Rebuttal Report
Principal Components Analysis of Geochemical Data from the Illinois River Watershed
Northwest Arkansas and Eastern Oklahoma

Prepared for:
Tyson Foods, Inc.
Tyson Poultry, Inc.
Tyson Chicken, Inc.
Cobb-Vantress, Inc.
Cal-Maine Foods, Inc.
Cal-Maine Farms, Inc.
Cargill, Inc.
Cargill Turkey Production, LLC
George's, Inc.
George's Farms, Inc.
Peterson Farms, Inc.
Simmons Foods, Inc.
Willow Brook Farms, Inc.

Prepared by:
Glenn W. Johnson, Ph.D., P.G.
GeoChem Metrix, Inc
9143 S. Peruvian Cir.
Sandy, Utah 84093

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Glenn W. Johnson, Ph.D.

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Appendices

Appendix A PCA Methodology and its Application by Olsen

Appendix B Curriculum Vita of Glenn W. Johnson

1.0 Introduction and Overview

This report provides a critical review and rebuttal to the opinions of Dr. Roger L. Olsen of CDM Companies, Inc. (Olsen, 2008a), as well as a reanalysis of the data upon which his opinions are based. The issue in dispute is the degree to which a series of principal components analysis (PCA) runs conducted by Olsen, support his conclusions with regard to sources of phosphorus, bacteria and other constituents in the Illinois River Watershed in Northwest Arkansas and Eastern Oklahoma. A map of the study area is shown as Figure 1-1.

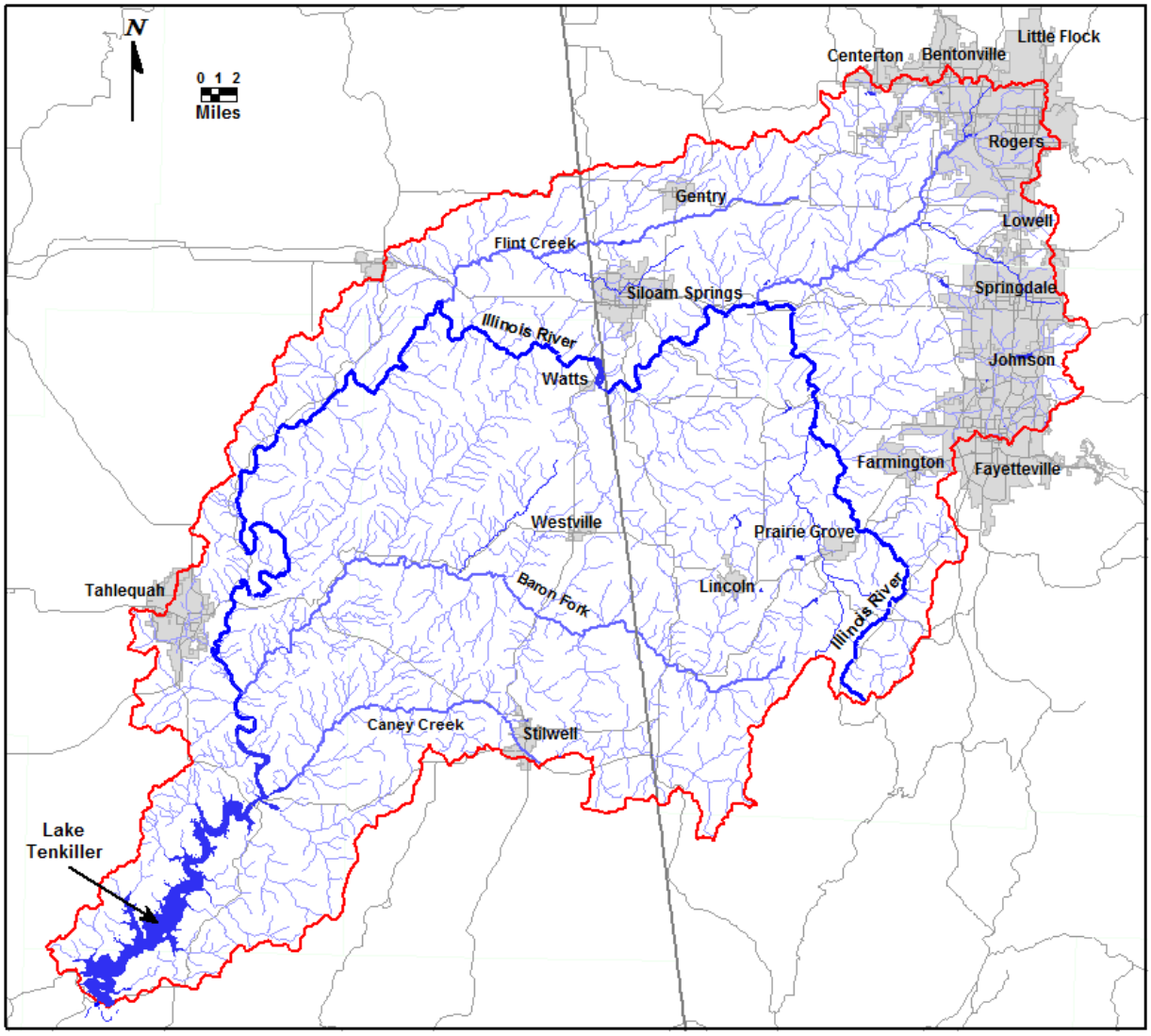

Figure 1-1. Site map showing rivers, creeks, lakes and cities/towns.
Gray shaded areas indicate regions of human population density > 400 people/mi^2, based on ESRI (2006) data.

Olsen's primary opinion based on his PCA, is summarized at the beginning of his report, in the following quote:

> *"Principal components analysis (PCA) identified two major sources of contamination in the IRW: poultry waste disposal and WWTP discharges. Poultry waste is by far the dominant contamination source in the IRW when compared to other sources. Cattle waste contamination was unique from both poultry waste and WWTP effluent, and was identified in some samples with documented cattle manure contamination. However, chemical contamination from cattle waste is not dominant in the basin and only represents a minor source. In the PCA, the chemical and bacterial composition of poultry waste creates a distinct chemical signature that contains both phosphorous and bacteria."*[1]

Olsen supports his application of PCA to IRW data sets by citing a number of papers in the literature where PCA and related methods were applied to environmental chemical data. There are indeed, many PCA applications in the literature. I have published such papers myself.[2] Olsen has not.[3] I have also served as a peer-reviewer for PCA case-study papers submitted to a number of journals.[4] There are numerous pitfalls for the unwary and/or inexperienced PCA practitioner. The mere existence of the literature cited by Olsen does not validate his work, nor does it give him license to err in PCA implementation, to misinterpret the results or to conceal lines of evidence that contradict his opinion. In this report, I will show that Olsen did all of this, and that his PCA does not identify sources of contamination in the IRW. Rather, it reflects the degree to which a small handful of chemicals exhibit a preference to be in solution, or to be associated with the particles in the suspended solids phase.

1.1 Qualifications

The conclusions and opinions in this report are based on my professional experience and education, and my opinions are supported to a reasonable degree of scientific certainty. My expertise is in the area of environmental forensics, with a particular focus on the application of multivariate statistical methods (including PCA) to environmental geochemical data. I received my M.S. in Geology at the University of Delaware in 1988 and my thesis focused on multivariate statistical analysis applied to geological data. I spent seven years in environmental consulting with Roux Associates, Inc. (West Deptford, New Jersey) and McLaren/Hart Environmental Engineering, Corp (Philadelphia, PA). During that time, I worked on a number of environmental contamination projects under a variety of regulatory authorities, including CERCLA, RCRA and a number of State regulatory authorities. I received my Ph.D. in Geological Sciences from the University of South Carolina in 1997, and my dissertation concerned development and application of a PCA based receptor modeling method to environmental geochemical data. Since 1995, I have been a research faculty member at the Energy & Geoscience Institute (EGI), Department of Civil and Environmental Engineering at the University of Utah. My current position is Research Associate Professor. My research at EGI focuses on development and deployment of multivariate statistical methods in geology, environmental chemistry, and environmental forensics. My environmental forensics work has focused on sources, fate and

[1] Olsen (2008a). p. 1-2. Bullet 3.
[2] Johnson, et al., 2007; Magar, et al., 2005; DeCaprio, et al., 2005; Johnson and Ehrlich, 2002; Johnson, 2002; Johnson, et al., 2000; Jarman, et al., 1997; Dore, et al., 1996; Ehrlich, et al., 1994.
[3] See Olsen 9/11/08 Deposition. p. 306. Lines 2-8.
[4] See Johnson CV: Appendix B, p. 14.

alteration of contaminants in soil, sediment, water and biota. I am the President and Chief Scientist of GeoChem Metrix, Inc. in Sandy, Utah - a service firm that specializes in analysis of chemical data and environmental forensics, and it is under that affiliation that this work has been performed.

I have spent a good portion of my career focusing on the development and deployment of PCA-based methods in environmental geochemistry and environmental forensics. I have published methodological papers/tutorials on the subject, as well as case-study/application papers. I have taught short courses on multivariate methods (including PCA) for the International Society of Environmental Forensics, the Association of Environmental Health and Soils, and the Society of Environmental Toxicologists and Chemists.

My curriculum vita is included as Appendix B of this report. My CV includes all of my publications as well as a summary of testimony provided in other cases. My billing rate for work conducted in this matter is $175/hour for data analysis and report preparation, and $225/hour for deposition and trial testimony

1.2 Data and Information Considered

The focus of my work on this project has been to review and critique the multivariate data analyses presented by Roger Olsen in his May 14, 2008 report (Olsen, 2008a). Thus, a primary objective of my work was to first understand exactly what data sets were used and considered by Olsen. I identified the following data sets produced by Olsen and/or his CDM colleagues, as summarized below.

The data considered in Olsen's PCA runs are contained within a Microsoft Access database entitled IllinoisMaster.mdb.[5] For use in his PCA, two primary subsets of the database were extracted and saved in the Excel files named: (1) PCA_Main_Database_Water.xls; and (2) PCA_Main_Database_Solids.xls.[6] These files contain approximately 50 data fields. Individual Excel subdatabase spreadsheets were then extracted from these files for use in PCA.[7] These files contained data for nine variables.[8] The PCA reproductions presented in this report start with these subdatabase files. Cowan (2008) addresses the degree to which these files can be recreated from the original Microsoft Access database.

Using these files as his source data, Olsen performed PCA on a number of permutations of the water data that are presented in his report (22 PCA runs – numbered SW1 through SW22) and solids data (8 PCA runs – numbered SD1 through SD8).[9] These individual PCA runs differed by (1) whether solids or water samples were considered; (2) which groups of samples were included in the analyses (i.e. USGS base flow samples, Lake Tenkiller samples, etc.); (3) which analytes (chemical parameters and bacteria) were included in the analyses; and (4) the criteria used for inclusion of samples with missing data.

The numbers of samples and analytes in each PCA run are summarized in Olsen's Table 6.11-7a and 6.11-7b. Individual input matrices and results for each PCA run were provided by Olsen in

[5] Olsen (2008a). pp. 4-1 to 4-2.
[6] Olsen (2008a). p. 6-35.
[7] Olsen (2008a). p. 6-39.
[8] Subdatabase files contained data for the following nine fields: EDA_Group; EDA_Sample; EDA_Location; EDA_Variable; EDA_Value; EDA_ValOp; EDA_UnitsID; EDA_Y; and EDA_X. Olsen (2008a) pp. 6-36 to 6-37.
[9] In addition, there PCAs run in preparation for the February Preliminary Injunction (PI) hearing, and "preliminary" PCAs run after the PI, that were not includes in Olsen's report. See Olsen deposition testimony September 10 and 11, 2008. P. 371-376.

the form of spreadsheets with filenames keyed to the PCA run numbers. For example, for Olsen's primary water PCA run SW3 (573 surface water samples, 26 analytes) the input data matrix was included in Olsen's document production as the file '*Crosstab_Water_0427_SW_3.xls*'. The results (scores, loadings, PC coefficients, eigenvalues, percent variance explained, and rotations) were included in the produced file '*Results_Water_0427_SW_3.xls'*.

The results files contain the digital data used for Olsen's PCA related graphics. These files were useful in evaluating Olsen's PCA, because it allowed plotting of data in alternative ways to that presented by Olsen. For example, Olsen claims to have done a spatial analysis whereby he evaluated the efficacy of his poultry fingerprint criterion by comparison to purported ground-truth data, such as poultry house density data.[10] This was based on his opinion that poultry house density is a surrogate for poultry waste land applications.[11] Elsewhere in his report, Olsen presents a map of poultry house density data, but curiously, he never shows PCA results plotted over that basemap. As Olsen's poultry house data was produced as GIS shapefiles, it was relatively easy to re-plot Olsen's PCA results on his poultry-house density basemap.

The data described above were produced by Olsen in Excel, SYSTAT and Microsoft Access, and GIS (shapefile) formats. In addition I have reviewed Olsen's correspondence and data provided in his considered materials, two errata submitted by Olsen (dated July 25, 2008 and September 24, 2008), his testimony in connection with the Preliminary Injunction ("PI" - February 2, 2008 deposition testimony; February 21-22 hearing testimony), and his September 2008 deposition testimony. I have also considered scientific literature that I have acquired in my experience, and I visited the Illinois River watershed on July 16, 2008.

1.3 Opinions

My primary opinions are summarized below. The bases of these opinions are expanded upon throughout the remainder of the main body of this report and Appendix A.

- **Fallacy of the "Unique Poultry Waste Signature."** Olsen's PCA cannot differentiate between poultry and other sources in the IRW. Olsen's sampling included collection of a few samples designed to characterize sources other than poultry (e.g. cattle and waste-water treatment plants), but his PCA cannot distinguish between these source categories. In addition, there are multiple other sources not considered by Olsen at all (spray irrigation, sludge application, biosolids application, nursery runoff, golf courses, wildlife, swine lagoons, septic systems, runoff from dirt roads, and commercial fertilizer application).[12]
- **Errors in Assumptions of the PCA Method**. Olsen made fundamental errors related to basic assumptions of the PCA method. The most consequential of these were (1) his assumption that unique source signatures will be conserved in the environment; and (2) the assumption that a principal component *equals* a source-related fingerprint.[13] These assumptions are addressed in more detail in Appendix A.
- **Errors of PCA Implementation**. Olsen made a number of errors in implementation of PCA: (1) he ignored results of goodness-of-fit diagnostics that suggested that he should retain more than 2 principal components; (2) the data transformations used were not

[10] See Olsen (2008a). pp. 6-34. Steps 12 and 13.
[11] Olsen (2008a). p. 6-30. 4th paragraph.
[12] Olsen Deposition. 9/11/08. pp. 521-534.
[13] Olsen (2008a). p. 6-59. Summary Observations. 1st sentence.

appropriate for this type of analysis; (3) rather than use PC scores calculated and reported by SYSTAT, Olsen chose to calculate PC scores himself, and in the process he did the calculations incorrectly; and (4) he did not evaluate goodness-of-fit on a variable-by-variable basis, so he is apparently unaware that several parameters that he considers diagnostic of his "*unique poultry waste signature*" (bacteria, arsenic, copper, zinc) exhibit a poor fit in his model. These mathematical/methodological problems are addressed in more detail in Appendix A.

- **Data Quality Problems.** There are problems with the quality of this data set, such that it is doubtful that a correctly implemented PCA would have yielded results that would allow differentiation of source fingerprints. Problems include the potential bias introduced by multiple labs using multiple analytical methods, a high incidence of missing data (especially for bacteria), missing data substitution strategies, and sample representativeness problems. The basis of this opinion is addressed primarily within Appendix A of this report, and is also addressed by Cowan (2008).
- **Major Contradictions to Olsen's Interpretations and Opinions**. Even if we ignore the problems of data quality, assumptions, and implementation, and accept Olsen's PCA results at face value, a detailed review of Olsen's interpretations reveals major contradictions. Olsen was aware of many of these, but presented only examples that supported his opinion. In one instance, Olsen changed the representation of results on a map, such that his PCA results appear to support his interpretation. In so doing, he never disclosed that subjective decision to the reader.
- **Failure to Recognize Influence of Total Concentration and Geochemical Partitioning on the PCA**. By assuming from the outset that source signatures control this data set, Olsen completely missed the two primary controls on the surface water and groundwater data sets: (1) total concentration; and (2) how chemicals redistribute in the environment according to their affinity for the dissolved phase versus association with suspended particulate matter. Olsen's PCA cannot be used to infer <u>any</u> source of contamination to the IRW, let alone poultry.

2.0 PCA Summary and Its Application by Olsen

2.1 Principal Components Analysis (PCA) Overview

Olsen conducted a series of principal components analyses (PCA) of water and solids data. The objective of PCA is to reduce the dimensionality of a data set in which there are a large number of interrelated (i.e., correlated) variables, such that similarities and differences between samples may be viewed on a single plot, with minimal loss of information. This dimensionality reduction is achieved by transforming the data to a new set of uncorrelated (i.e. mutually orthogonal) reference variables, which are termed principal components (PCs). The PCs are sorted such that each in turn, accounts for a progressively smaller percentage of variance. If the significant sources of variability can be accounted for by a small number of PCs, then relationships between multivariate samples may be assessed by simple inspection of a 2 or 3-dimensional plot, referred to as a principal components scores plot (*PC scores plot*). An example scores plot is shown below (Figure 2-1).

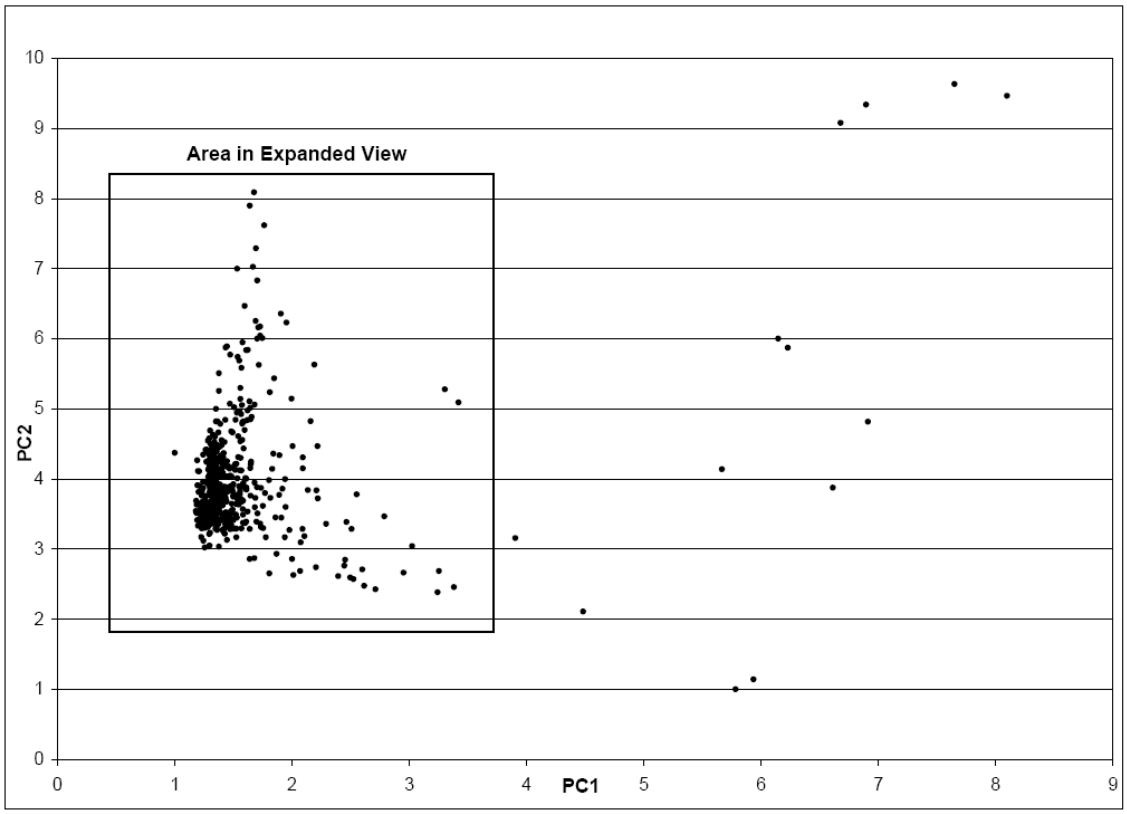

Figure 2-1. Olsen's scores plot for PCA run SW3 (full range view).
This figure is a direct copy of Olsen Figure 6.11-18a.

Figure 2-1 is a direct copy of Olsen's Figure 6.11-18a, and is a scores plot from Olsen's primary PCA run: SW3. Each of the black dots on this plot represents one of the 573 samples in SW3. The main thing to keep in mind in viewing such a plot is that samples that plot close to each other have similar chemical compositions. Samples that plot a great distance from each other have different chemical compositions.

2.2 Olsen's PCA Methodology

The term "PCA" is not a definitive statement of one's methodology. There are numerous data pretreatment methods, transformations, goodness-of-fit diagnostics, and other data analysis options that can be done under the umbrella term "PCA." Therefore, merely saying that one has performed a PCA is insufficient to understand exactly what calculations might have been done. As such, Olsen's actual PCA methods are provided in Appendix A. This includes a detailed discussion of the mathematics of PCA, a discussion of the difference between PCA and factor analysis[14] and a presentation of the calculations actually employed by Olsen. For a more detailed discussion of the general methodology of PCA and related methods, the reader is referred to a book chapter I wrote on the subject.[15]

Olsen performed his PCA using three software tools: Microsoft Excel, SYSTAT and EDAnalyzer. Excel was used to perform transformations, prepare the data for the actual PCA calculation, and calculation of scores on the back-end of the PCA. The PCA itself was done using the commercial statistical software package: SYSTAT (specifically SYSTAT's Factor Analysis module). In addition, Olsen used an in-house, proprietary software program ('EDAnalyzer') which is an Excel Add-In that reportedly serves as an interface to control graphical output and the various inputs/outputs between Excel and SYSTAT. EDAnalyzer was developed by CDM, and was used to do exploratory analysis, set up instructions for Excel, and set desired parameters for subsequent PCA of the data.[16]

2.2.1 Results Presented by Olsen

PCA results were provided in the form of data files as described in Section 1.2. Olsen presented these results graphically in a number of formats as follows:

- **Scree Plots**. These plots show the percentage of variance (a function of eigenvalues) associated with each principal component. The percent variance is plotted as a ski-slope shaped curve/line graph (e.g. Olsen Figures 6.11-1, 6.11-3, 6.11-5, 6.11-7 and 6.11-9). Data for these graphs are included in results spreadsheets under the row heading "Percent of Total Variance Explained."
- **Percent Variance Bar Graphs**. These bar graphs show the same information as a scree plot, but the data is plotted alternatively as a bar graph, rather than a line graph (e.g. Olsen Figures 6.11-2, 6.11-4, 6.11-6 and 6.11-8).
- **Loadings Bar Graphs.** These plots graphically illustrate the principal components loadings, which are correlation coefficients of the principal components with respect to individual chemicals included in the analysis (Olsen Figures 6.11-10, 6.11-12, 6.11-14a, 6.11-14b, 6.11-16, 6.11-18).
- **PC Coefficients Bar Graphs.** Principal component coefficients are equal to the loadings divided by the corresponding eigenvalues. Visually they should look identical to the loadings bar graphs, the only difference being that scaling by eigenvalues changes the scale of the y-axis.
- **Scores Plots.** Scores values are included in each results spreadsheet, and were used to plot principal components scores plots (Olsen Figures 6.11-18a-e, 6.11-19a-d, 6.11-20a-f, 6.11-21a-d, 6.11-22a-d, and 6.11-25). One of Olsen's scores plots (from his PCA run SW3) is presented above as Figure 2-1.

[14] Olsen maintains that he is doing *principal components analysis*, not *factor analysis*. The distinction between these (and which one Olsen used) was a point of contention during the PI process. As such, Appendix A addresses the distinction between the two, as well as discussion of the reasons for the stigma associated with '*factor analysis*.'

[15] Johnson, et al. (2007).

[16] Olsen (2008a) p. 6-36; p. 6-40. Deposition Testimony (9/11/08). p. 308-313.

- **Scores Maps.** One of Olsen's most consequential interpretations is that principal component 1 (PC1) is equivalent to "*poultry waste*."[17] This is an entirely subjective and unsupportable conclusion that will be addressed in detail elsewhere in his report. Be that as it may, given that interpretation, Olsen established a criterion whereby samples with PC1 > 1.3 were considered to be '*poultry waste impacted*' and he presented maps whereby samples above this threshold are shown as red-shaded circles. Samples with PC1 scores < 1.3 are shaded green. These maps are referred to within my report as Olsen's "red-dot / green-dot maps."

In addition to the graphics summarized above, the results of Olsen's PCA runs (scores, loadings, PC coefficients, eigenvalues, percent variance explained, and rotations) were provided digitally in a series of Excel files, the names of which are keyed to the PCA run number (e.g. SW3 results are in file '*Results_Water_0427_SW_3.xls'*. The results files contain the digital data used for most of the PCA related graphics listed above. The PC scores for each of Olsen's four major PCA runs were also included in Appendix F of his report.

2.2.2 Methodological Problems

On pages 6-32 through 6-66 of his report, Olsen describes his PCA methods (data management practices, preparation steps, data preprocessing options, calculations, back-calculations, and interpretations). To check these described methods I attempted to reproduce Olsen's primary PCA run (SW3) using the normalizations and transformations that he indicated. The method descriptions in Olsen's report were ultimately insufficient to reproduce his analyses. I was able to fill in these gaps by trial and error, by matching matrices to the results reported in Olsen's production material. To the extent that I found errors or gaps in his method descriptions, I have clarified what Olsen actually did in Appendix A. In so doing, I identified a number of key errors and concerns with respect to Olsen's assumptions, the quality of his data, his PCA implementation, and its general application to this environmental chemical data set. These problems are summarized below, and are outlined in detail in Appendix A.

2.2.2.1 Faulty Assumptions

Olsen's PCA carries with it, two basic assumptions that are fundamentally wrong.

- Reification of Factors. *Reification* is a term that refers to the assumption that principal components or factors are "things" that can be *equated* with physical or chemical phenomena. They are not. Rather, principal components are abstract sets of coordinates that allow us to plot data on simple two or three dimensional graphs. But Olsen consistently interprets PC1 as "*poultry waste*" and PC2 as "*waste water treatment plant effluent.*"[18] *Reification* of principal components and factors has been criticized in the literature for more than 25 years. (See Appendix A: Sections A1.2, A1.3; A1.4.2, A2.5, A2.5.1).
- *A priori* Assumption of a Source-Driven System. PCA and related methods have been successfully used in the literature to identify chemical patterns related to source. But source patterns do not always drive a PCA. What does drive is systematic variability, regardless of where it comes from. PCA can just as easily reflect alteration processes or even systematic error or bias. It depends on the data set being studied. But Olsen never discusses or explores his PCA interpretation in any context other than sources. Therefore, his interpretation carries the implicit assumption that differences in chemical patterns in

[17] Olsen (2008a). p. 6-60. Also see Figure 6.11-18c.
[18] Olsen (2008a). p. 6-59. Summary Observations. 1st sentence.

the IRW are due to differences in sources, and only sources. But Olsen has acknowledged that some chemicals used in his PCA (e.g. sodium) are preferentially found in the dissolved fraction of water[19] and that others (e.g. iron and aluminum) are preferentially associated with suspended sediment in water.[20] When Olsen's PCA is evaluated in context of preferential affinity of these analytes, his so called "*poultry signature*" is actually related to nothing more than suspended particulate matter in a sample. This issue is explored further in Section 4.2.

2.2.2.2 Data Concerns

There are numerous problems with the data set analyzed by Olsen using PCA, such that it is doubtful that a correctly implemented PCA would yield results that would allow inference of source fingerprints with any degree of confidence. These issues are summarized below, and are discussed in detail in Appendix A (Section A2.1). These issues are also addressed in the expert report of Cowan (2008).

- High Incidence of Missing Data. CDM and Lithochimea collected 2,325 individual water samples that were originally considered for use in Olsen's primary PCA run (SW3: see Table 2-1). Only 267 samples (11.5%) had full data records for all 26 variables used in Olsen's PCA run SW3. Olsen got the number of samples in SW3 up to 573 by allowing samples with up to 6 missing data points in the analysis. Of the 26 variables in SW3, bacteria (total coliforms, E. coli, enterococcus, fecal coliform) were the most problematic in terms of missing data. The percentage of missing data for bacteria variables ranged from 28 to 41 percent of the samples (see Appendix A, Section A2.1 and Table 2-1).
- Missing Data Substitution. In order to be able to use samples with up to 6 missing data points, Olsen had to come up with a missing data substitution scheme. The scheme employed was substitution of the mean (average) for all samples in the data set where that variable was not missing. This presents a series problems that discussed in more detail in Appendix A (Section A2.1).
- Multiple Analytical Methods. Phosphorus (P) is one of the primary chemicals of concern in the IRW study. However, the P data in Olsen's data base were run by different labs and by different methods. To the extent that there is a potential bias between these methods (and Olsen acknowledges that there is) this could contribute systematic variability to a PCA (Appendix A: Section A2.1).
- General Data Management Issues. From a database management standpoint, there are problems with the reproducibility of the data going from the Access database into the PCA, as outlined by Cowan (2008).

2.2.2.3 Errors in Calculation and Implementation

Olsen demonstrates a lacks of understanding and/or experience in implementation of PCA. Major mistakes in implementation include:

- Errors in Calculation of Principal Component Scores. While Olsen's software package SYSTAT reports PCA scores, Olsen did not use them. Instead he calculated them himself in Excel. In so doing he failed to correctly back-calculate his data (see Appendix A: Section A2.3).
- Failure to use more sophisticated PCA goodness-of-fit diagnostics. Olsen relied primarily on the percent variance criterion for determining the number of significant principal

[19] Olsen (2008a). p. 3-18. 4th paragraph. Olsen Deposition. 9/10/08. p. 116-117.
[20] Olsen Deposition. 9/10/08. p. 77.

components, and as a result his analysis focuses primarily on 2 PC models. In Appendix A, using a graphical variable-by-variable goodness of fit diagnostic method, I show that Olsen's 2 principal component model for surface water exhibits a very poor fit for several variables that he claims are important constituents of his "*unique poultry waste signature"* (arsenic, copper, zinc, total coliforms, E. coli, enterococcus, fecal coliforms). Olsen was aware of this method, but opted not to use it. Olsen was also aware of SYSTAT results indicating up to 5 principal components, but he ignored that information. (Appendix A: Section A2-4).

2.2.2.4 Errors in Interpretation

Olsen's PCA interpretations are not consistent with the purported independent ground-truth information (poultry-house density data) presented in his report. As a result, what Olsen calls a '*unique poultry-specific biological and chemical signature'* is neither unique nor poultry-specific. Olsen either failed to recognize or failed to disclose information that contradicted his opinion. These issues are discussed in more detail in the summaries of Olsen's major PCA runs (Section 2.3) and in discussion of the major contradictions in Olsen's theory (Section 3.0).

2.2.2.5 Failure to Adequately Characterize Other Sources

In Olsen's SW3 PCA run (surface water samples), collected sample to characterize the signature of potential sources. The vast majority of these were presumed from the outset to reflect the impact of the application of poultry-litter impact (64 edge-of-field samples).[21] Only six samples were collected with the intent of characterizing other potential sources. Two were collected with the intent of characterizing the impact of cattle (surface waters from cow-pastures where poultry-litter had never been applied).[22] Four were collected to characterize waste-water treatment plant samples (WWTP) effluent.[23] Other potential sources in the watershed were never evaluated, sampled or characterized (at least not for the 26 parameters used in Olsen's PCA). In deposition testimony, Olsen acknowledged that he had collected no samples to characterize sludge application, wastewater disposal by spray irrigation, biosolids application, nursery runoff, golf course runoff, wildlife feces, swine lagoon input, septic systems, runoff from dirt roads, or commercial fertilizer applications.[24]

[21] Olsen (2008a). p. 6-6 & Figure 6.4-2a. Olsen Deposition. 9/10/08. pp. 51-52.
[22] Olsen Deposition. 9/10/08. pp. 53. (Lines 1-5).
[23] Olsen (2008a). p. 6-4.
[24] Olsen Deposition. 9/11/08. pp. 521-534.

2.3 Summary of Olsen's Major PCA Runs

Olsen did 22 PCA runs for water, and 7 PCA runs for solids. The results of most of these are never discussed in Olsen's report. His opinions are based primarily on "*four major PCA runs*"[25] designated as such because they are "*the most important to the investigation or project objectives.*"[26] The four major runs cited by Olsen were SW3, SW17, SD1, and SD6. I have added a fifth to that list (SW22) because it forms the basis of Olsen's opinion regarding the impact of cattle in the IRW. These five PCA runs were included in a category Olsen refers to as "*investigative runs,*" implemented for the direct purpose of source identification in the watershed.[27] Most of the other PCA runs fall into a category Olsen calls '*sensitivity runs*' which were implemented to evaluate the effect of different permutations of the database (i.e. number of parameters, missing data cutoff criteria, groups or types of samples included, etc.). Each of Olsen's five major PCA runs are discussed in the remainder of this section of the report, along with a critical review of the opinions that Olsen draws from them.

2.3.1 SW3: Surface Water

SW3 was the PCA run relied upon by Olsen to reach the most consequential opinion of his report: that poultry was "*by far the dominant contamination source*" in surface waters of the IRW.[28] As such, this is the PCA run that I address in greatest detail throughout my report. Table 2-1 shows the total number of samples considered (2,325) as well as the number of sample per group (EDA_Group). Only 573 samples met Olsen's missing data criterion. Even then, some variables had much higher incidence of missing data, especially bacteria (coliform, E. coli, enterococcus, and fecal coliform). Variables missing in more than 10% of the samples are shown in red text. Appendix A (Section A2.1) includes further discussion of the missing data problem and the substitution method used by Olsen.

Olsen performed PCA on this 573 by 26 matrix after implementing a log transformation. Transformations are discussed in Appendix A (Section A2.2). He implemented PCA using the Factor Analysis module within the commercial software package SYSTAT (Section A2.3). Olsen used the SYSTAT-reported eigenvalues, percent variance accounted for, loadings, and coefficients (Section A2.3) but chose to calculate scores himself (outside of SYSTAT – in Excel) and in so doing failed to undo the log transformation (Section A2.3). SYSTAT's criteria indicated the presence of five significant principal components, but Olsen ultimately ignored that information and reports only the results of the first 2 principal components. His justification for a 2 PC model was that it accounted for 56.2 percent of the variance.[29] In Appendix A (Section A2.4) I discuss this decision, and I evaluate the goodness of fit of Olsen's SW3 PCA run using more sophisticated methods. In that discussion, I make it clear that for several key parameters that Olsen considers important parameters in his *unique poultry waste signature*[30] (copper, arsenic, zinc, and four bacteria variables) Olsen's 2 PC model does a poor job of recreating the original data.

The remainder of this section is a summary and discussion of Olsen's interpretation of SW3 results. Bearing in mind the numerous methodological problems discussed in Section 2.2.2, for purposes of this discussion, I take Olsen's PCA results at face value, and summarize his interpretations based on those results.

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[25] Olsen (2008a). p. 6-51. Last paragraph.
[26] Olsen p. 6-50. See also Table at the top of page 6-52.
[27] Olsen (2008a). p. 6-50. Olsen's four major PCA runs and SW22 were also considered 'investigative runs'
[28] Olsen (2008a). p. 1-2.
[29] Olsen (2008a). pp. 6-50 to 6-52. Figure 6.11-1.
[30] Olsen (2008a). p. 1-2 (3rd bullet), and p. 6-27.

Table 2-1. Summary of Olsen PCA Run SW3.

PCA Run SW3 573 Samples 26 Variable = 6 Missing Data Points Allowed Per Sample		Sample Summary		Variable Summary			Transformation Used for PCA
	EDA_Group	Total Number of Water Samples Available in CDM Database, for this Group	Number of Samples that Meet Missing Data Criterion	EDA_Variable	Number of Samples with Data Reported	Percent Missing Data	
SW3	SW - Edge of Field	89	65	AL_T	573	0%	Log10
0427_SW_3	SW - Lake - Tenkiller	533	29	ALKALINITY	565	1%	Log10
	SW - Stream - BFC	960	88	AS_T	569	1%	Log10
Surface Water Only	SW - Stream - Forest	2	0	BA_T	573	0%	Log10
	SW - Stream - HFC	152	20	CA_T	573	0%	Log10
	SW - Stream - High Flow - BFC	55	48	CL	563	2%	Log10
	SW - Stream - High Flow - HFC	240	177	**COLIFORMS**	**412**	**28%**	Log10
	SW - Stream - NA	10	0	CU_T	569	1%	Log10
	SW - Stream - PA - BFC	12	0	**ECOLI**	**340**	**41%**	Log10
	SW - Stream - PA - HFC	22	0	**ENTERO**	**410**	**28%**	Log10
	SW - Stream - Synoptic	24	1	FE_T	573	0%	Log10
	SW - Stream - USGS - BFC	107	60	**FECAL**	**410**	**28%**	Log10
	SW - Stream - USGS - HFC	115	81	K_T	573	0%	Log10
	SW - Stream - WWTP	4	4	MG_T	573	0%	Log10
	Total	**2325**	**573**	MN_T	573	0%	Log10
				NA_T	573	0%	Log10
				NI_T	569	1%	Log10
				NO2_NO3	564	2%	Log10
				P_SOL_REAC	559	2%	Log10
				P_T	571	0%	Log10
				P_TD	572	0%	Log10
				SO4	563	2%	Log10
				TDS	538	6%	Log10
				TKN	**505**	**12%**	Log10
				TOC	551	4%	Log10
				ZN_T	569	1%	Log10

Information from Olsen-produced spreadsheet '*PCA_Water_Runs_Table.xls*' as attachment to 5/9/08 email from Chappell to Olsen.

Olsen began his SW3 interpretation by plotting PC loadings as bar graphs and noting which analytes had the highest loadings. A direct copy of Olsen's Figure 6.11-10 is shown below as Figure 2-2. Pointing to these bar graphs, Olsen reported a similarity between PC1 (left panel of Figure 2-2) and presumed "*poultry-waste impacted water*."[31] That led him to conclude that *"PC1 has been identified as associated with poultry waste."*[32] Olsen follows similar logic with respect to PC2 loadings (right panel of Figure 2-2) and ultimately opined that "*PC2 has been identified as associated with WWTP effluent."*[33]

There are serious flaws in the logic that led to these conclusions. Olsen justifies his interpretation with a poorly reasoned, apples-to-oranges comparison of loadings (presented in abstract units of the PCA: log-transformed, correlation coefficients) to chemical data (in units of concentration). But the problem goes beyond units and stoichiometry. Olsen also makes the fundamental mistake of *reification* – equating a principal component with a *thing* with physical or chemical meaning. Olsen *reifies* or equates PC1 with "*poultry-waste*", and PC2 with WWTP effluent. Reification has been criticized in the literature for more than 25 years. The problems of reification of principal components are discussed in more detail in Appendix A (Sections A1.2, A1.3; A1.4.2, A2.5, A2.5.1).

[31] Olsen (2008a). p. 6-57. 2nd paragraph.
[32] Olsen (2008a). p. 6-57. 3rd paragraph.
[33] Olsen (2008a). p. 6-57. 3rd paragraph.

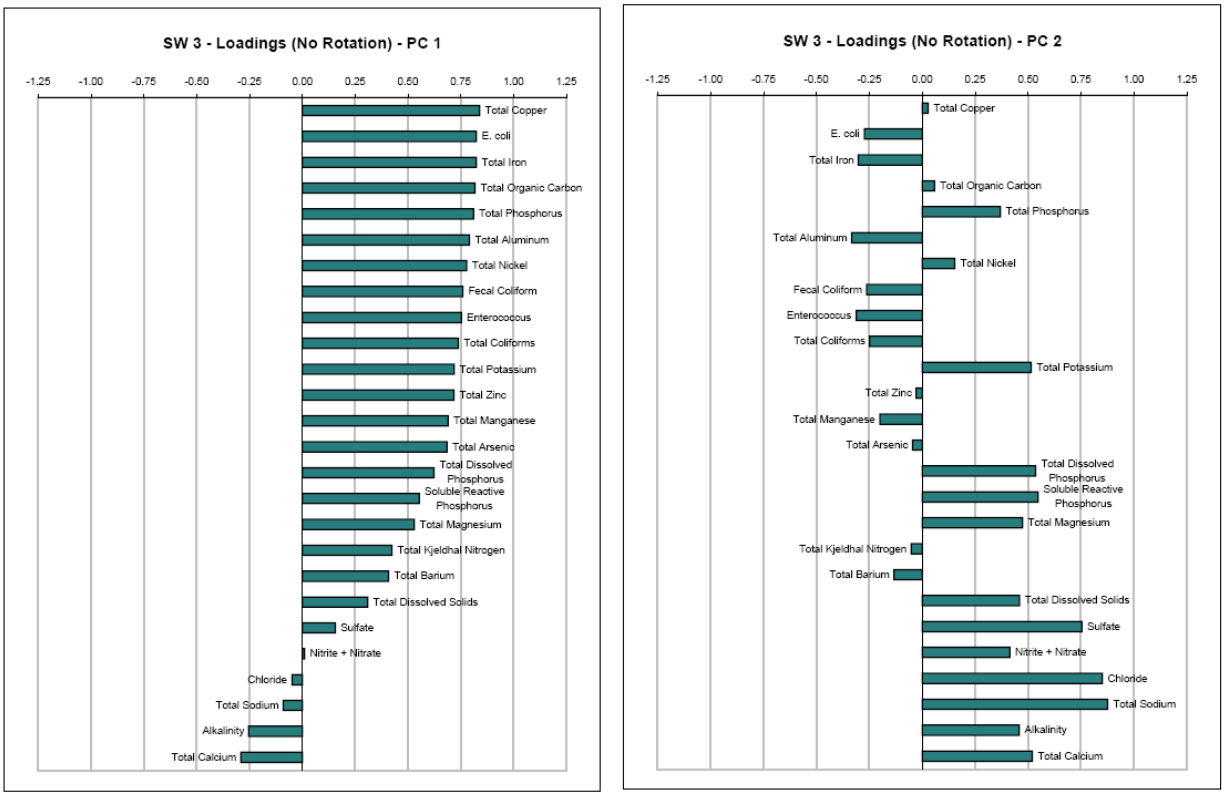


Figure 2-2. Olsen's loadings bar graphs for PCA run SW3.
Direct copy of Figure 6.11-10 of Olsen's Report

Based on Olsen's opinion that PC1 equals poultry and PC2 equals WWTP, he ultimately classified samples in SW3 with respect to their supposed predominant impact. Figure 2-3 is a direct copy of Olsen's Figure 6.11-18c, and shows his interpretation of the limits of dominant impact from his two supposed primary sources: "*Poultry-waste Dominant Impact*" and "*WWTP Dominant Impact*." To the reader unfamiliar with PCA, the red circled regions of Figure 2-3 may be misleading. These circles are not the objective results of the PCA method. They are not determined by SYSTAT or by any mathematical procedure. Rather, they represent a <u>subjective interpretation</u> on Olsen's part.

The limits of the two red ovals (shown graphically on the figure) were also defined numerically by Olsesn, as is seen in the quote below.

> *"The two groups were selected by examining the locations and chemistry/bacterial composition of the individual samples. <u>For the "WWTP dominant impact" group, the PC2 scores were selected to be above a value of **4.7**</u>. As shown on Table 6.11-11, samples below about a score of 4.8 are typically not in locations downgradient of WWTP discharges so cannot be impacted by WWTPs. <u>For the "poultry-waste dominant impact" group, a PC1 score of greater than **1.3** was selected</u>. This is a conservatively high value and could have been set lower to include more samples."*[34]

As is made clear in this quote, Olsen considers any sample exhibiting a PC2 scores greater than 4.7 to be impacted by WWTP effluent, and any sample with a PC1 score greater than 1.3 to be impacted by poultry.

[34] Olsen (2008a). p. 6-59 to 6-60 (emphasis added).

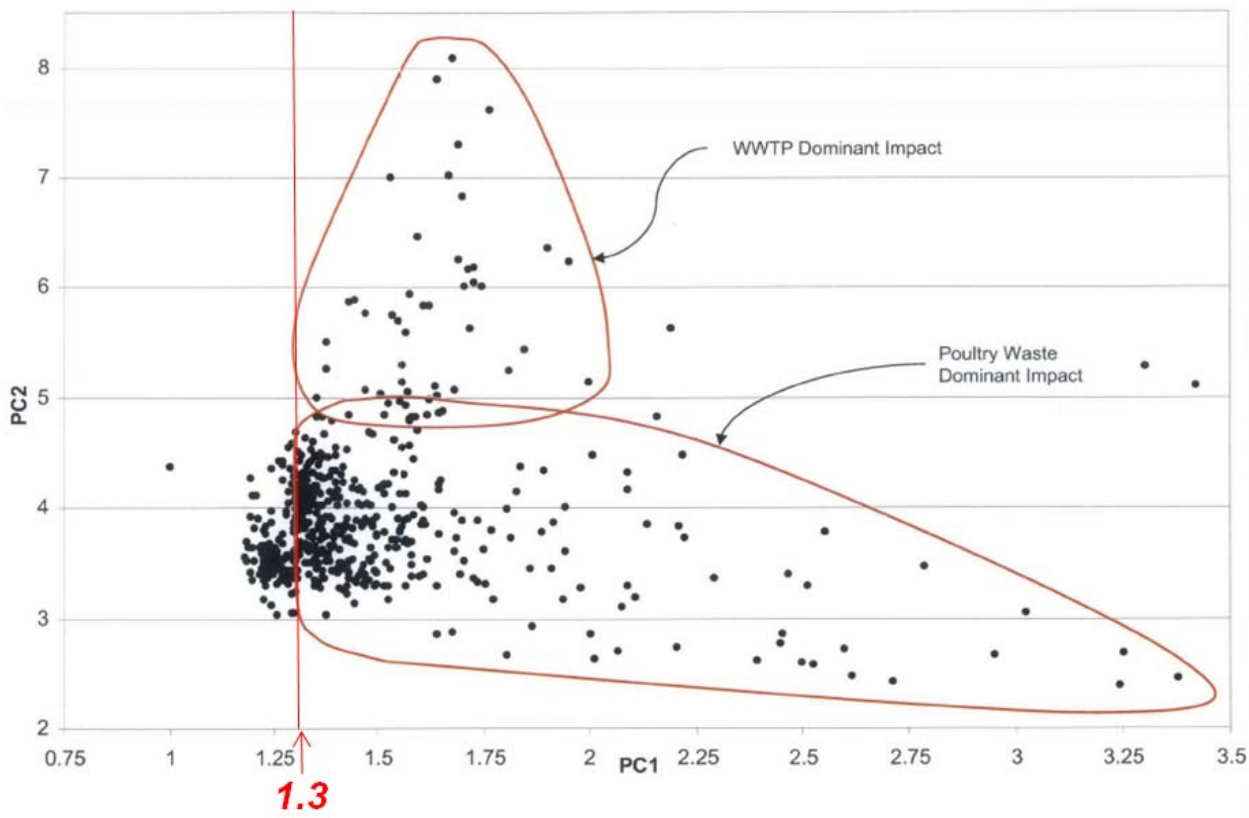


Figure 2-3. Olsen's PCA scores-plot for PCA run SW3 (zoomed in on 'expanded view' area).
This figure is a direct copy reproduction of Olsen Figure 6.11-18c. The red ovals and annotation *"Poultry-Waste Dominant Impact"* are Olsen's. I added the PC1=1.3 line.

Olsen's conclusion of a 1.3 PC1 poultry-impact threshold (highlighted in quote above) is the most consequential decision of his entire PCA. Olsen and his colleagues have repeatedly referred to Olsen's *"poultry signature."* But such a term is not a precise description of a PCA-based criterion. Figure 2-3 clarifies Olsen's actual numerical criterion. When he and other plaintiff experts testified at the Preliminary Injunction with regard to Olsen's "*unique poultry waste signature*" [35] or "*chemical fingerprint*"[36] it is the 1.3 PC1 threshold to which they were referring. A sample that supposedly exhibits Olsen's "*unique poultry waste signature"* is a sample that plots to the right-side of the PC1=1.3 line on Figure 2-3.

This threshold is entirely arbitrary, and Olsen has acknowledged as much. He has testified that there are samples with PC1 scores less than 1.3 that he believes <u>may be</u> impacted by poultry[37] and he has acknowledged samples with PC1 scores greater than 1.3 that he concedes <u>are not</u> impacted by poultry.[38] The arbitrary nature of this threshold discussed in more detail in Appendix A (Section A2.5.2).

Part of the reason that the 1.3 PC1 threshold is arbitrary is that it is not supported by the data Olsen supposedly relied upon to validate the threshold. The basis of Olsen's conclusion of a 1.3 PC1 threshold for poultry, and a 4.7 PC2 threshold for WWTP was his "*spatial analysis.*" That

[35] See PI Hearing Transcript: Olsen at p. 806; Teaf at p. 210; Harwood at p. 672;
[36] See PI Hearing Transcript: Olsen at p. 815;
[37] Olsen Deposition. 9/11/08. p. 330 (Line 19) to 331 (Line 20). See also, quote in Section 2.3.1 of the main report.
[38] Olsen Deposition. 9/10/08. p. 274. (emphasis added).

analysis involved testing his PCA interpretation against purported independent ground-truth information (i.e. data not included in the actual PCA such as poultry house density data and the locations of waste water treatment plants).[39] In support of his poultry impact threshold (PC1>1.3) Olsen presented the following discussion, based on poultry-house density:

> *"The value* [the 1.3 PC1 threshold] *was selected by examining the locations and scores of samples, particularly the scores of reference samples and samples in* ***low poultry house density*** *areas. In summary, the samples with PC1 scores below approximately 1.3 include all samples from reference locations (six total), 9 out of 10 samples from HFS30 (small watershed location with* ***low poultry house density****) and 10 out of 11 samples from HFS28A (small watershed with* ***low poultry house density****). The one sample from HFS30 and the one sample from HFS28A with higher PC1 scores were collected during extreme flow events. Overall 441 of the 573 samples (77%) had PC1 scores higher* [than] *1.3 and show some poultry contamination."*[40]

Note that this discussion addresses only five sampling locations (2 high flow sampling stations in the watershed (HFS28A and HFS30) and 3 base-flow reference stream locations (six samples from three locations) outside the watershed). This constitutes 27 of 573 SW3 samples (<5%) collected from 5 of 175 sample locations (< 3%). Olsen's report makes no mention of samples that contradict his poultry impact threshold, so the clear implication is that this subset of the data is representative of Olsen's spatial analysis a whole. This is not the case, and much of the remainder of this report will focus on the numerous inconsistencies in Olsen's theory, as revealed by the spatial analysis.

The bottom-line illustration of Olsen's interpretation of SW3 with respect to his poultry impact interpretations was his Figure 6.11-23 (reproduced below as Figure 2-4). On that map, a green dot (●) indicates a SW3 surface water sample location with an average PC1 score less than 1.3. A red dot (●) indicates a SW3 surface water sample location with an average PC1 score greater than 1.3. As such red-dots on his figure represent "*poultry impacted*" samples (see legend on Figure 2-4). In deposition testimony, Olsen confirmed this, but included the caveat/qualifier that a red dot in this map indicates only that "*There's some poultry contamination. Nothing about dominance.*"[41] In other words, a sample classified by Olsen as "WWTP dominant" would plot on this map as a red-dot, because all samples in his "*WWTP Dominant Impact*" area exhibit PC1 scores greater than 1.3 (see Figure 2-3).

The 1.3 PC1 threshold and this map then led Olsen to conclude that "*78 percent of the locations sampled in the IRW show some poultry contamination. Locations with PC1 scores higher than 1.3 are shown in red; those with scores less than 1.3 are shown in green."*[42] This is the basis of Olsen's flagship opinion coming out of his PCA: that "*Poultry waste is by far the dominant contamination source in the IRW when compared to other sources."*[43] Clearly, the validity of this opinion is directly dependent on the validity of the 1.3 threshold, which in turn is dependent on the validity of Olsen's spatial analysis. As such, the spatial analysis deserves scrutiny that goes beyond the five sample locations discussed by Olsen in the above quote.

[39] Olsen (2008a). p. 6-34: Steps 12 and 13.
[40] Olsen (2008a). p. 6-59 to 6-60. (emphasis added).
[41] Olsen Deposition (9/11/08). p. 339 (Lines 12-13).
[42] Olsen (2008a). p. 6-60. 2nd paragraph, as corrected by Olsen's errata (Olsen, 2008b – page 7).
[43] Olsen (2008a). p. 1-2. Bullet 3.

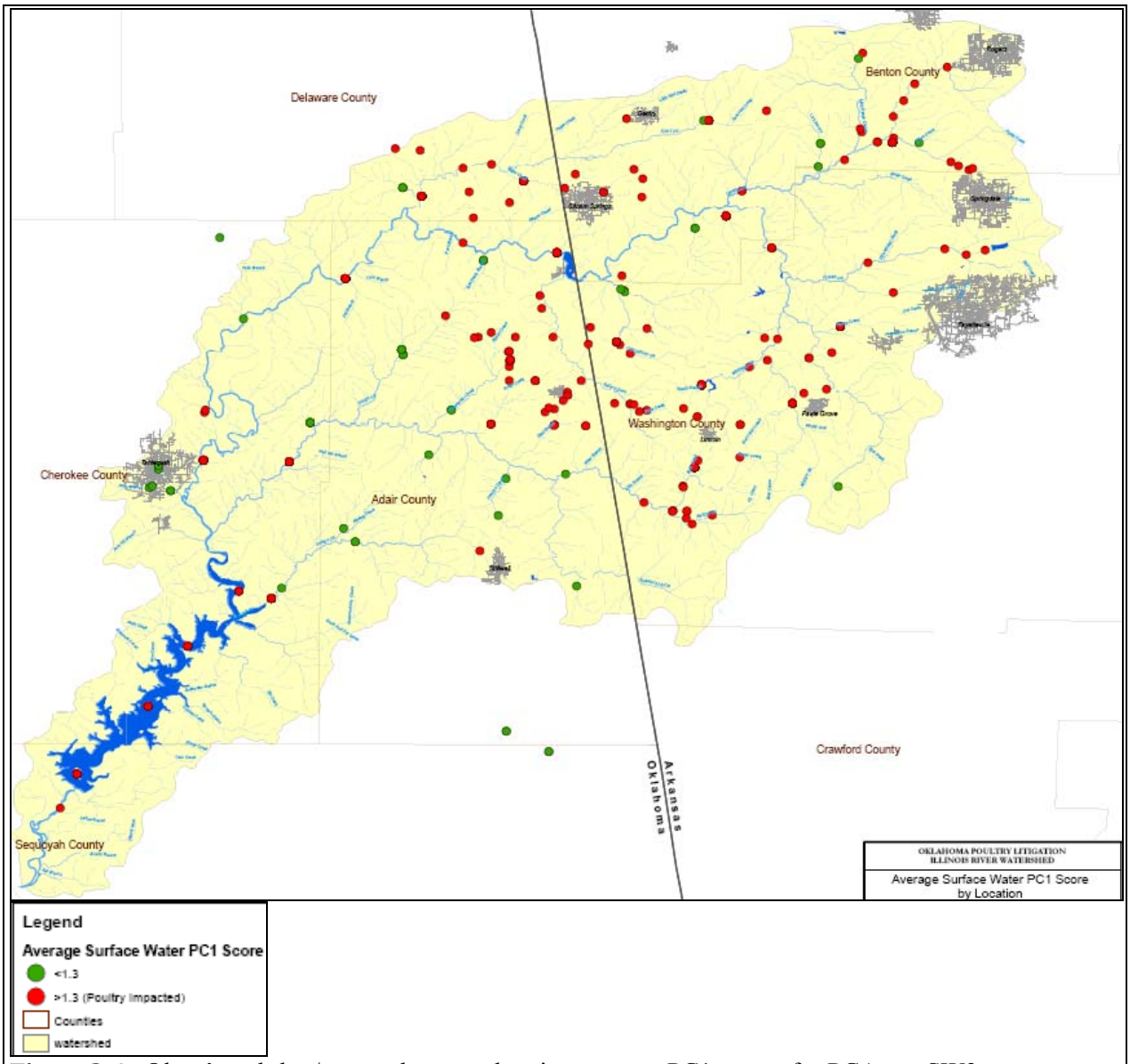


Figure 2-4. Olsen's red-dot / green-dot map showing average PC1 scores for PCA run SW3.
This figure is direct copy of Olsen's Figure 6.11-23. On this map, if multiple samples were collected from a location, the average of all PC1 scores from that location was taken. All locations that exhibit an average PC1 score > 1.3 (using Olsen's PCA run SW3) are shown as red circles (●) and are classified as 'poultry-impacted' or so the legend indicates. Olsen admitted in deposition testimony that this is actually not true. This is discussed in more detail in Sections 3.1 and 3.2.

