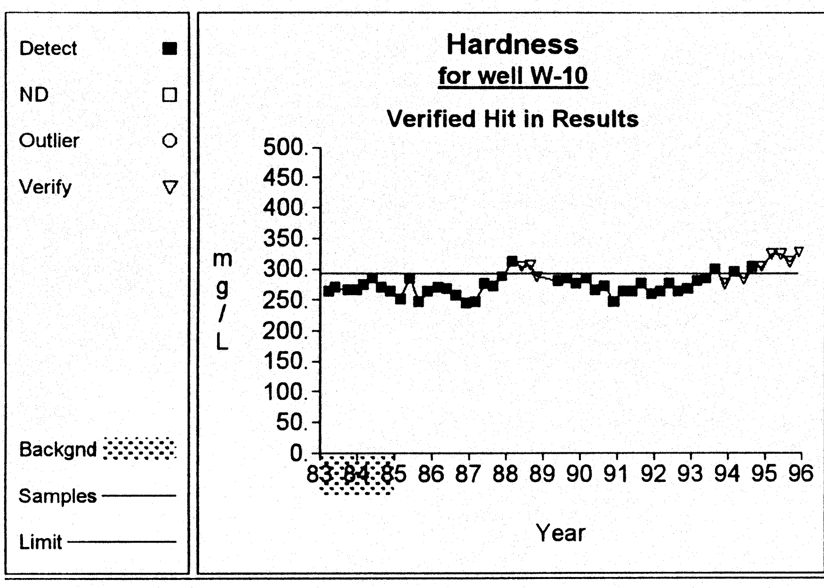
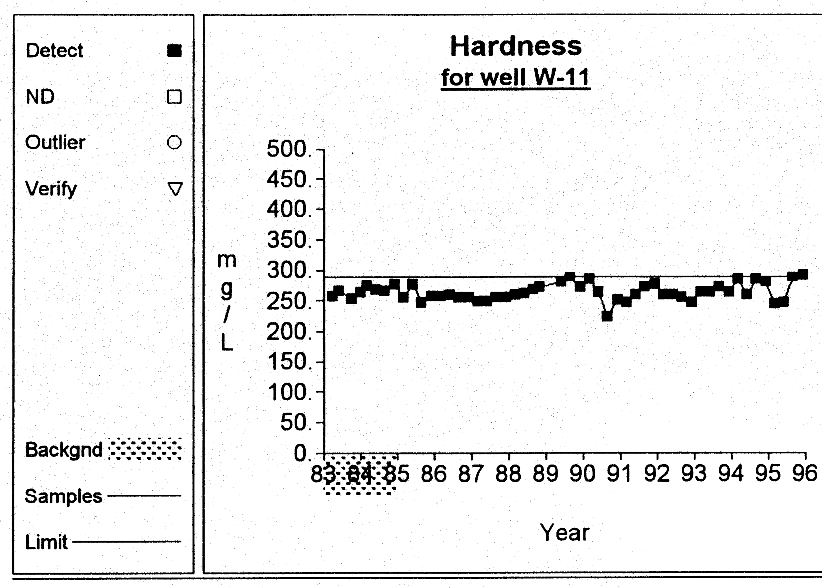
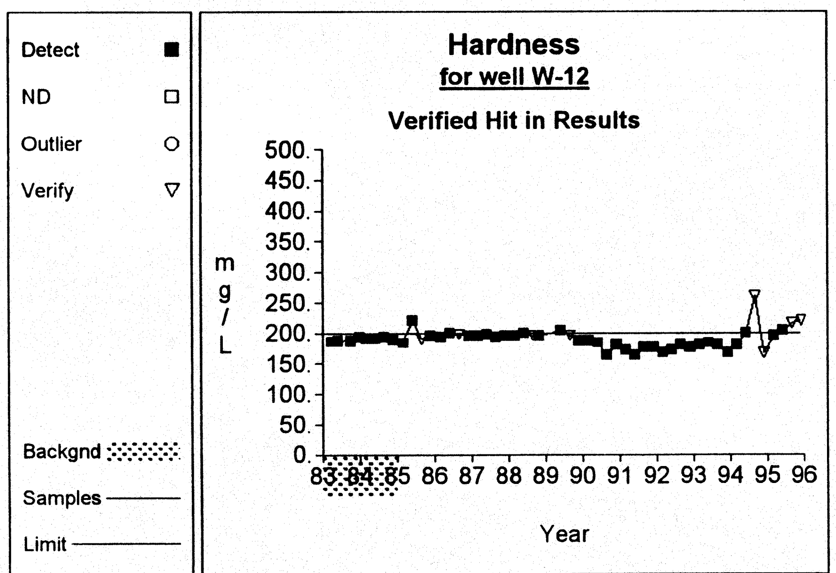
2966 Case Study: Intra-Well Prediction Limits



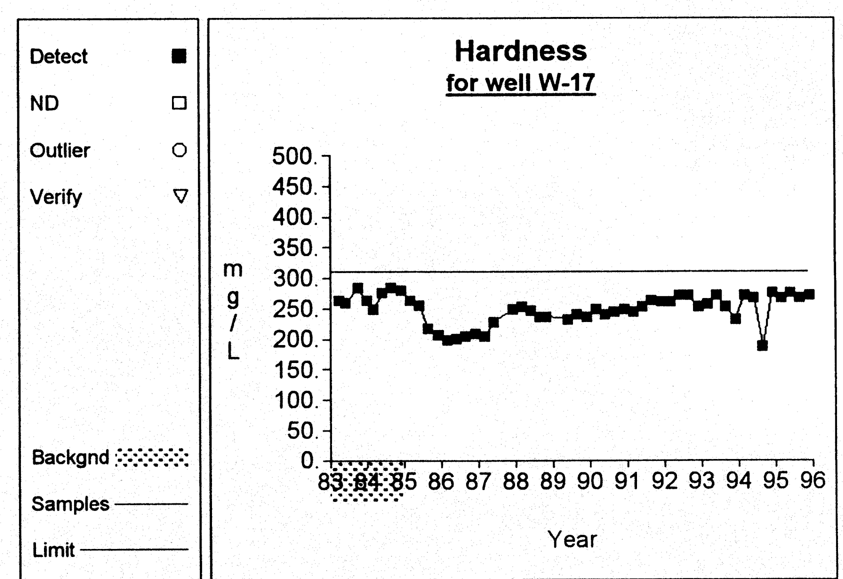
Graph 31



Graph 32

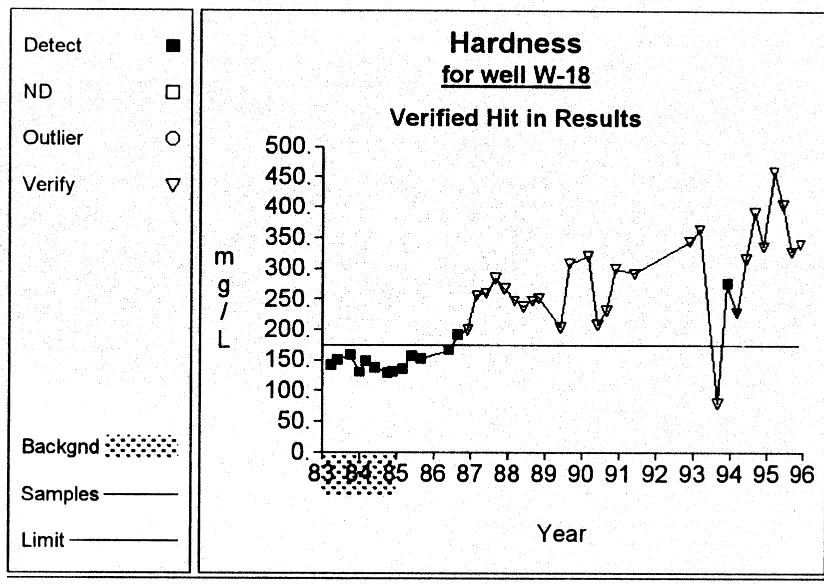


Graph 33



Graph 34

2966 Case Study: Intra-Well Prediction Limits



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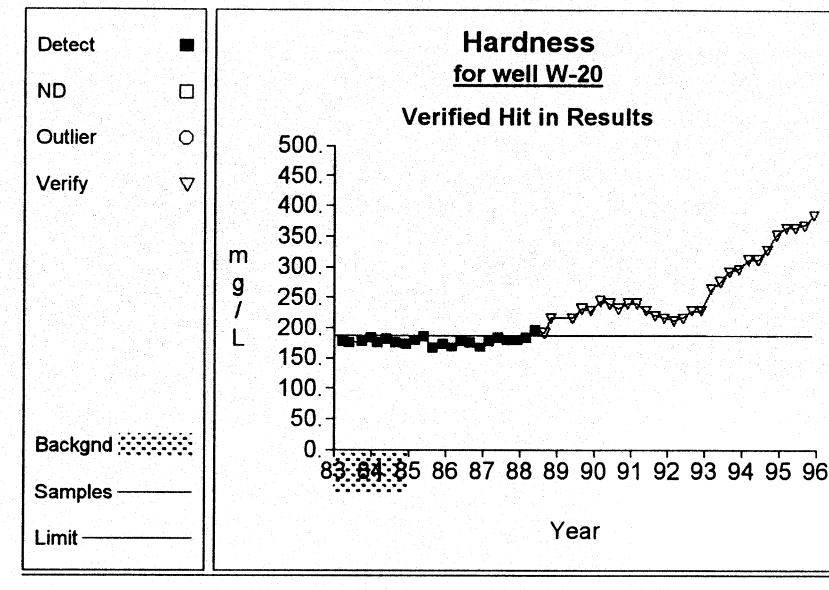

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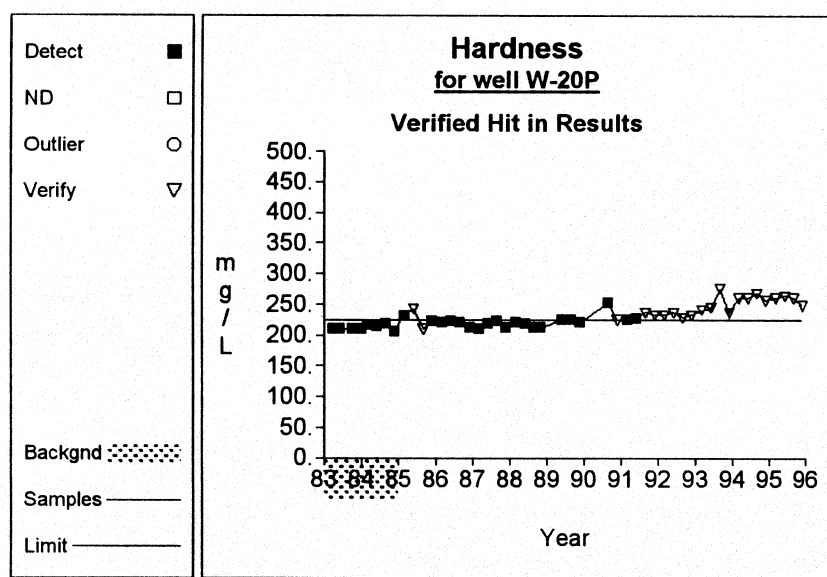

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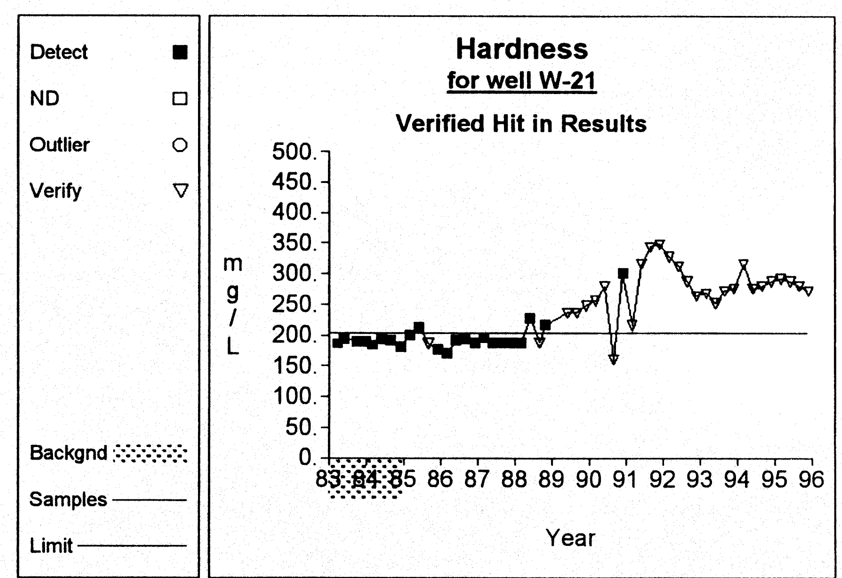

Graph 38

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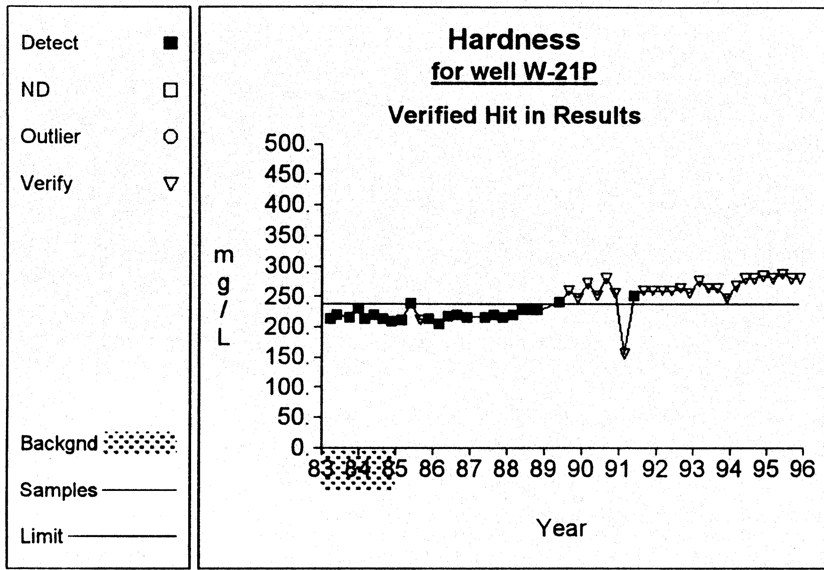
2966 Case Study: Intra-Well Prediction Limits



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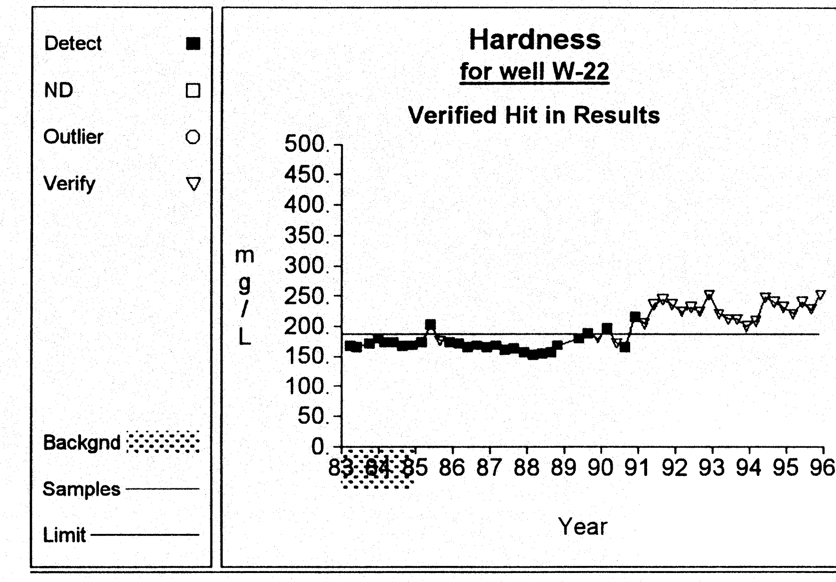

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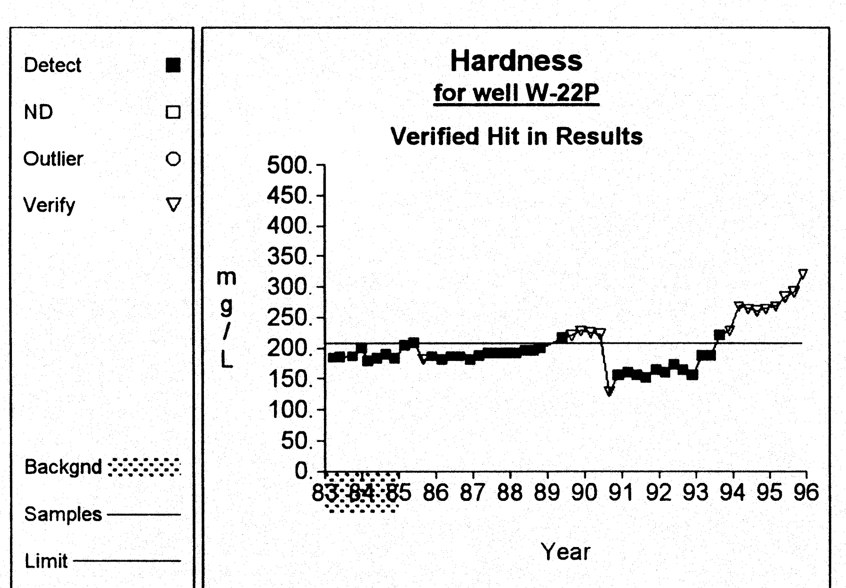

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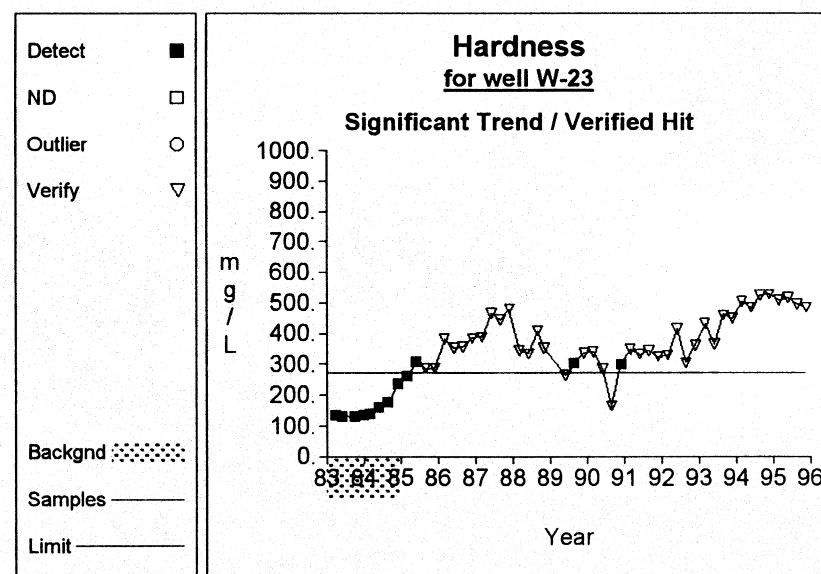

Graph 42

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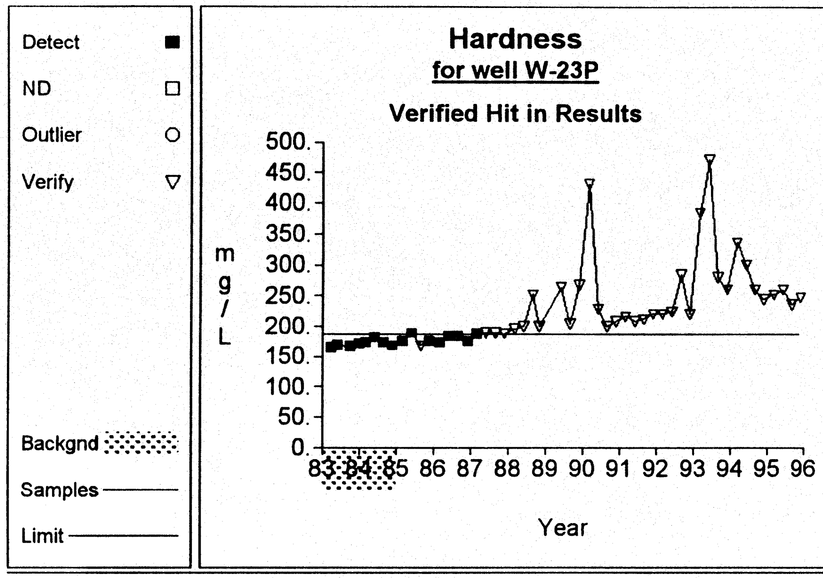
2966 Case Study: Intra-Well Prediction Limits



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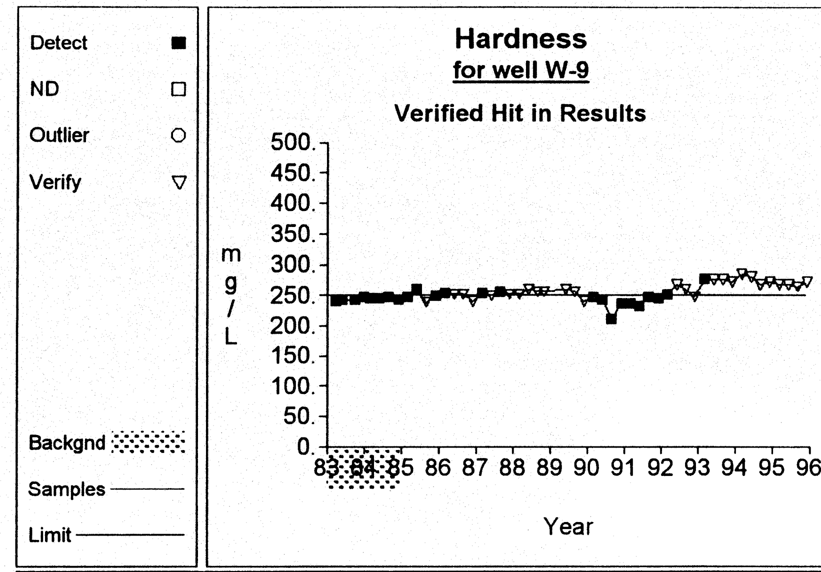
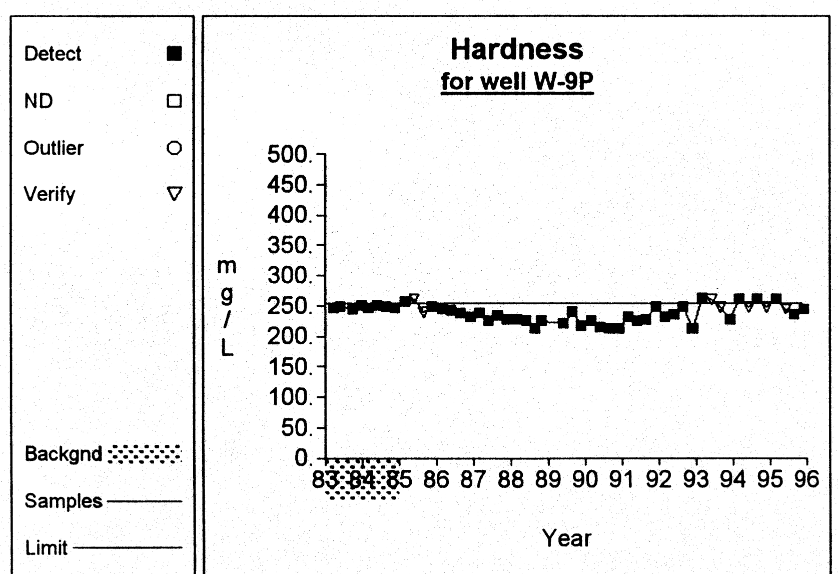


Graph 44



Graph 45

2966 Case Study: Table 1

Summary Statistics and Intermediate Computations for Combined Shewart-Cusum Control Charts

Constituent	Units	Well	N	Mean	SD	S(i-1)	S(i)	Limit
Alkalinity	mg/L	W-10	8	236.925	8.505	463.760	494.330	275.196
	mg/L	W-11	8	246.175	5.847	285.844	301.822	272.487
	mg/L	W-12	8	178.975	5.762	197.500	212.763	204.906
	mg/L	W-17	8	255.063	12.611	255.063	255.063	311.811
	mg/L	W-18	8	133.425	7.492	3730.831	3893.914	167.139
	mg/L	W-20	8	169.975	6.804	2174.613	2345.834	200.592
	mg/L	W-20P	8	181.863	36.830	236.401	397.708	347.597
	mg/L	W-21	8	179.225	5.555	2165.375	2224.594	204.224
	mg/L	W-21P	8	202.875	9.156	1015.028	1058.996	244.079
	mg/L	W-22	8	162.713	4.847	1055.089	1123.530	184.522
	mg/L	W-22P	8	178.738	7.835	709.589	815.017	213.993
	mg/L	W-23	8	147.662	37.709	7522.044	7784.672	317.355
	mg/L	W-23P	8	157.438	2.129	2614.357	2682.791	167.017
	mg/L	W-9	8	230.787	3.388	546.337	572.162	246.032
	mg/L	W-9P	8	225.287	4.934	225.287	225.287	247.492
Conductivity	MICR	W-10	8	517.875	42.549	651.603	551.179	709.345
	MICR	W-11	8	489.375	31.332	489.375	489.375	630.369
	MICR	W-12	8	374.875	26.107	392.912	374.875	492.355
	MICR	W-17	8	493.625	59.457	493.625	493.625	761.181
	MICR	W-18	8	265.750	9.603	7649.165	7969.812	308.963
	MICR	W-20	8	338.000	16.759	3617.754	3742.995	413.415
	MICR	W-20P	8	406.250	25.600	598.401	546.551	521.450
	MICR	W-21	8	361.250	23.414	3893.659	4282.995	466.613
	MICR	W-21P	8	410.000	24.495	1562.143	1517.648	520.227
	MICR	W-22	8	337.125	23.000	1315.134	1310.010	440.623
	MICR	W-22P	8	366.625	25.629	873.102	910.848	481.955
	MICR	W-23	8	302.500	63.552	12081.316	12325.264	588.484
	MICR	W-23P	8	323.500	21.119	4161.176	4176.557	418.534
	MICR	W-9	8	451.875	26.984	484.157	451.875	573.302
	MICR	W-9P	8	463.125	33.374	463.125	463.125	613.309
Hardness	mg/L	W-10	8	269.663	7.325	487.789	538.801	302.625
	mg/L	W-11	8	265.525	7.539	280.461	299.397	299.450
	mg/L	W-12	8	190.213	2.801	227.171	254.158	202.818
	mg/L	W-17	8	269.512	13.027	269.512	269.512	328.134
	mg/L	W-18	8	140.488	10.463	3731.975	3921.025	187.571
	mg/L	W-20	8	177.800	3.283	2467.149	2670.066	192.573
	mg/L	W-20P	8	211.762	3.913	867.784	900.109	229.369
	mg/L	W-21	8	188.600	4.837	2401.807	2480.371	210.365
	mg/L	W-21P	8	216.787	6.418	1199.035	1255.830	245.668

* - Insufficient Data
** - Detection Frequency < 25%
*** - Zero Variance

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2966 Case Study: Table 1 - Continued

Summary Statistics and Intermediate Computations for Combined Shewart-Cusum Control Charts

Constituent	Units	Well	N	Mean	SD	S(i-1)	S(i)	Limit
Hardness	mg/L	W-22	8	170.525	5.152	1190.588	1266.911	193.711
	mg/L	W-22P	8	186.075	6.602	737.335	864.658	215.784
	mg/L	W-23	8	154.075	36.476	7919.931	8213.380	318.217
	mg/L	W-23P	8	170.787	5.405	2682.071	2753.878	195.112
	mg/L	W-9	8	243.600	2.209	621.855	648.046	253.541
	mg/L	W-9P	8	247.488	2.382	247.488	247.488	258.205

* - Insufficient Data
** - Detection Frequency < 25%
*** - Zero Variance

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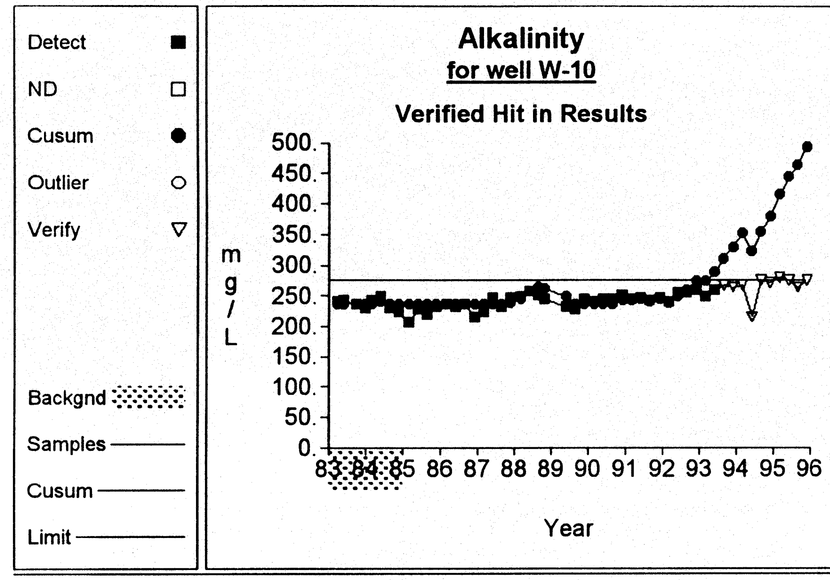
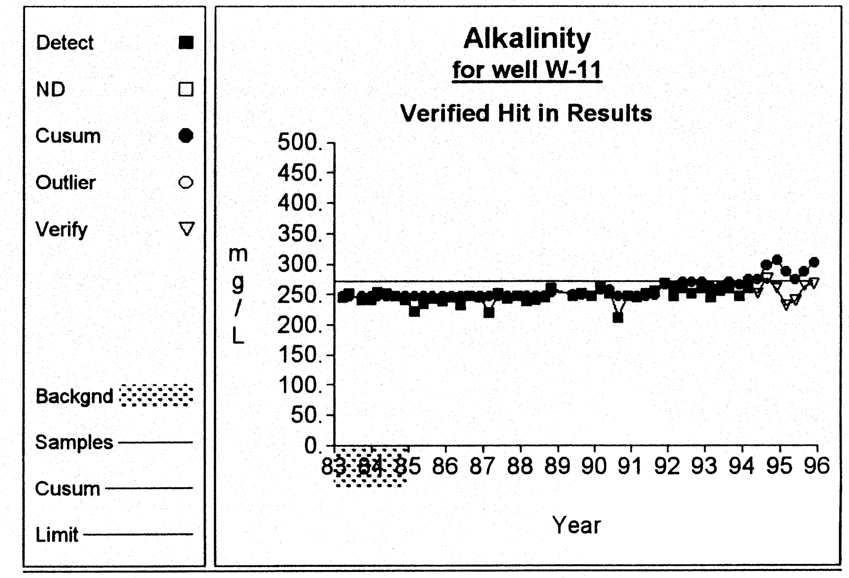
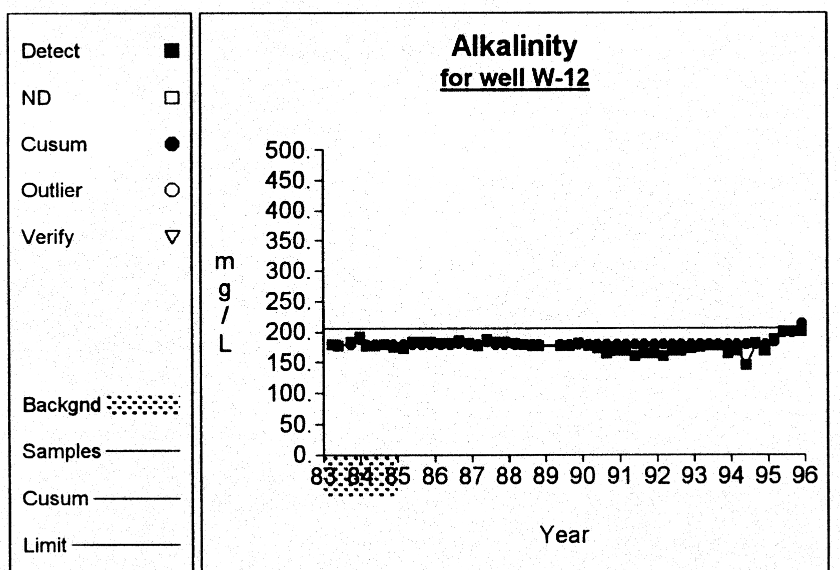
2966 Case Study: Intra-Well Control Charts



