Support to the U.S. Nuclear Regulatory Commission Safety Culture Initiative

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1. Introduction

The U.S. Nuclear Regulatory Commission's (NRC) primary mission is to regulate the nuclear power industry to ensure public safety and health. The NRC accomplishes this mission of monitoring nuclear power plant performance through their Reactor Oversight Process (ROP). In its continuing efforts to improve the safety of commercial nuclear power, the NRC has undertaken an effort to enhance the ROP through inclusion of safety culture initiatives into the inspection program for nuclear power plants. Specifically, the Commission issued a memorandum directing staff to develop guidance on how to include safety culture within the framework of the cross-cutting areas of the ROP [1]. The NRC has been working with stakeholders to establish a structure and approach for this initiative. As a first step, the NRC accepted the definition of safety culture used by the International Nuclear Safety Advisory Group (INSAG): "That assembly of characteristics and attitudes in organizations and individuals which establishes that, as an overriding priority, nuclear plant safety issues receive the attention warranted by their significance." [2] From this, a performance-based approach for including safety culture in a way that is consistent with the existing ROP has been developed. Specifically, the approach, "Relies on industry assessments and evaluations by licensees and/or Institute of Nuclear Power Operations to the extent practical, with NRC staff reviewing results to ensure consistency between these assessments and the staff's perceptions regarding the health of a licensee's safety culture." [3]

The Idaho National Laboratory (INL) was tasked to assist the NRC with this work by identifying information and measures from existing inspections that could help determine potential or actual performance problems associated with safety culture. INL was also asked to support the development of a methodology and algorithm for trending and assessing inspection information and measures relative to safety culture. This letter report describes the work completed by the INL to address this NRC tasking.

2. Technical basis supporting the assessment of safety culture

As a first step to helping establish a technical basis, the INL conducted a series of analyses to test the relationships between human performance, and Safety Conscious Work Environment (SCWE). SCWE is an environment in which employees are encouraged to raise safety concerns both to their own management and to the NRC without fear of harassment, intimidation, retaliation, or discrimination. Testing this relationship would establish whether human performance data could be used as information or measures to assess safety culture. The purpose of this analysis was to attempt to provide an empirical basis for the belief that human performance affects nuclear plant safety culture and safety performance. Specifically, the goal of the analysis was to begin establishing a clearer relationship between human performance outcomes and overall plant safety and performance through providing an empirical basis for the relationship between human performance and a plant's SCWE.

The data for the analysis came from two readily available sources. The human performance data were obtained from the NRC's Human Factors Information System (HFIS). Data indicative of SCWE were obtained from the NRC allegations database. It is recognized that measures obtained from these two data sources may not be the best or most complete measures of either human or plant safety performance. However, the HFIS data comes from the coding of inspection reports (IRs) and licensee event reports (LERs). Moreover, the HFIS coding process has been in place for a number of years, so it is a relatively rich data source, and it also serves as a method to document safety culture related information in a consistent and reliable manner. It is also important to note that because the investigation was meant to be exploratory in nature, these data were deemed sufficient. Promising results from these limited data may justify further effort in acquiring better data measures for more definitive modeling.

2.1 Data Details

HFIS data were available by facility while the allegations data obtained were aggregated by site only. Hence the HFIS data were combined over facilities within each site. Data for a total of 64 sites were analyzed.

Allegations data consisted of the (1) total number of allegations and (2) substantiated allegations for the years 2001 through 2004. (Allegations for the first part of 2005 were also available, but not used.) The NRC defines an allegation as:

> …a declaration, statement, or assertion of impropriety or inadequacy associated with NRC-regulated activities, the validity of which has not been established. This term includes all concerns identified by sources such as individuals or organizations, and technical audit efforts from Federal, State, or local government offices regarding activities at a licensee's site.

Substantiated allegations are those deemed to be valid after investigation.

The HFIS data analyzed were the number of human performance related "hits" or causal factors extracted from IRs and LERs. These data were available for the years 2000 through 2004 but because of a coding criteria change, only data from 2001 to 2004 were used. The HFIS hits were also categorized into seven types:

- communications
- human-system interface and environment
- management and supervision (including corrective action problems)
- organizational issues (staffing and overtime)
- procedures and reference documents
- training
- work factors.