In Olsen's quote above, he points to data from only two high-flow sampling stations, both of which he claims (1) have average PC1 scores less than 1.3; and (2) are located in low poultry-house density subbasins within the IRW.[44] Figure 2-5 shows Olsen's average PC1 scores for <u>all</u> high-flow samples (including the two cited by his quote above: HFS28A and HFS30). On my map, I have plotted red-dots and green-dots based on Olsen's 1.3 PC1 threshold (just as Olsen did in his Figure 6.11-23 – Figure 2-4 above). However, my map is different from Olsen's Figure 6.11-23 in that (1) I have plotted only high-flow samples, and (2) I used Olsen's poultry house density data (rather than a generic yellow shaded area) as my basemap.

[44] Olsen (2008a). p. 6-60.

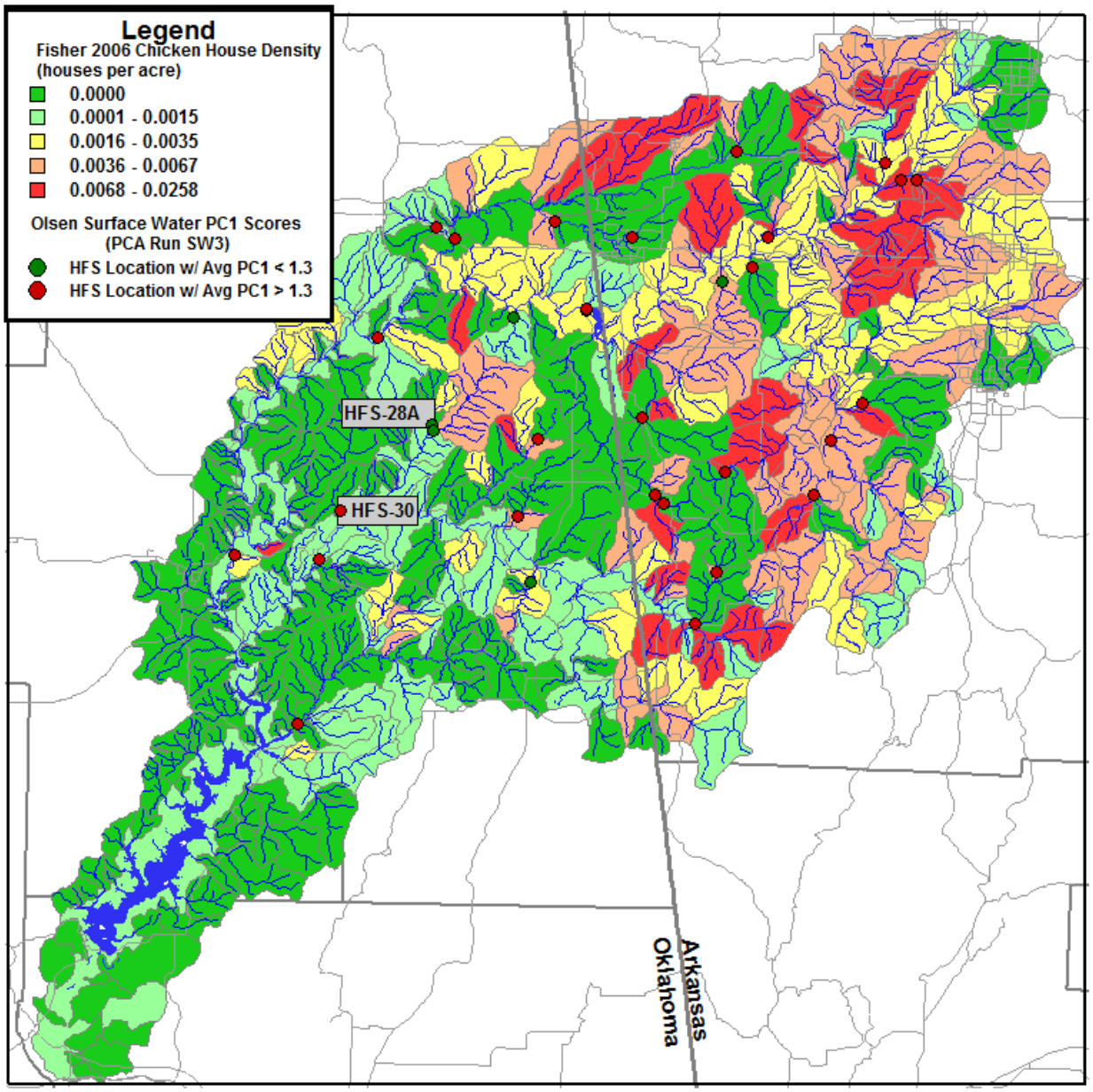


Figure 2-5. PC1 scores map for high-flow sample stations, plotted over Olsen's poultry house density data.

The two high-flow sample stations cited by Olsen in support of his 1.3 PC1 criterion (HFS-28A and HFS-30 - p. 6-60 of his report) are labeled. Poultry house data were produced as GIS shape files by Olsen in his production of materials relied-upon.

Having plotted PC1 scores over the data supposedly relied upon by Olsen for his spatial analysis, there are clearly problems with his interpretation. Both high-flow stations cited by Olsen in the quote above (HFS-28A and HFS-30) are located in low poultry-house density areas (just as Olsen said). HFS-28A plots as a green-dot within a low poultry-house density area (again, just as Olsen indicated). But HFS-30 is shown as a red-dot within a low poultry-house density area (i.e. HFS-30 had an average PC1 score > 1.3). This contradicts Olsen's statement in the quote above, and the HFS-30 data are <u>not</u> consistent with Olsen's assertion of a *conservative* 1.3 PC1 poultry-impact threshold. The seven high flow samples collected at HFS-30 yielded an average

PC1 score greater than 1.3 (1.3022) and by the criteria stated in Olsen's report, should have been shown on his figure as a red-dot, not a green-dot.[45]

The inconsistency in Olsen's spatial analysis is not limited to HFS-30. If we scan across the map above (Figure 2-5) we see many red-dots plotting in green sub-basins. Olsen's spatial analysis discussion in his report never acknowledges such samples that contradict his theory, only the two high-flow stations that supposedly support it. In subsequent deposition testimony, Olsen acknowledged that there were *"a few minor exceptions"* to his 1.3 criterion.[46] Through the course of his September 2008 deposition, Olsen eventually conceded that there were: (1) cow-pasture edge of field samples that had PC1 scores greater than 1.3 (2 locations); (2) cattle impacted springs that had PC1 scores greater than 1.3 (two locations); (3) waste-water treatment plant effluent samples that had PC1 scores > 1.3 (three locations); and (4) samples collected in Tahlequah, Oklahoma (an area of high human population density, but low poultry house density) that had PC1 scores > 1.3 (six samples from five locations). There are also major contradictions to Olsen's theory with regard to base-flow samples. These contradictions to Olsen's poultry impact criteria and his spatial analysis are explored in greater detail in Section 3.0.

2.3.2 SW17: Surface Water Plus Wells, Springs and Geoprobe Samples

PCA run SW17 included the same 573 sample, 26 variable data set used for SW3, plus 126 additional groundwater samples (17 geoprobes, 49 springs and 60 wells – Table 2-2). Geoprobe is a field method that allows collection of shallow groundwater using a direct push method.[47] Well samples represent generally deeper groundwater collected from existing groundwater wells.[48] Springs are surface water features, but were classified by Olsen as 'groundwater' because they are presumably fed, at least to some degree, by groundwater seeps.[49]

The addition of these samples brought the total number in SW17 to 699. The sample types, number of samples, number of variables, missing data criterion, and transformations used for this PCA run are shown on Table 2-2 below. Variables that had ≥10% missing data are shown in red text.

[45] This explains why in deposition testimony, Olsen changed the PC1 threshold from 1.3 (as indicated in his report) to 1.30226 (See Olsen Deposition 9/10/08. p. 218 (Lines 5-7) and p. 219 (Lines 13-18)). Apparently, Olsen not only believes that his PC1 threshold is not arbitrary, but that it is precise to the fifth decimal place.
[46] Olsen Deposition. 9/10/08. p. 274.
[47] Olsen (2008a). p. 6-17. Bullet 5.
[48] Olsen (2008a). p. 6-17. Bullet 6.
[49] Olsen (2008a). p. 6-17. Bullet 7.

Table 2-2. Summary of Olsen PCA Run SW17.

PCA Run SW17 **699** Samples **26** Variable ≤ **6** Missing Data Points Allowed Per Sample		Sample Summary		Variable Summary			
	EDA_Group	Total Number of Water Samples Available in CDM Database, for this Group	Number of Samples that Meet Missing Data Criterion	EDA_Variable	Number of Samples with Data Reported	Percent Missing Data	Transformation Used for PCA
SW17	GW - Geoprobe	19	17	AL_T	699	0%	Log10
0428_SW_17	GW - Spring	57	49	ALKALINITY	691	1%	Log10
	GW - Well	62	60	AS_T	695	1%	Log10
Surface	SW - Edge of Field	89	65	BA_T	699	0%	Log10
Water and	SW - Lake - Tenkiller	533	29	CA_T	699	0%	Log10
Groundwater	SW - Stream - BFC	960	88	CL	689	1%	Log10
	SW - Stream - Forest	2	0	**COLIFORMS**	**537**	**23%**	Log10
	SW - Stream - HFC	152	20	CU_T	695	1%	Log10
	SW - Stream - High Flow - BFC	55	48	**ECOLI**	**447**	**36%**	Log10
	SW - Stream - High Flow - HFC	240	177	**ENTERO**	**527**	**25%**	Log10
	SW - Stream - NA	10	0	FE_T	699	0%	Log10
	SW - Stream - PA - BFC	12	0	**FECAL**	**523**	**25%**	Log10
	SW - Stream - PA - HFC	22	0	K_T	699	0%	Log10
	SW - Stream - Synoptic	24	1	MG_T	699	0%	Log10
	SW - Stream - USGS - BFC	107	60	MN_T	699	0%	Log10
	SW - Stream - USGS - HFC	115	81	NA_T	699	0%	Log10
	SW - Stream - WWTP	4	4	NI_T	695	1%	Log10
	Total	**2463**	**699**	NO2_NO3	690	1%	Log10
				P_SOL_REAC	685	2%	Log10
				P_T	697	0%	Log10
				P_TD	698	0%	Log10
				SO4	689	1%	Log10
				TDS	656	6%	Log10
				TKN	**631**	**10%**	Log10
				TOC	677	3%	Log10
				ZN_T	695	1%	Log10

Information from Olsen-produced spreadsheet '*PCA_Water_Runs_Table.xls*' attachment to 5/9/08 email from Chappell to Olsen.

Olsen reported the same types of results for SW17 as he did for SW3. Scree-plots and average eigenvalue criteria indicated five significant principal components, but like SW3 he looked only at the first 2 principal components, and cited the 50.1 percent of the variance accounted for (barely half) to justify that decision.[50] In terms of interpretation, Olsen reported that:

> "*A similar evaluation of PC1 scores was performed for the SW17 run as for the SW3 run where the PC scores for reference samples and samples from locations in areas of low poultry house density were evaluated. This resulted in determination that the same threshold PC1 score could be used to determine poultry waste impact (samples with PC1 > 1.3).*"[51]

Note in the first underlined portion of the quote, that Olsen cites a similar spatial analysis as he did for SW3, with respect to his poultry house density data. As indicated in the second and third underlined portions of the quote, that analysis led Olsen to conclude an identical poultry-impact threshold for SW17 (PC1 > 1.3).

Olsen then presented the groundwater equivalent of his red-dot green-dot map, showing the locations of samples with PC1 scores greater than 1.3. This map is reproduced below as Figure 2-6.

[50] Olsen (2008a). pp. 6-50 to 6-52.
[51] Olsen (2008a). p. 6-61. 2nd Paragraph. Emphasis added.

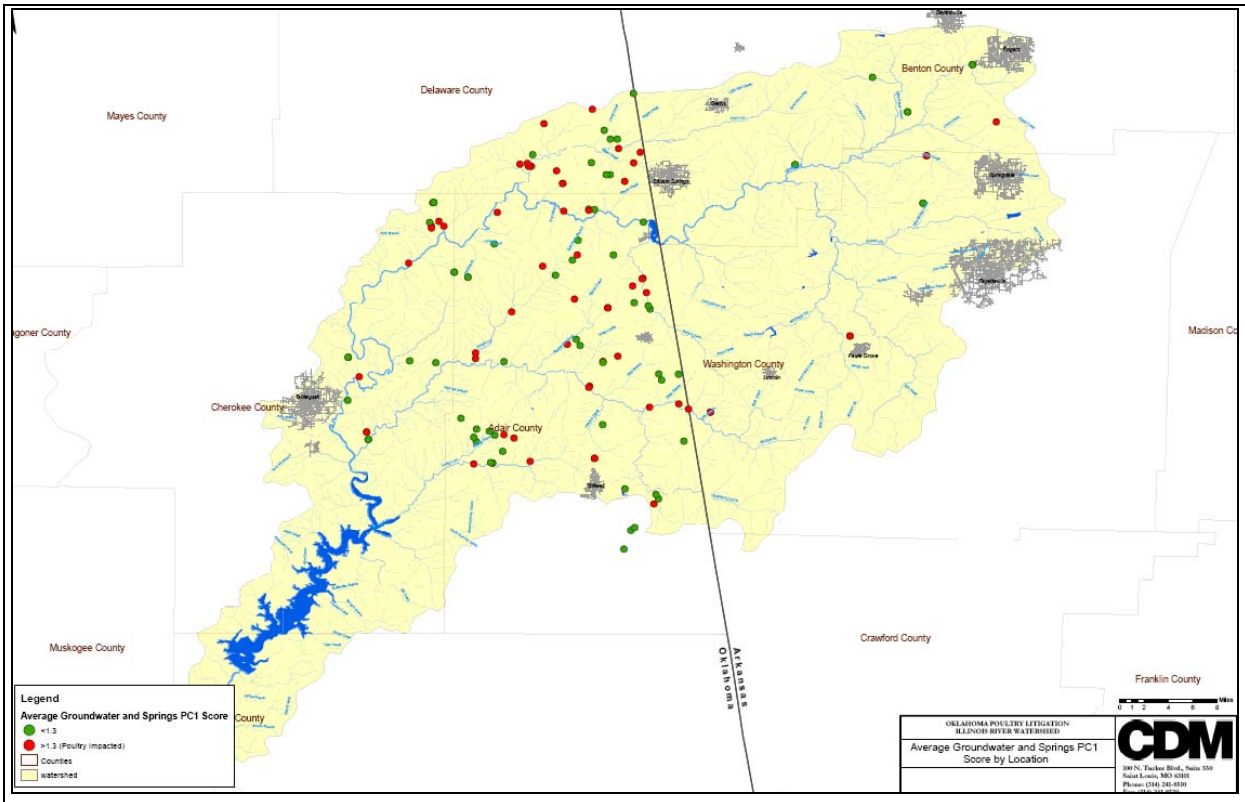


Figure 2-6. Direct copy of Olsen's Figure 6.11-24: average groundwater and spring PC1 scores.

Once again, Olsen showed his classification of groundwater on a generic base map. Figure 2-7, below, shows the same information plotted over Olsen's poultry house density data. Once again, there are numerous red-dots plotting in green areas and vice versa. Olsen addressed this inconsistency, at least in part, by pointing out that *"The three wells known to be greater than 150 ft in depth (actual depth = 203 to 803 ft) did not show poultry waste contamination."* These three wells were not identified by Olsen, and even if they were, it cannot explain all the inconsistencies observed here. Olsen's groundwater spatial analysis does not support his PC1>1.3 poultry impact classification.

Based on his 1.3 PC1 criterion, Olsen then reported that 51 of 112 locations on his groundwater red-dot / green-dot map (46%) plotted as red-dots.[52] By his criterion, less than half of the groundwater samples in the IRW are impacted by poultry litter. Even then, that number does not describe Olsen's presumed impact to homeowner wells, because domestic wells were just one of three categories of samples included as "*groundwater*." As indicated on Table 2-3 below (reproduced from the table on page 6-61 of Olsen's report) the percentage of homeowner wells that exhibit PC1 scores > 1.3 is only 40%.

[52] Olsen (2008a). p. 6-61. 2nd paragraph.

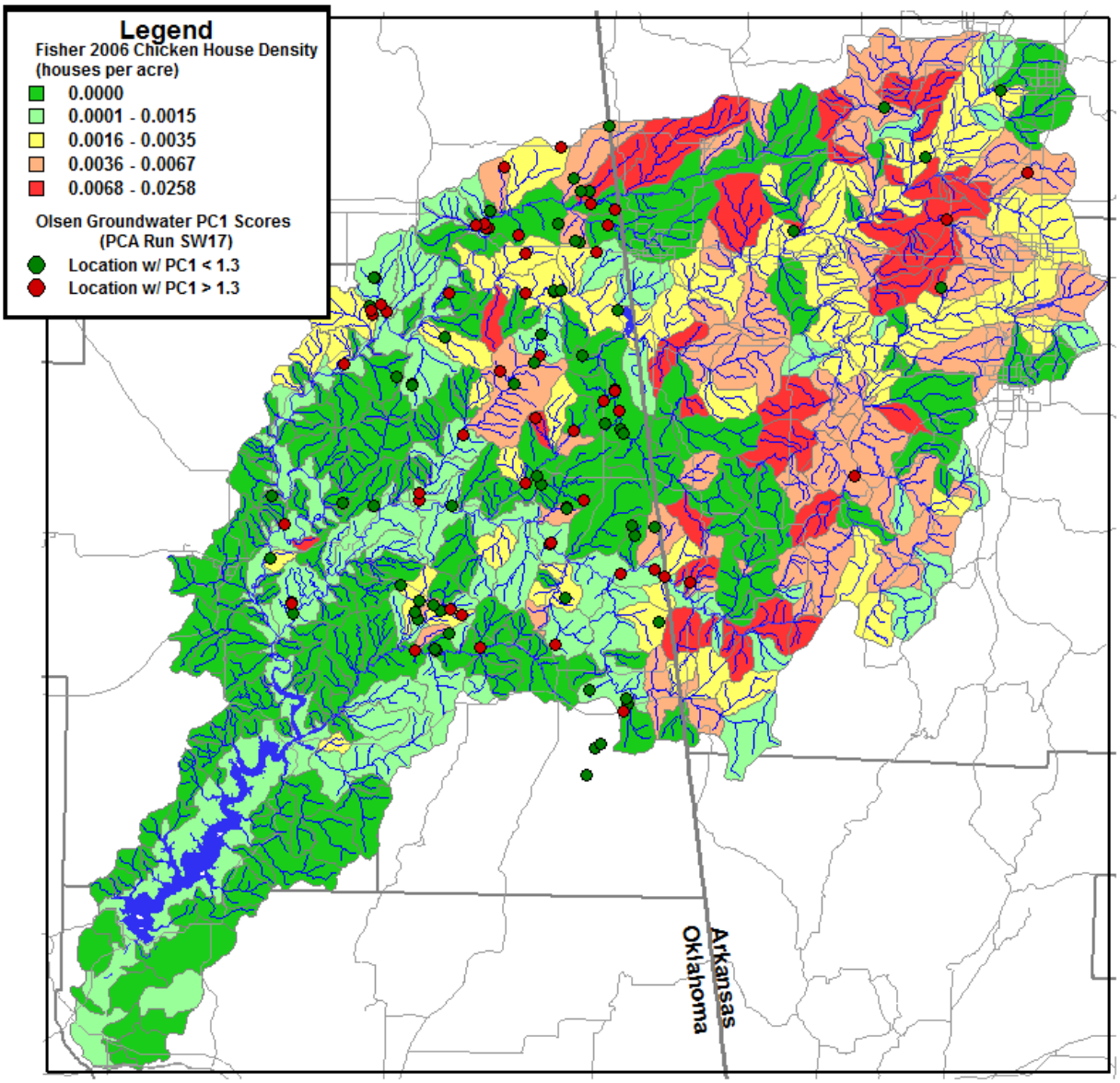


Figure 2-7. Olsen's red-dot/green-dot map for groundwater, plotted on poultry-house density map instead of generic base map.

Table 2-3. Sample Counts and Percentage of SW17 Groundwater Samples Exceeding Olsen's 1.3 PC1 Threshold

Sample Type	Sample Counts	Percent > 1.3
Geoprobe	16/17	94
Springs	19/49	39
Existing Wells	24/60	40

Reproduced from Olsen (2008a) p. 6-61

Recall also that, according to Olsen, a PC1 score greater than 1.3 means only that there is some poultry-impact. It says nothing about dominance.[53] According to Olsen, in order to be classified as "*poultry-waste impact dominant*" a sample must exhibit a PC1 score > 1.3 and a PC2 score < 4.7 to 5.0.[54] Only 15 percent of groundwater wells meet this criterion (9 out of 60: Figure 2-8).

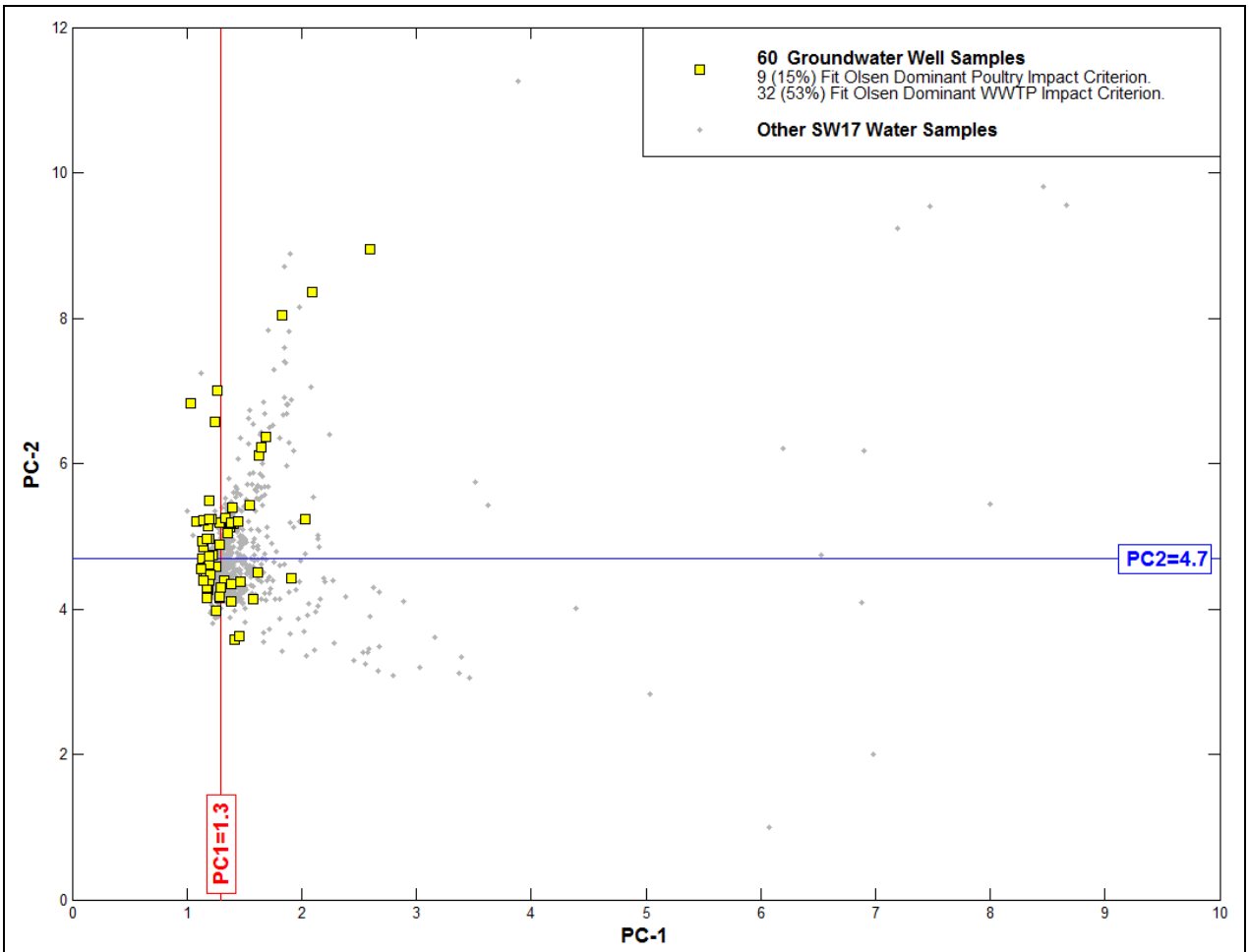


Figure 2-8. Scores plot for SW17 with groundwater samples (homeowner wells) highlighted.

Assuming that Olsen's PC1 and PC2 thresholds have any validity, groundwater is not nearly the poultry-impact problem that Olsen's claims for surface water. But once again the validity of Olsen's criteria is not supported by his spatial analysis. The locations of the nine well samples classified by Olsen's criteria as "*poultry-waste impact dominant*" are shown on Figure 2-9 with respect to Olsen's poultry-house density base map. The majority of these samples (six of nine) are located in areas of low poultry house density. Four plot in sub-basins that Olsen's map indicates have zero poultry-house density (dark-green). Two more plot within Olsen's second-lowest poultry house density classification (light-green). None of these nine samples plot within Olsen's maximum poultry-house density classification sub-basins (red).

[53] Olsen Deposition (9/11/08). p. 339 (Lines 12-13).
[54] Olsen Deposition (9/10/08). p. 279 (Lines 14-21).

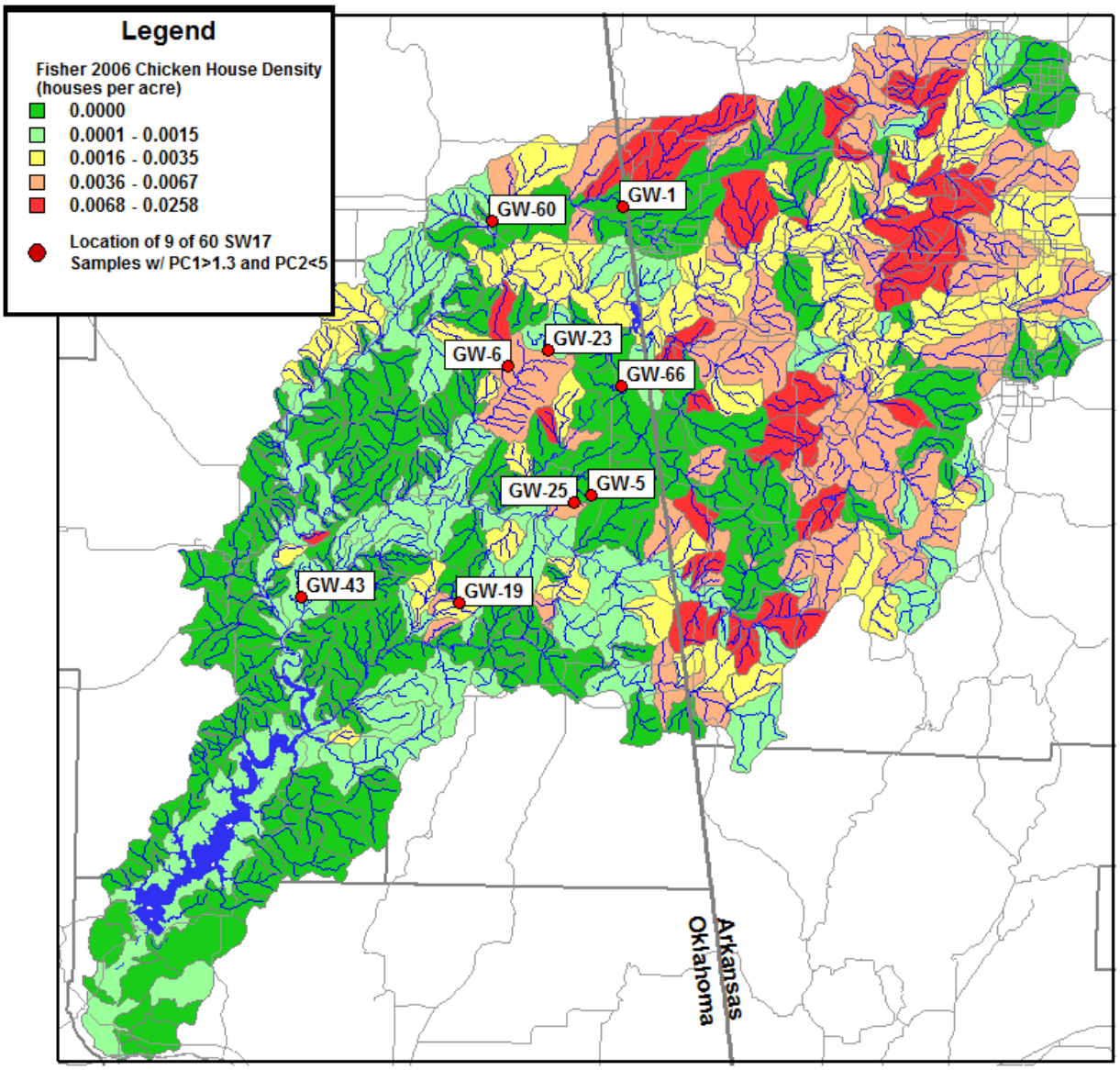


Figure 2-9. Locations of the nine (out of 60) SW17 groundwater wells classified by Olsen as "*poultry-waste impact dominant*"

Note: The majority of these nine samples plot in areas of low-poultry house density. Four plot in zero poultry house density sub-basins (dark-green). Two plot within the second lowest poultry house density classification of sub-basins (light-green). None plot in Olsen's maximum poultry-house density classification sub-basins (red).

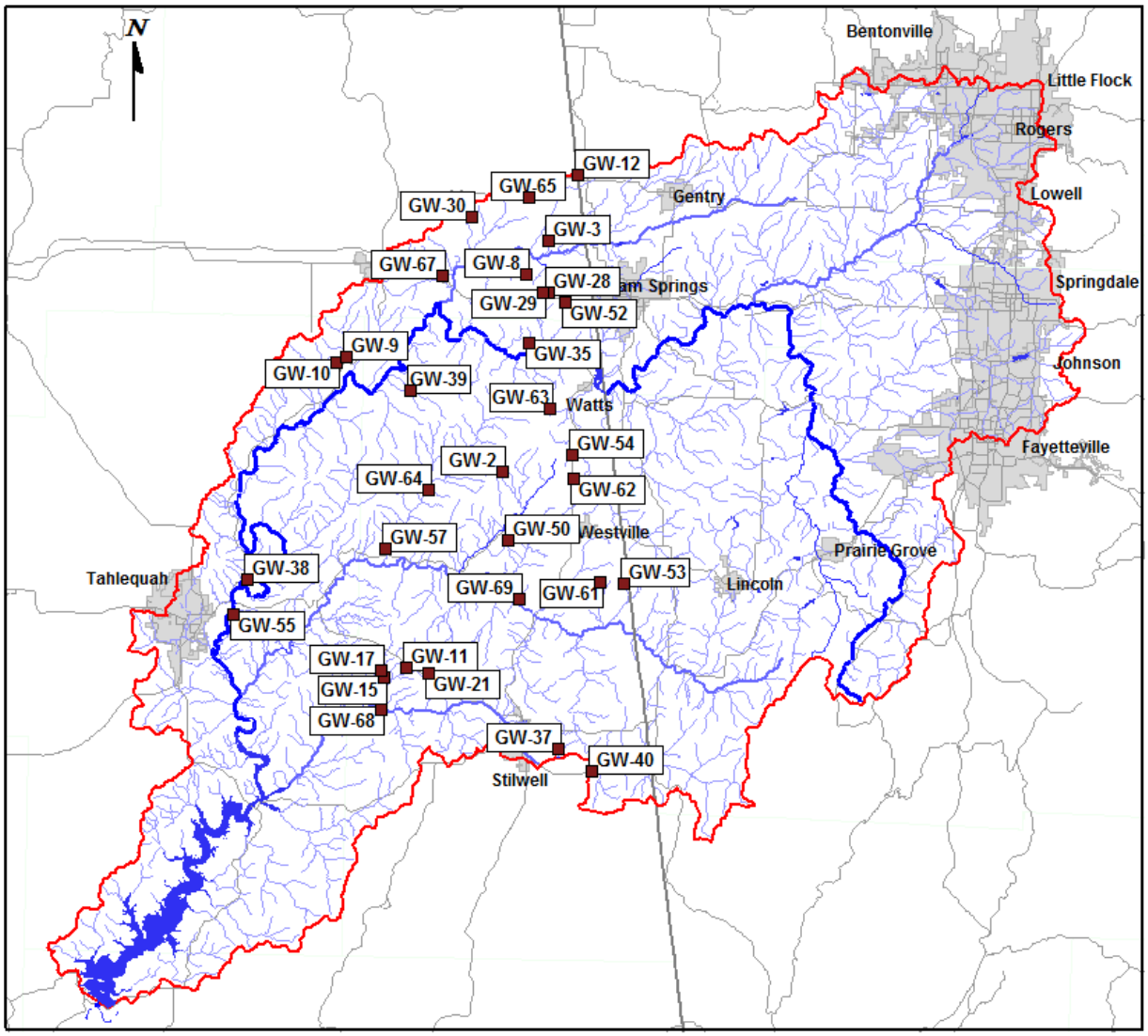
When Olsen discussed PC2 scores for SW17, he reported that:

> *"In addition to the samples showing poultry waste impact, some of the groundwater samples have higher PC2 scores than the typical samples identified as being impacted by poultry waste contamination (relatively lower PC2 scores). These groundwater samples potentially show human waste impact. Overall about 20 wells may show potential human impact."*[55]

In this quote, Olsen points to 20 groundwater samples that exhibit PC2 scores above his WWTP threshold of 4.7. In deposition he acknowledged that there were actually 29 SW17 samples with PC2 scores above his WWTP threshold. But even that number is wrong. There are actually 32 groundwater samples in Olsen's PCA run SW17 with PC2 scores greater than 4.7. As such, the number of wells that Olsen would classify as predominantly WWTP impacted is 32 of 60, or 53%. Olsen's WWTP criterion indicates that the majority of the wells sampled show evidence of WWTP impact. The locations of these wells are shown on Figure 2-10.

There is another important point within the above quote. Regardless of whether Olsen believes the number is 20, 29 or 32, his conclusion is that they "*potentially show human waste impact*." But Olsen's original interpretation of PC-2 was more much more specific than '*human waste.*' He identified PC2 as "*associated with WWTP effluent*."[56] The implication in Olsen's interpretation of data from groundwater wells is that he equates the chemical fingerprint of large-scale WWTP effluent with untreated and/or small-scale, domestically treated human waste (i.e. septic tanks). Olsen has apparently concluded that the chemical/biological signatures of treated WWTP effluent and septic tank inputs are identical, but he never discusses the basis of such an opinion.

[55] Olsen (2008a). p. 6-61. 4th paragraph.
[56] Olsen (2008a). p. 6-57. 3rd paragraph.



Sample	Date	Owner	Address	PC2 Score
GW-02	7/07/06	Collins	Westville, OK 74965	5.166
GW-03	7/11/06	Saunders	55286 S. 706 Rd. Colcord, OK 74338	6.575
GW-08	7/13/06	Glenn	56492 S. 700 Rd. Colcord, OK 74338	4.969
GW-09	7/18/06	Schwabe	4053 Hwy 10 Kansas, OK 74347	5.400
GW-10	7/18/06	Schwabe	4053 Hwy 10 Kansas, OK 74347	5.118
GW-11	7/19/06	Brown	Rt. 4 Box 2065 Stilwell, OK 74960	4.962
GW-12	7/20/06	Blagg	50769 S 725 Rd. Colcord, OK 74338	5.189
GW-15	7/20/06	Welch	Rt. 4 Box 2375 Stilwell, OK	6.826
GW-17	7/20/06	Peteet	PO Box 912 Stilwell, OK 74960	4.859
GW-21	7/24/06	Baird	Rt. 3 Box 825 Stilwell, OK 74960	5.244
GW-28	7/26/06	Millican	6482 Pine Dr. Colcord, OK 74388	4.881
GW-29	7/26/06	Granderson	57274 So. 711 Rd. Colcord, OK 74338	5.493
GW-30	7/26/06	Potter	53290 So. 670 Rd. Colocord, OK 74338	5.232
GW-35	8/10/06	Hester	Rt 2 Box 375, Watts OK 74964-9513	7.010
GW-37	8/10/06	Rogers	Rt 2 Box 1751-A Stilwell, OK 74960	5.206
GW-38	8/10/06	Fite	Hwy 10, north of Hwy 62 intersection	5.045

Sample	Date	Owner	Address	PC2 Score
GW-39	8/10/06	Oakball	Rt 1 P.O. Box 1038	4.741
GW-40	8/15/06	Faubian	Rt. 6 Box 1339, Stilwell, OK 74960	8.942
GW-50	1/22/07	Beaver	Rt. 2 Box 431, Westville, OK	5.135
GW-52	1/22/07	Ames	4795 Cedar Dr. W Siloam Springs (Colcord)	6.116
GW-53	1/22/07	McCoy	RR1 Box 49	4.936
GW-54	1/23/07	Reese	Rt 1 Box 154 Watts, OK 74964	6.228
GW-55	1/23/07	McAlpine	12979 S 543 Rd, Tahlequah, OK	4.731
GW-57	1/23/07	Blagg	50769 S 725 Rd. Colcord, OK 74338	8.358
GW-61	7/11/07	Choate	PO Box 897, Westville, OK	5.215
GW-62	7/11/07	Scism	RR2 Box 567, Westville, OK	5.229
GW-63	7/10/07	Dixon	Rt. 1 Box 450, Watts, OK 74964	5.242
GW-64	6/28/07	Kuelbs	Rt 2 Box 584, Westville, OK 74965	5.427
GW-65	7/10/07	Kustanborter	21213 State Highway 116, Colcord, OK	5.181
GW-67	7/11/07	Sewell	P.O. Box 16478 E 567 Rd, Del. County, OK	8.035
GW-68	7/10/07	Turner	RR01 Box 1010, Stillwell, OK	6.373
GW-69	7/30/07	Vance	Rt 2 Box 181, Westville, OK 74965	5.198

Figure 2-10. Locations, sample-dates and PC2 scores for 32 (out of 60) groundwater wells classified by Olsen as impacted by human waste.

2.3.3 SW22: Surface Water Plus Springs

SW22 was not included in Olsen's list of "*four major PCA runs*"[57] which he designated as such because they were "*the most important to the investigation or project objectives.*"[58] This is curious because SW22 forms the basis of Olsen's cattle manure impact argument, which would seem to be important to project objectives. As such, I have included it in this discussion. SW22 included the same 26 variables used in SW3 and SW17, but the samples differed. SW22 included all surface water samples included in SW3, as well as the 49 spring samples in SW17. Unlike SW17, SW22 did not include the geoprobe or groundwater well samples. This resulted in a data set with 622 samples and 26 variables. Sample types, number of samples, number of variables, missing data criterion, and transformations used for SW22 are shown on Table 2-4 below. Variables that had ≥10% missing data are shown in red text. Once again, a 2 principal component model was chosen by Olsen, which this time accounted for 55% of the variance.

Table 2-4. Summary of Olsen PCA Run SW17.

PCA Run SW22 622 Samples 26 Variable = 6 Missing Data Points Allowed Per Sample		Sample Summary		Variable Summary			Transformation Used for PCA
	EDA_Group	Total Number of Water Samples Available in CDM Database, for this Group	Number of Samples that Meet Missing Data Criterion	EDA_Variable	Number of Samples with Data Reported	Percent Missing Data	
SW22	GW - Spring	57	49	AL_T	622	0%	Log10
0504_SW_22	SW - Edge of Field	89	65	ALKALINITY	614	1%	Log10
	SW - Lake - Tenkiller	533	29	AS_T	618	1%	Log10
Surface	SW - Stream - BFC	960	88	BA_T	622	0%	Log10
Water Plus	SW - Stream - Forest	2	0	CA_T	622	0%	Log10
Springs	SW - Stream - HFC	152	20	CL	612	2%	Log10
(No Other	SW - Stream - High Flow - BFC	55	48	**COLIFORMS**	**460**	**26%**	Log10
Groundwater	SW - Stream - High Flow - HFC	240	177	CU_T	618	1%	Log10
Samples)	SW - Stream - NA	10	0	**ECOLI**	**370**	**41%**	Log10
	SW - Stream - PA - BFC	12	0	**ENTERO**	**450**	**28%**	Log10
	SW - Stream - PA - HFC	22	0	FE_T	622	0%	Log10
	SW - Stream - Synoptic	24	1	**FECAL**	**446**	**28%**	Log10
	SW - Stream - USGS - BFC	107	60	K_T	622	0%	Log10
	SW - Stream - USGS - HFC	115	81	MG_T	622	0%	Log10
	SW - Stream - WWTP	4	4	MN_T	622	0%	Log10
	Total	**2382**	**622**	NA_T	622	0%	Log10
				NI_T	618	1%	Log10
				NO2_NO3	613	1%	Log10
				P_SOL_REAC	608	2%	Log10
				P_T	620	0%	Log10
				P_TD	621	0%	Log10
				SO4	612	2%	Log10
				TDS	587	6%	Log10
				TKN	**554**	**11%**	Log10
				TOC	600	4%	Log10
				ZN_T	618	1%	Log10

Information from Olsen-produced spreadsheet '*PCA_Water_Runs_Table.xls*' as attachment to 5/9/08 email from Chappell to Olsen.

SW22 forms the basis of Olsen's cattle-manure impact argument on page 6-61 and 6-62 of his report, and that argument is reproduced below, in its entirety:

> ***"Evaluation of Potential Impact of Cattle Manure***
>
> *The potential impact due to cattle manure was previously discussed in Section 6.4.2. These mass balance calculations indicate that any impact or contamination from cattle manure would be small (< 10-15 percent) compared to the impact due to poultry waste disposal. Previous steps in this subsection (i.e. step 12 discussing waste characteristics) show that cattle manure and cattle manure*

[57] Olsen (2008a). p. 6-51. Last paragraph.
[58] Olsen p. 6-50. See also Table at the top of page 6-52.

leachate are very different in chemical composition when compared to poultry waste and poultry waste leachate. Therefore, if cattle waste provides a major impact on contamination in the IRW, a dominant signature should be observed in the PCA. To assist in this evaluation, samples with known cattle contamination were evaluated. The chemical and bacterial compositions of these samples have been previously provided in ***Tables 6.11-10 and 6.4-2a).*** *The four samples documented with cattle contamination are: SPR-LAL16-SP2, SPR-26, EOF-CP-1B and EOF-CP-1A.* ***Figure 6.11-25*** *shows the PC1 vs PC2 score plot for PCA run SW22 (surface water and springs). Also shown on this figure are the locations of the four samples with potential cattle contamination. Two of the samples (the springs) plot in the WWTP impact area while the other two samples plot on the edge of the poultry waste impacted area. These four samples have very different PC scores and no consistent relation or group is observed in the PCA. If cattle contamination contributed a significant impact to contamination in the IRW, a clear signature and associated group should be observed in the PCA and the four samples with cattle contamination would be in the group. Based on the mass balance calculations, the comparison of chemical composition and the PCA analyses, cattle waste is not a major source of chemical contamination in the IRW."*[59]

Olsen did not show loading bar-graphs, coefficient bar graphs or scree plots for this PCA run, but he did produce a single scores plot (referenced in the quote above and reproduced below as Figure 2-11).

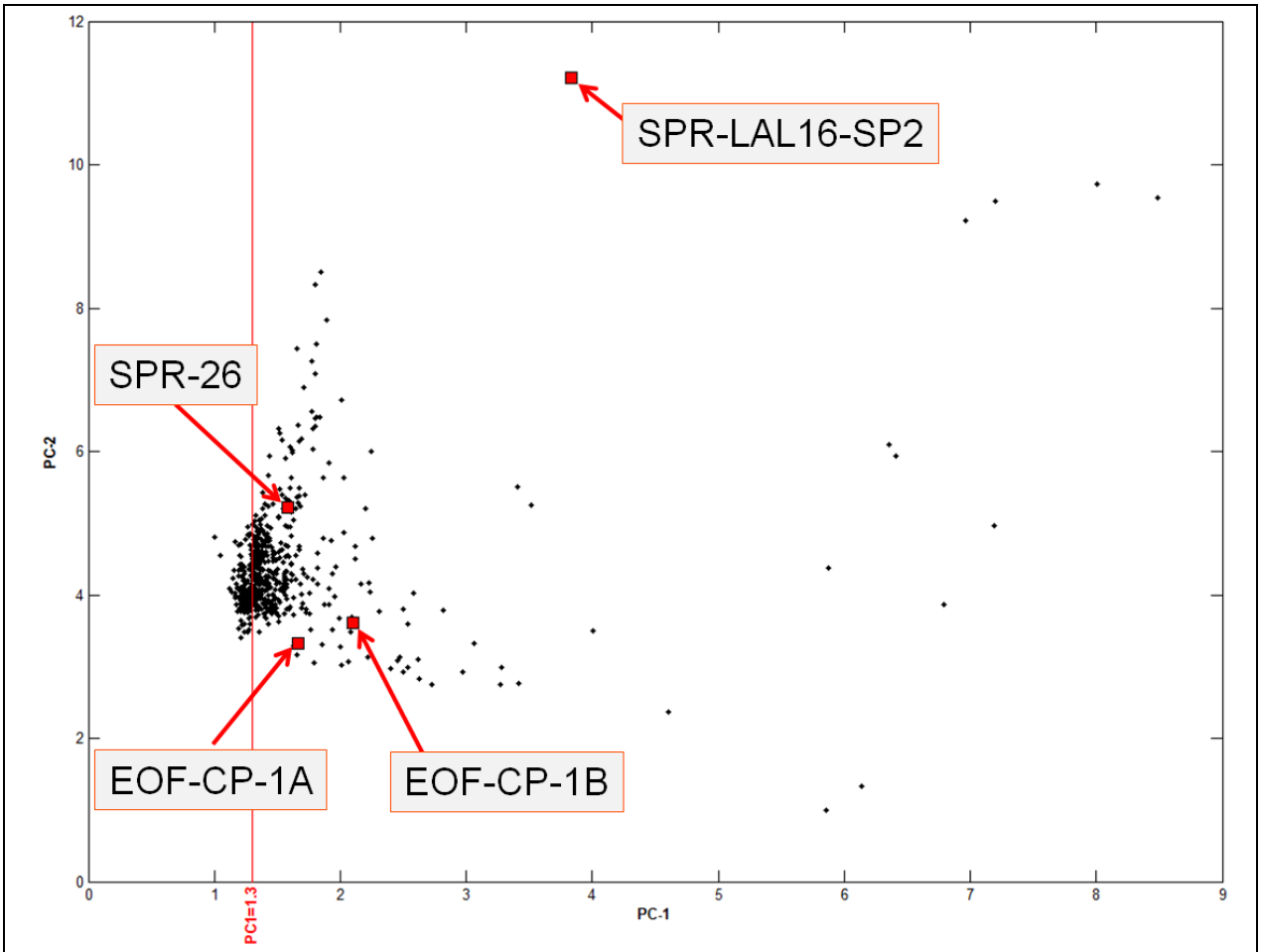


Figure 2-11. SW22 scores plot: Samples with known cattle contamination plotted as red squares.
Reproduction of Olsen Figure 6.11-25. Annotation of sample -names for Olsen's four cattle-impacted samples, and Olsen's PC1 poultry-impact threshold (1.3) have been added. The sample shown as SPR-26 is actually the average scores from two individual samples (See Section 3.3.2).

[59] Olsen (2008). p. 6-61 to 6-62. Emphasis added.

On this graph, the "*four samples documented with cattle contamination*"[60] are plotted as red squares. All other SW22 samples are plotted as black dots. The four cattle impacted samples plot across a wide area of the scores plot, and it is this range of variation that is the basis of Olsen's argument, quoted above. There are major problems with this argument, and they will be discussed in detail in Section 3.3 of this report. But two of the most important problems are summarized here. First, note that all four of Olsen's "*samples documented with cattle contamination*"[61] exhibit PC1 scores greater than 1.3. Second, two of the four cattle impacted samples were edge-of-field samples collected from cow pastures (EOF-CP) where poultry litter had never been applied.[62] Unlike the spring samples (SPR), these two EOF-CP samples were included in SW3 (the PCA run that formed the basis of Olsen's poultry-impact arguments). If we highlight the EOF-CP samples on Olsen's SW3 scores plot, we see that both plot within Olsen's "*poultry-waste dominant impact*" area (Figure 2-12).

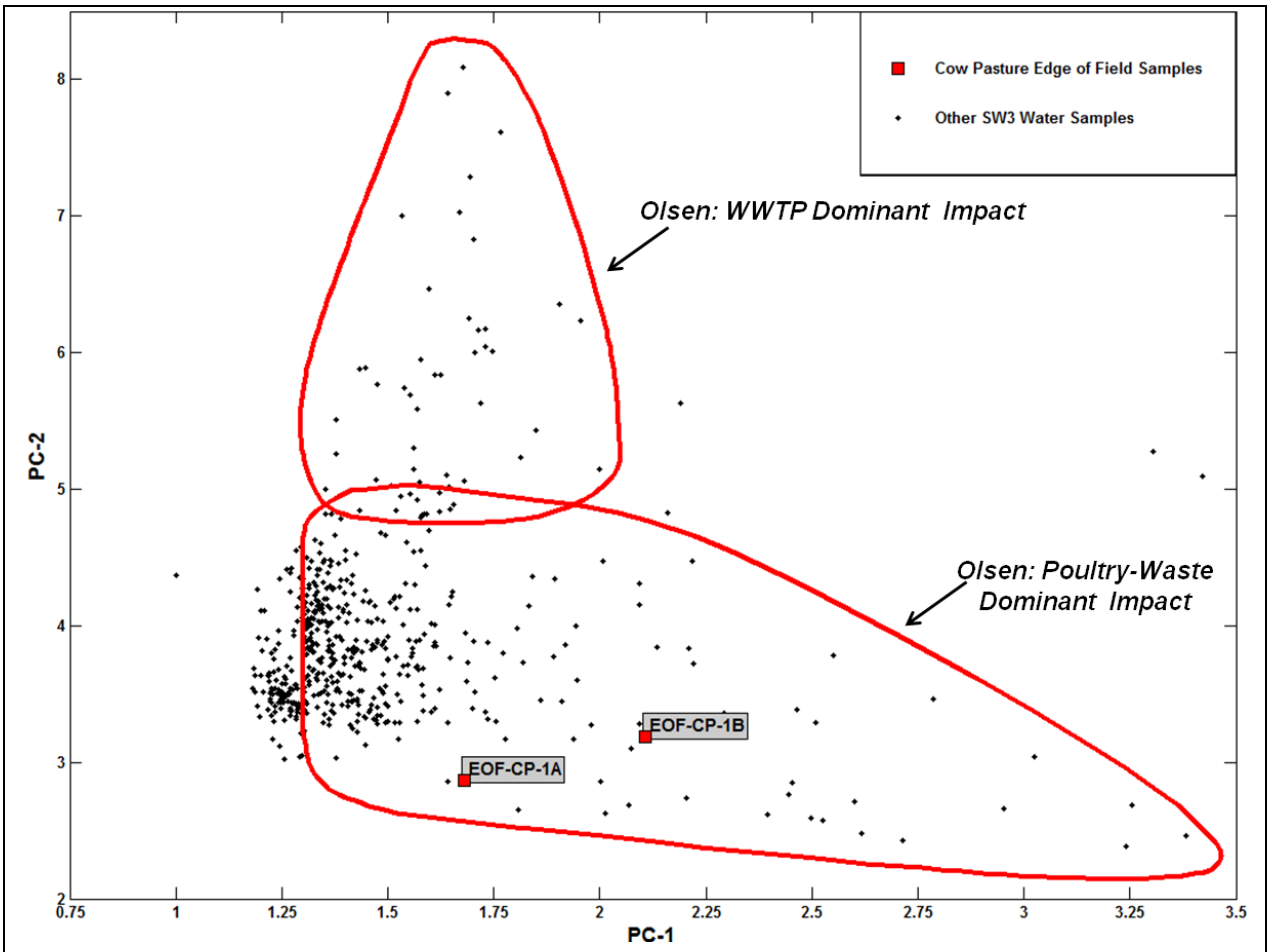


Figure 2-12. SW3 scores plot with cattle impacted edge-of-field samples highlighted.

[60] Olsen (2008a). p. 6-62 (line 5).
[61] Olsen (2008a). p. 6-62. Lines 4-6.
[62] See Field CDM/Lithochimea field notes from March 31, 2008 (STOK005374).

If one wishes to successfully challenge Olsen's criteria for a "*unique poultry waste signature*" they need look no further than this figure. This contradiction to Olsen's theory was never disclosed in his report. In addition, one could not see it for themselves on his score plots, because he did not use a unique symbol for EOF-CP samples. Rather, Olsen showed EOF-CP samples on his SW3 score plots using the same symbol shape and color used for all other EOF samples.[63]

In Olsen's discussion of SW22 in his report, he never disclosed that all four cattle impacted samples exhibited scores greater than 1.3, or that two of them plot squarely within his *poultry-waste dominant impact* area. As discussed in Section 3.3 of this report, these omissions were not because he failed to recognize these contradictions, or their significance. Section 3.3 will provide a detailed review of Olsen's cattle impact argument, as well as a summary of how that argument evolved from the February 2008 PI hearing, to the subsequent collection of the cow-pasture edge of field samples in March 2008, to his May 14 expert report, and ultimately to his September 2008 deposition testimony.