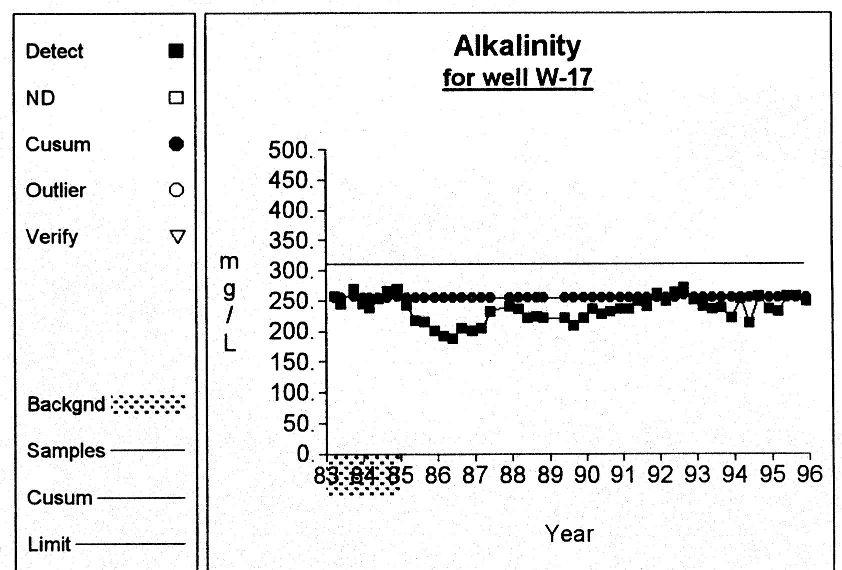
Graph 1



Graph 2



Graph 3



Graph 4

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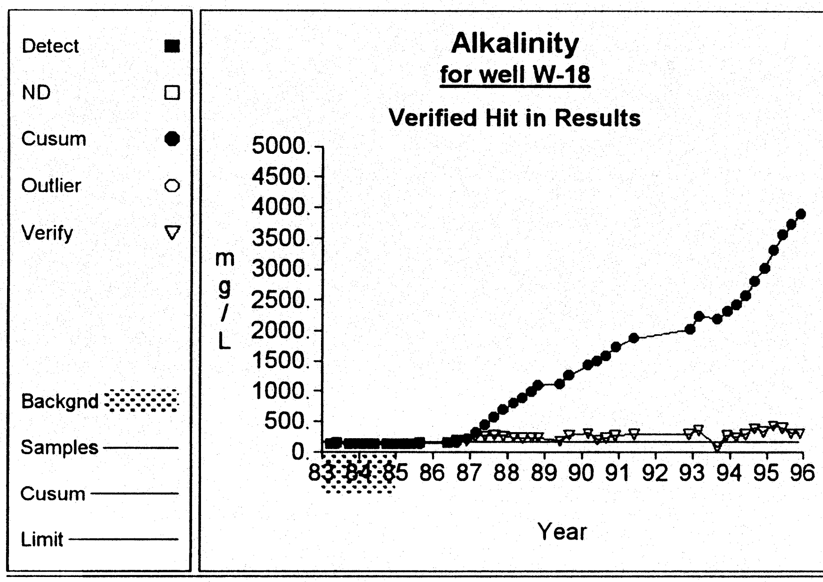
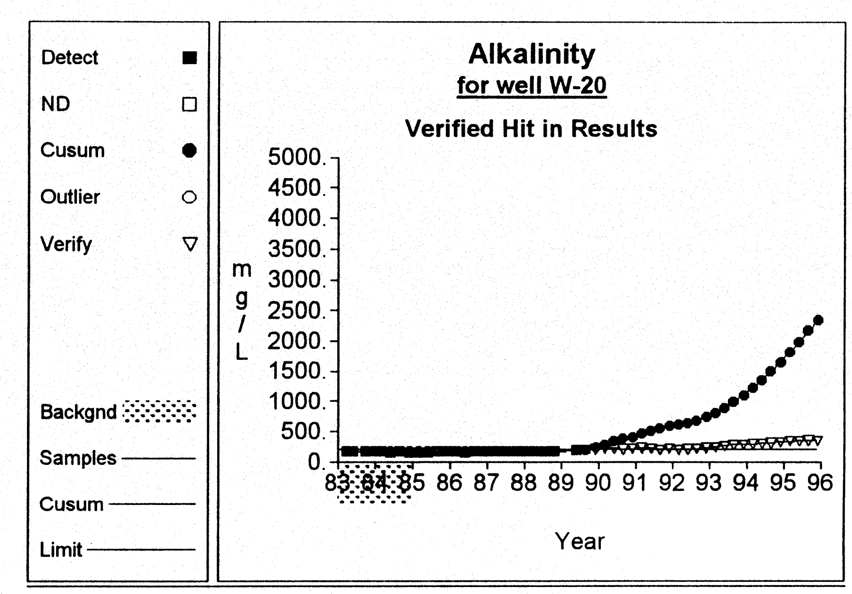
2966 Case Study: Intra-Well Control Charts



Graph 5



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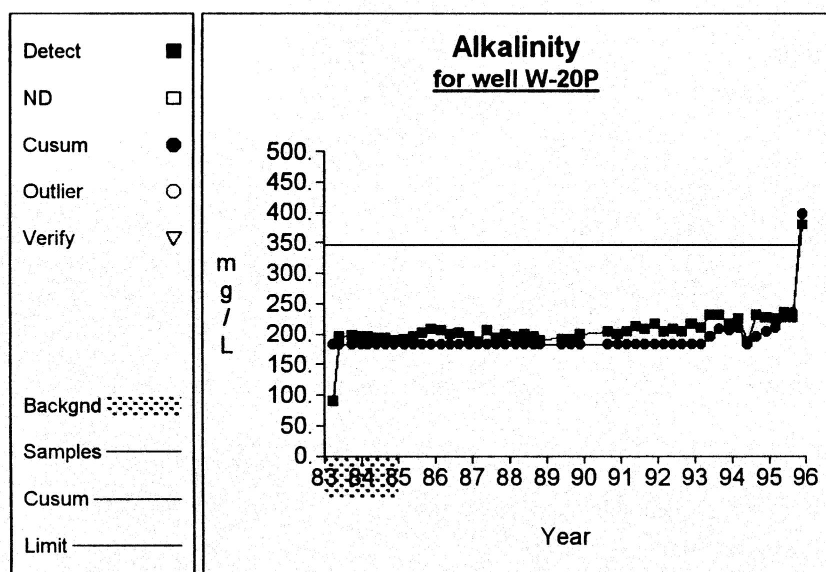

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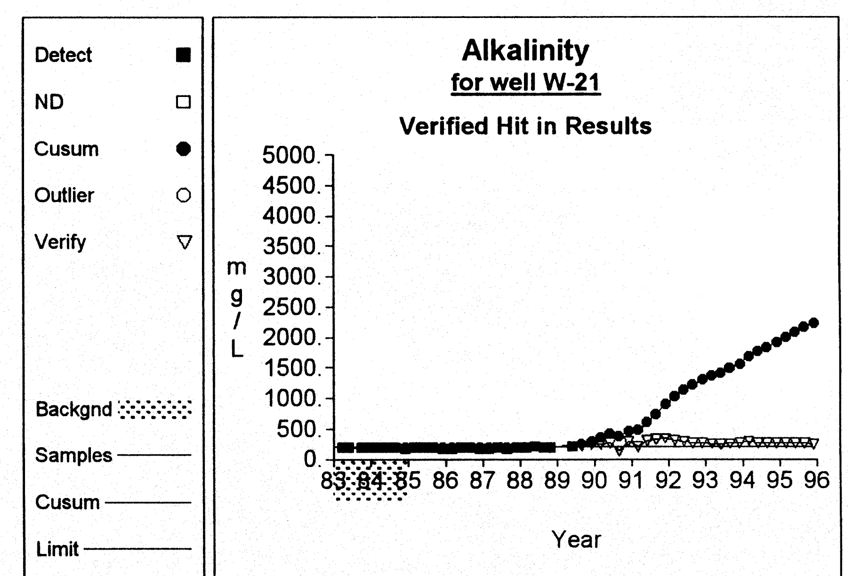

Graph 8

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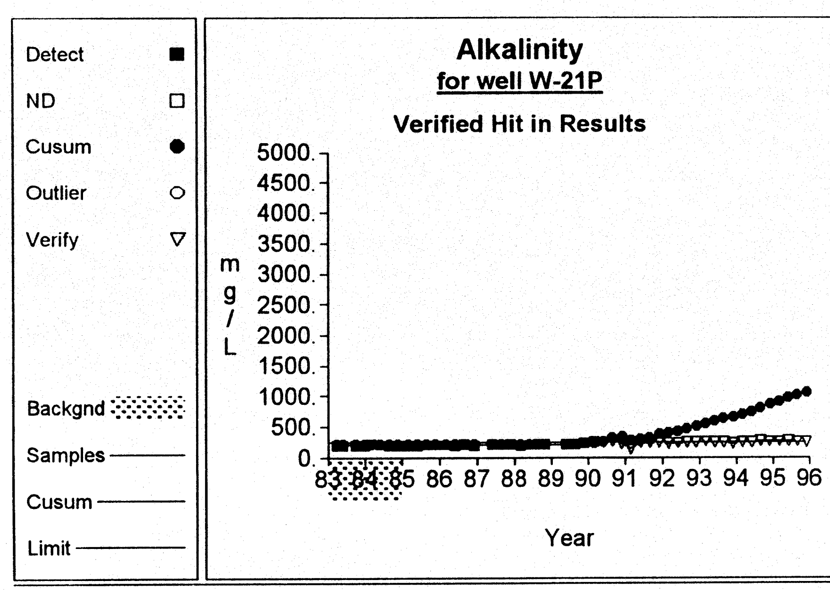
2966 Case Study: Intra-Well Control Charts



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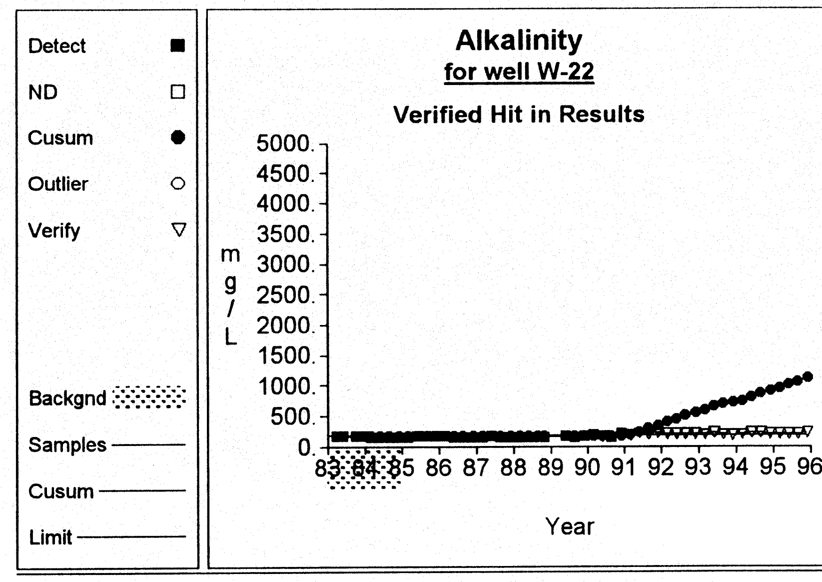
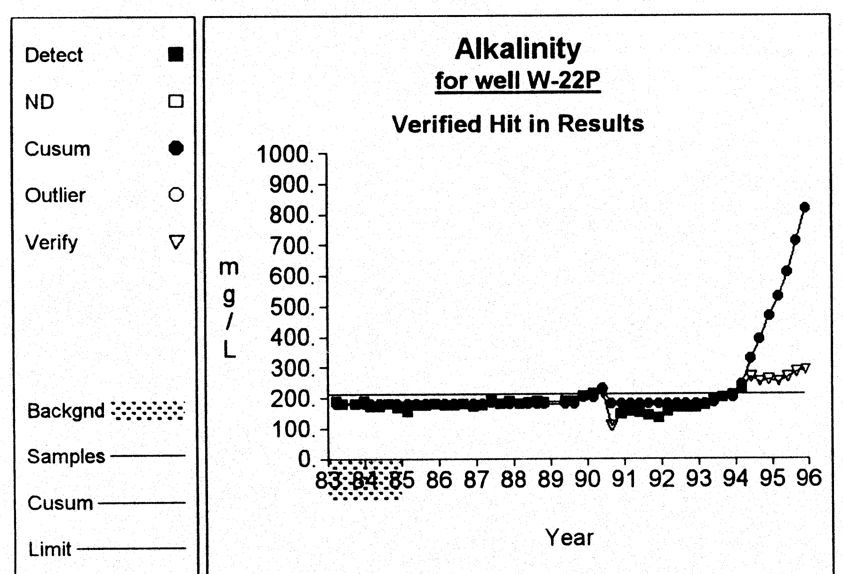


Graph 10



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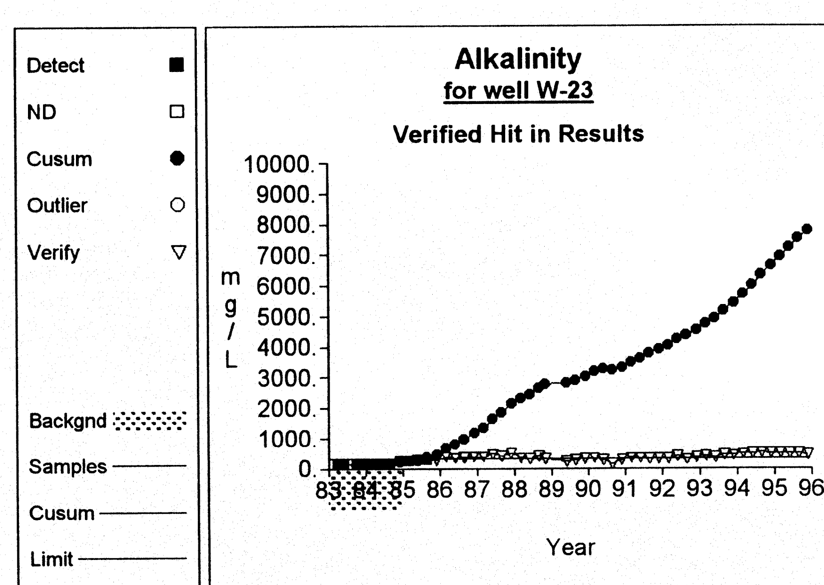

Graph 12

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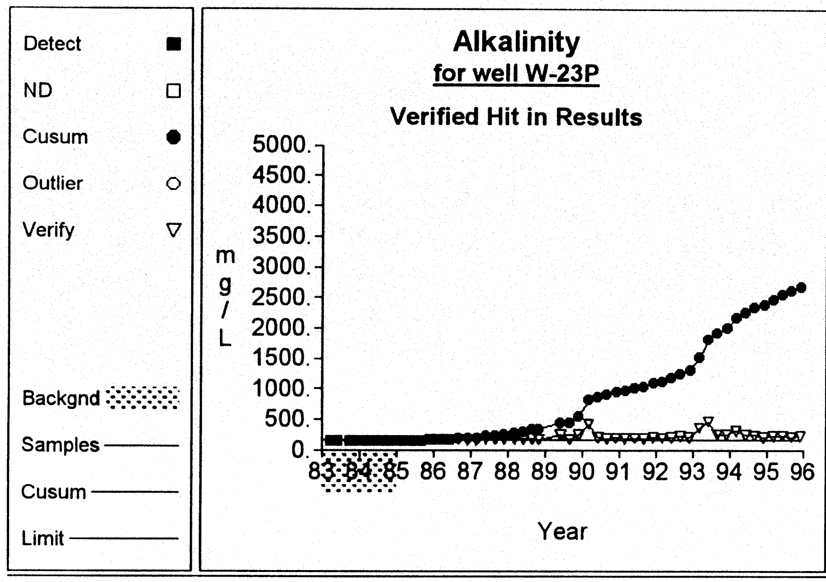
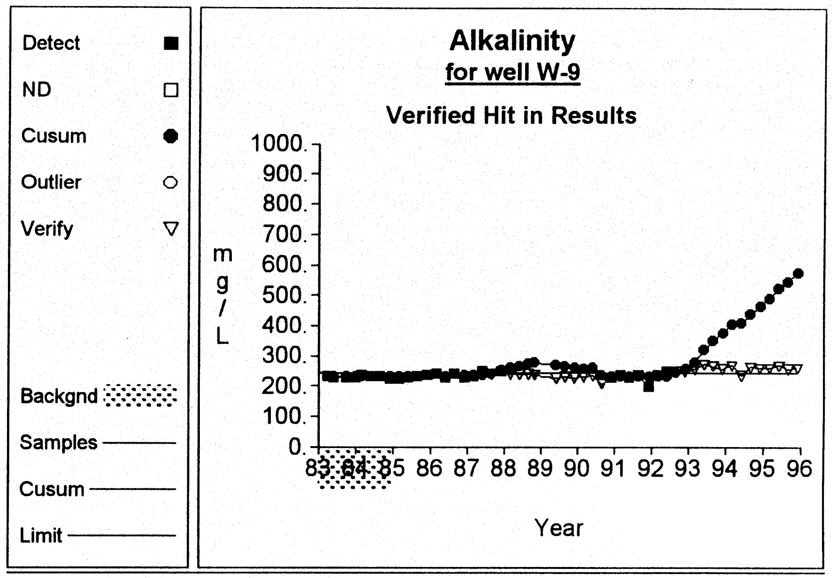
2966 Case Study: Intra-Well Control Charts



Graph 13



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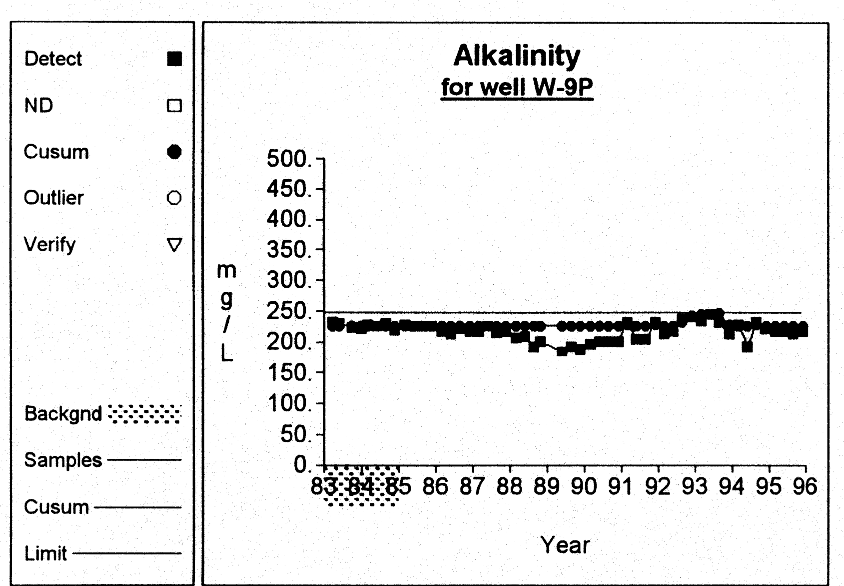
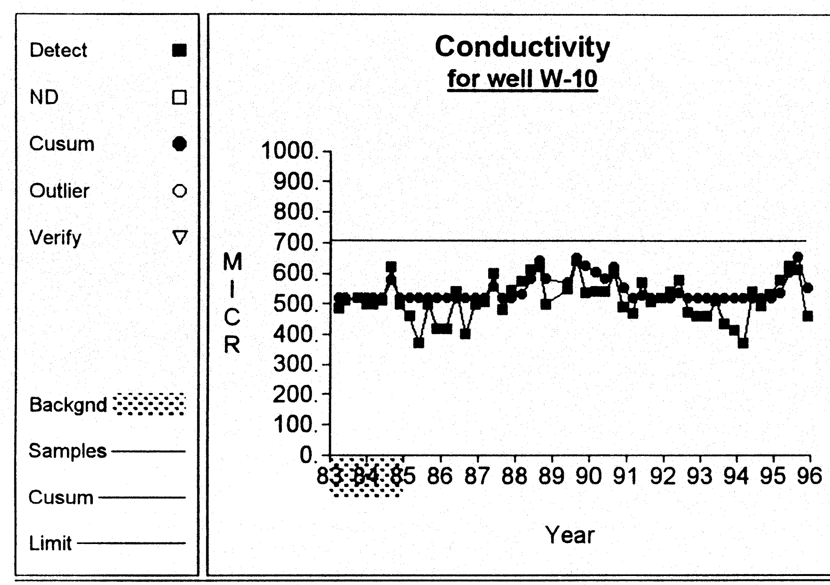


Graph 15

2966 Case Study: Intra-Well Control Charts



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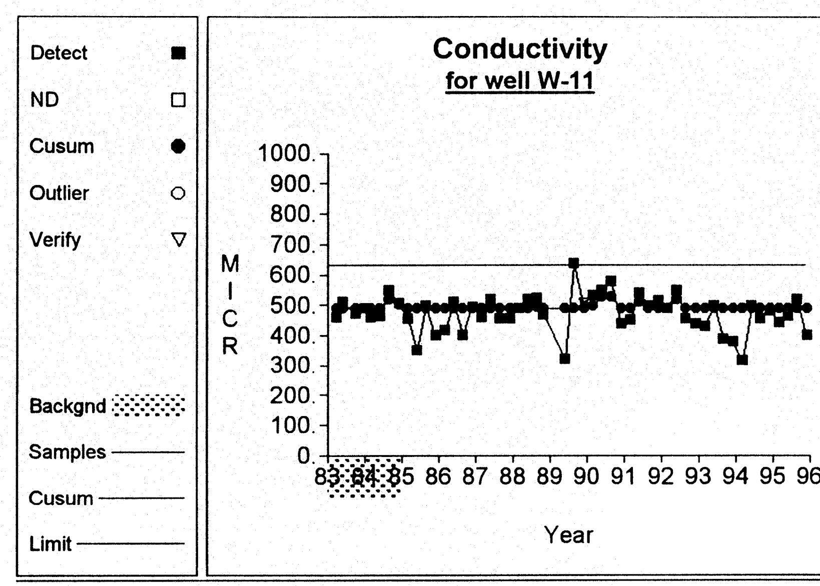

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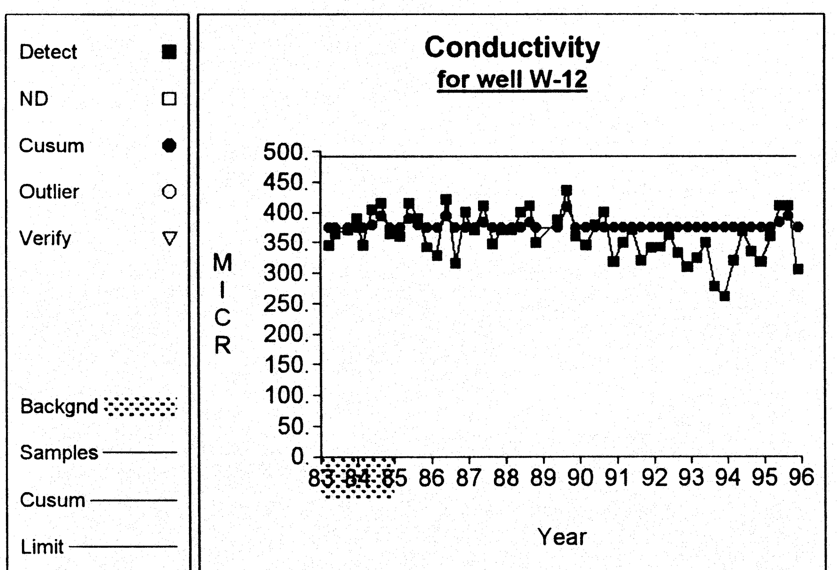

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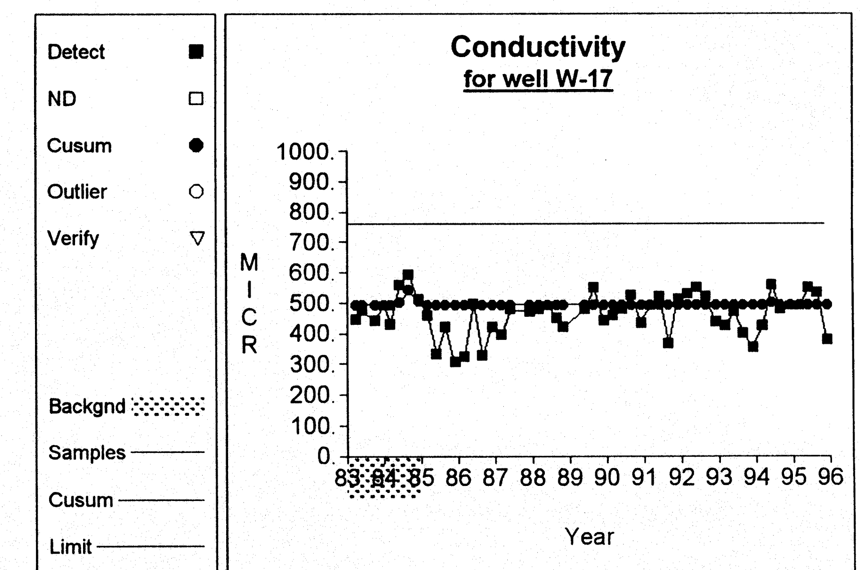

Graph 19

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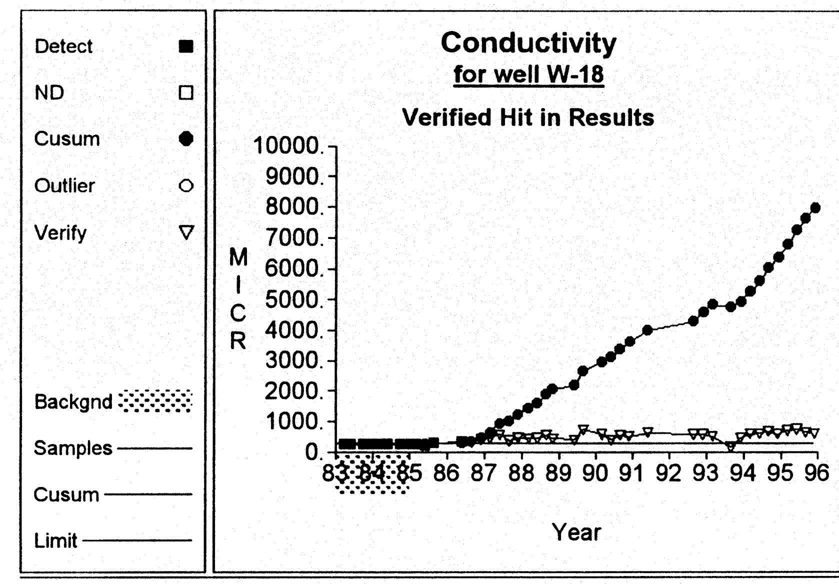
2966 Case Study: Intra-Well Control Charts



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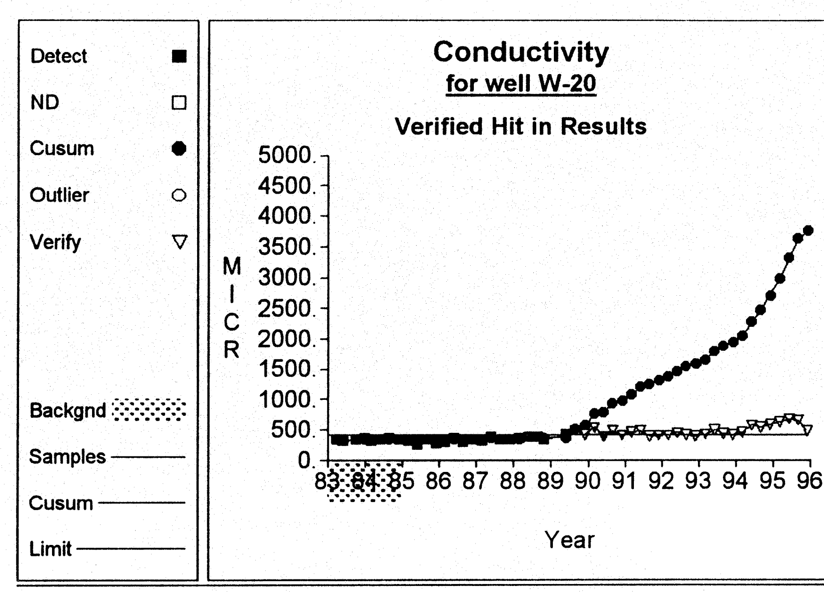

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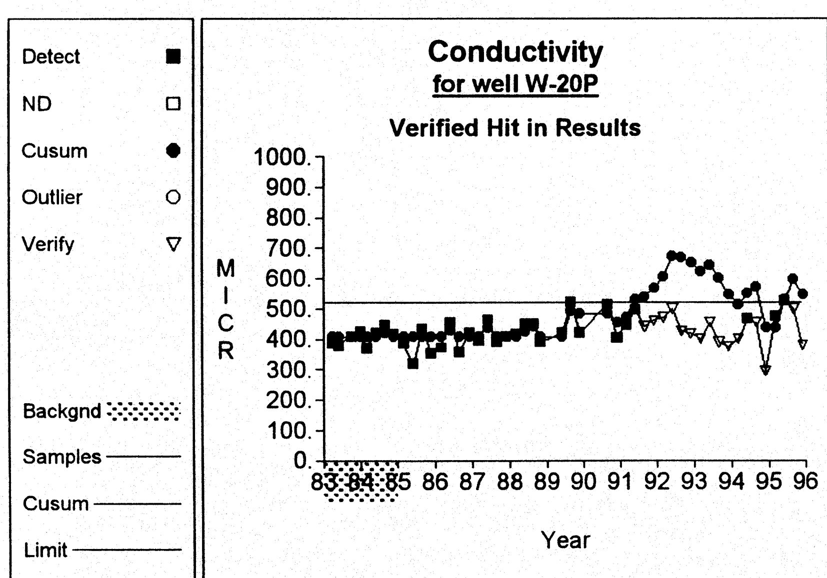