The overall total HFIS hits, as well as, those for each of the seven categories were considered in the analysis.

2.2 Statistical Modeling and Analysis

The most obvious statistical modeling and analysis techniques that could be use to support the development of a methodology and algorithm for trending and assessing inspection information and measures relative to safety culture are standard correlation and regression techniques. As a result, preliminary analysis of the data was performed using these techniques. However, the data being analyzed are count data, which do not necessarily meet the usual assumptions (additivity of effects, normality, equal variances) associated with the standard tests. Hence generalized linear methods using log-Poisson models were employed. More information on log-Poisson models is provided in Appendix A.

2.3 Results

Two series of analyses were performed, as it is intuitive that the relationship between human performance and allegations is reciprocal, and both relationship directions need exploration. First, because human performance data could be indicative of safety culture, regression analyses were performed using HFIS data to predict allegations. It also is likely that safety culture contributes to human performance issues at a plant, so a second set of regressions were performed using allegations to predict HFIS results. Before this was done, however, correlational analyses were performed to examine the nature of the relationship between human performance (as measured by HFIS hits) and safety culture (as measured by allegations).

Table 1 shows the standard Pearson's bivariate correlations of the allegations and HFIS hits for the years 2001 through 2004. Correlations greater than $r = .17$ are significant at the $p = 0.05$ level based on the standard significance test for correlations. Because these correlations do not meet the assumptions of constant variance and normality associated with the significance test, the significance results should be interpreted with considerable caution. But they do serve as a general indication of the degree of association between the variables and, in particular the potential for HFIS hits to predict allegations. For comparison, Table 2 gives the nonparametric Kendall's Tau correlations, which show a similar pattern of results although the correlations do not range as high as those attained in Table 1.

Variable	Allegations 2001	Allegations 2002	Allegations 2003	Allegations 2004	HFIS CF hits 2001	HFIS CF hits 2002	HFIS CF hits 2003	HFIS CF hits 2004
Allegations 2001	1.00	0.41	0.42	0.33	0.50	0.45	0.36	0.16
Allegations 2002	0.41	1.00	0.69	0.61	0.46	0.42	0.59	0.51
Allegations 2003	0.42	0.69	1.00	0.54	0.40	0.17	0.37	0.53
Allegations 2004	0.33	0.61	0.54	1.00	0.43	0.41	0.49	0.52
HFIS CF hits 2001	0.50	0.46	0.40	0.43	1.00	0.47	0.39	0.23
HFIS CF hits 2002	0.45	0.42	0.17	0.41	0.47	1.00	0.65	0.37
HFIS CF hits 2003	0.36	0.59	0.37	0.49	0.39	0.65	1.00	0.64
HFIS CF hits 2004	0.16	0.51	0.53	0.52	0.23	0.37	0.64	1.00

Table 1. Pearson's correlations for allegation and HFIS hit data.

Variable	Allegations 2001	Allegations 2002	Allegations 2003	Allegations 2004	HFIS CF hits 2001	HFIS CF hits 2002	HFIS CF hits 2003	HFIS CF hits 2004
Allegations 2001	1.00	0.32	0.27	0.43	0.29	0.19	0.25	0.24
Allegations 2002	0.32	1.00	0.37	0.35	0.17	0.19	0.31	0.18
Allegations 2003	0.27	0.37	1.00	0.35	0.28	0.20	0.28	0.29
Allegations 2004	0.43	0.35	0.35	1.00	0.19	0.15	0.27	0.29
HFIS CF hits 2001	0.29	0.17	0.28	0.19	1.00	0.35	0.31	0.37
HFIS CF hits 2002	0.19	0.19	0.20	0.15	0.35	1.00	0.47	0.31
HFIS CF hits 2003	0.25	0.31	0.28	0.27	0.31	0.47	1.00	0.40
HFIS CF hits 2004	0.24	0.18	0.29	0.29	0.37	0.31	0.40	1.00

Table 2. Kendall's tau nonparametric correlations for allegation and HFIS hit data.