2.3.4 SD1: Solids (Manure, Litter, Soils, Sediment – No Cores)

Olsen's PCA run SD1 included 32 variables measured in 203[64] solids samples. Solids samples were from three major groups: soil/sediment; cattle manure, and poultry litter. The soil/sediment group was comprised of surface soils, Lake Tenkiller sediments (grab samples only – no core samples), small reservoir sediments and stream sediment. Up to 6 missing data points were allowed per sample. The sample types, number of samples, number of variables, missing data criterion, and transformations used for this PCA run are shown on Table 2-5 below. Variables that had ≥10% missing data are shown in red text.

[63] See Olsen (2008a) Figures 6.11-18c; 6.11-18d; and 6.11-18e

[64] Olsen reported that SD1 had 203 samples but the results file produced for this run ('Results_Solids_0501_SD_1.xls') reported scores for only 202 samples. See Olsen (2008a - Table 6.11-7b). The missing sample appears to be a poultry litter sample. Olsen does not explain the reason for this discrepancy.

Table 2-5. Summary of Olsen PCA Run SD1.

PCA Run SD1 **203** Samples **32** Variable = **6** Missing Data Points Allowed Per Sample		Sample Summary		Variable Summary			Transformation Used for PCA
	EDA_Group	Total Number of Solids Samples Available in CDM Database, for this Group	Number of Samples that Meet Missing Data Criterion	EDA_Variable	Number of Samples with Data Reported	Percent Missing Data	
SD1	SD - Cow Manuare	10	10	AL_T	203	0%	Log10
0502_SD_1	SD - Litter	20	19	AS_T	203	0%	Log10
	SD - Litter - Plus Soil	1	1	BA_T	203	0%	Log10
Solids	SD - Sediment - Lake - Small IRW Reservoirs	12	12	BE_T	203	0%	Log10
Analysis	SD - Sediment - Lake - Tenkiller - Grab	15	15	CA_T	203	0%	Log10
	SD - Sediment - Stream	125	77	CO_T	203	0%	Log10
	SD - Soil - Surface	86	69	**COLIFORMS**	**179**	**12%**	Log10
	Total	**269**	**203**	CR_T	203	0%	Log10
				CU_T	203	0%	Log10
				ECOLI	**113**	**44%**	Log10
				ENTERO	**120**	**41%**	Log10
				FE_T	203	0%	Log10
				FECAL	**155**	**24%**	Log10
				HG_T	203	0%	Log10
				K_T	203	0%	Log10
				MG_T	203	0%	Log10
				MN_T	203	0%	Log10
				NA_T	203	0%	Log10
				NH4_WS	**157**	**23%**	Log10
				NI_T	203	0%	Log10
				NITROGEN	203	0%	Log10
				OM	198	2%	Log10
				P_MEHLICH	**167**	**18%**	Log10
				P_T	202	0%	Log10
				P_WS	**181**	**11%**	Log10
				PB_T	203	0%	Log10
				PH	195	4%	None
				SALTS	203	0%	Log10
				SO4_WS	**157**	**23%**	Log10
				STAPH	**179**	**12%**	Log10
				V_T	203	0%	Log10
				ZN_T	203	0%	Log10

Information from Olsen-produced spreadsheet '*PCA_Solids_Runs_Table.xls*' as attachment to 5/9/08 email from Chappell to Olsen.

Once again, a 2 principal component model was chosen, accounting for 55% of the variance.[65] He presents 2 PC score plots for SD1 in Figures 6.11-20a through 6.11-20f. One of those (Figure 6.11-20c) is presented below as Figure 2-13

[65] Olsen (2008a). p. 6-52. Table at top of page

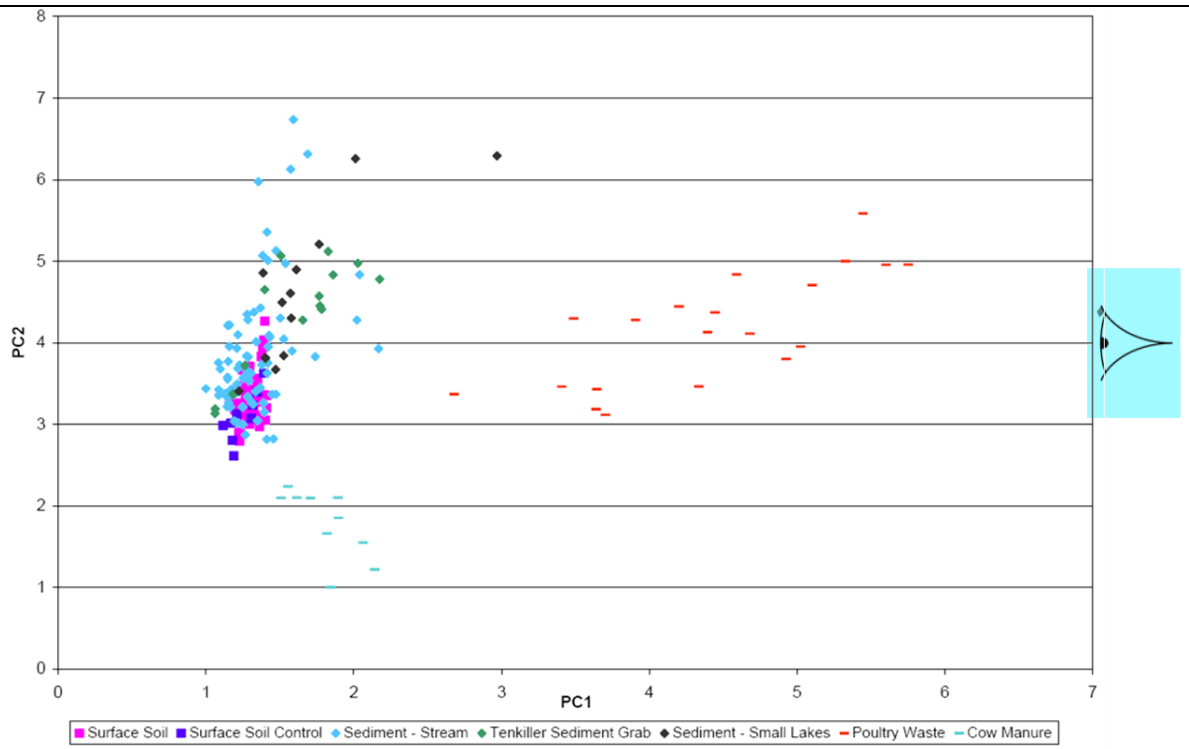


Figure 2-13. Direct copy of Olsen's Figure 6.11-20c: SD1 scores plot – varimax rotation.
Eye symbol on the right has been added, and shows viewer's perspective for Figure 2-14.

The primary conclusion drawn from this plot was that cow manure samples plot separately from the poultry litter samples:

> *"cattle manure plots on the figure in a distinctly different group than the poultry waste. These two groups are most clearly separated using the varimax rotation. However, the separate groups are also observed on the PC1 vs PC2 figure using no rotation (Figure 6.11-20f). These figures show that cattle manure and poultry waste have distinct chemical/bacterial signatures."* [66]

On this plot, we see that there is separation between cattle manure (blue dashes), poultry litter (red dashes) and soil/sediment (all other symbols). But, one of the basic aspects of interpreting a scores plot is that samples that plot close together have similar chemical composition. Those that plot farther away have different chemical compositions. Given that, note that soil/sediment samples generally plot closer to cattle manure then they do to poultry litter. Olsen's PCA plot shown above suggest that soil and sediments are more similar in composition to cattle manure than poultry litter, but he never acknowledges this. But, for the first and only time in his report, he called on the scores from a third principal component in his discussion of this PCA run.

Figure 2-14 is a direct copy of Figure 6.11-20e from Olsen's report. In contrast to the PC1 vs PC2 graphs (Figure 2-13) the red-dashes (poultry litter) plot directly on top of the soil/sediment samples, and both appear to be separated from the cow manure samples (blue dashes).

[66] Olsen (2008a). p. 6-56. 2nd paragraph

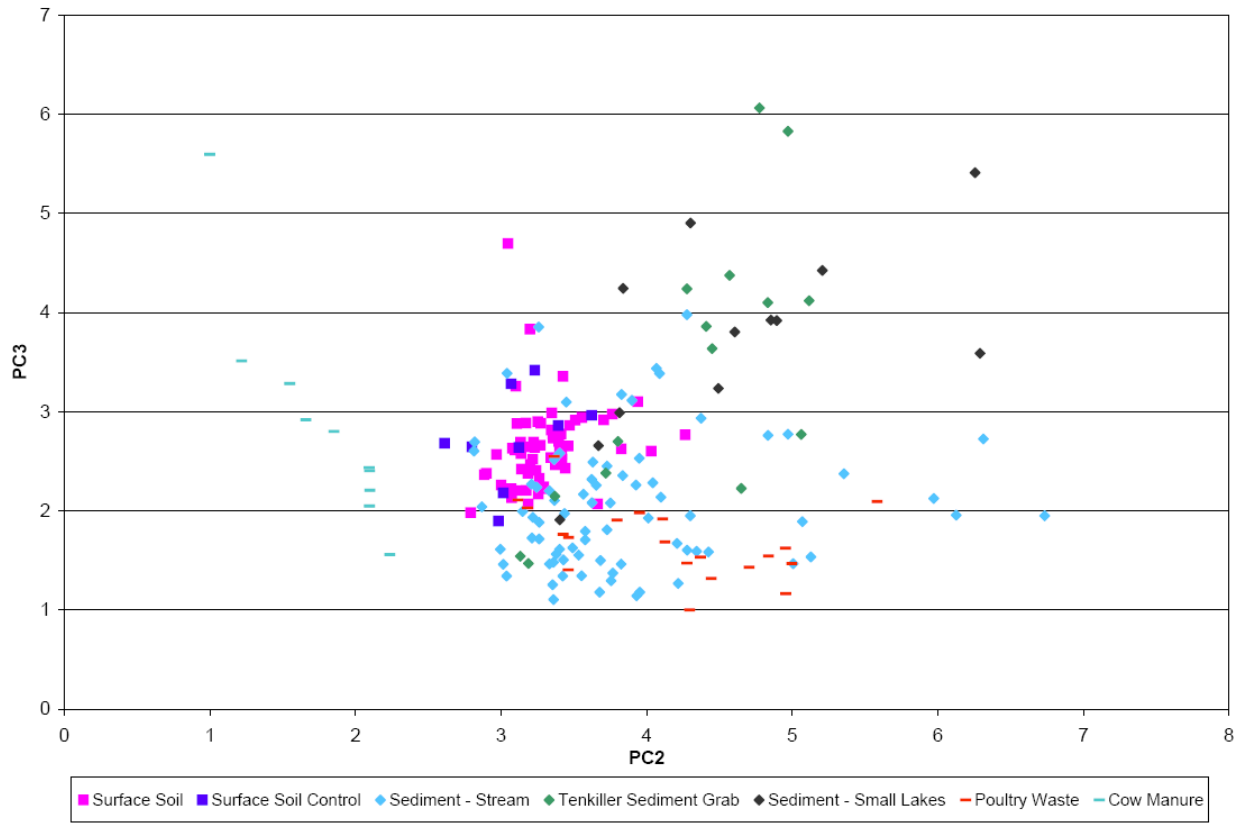


Figure 2-14. Direct copy of Olsen's Figure 6.11-20e. SD1 PC2 vs. PC3 scores plot .

Pointing to this second graph, Olsen makes the point that:

> *"cattle waste is distinct from the soils, and sediment samples. The poultry waste samples are closely related [to] the soil and sediment samples."*[67]

Olsen's statement is misleading, and demonstrates a basic lack of understanding of PCA. Figure 2-14 shows the same PCA results as Figure 2-13. Nothing has changed with respect to distance and separation of poultry litter samples compared to other samples. The only thing that has changed is our angle of view. In Figure 2-14 we are looking at the data from the perspective of the eye symbol that I added to the right side of Figure 2-13. In the second view (Figure 2-14) we are just looking down the barrel of PC1. That allows us to see where samples plot across a different 2-dimensional slice (PC2 vs PC3). We can no longer see the separation along the PC1 axis, but that separation did not suddenly vanish. On Figure 2-14, the poultry litter samples appear to overlap sediment/soil samples, but that is only because we can't tell how close the symbols are to our eye.

Olsen's argument is like holding your thumb in front of your face, directly in the line of sight between your eyes and the moon, and concluding that because your thumb and the moon overlap in your field-of-view, your thumb must be closer to the moon than it is to the tree 20 feet to your left. At best, Olsen's argument demonstrates a fundamental lack of understanding of PCA. At worst, he is fully aware that poultry litter samples are not closer to soil/sediments on the second figure, in which case he is purposely deceiving the reader.

[67] Olsen (2008a). p. 6-62. 2nd paragraph.

2.3.5 SD6: Solids (Manure, Litter, Soils, Sediment – Including Cores)

Olsen's final "*major PCA run*" was solids-run SD6. This PCA run included all samples in SD1, along with samples from sediment cores collected from Lake Tenkiller. Six cores were collected in Lake Tenkiller, but one was discarded (see Olsen report – Figure 2.12-1). As such, this PCA run differs from SD1 in that it includes an additional 88 sediment samples collected from 5 cores. Olsen indicates that this is the only difference, but as seen in Table 2-6, it also differs in that it included just 23 variables (rather than 32 variables in SD1). Nine variables missing in more than 10% of the SD1 samples have been removed from SD6. Up to 5 missing data points were allowed per sample, and Olsen's final SD6 data set had 299 samples and 23 variables.

Table 2-6. Summary of Olsen PCA Run SD6.

PCA Run SD6 **299** Samples **23** Variable ≤ **5** Missing Data Points Allowed Per Sample	EDA_Group	Sample Summary: Total Number of Solids Samples Available in CDM Database, for this Group	Sample Summary: Number of Samples that Meet Missing Data Criterion	EDA_Variable	Number of Samples with Data Reported	Percent Missing Data	Transformation Used for PCA
SD6	SD - Cow Manuare	10	10	AL_T	299	0%	Log10
0501_SD_6	SD - Litter	19	19	AS_T	299	0%	Log10
	SD - Litter - Plus Soil	1	1	BA_T	299	0%	Log10
Solids	SD - Sediment - Lake - Small IRW Reservoirs	12	12	BE_T	299	0%	Log10
Analysis	SD - Sediment - Lake - Tenkiller - Core	88	88	CA_T	299	0%	Log10
	SD - Sediment - Lake - Tenkiller - Grab	15	15	CO_T	299	0%	Log10
Core Samples	SD - Sediment - Stream	121	85	CR_T	299	0%	Log10
Added	SD - Soil - Surface	85	69	CU_T	299	0%	Log10
	Total	**351**	**299**	FE_T	299	0%	Log10
				HG_T	299	0%	Log10
				K_T	299	0%	Log10
Reduced				MG_T	299	0%	Log10
Analyte List:				MN_T	299	0%	Log10
Analytes				NA_T	299	0%	Log10
Missing in >				NI_T	299	0%	Log10
10% of				NITROGEN	294	2%	Log10
Samples				OM	288	4%	Log10
Removed				P_T	298	0%	Log10
				PB_T	299	0%	Log10
				PH	282	6%	None
				SALTS	290	3%	Log10
				V_T	299	0%	Log10
				ZN_T	299	0%	Log10

Information from Olsen-produced spreadsheet '*PCA_Solids_Runs_Table.xls*' as attachment to 5/9/08 email from Chappell to Olsen.

Olsen's discussion of SD6 is a single, short paragraph.[68] He reports that Lake Tenkiller cores show a general decrease in PC2 scores from shallow to deep, but beyond that statement, he presents no conclusions or opinions based on this analysis. Rather, he just repeats the opinions of Bert Fisher, as paraphrased earlier in his report. Given that no new opinions are presented in context of SD6, it is not clear why Olsen designated SD6 as one of four "*major PCA runs*."

[68] Olsen (2008a). p. 6-62. 3rd paragraph.

3.0 Major Contradictions to Olsen's Interpretations

If we ignore problems of Olsen's methods, assumptions and implementation, and accept his PCA results at face value, there are major problems with his interpretation. Some of these were discussed briefly in Section 2.3, as part of my summary of Olsen's major PCA runs. In Section 2.3, I presented several examples where the purported ground-truth data and spatial-analysis that Olsen claimed to have used to evaluate the efficacy of his opinion conflict with his theory of a *unique poultry waste signature* based on PC1 scores greater than 1.3. In this section I will review these conflicts in more detail and will show that in each case, Olsen either concealed conflicting information from the reader and/or presented a convoluted explanation, based on speculation, in order to explain it away. These contradictions are not evident in Olsen's report because he was selective in the examples presented and cited only a few instances that supported his theory.

3.1 Tahlequah

As part of my evaluation of Olsen's PCA methodology, I reproduced SW3, and re-plotted his red-dot green-dot map. Reproduction of that figure, using my calculated PCA scores is shown below as Figure 3-1. Note on this figure that there are five sample locations within Tahlequah, Oklahoma. All five show an average PC1 score greater than Olsen's 1.3 poultry-impact threshold. But Tahlequah is an area of low poultry house density.[69] In Tahlequah, Olsen's spatial analysis does not support his theory.

Comparing my map (Figure 3-1) to Olsen's red-dot green-dot map (Figure 6.11-23 of his report – reproduced as Figure 2-4 above) shows that he plotted these same Tahlequah samples as green-dots. Olsen's map is wrong, as is shown on the table below. The scores on Table 3-1 were taken directly from Olsen's Appendix F, and show the PC-1 scores for six Tahlequah samples in PCA run SW3.[70] All six had scores greater than 1.3. They should have been plotted as red-dots on Olsen's map.

Table 3-1. SW3 PC Scores for Tahlequah Samples

SW 3 Principal Component Scores	PC Size (No Rotation) normalized to 1	
EDA_Sample	PC 1	PC 2
RBS-0000574:8/10/2006:SW:S:0:-	1.4882282937	4.0293605941
RBS-0000577:8/10/2006:SW:S:0:-	1.4424297706	4.1783520334
RBS-0000578:8/10/2006:SW:S:0:-	1.3581186422	4.0013116585
RBS-0000625:8/10/2006:SW:S:0:-	1.3229373421	3.8085145848
RBS-0000630:8/11/2006:SW:S:0:-	1.6215165533	3.5363092996
RS-578:5/2/2007:SW:S:0:-	1.3022140797	3.8250842056

Data from Olsen (2008a): Appendix F.

[69] See Olsen Figure 2.5-1 as well as Figures 2-5 and 2-7 of this report.

[70] There were two sample from station 578, so in accordance with Olsen's method description, the average of those two samples' PC1 scores is shown as one of the five Tahlequah locations on the above map.

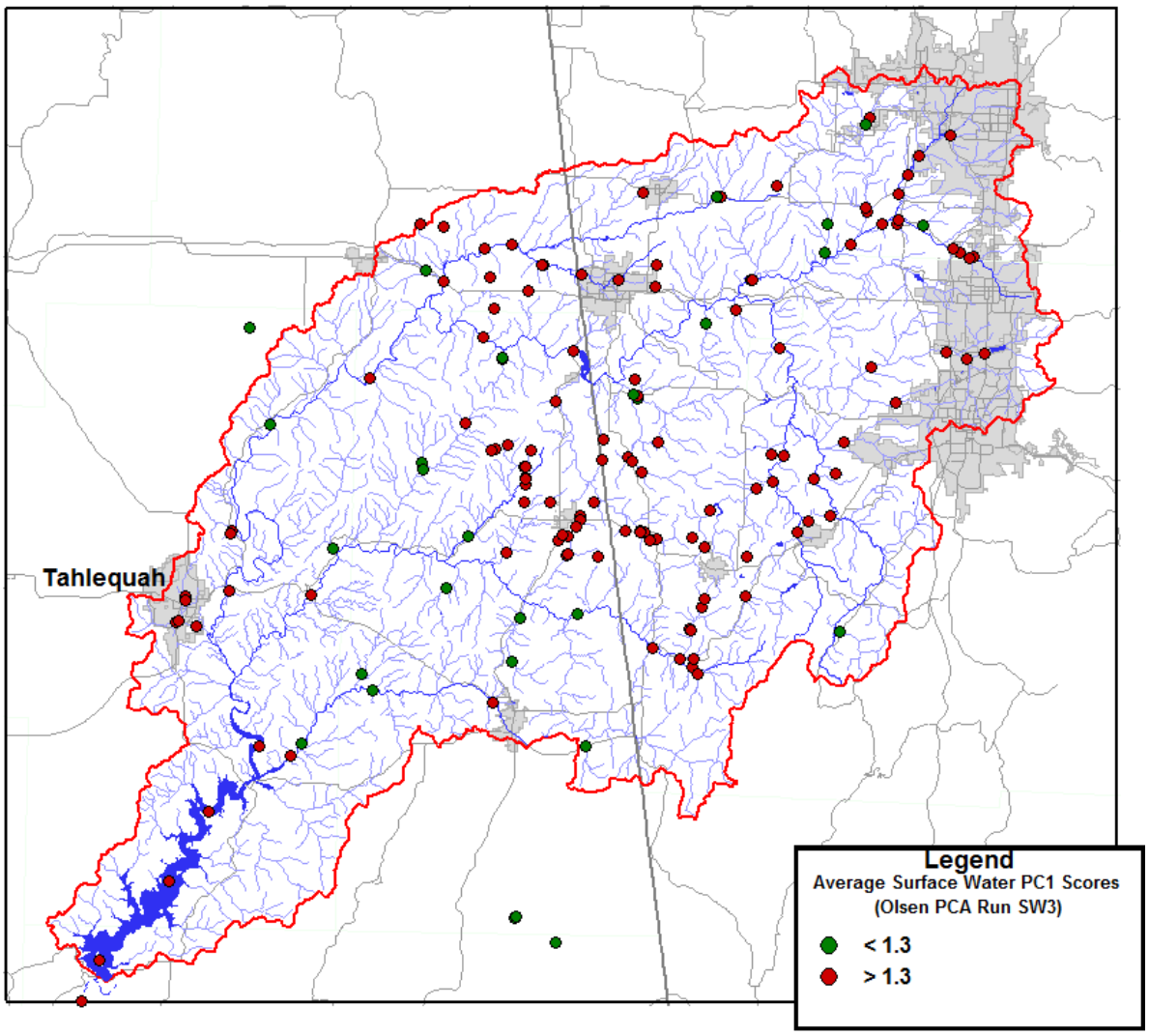


Figure 3-1. Reproduction of Olsen Figure 6.11-23.
Map generated using PC1 scores reported in Olsen's Appendix F, and the 1.3 PC1 threshold criteria indicated by Olsen. Note that in contrast to Olsen's Figure 6.11-23, all Tahlequah samples on this figure plot as green dots rather than red-dots.

In addition, when we highlight these six Tahlequah samples on Olsen's SW3 scores plot (Figure 3-2) we see that all six not only exceed his 1.3 poultry-impact threshold, they all plot within Olsen's "*Poultry Waste Dominant Impact*" area. Olsen appears to have changed the color of the Tahlequah samples on his Figure 6.11-23 because the PCA results did not agree with his theory. But nowhere on his red-dot green-dot map, and nowhere in the text of his report does he disclose this to the reader. Four months after submitting his report, in deposition testimony, Olsen did acknowledge it. After confirming that the Tahlequah samples were shown as green dots on his figure, Olsen was asked to turn to his table that lists Principal Component 1 scores, whereupon Olsen interjected the following:

> ***Q*** *Okay. Dr. Olsen, could you go to the table that reports your Principal Component 1 scores for SW3?*
> ***A*** *Yeah. Let me cut you short here now that we brought those up. Those were above 1.3, but* <u>*based on the spatial analysis*</u>*, I decided that those were not impacted by poultry, and* <u>*I colored them green*</u> *to this analysis of the percent.*[71]

[71] Olsen Deposition 9/11/08. p. 405.

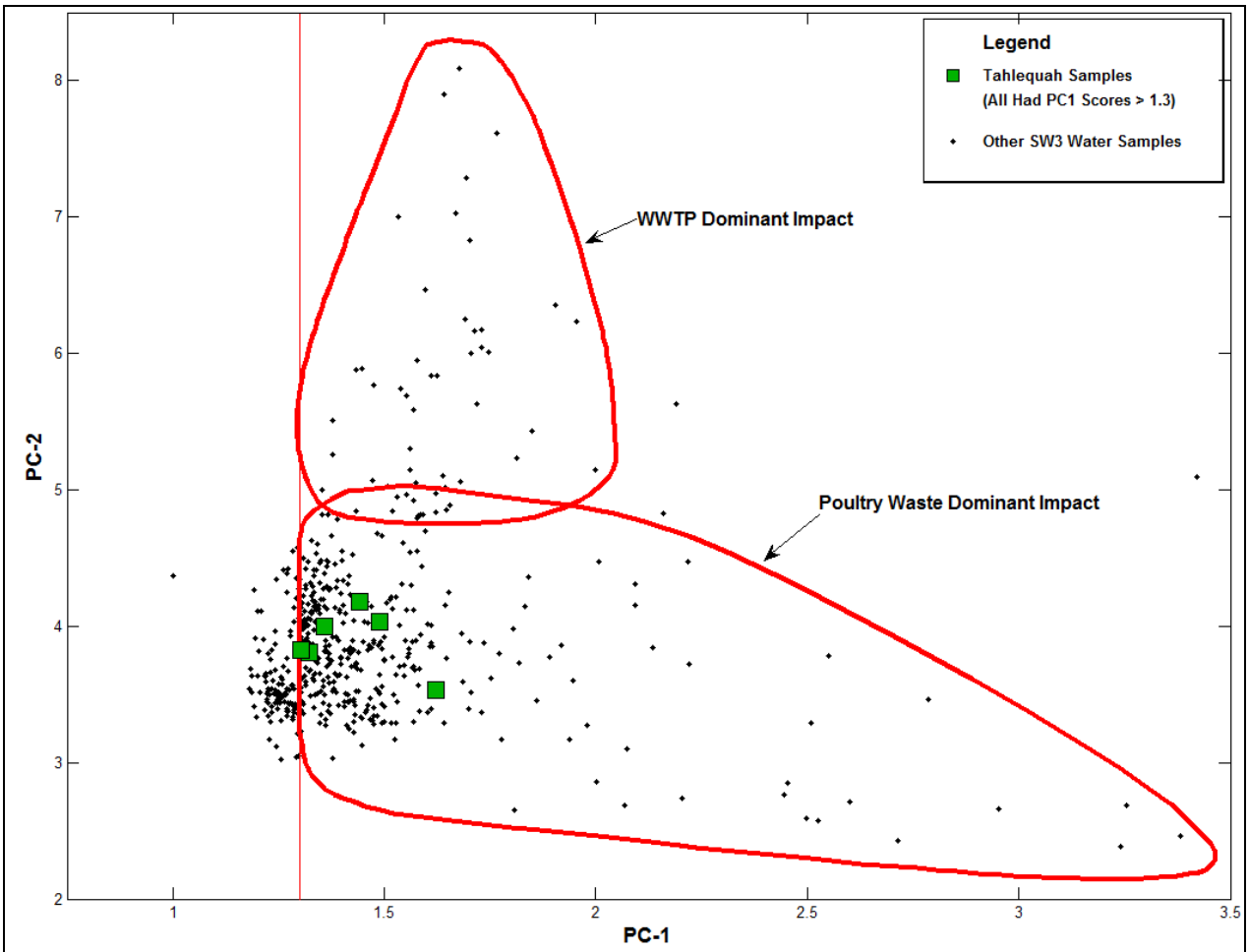


Figure 3-2. Olsen's SW3 scores plot (expanded view) with the six Tahlequah samples highlighted.

Olsen then acknowledged that (1) his decision to change the Tahlequah was subjective; (2) it was made as a result of his spatial analysis, (3) he never disclosed it to the reader, (4) his treatment of the Tahlequah data is misleading, and (5) he should have disclosed all of this in his report.[72] But consider this also in context of Olsen's original rationale for conducting a spatial analysis. The spatial analysis was offered by Olsen as a confirmatory line of evidence in support of his opinion that samples with PC1 scores greater than 1.3 exhibit a *unique poultry waste signature*.[73] In reporting the results of the spatial analysis, he discussed only five sample locations, all of which were consistent with Olsen's interpretation.[74] This was offered by Olsen as evidence that his 1.3 PC1 threshold was supported by an independent data set: poultry house density.[75] Olsen now admits that he knew that PC1 scores in Tahlequah did not support that theory, and offers this same spatial analysis as the justification to veto his own criterion.

Clearly, Olsen's spatial analysis serves more than one purpose. When it supports his opinion, it is offered as an independent line of evidence, used to validate his *unique poultry waste signature* criterion. But when it contradicts his opinion, it is used quite differently. The spatial analysis

[72] Olsen Deposition 9/11/08. p. 408-409.
[73] Olsen (2008a). p. 6-34 (Steps 12 and 13 bullets); p. 6-57 (4th paragraph); p. 6-59 (2nd paragraph). p. 6-60 (1st paragraph). Olsen Deposition testimony (9/10/08; p. 220).
[74] These 5 were consistent with Olsen's theory, if we grant him the latitude to round HFS30 data down from 1.30226 to 1.3 – see Section 2.3.1.
[75] Olsen (2008a). p. 6-59 to 6-60.

becomes the justification to recolor red-dots as green-dots, and make them appear to be consistent with his theory. Olsen's spatial analysis is instrument of convenience.

3.2 Waste Water Treatment Plant Samples

Waste water treatment plant samples (WWTP) are another example of where Olsen's PCA interpretation is not supported by his spatial analysis. Olsen collected four samples with the intent of characterizing the chemical/bacterial composition of WWTP sources. Three of these were actual effluent samples collected at the Siloam Springs, Springdale and Rogers plants (Figure 3-3). The fourth was given the sample name 'Lincoln WWTP', and was collected just downstream of the Lincoln WWTP (Figure 3-3).

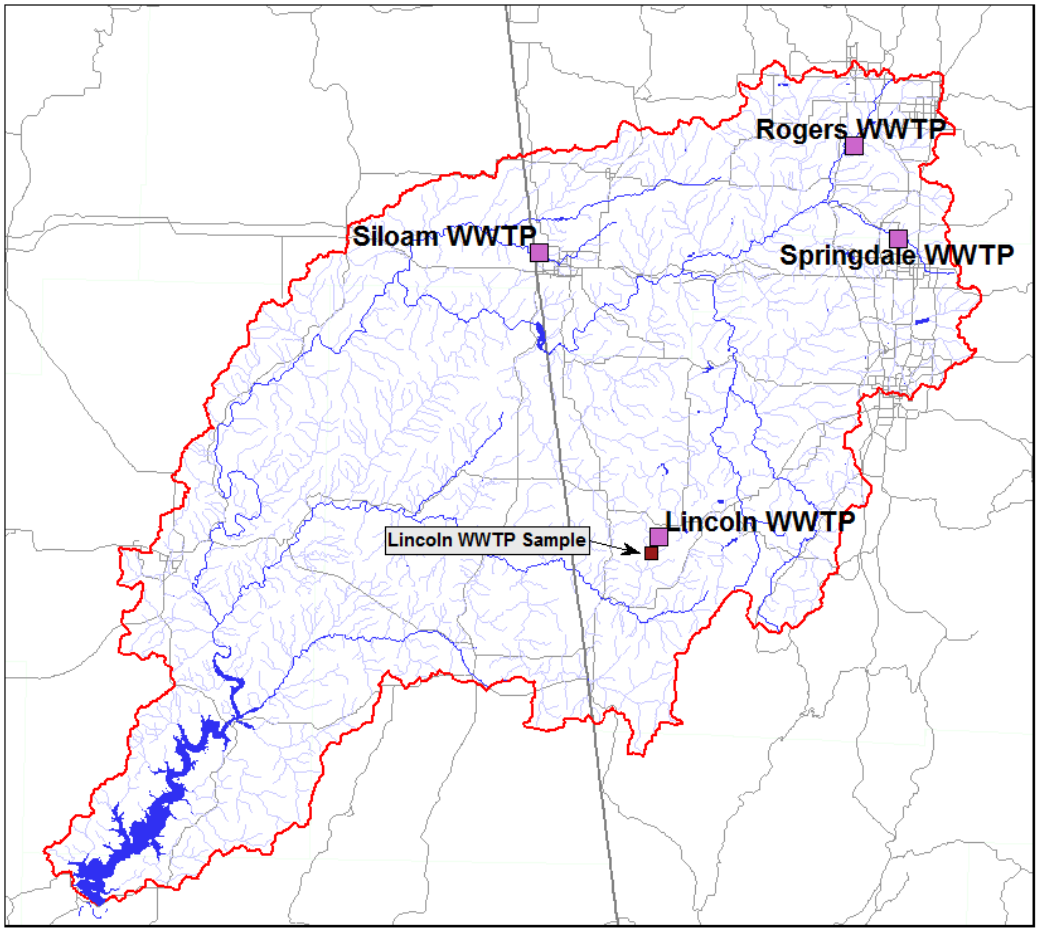


Figure 3-3. Map showing locations of Olsen's WWTP samples.
Rogers, Springdale and Siloam Springs WWTP samples were actual effluent samples. Lincoln was a surface water sample collected <2,000 feet downstream of the Lincoln WWTP (See Figure 3-5).

All four of these samples were included in Olsen's SW3 PCA run. Figure 3-4 shows the SW3 scores plot, with these samples highlighted and labeled. The three effluent samples plot within Olsen's WWTP Dominant Impact area, but they also exhibit PC1 scores above his 1.3 PC1 threshold for poultry impact. The fourth sample ("Lincoln") collected downstream of the Lincoln WWTP actually plots within Olsen's "*poultry waste dominant impact*" area. The fact that all four samples yield PC1 scores greater than 1.3 is a major contradiction to Olsen's theory of a PC1 threshold of 1.3 for determining the presence of a unique poultry signature.

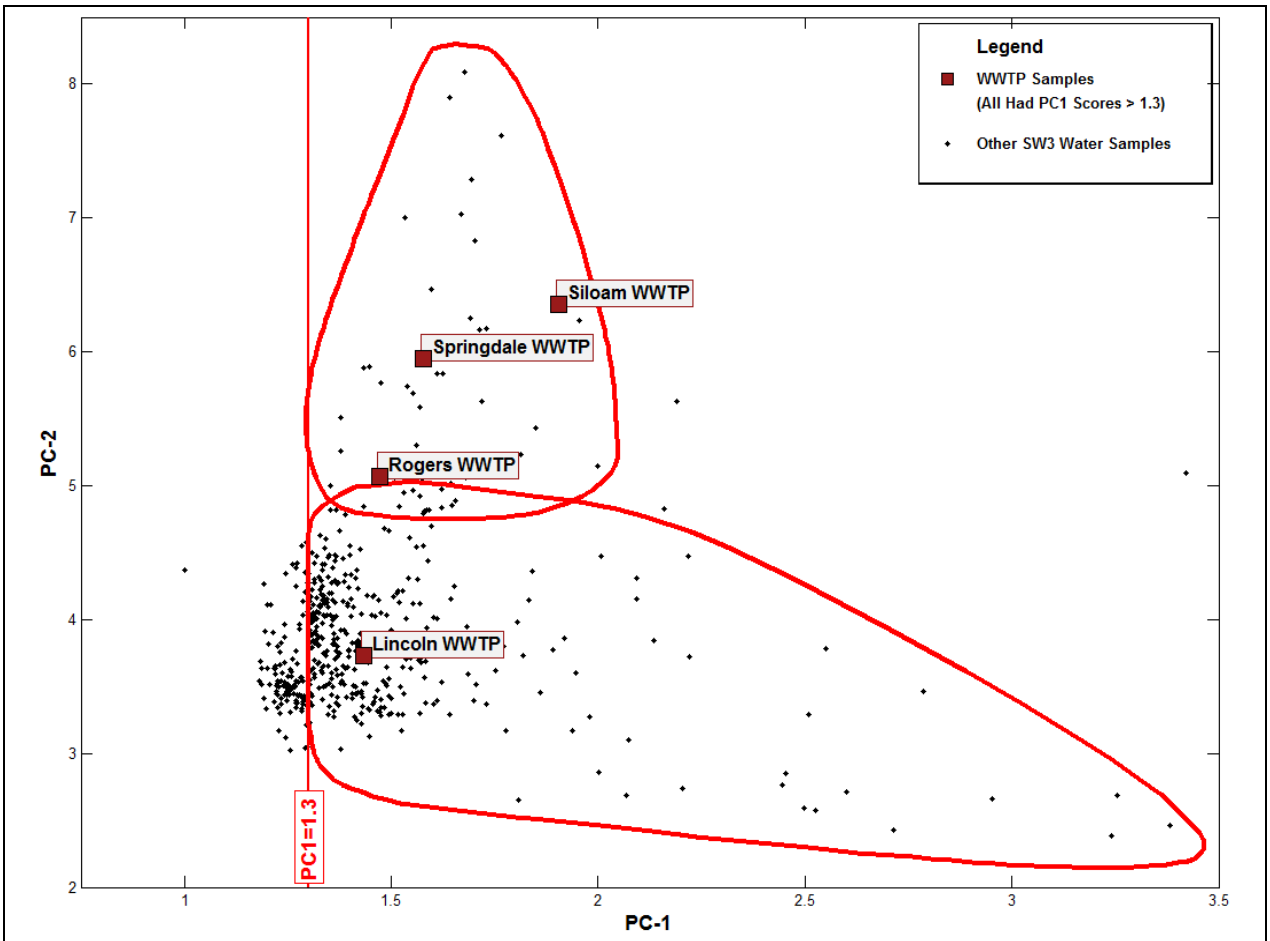


Figure 3-4. Olsen's SW3 scores plot (expanded view) with the four WWTP samples highlighted. All exhibit PC1 scores above Olsen's poultry impact threshold.

Like Tahlequah, Olsen's PCA classification of these samples as "*poultry impacted*" is not supported by his spatial analysis. But unlike Tahlequah, Olsen did not veto his 1.3 criterion. He showed them as red-dots on his Figure 6.11-23, and counted them among his poultry-impacted samples in his percentage calculations. In deposition, Olsen acknowledged that the three WWTP effluent samples all had PC1 scores greater than 1.3 and conceded that (1) they should not have been classified as poultry-impacted samples; and (2) they needed to be removed from his poultry-impact percentage calculations.[76] Two weeks later (9/24/08) Olsen submitted an erratum where the WWTP effluent samples (Siloam, Springdale and Rogers – but not Lincoln) were removed from his percentage calculations. The revised text neither acknowledged nor explained the inconsistency of having all WWTP effluent samples exhibit PC1 scores greater than 1.3. Even though the Siloam, Springdale and Rogers WWTP samples span a wide range of Olsen's "WWTP Dominant Impact" area (Figure 3-4) Olsen maintains that all other samples within the WWTP red-oval are poultry impacted. He makes no change in the classification of stream water samples as a result of his original error in classification of the three WWTP effluent samples.[77]

Olsen acknowledged that the intent of the Lincoln sampling was to get as close to the POTW outfall as possible.[78] But in contrast to Siloam, Rogers and Springdale, he did not change his

[76] Olsen Deposition. 9/10/08. pp. 274-275. 9/11/08. pp. 335-336.
[77] Olsen Deposition. 9/11/08. pp. 335-336.
[78] Olsen Deposition. 9/11/08. pp. 557-558.

classification of Lincoln WWTP as '*poultry impacted.*'[79] Neither did he address the degree to which his spatial analysis supported a conclusion of poultry-impact in this area, downstream of Lincoln.[80] Figure 3-5 shows a map of the location of the Lincoln WWTP sample, in relation to Olsen's poultry house density data and the Lincoln POTW. It is located in an area of low poultry house density, within a 1.5 km of Lincoln and its POTW outfall. A spatial analysis does not support the classification of this sample within the '*predominantly poultry-waste impact*' area of the scores plot.

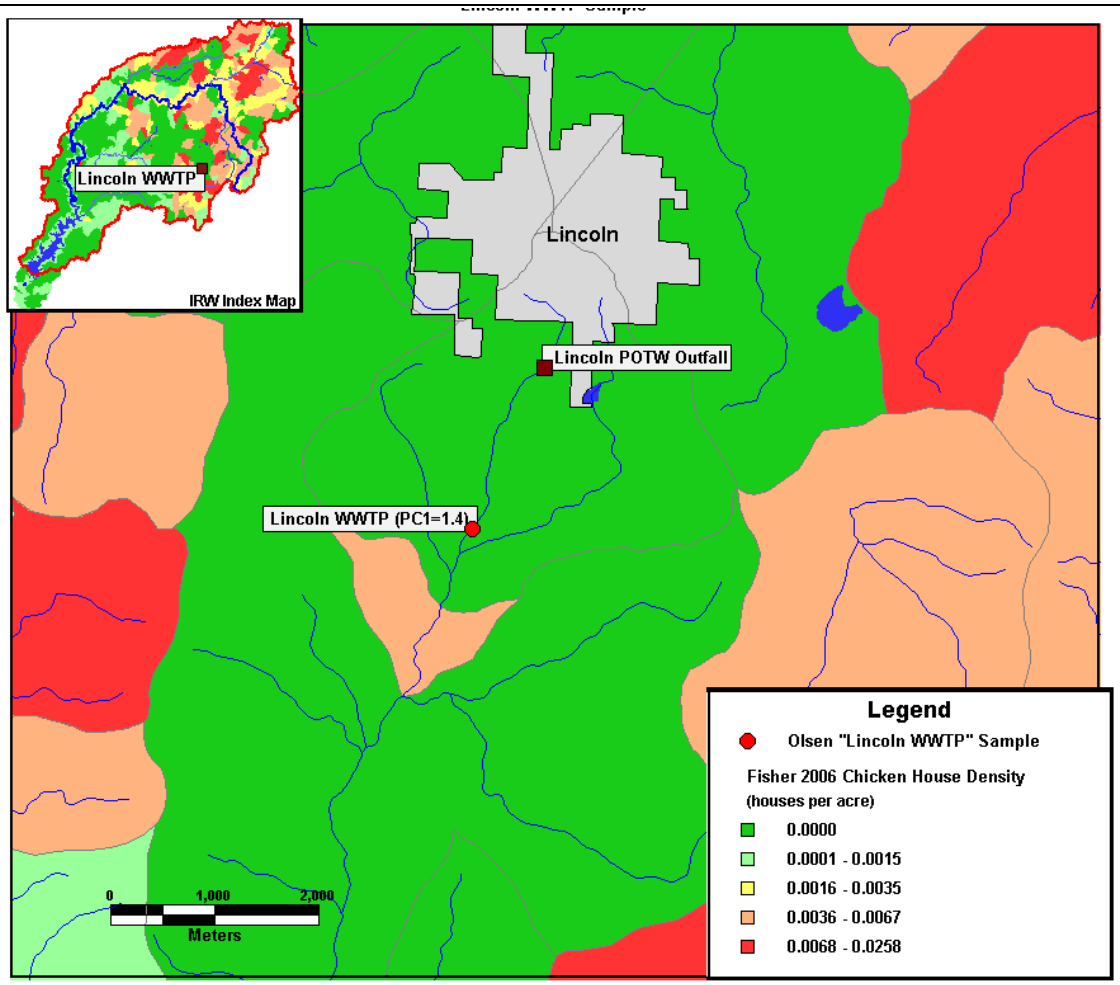


Figure 3-5. Location of Lincoln WWTP sample with respect to poultry house density & Lincoln POTW. Poultry House Density data from Olsen production. Lincoln POTW location from Jarman (personal communication).

[79] Olsen Deposition. 9/10/08. pp.276-277.
[80] Olsen Deposition. 9/11/08. pp. 558-559.

3.3 Cattle Impacted Samples

In Section 2.2.3, I briefly summarized the argument Olsen used to try to dismiss cattle manure as a source of contamination in the IRW. This section provides a more detailed critical review of that argument, as well chronological summary of how Olsen's cattle-impact argument has changed over time.

3.3.1 History of an Ever-Changing Cattle Impact Argument

3.3.1.1 February 2008: The Cattle Argument at the Time of the PI Hearing

As part of the Preliminary Injunction (PI) process, Olsen testified that his PCA differentiated three sources of contamination in the IRW: (1) poultry, (2) waste water treatment plants; and (3) cattle waste. Olsen testified to his ability distinguish between poultry, wastewater and cattle, and concluded that cattle waste inputs were not an important contributor.[81]

In that testimony, Olsen made it clear that he believed his PCA gave him the ability to distinguish between these three sources, but, he did not articulate a specific PCA criterion for what he considered "cattle impacted" (i.e. was it PC1 > 1.3, or PC2 > 4.7, or PC3>2). Two weeks after this deposition, in a February 14, 2008 email to counsel and members of his technical team[82] Olsen included the two hand-annotated PCA scores plots shown below (Figure 3-6).

The general shape of the data cloud is very similar to what we see in the SW3 and SW22 score plots presented by Olsen in his May 14 final report (see Figures 2-1 and 2-9 of this report). Most of the data plot within an L-shaped data cloud. His annotation of these graphs indicate that he interpreted samples located along the bottom of the "L" as "*poultry dominance*" and samples plotting along the vertical part of the "L" as *WWTP dominance.*" This is essentially the same interpretation as is reflected in his final report. But the cattle criterion is different. His hand-annotated PC scores plots show cattle-impacted samples all plotting away from (to the upper right of) the main part of the L. This hand-annotated scores plot sheds light on Olsen's subsequent PI hearing testimony:

> *"My conclusion is that the cattle signature is not significant. I went to specific samples that I knew had cattle waste in it and I could see a distinct difference, particularly with the poultry waste. So* ***I knew what I was looking for*** *and it just wasn't a dominant signature across the basin. I found it in, like, significantly in one spring sample and I found it not significant in three other spring samples. I found it significant in four edge of field samples and not so significant in five others. So it's just not a dominant signature across the basin. If it would have been, I would have found it."*[83]

This February 2008 testimony provides no hint of the cattle criteria that is ultimately reflected in his May 2008 report. Olsen says nothing about cattle-impacted samples "*exhibiting very different PC scores"* or the observation that some cattle impacted samples plot within both his WWTP and poultry dominant impact areas. Specifically, Olsen does not identify cattle impacted samples plotting in his WWTP oval or his poultry-impact oval. Instead he testified the he knew exactly what he was looking for, he saw distinct differences between cattle and poultry, and if cattle had been more dominant, he would have seen it. But bear in mind: this testimony predates both the collection of the cow-pasture edge of field samples (March 31, 2008), and Olsen's May 14, 2008 expert report.

[81] See Olsen PI Deposition. 2/2/08 pp. 93-97; 100-102. Preliminary Injunction Hearing. 2/ 21/08. pp. 844-845.
[82] OlsenCORR0015829-15833
[83] Olsen Preliminary Injunction Hearing Testimony. February 21, 2008. pp. 844-845. Emphasis added.

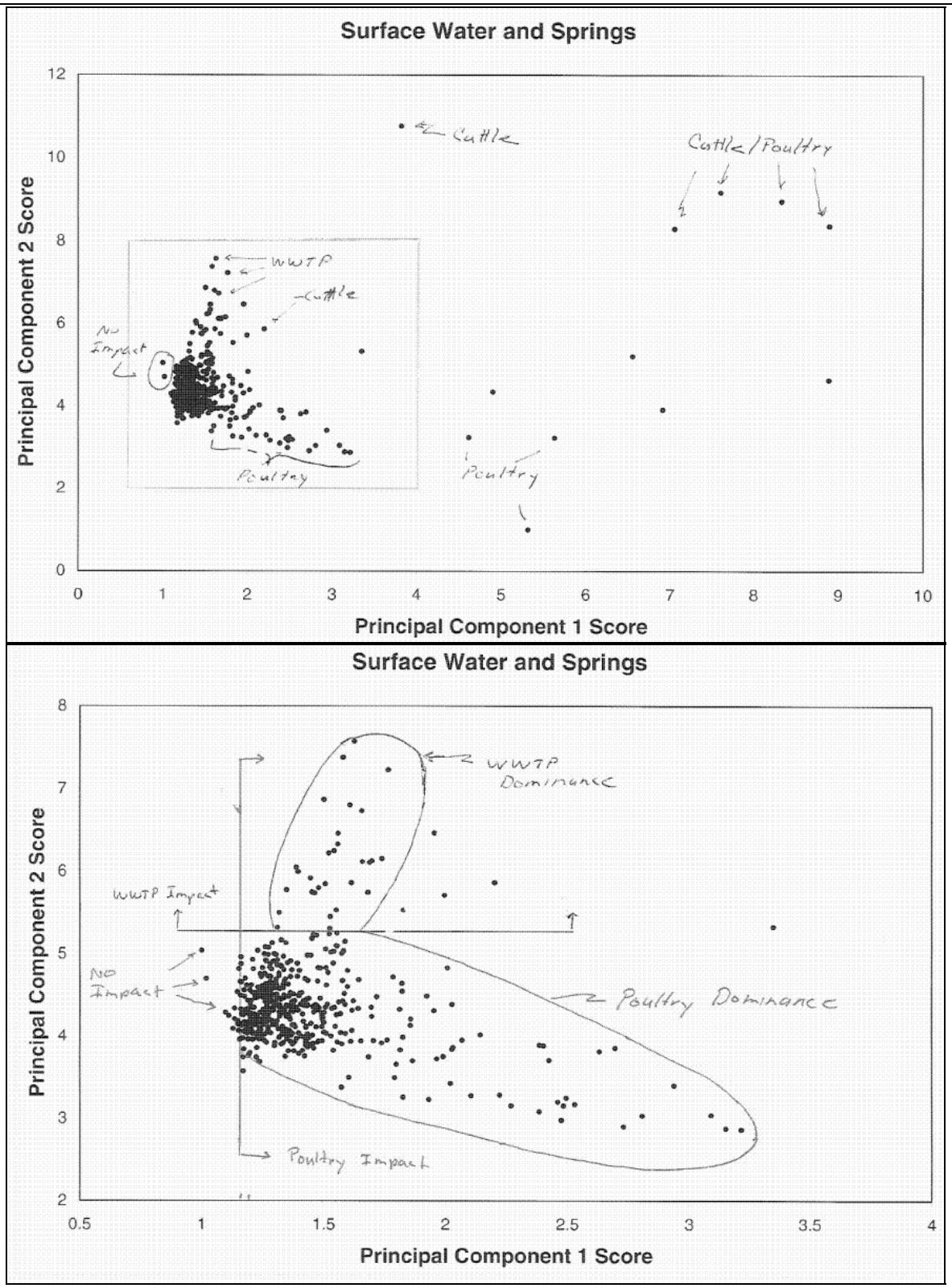


Figure 3-6. Olsen's hand-annotated scores plots: February 14, 2008 (surface-water and springs)
The lower scores plot is a zoom-in on the box-framed area shown in the upper plot. (Source: OlsenCORR0015833).

3.3.1.2 May 2008: The Cattle Argument in Olsen's Report.

The cattle manure argument that appears in Olsen's report (pages 6-61 and 6-62 of his report) is summarized and reviewed in Section 2.3.3 of this report, and differs from that presented as part of his February PI testimony. His PI testimony indicated that he believed that there was distinct separation between cattle and poultry samples on a scores plot. In contrast, his May 2008 report, points to "*four samples documented with cattle contamination*"[84] that plot across a wide ranging area of the scores plot, including areas of WWTP and poultry dominance. Most importantly, two of these four samples (cow-pasture edge of field samples collected after the PI hearing) actually plot within Olsen's '*poultry-waste impact dominant*' area (see Figure 2-9). As a result, we get a new argument in May 2008, as seen in the following three quotes:

- "*if cattle waste were a major impact on contamination in the IRW, a dominant signature should be observed in the PCA.*"[85]
- *"These four samples have very different PC scores and no consistent relation or group is observed in the PCA."* [86]
- "*If cattle contamination contributed significant impact to contamination in the IRW, a clear signature and associated group should be observed in the PCA and the four samples would be in a group."* [87]

Olsen's May 2008 opinion has not changed, but the argument that gets him there has. Olsen no longer expects cattle-impacted samples to be distinctly separated from poultry and/or WWTP-impacted samples on a scores plot. Instead he points to two samples that plot within the poultry-impact area, another that plots within the WWTP impacted area, and a fourth that plots separately from both areas, and cites this range of variability as evidence that there is no dominant signature for cattle.

As pointed out in Section 2.3, this argument completely ignores a major contradiction to Olsen's PCA interpretation. All "*four samples documented with cattle contamination*"[88] exhibit PC1 scores greater than 1.3. Olsen's report never acknowledges this. Nor did he acknowledge that the two cow pasture edge of field samples collected after the PI hearing (EOF-CP-1A and EOF-CP-1B) actually plot within his poultry- dominant area.

Olsen also concealed another interesting bit of information that contradicts his argument. Olsen's Figure 6.11-25 (SW22 scores plot reproduced here as Figure 2-9) shows cattle-impacted sample SPR-26 plotting as a single sample. With respect to that sample, Olsen wrote that "*one of the spring samples (SPR-26) plots within the WWTP impact area*."[89] There are actually two SPR-26 samples in SW22. Only one of these plots within Olsen's *WWTP impact area*. The other plots within Olsen's *poultry-waste dominant impact* group (PC1>1.3, PC2<4.7: see Figure 3-7 below). Olsen concealed this by taking the average of the two SPR-26 scores, and plotted the average on his Figure 6.11-25. Had Olsen not taken the average, his cattle impact argument would appear even weaker, because three of five "*samples documented with cattle contamination*"[90] would have plotted within an area of the scores plot that he interpreted as predominantly impacted by poultry. This graphical slight-of-hand obscures the fact that his "*unique poultry waste signature*" is not that unique.

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[84] Olsen (2008a). p. 6-62 (line 5).
[85] Olsen (2008a). p. 6-61 (last line) through p. 6-62 (2nd line). (emphasis added).
[86] Olsen (2008a). p. 6-62 (lines 13-14).
[87] Olsen (2008a). p. 6-62 (lines 14-17).
[88] Olsen (2008a). p. 6-62. Lines 4-6.
[89] Olsen (2008a). p. 6-62. 1st paragraph.
[90] Olsen (2008a). p. 6-62. Lines 4-6.