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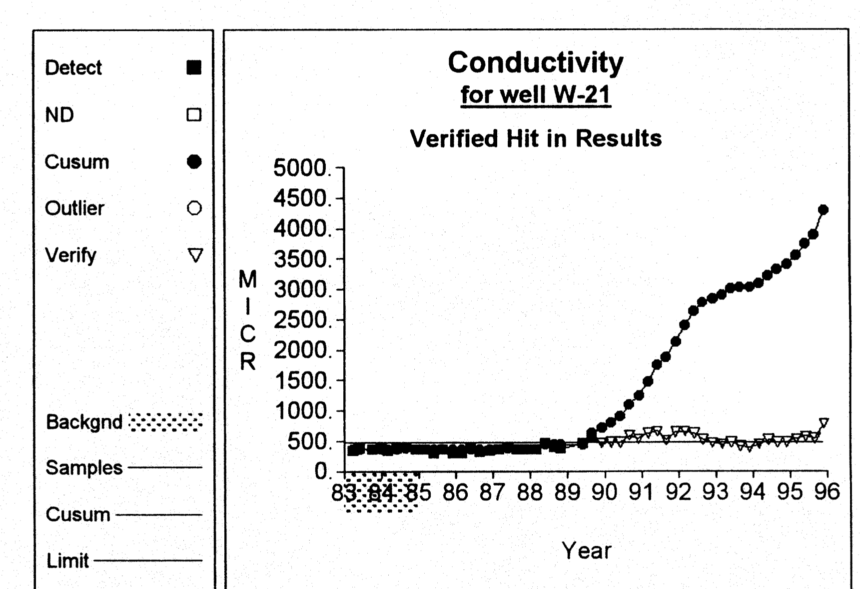

Graph 23

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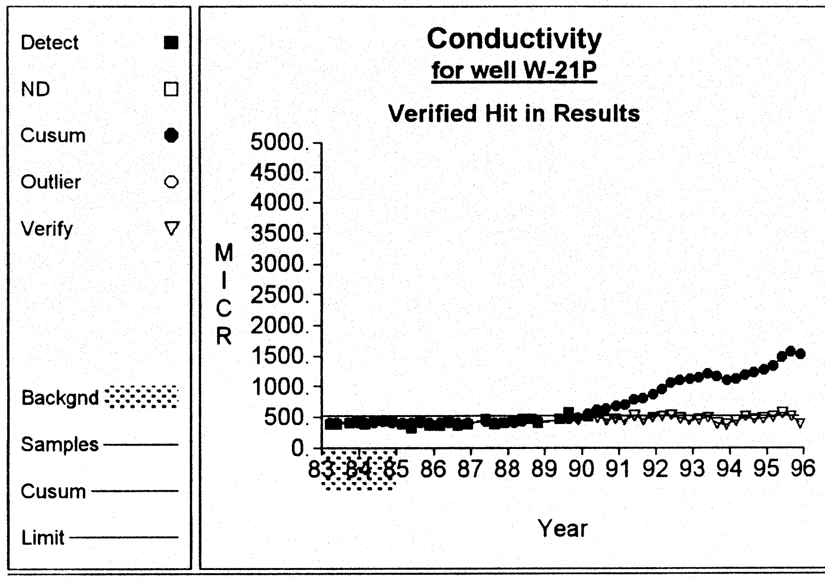
2966 Case Study: Intra-Well Control Charts



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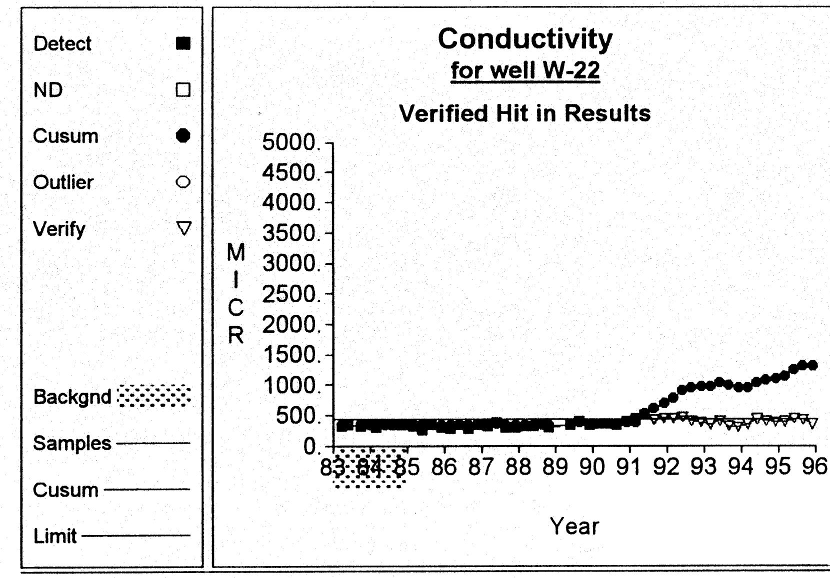

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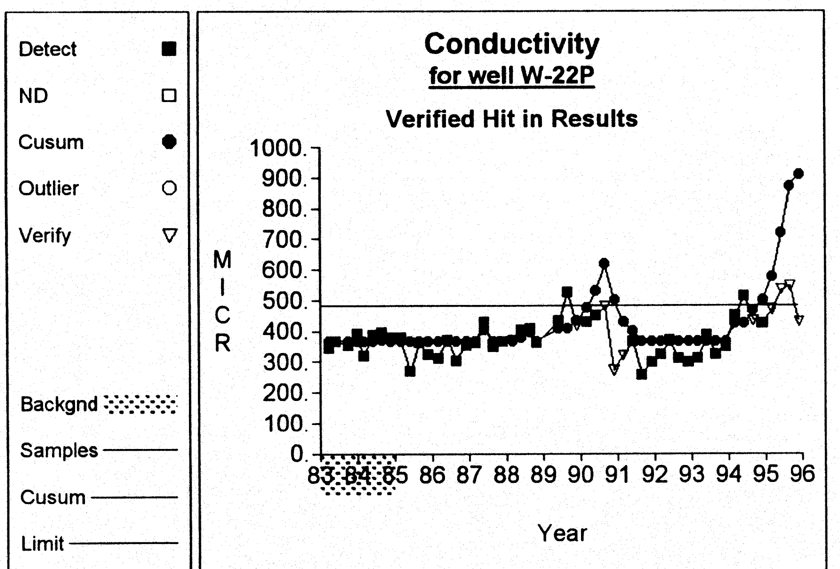

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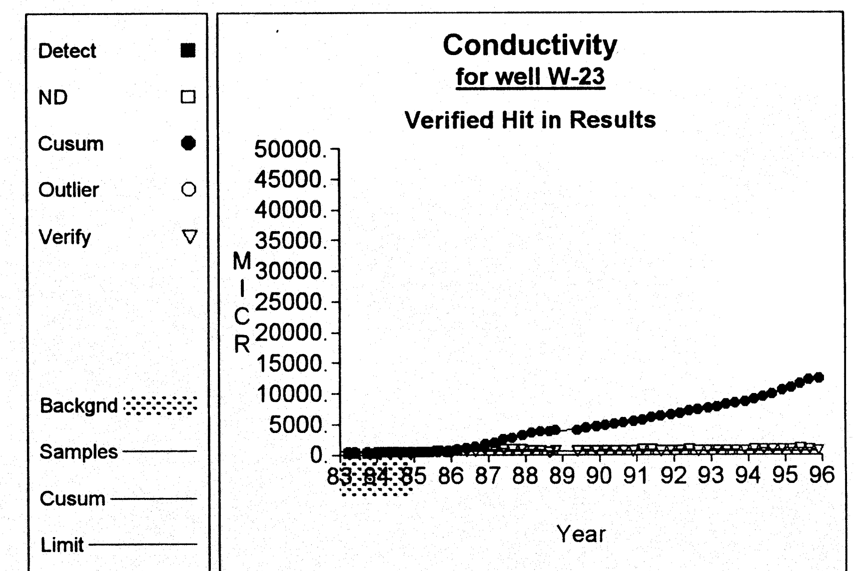

Graph 27

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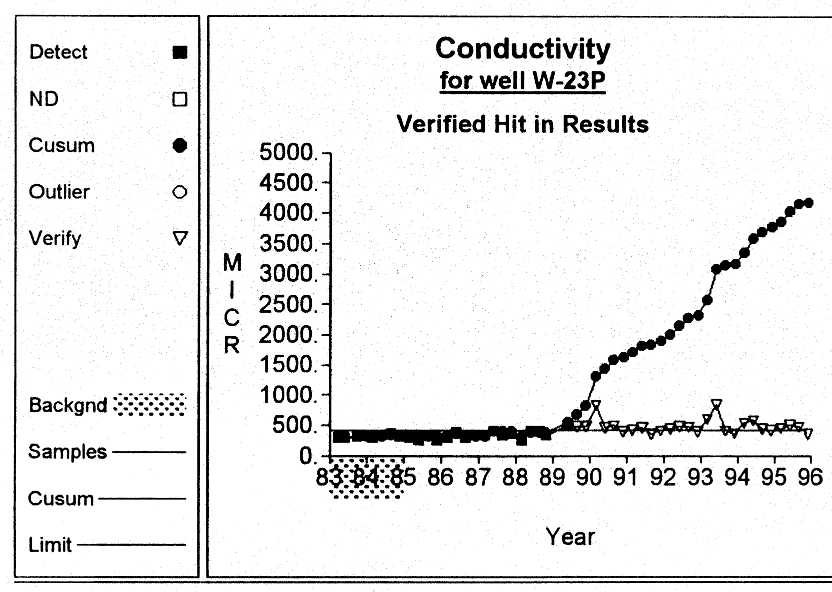
2966 Case Study: Intra-Well Control Charts



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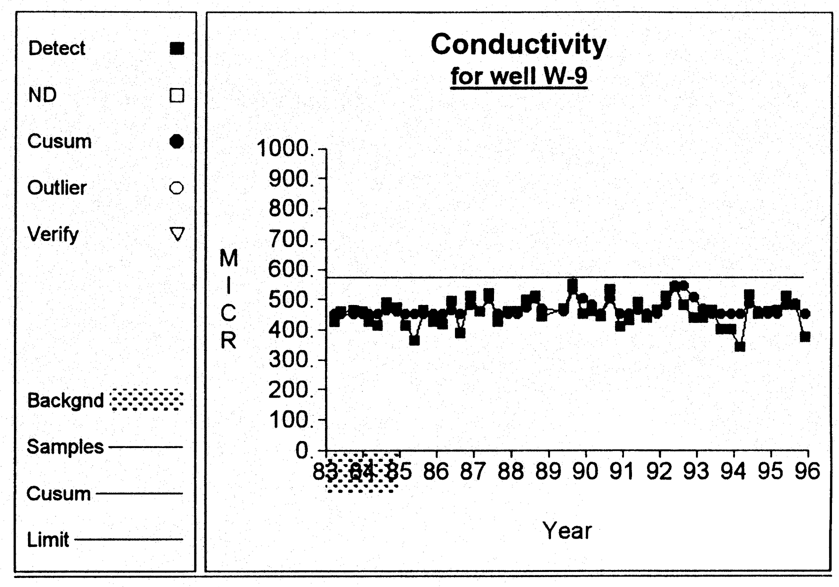

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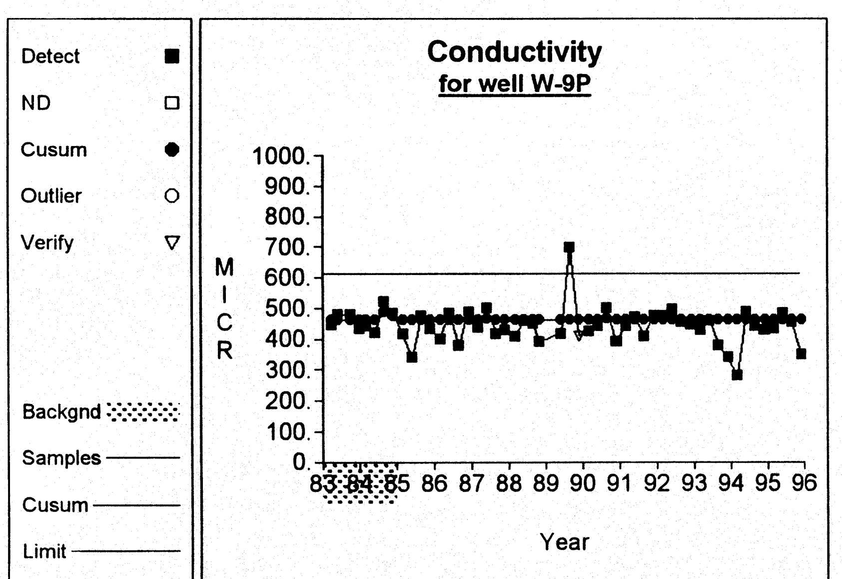

Graph 30

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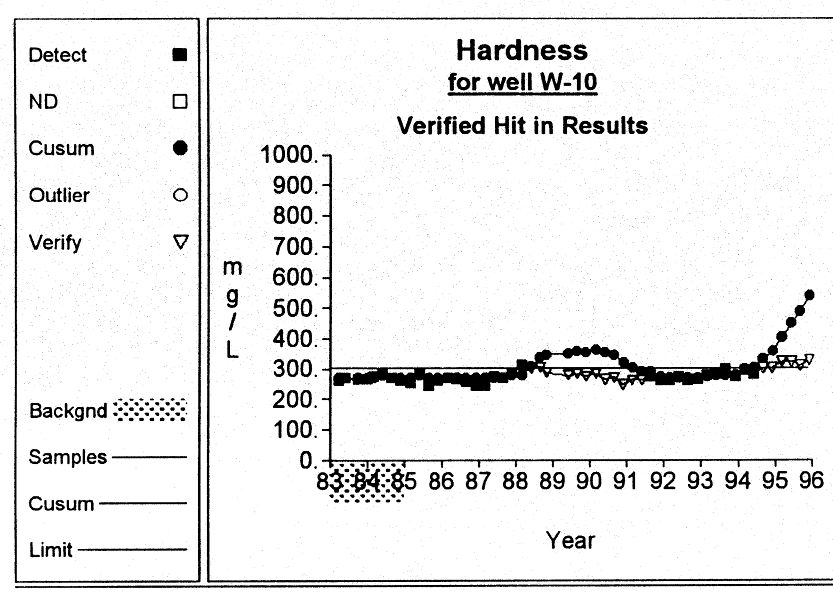
2966 Case Study: Intra-Well Control Charts



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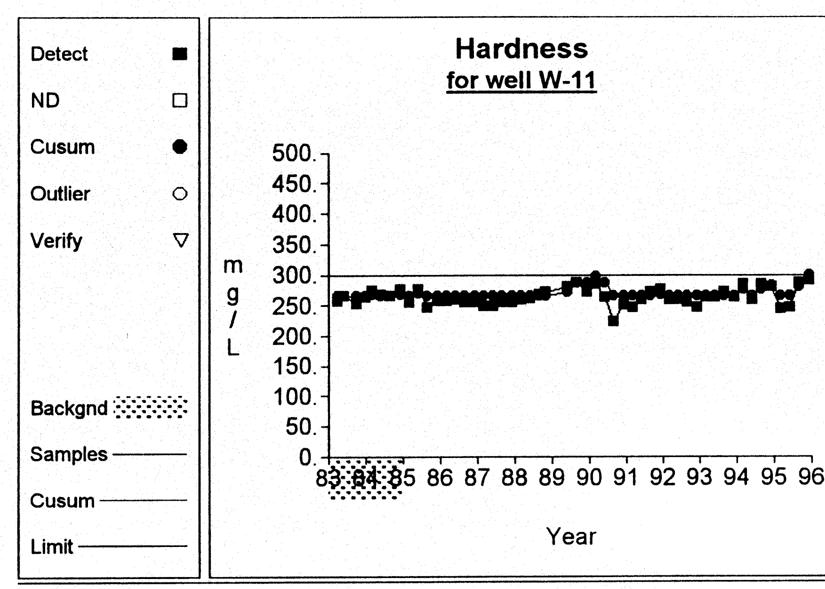

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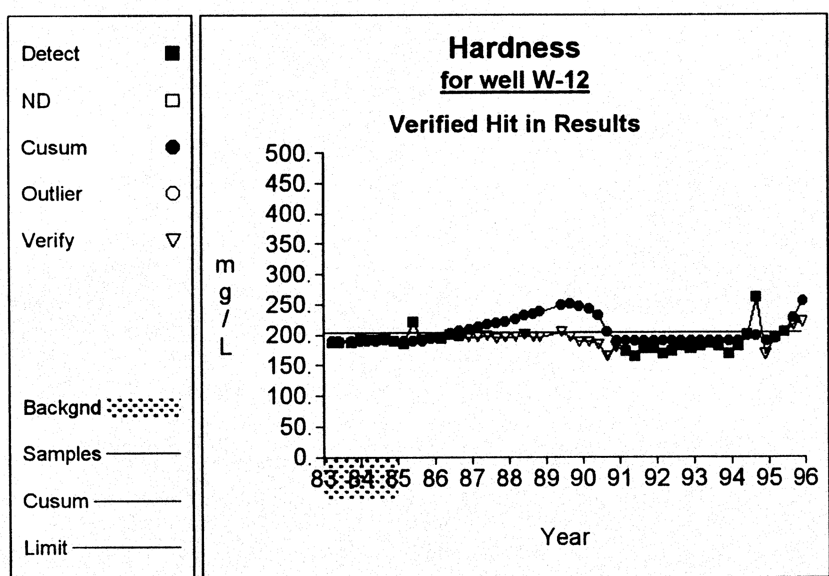
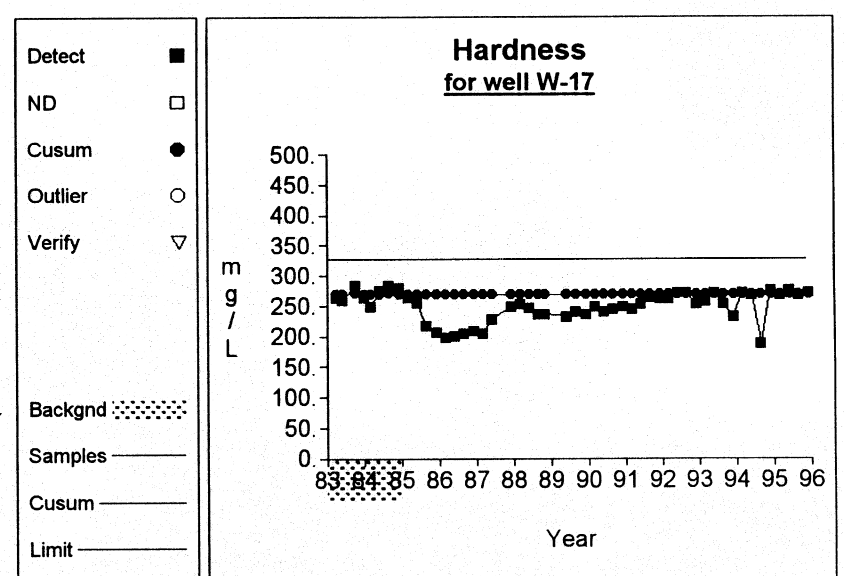


Graph 33



Graph 34

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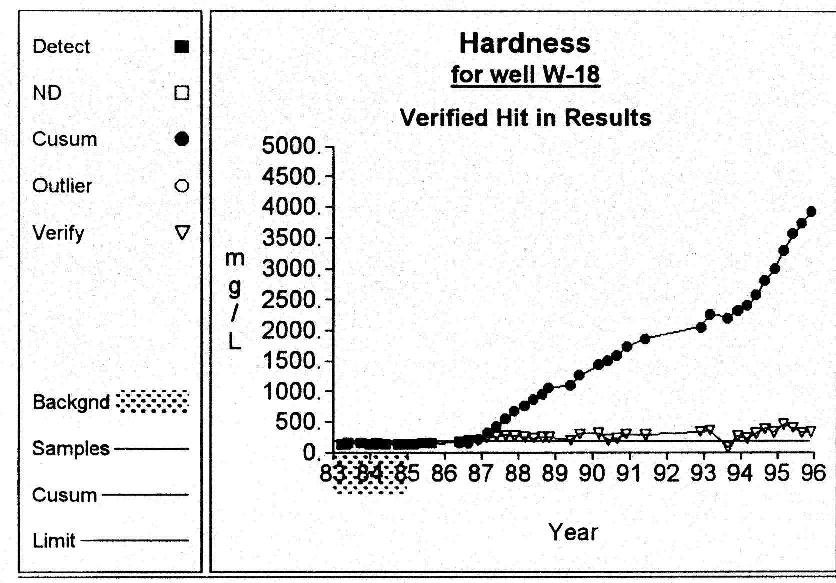
2966 Case Study: Intra-Well Control Charts



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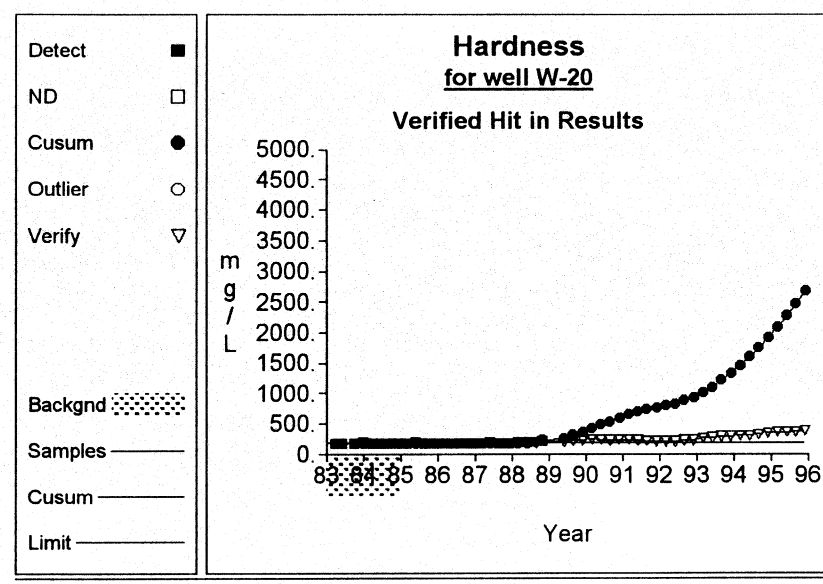
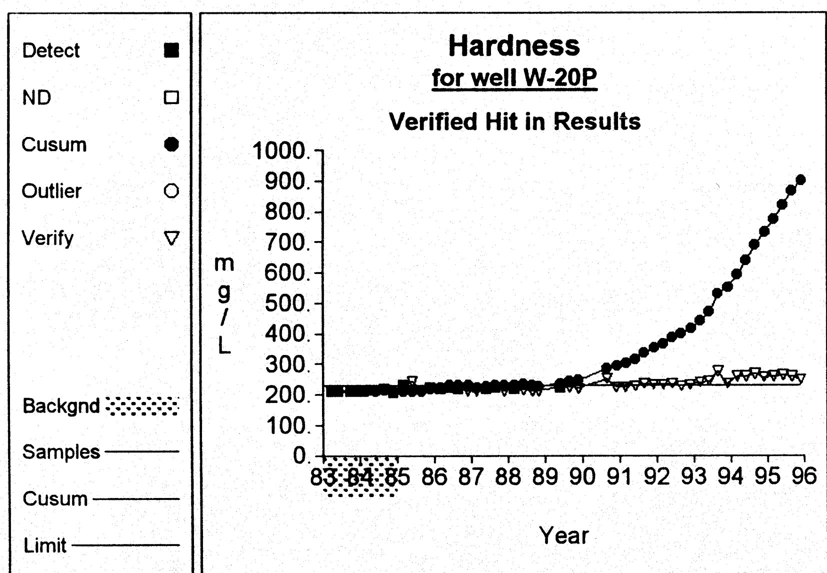
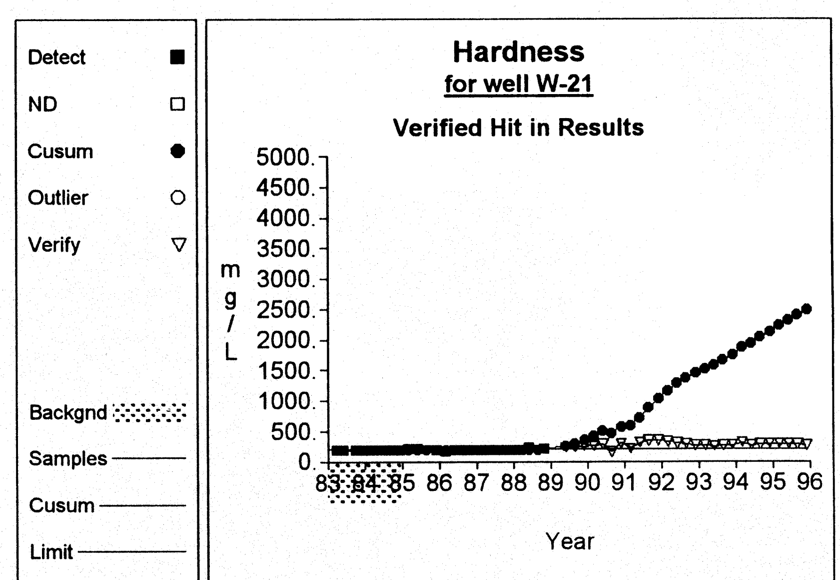


Graph 36



Graph 37



Graph 38

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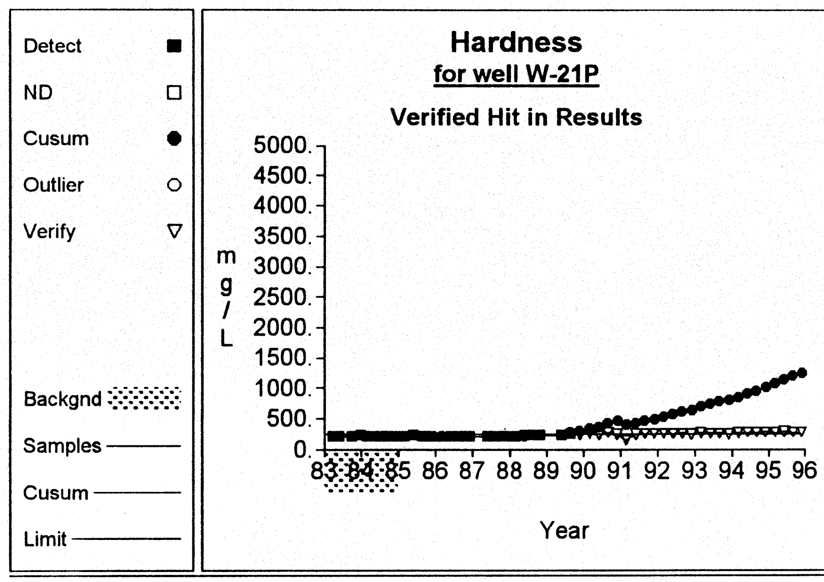
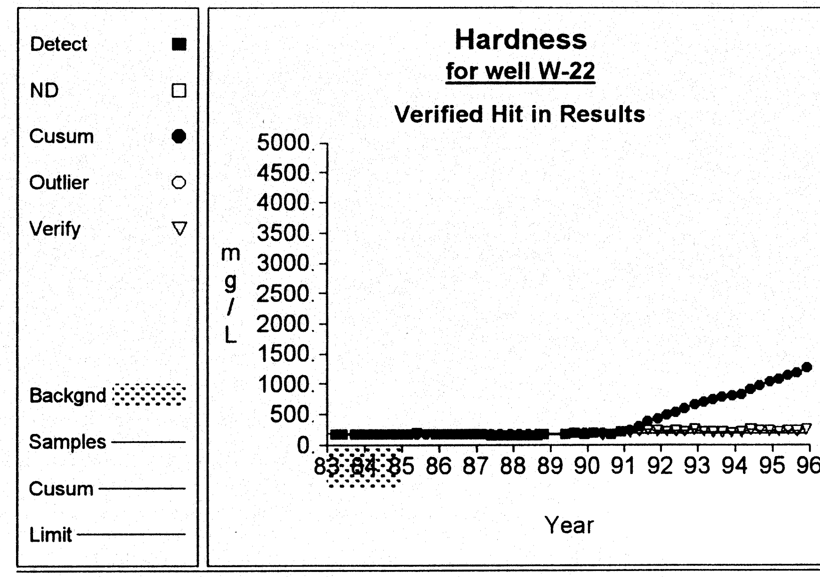
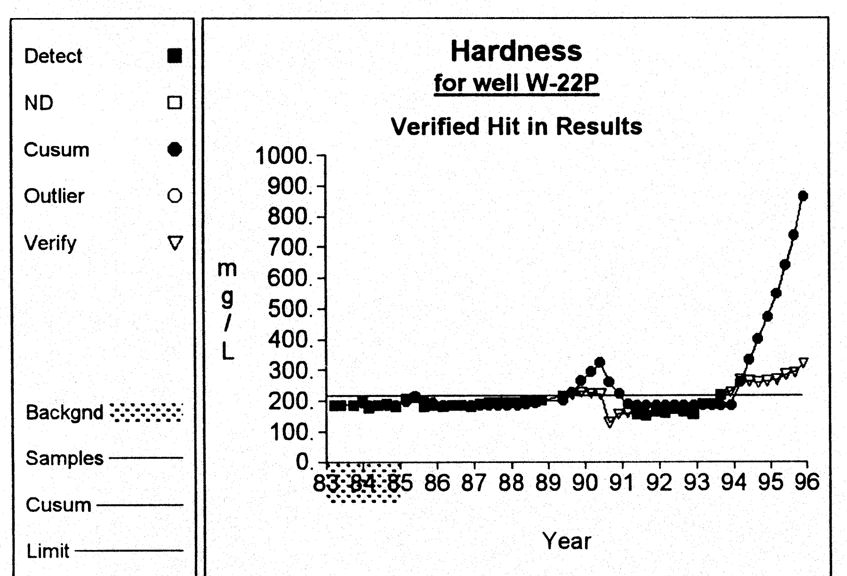
2966 Case Study: Intra-Well Control Charts