Table 1 shows reasonably strong bivariate correlations between, for example, HFIS hits in 2003 and allegations in 2004. The corresponding Kendall's tau correlation in Table 2 is smaller but still significant. However, as might be expected, allegations in 2003 are themselves also correlated with allegations in 2004. The autocorrelations holds true for other years as well, and for HFIS hits. Hence any rigorous assessment of allegations vs. HFIS hits should control for the effects of this autocorrelation.

2.4 Regression Series 1

The first set of regression analyses examined how well HFIS hits and allegations predict allegations for the following year. As mentioned above, the correlation between allegations of two consecutive years needed to be controlled for in the analysis. To achieve this, log-Poisson models with terms for both the previous year's allegations and HFIS hits were analyzed.

Results of the log-Poisson model analysis for the dependent variable 2004 allegations are shown in Table 3. Both the effects of 2003 allegations and 2003 HFIS hits are statistically significant in this model. So, even after controlling for the previous year's allegations, there is still significant predictive power afforded by HFIS hits.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	1.234763	0.152967	65.15841	0.000000
Allegations 2003	2	0.039938	0.012120	10.85864	0.000983
HFIS CF hits 2003	3	0.003773	0.001365	7.64462	0.005694

Table 3. Log-Poisson model results for the prediction of 2004 allegations.

The same analysis was also repeated using 2003 and 2002 allegations as the dependent variable and the previous year's allegations and HFIS hits as independent variables. These results are show in Tables 4 and 5.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	1.276446	0.177009	52.00112	0.000000
Allegations 2002	2	0.069715	0.010946	40.56582	0.000000
HFIS CF hits 2002	3	-0.003068	0.003083	0.99083	0.319540

Table 4. Log-Poisson model results for the prediction of 2003 allegations.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	1.423964	0.174160	66.85013	0.000000
Allegations 2001	2	0.030140	0.016768	3.23079	0.072266
HFIS CF hits 2001	3	0.002822	0.001421	3.94295	0.047068

Table 5. Log-Poisson model results for the prediction of 2002 allegations.

Tables 4 and 5 show that the previous year's HFIS data was a marginally significant predictor of allegations for 2001, but not significant at all for 2002. Furthermore, the effect of the 2001 allegations on 2002 allegations was not statistically significant. Still there is some positive evidence that a relationship between human performance and plant performance can be established.

To further explore the relationship between allegations and HFIS counts, the single variable for the total HFIS counts was replaced by separate variables for the counts in each of the seven categories of HFIS hits. This modeling effort identifies which of the seven categories contribute the most to the relationship observed between the total counts. Results for the full model for predicting 2004 allegations, given in Table 6, show that the only category with a significant effect was communications.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	1.226254	0.177466	47.74504	0.000000
Allegations 2003	2	0.061441	0.018843	10.63197	0.001111
Communications 2003	3	0.043200	0.020518	4.43277	0.035255
Human-System 2003	4	-0.055790	0.048203	1.33958	0.247107
Management 2003	5	0.010698	0.010203	1.09952	0.294370
Organization 2003	6	-0.091680	0.096491	0.90276	0.342042
Procedures 2003	7	-0.001344	0.015031	0.00800	0.928745
Training 2003	8	-0.016587	0.029501	0.31611	0.573954
Work Factors 2003	9	-0.001579	0.006393	0.06104	0.804867

Table 6. Results for model predicting 2004 allegations with all seven HFIS categories included.

2.5 Substantiated allegations

Models were also considered using substantiated allegations rather than total allegations for the dependent variable. It might seem that the total number allegations received is not as good a measure as substantiated allegations because some allegations received may not ultimately be validated. However, substantiated allegations involve a time lag, so data for recent years may be incomplete until the NRC completes their investigation into the allegation. Modeling results for the prediction of 2004, 2003, and 2002 substantiated allegations based on the previous years substantiated allegations and HFIS hits are given in Tables 7-9. Note that the order of the items listed in the Effect column is different than the order listed in Tables 3-5, but that this has no effect on the outcome of the analysis.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	-0.298588	0.223113	1.790996	0.180805
HFIS CF hits 2003	2	0.005800	0.001901	9.306996	0.002283
Sub. Allegations 2003	3	0.103716	0.054153	3.668129	0.055462