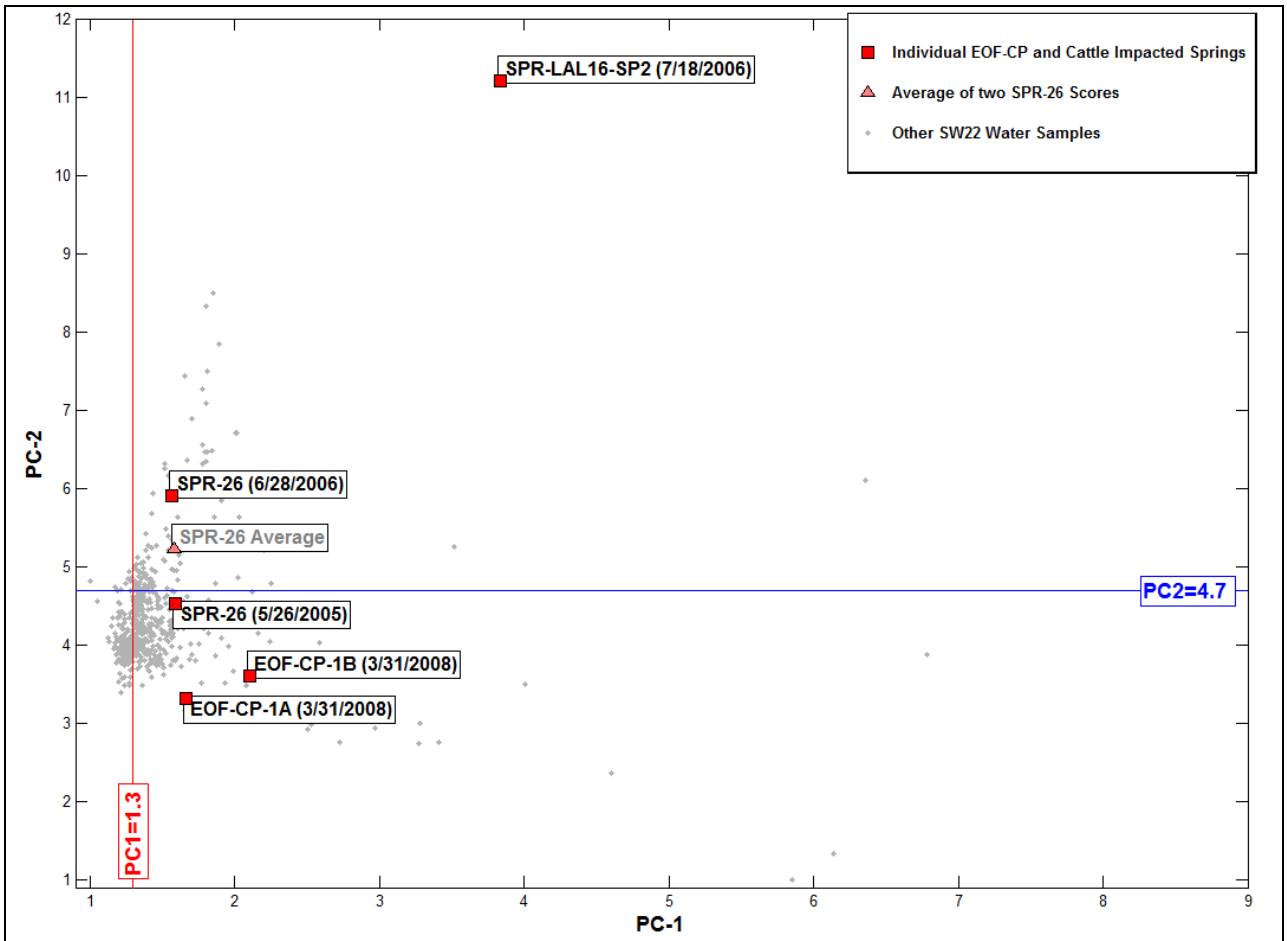

Figure 3-7. SW22 scores plot with cattle impacted edge-of-field (CP) and cattle impacted spring (SPR) samples highlighted.

Moving beyond this bit of deception, let's explore the logic Olsen's May 2008 cattle-impact argument in more detail. The argument is based on Olsen's premise that if cattle had a major impact, we would expect to see known cattle-impacted samples plotting as a single, clear and distinct group. According to Olsen, the fact that they do not (i.e. they plot across a wide ranging area of the scores plot) constitutes evidence that cattle-waste is not a major contributor. What if another group of samples, related to another suspected source, exhibited a similar wide range of variability? If we follow Olsen's logic, we should similarly conclude that it is not a "*dominant signature.*" With the exception of the two cow-pasture edge-of-field samples, Olsen claims that all other edge-of-field (EOF) samples reflect primarily poultry litter impacts.[91] SW3 included 63 EOF samples. These 63 samples (and the 2 EOF-CP samples) are highlighted on the SW3 scores plot in Figure 3-8.

[91] Olsen Deposition. pp. 51-52.

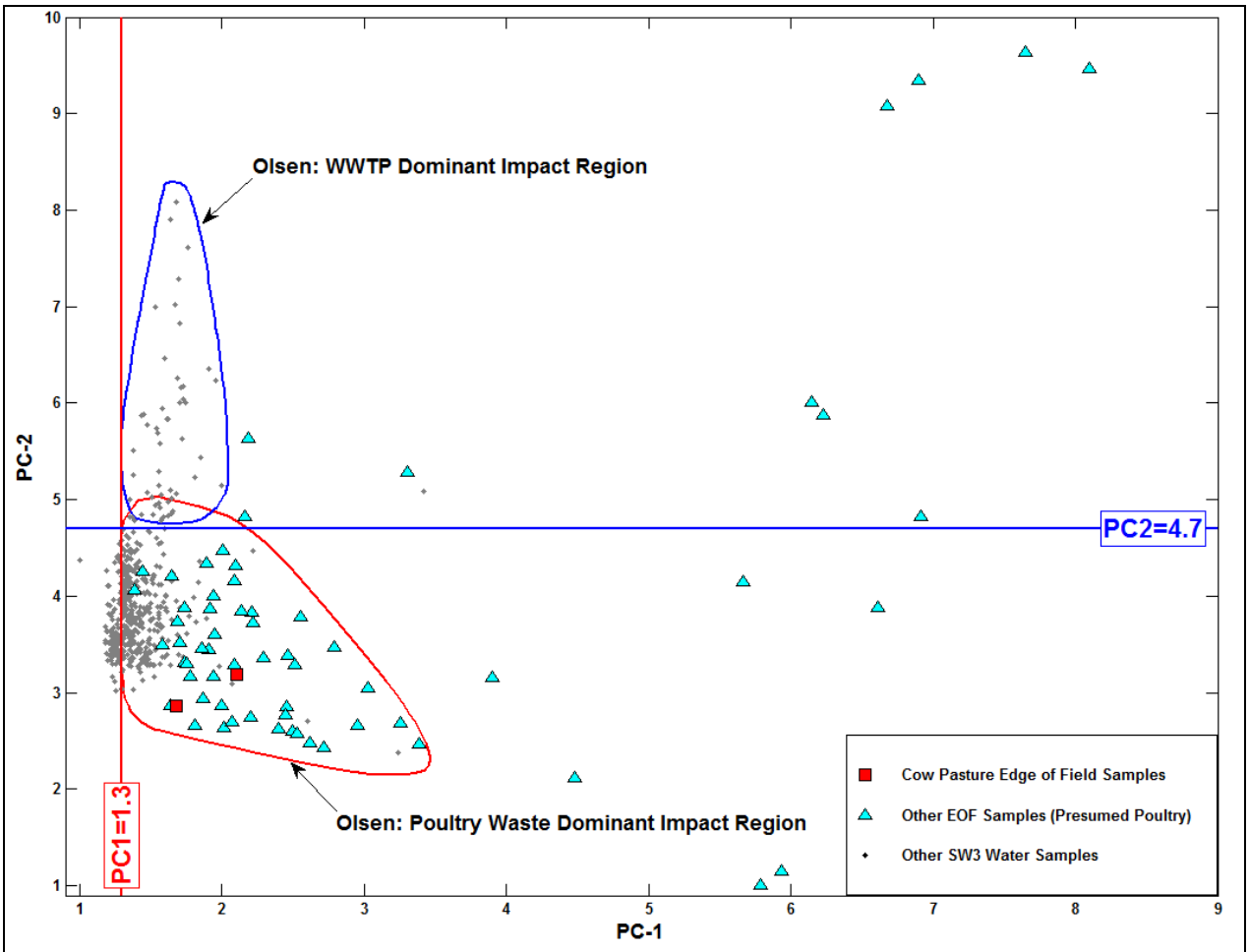

Figure 3-8. SW3 scores plot with EOF-CP and other EOF (presumed poultry) samples highlighted.

Note that the edge-of-field samples that Olsen presumes are poultry-impacted do not exhibit a "*clear signature and associated group.*" They have very different PC scores and no consistent relation or group is observed. This is exactly what Olsen described for the four cattle impacted samples in SW22[92] and was the rationale for dismissing cattle as a contributor to the IRW. The range of variability of the 63 presumed poultry-impacted EOF samples spans almost the entire range of the scores plot. Along the PC1 axis EOF scores range from very near Olsen's 1.3 poultry-impact threshold up to his maximum PC1 score of 8.1. Along the PC2 axis the EOF scores span the entire range from the minimum to maximum. Ten EOF samples actually exceed Olsen's "WWTP dominant impact" threshold of 4.7. Olsen's May 2008 cattle impact argument is poorly reasoned. In developing it, he relies on a conveniently ambiguous definition of "dominant signature." His logic is flawed because when you turn the same method to suspected poultry-impacted edge of field samples (the source that he claims is the dominant contributor to IRW surface waters) we see a similar range of variability. If you buy the premise of Olsen's May 14 cattle argument (i.e. what he would expect to see if cattle manure impacts were significant) the same logic should have led him to dismiss poultry as a significant source.

[92] Olsen (2008a). p. 6-62 (lines 13-17).

3.3.1.3 September 2008: The Cattle Argument Provided in Deposition Testimony.

Between Olsen's May 2008 report and his September 2008 deposition testimony, Olsen's cattle argument changed yet again. In May, the two EOF-CP samples (EOF-CP-1A and EOF-CP-1B collected on the property of Ed Fite) were characterized by Olsen as "*samples documented with cattle contamination.*"[93] In his September testimony, Olsen acknowledged that they exhibited PC1 scores greater than 1.3[94] and backed off of his position that they represent cattle-impact. He opined instead that they represent poultry-impact.[95] But he also confirmed that that (1) these samples were collected with the intent of capturing runoff representative of a pasture where cattle had been grazed,[96] (2) he had no evidence that poultry litter was ever applied on the property where the EOF-CP samples were collected,[97] and (3) his opinion that EOF-CP samples are poultry-impacted is speculation.[98] In deposition, Olsen offered caveats regarding the representativeness of the EOF-CP samples,[99] advised caution in how those data should be considered,[100] but conceded that his May 14 report included no such cautions.[101]

There is no evidence to support Olsen's speculation that the cattle edge-of-field samples are impacted by poultry.[102] The CP-EOF samples were collected on March 31, 2008 on the property of Ed Fite. Field notes taken at the time of their collection state: "*This field has never been applied with poultry waste*."[103] In addition, when you look at these data in context of Olsen's spatial analysis (in particular his poultry-house density data) it does not support Olsen's speculation (Figure 3-9). These samples were collected in an area of low poultry house density.

Olsen's most recent cattle argument is not only based on speculation, it is contradicted by the very data that he relied on elsewhere to justify his interpretations.

[93] Olsen (2008a). p. 6-62. Lines 4-6.
[94] Olsen Deposition 9/11/08. pp. 369.
[95] Olsen Deposition. 9/10/08 p. 282. (Lines 15-24). 9/11/08. p. 388 (Lines 1-17).
[96] Olsen Deposition 9/10/08. pp. 52-53.
[97] Olsen Deposition. 9/10/08. p. 54.
[98] Olsen Deposition. 9/11/08. p. 388 (Lines 18-19).
[99] Olsen Deposition 9/10/08. pp. 52-53.
[100] Olsen Deposition. 9/10/08. p. 55 (Lines 15-25).
[101] Olsen Deposition. 9/10/08. p. 56 (Lines 5-8).
[102] Olsen Deposition. 9/11/08. p. 388 (Lines 18-19).
[103] See Field CDM/Lithochimea field notes from March 31, 2008 (STOK005374).

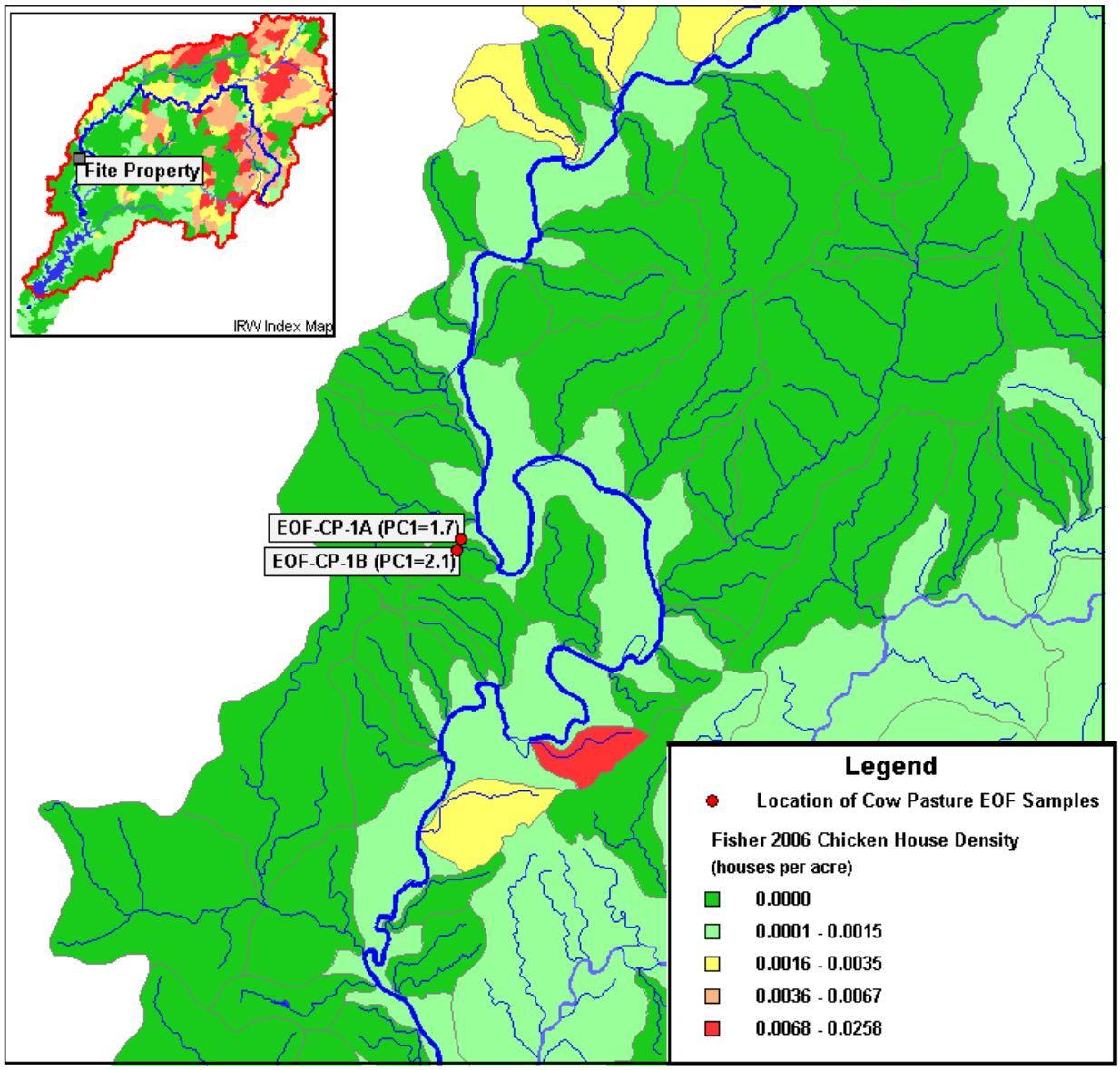

Figure 3-9. Locations of EOF-CP samples plotted on Olsen's poultry house density basemap.
Note that the EOF-CP samples are located in area of zero poultry-house density, yet the PC1 scores of both samples both yielded PC1 scores greater than Olsen's 1.3 poultry impact threshold.

3.3.2 Olsen was Aware of This "Problem" and Concealed It

In his May 14 report, Olsen never acknowledged that his "*samples documented with cattle contamination*"[104] all had PC1 scores > 1.3, or that there was overlap between EOF-CP and other EOF samples. However, it is clear from emails produced by Olsen that his failure to disclose it was not because he missed these points, or failed to appreciate their significance. Emails between Olsen and an associate that ran the statistical software for him, indicate that within the final two weeks before Olsen's report was due, they were actively trying to find a PCA run that would yield a scores plot with distinct separation between poultry EOF and cow pasture EOF samples. The emails below were exchanged on May 2, 2008, after nineteen PCA runs (out of 22 total in his report) had been completed.

Fri 5/2/2008 8:30 AM
From: Richard Chappell
To: Roger Olsen
Subject: PCA run SW 19 posted

Water_0502_SW_19
Same as SW 18 but removed the two FAC samples - so it's just EOF and Manure Leachate.

Fri 5/2/2008 9:54 AM
From: Olsen, Roger
To: Chappell, Richard
Subject: Looked at runs - one more

I looks at the runs - good confirming things.
I think we should run an EOF only run - see if the EOF - CP will break out. Thanks.

Fri 5/2/2008 11:06 AM
From: Richard Chappell
To: Roger Olsen
Subject: RE: Looked at runs - one more

Posted: **Water_0502_SW_20**
EOF only run, 26 variables, >=20 cutoff, total metals. On **R_PC_Plot** the CD [sic] samples are indicated on the variomax plots (and a few of the no rotation plots) as yellow symbols - they don't seem to break out, although they are kind of toward the edge on alot of the plots. I'm looking at the chemistry some more to see if there are any particular variables that differ from the rest of the EOF - if so, we may be able to break them out using a reduced set of variables.

Have you received any further information about those samples?

Recall that Olen's February 2008 cattle-impact criterion was based on separation of presumed cattle impacted samples and poultry-impacted samples on a PCA scores plot (see Section 3.3.1.1). But the March 2008 cow-pasture edge-of-field samples (CP) did not support that criterion. Those two samples plotted squarely within Olsen's "*poultry-waste dominant impact*" area (see SW3 scores plot: Figure 2-12). On May 2, after 19 PCA runs, Olsen was apparently still trying to find a way to "*see if the EOF - CP will break out.*" That is, he was trying to find a PCA run that supported his February PI testimony. SW20 was run with that specific purpose.

The SW20 varimax plots referred to in the 3rd email were not included in Olsen's production, but the results spreadsheets for PCA run SW20 were. It is a simple matter to make a varimax scores plot using those results (Figure 3-10 below). On this plot, we see exactly what was reported to Olsen in the email above: there is no separation between EOF-CP and other EOF samples.

[104] Olsen (2008a). p. 6-62. Lines 4-6.

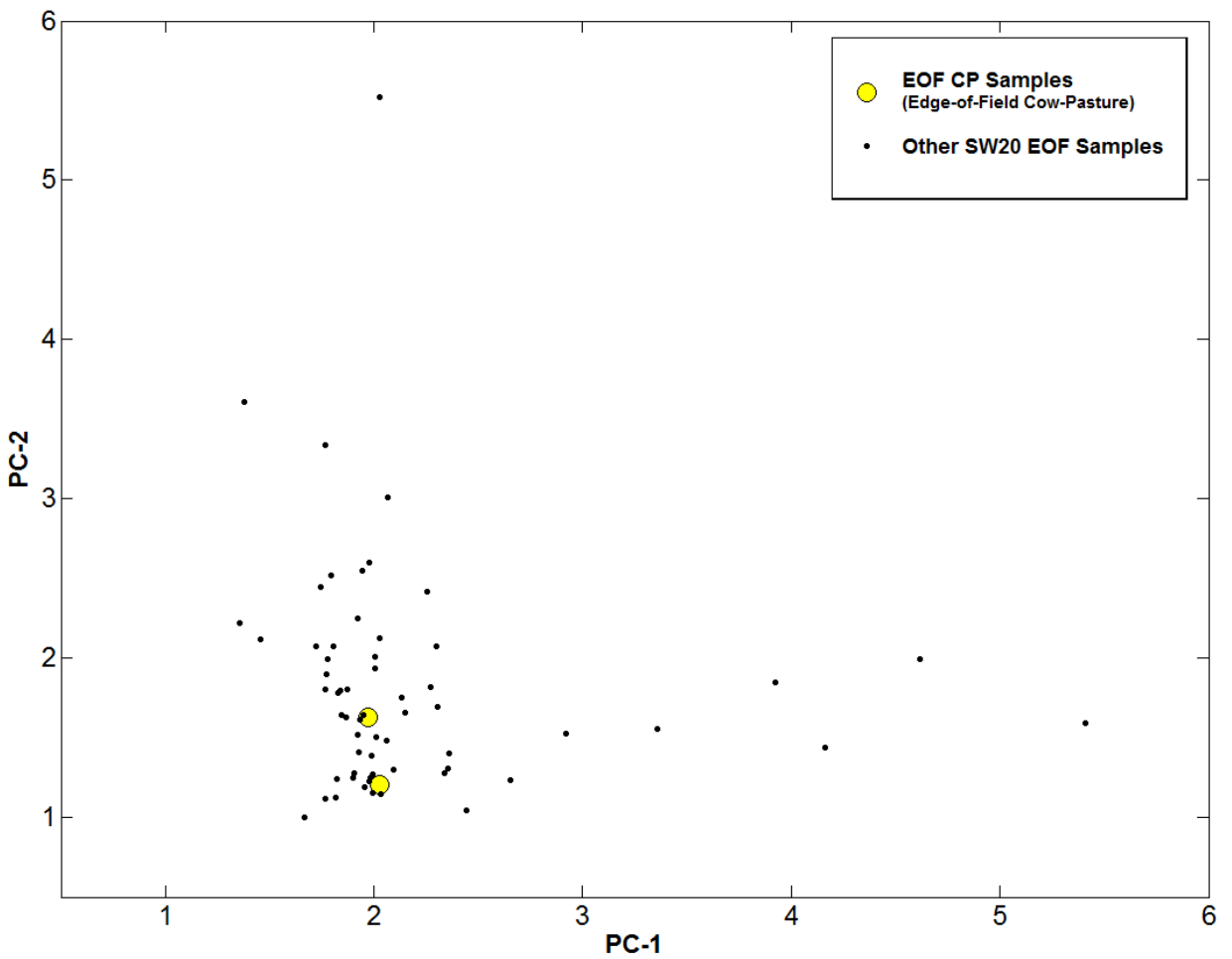

Figure 3-10. SW20 Scores Plot (Varimax Rotation).
Data taken from Spreadsheet ('Results_Water_0502_SW_20.xls') produced as part of Olsen considered materials. Note lack of separation between EOF CP and other edge-of-field samples.

In the same email where Olsen's associate (Chappell) reported the failure to get separation, he reported that "*I'm looking at the chemistry some more to see if there are any particular variables that differ from the rest of the EOF - if so, we may be able to break them out using a reduced set of variables.*" Two and a half hours later, the results of that analysis were back, in the form of PCA Run SW21.

Fri 5/2/2008 1:37 PM
From: Richard Chappell
To: Roger Olsen
Subject: RE: Looked at runs - one more
Attachments: Comparison_EOF_CP_Chemistry_26.xls; R_PC_Plot_Water_0502_SW_21.zip

I compared the 26 variables (see attached) then picked the 14 variables that were most different between the two CP samples and the EOF and ran a PCA. It put them more on the edge, generally, but still no distinct separation (see attached).

In this attempt to get "*distinct separation*" Chappell first conducted a comparison of the 26 variables in Olsen's main PCA water run (SW3). Based on that analysis, he identified 14 that he thought gave him the best chance of distinguishing between EOF-CP and other EOF samples. He

then ran a PCA using only those variables. Despite cherry-picking the variables with the specific objective of getting separation between EOF-CP and other EOF samples, this attempt failed: "*still no distinct separation (see attached).*" This time, the score plots were included as an attachment to the email (Figure 3-11).

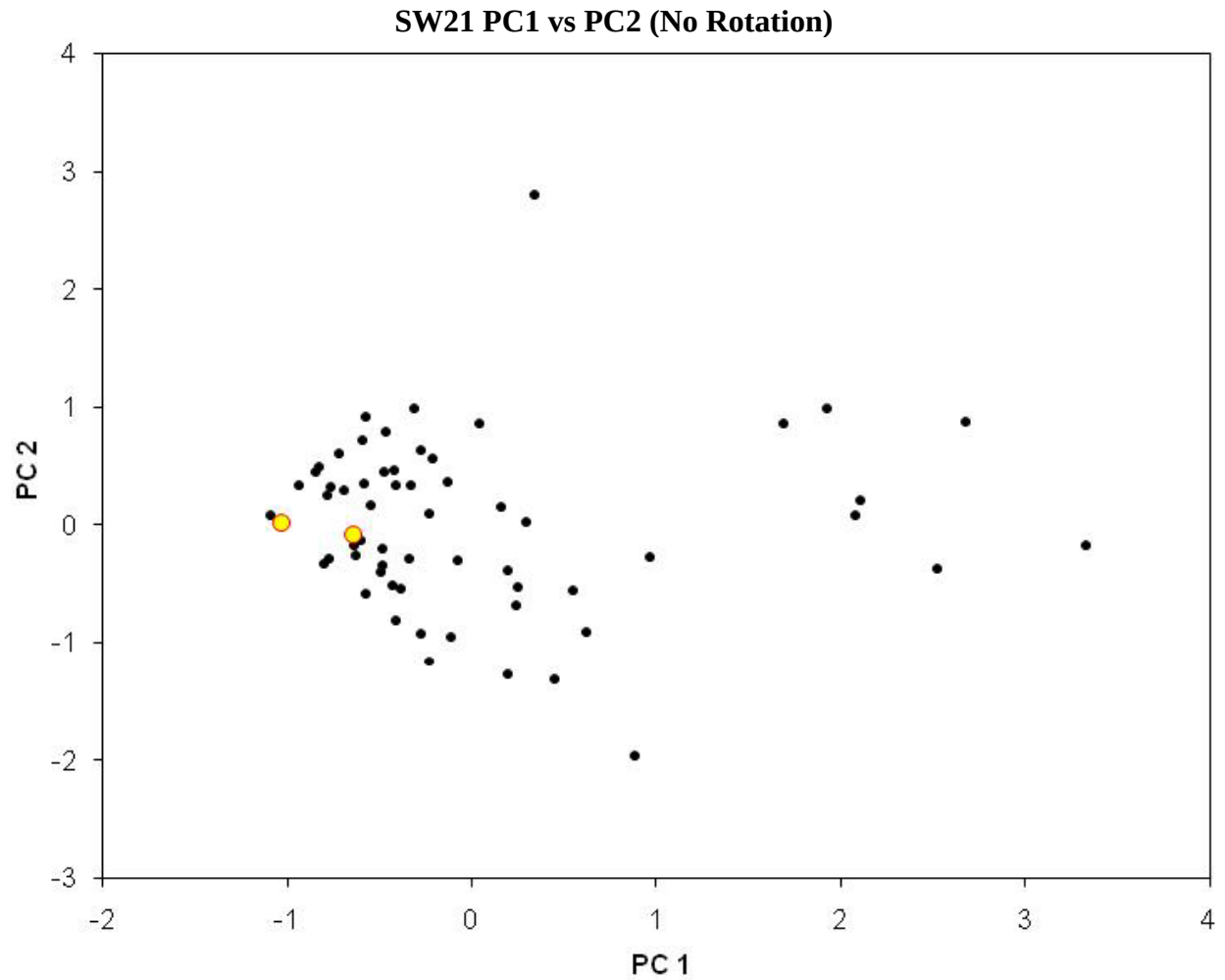

Figure 3-11. SW21 Scores Plot (No Rotation).
Plot included in spreadsheet ('R_PC_Plot_Water_0502_SW_21.xls') produced as part of Olsen considered materials, as attachment to 5/2/08 email from Chappell to Olsen. The yellow circles are the EOF-CP samples. The black dots are all other EOF samples in SW21. Note: no separation between EOF CP and other edge-of-field samples.

These emails make it clear that that as of Friday May 2, 2008, Olsen was holding out hope that the new cow-pasture edge-of-field data would support his concept of a distinct cattle signature, as per his PI testimony. He was looking for distinct separation between presumed cattle and poultry impacted samples. But PCA runs that included the new CP samples showed no such separation. He ran SW20 and SW21 with a specific objective: "*see if the EOF-CP will break out.*" They did not break out, and it was at this point that his cattle impact criterion changed. Two days after SW21 was run, (Sunday May 4 – ten days before the final report was due) Olsen ran one final PCA (SW22)[105] which became the basis of the cattle impact argument that appears his report (pages 6-61 and 6-62) and which is reviewed in Sections 2.3.3 and 3.3.1.3 of this

[105] See Olsen/Chappell email exchange. 5/4/08. 3:47 pm and 4:47 pm.

report. With this final PCA run, the criterion for distinguishing between cattle and poultry was no longer distinct separation, but rather the variability of scores.

Little of this is ever discussed in Olsen's report. But a detailed review of these PCA runs, the timing of emails that describe their purpose, and interpretation in context of the spatial analysis, indicate that he was well aware of evidence that contradicted his theory, and was less than forthcoming in his report.

- Olsen did not acknowledge in his report that all four cattle-impacted samples yielded PC1 scores above his *unique poultry waste signature* threshold.
- The score plots presented in Olsen's report from his primary PCA run (SW3) did not use a unique symbol for EOF-CP samples, so the reader cannot look at his figures and see that the two cow pasture edge-of-field samples plot within the boundaries of his "*poultry waste dominant impact*" area.
- In his report, Olsen never discussed the rationale for, or results from SW20 and SW21. But these PCA runs were implemented with the specific objective of getting separation between presumed cattle and poultry-impacted samples. They failed to meet that objective.
- In section 2.3.3 I noted that it was curious that PCA run SW22 was not included in Olsen's list of four "*major PCA runs*" [106] selected as such because they were "*the most important to the investigation or project objectives*."[107] This now makes a bit more sense. PCA run SW22 (and the associated cattle-impact argument in Olsen's report) was an afterthought. SW22 was run more than 2 months after Olsen's PI testimony, just 10 days before his report's due-date, and done so only when repeated PCA runs failed to support Olsen's previous argument, which had been based on distinct separation.
- Olsen's red-dot green-dot map ultimately shows the cattle edge-of-field samples as poultry impacted. But his spatial analysis does not support such an interpretation. The spatial analysis was supposedly an independent line of evidence in support of his interpretation.[108] In reporting the results of that effort, he presented just five examples, all of which were consistent with his interpretation.[109]
- The email exchanges quoted above indicates that these were not errors of omission. Olsen was fully aware of this contradictory evidence and its significance, and did not disclose it in his report.

In deposition, four months after his report, Olsen was confronted with these conflicting lines of evidence. Olsen now claims the EOF-CP samples (previously described "*samples documented with cattle contamination*"[110]) must considered with caution, and that they represent poultry impact, not cattle. Given three versions of Olsen's argument now, it is curious that his opinion never changes, only the argument necessary to get him there.

[106] Olsen (2008a). p. 6-51. Last paragraph.
[107] Olsen (2008a). p. 6-50. 3rd paragraph.
[108] Olsen (2008a). p. 6-34 (Steps 12 and 13 bullets); p. 6-57 (4th paragraph); p. 6-59 (2nd paragraph). P. 6-60 (1st paragraph). Olsen Deposition testimony (9/10/08; p. 220).
[109] Olsen (2008a). p. 6-59 to 6-60
[110] Olsen (2008a). p. 6-62 (line 5).

3.4 High Flow Sample Stations

As discussed in Section 2.3.1, Olsen's spatial analysis discussion relied in large part on results from two high-flow sampling stations in areas of low poultry house density: HFS28A and HFS30. I pointed out that these two stations represent only a fraction of the high-flow samples included in Olsen's PCA. Pointing to Figure 2-5, I noted that there were numerous instances of red-dots (supposedly poultry impacted) plotting in green sub-basins (areas of low poultry house density), and that this suggests that Olsen's spatial analysis is not as consistent with his poultry-impact classification as he might have us believe. In this section, I will present a more detailed review of some of the high-flow-station data that contradict Olsen's interpretation.

Figure 3-12 shows the location of high flow sample station HFS-05. Twenty high flow samples were collected from this station, between June 2005 and June 2006. For Olsen's SW3 PCA run, The PC1 scores for all 20 samples exceeded 1.3. The average PC1 score was 1.52, and the maximum was 2.22. But this map shows that it is located at or near the downstream boundary of a zero poultry house density sub-basin. This sub-basin is located just west of Fayetteville, Arkansas (the largest city in the IRW – see inset map). To the extent that Olsen's PC1 scores reflect contamination, it would certainly seem that urban runoff would be a more plausible explanation for the water quality at the HFS-05 sample station.

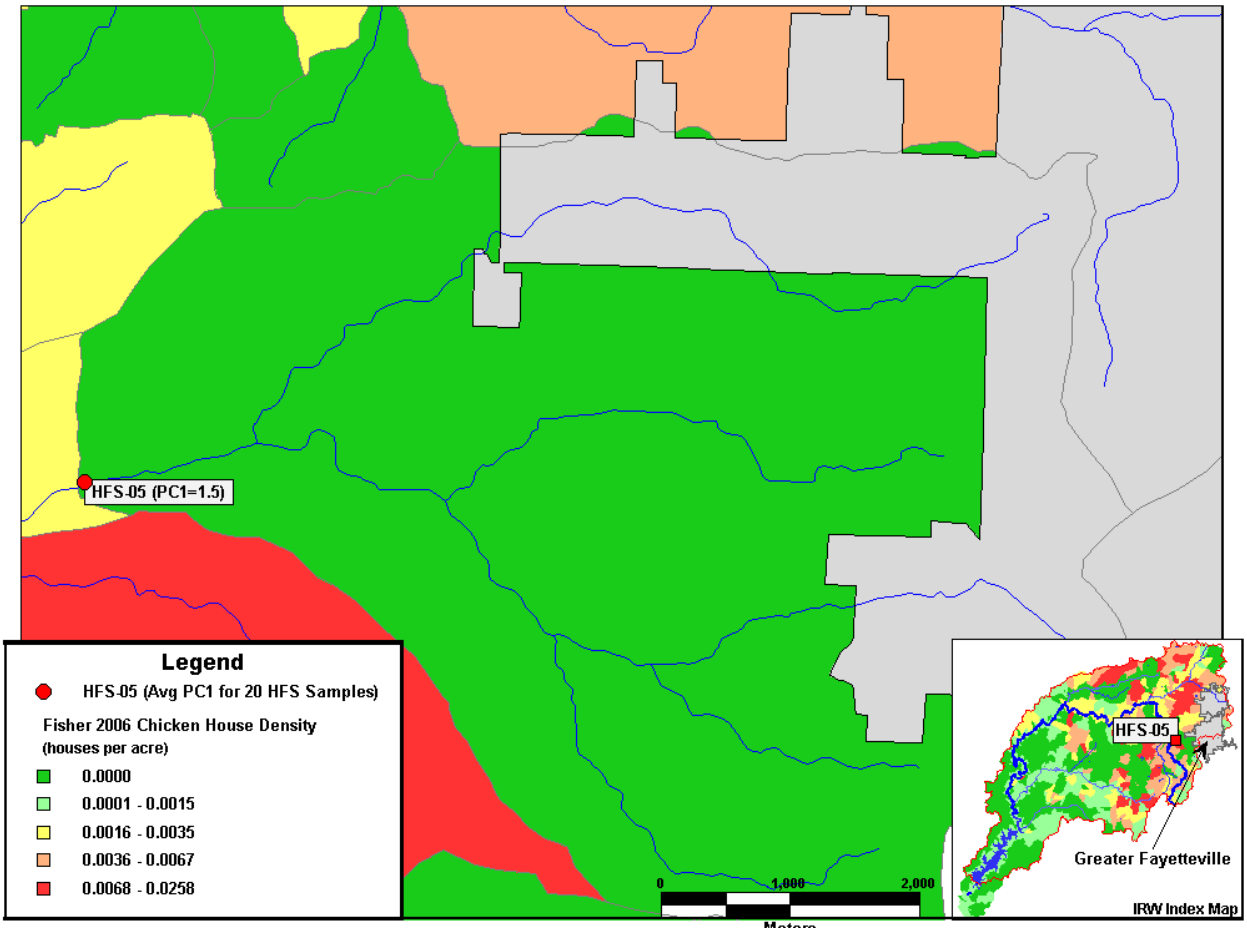

Figure 3-12. Location of HFS-05 plotted over Olsen poultry house density data and greater Fayetteville Area (gray shaded area).

A second example is HFS-22 near Lincoln, Arkansas. Figure 3-13 shows its location at the downstream edge of a zero poultry-house density area. This is the same area where Olsen

collected his Lincoln WWTP sample (Section 3.2) and that sample is shown on Figure 3-13 along with HFS-22. Fifteen high-flow samples were collected at HFS-22 between May 2005 and May 2006. All but one yielded PC1 scores greater than 1.3 (average=1.64 | range: 1.24 to 2.00). Like Olsen's "Lincoln WWTP" sample, HFS-22 is located downstream of both the city of Lincoln and its sewage treatment plant (POTW outfall - Figure 3-13).

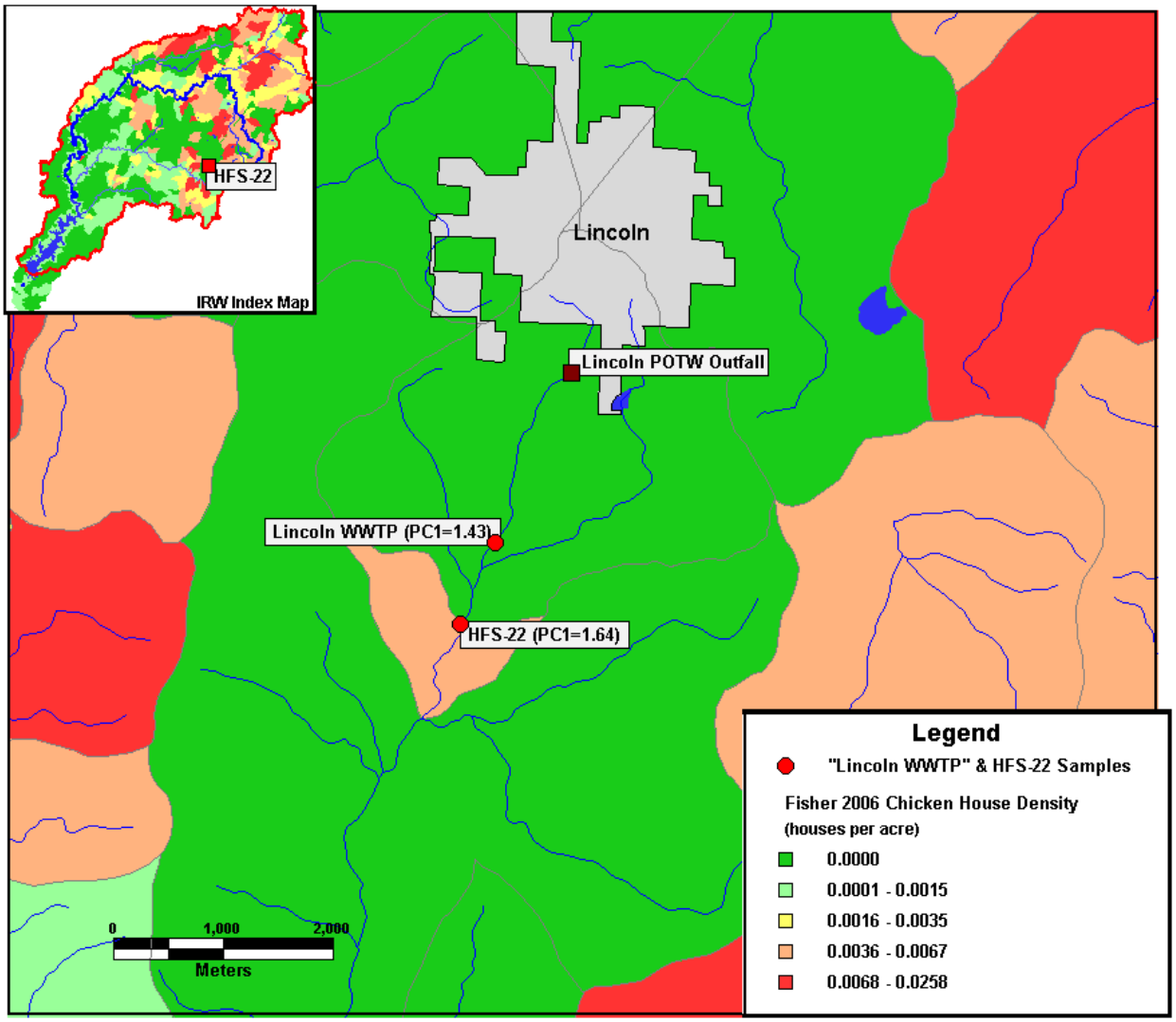

Figure 3-13. Locations of HFS-22 and Lincoln WWTP samples, plotted over Olsen poultry-house density data.
PC1 score shown for HFS-22 is the average of 15 high-flow samples collected at this location.

To the extent that Olsen's PC1 scores reflect contamination, his spatial analysis suggests that urban runoff and/or WWTP impacts are more plausible explanations. Elsewhere in his report, Olsen acknowledges this. In his discussion of sources of phosphorus in context of poultry house density, Olsen acknowledged that HFS-22 was sampled to provide information on the mass loads contributed by this type of WWTP facility. In the same discussion, he indicated that HFS-22 was excluded from the phosphorus statistical analysis because the stream water quality at this site is dominated by effluent from the Lincoln wastewater treatment plant.[111] These cautions and caveats were apparently not taken into consideration in the spatial analysis performed in support

[111] Olsen (2008a). p. 6-29. Final paragraph.

of Olsen's PCA interpretation. While acknowledging that this sample is dominated by wastewater treatment plant effluent, and aware that it is located in a low poultry-house density area, it did not influence his choice of a 1.3 PC1 poultry-impact threshold. This illustrates both the internal inconsistency in Olsen's report, and the arbitrary nature of his '*unique poultry waste signature*' criterion.

The third and fourth examples (HFS-04 and RS-336) are in or downstream of Siloam Springs, Arkansas (Figure 3-14). Both are located on Sager Creek, and both are located within a sub-basin that Olsen's data shows as having zero poultry house density.

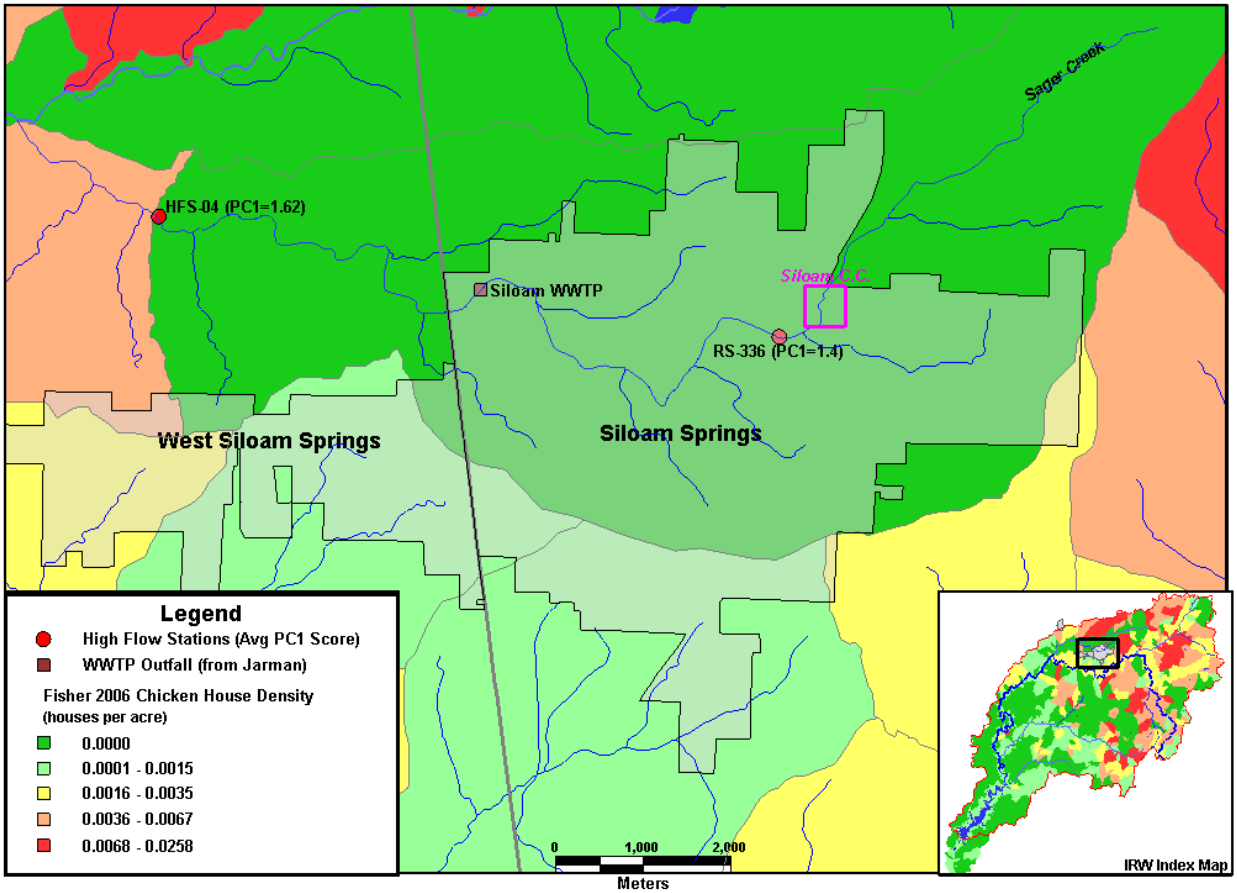

Figure 3-14. Siloam Springs high-flow samples plotted over poultry-house density.
Also shown: (1) Location of Siloam Springs WWTP; (2) Location of Siloam Springs Country Club (golf course); (3) city limits of Siloam Spring, Arkansas and West Siloam Springs, Oklahoma, based on ESRI (2006) data.

Nineteen samples were collected from high-flow sample station HFS-04 between May 2005 and May 2006. All 19 yielded PC1 scores greater than 1.3 (average=1.62 | range is 1.48 to 1.73). Like the Lincoln sample, HFS-04 is located downstream of both the city of Siloam Springs and its waste-water treatment plant (Figure 3-14). Once again, to the extent that Olsen's PC1 scores reflect contamination, his spatial analysis suggests that urban runoff and/or WWTP impacts are more plausible explanations. Once again, Olsen acknowledged this elsewhere in his report. In the same discussion of HFS-22 (in context of phosphorus concentrations and poultry house density, as discussed above) Olsen indicated that HFS-04 was excluded from the phosphorus statistical analysis because the stream water quality at this site is "*dominated by effluent from the City of Siloam Springs wastewater treatment plant*."[112] This was apparently not taken into

[112] Olsen (2008a). p. 6-29. Final paragraph.

account in context of Olsen's PCA. Rather, HFS-04 was classified by Olsen as poultry-impacted and plotted as a red-dot on his red-dot / green-dot map. This contradiction, as revealed by this spatial analysis did not influence his choice of a 1.3 PC1 poultry-impact threshold. Once again, this illustrates both the internal inconsistency in Olsen's report, and the arbitrary nature of his '*unique poultry waste signature'* criterion.

The fourth example is shown on this same map. RS-336 is located within the city limits of Siloam Springs, within the same zero poultry house density sub-basin as HFS-04. Only one high-flow sample was collected at RS-336 (5/10/2007), but it yielded a PC1 score of 1.4. This sample-station is located immediately downstream of a golf-course (Siloam Springs Country Club). To the extent that Olsen's PC1 scores reflect contamination, it would seem that urban runoff and/or fertilizer application would be a more plausible explanation.

In summary, Olsen's discussion of his spatial analysis cites 15 high-flow samples collected from 2 sample stations located in areas of low poultry house density. Those samples yielded average PC1 scores below or near or his 1.3 threshold, and that was cited by Olsen as a line of evidence in support of his purported *unique poultry waste signature* criterion. In this section of my report, I have presented data from 45 high flow samples, collected at 4 locations. Using the same spatial analysis criteria as Olsen (locations with respect to urban areas, locations with respect to WWTPs, and the Olsen/Fisher poultry house density data) it is clear that his 1.3 criteria is not supported by his own data.

3.5 Base Flow Sample Stations

If we look at base-flow samples in relation to Olsen's poultry house density data we see a similar pattern, or lack thereof. Figure 3-15 shows numerous red-dots plotting in green sub-basins.

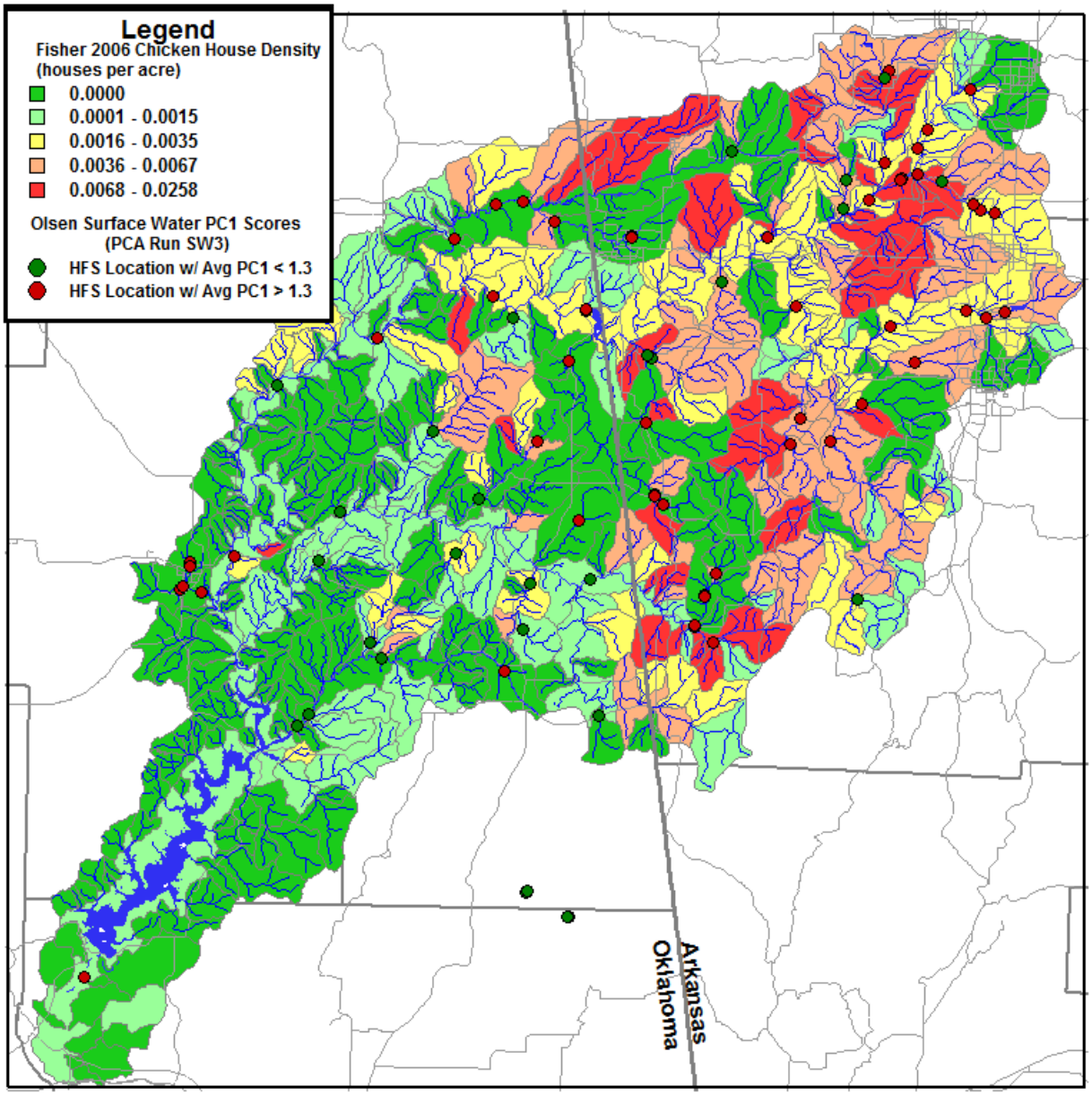

Figure 3-15. Base-flow sample PC1 scores map, plotted over poultry house density data.

However, if we plot these same base-flow results over a map showing human population centers, we see a more consistent pattern (Figure 3-16). Many of the red-dots that are anomalous with respect to poultry-house density data (Figure 3-15) are located in and immediately downstream of cities, towns, and/or WWTPs. This is particularly evident in streams that drain the greater Fayetteville/Bentonville urban areas. But it is also apparent in base-flow samples downstream of Siloam Springs, Tahlequah,[113] Stillwell, Watts, Prairie Grove, Westville, and Lincoln.

[113] Note that the Tahlequah base-flow samples shown on Figure 3-16 are the same samples that Olsen changed on his red-dot / green-dot map (Section 3.1). The coincidence of red-dots and urban areas for base-flow samples provides a plausible explanation for why the Tahlequah data did not fit Olsen's theory.

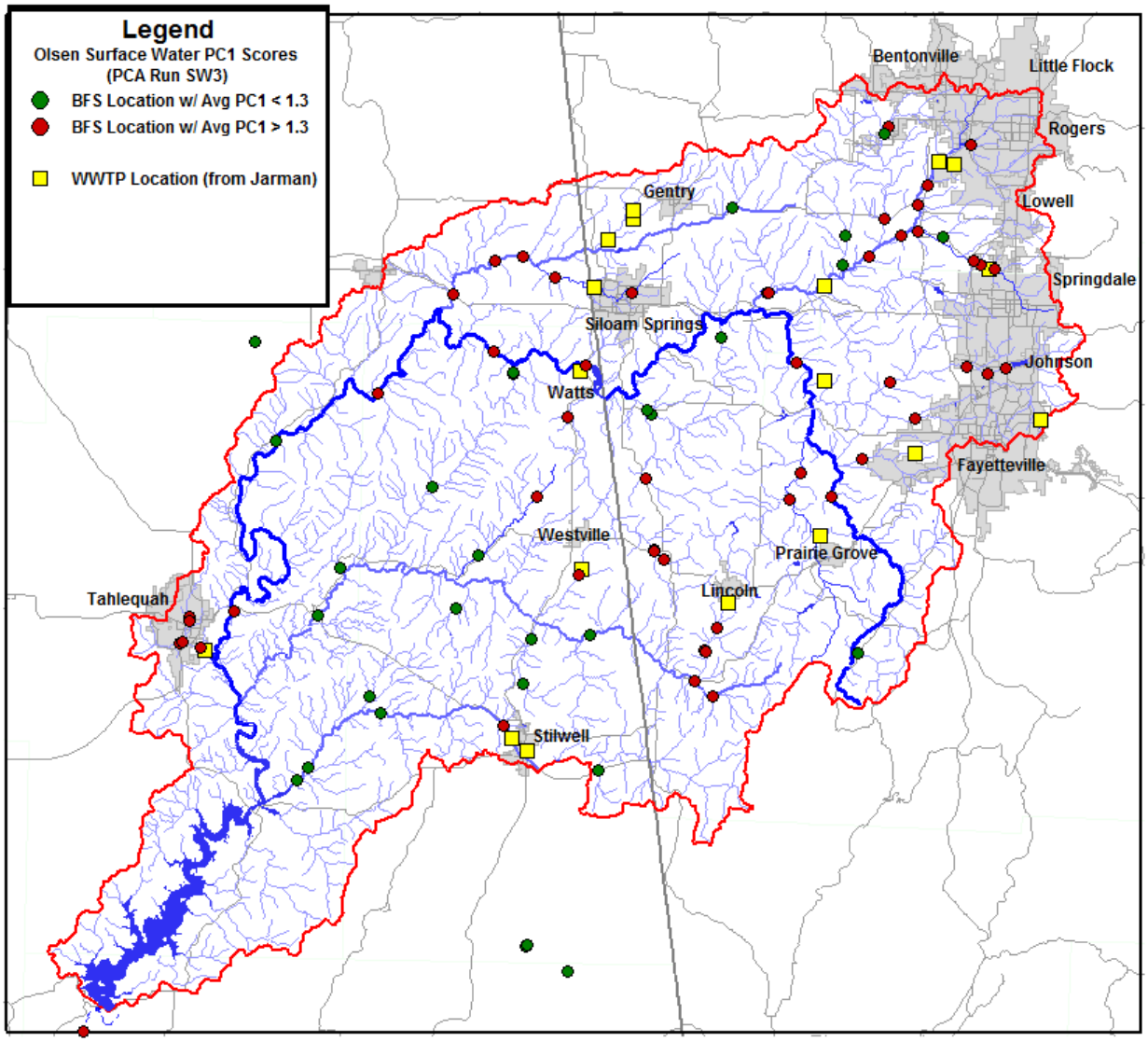

Figure 3-16. Base-flow PC1 scores map, plotted with respect to urban areas and WWTP Locations
Olsen's PC1 threshold plotted over basemap showing areas of high human population density and WWTP locations WWTP locations from Jarman, personal communication. Gray shaded areas indicate regions of human population density > 400 people/mi^2, based on ESRI (2006) data.