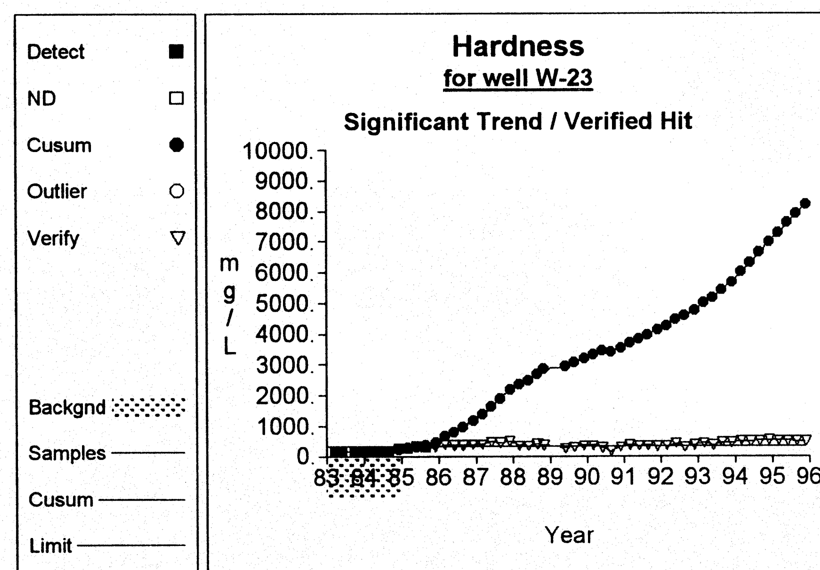
Graph 39



Graph 40

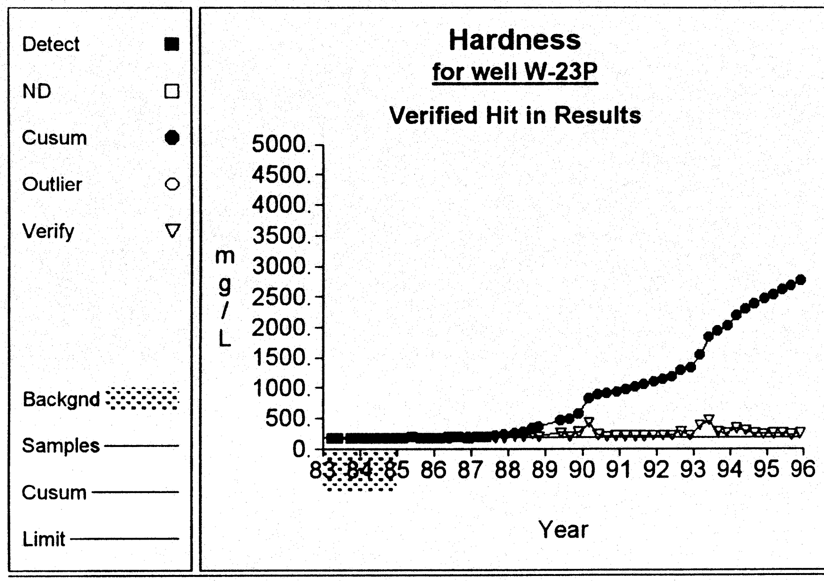


Graph 41

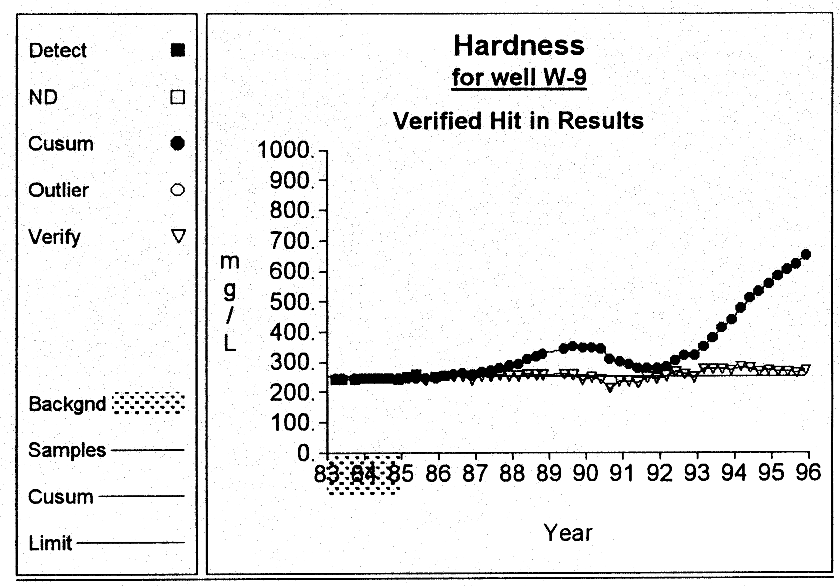


Graph 42

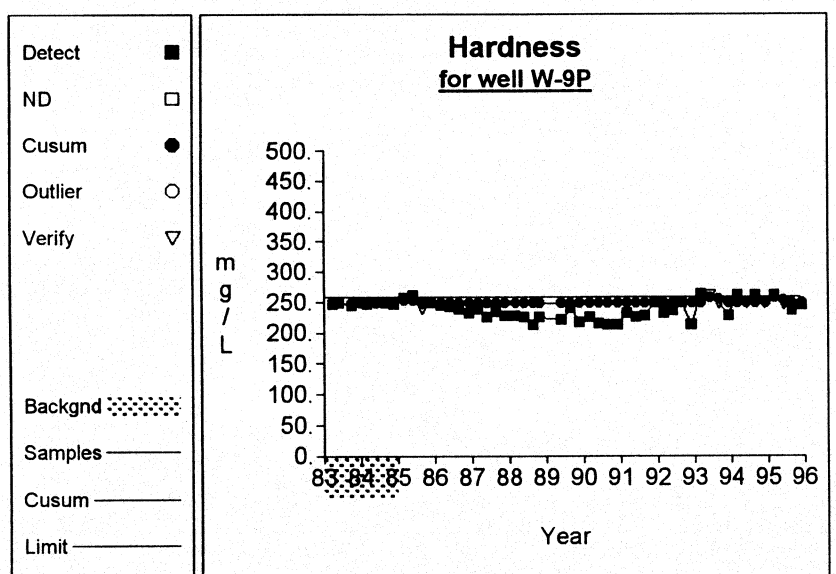
2966 Case Study: Intra-Well Control Charts



Graph 43



Graph 44



Graph 45

2966 Case Study: Table 1

Summary Statistics and Intermediate Computations for Intra-Well Prediction Limits

Constituent	Units	Well	N	Mean	SD	Factor	Limit
Alkalinity	mg/L	W-10	25	235.496	12.211	2.541	266.525
	mg/L	W-11	25	242.456	9.041	2.541	265.428
	mg/L	W-12	25	179.752	4.625	2.541	191.503
	mg/L	W-17	24	228.771	24.283	2.551	290.712
	mg/L	W-18	23	183.148	55.121	2.562	324.347
	mg/L	W-20	25	170.792	9.461	2.541	194.833
	mg/L	W-20P	25	192.756	21.824	2.541	248.211
	mg/L	W-21	25	181.352	10.310	2.541	207.550
	mg/L	W-21P	24	204.583	7.217	2.551	222.992
	mg/L	W-22	25	160.908	8.092	2.541	181.471
	mg/L	W-22P	25	179.516	8.227	2.541	200.422
	mg/L	W-23	25	281.812	112.164	2.541	566.820
	mg/L	W-23P	25	170.020	19.355	2.541	219.202
	mg/L	W-9	25	234.612	6.527	2.541	251.198
	mg/L	W-9P	25	217.052	11.706	2.541	246.797
Conductivity	MICR	W-10	25	509.320	65.588	2.541	675.978
	MICR	W-11	25	466.400	54.160	2.541	604.021
	MICR	W-12	25	375.360	29.590	2.541	450.548
	MICR	W-17	24	445.792	71.721	2.551	628.740
	MICR	W-18	23	355.478	106.569	2.562	628.466
	MICR	W-20	25	338.560	38.396	2.541	436.124
	MICR	W-20P	25	405.400	35.342	2.541	495.205
	MICR	W-21	25	360.040	43.316	2.541	470.106
	MICR	W-21P	24	407.417	39.410	2.551	507.944
	MICR	W-22	25	323.200	32.087	2.541	404.733
	MICR	W-22P	25	363.520	38.352	2.541	460.971
	MICR	W-23	25	500.600	194.489	2.541	994.797
	MICR	W-23P	25	338.320	56.851	2.541	482.779
	MICR	W-9	25	453.560	39.050	2.541	552.787
	MICR	W-9P	25	441.560	41.999	2.541	548.280
Hardness	mg/L	W-10	25	272.652	17.988	2.541	318.360
	mg/L	W-11	25	261.848	8.922	2.541	284.520
	mg/L	W-12	25	195.068	6.947	2.541	212.720
	mg/L	W-17	24	241.129	27.921	2.551	312.351
	mg/L	W-18	23	190.604	53.857	2.562	328.566
	mg/L	W-20	25	181.736	12.301	2.541	212.994
	mg/L	W-20P	25	216.884	7.977	2.541	237.154
	mg/L	W-21	25	193.792	14.958	2.541	231.801
	mg/L	W-21P	24	219.346	8.719	2.551	241.587

* - Insufficient Data
** - Detection Frequency < 25%
*** - Zero Variance

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2966 Case Study: Table 1 - Continued

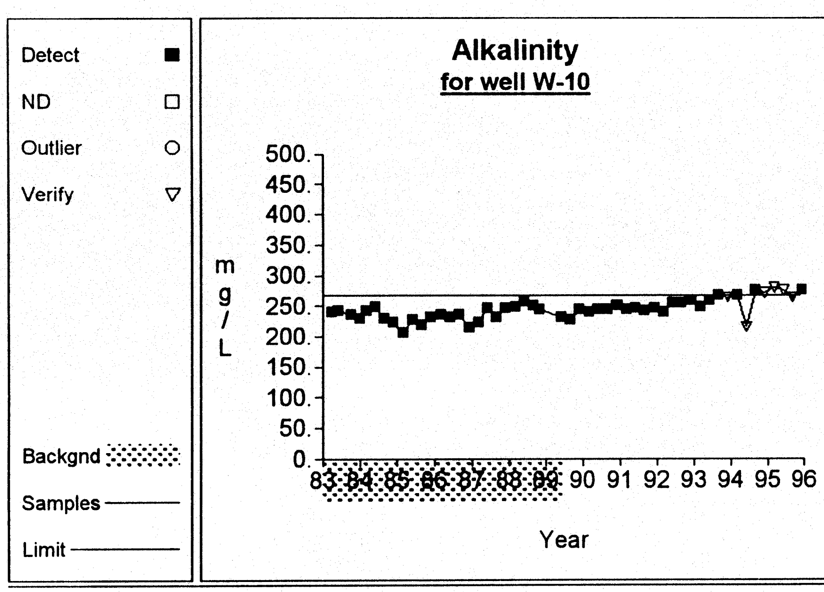
Summary Statistics and Intermediate Computations for Intra-Well Prediction Limits

Constituent	Units	Well	N	Mean	SD	Factor	Limit
Hardness	mg/L	W-22	25	168.528	10.430	2.541	195.031
	mg/L	W-22P	25	190.584	9.517	2.541	214.767
	mg/L	W-23	25	293.104	113.196	2.541	580.736
	mg/L	W-23P	25	186.452	23.986	2.541	247.400
	mg/L	W-9	25	249.512	6.490	2.541	266.003
	mg/L	W-9P	25	238.876	12.225	2.541	269.939

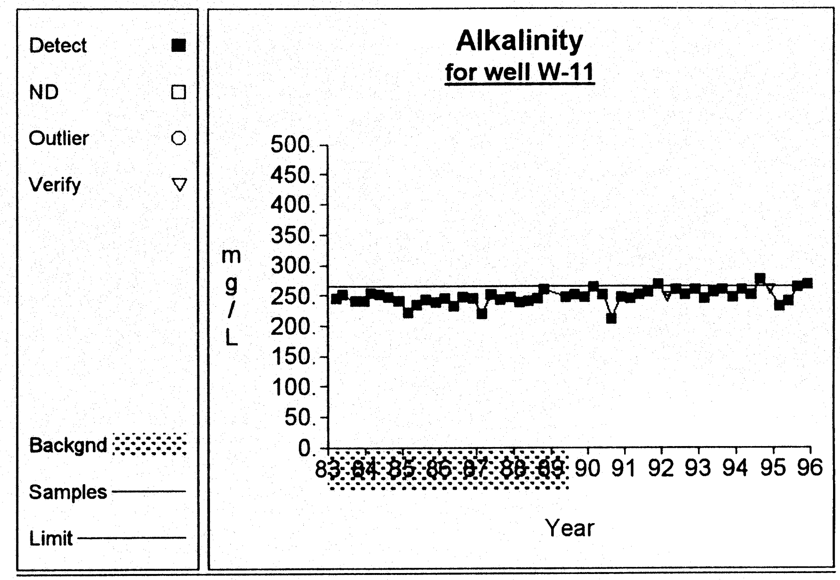
* - Insufficient Data
** - Detection Frequency < 25%
*** - Zero Variance

Prepared by: UW-Madison, CEE Department

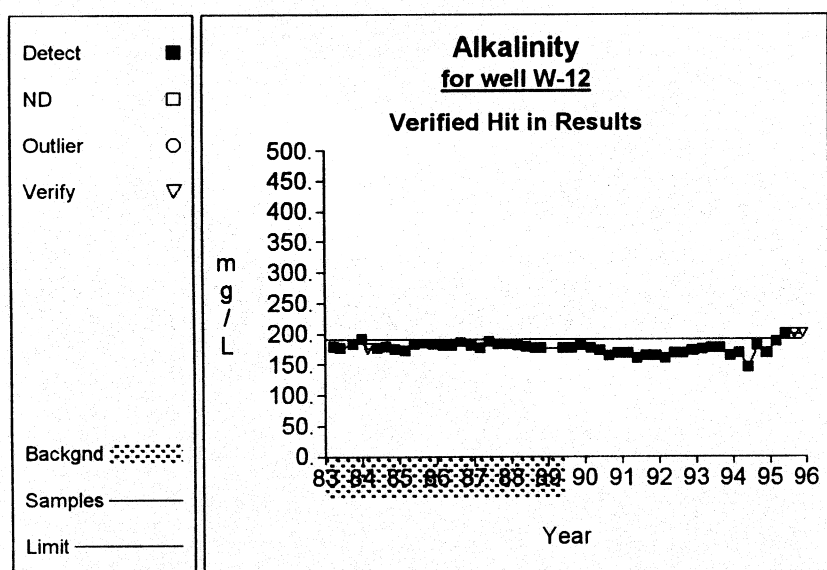
2966 Case Study: Intra-Well Prediction Limits



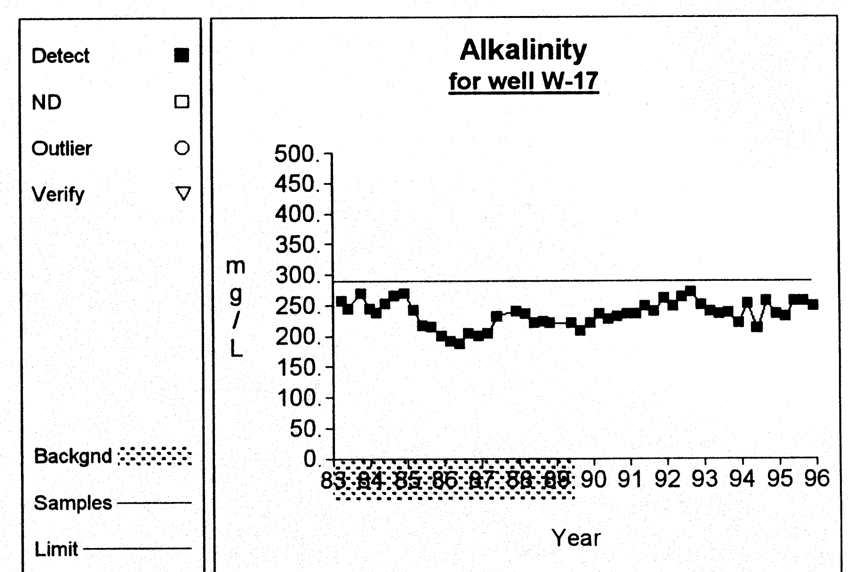
Graph 1



Graph 2



Graph 3



Graph 4

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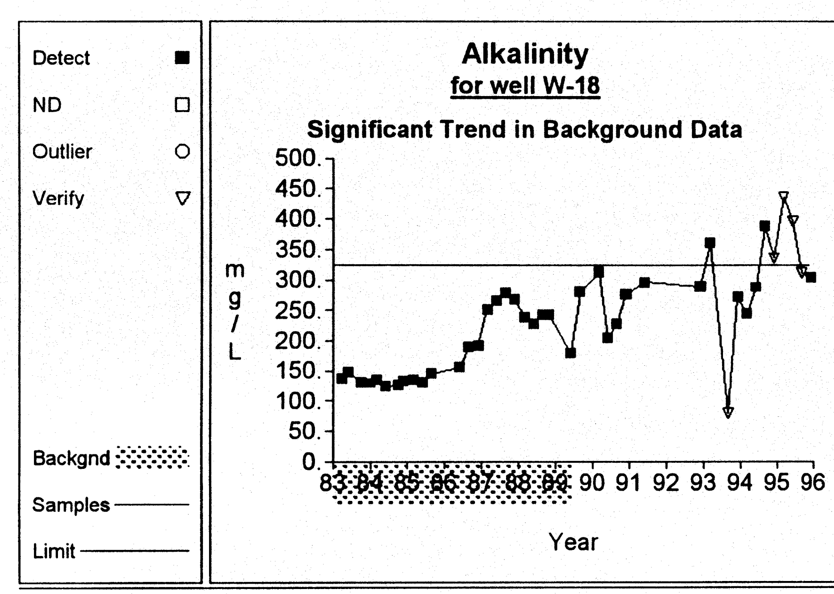
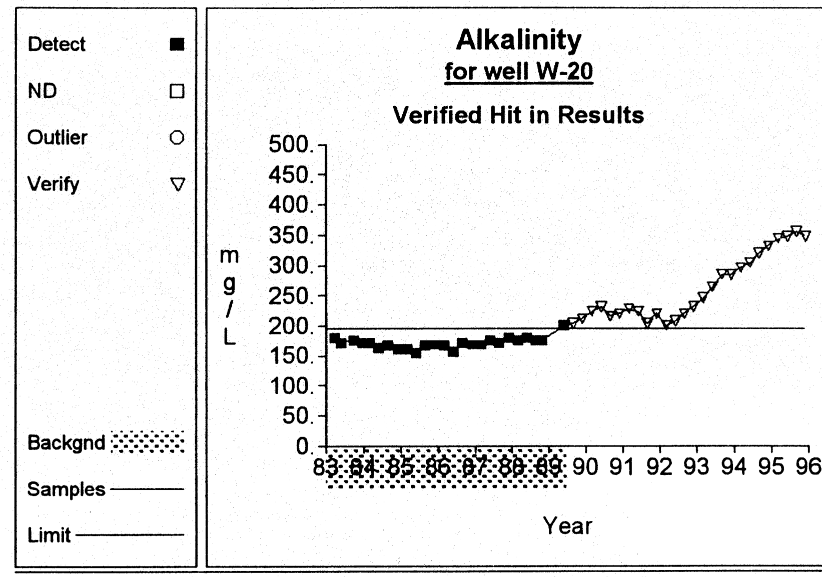
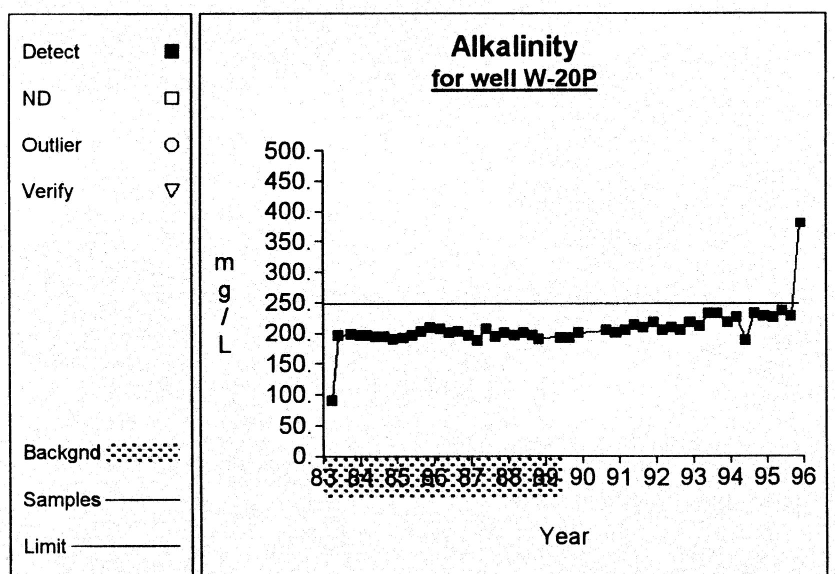
2966 Case Study: Intra-Well Prediction Limits



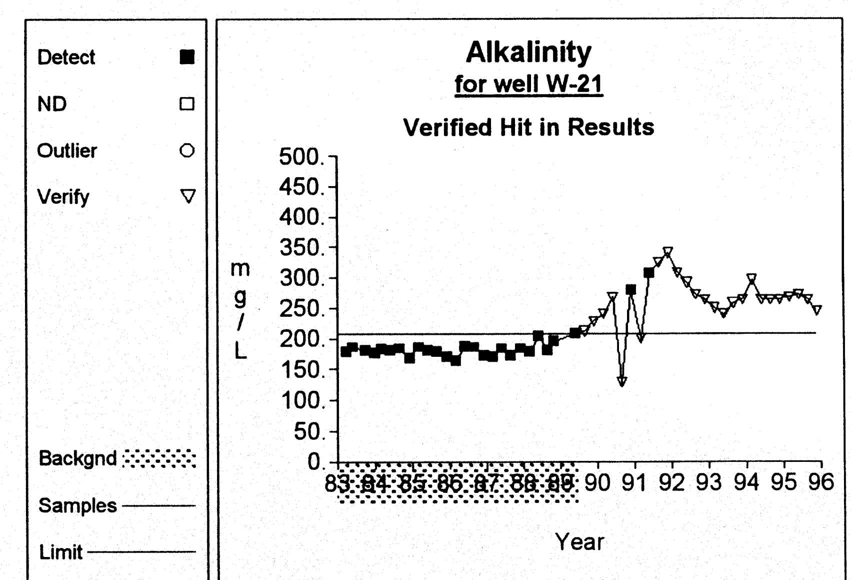
Graph 5



Graph 6



Graph 7



Graph 8

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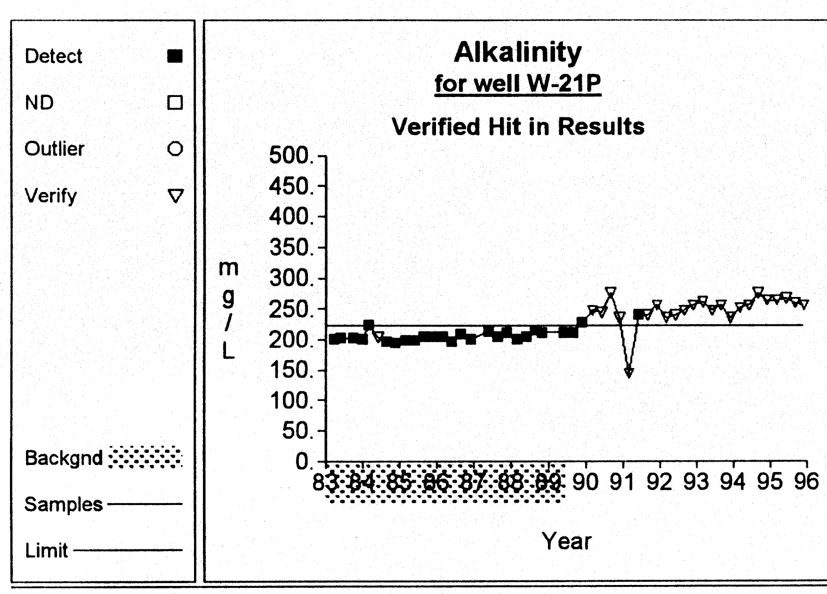
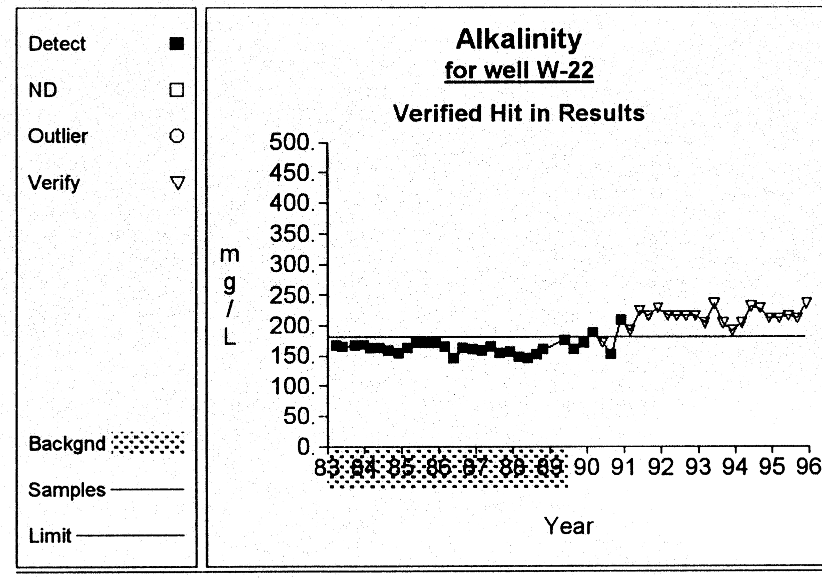
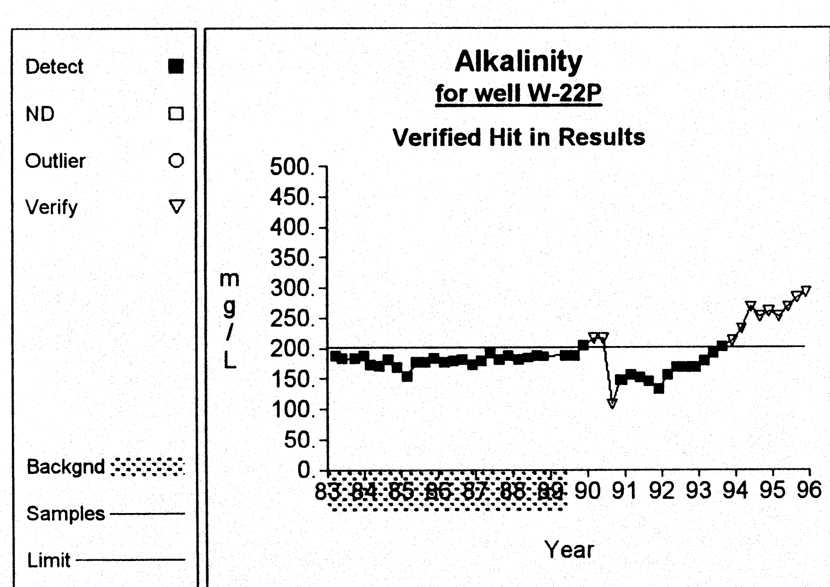
2966 Case Study: Intra-Well Prediction Limits



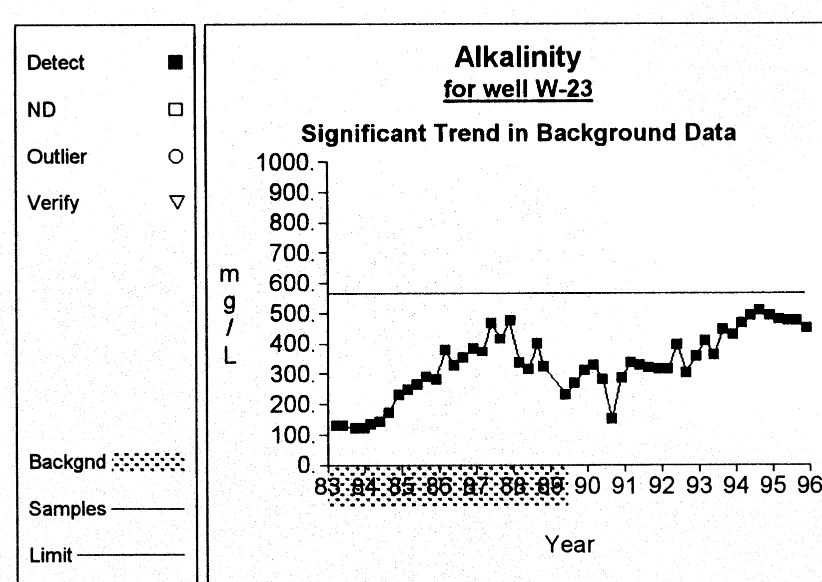
Graph 9



Graph 10



Graph 11



Graph 12

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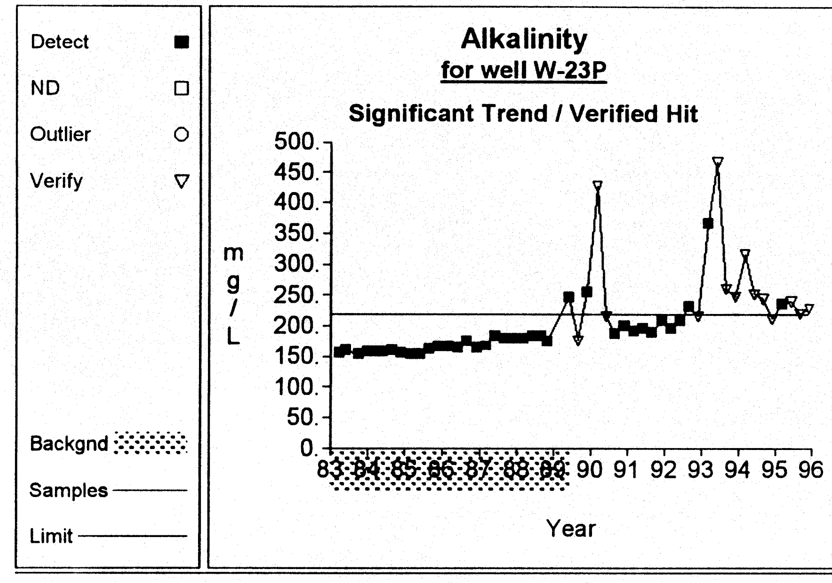
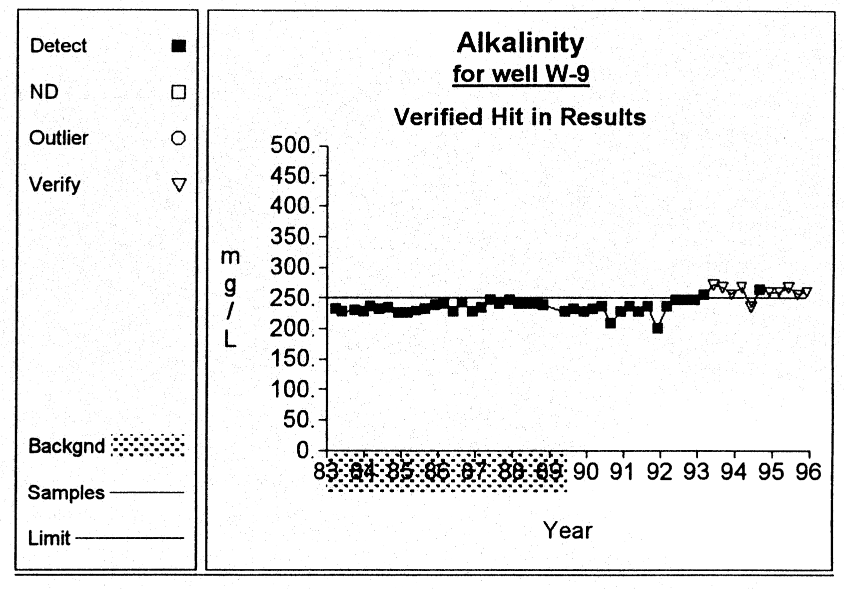
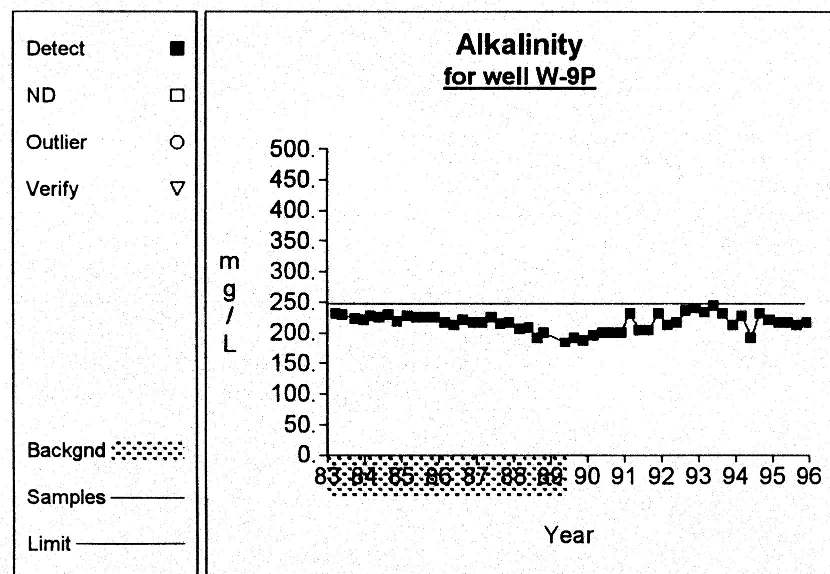
2966 Case Study: Intra-Well Prediction Limits