Table 7. Log-Poisson model results for the prediction of 2004 substantiated allegations.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	0.223128	0.213832	1.08883	0.296730
HFIS CF hits 2002	2	-0.001558	0.003596	0.18772	0.664818
Sub. allegations 2002	3	0.174286	0.036858	22.35950	0.000002

Table 8. Log-Poisson model results for the prediction of 2003 substantiated allegations.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	0.203932	0.155210	1.72635	0.188878
HFIS CF hits 2001	2	0.004604	0.000993	21.48384	0.000004
Sub. allegations 2001	3	0.058340	0.030288	3.71019	0.054081

Table 9. Log-Poisson model results for the prediction of 2002 substantiated allegations.

The model results for substantiated allegations follow the same pattern in regard to HFIS hits as did the models for total allegations, i.e., significant effects for HFIS hits for 2004 and 2002 substantiated allegations, but not for 2003. Since there was a maximum of 15 substantiated allegations in any one year, it was not reasonable to consider breaking the substantiated allegations data analysis down by the seven categories of HFIS hits.

2.6 Regression Series 2

The first analysis treated allegations as the dependent variable in the log-regression models employed. That is, HFIS data for a particular initial year was used to predict allegations for the following year (after controlling for the allegations in the initial year). It was also of interest to consider the opposite relationship, i.e., that of using allegations in an initial year to predict HFIS hits in the following year, controlling for the HFIS hits in the initial year. For example, if a safety conscious work environment is an effective measure, then allegations such as those reported to the NRC should be true indicators of potential human performance issues at a facility. This should lead to them being significant indicators of conditions leading to events resulting in HFIS hits. Conversely, the absence of such effects might suggest a lack of relevance of the allegations process data as a useful tool for identifying potential problem areas (although they may be useful for other reasons). In this analysis the same types of log-Poisson models used previously for predicting allegations from HFIS hits are used to examine the opposite relationship.

2.7 Analysis Results

The initial correlations shown in Tables 1 and 2 indicate that the correlations of one year's allegations with the next year's HFIS hits are sometimes noticeably stronger than the corresponding correlation of one year's HFIS hits with the following year's allegations. This suggests that modeling in the direction of predicting HFIS hits from allegations may yield stronger results than the reverse models did.

2.8 Allegations reported

Tables 12-14 show the results of the analysis of the data for predicting HFIS hits for the years 2002-2004 using allegations from the previous year as well as controlling for HFIS hits from the previous year. These results should be compared to those in Tables 3-5 above. In all the tables below, significant effects are those with $p < 0.05$.

The tables show that reported allegations were significant contributors to the models for HFIS data in all three years. This contrasts with the results for the previous analysis of HFIS hits as a predictor for allegations, which showed significant effects only for the years 2004 and 2002.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	3.578429	0.118512	911.7232	0.000000
Allegations 2003	2	0.031132	0.009709	10.2810	0.001344
HFIS CF hits 2003	3	0.005591	0.001023	29.8849	0.000000

Table 10. Log-Poisson model results for the prediction of 2004 HFIS hits.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	3.599460	0.125428	823.5356	0.000000
Allegations 2002	2	0.028996	0.008308	12.1803	0.000483
HFIS CF hits 2002	3	0.007711	0.001557	24.5373	0.000001

Table 11. Log-Poisson model results for the prediction of 2003 HFIS hits.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	3.578206	0.116064	950.4559	0.000000
Allegations 2001	2	0.027396	0.011492	5.6836	0.017125
HFIS CF hits 2001	3	0.002250	0.001026	4.8046	0.028384

Table 12. Log-Poisson model results for the prediction of 2002 HFIS hits.

2.9 Substantiated allegations

As before, the analysis was repeated using only substantiated allegations. These results are given in Tables 13-15. (Note that the order of the items listed in the Effect column is different than the order listed in Tables 10-12, but that this has no effect on the outcome of the analysis.) Again, substantiated allegations were significant predictors for all three years, compared to only 2004 and 2002 when HFIS hits were used to predict substantiated allegations.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	3.597297	0.129010	777.5055	0.000000
HFIS CF hits 2003	2	0.005823	0.001147	25.7809	0.000000
Sub. Allegations 2003	3	0.073752	0.033122	4.9580	0.025971

Table 13. Log-Poisson model results for the prediction of 2004 HFIS hits using substantiated allegations only.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	3.629283	0.126833	818.8012	0.000000
HFIS CF hits 2002	2	0.008069	0.001588	25.8236	0.000000
Sub. allegations 2002	3	0.067289	0.023770	8.0137	0.004643

Table 14. Log-Poisson model results for the prediction of 2003 HFIS hits using substantiated allegations only.

Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept	1	3.586536	0.113641	996.0469	0.000000
HFIS CF hits 2001	2	0.002659	0.000938	8.0438	0.004566
Sub. allegations 2001	3	0.055629	0.022906	5.8980	0.015158

Table 15. Log-Poisson model results for the prediction of 2002 HFIS hits using substantiated allegations only.

2.10 Categories of HFIS hits

In the previous analysis it was possible to examine the effects of the seven categories of HFIS hits on allegations by putting all seven categories of hits in the same model as independent variables. When considering the reverse relationship, it was necessary to consider a separate model for each of the seven categories as the dependent variable. Repeating the model for each category over each of three years resulted in the fitting of 21 different models. Rather than showing detailed results for each model, a summary is given in Table 18. In the table, an "x" indicates models in which allegations from the previous year were a significant predictor ($p < 0.05$) of the HFIS category hits for the indicated year (after controlling for hits in the same category in the previous year).

HFIS Category	2004	2003	2002
Communications	x		x
Human Systems			
Management	x	x	x
Organization		x	
Procedures	x	x	
Training	x	x	x
Work Factors	x	x	

Table 16. Models containing allegations as a significant ($p < 0.05$) predictor of HFIS hits by category.

The results in Table 16, showing a large number of significant effects, differ considerably from those found when the seven categories of HFIS hits were used to predict allegations. In that case, only communications was found to be important, and then only for the years 2004 and 2002. One possible explanation for the difference is that the correlations across the seven HFIS categories made it difficult for more than one category to be significant when they were all included in the same model. In the current case, where only one category is considered at a time, such correlations do not enter into the calculations.

3. Discussion

These preliminary analyses provide basic support for the premises that human performance data can be used to predict nuclear power plant safety culture via human performance's ability to predict aspects of SCWE, and those aspects of safety culture can predict human performance. The explanatory power of the models analyzed was not terribly strong, but this is to be expected given the general nature of the measures used. A number of the types of hits included in the HFIS data do not relate directly to allegations. There are also many types of allegations, some of which would be expected to be more strongly related to human performance issues than others. More detailed study to filter both the HFIS and allegation data for the most relevant cases should improve the predictive capability of the models.

In addition to refining measures based on HFIS and allegations data, future tasks could include the acquisition and analysis of additional currently available human and plant performance data (e.g., ROP data) so that more refined measures can be developed. Further analysis could also include an investigation of the ability of these types of models to identify specific facilities that are likely to have problems.

Another issue is whether there are models other than the log-Poisson model that might work as well or be more theoretically appropriate for these data. In supplemental analysis, two other modeling/analysis methods were briefly examined. One was to simply do a logarithmic transformation of all the count data (both independent and dependent variables) and then apply standard regression techniques. The other used the generalized linear model approach, but with a linearly additive Poisson model (linear-Poisson for short) rather than the log-Poisson model (which is linear in the logs of the dependent variable).

Applying a logarithmic transformation to the data was fairly effective in stabilizing the variance and producing data that more closely approximate a normal distribution. Hence standard regression analysis had more validity. However, one problem with this approach is that logarithms of zero counts do not exist. In this case they can be either ignored, or a small number can be added to each count to make it non-zero. The decision to ignore data or to add a value to each observation and what that value should be has no real theoretical basis so adds a degree of arbitrariness to the results.

Choosing between a log-Poisson and a linear Poisson model on theoretical grounds depends on the assumed form of underlying structure from which the allegation counts are derived. If the allegations all derive from the same base distribution (because they are all relate to the same or similar processes) and the HFIS hits represent measures of factors that modify single base distribution (i.e., change its mean), then a multiplicative model is probably the most appropriate form. However, if the allegations come from two or more distinct areas or processes, each modified differently by factors contributing to HFIS hits, then the resulting distribution of allegations may be best represented by a simple sum of Poisson distributions (one for each distinct area or process).