This map and its comparison to Figure 3-15 (same PCA results plotted over poultry-house density data) makes it clear that Olsen's 1.3 PC1 criterion for a '*unique poultry-specific biological and chemical signature'* is neither unique nor poultry-specific. Whatever is driving PC1 (see alternative interpretation: Section 4.2) it is in large part coming from areas of high human population, in absence of poultry.

4.0 Alternative Interpretation of Olsen's PCA

As discussed in Sections 2.0 and 3.0, there are major problems and inconsistencies with Olsen's PCA. The data simply do not support his interpretations. In this section, I present alternative interpretations/explanations of Olsen's PCA.

4.1 An Alternative PC1 Poultry-Impact Threshold

It is my opinion that Olsen's 1.3 PC1 criterion is arbitrary, and that there is no PC1 threshold that can be applied as an indicator of poultry-impact because PC1 does not equal poultry. But in the end, making such an argument is hardly necessary. Taking Olsen's interpretation at face value, a critical review shows contradictions at every turn. SW3 included a number of samples collected to characterize sources other than poultry (cattle edge-of-field; WWTP and Tahlequah), and every single one of them yielded PC1 scores greater than 1.3 (Section 3.1, 3.2 and 3.3). In addition there were many high-flow and base-flow stream samples that are contradicted by Olsen's spatial analysis (Sections 3.4 and 3.5).

But what would happen if Olsen had tried to preserve his opinion that PC1 equals '*poultry waste impact'*, and just changed the PC1 threshold to a value better supported by the spatial analysis. The first step would be to define a more reasonable threshold. If we were to just move the PC1 threshold up to a value greater than that observed for the samples that contradict Olsen's opinion, it would be both reasonable and '*conservative.*'[114] What's more, Olsen would not have had to veto PCA results or speculate about potential poultry litter application in cow-pastures or wastewater treatment plants. This would alleviate many problems for Olsen.

The maximum PC1 score for cattle edge-of-field; WWTP and Tahlequah samples was 2.11 (sample EOF-CP1B). A PC1 threshold of 2.12 would be conservative in that it would exceed the PC1 scores for all of these samples (Figure 4-1).

[114] Olsen repeatedly claims to have been '*conservative'* in establishing his 1.3 threshold. See Olsen 2008a: p. 6-60 (1st paragraph); Olsen Deposition, 9/10/08 pp. 218 (line 14) to 219 (line 6); Olsen Deposition, 9/10/08 p. 222 (Lines 3-12); Olsen Deposition, 9/11/08 pp. 330 (line 24) to -332 (line 5); Olsen Deposition, 9/11/08 pp. 472 (line 3-17). Olsen Deposition, 9/11/08 pp. 484 (line 5-8). Olsen Deposition, 9/11/08 pp. 485 (line 8-24).

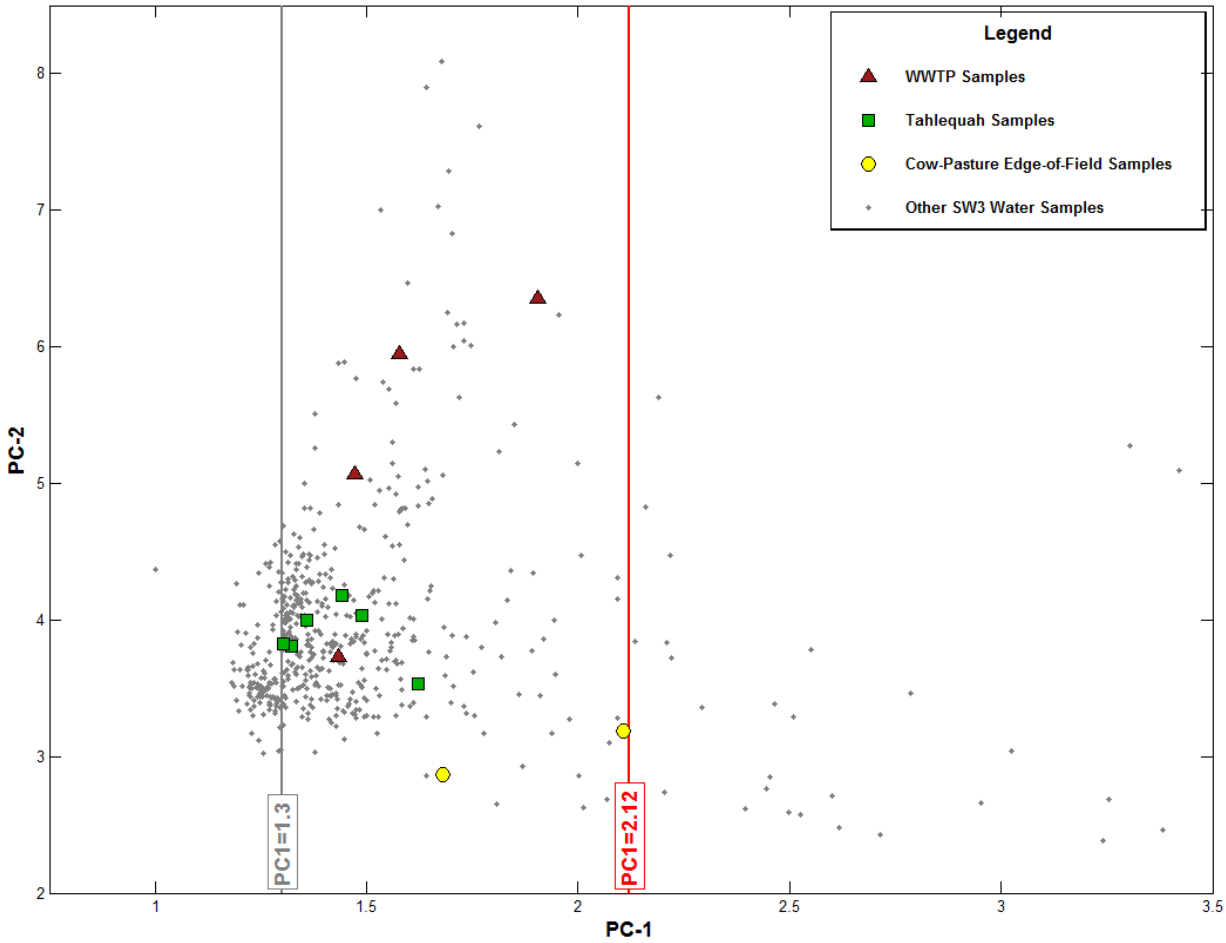

Figure 4-1. SW3 scores plot with known, non-poultry impacted samples highlighted.

Given this new threshold, Olsen's red-dot / green-dot map would be as shown on Figure 4-2. Looking at these results in context of a spatial analysis, this would seem to solve a lot of problems for Olsen. The three reference stream locations and two high flow locations cited in his spatial analysis discussion[115] are well below 2.12, so this more conservative PC1 threshold still supports the argument that appears in his report. The 2.12 threshold is in fact better, because Olsen doesn't have to round HFS-30 PC1 score down from 1.3022 to 1.3 to support his argument (see Figure 2-5). All Tahlequah scores are below the 2.12 threshold, so there is no need to make the subjective decision to veto his PCA results, and manually change the color of the Tahlequah sample from red-dots to green-dots. All WWTP effluent samples exhibit PC1 scores <2.12, so there is no need to veto those results either. The two EOF-CP samples are below a 2.12 threshold, so there is no need to speculate about poultry impact in cow pastures that reportedly have never had poultry litter applied to them. In addition, we no longer see as many red-dots plotted for samples down-stream of urban areas with low poultry-house density (Lincoln, Westville, Rogers, Fayetteville). A 2.12 PC1 threshold would to make for a simpler, more lucid story, without Olsen having to abandon his theory that PC1 equals poultry.

[115] Olsen (2008a). p. 6-59 to 6-60.

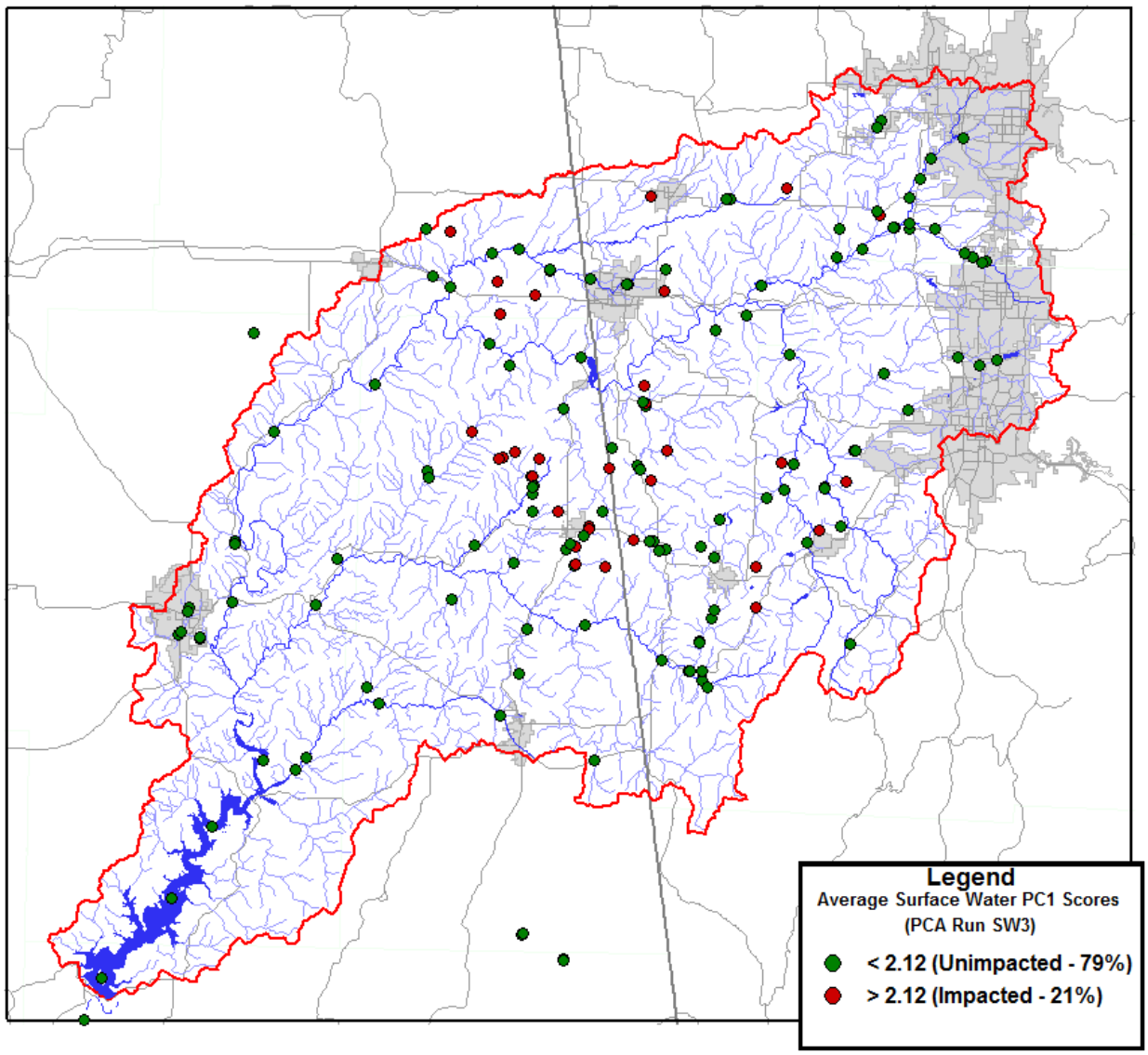

Figure 4-2. Olsen's red-dot / green-dot map using a PC1 threshold of 2.2.

However, this threshold yields a very different estimate of water samples supposedly impacted by poultry. Seventy-nine percent (79%) of IRW sample stations would now be classified by as unimpacted by poultry, and plot as green dots (Figure 4-2). Of that 21%, only one sample (SN-SBC2) is a river, stream or lake water sample. In other words, all but one of the red-dots on Figure 4-2 are edge-of-field samples. What's more, even that single stream sample with a PC1 score greater than 2.12 does not support the theory of a poultry source. A map showing the location of SN-SBC2 is provided as Figure 4-3. It is located in an area of low poultry house density, less than 500 meters downstream of the Westville WWTP.

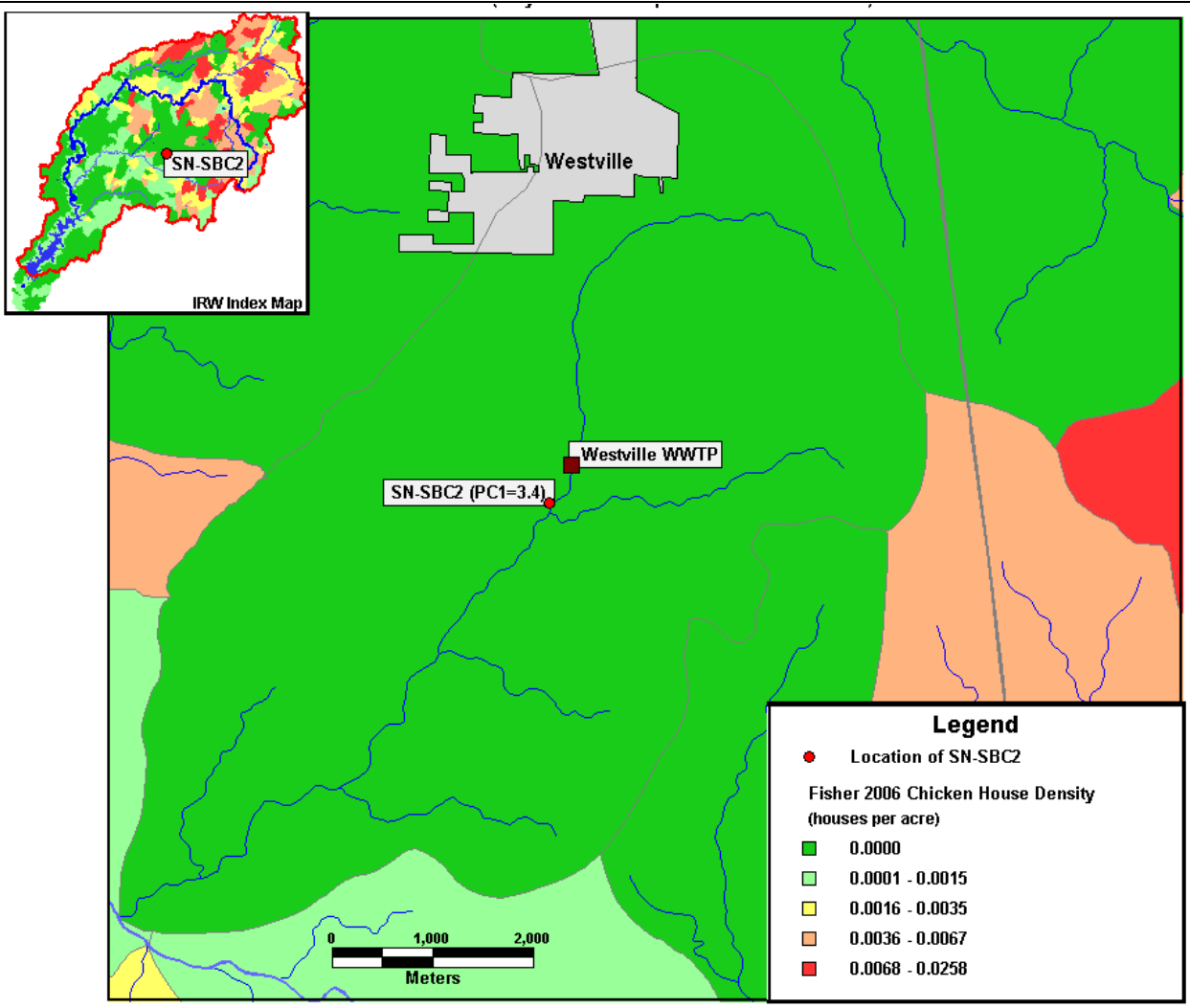

Figure 4-3. Location of SN-SBC2, in relation to poultry house density data and Westville WWTP.

This exercise shows that even if you overlook issues of faulty assumption and errors in implementation, accept at face-value Olsen's PCA interpretation that PC-1 equals poultry, and try to salvage the theory with a more reasonable threshold, the inevitable conclusion is still that Olsen's PCA does not support an opinion that "*poultry waste is by far the dominant contamination source in the IRW.*"[116] Olsen could not propose a more realistic PC1 threshold without simultaneously concluding minimal poultry impact to surface waters of the IRW.

4.2 PCA Interpretation In Context of Concentration and Differential Partitioning.

In Section A2.2 of Appendix A, I pointed out that Olsen did not do a transformation to normalize out the effect of widely differing concentrations. I also pointed out that, as a result, I would expect that the total concentration of samples would exert tremendous influence on where samples plotted on a scores plot. This turns out to be the case. To show this, I have re-plotted Olsen's SW3 scores plot, with colors assigned to symbols as a function of the sum concentration for all chemical variables (Figure 4-4). Bacteria was omitted from this sum for several reasons:

[116] Olsen (2008a). p. 1-2. Bullet 3.

(1) bacteria were reported in different units (org/100ml rather than mg/L); (2) bacteria data were missing from more than a quarter of the samples in SW3 (Appendix A: Section A2.1); and (3) bacteria has essentially no predictive ability in this PCA model whatsoever (See Appendix A, Section A2.4 & Figure A-5).

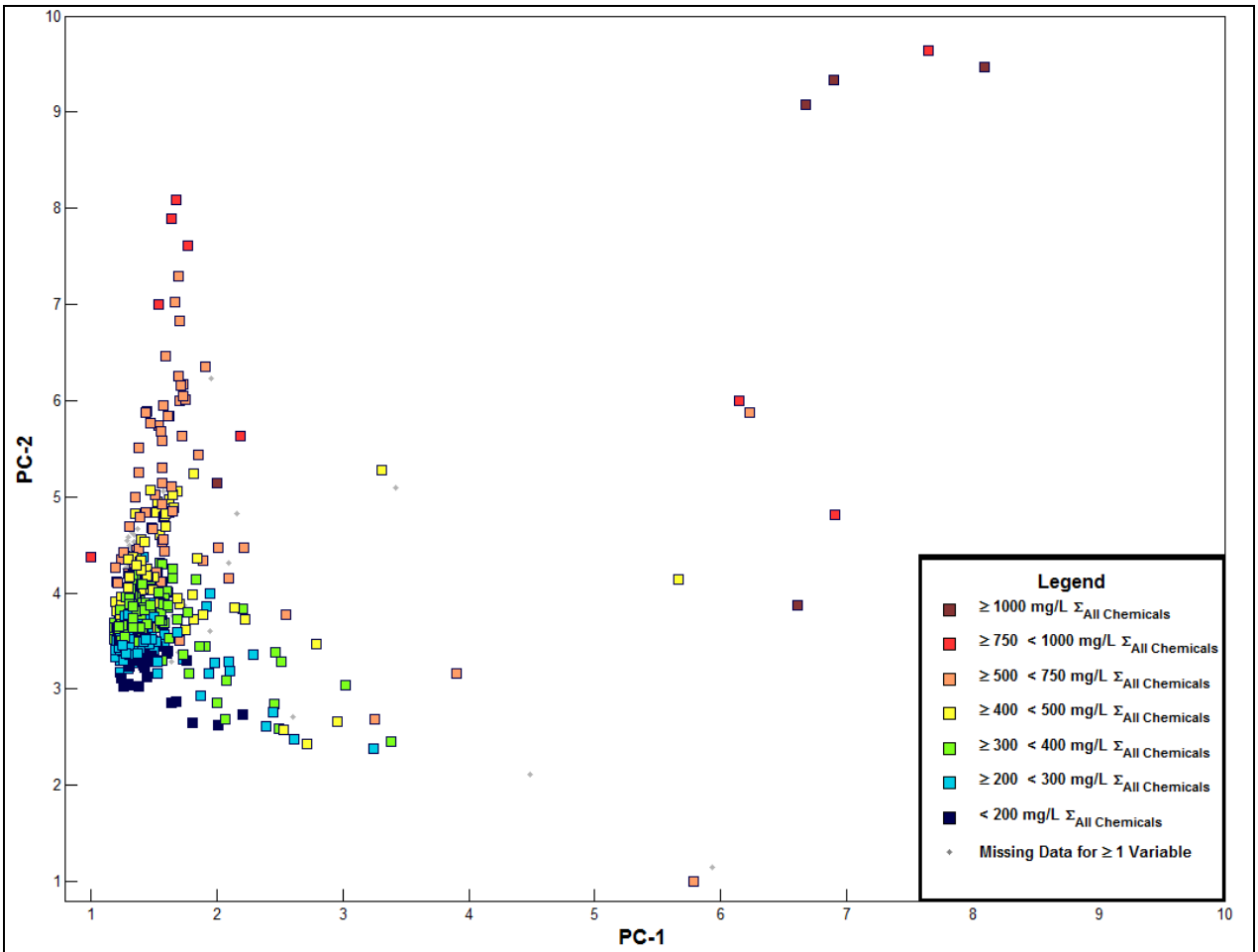

Figure 4-4. SW3 scores plot with symbol colors plotted as a function of total concentration.

The pattern here is exactly what we would expect from a PCA where no sample-normalization was done. Sample scores are strongly controlled by total concentration. Low-concentration samples (blue squares) plot at the bottom left corner of the data cloud (the corner of the "L"). As you move away from that corner of the scores plot, samples increase in total concentration, transitioning from blue to hotter colors: yellow, orange, red, and then brown. In general, a PCA scores plot that shows a "V" or "L" shaped data cloud is a tell-tale sign that the PCA did not include a transformation to normalize out concentration.

It is also clear on this plot that the greatest density of samples is along one of two trends: (1) along the bottom of the L; and (2) along the left side of the L. These two trends are labeled on Figure 4-5, below. A few samples do not plot within one of these two trends (e.g. samples plotting to the extreme upper-right), but these exceptions are primarily edge-of-field samples. The vast majority of IRW stream and lake surface-water samples plot within one of these two trends.

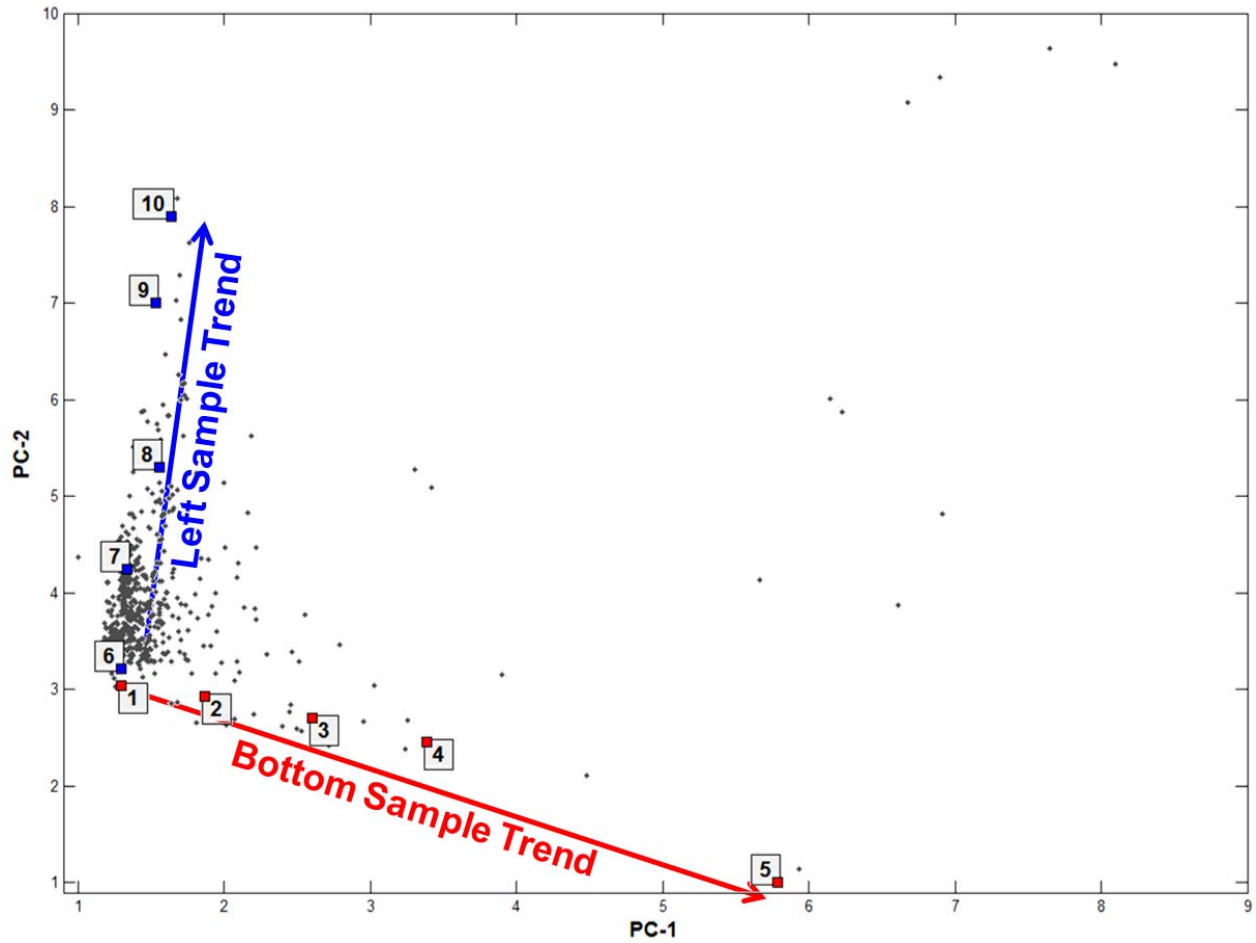

Figure 4-5. SW3 scores plot showing samples along bottom trend (red) and left trend (blue). Numbered samples are shown as bar-graphs on Figures 4-6 and 4-9.

Note on Figure 4-5 that there are numbered samples along each of these two trends. Samples 1 through 5 are shown along the bottom trend as red squares. Samples 6 through 10 are shown along the left trend as blue squares. Bar-graphs for the five samples along the bottom trend (red) are shown on Figure 4-6. Several observations can be made with regard to these five samples. First, note the bacteria data on the far right. All bacteria data were missing from the two lowest concentration samples (samples 1 and 2). The gray bars indicate missing data, and the height of the bars represents the mean (average) concentrations that were substituted for missing data. There is wide variation in bacteria concentrations and no discernable trend or pattern is observed as one moves to the right along the bottom sample trend.

Note also, that the three variables highlighted by pastel red shading: total phosphorus (P_T), total iron (FE_T) and total aluminum (AL_T) increase in concentration as you move to the right along the bottom trend. Iron and aluminum are not as soluble as ions such as sodium and chloride. As such, Fe and Al are generally associated with suspended sediment fraction of natural waters. Sorption of phosphorous to suspended particulate matter is common, with phosphate ions taken up from water by alumina, clay particles, and freshly precipitated iron and aluminum hydroxides (Stumm and Morgan, 1970). As such, particulate-bound phosphorus constitutes much of the phosphorus in runoff from cultivated land (Sharpley and Smith, 1990). As a result, total phosphorous in natural waters has been observed to correlate with total suspended solids (TSS - Sullivan, et. al., 2005).

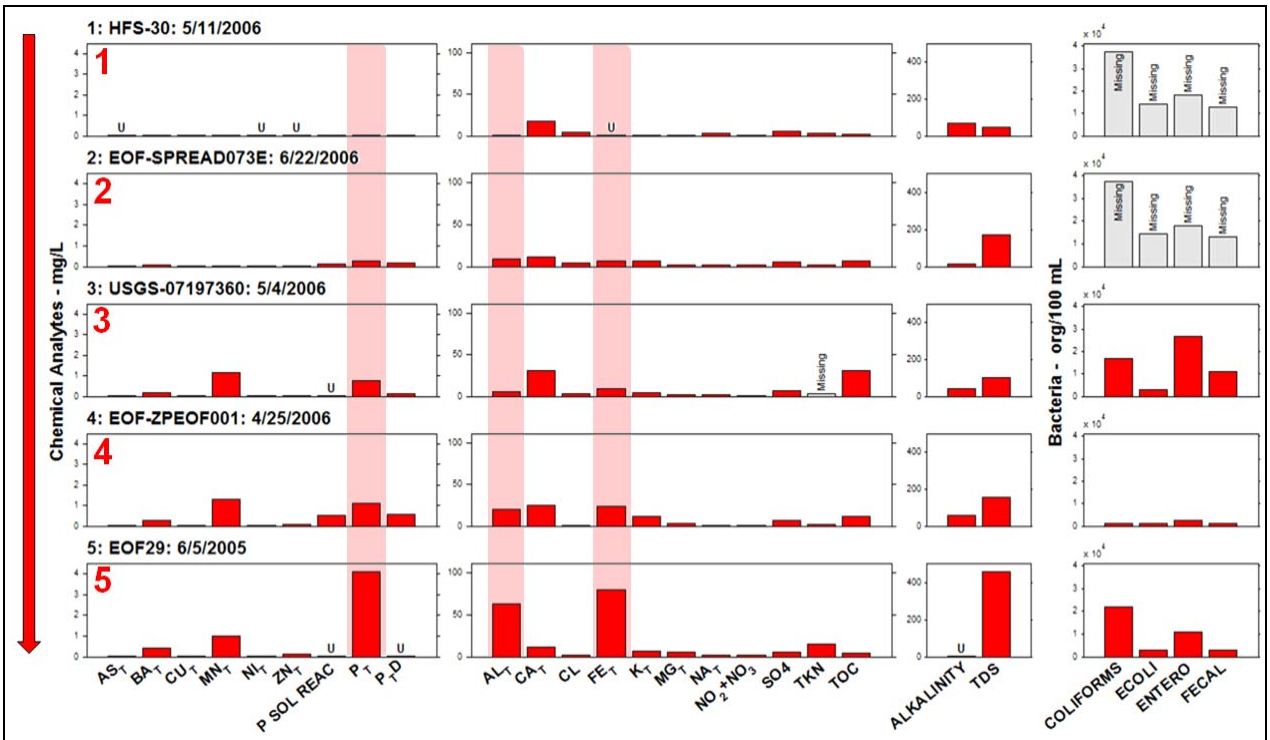

Figure 4-6. Bar graphs for the five bottom-trend samples indicated on Figure 4-5.

These observations suggests that the 'bottom trend' on Olsen's SW3 scores plot is associated with TSS, and that total phosphorous increases along this trend as a function of its association with suspended particulate matter.

But, the bar-graph above represents only five samples. If this interpretation is true, we should see increasing Fe and Al concentrations in all samples along this trend. Figure 4-7 shows Olsen's SW3 scores plot, with the symbol-color keyed to the concentration of total iron plus total aluminum. The trend suggested by the five samples discussed above, is observed for the data set as a whole. The concentration of total iron + total aluminum increases in samples along the bottom trend of Olsen's SW3 scores plot.

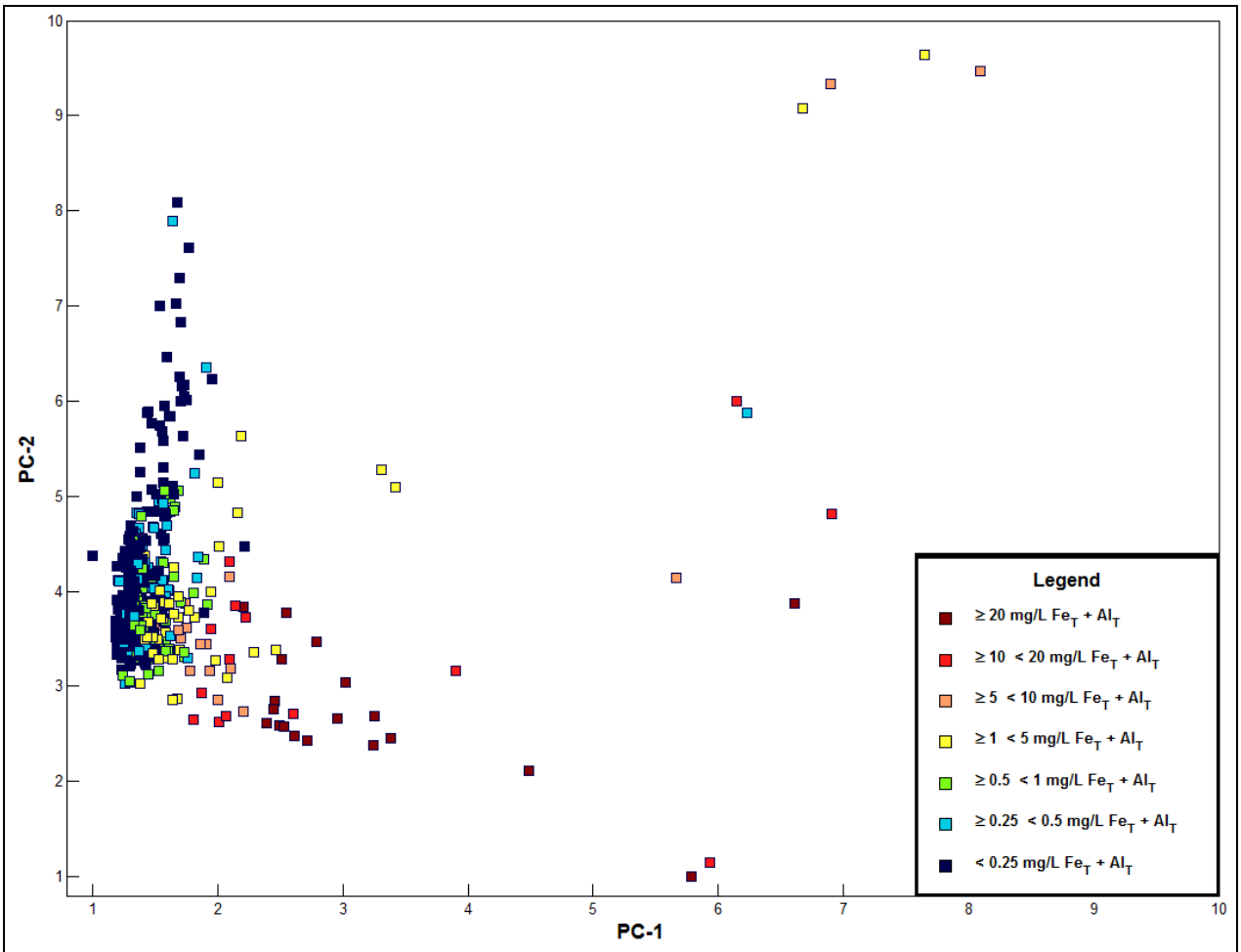

Figure 4-7. Olsen's SW3 scores plot, with symbol colors reflecting total Iron + total Aluminum.

If the sum of total iron and total aluminum reflects suspended sediment, then plotting PCA scores as a function of total suspended solids (TSS) should show a similar pattern. TSS was not included as a variable in Olsen's PCA, but it was provided in Olsen's database.[117] Figure 4-8 shows Olsen's SW3 scores plot, with the data plotted as a function of reported TSS concentrations. We see the same pattern that we saw for iron + aluminum. As you move from left to right across the bottom trend of Olsen's SW3 scores plot, TSS increases in concentration.

Clearly one of the major controls on Olsen's SW3 PCA run is the degree to which a water sample has high concentrations of suspended sediment. Samples that plot along this trend do so as a function of turbidity and suspended sediment, not poultry impact. In addition, consider that the muddier a water sample is, the higher the suspended sediment concentration will be. To the extent that edge-of-field samples exhibit high PC1 scores, it reflects preferential sampling of muddy water in EOF samples. This explains why Olsen could never get the cattle edge-of-field samples to "break out" from other edge of field samples: EOF samples would be expected to have high TSS, regardless of whether they are collected from a cow pasture, a road-side ditch, or a mud-puddle near a field where poultry litter might have been applied.

[117] TSS data are contained in the spreadsheet "PCA_Main_Database_Water.xls" within the worksheet 'Water (Out)'. TSS was included as an analyte for CDM/Lithochimia-collected samples, but not for USGS samples.

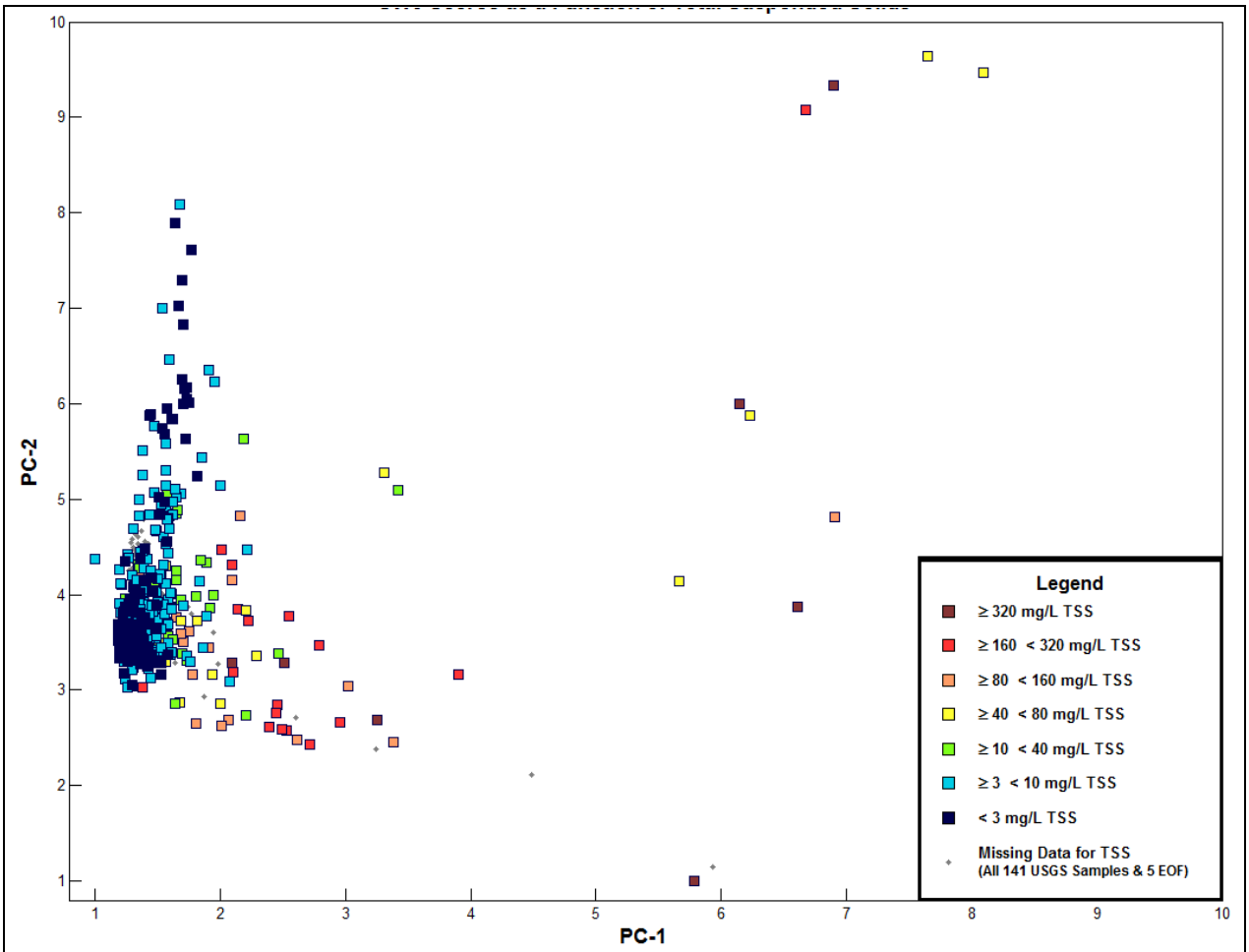

Figure 4-8. Olsen's SW3 scores plot, with symbol colors reflecting Total Suspended Solids (TSS).

None of this should come as a surprise to a geochemist, and it should not surprise Olsen. The following testimony came in context of a line of questioning related to the potential effects of stream-bank erosion (i.e. an input of suspended sediments) on Olsen's analysis:

> ***Q*** *What would you have expected to have seen in terms of a different composition?*
> ***A*** *You know, stream banks would have had more iron, more aluminum, you know, generally more highly elements that are in the sediments.*
> ***Q*** *Okay.*
> ***A*** *More silica. You know, we didn't analyze for silica. So more iron, more aluminum. We would have seen those types of things.*
> ***Q*** *Did you evaluate those samples for iron and aluminum concentrations to determine whether stream impact -- I'm sorry, stream bank erosion may be having an effect on those samples?*
> ***A*** *That was all in the principal component analysis, so it would have related to a change in chemical composition that in my opinion you would have been able to see if it was major.* [118]

In this quote, Olsen acknowledges that iron and aluminum are preferentially associated with suspended sediment in water. He says that if suspended sediment were a controlling factor, we would have seen it in his PCA results. We do see it in his PCA. Olsen just failed to recognize it. Clearly, suspended sediment, iron and aluminum exert a strong control on total phosphorus, and in turn on where samples plot on Olsen's SW3 scores plot.

[118] Olsen Deposition. 9/10/08. p. 77-78.

Going through the same process for the left trend (blue squares – samples 6 through 10 on Figure 4-5), the bar-graphs for these samples are shown on Figure 4-9. Again, the bacteria data exhibit a wide range of variability, with the highest values observed in otherwise low concentration samples, where missing data has been substituted.

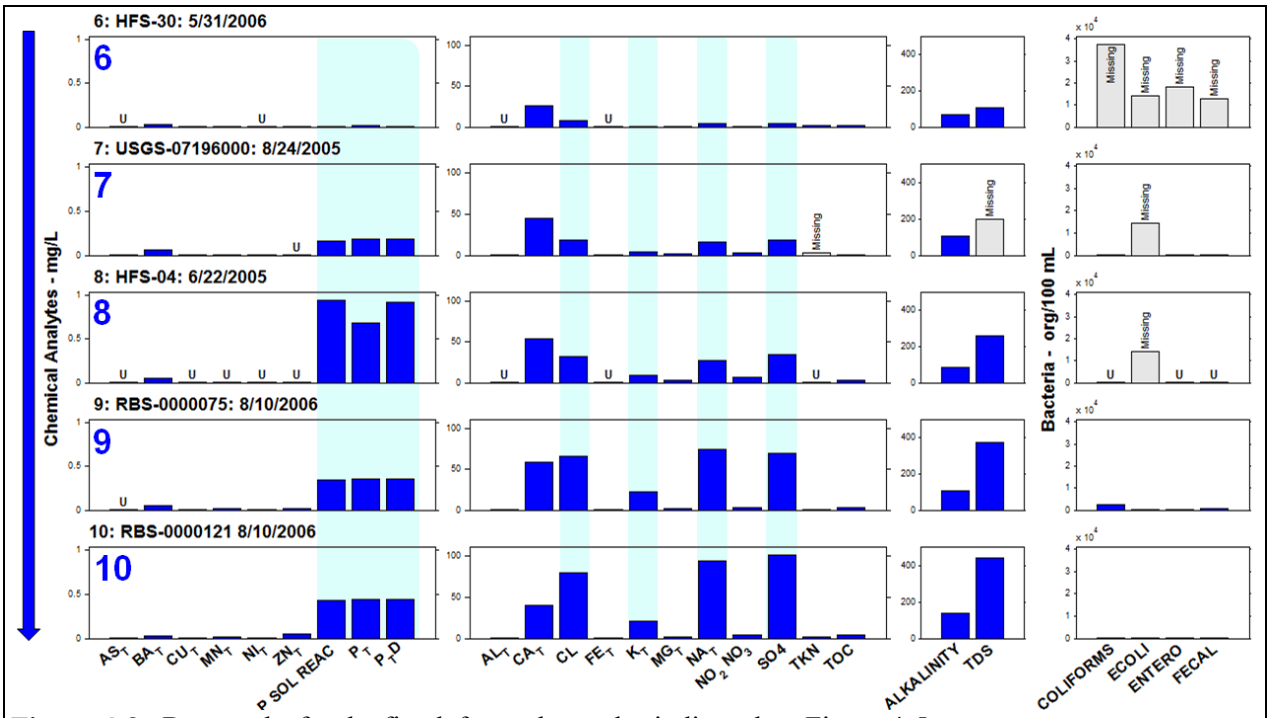

Figure 4-9. Bar graphs for the five left-trend samples indicated on Figure 4-5.

Variables shown with blue shading (total sodium (NA_T), total potassium (K_T), chloride (CL) and sulfate (SO_4)) all increase in concentration along this trend. These analytes are more soluble in water (Freeze and Cherry, 1979) so in contrast to iron and aluminum, they prefer to be in dissolved-phase rather than adsorbed to particulates. Once again, this should come as no surprise, and Olsen testified that for highly soluble analytes like sodium and potassium, the concentration reported as "total" should roughly equal their reported "dissolved" concentrations, because they are typically found entirely in solution.[119]

Note that all of these samples have low iron, aluminum and TSS (Figure 4-5 and 4-8). Note also that the two soluble forms of phosphorus (P_TD and P_SOL_REAC) are close to equal in each sample and are also close to the reported concentrations of total phosphorus. This suggests that the general increase in P concentrations in these samples (sample 8 being the exception) reflects dissolved phase phosphorus, rather than particle-bound phosphorus.

As for the bottom trend, I picked just five samples to show on Figure 4-9. Figure 4-10 shows Olsen's SW3 scores plot, with the symbol color keyed to the concentration of $NA_T + K_T + Cl + SO_4$. The trend observed in the bar-graphs above, is evident for the data set as a whole. The concentration of highly soluble analytes increases as you move up along the left trend of Olsen's SW3 scores plot. Clearly, the primary controls on Olsen's PCA are related to elementary geochemistry: whether an analyte is preferentially associated with the dissolved phase or particulate/suspended solids phase. To the extent Olsen's PCA model reflects real-world geochemistry, it is controlled by solution/adsorption processes, not sources.

[119] Olsen (2008a). p. 3-18. 4th paragraph. Olsen Deposition. 9/10/08. p. 116-117.

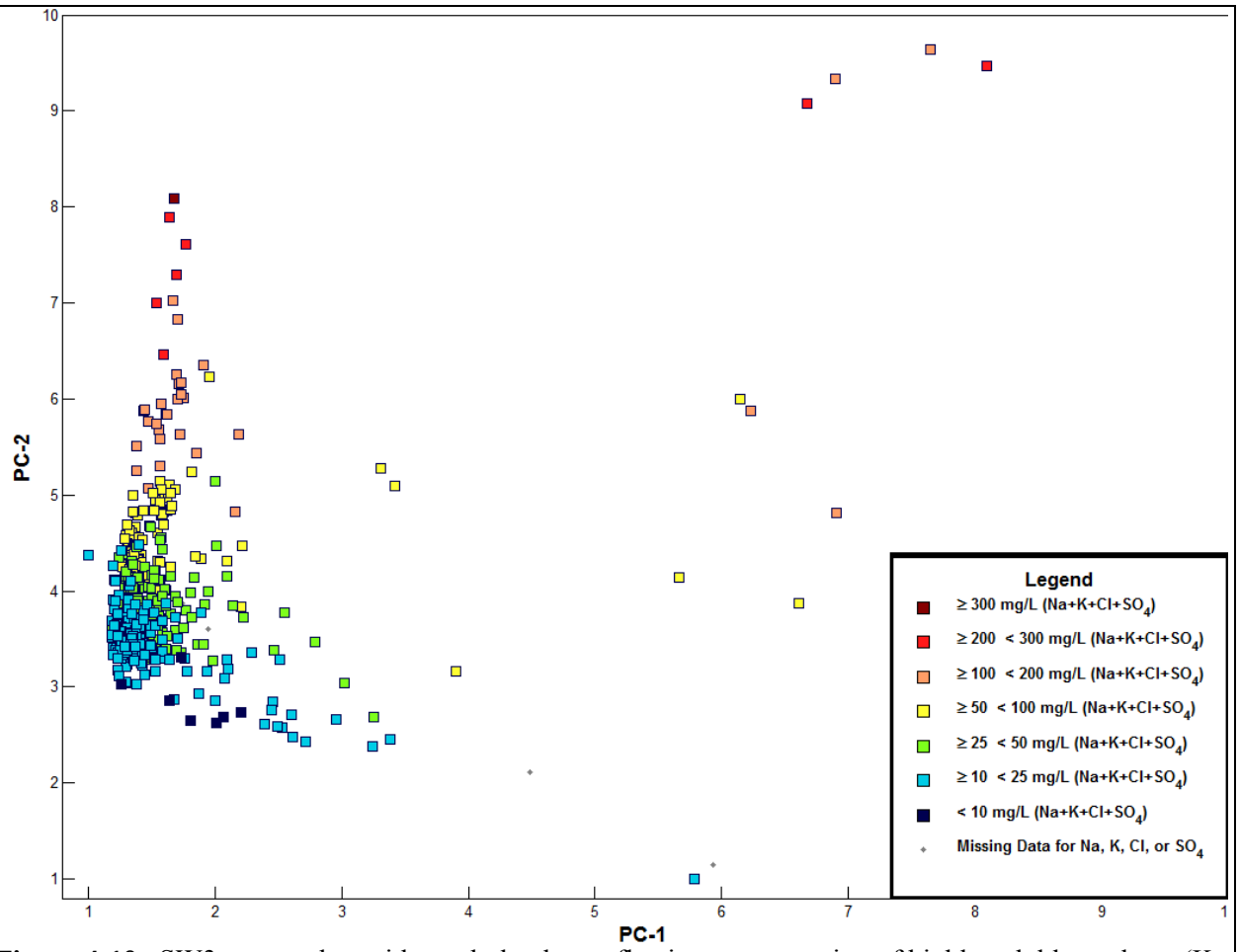

Figure 4-10. SW3 scores plot, with symbol colors reflecting concentration of highly soluble analytes (K, Na, Cl and SO_4).

Given this alternative interpretation of Olsen's PCA, let's revisit his interpretation and see how they compare. Olsen claimed that PC1 equals poultry, and that 1.3 is an appropriate threshold for delineating poultry-impacted versus non-impacted. But that theory had major problems. To explain away the contradictions, Olsen had to do one of three things: (1) ignore the contradictions (e.g. base-flow and high-flow samples that plot as red-dots in areas of zero poultry house density); (2) veto his own rule (e.g. Tahlequah, WWTP effluents) or (3) speculate about poultry impact in areas where there is no evidence of the application of poultry litter (e.g. cow-pasture edge-of-field samples). A simpler explanation is that PC1 does not *equal* poultry. As samples increase in PC1 scores, they do so as a function of suspended particulate matter. Regardless of the source (cattle, WWTP, poultry, soil erosion, contribution from urban sources like Tahlequah), total phosphorus and PC1 scores increase as a function of suspended sediment.

Olsen interpreted PC2 as WWTP effluent. PC2 does not *equal* anything, but the samples along the left trend (roughly parallel to PC2) generally increase in concentrations of water-soluble cations and anions (Na, K, Cl, and SO_4) as PC2 scores increase. As such, samples that plot within Olsen's "*WWTP-dominant impact*" area do so because they had high reported concentrations of soluble ions. Regardless of source, water samples with higher concentrations of dissolved salts will plot along this trend with high PC2 scores. This simple explanation alleviates the need to explain away anomalies like the majority of groundwater well samples in

SW17 exhibiting the "*WWTP fingerprint*" even though those wells are located nowhere near a waste-water treatment plant (See Section 2.3.2).

Once again, none of this should come as a surprise to Olsen. He is well aware that the samples he presumes to be '*poultry impacted'* have high TSS concentrations, and that samples presumed to be '*WWTP impacted*" have low TSS concentrations. In his report he stated that *"total suspended solids were found to be 10 to 100 times greater in the poultry EOF than in the WWTP*."[120] Olsen claims to have used PCA to discover unique chemical/biological signatures related to poultry and WWTP effluent. What he has actually discovered is nothing more profound than the distinction between muddy water and salty water.

[120] Olesen (2008a). p. 6-7 (2nd paragraph – lines 8-10) and 6-8 (1st paragraph – lines 9-11).

5.0 Summary and Conclusions

In the introduction of this report, I pointed out that Olsen cited a number of papers in the literature where PCA had been applied to environmental chemical data, but that the existence of such literature does not guarantee that its application to IRW will yield contaminant source signatures. Nor does it exonerate one from errors of implementation or misinterpretation of results. Nor does it justify concealing data/evidence that contradicted one's opinion. Olsen did all of this, and when one carefully dissects his analysis, it is clear that his PCA does not identify sources of contamination in the IRW.

PCA can be a useful tool in analysis of environmental chemical data, but there is no guarantee that the results will yield chemical fingerprints related to source. Its success in this regard depends on the analyst having a good understanding and sensitivity to the chemical system under study, the mathematics of the method, and its assumptions. There are numerous pitfalls for the unwary and inexperienced. In Olsen's application of PCA, he fell into a number of traps, many of which were identified in the literature, and cautioned against 20-30 years ago (e.g. reification of factors, interpretation of loading bar graphs as chemical compositions, and use of the percent-variance criterion for determining the number of significant principal components). Many of these pitfalls are errors of assumption. But Olsen also made errors in mechanical implementation of PCA, such as failure to do a sample normalization transformation, and incorrect back-calculation of scores.