Graph 13

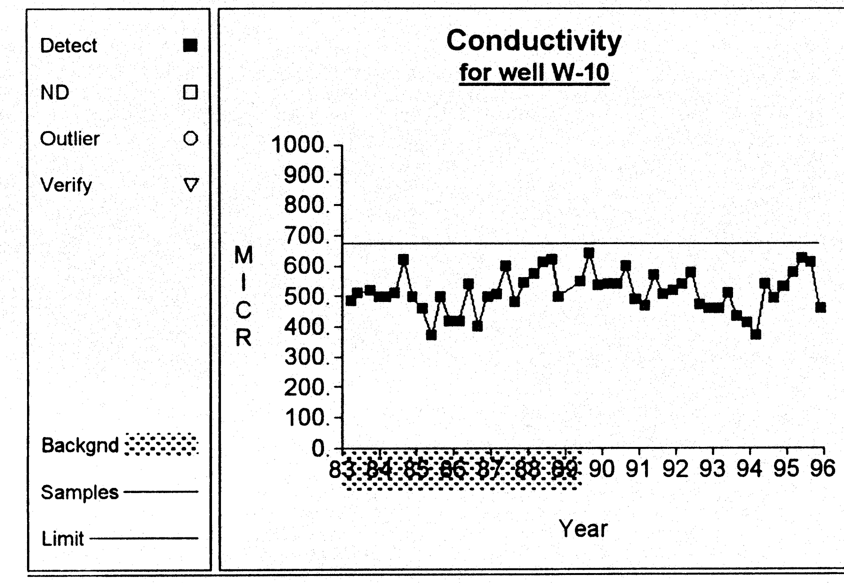


Graph 14

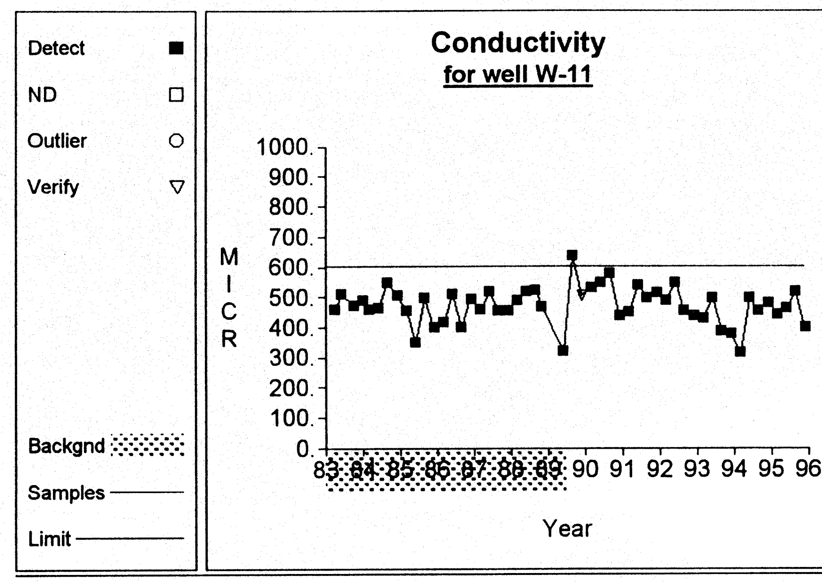


Graph 15

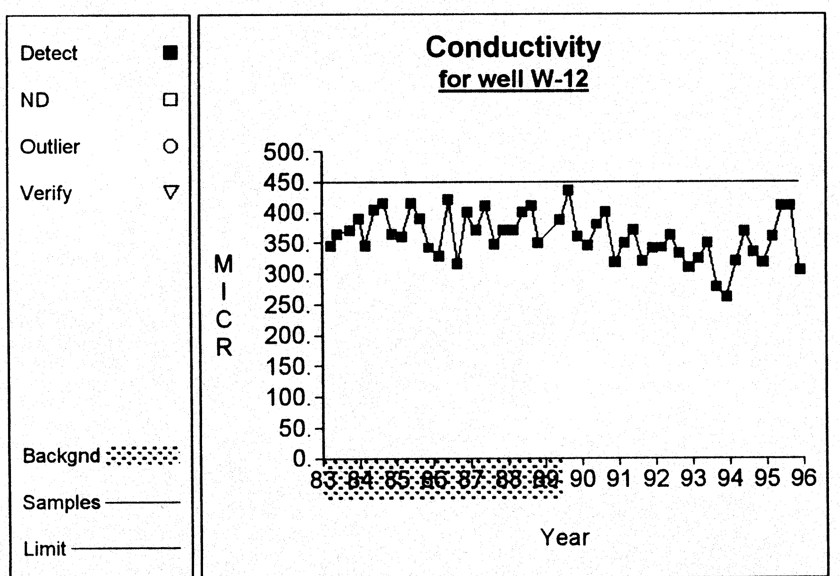
2966 Case Study: Intra-Well Prediction Limits



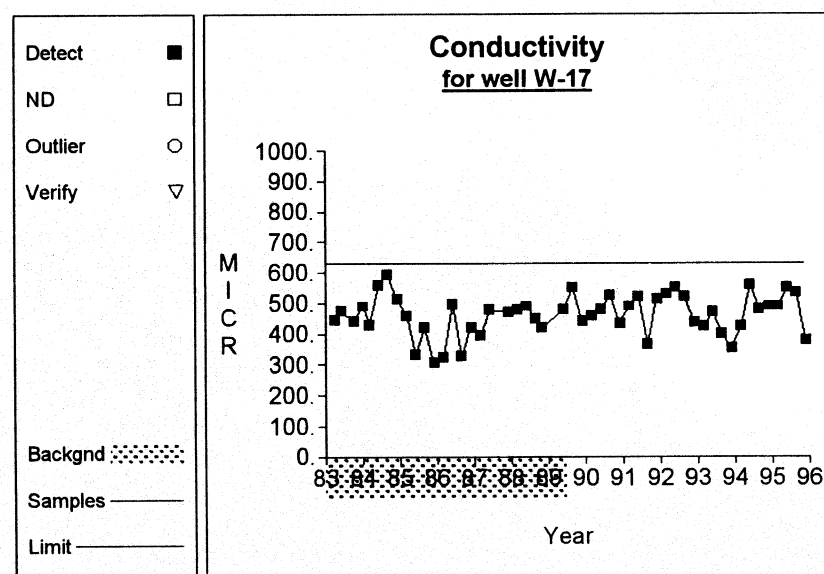
Graph 16



Graph 17



Graph 18



Graph 19

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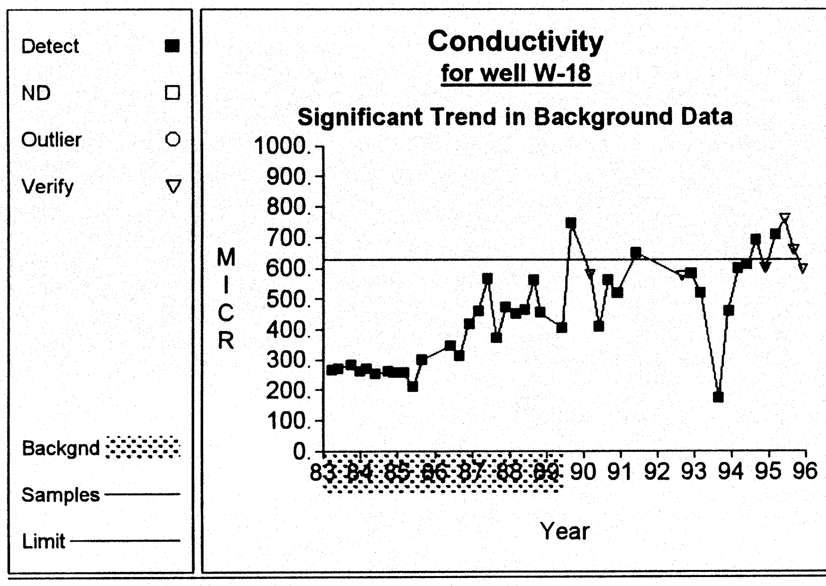
2966 Case Study: Intra-Well Prediction Limits



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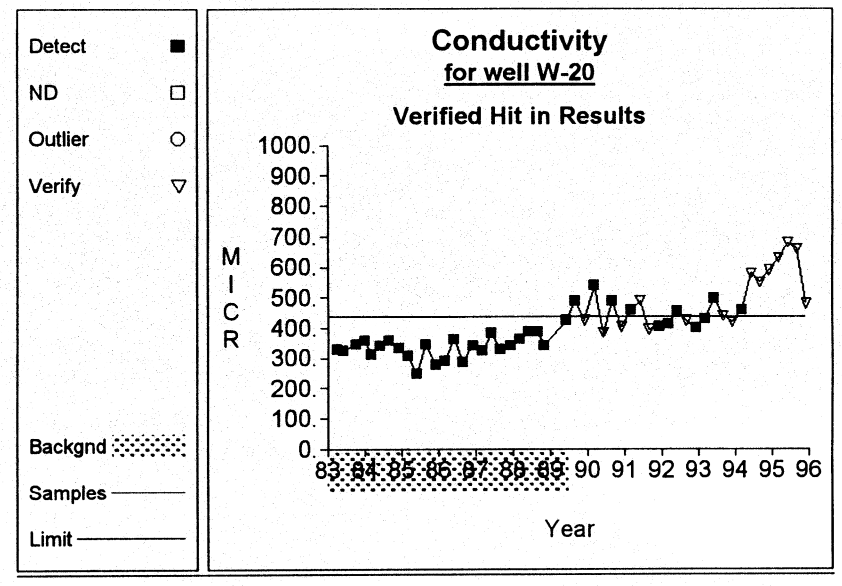
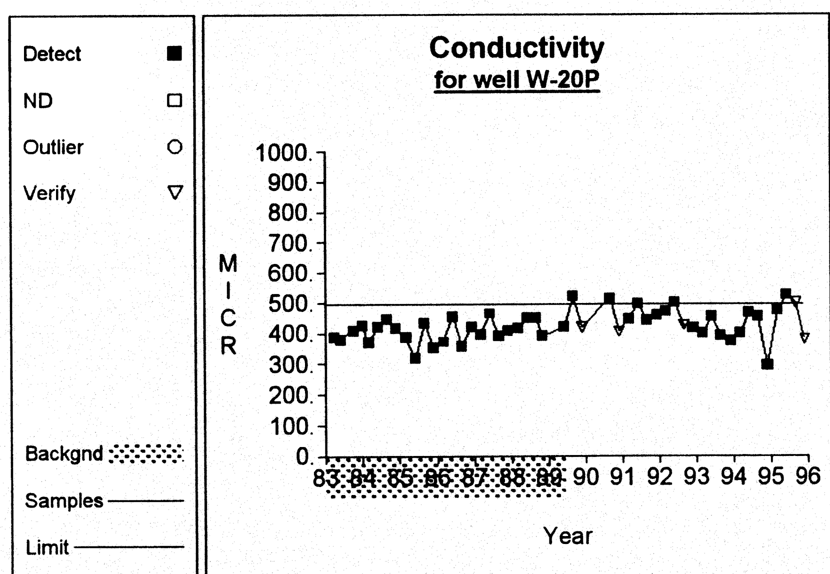
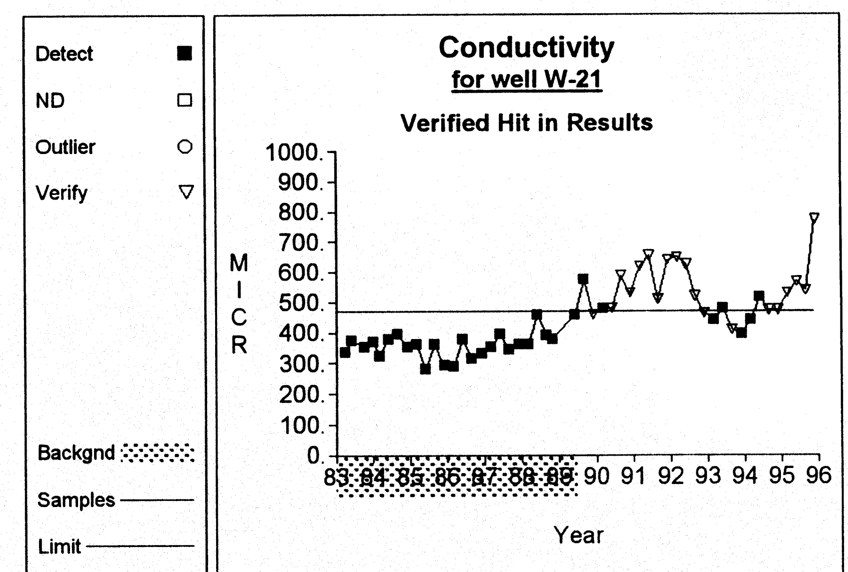


Graph 21



Graph 22



Graph 23

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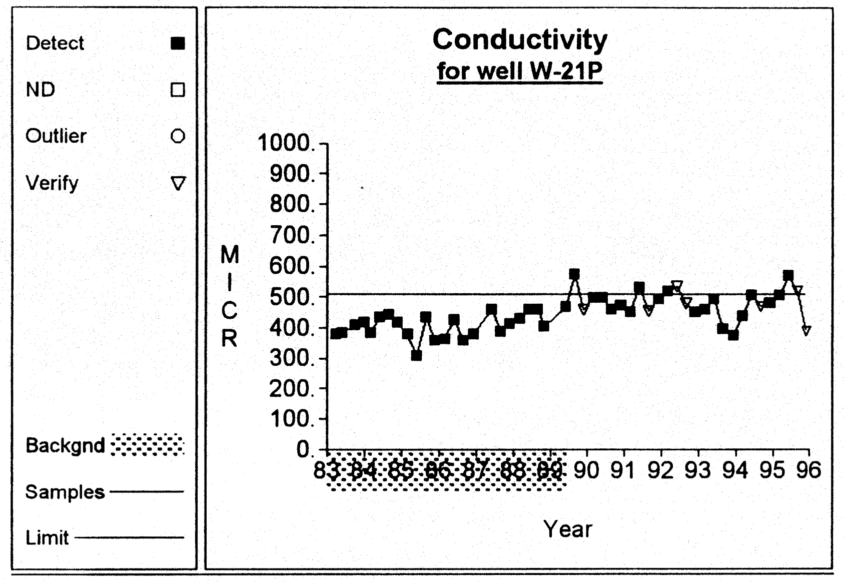
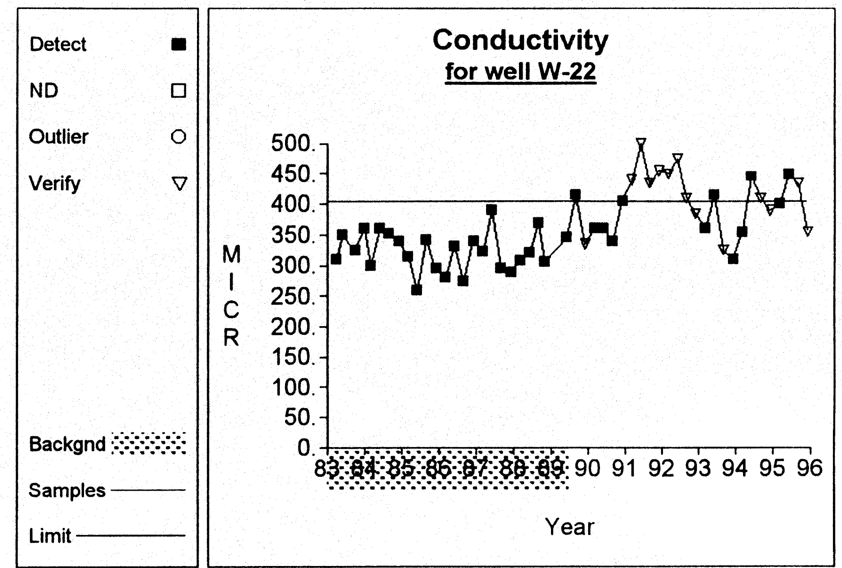
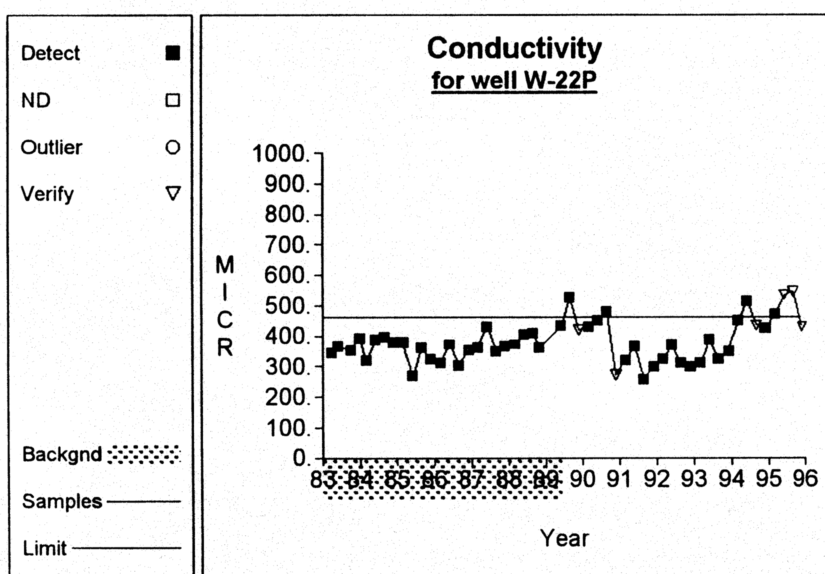
2966 Case Study: Intra-Well Prediction Limits



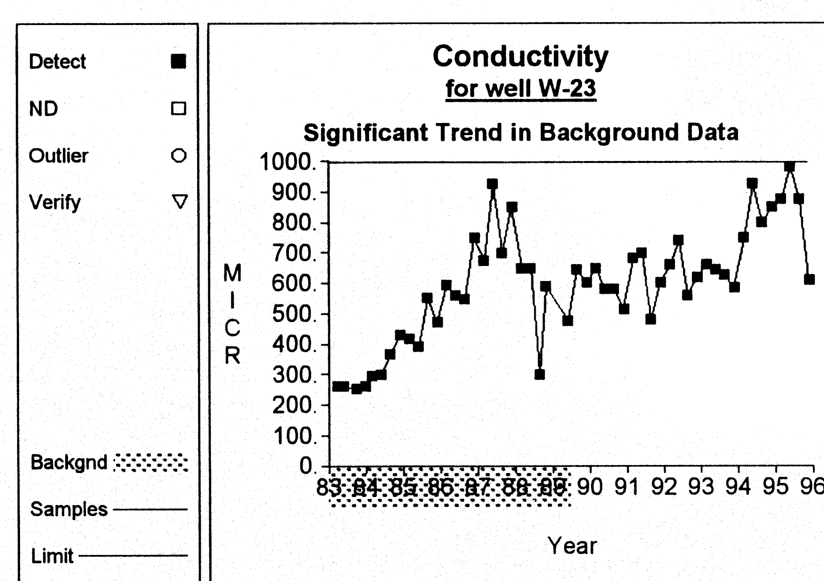
Graph 24



Graph 25



Graph 26



Graph 27

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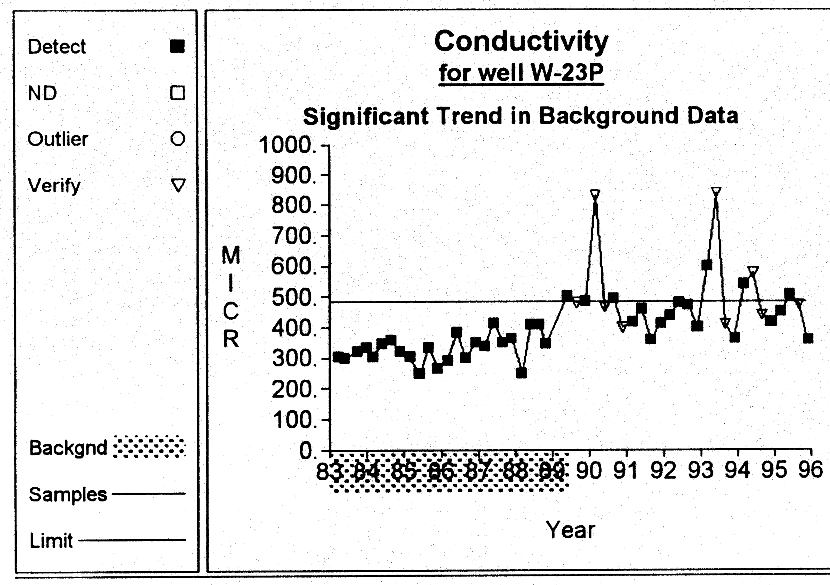
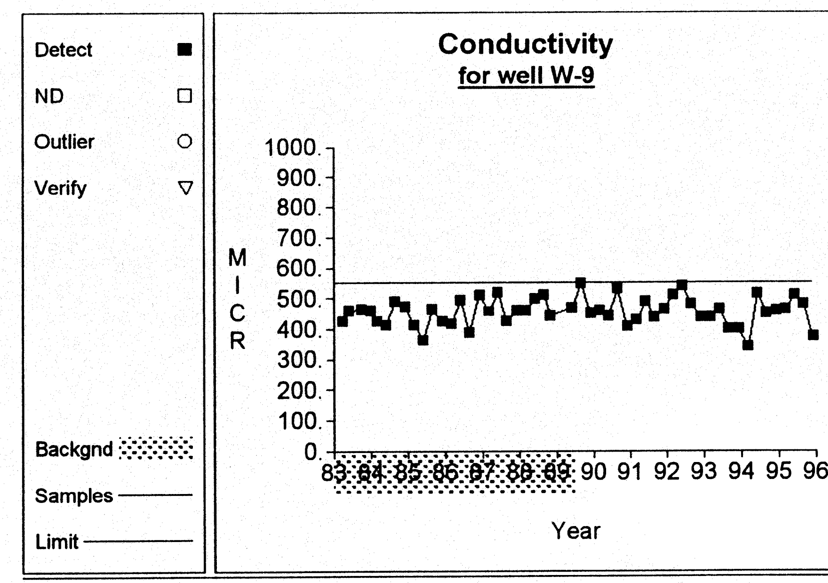
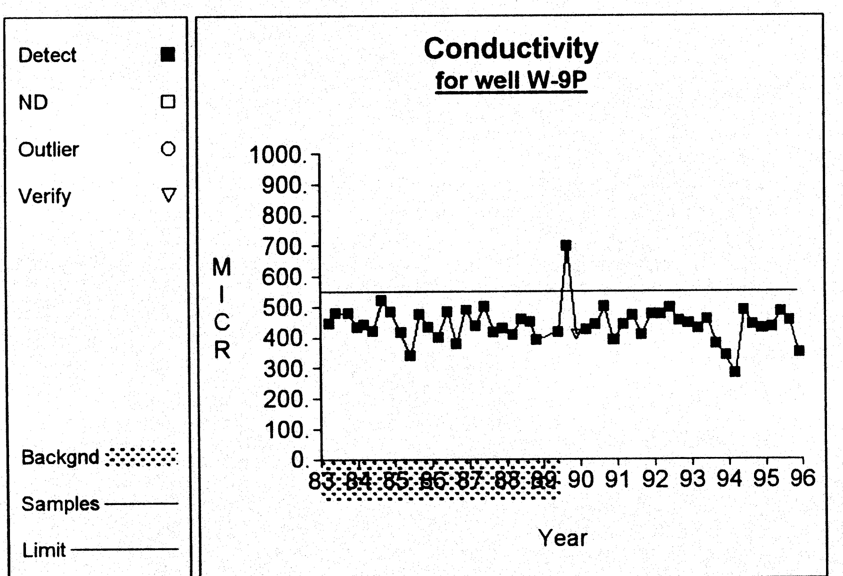
2966 Case Study: Intra-Well Prediction Limits



Graph 28



Graph 29



Graph 30

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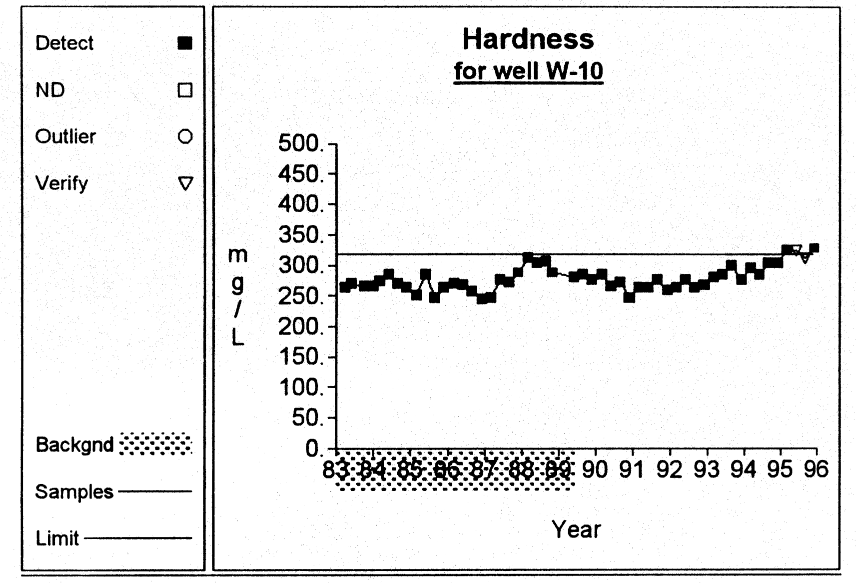
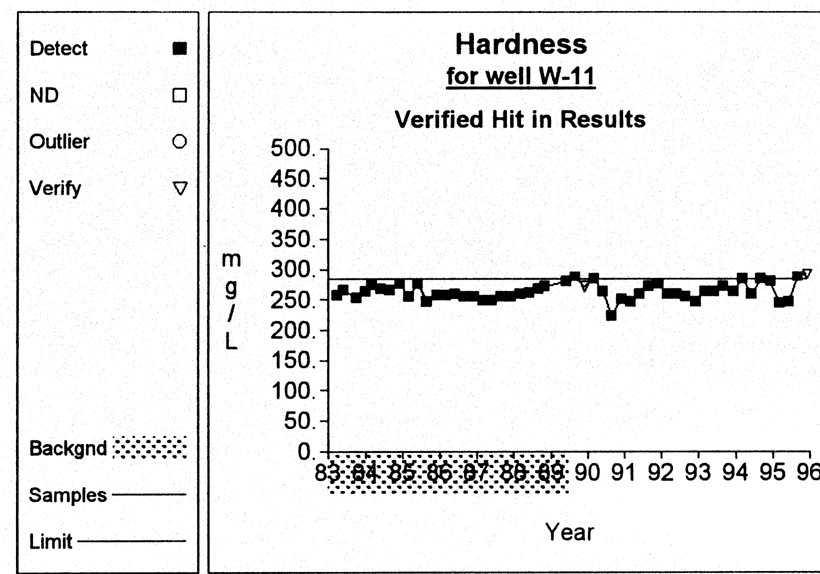
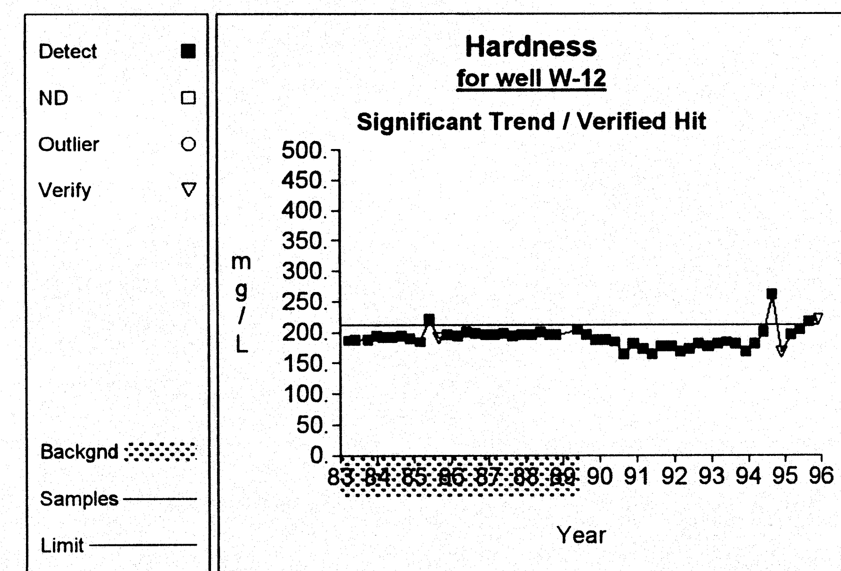
2966 Case Study: Intra-Well Prediction Limits