It is often the case that these model assumptions do not make a big difference in the results over the range in which the observed data occur. That was the case in this analysis where cursory analysis using the two alternative methods just described yielded essentially the same results in terms of the significance of HFIS effects as did the log-Poisson model. There are other considerations to be taken into account in choosing between such models. But for this preliminary look, the results are encouraging in that they show robust results across models and analysis methods. Given this, it makes sense to pursue these models further and to attempt to make a more complete determination of the best representation for the data. The only question that remains is whether existing NRC documentation, trending methods, and assessment actions can be modified in a way that not only accepts the approach proposed in this report, but does so in a way that agrees with stakeholders.

4. References

1. SRM-SECY-04-0111. (2004) Recommended Staff Actions Regarding Agency Guidelines in the Areas of Safety Conscious Work Environment and Safety Culture.
2. International Nuclear Safety Advisory Group. (1992) Safety Culture. Safety Series No. 75-INSAG-4
3. Safety Culture Initiative summary Results. (2005) http://www.nrc.gov/what-we-do/regulatory/enforcement/sc-ml0601705020.pdf
4. Agresti, A. (1996) An Introduction to Categorical Data Analysis. New York: John Wiley and Sons, Inc.
5. McCullagh, P., and Nelder, J. A. (1983) Generalized Linear Models. New York: Chapman and Hall.

Appendix A

Although other methods are sometimes used (e.g., transformations of the data to achieve near-normality), the most common approach used when analyzing count data is to employ models and analysis methods that assume a Poisson distribution for the counts. Maximum likelihood methods are used to derive results based on the Poisson assumption. The Poisson assumption can lead to a variety of functional forms for the analysis model, but again the most common form used is a log-Poisson model (a loglinear model with a Poisson-like error term). Such a model was used in this analysis. (Other model representations are discussed briefly in the discussion section below.)

Log-Poisson models are one type of a broad class of models called generalized linear models. (Ordinary regression models, ANOVA models, and logistic regression models are other examples of types of models that can be described as generalized linear models.) An introductory discussion of generalized linear models and log-Poisson models in particular can be found in Agresti [4].

In the log-Poisson model it is assumed that the counts of allegations for each facility follow a Possion probability distribution, i.e.,

$$P(Y = y) = \frac{e^{-\mu}\mu^{y}}{y!} \qquad y = 0, 1, 2, \ldots \qquad (1)$$

where Y is the variable representing the allegation counts, y is a specific count value for Y, and μ is the mean of the Poisson distribution. The loglinear designation comes from the further assumption that the natural logarithm of the mean μ is a dependent variable that is a linear function of some set of independent variables:

$$\ln(\mu) = \alpha + \beta_1 x_1 + \ldots + \beta_k x_k \qquad (2)$$

where α is a constant, $x_1 \ldots x_k$ are the values of k relevant human reliability variables thought to be predictors of allegations, and $\beta_1 \ldots \beta_k$ are unknown parameters to be estimated from the data.

Based on these models, the data were analyzed using generalized linear model methods. For a review of general linear model methods, see McCullagh and Nelder [5]. These methods give maximum likelihood results for parameter estimates as well as related asymptotical standard errors, significance tests for parameters in the model (based on the Wald statistic), goodness of fit results, etc. This method of analysis does not assume normality or equal variances as do standard regression models. It does assume independence of observations as well as the Poisson distribution for the counts (with the modification for over-dispersion discussed below).

Even though the counts for a particular site in a particular year may approximate a Poisson distribution, the variation from one site to another, as well as the year-to-year variation produces more dispersion in the data than what would be suggested by a simple Poisson error. This condition is referred to as over-dispersion. Hence, rather than using the standard Poisson relationship (where the variance is assumed to be equal to the mean), the models were analyzed assuming the less restrictive assumption that the variance is some constant multiple of the mean. The maximum likelihood parameter estimates remain the same as in the pure Poisson model, but the tests of significance are modified to account for the additional dispersion.