Olsen also made an error in the basic philosophy of data analysis. PCA is considered a statistical method. But within statistics, there is a distinction between classical hypothesis testing methods and exploratory data analysis (EDA) methods. PCA falls in the latter category. In layman's terms, exploratory data analysis is more like detective work than hypothesis testing. One may reasonably carry a working hypothesis into an investigation, and Olsen clearly had his.[121] But the analyst must allow himself to be surprised by the data, and must entertain alternative theories if and when the data reveal the unexpected. Olsen did not do this. When faced with new data and/or PCA results that contradicted his theory of a predominant poultry source, his opinions did not change. Rather, the logic of his argument became more complicated (often to the point of sheer speculation) and/or new arguments were presented to fit the existing theory (e.g. cattle edge of field samples - Section 3.3). In the end, Olsen tells us that samples with PC1 scores less than 1.3 might be impacted by poultry, and he concedes that there are samples with PC1 scores greater than 1.3 are not impacted by poultry. He is left with a completely arbitrary poultry-impact threshold that can be vetoed when convenient.

But dissenting lines of evidence were not just dismissed or explained away, they were concealed. Olsen relied on a spatial analysis where he compared principal component scores to poultry house density data. He was clearly aware of contradictory results, but in a discussion of the spatial analysis, offered in support of his 1.3 PC1 threshold, he presented only a few examples that supported his theory. Contradictory results are not evident on Olsen's maps or score plots because of misleading annotation and/or use of data symbols that obscure the contradictions. In Tahlequah, Olsen made the subjective decision to override the PCA results, and changed the color of the Tahlequah samples to fit his theory. This was never disclosed in annotation of his map or in the text of his report. The four known cattle impacted samples in Olsen's analysis are classified as poultry impacted by his PCA (SW3 PC1 scores > 1.3) but the reader can't tell that

[121] From the time CDM began work on this project, the project has carried the acronym 'OPL' (Oklahoma Poultry Litigation), so it is clear what the initial working hypothesis was.

by looking at his score-plots, because Olsen used the same symbol to plot EOF-CP and all other edge-of-field samples. Olsen also never discussed in his report, that after multiple PCA runs had failed to show separation between presumed poultry and cattle impacted samples, he ran two PCAs with the explicit objective of getting separation between these two groups of samples. Those attempts failed, and the cattle argument that appears in Olsen's report mentions none of this. Instead, Olsen advanced a new argument (based on a different criterion) that somehow led to the same opinion expressed during the PI. Olsen's opinion never changes, only the argument necessary to explain new data.

Even in the absence of these errors, it is doubtful that a properly implemented PCA, applied to these data, would yield unambiguous results with regard to sources. One reason is data quality. Olsen collected 2,325 individual samples of the type included in his primary surface water PCA run. Only 267 (11.5%) had data for all 26 variables in Olsen's PCA run. Of these 26 variables, the four bacteria variables (total coliforms, E. coli, enterococcus, fecal coliform) were the most problematic: missing in 28 to 41 percent of samples in Olsen's PCA. The missing data substitution method employed by Olsen violates the assumptions inherent in a multivariate data analysis, and likely contributes more noise to the system. Another concern is Olsen's use of data from multiple analytical methods. To the extent that there is bias between analytical methods, it can result in non-random variability. Phosphorus was one such analyte, run by different methods, and by different laboratories. Bacteria and phosphorus are not secondary parameters in the analysis. They are in fact the two parameters cited in Olsen's summary PCA opinion, where he claims to have identified a "*distinct chemical signature that contains both phosphorus and bacteria.*"[122]

But most importantly, Olsen's PCA applied to this data set did not resolve sources because these chemicals are not conservative in the environment. That is, they do not behave similarly in an aqueous environment. Diagnostic chemical differences and ratios that might be observed in the original presumed source materials (i.e. poultry litter, cattle manure, and WWTP effluent) are not preserved once those constituents are in water. Olsen's analysis was doomed from the start because he assumed a geochemical system controlled by unchanging ratios of source-diagnostic chemicals/bacteria. As discussed in Section 4.0, the actual controls on this system are the degrees to which a few key chemicals (in particular total sodium, chloride, total iron and total aluminum) have a preferential affinity for dissolved phase, or tend to be associated with suspended particulate matter. Olsen has not discovered unique chemical/biological signatures related to poultry and WWTP effluent. Rather, his PCA does nothing more than distinguish between turbid water and salty water. To the extent that total phosphorus is explained by his analysis, it is because variability of total phosphorus is a function of its association with iron, aluminum and suspended particulate matter. The other key parameters in Olsen's supposed poultry signature (bacteria, copper, arsenic, and zinc[123]) exhibit an extremely poor fit in Olsen's model.

The use of mathematical techniques such as PCA carries with it the aura of precision and exactitude. The associated jargon and the fact that it is mathematically complex is daunting, such that somebody who understands the method a little can often intimidate a skeptic that doesn't understand it at all. But it is not magic, and it does not give one special powers to see things in the data that are otherwise unobservable. The mathematics of PCA may be objective and straightforward, but the interpretation is entirely subjective. It is therefore incumbent upon the

[122] Olsen (2008a). p. 2-1. 3rd bullet – final sentence.
[123] Olsen (2008a). p. 1-2 (3rd bullet), and p. 6-27.

data analyst to evaluate the efficacy of that interpretation in an open and honest manner. Olsen failed to do this. When we dig just a little deeper into his analysis, his theory of a source driven, poultry dominated system falls apart.

But in conclusion, putting aside the problems of assumptions, philosophy of data analysis, methodology and logic, consider this. Olsen's SW3 and SW22 PCA runs included 15 samples presumed or collected with intent of characterizing sources other than poultry (2 cattle edge-of-field; 3 cattle impacted springs; 4 WWTP; and 6 Tahlequah urban stream samples). Every single one yielded a PCA score which fits Olsen's criterion for exhibiting his *unique poultry waste signature*. Olsen's PC1 threshold is without a doubt, not unique and he has failed to establish a poultry-specific biological and chemical signature.

6.0 References

Cowan C. (2008). Expert Report of Charles Cowan.

DeCaprio, A. P., Johnson, G. W., Tarbell, A. M., Carpenter, D. O., Chiarenzelli, J. R., Morse, G. S., Santiago-Rivera, A. L., Schymura, M. J., and Akwesasne Task Force on the Environment. 2005. PCB exposure assessment by multivariate statistical analysis of serum congener profiles in an adult Native American population. *Environ. Res.* 98, 284-302.

Doré, T.J., A.M. Bailey, J.W. McCoy, and G.W. Johnson. 1996. An examination of organic/carbonate-bound metals in bottom sediments of Bayou Trepagnier, Louisiana. *Transactions of the Gulf Coast Assoc.of Geological Societies*. **46:** 109-116.

Ehrlich, R., R.J. Wenning, G.W. Johnson, S.H. Su, and D.J. Paustenbach. 1994. A mixing model for polychlorinated dibenzo-p-dioxins and dibenzofurans in surface sediments from Newark Bay, New Jersey using polytopic vector analysis. *Arch. Environ. Contam. Toxicol*. **27:** 486-500.

ESRI (2006). U.S. MapData Places. ESRI. Redlands, California, USA. 10/1/2006.

Freeze, R.A., and J.A. Cherry. 1979. Groundwater. Prentice Hall. Englewood Cliffs, NJ. 604 pp.

Jarman, W.M., G.W. Johnson, C.E. Bacon, J.A. Davis, R.W. Risebrough, and R. Ramer. 1997. Levels and patterns of polychlorinated biphenyls in water collected from the San Francisco Bay and Estuary, 1993-1995. *Fresnius J. Anal. Chem.* **359**: 254-260.

Johnson, G.W., Jarman, W.M., Bacon, C.E., Davis, J.A., Ehrlich, R., and Risebrough, R. (2000). Resolving polychlorinated biphenyl source fingerprints in suspended particulate matter of San Francisco Bay. *Environ. Sci. Technol.* **34**: 552-559.

Johnson, G.W. 2002. Forensic Analysis. In: *Encyclopedia of Environmetrics* (El-Shaarawi and Piegorsch, eds.) Wiley, Chichester. Vol. 2, 796-806.

Johnson, G.W. and Ehrlich, R. (2002). State of the Art Review: Multivariate Statistical Methods in Environmental Forensics. *Environmental Forensics.* **3**: 59-79.

Johnson, G.W., Ehrlich, R., Full, W., and Ramos, S. (2007). Chapter 7: Principal components analysis and receptor models in environmental forensics. In: *An Introduction to Environmental Forensics.* 2nd Edition. (B. Murphy and, R. Morrison eds.). Elsevier. Amsterdam. pp. 207-272.

Magar, V.S., Johnson, G.W., Brenner, R., Durell, G., Quensen, J.F., III, Foote, E., Ickes, J.A., Peven-McCarthy, C. 2005. Long-term recovery of PCB-contaminated sediments at the Lake Hartwell Superfund Site: PCB Dechlorination I – End-Member Characterization. *Environ. Sci. Technol.* **39**: 3538-3547.

Olsen, R.L. (2008a). Expert Report of Roger L. Olsen. Prepared for A. Drew Edmondson, Attorney General of the State of Oklahoma. May 14, 2008. 170 pp. 72 tables. 153 figures.

Olsen, R.L. (2008b). Errata for Expert Report of Roger L. Olsen. Prepared for A. Drew Edmondson, Attorney General of the State of Oklahoma. July 25, 2008. 12 pp.

Olsen, R.L. (2008c). Transcript of Deposition of Roger Olsen, Ph.D. February 2, 2008.

Olsen, R.L. (2008d). Transcript of Deposition of Roger Olsen, Ph.D. September 10-11, 2008.

Sharpley, A.N., and S.J. Smith. (1990). Phorphorus transport in agricultural runoff: The role of soil erosion. In Boardman, Foster and Dearing (eds). Soil Erosion on Agricultural Land. Wiley. New York

Stumm, W. and J.J. Morgan. (1970). Aquatic Chemistry. Wiley. New York. 583 pp. (1st Edition - 3rd Edition 1996).

Sullivan, T.J., K.U. Snyder, E. Gilbert, J.M. Bischoff, M. Wustenberg, J. Moore, and D. Moore. 2005. Assessment of water quality in association with land use in the Tillamook Bay Watershed, Oregon, USA. *Water, Air and Soil Pollution*. **161:** 3-23.

Appendix A

PCA Methodology and its Application by Olsen

Appendix A: PCA Methodology and its Application by Olsen

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A1 Principal Components Analysis (PCA) Overview

Roger Olsen conducted a series of principal components analyses (PCA) of water and solids data from the Illinois River Watershed (IRW). Because much of the main part of my report is a critical review of Olsen's PCA implementation and interpretation, a review of the method is in order. PCA is an exploratory data analysis tool, often used in environmental forensics investigations (Johnson, et al., 2007). The objective is to reduce the dimensionality of a data set in which there are a large number of interrelated (i.e., correlated) variables, such that similarities and differences between samples may be viewed on a single plot, without loss of information. This dimensionality reduction is achieved by transforming the data to a new set of uncorrelated (i.e. mutually orthogonal) reference variables, which are termed principal components (PCs). The PCs are sorted such that each in turn, accounts for a progressively smaller percentage of variance. If the vast majority of variance between samples can be accounted for by a small number of PCs, then relationships between multivariate samples may be assessed by simple inspection of a 2 or 3-dimensional plot, referred to as a principal components scores plot (*PC scores plot*). As such, PCA and related methods are often referred to as "*dimensionality reduction*" methods.

On page 6-32 of his report, Olsen cites a list of publications where PCA has been applied to environmental data. It is true that PCA can be a useful in such investigations, and that there are numerous case studies in the literature where it has been successfully applied. I have published such peer-reviewed papers and book chapters myself.[1] Olsen has not.[2] But Olsen's literature citations imply that the mere existence of such literature supports the supposition that PCA applied to IRW data will result in unique chemical/biological signatures related to source. This is not true, and the fact that there is a large body of literature does not give Olsen, or anybody else, license to abuse the method, make mistakes in its implementation, misinterpret the results, or conceal information that contradicts their *a priori* theory. The success of PCA depends on the environmental system under study, and the quality of the data being analyzed. It also depends on the analyst having an understanding of the chemical system, and the mathematics/assumptions of the method. There are numerous pitfalls for the unwary and inexperienced. The purpose of this Appendix is to outline the PCA method in more detail, and to evaluate Olsen's implementation and interpretation with respect to the aforementioned pitfalls.

A1.1 Mathematics of PCA

Mathematically PCA involves an operation called "*eigenvector decomposition.*" This operation is common to many multivariate methods, including PCA, factor analysis, self modeling curve resolution, polytopic vector analysis, and target transformation factor analysis.[3] PCA involves decomposition of a covariance or correlation matrix into a set of eigenvectors. Olsen's analysis used the correlation matrix option. Eigenvector decomposition may be done using one of several methods[4] but given the same data pretreatment (i.e. transformations, substitution schemes for censored data, etc.) the calculated principal components scores and loadings should be the same, regardless of the algorithm. The result is a set of eigenvectors or principal components that serve as an alternative orthogonal coordinate system in which one may plot the data. Another result of this set of mathematical calculations is a set of '*eigenvalues*' which are a function of the amount of variance accounted for by each principal component. Other matrices that result from a PCA include

[1] Johnson, et al., 2007; Magar, et al., 2005; DeCaprio, et al., 2005; Johnson and Ehrlich, 2002; Johnson, 2002; Johnson, et al., 2000; Jarman, et al., 1997; Dore, et al., 1996; Ehrlich, et al., 1994.
[2] See Olsen 9/11/08 Deposition. p. 306. Lines 2-8.
[3] Johnson, et al., (2007); Malinowski (1991).
[4] See Malinowski (1991); Johnson et al., (2007)

scores and *loadings*. PCA and factor analysis texts vary in both jargon and matrix nomenclature, but the equations below will replicate matrices as reported by SYSTAT (the commercial software package used by Olsen to implement his PCA).

To calculate the various matrices that consitute the results of a PCA, one starts with a raw data matrix **X**, with *m* rows (samples) and *n* columns (variables/chemicals) reported in units of concentration (e.g. mg/L or organisms/100 mL). In the case of geochemical data, we usually have many more samples than variables (i.e. $m > n$). As this is the case for Olsen's data,[5] the matrix descriptions and calculations below are for the case where $m>n$.

Transformatons are usually applied to **X** in order to optimize the analysis. Transformations actually used by Olsen are discussed in Section A2.2. To the extent that transformations are done, I will refer to the transformed matrix as $\mathbf{X_{tran}}$. Given the *n* x *n* correlation matrix **C** of transformed matrix $\mathbf{X_{tran}}$ PCA may be accomplished through a singular value decomposition as shown in this equation:

$$\mathbf{C = U\,\Lambda\,V^t}$$

where **V** is the matrix of eigenvectors (*n* x *n*) and **Λ** is the diagonal matrix (*n*x*n*) of eigenvalues. For principal components analysis, the equation above is typically re-expressed in terms of two additional matrices: '*scores*' (**S**) and '*loadings*' (**L**). The loadings matrix may be calculated by multiplying the eigenvectors by the square root of the eigenvalues:

$$\mathbf{L = V\ \Lambda^{1/2}} \qquad (\mathbf{L}= n\text{x}n \text{ loadings matrix})$$

If we scale the columns of the loadings matrix **L** by the eigenvalues (**Λ**) we get a matrix that SYSTAT referes to as '*factor coefficients*' (designated here as **F**). We can then calculate the scores **S,** by multiplying transformed matrix $\mathbf{X_{tran}}$ by **F**:

$$\mathbf{S= X_{tran}\,F} \qquad (\mathbf{S}=m\text{x}n \text{ scores matrix})$$

This equation will recreate scores as reported by SYSTAT, but it will <u>not</u> recreate the scores reported and used by Olsen in his report. Olsen calculated scores outside of SYSTAT, within EDAnalyzer, and his method is discussed in more detail in Section A2.3.

A typical objective of PCA is to reduce the dimensionality of the data set, but the scores and loadings reported from the equation above are still of full rank (i.e. they still have *n* columns). The dimensionality of the data is not reduced until one decides how many of the *n* PCs are '*significant*.' If higher numbered principal components can be considered '*noise*' we can reduce the dimensionality of the system by looking at only the first *k* principal componenets, where *k* is some number less than *n*. In Olsen's case, he ultimately determined that 2 principal components were 'significant' (i.e. k=2). With one exception (PCA Run SD1 – see Section 2.3.4 of the main body of this report) Olsen considered/interpreted/plotted only the first two columns of matrix **S** and the first two columns of **L**.

Scores and loadings matrices may be multipled together to get an estimate of matrix $\mathbf{X_{tran}}$ using a reduced number of principal components. The comparison of such an estimate to the original data matrix is a common characteristic of many methods designed to help an analyst determine the number of significant principal components. However, because $\mathbf{X_{tran}}$ represents a transformation of the original data matrix, **X,** a '*back-calculation*' is necessary in order to get the estimate of **X** ($\hat{\mathbf{X}}$)

[5] For SW3 (and all of Olsen's PCA runs) $m>n$. For example, in the case of Olsen's SW3 PCA run, there were m=573 samples and n=26 variables.

back in the originally measured units. As an example, if one chooses to do a log transformation prior to eigenvector decomposition (as Olsen did) they will need to take the inverse of that transformation in order to get an estimate of $\hat{\mathbf{X}}$ in the units of the raw data matrix (e.g. mg/L). This is discussed in more detail in Section A1.3.

A1.2 A Geometric Description of PCA.

The above description tells one, in mathematical terms, how to calculate principal components. But it provides little in the way of an intuitive feel for what a principal component is. Geometrically, the first principal component is essentially a linear regression line through the data cloud, along the direction of greatest density of data points. Successive PCs are calculated such that higher numbered principal component axes (PCs 2, 3 and higher) meet the following criteria: (1) each must account for as much of the remaining variance as is possible, and (2) the new PC axes must be mutually orthogonal (i.e. at a 90° angle) with respect to all PCs previously resolved. Successively higher numbered eigenvectors (principal components) account for successively smaller percentages of the variance.[6]

A graphical PCA example is provided in Figure A-1 below. This figure shows a data set with three measured variables (a three-dimensional system). The sample points that are plotted there (black dots) define a 3 dimensional, slightly flattened cigar-shaped data cloud. If we were to do a principal component analysis of this data set, PCA would calculate a set of three eigenvectors, plotted within this three dimensional data cloud. As indicated in the previous paragraph, the first eigenvector plots along the longest axis of the data cloud (i.e. the '*length*' axis of the cigar). To the extent that one considers the slightly flattened dimension of the 'cigar' unimportant to one's concept of a 'cigar shape' we can get a realistic understanding of the size and limits of this geometry by plotting the data on the first two axes. We have reduced the three dimensional (x, y and z) data to two dimensions (eigenvectors 1 and 2) without loss of much information.

[6] Malinowski (1991). p. 47; Johnson et al., (2007)

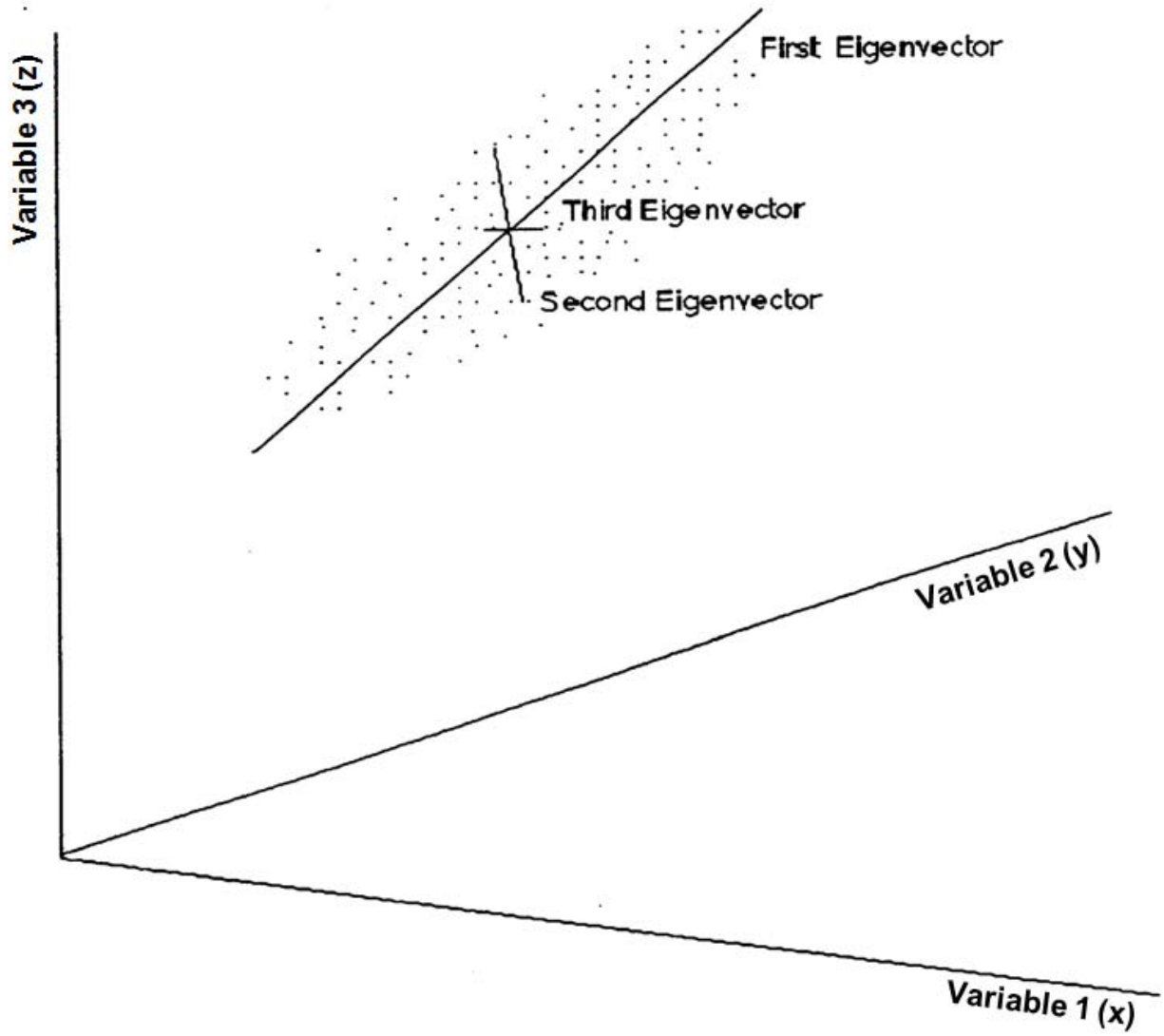

Figure A-1. Example of three eigenvectors plotted in three dimensional variable space.
Example taken from Brown (1994).

Now let us consider a system related to environmental chemistry. Figure A-2 shows a scores plot from a PCA of a polychlorinated biphenyl (PCB) data set (24 samples and 56 chemicals). I have published this example in both an environmental forensics book chapter and a journal article.[7] In terms of dimensionality, this system can be thought of as 24 sample vectors plotted in 56 dimensional space. We cannot plot a 56 dimensional vector on a 2 dimensional graph, at least not without some sort of mathematical calculation such as PCA. When we do a PCA/eigenvalue decomposition of these data, it turns out that two principal components achieve the goal of dimensionality reduction, because 2 PCs account for more than 92% of the variance in this data set. Having begun with a high dimensional system (24 samples plotted in 56 space) we can now plot those samples on a two dimensional '*scores plot*' with very little loss of information.

[7] Johnson, et al., (2007). Johnson, et al. (2002); Johnson and Ehrlich (2002).

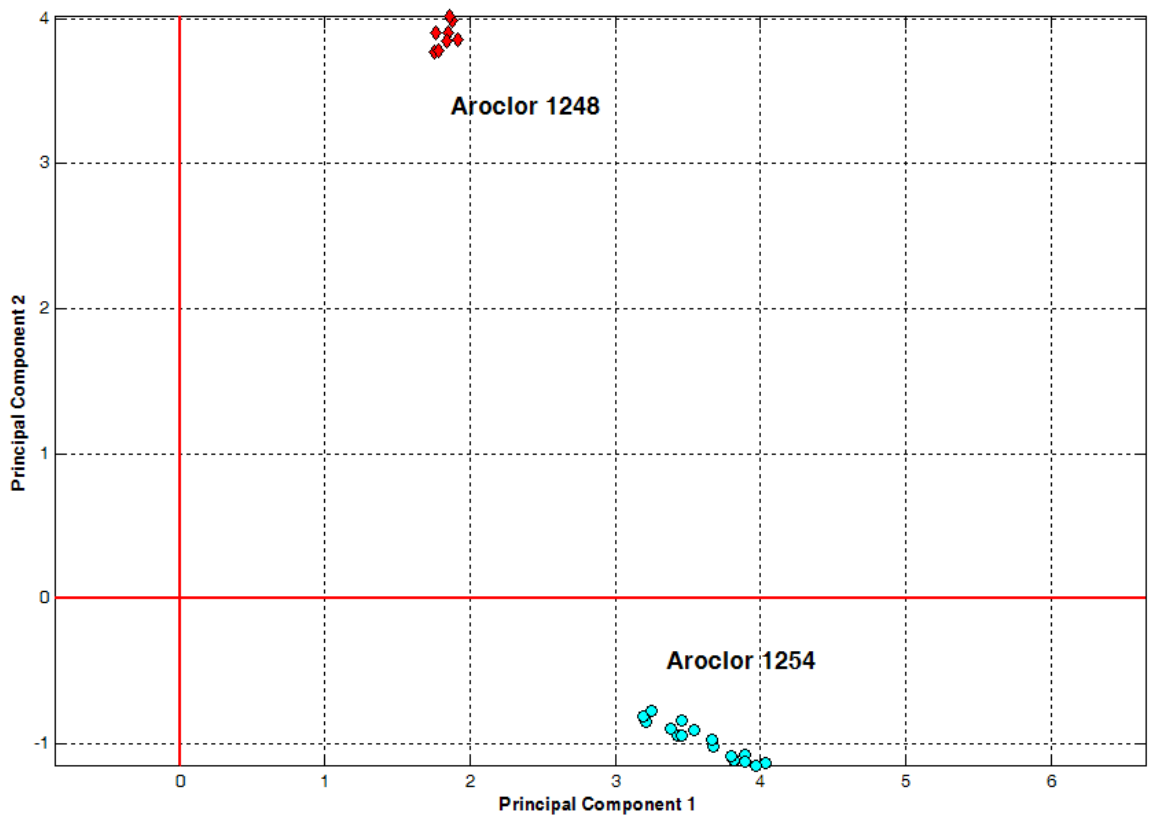

Figure A-2. Two principal component score-plot of PCB data set published by Johnson, et al., (2007). Two PCs may account for >92% of the variance of Data Set 1, but are insufficient to allow distinction of the two Aroclor 1254 variants (see Section A1.3).

In terms of the matrices described in Section A1.1, we plot the first column of matrix **S** on the x-axis, and the 2nd column of **S** on the y-axis. To interpret such a plot, the main thing to keep in mind is that samples that plot close to each other have similar chemical compositions. Samples that plot a great distance from each other have different chemical compositions. On this plot, there are two distinct, well separated clusters, and we are clearly looking at two groups of samples with different chemical compositions.

Understanding and correctly interpreting a PCA scores plots depends to a great extent on the user understanding exactly what a principal component is (and more importantly what it is not). Note that the data on this figure do not define a data cloud geometry anything at all like Figure A-1, so it would be naïve to equate principal component 1 with "*cigar length*." Note also that the two source clusters do not plot directly on either of the two principal components, so it is equally naïve to make the claim that "PC1 equals Aroclor 1254" or that "PC 2 equals Aroclor 1248." When applying PCA to environmental chemical data, you cannot assume that principal components are equivalent to sources. Rather they merely serve as an alternative cartesian coordinate system that allows plotting of data on a simple graph. The practice of equating a principal component to a "thing" with chemical or physical meaning is termed '*reification*' and will be discussed in more detail later in this Appendix (Section A1.4).

Correctly interpreting a PCA scores plot also depends on having sensitivity to what are referred to as "*data pathologies*." All chemical systems are not the same, and different types of data manifests themselves differently on a scores plot. The data set shown above is a very simple system: a two source, "*hard-clustered*" data set. There are two distinctly separate clusters of samples related to

the chemical composition of different sources: Aroclor 1248 (A1248) or Aroclor 1254 (A1254). A *hard-clustered* or *crisp* data set is one in which each and every sample can be unambiguously classified into one, and only one group (in this case, it is either "Aroclor 1248" or "Aroclor 1254"). No samples are mixtures of say 50% A1248and 50% A1254. If there were such a mixture on this plot, it would plot about half way between the two clusters.

In contrast to a *hard-clustered* system, Figure A-3 shows a scores plot for data with similar sources, but a very different data pathology. This data set has samples (blue dots) that are mixtures of three sources, but not a single sample has a pure, 100% contribution from any single source. If it did, the single-source samples would plot at or very near the corners of the gray shaded triangle. One of the most common mistakes in the application of PCA to environmental chemical data is to look at a mixed or gradational data set and interpret it as if it were a hard clustered data set. It would be naïve, simplistic and wrong to look at Figure A-3 and set some arbitrary rule based on a hard-partition threshold, and make a statement such as *"all samples with PC2 scores > 0 are impacted by Aroclor 1248, and all samples with PC2 scores < 0 are not."* Such a statement imposes a hard-clustered conceptual model upon a data pathology that is anything <u>but</u> clustered.

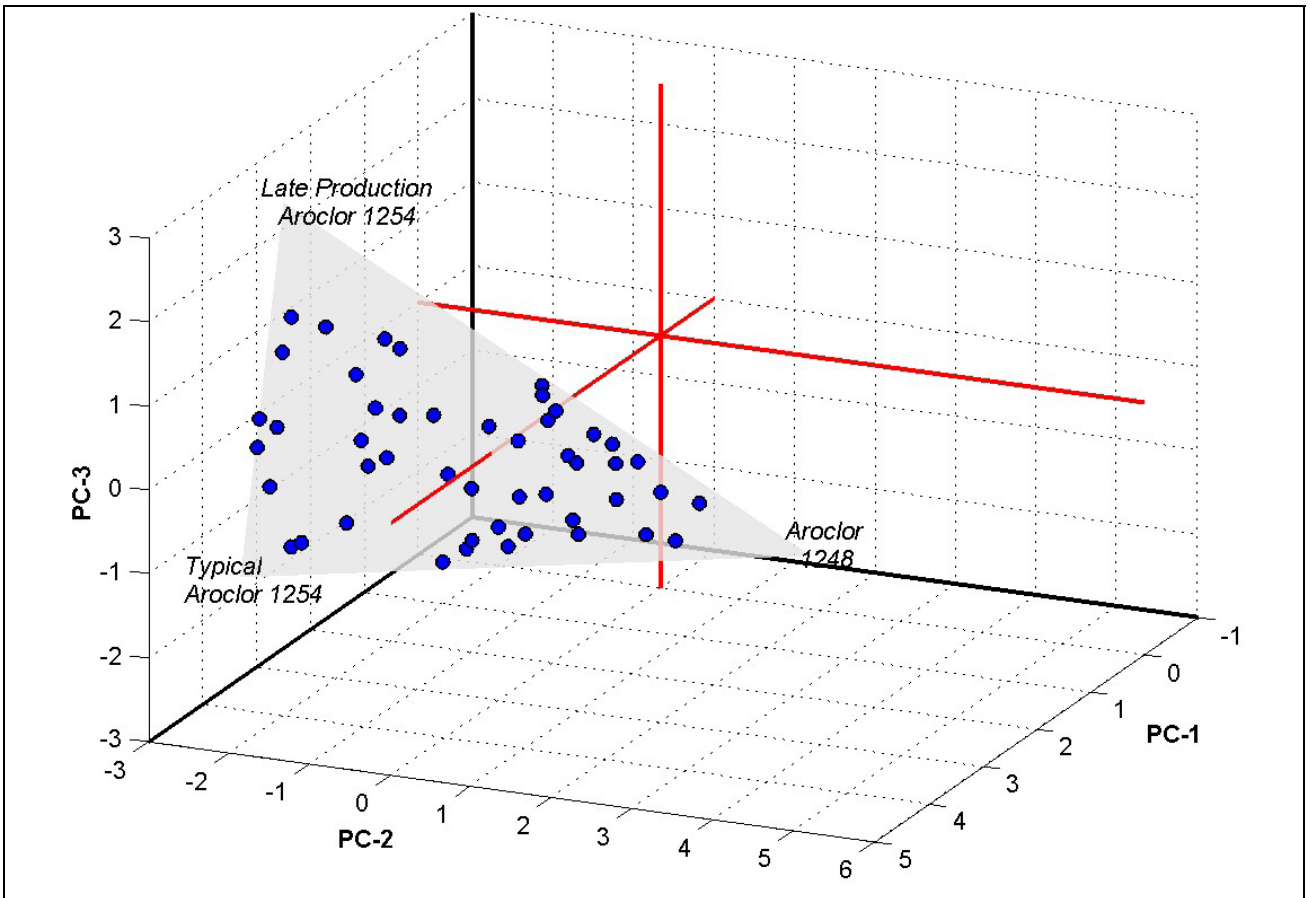

Figure A-3. Three PC scores plot for 3 source, mixed PCB data set published by Johnson, et al., (2007).

A1.3 Determining The Number of Significant Principal Components.

One of the most difficult aspects of PCA is determining the number of "significant" eigenvectors or principal components. Numerous methods have been proposed for this determination (Cattell, 1966; Exner, 1966; Malinowski, 1977; Miesch, 1976a; Wold, 1978; Ehrlich and Full, 1987; Henry et al., 1999, Johnson, et al., 2007). The spirit and intent of these methods are similar: the estimated

data set, as back-calculated from reduced dimensional principal component space ($\hat{\mathbf{X}}$), should reproduce the measured data (**X**) with reasonable fidelity. A common method used to justify one's choice of number of principal components retained is the percent variance criterion. Using this method, the analyst will show a principal component scores plot, and justify the choice of 2 or 3 PCs with a statement like "*2 PCs accounts for 76% of the variance*." The tacit assumptions in such a statement are that the remaining 24% is (1) random noise, and (2) irrelevant to the problem under study. There is no objective criterion to determine what percentage of variance is "significant." Malinowski addressed this problem more than 15 years ago:

> *"In practice, eigenvectors having large variances are considered to be primary eigenvectors, whereas eigenvectors having small variances are considered to be secondary eigenvectors. Unfortunately, classifying the variance as large or small presents a problem. It is at this critical point in the process that various investigators diverge. Often, the factor analyst gives no justification for the cutoff point used in the variance classification, thus casting doubt on the conclusion."*[8]
>
> *"In general the method can be deceptively misleading and is not recommended unless one can make an accurate estimate of the true variance in the data."* [9]

Ehrlich and Full (1987) expressed a similar, if more visceral objection, presented within context of the application of PCA and factor analysis to geochemistry:

> *"In the framework of our discussion, we mentioned that each eigenvalue represents a portion of the total variance of the system. If eigenvalues are arranged in order of the decreasing variance accounted for (the usual case), can we say that the first eigenvalue is most important because it is associated with the most variance? The answer is, of course, no.* [10]

And later, they state:

> *A common erroneous statement made by ignorant practitioners of factor analysis is that 'only the first k eigenvalues .. will be considered inasmuch as they account for 70% of the variance'."*[11]

To illustrate the potential problems with the percent variance criterion, refer back to the PCA scores plot in Figure A-2. That 2 PC model accounted for 92% of the variance, a seemingly impressive number. The associated scores plot showed two distinct and interpretable clusters. All of the red diamonds on that figure were Aroclor 1248 (a PCB product) and all cyan circles were Aroclor 1254 (another PCB product). This all seems to tie together to tell a nice simple story. It appears to be an impressively simple, hard-clustered, two source system that accounts for the vast majority of the variance. It certainly seems safe to assume that the remaining 7.5% of the variance is random noise. But, these conclusions and assumptions are wrong. It is not a 2-source system: it is a 3-source system. I know, because I created this data set by combining compositions of published PCB sources,[12] and have used this data set as an example in my publications.[13] Figure A-4 shows a three component scores plot for the same data shown in Figure A-2.

[8] Malinowski (1991). p. 111 (emphasis added).
[9] Malinowski (1991). p. 112.
[10] Ehrlich and Full (1987). p. 39 (emphasis added).
[11] Ehrlich and Full (1987). p. 39 (emphasis added).
[12] Frame, et al., (1996)
[13] Johnson, et al. (2007); Johnson, et al., (2002); Johnson and Ehrlich (2002).

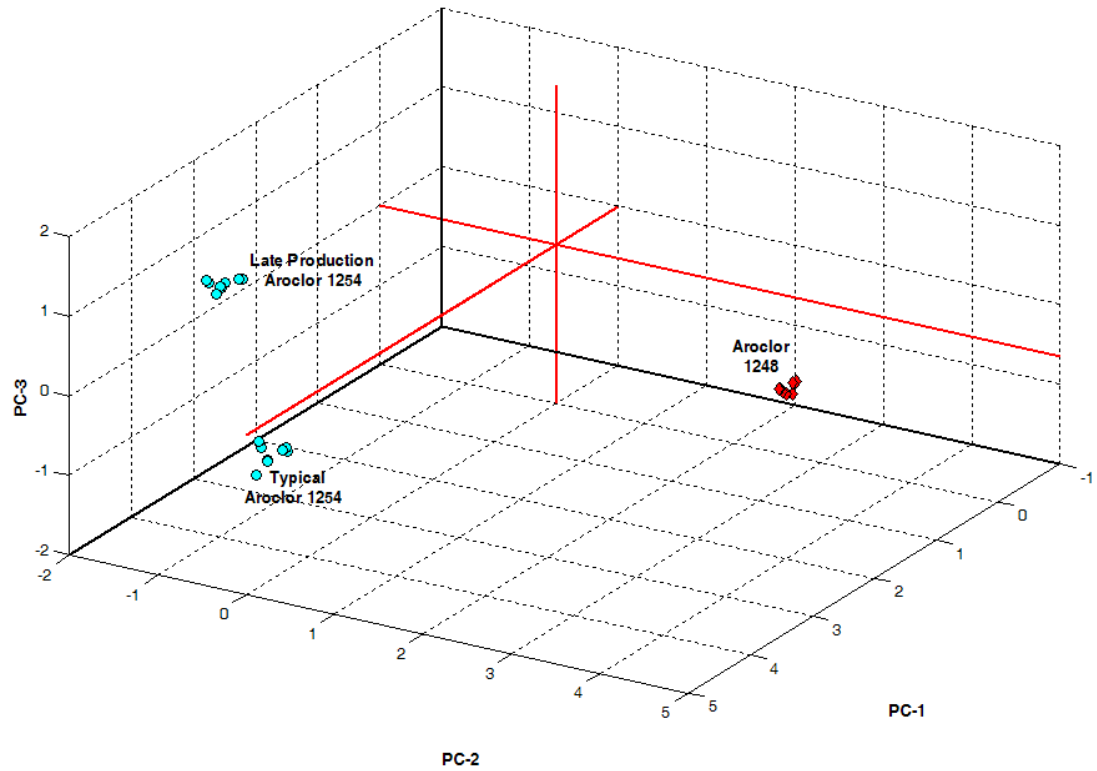

Figure A-4. Three principal component score- plot of hard-clustered data set shown in Figure A-2. Three PCs account for 97.5% of the variance, and allow clear distinction of the three PCB sources.

A three component solution accounts for 97.5% of the variance; an incremental increase over that accounted-for by two PCs. But that small percentage of variance is *not* random. The three-PC scores plot clearly distinguishes three clusters, rather than two, and effectively allows the analyst to infer the presence of the third source. As it turns out, there are two variants of the PCB product Aroclor 1254. While the chemical patterns of both A1254 variants are more similar to each other than either is to Aroclor 1248, they undoubtedly have distinctly different chemical fignerprints (Johnson, et al., 2008). The variance accounted for by the compositional difference between A1248 and undifferentiated A1254 is much greater than the variance accounted for by the compositional difference between the two types of A1254. That is why we don't see the difference in A1254 variants until we look at a 3 PC plot. This does not mean that Aroclor 1248 is "more important" than Late Production Aroclor 1254. Variance is not an function of scientific importance.

In addition, while this system requires three PCs to differentiate three sources, you cannot *reify* the PCs. In other words, one cannot make the statement that "PC1 is Typical A1254" or that "PC2 is A1248" or that "PC3 is Late Production A1254". I point this out because one of the issues in dispute in Olsen's PCA application is his *reification* of principal components. Olsen ultimately concludes that his principal components *are* sources. Principal components are abstract sets of orthogonal axes that allow us to plot the data in reduced dimensional space. They are not "things" that can be *equated* with physical or chemical reality. This issue is dicussed in more detail in Section A1.4, in context of the distinction between '*PCA*' and '*factor analysis*' and the reasons why many workers prefer to steer clear of the latter term.

Other methods have been used in the literature to determine the number of principal components to retain in a PCA. The scree test (Cattell, 1966) is closely related to the percent variance method, but rather than reporting a scalar value of the cumulative percent variance accounted for by retained PCs, the eigenvalues or percent variance are plotted on a graph. The scree test is based on the supposition that the residual variance, not accounted for by a *k* principal component model, should level off at the point where the principal components begin accounting for random error. When residual variance is plotted versus principal component number, the point where the curve begins to level off should show a noticeable inflection point, or 'knee.' The problem with this criterion is that often there is no unambiguous inflection point, and when such is the case, the decision as to the number of significant principal components is arbitrary.[14]

Another method used is the "average eigenvalue" method. This criterion is based on the rationale that only those principal components whose eigenvalues are above the average eigenvalue should be retained for the model. This criterion was first proposed by Kaiser (1960). In those cases where PCA is performed on the correlation matrix, the average eigenvalue will be 1.0. As such, this index is also referred to as the *eigenvalue-one* criterion.[15]

Scree plots and average-eigenvalue are slightly more useful than the percent variance criterion, because there is at least some stated objective criteria associated with their use (as opposed to just reporting percent variance accounted for by 2 PCs, and moving on) but they can still be problematic. As I point out in my PCA book chapter, these and other commonly used methods often yield ambiguous and/or contradictory results, in part because they are 'single-index' methods. Each involves calculation of a single numerical value or statistic, which represents the data set as a whole, as a function of the number of principal components retained. The data analyst typically compares the behavior of the index as additional PCs are retained, relative to some rule-of-thumb cutoff criterion (e.g. stopping at 70% variance, stopping at the average eigenvalue, and/or looking for an inflection point on a scree plot). The idea of a rule-of-thumb decision criterion is troublesome because we have very little information to evaluate the efficacy of these rules. The scree plot and average eigenvalue methods are included within SYSTAT (the software used by Olsen for his PCA runs). However, Olsen ultimately ignored the results of these two methods and relied primarily on the percent variance criteria (Section A2.4).

A better approach was first proposed by Miesch (1976a) whereby a goodness-of-fit index is calculated not just for the data set a whole, but on an individual, variable-by-variable basis. An extension of Miesch's method, the CD scatter-plot method[16] will be discussed in more detail in my critical review of Olsen's method of determining the number of "significant" principal components.

A1.4 Factor Analysis vs. Principal Components Analysis

The distinction between factor analysis and PCA was a topic of disagreement during the PI hearing. Olsen's '*factor analysis*' was criticized[17] by citing literature where factor analysis was characterized as "*a controversial and poorly understood methodology that extends the beguiling promise of instant insight to the researcher faced with more data than comprehension.*" This quote is from John Davis' book *Statistics and Data Analysis in Geology*, and falls within his discussion of the

[14] See Johnson, et al., (2007). p. 225.
[15] Malinowski (1991). P. 114.
[16] Johnson, et al., (2000; 2002; 2007)
[17] See Huber (2008).

sordid history of factor analysis in the social sciences. Olsen maintains what he is not doing *factor analysis* at all, but rather *principal components analysis.*[18] Olsen makes this claim despite the fact that he used SYSTAT's "Factor Analysis" module[19] to perform his calculations. Results reported in documents produced before the PI carried terminology such as '*factor scores*.'[20] After the PI hearing, Olsen had changes made CDM's in-house software EDAnalyzer[21] such that the term '*factor*' would no longer appear in any of his output files.[22] Clearly, the distinction between *PCA* and *factor analysis* was important to Olsen, and he wanted to distance himself from the latter term. The question is why. The purpose of this section is to describe what is meant by the terms *PCA* and *factor analysis*, to offer some insight to the stigma associated with the latter term, and to bring the related criticisms of Olsen's method into sharper focus.

A1.4.1 PCA and Factor Analysis: The Distinction

To the extent that there are differences between PCA and factor analysis, it is best to understand from the very outset that there is little agreement on terminology across scientific disciplines (e.g. chemometrics, psychometrics, engineering, mathematical geology, etc.). Malinowski (1991) considers "*principal components analysis"* to be synonymous with what he calls "*principal factor analysis"* and as such, PCA is a subset within the larger realm of factor analysis. Jackson (2003) makes a clear distinction between the two methods, says that the two methods are mutually exclusive, and that practitioners such as Malinowski are doing both procedures a disservice by making one a subset of the other. So what Malinowski calls *factor analysis*, Jackson calls *PCA*. But the problem does not end with Jackson and Malinowski. The definitions and distinctions between factor analysis and PCA depend on whom you ask, and on the corner of scientific literature that person worked in as part of their education and training. What's more, the interdisciplinary differences in jargon extend beyond the terms '*PCA'* and '*factor analysis*.' For example, the terms '*scores'* and '*loadings'* have different definitions, depending on the literature being read. In the mathematical geology literature, a matrix of samples with respect to a '*factor analysis'* is termed '*loadings.*' The matrix of variables is termed '*scores'* (e.g. Miesch, 1976a; 1976b). But exactly the opposite terminology is used in the chemometrics literature. A chemometrician would call a geologist's scores matrix '*loadings*' and vice versa.[23]

It is important to appreciate the existence of cross-discipline jargon issues, because in this Appendix, I cite literature from various disciplines. While the citations are relevant, the jargon may not make it immediately obvious. But having now more clearly recognized the issue for what it is, let's cut to the chase: I am more concerned with understanding Olsen's actual calculations and subsequent interpretations, than I am in the jargon he or anybody else might prefer in labeling it. To minimize jargon-related confusion, I will, whenever possible, use terms such as "*PCA*" "*scores*" and "*loadings*" in the manner apparently preferred by Olsen. The reader is free to label the method and the resultant matrices using whatever jargon they prefer.

A1.4.2 The Stigma of Factor Analysis

Given the ambiguous distinction between *PCA* and *factor analysis*, one might ask why Olsen is so adamant that his method should be called *PCA*. As John Davis made clear (see quote above) factor

[18] See Olsen PI Deposition Testimony. 2/2/08. p. 244.
[19] SYSTAT (2007).
[20] See PCA Results files in State's 01/21/2008 PI document production: PI-Olsen00028615 ('*Results_SW_0120_A.xls'*)
[21] EDAnalyzer is CDM proprietary software - an Excel add-in program - used to facilitate the PCA. It serves as an interface between Excel and SYSTAT, and defines transformation, data analysis options for PCA, and reporting. See Olsen (2008a) p. 6-46 and Olsen deposition (9/11/08). p. 308.
[22] See 4/21/08 8:13 am email from Chappell to Olsen (OlsenCORR0016188.0001)
[23] Johnson et al. (2007). p. 222.

analysis has a controversial history based on how it was used by social scientists in the study of intelligence. In the early 20th century: factor analysis was an important part of the science used to support theories of innate, hereditary intelligence of groups of people, as defined by race and/or social class. Therefore, for better or for worse, the term '*factor analysis*' carries a stigma that '*PCA*' does not.

Much of the stigma can be traced to the 1981 book "The Mismeasure of Man" by Stephen J. Gould (Gould's 1996 2nd Edition is cited here). This book was in large part an indictment of *factor analysis* as applied to data from intelligence testing of children. Gould made the case that a large body of factor-analysis-based psychometric research of the early 20th century was used to support *a priori* theories of a quantifiable, scalar metric of intelligence. Applying factor analysis to intelligence test data, the chief proponents of factor analysis (Cyril Burt and before him, Charles Spearman) ultimately equated a factor axis (i.e. principal component 1) with the concept of "*general intelligence.*" Factor scores were then used as a method of ranking grade-school students, to determine if they had an aptitude for university, or if they were destined for the technical trades. That and related research was then used to argue that people of certain races and/or social classes were innately less intelligent. As a result, the term '*factor analysis*' carries with it the stigma of class-systems, racism and the limitation of children's educational opportunities based on standardized test scores.

But Gould's indictment of factor analysis had little to do with a whether it was mathematically valid. Gould acknowledged that he himself successfully used factor analysis in his own field of research (paleontology), and he conceded that "*its mathematical basis is unassailable.*"[24] Neither did Gould make much of a distinction between factor analysis and PCA.[25] Rather, '*factor analysis*' takes the rap because that was the name applied to the method used by Spearman and Burt. Gould's indictment of factor analysis was based not on mathematics or jargon, but rather on the *a priori* prejudices of the scientists involved, how that predetermined their interpretations, and the flawed logic used to defend those interpretations.

Based on activities later in his career, Burt was accused of academic fraud, and in particular fabrication of data (Hearnshaw, 1979). But in terms of factor analysis (the focus of Burt's early career), the primary problems pointed out by Gould were (1) that factor analysis interpretations supporting theories of innate intelligence were predestined based on Burt's *a priori* theory and bias; and (2) '*reification*' – equating a principal component with a "*thing*" like general intelligence. In terms of Burt's *a priori* bias, Gould argues that Burt's preexisting opinions were imposed on his interpretations, such that Burt's conclusions were little more than a self-fulfilling prophesy.[26] With regard to reification, Gould pointed out that an eigenvector, principal component or factor is an abstract line through multivariate space, not a "thing" with physical reality. Whether one prefers to call this line "*Factor-1*" or "*PC-1*" was not the point. Rather it was whether or not you can equate a factor with a *thing* like intelligence.[27]

Gould's criticism of *reification* went beyond Burt's work, as made clear when Gould wrote: "*The history of factor analysis is strewn with the wreckage of misguided attempts at reification.*"[28] Nor is the objection to reification limited to Stephen J. Gould. It has also been criticized in application

[24] Gould (1996). p. 268.
[25] In fact, Gould acknowledges that the example he provides to explain the method of *factor analysis*, is technically *PCA*, not *factor analysis* (see Gould, 1996; footnote on pages 276-277).
[26] See Gould (1996). p. 304
[27] Gould (1996). P. 280.
[28] Gould (1996). p. 298.

to chemical data. Malinowski (1991) discussed PCA (which he terms "principal factor analysis"[29]) in context of chemistry applications. Using the term "abstract factors" to refer to the orthogonal PCA scores and loadings, Malinowski made the following points.

> "*Principal factor analysis yields an abstract solution consisting of a set of abstract eigenvectors and an associated set of abstract eigenvalues. Each principal eigenvector represents an abstract factor*"[30]
>
> "*Unfortunately, no physical meaning can be attached to the resulting matrices since they represent mathematical solutions only.*"[31]
>
> "*The row and column factors in their abstract forms are not recognizable as physical or chemical parameters, since the reference axes were generated to yield a purely mathematical solution. For scientific purposes we seek chemically recognizable factors.*"[32]

The inability to interpret abstract principal components loadings in real chemical context was ultimately the reason why chemists developed target transformation factor analysis (Malinowski, 1991; Hopke, 1989); why geologists developed polytopic vector analysis (Ehrlich and Full, 1987), why chemometricians developed alternating least squares (ALS: Tauler, et al., 1993; Tauler, 1995) and why scientists/engineers studying air pollution developed extended self-modeling curve resolution (Kim and Henry, 1991; Henry, 2003). All of these methods use principal components analysis as a mathematical basis, but they do not reify orthogonal PCs as sources.[33]

Given this dubious history, most now try to steer clear of the term '*factor analysis*' in favor of the mathematically similar, but less controversial '*principal components analysis.*' Roger Olsen is no exception. Even though he uses SYSTAT's "*Factor Analysis Module*", he would prefer that we call it *principal components analysis*. But focusing the argument on the jargon misses the point. Regardless of the terminology preferred by Olsen or anybody else, his work is best judged on the validity of assumptions, the logic of the application and the defensibility of interpretations. As shown throughout the main body of my report and this appendix, even if we agree to call Olsen's method *PCA*, he has repeated key mistakes of factor analysts such as Cyril Burt. He came into the process with an *a priori* opinion of a predominant poultry-waste impact in the IRW[34] and that opinion never changed regardless of what new data showed (see Section 3.3.2). Olsen consistently reified principal component 1 as '*poultry waste*' or '*the chicken signature*', and principal component 2 as '*WWTP effluent*'.[35] Contradictory data were ignored, rationalized to fit his *a priori* theory, and/or concealed (Section 3.0). In one case, PCA results that contradict Olsen's theory were actually altered so that a map would appear to better fit Olsen's theory (Section 3.1: Tahlequah). Whether this was done under the guise of *PCA* or *factor analysis* is hardly the point.

A2 Steps in Olsen's PCA

There are numerous data pretreatment options, transformations, goodness-of-fit diagnostics, and other data analysis decisions that can be done under the umbrella term "PCA." Add to this the confusion of different jargon used in different sub-disciplines, (see Section A1.2) we see that "PCA" is not definitive statement of one's entire methodology. On pages 6-32 through 6-66 of his

[29] Malinowski (1991). p. 19.
[30] Malinowski (1991). p. 19.
[31] Malinowski (1991). p. 57.
[32] Malinowski (1991). p. 61.
[33] See Johnson, et al. (2007) for review and comparison of these methods, as applied to a common environmental chemical data set.
[34] From the time CDM began work on this project, the project carried the acronym 'OPL' (Oklahoma Poultry Litigation), so it is clear what Olsen's the initial working hypothesis was.
[35] See Olsen (2008a: p. 6-57. 3rd paragraph), Olsen 2/2/08 deposition testimony (p. 102 lines 17-18; p. 115 lines 21-22; p. 263 lines 7-9; p. 264 line 22; p 265 line 1) and Olsen 9/11/08 deposition testimony (p. 337 lines 12-14).

report, Olsen describes his data management practices, preparation steps, preprocessing options, calculations, back-calculations, and interpretations. While that section of Olsen's report comprises 35 pages of text, his descriptions were ultimately insufficient to reproduce the analyses. I was able to fill in these gaps by trial and error, by matching matrices to the results reported in Olsen's production material.

To check Olsen's methodology, I reproduced his PCA run SW3, which was the primary basis of his opinion that poultry-waste was "*by far the dominant contamination source*" in surface waters of the IRW.[36] I used the normalizations and transformation that he indicated as a starting point. To the extent that I found errors or gaps in his method descriptions, I will clarify those ambiguities within this section of Appendix A. I reproduced Olsen's SW3 analysis by (1) implementing PCA using the scientific computing package Matlab (the Mathworks, Natick, Mass) (2) checking these results against PCA results reported by Olsen in spreadsheet files contained in his production materials, and (3) by checking results against results reported by SYSTAT (the software that Olsen used for his PCA) applied to the same data sets.