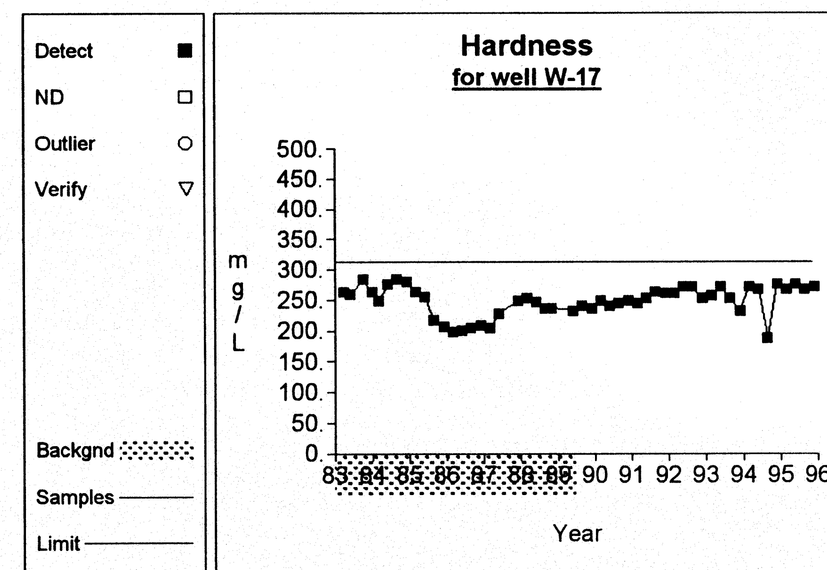
Graph 31



Graph 32



Graph 33



Graph 34

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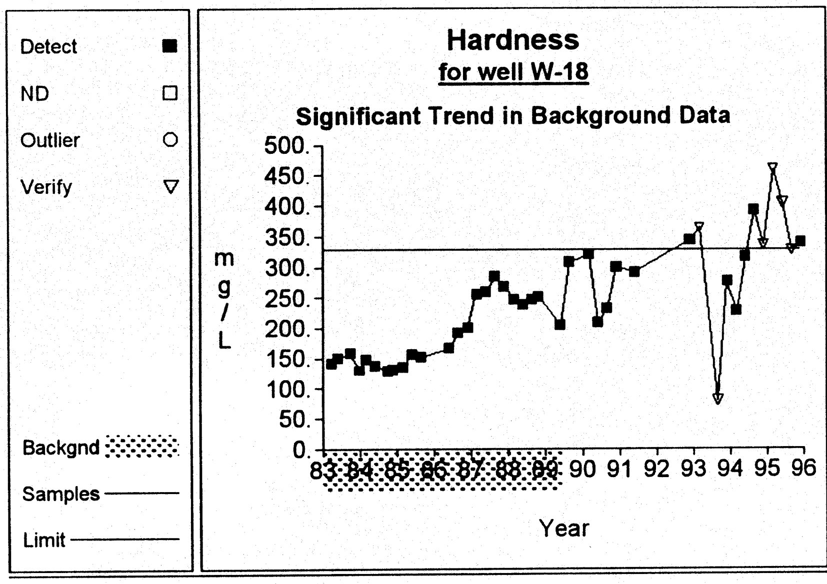
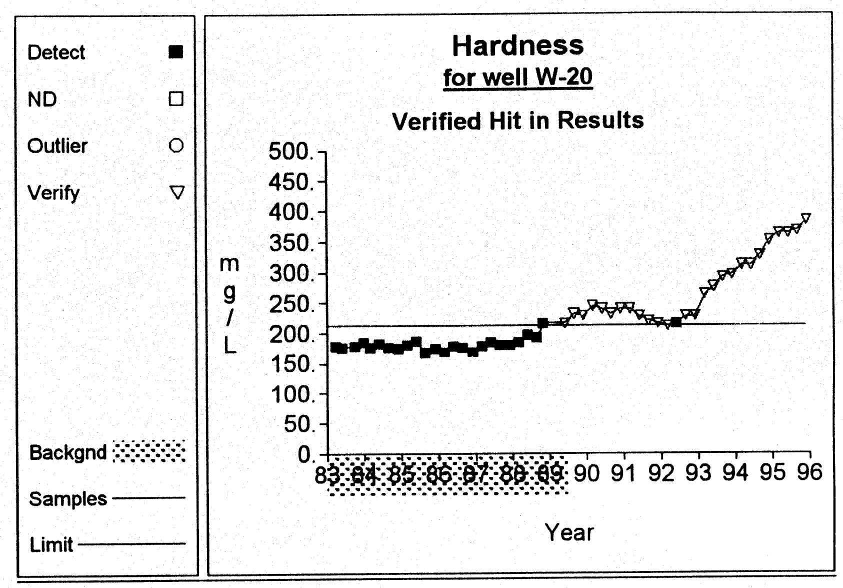
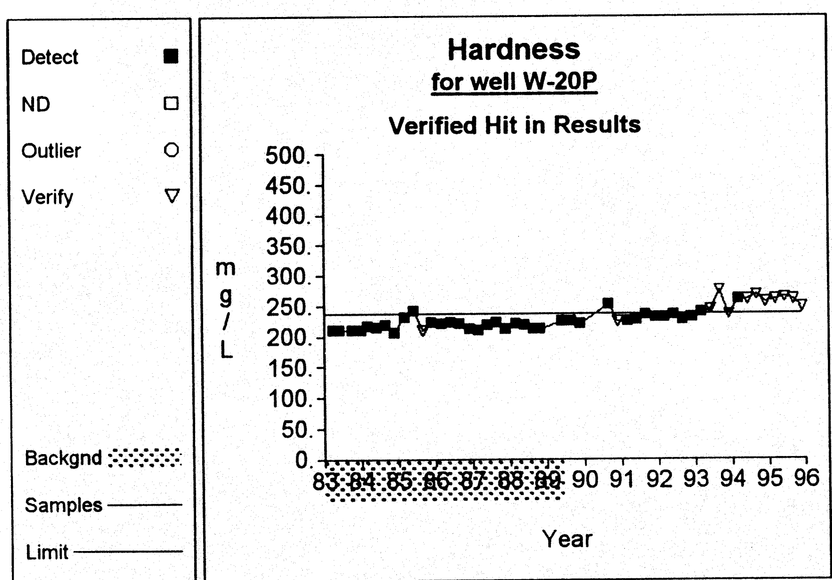
2966 Case Study: Intra-Well Prediction Limits



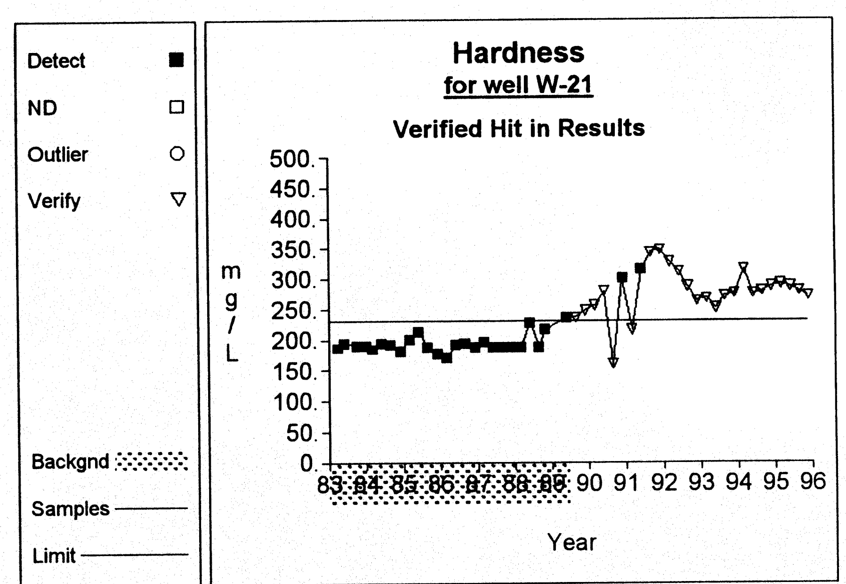
Graph 35



Graph 36



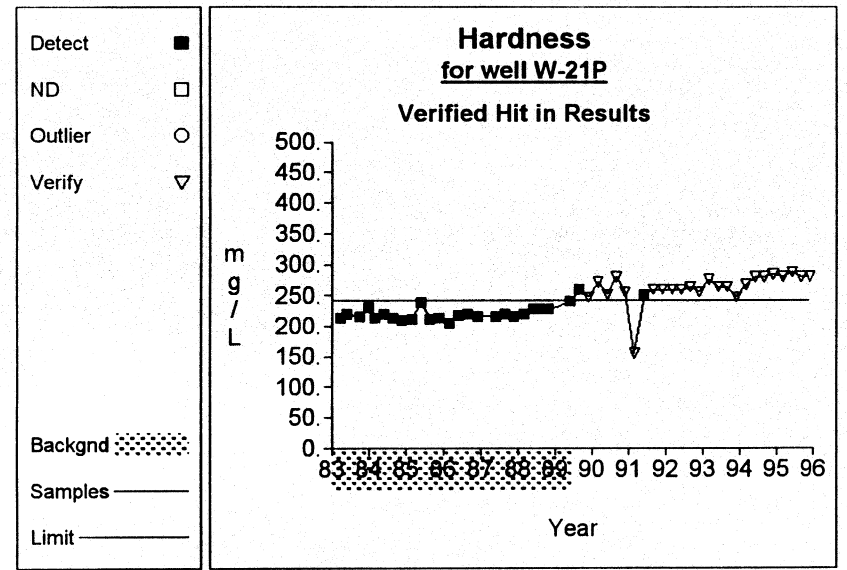
Graph 37



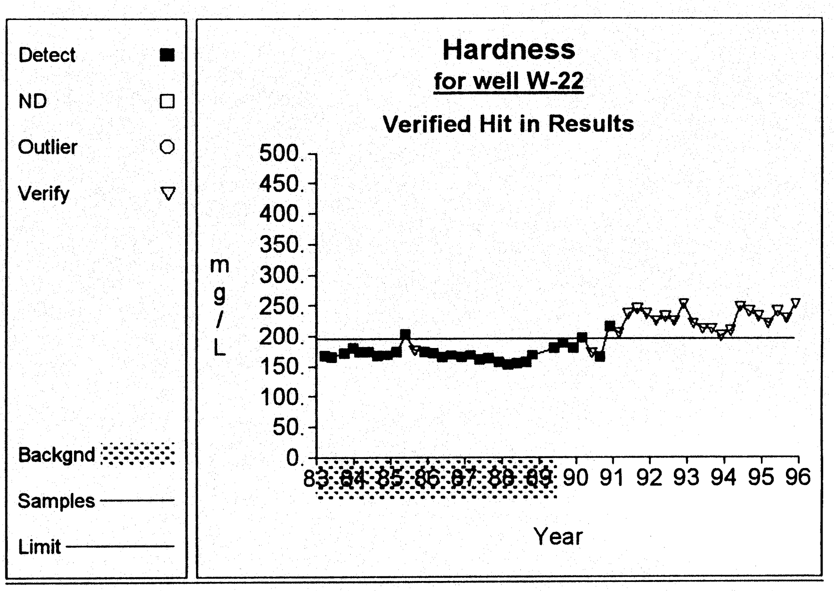
Graph 38

Prepared by: UW-Madison, CEE Department

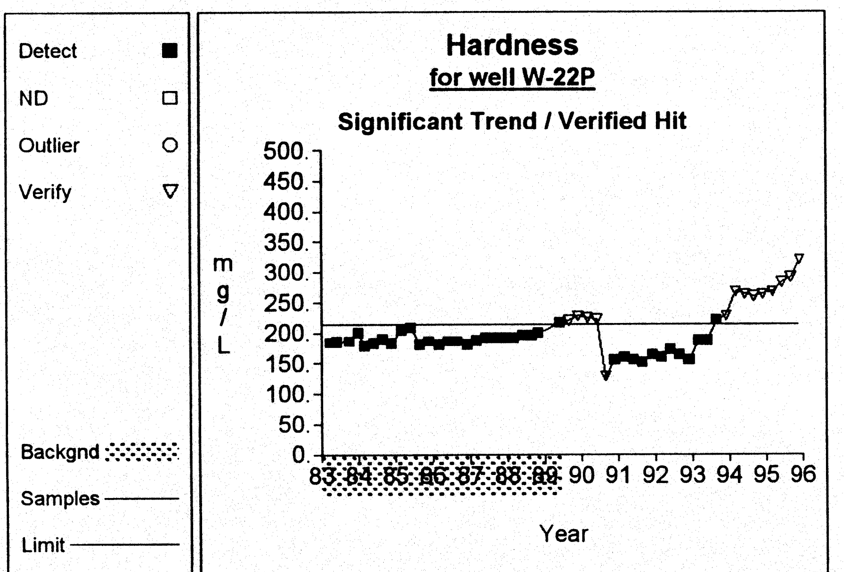
2966 Case Study: Intra-Well Prediction Limits



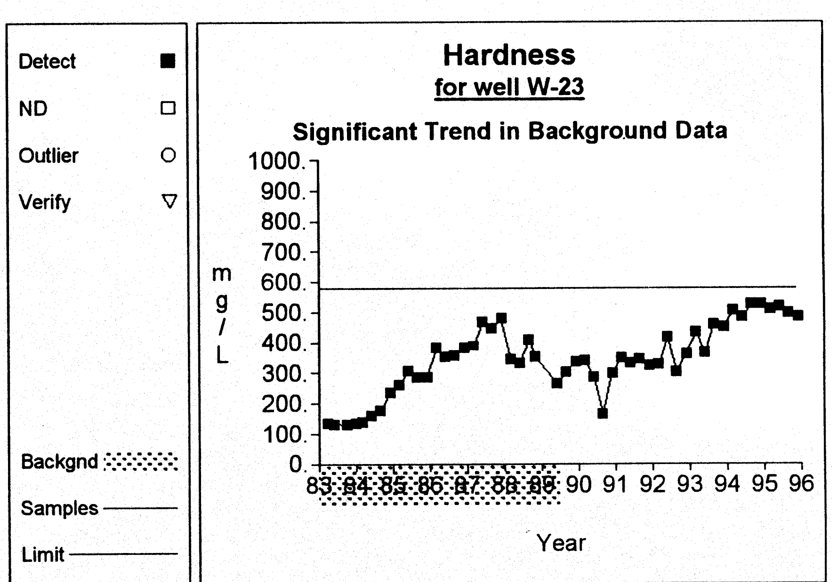
Graph 39



Graph 40



Graph 41



Graph 42

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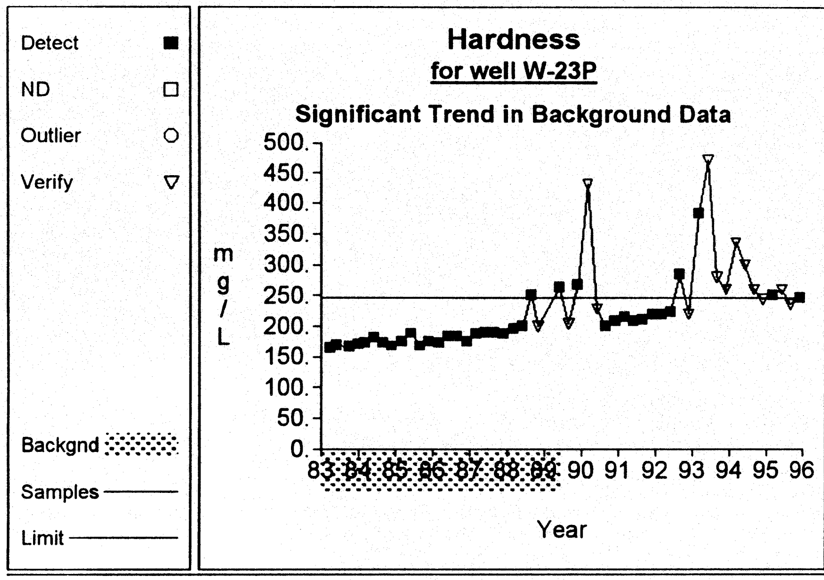
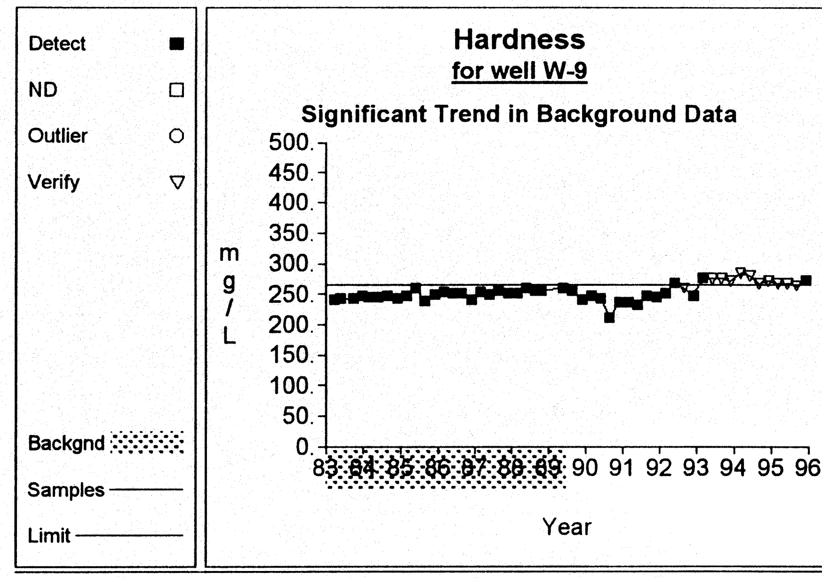
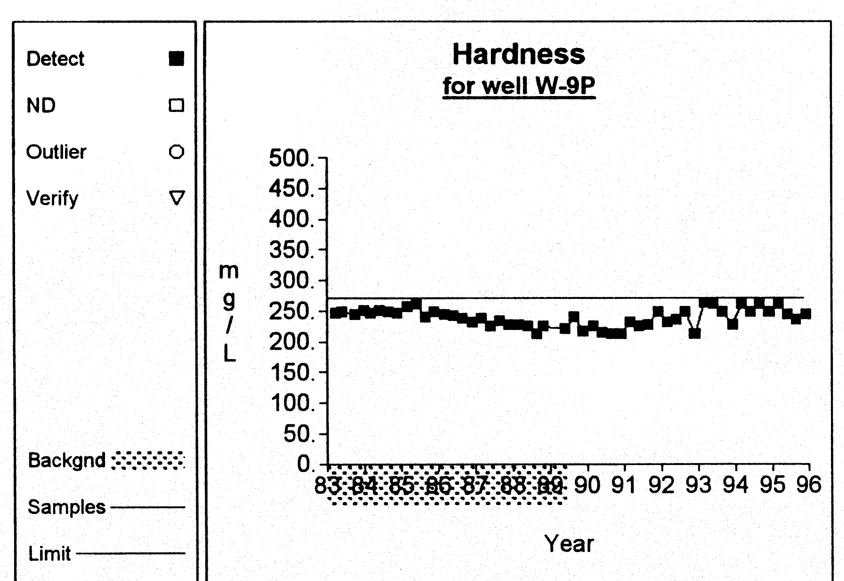
2966 Case Study: Intra-Well Prediction Limits



Graph 43



Graph 44



Graph 45

Prepared by: UW-Madison, CEE Department

2966 Case Study: Table 1

Summary Statistics and Intermediate Computations for Combined Shewart-Cusum Control Charts

Constituent	Units	Well	N	Mean	SD	S(i-1)	S(i)	Limit
Alkalinity	mg/L	W-10	25	235.496	12.211	466.060	497.406	284.341
	mg/L	W-11	25	242.456	9.041	333.437	352.200	278.618
	mg/L	W-12	25	179.752	4.625	201.311	218.090	198.251
	mg/L	W-17	24	228.771	24.283	246.805	247.822	325.902
	mg/L	W-18	23	183.148	55.121	1480.928	1560.439	403.633
	mg/L	W-20	25	170.792	9.461	2143.594	2313.706	208.637
	mg/L	W-20P	25	192.756	21.824	331.392	502.268	280.052
	mg/L	W-21	25	181.352	10.310	2030.984	2085.900	222.592
	mg/L	W-21P	24	204.583	7.217	1091.697	1137.701	233.450
	mg/L	W-22	25	160.908	8.092	1077.453	1146.476	193.278
	mg/L	W-22P	25	179.516	8.227	718.337	824.651	212.426
	mg/L	W-23	25	281.812	112.164	1146.463	1228.528	730.467
	mg/L	W-23P	25	170.020	19.355	1657.678	1701.141	247.442
	mg/L	W-9	25	234.612	6.527	472.015	492.508	260.721
	mg/L	W-9P	25	217.052	11.706	217.052	217.052	263.877
Conductivity	MICR	W-10	25	509.320	65.588	648.788	550.277	771.670
	MICR	W-11	25	466.400	54.160	479.380	466.400	683.041
	MICR	W-12	25	375.360	29.590	400.255	375.360	493.720
	MICR	W-17	24	445.792	71.721	554.297	445.792	732.676
	MICR	W-18	23	355.478	106.569	2901.945	3062.540	781.755
	MICR	W-20	25	338.560	38.396	3228.563	3341.206	492.144
	MICR	W-20P	25	405.400	35.342	583.264	531.358	546.769
	MICR	W-21	25	360.040	43.316	3555.281	3936.753	533.305
	MICR	W-21P	24	407.417	39.410	1490.147	1443.173	565.055
	MICR	W-22	25	323.200	32.087	1644.832	1652.566	451.548
	MICR	W-22P	25	363.520	38.352	869.818	907.534	516.926
	MICR	W-23	25	500.600	194.489	1801.799	1765.332	1278.556
	MICR	W-23P	25	338.320	56.851	3088.485	3067.526	565.725
	MICR	W-9	25	453.560	39.050	477.865	453.560	609.761
	MICR	W-9P	25	441.560	41.999	441.560	441.560	609.556
Hardness	mg/L	W-10	25	272.652	17.988	383.508	425.365	344.604
	mg/L	W-11	25	261.848	8.922	281.308	304.768	297.538
	mg/L	W-12	25	195.068	6.947	198.790	218.512	222.855
	mg/L	W-17	24	241.129	27.921	280.850	290.780	352.813
	mg/L	W-18	23	190.604	53.857	1553.668	1662.671	406.034
	mg/L	W-20	25	181.736	12.301	2170.797	2363.835	230.942
	mg/L	W-20P	25	216.884	7.977	650.412	675.545	248.793
	mg/L	W-21	25	193.792	14.958	2069.493	2136.483	253.625
	mg/L	W-21P	24	219.346	8.719	1106.556	1160.671	254.223

* - Insufficient Data
** - Detection Frequency < 25%
*** - Zero Variance

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2966 Case Study: Table 1 - Continued

Summary Statistics and Intermediate Computations for Combined Shewart-Cusum Control Charts

Constituent	Units	Well	N	Mean	SD	S(i-1)	S(i)	Limit
Hardness	mg/L	W-22	25	168.528	10.430	1151.764	1227.414	210.248
	mg/L	W-22P	25	190.584	9.517	728.809	851.087	228.653
	mg/L	W-23	25	293.104	113.196	1253.091	1359.089	745.890
	mg/L	W-23P	25	186.452	23.986	1746.533	1790.092	282.396
	mg/L	W-9	25	249.512	6.490	446.578	464.199	275.472
	mg/L	W-9P	25	238.876	12.225	266.386	262.342	287.775

* - Insufficient Data
** - Detection Frequency < 25%
*** - Zero Variance

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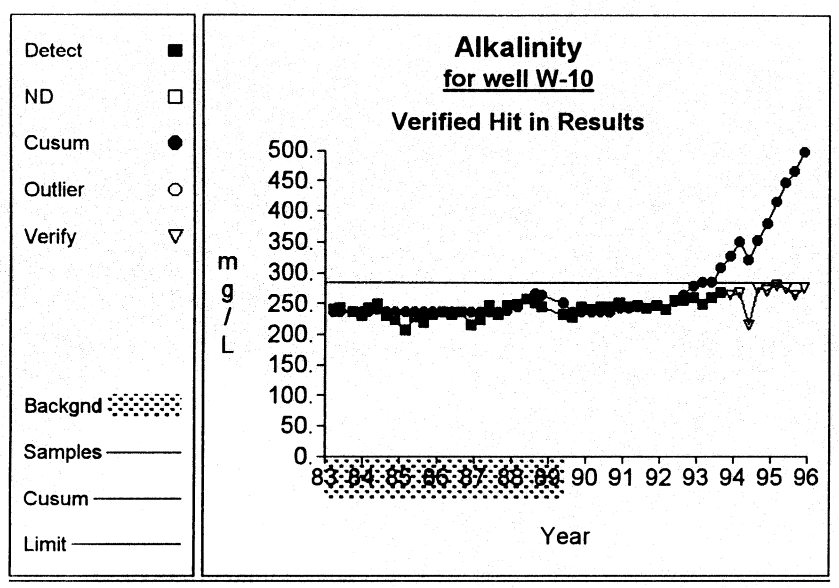
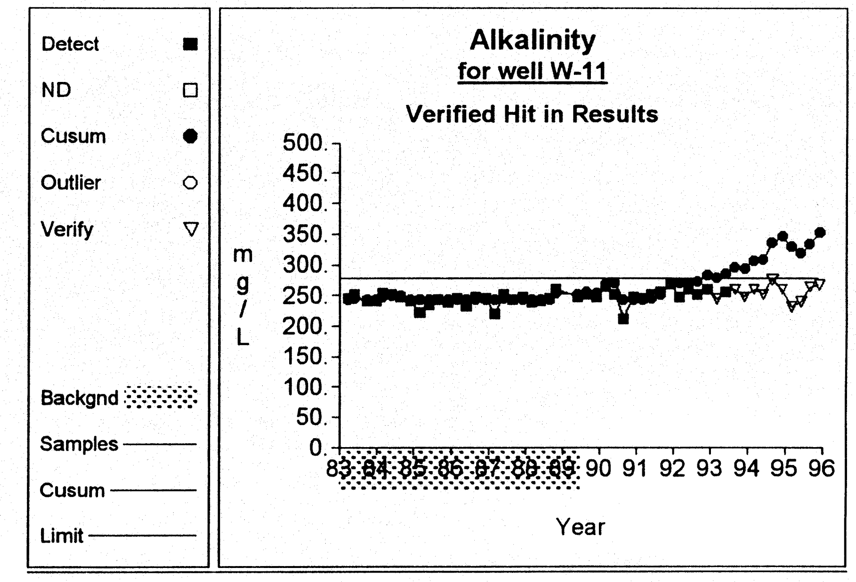
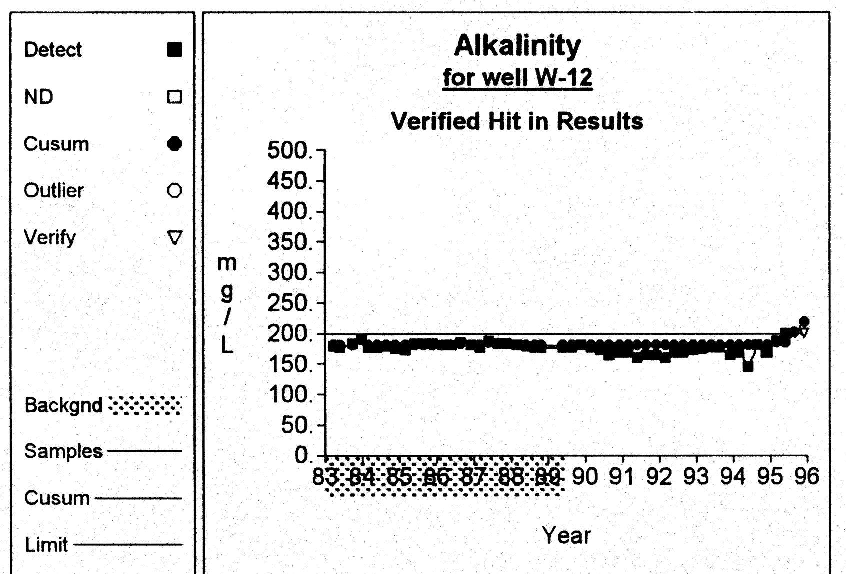
2966 Case Study: Intra-Well Control Charts



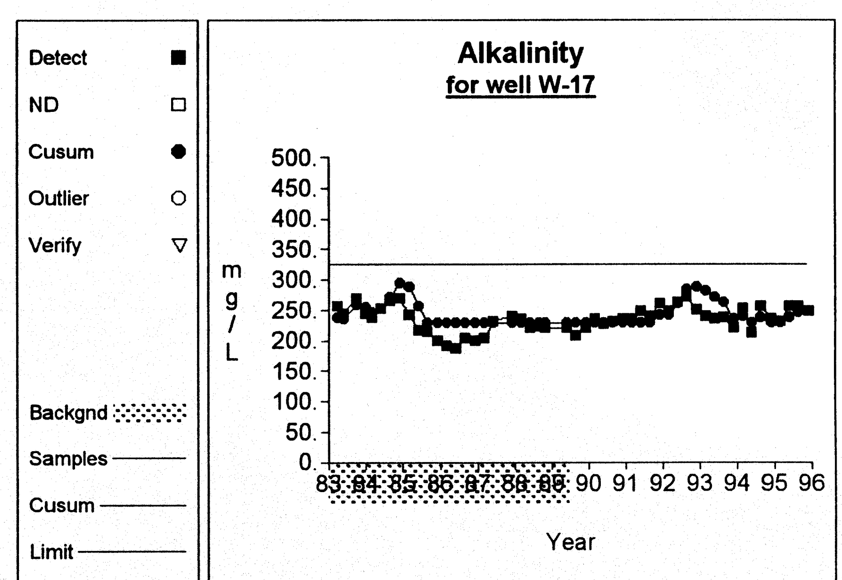
Graph 1



Graph 2

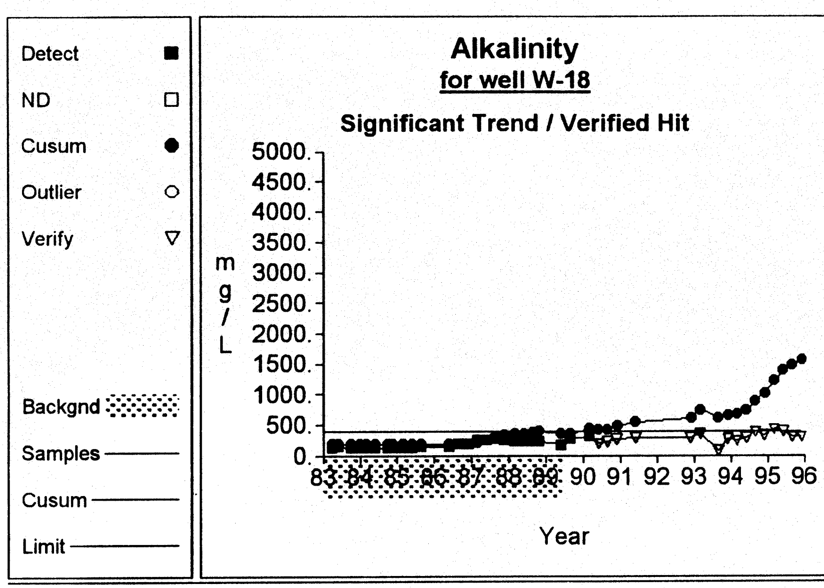


Graph 3



Graph 4

2966 Case Study: Intra-Well Control Charts



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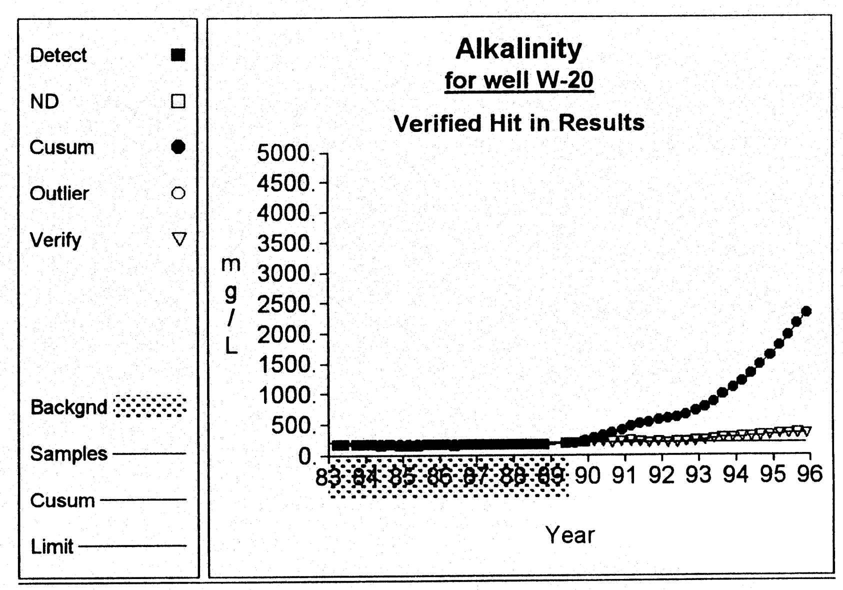