A2.1 Data Screening

Prior to implementation of PCA, Olsen performed a series of preprocessing steps using an Excel add-in program called 'EDAnalyzer.' This program is a CDM-developed application used to do exploratory analysis, and set desired parameters for subsequent PCA of the data.[37] The actual PCA itself was not done in EDAnalyzer, but rather EDAnalyzer linked to SYSTAT's Factor Analysis module.[38]

One of the goals of the data screening process is identification and handling of missing data. The data sets analyzed by Olsen had a surprisingly high incidence of missing data. Many analytes of interest in Olsen's PCA were not routinely analyzed in all samples collected, or were missing from the database because the data were rejected. For SW3, 573 samples from 10 groups were included in the PCA. However, if you look at all water samples in those 10 groups, there are 2,325 individual water samples (see Table 2-1: p. 12 of the main report). Of those 2,325 samples only 11.5% (267 samples[39]) included analyses for all 26 analytes in that PCA run. The vast majority of water samples considered by Olsen for this PCA had missing data.[40] By allowing inclusion of samples with data reported for at least 20 of 26 variables (i.e. up to six missing data points per sample were allowed in SW3) Olsen was able to get the number samples analyzed in SW3 up to 573 (still only about ¼ of the available samples).[41]

This entire practice was puzzling, because (1) it is not possible to calculate principal components using a matrix with missing data (aka "holes" in the matrix); (2) while SYSTAT allows samples with missing data to be input into a PCA, the software will by default, delete such samples from the analysis[42] and will not return principal component scores for them. But the PCA results produced by Olsen[43] include scores for <u>all</u> samples, <u>including</u> those with missing data.

[36] Olsen (2008a). p. 1-2.
[37] Olsen, p. 6-40.
[38] Olsen, p. 6-40.
[39] See Olsen Table 6.11-7a. Summary for PCA Run SW15 (Same as SW3 with no missing data allowed)
[40] To clarify, when I say missing data, I do not mean that a chemical or bacterial analyte were sampled for but not detected (i.e. non-detect). Rather I mean that the chemical or bacterial analyte was not sampled for or the data were rejected.
[41] See Table 6.11-7a and text on page 6-40, 3rd paragraph
[42] Systat (2007). p. I-492
[43] For example, see SW3 result produced by Olsen in the file '*Results_Water_0427_SW_3.xls*'

Olsen attempted to avoid this limitation with a work-around: he substituted the average (mean) concentration for missing data, prior to running PCA.[44] As an example, if a sample was missing data for total phosphorus, Olsen's substitution method would assign the mean phosphorus concentration for all samples in which phosphorus was measured. This was done regardless of the concentration of related chemicals (e.g. total dissolved phosphorus) in the sample with missing total P, and regardless of whether that sample was collected from an edge of field location, a stream adjacent to a golf course, a waste water treatment plant or a head-water stream. This is at best, a kluge: a clumsy and inelegant work-around designed to circumvent a fundamental data quality problem. For a number of reasons, it is inappropriate. There is a philosophical objection: the mean is a univariate measure of central tendency. An underlying assumption of PCA is that we are dealing with a multivariate system. The substitution of a univariate estimate for missing data in a multivariate system subverts the underlying conceptual model. For example, if *E.coli* data were missing in a base-flow stream sample and in an edge of field sample, both samples would be assigned the exact same value (the average of all reported *E. coli* measurements) in that PCA run. In addition, Cowan (2008) clearly and empirically shows that Olsen's method of missing-data substitution actually adds artificial variability to the system, and alters where in the data cloud the principal components will be located.

Be that as it may, Olsen established a criterion for each of his PCA runs where some allowable number of missing data points would be tolerated in samples. For PCA run SW3 he set that number at 20. Given 26 variables, that means that he would retain samples that had ≤ 6 missing data points. That criterion tells us about missing data allowed as a function of samples, but Olsen's report never tells the reader about missing data with respect to variables. This leaves the impression that missing data are spread evenly across all variables, but that is not the case. Some of the variables in SW3 (particularly bacteria) have extremely high occurrences of missing data. As is shown on the table below, for his four bacteria variables, data are missing in more than a quarter of samples. Of these four, the worst case is *E. coli*, where 41% of the samples have missing data.

EDA_Variable	# Missing Data Points in SW3	% Missing
COLIFORMS	**161** of **573**	28%
ECOLI	**233** of **573**	41%
ENTERO	**163** of **573**	28%
FECAL	**163** of **573**	28%

Olsen acknowledged in deposition testimony that he was aware that *E. coli* and other bacteria were often missing, and that this was due to high rates of rejected data.[45]

Many samples had no bacteria data reported at all, but other bacteria results had multiple reported values in the database (i.e. duplicate values). An example set of duplicate analyses for one bacteria analyte (coliforms) is shown below. In this case, surface water sample BS-REF3, collected on September 1, 2005, includes four results and the four reported values exhibit a wide range (ranging from non-detect to 900 organisms per 100 mL).[46]

[44] On page 6-53 Olsen indicates that he did his substitution for missing data after PCA loadings and coefficients were calculated (Step 11: calculate PC scores). This is not the case. To reproduce Olsen's reported PC loadings, coefficients and scores one must substitute the mean for missing data prior to transformation and eigenvector decomposition.

[45] Olsen Deposition. 9/11/08. pp. 424-425.

[46] These data were taken from Olsen's subdatabase spreadsheet used as the source for his PCA run SW3: "Subdatabase_Water_0427.xls"

EDA_Location	Date	EDA_Variable	EDA_Value	EDA_ValOp	EDA_UnitsID
BS-REF3	9/1/2005	COLIFORMS	1	U	org/100mL
BS-REF3	9/1/2005	COLIFORMS	900		org/100mL
BS-REF3	9/1/2005	COLIFORMS	40		org/100mL
BS-REF3	9/1/2005	COLIFORMS	900		org/100mL

For use in PCA, duplicate analyses such as this (or in this case quadruplicates) Olsen would calculate the average of the replicate values, and use that average (mean) number in his PCA. The average of these four values is 460 org/100ml. Olsen's SW3 PCA run used a value of 313.5[47] for the variable 'coliforms' in BS-REF3 (which is the average of the first three data points, and substituting ½ the detection limit (0.5 org/100 mL) for the "U" qualified (non-detect) result. Olsen did not use the second 900 org/100mL value in his mean calculation, which suggests perhaps this second 900 was duplicate of the first 900 data-entry, rather than a true duplicate, but this is not explained by Olsen. Regardless, note that the average value used by Olsen for 'COLIFORMS' in 'BS-REF3' (313.5 org/100 mL) is not near any of the actual, measured values (see Cowan, 2008).

Myoda (2008) addresses the high incidence of missing bacteria data in more detail, as well the high variability of those data. Myoda also addresses other bacteria data quality concerns (e.g. more than 60% of the bacteria data that were retained for Olsen's analysis were not analyzed by the lab within the method-prescribed holding times). In Section A2.4 of this appendix, we will see that all four bacteria variables exhibit very poor goodness-of-fit in the PCA. This presents a major problem for Olsen's ultimate conclusions, because bacteria is one of two major constituents of his poultry fingerprint. In his summary of major opinions at the beginning of his report, Olsen says *"In the PCA, the chemical and bacterial composition of poultry waste creates a distinct chemical signature that contains both phosphorus and bacteria."*[48]

There is also a data quality concern for the second analyte highlighted in Olsen's quote above. Phosphorus (P) is a key part of Olsen's "*unique poultry waste signature*." Olsen's SW3 PCA run included 3 different forms of phosphorus (soluble reactive P, total P, and total dissolved P). These parameters were analyzed by three different laboratories (A&L, Aquatic Research, and the USGS). The majority of analyses in Olsen's database were conducted by Aquatic Research, but hundreds of analyses were also run by the A&L and USGS labs. In addition the database includes different analytical methods. The number of samples in SW3, broken out by method, are summarized on the table below. The samples collected by CDM/Lithochimea were analyzed by three different methods (365.2, 6020, and 4500), and by two different labs (A&L and Aquatic). The USGS samples were analyzed by a 3rd lab (USGS's lab) using yet different methods (P00665, P00666 and P00671). The USGS methods are not discussed in Olsen's text.

In some instances, a single sample would have P data reported from multiple phosphorus methods, and some methods were considered more reliable than others. For example, Olsen reported that method 365.2 was more susceptible to interference in the sample matrix, so those analyses had greater potential to be biased high.[49] Therefore, in instances where data were available from both methods 365.2 and SM4500, the SM4500 results were chosen by Olsen for use in his PCA.[50] In addition, there are instances where there are no P data reported at all (see missing data for total P and soluble reactive P on the table below).

[47] See REF3 data for SW3 input matrix, in Olsen produced spreadsheet "Crosstab_Water_0427_SW_3.xls"
[48] Olsen summary of major opinions (Olsen, 2008a; p. 1-2 3rd bullet, final sentence)
[49] Olsen (2008a). p. 3-5.
[50] See 'Water (P Protocol)' worksheet within Olsen produced Excel spreadsheet 'PCA_Main_Database_Water.xls'

Total Dissolved P		Number of Samples in SW3
P Protocol Code	**Param ID (Method)**	
P_TD_365	Total Dissolved P (365.2)	58
P_TD_4500	Total Dissolved P (4500PF)	349
P_TD_6020	Total Dissolved P (6020)	24
USGS P00666	Dissolved P (USGS P00666)	142
	Total	**573**

Total P		Number of Samples in SW3
P Protocol Code	**Param ID (Method)**	
P_T_365	Total P (365.2)	40
P_T_4500	Total P (4500PF)	345
P_T_6020	Total P (6020)	28
P_T_ortho	Total ortho P (365.2)	17
USGS P00665	Total P (USGS P00665)	142
Missing Data		***1***
	Total	**573**

Soluble Reactive P		Number of Samples in SW3
P Protocol Code	**Param ID (Method)**	
P_SOL_REAC_365	Dissolved Ortho P (365.2)	69
P_SOL_REAC_4500	Soluble Reactive P (4500PF)	349
USGS P00671	Orthophosphate (USGS P00671)	142
Missing Data		***13***
	Total	**573**

Data Compiled from Olsen Produced Spreadsheet: 'PCA_Main_Database_Water.xls'

The mixing and matching of data from multiple labs, using multiple analytical methods (especially when there is suspected bias between methods) can be problematic in application of eigenvector methods such as PCA. When PCA is used for chemical fingerprinting/source identification (as is the case here) the data analyst often makes the tacit assumption that systematic variability is related to differences in sources. But there are many potential causes of systematic variability (e.g. degradation, and bias introduced by data from multiple lab methods). To the extent that there may be bias between these methods (and Olsen acknowledges that there is) this could contribute systematic variability to a PCA.

A2.2 Data Transformations

Prior to implementation of PCA, Olsen also undertook a series of data transformations. Such transformations are commonly done in PCA, in order to condition the data matrix, and/or optimize the analysis. Olsen used two transformations prior to his PCA. The first was a log transform. He replaced every data point in the matrix with base 10 log of that value. In general, log transformations are useful in situations where variables are log-normally distributed, and if the method being used requires an assumption of normally distributed data. In my experience with PCA, such a transformation is not really necessary because PCA used in an exploratory data analysis mode (as Olsen uses it here) does not require any assumption regarding data distributions.

The second transformation done by Olsen was a homogeneity of variance normalization, which may be accomplished by calculating principal components from a correlation matrix.[51] This transformation has the effect of creating homogeneity of variance, such that the variance of high concentration analytes does not dominate the analysis.[52] In Olsen's workflow, these transformations are chosen by the user in EDAnalyzer, and implemented in Excel, prior to passing the transformed matrix to SYSTAT for the actual eigenvector decomposition / PCA.[53]

It is worth mentioning a transformation that Olsen did not do. Olsen's PCA method did not include sample normalization. Such a transformation is commonly done in environmental and geochemical studies, because concentrations can vary widely due to dilution (Johnson, et al., 2007). In the case of many (if not most) environmental chemistry studies, concentrations will vary dramatically, often by orders of magnitude. Without a sample normalization transformation, the main source of variability that drives differences in principal component scores will be total concentration rather than the ratios of key analytes. Therefore, sample normalization transformations are almost always employed. The common ones are (1) transformation to percent of total concentration, and (2) normalization to a key analyte (a 'normalization variable'). I discuss both of these transformations in my PCA book chapter (Johnson, et al., 2007). Olsen used no such transformation in his PCA. As a result, there is every reason to suspect that his score plots reflect primarily the differences in total concentration of the samples rather than differences in the ratios of source-diagnostic analytes. In Olsen's PCA, I would expect two samples with identical proportions of analytes, but which differed in total concentration due to attenuation, to plot a great distance from each other on a scores plot. Olsen specifically stated in deposition testimony that attenuation of samples does not affect his PCA,[54] so it appears that he is unaware of this, and is under the impression that the two transformations he used somehow normalize out the concentration effect. He is wrong. Without a sample normalization step, differences in total concentration due to attenuation will have a strong effect on PCA scores, as is demonstrated in Section 4.0 of the main report.

A2.3 Eigenvector Decomposition and Calculation of Scores and Loadings

The transformed matrices were then submitted to SYSTAT to perform eigenvector-decomposition, calculation of eigenvalues, and percent variance accounted-for, principal component loadings, coefficients and scores. These were reported by SYSTAT for unrotated principal components and for a number of rotation schemes (e.g. varimax rotation: Kaiser, 1958). In my reproduction of Olsen's SW3 PCA run (using Matlab) I was able to match my results with those produced by SYSTAT. With the exception of scores, these also matched results reported in Olsen's results spreadsheets.[55]

The PC scores that I calculated (using equations given in Section A1.1) and matched with the SYSTAT output did not match those reported in Olsen's results spreadsheets. This is because Olsen calculated scores outside of SYSTAT, in Excel using instructions defined in EDAnalyzer. The method for external scores calculation, was described by Olsen in his report as follows:

> *"To calculate a PC score for each individual sample, the PC coefficient is multiplied by the standardized parameter concentration. This is performed for all parameters (variables) in a*

[51] Use of a correlation matrix in PCA is essentially the same as doing the autoscale transform (i.e. transform all variable to $\mu=0$, $\sigma=1$) prior to PCA (Johnson, et al., 2007). In SYSTAT, the correlation matrix is the default option for matrix extraction. Olsen did the equivalent of an autoscale, by calculating principal components from a correlation matrix , but it was the correlation matrix calculated after his log-transformation.

[52] See Johnson, et al., 2007 for general discussion of homogeneity of variance transforms.

[53] See Olsen Deposition (9/11/08). pp. 312-313.

[54] Olsen Deposition. 9/11/08. p. 565-566.

[55] For example, Olsen's SW3 results are reported in Olsen's produced file: "Results_Water_0427_SW_3.xls"

particular PCA run. The product values for all 25 parameters are summed to yield one PC score for each PC."[56]

So to reproduce Olsen's reported scores, he says that one needs to multiply "*standardized parameter concentration"* by "*PC coefficients.*" The latter matrix was easy to find. It is matrix **F** in the set of equations given in Section A1.1, and they are clearly identified in Olsen's results spreadsheet. What Olsen meant by "*standardized parameter concentration"* was not at all clear. By trial and error, I determined that what he meant was an autoscale transformation of the raw concentrations matrix (prior to the log transformation) with the average of reported variable concentrations substituted for missing data.

I discussed the autoscale transformation (also known as the Z transform) in my PCA book chapter. Given a matrix **X** with i=1,2…m samples and j=1,2…n variables, composed of raw concentration data in the originally measured units (e.g. mg/L) we calculate the mean ($\bar{x}$) and standard deviations (s_j) for each column of variables (j = 1,2…n), and then calculate the autoscaled matrix **Z** as follows:

$$\mathbf{Z}_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j}$$

Olsen's "<u>*standardized parameter concentration*</u>" matrix is **Z**. Olsen's PC scores matrix (designated $\mathbf{S_o}$ to differentiate it from the SYSTAT reported scores **S** – see Section A.1.1) is then calculated by multiplying the matrix **Z** by the SYSTAT-reported factor coefficients matrix **C**.

$$\mathbf{S_o} = \mathbf{Z} * \mathbf{C}$$

Using this equation, I did get scores that closely matched those reported in the PCA results spreadsheets produced by Olsen.[57] But they still do not match the scores shown on Olsen's figures (e.g. Figure 6.11-18 for SW3). That is because, after calculating $\mathbf{S_o}$ Olsen did one final transformation. He normalized each column of his scores matrix such that the minimum score would equal +1.0. The reason given for this transformation was that "*mapping was facilitated by rescaling the PC scores such that the lowest score for a particular PC was assigned a value of one*."[58] If the minimum score of each column j of $\mathbf{S_o}$ is defined as min($\mathbf{So}_j$), Olsen's translated scores may be calculated by:

$$\mathbf{S}_{Tj} = \mathbf{So}_j + |\min(\mathbf{So}_j)| + 1$$

Where the vertical brackets (| |) indicate absolute value. It is odd that Olsen is calculating scores using a **Z** matrix from the raw concentrations matrix **X**, but in his transformations done prior to his PCA, he did not use the **Z** transformation (at least not applied to the raw data). He first did a log transformation of **X**, and performed a PCA on the correlation matrix of the transformed data. Olsen's scores back-calculation method is incorrect because he does not undo the log transformation, and instead calculates scores using a transformed matrix never calculated prior to PCA. Olsen does not explain why he did this. In fact, his deposition testimony indicates that he is not even aware that he did this.[59]

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[56] Olsen (2008a). p. 6-53. (emphasis added).

[57] In my reproduction of Olsen's SW3 PCA run, the vast majority of PC1 and PC2 scores matched those reported by Olsen There were slight differences in scores of a few samples that had missing data.

[58] Olsen (2008a). p. 6-54.

[59] Olsen deposition testimony. 9/11/08. p. 315. Olsen states three times that the only difference between his scores and SYSTAT's scores was the normalization to set the minimum for each PC at +1.0. This is incorrect. Olsen is apparently unaware that his

A2.4 Determining the Number of Significant Principal Components

Olsen used three methods to determine the number of "significant" principal components: (1) cumulative percent variance, (2) scree plots, and (3) the average eigenvalue criterion.[60] All of these were discussed above in Section A1. Olsen's scree plot for SW3 is shown below as Figure A5.

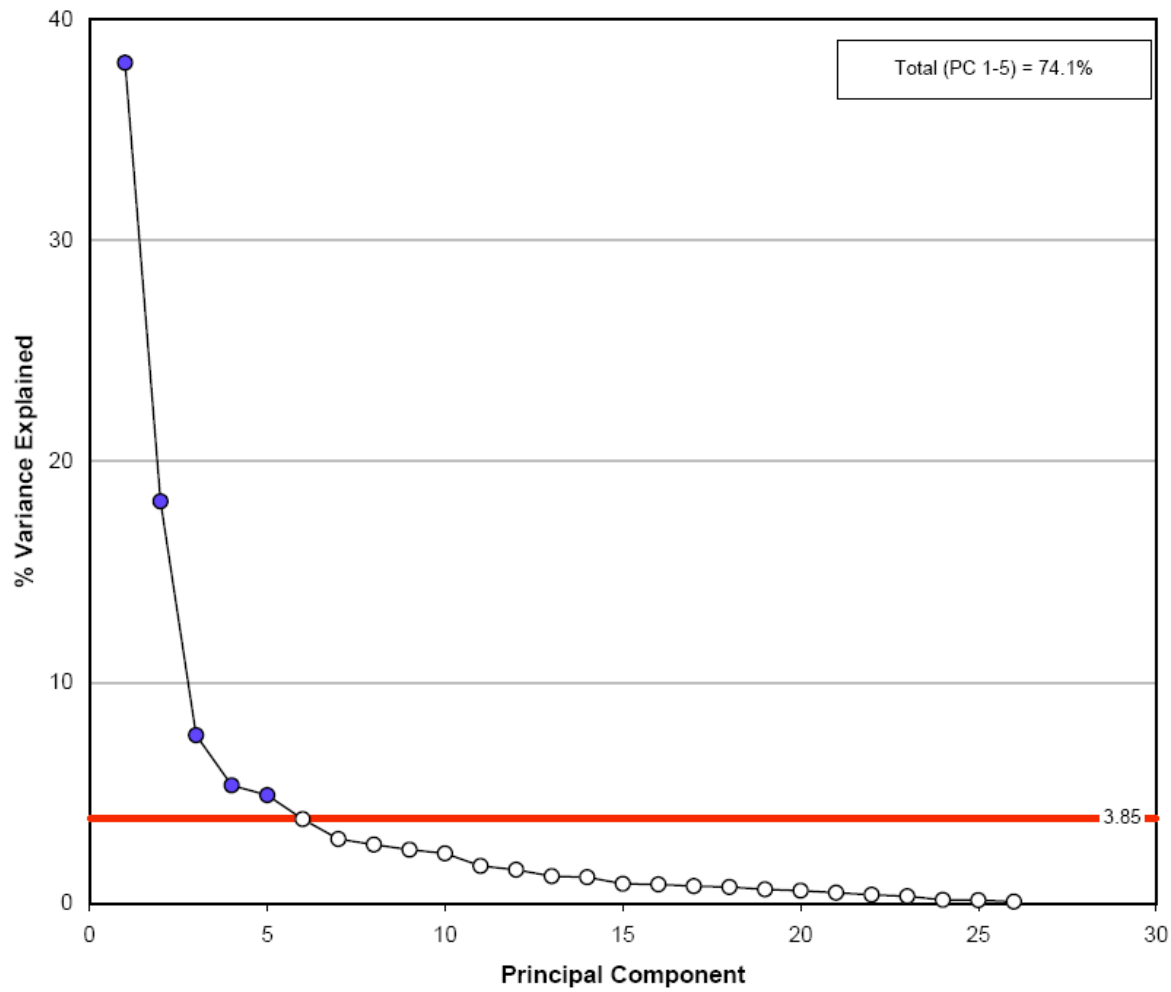

Figure A-5. Direct copy of Olsen's SW3 scree-plot, indicating 5 significant principal components. By this criterion, samples that plot as blue dots, above the average percentage of variance (3.85) are considered significant and should be retained for the PCA. Olsen only retained 2 PCs for his SW3 PCA run.

The average eigenvalue criteria and scree plots indicated 5 principal components for Olsen's PCA run SW3 (shown above) as well as for SW17, and SD1.[61] For PCA run SD6, four significant PCs were indicated.[62] For SW3, Olsen concluded that there were five "significant" principal components because (1) 5 PCs accounted for 74.1% of the variance in that data set; and (2) the first five principal components each accounted for greater than the average eigenvalue 3.85.[63] But

EDAnalyzer is doing a log transformation on the way into PCA but failing to undo it as part of the calculation of scores on the back end of the analysis.

[60] Olsen (2008a). p. 6-50.

[61] See Olsen (2008a) Figure 6.11-5

[62] See Olsen (2008a) Figure 6.11-7

[63] Olsen (2008a) p. 6-50. Last paragraph. See also Olsen's Figure 6.11-1.

Olsen's subsequent interpretations focused solely on the 2 principal component solution, and his justification is based on the percent variance criterion, as is seen in the following quotes.

> *"The term "significant" in this context means that a relatively high percentage of the total variance is accounted for by a small number of PCs.*
>
> *Experience has shown that the objectives of PCA can be met in a data set or environmental system dominated by a relatively few number of source impacts that exhibit mutual correlation among their parameters. In such cases a correspondingly high percentage of the total variance is explained by only a few PCs, typically 2-3 PCs"*[64]

> *"These results all clearly show that the top five PCs are significant (above random noise), and that the top two are most significant. The results were used to establish the top 2 PCs (PC1 and PC2) as representing the dominant signals or signatures related to impacts in the watershed. The dominant PC1 and PC2 signatures also proved to be interpretable as to source identification because they are so dominant – see steps 12 and 13. On the other hand, PCs 3, 4 and 5 generally were less readily interpretable (because they are so much closer to random noise or background variation)."*[65]

In the first quote, Olsen is making the age-old mistake discussed in Section A1.3 of equating variance with scientific significance. Based on what "*experience has shown*" and the fact that he was not able to interpret PCs 3, 4 and 5, he concludes that the PCs 3, 4 and 5 are "*closer to random*" and from that point on in his report, Olsen addresses primarily 2 PC solutions. As is shown in the table below,[66] two PCs account for as little as 50%, of his four primary PCA runs. As was discussed in Section A1.3, the assumption inherent in this method (and in fact the assumption explicitly stated by Olsen in the quote above) is that the residual variance not accounted for by 2 PCs is random noise. In the case of his primary SW3 PCA run, 44% of the variance in the system is ***not*** accounted for.

Run	Groups	Rotation	Variance Explained by PC1 (%)	Variance Explained by PC2 (%)	Variance Explained by PC1 and PC2 (%)
SW 3	Surface Waters	No Rotation	38.0	18.2	56.2
SW 17	Surface Waters and Groundwaters	No Rotation	34.2	15.9	50.1
SD 1	Solids (wastes, soils, sediments)	Varimax	38.3	16.7	55.0
SD 6	Solids and Core Samples	No Rotation	38.5	28.5	67.0

This section of Olsen's report (as quoted above) is more rationalization than analysis. Olsen is trying to convince the reader that the average eigenvalue criterion is wrong, and the 43.8% of the variance unexplained by his 2 component SW3 model is random, based on what "*experience has shown*" and because "*PCs 3, 4 and 5 generally were less readily interpretable.*" In so doing, he disregards evidence of a five component system by relying solely on percent-variance. Thus, he is revisiting problems pointed out more than 20 years ago by Ehrlich and Full (1987), as quoted below:

[64] Olsen (2008a) p. 6-50. 1st and 2nd paragraphs. (emphasis added).
[65] Olsen (2008a). p. 6-51. (emphasis added).
[66] Table reproduced from on page 6-52 of Olsen (2008a).

(1) *"If eigenvalues are arranged in order of the decreasing variance accounted for (the usual case), can we say that the first eigenvalue is most important because it is associated with the most variance? The answer is, of course, no.*

(2) "*A common erroneous statement made by ignorant practitioners of factor analysis is that "only the first k eigenvalues ... will be considered inasmuch as they account for 70% of the variance."*[67]

This is also a classic example of a problem I pointed out in my book chapter. Regardless of the actual complexity of a data set, and regardless of the results of goodness-of-fit diagnostics such as the average eigenvalue criteria, there is subtle pressure on naïve practitioners to rationalize an excuse such that they end up with a 2 PC system, not because of the inherent simplicity of the system, but because it is easier to plot 2 PCs than it is to plot 5.[68] Olsen focuses his attention on the first 2 principal components, and then rationalizes in order to dismiss evidence of a more complicated system.

As discussed in Section A1, and in several of my papers and book chapters, when faced with quite reasonable and common environmental chemistry data pathologies, 'single index methods' such as the percent variance criterion, the scree-test, and the average eigenvalue criterion can yield ambiguous and conflicting results.[69] A better approach is through use of graphical diagnostics to evaluate goodness of fit on an analyte-by-analyte basis, in particular the Miesch coefficient of determination (CD) accompanied by CD scatter-plots.[70]

I have reproduced Olsen's SW3 PCA using the transformations and missing-data substitution criteria indicated by Olsen. I did a singular value decomposition (svd) of the **Z** transform of the log-transformed data (which is equivalent to doing svd of the correlation matrix of log-transformed data) using the equations provided in Section A1.1. I then back-calculated an estimate of the original 573 by 26 data matrix (based on 2 principal components), calculated Miesch CDs and generated a scatter-plot array for Olsen's SW3 PC model (Figure A-6). In order to get the results into the units of the original variables (mg/L for chemical species; org/100ml for bacteria) I had to deviate from Olsen's back-calculation method (because he failed to undo his log-transformation in his calculation of scores). I did my back-calculation by first undoing the correlation matrix (**Z**-transform) and then undoing the log-transform. I first calculated the 2 principal component estimate of **Z** ($\hat{\mathbf{Z}}$), using only the first two columns or rows of matrices **U**, **Λ** and **V**:

$$\hat{\mathbf{Z}}_{573x26} = \mathbf{U}_{573x2}\, \mathbf{\Lambda}_{2x2}\, \mathbf{V}^{T}{}_{2x26}$$

I then back-calculated an estimate of $\mathbf{X}_{log}$ (by undoing the **Z** transform):

$$\hat{\mathbf{X}}\mathrm{log}_{ij} = \hat{\mathbf{Z}}_{ij} * \mathrm{stdev}(\mathbf{X}\mathrm{log}_j) + \mathrm{mean}(\mathbf{X}\mathrm{log}_j)$$

And finally to get an estimate of **X** (2 PC estimate of the data - in the originally reported units) I undid the log transformation:

$$\hat{\mathbf{X}}_{ij} = 10^{\hat{\mathbf{X}}\mathrm{log}_{ij}}$$

The scatter-plots shown in Figure A-6 are then constructed by plotting each column **X** on the x-axis versus each column of $\hat{\mathbf{X}}$ on the y axis.

[67] See the full quote in Section A1.3. From Ehrlich and Full (1987). p. 39.
[68] Johnson et al., (2007). p. 231.
[69] Johnson et al., (2007). p. 225-226.
[70] Johnson, et al., (2007). pp. 226-230.

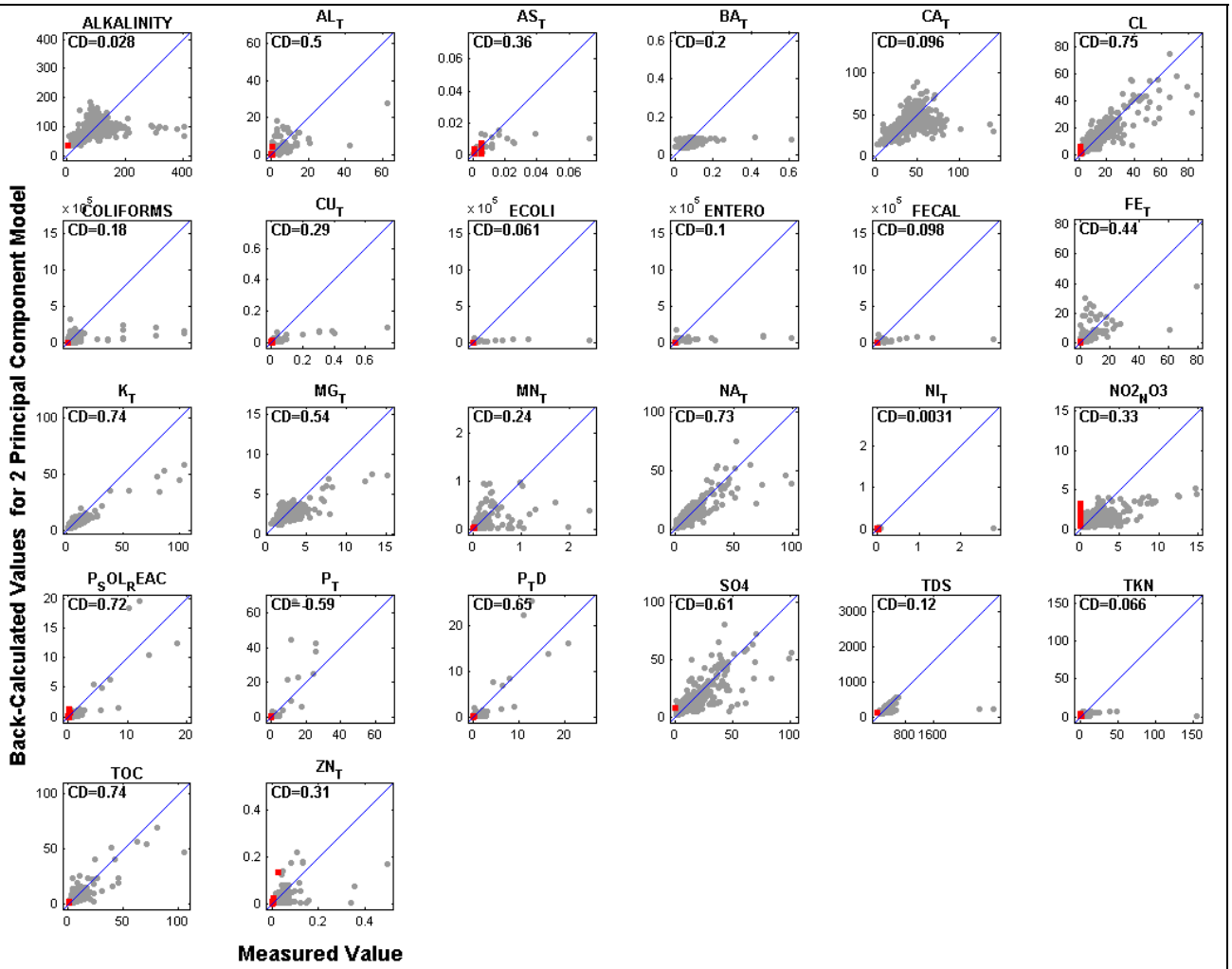

Figure A-6. CD scatter-plots showing 2 principal component goodness-fit for each of 26 analytes used in Olsen's SW3 PCA (573 samples | 26 variables).
Red squares indicate samples that were reported as "non-detect." For these samples, half the detection limit was substituted.

The "CD" indicated at the top left of each scatter-plot was proposed by Miesch (1976a). Miesch provided a method to calculate a coefficient of determination (CD) between each variable in the original matrix (**X**), and its back-calculated reduced dimensional equivalent $\hat{\mathbf{X}}$. The formula for the Miesch CDs is:

$$r_j^2 \cong \frac{s(x)_j^2 - s(d_j)^2}{s(x)_j^2}$$

where $s(x)_j^2$ is the variance of values in the jth column of **X**, and $s(d_j)^2$ is the variance of residuals between column j of **X** and column j of $\hat{\mathbf{X}}$. Miesch used the '≅' in this equation because he recognized that this was not a r^2 or CD as defined for a least squares regression line of $\mathbf{X}_j$ vs $\hat{\mathbf{X}}_j$. It is the r^2 with respect to a line of <u>one-to-one</u> back-calculation between $\mathbf{X}_j$ and $\hat{\mathbf{X}}_j$. On Figure A-6, there is one scatter-plot for each of the 26 chemicals in the analysis. The x axis on each plot (Measured Value) is actual concentration used by Olsen at the beginning of the PCA - the measured concentration of that analyte in the original units. The y axis is a back-calculated estimate from a 2

PC model.[71] Non-detects (censored data points) are indicated as red shaded squares (■). When an insufficient number of principal components are retained we expect to see low CDs and great deviation of points away from the 1:1 fit line.

For Olsen's two PC model for SW3, we see a good fit for some variables (e.g. soluble reactive phosphorus ($P_{Sol\ Reac}$) and chloride (Cl) both exhibit CDs greater than 0.7 and a relatively uniform scatter about the 1:1 fit line). Note also that all three forms of phosphorus in Olsen's 2 PC model exhibit CDs ≥ 0.59. Olsen's 2 PC model does a relatively good job of back-calculating phosphorus. But Olsen's ultimate opinion of poultry impact is based on more than just phosphorus. Olsen opines that poultry-waste disposal is "*by far the dominant contamination source in the IRW*" and "*In the PCA, the chemical and bacterial composition of poultry-waste creates a distinct chemical signature that contains both phosphorus and bacteria*."[72] Elsewhere, Olsen says that poultry-waste is also characterized by copper (CU_T) arsenic (AS_T) and zinc (ZN_T).[73] If we look at all contaminants that Olsen suggests should be associated with poultry waste (P, CU_T, AS_T, ZN_T, COLIFORMS, ECOLI, ENTERO, and FECAL) we see a very poor fit with this PCA model for all except phosphorus. It is especially poor for bacteria. E. coli, enterococcus, coliforms and fecal coliform all exhibit CDs < 0.2 and an extremely poor fit with respect to the 1:1 line that bisects each graph. Olsen's 2PC model cannot accurately back-calculate any of the co-contaminants that he suggests should be associated with poultry derived phosphorus.

A2.5 Interpretation of Results

The real key to any PCA-based data analysis is the logic of one's interpretations on the back end of an analysis. As discussed in Section A1.3 Gould's primary objection to factor analysts as applied by psychometricians, was not the mathematics, but rather the interpretation of the results; and specifically (1) the practice of reification (assuming that a principal component necessarily represents some real entity such as "intelligence" or "poultry litter") and (2) the *a priori* prejudices of its practitioners; and (3) how those *a priori* prejudices predestined their interpretation. As will be shown below and in the main body of this report, Olsen's PCA interpretation revisits all of these problems.

A2.5.1 PC Loadings and Coefficients

Olsen began his interpretation by plotting PC loadings as bar graphs and observing which analytes had the highest loadings. A direct copy of Olsen's Figure 6.11-10 (loadings bar graph for SW3) is included in the main body of this report, as Figure 2-2. Based on that graph, Olsen reported a similarity between the PC1 loadings graph and the composition of poultry-waste impacted water[74] and that led to one of Olsen's primary conclusions in his PCA: "*PC1 has been identified as associated with poultry waste.*"[75] Olsen follows similar logic with respect to PC2[76] and reported that "*PC2 has been identified as associated with WWTP effluent.*"[77]

Olsen is essentially telling us that the bar graph in the left panel of his Figure 6.11-10 (Figure 2-2 of this report) looks like poultry-waste impacted water and that the bar-graph on the right looks like

[71] An interesting side note: Olsen was aware of the CD scatter-plot method (See Olsen Deposition 9/11/08 Exhibit 17 – 4/29/08 email from Chappell to Olsen).
[72] Olsen (2008a). p. 1-2 (3rd bullet).
[73] Olsen (2008a). p. 6-27.
[74] Olsen (2008a). p. 6-57. 2nd paragraph.
[75] Olsen (2008a). p. 6-57. 3rd paragraph.
[76] Olsen (2008a). p. 6-57. 2nd paragraph.
[77] Olsen (2008a). p. 6-57. 3rd paragraph.

WWTP effluent. For the reasons that follow, it is impossible to support such conclusions with anything but conjecture.

When Olsen tells us that the PC1 loadings bar graph looks like "*runoff from fields with poultry waste*" he is talking about 89 'edge of field' samples that he believes are impacted primarily by poultry. But in deposition testimony on September 10, 2008, Olsen acknowledged that these samples were impacted by *"both poultry and cattle waste"*[78] and that he did not try to document the extent to which his 89 edge of field samples were impacted by cattle.[79] Olsen's PCA interpretation *presumes* that his edge-of-filed samples are representative of a single source (poultry) while acknowledging elsewhere that they are not.

The second sample type that Olsen says shows similarity to his PC-1 loadings bar graph is "*leachate from poultry waste*."[80] He is referring to data from synthetic precipitation leachate procedure (SPLP) experiments, which CDM conducted for both cattle manure and poultry litter. The data from these SPLP experiments are reported in Tables 6.4-2a and 6.4-2b of Olsen's report. With respect to PC1 loadings bar graph, Olsen points out that 17 parameters had loadings greater than 0.5 and that all of these parameters have high concentration in leachate from poultry waste. [81] But if one carefully compares these 17 parameters to Olsen's Table 6.4-2a, ten of these 17 parameters were ***not even measured*** in SPLP samples.[82] The SPLP procedure requires filtering[83] so only dissolved metals and dissolved phosphorus were reported. The following SW3 variables, with loading greater than 0.5, were not measured in Olsen's poultry leachate experiments: Total Aluminum, Total Arsenic, Total Copper, Total Iron, Dissolved Potassium, Total Magnesium, Total Manganese, Total Nickel, Total P, and Total Zinc. The distinction between dissolved and total analyte measurements is not trivial. These are fundamentally different measurements that reflect concentrations associated with the particulate fraction versus the dissolved phase. In particular, total phosphorus (an analyte of primary concern in this litigation) is strongly tied to total suspended solids measurements (see Section 4.2) but is not measured in the SPLP data. Even if the PC loadings and the SPLP chemical data were in the same units, the lack of total P data in the SPLP results makes it such that Olsen's PCA and SPLP data sets are not comparable.

But moving beyond issues of data comparability and Olsen's presumption that edge-of-field samples represent impact from a single source, his argument is still fundamentally flawed. It is based on a comparison of loadings (which are reported in abstract units of correlation coefficients of a log-transformed data matrix) to the chemical data in Table 6.4-2a and 6.4-2b (which are reported in units of concentration - mg/L or organisms/100mL). This is an apples and oranges comparison, and was recognized as such more than 30 years ago, by a geochemist with the USGS: A.T. Miesch:

> *"Models of the type represented … are difficult to interpret because the factor scores* [Miesch's '*scores*' are '*loadings*' in Olsen/SYSTAT terminology] *are normalized and therefore dimensionless."*[84]

Olsen's loading graphs have the same problem. The loadings are in abstract, unitless metric of a correlation matrix of log–transformed data. This problem of trying to interpret scores and loadings in abstract units was ultimately the impetus for Miesch (1976a) outlining methods of back-calculation, to allow evaluation of scores and loading in the originally measured units.

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[78] Olsen Deposition. 9/10/08. p. 61. Lines 19-25.
[79] Olsen Deposition. 9/10/08. p. 62. Lines 7-13.
[80] Olsen (2008a). p. 6-57. 2nd paragraph.
[81] Olsen (2008a). p. 6-57. 2nd paragraph.
[82] Compare the analytes in Olsen's
[83] Olsen (2008a). p. 6-55.
[84] Miesch (1976a). p. G5.

Another issue is that Olsen's logic for PC-1 being poultry waste is based in part on the observation that the vast majority of PC-1 loadings are greater than zero. This comes as no surprise to anybody who has looked at chemical data using PCA-based methods. Given compositional data[85] the first principal component will always yield primarily positive loadings. The explicit constraint of PCA, that all principal components are mutually orthogonal (i.e. at a 90 degree angle with respect to all other principal components) means that loadings on PC2, PC3, etc. will necessarily have more negatives. That in turn means that it is impossible to interpret loadings bar graphs as source compositions unless source fingerprints are uncorrelated. This difficulty is reflected in Olsen's quote above. He interprets PC1 loadings like a chemical bar graph, and it seems reasonable because the majority of bars are positive. The PC2 interpretation is a bit more difficult, but he manages an argument based on an observation of seven out of 26 parameters with loadings > +0.5 (while avoiding any discussion of the meaning of a -0.33 loading for Total Aluminum, or a -0.31 loading for Enterococcus). He does not attempt to interpret principal component loadings beyond PC2, and in fact he points to the difficulty in interpreting higher numbered PCs as part of his rationale for dismissing evidence of five significant PCs.

As it turns out, the difficulty in interpreting negative loadings was also recognized by Miesch more than 30 years ago:

> *"Composition scores for the first axis of a principal component model tend to be all nonnegative, as do the composition loadings of the first end-member. The scores and loadings of subsequent axes tend to be positive and negative in about equal number."*[86]

This led Miesch to develop an extension to PCA: oblique rotation with explicit non-negative constraints. This is the fundamental basis of a number of receptor modeling techniques.

Ultimately, Olsen is trying to interpret orthogonal principal component loadings (reported in abstract units) as one might interpret bar graphs of chemical compositions. This is essentially *reification* – equating a principal component with a "thing" with physical or chemical meaning. Olsen is taking abstract axes, defined in multivariate space, and assigning them a chemical/physical interpretation in terms of source. *Reification* was one of the major problems in implementation of factor analysis by early 20th century psychometricians (see section A1.4.2). Where Charles Pearson and Cyril Burt *equated* their Factor 1 with the innate general intelligence of a child, Olsen is *equating* PC1 with a *poultry signature* and PC2 with *WWTP signature*. What's more, Olsen's reification of PC1 is not limited to the two paragraphs on page 6-57 of his report. He has consistently made similar statements in testimony before and after his May report.[87] Olsen *reifies* PC-1 as poultry, PC-2 as WWTP and justifies that interpretation with a poorly reasoned, apples-to-oranges comparison of loadings to chemical data from samples of indeterminate source, and/or mismatched analytes.

A2.5.2 Score Plots and Source-Impact Thresholds

Based on his theory that PC1=poultry and PC2=WWTP, Olsen ultimately classified each sample in his PCA with respect to whether it reflected a predominant impact by poultry-waste or WWTP effluent. The interpretations described in his report were made primarily with respect to PCA run

[85] Chemical data is 'compositional data' and is always reported by a lab is non-negative values (e.g. phosphorus concentrations are never reported as -20 mg/L).

[86] Miesch (1976a). P. G10.

[87] In deposition testimony prior to the preliminary injunction (PI) hearing, Olsen referred to "*the chicken signature, which is principal component 1*" (p. 102 lines 17-18 – see also p. 264 line 22). In testimony at the Preliminary Injunction Hearing itself, Olsen repeatedly refers to 'principal component 1' as 'the poultry signature' and 'principal component 2' as the 'waste water treatment plant signature.' See PI hearing transcript, Volume III; pp. 819-842, and in particular, p. 824; lines 16-19. Olsen 9/11/08 deposition testimony (p. 337 lines 12-14).

SW3. Olsen presented PC1 vs. PC2 score plots as Figures 6.11-18a through 6.11-18e of his report (Figures 6.11-18a and c are reproduced in the main body of this report as Figures 2-1 and 2-3).

Figure 6.11-18c (Figure 2-3 of my main report) was the scores plot with the two red ovals identifying the inferred limits of Olsen's supposed primary sources: "*Poultry-waste Dominant Impact*" and "*WWTP Dominant Impact*." If we look at that scores plot in the context of the data pathologies discussion (Section A1.2) we see a major problem with Olsen's interpretation. The SW3 data set appears to be more gradational than "*hard-clustered.*" Yet Olsen is establishing hard cluster boundaries within this system. He established a 1.3 PC1 poultry impact threshold, and in so doing, he drew a hard partition (a vertical line) through the densest clustering of samples. Another hard partition threshold, at PC2=4.7 demarcates his dividing line for WWTP impact. [88]

In deposition, Olsen was asked to explain this hard-partition, and in particular the 1.3 PC1 criterion. Olsen responded by saying that samples with PC1 scores below the 1.3 threshold may also be impacted by poultry and that it his opinion, any sample with a PC1 score>1 is potentially impacted by poultry waste.[89] Olsen chose his threshold at 1.3 PC1 in order to be "*conservative*."[90]

Similarly Olsen indicated in deposition testimony that the text of his report needed clarification with respect to its implication that PC1>1.3 indicates a <u>predominant</u> poultry-waste impact. This, he says is not the case.[91] A PC1 score > 1.3 indicates (in Olsen's opinion) that a sample is impacted by poultry waste to some degree. But to be considered "predominantly" impacted by poultry-waste, a sample must exhibit a PC-1 score greater than 1.3 <u>and</u> a PC2 score less than 5.[92] Given that PC2=4.7 is his threshold for WWTP dominance, there is an overlap[93] in Olsen's WWTP-dominant versus poultry-dominant areas. For samples that plot within this PC2 overlap region (between 4.7 and 5.0) there is some uncertainty as to which source Olsen would consider to be "dominant."

In Figure A-7 below, I have annotated Olsen's SW3 scores plot to show his two thresholds (PC1=1.3 and PC2=4.7) and I have added a gradational red and blue shaded regions to show the range of PC1 and PC2 scores where Olsen's poultry and WWTP classifications are uncertain.

[88] Olsen (2008a). p. 6-59 to 6-60.
[89] Olsen Deposition. 9/11/08. p. 333. Lines 3-21.
[90] Olsen Deposition. 9/11/08. p. 330 (Line 19) to 331 (Line 20). See also, quote in Section 2.3.1 of the main report.
[91] Olsen Deposition. 9/10/08. p. 277. Lines 15-25.
[92] Olsen Deposition. 9/10/08. p. 278 (Line 22) to 279 (Line 21). But Olsen still qualifies this by noting that there were two "cow samples" that fit the criteria of this new rule, and that those samples need more investigation.
[93] Olsen Deposition. 9/10/08. p. 279 (Line 7-13).

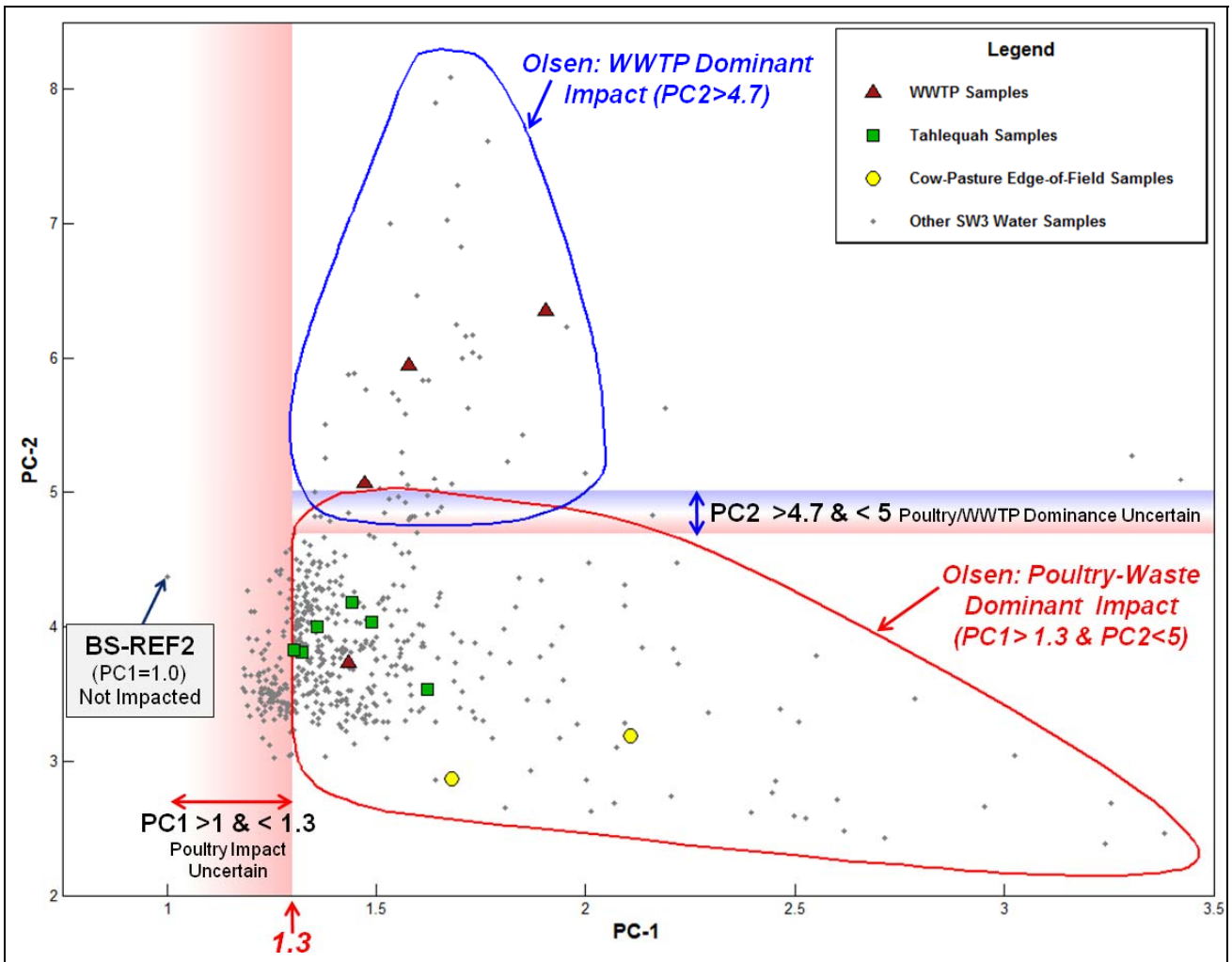

Figure A-7. PCA scores plot for SW3, showing Olsen's interpretation as modified in deposition testimony. Olsen's deposition testimony acknowledged uncertainty in PC1 threshold (gradational red shading) and PC2 thresholds (gradational red-to-blue shading) and contradictions to his poultry and WWTP impact classifications (WWTP, Tahlequah and cow-pasture (CP) samples).

So Olsen's testimony is that the 1.3 PC1 and 4.7 PC2 values are not hard partitions. There is a gradient: a region of uncertainty. He claims that he could have set the poultry impact threshold even lower than 1.3, but decided to be "*conservative*" and set it at the upper end of this gradient.[94] This purported effort to be "*conservative*" implies that if a sample has a PC1 score greater than 1.3, then it definitely must be impacted by poultry waste. When asked about this in deposition, Olsen's response was not exactly unequivocal.

> ***Q*** *Okay. For purposes of your principal component analysis work in this case and your opinions about the source of contamination in particular samples, do I understand correctly that you've concluded that all samples with a Principal Component 1 score of greater than 1.3 are in your opinion impacted predominantly by poultry litter?*
>
> ***A*** *There may be a few minor exceptions in there. I'd have to go review it. There's some question about the CP samples*[95] *that we collected this morning, so, you know, that needs further analysis. So there's -- and a few samples I couldn't verify locations of so I kind of excluded them, so there's a very, very few, but generally that statement is true.*

[94] Olsen Deposition (9/10/08). pp. 218 (Line 17) to 219 (Line 6).
[95] "CP samples" are cow-pasture edge-of-field samples.

> ***Q*** *Well, Dr. Olsen, in your report you said that a Principal Component 1 score of 1.3 or greater is consistent with and supports your opinion that that sample reflects contamination from poultry litter; is that right?*
> ***A*** *Yeah, and I need to clarify that a little bit more. There were some -- in that particular count, I included inadvertently some of the wastewater treatment plant discharges, so I need to take that out of those percentages and analysis.*
> ***Q*** *I didn't really ask about percentages so I'm confused as to exactly what you are talking about. What are you talking about?*
> ***A*** *There were three wastewater treatment samples that were scored and typically those had a principal component score of above 1.3, and I would say that those probably weren't contaminated by poultry.* [96]

The "*few minor exceptions*" cited in quote above are neither few nor minor. As it turns out, every sample collected by Olsen to characterize sources other than poultry yielded PC1 scores greater than 1.3. I have plotted a number of these on Figure A-7. The brown triangles are the "*wastewater treatment plant discharge"* samples referenced in the quote above. All four yielded PC1 scores greater than 1.3. Three of these were actual effluent samples from the Siloam Springs, Rogers and Springdale. They all plot within Olsen's '*WWTP impact dominant'* area on Figure A-7, but they also have PC1 scores greater than 1.3. As such, they should be classified by Olsen as '*poultry impacted.'* But with regard to these three samples, Olsen testified as follows:

> "*what I'm just trying to do is clarify the text there when I said that anything above 1.3 had poultry contamination … that's probably not true, and so I'm just trying to clear that up, and these are three examples*".[97]

In addition, note on Figure A-7 that Olsen's fourth WWTP sample (Lincoln) does not even plot within his '*WWTP dominant impact*' area, but rather within his '*poultry-waste impact dominant'* area (Section 3.2).

The two yellow circles on Figure A-7 are the '*CP samples*' referenced in Olsen's quote above. These are edge-of-field samples were collected from a cow-pasture (CP) where poultry litter had never been applied.[98] Both plot within Olsen's '*poultry-waste impact predominant'* area (Section 3.3).

The green squares are not among the '*few minor exceptions*' discussed in Olsen's quote above, but they deserve mention here. These six samples are base-flow stream-water samples from Tahlequah, Oklahoma. All six yielded PC1 scores above 1.3, but given that Tahlequah is an area of zero poultry house density, Olsen concedes that they too are not impacted by poultry[99] (Section 3.1).

There were also numerous high-flow and base-flow stream samples in Olsen's SW3 PCA run that were collected in areas of low poultry-house density, but which Olsen's PCA classification would indicate are poultry-impacted (see Sections 3.4 and 3.5).

Regardless of all the technical/methodological problems discussed in this report, one needs look no farther than Figure A-7 to see that Olsen's poultry and WWTP signature criteria are meaningless. We see a sample collected to characterize WWTP effluent that plots outside of his '*WWTP dominant impact'* area (and within his '*poultry-waste impact dominant'* area). We see samples with PC1 scores less than 1.3 that Olsen believes may be impacted by poultry. We see samples with PC1 scores greater than 1.3 that Olsen concedes are not impacted by poultry (Figure A-7). Olsen's PC1 and PC2 thresholds are entirely arbitrary.

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[96] Olsen Deposition. 9/10/08. p. 274. (emphasis added).
[97] Olsen Deposition. 9/10/08. pp. 276-278.
[98] See Field CDM/Lithochimea field notes from March 31, 2008 (STOK005374).
[99] Olsen Deposition 9/11/08. p. 405.

A2.5.3 Spatial Analysis

The basis of Olsen's establishment of thresholds for PC1 (poultry impact) and PC2 (WWTP impact) was his "spatial analysis" of principal components scores. His rationale for that exercise was that he wanted to evaluate the viability of that interpretation in context of independent data. The basic idea is that methods such as principal components analysis are not classical statistical methods that allow one to test a formal hypothesis in terms of statistical probabilities.[100] Rather they are '*exploratory data analysis*' methods that expedite the process of *forming* (rather than testing) a hypothesis that can explain the observed data. For an interpretation of a PCA to be viable, it must be consistent with other lines of evidence. Having formed a hypothesis that PC1 equals poultry waste, and that PC2 equals WWTP effluent, Olsen needed to test it against purported ground truth data (e.g. locations of waste water treatment plants, areas of high poultry house density, areas of low poultry house density, etc.).[101] Olsen describes his spatial analysis in general, in the following quote:

> *"As previously discussed in Section 12, a spatial evaluation was performed to evaluate the individual sample PC scores in relation to distance from source, sample group, sample condition and reference locations. In this step the individual PC scores are evaluated to determine the magnitude of impact or contamination from sources across the basin."*[102]

With respect to his PC1 poultry waste threshold (PC1>1.3) Olsen presented this discussion of his spatial analysis to support that value:

> *"The value* [the 1.3 PC1 threshold] *was selected by examining the locations and scores of samples, particularly the scores of reference samples and samples in low poultry house density areas. In summary, the samples with PC1 scores below approximately 1.3 include all samples from reference locations (six total), 9 out of 10 samples from HFS30 (small watershed location with low poultry house density) and 10 out of 11 samples from HFS28A (small watershed with low poultry house density). The one sample from HFS30 and the one sample from HFS28A with higher PC1 scores were collected during extreme flow events. Overall 441 of the 573 samples (77%) had PC1 scores higher [than] 1.3 and show some poultry contamination."*[103]

So, in terms of his spatial analysis to evaluate the efficacy of his PC1 threshold, the primary information relied upon by Olsen was poultry house density data. This data was presented by Olsen in the form of a map (Figure 2.5-1 of his report: reproduced below as Figure A-8). The map was presented in context of identifying the locations of groundwater samples, but curiously it was never presented as the base map for plotting his PCA scores. Instead, a generic base map was used. The poultry house density data used to generate the map shown below were produced by plaintiff's experts. As such it was relatively straightforward to plot Olsen's PCA results over his poultry-house density base-map (and this is done on a number of figures in the main body of this report).

Note in the quote above, that Olsen does not cite an exhaustive list of samples that he evaluated in context of poultry house density. He cites only 25 samples from five sampling stations, and these he says are consistent with his PC1 interpretation. But Olsen's SW3 PCA run included 573 samples, from 175 different sampling locations. Olsen's discussion on page 6-60 gives the clear impression that his 1.3 PC1 poultry-impact criterion is consistent with poultry house density data, but as pointed out in the main body of this report (Sections 2.3.1 and 3.0) this is not the case.

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[100] See Johnson, et al. (2007). Section 7.1.1 Philosophy and Approach: A Case for Exploratory Data Analysis
[101] Olsen (2008a). p. 6-34: Steps 12 and 13.
[102] Olsen (2008a). p. 6-59.
[103] Olsen (2008a). p. 6-59 to 6-60.

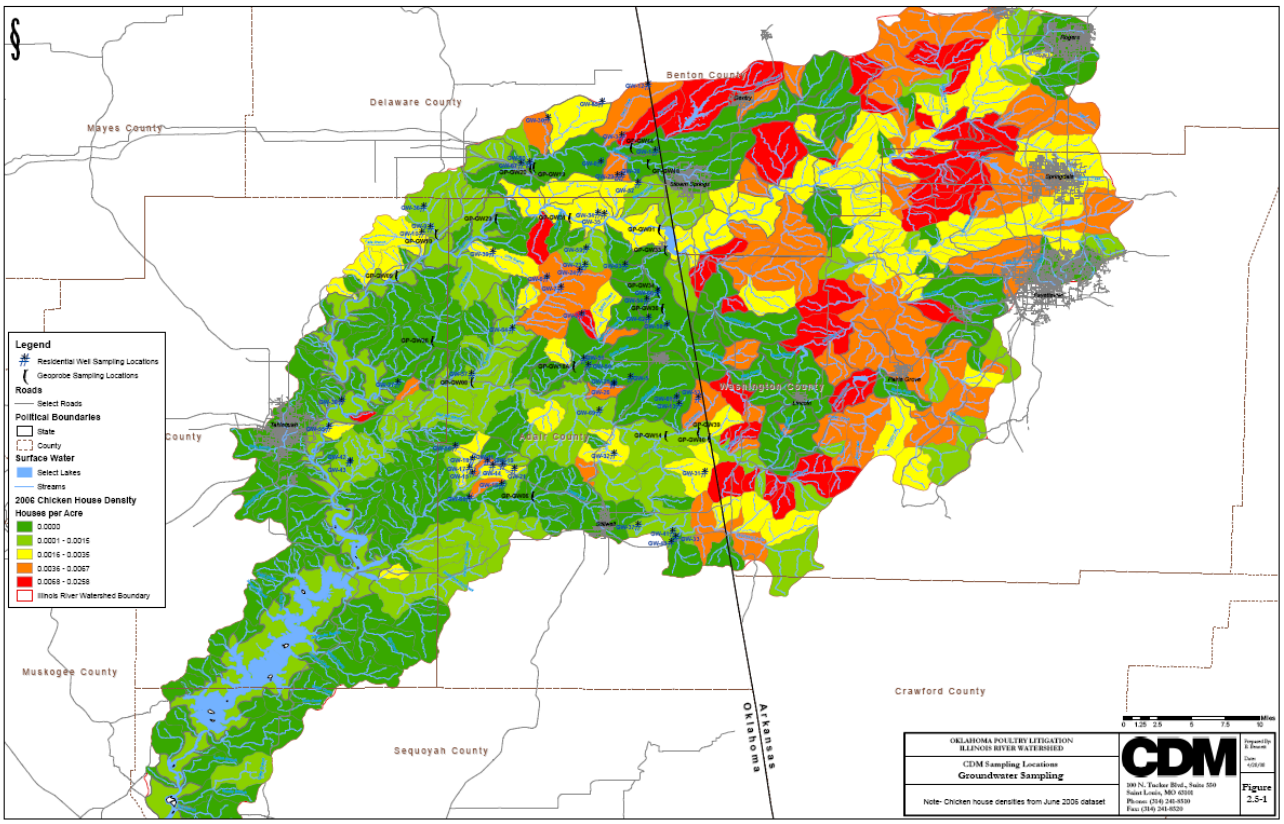

Figure A-8. Poultry house densities as shown on Olsen's Figure 2.5-1.
Figure reproduced as a direct copy of Olsen Figure 2.5-1. Data reportedly from Fisher's 2006 data.

A2.5.3 The Red-Dot / Green-Dot Map

The bottom line map used to illustrate Olsen's interpretation of samples that have been impacted by poultry-waste, was his Figure 6.11-23 (reproduced in the main body of this report as Figure 2-4). This map then led directly to Olsen's most important conclusions/opinions coming out of his PCA: that 78% of surface water locations in the IRW show some poultry contamination.[104] Olsen's red-dot / green-dot maps and the conclusions drawn from them are critically reviewed in the main body of this report.

[104] Olsen (2008a). p. 6-60. 2nd paragraph, as corrected by Olsen's errata (Olsen, 2008b – page 7).

A3 References

Brown, S.B. (1994). Course notes and material from CHEM 623. Graduate Level Class in Chemometrics. Spring, 1994. University of Delaware.

Cattell, R.B. 1966. The scree test for the number of factors. *Multivariate Behav. Res.* **1**: 245-276.

Cowan C. (2008). Expert Report of Charles Cowan.

DeCaprio, A. P., Johnson, G. W., Tarbell, A. M., Carpenter, D. O., Chiarenzelli, J. R., Morse, G. S., Santiago-Rivera, A. L., Schymura, M. J., and Akwesasne Task Force on the Environment. 2005. PCB exposure assessment by multivariate statistical analysis of serum congener profiles in an adult Native American population. *Environ. Res.* 98, 284-302.

Davis, J.C. (1986). Statistics and Data Analysis in Geology. 2nd Edition. Wiley. 646 p. (3rd edition: 2002)

Doré, T.J., A.M. Bailey, J.W. McCoy, and G.W. Johnson. 1996. An examination of organic/carbonate-bound metals in bottom sediments of Bayou Trepagnier, Louisiana. *Transactions of the Gulf Coast Assoc.of Geological Societies*. **46:** 109-116.

Ehrlich, R., and W.E. Full WE. 1987. Sorting out Geology, Unmixing Mixtures. In: Size, W., *Use and Abuse of Statistical Methods in Earth Sciences*. Oxford University Press.

Ehrlich, R., R.J. Wenning, G.W. Johnson, S.H. Su, and D.J. Paustenbach. 1994. A mixing model for polychlorinated dibenzo-p-dioxins and dibenzofurans in surface sediments from Newark Bay, New Jersey using polytopic vector analysis. *Arch. Environ. Contam. Toxicol*. **27:** 486-500.

Exner, O. 1966. Additive physical properties. *Collection of Czechoslovak Chemical Communications*. 31: 3222-3253.

Frame, G.M., Cochran, J.W., and Bøwadt, S.S. (1996) Complete PCB congener distributions for 17 Aroclor mixtures determined by 3 HRGC systems optimized for comprehensive, quantitative, congener-specific analysis. *Journal of High Resolution Chromatography* 19, 657–668.

Gould, S.J. (1996). The Mismeasure of Man. 2nd Edition. W.W. Norton & Co. New York. 432 pp. (1st edition: 1981).

Hopke, P.K. (1989) Target transformation factor analysis. *Chemometrics and Intelligent Laboratory Systems* 6, 7–19.

Hearnshaw, L.S. (1979). Cyril Burt psychologist. Hodder and Stoughton. 370 pp.

Henry, R.C. (1987). Current factor analysis receptor models are ill-posed. *Atmospheric Environment*. (21) 1815-1820.

Henry, R.C., Park, E.S., and Spiegelman, C.H. (1999) Comparing a new algorithm with the classic methods for estimating the number of factors. *Chemometrics and Intelligent Laboratory Systems* 48, 91–97.

Henry, R.C. (2003). Multivariate receptor modeling by N-dimensional edge detection, *Chemometrics Intell. Lab. Sys*. 65, 179-189.

Hopke, P.K. 1989. Target transformation factor analysis. *Chemometrics and Intelligent Laboratory Systems*. **6**: 7-19.

Huber, W.A. (2008). Declaration of William A. Huber, Ph.D. 2/7/08. (Engel00000114)

Jarman, W.M., G.W. Johnson, C.E. Bacon, J.A. Davis, R.W. Risebrough, and R. Ramer. 1997. Levels and patterns of polychlorinated biphenyls in water collected from the San Francisco Bay and Estuary, 1993-1995. *Fresnius J. Anal. Chem.* **359**: 254-260.

Jackson, J.E. (2003). A User's Guide to Principal Components. Wiley. 569 pp.

Johnson, G.W., Jarman, W.M., Bacon, C.E., Davis, J.A., Ehrlich, R., and Risebrough, R. (2000). Resolving polychlorinated biphenyl source fingerprints in suspended particulate matter of San Francisco Bay. *Environ. Sci. Technol.* **34**: 552-559.

Johnson, G.W. 2002. Forensic Analysis. In: *Encyclopedia of Environmetrics* (El-Shaarawi and Piegorsch, eds.) Wiley, Chichester. Vol. 2, 796-806.

Johnson, G.W. and Ehrlich, R. (2002). State of the Art Review: Multivariate Statistical Methods in Environmental Forensics. *Environmental Forensics.* **3**: 59-79.

Johnson, G.W., Ehrlich, R., Full, W., and Ramos, S. (2007). Chapter 7: Principal components analysis and receptor models in environmental forensics. In: *An Introduction to Environmental Forensics.* 2nd Edition. (B. Murphy and, R. Morrison eds.). Elsevier. Amsterdam. pp. 207-272.

Johnson, G.W. Hansen, L.G., Hamilton, M.C., Fowler, B., and Hermanson, M.H. 2008. PCB, PCDD and PCDF congener profiles in two types of Aroclor 1254. *Environmental Toxicology & Pharmacology.* 25: 156-163.

Kim, B.M. and Henry, R.C. (1991) Extension of self-modeling curve resolution to mixtures of more than 3 components Part 2 – finding the complete solution. *Chemometrics and Intelligent Laboratory Systems* 49, 67–77.

Kaiser, H.F. 1958. The varimax criterion for analytic rotation in factor analysis. *Psychometrika*. **23:** 187-200.

Kaiser, H.F. 1960. *Educ. Psychol. Meas*. **20**: 141 (1960).

Magar, V.S., Johnson, G.W., Brenner, R., Durell, G., Quensen, J.F., III, Foote, E., Ickes, J.A., Peven-McCarthy, C. 2005. Long-term recovery of PCB-contaminated sediments at the Lake Hartwell Superfund Site: PCB Dechlorination I – End-Member Characterization. *Environ. Sci. Technol.* **39**: 3538-3547.

Malinowski, E.R. 1977. Determination of the number of factors and the experimental error in a data matrix. *Analytical Chemistry*. 49: 612-617.

Malinowski, E.R. 1991. *Factor Analysis in Chemistry*. 2nd Edition. Wiley & Sons, Inc. New York. 350 p. (also, see 3rd edition 2002).

Miesch, A.T. (1976a) Q-mode factor analysis of geochemical and petrologic data matrices with constant row sums. *Geological Survey Prof. Paper*, 574-g, pp. 1–47.

Miesch, A.T. (1976b) Interactive computer programs for petrologic modeling with Extended Q-mode factor analysis. *Computers and Geosciences* 2, 439–492.

Myoda, S. (2008). Expert Report of Sam Myoda.

Olsen, R.L. (2008a). Expert Report of Roger L. Olsen. Prepared for A. Drew Edmondson, Attorney General of the State of Oklahoma. May 14, 2008. 170 pp. 72 tables. 153 figures.

Olsen, R.L. (2008b). Errata for Expert Report of Roger L. Olsen. Prepared for A. Drew Edmondson, Attorney General of the State of Oklahoma. July 25, 2008. 12 pp.

Olsen, R.L. (2008c). Transcript of Deposition of Roger Olsen, Ph.D. February 2, 2008.

Olsen, R.L. (2008d). Transcript of Deposition of Roger Olsen, Ph.D. September 10-11, 2008.

SYSTAT Software, Inc. (2007). Chapter 12: Factor Analysis. In: SYSTAT 12 Statistics_I_II_III_IV Users Guide. pp. I453-I493.

Tauler, R., Kowalski, B., and Fleming, S. (1993). Multivariate curve resolution applied to spectral data from multiple runs of an industrial process. *Anal. Chem.* 65, 2040-2047.

Tauler, R. (1995) Multivariate curve resolution applied to second order data. *Chemom. Intell. Lab. Sys*. 30, 133-146.

Wold, S. 1978. Cross-validatory estimation of the number of components in factor and principal components analysis models. *Technometrics*. 20: 397-405.

Appendix B

Curriculum Vita of Glenn W. Johnson

CURRICULUM VITA

Glenn Wilbur Johnson
Born March 1, 1960. Wilmington, North Carolina

CURRENT POSITIONS

President, GeoChem Metrix, Inc. (Environmental and Data Analysis Consulting). 9143 S. Peruvian Cir. Sandy, Utah 84093. Tel: (801) 571-9372. Fax: (801) 571-9373. Email: gjohnson@gcmetrix.com

Research Associate Professor, Energy & Geoscience Institute, Department of Civil and Environmental Engineering, University of Utah, 423 Wakara Way, Suite 300, Salt Lake City, UT, 84108, Tel: (801) 581-6151 Fax: (801) 585-3540 Email: gjohnson@egi.utah.edu

RESEARCH INTERESTS

Environmental Chemometrics / Receptor Modeling. Development and application of principal components analysis based pattern recognition methods for analysis of environmental chemical data.

Environmental Forensics. Determination of contaminant sources and alteration processes in complex environmental systems.

Source, Fate and Transport of Persistent Organic Pollutants. Study of natural alteration and attenuation processes that affect dibenzo-*p*-dioxins, dibenzofurans, polychlorinated biphenyls and polycyclic aromatic hydrocarbons.

Biostratigraphy and Paleoecology. Application of quantitative and graphical methods applied to micropaleontological data.

PROFESSIONAL EXPERIENCE

April 1988-June 1989. **Environmental Scientist**, Roux Associates, Inc. Cherry Hill, New Jersey.

June 1989 - July 1995. **Senior Geoscientist / Project Manager**, McLaren/Hart Environmental Engineering Corp. Philadelphia, Pennsylvania

August 1995 - Present. **Research Associate Professor,** Energy and Geoscience Institute, Department of Civil & Environ. Engineering, University of Utah, Salt Lake City, Utah.

October, 1998 – Present. **President, Chief Scientist,** GeoChem Metrix, Inc. Sandy, Utah

EDUCATION

Ph.D. 1997. Geology, University of South Carolina, Columbia, South Carolina, Dissertation: *Application of Polytopic Vector Analysis to Environmental Geochemistry Investigations*

M.S. 1988. Geology, University of Delaware, Newark, Delaware. Thesis: *Pleistocene Planktonic Foraminiferal Biostratigraphy and Paleoecology - Northeast Gulf of Mexico.*

B.S. 1985. Geology, East Carolina University, Greenville, North Carolina.

B.M. 1982. Music. East Carolina University, Greenville, North Carolina

CERTIFICATIONS AND PROFESSIONAL AFFILIATIONS

Professional Geologist, Commonwealth of Pennsylvania, Registration Number PG-002729
Professional Geologist, State of Utah, Registration Number 5537643-2250
Member, Society of Environmental Toxicologists and Chemists
Member, Sigma Xi, the Scientific Research Society
Member, International Society of Environmental Forensics

PUBLICATIONS/PRESENTATIONS

Peer-Reviewed Papers

Johnson, G.W. Hansen, L.G., Hamilton, M.C., Fowler, B., and Hermanson, M.H. 2008. PCB, PCDD and PCDF congener profiles in two types of Aroclor 1254. *Environmental Toxicology & Pharmacology*. 25: 156-163.

Gary, A.C., Wakefield, M.I., Johnson, G.W. and Ekart, D.D. (In Press). Application of fuzzy-c-means clustering to paleoenvironmental analysis: Example from the Jurassic, Central North Sea, UK. SEPM Special Publication: Geologic Problem Solving with Microfossils. Accepted February 2007.

Hermanson M.H., Johnson, G.W. 2007. Polychlorinated biphenyls in tree bark from Anniston, Alabama. *Chemosphere*. 68: 191-198.

Carpenter, D.O., DeCaprio, A.P., O'Hehir, D., Akhtar, F., Johnson, G., Scrudato, R.J., Apatiki, L., Kava, J., Gologergen, J., Miller, P.K., Eckstein, L. 2005. Polychlorinated biphenyls in serum of the Siberian Yupik people from St. Lawrence Island, Alaska. *International Journal of Circumpolar Health*. ***64***: 322-335.

Magar, V.S., Johnson, G.W., Brenner, R., Durell, G., Quensen, J.F., III, Foote, E., Ickes, J.A., Peven-McCarthy, C. 2005. Long-term recovery of PCB-contaminated sediments at the Lake Hartwell Superfund Site: PCB Dechlorination I – End-Member Characterization. *Environ. Sci. Technol.* **39**: 3538-3547.

Magar, V.S., Brenner, R., Johnson, G.W., Quensen, J.F., III. 2005. Long-term recovery of PCB-contaminated sediments at the Lake Hartwell Superfund Site: PCB Dechlorination II – Rates and Extent. *Environ. Sci. Technol.* **39:** 3548-3554.

DeCaprio, A. P., Johnson, G. W., Tarbell, A. M., Carpenter, D. O., Chiarenzelli, J. R., Morse, G. S., Santiago-Rivera, A. L., Schymura, M. J., and Akwesasne Task Force on the Environment. 2005. PCB exposure assessment by multivariate statistical analysis of serum congener profiles in an adult Native American population. *Environ. Res.* 98, 284-302.

Nash, G.D. G.W. Johnson, and S. Johnson. 2004. Hyperspectral Detection of Geothermal System Related Soil Mineralogy Anomalies in Dixie Valley, Nevada: A Tool For Exploration. *Geothermics*. **33**: 695-711..

Collister, J. R. Ehrlich, F. Mango, and G.W. Johnson. 2004. Modification of the petroleum system concept: Origins of alkanes and isoprenoids in crude oils. *American Assoc. Petroleum Geologists Bulletin*. **88**: 587-611.

Johnson, G.W. and Ehrlich, R. 2002. State of the Art Review: Multivariate Statistical Methods in Environmental Forensics. *Environmental Forensics.* **3**: 59-79

PUBLICATIONS / PRESENTATIONS (Continued)

Peer-Reviewed Papers (Continued)

Johnson, G.W., Jarman, W.M., Bacon, C.E., Davis, J.A., Ehrlich, R., and Risebrough, R. 2000. Resolving polychlorinated biphenyl source fingerprints in suspended particulate matter of San Francisco Bay. *Environ. Sci. Technol.* **34**: 552-559.

Chiarenzelli, J., Bush, B., Casey, A., Barnard, E., Smith, R., O'Keefe, P., Gilligan, E., and Johnson, G., 2000. Defining sources of airborne polychlorinated biphenyls: evidence of influence from microbially dechlorinated congeners from river sediment. *Can. J. Fish. Aquat. Sci.* **57** (Supplement 1): 86-94.

Huntley, S.L., H. Carlson-Lynch, G.W. Johnson, D.J. Paustenbach, and B.L. Finley. 1998. Identification of historical PCDD/F sources in Newark Bay Estuary subsurface sediments using polytopic vector analysis and radioactive dating techniques. *Chemosphere*. **36:** 1167-1185.

Jarman, W.M., G.W. Johnson, C.E. Bacon, J.A. Davis, R.W. Risebrough, and R. Ramer. 1997. Levels and patterns of polychlorinated biphenyls in water collected from the San Francisco Bay and Estuary, 1993-1995. *Fresnius J. Anal. Chem.* **359**: 254-260.

Doré, T.J., A.M. Bailey, J.W. McCoy, and G.W. Johnson. 1996. An examination of organic/carbonate-bound metals in bottom sediments of Bayou Trepagnier, Louisiana. *Transactions of the Gulf Coast Assoc.of Geological Societies*. **46:** 109-116.

Ehrlich, R., R.J. Wenning, G.W. Johnson, S.H. Su, and D.J. Paustenbach. 1994. A mixing model for polychlorinated dibenzo-p-dioxins and dibenzofurans in surface sediments from Newark Bay, New Jersey using polytopic vector analysis. *Arch. Environ. Contam. and Toxicol*. **27:** 486-500.

Wenning, R.J., D.J. Paustenbach, G.W. Johnson, R. Ehrlich and H. Bedbury. 1993. Chemometric analysis of potential sources of polychlorinated dibenzo-p-dioxins and dibenzofurans in surficial sediments from Newark Bay, New Jersey. *Chemosphere*. **27:** 55-64.

Martin, R.E., E.D. Neff, G.W. Johnson, and D.E. Krantz. 1993. Biostratigraphic expressions of Pleistocene sequence boundaries, Gulf of Mexico. *Palaios*. **8**: 155-171.

Martin, R.E., G.W. Johnson, E.D. Neff, and D.E. Krantz. 1990. Quaternary planktonic foraminiferal assemblage zones of the northeast Gulf of Mexico, Colombia Basin (Caribbean Sea), and Tropical Atlantic Ocean: graphic correlation of microfossil and isotope stage boundaries. *Paleoceanography*. **5**: 531-555.

Book Chapters

Johnson, G.W., Ehrlich, R., Full, W., and Ramos, S. (2007). Chapter 6: Principal components analysis and receptor models in environmental forensics. In: *An Introduction to Environmental Forensics.* 2nd Edition. (R. Morrison and B. Murphy, eds.). Elsevier. Amsterdam. pp. 207-272.

Johnson, G.W., Quensen, J.F., III, Chiarenzelli, J., and Hamilton, C. (2006). Chapter 10: Polychlorinated Biphenyls. In: *Environmental Forensics: A Contaminant Specific Guide* (R. Morrison and B. Murphy, eds.). Elsevier. Amsterdam. pp. 187-225.

PUBLICATIONS / PRESENTATIONS (Continued)

Book Chapters (Continued)

Gary, A.C., G.W. Johnson, D.D. Ekart, E. Platon, and M.I. Wakefield. (2005). A Method for Two-Well Correlation using Multivariate Biostratigraphical Data. In: *Recent Developments in Applied Biostratigraphy*. (A.J. Powell & J.B. Riding, Eds). The Micropaleontological Society Special Publication. pp. 205-217. Micropaleontological Society. London

Johnson, G.W., Ehrlich, R., and Full, W. 2002. Principal components analysis and receptor models in environmental forensics. In: *An Introduction to Environmental Forensics* (R. Morrison and B. Murphy, eds.). Academic Press. San Diego. pp. 461-515.

Johnson, G.W. 2002. Forensic Analysis. In: *Encyclopedia of Environmetrics* (El-Shaarawi and Piegorsch, eds.) Wiley, Chichester. Vol. 2, 796-806.

Magar, V.S., J. Ickes, J.E. Abbott, R.C. Brenner, G. S. Durell, C. Peven-McCarthy, G.W. Johnson, E.A. Crecelius, and L.S. Bingler. 2002. Natural Recovery of PCB-Contaminated Sediments at the Sangamo-Weston/Lake Hartwell Superfund Site. In R.E. Hinchee, A. Porta, and M. Pellei (Eds.), *Remediation and Beneficial Reuse of Contaminated Sediments*, ***1(3),*** 413-418. Battelle Press, Columbus, OH.

Selected Presentations at Professional Meetings / Proceedings Contributions

Johnson, G.W. (2006). Data analysis: PCB congener profiles. Invited Presentation. NIEHS/EPA Fourth PCB Workshop. Zakopane, Poland, September 6 - 10, 2006.

Hermanson, M. H. Johnson, G. W., Carpenter, D.O. (2006). Routes of Human Exposure to PCBs in Anniston, Alabama. ACS Division of Environmental chemistry, 232rd National Meeting, 46(2): 1117-1122.

Hermanson, M. H. Johnson, G. W., Matthews, K., Isaksson, K., Teixeira, C., van de Wal, R. S. W., Muir, D. C. G. (2005). Historic PCB congener profiles in an ice core from Svalbard, Norway. *Organohalogen Compounds* 67, 936-939.

Johnson, G.W., (2005). Keynote Speaker: Identifying Polychlorinated Biphenyl Sources in Environmental Media. The 15th Annual Goldschmidt Conference: University of Idaho, Moscow, Idaho, USA, May 20 – 25, 2005.

Ramos, S., Rohrback, B., Johnson, G., and Kaufman, R. (2005). Using gas chromatography and curve resolution to quantify contributions to mixed crude oils. Pittsburgh Conference on Analytical Chemistry and Applied Spectroscopy. Orlando, FL. Feb. 27 – Mar. 4, 2005.

Johnson, G.W. (2005). Distinguishing Between Two Types of Aroclor 1254: Considerations for Environmental Forensics Investigations. Society of Environmental Toxicology and Chemistry 26th Annual Meeting. Baltimore, MD. November 13-17, 2005.

Johnson, G.W. Gary, A.C., and Ekart, D.D. (2005). A New Approach to the Analysis of Assemblages within Biostratigraphical Data. North American Micropaleontology Section of the Society for Sedimentary Geology (NAMS-SEPM) International Conference on Geological Problem Solving with Microfossils. Rice University. Houston, TX. March 6-11, 2005.

PUBLICATIONS / PRESENTATIONS (Continued)

Selected Presentations at Professional Meetings / Proceedings Contributions (Continued)

Johnson, G.W., V.S. Magar, J.F. Quensen, III ,G. Durell, and R. Brenner. 2003. PCB Source and Natural Alteration Patterns in Sediments of Lake Hartwell and Twelve-Mile Creek, South Carolina. International In-Situ and On-Site Bioremediation Symposium. Orlando, Florida. June 2-5, 2003.

Nash, G.D. and G.W. Johnson. 2002. Soil Mineralogy Anomaly Detection in Dixie Valley, Nevada using Hyperspectral Data. Proceedings: Twenty-Seventh Workshop on Geothermal Reservoir Engineering, Stanford University, January 28-30, 2002.

Ickes, J., Brenner, R. Magar, V.S., Durrell, G., Johnson, G. Crecelius, E., Abbott, J., Peven McCarthy, C., and Bingler, L., 2001. Natural Recovery of PCB-contaminated sediments at the Sangamo-Weston/Lake Hartwell Superfund Site. In: (Leeson, Foote, Banks, and Magar, eds.) *Wetlands and Sediments*. *The Sixth International In-Situ and On-Site Bioremediation Symposium*. ***6(5)***. Battelle Press. pp. 231-236.

Johnson, G.W., and Chiarenzelli, J.C. 2000. Implications of volatilization on PCB source profile interpretation. Society of Environmental Toxicologists and Chemists 21st Annual Meeting. Nashville, Tennessee. November 12-16, 2000. Programs with Abstracts. 14.

Johnson, G.W. and Quensen, J.F. III. 2000. Implications of PCB dechlorination on linear mixing models. *Organohalogen Compounds*. **45**: 280-283. Presented at 20th International Symposium on Halogenated Environmental Organic Pollutants & POPs (Dioxin 2000). Monterey, California. August 13-17, 2000.

Johnson, G.W. 1999. Unmixing sources of polychlorinated biphenyls in San Francisco Bay. Association of Environmental Health of Soils, Conference on Contaminated Soils and Waters, Oxnard, California, March 8-11, 1999.

Johnson, G.W. and G.D. Nash. 1998. Unmixing AVIRIS hyperspectral data from Dixie Valley, Nevada. In: Proceedings, Twenty-Third Workshop on Geothermal Reservoir Engineering, Stanford University, **23**: 240-245.

Moore, J.N., T.S. Powell, D.I Norman, and G.W. Johnson. 1997. Hydrothermal alteration and fluid-inclusion systematics of the reservoir rocks in Matalibong-25, Tiwi, Philippines. Twenty Second Annual Workshop: Geothermal Reservoir Engineering. Stanford University. **22**: 447-456.

Schumacher, D., G.W. Johnson and R. Ehrlich. 1996. Statistical unmixing of crude oil geochemical data as a method for assessing reservoir compartmentalization: An example from the Eugene Island Block 330 Field, Offshore Louisiana. American Association of Petroleum Geologists/EAGE Research Symposium on Compartmentalized Reservoirs. The Woodlands, Texas. October 20-23, 1996.

Martin, R.E., Neff, E., Johnson, G.W., and Krantz, D.E. 1991. Ecostratigraphic datums and sequence stratigraphy: application to the Marine Quaternary. Society of Economic Paleontologists and Mineralogists/American Association of Petroleum Geologists Special Session "Biostratigraphic Aspects of Sequence Stratigraphy". *American Association of Petroleum Geologists Bulletin* **75**: 630.

PUBLICATIONS / PRESENTATIONS (Continued)

Selected Presentations at Professional Meetings / Proceedings Contributions (Continued)

Johnson, G.W., Johnson, B., Wehmiller, J.F., and Martin, R.E. 1989. High resolution biostratigraphy and aminostratigraphy of ODP Hole 625B; Northeast Gulf of Mexico: *Am. Assoc Petrol. Geol. Bull.* **73**: 368-369.

Martin, R.E., and Johnson, G.W. 1989. Comparative ecostratigraphy of the Pleistocene: ODP Site 625 and DSDP Site 502. *American Association of Petroleum Geologists Bulletin* **73**: 387.

Johnson, G.W., and Martin, R.E. 1987. Quaternary planktonic foraminiferal paleoecological models: Northeast Gulf of Mexico: In: Barnette, S.C. and Butler, D.M., eds., Innovative Biostratigraphic Approaches to Sequence Analysis: New Exploration Opportunities. Society of Economic Paleontologists and Mineralogists, p. 83. Also: *American Association of Petroleum Geologist Bulletin* **72**: 202 (March, 1988).

Technical Reports

Johnson, G.W., Gary, A.C. and Ekart, D. (2006) TACSWorks 4.0 Quick Start User's Guide (Version 4.0). Technical Alliance for Computational Stratigraphy. Energy & Geoscience Institute at the University of Utah. April, 2006.

Johnson, G.W., Gary, A.C. and Ekart, D. (2003) TACSWorks 2.0 Quick Start User's Guide (Version 2.0). Technical Alliance for Computational Stratigraphy. Energy & Geoscience Institute at the University of Utah. December, 2003.

Johnson, G.W. (2002). Evaluation of Sources of PCBs in Sediments Adjacent to the Former Rockwell Facility - Allegan, Michigan. Energy & Geoscience Institute at the University of Utah. Technical Report 01-00059-5000-50500961. September, 2002.

Johnson, G.W. (2002). Summary Report: A Feasibility Study to Evaluate Statistical Unmixing as a Stratigraphic Tool. Energy & Geoscience Institute at the University of Utah. Technical Report No. 5000-50500865-06-2002. June, 2002.

Johnson, G.W., Ekart, D. and Gary, A.C. (2002) TACS Bioslot Software User's Guide (Version 1.1β) Energy & Geoscience Institute at the University of Utah. Technical Report 50500625-05-2002. May, 2002.

Sikora, P.J., Skowron, G., and Johnson, G. (2001). Regional Biofacies Study for the Ekofisk Field, Norwegian North Sea. Energy & Geoscience Institute at the University of Utah. Technical Report No. 01-00059-50500674-03-2001.

Magar, V., Durrell, G., Johnson, G., Crecelius, E., Ickes, J., Abbott, J., Peven-McCarthy, C., and Brenner, R. (2000). Natural Recovery of Persistent Organics in Contaminated Sediments at the Sangamo-Weston/Twelve Mile Creek/Lake Hartwell Superfund Site. Technical Report submitted to USEPA (USEPA Work Assignment No. 4-30 - Contract No. 68-C5-0075). September 29, 2000. Battelle, Columbus, Ohio. (EGI subcontractor to Battelle).

Collister J.W., Johnson G.W., Ehrlich R., Shlygin D. and Wavrek D.A. (1998). Geology and hydrocarbon potential of the North and Central Caspian Depressions. Volume 3. Organic Geochemistry. EGI Technical Report 5-20894-12-98.

PUBLICATIONS / PRESENTATIONS (Continued)

Technical Reports (Continued)

Collister J.W., Ehrlich R., Dahdah N.F., Curtiss D.K., Johnson G.W. and Shlygin D. (1998). Pliocene "Red Series" Reservoir Characterization and Organic Geochemistry of Hydrocarbons and Source Rocks, Western Turkmenistan Onshore and Offshore Shelf. Volume III: Properties and Origins of Oils and Gas. EGI Technical Report No. 98-5-20982.

Collister J.W., Johnson G.W., and Ehrlich R. (1997). Chemical fingerprinting of geochemical data to assess reservoir compartmentalization: An example using Yemen crude oils. EGI Technical Report 97-2-20972.

Collister J.W., Ehrlich R. and Johnson G.W. (1997). Petroleum Systems of the Timan Pechora Basin, Russia. Volume 3a: Organic Geochemistry. EGI Technical Report No. 97-05-20940.

McLaren/Hart Environmental Engineering Corp. (1994). *Expanded Hydrogeological Report for the BP Oil, Inc. Marcus Hook Refinery and Adjacent Area.* Prepared for B.P. Oil Inc., Marcus Hook, PA. Prepared by G.W. Johnson & T.E. Rodriguez. November, 1994.

Perception and Decision Systems, Inc. (1994). *A Major Ion Hydrochemical Model for Groundwater at the Wake/Chatham County Preferred Site: N.C. Low-Level Radioactive Waste Disposal Facility.* Prepared for RUST Environment and Infrastructure, Aiken, SC. Prepared by G.W. Johnson and R. Ehrlich.

McLaren/Hart Environmental Engineering Corp. (1993). *RCRA Facility Investigation Task V: RFI Report: Marcus Hook Processing, Inc., Marcus Hook Pennsylvania.* Prepared for Marcus Hook Processing, Inc. Valley Forge, PA. Revision 1.0: . Prepared by G.W. Johnson & T.E. Rodriguez. September, 1993.

McLaren/Hart Environmental Engineering Corp. (1992). *RCRA Facility Investigation Task I: Description of Current Conditions. Marcus Hook Processing, Inc., Marcus Hook Pennsylvania.* Prepared for Marcus Hook Processing, Inc. Valley Forge, PA. Revision 1.0: Prepared by G.W. Johnson & T.E. Rodriguez. July, 1992.

McLaren/Hart Environmental Engineering Corp. (1992). *Site Characterization and Free Product Recovery Report. Rollins Truck Leasing, Harrisonburg, Virginia.* Prepared for McDonnell Douglas Truck Services, Fort Washington, PA. Prepared by G.W. Johnson & Z. Karpa. May, 1992.

Theses/Dissertations

Johnson, G.W. 1997. Application of Polytopic Vector Analysis to Environmental Geochemistry Investigations. Ph.D. Dissertation. Department of Geological Sciences. University of South Carolina. Columbia, S.C. 244 pp.

Johnson, G.W. 1988. Pleistocene Planktonic Formaminiferal Biostratigraphy and Paleoecology: Northeast Gulf of Mexico. M.S. Thesis. University of Delaware. Dept. Geology. University of Delaware, Newark, DE. 256 p.

CURRENT UNIVERSITY FUNDING

Project: Biostratigraphic Integration Interpretation Workspace Phase 2
Funding Agency: British Gas and BP-Amoco.
Awardee: University of Utah, Anthony C. Gary, P.I.; Glenn Johnson, Co Investigator
Project Dates: January 1, 2008 – December 31, 2008 (Extended into 2009).
Budget: $65,000
Status: Beta Softwre to be Delivered in December, 2008.

Project: Integrated Forensics Approach to Fingerprint PCB Sources using Rapid Screening Characterization (RSC) and Advanced Chemical Fingerprinting (ACF)
Funding Agency: Department of Defense (DoD) Environmental Security Technology Certification Program (ESTCP)
Awardee: Space and Naval Warfare Systems Command (SPAWAR), James Leather, P.I.; Glenn Johnson, Co Investigator, University of Utah under subcontract to SPAWAR.
Project Dates: March, 2008 – February, 2011.
Budget: FY08: $69,159
Status: Project Awarded – FY08 work under way.

RECENT UNIVERSITY FUNDING

Project: Biostratigraphic Integration Interpretation Workspace
Funding Agency: Technical Alliance for Computational Stratigraphy
Awardee: University of Utah, Anthony C. Gary, P.I.; Glenn Johnson, Co Investigator
Project Dates: January 1, 2005 – December 31, 2005 (Extended into 2008).
Budget: $220,000
Status: Software delivered to sponsors March, 2008.

Project: PCB Congener Patterns in Adult Mohawks (Proj # 54500989, 54501133, 54501133)
Funding Agency: Agency for Toxic Substances & Disease Registry (ATSDR).
Primary Awardee: University at Albany, Anthony DeCaprio, P.I.
Subaward: University of Utah, Glenn W. Johnson, P.I.,
Project Dates: October 1, 2004 - September 30, 2007
Budget: UU Subaward: $39,000
Status: Completed September 2007

Project: Emigrant Slimhole Drilling Project, Fish Lake, Nevada – GRED III
Funding Agency: Department of Energy (DOE)
Primary Awardee: Esmeralda Energy Company, John E. Deymonaz, PI
Subaward: University of Utah, Jeff Hulen, Greg Nash, Co-PIs, Glenn Johnson, Investigator
Project Dates: January, 2005 – December, 2007
Budget: $740,000 – UU Subaward: $153,078
Status: Project Completed.

RECENT UNIVERSITY FUNDING (Continued)

Project: PCB Fingerprinting in Sediments of Twelve Mile Creek, Lake Hartwell, SC (Proj # 54900561, 54900493,
Funding Agency: US Environmental Protection Agency (USEPA)
Primary Awardee: Battelle Memorial Institute, Victor Magar, P.I.
Subaward: University of Utah, Glenn W. Johnson, P.I.,
Project Dates: August 31, 2000 – March 30, 2005
Budget: UU Subaward: $26,212

Project: Analytical and Modeling Methods for Biostratigraphy (Proj # 50501006)
Funding Agency: Technical Alliance for Computational Stratigraphy
Awardee: University of Utah, Anthony C. Gary, P.I.; Glenn Johnson, Co Investigator
Project Dates: January 1, 2004 – December 31, 2004
Budget: $110,000

Project: Biostratigraphic Preprocessor (Proj # 50501108)
Funding Agency: Technical Alliance for Computational Stratigraphy
Awardee: University of Utah, Anthony C. Gary, P.I.; Glenn Johnson, Co Investigator
Project Dates: December 16, 2002 – December 15, 2004
Budget: $220,002

Project: PCB Congener Patterns in Adult Mohawks (Proj # 54500989, 54501133, 54501133)
Funding Agency: Agency for Toxic Substances & Disease Registry (ATSDR).
Primary Awardee: University at Albany, Anthony DeCaprio, P.I.
Subaward: University of Utah, Glenn W. Johnson, P.I.,
Project Dates: September 30, 2001 – September 29, 2004
Budget: Total Grant: $225,000 – UU Subaward: $35,514

ENVIRONMENTAL CONSULTING EXPERIENCE

Expert Witness Testimony

- Superior Court of the State of Washington for King County (*City of Seattle v. Michael O. Malarkey, et al.*). Subject: Sources of polychlorinated biphenyls (PCBs) in soils and sediments at a former asphalt manufacturing facility along the Duwamish Waterway in Seattle, WA. Deposition testimony in June 2008. Clients: Stoel Rives, LLP and the Port of Seattle. Case settled in July 2008.
- United States District Court for the Central District of California. (*Angeles Chemical Company, et al., v. McKesson Corporation*). Subject: Sources of Chlorinated VOCs in Groundwater Beneath Neighboring Solvent Packaging Facilities. Rebuttal Report in March, 2008. Clients: Caufield & James, LLP and Angeles Chemical Company. Case Ongoing. Expert that Johnson Rebutted Disqualified in May 2008.
- Arbitration in the matter of allocation of cleanup costs for PCBs in soil and sediments in Union City, Indiana. Subject: Sources of polychlorinated biphenyls (PCBs) in sediments of Little Mississinnewa River and floodplain. Report in November 2004. Rebuttal Report in July, 2007. Deposition testimony in August, 2007. Case settled in September, 2007. Client: Hanna Associates, Inc.; Eastman & Smith, Ltd and United Technologies, Inc.

ENVIRONMENTAL CONSULTING EXPERIENCE (Continued)

Expert Witness Testimony (Continued)

- United States District Court, Southern District of California (*San Diego Unified Port District v. TDY Industries, Inc., et al.*). Subject: Sources of polychlorinated biphenyls (PCBs) in sediments from a storm water conveyance system leading to a lagoon in San Diego Bay, California. Deposition testimony in January, 2007. Case settled March, 2007. Client: Latham & Watkins, LLP; counsel for defendant General Dynamics.
- United States District Court for the Northern District of Mississippi- Western Division (Fred Beck, et al., vs. Koppers Industries et al., Civil Action No. 3:03CV-60-P-D). Subject: Sources of polychlorinated dibenzo-p-dioxin and dibenzofurans (PCDD/Fs) in soil and sediment. Expert Reports in 2005. Depositions: in 2005 and 2006. Trial testimony: in April 2006. Client: Consortium of Residents of Grenada, Mississippi (represented by Lundy & Davis).
- Circuit Court of Copiah County, Mississippi (Kellum et al., vs. Kuhlman Corporation et al., Civil Action No. 2001-0313 thru 2001-0324). Subject: Sources of polychlorinated biphenyls (PCBs) in soil, sediment, tree bark and blood. Expert Reports in 2003. Depositions: 2003 and 2005. Client: David Nutt & Associates and a Consortium of Residents of Crystal Springs, Mississippi.

Other Litigation / Arbitration Support

- Litigation support and expert report preparation: Former Campbell Shipyard, San Diego, California. San Diego Unified Port District v. ExxonMobil, et. al., United States District Court, Southern District of California. Case No. 03 CV 1053 DMS (POR). Conducted data analysis and developed opinions regarding sources of PCBs in sediment at the former Campbell Shipyard, San Diego Bay. Case settled in October 2006 prior to submittal of expert reports, and/or deposition testimony (2006).
- Consulting expert for confidential client in anticipation of litigation. Data analysis and consultation calls on expertise in environmental forensics, sources, fate and transport of PCDD/F in sediments of a U.S. river/estuary with multiple potential point and non-point sources of PCDD/F. (2002-Present).
- Consulting expert in anticipation of litigation. Data analysis and consultation calls on expertise in environmental forensics, sources, fate and transport of PCDD/F in sediments of a Pacific Northwest U.S. river near three industrial facilities. (2004-2005).
- Consulting expert in anticipation of litigation. Developed field sampling strategy and performed PCB fingerprinting using congener-specific data from storm sewer sediments near an industrial facility in upstate New York (2003).
- Consulting expert in anticipation of litigation. Performed PCB fingerprinting using congener-specific data from sediment cores collected offshore of a major west-coast U.S. city. Work performed for a confidential client in anticipation of litigation (1999).
- Developed a quantitative receptor model for PAH in sediments Thea Foss Waterway, Tacoma, WA. The project was part of a series of investigations in support of a cleanup-cost allocation / arbitration process (1999-2001).

ENVIRONMENTAL CONSULTING EXPERIENCE (Continued)

Other Litigation / Arbitration Support (Continued)

- Developed a multivariate statistical model to help determine sources of pesticides in residential soils near a manufacturing plant in Texas. The project was conducted for a confidential client in anticipation of environmental litigation (1999).
- Utilized multivariate statistical techniques to develop a quantitative source apportionment model to account for sources of chromium in groundwater near two electroplating facilities in Greenville, South Carolina (1997).
- Developed a mixing model for dioxin and dibenzofuran residues in sediments in a major industrialized waterway. The model was used to show that the assertion of single industrial source of contamination to the estuary was untenable. Specific chemical fingerprints were resolved, and their relative contributions to sediments were quantified (1992-1994).
- Performed hydrogeologic technical review and wrote summary documents for the development of expert witness testimony for a plaintiff in two civil actions in Superior Court, State of New Jersey (1988-1989).

Environmental Site Assessment / Hydrogeologic Investigations

- Project Manager for investigation of an unregistered solid waste landfill in a wetlands area of the New Jersey Pinelands, Atlantic County, New Jersey. Scope of work included pre-investigation review of site-specific historical information, aerial photographs, environmental setting and applicable state and federal regulations that would apply to investigation and remediation. Site investigation included wetlands delineation & contaminant characterization of landfill soils, and groundwater beneath the landfill (1992).
- Used a non-parametric statistical technique (Mann-Whitney U Test) to analyze groundwater contaminant trends over a four year time period at a manufacturing facility in southern New Jersey. The statistical analyses demonstrated that groundwater quality was improving at the site. The results of the test were incorporated into a position paper to the New Jersey Department of Environmental Protection and Energy recommending that the facility's NJPDES permit be allowed to expire at the conclusion of the permit term (1991).
- Used MODFLOW, the USGS modular three dimensional finite difference flow model to simulate groundwater flow in a water-table aquifer in Hainesport, Burlington County, NJ. The model was used to determine placement of extraction and reinjection wells in conjunction with the design of a groundwater treatment system (1991).
- Supervised the technical development of the Sampling Analysis and Monitoring Plan and the Quality Assurance Project Plan prepared as part of a Remedial Design Work Plan for an EPA-lead Superfund site in Burlington County, New Jersey. The scope of work included a soil-gas survey, an electromagnetic conductivity survey, a ground penetrating radar survey, an exploratory excavation/drum sampling program, and a 72-hour pumping test (1989-1991).

ENVIRONMENTAL CONSULTING EXPERIENCE

Environmental Site Assessment / Hydrogeologic Investigations (Continued)

- Wrote the scope of work for an investigation of environmental setting for a RCRA Facility Workplan at a polymer manufacturing facility in Gloucester County, New Jersey. The work plan included monitoring well installation and sampling, borehole geophysics, pumping tests, geotechnical/geochemical sampling and in-situ infiltration tests (1989-1990).
- Field team member for New Jersey ECRA Sampling Plan and Clean-up Plan activities at five ECRA sites in New Jersey. Activities included installation of monitoring wells, test-pit excavation, soil and ground water sampling and continuous ground water monitoring using electronic data loggers (1989-1990).
- Project Hydrogeologist for environmental programs at a UST site in South Brunswick, New Jersey. Responsibilities included oversight and implementation of UST excavation and soils disposition, monitoring well installation, soil gas surveys, ground water sampling and monitoring for VOCs and semivolatile compounds, data analysis, report preparation, clean-up plan preparation, preparation of discharge permit applications (NJPDES), and preparation for negotiations with NJDEPE Bureau of Underground Storage Tanks (1989-1991).
- Auditor for comprehensive compliance audits performed at hazardous waste treatment, storage and disposal facilities in Baltimore, MD and Fort Wayne, IN. Conducted for the Commercial Hazardous Waste Management Evaluation Group (CHWMEG), a consortium of approximately 30 corporations that utilize a number of TSDF facilities across the nation (1989-1990).
- Project Manager for Phase II environmental assessments at four commercial printing facilities in Florida, New York and Connecticut. The project was conducted as part of a real estate transaction to assess potential liability associated with underground tanks and septic systems (1990).
- Project Hydrogeologist responsible for oversight of soil boring and monitoring well installation; well-development, soil sampling, groundwater sampling, UST removal, post-excavation sampling and report preparation. Various clients and projects (1989-1993).
- Liaison between major oil company and the New Jersey Department of Environmental Protection - Bureau of Underground Storage Tanks to expedite compliance with state and federal UST registration requirements (1988-1989).
- Field geologist responsible for quarterly bail & gauge, groundwater sampling and other related activities at former ARCO service stations in Pennsylvania, New Jersey, Delaware and Maryland (1988-1989).

TEACHING

University Teaching

2005 & 2007, Taught CVEEN 6630: Ecological Systems and Engineering, Department of Civil and Environmental Engineering, University of Utah. (Graduate level only).

2000-2004, Taught CVEEN 5630/6630 Ecological Systems and Engineering, Department of Civil and Environmental Engineering, University of Utah. (Dual listed class: Graduate and Undergraduate)

2000-2008. Served on Graduate Committees at the University of Utah for M.S. and Ph.D. Candidates within the Department of Civil and Environmental Engineering and the Department of Chemical Engineering.

Fall Semester, 1993, Hydrogeology, School of Engineering, Widener University, Chester, PA

1985-1987, Graduate Teaching Assistantship, Department of Geology, University of Delaware. Taught labs for Introductory Geology, Mineralogy, and Paleontology.

Short Courses

Introduction to Environmental Forensics. Workshops presented by *Association of Environmental Health Sciences (AEHS)*
March 21, 2002, San Diego, California
August 14, 2001, Imperial College, London, England, United Kingdom

Introduction to Environmental Forensics. Workshops presented by *International Society of Environmental Forensics (ISEF).*
September 25-26, 2006. Baltimore, Maryland.
November 9-10, 2004. Charleston, South Carolina.
November 4-5, 2003. San Diego, California
April 14-15, 2003. Honolulu, Hawaii
September 23-24, 2002. Santa Fe, New Mexico

Johnson, G.W. and Haddad, R.I. (2000-2002). Use of Chemometric Methods in Environmental Forensics Investigations. Society of Environmental Toxicology and Chemistry Short Course. SETAC 21st - 23rd Annual Meetings. Nashville, TN; Baltimore, MD; and Salt Lake City, UT.

Johnson, G.W. An Environmental Forensics Case Study: PCB Source Identification in San Francisco Bay. International Business Communications 2nd Annual Executive Forum on Environmental Forensics. Marriott Metro Center. Washington, D.C. June 24-25, 1999.

Johnson, G.W., Gary, A.C., and Yarus, J. Applied Multivariate Analysis of Geological Data. EGI. Short Course: EGI Instructional Services Catalogue. (http://associates.egi.utah.edu/) 1998-Present.

Zmuda, J. Chapman, P.H., Rodriguez, T.E., Johnson, G.W., Swetits, F.W., Wideman, J.A., Perkins, E.E., Mathre, O.B., Shmookler, M., Snyder, D., and Abercrombie, D. (1994). Environmental Sampling, Laboratory and Data Analysis, Executive Enterprises, Inc. November 9-10, 1994.

Peer Review / Editorial

1995-2007 Served as peer-reviewer for manuscripts submitted to the following journals: *AAPG Bulletin, Chemosphere, Journal of Chemometrics; Chemometrics and Intelligent Laboratory Systems; Environmental Forensics; Environmental Pollution; Environmental Science & Technology; Environmental Toxicology & Chemistry; Geochemistry-Geophysics-Geosystems (G^3); Geothermics; Integrated Environmental Assessment and Management; Organic Geochemistry; Journal of Volcanology, Geothermal Research, and Water Science.*

2000 Technical Reviewer for USEPA Receptor Modeling Software (Project Manager: Charles Lewis, USEPA, Research Triangle, North Carolina.

2001 Magar, V.S., Johnson, G., Ong, S.K. and Leeson, A. (Editors) (2001). *Bioremediation of Energetics, Phenolics and Polycyclic Aromatic Hydrocarbons.* The Sixth International In Situ and On-Site Bioremediation Symposium. ***6(3)***. Battelle Press. Columbus, OH.

2001-2005 Member, Editorial Board. *Environmental Forensics.*

2005 Peer Reviewer for Department of Defense (DoD) Strategic Environmental Research and Development Program (SERDP) research proposals.