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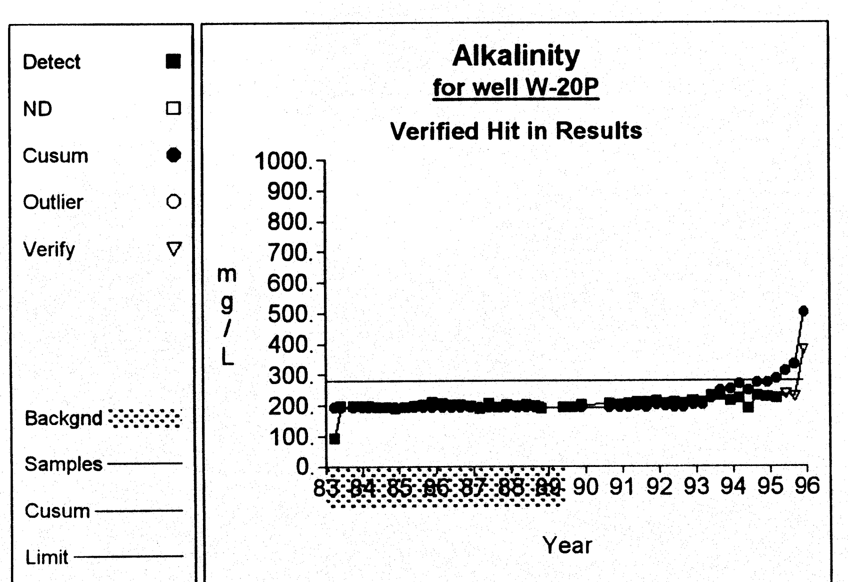

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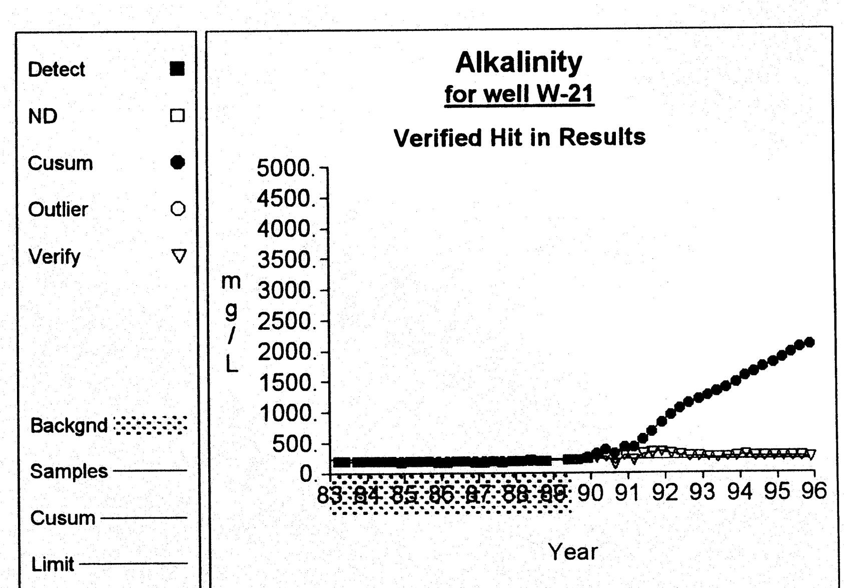

Graph 8

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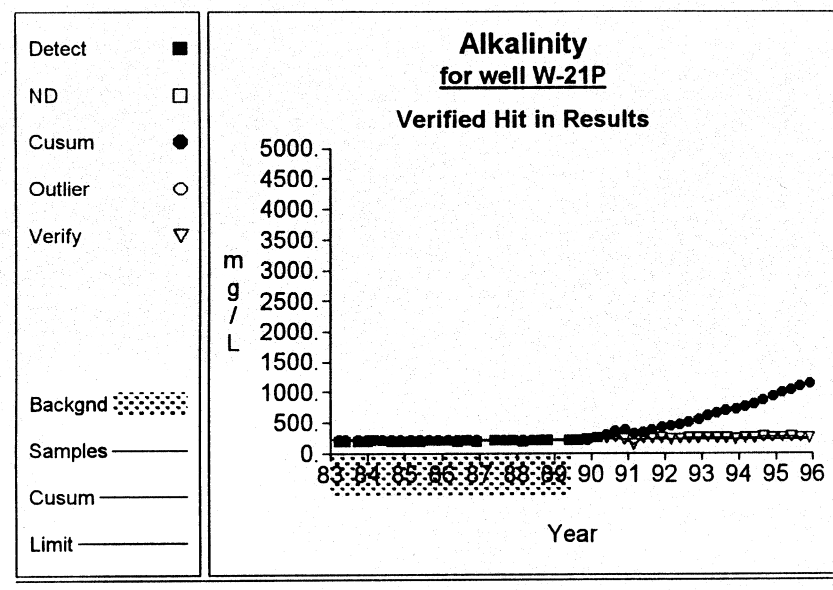
2966 Case Study: Intra-Well Control Charts



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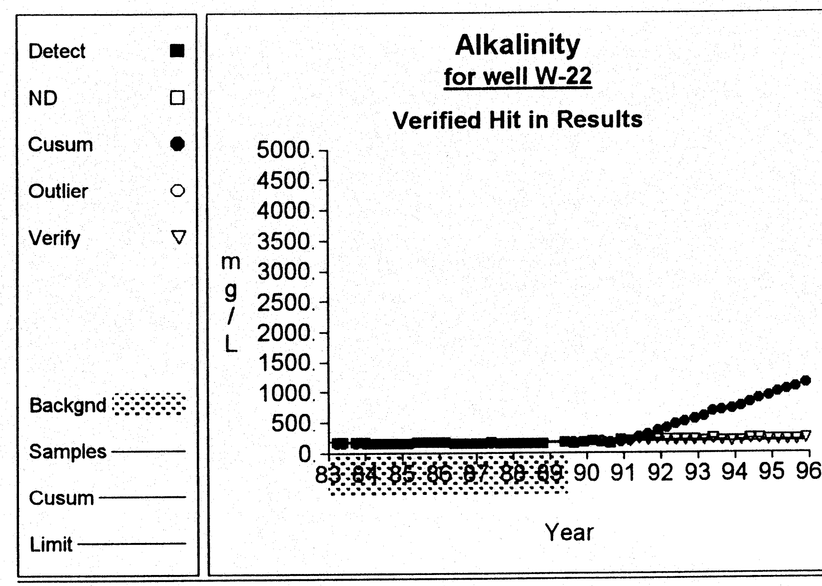

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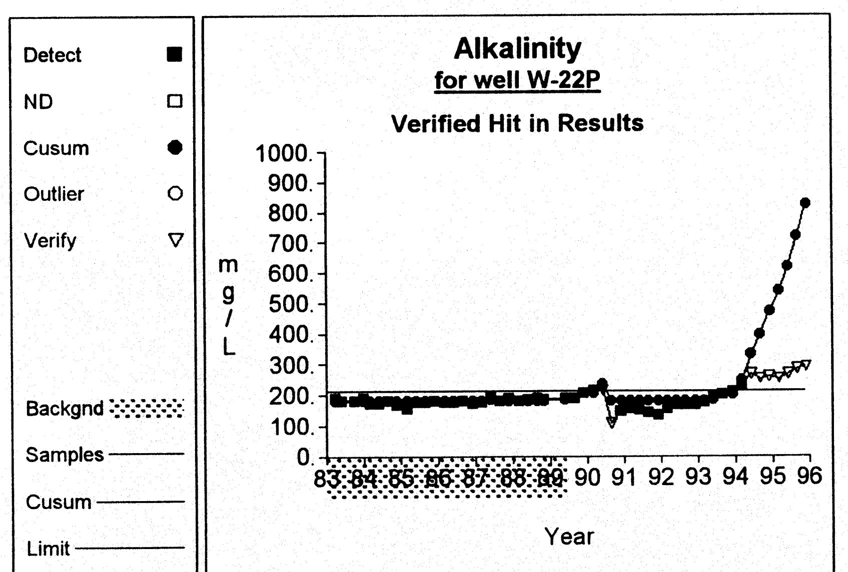

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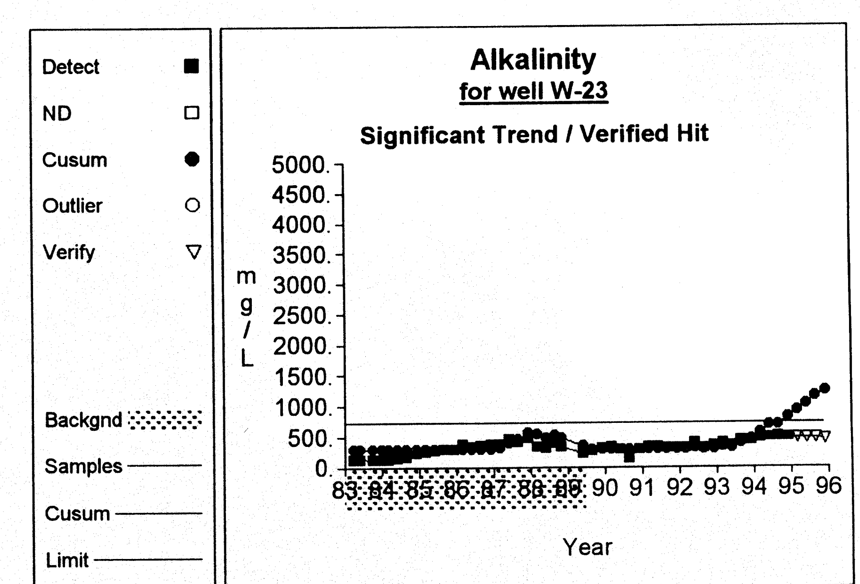

Graph 12

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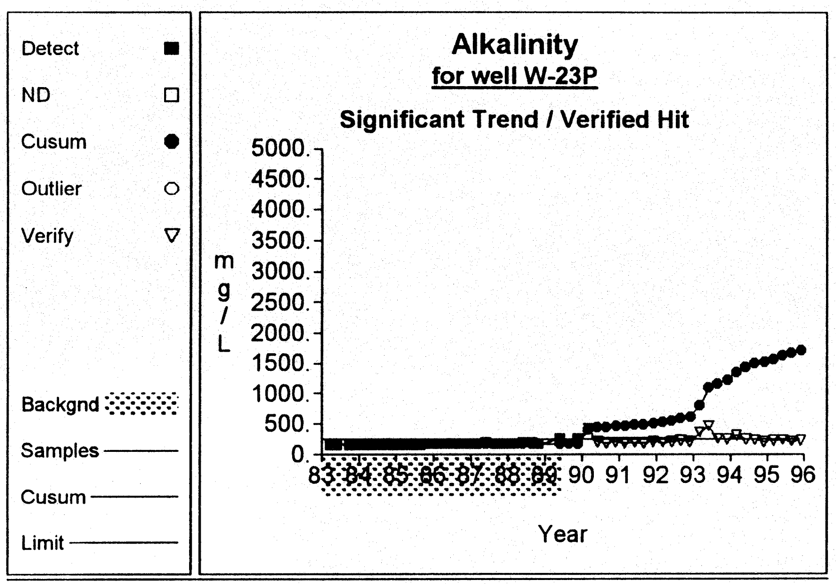
2966 Case Study: Intra-Well Control Charts



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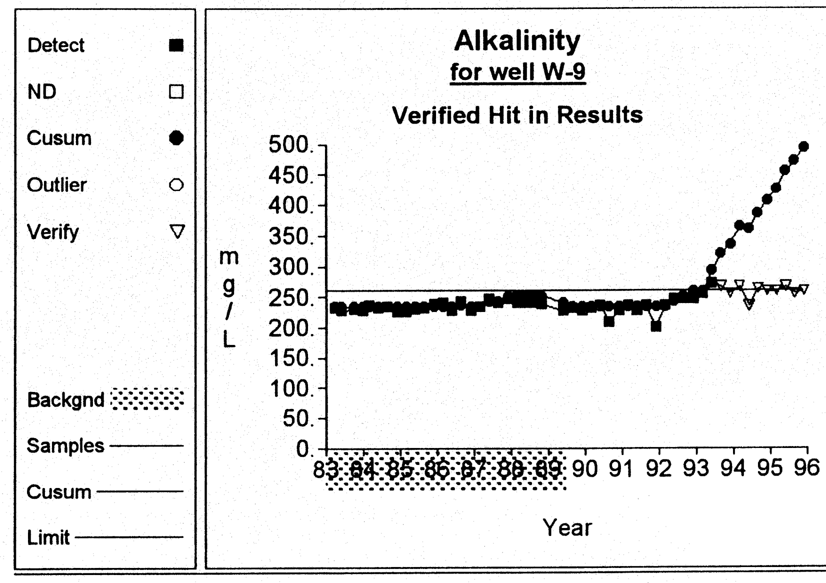

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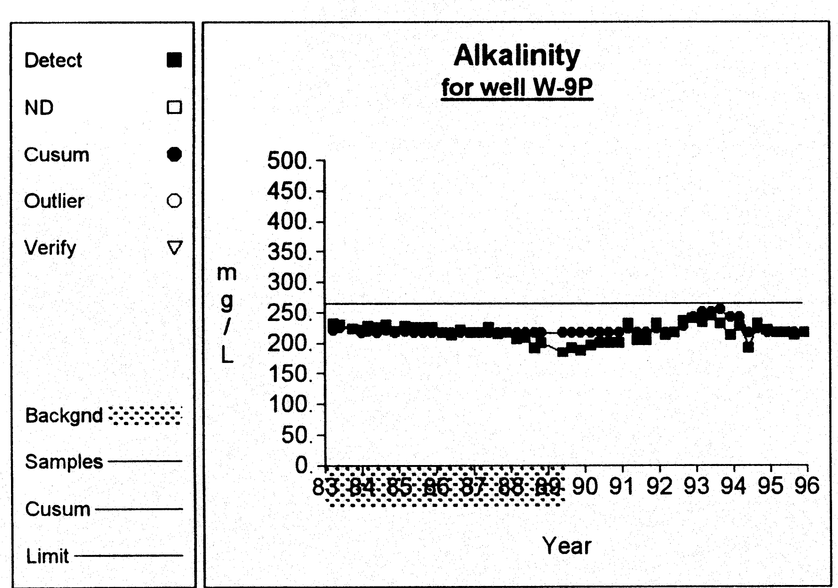

Graph 15

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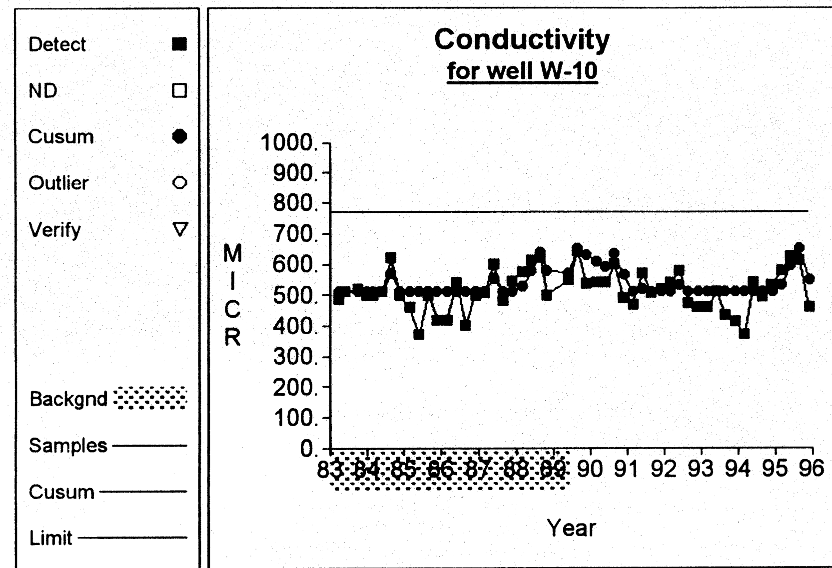
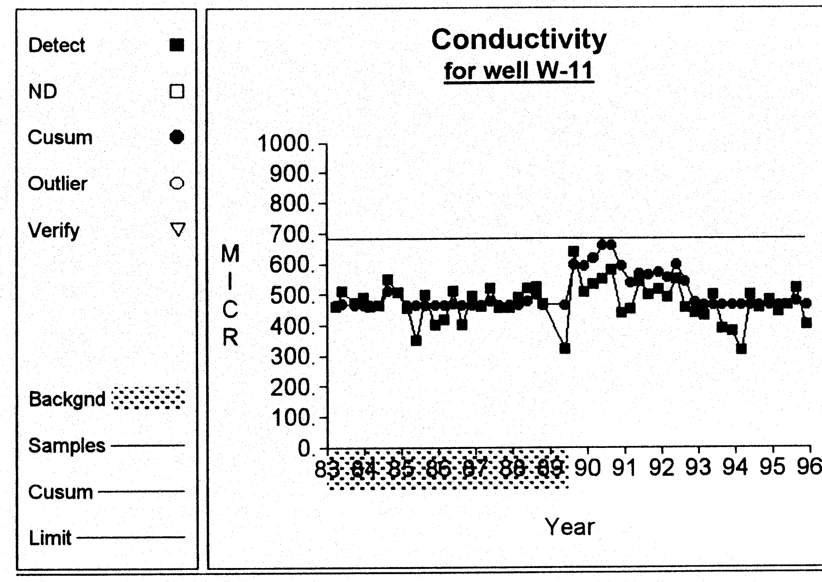
2966 Case Study: Intra-Well Control Charts



Graph 16



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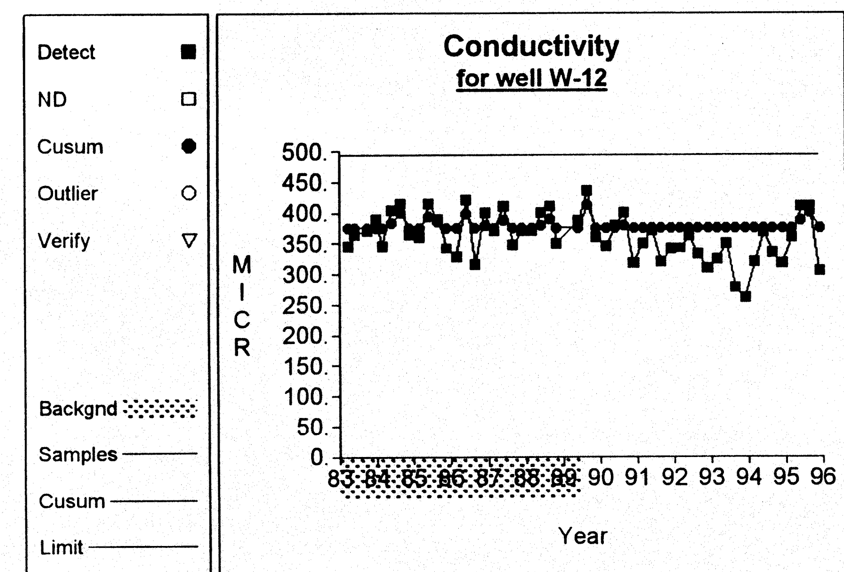

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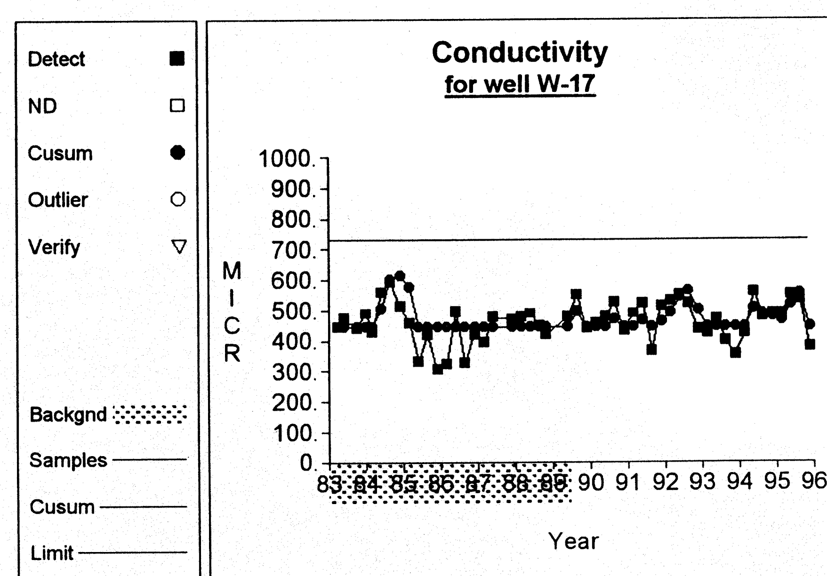

Graph 19

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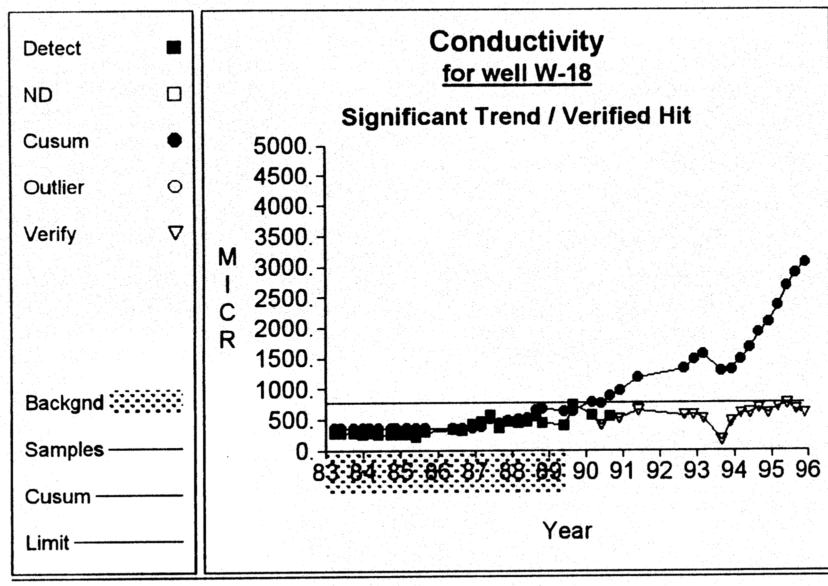
2966 Case Study: Intra-Well Control Charts



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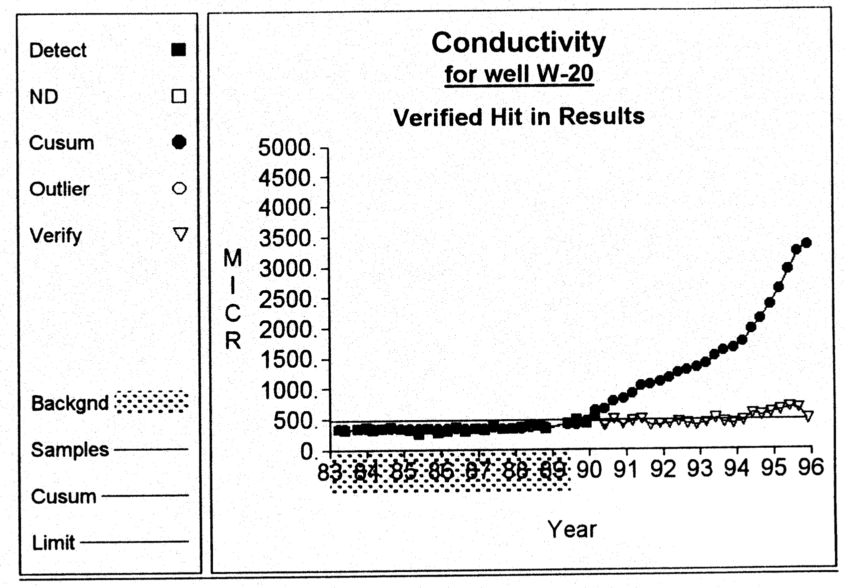

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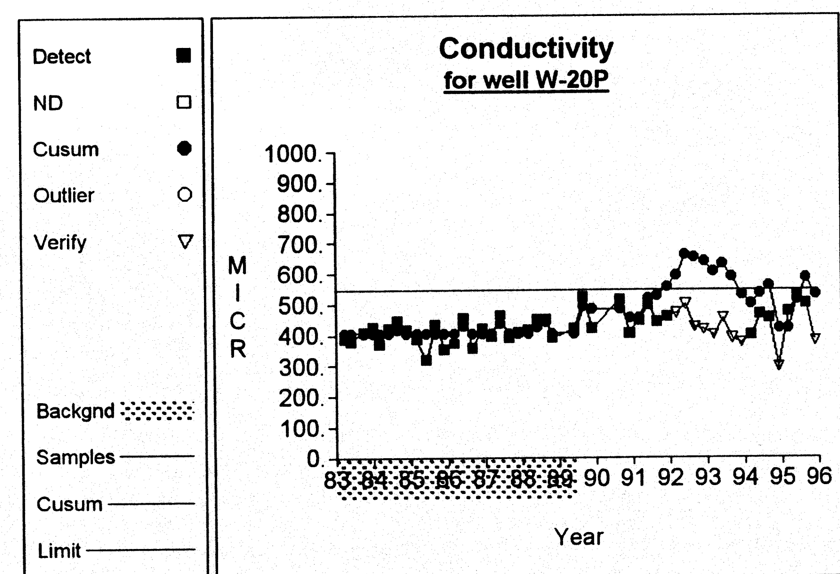

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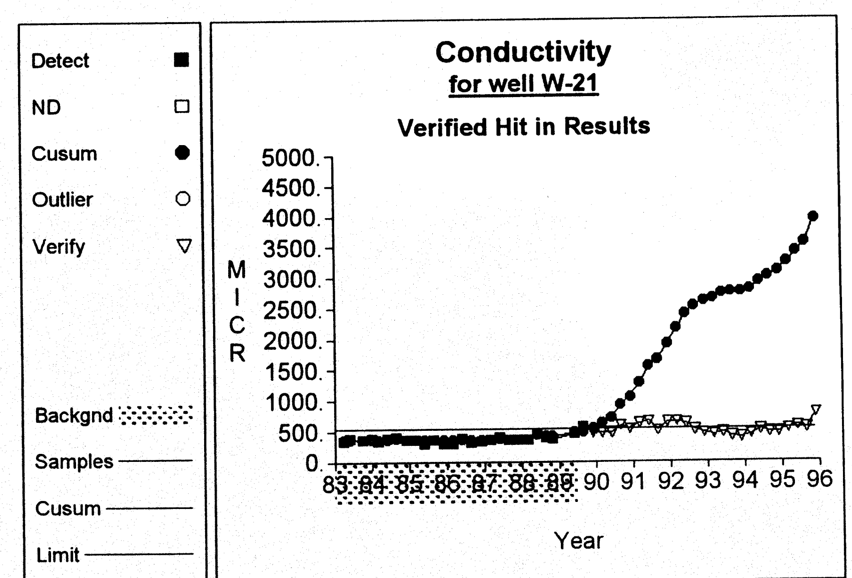

Graph 23

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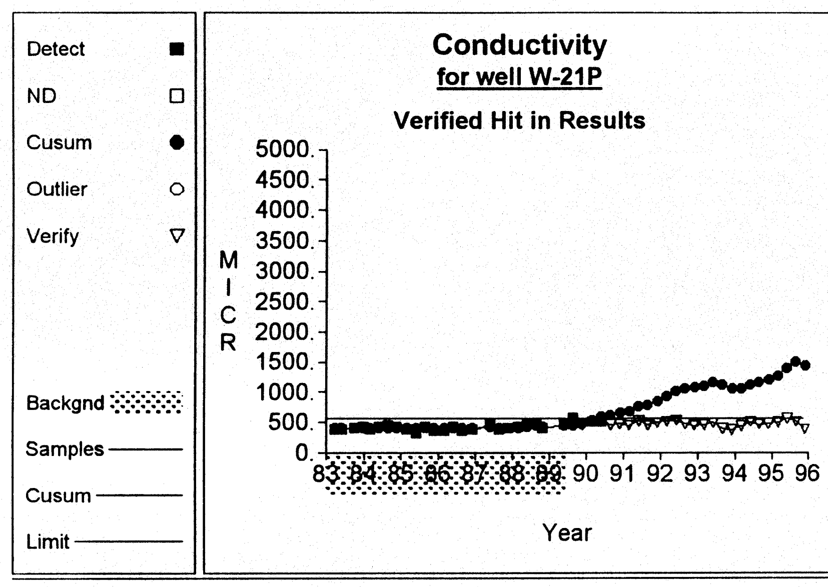

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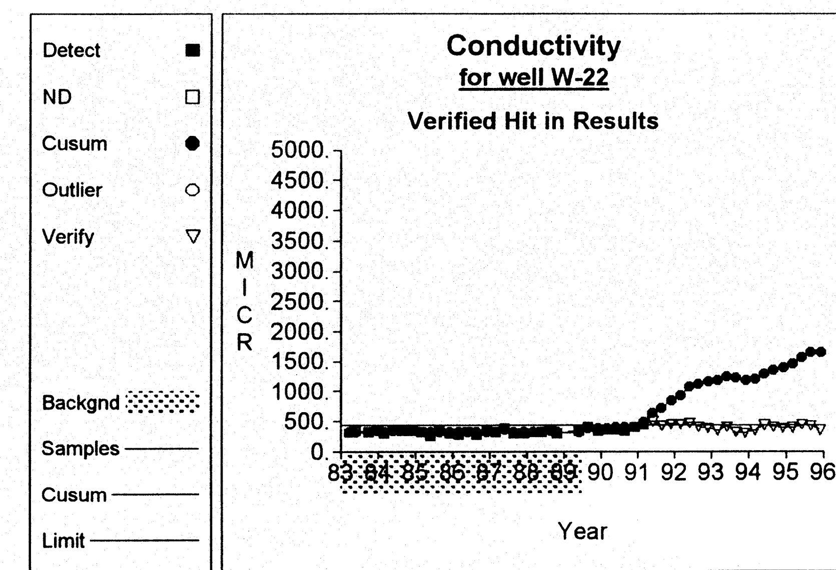

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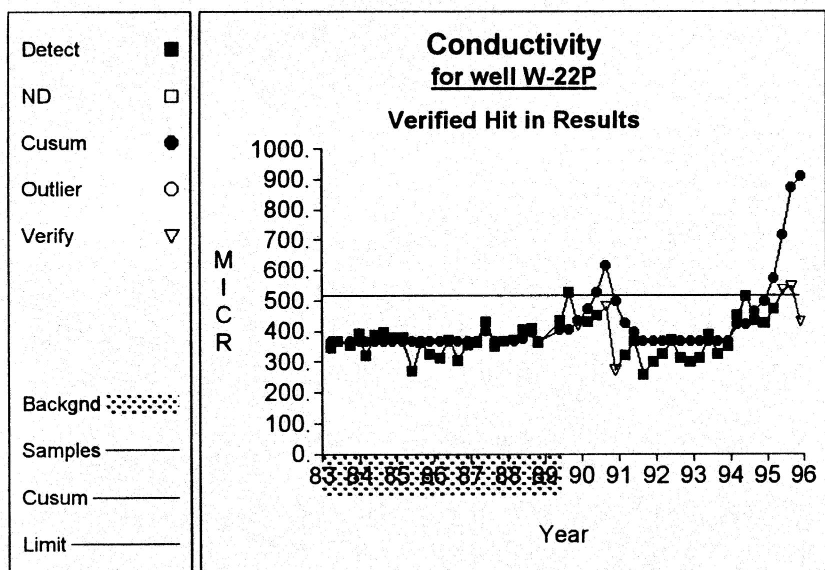

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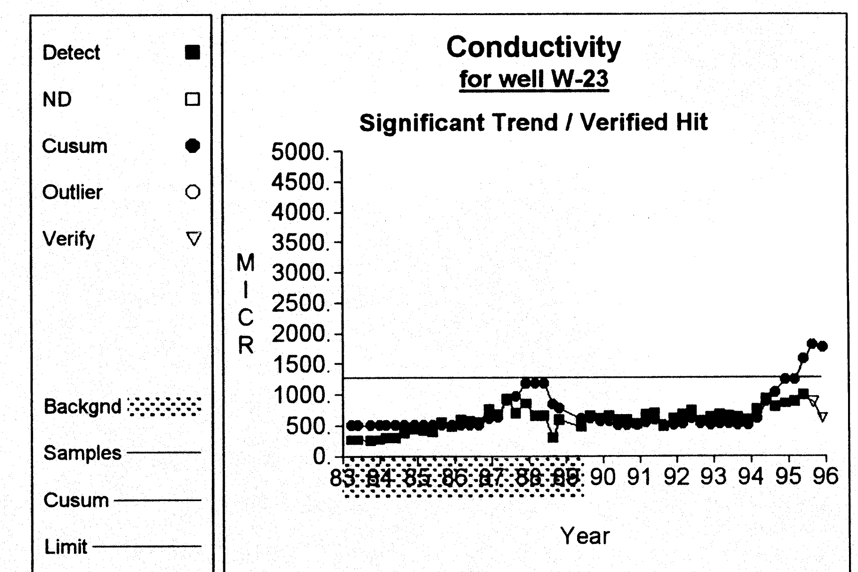

Graph 27

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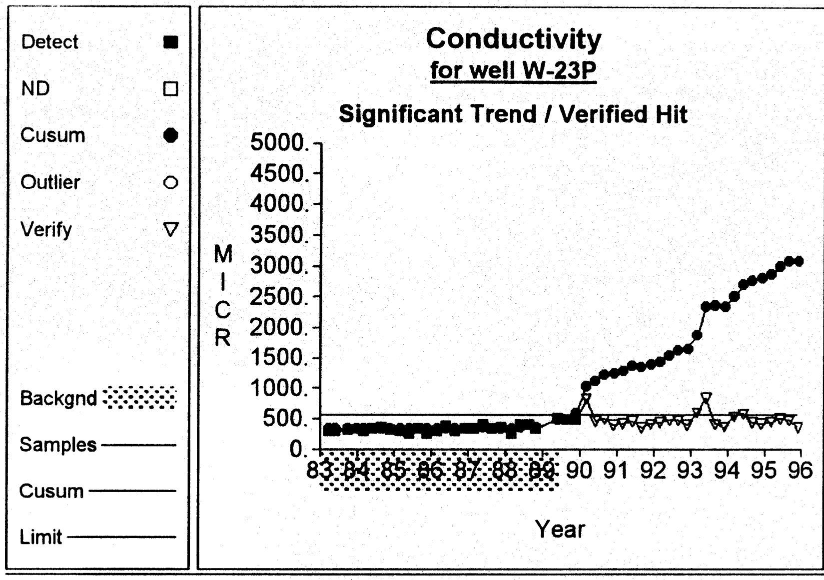

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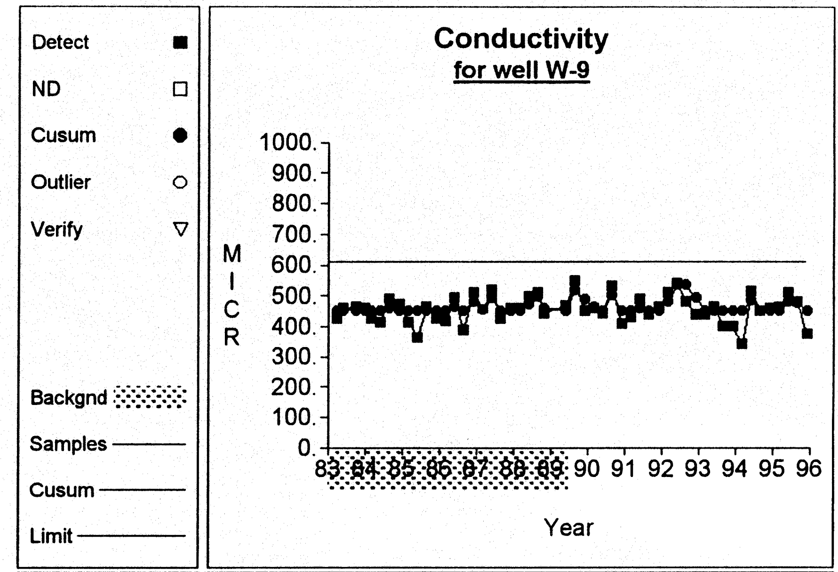

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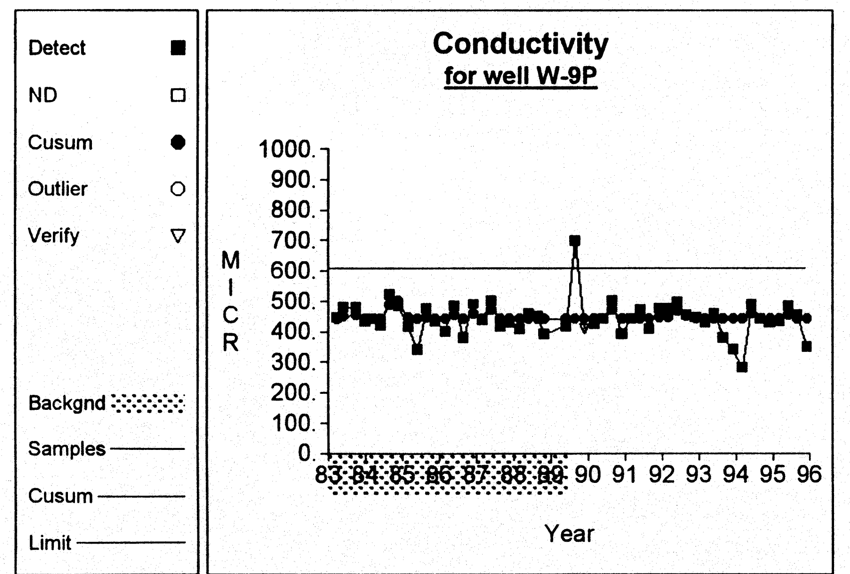

Graph 30

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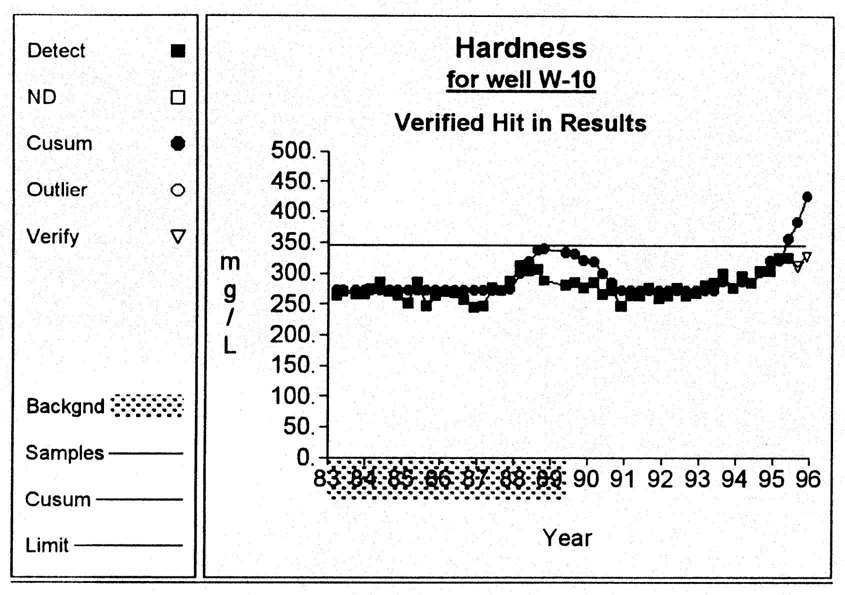
2966 Case Study: Intra-Well Control Charts



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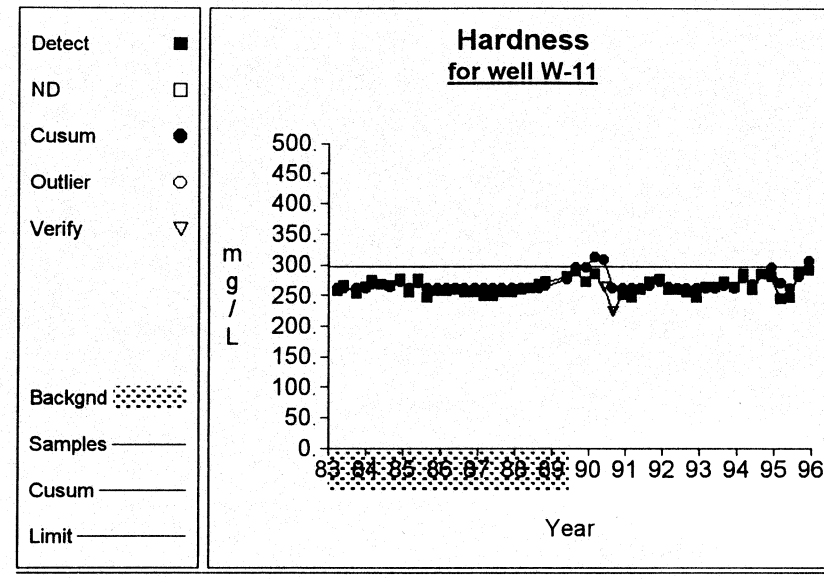

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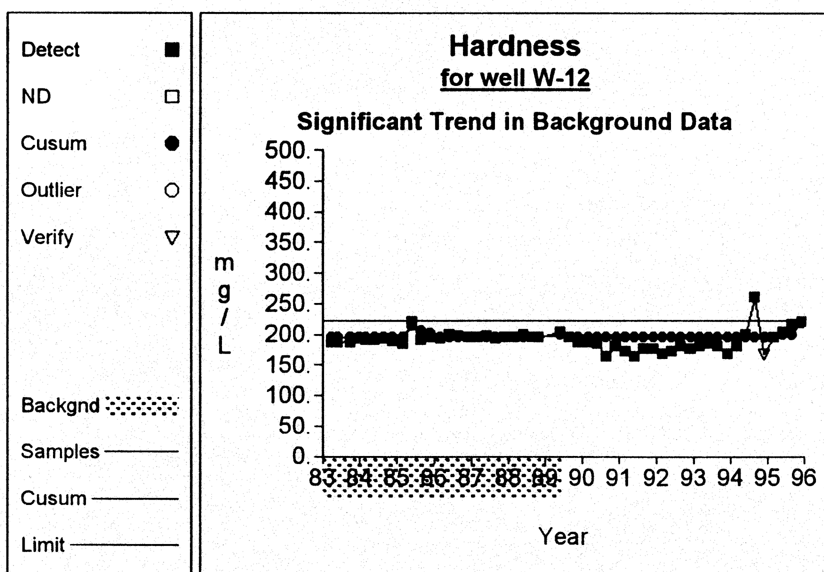

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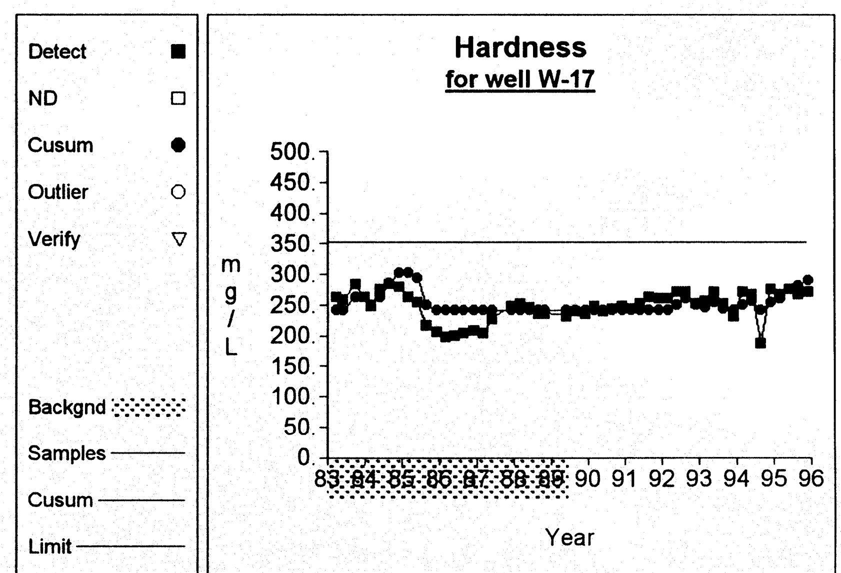

Graph 34

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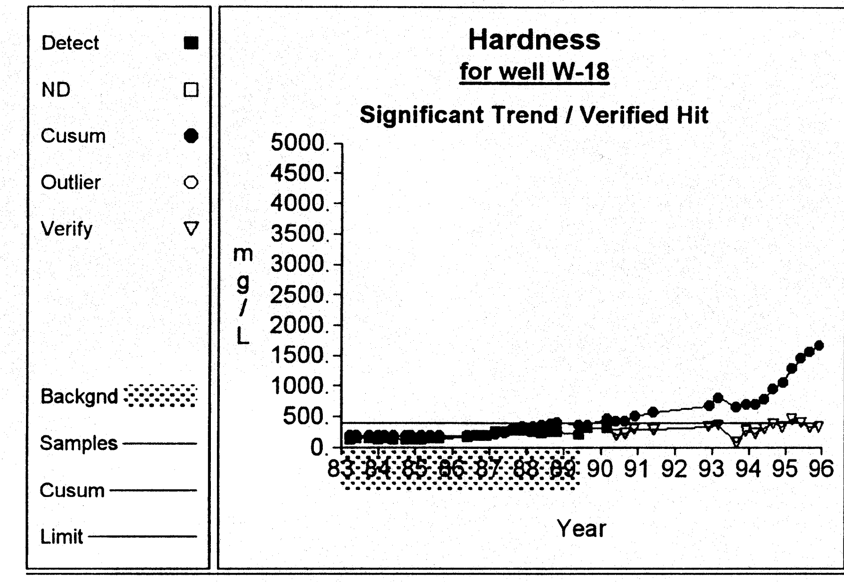
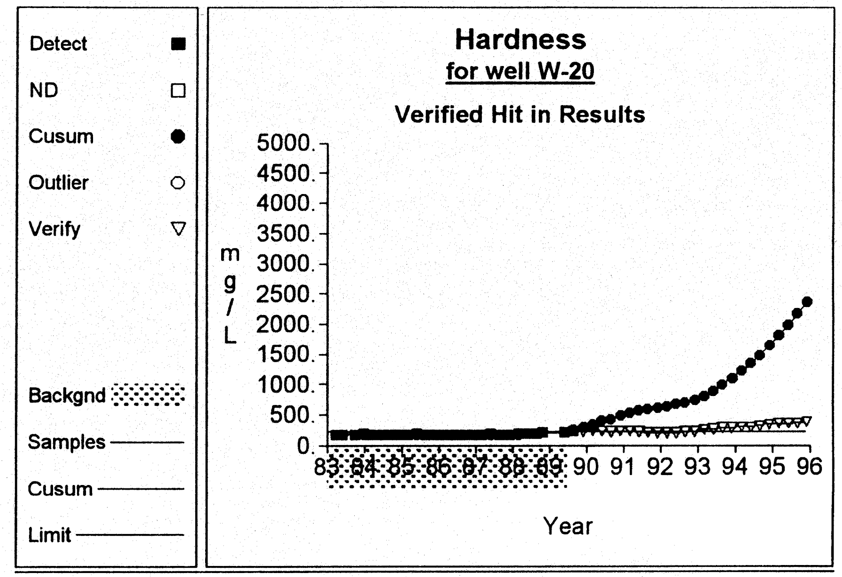


Graph 35



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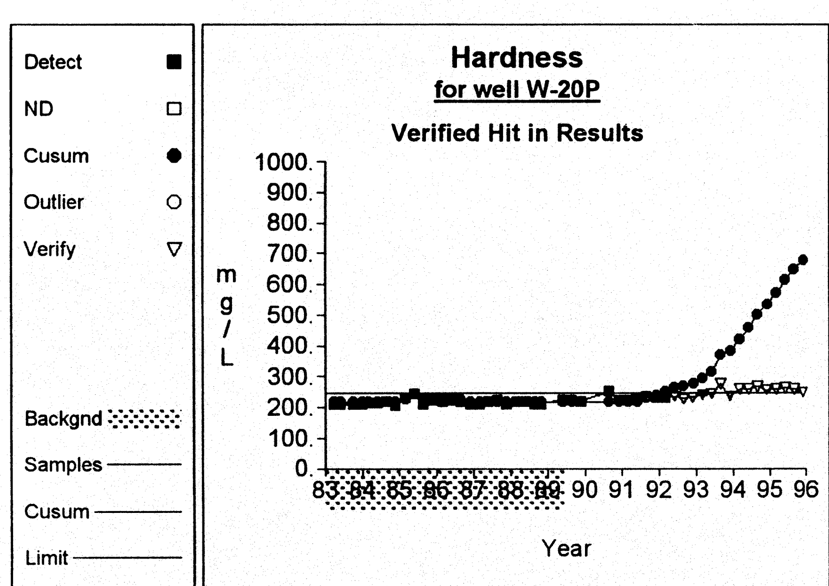

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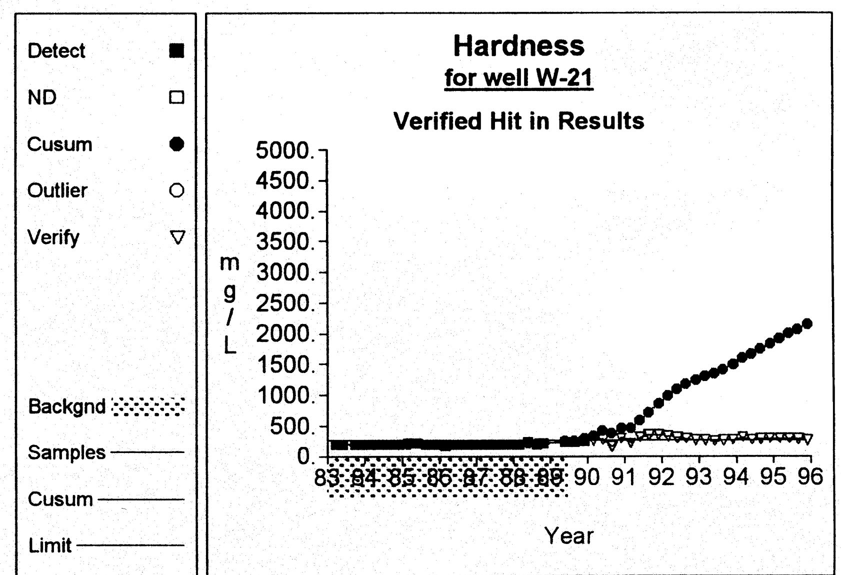

Graph 38

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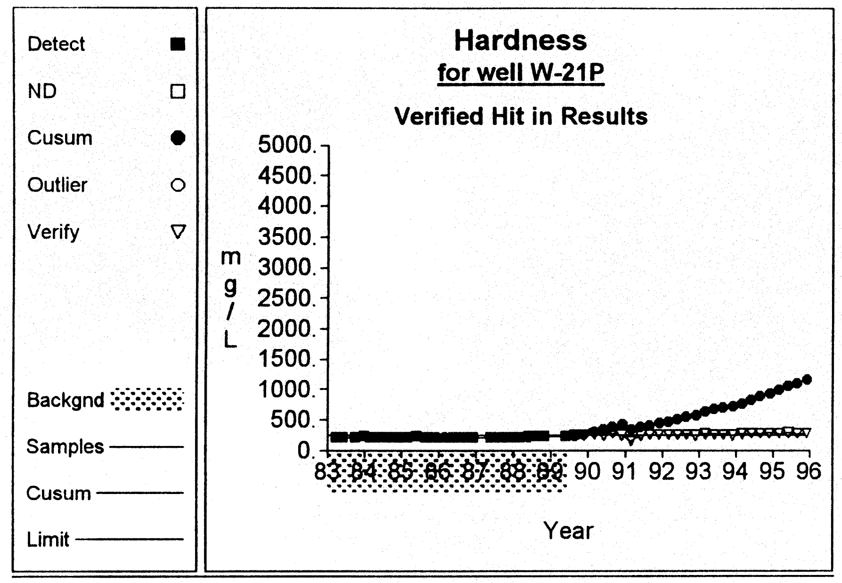
2966 Case Study: Intra-Well Control Charts



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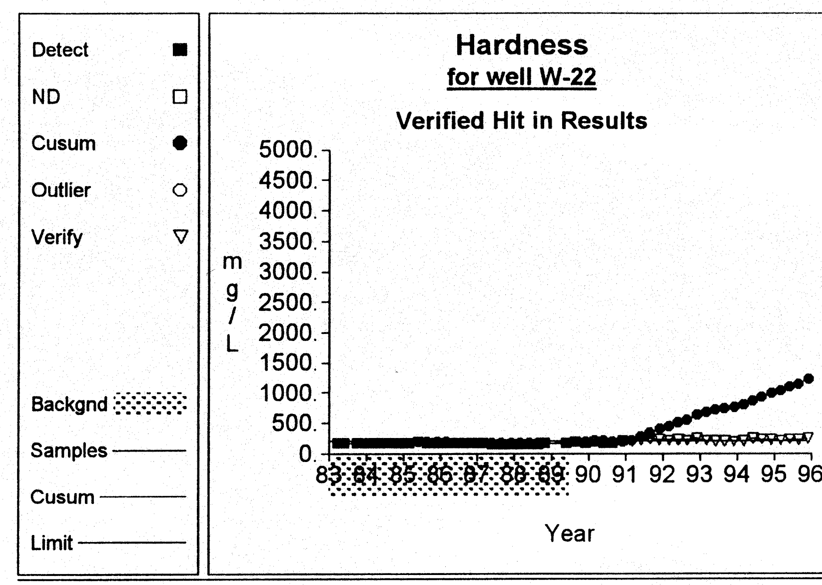

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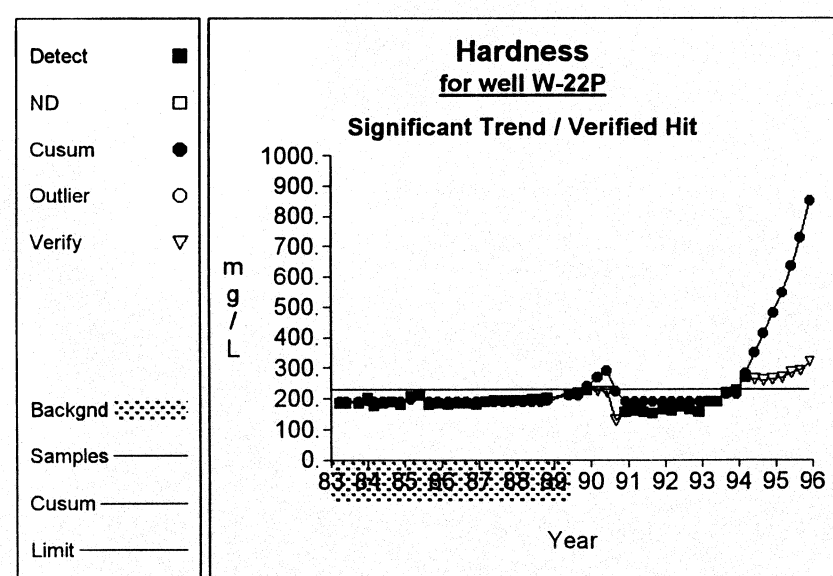

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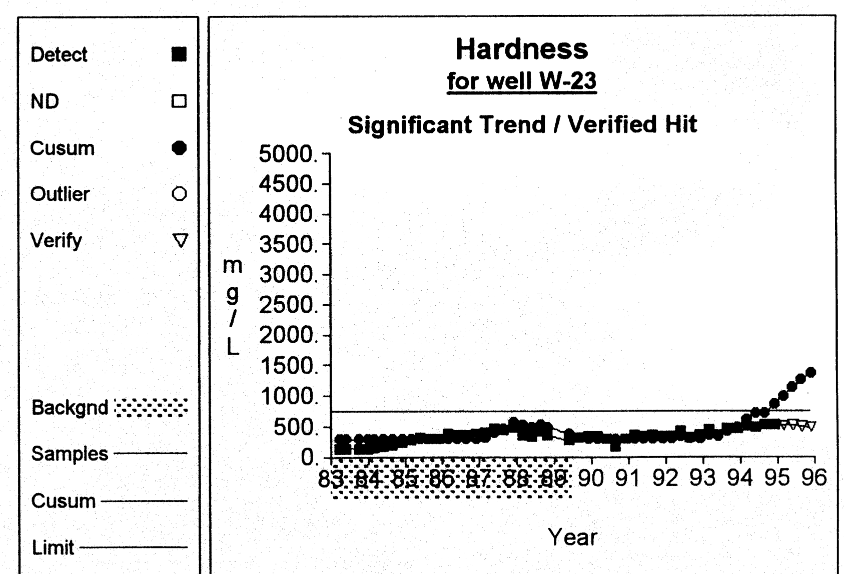

Graph 42

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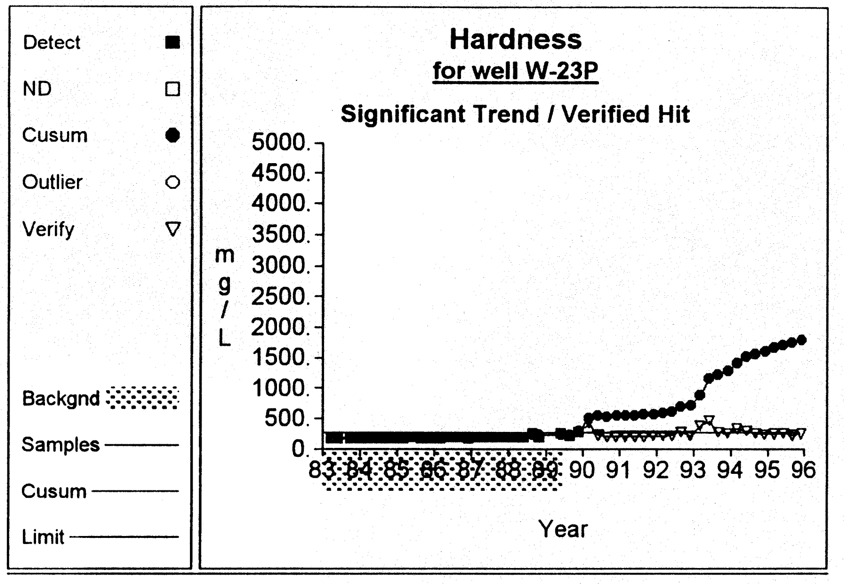

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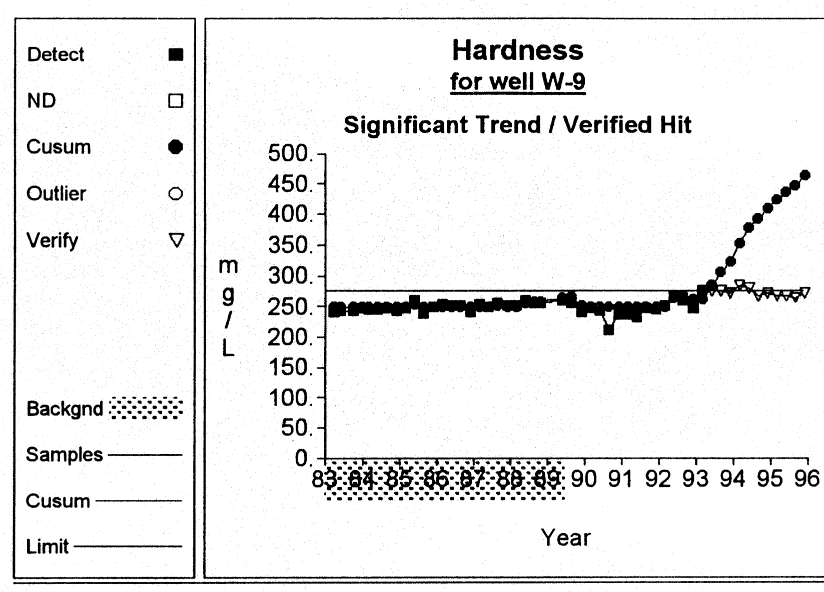

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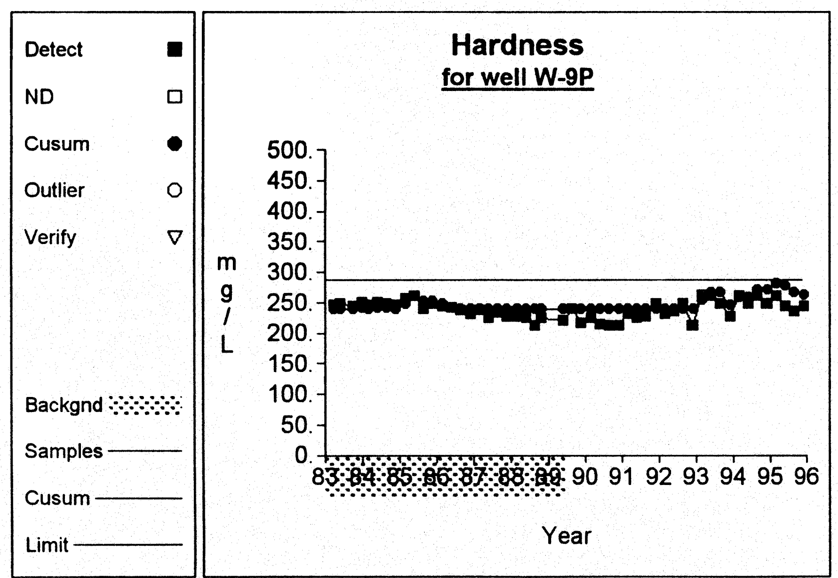

Graph 45

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